Christian Breitwieser, Dipl.-Ing.

A Tactile Hybrid Brain-Computer Interface Utilizing a Common Implementation Platform

DISSERTATION

zur Erlangung des akademischen Grades

Doktor der technischen Wissenschaften

eingereicht an der

Technischen Universität Graz

Betreuer

Univ.-Prof. Dipl.-Ing. Dr.techn. Gernot R. Müller-Putz

Institut für Neurotechnologie/Institute of Neural Engineering

Graz, July 2017

EIDESSTATTLICHE ERKLÄRUNG

AFFIDAVIT

Ich erkläre an Eides statt, dass ich die vorliegende Arbeit selbstständig verfasst, andere als die angegebenen Quellen/Hilfsmittel nicht benutzt, und die den benutzten Quellen wörtlich und inhaltlich entnommenen Stellen als solche kenntlich gemacht habe. Das in TUGRAZonline hochgeladene Textdokument ist mit der vorliegenden Dissertation identisch.

I declare that I have authored this thesis independently, that I have not used other than the declared sources/resources, and that I have explicitly indicated all material which has been quoted either literally or by content from the sources used. The text document uploaded to TUGRAZonline is identical to the present doctoral dissertation.

Datum / Date

Unterschrift / Signature

Abstract

Brain-Computer interfaces (BCIs) provide a communication channel which directly translates brain signals into different kinds of control commands. Most BCI systems nowadays rely on rhythms of mainly sensorimotor but also other areas or visually evoked P300, which either achieve low classification rates or are only applicable for persons who have remaining muscular control of their eyes.

The aim of this thesis was to investigate the rarely explored field of tactile BCIs and to develop a tactile hybrid BCI (hBCI) which incorporates different tactile modalities. Such hBCIs, which combine different kinds of input channels, are used to increase overall BCI performance and stability. To reach the goal of such a tactile hBCI, a common platform for BCI development was implemented which facilitates the creation of hBCIs and the integration of already existing BCI systems or individual BCI components with each other. One study in this thesis was carried out to investigate the stability of somatosensory evoked potentials (SSSEPs) upon vibratory tactile stimulation. Another study investigated the feasibility of using vibratory stimulation of multiple fingers on one hand for a tactile BCI which relies on attention modulation. In parallel to these studies, the already mentioned common implementation platform was developed. The new components and interfaces were used in the studies mentioned before to validate their functionality in real-world BCI scenarios. Different libraries for raw data exchange, classification results delivery, and distributed event processing were implemented, as well as tools like a data acquisition software called SignalServer and an online scope for real time data visualization. Moreover, the developed code is open source and available on GitHub in the tools4BCI project. A final hBCI study, which utilized all components of the common implementation platform, finally brought the development and the BCI parts of this thesis together. The study used SSSEPs and transient tactile event-related potentials (tERPs) as features. These feature types were fused together using two different fusion methods. All studies included screening measurements to identify optimal individual tactile stimulation frequencies.

This thesis demonstrates that the brain response upon vibratory stimulation is stable over time and similar across individual fingers of one hand. However, it was not possible to achieve a classification above chance for SSSEP when the participants focused their attention on a specific finger on one hand while another non-target finger was stimulated at the same time. The final study proved the functionality of the components of the common implementation platform. This study also showed that a classification above chance, with SSSEP as a feature, is possible, which might be related to a selection of person dependent stimulation frequencies. Fusing tERP and SSSEP can significantly enhance the classification accuracy even further. Participants who showed a higher relative band power increase during the screening also achieved higher accuracy in the later BCI task. It was finally shown that individual modalities might be better suited to detecting different BCI "states". SSSEP appears to be the better choice for identifying non-control (or idle) states, whereas tERP was better suited to detecting focused attention on left-hand or right-hand stimulation.

Zusammenfassung

Sogenannte BCIs (Brain-Computer Interfaces) ermöglichen eine direkt Umsetzung von Hirnsignalen in unterschiedliche Kommandos und eröffnen dadurch einen zusätzlichen Kommunikationskanal. Aktuelle BCI-Systeme nutzen zumeist Oszillationen des Motorcortex oder anderer Hirnregionen oder verwenden visuell evozierte P300 Potentiale. Derartige BCI-Systeme erreichen oftmals eine niedrige Klassifikationsrate oder benötigen eine verbleibende Kontrolle über die motorischen Fähigkeiten der Augen.

Ziel dieser Arbeit war es, das aktuell wenig erforschte Feld taktiler BCIs genauer zu untersuchen und schlussendlich ein hybrides BCI (hBCI) zu erstellen, welches auf mehreren taktilen Modalitäten aufbaut. Derartige hBCIs verwenden mehrere unterschiedliche Eingangssignale, um die Genauigkeit als auch die Stabilität aktueller BCIs zu verbessern. Ein weiteres Ziel war es, eine gemeinsame Plattform zu entwickeln, welche die Erstellung von hBCIs erleichtert und eine Integration mehrerer unterschiedlicher BCI-Systeme oder -Komponenten ermöglicht. In der ersten Studie dieser Arbeit wurde die Stabilität somatosensorisch evozierter Potentiale (SSSEPs) über die Zeit untersucht. Eine weitere Studie widmete sich der Untersuchung, ob die Erstellung eines BCIs, das auf einer Fokussierung der Aufmerksamkeit basiert, möglich ist, indem zwei Finger einer Hand stimuliert werden und ein Teilnehmer sich auf eine der Stimulationen konzentriert. Parallel zu diesen Studien wurde die bereits genannte Plattform entwickelt. Die neu entwickelten Komponenten wurden bereits in den genannten Studien verwendet, um deren Funktionalität in echten BCI-Systemen zu testen. Unterschiedliche Bibliotheken zur Übertragung von Biosignal-Rohdaten, zur Übermittlung von Klassifikationsergebnissen oder zur Verteilung von Events in BCI-Systemen wurden innerhalb dieser Plattform entwickelt sowie unterschiedliche Hilfsmittel wie beispielsweise eine Software namens „SignalServer“ zur Datenakquise oder ein Signal-Visualisierungswerkzeug, um die gewonnenen Rohdaten live zu analysieren. Der erzeugte Code ist in dem „tools4BCI“ Projekt als Open-Source auf GitHub verfügbar. Eine finale hBCI Studie, in der alle Komponenten des tools4BCI Projektes zum Einsatz kamen, führte schlussendlich den Entwicklungsteil als auch den BCI Teil zusammen. Diese Studie basierte auf dem Einsatz von SSSEPs als auch von taktilen transienten Event-basierten Potentialen (tERPs) als Klassifikationsfeatures, wobei beide Feature-Typen zu einem finalen Ergebnis anhand von unterschiedlichen Strategien fusioniert wurden. In allen durchgeführten Studien wurde eine anfängliche „Screening“-Messung durchgeführt, um optimale personenspezifische Stimulationsfrequenzen zu bestimmen.

Es konnte in dieser Arbeit gezeigt werden, dass SSSEP Muster, hervorgerufen durch taktile Stimulation, auch über einen längeren Zeitraum stabil sind und sich des Weiteren nicht zwischen den einzelnen Fingern einer Hand unterscheiden. Es war jedoch nicht möglich, ein BCI zu erstellen, in dem mehrere Finger einer Hand taktil stimuliert wurden und ein Teilnehmer sich auf einen spezifischen Stimulus konzentrieren musste. Die letzte Studie, in der alle Komponenten des tools4BCI Projektes zum Einsatz ka-

men, zeigte die Funktionalität der entwickelten Plattform und ihre Einsatzbereitschaft zur Anwendung in anderen BCI-Systemen. In dieser Studie wurde ebenfalls eine signifikante Klassifikation über dem Zufallslevel für die SSSEP-Komponente erreicht. Dieses Ergebnis wurde höchstwahrscheinlich durch die Verwendung personenspezifischer Stimulationsfrequenzen erreicht. Zusätzlich konnte durch eine Fusionierung von SSSEP und tERP ein signifikant höheres Klassifikationsergebnis erzielt werden als durch die unterschiedlichen Modalitäten alleine. Des Weiteren erreichten Teilnehmer, welche bereits in der Screening-Messung eine höhere relative Bandleistung bei taktiler Stimulation aufzeigten, auch ein signifikant höheres Klassifikationsergebnis. Schlussendlich wurde entdeckt, dass sich SSSEP besser zu Erkennung eines Ruhezustandes eignet und tERP die bessere Wahl darstellt, um unterschiedliche BCI-Kommandos, wie beispielsweise eine fokussierte Aufmerksamkeit auf eine Stimulation der linken oder rechten Hand, zu erkennen.

Acknowledgments

At this point I would like to thank everybody who played a role in the completion of this thesis.

Foremost, I would like to thank Gernot, who supervised me, acted as a mentor and who provided support and advice in many aspects of this thesis.
I also would like to thank Christa Neuper and Gert Pfurtscheller, who gave me the possibility to start my work at the former Institute of Knowledge Discovery and also provided proficient advice.

My special thanks goes to all my former colleagues at the BCI Lab, to Christoph, Alex, Martin, Günther, Vera, Theo, Patrick, Clemens, Reini, Robert, and all the others for lots of fruitful discussions, funny moments, and a really great place to work. I also would like to thank all the colleagues and teams from the TOBI project for the great collaboration. To name only a few: Febo, Martijn, Michele, Francesco, Luigi, Rüdiger, Andrea, José, and all the others who made the project a success.

Moreover, I want to thank my colleagues at Ranorex for their assistance and flexibility. Additionally, I want to say thank you to my family and my friends who supported me during this long endeavor and who also backed me up in harder times and especially my grandmother, who did not live to see this final thesis, but who always supported me and guided me the right direction.
I also want to thank Mario, who accepted the challenge to proofread this thesis.

Last but not least I want to thank you, Bianca, for your patience in stressful moments, your understanding, and for always being there when I need you.

This thesis was supported by the European ICT Programme Project FP7-224631 Tools for Brain-Computer Interaction (TOBI).

Table of Contents

Abbreviations

AEP Auditory Evoked Potential 5
ALS Amyotrophic Lateral Sclerosis 1, 10, 12, 16, 40, 42
ANN Artificial Neuronal Network 8
ANOVA Analysis of Variance 24, 28

BCI Brain-Computer Interface 1–19, 21–25, 27, 31–46
BOLD Blood-Oxygen-Level Dependent 4
BPwr Band power 5, 8, 23, 24, 27, 29, 35, 40, 45

CAR Common Average Reference 7
CDMA Code Division Multiple Access 37
CNS Central Nervous System 1, 2, 12
CSP Common Spatial Pattern 7, 36, 37

ECG Electrocardiogram 39
ECoG Electrocorticogram 3, 4
edf European Data Format 14, 15
EEG Electroencephalogram 3–5, 7, 10–15, 19–21, 23, 26, 35, 36, 38, 39, 41, 42
EMG Electromyogram 12, 19, 39
EOG Electrooculogram 15, 20
EP Evoked Potential 5, 6, 8
EPFL École Polytechnique Fédérale de Lausanne 33
EPSP Excitatory Postsynaptic Potential 3
ERD Event-Related Desynchronization 5
ERD/S Event-Related Desynchronization/Synchronization 5, 6, 8
ERP Event-Related Potential 5, 27, 37, 40
ERS Event-Related Synchronization 5

FDMA Frequency Division Multiple Access 37
fMRI Functional Magnetic Resonance Imaging 4, 7
FTP File Transfer Protocol 19

gdf General Data Format for Biomedical Signals 14, 15, 33
GPL GNU General Public License 20, 35

hBCI Hybrid Brain-Computer Interface 11–13, 15, 16, 18, 20, 21, 27, 30–32, 39–42, 44–46
HTTP Hypertext Transfer Protocol 19

ICA Independent Component Analysis 7
IP Internet Protocol 34
IR Interaction Ratio 36
IT Information Technology 33, 45

ITR Information Transfer Rate 11, 12, 15, 36, 39, 46

LAS Lock-in Amplifiers System 8
LDA Linear Discriminant Analysis 8, 28
LFP Local Field Potential 3
LGPL GNU Lesser General Public License 20, 22, 35
LSL Lab Streaming Layer 15, 41–44

MEG Magnetoencephalography 4
MI Motor Imagery 5, 6, 8, 12–16, 22, 35, 37–41
MRCP Movement-Related Cortical Potential 5
MRI Magnetic Resonance Imaging 4, 37, 41
MTU Maximum Transmission Unit 34

NIRS Near-Infrared Spectroscopy 4, 12, 15, 20

OS Operating System 22

PCA Principal Component Analysis 7

SaaS Software as a Service 33
SAO Somatosensory Attentional Orientation 11, 41
SCI Spinal Cord Injury 1
SCP Slow Cortical Potentials 5
SEP Somatosensory Evoked Potential 5
SHM Shared Memory 34
SMR Sensorimotor Rhythm 11, 39
SNR Signal to Noise Ratio 3, 5–8, 27, 36, 38
SSEP Steady-State Evoked Potential 5, 6, 8
SSSEP Steady-State Somatosensory Evoked Potential 6, 9–11, 16, 23–25, 27–30, 32, 35, 37–41, 44, 45
SSVEP Steady-State Visually Evoked Potential 6, 10–13, 15, 16, 35, 37–39, 45
SVM Support Vector Machine 8

TCP Transmission Control Protocol 19, 34
TDMA Time Division Multiple Access 37
tERP Transient Event-Related Potential 9, 11, 27–30, 32, 37, 39–41, 44
TiA TOBI Interface A 18–20, 26, 33, 34, 42, 43
TiD TOBI Interface D 21, 22, 33, 34
TOBI Tools for Brain-Computer Interaction 12, 18, 33, 42

UDP Universal Datagram Protocol 19

VEP Visually Evoked Potential 5

XML Extended Markup Language 19, 21, 34

1. Introduction

Getting up in the morning, walking into the bathroom, brushing your teeth, saying hello to somebody, etc. are common things everybody does; but rarely do we think about the functions which are necessary to perform such basics tasks, as getting out of bed alone or simply saying hello to someone. And hardly anyone thinks about what happens when these things become problematic or outright impossible to accomplish. All the aforementioned tasks have one thing in common; they rely on voluntary control of the motor abilities. When these motor abilities degrade or are lost, the consequences are disability and, in the worst cases, even becoming completely locked in the own body. Various reasons can lead to such disorders. A baby can already be born with them, but accidents like car crashes can also result in damages such as spinal cord injury (SCI), which can in turn lead to disorders as mentioned above. People affected by a spinal cord injury might lose the capability of moving their feet (paraplegic), but are still able to move the upper body and their arms. Other people affected by an SCI, e.g., in the cervical spine, can partly or completely lose all motor functions of their arms as well. They might even need artificial respiration, depending on the location of the lesion. All the mentioned impairments originate from a loss of voluntary motor control.

Diseases can also leave behind irreparable damage to the body. For example, the peripheral nervous systems can suffer damage, as is the case in Amyotrophic Lateral Sclerosis (ALS) or the central nervous system (CNS) can come to harm by conditions such as stroke, cerebral palsy, etc.

The results are largely the same; people can lose their motor skills up to losing any communication capabilities that would allow them to stay in touch with their environment.

Humans have been thinking about the curiosities of the brain since time immemorial. Nearly everybody has at least once thought about how great it would be to read someone's mind or to control devices purely by willpower and thought. These ideas were frequently picked up in science-fiction films or prominent series such as "Star Trek". For example, the episode "The Menagerie" from 1966 shows captain Christopher Pike in a mind controlled wheelchair. This is just one example of what people would call "mind control".

These days, the system Christopher Pike used has become known as brain-computer interface; usually just referred to as BCI [1, 2, 3, 4, 5, 6, 7, 8, 9].

1.1. Brain-Computer Interfaces (BCI)

Brain-computer interfaces were introduced the very first time in literature by Jacques J. Vidal in 1973 [10]. A brain-computer interface (BCI) is a system which offers an additional communication or control channel without involving any voluntary muscular control. A definition from Wolpaw et al. [1] describes a BCI as a system

where the user wants to achieve a certain goal. The BCI only utilizes and processes directly measured brain activity in real-time and provides feedback to the user. Such a BCI is designed to replace, restore, enhance, or improve the output of the CNS by measuring and processing CNS signals.
Typical BCI systems consist of the following six characteristics:

- Type of brain signal
- Signal recording
- Experimental strategy
- Mode of operation
- Signal processing
- Type of feedback

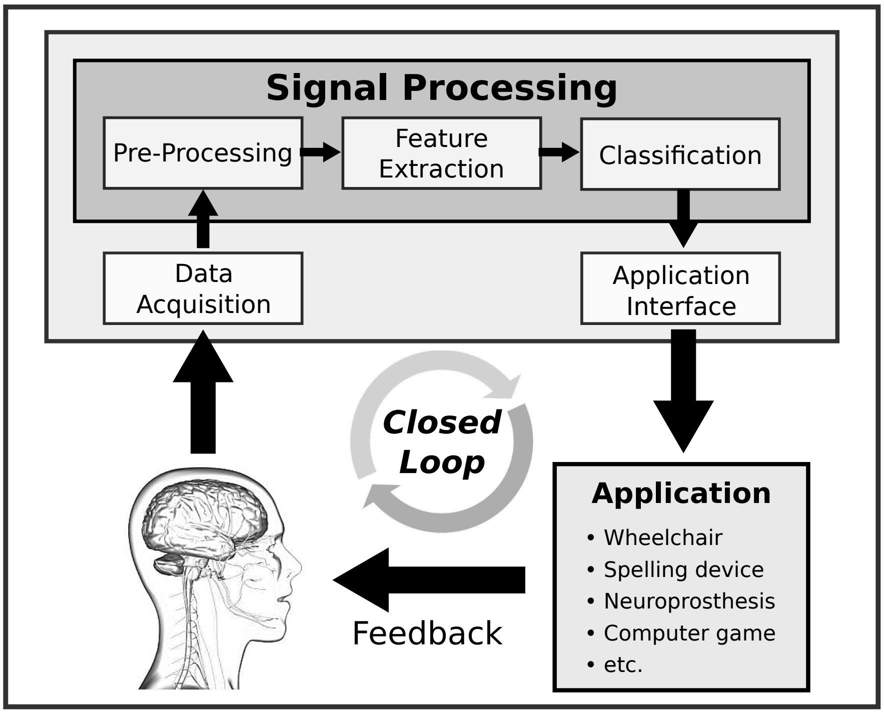


Figure 1.1.: This illustration shows the common closed loop operating principle of BCI systems. Brain signals like an EEG are acquired from the human brain. This data is subsequently processed in the pre-processing, the feature extraction, and the classification modules. The classification results are sent to an application like a neuroprosthesis [11, 12], a speller [13], etc. through an application interface. The reaction of the application, like the movement of a neuroprosthesis, is observed by the BCI user, who thus gets feedback in this manner. All within this closed loop is done in real-time.

Moreover, BCIs can also operate in a passive manner by detecting different mental states like fatigue or drowsiness or can be used to identify wrong commands delivered by a BCI using error-potentials [14]. These kinds of BCIs can be described as "passive" BCIs [15, 16, 17, 14] and neither require active feedback nor do they have to be goal-oriented as mentioned above.

1.1.1. Types of Brain Signals and Signal Recording

Different types of brain signals which measure the brain activity can be utilized for BCI purposes. For example, brain activity can be directly measured by recording electrical activity. The electrical signals are thought to be primarily generated by postsynaptic

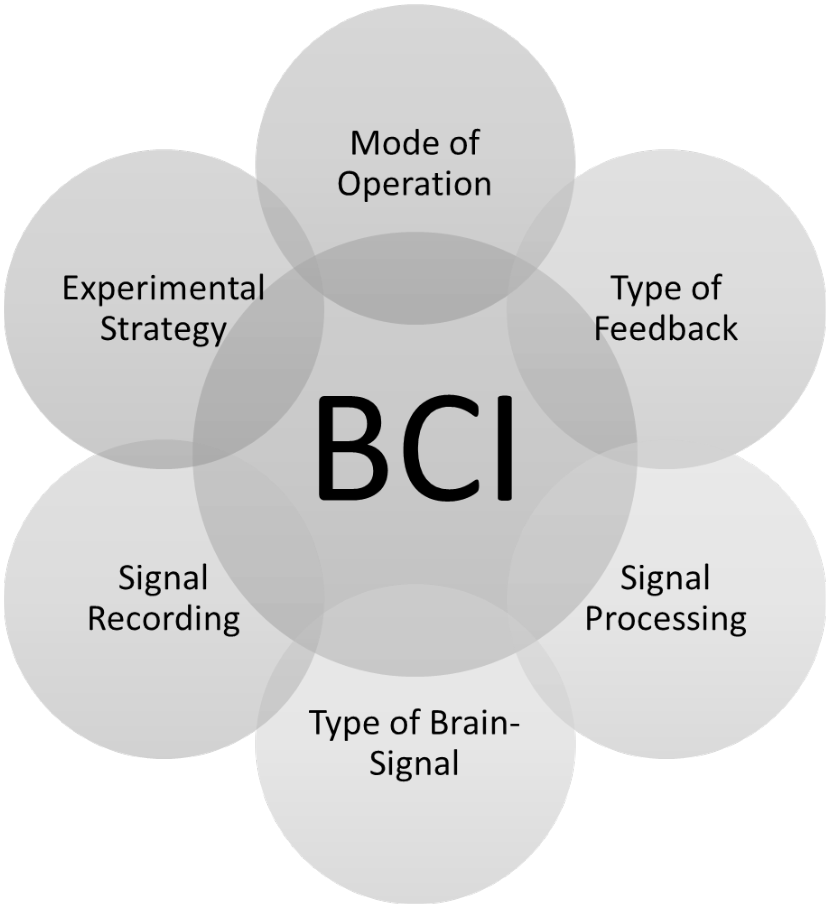


Figure 1.2.: This drawing illustrates the six characteristics of a BCI.

potentials [18]. Excitatory postsynaptic potentials (EPSPs) trigger neuronal action potentials, whereas inhibitory postsynaptic potentials (IPSPs) inhibit the propagation of action potentials. This electric activity can be measured with systems like the electroencephalogram (EEG) [19], which is a non-invasive and low cost method to directly measure electric brain activity. It provides excellent time resolution but only limited spatial resolution. The limitation in spatial resolution occurs because a single EEG electrode records the brain activity of a large population of neurons. EEG furthermore only provides a poor signal to noise ratio (SNR) because electrodes are directly placed on the skin. The electrical signal is thus attenuated and influenced by the skull, by cerebrospinal fluid, and by tissue between the cortex and the electrodes.

Invasive methods, which require surgical intervention, like recording an electrocorticogram (ECoG), local field potentials (LFPs) or the recording of single neuron spiking activity, provide a better spatial resolution and a higher SNR. In case of ECoG, an electrode grid is placed on the surface of the cortex [20, 21, 22, 23]. LFP and single or multi neuron measurements are accomplished by planting micro-arrays directly into the cortex, resulting in excellent SNR and spatial resolution [24, 25, 26]. However, these methods carry the risk of an infection because of the surgical procedure. Such invasive methods are thus less frequently used in BCI research compared to EEG based measurements. They are often used in experiments with primates [27, 28, 29] or sometimes in BCI experiments that involve participants who are epilepsy patients in need of surgical intervention [30, 31, 32].

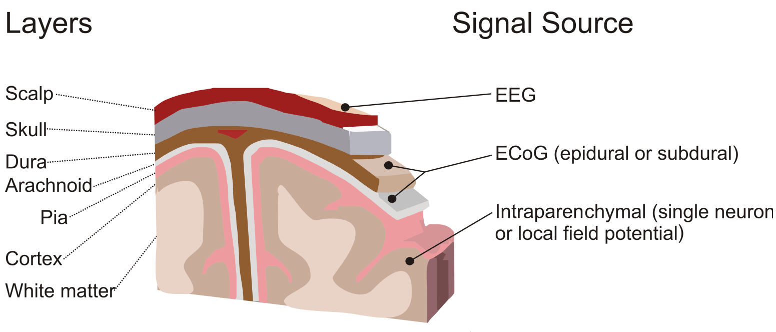


Figure 1.3.: This illustration shows the layers of the human brain and the related data acquisition methods. EEG electrodes are placed directly at the scalp and thus non-invasive. ECoG is measured on the dura or directly on the arachnoidal matter and is thus an invasive method. Single neuron or local field potential measurements are performed directly on or in the cortex and are thus highly invasive.
Modified from: http://www.schalklab.org/research/brain-computer-interfacing *(visited on July 16 2017)*

Electrical activity implicitly generates magnetic fields as well. This magnetic activity can be measured utilizing magnetoencephalography (MEG) [33, 34, 35]. MEG provides a better spatial resolution, because magnetic fields are less influenced by the skull and tissue around the brain. However, MEG systems are sensitive to environmental influences and are much more expensive than EEG amplifiers. Moreover, the brains magnetic fields are in the order of 0.1 µT (compared to the earth's magnetic field: 25-65 µT), making extensive shielding against external influences necessary.
The aforementioned systems all rely on electrical activity or its effects. But neural activity also consumes energy, resulting in different blood oxygenation levels. The location and the level of oxygenation change depends on brain activation as well as the activated cortical region and is thus an indirect way to measure brain activity. The blood oxygenation level can be measured with near-infrared spectroscopy (NIRS) [36, 37, 38, 39, 40] or functional magnetic resonance imaging (fMRI) [41, 42]. NIRS utilizes the effects of a different light absorption level for different wave lengths, which depends on the oxygenation level of the blood. By contrast, fMRI measures the hemodynamic response between oxygenated and deoxygenated hemoglobin, also known as the blood-oxygen-level dependent (BOLD) signal [43]. Both methods achieve good spatial resolution, but they only achieve low time resolution in the range of seconds.
Various kinds of BCIs have already been realized using NIRS, magnetic resonance imaging (MRI), ECoG, highly invasive methods, etc. However, EEG is currently the most frequently used data acquisition method in the BCI field. This is the case because of very good time resolution, acceptable spatial resolution, but mainly because of low hardware costs and minimal environmental requirements. The placement of EEG electrodes is rather simple and an extensive environmental shielding is only necessary in case of high frequency EEG measurements [44, 45].
All measurements conducted in this thesis were based on EEG.

1.1.2. Experimental Strategy

Different kinds of mental strategies can be used for BCI operation. Prominent examples for strategies which are used in BCIs would be mental imagination with the prominent example of motor imagery (MI) [46, 47, 48], focused attention on an external stimulus [49, 50], or neurofeedback [51, 52].
In case of an MI BCI, a user imagines the movement of his feet, his hand, or of other body parts, which in turn activates similar regions of the brain as the real movement execution [53, 12]. Areas in the sensory and the motor cortex are activated. The band power (BPwr) changes in the related cortical area during such a movement imagination. These changes in BPwr are described by the event-related desynchronization/synchronization (ERD/S) effect [54, 48, 55, 56]. The BPwr initially decreases (desynchronization) compared to a prior reference period. This effect, which most frequently occurs between 8 Hz and 12 Hz (μ frequency band) and between 13 Hz and 30 Hz (β frequency band), is called event-related desynchronization (ERD) [55, 56]. This decrease is followed by a BPwr increase (mainly in the β frequency band) subsequent to the completion of the imagined movement. This effect is called event-related synchronization (ERS) [57, 58, 59, 60, 61] or β -rebound (post movement β synchronization). Both effects occurring together form the ERD/S effect. This kind of BPwr inhibition and increase can be detected by BCI systems and has evolved into a standard BCI strategy. Moreover, such a movement imagination is just one way of using a mental task to control a BCI. Doing mental arithmetic would be another example, where people perform a cognitive task to control a BCI [62]. Neurofeedback and the modulation of slow cortical potentials (SCP) [51, 13, 63, 64], frequently used in the early days of BCI, are another option to control a BCI [65, 52]. However, modulating SCPs often requires a vast amount of user training [66].

Another well-established strategy in BCI research is utilizing the effects of event-related potentials (ERPs) [67, 68]. An ERP describes the brain response to an internal or external event. For example, an auditory evoked potential (AEP) [69, 70] is evoked by an auditory, a visually evoked potential (VEP) [71, 72] by a visual stimulus, a movement-related cortical potential (MRCP) [73, 74] is evoked by a movement intention, and a somatosensory evoked potential (SEP) [75] is triggered by a tactile stimulation. The aforementioned MRCP describes an ERP which is based on an internal event, whereas AEPs, VEPs, or SEPs are based on an external stimulus. These evoked potentials (EPs) [76, 77, 78, 79] form a subset of ERPs because they require an external stimulus to be present. The P300 potential [80] is a prominent example for an EP which has been used in BCIs for a long time. P300 has mainly been used in vision based BCIs [50, 81, 82] as well as auditory [83, 84], or tactile BCIs [85]. The P300 potential occurs in case of appearance and recognition of a target event in a sequence of non-targets. The experimental paradigm leading to P300 effects is called an "Oddball" paradigm. The P300 depicts a positive EEG amplitude increase which occurs around 300 ms after the occurrence of the target event [86, 87, 88] – an acoustic, a visual, or a tactile stimulus. It can be difficult for a BCI to detect a single trial P300. Multiple P300 potentials which belong to the same target event are thus frequently averaged to increase SNR. Such an averaging is possible because the P300 is time- as well as phase-locked.
When stimuli are applied in a steady-state manner, the brain reacts with a stable oscillation at the same frequency as the external stimulus. Such an oscillation is called steady-state evoked potential (SSEP) [89]. To operate a BCI which relies on SSEPs, the

user shifts his attention to a target stimulation within a multitude of other stimuli with a different frequency. A frequently used experimental design relies on multiple flashing lights where every light flashes with a different frequency. Such flashing or flickering lights induce steady-state visual evoked potentials. If the user shifts his attention to such a flickering light, the amplitude of the related steady-state visually evoked potential (SSVEP) [90, 91, 49, 92] component increases in contrast to the other SSVEP components. SSEPs have already been successfully used for visual, auditory [69] and tactile BCIs.

Steady-State Somatosensory Evoked Potentials: Applying steady-state tactile stimulation elicits so-called steady-state somatosensory evoked potential (SSSEP) [93, 94, 95]. Only a limited number of studies which utilize SSSEP for BCIs purposes have been accomplished so far. Tactile stimulation was mostly applied at the fingertips, as carried out by Giabbiconi et al. [96] or Severens at al. [97] or at the palm, as performed done by Tobimatsu et al. [94]. Other stimulation locations like the abdomen, the wrist, or the feet are less frequent. Exploring SSSEPs for BCI usage is a major topic in this thesis. This type of BCIs could combine the advantages of EP-based BCIs (like a high classification rate and a short amount of training) and do not require a functional visual system, which is needed for visual P300 BCIs.

1.1.3. Mode of Operation and Type of Feedback

As stated in section 1.1, the data processing in BCIs has to be done in real-time and the user also receives feedback. However, the BCI can operate in different manners; in a synchronous or an asynchronous way. In case of synchronous operation, the BCI itself defines the sequence. The user has to follow the instructions of the BCI like performing an MI. In this case, only data from a defined time window is processed. The advantage of such a BCI-type is the well-known sequence of the experiment. The time windows which contain a BCI "action" (like MI or focused attention) are known. These kinds of BCIs are computer driven and thus frequently used to train BCI classifiers or to test new strategies. However, synchronous BCIs are not practical in real-world situations. Users are only able to operate the BCI in certain time windows, which reduces the freedom of operation. The user is thus unable to deliver a command at a voluntary point of time and thus has to wait for the next time slot. This results in an unnatural way of interaction and a reduced user experience.
In contrast, asynchronous BCIs provide the possibility for a user to deliver a command at a voluntary point of time. The BCI is active the whole time and tries to detect BCI actions. From a user's point of view, this is the perfect kind of operation. To achieve such an asynchronous mode of operation, the BCI has to constantly analyze incoming data in real-time and has to locate user commands in the data stream. However, as discussed in the previous section, the SNR of a target signal like a P300 potential or an ERD/S pattern can be low. As a consequence, it may happen, that user commands are not or wrongly detected. Especially the detection of non-control (or idle) phases where the user does not deliver any commands can become hard to recognize. Methods to increase the SNR like data averaging are hardly possible, because triggers describing a command onset are not available. To sum up, asynchronous BCIs would provide a natural way of interaction for the user. However, it is a major challenge to detect user commands on a single trial basis in a continuous data stream with satisfying

classification accuracy.

The mode of operation (synchronous or asynchronous) is also tightly coupled with the type of feedback, presented to the BCI user. The feedback can be realized in a multitude of variations. It can be presented in an abstract manner like manipulating a bar on a computer screen or very realistically like animating a hand movement in a virtual environment. The feedback can also be provided in a discrete manner like a circle which just toggles its color or in a continuous way like a bar which continuously moves depending on classification results. Moreover, the feedback can be implicitly provided by the app itself. Examples would be the letters selected in a P300 speller, the direction a BCI controlled wheelchair moves, or a BCI operated neuroprosthesis. The user thus gets informed by the feedback if the BCI was able to decode the command correctly, for example, if the correct letter in a P300 speller was detected. Such feedback is an important component in a BCI; it can influence the classification rate, can be beneficial in terms of motivation, and can also help users to adapt and fine tune their "internal" strategy (like the thought of a movement imagination) to reach better results.

1.1.4. Signal Processing

Data acquisition is the first step in a BCI where brain-signals are acquired from hardware devices like EEG amplifiers, fMRI scanners, etc. This data is subsequently processed in the BCI processing chain. The signal-processing chain in BCI systems generally consists of the following parts: (i) signal pre-processing, (ii) feature extraction, and (iii) classification.
The pre-processing step is frequently used to increase the SNR of a "target" signal and to remove interfering signal components or spatial effects from the raw data. Common pre-processing methods are low-, high-, notch-, or bandpass filtering, applied to the raw data. To a certain extent, this kind of filtering can already be done directly in the acquisition hardware. Examples would be the removal of local power supply interference at 50 or 60 Hz, or a broadband bandpass filtering, e.g., from 0.5–500 Hz. Such a bandpass filter is applied for two reasons: to remove biological artifacts like the effects of sweating, which could result in a low frequency electrode potential drift, and to filter frequency ranges which are not of interest for the experiment.
Spatial filters can be applied in the pre-processing step to amplify or damp effects which are spatially distributed. Examples for generalized spatial filters are: (i) bipolar filters encompassing an electrode-pair, (ii) Laplacian filters [98] encompassing an array of electrodes [99], or (iii) common average reference (CAR) encompassing all electrodes [100, 101]. Spatial filtering can also be done in a subject specific manner, creating individual filter arrangements. One example for such a filtering method would be common spatial patterns (CSPs) [102, 103, 104, 105]. Moreover, common signal processing methods like principal component analysis (PCA) or independent component analysis (ICA) can also be used as a spatial filtering method.
The output of the pre-processing step thus results in a signal which is still equivalent to the raw data (e.g., an EEG signal in μV), where interfering signals are attenuated and the SNR of the "target" signal is increased.

The output from pre-processing is further processed in the feature extraction step [106]. Different kind of features used in EEG based BCI systems comprise (logarithmic)

BPwr [46, 107, 108], autoregressive parameters [109, 110, 111, 112], brain connectivity [113, 114, 115], the output of lock-in amplifiers system (LAS) [116, 117], features in the frequency domain as Fourier transformation results [117, 118], or features in the time domain like like amplitudes of EPs at given latencies or from a spectral band [119]. The individual type of feature used in a BCI is usually tightly coupled with the experimental strategy. Band power features are often used in MI based BCIs. In contrast, features in the frequency domain or LAS are frequently used in BCIs which rely on SSEP. To obtain meaningful feature values, a feature selection has to get carried out. For example, in case of BPwr features, optimal frequency bands have to be selected. The feature selection can be done in a manual way, like visually inspecting ERD/S plots to identify frequency ranges for band power feature. The feature selection process can also be automated to automatically select or even update features without the need for manual interaction.

The resulting features are subsequently classified by a certain classifier. A binary classifier can be realized by a threshold detector, which classifies a single feature. If the feature value is below a threshold, the classifier detects class one. If it exceeds the threshold, class two is detected. However, current BCIs usually utilize more than just one feature. More advanced classifiers are thus used in current BCI systems.
Supervised learning methods are common in BCI research because the SNR can still be low even after pre-processing and feature extraction. The available data is therefore split into dedicated training and test sets. A common classification method used in BCI research is the linear discriminant analysis (LDA). The LDA is based on a linear transformation, maximizing the separability between classes utilizing a linear hyperplane [120, 121]. This separation is achieved by maximizing the ratio of between-class variance to the within-class variances. Different kinds of extension to the original LDA, which was introduced by Ronal Fisher in 1936 [122], have been developed so far. Examples are a step-wise LDA or a shrinkage LDA, which try to increase classification results compared to the original LDA. This is done by calculating classifier weights in a step-wise manner or by applying shrinkage and the regularization of variances for example.
Other classification methods (linear or non-linear) which are often applied in BCI research comprise support vector machines (SVMs) [121, 123, 124], artificial neuronal networks (ANNs) [125, 126], restricted Boltzmann machines [127], decision trees [128], hidden Markov models [129], and many more [130]. Classification results are subsequently mapped to distinct class labels.
As mentioned above, supervised learning is frequently used in BCI research. Because early feedback to the user can increase motivation, which in turn can influence the overall performance [131, 132, 133], the first classifier in a BCI experiment is often trained at an early stage with a reduced number of training trials. Moreover, users can modify their "internal" mental strategy (as already mentioned before) during an experiment or between sessions, which can lead to different brain activation patterns. Additionally, effects like operant conditioning or the creation of some kind of somatosensory memory [134] can also lead to different activation patterns. Classifiers are thus usually updated, for example, when more trials are available or from session to session. This update procedure can be done in a manual or automated manner. Automatic classifier update strategies can even encompass automatic feature selection with subsequent classifier recalculation. This kind of automated processing is a key component in adaptive BCIs [135, 136, 137, 138, 139].

1.2. Tactile Brain-Computer Interfaces and the Somatosensory System

Tactile BCIs usually rely on an attention modulation paradigm. Tactile stimulation can be applied in a steady-state manner to elicit SSSEPs as shown by Müller-Putz et al. [116] or by single pulses to induce transient event-related potentials (tERPs), as performed by Brouwer and Erp [85].

1.2.1. Physiological Background of the Somatosensory System

In case of SSSEPs, a vibratory stimulus is applied to the skin to stimulate the available mechanoreceptors. The human skin contains different types of such mechanoreceptors which respond to mechanical pressure or distortion [140]. These four receptors are: (i) Meissner corpuscles, (ii), Pacinian corpuscles, (iii) Merkel disks, and (iV) Ruffini endings.

Meissner corpuscles (sometimes simply called "tactile" corpuscles), are mostly found in the fingertips or the eyelids and are less frequent in the palm. The Meissner corpuscles respond to touch and pressure as well as low frequency vibration (3–40 Hz) and have a small receptive field. These receptors further respond when moving the skin across a surface or when rubbing an object against the skin.

Pacinian corpuscles are also able to detect pressure changes and vibratory stimulation. Their optimal sensitivity for vibratory stimulation at the fingertips is around 250–300 Hz and thus higher than the optimal frequency for Meissner corpuscles. These corpuscles, which have a large receptive field, are best suited to detect rapidly changing stimulation.

Merkel disks are slowly adapting receptors which respond to light touch. These receptors have small receptive fields with well-defined borders and allow the exact determination of a stimulus location.

Ruffini endings, also known as bulbous corpuscles, are slowly adapting mechanoreceptors too and are able to detect stretching of the skin or deformation in a joint. These receptors thus provide viable information when moving the body or when gripping objects.

Considering the mentioned mechanoreceptors, the Pacinian and the Meissner corpuscles are most interesting for a usage in an SSSEP BCIs. Both react to vibratory stimulation and are rapidly adapting. Afferent sensory information is "filtered" within each relay nucleus to sharpen the contrast of incoming signals. The sensory information is subsequently "routed" through the Thalamus and forwarded to the primary somatosensory cortex (for more detailed information see Kandel et al. [140]). A focused attention on tactile stimulation, the key component of a tactile BCI based on attention modulation, is mediated in the primary somatosensory cortex [141]. If the tactile information is of certain interest or the person focuses their attention on the stimulus, an activation of certain areas in the secondary somatosensory cortex becomes visible as well [142].

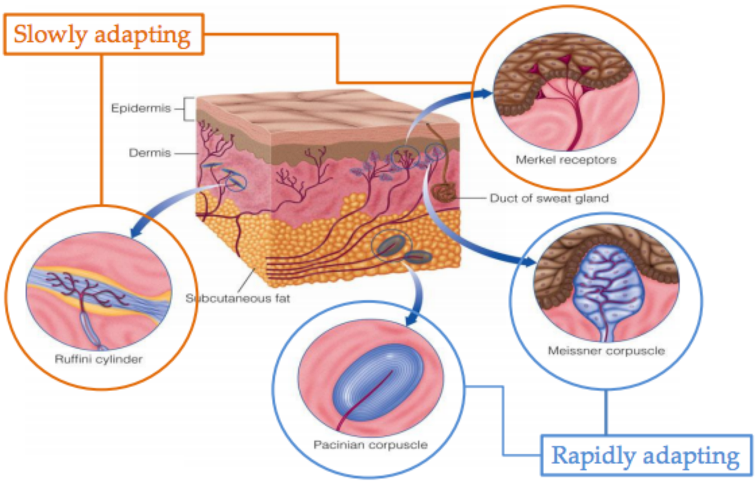


Figure 1.4.: This figure shows the individual mechanoreceptors of the human skin as well as their location and their shape.
Modified from: http://wiki.bethanycrane.com/somaticsenses *(visited on July 16 2017)*

1.2.2. BCIs Based on Tactile Stimulation

As mentioned above, tactile BCIs usually rely on an attention modulation paradigm. To be precise, the amplitude of harmonics of the stimulation frequency within the EEG are modulated when switching the attention to an individual stimulus, e.g. a vibratory stimulation of the index finger. The amplification or attenuation of the harmonics in a certain brain area is then detected by the BCI. Such an SSSEP based BCI thus shares certain similarities with SSVEP based BCIs which rely on a steady-state visual stimulus.
Moreover, a transient tactile stimulation can elicit a P300 potential [143, 144]. The processing methods of a BCI based on such tactile transient evoked potentials [85, 145, 146] are similar to the ones used in a visual P300 BCI (e.g., using a P300 speller).
SSVEP and visual P300 based BCIs have already been investigated in great detail and lots of studies have been conducted [147, 81, 82, 148, 149, 150, 151, 152]. Different kinds of modifications to improve performance were introduced, like optimized flashing patterns, utilizing colors or pictures, etc. [153, 154, 155, 156]. However, these kinds of BCIs require a functional visual system as well as the remaining ability of voluntary eye control. Unfortunately, such functionality can become impaired, e.g., as a result of a disease or an accident. In case of ALS, motor skills are lost and people might not be able to even move their eyes or eyelids in later stages of the disease. The sensory system however remains functional in contrast to the loss of motor skills. BCIs using the somatosensory system are thus reasonable alternatives to vision based BCIs.
However, tactile BCIs are still rather unexplored. This might be related to a more complex measurement setup like the need for a tactile stimulation controller or the availability of appropriate tactile stimulators. Different kinds of stimulators have been used in the available literature so far. The most common ones are: (i) motor driven mechanical stimulators [157], (ii) stimulators operated by magnetic fields, similar to a loudspeaker [116], or (iii) braille stimulators [158].
To achieve maximum stimulation efficiency, an appropriate stimulator has to be chosen which has to reproduce the stimulation pattern with minimal interfering or damping effects. Selecting an appropriate stimulation pattern is crucial as well. In case of SSSEP

based BCIs, a carrier frequency around 250 Hz is usually used to stimulate Pacinian corpuscles. This carrier frequency is further modulated with frequencies between 15 and 35 Hz. A rectangular modulation pattern achieved the best results, beating triangular and sinusoidal frequency modulation [159]. Such a combined stimulation pattern stimulates a maximum amount of the rapidly adapting mechanoreceptors, namely the Meissner and Pacinian corpuscles. In case of tactile tERP based BCIs, short stimulation pulses are used, which are usually also modulated with a carrier frequency around 250 Hz.

The first step towards tactile BCIs which rely SSSEP has been done by Tobimatsu et al. [94] and Snyder [93]. These research groups showed that the somatosensory cortex reacts to tactile stimulation in a similar manner as the visual cortex when observing a flickering light. The EEG amplitude of the harmonics from a steady-state tactile stimulation increases or decreases when shifting the attention to or away from a certain target stimulus. Moreover, people show a different brain response when applying tactile stimulation [94], resulting in so-called resonance-like frequencies [160]. This amplitude modulation was first used by Müller-Putz et al. [116] to create a BCI which was solely relying on SSSEP. The participants achieved a classification performance of up to 80 % with this kind of BCI. The following years, other BCI systems based on tactile stimulation evolved as well. Severens et al. [97] presented a study using braille stimulators and discovered an interaction effect when stimulating two fingers of one hand. Adler et al. [157] showed that enhanced complexity of the stimulation pattern, which makes transient events harder to recognize, increases the response EEG amplitude. Furthermore, Spitzer et al. [134] discovered an interesting phenomenon. When switching the attention to tactile stimulation and trying to keep this stimulation in memory, a prefrontal activity in the EEG beta-range (20-25 Hz) was observed. The effect described by Spitzer et al. has already been turned into a BCI application by Yao et al. [161]. Moreover, it was shown by Yao et al. [162], that a user can even control a BCI by somatosensory attentional orientation (SAO) without the need for any tactile stimulation.

However, compared to sensorimotor rhythm (SMR) or SSVEP based BCIs, tactile BCIs, and especially those relying on SSSEP, are rather unexplored [163].

1.3. Hybrid Brain-Computer Interfaces (hBCI)

As discussed above, different kinds of experimental strategies can be used to operate a BCI. In case of tactile BCIs, the SSSEP and tERP based BCIs have already been discussed in more detail. Common performance measures for BCIs are usually the classification rate or the information transfer rate (ITR). Unfortunately these rates vary between individuals. An individual could achieve a reasonable performance with one experimental strategy. However, another person might just reach the chance-level with the same BCI. In former days it was usual to investigate a single strategy only and use it within a BCI. This approach frequently lead to poor results for a couple of subjects. A new approach, called hybrid brain-computer interface (hBCI), involves the integration of multiple input signals into common BCIs to enhance overall performance. A definition by Pfurtscheller [164] depicts the characteristics of an hBCI to be similar to a common BCI. Thus, an hBCI also has to: (i) rely on signals being directly recorded from the brain; (ii) comprise at least one brain signal which the user is able to modulate to achieve a certain goal; (iii) be based on real-time signal processing; and (iv) provide

feedback to the user. However, this hBCI definition does not permit the inclusion of external signals to enhance overall system performance. An extended definition for hBCI systems that also includes external information is provided by Müller-Putz et al. [165]. It evolved as part of the large scale EU project Tools for Brain-Computer Interaction (TOBI).
The definition from Pfurtscheller et al. supports BCI systems which are created and run under laboratory conditions to study brain signals, the interaction of different experimental strategies, etc., but are not designed to support a BCI user in a maximum way. A BCI is intended to replace, restore, enhance, supplement, or improve the output of the CNS and to provide an additional or maybe even a last communication channel for severely disabled people. However, it is often a long process until a user, like an ALS patient, has to completely rely on a BCI because all remaining communication channels have been lost [4]. Such users could still have some remaining muscular functionality and the capability of intentional movement control. Ignoring this functionality would only hamper an already disabled person. Involving any additional information source to maximize the ITR or the performance in general is thus a reasonable step.
The already mentioned EU project TOBI defined an hBCI as a system where the BCI itself is an existing, but optional control channel [165, 166]. The user can decide freely whether to utilize the BCI channel or other input channels like a shoulder joystick, a mouth-mouse, etc. The combination of different input signals to a final output signal was called “fusion”. The term “switching” was introduced for cases when one signal is directly forwarded to the output. A switch between signals can occur if, e.g., the quality of one signal falls below a certain quality measure [167] or due to altered environmental conditions, like a wheelchair driving towards stairs. Such context or location aware computing is becoming more prominent day by day [165]. This can also be integrated in hBCI systems. For example, a small robot with context and location awareness can assist a BCI user. Moreover, a navigation and steering system which is integrated in a BCI operated wheelchair can help a person to get from point A to point B with a minimum of BCI commands. A new term called “shared control” was introduced into the BCI field, describing the integration of external intelligence into BCI systems. Shared control operates in a target oriented manner which assists the user to reach a desired goal. It can further inhibit potentially dangerous BCI commands, like moving a wheelchair too close to stairs. A general architectural illustration of an hBCI is presented in Figure 1.5.

Different kinds of hBCI systems have already been successfully investigated. The combination of an EEG based MI BCI with electromyogram (EMG) from residual muscular activity significantly increased overall performance [168, 169]. A combined classification of EEG and EMG together within a data fusion outperformed the classification rates of EEG and even of EMG. The effect of fusing both kinds of input signals was investigated by continuously adapting weights for the individual signal types within fusion. A mixture of both signal types achieved best results. Other examples for successful hBCI setups include: (i) the combination of EEG and NIRS [170], linking two different brain signal types, (ii) the combination of MI and SSVEP [171], combining two different kinds of experimental strategies, (iii) the combination of MI with external input, e.g., from a joystick, merging a BCI and an assistive device [167], or (iv) the combination of a BCI with inputs from a wheelchair or a robotic device to increase user presence and awareness [172, 173].
This list provides only a short excerpt of introduced hBCI systems. They are presented in more detail by Müller-Putz et al. [166]. Despite the differences between the

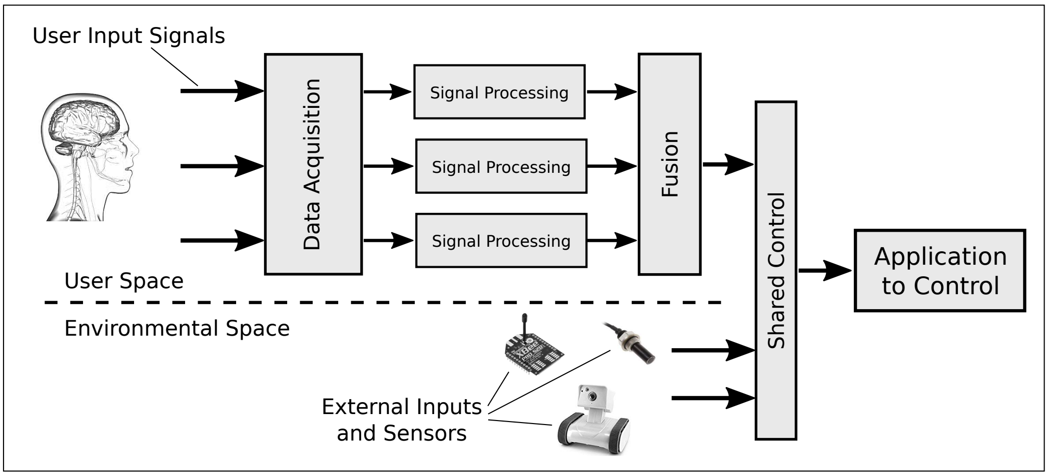


Figure 1.5.: This figure illustrates the architecture of an hBCI system which utilizes three processing streams. These processing streams are fused to a final result in the fusion module. Shared control incorporates information from external devices like sensors or robots. The output from shared control, which integrates information from the user as well as information from the environment, is finally sent to the application.

aforementioned BCI systems, they all have one thing in common. The hBCI approach usually outperforms the "old fashioned" BCI when compared to a common single modality based BCI. Because common BCIs frequently achieve low classification accuracies, applying hBCI mechanisms makes perfect sense. Furthermore, fusing different kinds of experimental strategies can increase the applicability of BCI systems across different end users. It could also happen that a BCI user achieves good results with one experimental strategy like SSVEP, but achieves a poor classification with an MI based BCI. Fusing different kinds of experimental strategies within an hBCI can thus also increase the overall performance across users because a fusion logic can inhibit the poor channel.

1.4. The Architecture of BCI Systems

Various BCI systems have been developed since the beginning of BCI research. All these BCI systems had to fulfill the requirements regarding real-time processing and user feedback. However, former BCI systems usually processed a single type of data, for example, multiple EEG channels. Moreover, an experiment typically dealt with one experimental strategy, such as MI, at a time. The introduction of hBCIs thus brought with it various additional requirements for BCI systems and their underlying architecture.

1.4.1. An Overview of BCI Systems

BCI research, pioneered by Jacques Vidal, was only done by very few laboratories in the 1990s. This number has vastly grown since the times when Farwell and Donchin created the first P300 speller in 1988 [50] or since the groups around Pfurtscheller, Birbaumer, and Wolpow started their research on brain-computer interfaces [8, 13, 1]. Together with a growing number of research groups performing BCI research, the number of BCI systems began to grow too. Lots of laboratories developed their very own BCI system, such as the Graz BCI [174], the EPFL BCI, the Berlin BCI, xBCI [175], Fieldtrip [176], and many more. In parallel to the evolvement of these custom BCIs, different publicly available BCIs were developed too. Prominent ones include BCI2000[1], initiated by Gerwin Schalk and colleagues [177, 178], OpenViBE[2], developed by the group around Anatole Lécuyer [179] at the French Institute for Research in Computer Science and Automation (INRIA), or the Body Language Framework (BF++)[3], created by Luigi Bianchi [180]. Moreover, the emerging open-source project OpenBCI[4], which specializes on low-cost sensory hardware and open-source software for BCIs, is becoming more and more popular. OpenBCI, founded by a Kickstarter campaign[5], intends to make BCI systems affordable for everybody from scientists to high school students, take BCIs into classrooms, and thus expand the overall BCI community.

Furthermore, various companies, like g.tec (Austria), ANT neuro (The Netherlands), Brain Products (Germany), or EMOTIV (USA) also offer or develop proprietary BCI systems or components for BCIs. A recent trend further includes the output of BCI (or BCI like) systems for gaming and thus for a broader audience [181, 182]. Different low cost EEG or biosignal amplifiers have been developed by various companies. NeuroSky used BCI input to control their game "NeuroBoy", or Mattel, which used the system from Neurosky, utilized a BCI-like input for their game "MindFlex". Even the flash drive manufacturer OCZ developed their "Neural Impulse Actuator" which was intended to provide joystick-like control.

This is just a small excerpt of available systems. Because many laboratories build custom BCI systems, it is hard to estimate the number of different BCI systems and frameworks being used right now.

1.4.2. Capabilities and Limitations of BCI Current Systems

BCI systems need to fulfill the basic requirements like online data processing of brain signals and have to be able to provide real-time feedback to the user. However, these systems differ in various manners like the supported operating systems, the available methods for pre-processing, feature extraction or classification, or the support for different experimental strategies like MI, P300, etc. Some BCI systems, such as OpenViBE, BCI2000 or NPX, are completely custom built and based on programming languages like C, C++, Java, Python, etc. Other systems like the Graz BCI, the Berlin BCI or the EPFL BCI utilize existing platforms like Matlab as an underlying framework. Usually, BCI systems also include the possibility to save data in different file formats like the European data format (edf) [183], NPX [184], the general data format for biomedical signals (gdf) [185], XDF[6], or individual system specific formats. Moreover, BCI systems provide support for various data acquisition devices, real-time data monitoring, different pre-processing, feature extraction and classification algorithms, as well as pre-existing feedback systems like P300 spellers, bar based feedbacks, up to complete 3D feedback mechanisms [179]. Tools like BCI2000 or OpenViBE enable a quick step into BCI research and a fast ramp up. The availability of the aforementioned

[1] BCI2000 *(visited on July 16 2017)*
[2] OpenViBE *(visited on July 16 2017)*
[3] Body Language Framework (BF++) *(visited on July 16 2017)*
[4] OpenBCI *(visited on July 16 2017)*
[5] OpenBCI Kickstarter Campaign *(visited on July 16 2017)*
[6] XDF specifications *(visited on July 16 2017)*

tools might also have influenced a fast growth of the BCI community during the last years.
However, the diversity in individual BCI frameworks has introduced a problem to the field of BCI research. The aforementioned systems have become partly or completely incompatible with each other up to a certain extend. Loading existing data files in a standard format as gdf or edf mostly works. However, a real-time interaction between different BCI systems is mostly impossible or at least hard to realize. These incompatibilities create significant issues, especially when laboratories and research groups need to collaborate. Furthermore, common BCI systems are usually designed to process a single data stream of a certain type (e.g., EEG, NIRS. . .) at a time. But at the time of starting to write this thesis, these system were unable to acquire and process different data streams of a different type (e.g., EEG, electrooculogram (EOG), Joysticks. . .) at the same time or were incapable of acquiring data from external sensors or intelligent devices like robots. For the new hBCI trend, the support of different kinds of signal types, biological as well as non-biological, is a crucial requirement.

1.4.3. Common Implementation Platform

To establish compatibility and exchangeability of modules between laboratories and research groups, some kind of common ground for online data exchange is necessary. A lack of standardization has already been mentioned by P. Brunner et al. [186] when investigating issues in BCI development. Considering the architecture and the data processing chain of BCI systems, they are all built according to the structure presented by Mason and Birch [187]. All BCI systems need a data acquisition system, a data processing chain, which usually consists of pre-processing, feature extraction, and classification, and an application interface. Thus, BCIs follow the structural definitions presented in Figure 1.1. These components process data and subsequently provide the processed data to the next module in the BCI chain. Thus, the data connections between the individual modules are key components to establish a common ground for real-time data exchange. By providing well known or standardized interfaces and communication protocols, it would become possible to replace or even share modules. The Lab Streaming Layer (LSL)[7] developed at the Swartz Center for Computational Neuroscience, UCSD, or the common implementation platform presented in this thesis are working towards the goal of a standardized communication within or between BCI systems.

1.5. Aim of this Thesis

BCIs which rely on the somatosensory system are rare compared to the amount of studies which have been done on BCIs based on MI, visual P300 paradigms, or SSVEP. However, BCIs which rely on MI often need intense training or do not reach a sufficient classification accuracy. Visual P300 paradigms or SSVEP based BCIs seem to be a better alternative, as they often provide higher ITRs and can be rapidly set up even without or with a low amount of training. However, these BCIs require a functional visual system, which can be impaired in potential end users. BCIs which rely on the somatosensory system are a reasonable option in this case because the

[7] LSL Repository *(visited on July 16 2017)*

neuronal pathways for somatosensation remain functional, event in the case of ALS, which affects the motor functions. It could further be used for patients which are in a vegetative state, where a vision-based BCI is not an option either [188].
However, many topics related to somatosensory BCIs had been unexplored. For example, influences on the BCI performance of different stimulation devices or of person-dependent stimulation frequencies have not been investigated. Moreover, the stability of an SSSEP tuning curve or the possibility to assign a focused attention target to a single finger in an SSSEP based BCI (while the other fingers on the same hand are potential targets too) and then detect a focused attention on it, have not been investigated. BCIs which rely on the tactile system unfortunately come with increased hardware effort because a tactile stimulation device and a stimulation controller are necessary. This increased effort is a drawback compared to MI based BCIs or BCIs which rely on the visual system (like SSVEP or a visual P300), where just a computer screen or flickering lights (e.g., an LED) are necessary in addition to a common BCI environment. As mentioned above, the knowledge regarding somatosensory BCIs is rare and it is an open question if the increased effort that comes with a tactile BCI came with enough advantages to be a reasonable option to other BCI types. One aim of this thesis was therefore to shed more light on some questions around tactile BCIs.
As mentioned before, the hardware effort of tactile BCIs is higher than for common BCIs, such as those based on MI. The increased hardware effort is accompanied by increased software complexity because the tactile stimulation requires external commands. Moreover, the stimulation device itself also produces valuable information which needs to be stored for later offline analysis. Additionally, hBCIs are becoming more and more popular, but they are also increasing complexity. Another goal of this thesis is to provide a common implementation framework to facilitate the compatibility and exchangeability within BCI systems. Introducing hBCI principles in tactile BCIs would thus further increase their complexity and could render the applicability too complex from a general point of view. The common implementation platform introduced in this thesis was meant to reduce this complexity and also make the increased hardware effort for tactile BCIs a negligible issue. For example, one goal was to make it possible to control a stimulation device like any other comparable component in the BCI processing chain.
This goal was finally validated with a hybrid tactile BCI which relies on easily exchangeable and replaceable components. Sending commands to components such as a tactile stimulation device should not be more complex than sending a message to a screen showing instructions to a participant. Moreover, the applicability of hBCI methods, like fusing classification results was explored in this thesis and if such a tactile hBCI can further reach a sufficient classification accuracy [51].

1.6. Structure and Organization of this Thesis

Chapter 1 covers the main topics addressed in this thesis. This chapter provides a general overview of BCIs in conjunction with an overview of basic topics related to BCIs. Somatosensory BCIs, hybrid BCIs, and BCI platforms are addressed in more detail as these fields of research are most relevant for this thesis. Moreover, the aim of this thesis is outlined.
Chapter 2 introduces the main publications which are relevant for this thesis and provides a short summary for the individual publications.
Chapter 3 summarizes and discusses the outcomes of the publications presented in chapter two. This chapter further analyzes the impact of the individual publications on this thesis and provides a discussion of the scientific contributions to the BCI community.
Finally, a conclusion is provided in **Chapter 4** together with an outlook in **Chapter 5** on future directions of somatosensory BCIs and the current trend on BCI platforms.

2. Methods and Results

2.1. Establishing a Common Implementation Platform

2.1.1. Introducing a Concept to Standardize Raw Biosignal Transmission

C. Breitwieser, C. Neuper, and G. R. Müller-Putz. “A concept to standardize raw biosignal transmission for brain-computer interfaces.” In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. 2011, pp. 6377–6380. DOI: 10.1109/IEMBS.2011.6091574 [189]

As presented in the introduction, BCI systems are usually divided into the segments: (i) data acquisition, (ii) signal processing, (iii) an application interface, and (iv) the application itself. Mason and Birch [187] introduced a general BCI scheme (shown in figure 2.1) that also follows the aforementioned segmentation. An open source interface for raw data exchange, called TOBI interface A (TiA), is introduced in this paper, which aims to facilitate a common methodology to exchange raw data between acquisition devices and BCI systems.

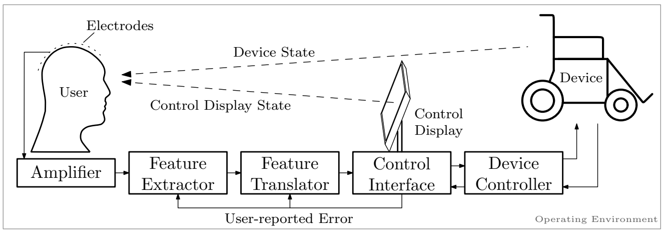


Figure 2.1.: Functional model for BCI systems introduced by Mason and Birch.

Contribution to this Thesis:

This publication describes a concept to standardize the raw data transmission between data acquisition devices and subsequent processing modules and is the first step towards the common implementation platform. Keeping the requirements of hBCI in mind, it is necessary to support different kinds of signal types (biological and non-biological ones) in the same manner. An interface is presented in this paper that is designed to provide data transmission of the acquired signals over a network to multiple clients. An initial prototype implementing this interface, called TiA, is introduced in this paper together with first benchmarking results. All developed components like TiA finally form a common implementation platform and are open source available at github[1]. The development was supported by the large scale EU project “TOBI”. The naming of the individual interface thus refers to the TOBI project (e.g., TiA . . . TOBI interface A).

[1] https://github.com/tools4BCI (visited on July 16 2017)

2.1.2. Introducing a Common Protocol for Raw Biosignal Transmission in BCI Systems

C. Breitwieser, I. Daly, C. Neuper, and G. R. Müller-Putz. "Proposing a standardized protocol for raw biosignal transmission." In: *IEEE Transactions on Biomedical Engineering* 59.3 [2012], pp. 852–859. DOI: 10.1109/TBME.2011.2174637 [190]

Introducing a common interface for raw data exchange within BCI systems is an essential part of this thesis. This publication presents a full blown implementation of the TiA interface as well as a data acquisition software called "SignalServer". A cross-platform TiA library was implemented in C++ and embedded in the SignalServer, which was also realized in C++. Moreover, TiA clients for different systems and programming languages were implemented to facilitate the usage of the newly designed system. Figure 2.2 shows the client-server architecture of the overall system. The communication is split into two different streams, inspired by the design of File Transfer Protocol (FTP). A control connection (realized with the Transmission Control Protocol (TCP)) is used to exchange Hypertext Transfer Protocol (HTTP) oriented control commands using Extended Markup Language (XML) for command encoding. A second data connection can be realized with either TCP or Universal Datagram Protocol (UDP). The desired data connection protocol is chosen by the client with commands sent over the control connection. TCP guarantees data delivery at the cost of an additional protocol communication overhead. UDP has a reduced overhead and the possibility to broadcast data to multiple clients at the cost of non-guaranteed data delivery. Figure 2.3 shows an illustration of a TiA data packet containing an EEG as well an EMG signal with different block sizes.

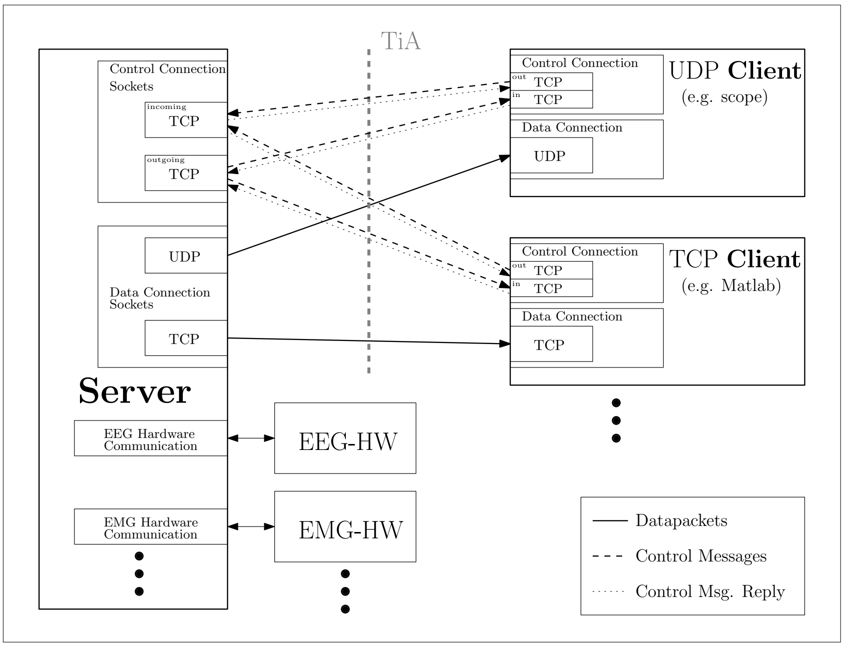


Figure 2.2.: Client–server architecture showing two clients (signal scope and Matlab [The MathWorks Inc., Natick, USA]) using TiA. A server acquires data from different devices at the same time. The communication is split into a control- and a data connection. The control connection is used to exchange messages and commands between client and server; the data connection is used to stream data from the server to a connected client. The clients between a data connection use TCP or UDP.

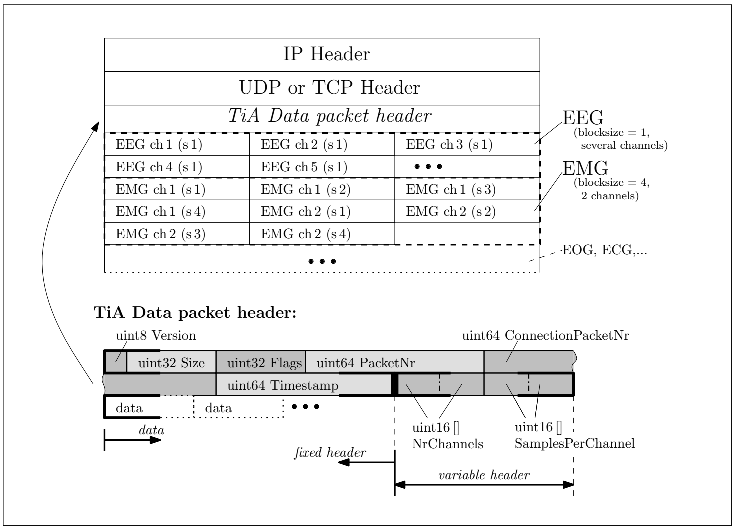


Figure 2.3.: Illustration of content from a TiA packet, showing the header and data section from an exemplary packet. EEG and EMG are presented as exemplary data. EEG ch 1 (s 1) depicts the "EEG" signal type from channel one with a block size of one. An EMG data content is shown with a block size of four.

TiA and the SignalServer were designed to meet the requirements of hBCI systems. Both thus support a broad range of biological signal types like EEG, EOG, NIRS, etc., as well as non-biological ones like signals from joysticks, buttons, trigger lines, etc. Furthermore, TiA provides the possibility for multiple clients to receive individual data streams. The clients can select the desired signal types, individual channels and can also request a downsampled data stream to save bandwidth. The TiA library as well as the SignalServer are open-source; TiA is licensed under the GNU Lesser General Public License (LGPL) and the SignalServer is licensed under the GNU General Public License (GPL).

Contribution to this Thesis:

This publication describes the protocol, the communication steps, the data packet structure and other specifications in detail. It is another step towards the common implementation platform by providing the first open-source available components. It further shows benchmarking results which indicate the low resource requirements and minimal processing time of the SignalServer and the TiA library. The memory consumption of the SignalServer is less than 2 MB and the data processing time of a data packet within the server is around 20 µs. The client needs around 10-15 MB memory, mainly depending on the buffer settings. The CPU utilization is very low; 250 channels acquired with a packet rate of 2 kHz merely consumed a maximum of 13 % of the CPU at the server and 11 % at the client on an old Intel Core2Duo 6300@1.86 GHz from 2006[2]. The transmission time from the TiA server to a connected client was around 0.2 ms on a 100 MBit Ethernet network.

[2]Specifications Intel Core2 Duo Processor E6300 *(visited on July 16 2017)*

2.1.3. Introducing a Bus-Oriented Event-Delivery System which Fulfills the Needs of Today's BCI Systems

C. Breitwieser, M. Tavella, M. Schreuder, F. Cincotti, R. Leeb, and G. R. Müller-Putz. "TiD – Introducing and Benchmarking an Event-Delivery System for Brain-Computer Interfaces." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* accepted [2017]. DOI: 10.1109/TNSRE.2017.2728199 [191]

Reliable and flexible event delivery is a crucial requirement for BCI systems. Former BCIs usually dealt with a single data stream, like EEG channels with a fixed sampling rate. The data was processed in a common processing pipeline as described by Mason and Birch [187] (see Figure 2.1). Events were frequently related to a specific sample in the raw data and also transmitted together with the raw data, for example as done by the "DataRiver" from ERICA [192].
This makes sense in common BCIs, but can introduce problems in BCIs with multiple data streams, like an hBCI which processes different signal types. Binding an event to the raw data might lead to an event duplication across the individual streams. A different processing delay of the individual processing lines would further increase the complexity to handle events. Duplicated events might arrive at different times at the location where the data streams are fused to a final result. Moreover, an event source beyond the processing line would be hard to realize.

Contribution to this Thesis:
This publication introduces a new event distribution mechanism called TOBI interface D (TiD). TiD acts in a bus-oriented manner, as illustrated in Figure 2.4. It is another viable component of the common implementation platform because it provides a system for message exchange within and even beyond the borders of a BCI system.

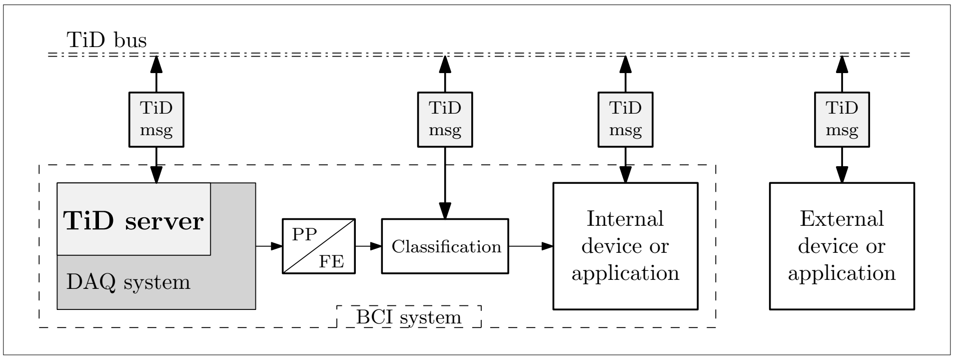


Figure 2.4.: Illustration of the TiD operating principle. A TiD message can be created by different clients like the classification module or another "internal" application within the BCI processing chain, but also from "external" applications outside the chain. A TiD message is sent to the TiD server, which dispatches the message to the clients. The TiD architecture thus operates in a bus oriented manner, where clients can subscribe freely to receive events.

Multiple clients can connect to a single TiD server. This server dispatches incoming messages to the connected clients. Shared memory and socket based transmission methods are provided by TiD. The TiD messages are based on XML to keep them extensible and human readable (e.g. for debugging purposes). The bus-oriented principle thus allows an event delivery which is detached from the common BCI processing pipe. Detailed specifications regarding the TiD architecture, and the TiD message

format are available in this publication and at arXiv.org. The TiD library is open source[3] and licensed under the LGPL.
The TiD library was extensively tested for stability and performance. Detailed benchmarking results are available in this publication. It further contains guidance values regarding damping effects which can occur when raw data is aligned on events distorted by a trigger jitter. Such a time jitter can occur and depends on the selected delivery method like a delivery over Ethernet. An attenuation of 3 dB becomes visible at frequencies around 1–3 kHz for network delivery or higher than 10 kHz for shared memory, but also depends on the chosen operating system (OS). Figure 2.5 shows a latency distribution together with a damping curve. The 3 dB attenuation in this case becomes visible at 1071 Hz, so it will not influence a common BCI system at all which relies on a standard MI or on a visual P300 paradigm, for example.

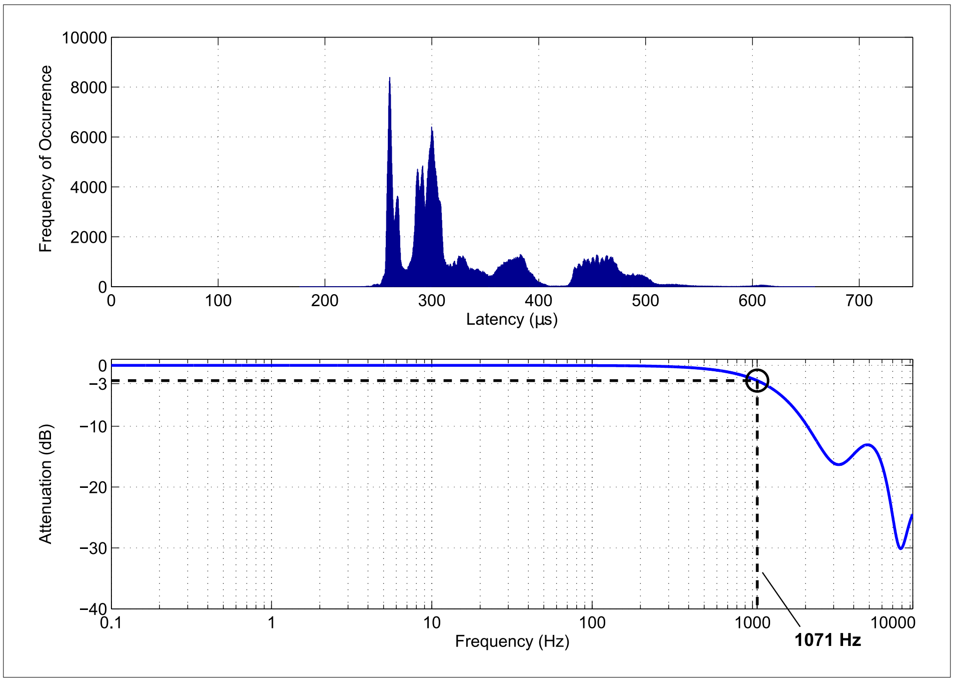


Figure 2.5.: The upper plot presents the latency distribution for 10^6 messages of a Linux server/arrangement with five connected clients. The lower plots shows the damping curve caused by the TiD latency jitter which takes place when averaging data aligned by the TiD events. A 3 dB attenuation occurs at 1071 Hz as indicated by the black dashed lines.

[3] https://github.com/tools4BCI/core (*visited on July 16 2017*)

2.2. Towards a Tactile Hybrid BCI which Utilizes the Introduced Common Implementation Platform

2.2.1. Investigating the Stability and Distribution of SSSEPs

C. Breitwieser, V. Kaiser, C. Neuper, and G. R. Müller-Putz. "Stability and distribution of steady-state somatosensory evoked potentials elicited by vibro-tactile stimulation." In: *Medical and Biological Engineering and Computing* 50.4 [2012], pp. 347–357. DOI: 10.1007/s11517-012-0877-9 [193]

This paper analyzes the stability of SSSEPs over time across multiple persons. Tobimatsu et al. and Snyder et al. described a characteristic EEG response when applying steady-state tactile stimulation. Moreover, Müller et al. [160] showed the emergence of so-called resonance-like frequencies and a tactile BCI which utilizes focused attention on a vibratory stimulus to elicit SSSEPs was successfully realized by Müller-Putz et al. [116]. However, at the time this thesis was started, additional information regarding SSSEP being used in BCIs was rare. For example, it was uncertain if these resonance-like frequencies are different across the individual fingers, or across different people, or if they are even stable over time. The existence of this kind of stability is a relevant piece of information when conducting multiple BCI sessions over an extended time window. Moreover, a different response of the single fingers might make it necessary to run individual screenings to identify an optimal stimulation frequency.

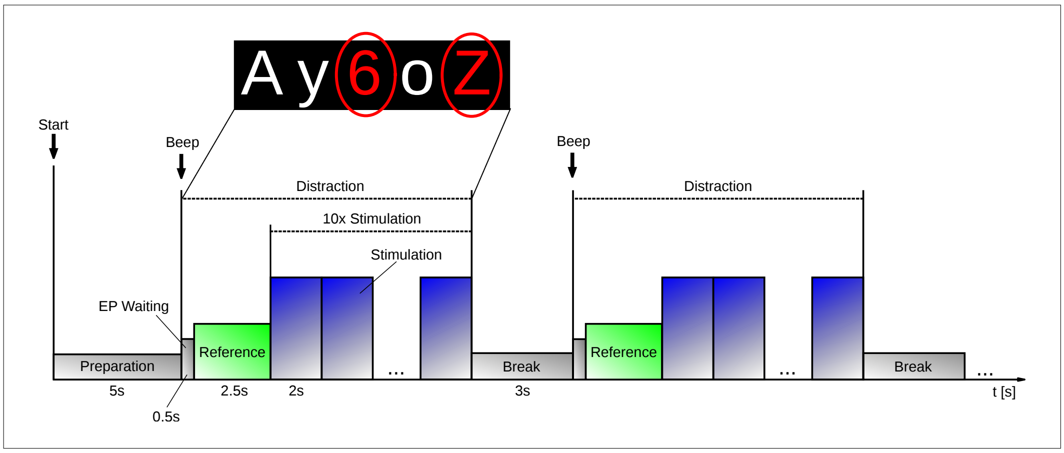


Figure 2.6.: Illustration of the paradigm used to determine the stability and the distribution of the SSSEPs. Every trial consists of a short period to wait for EPs, a reference period, and ten blocks lasting two seconds each where vibratory stimulation was applied with different frequencies. Each trial was followed by a short break. A visual distraction paradigm was presented during the trials where people had to count red-colored characters. The same paradigm was used for both sessions.

Nine subjects participated in this study (eight male, one female). The subjects' fingers of the right hand were stimulated with different stimulation frequencies from 19–31 Hz. The subjects were distracted using a counting task to avoid focusing on a specific finger during the tactile stimulation. An illustration of the paradigm sequence is available in Figure 2.6. All subjects participated in two sessions with at least two weeks between the sessions. The relative BPwr increase based on SSSEPs was individually analyzed for every single subject. It was shown that the SSSEP response was stable over time for all subjects. The tuning curves for relative BPwr increase were similar for both sessions. Furthermore, the tuning curves had a similar shape across the different fingers. Figure 2.7 shows the relative BPwr increase of all fingers for one subject from both sessions. Moreover, an analysis of variance (ANOVA) for repeated measures confirmed that the resonance-like frequencies with the highest amplitude increases were significantly different across the individual subjects.

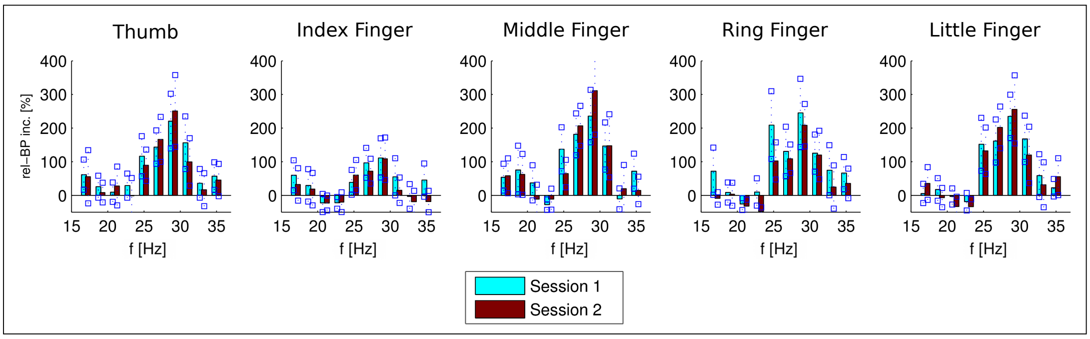


Figure 2.7.: This figure shows the relative BP increase tuning curves for one subject for different stimulation frequencies of all five fingers. The blue-colored bars show the BP increase of the first session and the red-colored bars from the second session.

Contribution to this Thesis:

This paper provides important information for running tactile BCI systems which rely on SSSEP, because it investigates the stability of the SSSEP tuning curves over time and their distribution. It answers the question, if person-dependent screening is necessary and if this screening should be repeated regularly.
Based on the results of this paper, it is recommended to perform a screening session for SSSEPs' resonance-like frequencies because the relative BPwr tuning curves are person-dependent. The screening session needs to be done only once because the tuning curves are stable over time; at least over a time period of two to four weeks. It is hypothesized that the response is also stable over a longer period of time, but this was not validated within this paper. If no screening is done for whatever reason, it is suggested that stimulation frequencies between 19 Hz and 29 Hz be used because this range showed the highest BPwr increase values across the subjects.

2.2.2. Is it Possible to Realize an SSSEP based BCI Utilizing Focused Attention on Two Fingers on the Same Hand?

C. Breitwieser, C. Pokorny, C. Neuper, and G. R. Müller-Putz. "Somatosensory evoked potentials elicited by stimulating two fingers from one hand - Usable for BCI?" In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2011, pp. 6373–6376. DOI: 10.1109/IEMBS.2011.6091573 [194]

Considering tactile BCIs where the stimulation is applied to the fingertips, a theoretical number of ten classes would be possible. However, is has to be investigated first if it is possible to realize an SSSEP based BCI where only two fingers on the same hand are stimulated. This study investigates the feasibility of such a BCI. Subject specific stimulation frequencies were determined in a screening prior to the actual measurement. The stimulation with two different frequencies was applied to the thumb and the middle finger of the right hand with a custom built tactile stimulation generator [195] using C2 tactors (Engineering Acoustics, Inc., Casselberry, FL, USA). Fourteen healthy subjects participated in this study (50 % male, 50 % female). The subjects had to focus their attention on a specific finger according to instructions presented on a screen. The paradigm sequence is illustrated in Figure 2.8. The subjects received no feedback during this study and the recorded data was analyzed after the measurements.

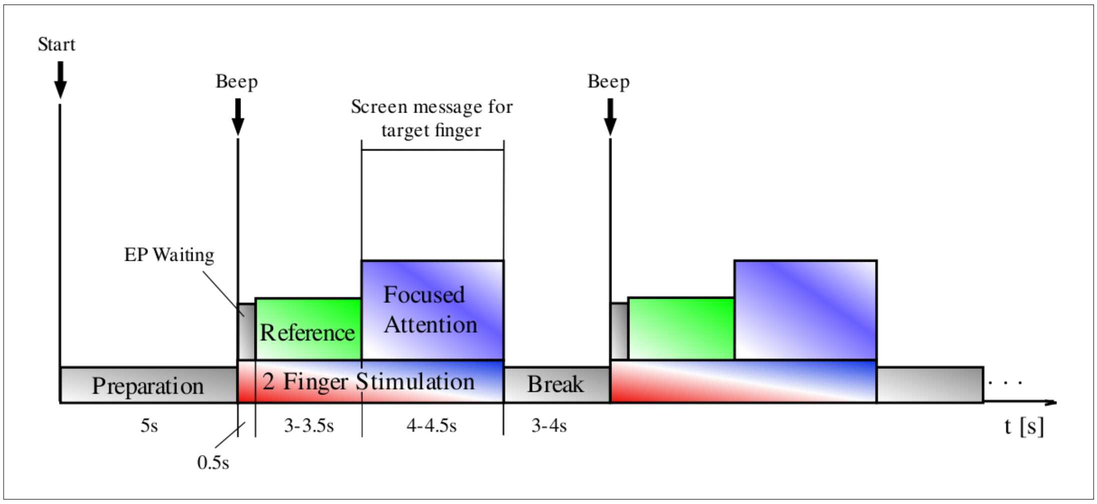


Figure 2.8.: Graphical illustration of the measurement paradigm used to determine if a stimulation of two fingers on the same hand is a feasible setup for a BCI. Every trial was introduced with an acoustic beep, followed by a short waiting period for potential EPs, a reference period, a period where the subject had to perform a focused attention task, and a short break before the start of the next trial. The thumb and the middle finger of the right hand were stimulated during whole trial with two different frequencies, that were determined in a prior screening.

Contribution to this Thesis:

This publication provides insights into the possibility of using multiple fingers on one hand as individual targets in a focused-attention based BCI. The participants were unfortunately hardly able to focus their attention on the stimulation of an individual finger.

All subjects except one achieved a classification above the chance level for at least one class (thumb or middle finger) against the reference period. The subjects were thus able to focus their attention actively on the stimulation. However, only two subjects barely reached the chance level when classifying the focused attention on the thumb vs. the middle finger. All other subjects stayed below chance, mostly around 55 %. Figure 2.9 shows the classification accuracy averaged over trials for one participant. The classification accuracies against the reference period clearly cross the chance level border at 61 %, but the classification of one finger against the other stays below chance. The experiment in this study was based on the existent components from the tools4BCI project at this time. The SignalServer was used for data acquisition of 48 EEG where a high sampling rate of 1.2 kHz was chosen as an implicit stress- and performance test. TiA was used for data transmission and a first version of the signal scope was utilized for real-time signal monitoring.

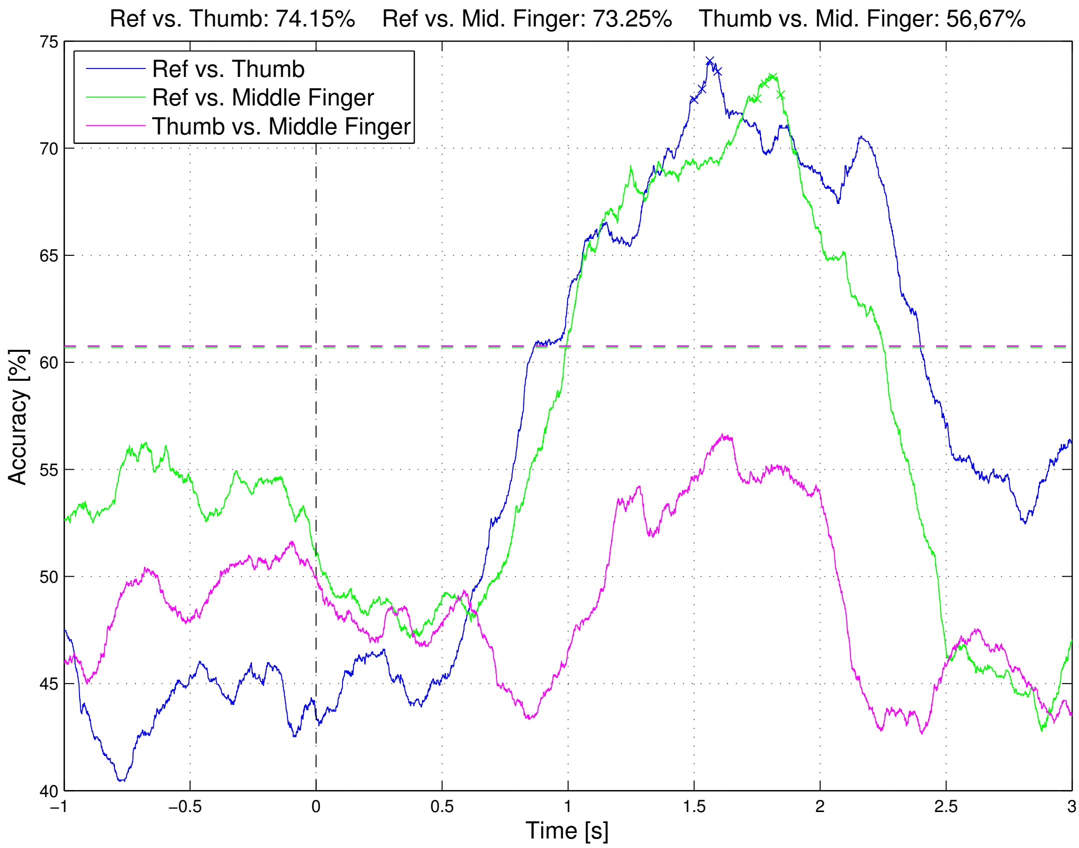


Figure 2.9.: This figure shows the classification accuracies averaged over trials of the reference period against a focused attention on one finger as well as the accuracy of focused attention on one finger against the other. The blue line shows the accuracy of thumb vs. reference, the green line middle finger vs. reference, and the magenta colored line shows thumb vs middle finger. The dashed horizontal line highlights the chance level at 61 % (significance level of 5 %, 79 trials per class [196]). The dashed vertical line indicates the start of the trial where the subjects were instructed to focus their attention on a target finger.

2.2.3. Introducing A Hybrid Three-Class BCI which is Based on SSSEPs and tERPs

C. Breitwieser, C. Pokorny, and G. R. Müller-Putz. "A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERPs." In: *Journal of Neural Engineering* 13.6 [2016]. DOI: 10.1088/1741-2560/13/6/066015 [197]

This article relies on insights gained in the former studies performed in this thesis and on the components developed for the common implementation platform. It concludes the attempts to create an hBCI based on the somatosensory system utilizing components available in the tools4BCI project. Former studies, such as that by Severens et al. [158] indicated that tactile ERP based BCIs might outperform BCI systems which purely rely on SSSEP. Severens et al. [158] conducted a study combining SSSEP and tactile tERP within an hBCI arrangement. Classifying tERP achieved higher accuracies than classifying SSSEP. However, the same "standard" stimulation frequencies were used for all subjects who participated in the study. Fourteen healthy subjects participated in this study (50 % male, 50 % female). The experiment consisted of two main parts.

In the first part, all subjects performed a screening paradigm to determine optimal tactile stimulation frequencies for the second part of the experiment. Screening was applied in the same manner as in our prior studies [194, 193]. The only difference was that the index fingers of both hands were stimulated. The fingers were stimulated with random frequencies from 17 to 35 Hz in 2-Hz steps. Every frequency was stimulated 40 times to achieve an adequate SNR for later tuning curve calculations. In the second part, the index fingers of the left and the right hand were stimulated with the two frequencies which achieved highest relative BPwr increase values during the screening. The paradigm sequence is similar to our prior study [193]. The main differences were that a third "idle" class, which represents a non-control state, was introduced and that the subjects received online feedback. Short pseudo-random twitches [160] were inserted into the steady-state stimulation paradigm to induce tERPs.

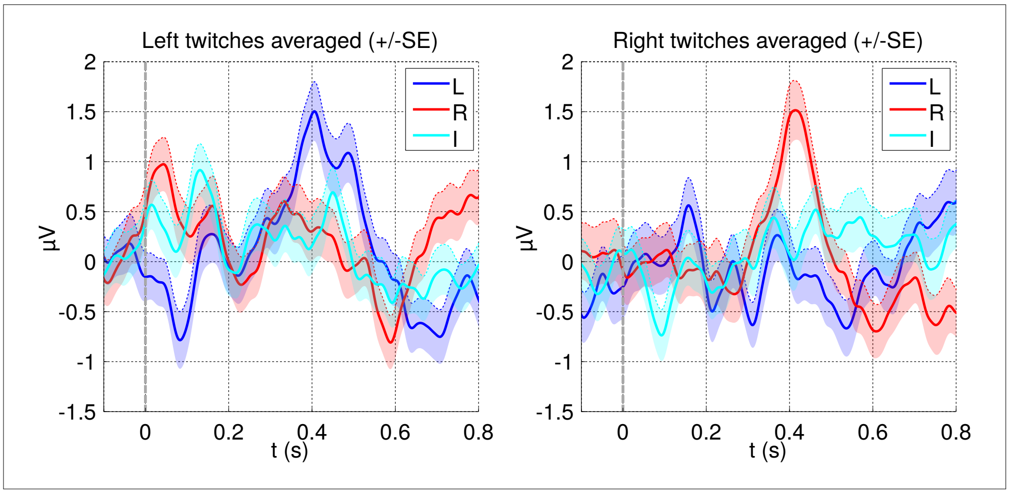


Figure 2.10.: This figure shows the tERP response of one subject averaged over trials for a target and a non-target class of channel Pz. The response to left hand target twitches is shown in the left image and the response for right target twitches in the right image. The standard error is depicted by the shaded area.

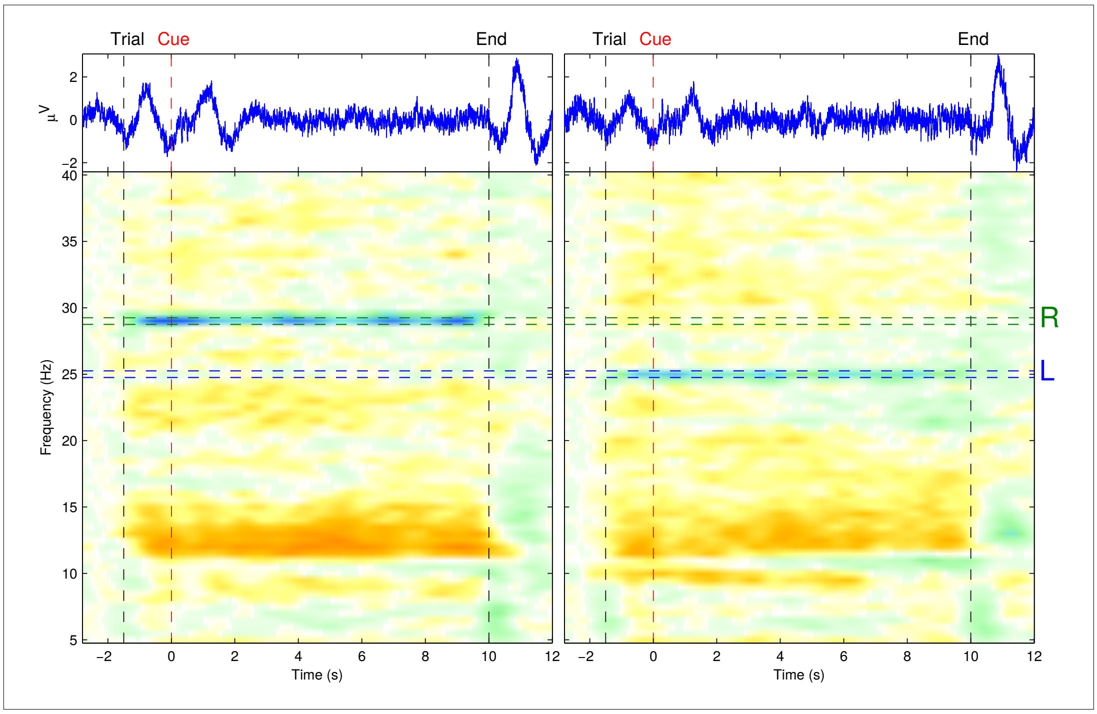
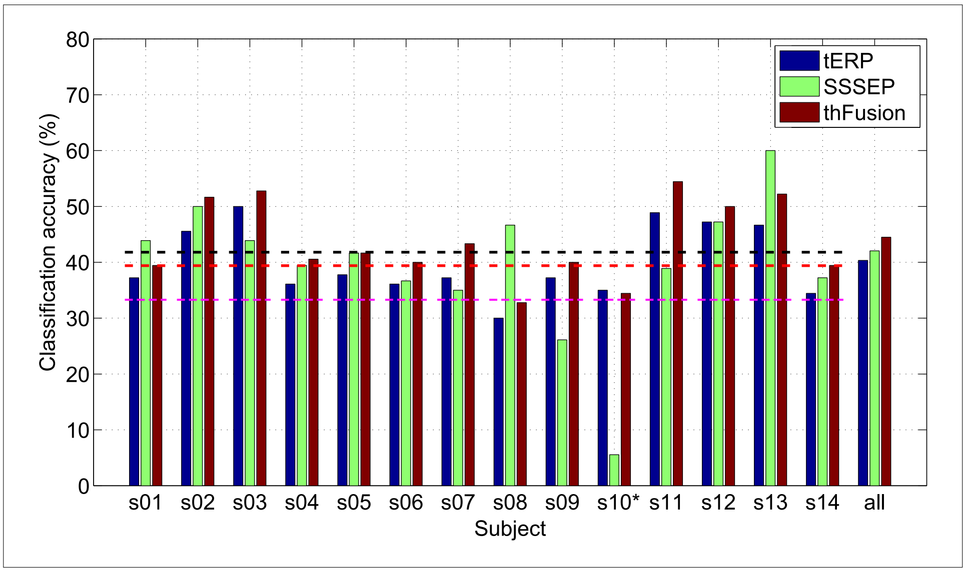


Figure 2.11.: This figure presents an averaged time/frequency map over all trials from one subject. The left part of the image shows the channel FC3-CP3 and the right one FC4-CP4. The averaged time domain signal is shown in blue at the very top. ERPs are clearly visible (due to trial start/stop or the cue).
The stimulation frequencies are shown as green and blue dashed lines. The emergence of SSSEP patterns at 25 Hz and 29 Hz are clearly visible.

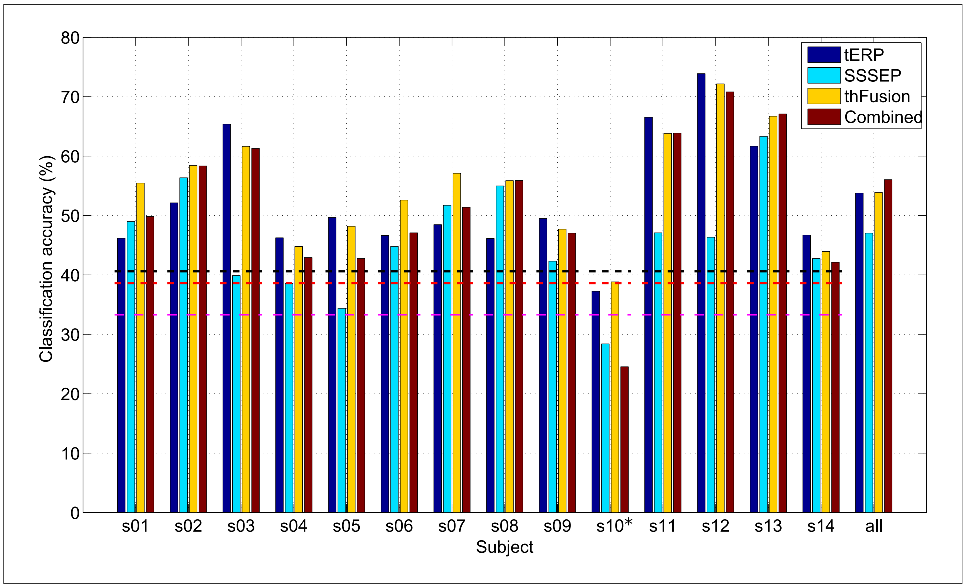
Subjects had to focus their attention either on a target finger or remain in a "rest" state without focusing on any finger. In case of a focused attention task, the subjects were instructed to count the twitches on the respective target finger. Both components (SSSEP and tERP) were classified in parallel during runtime and in succession fused to a final result utilizing a threshold-based fusion. The successful emergence of a tERP, induced by the twitches, as well as the formation of a stable SSSEP pattern can be seen in the Figures 2.10 and 2.11. The recorded data was also analyzed offline. Another fusion strategy was tested in the offline analysis. This combined fusion combines SSSEP and tERP into one feature vector, which was in succession classified by a shrinkage LDA classifier. Moreover, because the initial number of features was different between SSSEP and tERP, a feature balancing was accomplished by introducing additional features for SSSEP.

The final results for the online paradigm and also for a later offline analysis, considering all recorded data, are shown in Figure 2.12. As visible, fusion achieved better results in most cases than classifying a single modality. Additionally, fusing the data with a combined classifier achieved highest results. Statistical analysis, done with two ANOVAs for repeated measures, revealed that a combined classification achieved significantly higher accuracies than the classification of a single modality. However, for individual subjects (like s03 or s12 – see Figure 2.12b), classifying tERP alone resulted

in a higher accuracy than any fusion. Most likely because SSSEP only reached accuracies just above chance and thus had a negative effect on the final fusion. Moreover, it became visible that different modalities might be better suited for certain class-types. The SSSEP classifier reached significantly higher classification results for the idle class than the tERP classifier ($p<0.00001$).
By contrast, the classes related to a focused attention were detected with a higher accuracy by the tERP classifier. Furthermore, it became apparent that subjects with a higher relative BPwr increase in the screening session also achieved higher classification in the online experiment.



(a) Online classification accuracies for tERP, SSSEP and threshold based fusion.



(b) Offline classification accuracies with feature balancing for tERP, SSSEP, threshold based fusion, and combined fusion.

Figure 2.12.: These figures show the classification accuracies for all subjects from the online experiment and for a later offline analysis with feature balancing. The rightmost bars represent the accuracies averaged over all participants, except s10. The red dotted line indicates the 5 % chance level, the black dotted line the 1 % chance level and the theoretical chance level of 33.3 % is indicated by the black dotted line.

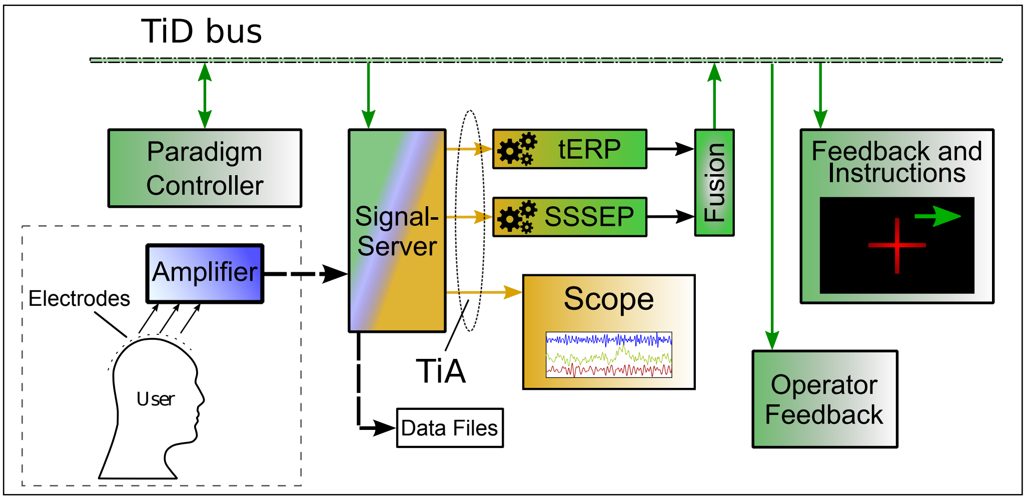


Figure 2.13.: This figure illustrates the measurement system showing all connected components. Raw data was acquired by the SignalServer and forwarded to the subsequent processing modules (tERP and SSSEP) using TiA. An online scope was used for raw data inspection during the measurement. The processed data from the tERP and SSSEP modules was fused to a final result by the "Fusion" module. This final result was distributed via the TiD bus. A paradigm controller was in charge of the measurement sequence. Events to control the measurement (e.g., visual cue, acoustic beep. . .) were sent at appropriate points in time. Modules connected to the TiD bus reacted on events, like the "Feedback and Instructions" module which showed the respective cues upon an event arrival. An "Operator Feedback" was displayed to the measurement operator to observe the measurement sequence. The SignalServer saved incoming events together with the acquired raw data in a data file for later analysis.

Contribution to this Thesis:

The experiment utilized all existing components from the common implementation framework and brought together the findings from the other studies introduced in this thesis. With this experiment, the final goal of a tactile hBCI system which uses the common implementation framework and which was built on exchangeable components was reached.

The individual components and how they were connected are shown in Figure 2.13. With this article, the successful setup of a tactile hBCI system was presented. Furthermore, it was demonstrated that classifying SSSEP can achieve comparable results to classifying tERP. Additionally, this experiment can be seen as a reference setup for the common implementation platform as it utilized all existing components available in the tools4BCI project.

2.3. Additional Publications

2.3.1. Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI

G. R. Müller-Putz, C. Breitwieser, F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. d. R. Millán. "Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI." In: *Frontiers in Neuroinformatics* 5.November [2011], p. 30. DOI: 10.3389/fninf.2011.00030 [165]

This paper introduces a concept for hBCI systems. The presented concept relies on the interfaces and the structure of the common implementation platform presented in this thesis. This publication presents a prototype system, showing the individual components of the hBCI interacting with each other. Data fusion and shared-control concepts are also introduced in this paper to pave the way for new BCI systems. These new types of BCIs can deal with multiple signal streams and are also able to integrate external information provided by smart sensors or intelligent devices such as robots for example.

2.3.2. BCI Software Platforms

C. Brunner, G. Andreoni, L. Bianchi, B. Blankertz, C. Breitwieser, S. Kanoh, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, G. R. Müller-Putz, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, and G. R. Müller-Putz. "BCI Software Platforms." In: *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*. Ed. by B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. Chap. BCI Softwa, pp. 303–331. DOI: 10.1007/978-3-642-29746-5_16 [198]

This book chapter provides an insight into existing BCI software platforms. A brief overview of the individual systems is provided and the strengths and limitations of the individual platforms are discussed.

3. Discussion

3.1. Overview

The overall goal of this thesis was the creation of a multimodal tactile hBCI system which utilizes different signal modalities, namely tERP and SSSEP, processes them in parallel at runtime, and fuses them together into a final result. Common BCI systems, the Graz BCI included, were not capable of fulfilling the needs of hBCI operations necessary to achieve the desired goal. For this reason, a general framework to interconnect individual BCI components was developed. These components were required to be easily exchangeable and also follow a common concept to establish a common ground for generalized BCI data exchange. To realize this goal, a common implementation platform was developed, which is now freely available under the tools4BCI project. In parallel to the development of components for tools4BCI, studies to extend the knowledge around tactile BCIs were conducted. This work was then merged together in a final hBCI study, realizing a tactile hBCI system with multimodal fusion.

The contributions of this thesis can thus be summarized as follows:

- Design of an architecture for modular BCI data exchange
- Creation of the common implementation platform
- New insights on the stability of SSSEP over time and on the meaningfulness of a screening for resonance-like frequencies in SSSEP
- Strategies how to fuse SSSEP and tERP in a tactile hBCI
- New general insights on SSSEP and tERP as features in tactile BCIs

3.2. Common BCI Communication and Interaction

As mentioned in the introduction, the first BCI was developed in the 1970s by Vidal [10]. However, for a long time hardly any further BCI research was conducted, until the subject saw a rise in popularity in the 90s. Leading researchers at the time included, among others, the groups around Wolpaw et al., Pfurtscheller et al., or Birbaumer et al. Since this time, BCI research has evolved and new fields have been discovered. However, also environmental conditions have changed as well. In the early days, computers were rare and expensive; data being stored on punch cards was daily business. Later on, analog data recordings were used and it was possible to store some hundred bytes, maybe some kilobytes of data. Nowadays, storing terabytes is not a problem at all; this is an increase of 10^9! Also the way we use computers has changed drastically. In former days, multiple people usually shared one computer; nowadays it has become common for one person to own more than one PC. Even our mobile phones are more powerful than the computers used to control the first space rockets.

All these changes also affected BCI research, BCI systems, and their architecture.
At the time this thesis was started, two "major" BCI systems were publicly available: BCI2000 [177] and OpenViBE [179]. Moreover, other BCI systems or frameworks like xBCI [175], rtsBCI [174], or FieldTrip [176] existed as well. These systems and frameworks were mostly developed by a single laboratory and less widespread than BCI2000 or OpenViBE. Generally speaking, the majority of BCI systems and frameworks at that time were built in a monolithic manner. Features to exchange data or to interact with other systems were mostly unavailable. However, the trend in information technology (IT) has been shifting more and more towards small interconnected systems which are easily deployable and scalable. This trend is reflected in systems like docker [199] and the ongoing emergence of software as a service (SaaS) systems. Generally speaking, software tasks which were formerly performed on a single computer and in a single application are becoming increasingly distributed. These trends also influence BCI research and the development of BCI systems. Research cooperation has become part of daily business, as in the large scale EU project TOBI for instance. Many different laboratories worked together on one project, but individual labs had a different research focus. This research focus led to different BCI systems which were partly incompatible with each other. The common implementation platform developed in this thesis shows and provides approaches to realize an integration between different systems. It provides mechanisms to connect different BCI systems or their components. The core idea in the common implementation platform was to establish well defined interfaces between individual components rather than specifying or replacing the "modules" (like data acquisition or classification) themselves. This approach carries the advantage that existing systems can still be used, but would gain compatibility to other systems which also fulfill the interface definitions. It also has the benefit being reusable by other people; the burden to "reinvent" the wheel would disappear. In times of agile software development, reusability is crucial to speeding up development.
The interfaces designed in this thesis were required to introduce a common data exchange at the following steps in the BCI processing chain: (i) between data acquisition and pre-processing, (ii) between classification and subsequent application modules, and (iii) between all modules to exchange meta information on an event basis. These interfaces and their general intention are further discussed in more detail by Müller-Putz et al. [165]

The following interfaces were developed as a result:

- **TiA:** For raw data transmission [190]
- **TiC:** To transmit classification results *(this interface was designed in this thesis, but developed together with Michele Tavella from École Polytechnique Fédérale de Lausanne (EPFL))*
- **TiD:** For event delivery between modules [191]

Different tools [165], important for operating a BCI, were developed as well:

- **SignalServer:** The SignalServer provides a cross-platform data acquisition system which is able to acquire data from multiple devices at the same time. It supports data transfer via TiA and also includes a TiD server for event dispatching. Acquired data can be saved to gdf files using libgdf [1]. Events are aligned to the acquired data and can be stored together with the acquired data in a gdf file.

[1] `https://github.com/mbillingr/libgdf` *(visited on July 16 2017)*

- **TiA Scope:** The TiA scope provides a monitoring tool for real-time data visualization [200]. It is able to receive data via TiA and visualize this data for real-time inspection. The TiA scope is built upon the Qt framework [2] and is thus cross-platform compatible. Many thanks go to Christoph Eibel for implementing the scope and to Reinmar Kobler for feature extension.
- **Python and Matlab bindings:** Different language bindings for the individual libraries are also available. The TiA library provides a wrapper for Matlab and Matlab Simulink. Furthermore, Python, Matlab, and Matlab Simulink wrappers are provided within the tools4BCI core library package. Many thanks go to Martin Billinger, Max Sagebaum and Michele Tavella for their assistance.

The aforementioned libraries provide the methods to interconnect different BCIs or individual modules. Due to the real-time requirements of BCI systems, the processing as well as the data transmission have to be done in a minimal amount of time to avoid violations of real-time constraints. The TiA as well as the TiD library were tested in great detail to obtain an estimate of their resource requirements and their timing behavior. In the case of TiA, which is designed for raw data transmission, an efficient data model with a binary packet structure was chosen to reduce the data overhead. The packet header of a TiA packet is just 33 bytes long. Assuming a maximum transmission unit (MTU) of 1500 bytes for Ethernet and 40 bytes overhead for TCP/Internet Protocol (IP), 1427 bytes remain for dynamic signal data, with a minimal overhead of just 4 bytes per signal type. A single TCP packet, transferred in a single Ethernet frame, can thus transmit data from 355 channels (single precision), resulting in a high transmission efficiency. Furthermore, the transmission delay of a TiA packet amounts to approximately 150 µs. Considering these values, a data packet from a BCI setup with 256 channels, 6 kHz sampling rate, and a block size of one, would still contain all channels and will arrive at the client before the next sample is acquired. Additionally, the resource footprint of the TiA server as well as the client is minimal (less than 15 MB – mainly dependent on buffer size settings). This facilitates operation on devices with limited resources such as Raspberry Pis or other embedded systems.
Considering TiD and event processing, minimum transmission delay and minimum delay jitter are important requirements. Transmission efficiency is a negligible requirement because events mostly occur at a lower rate than the raw data is acquired. However, events have to deliver flexible data content to a multitude of clients. Moreover, these clients might not be connected to the common BCI processing pipeline. The TiD interface, which is responsible for event delivery, was thus designed in a bus-like manner. Clients can subscribe to the event bus freely. XML was used as an event delivery format due to a vast amount of libraries which are able to parse XML. Furthermore, it is possible to extend XML messages without violating backwards compatibility. In depth tests of the TiD framework showed an approximate transmission delay of around 400-800 µs (client to client via the TiD server). The 3 dB signal attenuation when averaging trials aligned by TiD events becomes visible at different frequencies. These frequencies are mostly dependent on the underlying transmission method and the operating system. For example, the 3 dB edge frequency is located at 1 kHz for a GBit connection and homogeneous Linux or Windows environments. It is even beyond 10 kHz when running the server on Linux and the clients on Windows. In case of shared memory (SHM) operations, the transmission delay is reduced to around 50-80 µs with a 3 dB edge frequency at 4–10 kHz, mainly dependent on the number of clients attached to the SHM.

[2] https://www.qt.io (*visited on July 16 2017*)

These results show the applicability of the implemented interfaces for BCI systems and ensure that the data or event transmission does not violate real-time requirements of common BCI systems. Adding these interfaces to the respective components of an existing BCI system would make them compatible and exchangeable with other systems using the same interface.
One intention of this thesis was thus to establish a common ground to interconnect components from different BCI systems with each other. To provide certainty that the interfaces do not hamper existing BCI operations, the created framework was tested intensively. Furthermore, the whole framework is open-source available [3]. The SignalServer is licensed under the GPL; all libraries are licensed under the LGPL. The framework can thus be used and extended freely.

3.3. Usability of Somatosensory Evoked Potentials for Brain-Computer Interfaces

Investigating tactile BCIs, mainly based on SSSEP, was another main topic of this thesis. At the time this thesis was started, knowledge regarding tactile BCIs, and especially regarding SSSEP based BCIs was still rare. Snyder [93], G. Müller et al. [160], the groups around Tobimatsu et al. [94, 95], or around Adler or Giabbiconi et al. [157, 96, 141] had already gained valuable knowledge regarding the involved brain areas or tuning curves. This knowledge was finally brought together by Müller-Putz et al. [116] in a study showing the feasibility of SSSEP for BCI systems where one subject even reached a classification rate of 84 %.
However, compared to the vast number of studies in the fields of MI, P300, or SSVEP based BCIs, there were few works on tactile BCI systems, especially those based on SSSEP. Certain similarities exist between the latter and the well-established field of SSVEP related BCI research, like the possibility to modulate the EEG amplitude through focused attention on a certain stimulus. However, the underlying physical system and the neural pathways or the involved brain regions are completely different and certain characteristics remained unexplored.
For example, at the time this thesis was begun, it was unknown if the tuning curves introduced by G. Müller et al. [159] are stable over time – an essential factor for operating a BCI system. It was also uncertain if the remaining fingers would show a similar tuning curve or not. An individual screening for every finger might thus be necessary. In the worst case, if the response changes over time, it could become necessary to perform a screening in regular intervals to keep pace with the changes.
The first paper investigates the stability and the distribution of SSSEP tuning curves and resonance-like frequencies. It was confirmed that the tuning curves are stable over time; at least for a time window of several weeks. We further showed that these curves are similar over all fingers and different across individuals. We also confirmed the findings by Snyder [93] that the resonance-like frequency is around 25 Hz. Results from the last study in this thesis showed that subjects who had a higher relative BPwr increase also achieved better classification results. It is thus hypothesized that screening for optimal stimulation frequencies is a necessary step to operate an SSSEP based BCI with optimal parameters. Stimulating with a non-optimal frequency might lead to deteriorated classification results because of the relation between the relative BPwr increase and the classification rate.

[3] `https://github.com/tools4BCI` *(visited on July 16 2017)*

An important characteristic value of BCIs is the ITR, which is also influenced by the number of classes being used. Increasing the number of classes which a BCI is able to recognize can boost the ITR. Utilizing focused attention on individual fingers could significantly increase the ITR. In theory, a two classes BCI could become a ten classes BCI. The second tactile BCI related study (see section 2.2.2) investigated a first step towards this goal in more detail. Subjects performed a focused attention task, switching their attention to either the thumb or the middle finger on the same hand. The attempt using different fingers on one hand unfortunately did not turn out to be a fruitful methodology. The classifier was able to detect if the participant focused his/her attention on any finger or if he/she did not. However, it was hardly possible to identify the individual target finger. A potential reason might be related to the receptive fields of the somatosensory receptors. Participants reported in the related study that it was hard to shift the attention on the stimulation of a specific finger. This could be related with the fact that especially Pacinian corpuscles have large receptive fields, which are stimulated by the 200 Hz carrier. It is hypothesized that such a carrier might even hamper such a paradigm where multiple fingers from one hand are stimulated. Moreover, Severens et al. [97] showed a significantly larger interaction ratio (IR) when stimulating adjacent fingers compared to stimulating distant fingers. This indicates that stimulating multiple fingers on one hand causes a certain sensory interaction. However, the IR was not analyzed in the study accomplished in this thesis. The fingers (thumb and middle finger) might have been too close together and a stimulation of, e.g., the index finger and the little finger might have brought different results. This remains an open question. A single EEG electrode further records the activity of a large population of neurons. The spatial resolution of the applied electrode setup might not have been sufficient. The SNR of an amplitude increase due to focused attention could thus have been too low for a classifier. The bipolar channel FC3–CP3 was used for classification in the present study to obtain comparable results with the work from Müller-Putz et al. [116], who also used such a combination. The influence of a different channel setup is therefore still an open question. More advanced spatial filters like CSP [102, 103] can improve the class separability and increase the classification rate [201] and would thus be a reasonable future step.

Various other parameters which could influence the performance of tactile BCIs also remain rather unexplored.

Stimulator position and stimulation locations: The stimulator position and the number of parallel stimulation locations might influence the results. The stimulators are placed on the fingertips in most studies. However, a placement on other body parts (as done by Brouwer and Erp [85] or Herweg et al. [202]) was rarely mentioned in literature. Moreover, multiple (maybe close) body locations (e.g., fingers) could be stimulated in parallel with the same pattern. This could increase the classification accuracy, because a larger brain area would be involved, increasing the SNR in succession. Even the body posture can have an influence on the tactile discrimination [203] and, in turn, on the classification rate. Investigating such influences in more detail might thus be a reasonable endeavor for future studies.

Stimulation amplitude and stimulation pattern: The stimulation amplitude could also have an impact on the classification rate. The individual mechanoreceptor types react to different stimulation frequencies, as discussed by Kandel et al. [140], and thus

influence the emergence of SSSEP tuning curves. However, an effect of the stimulation amplitude on the classification accuracy, especially in case of steady-state stimulation, has not been explored so far.
Moreover, the stimulation pattern itself can have an influence on the classification rate too. Adler et al. [157] showed in their studies that the SSSEP amplitude significantly increases under conditions of high perceptual load, as in the case of a target stimulus which is difficult to perceive. Furthermore, G. Müller et al. [159] investigated the influence of different stimulation characters (sinusoidal, rectangular, and triangular) on SSSEP and showed a maximum SSSEP amplitude for rectangular stimulation patterns. However, the influences on the classification rate of different stimulation patterns (hard or simple to perceive), their characteristics (rectangular, sinusoidal, the duty-cycle of a rectangular pattern, etc.), or the stimulation amplitude, as discussed above, are unknown. Sutter [204, 205] presented a very interesting approach of a stimulation pattern called "m-sequence". The concept behind SSSEP is similar to frequency division multiple access (FDMA) and tERP to time division multiple access (TDMA). In contrast to the two other systems, the m-sequences rely on a code division multiple access (CDMA) approach [206]. Such an m-sequence based BCI has already been successfully tested in the visual domain [207, 208, 209] and outperformed common SSVEP based BCIs. Utilizing an m-sequence based tactile stimulation pattern might be a reasonable next step.

Stimulation device: The stimulation device can further influence the BCI performance. Different kinds of stimulators were used in the available literature. These stimulators range from magnetic ones (like the "C2" tactors used in this thesis [194, 197]), over Braille stimulators (as used by Severens et al. [97, 158]), to mechanical stimulators (as used by Giabbiconi et al. [141, 96]). Even pneumatic stimulators exist, which are designed to meet the requirements for MRI studies [210]. All these stimulators have different characteristics (applied force, linearity, harmonics, . . .) and could therefore also elicit a different cortical response. It is still an open question if a specific stimulator type is an optimal choice to elicit SSSEP or tERP or if it is irrelevant which type of stimulator is used.

Training: BCI training can have an effect on brain activation patterns [211] in case of MI based BCIs [212] and increase classification accuracy [9]. This also applies to auditory BCIs [213, 214], or to tactile ERP based BCIs [202, 215]. Training might thus also increase the classification accuracy of the tERP component of the BCI. However, it is unknown if BCI training also significantly increases classification of the SSSEP component, but it seems to be very likely. Preuschhof et al. [216] could show that the neural activation was significantly higher in conditions where subjects already had tactile memory compared to naive ones.

Involved brain areas: As shown by Giabbiconi et al. [141], sustained spatial attention to vibratory stimulation is mediated in the primary somatosensory cortex. In contrast, the secondary somatosensory cortex seems to be involved as well when performing a tactile attention task [217, 142]. In this thesis, merely bipolar channels have been used. As already discussed, CSP might increase the classification accuracy. Using more advanced spatial filtering techniques as beamforming [218] or source localization methods [219] might be meaningful in this case, because the involved regions are located deeper in the brain and thus won't have a SNR as high as from signals which originate directly from the primary somatosensory cortex. Because different brain areas are involved when processing a tactile stimulation, the connectivity [115] between these brain areas could be used as an additional feature. Such connectivity measures were already successfully applied in case of MI [113, 114] or SSVEP [16] based BCIs.

Twitches: The twitches applied in the studies in this thesis were introduced to assist the subjects in the attention modulation task when focusing on a specific stimulation. However, these twitches might have had negative effects as well. Briefly summarized, a so-called twitch [116] is a short amplification or attenuation of the steady-state tactile stimulation. Such twitches can further be used as a second input channel. It might even be possible to detect so-called "blocking features" [220] and use them as features in a BCI. However, these twitches interrupt the steady-state stimulation for a short time and could thus hamper the emergence of a stable SSSEP pattern [146]. The twitches could thus be beneficial to boosting BCI performance, but they could also reduce the classification rate. Influencing factors like an optimal shape or pattern of a twitch, an optimal length or duty cycle, a meaningful time between twitches, or a parallel stimulation with two stimulators, where one applies a vibratory stimulus and the other one creates the twitches, are open questions.

Habituation to somatosensory input: Another issue that might hamper tactile BCIs could be related to an inhibition of afferent tactile pathways. An example would be putting on ones socks. At the beginning, the person still feels the socks, but after a while, the signals are inhibited. Such sensory gating and inhibition inhibits the response to irrelevant external stimuli, which is an essential part of the overall cognitive system [221]. The pulvinar nuclei in the thalamus seems to play a major role, deciding which signals reach the somatosensory areas of the brain and which are inhibited [222]. A tactile stimulation over a prolonged time might therefore be inhibited or at least attenuated.

Person specific influences: Another important aspect which might influence overall BCI performance are individual differences. It is already known that people show different tuning curves when applying vibratory tactile stimulation [194]. However, the involved persons were randomly picked. Herweg et al. [202] investigated an interesting aspect where participants with normal vision and blind people performed the same tactile BCI experiment. It turned out that the blind subject group achieved better results than the other. These findings are also in line with the findings from Burton et al. [223, 224]. They determined an additional activation even in parts of the occipital cortex in the blind subjects group when performing sensory tasks. It would be interesting to know if an increased mental activity or a higher EEG amplitude response would also occur in people who need higher tactile and sensory skills – like piano players, for example.

3.4. Hybrid Brain-Computer Interfaces based on Tactile Stimulation

The last major part of this thesis was the setup of an hBCI system which involves tactile stimulation and combines multiple processing streams to a final result. This hBCI was further required to utilize the components developed in the common implementation platform. An hBCI can use different strategies to merge processing streams to a final result. One attempt is to switch between individual input channels, e.g., if the signal quality of one channel becomes worse [167]. In another attempt, the results of the individual input streams can be fused together to a final result. Various strategies are already presented in literature how the results from hBCI processing streams can be fused. These examples encompass fusing different tactile modalities [158, 225], fusing the input from an EEG based BCI with EMG [169], fusing MI with electrocardiogram (ECG) [226] or with P300 [227], or combining SSVEP with P300 [228, 229]. Moreover, Fazli et al. [230] presents and reviews different data fusion techniques for SMR based BCIs.

The hBCI developed in this thesis followed the second approach, fusing SSSEP with a tactile tERP. In contrast to the findings of Severens et al. [158], it was possible to classify SSSEP above chance in this thesis. As discussed above and also mentioned by Severens et al., a potential major influence might have been the selection of person dependent stimulation frequencies. Nevertheless, Severens et al. [158] showed that an SSSEP component which is classified at the chance level hardly affected the final hBCI performance. This is in line with the findings in this thesis or with the findings from, e.g., Allison et al. [171].

In case of the hBCI in this thesis, the mental workload for the subject is the same compared to a standard SSSEP or tactile tERP BCI based on attention modulation and uses only one modality. Combining different experimental strategies to hybrid systems is thus a reasonable step. An hBCI can increase classification accuracy or can also ensure the BCI functionality if an input stream deteriorates.

Moreover, different fusion strategies can significantly increase the classification results, as shown in this thesis [197]. Comparing the "combined fusion" with the "threshold based fusion", the combined approach outperformed the other. Considering the second approach in more detail, it became visible that the threshold based fusion approach using a probabilistic generative model [121] had a preference for one class; in this case for the tERP class. This happened due to a different number of features being used by the two classifiers. When applying fusion principles, the fusion approach thus has to be picked with care to avoid effects such as the mentioned one.

Generally speaking, tactile BCIs can have advantages compared to other BCI strategies. In most BCIs which use the visual system, the user needs to focus his view on a certain stimulus, which requires muscular activity. However, some approaches exist which do not require muscular activity. Nevertheless, in the vast majority of vision BCIs, muscular control is mandatory. No muscular activity is needed in tactile BCIs in every variant. Nevertheless, subjects reported it is hard to focus on a single stimulation and it is even harder to focus on individual fingers. Current tactile BCI approaches are thus limited in the maximum number of classes they can identify and thus also have a low ITR compared, e.g., visual P300 BCIs.

3.5. Relations to the State of the Art

Nowadays, most tactile BCIs rely on tERP features and an oddball paradigm. BCIs which utilize steady-state signals are rare and seem to cause troubles. As described by Severens et al. [158], classifying ERP resulted in a higher accuracy than classifying SSSEP, which was hardly above chance for multiple subjects. Also in the BCI system introduced by Müller-Putz et al. [116] only one subject reached excellent results. The others were close to the chance-level as well. In contrast, successful tactile tERP based BCI setups were demonstrated by Brouwer and Erp [85] or Herweg et al. [202], for example. This thesis contributes to the current state of the art by showing a successful BCI setup where the SSSEP modality also performs above chance. One of the main differences to other studies was the screening for person dependent resonance-like frequencies. Screening measurements were conducted for all subjects who participated in experiments in this thesis. The assumption in this thesis is that the selection of stimulation frequencies needs to be done for every person individually. The very first study showed individual tuning curves and also person dependent resonance-like frequencies [194]. Moreover, subjects who showed higher relative BPwr increase values also achieved higher classification results in a BCI experiment [197]. However, first results from another study accomplished in this thesis did not show any significant correlation between the BPwr and the classification accuracy [231]. Nevertheless, these results might stem from an insufficient number of subjects..

In any case, it is currently unknown if selecting an optimal stimulation frequency is necessary to reach classification results significantly better than when using standard frequencies like 23 and 26 Hz. Many things point to a relationship between the relative BPwr increase and the classification rate of SSSEP features. As already mentioned, Severens et al. [158] could not reach classification rates above chance for their SSSEP component with standard frequencies. In their discussion, they also hypothesized that this might be related to the fact that standard frequencies were used. In contrast, a classification above chance was reached in this thesis for the SSSEP component too [197]. It is thus strongly suggested to screen subjects for an optimal tactile stimulation frequency to achieve reasonable classification accuracies.

At the current state of the art, the functionality of tactile BCIs for patients is unfortunately not fully proven. Severens et al. [232] compared a spelling task using a Hex-O-Spell paradigm [233] with a tactile speller. The ALS patients achieved results around 77 % with the Hex-O-Spell paradigm, which is above the suggested level of 70 % by Kübler et al. [51]. However, only a 66 % classification accuracy was reached with the tactile speller. The results are thus lower than the ones which were achieved with a visual speller for ALS patients with minor disabilities (92 % accuracy [234]), or with major disabilities (79 % accuracy [235]). Mak et al. [236] showed that ALS patients can even achieve a 100 % accuracy using a visual P300 speller. Kaufmann et al. [237] compared the visual, the tactile, and the auditory modality with each other in a case study with a locked-in patient. In contrast to the findings of Severens et al., Kaufmann et al. showed the feasibility of a tactile BCI for a patient who did not profit from a visual BCI. The usability of tactile BCIs for potential end-users looks promising, as demonstrated by Kaufmann et al. [237], but is thus still a rather unexplored field.

Spitzer et al. [134] showed a very interesting phenomenon in their paper: an oscillation which emerges after a tactile stimulation, but which occurs in a different frequency range than the tactile stimulation itself. Yao et al. [161] turned this approach into a tactile BCI utilizing the aforementioned oscillation. They finally created an hBCI system by combining an MI task with the approach mentioned before. Furthermore,

Yao et al. [162] showed a successful BCI setup based on SAO (Somatosensory Attentional Orientation), which does not require any tactile stimulation anymore. These are different strategies for potential hBCI setups utilizing the somatosensory system.
However, there is still a multitude of other possible combinations. For example, up to now, the blocking feature has only been investigated by Xu et al. [220] for BCIs based on the visual domain and further by Pokorny et al. [146] for tactile BCIs. An hBCI system, combining this blocking effect with other modalities would thus be a reasonable next step. Investigating if the blocking affect still occurs in case of a parallel stimulation, applying vibratory stimulation and the twitches separately, could be another future direction. Moreover, bringing hybrid tactile BCIs and MI BCIs together, for example, as an MI, tERP and SSSEP based hBCI, would be another possible combination which even uses three modalities. However, at this point it is unknown if the workload for the subject would be still bearable. Nevertheless, Adler et al. [157] demonstrated that the EEG amplitude increases in case of high perceptual load. A high workload might thus even contribute to an increased classification rate, but this is just hypothesized.

Considering the common implementation platform introduced in this thesis, it is one step towards a common communication protocol. P. Brunner et al. [186] have already criticized the lack of standardization among BCI systems. The interfaces provided by the tools4BCI platform could introduce compatibility within different BCI tools and thus facilitate and speed up research. LSL [238] provides another approach to interconnect distributed BCI components with one interface. The underlying principle resides on multiple data sinks and sources, called "inlets" and "outlets", which synchronize the timing between the individual connected clients and continuously trace the network delay. The whole LSL project is publicly available on GitHub[4] and licensed under the MIT license. It can thus be used and extended without any restrictions. Moreover, the project is still highly active with regular commits. However, a brief latency benchmarking of LSL and TiD carried out recently revealed that events, delivered by TiD, reach the even sinks earlier than packets, delivered by LSL under the same conditions. It is thus upon the BCI developer to choose the right protocol and to decide how crucial fast event delivery is.
Another approach, the so-called "DataRiver", presented in "ERICA" [192], utilizes a centralized data flow, which is more similar to the common BCI processing pipeline. This implicitly removes synchronization issues, because data and events are transmitted in one stream. However, this makes an interaction with external event sinks which are not connected the data stream more difficult. Another popular framework used in MRI and BCI research is "FieldTrip". This framework [176] utilizes a centralized server approach, called the FieldTrip buffer[5,6]. However, FieldTrip mainly addresses Matlab users. The communication protocol is open-source and publicly available, but it is not the intention of the FieldTrip project to provide or standardize a communication system between clients. This is an extract from the FieldTrip website[6]: *"We do not aim to provide or specify: (i) any kind of remote procedure calls, or direct communication between clients, . . . , merging data from different acquisition systems"*.
BCI2000 [177, 178] or OpenViBE [179] are also open-source and thus publicly available.

[4] LSL Repository *(visited on July 16 2017)*
[5] FieldTrip Overview *(visited on July 16 2017)*
[6] FieldTrip Protocol *(visited on July 16 2017)*

However, both BCI2000 and OpenViBE use custom message formats[7,8,9], which also fulfill application-specific needs. These message formats are thus hardly able to be used as a common data or event delivery protocol. OpenBCI defines different data formats (Cython and Ganglion)[10,11], which could be used for data exchange, but these formats are hardware specific and are not designed as a common protocol for different BCI systems. OpenBCI follows the strategy to integrate their protocols in the data acquisition component of OpenViBE or to act as a data source for LSL, for example.

3.6. Limitations

This sections summarizes the limitations of the individual studies and experiments as well as the limitations of the common implementation platform. Some compromises had to be made to realize the individual studies or implementations.

Subjects who participated in studies in this thesis were not all naive ones. Some of them had already taken part in other BCI experiments and a few had even attended a tactile BCI study. The overall results are thus a mixture of naive subjects and ones with BCI experience. However, the experienced subjects did not attend a tactile BCI experiment for at least several months before participating in an experiment in this thesis. This fact reduces the limitation of a mixed subject pool.
Moreover, a tactile BCI would be most beneficial for patients who have lost their motor skills, but who still have a working sensory system, like ALS patients. However, no study was carried out in this thesis which involves patients. First screening results from people in a vegetative state, discovered by Pokorny et al. [188], did not show very promising results [188]. The decision to exclude patients was made due to limited access to these people. Including experiments with potential end-users who would benefit from such a BCI would definitely have been an enrichment for this thesis.
Another limitation was related to the mounting and positioning of the tactile stimulators. An initial design with tactors being placed in a fixed shape of a hand was redesigned to a flexible "clip-on" system, as presented by Pokorny et al. [146]. These clips have the advantage of flexible and rapid mounting and can be placed individually. However, with these clips, it is impossible to control the pressure which is applied to the fingertips. This might have influenced the overall classification results. Due to this limitation, the experiments were done in a single session and the subjects were asked to wear the tactors during the whole measurement if possible to avoid any repositioning.
Potentially existent higher harmonics of the stimulation frequency in the EEG were not considered as well. This was done due to an already high number of unknown parameters which could have influenced the BCI. The overall classification accuracy might thus improve when using higher harmonics.

The common implementation platform is also limited at several points. Initially, the framework was intended be used for realizing an hBCI within TOBI, which had rather little requirements like supporting only one EEG amplifier with 16 channels.

[7] BCI2000 Signal Format *(visited on July 16 2017)*
[8] OpenViBE Architecture *(visited on July 16 2017)*
[9] OpenViBE Stream Structures *(visited on July 16 2017)*
[10] OpenBCI Cython data format *(visited on July 16 2017)*
[11] OpenBCI Ganglion data format *(visited on July 16 2017)*

The final tools4BCI project emerged out of these initial requirements and still carries a couple of these initial limitations with it. A major limitation is based on the initial design decision of a single and central TiA server which is attached to the data acquisition and distributes the data to the connected clients. In contrast, LSL operates on distributed data sources among a network and takes care of the synchronization.
In the SignalServer, the synchronization has to be done on a hardware layer. The SignalServer and TiA do not carry out a synchronization of raw data based on timestamps. It is assumed that the acquired data is already synchronized. This is a big limitation compared to LSL, for example, which at least provides a packet synchronization that is necessary in case of distributed data sinks and sources. However, such a synchronization can only synchronize packets to compensate a varying network transmission delay. Even this kind of synchronization cannot cope with clock-drifts or different data-acquisition delays within amplifiers.
In the common implementation platform an individual interface needs to be selected for a specific stage in the BCI processing chain. At the moment, there is no abstraction layer available which automatically detects the optimal interface type. Additionally, TiA only provides one timestamp per packet. Sticking single samples within a packet to individual timestamps is not possible yet. In case of block-based transmission, the individual samples are assumed to be equally time-shifted according to the sampling rate for the respective signal type.

4. Summary and Conclusion

This thesis comprises online as well as offline BCI studies using the somatosensory system and includes the development of a common implementation platform to realize BCI and hBCI studies.

At the very beginning of writing this thesis, an hBCI was a new concept to set up BCI system and improve the overall classification accuracy and user experience. The BCI frameworks which were available at that time were mostly unable to fulfill the new needs of hBCIs. The tools4BCI project, which is the result of the common implementation platform, is now publicly available on GitHub and provides tools which help to fulfill the new requirements. The definition of the introduced interfaces might be the very fist step towards some standardization in BCI, and in future maybe even in neuroscience data exchange. Tools like the framework developed in this thesis or LSL could help connect formerly incompatible systems with each other.

The components developed for the common implementation platform were thoroughly tested and utilized in the BCI experiments to achieve the overall goal of this thesis: the creation of a tactile hBCI system. Creating the components needed for such an hBCI was one part. Different studies were also conducted to gain additional knowledge in the rather unexplored field of tactile BCIs [163]. During the initial phase of this thesis, merely one functional tactile BCI system utilizing SSSEP, developed by Müller-Putz et al. [116], was described in literature. Thus, many things like stability of patterns induced by tactile stimulation or the possibility to classify stimulation on different fingers on one hand was unknown. With this thesis, additional knowledge was gained from utilizing the somatosensory system for BCIs. Moreover, the gained knowledge and the developed components of the common implementation platform were finally assembled together to an hBCI experiment, demonstrating a successful fusion of SSSEP and tactile tERP. It was also demonstrated that fusing different BCI modalities can significantly increase the classification accuracy, and that single modalities might be better suited for different classes, like a non-control state. Finally, the results initially demonstrated by Müller-Putz et al. [116] were reproduced, in contrast to the findings of Severens et al. [158], who achieved a random classification with the SSSEP modality.

5. Outlook

As mentioned multiple times, a lot of questions are still open when dealing with tactile BCIs. Moreover, hBCIs are becoming more common, but are still a new concept compared to the “classic” BCI. Additionally, computer science, or the development in IT in general, is progressing rapidly. Considering the common implementation platform, which stores the acquired data in files like .gdf [185], a new alternative might appear with databases like influxdb[1], which are designed to store time series. The acquired data might even be stored in cloud environments, as already commercially offered by Qusp[2]. Moreover, new programming languages, featuring highly parallelized processing, like “Go”[3] or “Rust” [4], could simplify the development of systems with real-time capabilities. These languages offer an efficient and simple binding to the C-interface, making the creation of different language bindings straightforward.
These trends might influence the overall communication within BCI systems and might also influence the development of BCI systems in general. A potential future step for the common implementation platform would be extending the functionality of the SignalServer to store acquired data directly in such a time series database. Time will show if a standardization will take place in BCI or neuroscience research.

One possible step concerning tactile BCIs would be to investigate the necessity of a screening for optimal SSSEP stimulation frequencies in more detail. It was discovered in this thesis that subjects who showed a high relative BPwr increase also achieved higher classification results. However, it is unknown if these subjects would have achieved comparable results with standard stimulation frequencies or if a screening of both hands is necessary at all. Moreover, an influence of the stimulation position or the stimulator itself on the classification performance was also not investigated. Furthermore, testing the applicability of m-sequences for tactile BCI usage would be another option. Generally speaking, principles which have already been investigated, such as for SSVEP or visual P300 based BCIs, could be transferred and investigated in the somatosensory domain.
Furthermore, hBCIs are still a very young field of research. Papers, describing different fusion strategies have started to become available the recent years. However, many things like fusing tactile modalities are still unexplored. Pokorny et al. [146] provided an insight into the effects of twitches during a tactile stimulation. However, a blocking-feature effect of such twitches has not intentionally been used as a feature for tactile BCIs yet. Moreover, it was shown in this thesis that SSSEP might be better suited for detecting non-control states. Implementing a dedicated fusion approach which considers such a class-preference of SSSEP might further increase the overall performance.

[1] https://docs.influxdata.com/influxdb *(visited on July 16 2017)*
[2] https://qusp.io *(visited on July 16 2017)*
[3] https://golang.org/ *(visited on July 16 2017)*
[4] https://www.rust-lang.org *(visited on July 16 2017)*

In the opinion of the author, somatosensory hBCIs could be a reasonable alternative, especially for BCIs which require a functional visual system and for potential end-users who have no voluntary muscle control anymore. But it is uncertain if tactile BCIs will reach performance values at the level of ITR or classification accuracy already possible with visual P300 BCIs, for example. Moreover, the functionality of tactile BCIs still needs to be fully shown for these user groups, but some findings, such as those in Kaufmann et al. [237], already look promising.

List of the Author's Publications

Peer-Reviewed Journal Papers

C. Breitwieser, C. Neuper, and G. R. Müller-Putz (2011), "TOBI Interface A (TiA) – A Standardized Interface to Transmit Raw Biosignals", Int. J. Bioelectromagn., vol. 13, no. 2, pp. 64–65

C. Breitwieser, I. Daly, C. Neuper, and G. R. Müller-Putz (2012), "Proposing a standardized protocol for raw biosignal transmission", IEEE Trans. Biomed. Eng., vol. 59, no. 3, pp. 852–859

C. Breitwieser, V. Kaiser, C. Neuper, and G. R. Müller-Putz (2012), "Stability and distribution of steady-state somatosensory evoked potentials elicited by vibro-tactile stimulation", Med. Biol. Eng. Comput., vol. 50, no. 4, pp. 347–357

C. Breitwieser, C. Pokorny, and G. R. Müller-Putz (2016), "A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERPs", J. Neural Eng., vol. 13, no. 6

C. Breitwieser, M. Tavella, M. Schreuder, F. Cincotti, R. Leeb, and G. R. Müller-Putz (2017), "TiD – Introducing and Benchmarking an Event-Delivery System for Brain-Computer Interfaces", IEEE Trans. Neural Syst. Rehabil. Eng., *accepted*

G. R. Müller-Putz, **C. Breitwieser**, M. Tangermann, M. Schreuder, M. Tavella, R. Leeb, F. Cincotti, F. Leotta, and C. Neuper (2011), "TOBI hybrid BCI: principle of a new assistive method", Int. J. Bioelectromagn., vol. 13, no. 3, pp. 144–145

G. R. Müller-Putz, **C. Breitwieser**, F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. del R. Millán (2011), "Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI", Front. Neuroinform., vol. 5, no. November, p. 30

A. Kreilinger, V. Kaiser, **C. Breitwieser**, J. Williamson, C. Neuper, and G. R. Müller-Putz (2012), "Switching between manual control and brain-computer interface using long term and short term quality measures", Front. Neurosci., vol. 5, p. 147

C. Pokorny, **C. Breitwieser**, and G. R. Müller-Putz (2014), "A tactile stimulation device for EEG measurements in clinical use", IEEE Trans. Biomed. Circuits Syst., vol. 8, no. 3, pp. 305–312

C. Pokorny, **C. Breitwieser**, and G. R. Müller-Putz (2016), "The role of transient target stimuli in a steady-state somatosensory evoked potential-based brain-computer interface setup", Front. Neurosci., vol. 10, p. 152

Peer-Reviewed Conference Papers

C. Breitwieser, A. Kreilinger, C. Neuper, and G. R. Müller-Putz (2010), "The TOBI hybrid BCI – the data acquisition module", in Proceedings of the First TOBI Workshop 2010, vol. 11, no. 1, p. 58.

C. Breitwieser, C. Neuper, and G. R. Müller-Putz (2011), "A concept to standardize raw biosignal transmission for brain-computer interfaces", in Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, pp. 6377–6380.

C. Breitwieser, C. Pokorny, C. Neuper, and G. R. Müller-Putz (2011), "Somatosensory evoked potentials elicited by stimulating two fingers from one hand - Usable for BCI?", in 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 6373–6376.

C. Breitwieser, C. Neuper, and G. R. Müller-Putz (2011), "TiA – Standardizing Raw Biosignal Delivery in BCIs", in Proceedings of the 5th International Brain-Computer Interface Conference 2011, pp. 1–4.

C. Breitwieser, C. Pokorny, C. Neuper, and G. R. Müller-Putz (2011), "Correlating SSSEP Screening Results with BCI Performance", in Proceedings of the 5th International Brain-Computer Interface Conference 2011, pp. 152–155.

C. Breitwieser, M. Tavella, M. Schreuder, F. Cincotti, and G. R. Müller-Putz (2012), "A Novel Approach for Event Transmission within Brain-Computer Interfaces Systems", in Proceedings of the 3rd TOBI Workshop, pp. 85–86.

C. Pokorny, **C. Breitwieser**, C. Neuper, and G. R. Müller-Putz (2011), "Towards a Single-Switch BCI Based on Steady-State Somatosensory Evoked Potentials", in Proceedings of the 5th International Brain-Computer Interface Conference 2011, pp. 200–203.

C. Pokorny, **C. Breitwieser**, and G. R. Müller-Putz (2012), "Impact of Channel Selection on the Classification Accuracy in a Brain-Computer Interface based on Steady-State Somatosensory Evoked Potentials", in Proceedings of the 1st international DECODER Workshop, pp. 17–20.

C. Brunner, **C. Breitwieser**, and G. R. Müller-Putz (2013), "Sigviewer and Signalserver – Open Source Software Projects for Biosignal Analysis", in Proceedings of the BMT 2013, vol. 58, pp. 5–6.

A. Ottaviani, **C. Breitwieser**, A. Kreilinger, M. Tavella, M. Rohm, M. Schreuder, R. Leeb, and J. del R. Millán, G. R. Müller-Putz, R. Rupp, and F. Cincotti (2013), "Designing Wearable BCIs: A Software Framework", in Proceedings of the 4th TOBI Workshop, pp. 123–124.

T. Reiter, M. Cik, M. Haberl, **C. Breitwieser**, R. Scherer, M. Kröll, C. Horn, G. R. Müller-Putz, S. Lindstaedt, and M. Fellenforfer (2013), "Traffic incident detection with cellular network data", in 2013 International Symposium on Recent Advances in Transport Modelling (OPTIMUM 2013)

Books and Other Publications

C. Breitwieser and C. Eibel (2011), "TiA – Documentation of TOBI Interface A", CoRR, vol. abs/1103.4

C. Breitwieser, O. Terbu, A. Holzinger, C. Brunner, S. Lindstaedt, and G. R. Müller-Putz (2013), "iScope - Viewing biosignals on mobile devices", in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 7719 LNCS, pp. 50–56.

C. Breitwieser (2015), "TiD - Documentation of TOBI Interface D", CoRR, vol. abs/1507.0

C. Brunner, G. Andreoni, L. Bianchi, B. Blankertz, **C. Breitwieser**, S. Kanoh, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, G. R. Müller-Putz, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, and G. R. Müller-Putz (2013), "BCI Software Platforms", in Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications, B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 303–331.

Bibliography

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. "Brain-computer interfaces for communication and control." In: *Clinical Neurophysiology* 113.6 (2002), pp. 767–791. DOI: 10.1016/S1388-2457(02)00057-3 (cit. on pp. 1, 13).

[2] J. R. Wolpaw and D. J. McFarland. "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans." In: *Proceedings of the National Academy of Sciences of the United States of America* 101.51 (2004), pp. 17849–54. DOI: 10.1073/pnas.0403504101 (cit. on p. 1).

[3] J. P. Donoghue. "Connecting cortex to machines: recent advances in brain interfaces." In: *Nature neuroscience* 5 (2002), pp. 1085–1088. DOI: 10.1038/nn947 (cit. on p. 1).

[4] J. d. R. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb, C. Neuper, K. R. Müller, and D. Mattia. "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges." In: *Frontiers in Neuroscience* 4 (2010), p. 161. DOI: 10.3389/fnins.2010.00161 (cit. on pp. 1, 12).

[5] L. F. Nicolas-Alonso and J. Gomez-Gil. "Brain computer interfaces, a review." In: *Sensors* 12.2 (2012), pp. 1211–1279. DOI: 10.3390/s120201211 (cit. on p. 1).

[6] A. Kübler, B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer. "Brain-computer communication: unlocking the locked in." In: *Psychological bulletin* 127.3 (2001), pp. 358–75 (cit. on p. 1).

[7] M. A. Lebedev and M. A. Nicolelis. "Brain–machine interfaces: past, present and future." In: *Trends in Neurosciences* 29.9 (2006), pp. 536–546. DOI: 10.1016/j.tins.2006.07.004 (cit. on p. 1).

[8] G. Pfurtscheller, D. Flotzinger, and J. Kalcher. "Brain-Computer Interface—a new communication device for handicapped persons." In: *Journal of Microcomputer Applications* 16.3 (1993), pp. 293–299. DOI: 10.1006/jmca.1993.1030 (cit. on pp. 1, 13).

[9] G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlögl, B. Obermaier, and M. Pregenzer. "Current trends in Graz Brain-Computer Interface (BCI) research." In: *IEEE Transactions on Rehabilitation Engineering* 8.2 (2000), pp. 216–219. DOI: 10.1109/86.847821 (cit. on pp. 1, 37).

[10] J. J. Vidal. "Toward direct brain-computer communication." In: *Annual review of biophysics and bioengineering* 2 (1973), pp. 157–80. DOI: 10.1146/annurev.bb.02.060173.001105 (cit. on pp. 1, 32).

[11] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp. "EEG-based neuroprosthesis control: A step towards clinical practice." In: *Neuroscience Letters* 382.1-2 (2005), pp. 169–174. DOI: 10.1016/j.neulet.2005.03.021 (cit. on p. 2).

[12] C. Neuper, G. R. Müller-Putz, R. Scherer, and G. Pfurtscheller. "Motor imagery and EEG-based control of spelling devices and neuroprostheses." In: *Progress in Brain Research*. Vol. 159. 2006, pp. 393–409. DOI: 10.1016/S0079-6123(06)59025-9 (cit. on pp. 2, 5).

[13] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor. "A spelling device for the paralysed." In: *Nature* 398 (1999), pp. 297–298. DOI: 10.1038/18581 (cit. on pp. 2, 5, 13).

[14] P. W. Ferrez and J. del R. Millán. "Error-related EEG potentials generated during simulated brain-computer interaction." In: *IEEE Transactions on Biomedical Engineering* 55.3 (2008), pp. 923–929. DOI: 10.1109/TBME.2007.908083 (cit. on p. 2).

[15] T. O. Zander, C. Kothe, S. Jatzev, and M. Gaertner. "Enhancing Human-Computer Interaction with Input from Active and Passive Brain-Computer Interfaces." In: *Brain -Computer Interfaces*. Springer London, 2010, pp. 181–199. DOI: 10.1007/978-1-84996-272-8_11 (cit. on p. 2).

[16] Y. Zhang, P. Xu, Y. Huang, K. Cheng, and D. Yao. *SSVEP Response Is Related to Functional Brain Network Topology Entrained by the Flickering Stimulus*. eng. Ed. by D. R. Chialvo. 2013. DOI: 10.1371/journal.pone.0072654 (cit. on pp. 2, 38).

[17] L. C. Parra, C. D. Spence, A. D. Gerson, and P. Sajda. "Response error correction - A demonstration of improved human-machine performance using real-time EEG monitoring." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11.2 (2003), pp. 173–177. DOI: 10.1109/TNSRE.2003.814446 (cit. on p. 2).

[18] D. Purves, G. J. Augustine, D. Fitzpatrick, L. C. Katz, A.-S. LaMantia, J. O. McNamara, and S. M. Williams. *Neuroscience*. Sinauer Associates, 2001 (cit. on p. 3).

[19] H. Berger. "Über das Elektrenkephalogramm des Menschen." In: *Archiv für Psychiatrie und Nervenkrankheiten* 99.1 (1933), pp. 555–574. DOI: 10.1007/BF01814320 (cit. on p. 3).

[20] E. C. Leuthardt, G. Schalk, J. R. Wolpaw, J. G. Ojemann, and D. W. Moran. "A brain-computer interface using electrocorticographic signals in humans." In: *Journal of Neural Engineering* 1.2 (2004), pp. 63–71. DOI: 10.1088/1741-2560/1/2/001 (cit. on p. 3).

[21] E. C. Leuthardt, K. J. Miller, G. Schalk, R. P. N. Rao, and J. G. Ojemann. "Electrocorticography-based brain computer interface - The seattle experience." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14.2 (2006), pp. 194–198. DOI: 10.1109/TNSRE.2006.875536 (cit. on p. 3).

[22] E. C. Leuthardt, C. Gaona, M. Sharma, N. Szrama, J. Roland, Z. Freudenberg, J. Solis, J. Breshears, and G. Schalk. "Using the electrocorticographic speech network to control a brain-computer interface in humans." In: *Journal of Neural Engineering* 8.3 (2011), p. 036004. DOI: 10.1088/1741-2560/8/3/036004. arXiv: NIHMS150003 (cit. on p. 3).

[23] G. Schalk, J. Kubánek, K. J. Miller, N. R. Anderson, E. C. Leuthardt, J. G. Ojemann, D. Limbrick, D. Moran, L. A. Gerhardt, and J. R. Wolpaw. "Decoding two-dimensional movement trajectories using electrocorticographic signals in humans." In: *Journal of Neural Engineering* 4.3 (2007), pp. 264–75. DOI: 10.1088/1741-2560/4/3/012 (cit. on p. 3).

[24] E. M. Maynard, C. T. Nordhausen, and R. A. Normann. "The Utah Intracortical Electrode Array: A recording structure for potential brain-computer interfaces." In: *Electroencephalography and Clinical Neurophysiology* 102.3 (1997), pp. 228–239. DOI: 10.1016/S0013-4694(96)95176-0 (cit. on p. 3).

[25] D. A. Heldman, W. Wang, S. S. Chan, and D. W. Moran. "Local field potential spectral tuning in motor cortex during reaching." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14.2 (2006), pp. 180–183. DOI: 10.1109/TNSRE.2006.875549 (cit. on p. 3).

[26] P. R. Kennedy, D. Andreasen, P. Ehirim, B. King, M. T. Kirby, H. Mao, and M. M. Moore. "Using human extra-cortical local field potentials to control a switch." In: *Journal of Neural Engineering* 1.2 (2004), pp. 72–7. DOI: 10.1088/1741-2560/1/2/002 (cit. on p. 3).

[27] Z. C. Chao, Y. Nagasaka, N. Fujii, Chao, Z. C. Chao, Y. Nagasaka, and N. Fujii. "Long-term asynchronous decoding of arm motion using electrocorticographic signals in monkeys." In: *Frontiers in neuroengineering* 3.March (2010), p. 3. DOI: 10.3389/fneng.2010.00003 (cit. on p. 3).

[28] G. Santhanam, S. I. Ryu, B. M. Yu, A. Afshar, and K. V. Shenoy. "A high-performance brain–computer interface." In: *Nature* 442 (2006), pp. 195–198. DOI: 10.1038/nature04968 (cit. on p. 3).

[29] A. Jackson, C. T. Moritz, J. Mavoori, T. H. Lucas, and E. E. Fetz. "The neurochip BCI: Towards a neural prosthesis for upper limb function." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14.2 (2006), pp. 187–190. DOI: 10.1109/TNSRE.2006.875547 (cit. on p. 3).

[30] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn, and J. P. Donoghue. "Neuronal ensemble control of prosthetic devices by a human with tetraplegia." In: *Nature* 442 (2006), pp. 164–171. DOI: 10.1038/nature04970 (cit. on p. 3).

[31] E. a. Felton, J. A. Wilson, J. C. Williams, and P. C. Garell. "Electrocorticographically controlled brain-computer interfaces using motor and sensory imagery in patients with temporary subdural electrode implants. Report of four cases." In: *Journal of Neurosurgery* 106.3 (2007), pp. 495–500. DOI: 10.3171/jns.2007.106.3.495 (cit. on p. 3).

[32] J. L. Collinger, B. Wodlinger, J. E. Downey, W. Wang, E. C. Tyler-Kabara, D. J. Weber, A. J. C. McMorland, M. Velliste, M. L. Boninger, and A. B. Schwartz. "High-performance neuroprosthetic control by an individual with tetraplegia." In: *The Lancet* 381.9866 (2013), pp. 557–564. DOI: 10.1016/S0140-6736(12)61816-9 (cit. on p. 3).

[33] J. Mellinger, G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler. "An MEG-based brain-computer interface (BCI)." In: *NeuroImage* 36.3 (2007), pp. 581–593. DOI: 10.1016/j.neuroimage.2007.03.019. arXiv: NIHMS150003 (cit. on p. 4).

[34] E. Buch, C. Weber, L. G. Cohen, C. Braun, M. A. Dimyan, T. Ard, J. Mellinger, A. Caria, S. Soekadar, A. Fourkas, and N. Birbaumer. "Think to move: A neuromagnetic brain-computer interface (BCI) system for chronic stroke." In: *Stroke* 39.3 (2008), pp. 910–917. DOI: 10.1161/STROKEAHA.107.505313 (cit. on p. 4).

[35] L. Bianchi, S. Sami, A. Hillebrand, I. P. Fawcett, L. R. Quitadamo, and S. Seri. "Which physiological components are more suitable for visual ERP based brain-computer interface? A preliminary MEG/EEG study." In: *Brain Topography* 23.2 (2010), pp. 180–185. DOI: 10.1007/s10548-010-0143-0 (cit. on p. 4).

[36] G. Bauernfeind, R. Leeb, S. C. Wriessnegger, and G. Pfurtscheller. "Development, set-up and first results for a one-channel near-infrared spectroscopy system." In: *Biomedizinische Technik* 53.1 (2008), pp. 36–43. DOI: 10.1515/BMT.2008.005 (cit. on p. 4).

[37] G. Bauernfeind, R. Scherer, G. Pfurtscheller, and C. Neuper. "Single-trial classification of antagonistic oxyhemoglobin responses during mental arithmetic." In: *Medical and Biological Engineering and Computing* 49.9 (2011), pp. 979–984. DOI: 10.1007/s11517-011-0792-5 (cit. on p. 4).

[38] S. M. Coyle, T. E. Ward, C. M. Markham, E. Ward, and C. M. Markham. "Brain-computer interface using a simplified functional near-infrared spectroscopy system." In: *Journal of Neural Engineering* 4.3 (2007), pp. 219–26. DOI: 10.1088/1741-2560/4/3/007 (cit. on p. 4).

[39] R. Sitaram, H. Zhang, C. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu, and N. Birbaumer. "Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface." In: *NeuroImage* 34.4 (2007), pp. 1416–1427. DOI: 10.1016/j.neuroimage.2006.11.005 (cit. on p. 4).

[40] S. Luu and T. Chau. "Decoding subjective preference from single-trial near-infrared spectroscopy signals." In: *Journal of Neural Engineering* 6.1 (2009), p. 016003. DOI: 10.1088/1741-2560/6/1/016003 (cit. on p. 4).

[41] N. Weiskopf, K. Mathiak, S. W. Bock, F. Scharnowski, R. Veit, W. Grodd, R. Goebel, and N. Birbaumer. "Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI)." In: *IEEE Transactions on Biomedical Engineering* 51.6 (2004), pp. 966–970. DOI: 10.1109/TBME.2004.827063 (cit. on p. 4).

[42] R. Sitaram, N. Weiskopf, A. Caria, R. Veit, M. Erb, and N. Birbaumer. "fMRI brain-computer interfaces." In: *IEEE Signal Processing Magazine* 25.1 (2008), pp. 95–106. DOI: 10.1109/MSP.2008.4408446 (cit. on p. 4).

[43] O. J. Arthurs and S. Boniface. "How well do we understand the neural origins of the fMRI BOLD signal?" In: *Trends in Neurosciences* 25.1 (2002), pp. 27–31. DOI: 10.1016/S0166-2236(00)01995-0 (cit. on p. 4).

[44] T. Fedele, H. J. Scheer, G. Waterstraat, B. Telenczuk, M. Burghoff, and G. Curio. "Towards non-invasive multi-unit spike recordings: Mapping 1kHz EEG signals over human somatosensory cortex." In: *Clinical Neurophysiology* 123.12 (2012), pp. 2370–2376. DOI: 10.1016/j.clinph.2012.04.028 (cit. on p. 4).

[45] H. J. Scheer, T. Sander, and L. Trahms. “The influence of amplifier, interface and biological noise on signal quality in high-resolution EEG recordings.” In: *Physiological measurement* 27.2 (2006), pp. 109–117. DOI: 10.1088/0967-3334/27/2/002 (cit. on p. 4).

[46] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer. “EEG-based discrimination between imagination of right and left hand movement.” In: *Electroencephalography and Clinical Neurophysiology* 103.6 (1997), pp. 642–651. DOI: 10.1016/S0013-4694(97)00080-1 (cit. on pp. 5, 8).

[47] G. Pfurtscheller and C. Neuper. “Motor imagery and direct brain-computer communication.” In: *Proceedings of the IEEE* 89.7 (2001), pp. 1123–1134. DOI: 10.1109/5.939829. arXiv: 5.939829. [10.1109] (cit. on p. 5).

[48] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. Lopes da Silva. “Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks.” In: *NeuroImage* 31.1 (2006), pp. 153–159. DOI: 10.1016/j.neuroimage.2005.12.003 (cit. on p. 5).

[49] G. R. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller. “Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components.” In: *Journal of Neural Engineering* 2.4 (2005), pp. 123–130. DOI: 10.1088/1741-2560/2/4/008 (cit. on pp. 5, 6).

[50] L. A. Farwell and E. Donchin. “Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials.” In: *Electroencephalography and Clinical Neurophysiology* 70.6 (1988), pp. 510–523. DOI: 10.1016/0013-4694(88)90149-6 (cit. on pp. 5, 13).

[51] A. Kübler, N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N. P. Birbaumer. “Brain-computer communication: Self-regulation of slow cortical potentials for verbal communication.” In: *Archives of Physical Medicine and Rehabilitation* 82.11 (2001), pp. 1533–1539. DOI: 10.1053/apmr.2001.26621 (cit. on pp. 5, 16, 40).

[52] C. Neuper and G. Pfurtscheller. “Neurofeedback Training for BCI Control.” In: *Brain-Computer Interfaces: Revolutionizing Human–Computer Interaction*. Springer Berlin Heidelberg, 2010, pp. 65–78. DOI: 10.1007/978-3-642-02091-9 (cit. on p. 5).

[53] G. Pfurtscheller and C. Neuper. “Motor imagery activates primary sensorimotor area in humans.” In: *Neuroscience Letters* 239.2-3 (1997), pp. 65–68. DOI: 10.1016/S0304-3940(97)00889-6 (cit. on p. 5).

[54] G. Pfurtscheller and F. H. Lopes Da Silva. “Event-related EEG/MEG synchronization and desynchronization: Basic principles.” In: *Clinical Neurophysiology* 110.11 (1999), pp. 1842–1857. DOI: 10.1016/S1388-2457(99)00141-8 (cit. on p. 5).

[55] G. Pfurtscheller and A. Aranibar. “Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement.” In: *Electroencephalography and Clinical Neurophysiology* 46.2 (1979), pp. 138–146. DOI: 10.1016/0013-4694(79)90063-4 (cit. on p. 5).

[56] G. Pfurtscheller. “Central beta rhythm during sensorimotor activities in man.” In: *Electroencephalography and Clinical Neurophysiology* 51.3 (1981), pp. 253–264. DOI: 10.1016/0013-4694(81)90139-5 (cit. on p. 5).

[57] G. Pfurtscheller, A. Stancák, and C. Neuper. "Event-related synchronization (ERS) in the alpha band - An electrophysiological correlate of cortical idling: A review." In: *International Journal of Psychophysiology* 24.1-2 (1996), pp. 39–46. DOI: 10.1016/S0167-8760(96)00066-9 (cit. on p. 5).

[58] G. Pfurtscheller and C. Neuper. "Event-related synchronization of mu rhythm in the EEG over the cortical hand area in man." In: *Neuroscience Letters* 174.1 (1994), pp. 93–96. DOI: 10.1016/0304-3940(94)90127-9 (cit. on p. 5).

[59] C. Neuper and G. Pfurtscheller. "Evidence for distinct beta resonance frequencies in human EEG related to specific sensorimotor cortical areas." In: *Clinical Neurophysiology* 112.11 (2001), pp. 2084–2097. DOI: 10.1016/S1388-2457(01)00661-7 (cit. on p. 5).

[60] C. Neuper and G. Pfurtscheller. "Post-movement synchronization of beta rhythms in the EEG over the cortical foot area in man." In: *Neuroscience Letters* 216.1 (1996), pp. 17–20. DOI: 10.1016/S0304-3940(96)12991-8 (cit. on p. 5).

[61] G. R. Müller, C. Neuper, R. Rupp, C. Keinrath, H. J. Gerner, and G. Pfurtscheller. "Event-related beta EEG changes during wrist movements induced by functional electrical stimulation of forearm muscles in man." In: *Neuroscience Letters* 340.2 (2003), pp. 143–147. DOI: 10.1016/S0304-3940(03)00019-3 (cit. on p. 5).

[62] E. V. C. Friedrich, R. Scherer, and C. Neuper. "The effect of distinct mental strategies on classification performance for brain-computer interfaces." In: *International Journal of Psychophysiology* 84.1 (2012), pp. 86–94. DOI: 10.1016/j.ijpsycho.2012.01.014 (cit. on p. 5).

[63] B. Rockstroh, T. Elbert, W. Lutzenberger, and N. Birbaumer. "Operant control of slow brain potentials: A tool in the investigation of potential meaning and its relation to attentional dysfunctions." In: *Self-regulation of brain and behavior*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1984, pp. 226–239. DOI: 10.1007/978-3-642-69379-3_16 (cit. on p. 5).

[64] W. Lutzenberger, T. Elbert, B. Rockstroh, and N. Birbaumer. "The effects of self-regulation of slow cortical potentials on performance in a signal detection task." In: *The International Journal of Neuroscience* 9.3 (1979), pp. 175–183. DOI: 10.3109/00207457909147670 (cit. on p. 5).

[65] N. Birbaumer, A. Kübler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor. "The thought translation device (TTD) for completely paralyzed patients." In: *IEEE Transactions on Rehabilitation Engineering* 8.2 (2000), pp. 190–193. DOI: 10.1109/86.847812 (cit. on p. 5).

[66] A. Kübler and N. Birbaumer. "Brain-computer interfaces and communication in paralysis: Extinction of goal directed thinking in completely paralysed patients?" In: *Clinical Neurophysiology* 119.11 (2008), pp. 2658–2666. DOI: 10.1016/j.clinph.2008.06.019 (cit. on p. 5).

[67] M. D. Rugg and M. G. Coles. *Electrophysiology of mind: Event-related brain potentials and cognition*. Vol. 19. 6. Oxford University Press, 1995, pp. xii, 220. DOI: 10.1097/00004691-199605000-00011 (cit. on p. 5).

[68] Stefen J. Luck. *An introduction to the event-related potential technique*. MIT Press, 2005 (cit. on p. 5).

[69] N. J. Hill and B. Schölkopf. "An online brain–computer interface based on shifting attention to concurrent streams of auditory stimuli." In: *Journal of Neural Engineering* 9.2 (2012), p. 026011. DOI: 10.1088/1741-2560/9/2/026011. arXiv: NIHMS150003 (cit. on pp. 5, 6).

[70] J. W. Hall III. *Handbook of Auditory Evoked Responses*. Pearson, 1992 (cit. on p. 5).

[71] E. Courchesne, S. A. Hillyard, and R. Galambos. "Stimulus novelty, task relevance and the visual evoked potential in man." In: *Electroencephalography and Clinical Neurophysiology* 39.2 (1975), pp. 131–143. DOI: 10.1016/0013-4694(75)90003-6. arXiv: arXiv:1011.1669v3 (cit. on p. 5).

[72] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao. "A practical VEP-based brain-computer interface." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14.2 (2006), pp. 234–239. DOI: 10.1109/TNSRE.2006.875576 (cit. on p. 5).

[73] I. K. Niazi, N. Jiang, O. Tiberghien, J. F. Nielsen, K. Dremstrup, and D. Farina. "Detection of Movement Intention from Single-Trial Movement-Related Cortical Potentials." In: *Journal of Neural Engineering* 8.6 (2011). DOI: 10.1088/1741-2560/8/6/066009 (cit. on p. 5).

[74] M. Hallett. "Movement-related cortical potentials." In: *Electromyography And Clinical Neurophysiology* 34.1 (1994), pp. 5–13 (cit. on p. 5).

[75] G. Pfurtscheller, M. Woertz, G. Müller, S. Wriessnegger, and K. Pfurtscheller. "Contrasting behavior of beta event-related synchronization and somatosensory evoked potential after median nerve stimulation during finger manipulation in man." In: *Neuroscience Letters* 323.2 (2002), pp. 113–116. DOI: 10.1016/S0304-3940(02)00119-2 (cit. on p. 5).

[76] J. R. Hughes. *Human brain electrophysiology. Evoked potentials and evoked magnetic fields in science and medicine*. Vol. 73. 1. Elsevier, 1989, p. 84. DOI: 10.1016/0013-4694(89)90022-9 (cit. on p. 5).

[77] H. R. Chiappa K. *Evoked Potentials in Clinical Medicine*. Lippincott-Raven, 1997 (cit. on p. 5).

[78] E. Colon, S. Visser, J. de Weerd, and A. Zonneveldt. *Evoked Potential Manual*. Dordrecht: Springer Netherlands, 1983. DOI: 10.1007/978-94-017-1499-0 (cit. on p. 5).

[79] M. R. Nuwer. "Fundamentals of evoked potentials and common clinical applications today." In: *Electroencephalography and Clinical Neurophysiology* 106.2 (1998), pp. 142–148. DOI: 10.1016/S0013-4694(97)00117-X (cit. on p. 5).

[80] S. Sutton, M. Braren, J. Zubin, and E. R. John. "Evoked-Potential Correlates of Stimulus Uncertainty." In: *Science* 150.3700 (1965), pp. 1187–1188. DOI: 10.1126/science.150.3700.1187 (cit. on p. 5).

[81] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger. "How many people are able to control a P300-based brain-computer interface (BCI)?" In: *Neuroscience Letters* 462.1 (2009), pp. 94–98. DOI: 10.1016/j.neulet.2009.06.045 (cit. on pp. 5, 10).

[82] E. Donchin, K. M. Spencer, and R. Wijesinghe. "The mental prosthesis: Assessing the speed of a P300-based brain- computer interface." In: *IEEE Transactions on Rehabilitation Engineering* 8.2 (2000), pp. 174–179. DOI: 10.1109/86.847808 (cit. on pp. 5, 10).

[83] M. Schreuder, B. Blankertz, and M. Tangermann. "A new auditory multi-class brain-computer interface paradigm: Spatial hearing as an informative cue." In: *PLoS ONE* 5.4 (2010). Ed. by J. Yan, e9813. DOI: 10.1371/journal.pone.0009813 (cit. on p. 5).

[84] C. Pokorny, D. S. Klobassa, G. Pichler, H. Erlbeck, R. G. L. Real, A. Kübler, D. Lesenfants, D. Habbal, Q. Noirhomme, M. Risetti, D. Mattia, and G. R. Müller-Putz. "The auditory P300-based single-switch brain-computer interface: Paradigm transition from healthy subjects to minimally conscious patients." In: *Artificial Intelligence in Medicine* 59.2 (2013), pp. 81–90. DOI: 10.1016/j.artmed.2013.07.003 (cit. on p. 5).

[85] A. M. Brouwer and J. B. F. van Erp. "A tactile P300 brain-computer interface." In: *Frontiers in Neuroscience* 4 (2010). DOI: 10.3389/fnins.2010.00019 (cit. on pp. 5, 9, 10, 36, 40).

[86] J. Polich and A. Kok. "Cognitive and biological determinants of P300: an integrative review." In: *Biological Psychology* 41.2 (1995), pp. 103–146. DOI: 10.1016/0301-0511(95)05130-9 (cit. on p. 5).

[87] J. Polich. "Updating P300: An integrative theory of P3a and P3b." In: *Clinical Neurophysiology* 118.10 (2007), pp. 2128–2148. DOI: 10.1016/j.clinph.2007.04.019 (cit. on p. 5).

[88] R. M. Chapman and H. R. Bragdon. "Evoked Responses To Numerical and Non-Numerical Visual Stimuli While Problem Solving." In: *Nature* 203 (1964), pp. 1155–1157. DOI: 10.1038/2031155a0 (cit. on p. 5).

[89] D. Regan. "Steady-state evoked potentials." In: *Journal of the Optical Society of America* 67.11 (1977), pp. 1475–1489. DOI: 10.1364/JOSA.67.001475 (cit. on p. 5).

[90] S. T. Morgan, J. C. Hansen, and S. a. Hillyard. "Selective attention to stimulus location modulates the steady-state visual evoked potential." In: *Proceedings of the National Academy of Sciences of the United States of America*. Vol. 93. 10. 1996, pp. 4770–4774. DOI: 10.1073/pnas.93.10.4770 (cit. on p. 6).

[91] M. Middendorf, G. McMillan, G. Calhoun, and K. Jones. "Brain-computer interfaces based on the steady-state visual-evoked response." In: *IEEE Transactions on Rehabilitation Engineering* 8.2 (2000), pp. 211–214. DOI: 10.1109/86.847819 (cit. on p. 6).

[92] F. B. F.-B. Vialatte, M. Maurice, J. Dauwels, and A. Cichocki. "Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives." In: *Progress in Neurobiology* 90.4 (2010), pp. 418–438. DOI: 10.1016/j.pneurobio.2009.11.005 (cit. on p. 6).

[93] A. Z. Snyder. "Steady-state vibration evoked potentials: description of technique and characterization of responses." In: *Electroencephalography and Clinical Neurophysiology/ Evoked Potentials* 84.3 (1992), pp. 257–268. DOI: 10.1016/0168-5597(92)90007-X (cit. on pp. 6, 11, 35).

[94] S. Tobimatsu, Y. M. Zhang, and M. Kato. "Steady-state vibration somatosensory evoked potentials: Physiological characteristics and tuning function." In: *Clinical Neurophysiology* 110.11 (1999), pp. 1953–1958. DOI: 10.1016/S1388-2457(99)00146-7 (cit. on pp. 6, 11, 35).

[95] S. Tobimatsu, Y. M. Zhang, R. Suga, and M. Kato. "Differential temporal coding of the vibratory sense in the hand and foot in man." In: *Clinical Neurophysiology* 111.3 (2000), pp. 398–404. DOI: 10.1016/S1388-2457(99)00278-3 (cit. on pp. 6, 35).

[96] C. M. Giabbiconi, C. Dancer, R. Zopf, T. Gruber, and M. M. Müller. "Selective spatial attention to left or right hand flutter sensation modulates the steady-state somatosensory evoked potential." In: *Cognitive Brain Research* 20.1 (2004), pp. 58–66. DOI: 10.1016/j.cogbrainres.2004.01.004 (cit. on pp. 6, 35, 37).

[97] M. Severens, J. Farquhar, P. Desain, J. Duysens, and C. Gielen. "Transient and steady-state responses to mechanical stimulation of different fingers reveal interactions based on lateral inhibition." In: *Clinical Neurophysiology* 121.12 (2010), pp. 2090–2096. DOI: 10.1016/j.clinph.2010.05.016 (cit. on pp. 6, 11, 36, 37).

[98] B. Hjorth. "An on-line transformation of EEG scalp potentials into orthogonal source derivations." In: *Electroencephalography and Clinical Neurophysiology* 39.5 (1975), pp. 526–530. DOI: 10.1016/0013-4694(75)90056-5 (cit. on p. 7).

[99] G. Pfurtscheller, C. Neuper, and J. Berger. "Source localization using event-related desynchronization (ERD) within the alpha band." In: *Brain topography* 6.4 (1994), pp. 269–275. DOI: 10.1007/BF01211172 (cit. on p. 7).

[100] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw. "Spatial filter selection for EEG-based communication." In: *Electroencephalography and Clinical Neurophysiology* 103.3 (1997), pp. 386–394. DOI: 10.1016/S0013-4694(97)00022-2 (cit. on p. 7).

[101] J. W. Osselton. "Acquisition of EEG data by bipolar, unipolar and average reference methods: a theoretical comparison." In: *Electroencephalography and clinical neurophysiology* 19.5 (1965), pp. 527–528. DOI: 10.1016/0013-4694(65)90195-1 (cit. on p. 7).

[102] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller. "Optimal spatial filtering of single trial EEG during imagined hand movement." In: *IEEE Transactions on Rehabilitation Engineering* 8.4 (2000), pp. 441–446. DOI: 10.1109/86.895946 (cit. on pp. 7, 36).

[103] B. Blankertz, M. Kawanabe, R. Tomioka, F. Hohlefeld, V. Nikulin, and K.-R. Müller. "Invariant common spatial patterns: Alleviating nonstationarities in brain-computer interfacing." In: *Advances in neural information processing systems*. 2007, pp. 1–8 (cit. on pp. 7, 36).

[104] Z. J. Koles, M. S. Lazar, and S. Z. Zhou. "Spatial patterns underlying population differences in the background EEG." In: *Brain topography* 2.4 (1990), pp. 275–84 (cit. on p. 7).

[105] J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg. "Designing optimal spatial filters for single-trial EEG classification in a movement task." In: *Clinical Neurophysiology* 110.5 (1999), pp. 787–798. DOI: 10.1016/S1388-2457(98)00038-8 (cit. on p. 7).

[106] A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch. "A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals." In: *Journal of Neural Engineering* 4.2 (2007), R32–R57. DOI: 10.1088/1741-2560/4/2/R03 (cit. on p. 7).

[107] R. Leeb, C. Keinrath, D. Friedman, C. Guger, R. Scherer, C. Neuper, M. Garau, A. Antley, A. Steed, M. Slater, and G. Pfurtscheller. "Walking by Thinking: The Brainwaves Are Crucial, Not the Muscles!" In: *Presence: Teleoperators and Virtual Environments* 15.5 (2006), pp. 500–514. DOI: 10.1162/pres.15.5.500 (cit. on p. 8).

[108] R. Scherer, F. Lee, A. Schlögl, R. Leeb, H. Bischof, and G. Pfurtscheller. "Toward self-paced brain-computer communication: Navigation through virtual worlds." In: *IEEE Transactions on Biomedical Engineering* 55.2 (2008), pp. 675–682. DOI: 10.1109/TBME.2007.903709 (cit. on p. 8).

[109] A. Schlögl, D. Flotzinger, and G. Pfurtscheller. "Adaptive Autoregressive Modeling used for Single-trial EEG Classificaton." In: *Biomedizinische Technik* 42.6 (1997), pp. 162–167. DOI: 10.1515/bmte.1997.42.6.162 (cit. on p. 8).

[110] A. Schloegl, K. Lugger, and G. Pfurtscheller. "Using adaptive autoregressive parameters for a brain-computer-interface experiment." In: *Engineering in Medicine and Biology Society*. Vol. 4. IEEE, 1997, pp. 1533–1535. DOI: 10.1109/IEMBS.1997.757002 (cit. on p. 8).

[111] G. Pfurtscheller, C. Neuper, A. Schlogl, and K. Lugger. "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters." In: *IEEE Transactions on Rehabilitation Engineering* 6.3 (1998), pp. 316–325. DOI: 10.1109/86.712230 (cit. on p. 8).

[112] D. J. McFarland and J. R. Wolpaw. "Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis." In: *Journal of Neural Engineering* 5.2 (2008), pp. 155–62. DOI: 10.1088/1741-2560/5/2/006 (cit. on p. 8).

[113] I. Daly, S. J. Nasuto, and K. Warwick. "Brain computer interface control via functional connectivity dynamics." In: *Pattern Recognition* 45.6 (2012), pp. 2123–2136. DOI: 10.1016/j.patcog.2011.04.034 (cit. on pp. 8, 38).

[114] M. Billinger, C. Brunner, and G. R. Müller-Putz. "Single-trial connectivity estimation for classification of motor imagery data." In: *Journal of Neural Engineering* 10.4 (2013), p. 046006. DOI: 10.1088/1741-2560/10/4/046006 (cit. on pp. 8, 38).

[115] M. Hamedi, S.-H. Salleh, and A. M. Noor. "Electroencephalographic Motor Imagery Brain Connectivity Analysis for BCI: A Review." In: *Neural Computation* 28.6 (2016), pp. 999–1041. DOI: 10.1162/NECO_a_00838 (cit. on pp. 8, 38).

[116] G. R. Müller-Putz, R. Scherer, C. Neuper, and G. Pfurtscheller. "Steady-state somatosensory evoked potentials: Suitable brain signals for brain-computer interfaces?" In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14.1 (2006), pp. 30–37. DOI: 10.1109/TNSRE.2005.863842 (cit. on pp. 8–11, 23, 35, 36, 38, 40, 44).

[117] G. R. Müller-Putz, E. Eder, S. C. Wriessnegger, and G. Pfurtscheller. "Comparison of DFT and lock-in amplifier features and search for optimal electrode positions in SSVEP-based BCI." In: *Journal of Neuroscience Methods* 168.1 (2008), pp. 174–181. DOI: 10.1016/j.jneumeth.2007.09.024 (cit. on p. 8).

[118] G. R. Müller-Putz and G. Pfurtscheller. "Control of an electrical prosthesis with an SSVEP-based BCI." In: *IEEE Transactions on Biomedical Engineering* 55.1 (2008), pp. 361–364. DOI: 10.1109/TBME.2007.897815 (cit. on p. 8).

[119] G. E. Fabiani, D. J. McFarland, J. R. Wolpaw, and G. Pfurtscheller. "Conversion of EEG activity into cursor movement by a brain-computer interface (BCI)." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12.3 (2004), pp. 331–338. DOI: 10.1109/TNSRE.2004.834627 (cit. on p. 8).

[120] K. M. Adams. "Linear discriminant analysis in clinical neuropsychology research." In: *Journal of Clinical Neuropsychology* 1.3 (1979), pp. 259–272. DOI: 10.1080/01688637908414455 (cit. on p. 8).

[121] C. Bishop. *Pattern Recognition and Machine Learning*. Springer-Verlag New York, Inc., 2006. DOI: 10.1117/1.2819119. arXiv: arXiv:1011.1669v3 (cit. on pp. 8, 39).

[122] R. A. Fisher. "The Use of Multiple Measurements in Taxonomic Problems." In: *Annals of Eugenics* 7.2 (1936), pp. 179–188. DOI: 10.1111/j.1469-1809.1936.tb02137.x (cit. on p. 8).

[123] T. Solis-Escalante, G. Müller-Putz, and G. Pfurtscheller. "Overt foot movement detection in one single Laplacian EEG derivation." In: *Journal of Neuroscience Methods* 175.1 (2008), pp. 148–153. DOI: 10.1016/j.jneumeth.2008.07.019 (cit. on p. 8).

[124] C. Cortes and V. Vapnik. "Support-Vector Networks." In: *Machine Learning* 20.3 (1995), pp. 273–297. DOI: 10.1023/A:1022627411411. arXiv: arXiv:1011.1669v3 (cit. on p. 8).

[125] C. W. Anderson and Z. Sijercic. "Classification of EEG Signals from Four Different Subjects during Five Mental Tasks." In: *Proceedings of the Conference on Engineering Applications in Neural Networks (EANN96)* (1996), pp. 407–414 (cit. on p. 8).

[126] A. Hiraiwa, K. Shimohara, and Y. Tokunaga. "EEG Topography Recognition by Neural Networks." In: *IEEE Engineering in Medicine and Biology Magazine* 9.3 (1990), pp. 39–42. DOI: 10.1109/51.59211 (cit. on p. 8).

[127] R. Scherer, J. Faller, D. Balderas, E. V. C. Friedrich, M. Pröll, B. Allison, and G. Müller-Putz. "Brain-computer interfacing: More than the sum of its parts." In: *Soft Computing* 17.2 (2013), pp. 317–331. DOI: 10.1007/s00500-012-0895-4 (cit. on p. 8).

[128] A. K. Jain, R. P. W. Duin, and J. Mao. "Statistical pattern recognition: A review." In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 22.1 (2000), pp. 4–37. DOI: 10.1109/34.824819. arXiv: arXiv:1011.1669v3 (cit. on p. 8).

[129] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller. "Hidden Markov models for online classification of single trial EEG data." In: *Pattern Recognition Letters* 22.12 (2001), pp. 1299–1309. DOI: 10.1016/S0167-8655(01)00075-7 (cit. on p. 8).

[130] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi. "A review of classification algorithms for EEG-based brain-computer interfaces." In: *Journal of Neural Engineering* 4.2 (2007), R1. DOI: 10.1088/1741-2560/4/2/R01 (cit. on p. 8).

[131] S. C. Kleih, F. Nijboer, S. Halder, and A. Kübler. "Motivation modulates the P300 amplitude during brain-computer interface use." In: *Clinical Neurophysiology* 121.7 (2010), pp. 1023–1031. DOI: 10.1016/j.clinph.2010.01.034 (cit. on p. 8).

[132] E. M. Hammer, S. Halder, B. Blankertz, C. Sannelli, T. Dickhaus, S. Kleih, K. R. Müller, and A. Kübler. "Psychological predictors of SMR-BCI performance." In: *Biological Psychology* 89.1 (2012), pp. 80–86. DOI: 10.1016/j.biopsycho.2011.09.006 (cit. on p. 8).

[133] S. C. Kleih and A. Kübler. "Empathy, motivation, and P300 BCI performance." In: *Frontiers in human neuroscience* 7.October (2013), p. 642. DOI: 10.3389/fnhum.2013.00642 (cit. on p. 8).

[134] B. Spitzer, E. Wacker, and F. Blankenburg. "Oscillatory correlates of vibrotactile frequency processing in human working memory." In: *Journal of Neuroscience* 30.12 (2010), pp. 4496–4502. DOI: 10.1523/JNEUROSCI.6041-09.2010 (cit. on pp. 8, 11, 40).

[135] C. Vidaurre, A. Schlögl, R. Cabeza, R. Scherer, and G. Pfurtscheller. "A fully on-line adaptive BCI." In: *IEEE Transactions on Biomedical Engineering* 53.6 (2006), pp. 1214–1219. DOI: 10.1109/TBME.2006.873542 (cit. on p. 8).

[136] C. Vidaurre, C. Sannelli, K.-R. Müller, and B. Blankertz. "Co-adaptive calibration to improve BCI efficiency." In: *Journal of Neural Engineering* 8.2 (2011), p. 025009. DOI: 10.1088/1741-2560/8/2/025009 (cit. on p. 8).

[137] C. Vidaurre. "Machine-Learning-Based Coadaptive Calibration for Brain-Computer Interfaces." In: *Neural Computation* 816.3 (2011), pp. 791–816. DOI: 10.1162/NECO_a_00089 (cit. on p. 8).

[138] J. Faller, R. Scherer, U. Costa, E. Opisso, J. Medina, and G. R. Müller-Putz. "A co-adaptive brain-computer interface for end users with severe motor impairment." In: *PLoS ONE* 9 (2014). Ed. by D. Friedman, pp. 1–10. DOI: 10.1371/journal.pone.0101168 (cit. on p. 8).

[139] A. Schwarz, R. Scherer, D. Steyrl, J. Faller, and G. R. Müller-Putz. "A Co-Adaptive Sensory Motor Rhythms Brain-Computer Interface Based on Common Spatial Patterns and Random Forest." In: *2015 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'15*. IEEE, 2015, pp. 1049–1052. DOI: 10.1109/EMBC.2015.7318545 (cit. on p. 8).

[140] E. R. Kandel, J. H. Schwartz, T. M. Jessell, S. A. Siegelbaum, and A. J. Hudspeth. "The Somatosensory System: Receptors and Central Pathways." In: *Principles of Neural Science*. Vol. 4. McGraw-Hill New York, 2000. Chap. 22, pp. 369–385 (cit. on pp. 9, 36).

[141] C. M. Giabbiconi, N. J. Trujillo-Barreto, T. Gruber, and M. M. Müller. "Sustained spatial attention to vibration is mediated in primary somatosensory cortex." In: *NeuroImage* 35.1 (2007), pp. 255–262. DOI: 10.1016/j.neuroimage.2006.11.022 (cit. on pp. 9, 35, 37).

[142] H. Burton, R. J. Sinclair, and D. G. McLaren. "Cortical network for vibrotactile attention: A fMRI study." In: *Human Brain Mapping* 29.2 (2008), pp. 207–221. DOI: 10.1002/hbm.20384 (cit. on pp. 9, 37).

[143] S. Yamaguchi and R. T. Knight. "P300 generation by novel somatosensory stimuli." In: *Electroencephalography and Clinical Neurophysiology* 78.1 (1991), pp. 50–55. DOI: 10.1016/0013-4694(91)90018-Y (cit. on p. 10).

[144] S. Yamaguchi and R. T. Knight. "Anterior and posterior association cortex contributions to the somatosensory P300." In: *Journal of Neuroscience* 11.7 (1991), pp. 2039–2054 (cit. on p. 10).

[145] M. van der Waal, M. Severens, J. Geuze, and P. Desain. "Introducing the tactile speller: an ERP-based brain–computer interface for communication." In: *Journal of Neural Engineering* 9.4 (2012), p. 045002. DOI: 10.1088/1741-2560/9/4/045002 (cit. on p. 10).

[146] C. Pokorny, C. Breitwieser, and G. R. Müller-Putz. "The role of transient target stimuli in a steady-state somatosensory evoked potential-based brain-computer interface setup." In: *Frontiers in Neuroscience* 10 (2016), p. 152. DOI: 10.3389/fnins.2016.00152 (cit. on pp. 10, 38, 41, 42, 45).

[147] E. W. Sellers and E. Donchin. "A P300-based brain-computer interface: Initial tests by ALS patients." In: *Clinical Neurophysiology* 117.3 (2006), pp. 538–548. DOI: 10.1016/j.clinph.2005.06.027 (cit. on p. 10).

[148] U. Hoffmann, J. M. Vesin, T. Ebrahimi, and K. Diserens. "An efficient P300-based brain-computer interface for disabled subjects." In: *Journal of Neuroscience Methods* 167.1 (2008), pp. 115–125. DOI: 10.1016/j.jneumeth.2007.03.005 (cit. on p. 10).

[149] E. W. Sellers, D. J. Krusienski, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw. "A P300 event-related potential brain-computer interface (BCI): The effects of matrix size and inter stimulus interval on performance." In: *Biological Psychology* 73.3 (2006), pp. 242–252. DOI: 10.1016/j.biopsycho.2006.04.007 (cit. on p. 10).

[150] F. Piccione, F. Giorgi, P. Tonin, K. Priftis, S. Giove, S. Silvoni, G. Palmas, and F. Beverina. "P300-based brain computer interface: Reliability and performance in healthy and paralysed participants." In: *Clinical Neurophysiology* 117.3 (2006), pp. 531–537. DOI: 10.1016/j.clinph.2005.07.024 (cit. on p. 10).

[151] H. Serby, E. Yom-Tov, and G. F. Inbar. "An improved P300-based brain-computer interface." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 13.1 (2005), pp. 89–98. DOI: 10.1109/TNSRE.2004.841878 (cit. on p. 10).

[152] J. N. Mak, Y. Arbel, J. W. Minett, L. M. McCane, B. Yuksel, D. Ryan, D. Thompson, L. Bianchi, and D. Erdogmus. "Optimizing the P300-based brain-computer interface: current status, limitations and future directions." In: *Journal of Neural Engineering* 8.2 (2011), p. 025003. DOI: 10.1088/1741-2560/8/2/025003 (cit. on p. 10).

[153] T. Kaufmann, S. M. Schulz, C. Grünzinger, and A. Kübler. "Flashing characters with famous faces improves ERP-based brain–computer interface performance." In: *Journal of Neural Engineering* 8.5 (2011). DOI: 10.1088/1741-2560/8/5/056016 (cit. on p. 10).

[154] B. Z. Allison and J. A. Pineda. "ERPs evoked by different matrix sizes: Implications for a brain computer interface (BCI) system." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11.2 (2003), pp. 110–113. DOI: 10.1109/TNSRE.2003.814448 (cit. on p. 10).

[155] G. Townsend, B. K. LaPallo, C. B. Boulay, D. J. Krusienski, G. E. Frye, C. K. Hauser, N. E. Schwartz, T. M. Vaughan, J. R. Wolpaw, and E. W. Sellers. "A novel P300-based brain-computer interface stimulus presentation paradigm: Moving beyond rows and columns." In: *Clinical Neurophysiology* 121.7 (2010), pp. 1109–1120. DOI: 10.1016/j.clinph.2010.01.030 (cit. on p. 10).

[156] K. Takano, T. Komatsu, N. Hata, Y. Nakajima, and K. Kansaku. "Visual stimuli for the P300 brain-computer interface: A comparison of white/gray and green/blue flicker matrices." In: *Clinical Neurophysiology* 120.8 (2009), pp. 1562–1566. DOI: 10.1016/j.clinph.2009.06.002 (cit. on p. 10).

[157] J. Adler, C. M. Giabbiconi, and M. M. Müller. "Shift of attention to the body location of distracters is mediated by perceptual load in sustained somatosensory attention." In: *Biological Psychology* 81.2 (2009), pp. 77–85. DOI: 10.1016/j.biopsycho.2009.02.001 (cit. on pp. 10, 11, 35, 37, 41).

[158] M. Severens, J. Farquhar, J. Duysens, and P. Desain. "A multi-signature brain–computer interface: use of transient and steady-state responses." In: *Journal of Neural Engineering* 10.2 (2013). DOI: 10.1088/1741-2560/10/2/026005 (cit. on pp. 10, 27, 37, 39, 40, 44).

[159] G. Müller, C. Neuper, and G. Pfurtscheller. "Do various stimulation characters cause different steady-state evoked potentials in man?" In: *Proceedings 2nd European Medical & Biological Engineering Conference EMBEC '02. IFMBE Proceedings*. Technische Universität Graz, 2002, pp. 1312–1313 (cit. on pp. 11, 35, 37).

[160] G. Müller, C. Neuper, and G. Pfurtscheller. "„Resonance-like" Frequencies of Sensorimotor Areas Evoked by Repetitive Tactile Stimulation - Resonanzeffekte in sensomotorischen Arealen, evoziert durch rhythmische taktile Stimulation." In: *Biomedizinische Technik/Biomedical Engineering* 46.7-8 (2001), pp. 186–190. DOI: 10.1515/bmte.2001.46.7-8.186 (cit. on pp. 11, 23, 27, 35).

[161] L. Yao, J. Meng, D. Zhang, X. Sheng, and X. Zhu. "Selective Sensation Based Brain-Computer Interface via Mechanical Vibrotactile Stimulation." In: *PLoS ONE* 8.6 (2013). DOI: 10.1371/journal.pone.0064784 (cit. on pp. 11, 40).

[162] L. Yao, X. Sheng, D. Zhang, N. Jiang, D. Farina, and X. Zhu. "A BCI System based on Somatosensory Attentional Orientation." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 25.1 (2016), pp. 81–90. DOI: 10.1109/TNSRE.2016.2572226 (cit. on pp. 11, 41).

[163] J. B. F. Van Erp and A. M. Brouwer. "Touch-based Brain Computer Interfaces: State of the art." In: *IEEE Haptics Symposium, HAPTICS* (2014), pp. 397–401. DOI: 10.1109/HAPTICS.2014.6775488 (cit. on pp. 11, 44).

[164] G. Pfurtscheller. "The hybrid BCI." In: *Frontiers in Neuroscience* 4.April (2010), pp. 1–11. DOI: 10.3389/fnpro.2010.00003 (cit. on p. 11).

[165] G. R. Müller-Putz, C. Breitwieser, F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. d. R. Millán. "Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI." In: *Frontiers in Neuroinformatics* 5.November (2011), p. 30. DOI: 10.3389/fninf.2011.00030 (cit. on pp. 12, 31, 33, 125).

[166] G. R. Müller-Putz, R. Leeb, M. Tangermann, J. Hohne, A. Kubler, F. Cincotti, D. Mattia, R. R. Rupp, K.-R. Muller, J. d. R. Millán, G. Mueller-Putz, R. Leeb, M. Tangermann, J. Hoehne, A. Kuebler, F. Cincotti, D. Mattia, R. R. Rupp, K.-R. Mueller, J. del R. Millan, G. Muller-Putz, R. Leeb, M. Tangermann, J. Hohne, A. Kubler, F. Cincotti, D. Mattia, R. R. Rupp, K.-R. Müller, and J. d. R. Millan. "Towards Noninvasive Hybrid Brain–Computer Interfaces: Framework, Practice, Clinical Application, and Beyond." In: *Proceedings of the IEEE* 103.6 (2015), pp. 926–943. DOI: 10.1109/JPROC.2015.2411333 (cit. on p. 12).

[167] A. Kreilinger, V. Kaiser, C. Breitwieser, J. Williamson, C. Neuper, and G. R. Müller-Putz. "Switching between manual control and brain-computer interface using long term and short term quality measures." In: *Frontiers in Neuroscience* 5 (2012), p. 147. DOI: 10.3389/fnins.2011.00147 (cit. on pp. 12, 39).

[168] R. Leeb, H. Sagha, R. Chavarriaga, and J. d. R. Millán. "Multimodal fusion of muscle and brain signals for a Hybrid-BCI." In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10* 1 (2010), pp. 4343–4346. DOI: 10.1109/IEMBS.2010.5626233 (cit. on p. 12).

[169] R. Leeb, H. Sagha, R. Chavarriaga, and J. d. R. Millán. "A hybrid brain-computer interface based on the fusion of electroencephalographic and electromyographic activities." In: *Journal of Neural Engineering* 8.2 (2011), p. 025011. DOI: 10.1088/1741-2560/8/2/025011 (cit. on pp. 12, 39).

[170] S. Fazli, J. Mehnert, J. Steinbrink, G. Curio, A. Villringer, K. R. Müller, and B. Blankertz. "Enhanced performance by a hybrid NIRS-EEG brain computer interface." In: *NeuroImage* 59.1 (2012), pp. 519–529. DOI: 10.1016/j.neuroimage.2011.07.084 (cit. on p. 12).

[171] B. Z. Allison, C. Brunner, V. Kaiser, G. R. Müller-Putz, C. Neuper, and G. Pfurtscheller. "Toward a hybrid brain-computer interface based on imagined movement and visual attention." In: *Journal of neural engineering* 7.2 (2010). DOI: 10.1088/1741-2560/7/2/026007 (cit. on pp. 12, 39).

[172] T. Carlson and J. d. R. Millan. "Brain-controlled wheelchairs: A robotic architecture." In: *IEEE Robotics and Automation Magazine* 20.1 (2013), pp. 65–73. DOI: 10.1109/MRA.2012.2229936 (cit. on p. 12).

[173] T. Carlson, L. Tonin, S. Perdikis, R. Leeb, and J. d. R. Millán. "A hybrid BCI for enhanced control of a telepresence robot." In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. IEEE, 2013, pp. 3097–3100. DOI: 10.1109/EMBC.2013.6610196 (cit. on p. 12).

[174] R. Scherer, A. Schlögl, G. Müller-Putz, and G. Pfurtscheller. "Inside the Graz-BCI: rtsBCI." In: *Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course 2004*. 2004 (cit. on pp. 14, 33).

[175] I. P. Susila, S. Kanoh, K. I. Miyamoto, and T. Yoshinobu. "xBCI: A generic platform for development of an online BCI system." In: *IEEJ Transactions on Electrical and Electronic Engineering* 5.4 (2010), pp. 467–473. DOI: 10.1002/tee.20560 (cit. on pp. 14, 33).

[176] R. Oostenveld, P. Fries, E. Maris, and J. M. Schoffelen. "FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data." In: *Computational Intelligence and Neuroscience* 2011 (2011), pp. 1–9. DOI: 10.1155/2011/156869. arXiv: 156869 (cit. on pp. 14, 33, 41).

[177] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw. "BCI2000: A general-purpose brain-computer interface (BCI) system." In: *IEEE Transactions on Biomedical Engineering* 51.6 (2004), pp. 1034–1043. DOI: 10.1109/TBME.2004.827072 (cit. on pp. 14, 33, 41).

[178] G. Schalk and J. Mellinger. *A practical guide to brain-computer interfacing with BCI2000: General-purpose software for brain-computer interface research, data acquisition, stimulus presentation, and brain monitoring*. Springer Science & Business Media, 2010. DOI: 10.1007/978-1-84996-092-2 (cit. on pp. 14, 41).

[179] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer. "OpenViBE: An Open-Source Software Platform to Design, Test, and Use Brain–Computer Interfaces in Real and Virtual Environments." In: *Presence* 19.1 (2010), pp. 35–53. DOI: 10.1162/pres.19.1.35 (cit. on pp. 14, 33, 41).

[180] L. Bianchi, F. Babiloni, F. Cincotti, S. Salinari, and M. G. Marciani. "Introducing {BF++}: A {C++} framework for cognitive bio-feedback systems design." In: *Methods Inf Med* 42.1 (2003), pp. 104–110 (cit. on p. 14).

[181] A. Nijholt, B. Reuderink, and D. O. Bos. "Turning shortcomings into challenges: Brain-computer interfaces for games." In: *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering* 9 LNICST.2 (2009), pp. 153–168. DOI: 10.1007/978-3-642-02315-6_15 (cit. on p. 14).

[182] B. Blankertz, M. Tangermann, and K. R. Müller. "BCI Applications for the General Population." In: *Brain-Computer Interfaces: Principles and Practice*. Oxford University Press, 2012, pp. 364–372. DOI: 10.1093/acprof:oso/9780195388855.003.0023 (cit. on p. 14).

[183] B. Kemp and J. Olivan. "European data format 'plus' (EDF+), an EDF alike standard format for the exchange of physiological data." In: *Clinical Neurophysiology* 114.9 (2003), pp. 1755–1761. DOI: 10.1016/S1388-2457(03)00123-8 (cit. on p. 14).

[184] L. Bianchi, L. R. Quitadamo, M. Abbafati, M. G. Marciani, and G. Saggio. "Introducing NPXLab 2010: A tool for the analysis and optimization of P300 based brain-computer interfaces." In: *2nd International Symposium on Applied Sciences in Biomedical and Communication Technologies, ISABEL 2009*. IEEE, 2009, pp. 1–4. DOI: 10.1109/ISABEL.2009.5373621 (cit. on p. 14).

[185] A. Schlögl. "GDF - A general dataformat for biosignals." In: *Structure* 19 (2006), pp. 1–15. arXiv: 0608052 [cs] (cit. on pp. 14, 45).

[186] P. Brunner, L. Bianchi, C. Guger, F. Cincotti, and G. Schalk. "Current trends in hardware and software for brain-computer interfaces (BCIs)." In: *Journal of Neural Engineering* 8.2 (2011). DOI: 10.1088/1741-2560/8/2/025001 (cit. on pp. 15, 41).

[187] S. G. Mason and G. E. Birch. "A general framework for brain-computer interface design." In: *IEEE Engineering in Medicine and Biology Society* 11.1 (2003), pp. 70–85. DOI: 10.1109/TNSRE.2003.810426 (cit. on pp. 15, 18, 21).

[188] C. Pokorny, G. Pichler, D. Lesenfants, Q. Noirhomme, S. Laureys, and G. Müller-Putz. "Steady-State Somatosensory Evoked Potentials in Minimally Conscious Patients – Challenges and Perspectives." In: Proceedings of the 6th International Brain-Computer Interface Conference, Graz, 2014 (cit. on pp. 16, 42).

[189] C. Breitwieser, C. Neuper, and G. R. Müller-Putz. "A concept to standardize raw biosignal transmission for brain-computer interfaces." In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. 2011, pp. 6377–6380. DOI: 10.1109/IEMBS.2011.6091574 (cit. on pp. 18, 71).

[190] C. Breitwieser, I. Daly, C. Neuper, and G. R. Müller-Putz. "Proposing a standardized protocol for raw biosignal transmission." In: *IEEE Transactions on Biomedical Engineering* 59.3 (2012), pp. 852–859. DOI: 10.1109/TBME.2011.2174637 (cit. on pp. 19, 33, 76).

[191] C. Breitwieser, M. Tavella, M. Schreuder, F. Cincotti, R. Leeb, and G. R. Müller-Putz. "TiD – Introducing and Benchmarking an Event-Delivery System for Brain-Computer Interfaces." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* accepted (2017). DOI: 10.1109/TNSRE.2017.2728199 (cit. on pp. 21, 33, 85).

[192] A. Delorme, T. Mullen, C. Kothe, Z. Akalin Acar, N. Bigdely-Shamlo, A. Vankov, and S. Makeig. "EEGLAB, SIFT, NFT, BCILAB, and ERICA: New tools for advanced EEG processing." In: *Computational Intelligence and Neuroscience* 2011.Article ID 130714 (2011). DOI: 10.1155/2011/130714. arXiv: 130714 (cit. on pp. 21, 41).

[193] C. Breitwieser, V. Kaiser, C. Neuper, and G. R. Müller-Putz. "Stability and distribution of steady-state somatosensory evoked potentials elicited by vibrotactile stimulation." In: *Medical and Biological Engineering and Computing* 50.4 (2012), pp. 347–357. DOI: 10.1007/s11517-012-0877-9 (cit. on pp. 23, 27, 94).

[194] C. Breitwieser, C. Pokorny, C. Neuper, and G. R. Müller-Putz. "Somatosensory evoked potentials elicited by stimulating two fingers from one hand - Usable for BCI?" In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2011, pp. 6373–6376. DOI: 10.1109/IEMBS.2011.6091573 (cit. on pp. 25, 27, 37, 38, 40, 106).

[195] C. Pokorny, C. Breitwieser, and G. R. Müller-Putz. "A tactile stimulation device for EEG measurements in clinical use." In: *IEEE Transactions on Biomedical Circuits and Systems* 8.3 (2014), pp. 305–312. DOI: 10.1109/TBCAS.2013.2270176 (cit. on p. 25).

[196] M. Billinger, I. Daly, V. Kaiser, J. Jin, B. Z. Allison, R. M. Gernot, and C. Brunner. "Towards Practical Brain-Computer Interfaces." In: *Towards Practical Brain-Computer Interfaces*. Ed. by B. Z. Allison, S. Dunne, R. Leeb, J. del R Millán, and A. Nijholt. Biological and Medical Physics, Biomedical Engineering. Springer Berlin Heidelberg, 2013, pp. 333–354. DOI: 10.1007/978-3-642-29746-5 (cit. on p. 26).

[197] C. Breitwieser, C. Pokorny, and G. R. Müller-Putz. "A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERPs." In: *Journal of Neural Engineering* 13.6 (2016). DOI: 10.1088/1741-2560/13/6/066015 (cit. on pp. 27, 37, 39, 40, 111).

[198] C. Brunner, G. Andreoni, L. Bianchi, B. Blankertz, C. Breitwieser, S. Kanoh, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, G. R. Müller-Putz, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, and G. R. Müller-Putz. "BCI Software Platforms." In: *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*. Ed. by B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. Chap. BCI Softwa, pp. 303–331. DOI: 10.1007/978-3-642-29746-5_16 (cit. on pp. 31, 126).

[199] D. Merkel. "Docker: lightweight Linux containers for consistent development and deployment." In: *Linux Journal* 2014.239 (2014), p. 2. DOI: 10.1097/01.NND.0000320699.47006.a3 (cit. on p. 33).

[200] C. Breitwieser, O. Terbu, A. Holzinger, C. Brunner, S. Lindstaedt, and G. R. Müller-Putz. "iScope - Viewing biosignals on mobile devices." In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 7719 LNCS. 2013, pp. 50–56. DOI: 10.1007/978-3-642-37015-1_5 (cit. on p. 34).

[201] F. Lotte and C. Guan. "Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms." In: *IEEE Transactions on Biomedical Engineering* 58.2 (2011), pp. 355–362. DOI: 10.1109/TBME.2010.2082539 (cit. on p. 36).

[202] A. Herweg, J. Gutzeit, S. Kleih, and A. Kübler. "Wheelchair control by elderly participants in a virtual environment with a brain-computer interface (BCI) and tactile stimulation." In: *Biological Psychology* 121 (2016), pp. 117–124. DOI: 10.1016/j.biopsycho.2016.10.006 (cit. on pp. 36–38, 40).

[203] M. Riemer, J. Trojan, D. Kleinböhl, and R. Hölzl. "Body posture affects tactile discrimination and identification of fingers and hands." In: *Experimental Brain Research* 206.1 (2010), pp. 47–57. DOI: 10.1007/s00221-010-2396-y (cit. on p. 36).

[204] E. Sutter. "The Brain Response Interface-Communication through Visually Induced Electrical Brain Responses." In: *Journal of Microcomputer Applications* 15.1 (1992), pp. 31–45 (cit. on p. 37).

[205] E. E. Sutter. "Imaging visual function with the multifocal m-sequence technique." In: *Vision Research* 41.10-11 (2001), pp. 1241–1255. DOI: 10.1016/S0042-6989(01)00078-5 (cit. on p. 37).

[206] A. J. Viterbi. *CDMA: Principles of Spread Spectrum Communication*. Addison Wesley Longman Publishing Co., Inc., 1995, p. 272 (cit. on p. 37).

[207] G. Bin, X. Gao, Y. Wang, B. Hong, and S. Gao. "VEP-based brain-computer interfaces: Time, frequency, and code modulations." In: *IEEE Computational Intelligence Magazine* 4.4 (2009), pp. 22–26. DOI: 10.1109/MCI.2009.934562 (cit. on p. 37).

[208] G. Bin, X. Gao, Y. Wang, Y. Li, B. Hong, and S. Gao. "A high-speed BCI based on code modulation VEP." In: *Journal of Neural Engineering* 8.2 (2011). DOI: 10.1088/1741-2560/8/2/025015 (cit. on p. 37).

[209] M. Spüler, W. Rosenstiel, and M. Bogdan. "Online Adaptation of a c-VEP Brain-Computer Interface(BCI) Based on Error-Related Potentials and Unsupervised Learning." In: *PLoS ONE* 7.12 (2012), pp. 1–11. DOI: 10.1371/journal.pone.0051077 (cit. on p. 37).

[210] Y. Hao, B. Manor, J. Liu, K. Zhang, Y. Chai, L. Lipsitz, C. K. Peng, V. Novak, X. Wang, J. Zhang, and J. Fang. "Novel MRI-compatible tactile stimulator for cortical mapping of foot sole pressure stimuli with fMRI." In: *Magnetic Resonance in Medicine* 69.4 (2013), pp. 1194–1199. DOI: 10.1002/mrm.24330. arXiv: NIHMS150003 (cit. on p. 37).

[211] J. Toppi, M. Risetti, L. R. Quitadamo, M. Petti, L. Bianchi, S. Salinari, F. Babiloni, F. Cincotti, D. Mattia, and L. Astolfi. "Investigating the effects of a sensorimotor rhythm-based BCI training on the cortical activity elicited by mental imagery." In: *Journal of Neural Engineering* 11.3 (2014). DOI: 10.1088/1741-2560/11/3/035010 (cit. on p. 37).

[212] V. Kaiser, G. Bauernfeind, A. Kreilinger, T. Kaufmann, A. Kübler, C. Neuper, and G. R. Müller-Putz. "Cortical effects of user training in a motor imagery based brain–computer interface measured by fNIRS and EEG." In: *NeuroImage* 85 (2014), pp. 432–444. DOI: 10.1016/j.neuroimage.2013.04.097 (cit. on p. 37).

[213] S. Halder, I. Käthner, and A. Kübler. "Training leads to increased auditory brain–computer interface performance of end-users with motor impairments." In: *Clinical Neurophysiology* 127.2 (2016), pp. 1288–1296. DOI: 10.1016/j.clinph.2015.08.007 (cit. on p. 37).

[214] E. Baykara, C. Ruf, C. Fioravanti, I. Käthner, N. Simon, S. Kleih, A. Kübler, and S. Halder. "Effects of training and motivation on auditory P300 brain–computer interface performance." In: *Clinical Neurophysiology* 127.1 (2016), pp. 379–387. DOI: 10.1016/j.clinph.2015.04.054 (cit. on p. 37).

[215] A. Herweg and A. Kübler. "High performance with tactile P300 BCIs." In: *4th International Winter Conference on Brain-Computer Interface, BCI 2016*. 2016, pp. 1–2. DOI: 10.1109/IWW-BCI.2016.7457442 (cit. on p. 37).

[216] C. Preuschhof, H. R. Heekeren, B. Taskin, T. Schubert, and A. Villringer. "Neural correlates of vibrotactile working memory in the human brain." In: *The Journal of neuroscience : the official journal of the Society for Neuroscience* 26.51 (2006), pp. 13231–13239. DOI: 10.1523/JNEUROSCI.2767-06.2006 (cit. on p. 37).

[217] H. Burton, R. J. Sinclair, and D. G. McLaren. "Cortical activity to vibrotactile stimulation: An fMRI study in blind and sighted individuals." In: *Human Brain Mapping* 23.4 (2004), pp. 210–228. DOI: 10.1002/hbm.20064. arXiv: NIHMS150003 (cit. on p. 37).

[218] M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss. "Beamforming in noninvasive brain-computer interfaces." In: *IEEE Transactions on Biomedical Engineering* 56.4 (2009), pp. 1209–1219. DOI: 10.1109/TBME.2008.2009768 (cit. on p. 37).

[219] M. G. Wentrup, K. Gramann, E. Wascher, and M. Buss. "EEG source localization for brain-computer-interfaces." In: *2nd International IEEE EMBS Conference on Neural Engineering*. Vol. 2005. 2005, pp. 128–131. DOI: 10.1109/CNE.2005.1419570 (cit. on p. 37).

[220] M. Xu, H. Qi, B. Wan, T. Yin, Z. Liu, and D. Ming. "A hybrid BCI speller paradigm combining P300 potential and the SSVEP blocking feature." In: *Journal of Neural Engineering* 10.2 (2013). DOI: 10.1088/1741-2560/10/2/026001 (cit. on pp. 38, 41).

[221] C.-H. Cheng, P.-Y. S. Chan, D. M. Niddam, S.-Y. Tsai, S.-C. Hsu, and C.-Y. Liu. "Sensory gating, inhibition control and gamma oscillations in the human somatosensory cortex." eng. In: *Scientific Reports* 6 (2016), p. 20437. DOI: 10.1038/srep20437 (cit. on p. 38).

[222] M. T. Banich. "Cognitive neuroscience and neuropsychology (2nd Edition)." In: Houghton Mifflin College Division, 2004, pp. 49–50, 258–259 (cit. on p. 38).

[223] H. Burton, R. J. Sinclair, and S. Dixit. "Working memory for vibrotactile frequencies: Comparison of cortical activity in blind and sighted individuals." In: *Human Brain Mapping* 31.11 (2010), pp. 1686–1701. DOI: 10.1002/hbm.20966 (cit. on p. 38).

[224] H. Burton, A. Agato, and R. J. Sinclair. "Repetition learning of vibrotactile temporal sequences: An fMRI study in blind and sighted individuals." In: *Brain Research* 1433 (2012), pp. 69–79. DOI: 10.1016/j.brainres.2011.11.039 (cit. on p. 38).

[225] H. Mori, Y. Matsumoto, V. Kryssanov, E. Cooper, H. Ogawa, S. Makino, Z. R. Struzik, and T. M. Rutkowski. "Multi-command tactile brain computer interface: A feasibility study." In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Ed. by I. Oakley and S. Brewster. Vol. 7989 LNCS. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 50–59. DOI: 10.1007/978-3-642-41068-0_6. arXiv: arXiv:1305.4319v1 (cit. on p. 39).

[226] S. Shahid, G. Prasad, and R. K. Sinha. "On fusion of heart and brain signals for hybrid BCI." In: *2011 5th International IEEE/EMBS Conference on Neural Engineering, NER 2011*. 2011, pp. 48–52. DOI: 10.1109/NER.2011.5910486 (cit. on p. 39).

[227] H. Riechmann, N. Hachmeister, H. Ritter, and A. Finke. "Asynchronous, parallel on-line classification of P300 and ERD for an efficient hybrid BCI." In: *2011 5th International IEEE/EMBS Conference on Neural Engineering*. 2011, pp. 412–415. DOI: 10.1109/NER.2011.5910574 (cit. on p. 39).

[228] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, and D. Hu. "A novel hybrid BCI speller based on the incorporation of SSVEP into the P300 paradigm." In: *Journal of Neural Engineering* 10.2 (2013). DOI: 10.1088/1741-2560/10/2/026012 (cit. on p. 39).

[229] M. Wang, I. Daly, B. Z. Allison, J. Jin, Y. Zhang, L. Chen, and X. Wang. "A new hybrid BCI paradigm based on P300 and SSVEP." In: *Journal of Neuroscience Methods* 244 (2015), pp. 16–25. DOI: 10.1016/j.jneumeth.2014.06.003 (cit. on p. 39).

[230] S. Fazli, S. Dähne, W. Samek, F. Bießmann, and K. R. Müller. "Learning From More Than One Data Source: Data Fusion Techniques for Sensorimotor Rhythm-Based Brain-Computer Interfaces." In: *Proceedings of the IEEE* 103.6 (2015), pp. 891–906. DOI: 10.1109/JPROC.2015.2413993 (cit. on p. 39).

[231] C. Breitwieser, C. Pokorny, C. Neuper, and G. Müller-Putz. "Correlating SSSEP Screening Results with BCI Performance." In: *Proceedings of the 5th International Brain-Computer Interface Conference 2011*. Verlag der Technischen Universität Graz, 2011, pp. 152–155 (cit. on p. 40).

[232] M. Severens, M. Van der Waal, J. Farquhar, and P. Desain. "Comparing tactile and visual gaze-independent brain-computer interfaces in patients with amyotrophic lateral sclerosis and healthy users." In: *Clinical Neurophysiology* 125.11 (2014), pp. 2297–2304. DOI: 10.1016/j.clinph.2014.03.005 (cit. on p. 40).

[233] K. R. Müller and B. Blankertz. "Toward noninvasive brain-computer interfaces." In: *IEEE Signal Processing Magazine* 23.5 (2006), pp. 125–128. DOI: 10.1109/MSP.2006.1708426 (cit. on p. 40).

[234] G. Pires, U. Nunes, and M. Castelo-Branco. "Comparison of a row-column speller vs. a novel lateral single-character speller: Assessment of BCI for severe motor disabled patients." In: *Clinical Neurophysiology* 123.6 (2012), pp. 1168–1181. DOI: 10.1016/j.clinph.2011.10.040 (cit. on p. 40).

[235] F. Nijboer, E. W. Sellers, J. Mellinger, M. A. Jordan, T. Matuz, A. Furdea, S. Halder, U. Mochty, D. J. Krusienski, T. M. Vaughan, J. R. Wolpaw, N. Birbaumer, and A. Kübler. "A P300-based brain-computer interface for people with amyotrophic lateral sclerosis." In: *Clinical Neurophysiology* 119.8 (2008), pp. 1909–1916. DOI: 10.1016/j.clinph.2008.03.034. arXiv: NIHMS150003 (cit. on p. 40).

[236] J. N. Mak, D. J. McFarland, T. M. Vaughan, L. M. McCane, P. Z. Tsui, D. J. Zeitlin, E. W. Sellers, and J. R. Wolpaw. "EEG correlates of P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis." In: *Journal of Neural Engineering* 9.2 (2012), p. 026014. DOI: 10.1088/1741-2560/9/2/026014 (cit. on p. 40).

[237] T. Kaufmann, E. M. Holz, and A. Kübler. "Comparison of tactile, auditory, and visual modality for brain-computer interface use: A case study with a patient in the locked-in state." In: *Frontiers in Neuroscience* 7.7 JUL (2013), p. 129. DOI: 10.3389/fnins.2013.00129 (cit. on pp. 40, 46).

[238] C. A. Kothe and S. Makeig. "BCILAB: A platform for brain-computer interface development." In: *Journal of Neural Engineering* 10.5 (2013). DOI: 10.1088/1741-2560/10/5/056014 (cit. on p. 41).

Appendix A.

Publications

A.1. A Concept to Standardize Raw Biosignal Transmission for Brain-Computer Interfaces

C. Breitwieser, C. Neuper, and G. R. Müller-Putz. "A concept to standardize raw biosignal transmission for brain-computer interfaces." In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. 2011, pp. 6377–6380. DOI: 10.1109/IEMBS.2011.6091574 [189]

Distribution of dedicated work:

- **Christian Breitwieser**: 80
- Christa Neuper: 2 %
- Gernot R. Müller-Putz: 18 %

33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Concept to Standardize Raw Biosignal Transmission for Brain-Computer Interfaces

Christian Breitwieser, Christa Neuper, Gernot R. Müller-Putz

Abstract— **With this concept we introduced the attempt of a standardized interface called TiA to transmit raw biosignals. TiA is able to deal with multirate and block-oriented data transmission. Data is distinguished by different signal types (e.g., EEG, EOG, NIRS,…), whereby those signals can be acquired at the same time from different acquisition devices. TiA is built as a client-server model. Multiple clients can connect to one server. Information is exchanged via a control- and a separated data connection. Control commands and meta information are transmitted over the control connection. Raw biosignal data is delivered using the data connection in a unidirectional way. For this purpose a standardized handshaking protocol and raw data packet have been developed. Thus, an abstraction layer between hardware devices and data processing was evolved facilitating standardization.**

I. INTRODUCTION

Various brain-computer interface (BCI) systems have been built since 1973 when the idea of a BCI was mentioned the first time by Vidal [1]. All those BCIs have the similarity to deal with brain signals, a small subset of biosignals. To compare and summarize commonalities in BCI systems, Mason and Birch presented a common BCI structure in 2003 [2], shown in Fig. 1. The BCI was divided into distinct modules, each one with a specific responsibility inside the BCI processing chain. Those modules are connected with different interfaces, which can be seen as the key principle for standardization processes for BCI systems.

Tackling the first interface between "Amplifier" and "Feature Extractor", as shown in Fig. 1, commonalities like acquisition of various channels or a defined sampling rate can be found in different BCI system like OpenVibe [3], BCI2000 [4], rtsBCI [5], or xBCI [6]. Every one of those systems acquire data and transmit it for further processing. But as no standardized interface definition between acquisition and the first processing module is available, partly incompatible systems are the result. BCI systems dealing with other signal types than just brain signals like EEG (electroencephalogram) or NIRS (near infrared spectroscopy) are also mentioned in literature [7]–[11]. Such systems, called hybrid BCIs (hBCI), deal with different types of user inputs to form a more flexible BCI by also including assistive technology (joysticks, buttons,…). To deal with different kinds of signals in a standardized way, some kind of abstraction is needed. Additionally the type or manufacturer of a respective data acquisition source should be completely irrelevant for the following processing chain. Such a standardized abstraction layer would enhance flexibility and autonomy concerning used hardware.

Therefore an attempt of a standardized interface for raw biosignal transmission, especially for BCIs, called TiA (Tools for BCI – Interface A) was developed. With this interface it is possible to deal with different kinds of biosignals in a common way. It is a first step to decouple the data acquisition system from the BCI processing chain and provide ensured exchangeability.

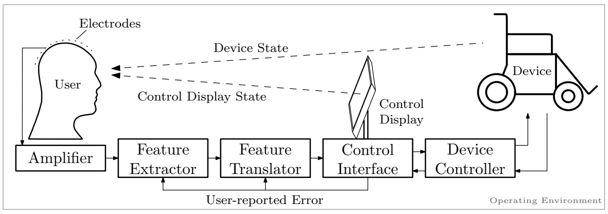


Fig. 1. Functional model from Mason and Birch (modified from [2]).

II. REQUIREMENT ANALYSIS AND DESIGN

Different BCI systems have already been built using pure brain control as well as hybrid combinations. EEG [12], magnetoencephalogram (MEG) [13], the NIRS signal [14], or the blood oxygen level dependent (BOLD) signal [15] have already been utilized to control a BCI just using mentioned brain signals. Developing hybrid BCI systems, the number of potential kinds of possible signals further increases. Signals like the electromyogram (EMG) [10] and the electrocardiogram (ECG) [16] have already been successfully combined with EEG to control a hybrid BCI. But also other signals like electrooculogram (EOG) or information delivered by various assistive devices (e.g. buttons or joysticks) or sensors could be used in combination with an arbitrary brain signal to form an hBCI system.

TiA evolves an abstraction layer between data acquisition and data processing. Therefore, a standardized possibility to distinguish between different kinds of signals beyond this abstraction is an important issue. For that purpose so-called "Signal Types" were introduced, allocating every different kind of signal a unique identifier.

When analyzing different kinds of signals transmitted be-

This work is supported by the European ICT Programme Project FP7-224631. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.

C. Breitwieser and G.R. Müller-Putz are with the Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria, 8010 Graz, Krenngasse 37, e-mail: c.breitwieser@tugraz.at, e-mail: gernot.mueller@tugraz.at

C. Neuper is with the Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria, 8010 Graz, Krenngasse 37, and the Department of Psychology, University of Graz, Austria, 8010 Graz, Universitätsplatz 2/III, e-mail: neuper@tugraz.at

tween data acquisition and data processing, various commonalities can be found. Signals are, or can be, divided into channels with related channel names and a defined scaling. Those channels can have a position or location and are acquired with a defined sampling rate. Single samples can be grouped together, forming blocks of samples.
Mason and Birch [2] showed a unidirectional transmission (see Fig. 1) from data acquisition (amplifier) to the first processing module (feature extraction). Using a client–server architecture is one possibility to address such a principle. In this case the data acquisition plays the server role and processing modules are the respective clients. Applying the client–server principle in this case easily facilitates the usage of multiple and potentially distributed processing chains (Mason and Birch merely show one processing chain in their models).

A. Design Principles

Information transmitted via TiA can be distinguished into two categories: (i) mutable and (ii) immutable information. Therefore, the data distribution is also split into two parts, initial meta information transmission to transmit immutable information and a continuous data stream to transmit mutable data to the client. Control messages using a defined handshaking protocol are used to transmit meta information. Mutable data (e.g., recorded voltage from an EEG channel) is delivered using a unidirectional binary data stream from the server to the client. Using the client–server principle similar or individual data streams can be established to multiple clients, only depending on the transmitted meta information. It is possible for an arbitrary number of clients to attach to the server at runtime. The client–server principle used for TiA is illustrated in more detail in Fig. 2.
A whitepaper concerning design and implementation of TiA (e.g., signal type flags) is available for download at arXiv.org [17].

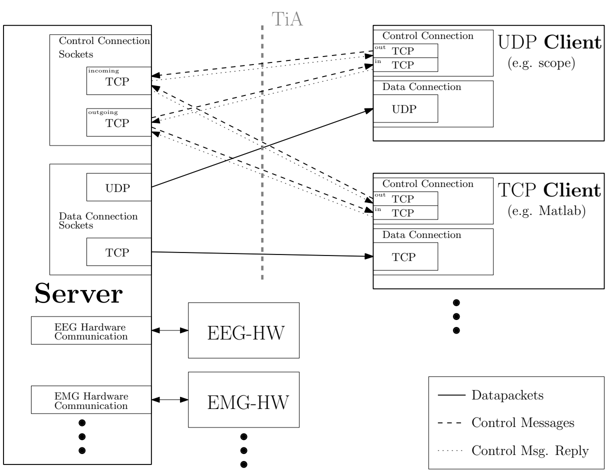


Fig. 2. TiA principle showing one server and two clients. An arbitrary number of clients can connect to the server choosing TCP or UDP for raw data transmission.

B. Software Design

A single data acquisition system, implementing the TiA interface, acquires data from different hardware devices. To set up a connection, HTTP-like (hyper text transfer protocol [18]) control messages are sent using two TCP (transmission control protocol [19]) connections. Messages sent over those connections are used for handshaking between client and server. Meta information can be optionally appended to this control messages. For mutable raw data transmission, a TCP or UDP (user datagram protocol [20]) connection can be chosen during the handshaking process.
The handshaking process is handled with two separated connections, whereby one connection is client–server oriented and the other one has a server–client orientation. The client–server connection is a mandatory requirement in TiA, supporting the server–client connection is optional. Incoming messages are always answered using the same connection on which the message was received.

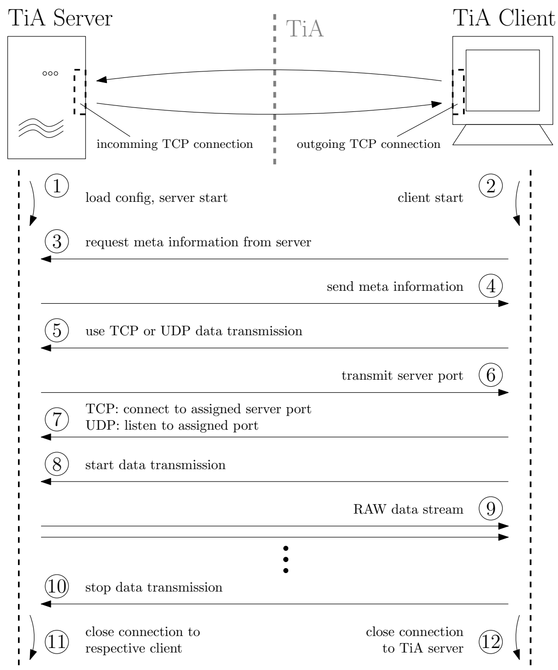


Fig. 3. TiA – client–server handshake. Steps 3–8 and 10 are done using the client–server control connection. During step 9 information is transmitted over the data connection; it represents the raw data stream from the server to the client.

1) Handshaking Process: Fig. 3 illustrates the steps between client–server communication. Information exchange is represented using arrows. Every message is transmitted in a standardized way using defined control messages and data packets. During steps 1 and 2 the client and server are started. In case of an error the startup is interrupted. In step 3 the client requests meta information from the server, the server responds with the meta information in step 4. For raw data transmission the client can choose whether to receive data via TCP or UDP. The desired raw data transmission protocol is sent to the server during step 5.

The server responds in step 6 with the respective port the client has to connect to (in case of TCP) or to listen to (in case of UDP). Subsequently in step 7 the client establishes a connection to (TCP) or starts listening (UDP) for data packets on the assigned port. To start data transmission, the client sends a message to the server during step 8. Starting in step 9, the server starts transmitting data packets to the client (the data packet is the same for TCP and UDP). In case of UDP, packets are broadcasted. The first connected client requesting UDP starts the broadcast and the last client disconnecting from the server stops the broadcast. If the client does not want to receive any more messages, a stop command is sent to the server during step 10. In case of TCP no more packets are delivered using the respective data connection. In case of UDP the broadcast is only stopped if the respective client was the last one requesting UDP. Otherwise UDP packets are further broadcasted. During step 11 the respective client is removed from the servers list of connected clients. Subsequently, in step 12, the client closes both the data and control connections to the server.
This handshaking procedure is mandatory to establish a connection. In case of an error during this handshaking procedure no connection is created.

2) Data Transmission: Mutable raw data is transmitted via TiA data packets using a binary data stream. Acquired data is encapsulated within those data packets. An exemplary data packet is visible in Fig. 4.

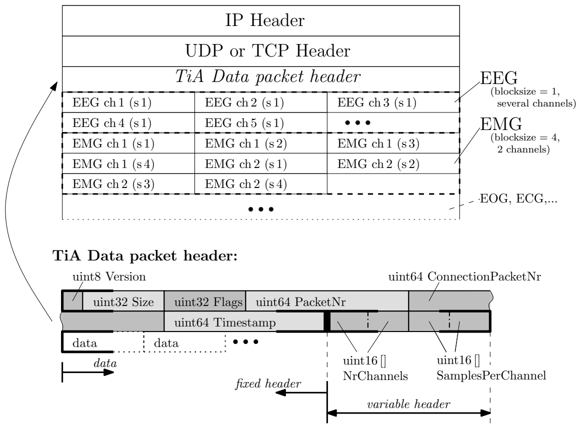


Fig. 4. Graphical representation of a TiA data packet. EEG and EMG content is shown as an example. EEG ch 1 (s 1) is an abbreviation for the signal type EEG, the first channel and the first sample. The block size for EEG is also one. For EMG an exemplary block size of four is used.

a) TiA Data Packet: The TiA data packet consists of three parts: (i) a fixed header; (ii) a variable header; and (iii) the raw data. By interpreting information stored in the fixed and variable header it is possible to correctly parse and read the whole data packet. The packet is equipped with a timestamp, a packet number, and a unique identifier per connection to facilitate proper timing and detect lost packets using UDP data transmission. Every signal type inside the data packet is identified with a unique flag. The number of channels and the block size can vary from packet to packet, but within TiA, a constant number of channels over time is assumed. Within the data packet raw data is stored as a 32 bit binary single precision floating point number (IEEE 754-2008 [21]). As a distinction between different signal types is possible within the data packet, data acquisition of multiple signal types at the same time and transmission within one data packet is possible. Different signal types can have different sampling rates and different block sizes, but within on signal type the sampling rate and the block size must be the same. Furthermore a single hardware device can acquire just one or also multiple signal types, as far as prior requirements are fulfilled. Detailed information concerning the data packet is available at arXiv.org [17].

b) Data Stream: A client has to perform the TiA handshaking process before receiving any data packets and has to choose either TCP or UDP for data transmission. Potential lost packets in case of UDP are not re-sent. If guaranteed data transmission is required, TCP has to be chosen. Using TCP for data transmission, a separate TCP connection from the client to the server is established and data packets are sent via this connection. The TiA data transmission is also restricted in some sense: for a single signal type only one block size and one sampling rate is allowed. But different signal types may have different sampling rates and block sizes.

III. Implementation and Testing

A. Implementation

A library and a first prototype called "signal server" using this TiA library, both written in C++, have been implemented and are available for download (http://bci.tugraz.at/downloads.html). The implementation is cross platform (Windows and Linux). During implementation a main focus was performance and stability. Up to now various hardware devices like generic joysticks and amplifiers from g.tec [Guger Technologies OG, Graz, Austria] and Brain Products [Brain Products GmbH, Gilching, Germany)] are supported by the signal server. To use those devices for BCIs, different clients using TiA have been written for Matlab [The MathWorks Inc., Natick, USA], Matlab Simulink, and BCI2000 [4]. Thus it is possible to stream data into these systems using TiA.

B. Testing

Testing measurements were accomplished using common personal computers (HP dc7700 workstation, Intel Core2Duo 6300@1.86 GHz, 4 GB Ram, Nvidia GeForce 9500 GT, Western Digital WD1002FAEX) using Windows Xp 32 bit and Debian unstable 64 bit.

1) Stability and Memory Consumption: The signal server was tested with a TiA client, both running on the same machine or on two different PCs connected via Ethernet. Long-term tests, lasting at least 10 hours, were performed under Linux (Debian unstable) and Windows XP to check for stability problems. In Linux additional memory leak tests using valgrind [22] were conducted. The tested version of the signal server and the TiA client showed no increasing memory consumption in ten tests on both operating systems. The required memory was constant also after a continuous operation longer than ten hours. This was achieved in both operating systems. No memory leak was detected by valgrind under Linux when closing the server or the client. The memory consumption of the server was always below 1MB, the client required less than 15 MB. The higher memory consumption of the client is caused by its receive buffer for incoming data packets. This value has been increased in comparison with the server to prevent the client from loosing data packets in case of reading delays.

2) Processing Time: A low processing time during data acquisition is essential. Acquired data has to be delivered as fast as possible to the clients. The processing time was measured from creation of a data packet (nearly the moment when data is read out from the respective data acquisition driver) until it's handover to the operating systems networking library functions. The timestamp stored inside the data packet was utilized to measure the delay. Packets were created with 10 kHz and 128 channels to simulate a high workload and sent using TCP over the loopback device (a virtual local network interface). Statistical values were computed over five minutes (resulting in $3 \cdot 10^6$ packets), the computer was idle except the signal server and client processes. According to the results, shown in Tab. I, the maximum packet rate for the signal server would be roughly 40 kHz (with a mean processing time of 25 µs per data packet). Using a higher sampling rate, new data would be available before older one was completely processed.

TABLE I

PROCESSING TIME OF A SINGLE TIA DATA PACKET.

	mean	std	median	min	max
Debian	19 µs	±3 µs	16 µs	7 µs	2817 µs
Windows	23 µs	±18 µs	18 µs	9 µs	3741 µs

IV. DISCUSSION

We have shown that it is possible to introduce an attempt of a standardized layer between the data acquisition module (Amplifier) and the first data processing module (Feature Extractor) into the functional model described by Mason and Birch [2]. A library and a data acquisition software have been written for this purpose and have been successfully integrated into different programs used for BCI purposes nowadays (BCI2000, Matlab). Performance and stability of the current implementation has been analyzed. Furthermore, using TiA, it is a simple process to add additional signal types.

By using TiA it becomes possible to decouple a BCI system from the used data acquisition hardware and make one step towards Masons standardized BCI model.

ACKNOWLEDGMENT

Special thanks to Christoph Eibel and Andreas Schuller from Graz University of Technology and Francesco Leotta from Fondazione Santa Lucia for their contributions.

REFERENCES

[1] J. J. Vidal, "Toward direct brain-computer communication." *Annu Rev Biophys Bioeng*, vol. 2, pp. 157–180, 1973.

[2] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design." *IEEE Trans Neural Syst Rehabil Eng*, vol. 11, no. 1, pp. 70–85, Mar 2003.

[3] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer, "Openvibe: An open-source software platform to design, test, and use brain-computer interfaces in real and virtual environments," *Presence: Teleoperators and Virtual Environments*, vol. 19, no. 1, pp. 35–53, 2010.

[4] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "Bci2000: a general-purpose brain-computer interface (bci) system." *IEEE Trans Biomed Eng*, vol. 51, no. 6, pp. 1034–1043, Jun 2004.

[5] R. Scherer, A. Schlögl, G. Müller-Putz, and G. Pfurtscheller, "Inside the graz-bci: rtsbci," in *Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course 2004*, 2004.

[6] I. P. Susila, S. Kanoh, K.-i. Miyamoto, and T. Yoshinobu, "xBCI: A generic platform for development of an online bci system," *IEEJ Trans Elec Electron Eng*, vol. 5, no. 4, pp. 467–473, 2010.

[7] J. D. R. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb, C. Neuper, K.-R. Müller, and D. Mattia, "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges." *Front Neurosci*, vol. 4, 2010.

[8] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Müller-Putz, C. Neuper, and N. Birbaumer, "The hybrid bci." *Front Neurosci*, vol. 4, p. 42, 2010.

[9] G. Pfurtscheller, T. Solis-Escalante, R. Ortner, P. Linortner, and G. R. Müller-Putz, "Self-paced operation of an ssvep-based orthosis with and without an imagery-based "brain switch:" a feasibility study towards a hybrid bci." *IEEE Trans Neural Syst Rehabil Eng*, vol. 18, no. 4, pp. 409–414, Aug 2010.

[10] R. Leeb, H. Sagha, R. Chavarriaga, and J. D. R. Millan, "Multimodal fusion of muscle and brain signals for a hybrid-bci." *Conf Proc IEEE Eng Med Biol Soc*, vol. 1, pp. 4343–4346, 2010.

[11] C. Brunner, B. Z. Allison, D. J. Krusienski, V. Kaiser, G. R. Müller-Putz, G. Pfurtscheller, and C. Neuper, "Improved signal processing approaches in an offline simulation of a hybrid brain-computer interface." *J Neurosci Methods*, vol. 188, no. 1, pp. 165–173, Apr 2010.

[12] G. Müller-Putz, B. C., F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. Millán, "Tools for Brain-Computer Interaction: A new concept for a hybrid BCI," *IEEE Trans Biomed Eng*, submitted 2011.

[13] J. Mellinger, G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler", "An meg-based brain-computer interface (bci)," *NeuroImage*, vol. 36, no. 3, pp. 581 – 593, 2007.

[14] S. M. Coyle, T. E. Ward, and C. M. Markham, "Brain–computer interface using a simplified functional near-infrared spectroscopy system," *Journal of Neural Engineering*, vol. 4, no. 3, p. 219, 2007.

[15] J.-H. Lee, J. Ryu, F. A. Jolesz, Z.-H. Cho, and S.-S. Yoo, "Brain-machine interface via real-time fmri: Preliminary study on thought-controlled robotic arm," *Neuroscience Letters*, vol. 450, no. 1, pp. 1 – 6, 2009.

[16] R. Scherer, G. R. Mller-Putz, and G. Pfurtscheller, "Self-initiation of EEG-based brain-computer communication using the heart rate response," *Journal of Neural Engineering*, vol. 4, pp. L23–L29, 2007.

[17] C. Breitwieser and C. Eibel, "TiA – Documentation of TOBI Interface A," *ArXiv e-prints*, Mar. 2011.

[18] R. Fielding, J. Gettys, J. Mogul, H. Frystyk, L. Masinter, P. Leach, and T. Berners-Lee, "Hypertext transfer protocol – http/1.1," United States, 1999.

[19] V. Cerf and R. Kahn, "A protocol for packet network intercommunication," vol. 22, no. 5, pp. 637–648, 1974.

[20] J. Postel, "User datagram protocol," Internet Engineering Task Force, RFC 768, August 1980.

[21] "Ieee standard for floating-point arithmetic," *IEEE Std 754-2008*, pp. 1 –58, 29 2008.

[22] N. Nethercote and J. Seward, "Valgrind: a framework for heavyweight dynamic binary instrumentation," *SIGPLAN Not.*, vol. 42, pp. 89–100, June 2007.

A.2. Proposing a Standardized Protocol for Raw Biosignal Transmission

C. Breitwieser, I. Daly, C. Neuper, and G. R. Müller-Putz. "Proposing a standardized protocol for raw biosignal transmission." In: *IEEE Transactions on Biomedical Engineering* 59.3 [2012], pp. 852–859. DOI: 10.1109/TBME.2011.2174637 [190]

Distribution of dedicated work:

- **Christian Breitwieser**: 80
- Ian Daly: 3 %
- Christa Neuper: 2 %
- Gernot R. Müller-Putz: 15 %

Proposing a Standardized Protocol for Raw Biosignal Transmission

Christian Breitwieser, Ian Daly, Christa Neuper, and Gernot R. Müller-Putz*

***Abstract*—In this paper, we propose a standardized interface called TiA (TOBI interface A) to transmit raw biosignals, supporting multirate and block-oriented transmission of different kinds of signals from various acquisition devices (e.g., EEG, electrooculogram, near-infrared spectroscopy signals, etc.) at the same time. To facilitate a distinction between those kinds of signals, so-called signal types are introduced. TiA is a single-server, multiple-client system, whereby clients can connect to the server at runtime. Information transfer between client and server is divided into control and data connections. The control connections use transmission control protocol (TCP) and transmit extensible-markup-language (XML)-encoded meta information. The data transmission utilizes a user datagram protocol (UDP) or TCP with a binary data stream. A standardized handshaking procedure for the connection setup and a standardized binary data packet has been defined. Thus, a standardized layer, abstracting used hardware devices and facilitating distributed raw data transmission in a standardized way, has been evolved. A cross-platform library, implemented in C++, is available for download.**

***Index Terms*—Biosignal, brain–computer interface, ECG, EEG, electromyogram (EMG), electrooculogram (EOG), multirate, NIRS, standard, transmission.**

I. Introduction

BRAIN–COMPUTER interfaces (BCIs) facilitate user interaction with a computer by processing different kinds of brain signals [1]. Different BCI systems [2] have been developed since a BCI was first mentioned in the literature by Vidal in 1973 [3]. Some of those systems are publicly available, for example, BCI2000 [4], OpenViBE [5], rtsBCI [6], xBCI [7], or FieldTrip [8], and some others are just internally used within individual groups, for example, Reading BCI [9] or Strathclyde BCI [10]. Each of these systems solves the working principle of a BCI system in its own way.

In [11], Mason and Birch introduced a common structure for BCI systems. Here, the common BCI "processing pipeline"—originally divided into the sections: 1) data acquisition, 2) preprocessing, 3) feature extraction, 4) classification, and 5) application—was modified and extended with a control interface, a device controller, and a device (see Fig. 1). Taking a closer look at the mentioned BCI systems, they can all be described with Mason and Birch's model. However, as a result of this diversity in BCI systems, it is becoming increasingly difficult for groups to collaborate with one another. This is despite the different systems fitting into the functional model shown in Fig. 1. In practice, this means that one of the groups has to switch to another system or partly reimplement/adapt their system to establish compatibility. As an example, adding new data acquisition (DAQ) hardware can be a huge effort for small systems with limited manpower behind their development. Furthermore, it is difficult for new hardware manufacturers to ensure compatibility with different BCI systems, as the support for their hardware has to be implemented first.

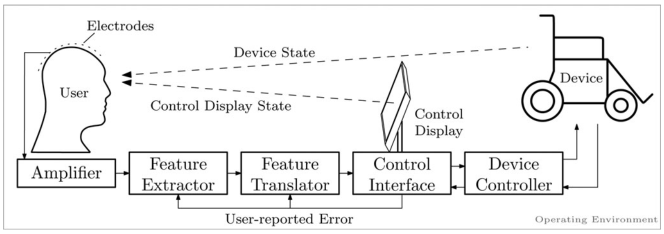


Fig. 1. Functional model from Mason and Birch (modified from [11]).

Mason and Birch showed in their work that BCI systems can be divided into individual modules, connected by individual interfaces (see Fig. 1). Furthermore, a number of the aforementioned popular BCI systems are all built in a modular way. For example, BCI2000 is constructed from three modules: signal acquisition, processing, and feedback; OpenViBE has modules devoted to acquisition, preprocessing, processing, and visualization of biosignals.

In this study, we tackled the first interface shown in Mason and Birch's model between "amplifier" and "feature extractor." Therefore, we attempted to introduce a standardized open-source protocol to transmit raw biosignal data. Such an interface would make BCI systems or, in general, systems processing biosignals independent of the specific amplifier used and introduce an abstraction layer. People would benefit from this standardization in various ways, shown in different exemplary scenarios.

Scenario 1: A new company wants to establish themselves in the market with a new product. Currently, they have to wait until their hardware is supported by the respective software systems, i.e., they have to wait for the developers of BCI2000 or OpenViBE to do the implementation. Using TiA, they merely

Manuscript received May 11, 2011; revised July 29, 2011 and September 30, 2011; accepted September 30, 2011. Date of publication December 21, 2011; date of current version February 17, 2012. This work was supported by the European ICT Programme Project FP7-224631. *Asterisk indicates corresponding author*.

C. Breitwieser and I. Daly are with the Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology, 8010 Graz, Austria (e-mail: c.breitwieser@tugraz.at; ian.daly@tugraz.at).

C. Neuper is with the Department of Psychology, University of Graz, 8010 Graz, Austria and with the Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria, 8010 Graz, Krenngasse 37 (e-mail: neuper@tugraz.at).

*G. R. Müller-Putz is with the Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology, 8010 Graz, Austria (e-mail: gernot.mueller@tugraz.at).

Digital Object Identifier 10.1109/TBME.2011.2174637

have to wrap their hardware driver with the TiA library and they are then automatically supported by every software system which is able to operate with TiA.

Scenario 2: A BCI researcher wants to try out some new hardware device with a customized system he or she has written. Without TiA, a lot of implementation to support the new device would be necessary, and the researcher would have to write his or her own module to interface with the new hardware device. However, if the researcher has already implemented a module in his or her system for supporting the TiA interface, then, so long as the new hardware device also supports TiA, a new device may be added to the system with minimal effort.

Scenario 3: A BCI developer wants to use components from two different BCI toolboxes, e.g., a preprocessing toolbox from BCI2000 in conjunction with a DAQ module from the OpenViBE toolbox. In this case, both the respective modules would have to be adapted to support one another. As TiA is an open source, the existing library can be integrated in BCI2000 acting as a client and in OpenViBE acting as a server. Thus, the OpenViBE data acquisition would also be usable with BCI2000.

However, there are already different protocols available to distribute raw data over the network. Proprietary examples would be, e.g., the brain products RDA protocol (Brain Products, Gilching, Germany); the Electrical Geodesic Amp Server (Electrical Geodesics, Inc., Eugene, OR); the Neuroscan amplifier communication protocol (Compumedics Neuroscan, Charlotte, NC); or the BioSemi ActiView + National Instruments LabView (BioSemi B.V., Amsterdam, The Netherlands+National Instruments Corp., Austin, TX). Usually a single proprietary protocol together with its acquisition software is bound and limited to hardware from the respective manufacturer and does not support devices from other manufacturers. Open-source alternatives would be the communication used within BCI2000 or OpenViBE, but they are extremely bound to the respective software framework (e.g., the internal BCI2000 states are useless for other BCI systems). As TiA is a flexible open-source approach, it would enhance compatibility between BCI toolbox modules and amplifiers, allowing users more freedom to mix and match modules.

Furthermore, according to the work of Brunner *et al.* [12], standardization is still an open issue within basic and clinical BCI research. TiA, as already briefly introduced in [13] would, therefore, be a first step toward such standardization, enhancing flexibility, and compatibility as shown in the aforementioned scenarios. TiA would save a lot of time and manpower allowing researchers to focus more on their actual work and less on writing code to support new hardware devices.

II. Methods

BCI systems can be built using various brain signals. Including hybrid systems [2], [14], the number of potential signal sources further increases the number of different kinds of signals that may be used for BCI purposes. Various brain signals have been used up to now for BCI purposes such as the EEG [1], magnetoencephalography signals [15], near-infrared spectroscopy signals [16], or the blood oxygen level-dependent signal [16].

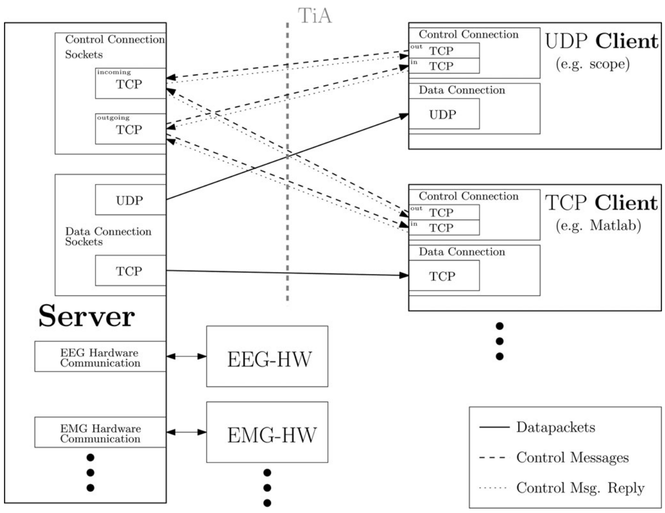


Fig. 2. Client–server principle for two exemplary clients (scope and MATLAB [The MathWorks Inc., Natick, MA]) using TiA. Multiple clients can connect to one server using a user datagram protocol (UDP) or transfer control protocol (TCP) data connection. The server is able to acquire data from various hardware devices at the same time. Both control connections for incoming and outgoing messages and the data connections are shown for both clients (see legend).

Furthermore, also hybrid BCIs have already been created using biosignals such as the electromyogram (EMG) [18] or the ECG [19]. Additional potential candidates might be the electrooculogram, input from different sensors, or signals from various assistive devices like buttons or joysticks.

To establish an interface that facilitates an abstraction for all these different types of biosignals, commonalities have to be analyzed. A distinction beyond this abstraction layer must still be possible, so all transmitted signals have to be divided into so-called signal types. Information concerning a specific signal type must not get lost during the abstraction process.

A. Requirements Analysis

Different signal types exhibit common and different attributes (e.g., impedance, channel position, etc.). Comparing different signal types used for BCI purposes, similarities concerning their usage and acquisition have been found. These similarities are a separation into distinct channels, individual channel names and channel positions, and a defined data or sampling rate with a defined scaling. Data might also be grouped together forming blocks of samples.

As seen in Mason's model [11] (see Fig. 1), the connection from data acquisition (amplifier) to the first processing module (feature extraction) is unidirectional. A meaningful way to establish such a communication principle is a client–server architecture, whereby the data acquisition can be seen as a server and connected processing modules as clients, shown in Fig. 2. Mason's model shows only a single processing chain. Using a client–server system, multiple processing streams can easily be built. This interface between the data acquisition and the following processing modules is called TiA. It is an interface to transmit raw biosignals from different sources with different signal types at the same time.

B. Design Principles

TiA is built as a single-server, multiple-client system. Thus, one server acquires data from all hardware devices and is, therefore, responsible for synchronization. A multiserver approach (multiple servers acquiring data from a single device) would allow more flexibility, as servers can be distributed over different computers and/or operating systems. The drawbacks are an increased and complex configuration and connection procedure as well as difficult synchronization issues. Due to this, a single-server system was chosen as a DAQ principle.

Analyzing information exchange between server and client(s), two types of information can be found: 1) mutable and 2) immutable. It is sufficient to transmit immutable information (e.g., channel names) during the connection setup and mutable information (e.g., channel values) as a data stream. Therefore, mutable raw data are distinguished from immutable meta information and transmitted in different ways. Meta information is encapsulated inside control messages with a defined handshaking protocol; raw data are transmitted via a binary data stream. The single-server system is able to deal with an arbitrary number of clients at runtime. In the case of multiple data sources, running potentially with different sampling rates, TiA is not in charge of data synchronization. This has to be done within the data acquisition part, passing already synchronized data to TiA. A schematic representation can be seen in Fig. 2.

The latest documentation for TiA (e.g., signal type flags) can be found at arXiv.org [19] and http://www.bcistandards.org.

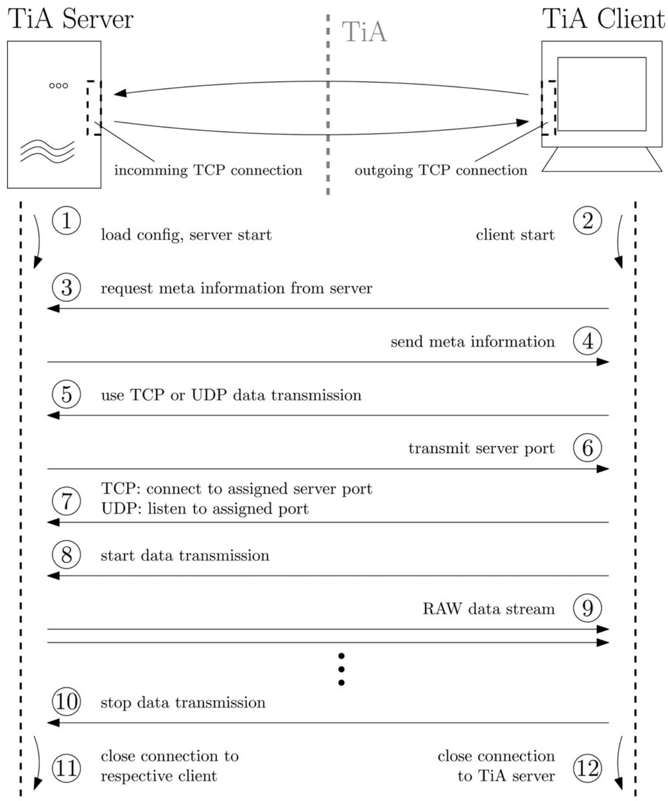


Fig. 3. TiA: Client–server handshake for the servers incoming TCP connection. Step 9 can be repeated indefinitely.

C. Software Design

Data acquisition is done using a single server acquiring data from all needed devices, while clients can attach to the server at runtime. The communication is divided into a hypertext transfer protocol (HTTP) [20] oriented control communication (using two TCP sockets) with optional meta information encoded in extensible markup language (XML) [21] (sending control messages) and raw data transmission. To facilitate distributed processing, the whole communication is handled using network sockets. Using TCP, it is ensured that no control message gets lost. Two TCP sockets are used, whereby one socket processes incoming messages from the client and the second can be used to send messages to the client. Every message is answered with a reply message, sent over the same socket at which the incoming message was received on. Using the server outgoing message socket, it is possible to inform connected clients about errors that occurred or important notifications. Using the server's outgoing socket from the client side is voluntary; a connection to the server's incoming socket is a mandatory requirement. Concerning the data connection, every client is free to choose either TCP or UDP [22], [23]. TCP can, therefore, be chosen, if reliable data transmission is mandatory (e.g., BCI data processing) and UDP if a potential packet loss is an acceptable issue (e.g., a scope application for monitoring the biosignal data stream).

1) Handshaking Process: Fig. 3 shows the handshaking procedure between a server's incoming TCP connection and a single client. Every arrow between the client and the server represents networking activity; the communication is done via defined control messages. Messages from the outgoing server connection are permitted at any time.

The client and server are started during steps 1 and 2 (startup is interrupted if an error occurs). In step 3, the client sends a meta information request to the server. In step 4, requested meta information is delivered by the server. The client is free to choose either TCP or UDP for data transmission. In step 5, this information is transmitted to the server. In step 6, the server responds with the respective port. During step 7, in the case of TCP, the client connects to this port or in the case of UDP, it starts listening on this port. In step 8, data transmission is started. Following this message, the server starts streaming raw data to the client during step 9 (UDP data packets are broadcasted into a given subnet). In the case of UDP, data broadcast is established by the first client. In step 10, data transmission is stopped. UDP broadcast is stopped if the last client sends the stop message. In the case of TCP, no more packets are transmitted over the respective connection. Steps 11 and 12 are used for server- and client-specific shutdown procedures (close connections, remove client from list, etc.).

A successful handshaking is a mandatory requirement to establish a connection; otherwise, the procedure is aborted. In the case of dropped connections, the data transmission is stopped to the respective client and its connection is shut down.

2) Data Transmission: During step 9 (see Fig. 3), raw samples are transmitted via a binary data stream. Sampled data are encapsulated in data packets (see Fig. 4).

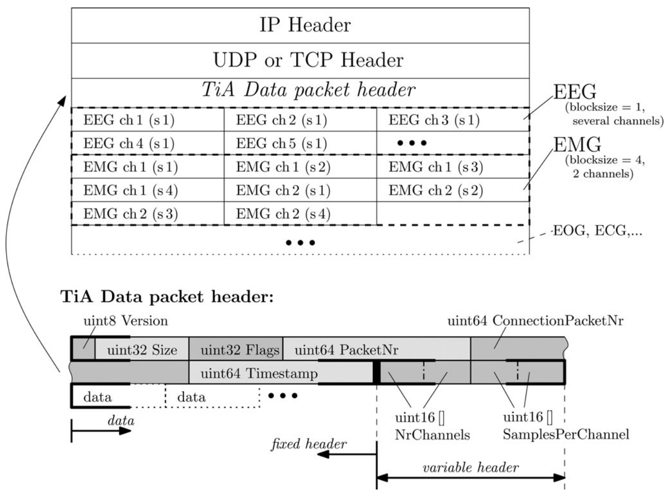


Fig. 4. Data packet structure. Exemplary content with EEG and EMG are shown in this figure. EEG ch 1 (s 1) represents a signal from type EEG, channel 1, first sample; block size is 1. For the signal type EMG, blocked samples are shown with a block size of 4. Borders between fixed and variable headers and data are highlighted with bold lines.

a) Data packet: The data packet is divided into three parts: 1) a fixed header, 2) a variable header, and 3) the raw data. The whole data transmission is using little-endian byte order [24]. All variables inside the fixed and the variable headers are unsigned integers (uint) with a different number of bits (e.g., uint16, i.e., unsigned integer using 16 bits).

The first variable inside the fixed header is the version number (uint8 Version) of the data packet. This variable is used to prevent an older client from reading a newer packet. The second variable (uint32 size) contains the size of the data packet in bytes. Thus, it is possible to determine whether a packet has already been completely received. The third variable (uint32 Flags) is used to indicate which signal types are stored inside the data packet. Every bit inside this integer represents a defined signal type. The packet number is stored in the fourth variable (uint64 PacketNr) and is a running ascending number, which is increased when a new data packet is produced. A data packet can be identified in the whole BCI system by its packet number. In the case of downsampling, the packet number is always increased by the downsampling factor. By this, also a downsampled data stream can still be aligned with the original data packets. The fifth variable (uint64 ConnectionPacketNr) is a unique number per client–server connection. Thus, it is possible to identify lost packets. This is useful when using UDP because here no guaranteed transmission is given. The sixth and last variable (uint64 Timestamp) inside the fixed header is a timestamp storing elapsed microseconds since the data acquisition starts. This ensures accurate timing information within a potentially distributed BCI system.

The variable header consists of two arrays storing uint16 variables. The number of uint16 values is the same as the number of signal types stored in the data packet. Both arrays always have the same length. The first variable array (uint16[] NrChannels) holds the number of channels for every signal type stored in the data packet. The second variable array (uint16[] SamplesPerChannel) stores the block size for every signal type stored in the respective data packet.

The length of both arrays can be determined by counting the amount of flags set in the fixed header. Combining the information from the fixed and variable headers, it is possible to parse the raw data section.

Following the variable header, the raw data are stored in samples in the data packet. Every sample is stored as a 32-bit binary single precision floating point number as defined in IEEE 754-2008 [25]. Signal types are stored in ascending order by means of their flags. If block-oriented transmission is used, samples are grouped into blocks from the same channel (e.g., block size = 2: ch1s1 ch1s2, ch2s1 ch2s2, etc.). Channels are sorted in ascending order by means of their channel number. Only one block size and one sampling rate are allowed per signal type. The number of channels from a signal type must not change during data acquisition.

The data packet is designed to be flexible in its use. Different signal types can have different sampling rates or different block sizes. Using a binary representation for the data packet reduces the needed bandwidth in case of a network transmission and facilitates higher sampling rates or a high number of acquired channels. By distinction between different signal types, data acquisition and transmission from different sources at the same time are easily possible.

b) Data stream: The data packets are delivered to attached clients in a unidirectional stream-oriented way. A client subscribes to the server for TCP or UDP data transmission. In the case of UDP, the data are broadcasted into a defined subnet with a defined port. The client itself has to take care to be inside this subnet. If the last UDP client unsubscribes from the server, UDP broadcasting is stopped. Lost packets are not resent into the subnet. For guaranteed data transmission, TCP has to be used. UDP data transmission is mainly provided for applications without the need to receive all data packets (e.g., scope application). In the case of TCP transmission, a single TCP connection is established between the server and every TCP client. A unique TCP port is assigned to every client and automatically transmitted during the initial handshake. A client-specific signal type, channel, and/or sampling rate selection is possible because of individual connections.

TCP packets are sent without Nagle's algorithm (congestion control) [26]. This ensures a data packet to be transmitted (nearly) immediately. Unfortunately, TCP traffic is not optimized by deactivating this algorithm.

TiA is used for testing and demonstration purposes in DAQ software called "SignalServer." The SignalServer is implemented in C++, is cross-platform, and supports multirate data acquisition from different sources at the same time.

D. Implementation—The SignalServer

The SignalServer, a cross-platform DAQ system, was implemented in C++ using the TiA library. It was designed to support multirate acquisition from different hardware devices at the same time with the focus on performance and stability.

E. Testing

To ensure the functionality of TiA and the SignalServer, various tests have been accomplished.

1) Performance and Network Delay: Performance measurements were done using a modern state-of-the-art PC (HP dc7700 workstation, Intel Core2Duo 6300@1.86 GHz, 4 GB RAM, Nvidia GeForce 9500 GT, Western Digital WD1002FAEX) using Windows Xp 32 bit and Debian unstable 64 bit. The CPU load and memory consumption were logged running the SignalServer under both operating systems. Tests were done in all possible combinations (Debian/Debian, Debian/Win, etc.).

Delivering acquired signals over a network connection, especially its latency has to be investigated in this case. Network latency was analyzed using a 1-Gbit Ethernet connection between two PCs (cable length 2 m), one running the SignalServer and the other one a simple client. In case of a packet transmission or a packet reception, the server and the client inverted a single pin on a parallel port. Thus, packet delay over the network could be measured by detecting rising and falling edges on the parallel port. Signals from respective pins from both parallel ports were recorded with a sampling rate of 25 kHz. Packets containing data from 250 artificial channels were sent with a packet rate of 100 Hz (this rate was chosen due to hardware limitations of the parallel port and its steepness of rising and falling edges).

To investigate the effects of additional network load, internet control message protocol (ICMP) packets [27] were sent with a fixed size and packet rate to generate a consistent load of 1 Mb/s (congestion control is deactivated by default in TiA to achieve near-real-time packet delivery).

For testing purposes, a C++ TiA client was implemented for just acquiring data packets over a network connection. CPU load, memory consumption, and network load were logged. An additional test was carried out with a packet rate of 2 kHz and 250 artificial channels to determine changes in CPU and memory usage compared to a packet rate of 100 Hz (parallel port signal was not recorded).

2) Processing Time: A short processing time (far below the data packet rate) inside the SignalServer and TiA is essential. Acquired data have to be delivered as fast as possible to the clients. The processing time was measured from creation of a data packet (which is the moment when data are read out from the respective DAQ driver) until it is handed over to the networking library functions. The timestamp stored inside the data packet was utilized to measure the delay. Packets were created with the rate of 10 kHz and 128 channels and sent using TCP over the loopback device. Statistical values were computed over 5 min (resulting in 3×10^6 packets); the computer was idle except the SignalServer and client processes (Debian unstable 64 bit and Windows XP 32 bit, Pentium Core2Duo 6300, 1.86 GHz). Within Windows, threads were set to real-time priority.

3) Stability: TiA was tested over a prolonged period of time using the SignalServer and a TiA client. Both systems running on a single machine or on two PCs connected via Ethernet. The tests lasted at least 10 h. Used operating systems were Linux (Debian unstable) and Windows XP.

TABLE I
CPU LOAD AND MEMORY CONSUMPTION FROM THE SIGNALSERVER FOR DIFFERENT OPERATING SYSTEMS (OS)

OS	packet rate	Server CPU	Server MEM	Client CPU	Client MEM
Debian	100 Hz	0–1 %	< 500 kB	0–1 %	< 10 MB
Win XP	100 Hz	0–1 %	< 1 MB	0–1 %	< 12 MB
Debian	2 kHz	11–12 %	< 800 kB	6–8 %	< 10 MB
Win XP	2 kHz	9–13 %	< 1.5 MB	5–11 %	< 12 MB

TABLE II
PROCESSING TIME INSIDE THE SIGNALSERVER FOR DIFFERENT OPERATING SYSTEMS (OS)

OS	packet rate	mean	std	median	min	max
Debian	10 kHz	19 µs	3 µs	16 µs	7 µs	2817 µs
Win XP	10 kHz	23 µs	4 µs	18 µs	9 µs	3741 µs

Memory consumption was logged and memory leaks were analyzed using valgrind [28] under Linux. Fourteen tests have been carried out: five running the client and the server in Windows and five running both in Debian unstable; four "mixed" tests were also performed, running either the server under Windows and the client in Debian or vice versa.

III. RESULTS

A. Testing

1) Performance and Network Delay: CPU load and memory consumption were logged during measurements with 250 channels under different operating systems and two packet rates of 100 Hz and 2 kHz. Results are shown in Table I.

Table III shows averaged packet delays according to various additional artificial network loads and different number of channels.

Memory consumption was constant during all the measurements; the client requires more memory than the server because of a bigger buffer size for incoming data.

2) Processing Time: Table II shows the processing time inside the SignalServer for a packet rate of 10 kHz and 128 acquired channels.

3) Stability: The tested version of the SignalServer and the TiA client showed no increasing memory consumption. The required memory was the same also after a continuous operation longer than 10 h. This was achieved in Windows and likewise in Linux. No memory leak was detected by valgrind under Linux when closing the server or the client.

B. Implementation—The SignalServer

Key goals of the SignalServer are performance, stability, and simplicity. To achieve those goals, only well-tested libraries, mainly from the boost library collection, are used (http://www.boost.org).

The SignalServer is designed to support data acquisition from various hardware devices at the same time. A list of devices already supported or planned for implementation in the near

TABLE III
MEASURED NETWORK DELAYS AND NETWORK LOAD USING A 1-GB ETHERNET CONNECTION

Packet rate	Channels	Resulting load	Additional load	Recording duration	mean	std	median	min	max
100 Hz	16	15.8 kB/s	-	10 min	0.17 ms	0.08 ms	0.2 ms	0.05 ms	0.5 ms
100 Hz	16	15.8 kB/s	1 MB/s	10 min	0.16 ms	0.07 ms	0.2 ms	0.05 ms	0.4 ms
100 Hz	250	107.2 kB/s	-	15 min	0.19 ms	0.07 ms	0.2 ms	0.05 ms	0.5 ms
100 Hz	250	107.2 kB/s	1 MB/s	15 min	0.21 ms	0.05 ms	0.2 ms	0.05 ms	0.8 ms

TABLE IV
LIST OF DEVICES SUPPORTED BY THE SIGNALSERVER

Name	Manufacturer	Type	Implementation	Testing
g.USBamp	g.tec (Guger Technologies, Graz, Austria)	multipurpose biosignal DAQ	done	done
g.Mobilab	g.tec (Guger Technologies, Graz, Austria)	mobile biosignal DAQ	done	done
Generic joysticks	independent	aperiodic user input	done	done
Software sine generator	-	testing signals	done	done
Generic mouse	independent	aperiodic user input	done	done
BrainVision BrainAmp Series	Brain Products (Gilching, Germany)	multipurpose biosignal DAQ	done	done
g.BSAmp	g.tec (Guger Technologies, Graz, Austria)	multipurpose biosignal DAQ	done	in progress
DAQ card	National Instruments (Austin, TX, USA)	multi I/O card	done	in progress
Adjustable EEG simulator	-	testing signals	done	in progress
Generic keyboard	independent	aperiodic user input	in progress	planned
NIRScout	NIRx Medical Techn., LLC.(Glen Head, NY, USA)	NIRS daq system	in progress	planned
g.USBamp (Linux)	g.tec (Guger Technologies, Graz, Austria)	multipurpose biosignal DAQ	planned	planned

future can be found in Table IV. Configuration is done via a local XML file.

C. Distribution of Software

The SignalServer and a TiA client and server library are already available as Debian packages for Debian unstable and Ubuntu 10.10 as 64- and 32-bit versions. A Windows installer for 32-bit systems is also available, tested under Windows XP and Windows 7.

Packages, tools, and an installer can be downloaded at
http://bci.tugraz.at/downloads.html or
https://sourceforge.net/p/tools4bci

D. Current Usage

1) SignalServer: The SignalServer is already in use for measurements at Graz University of Technology, Berlin Institute of Technology, Ecole Polytechnique Fédérale de Lausanne, Fondazione Santa Lucia, and Heidelberg University. Various measurements, mainly using g.tecs g.USBamp, or g.Mobilab, have been carried out.

2) MATLAB/Simulink: A client for MATLAB/Simulink has been built and tested using MATLAB R2010a and R2010b. The Simulink client is implemented as a C++ MATLAB S-Function using TiA. It supports multirate data acquisition and is able to deal with multiple signal types, creating individual block output ports for every signal type when initializing the model.

3) TiAScope: TiA has been integrated into an online remote scope to view acquired data in real time. This scope application is implemented in C++ using the Qt framework (http://qt.nokia.com/products) as a graphical user interface.

4) BCiScope: TiA has also been ported to Apple's iPod Touch [Apple, Cupertino, CA (http://www.apple.com)]. A portable scope application is currently in development, facilitating online signal monitoring, especially for measurements outside any laboratory.

5) Embedded Linux Platform: TiA has been successfully integrated into an embedded BCI system acquiring data from the g.tec g.Mobilab+ using bluetooth. The whole acquisition is done on a Linux embedded board [FOX Board G20—ARM 400 MHz CPU, 64 MB RAM (http://www.acmesystems.it)].

6) BCI2000 TiA Client: A TiA compliant source module has been developed for BCI2000 v2. The developed module supports only a subset of the features offered by the interface specification, in order to adapt to the BCI2000 elaboration model. At the moment, the TiA module for BCI2000 supports multiple signal acquisition but imposes a fixed sampling rate and buffer size (taken from the master device).

IV. DISCUSSION

With TiA, we were able to introduce a standardization layer between DAQ hardware devices and BCI software as described in Mason's model [11] to make a first step toward the recommendations proposed in [12]. A platform-independent library and DAQ software have been implemented, tested, and are available for download. This library has been successfully integrated into, e.g., BCI2000 and MATLAB, two programs used for BCI purposes nowadays. TiA and the SignalServer have successfully passed through various tests and have already proven their potential for portability and very low resource requirements.

A. Performance and Timing Issues

Signal transmission over a 1-Gbit Ethernet connection can be seen as stable and predictable over time, as every test was performed consistently. Using the maximum mean packet delay

(0.21 ms), a theoretical limit to receive a packet before the next one is created would be 4.7 kHz, based on the results shown in Table III. This value was similar to half of the round trip time of a packet sent to the second computer used in the measurements [29]. Introducing an additional load simulates concurrent network traffic caused by external programs like a web browser. As can be seen, the transmission delay was not affected by minor additional traffic.

Considering the processing time of a data packet, the theoretical limit based on the maximum mean value of 23 μs (see Table II) would be 43 kHz for processing data packets with a block size of one sample. This value is obviously dependent on the available processing power.

B. Portability

Both TiA and the SignalServer are cross-platform. This is a result of using portable libraries like boost or TinyXML for C++ [a.k.a. ticpp (code.google.com/p/ticpp)], and not relying on operating system-dependent inclusion of files. Porting the SignalServer and TiA to embedded systems or an iPod illustrates the low resource requirements of those approaches. Thus, using TiA and the SignalServer is also a step forward in building portable or even embedded BCI systems. Distributing TiA and the SignalServer directly to Mac OS X and also the iPad and the iPhone is planned as a next step. A major constraint at this point is a limited availability of operating system-independent hardware drivers.

C. Extendability

Extendability was and is an important focus during development of TiA and also the SignalServer. Using HTTP related message style for control messages simplifies parsing. Transmitting meta information by XML encoding ensures that it is simple to add new tags to the message. As TiA is based on an open-source approach, additional features can be added by everybody willing to contribute to the system.

Extending the SignalServer with new hardware support is a simple process. The respective hardware class derives itself from a base class, implements abstract methods, and registers itself at a factory. Once these steps are done, the respective hardware module is automatically ready to be used. To extend the SignalServer with new hardware a combination of the factory and the builder pattern [30] is used.

D. Flexibility

Applying TiA for raw data transmission can enhance flexibility of a system in multiple ways. Within a BCI, the raw data could be directly fed into, e.g., the preprocessing module or alternatively into the commonly used DAQ module of the respective system. Therefore, TiA would result in minimal changes to the original software platform. However, TiA does not prevent the user from building loops, e.g., a module is acting as server and a client at the same time.

E. Data Security

Currently TiA provides no encryption algorithm for data transmission. As personal data in terms of biosignals are transmitted, a violation in data privacy is a potential risk. Usage of secure sockets layer [31] secured connections is currently under discussion. Currently, TiA should only be used if it is running on the loopback interface or behind a firewall in a secure subnet. Otherwise, unauthorized access cannot be excluded. On the other hand, using encryption, especially for high-bandwidth data streams, could heavily increase actual resource requirements. This might affect portability, especially to embedded systems with limited hardware.

F. Outlook

Some optional handshaking commands for TiA are currently under development. The first extension is the possibility for the client to send a configuration for the DAQ system using TiA. Thus, the data acquisition can be remotely configured. Because every DAQ system being equipped with TiA might be configured in a different way, TiA will give no restrictions in this case. A binary representation of the configuration will be handed over to the data acquisition part and a potential error or incompatibility will be reported to the client trying to configure the system. A second extension will be the possibility for clients to select individual channels, signal types, and also a lower sampling rate. This could be useful for clients with limited processing power or network bandwidth (e.g., embedded devices). The third extension will be to keep alive messages to determine broken connections, especially for clients using UDP. Thus, it is possible to detect crashed clients or a crashed server.

Acknowledgment

The authors would like to thank all companies for their support during hardware integration. They are also grateful to F. Leotta from Fondazione Santa Lucia, and C. Eibel, A. Schuller, M. Rowies, and B. Kaltner from the Graz University of Technology for their contributions. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control.," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

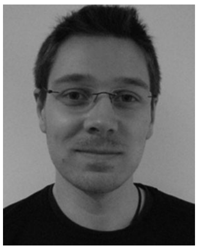
[2] J. D. R. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb, C. Neuper, K.-R. Müller, and D. Mattia, "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges," *Front Neurosci.*, vol. 4, pp. 1–15, 2010.

[3] J. J. Vidal, "Toward direct brain-computer communication.," *Annu. Rev. Biophys. Bioeng.*, vol. 2, pp. 157–180, 1973.

[4] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.

[5] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer, "OpenViBE: An open-source software platform to design, test, and use brain-computer interfaces in real and virtual

environments," *Presence: Teleoperat. Virt. Environ.*, vol. 19, no. 1, pp. 35–53, 2010.
[6] R. Scherer, A. Schlögl, G. Müller-Putz, and G. Pfurtscheller, "Inside the Graz-BCI: rtsBCI," in *Proc. 2nd Int. Brain-Comput. Interface Workshop Training Course*, 2004, pp. 81–82.
[7] I. P. Susila, S. Kanoh, K.-i. Miyamoto, and T. Yoshinobu, "xBCI: A generic platform for development of an online BCI system," *IEEJ Trans. Electr. Electron. Eng.*, vol. 5, no. 4, pp. 467–473, 2010.
[8] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, "FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Intell. Neurosci.*, vol. 2011, pp. 1–9, 2011.
[9] A. J. Portelli and S. J. Nasuto, "Toward construction of an inexpensive brain computer interface for goal oriented applications," in *Proc. Artif. Intell. Simul. Behav. Soc.*, Aberdeen, Scotland, 2008, pp. 2–7.
[10] G. Valsan, B. Grychtol, H. Lakany, and B. Conway, "The strathclyde brain computer interface," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, Sep. 2009, pp. 606–609.
[11] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 1, pp. 70–85, Mar. 2003.
[12] P. Brunner, L. Bianchi, C. Guger, F. Cincotti, and G. Schalk, "Current trends in hardware and software for brain–computer interfaces (BCIs)," *J. Neural Eng.*, vol. 8, no. 2, pp. 1–7, 2011.
[13] C. Breitwieser, C. Neuper, and G. R. Muller-Putz, "A concept to standardize raw biosignal transmission for brain-computer interfaces," in *Proc. IEEE Int. Conf. Eng. Medicine Biol. Soc. EMBC, 2011*, Sep. 2011, pp. 6377–6380.
[14] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Müller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Front Neurosci.*, vol. 4, pp. 1–11, 2010.
[15] J. Mellinger, G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler, "An MEG-based brain-computer interface (BCI)," *Neuroimage*, vol. 36, no. 3, pp. 581–593, 2007.
[16] S. M. Coyle, T. E. Ward, and C. M. Markham, "Brain–computer interface using a simplified functional near-infrared spectroscopy system," *J. Neural Eng.*, vol. 4, no. 3, pp. 219–226, 2007.
[17] N. Weiskopf, K. Mathiak, S. Bock, F. Scharnowski, R. Veit, W. Grodd, R. Goebel, and N. Birbaumer, "Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI)," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 966–970, Jun. 2004.
[18] R. Leeb, H. Sagha, R. Chavarriaga, and J. D. R. Millan, "Multimodal fusion of muscle and brain signals for a hybrid-BCI," in *Proc. IEEE Eng. Med. Biol. Soc.*, 2010, vol. 1, pp. 4343–4346.
[19] R. Scherer, G. R. Müller-Putz, and G. Pfurtscheller, "Self-initiation of EEG-based brain-computer communication using the heart rate response," *J. Neural Eng.*, vol. 4, pp. L23–L29, 2007.
[20] C. Breitwieser and C. Eibel, "TiA—Documentation of TOBI Interface A," *ArXiv e-prints*, 2011.
[21] R. Fielding, J. Gettys, J. Mogul, H. Frystyk, L. Masinter, P. Leach, and T. Berners-Lee, "Hypertext transfer protocol—HTTP/1.1," United States, 1999.
[22] T. Bray, J. Paoli, C. M. Sperberg-McQueen, E. Maler, and F. Yergeau, "Extensible markup language (XML) 1.0 (fifth edition)," World Wide Web Consortium, Recommendation REC-xml-20081126, 2008.
[23] V. Cerf and R. Kahn, "A protocol for packet network intercommunication," *IEEE Trans. Commun.*, vol. 22, no. 5, pp. 637–648, May 1974.
[24] J. Postel, *User Datagram Protocol*, Internet Engineering Task Force, RFC 768, 1980.
[25] D. Cohen, "On holy wars and a plea for peace," *Computer*, vol. 14, no. 10, pp. 48–54, 1981.
[26] *IEEE Standard for Floating-point Arithmetic*, IEEE Standard 754-2008, 2008, pp. 1–58.
[27] J. Nagle, "Congestion control in IP/TCP internetworks," *SIGCOMM Comput. Commun. Rev.*, vol. 14, pp. 11–17, 1984.
[28] J. Postel, "Internet Control Message Protocol," RFC 792, Sep. 1981.
[29] N. Nethercote and J. Seward, "Valgrind: A framework for heavyweight dynamic binary instrumentation," *SIGPLAN Not.*, vol. 42, pp. 89–100, 2007.
[30] P. Karn and C. Partridge, "Improving round-trip time estimates in reliable transport protocols," *SIGCOMM Comput. Commun. Rev.*, vol. 25, pp. 66–74, 1995.
[31] B. Meyer, *Object-Oriented Software Construction*, 2nd ed. Upper Saddle River, NJ: Prentice-Hall, 1997.
[32] A. O. Freier, P. Karlton, and P. C. Kocher, The SSL Protocol Version 3.0, Nov. 1996.



Christian Breitwieser received the B.Sc. and M.Sc. degrees in telematics from the Graz University of Technology, Graz, Austria, in 2007 and 2009, respectively, where he is currently working toward the Ph.D. degree at the Institute for Knowledge Discovery.

His research interests include software development, brain–computer interface (BCI) design, hybrid BCIs, and somatosensory brain signals for BCI purposes.

Ian Daly received the Ph.D. degree in cybernetics and the M.Eng. degree in computer science from the University of Reading, Reading, U.K.

Since May 2011, she has been a Postdoctoral Researcher in the Laboratory of Brain–Computer Interfaces at the Graz University of Technology, Graz, Austria. His research focuses on brain–computer interfaces, nonlinear dynamics, machine learning, signal processing, biosignal analysis, metaheuristic search techniques, and long-range phase synchronization in the EEG.

Christa Neuper recieved the Ph.D. degree in psychology from the University of Graz, Graz, Austria, in 1984.

She is currently the Principal of the University of Graz, Graz, Austria. She was the Head of the Institute for Knowledge Discovery at the Graz University of Technology, Graz, and the Full Professor of neuropsychology at the University of Graz. Since 1990, she has been involved in the pioneering development of motor imagery-based brain–computer interface (BCI) systems at the Graz University of Technology, which is one of the leading research institutes in brain–computer communication. She has also been a coinvestigator in a number of national and international research projects and has published more than 100 scientific papers and book chapters. Her main research interests include the study of brain dynamics of cognitive processes, functional brain diagnostics, the design of neurofeedback systems, and BCIs based on EEG and/or near-infrared spectroscopy.

Gernot R. Müller-Putz received the M.S. degree in biomedical engineering from the Graz University of Technology, Graz, Austria, in May 2000. He also received the Ph.D. degree from the Institute of Human-Computer Interfaces, Graz University of Technology in 2004. In 2008, he received the Habilitation in medical informatics with the title "Towards EEG-based Control of Neuroprosthetic Devices" at the faculty of informatics, Graz University of Technology.

Currently, he is an Associate Professor at the Graz University of Technology and the Head of the Institute for Knowledge Discovery. His research interests include brain–computer communication systems, noninvasive control of neuroprosthetics in spinal cord injured, the human somatosensory system and assistive technology.

A.3. TiD – Introducing and Benchmarking an Event-Delivery System for Brain-Computer Interfaces

C. Breitwieser, M. Tavella, M. Schreuder, F. Cincotti, R. Leeb, and G. R. Müller-Putz. "TiD – Introducing and Benchmarking an Event-Delivery System for Brain-Computer Interfaces." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* accepted [2017]. DOI: 10.1109/TNSRE.2017.2728199 [191]

Distribution of dedicated work:

- **Christian Breitwieser**: 50
- Michele Tavella: 15 %
- Martijn Schreuder: 10 %
- Febo Cincotti: 10 %
- Robert Leeb: 5 %
- Gernot R. Müller-Putz: 10 %

Introducing a flexible protocol for event delivery in neuroscience research

Christian Breitwieser, Michele Tavella, Martijn Schreuder, Febo Cincotti, Robert Leeb, Gernot R. Müller-Putz

***Abstract*—In this paper we introduce a flexible extended markup language (XML) based protocol for event distribution in neuroscience research. Events are commonly used to mark and describe incidents during an experiment, and are therefore critical for later data analysis or immediate real-time processing. However, different systems transmit events in varying ways, leading to incompatibilities and data misinterpretation. The new protocol, called TiD (Tools for brain-computer interaction - interface D) introduces a new standardized layer for flexible event distribution. TiD is a network based protocol, delivering messages in XML via a bus-like system using transmission control protocol (TCP) connections. A dedicated server dispatches TiD messages to potentially distributed clients. The TiD message is designed to be flexible and contains time stamps for proper event synchronization. TiD was tested extensively and its stability and low latency is demonstrated. The effect of an occurring event jitter is analyzed, whereas a 3 dB signal attenuation when averaging events is starting to become visible between 6–8 kHz. Mean event distribution times across operating systems are ranging from 0.27 ms to 0.43 ms over a network connection for 10^6 events. So the applicability of TiD for event delivery over network with distributed clients could be shown. Cross-platform libraries, implemented in C++ are available for download.**

***Index Terms*—standard, protocol, transmission, event, marker, jitter, Brain-Computer Interface, open source, C++**

I. Introduction

NEUROSCIENCE and the curiosity for the brain's anatomy/functionality or its respond to external events (e.g., an acoustic stimuli) are old fields of interest. Events could be an instruction to move an arm, an electrical stimulus, a flashing light on a computer screen, being used to store information relative to an instruction, etc. Brain activation and brain responses can get quantitatively recorded, for example, using EEG (Electroencephalography), NIRS (Near Infrared Spectroscopy) MEG (Magnetoencephalography), or fMRI (functional Magnetic Resonance Imaging); also together with external events. Potential applications for these techniques to measure brain activity are diagnostic systems [1], [2], systems to investigate brain functionality [3], or brain-computer interfaces (BCIs) to establish a non-muscular communication channel [4].

Events are an essential tool to mark and describe environmental occurrences in neuroscience research. They have been used, recorded and stored in many different ways for decades. Examples would be marking an event on paper in an analogue recording during the 1970s and storing an event in a biosignal data file on a personal computer (PC) nowadays [5], [6]. In analogous paper recordings, events could have been registered manually by use of a pen or also in an automated way. Nowadays, events are mainly stored in data files, potentially using an electrical connection or getting directly inserted by the acquisition hardware, which is connected to the event source. However, recorded data without events or without any event description could make the data worthless, as it might become impossible to determine exactly what happened during the recording. Events such as timing and descriptive information, are just as important as the recorded biosignal data itself. To support an upcoming necessity of event storage, e.g., the European Data Format (EDF) file format was extended to EDF+ to support events and annotations [5].

Unfortunately, events are stored and transmitted in various ways in different programs, tools, laboratories and institutions around the world. This could lead to miss-interpretations and needless waste of manpower to eliminate these issues. Furthermore, due to the cost reductions of common PCs, multiple computers, connected in different ways, are often used for measurements. For example one computer creates events and provides visual stimulation and another one records and stores the biosignal data. Accurate timing is a crucial issue in this case, which is often solved with the parallel port (often called LPT port) of a PC [7].

However, using a digital line (conducted with the LPT port) has two big issues. First, LPT ports are rare in today's computers, especially in notebooks. Alternatives like data acquisition cards with digital output capabilities would be suitable, but are usually an expensive replacement for the LPT port functionality. USB based LPT adapter systems seem to be an adequate replacement. However, insufficient real-time capabilities of USB drivers limit the usability of USB based LPT adapters. Second, the transmitted signal is a high or low signal without any additional meta-information. However, when loosing a descriptive trigger channel information, potentially stored elsewhere (e.g., in a text or .pdf file), might render the file uninterpretable. It would not be possible It would hardly becomes possible to distinguish the meaning of the individual lines. Thus, event transmission and

C. Breitwieser, and G.R. Müller-Putz are with the Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria, 8010 Graz, Inffeldgasse 13/4, e-mail: c.breitwieser@tugraz.at, gernot.mueller@tugraz.at

R. Leeb is with the Chair in Non-Invasive Brain-Machine Interface, Center for Neuroprosthetics, École Polytechnique Fédérale de Lausanne, Station 11, CH-1015 Lausanne, Switzerland., e-mail: robert.leeb@epfl.ch

M. Tavella: e-mail: michele.tavella@gmail.com

M. Schreuder is with the Machine Learning Laboratory, Berlin Institute of Technology, Germany, 10587 Berlin, Franklinstr. 28/19, e-mail: schreuder@tu-berlin.de

F. Cincotti is with the Neuroelectrical Imaging and Brain-Computer Interfaces Laboratory, Fondazione Santa Lucia, Italy, 00142 Rome, Via Ardeatina 306, e-mail: f.cincotti@hsantalucia.it

storage is not a trivial process. Accurate timing and descriptive meta-information are requirements for proper event delivery. Considering today's PC hardware, nearly all computers are equipped with at least 100 MBit, or 1 Gbit Ethernet networking cards. So using a network connection for event-transmission is an alternative to the LPT port. Furthermore, Ethernet coupled with transmission protocols like TCP/IP provide guaranteed data delivery.

In this paper, we propose an open source standardization attempt for a common event transmission protocol called TiD (TOBI interface D; TOBI... Tools for Brain Computer Interaction). It provides a dedicated efficient and flexible transmission protocol to ensure proper and reliable event delivery. TiD is designed to fit the needs of BCI research, which can be seen as an extended set of requirements to events used in neuroscience measurements with and without feedback. TiD is intended to be used for inter-process communication on localhost or over network but not within a single application, where a direct function call for event delivery is still the best choice. TiD should reduce the burdens of inter-process communication. This paper should also give an estimate of occurring effects (like delay and jitter). These estimates might also be interesting for people using tools, relying on event and data delivery over network. The effects of a timing jitter in event delivery can get carried over to other protocols as well. So one could use the testing part of the TiD framework to analyze his own network environment conditions get an idea of the occurring effects.

Considering BCIs, their functionality is based on real-time processing of biosignal data. Mason and Birch provided a functional BCI model, showing a common closed-loop structure for BCI systems [8] (see Fig. 1). Similar to neurofeedback paradigms in neuroscience, user-feedback is a crucial component in BCI systems. Data is acquired, processed, then sent to a device or application. Next, the user gets feedback based on the device's or application's actions. This concept is generalized in [9], presenting multiple processing streams and distinct logic like fusion and shared-control principles. Events are important for BCIs, as various modules might create, receive, and process events [9]. TiD is intended to embed event transmission in the standardization process, as introduced in [9]–[11] and requested in [12].

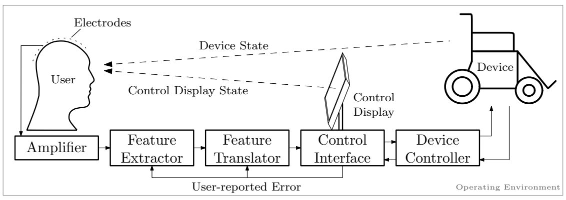


Figure 1. Mason and Birchs functional model (modified from [11]).

II. Methods

The term "event" is sometimes used in a vague and confusing manor. Too often, an event is treated the same way as a marker. To avoid ambiguities, events and markers are defined as follows in the context of this paper:

Marker: A marker marks some (potentially environmental) incident without any meta-information; it only provides time information. An example is a rising edge on a trigger channel. The meaning of a rising edge can change from recording to recording. It is not stored directly with the respective marker. So the information is provided elsewhere as in a text or .pdf file, describing the experiment and the meaning of hte trigger channels.

Event: An event, similar to a marker, provides timing as well as meta-information to distinguish events. Examples like the biosig project [6] or the "Hierarchical Event Descriptor" (HED) [13] are using event codes or an structured event description.

A. Requirements Analysis

Events and markers are both used to mark some incident during a measurement. As previously mentioned, timing accuracy is an important requirement. However, accuracy is a relative term. For example, with near-infrared spectroscopy (NIRS) measurements of slow haemodynamic responses, sampling rates below 50 Hz (or even 10 Hz) are sufficient. But when considering event-related potential (ERP) measurements [3], high resolution timing is a critical requirement. An occurring constant and stable delay over time during event transmission can be measured prior to or after a measurement. To correct the recorded data afterward, the delay just has to be subtracted from the event times. However, a trigger jitter [14] during the event transmission is a much bigger problem. ERPs are often averaged to increase signal-to-noise ratio. Any jitter influences the ERP calculation and distorts their recognition [14]. By measuring brainstem auditory evoked potentials (BAEPs), the first wave occurs at about 1.6 ms in adults [3]. Thus, millisecond response time and minimal jitter are important in this case.

Considering different kinds of analysis, it is possible to roughly distinguish between data processing during the recording in real-time or just after recording the data. Within this paper, performing data analysis during the recording is called "online analysis" while later on is called "offline analysis".

1) Offline Analysis: Measurements done for later offline data analysis are often based on a pre-defined paradigm with pre-defined event sequences. Within such a measurement, no data is processed during recording;. It only gets stored, so event processing time is a non-critical requirement. Such experiments can be set-up with a single event source and multiple clients, waiting for and processing incoming events.

2) Online Analysis: In measurements with online analysis, data is processed in (firm) real-time. [1] Considering e.g., BCI experiments, events can occur due to feature extraction, classification or feedback. These events are not pre-defined and usually have to be processed immediately, not breaking with potential real-time requirements. Furthermore, multiple event sources and multiple event sinks are possible [9].

[1]Within this paper, the term "real-time" can get interpreted as a firm real-time and is not related to any real-time operating system. A rare violation of the firm real-time condition is assumed not to have a harming effect.

B. Design Principles

To sum up the aforementioned requirements, accurate timing, fast event processing, flexible event delivery, and flexible events themselves are needed for proper event transmission. As flexibility is a major requirement, XML [15] messages are suitable for event encoding. In addition, various platform independent libraries are available for XML processing. A network-based approach with network sockets offers a flexible and platform independent way of event delivery ans also fulfills the requirements of distributed event processing [9].

C. Software Design

Event distribution via TiD is realized based on XML messages distributed over TCP networking sockets [16], ensuring guaranteed data transmission.

1) The XML Message:

```
<tid version="0.3.0.1"
 absolute="1330691458,821096"
 relative="34687,761248" >
   <description> beep </description>
   <block> 1732 </block>
   <family> biosig </family>
   <event> 785 </event>
   <value> 13,2 </value>
   <source> P300 detector </source>
</tid>
```

This exemplary TiD message contains one outer tag named `tid` which is holding two attributes with timing information. Additional elements are stored within nested tags. Following attributes are defined in a TiD root node:

- `version` – identifies the TiD message version to ensure compatibility by using distributed clients
- `absolute` – provides a timing reference in seconds, based on the local machine's system clock
- `relative` – holds a relative time value also in seconds (e.g., relative to the start of data acquisition; can be used for tracing purposes)

Following nested tags are defined TiD:

- `description` – holds event description
- `block` – specifies the data block the event belongs to
- `family` – indicates the respective family the event belongs to (e.g., BCI2000, biosig,…)
- `event` – holds a unique event code
- `value` – *optional:* value for the corresponding event (numeric or string)
- `source` – *optional:* holds the event source (like P300 detector)

Utilizing XML tags, the TiD message is able to deal with a flexible data content and allows event notations like defined in HED [13]. The content of all tags (e.g., family, event) can get defined freely. It is recommended to orient oneself at available event definitions as suggested by HED [13] or GDF [6]. More detailed information regarding the individual attributes is available in the TiD Documentation [17]. The XML message contains a block number, providing a way to link an event with recorded data. A block (also called a frame) describes a block of individual samples [11]. Due to hardware limitations, data might get delivered in a block oriented manner, as done by some EEG amplifiers. This delivery rate is lower as the actual sampling rate, because the amplifier waits until a filled block of samples becomes available. Without additional timing information for an event (like a timestamp or a related digital trigger line), an event can only get aligned to the start or the end of a block. Aligning events only to data blocks introduces an additional uniform distributed jitter based on the block size, independent of the applied event transmission or synchronization protocol. So timestamps or trigger lines are important to achieve a proper alignment, which could then be even better than the actual cycle duration.

2) Client/Server Architecture: TiD is built as a bus system like shown in Fig. 2. This achieves a flexible system where individual modules can act as an event sink and/or source [9], as done in a bus. Furthermore, this also fulfills the requirements for system with a single event source (server) and multiple event sinks (clients).

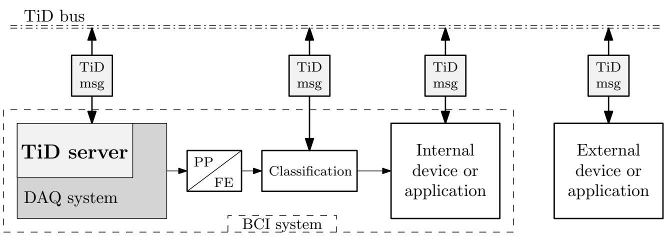


Figure 2. TiD bus operating principle shown in a BCI context with a single processing stream (PP… pre-processing, FE… feature extraction).

The architecture is divided into individual TiD clients and a single TiD server. Clients are just connected to the TiD server. This server dispatches an incoming messages from a client to the other connected clients. These clients are free to process or ignore received TiD messages. For proper synchronization with the raw data, the TiD message server has to be connected to the data acquisition system as shown in Fig.2.

3) Message Dispatching: Modules, which are connected to the raw data stream (like the classification module shown in Fig. 2) have to mark an outgoing event with the actual block number. The TiD server further distributes the event without any modification. An external module, like an external application, is not aware of the current block number. So the block number of an outgoing event is set to "-1", marking it invalid. The TiD server will then set the actual block number accordingly. Utilizing the TiD timestamps, the event can be aligned more precisely. This alignment needs proper clock synchronization using e.g., the precision time protocol (PTP) [18] which can achieve a clock accuracy in a microsecond range when being operated in a local area network. PTP operates in a hierarchical master/slave architecture, where clients get synced with a so-called "grandmaster". Further details regarding PTP can be found here: [18].

4) Timing Information: A TiD message contains an absolute and a relative timestamp with microseconds resolution. The timestamps are created from the local machines POSIX high resolution clock. So the clocks of the server and the clients need to get synchronized, e.g., using NTP (Network Time Protocol) or preferably PTP, which was mentioned above. This timing information is required for proper synchronization of the events, especially for block-oriented data transmission, so events can get aligned to samples within a data block. Transmitting data, for example, via TOBI interface A (TiA) [11], every TiA data packet is equipped with the reference timestamp, which is relative to the data acquisition start. Incoming events can also be aligned with a sub-block size accuracy, reducing jitter effects. Furthermore, utilizing relative timestamps and a proper clock synchronization, it becomes possible to trace the processing pipe latency. The TiD documentation [17] provides additional information, especially towards implementation, performance tuning, the used tags and attributes.

D. Implementation

The TiD implementation is separated into two distinct libraries to provide flexibility, with respect to network operations. Both libraries are written in cross-platform C++ and are shipped within a combined library package called TobiCore (http://tools4bci.sourceforge.net/tobicore.html). All TobiCore libraries are licensed under the LGPL V3 (lesser GNU public license version 3).

1) Tobiid: The tobiid library is responsible for TiD message parsing. It is capable of serializing and de-serializing TiD XML messages from and back to TiD message objects. Its current implementation is based on rapidxml (http://rapidxml.sourceforge.net).

2) Libtid: The cross-platform libtid library incorporates the tobiid library and provides network based TiD client, as well as a TiD server implementations. It utilizes various sub-libraries from the boost library collection (http://www.boost.org – used version: 1.55.0). To provide low latency on localhost, libtid also offers a shared memory based message dispatching utilizing message queues from boost::interprocess.

A complete TiD system has been integrated into the SignalServer data acquisition system [9]. Briefly summarized, the SignalServer supports multirate data acquisition from multiple hardware devices simultaneously (devices need to get synchronized on a hardware level), whereby the TiD server is connected to the data acquisition system. A TiA packet is equipped with a timestamp and a packet number, so aligning TiD messages is simple. Additional information can be found here: http://tools4bci.sourceforge.net/signalserver.html.

To support proper data and event saving, acquired data and received events are saved together in a .gdf file [6]. This is realized via the libgdf library (http://tools4bci.sourceforge.net/libgdf.html). For block-oriented data acquisition, events are re-aligned by interpolating timestamps for every sample in a block and then matching the event to the appropriate sample. To ease the event acquisition from embedded systems like an Arduino (http://www.arduino.cc/), which just provide digital trigger lines, a dedicated LPT TiD client is available too. This LPT TiD client simply reads data from the LPT port and converts it into TiD messages.

E. Testing

To ensure proper functionality of the libraries, black and white box tests have been conducted. Unit tests were done with the UnitTest++ framework (http://unittest-cpp.sourceforge.net). Single computer tests were performed on a common PC (for specifications, please see Appendix). For timing tests, boost::chrono (http://www.boost.org/doc/html/chrono.html) was used. All tests were carried out for 10^6 messages; mean, median, standard deviation, minimum and maximum values were computed. A sliding window of 5000 samples was further applied to the data with aforementioned calculations to provide some kind of visual down-sampling for later plotting.

1) Processing Time: TiD message processing needs to fast so, in addition to the data processing time, the additional TiD processing time does not then violate a (firm) real time condition. Tobiid and libtid have been tested regarding their processing times. As a TiD message may vary in its length, probably affecting processing time, the timing tests have been carried out for description lengths of 10, 50, and 100 characters. A random event number was assigned to the message and the block number was increased by one for every message.

a) Parsing tests: Within the tobiid library the TiD message serialization and de-serialization processing times were recorded. For the serialization test, 10^6 message objects were created and serialized to obtain a TiD message string. For the de-serialization test, TiD message strings were de-serialized to obtain the original object.

b) Dispatching tests: Within the libtid library, the times to send and receive a message within a TiD client and the dispatching time within the TiD server were measured. When sending a message via the client, the recorded values represent the processing time. This begun when a message was handed over to the libtid client methods until it was forwarded to the underlying networking or shared memory library. Through the receiving test, the latency of a message received by the network socket until it was handed over to the test routine was determined. The dispatching time represents the time from when a message arrived at the servers socket until it was forwarded to the sockets that the clients are connected to. The dispatching timing tests were performed for 3, 5, and 10 clients connected to the server, with one client operating as message source and all others as message sinks. The tested description length was 100 characters.

2) Message Transmission Delay and Jitter: TiD message delivery is based on an underlying network or SHM system. Unfortunately, every network or SHM system is characterized by a certain latency. This latency is affected by multiple factors like the performance of the TCP stack from the respective operating system or hardware based factors like the utilized networking card. To obtain some guidance levels, libtid was tested in regard to its transmission latency using SHM, the operating systems loopback device, a GBit, and a 100 MBit Ethernet connection between two PCs with a GBit or 100 Mbit switch in between. Those tests were carried out on Linux, as well as, Windows, with combinations of both operating systems on 3, 5, and 10 clients connected to the server, similar to the libtid processing time test. To estimate the GBit network latency, the server was running on the second PC, whereas the sending client, as well as the receiving clients, were running on the first PC. Tested description length was 100 characters. The time between sent TiD messages was 2 ms, far below the average event occurrence rate of 75 ms at a P300 speller [19]. The testing framework is also part of the TiD library. So one can use this framework and testing methods to get an estimate of his own environmental conditions and the effects to a measurement.

3) Stability: To ensure functionality over a prolonged time, tobiid and libtid were tested in multiple tests, lasting at least 10 h. During this time, memory consumption was logged using valgrind [20] under Linux. During this long term test, a TiD message was sent every 500 ms. Additional stress tests were carried out with one server and 50 connected clients. During these tests, every client acted as a sender as well as a receiver, sending a TiD message every 10-20 ms. This test was carried out to test the proper functionality of the TiD dispatcher.

4) Trigger Jitter Attenuation: A trigger jitter behaves like a low-pass filter for averaging across trials [21]. An averaged signal affected by a time shift is calculated the following way: S is the original signal, $\mathrm{X_m}$ the signal for averaging, and Θ_m the shift against the original signal:

$$\bar{x}[k] = \frac{1}{M}\sum_{m=1}^{M} x_m[k] = \frac{1}{M}\sum_{m=1}^{M} S[k+\Theta_m] \quad (1)$$

Applying a Fourier transform and estimating the expectancy value, $E\{\bar{X}(f)\}$ yields to the transfer function $H(f)$ based on the respective probability density function (PDF) $p(\Theta)$.

$$E\{\bar{X}(f)\} = E\{S(f)\cdot e^{j2\pi f\Theta_m}\} = S(f)\cdot E\{e^{j2\pi f\Theta_m}\} \quad (2)$$

$$H(f) = E\{e^{j2\pi f\Theta_m}\} = \int_{-\infty}^{\infty} p(\Theta)\cdot e^{j2\pi f\Theta}\, d\Theta \quad (3)$$

For a normal distribution, the respective 3 dB cutoff frequency would be equal to: $f_c = \frac{0.132}{\sigma}$ (σ in seconds). For a non-parametric PDF, the transfer function can be calculated based on the available discrete latency values:

$$H(f) = \sum_{\Theta=\Theta_{min}}^{\Theta=\Theta_{max}} p(\Theta)\cdot e^{j2\pi f\Theta} \quad (4)$$

No outliers were removed from the data set.

III. Results

A. Testing

1) Processing Time:

a) Parsing tests: The tobiid library has been tested for its serialization and de-serialization performance. The processing time for all description lengths was within the low microseconds range (around 3 µs) with a low standard deviation (STD) of max. 0.3 µs. So this affects the TiD processing time in a minor way. Due to this limited effect to the overall latency, it is not presented in Table I.

b) Dispatching tests: The libtid library has been tested for its latency to send and receive a TiD message on the client side and to dispatch a message in the server. Those test results include the processing time to process a message with tobiid. Statistical values for selected tests are presented in Table I. Considering the dispatching latency in the TiD server, this value was primarily dependent on the number of clients attached to the server. The most important results are the latencies occurring during network transmission.

2) Message Transmission Delay and Jitter: As client(s) and server might be running on the same machine, as well as being distributed over a network, both latencies have been tested. Tests have been carried out running the server or clients on Linux, Windows and the combination. Fig. 3 shows the client–server latencies for 3, 5, and 10 clients with a description length of 100 characters for SHM, remote, and localhost transmission. Time values are presented in Table I. Extensive plots for different client/server combinations are available in the supplementary material.

Table I

Processing times and latencies for tobiid and libtid on different operating systems (OS) for 10^6 messages. The given values resulted from the tests with a description length of 100 characters and in case of networking activity, with five clients attached to the server in case of GBit or 100MBit. The WiFi test was done with three clients connected.

Linux	mean	std	median	min	max
cl snd	15.0 µs	8.39 µs	12.80 µs	7.08 µs	203.9 µs
cl recv	20.2 µs	3.27 µs	19.99 µs	5.21 µs	171.0 µs
srv disp	49.5 µs	6.88 µs	57.77 µs	14.2 µs	236.5 µs
local lat	188.7 µs	55.8 µs	157.7 µs	74.2 µs	402.2 µs
SHM lat	56.2 µs	18.3 µs	50.5 µs	26.4 µs	308.0 µs
rem lat	336.2 µs	74.6 µs	303.2 µs	176.2 µs	658.4 µs
rem lat^{100M}	496.7 µs	36.9 µs	494.6 µs	391.6 µs	705.3 µs
rem lat^{Wifi}	1386 µs	1022 µs	1271 µs	809.9 µs	210 ms
Windows					
cl snd	21.0 µs	3.44 µs	21.1 µs	13.0 µs	220.4 µs
cl recv	17.1 µs	1.76 µs	16.8 µs	4.38 µs	215.7 µs
srv disp	46.3 µs	3.79 µs	46.7 µs	19.0 µs	132.8 µs
local lat	137.7 µs	4.2 µs	137.6 µs	122.6 µs	350.3 µs
SHM lat	81.3 µs	24.8 µs	77.4 µs	33.57 µs	287.2 µs
rem lat	512.2 µs	68.5 µs	548.4 µs	238.3 µs	1751 µs
rem lat^{100M}	799.7 µs	7.7 µs	801.7 µs	486.8 µs	4997 µs
rem lat^{Wifi}	1415 µs	2108 µs	1245 µs	907 µs	1108 ms
Remote latency – server/client					
Win/Lin	439.5 µs	34.7 µs	448.8 µs	260.4 µs	3812 µs
Lin/Win	434.8 µs	7.6 µs	432.8 µs	248.9 µs	650.6 µs
Win/Lin^{100M}	543.9 µs	27.2 µs	541.2 µs	391.7 µs	1257 µs
Lin/Win^{100M}	496.2 µs	134.2 µs	480.6 µs	406.5 µs	2023 µs
Win/Lin^{Wifi}	1452 µs	860 µs	1392 µs	808 µs	314 ms
Lin/Win^{Wifi}	1645 µs	3041 µs	1461 µs	956 µs	674 ms

3) Stability: No memory leaks have been detected in the prolonged tests in either the server or the client. Furthermore, running the automated test routine provided in libtid with its default values took roughly 31 hours to finish. All those tests succeeded without any error or message loss, indicating the stability of tobiid and libtid. Additionally, events were successfully sent using a high event rate with an event every

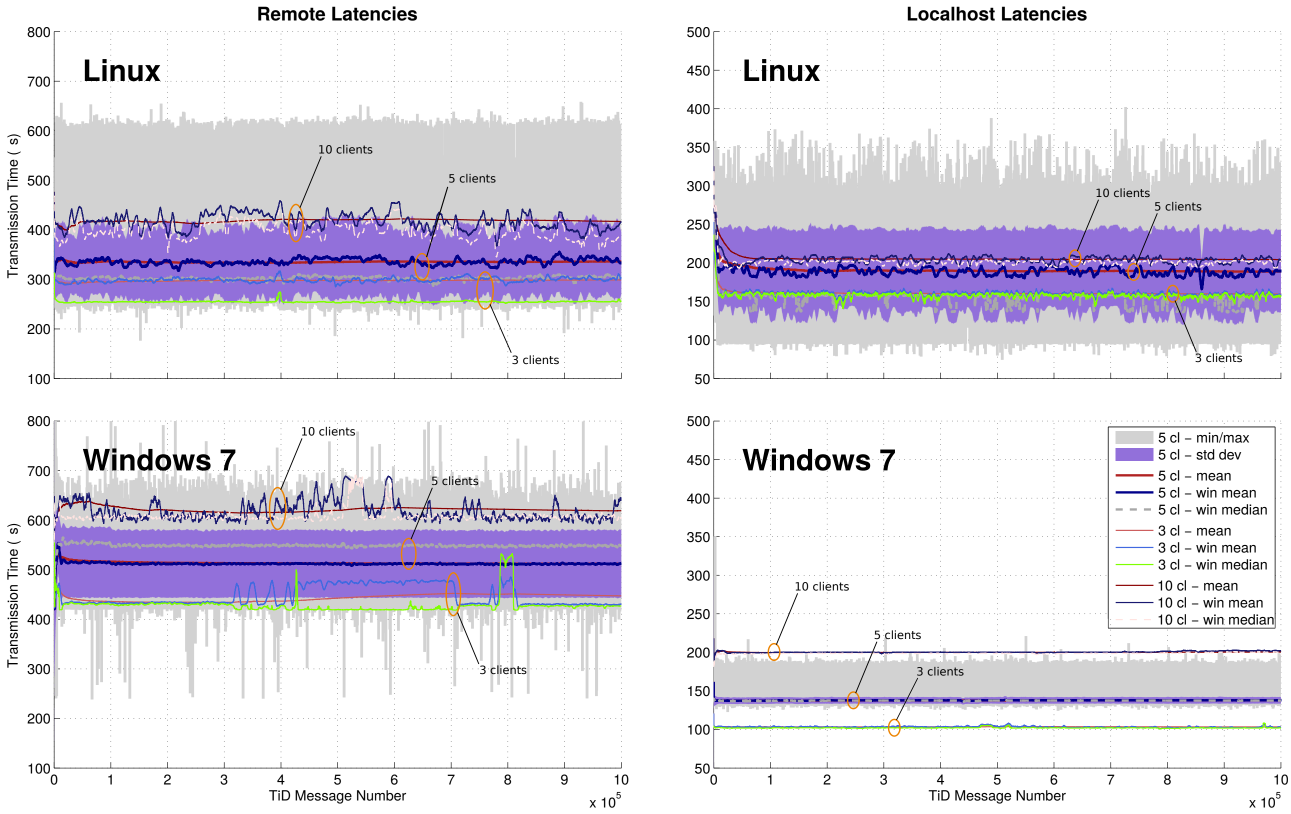


Figure 3. Server – client latency – sending a TiD message from a client via the TiD server to another client. The TiD server was running on a second computer with remote delivery (left column) or on the same machine for localhost delivery (right column). The upper figures represent the latency running both client and server on Linux, the lower one on Windows 7. The figures show the latencies for 3, 5, and 10 TiD clients with a description length of 100 characters. STD (purple region) and min/max values (grey region) are only shown for 5 clients. The red line shows the mean values, the blue line shows the windowed mean, and the black line shows the windows median (window size: both 5000 samples).

2 ms, compared to events occurring roughly every 75 ms using a P300 speller [19].

4) Trigger Jitter Attenuation: The upper image in Fig. 4 shows the jitter distribution for the remote latency test with a description length of 100 characters, running the server and five clients on two Linux systems. Statistical testing using a Lilliefors test [22] revealed that the trigger jitter is not normal distributed. The lower image in Fig. 4 depicts the attenuation caused by the jitter introduced with TiD. Thus, a 3 dB attenuation is reached at 1071 Hz, equal to a cycle duration of 0.9 ms. The cut off frequency f_c was for other equal server/client combinations as follows: Windows/Windows – 1.1 kHz, Windows/Linux – 2.4 kHz, Linux/Windows – >10 kHz. Additional histogram and attenuation plots are provided in the supplementary material.

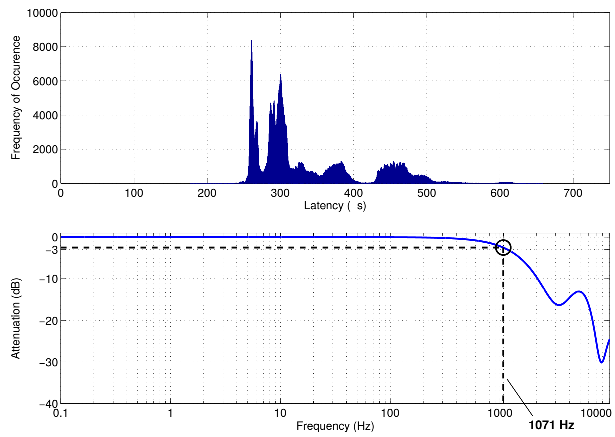


Figure 4. The upper plot shows the latency histogram of the remote TiD test (Linux, five clients, 100 characters description length). The lower plot depicts the amplitude attenuation in case of averaging caused by the TiD based trigger jitter. $f_{c,3\,dB}$ at 7815 Hz in highlighted with black dashed lines.

B. TiD as a User Interaction Event Delivery System

To illustrate the potential of TiD, a simple command line TiD client was coupled with an established test automation tool named Ranorex (Ranorex GmbH, Graz, Austria). This tool is intended to perform a user simulation for test automation purposes. Its operating principle was modified, listening for incoming TiD events. These TiD events were utilized to carry out user interaction commands within a browser for demonstration purposes. A short video illustrating this principle is available in the supplementary material. Commands are entered using the command line TiD client (this client could also be replaced with, e.g., a P300 speller) and then send to Ranorex. Information gathered by Ranorex, like available links on a website, is then transmitted back to the client using TiD messages. This gives the possibly to interact with every standard program in the world for experiments.

IV. Discussion

With TiD we could successfully introduce a powerful and flexible way for event distribution for BCI research, which is potentially of interest for the wider neuroscience community. The TiD design provides an extendable alternative to common event distribution methods like the LPT port. It includes event descriptions, event codes and timestamps for proper event interpretation. It eliminates issues like trigger lines without any further meta-information as well as the limitation of different hardware based approaches, where e.g., just eight trigger lines (similar to eight different events) are available. Two dedicated libraries have been developed, one for processing TiD messages, called tobiid and a second library, called libtid, providing a network layer for TiD message transmission. Both libraries have been tested in detail to prove stability as well as fast message processing and delivery. The TiD libraries are freely available including pre-compiled versions for Linux, Windows, and client implementations for different languages or systems (e.g., Python, Matlab). C++ demo code for TiD client and server examples is available in the supplementary material. It shows the simplicity, running either a TiD client or a server. In [10], different studies utilizing the TOBI framework, which also includes TiD, are presented. The utilization of the mentioned interfaces, including TiD, facilitated the accomplishment of these studies, which consisted of modules from different laboratories.

A. Compatibility with the Common BCI Processing Pipeline

At first glance, the TiD bus seems unnatural, compared to the common BCI processing stream, which consists of data acquisition, pre-processing, feature extraction, classification and application. A pipe implementation would look more natural at first appearance. However, in the TiD architecture, events are not strictly bound to the raw data. The bus oriented event delivery system comes up with many additional features, like the possibility to use modules outside the BCI processing pipeline; that later modules in the processing chain can interact with earlier modules (e.g. reset outputs); or that modules can subscribe to the event bus freely. Despite these features, this also introduces some minor issues: Potential problems are that events could "overtake" the raw data or that events arrive later than the raw data. This can be eliminated by synchronizing with the available timestamps. Considering the latency measurements, the problem of events arriving too late is also a minor one, as the event delivery time is in the microsecond range. The TiD architecture is a proper way to decouple events from the raw data and merge them back if needed and wanted. With regards to multiple processing streams, events are not duplicated; so events do not have to be forwarded by individual processing modules. This removes the forwarding burden for the respective module and eliminates the issue of duplicated events in multiple processing streams, which then might arrive at different times, introducing processing errors. No "duplicate event filter" or similar is needed. Additionally, TiD is not bound to a specific raw data transmission format. It can be used with TiA [11], as well as any other raw data delivery methods; so the raw data protocol does not have to be modified.

B. Comparison to other Data Distribution Systems

Another approach, delivering data with the so-called "lab streaming layer" (LSL), is presented in [23]. It is mentioned by LSL to be *"a system for the unified collection of measurement time series in research experiments that handles both the networking, time-synchronization, (near-) real-time access, as well as optionally the centralized collection, viewing and disk recording of the data"* [24]. LSL is designed to take away the synchronization burden from the user. Another strategy, using the "DataRiver" in "ERICA", as presented in [25], shares the idea of a centralized data flow principle, eliminating synchronization issues as well. TiD is not designed to resolve synchronization issues, as demonstrated by the presented examples. The goal of TiD is to provide a lightweight and common approach, delivering event information as fast as possible and offering timing information for a potential synchronization. TiD can easily get added to existing systems, without the need to redesign the data flow. The user is free to choose if a synchronization is necessary. As TiD is completely XML based, an incorporation with, e.g., LSL should not be an issue, as LSL streams can be equipped with XML metadata as well.

C. Performance and Timing Issues

Latencies are mostly within the millisecond or even microsecond range, as visible in Table I. As can be seen, a GBit connection should be the first choice due to the lowest latency. A 100 MBit connection also provides low latency and jitter values. In contrast, WiFi should be avoided in any case, as visible in the table. The maximum delay was more than a second! This might have occurred, as WiFi can easily get disturbed by other wireless networks or devices and is just a best effort network. Furthermore, it becomes nearly impossible to protect oneself from environment influences to a wireless network. So WiFi could get used, for example, as event monitor in an online scope for visual signal inspection; but not for any time critical calculations. In case of GBit or 100 MBit, low-pass effect caused by TiD is unnoticeable until frequencies in the low kHz range (shown in the supplementary material in more detail). A high CPU load is also causing no substantial effect to the jitter or delay. As the maximum delay, even over Ethernet network is below 5 ms, it can safely be used for event transmission. However, it is recommended to measure the individual timing influence of ones network. So one can get an estimate of the actual environmental conditions (being dependent of many influence factors like networking card, CPU, router/switch, ...) using the testing framework provided by TiD. It might even be interesting if TiD is not used at all, as a major influence to trigger jitter comes from the network. In case of very low latency requirements, the best way to deliver information is and will always be a direct function call within a single application. However, if this is not possible, utilizing shared memory provides very low latency with low jitter, as shown in Table I and in more detail in the supplementary material. In comparison, a trigger jitter occurring due to trigger alignment to blocks of data introduces a much higher low-pass filtering effect. In this case, the trigger jitter is uniformly distributed, based on the block size, and f_c equals to: $f_c = \frac{0.127}{\sigma}$ (σ in seconds). Assuming a sampling rate of 512 Hz and a block size of 16 samples, STD $\sigma = 9\,ms$ and therefore f_g = 14.1 Hz. Using TiD timestamps, event alignment within a data block is possible, eliminating this issue.

D. Portability, Extendability and Flexibility

Both, tobiid and libtid only use portable libraries. It is a simple process to port them to other operating systems like OS X, iOS or even embedded systems. Both libraries developed towards low resource requirements. Because TiD is entirely based on XML messages, it is simple to extend the TiD messages, introduce e.g., additional event families, add new tags, or extend existing ones. As TiD is storing the main information in tags, it allows more characters than simply using attributes to facilitate a grammar, as presented in [13]. Individual extensions are therefore not affecting a common TiD client. TiD can also be used to control systems, performing a user simulation, as shown within the video, available in the supplementary material. TiD is based on XML and provides cross-platform libraries, so an integration into other systems, such as Ranorex, is a simple step. In that way, interacting with different programs, running on other operating systems or being implemented in another programming language becomes possible.

TiD proved to match its low latency requirements and its potential for proper event distribution. However, those capabilities might not be enough. For example, BAEPs, can occur at 1.6 ms [3]. For these cases, the jitter introduced by TiD might be too high. The available LPT TiD client which converts a digital signal into TiD messages provides a way getting around this issue. So TiD messages together with trigger lines can also get used if lowest latency requirements need to be met.

ACKNOWLEDGMENT

This work was supported by the European ICT Programme Project FP7-224631. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein. Special thanks to Jim Trentadue for final editing.

REFERENCES

[1] G. Cruccu, M. Aminoff, G. Curio, J. Guerit, R. Kakigi, F. Mauguiere, P. Rossini, R.-D. Treede, and L. Garcia-Larrea, "Recommendations for the clinical use of somatosensory-evoked potentials," *Clin. Neurophysiol.*, vol. 119, no. 8, pp. 1705–1719, 2008.

[2] Y. Hu, K. D. K. Luk, W. W. Lu, and J. C. Y. Leong, "Application of time-frequency analysis to somatosensory evoked potential for intraoperative spinal cord monitoring," *J Neurol Neurosurg Psychiatry*, vol. 74, no. 1, pp. 82–87, 2003.

[3] D. Regan, *Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine*. Elsevier, 1989.

[4] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control." *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

[5] B. Kemp and J. Olivan, "European data format 'plus' (EDF+), an EDF alike standard format for the exchange of physiological data," *Clin. Neurophysiol.*, vol. 114, no. 9, pp. 1755–1761, 2003.

[6] A. Schlögl, "GDF - A general dataformat for biosignals," *eprint arXiv:cs/0608052*, 2006.

[7] N. Stewart, "A PC parallel port button box provides millisecond response time accuracy under linux," *Behav. Res. Methods.*, vol. 38, pp. 170–173, 2006, 10.3758/BF03192764.

[8] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design." *IEEE Trans Neural Syst Rehabil Eng*, vol. 11, no. 1, pp. 70–85, 2003.

[9] G. R. Müller-Putz, C. Breitwieser, F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. d. R. Millán, "Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI." *Front. Neuroinform.*, vol. 5, 2011.

[10] G. Müller-Putz, R. Leeb, M. Tangermann, J. Höhne, A. Kubler, F. Cincotti, D. Mattia, R. Rupp, K. Müller, and J. Millán, "Towards noninvasive hybrid brain-computer interfaces: Framework, practice, clinical application, and beyond," *Proc. IEEE*, vol. 103, no. 6, pp. 926–943, June 2015.

[11] C. Breitwieser, I. Daly, C. Neuper, and G. R. Müller-Putz, "Proposing a standardized protocol for raw biosignal transmission," *IEEE. Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 852–859, 2012.

[12] P. Brunner, L. Bianchi, C. Guger, F. Cincotti, and G. Schalk, "Current trends in hardware and software for brain–computer interfaces (BCIs)," *J. Neural Eng.*, vol. 8, no. 2, pp. 1–7, 2011.

[13] N. Bigdely-Shamlo, K. Kreutz-Delgado, K. Robbins, M. Miyakoshi, M. Westerfield, T. Bel-Bahar, C. Kothe, J. Hsi, and S. Makeig, "Hierarchical event descriptor (HED) tags for analysis of event-related EEG studies," in *Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE*, Dec 2013, pp. 1–4.

[14] A. Mouraux and G. Iannetti, "Across-trial averaging of event-related eeg responses and beyond," *Magn. Reson. Imaging.*, vol. 26, no. 7, pp. 1041–1054, 2008.

[15] T. Bray, J. Paoli, C. M. Sperberg-McQueen, E. Maler, and F. Yergeau, "Extensible markup language (XML) 1.0 (fifth edition)," World Wide Web Consortium, Recommendation REC-xml-20081126, 2008.

[16] V. Cerf and R. Kahn, "A protocol for packet network intercommunication," *IEEE J COM*, vol. 22, no. 5, pp. 637–648, 1974.

[17] C. Breitwieser, "TiD – Documentation of TOBI Interface D," *ArXiv e-prints*, 2015.

[18] "IEEE standard for a precision clock synchronization protocol for networked measurement and control systems," *IEEE Std 1588-2008 (Revision of IEEE Std 1588-2002)*, pp. c1 –269, 24 2008.

[19] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "A comparison of classification techniques for the P300 speller," *J. Neural Eng.*, vol. 3, no. 4, pp. 299–305, 2006.

[20] N. Nethercote and J. Seward, "Valgrind: a framework for heavyweight dynamic binary instrumentation," *SIGPLAN Not.*, vol. 42, pp. 89–100, 2007.

[21] W. Craelius, M. Restivo, M. A. Assadi, and N. El-Sherif, "Criteria for optimal averaging of cardiac signals," *IEEE Trans Biomed Eng*, vol. BME-33, no. 10, pp. 957–966, oct. 1986.

[22] H. W. Lilliefors, "On the Kolmogorov-Smirnov test for the exponential distribution with mean unknown," *J. Amer. Statist. Assoc.*, vol. 64, no. 325, pp. 387–389, 1969.

[23] C. Kothe and S. Makeig, "BCILAB: a platform for brain-computer interface development," *J. Neural Eng.*, vol. 10, no. 5, p. 056014, 2013.

[24] labstreaminglayer. (2014, 09) Lab streaming layer - distributed signal transport, time synchronization and data collection system for research use. [Online]. Available: https://code.google.com/p/labstreaminglayer/

[25] A. Delorme, T. Mullen, C. Kothe, Z. A. Acar, N. Bigdely-Shamlo, A. Vankov, and S. Makeig, "EEGLAB, SIFT, NFT, BCILAB, and ERICA: New tools for advanced EEG processing," *Intell. Neuroscience*, vol. 2011, pp. 10:10–10:10, Jan. 2011.

APPENDIX

Test systems: PC 1 – Intel Core i5@2.66 GHz, 8 GB RAM, Nvidia GeForce GT 9500, Realtek 8112L Gbit – Debian unstable 64 bit (g++ 4.8.5) and Windows 7 32 bit (msvc2012). PC 2 – Intel Core2Quad Q9450@2.66 GHz, 8 GB RAM, Nvidia GeForce GT 9500, Realtek 8110SC Gbit – Debian unstable 64 bit and Windows 7 32 bit; Linksys WRT320N Gbit Router (DD-WRT – v24-sp2); no other PCs attached

A.4. Stability and Distribution of Steady-State Somatosensory Evoked Potentials Elicited by Vibro-Tactile Stimulation

C. Breitwieser, V. Kaiser, C. Neuper, and G. R. Müller-Putz. "Stability and distribution of steady-state somatosensory evoked potentials elicited by vibro-tactile stimulation." In: *Medical and Biological Engineering and Computing* 50.4 [2012], pp. 347–357. DOI: 10.1007/s11517-012-0877-9 [193]

Distribution of dedicated work:

- **Christian Breitwieser**: 70
- Vera Kaiser: 5 %
- Christa Neuper: 2 %
- Gernot R. Müller-Putz: 23 %

Med Biol Eng Comput (2012) 50:347–357
DOI 10.1007/s11517-012-0877-9

ORIGINAL ARTICLE

Stability and distribution of steady-state somatosensory evoked potentials elicited by vibro-tactile stimulation

Christian Breitwieser · Vera Kaiser · Christa Neuper · Gernot R. Müller-Putz

Received: 20 July 2011 / Accepted: 7 February 2012 / Published online: 8 March 2012

Abstract Steady-state somatosensory evoked potentials (SSSEPs) have been elicited applying vibro-tactile stimulation to all fingertips of the right hand. Nine healthy subjects participated in two sessions within this study. All fingers were stimulated 40 times with a 200-Hz carrier frequency modulated with a rectangular signal. The frequencies of the rectangular signal ranged between 17 and 35 Hz in 2 Hz steps. Relative band power tuning curves were calculated, introducing two different methods. Person-specific resonance-like frequencies were selected based on the data from the first session. The selected resonance-like frequencies were compared with the second session using an ANOVA for repeated measures to investigate the stability of SSSEPs over time. To determine, if SSSEPs can be classified with a classifier based on unseen data, an LDA classifier was trained with data from the first and applied to data from the second session. Person-specific resonance-like frequencies within a range from 19 to 29 Hz were found. The relative band power of the resonance-like frequencies did not differ significantly between the two sessions. Significant differences were found for the two methods and the used channels. SSSEPs were classified with a hit rate from 51 to 96 %.

Keywords Steady-state somatosensory evoked potentials (SSSEP) · Stimulation · Vibration · Tactile · EEG

C. Breitwieser · V. Kaiser · C. Neuper · G. R. Müller-Putz (✉)
BCI Lab, Institute for Knowledge Discovery, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria
e-mail: gernot.mueller@tugraz.at

C. Breitwieser
e-mail: c.breitwieser@tugraz.at

C. Neuper
Department of Psychology, University of Graz, Universitätsplatz 2/DG, 8010 Graz, Austria

1 Introduction

A brain–computer interface (BCI) is a system facilitating communication and control without the need of any muscular activity [31]. For patients, e.g., who suffer from some sort of locked-in syndrome or amyotrophic lateral sclerosis (ALS), a BCI could be their last chance to stay in touch with their environment [16]. Different strategies can be used for BCI control-like sensory motor rhythms (SMR) [23] or evoked potentials (EPs) [6]. EPs can occur after different kinds of external stimulation (e.g., visual, auditory, tactile, etc.) [24]. A common way to gain control through a BCI using EPs utilizes the oddball paradigm to evoke P300 EPs [6]. Applying external stimulation in a repetitive manner with a certain frequency elicits so-called steady-state evoked potentials (SSEPs) [24] in the brain. Those SSEPs are related to the applied stimulation frequency. Affected brain regions depend on the kind of this stimulation. Visual stimulation (e.g., flickering lights) produces steady-state visual evoked potentials (SSVEP). SSVEPs can be recorded in the occipital regions of the brain whereas repetitive tactile stimulation (e.g., vibratory stimulation) elicits steady-state somatosensory evoked potentials (SSSEP) in the somatosensory cortex [26].

As already mentioned, a BCI might be the last remaining communication channel for completely paralyzed persons. SSVEPs as well as SSSEPs have already been successfully used for BCI control [19, 20]. A major drawback of BCIs utilizing a person's visual system is the requirement that this system is still functional. As an example, patients who suffer from ALS can lose control over their eyelids [11] or they do not have full control over their eye muscles any more. As exemplarily shown in [7] and [10] the somatosensory system of ALS patients is still functional (with potential abnormalities regarding to the form of evoked potentials). Based on these findings, using a somatosensory BCI, e.g., based on SSSEP, might be suitable for patients suffering from some kind of locked-in syndrome because they are completely independent of a muscular component. Patients could gain control shifting their attention to a certain target stimulus, as presented in [19] with healthy subjects.

Tobimatsu et al. [28] and Müller et al. [17] investigated the emergence of tuning curves based on vibro-tactile stimulation. Tobimatsu et al. reported a narrow tuning curve with a person independent maximum at 21 Hz by stimulating the whole palm. Findings from Müller et al. [17] show a broad person-dependent tuning curve with person-specific resonance-like frequencies stimulating only the index finger. However, none of both studies analyzed the stability of those tuning curves over time, regardless of being broad or narrow. For BCI usage, a stable response on external stimulation is very useful to avoid unnecessary screening sessions to determine an optimal stimulation frequency. A proper tool to investigate potential resonance-like frequencies and their stability are tuning curves based on relative band power (BP) changes [17]. Other ways to show cortical activity elicited by repetitive stimulation would exemplarily be FFT (fast fourier transform) spectra as, e.g., shown in [25] or time/frequency maps as shown in [27]. However, the big advantage of relative BP tuning curves is a compact representation showing the relation between a reference period without stimulation and a stimulation period. Furthermore, an emergence of a potential tuning curve is very well visible. Such an emergence becomes hard to recognize using, e.g., FFT spectra.

Within this work we analyzed the stability and the distribution of SSSEPs evoked by vibro-tactile stimulation of all five fingers from the right hand using relative BP values. As the density of mechanoreceptors (especially Meissner and Pacinian corpuscles) is different on every finger, all five fingers were stimulated [14]. Thus, SSSEP resonance-like frequencies based on tactile stimulation being potentially finger-dependent were also analyzed within this work. Due to the long measurement duration, this was done in two different ways. The first one is similar to [17], the second one is taking cortical changes over time into account. Phase locking effects were not investigated as, e.g., done in [8].

2 Methods

2.1 Measurement setup

Vibro-tactile stimulation was generated by five audio transducers (12 mm KSQG706BP Magnetic Transducer, Kingstate Electronics Corp., Taiwan), similar to [19]. This stimulation was applied to the fingertips of all five fingers of the right hand through a round 50 mm^2 metal plate (∅ 8 mm, height 1 mm) mounted on the audio transducers surface. A carrier frequency of 200 Hz modulated with a rectangular signal was used for stimulation [18]. The rectangular modulation ranged between 17 and 35 Hz in 2 Hz steps and a duty cycle of 50 %. Figure 1 shows an example of the applied stimulation signal. This signal was created with 2 kHz, whereby a first-order hardware low-pass filter with an edge frequency at 300 Hz was used to smooth the 200-Hz sine. The system used for the measurement was driven by a Matlab realtime Simulink model (The MathWorks Inc., Realtime Windows Target, Natick, USA).

Nine subjects participated in the study, eight male and one female, one participant was left handed. The mean age was 26.9 years (SD = 1.7). All subjects participated in two sessions with at least 2 weeks in between (mean 28 days, SD ±17.5, min. 13, max. 64).

A model of the shape of the right hand was produced for mounting the audio transducers. Those were placed at the fingertips of the hand form to cover regions with the highest density of Pacinian and Meissner corpuscles [14]. Participants were seated in a comfortable armchair during the measurement, the form mounted under the participants right hand. All participants listened to white noise over two in-ear headphones to avoid auditory influences from the stimulation device. They were introduced to the measurement and stimulation procedure and gave their informed consent in participating to the measurement. Three bipolar EEG channels over C3, Cz, and C4 (international 10-20 system) were recorded using a bipolar EEG amplifier (Guger Technologies OEG, Graz, Austria). Those electrode positions were chosen, as various studies show activation in different cortical regions [2, 3, 9, 21, 25, 27], also

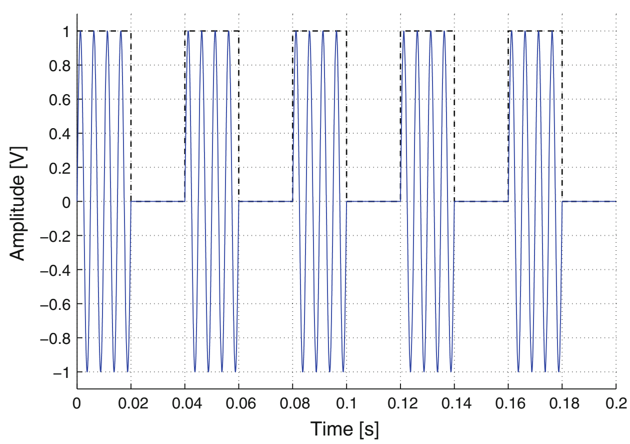


Fig. 1 Signal used for tactile stimulation. A 200-Hz sine modulated with a 25-Hz rectangular signal (duty cycle 50 %) is shown as an example

including the primary somatosensory cortex. Furthermore, according to Giabbiconi et al. [9]: "Sustained spatial attention to vibration is mediated in primary somatosensory cortex" and attention modulation is the operating principle of an SSSEP-based BCI. However, due to hardware limitations a trade-off had to be made and more electrodes also covering frontal or parietal regions could unfortunately not be recorded.

Ag/AgCl electrodes were used, positioned 2.5 cm anterior and 2.5 cm posterior to C3, Cz, and C4. The ground electrode was placed at position Fpz. All impedances were kept below 5 kΩ. A hardware high-pass filter at 0.5 Hz, a low-pass filter at 100 Hz, and a notch filter at 50 Hz were applied. The same Matlab system was used for EEG-recording and stimulation signal generation, thus the sampling rate was also 2 kHz. The whole measurement was done in a shielded room. Validation measurements were conducted prior to the measurement series. The measurements were accomplished running the stimulation unit with and without the participants touching the stimulator and with the stimulator running and no subject participating. This was done to verify that the measured signals are not contaminated by any stimulator artifacts.

2.2 Stimulation paradigm

Figure 2 shows an illustration of the measurement paradigm. Before the start of the first trial, a 5 s break was inserted. A beep signalized the beginning of the trial. The first 0.5 s were not used for any calculations as being potentially influenced by EPs caused by the auditory event (marked as EP waiting, see Fig. 2). The next 2.5 s were used as reference period without applying any stimulation. Subsequently, randomly selected fingers from the participant were stimulated within randomly selected frequencies ten times for 2 s within one trial. Every single stimulation interval was therefore completely based on a random process. Thus, the stimulation order of different trials was (theoretically) never the same to avoid any adoption effects. No finger was stimulated two times consecutively, but the stimulation of two different fingers with the same frequency in a row was possible. Following the stimulation block, a 3 s break was inserted. After this break the trial started anew. Each frequency was applied 40 times to every finger, thus altogether 2,000 stimulations were done, distributed over 200 trials. A session was divided into 20 runs with about 6 min duration each, consisting ten trials.

During all trials, participants were visually distracted, by counting highlighted characters (letters, numbers, and symbols highlighted in red color) on a computer monitor in front. This was done to avoid that the participants shift their attention to the stimulated finger. About 20 % of all characters were red colored with a mean display time of 0.7 s per character, resulting in about 70 characters to count in 6 min. Participants were asked for the number of highlighted characters after every run.

2.3 Data analysis

Before analysis, all data were visually inspected for EMG (electromyogram) artifacts. Time segments (reference or stimulation) containing EMG artifacts were discarded for further calculations. All data were downsampled to 512 Hz, applying an FIR filter to avoid aliasing. To reduce the effect of evoked potentials caused by the stimulation onset, the first 0.5 s of every stimulation period were not used.

Furthermore, FFT spectra were calculated for every finger, channel and session. Those spectra were averaged over the respective reference and stimulation intervals. This was done to ensure that the obtained relative BP increase was caused by the stimulation and not accidentally by event-related synchronization or desynchronization

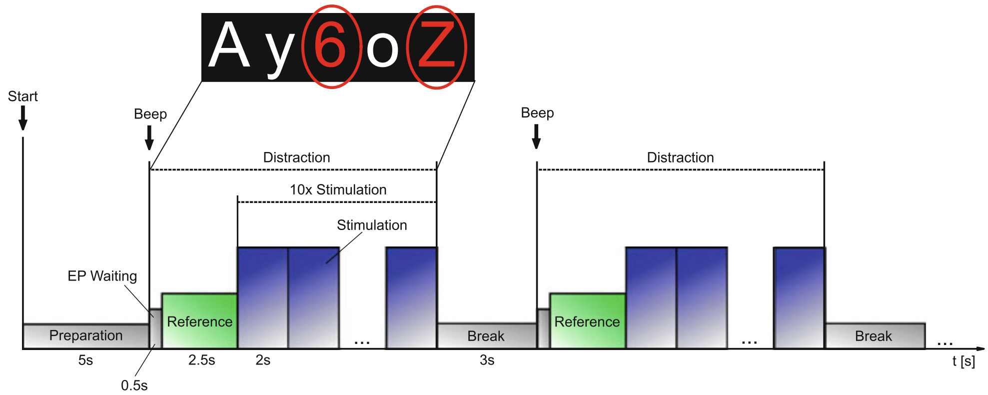


Fig. 2 Graphical illustration of the measurement paradigm. The reference period without stimulation is *green colored*, stimulation intervals are *blue colored*. A visual distraction was given during the whole trial starting with a beep and ending after one reference and ten stimulation periods. The visual distraction is illustrated within the *black bar*

processes (ERD/S). As shown in [27], tactile stimulus processing is accompanied by frequency-dependent responses and might therefore influence further calculations. FFT spectra for subject s2 are presented in the online supplementary material.

2.3.1 Determination of resonance-like frequencies

BP tuning curves were computed to determine the participants resonance-like frequencies as described in [17]. Therefore the recorded channels were bandpass-filtered ten times with the stimulation frequencies as center frequency and a bandwidth of 2 Hz to obtain ten frequency bands. A fifth-order butterworth filter was applied for this purpose. The mean BP of the last 1.5 s of every stimulation block and the last 2.5 s of the reference intervals were computed.

$$\mathrm{BP} = \frac{1}{N} \cdot \sum_{n=1}^{N} x[n]^2 \tag{1}$$

BP values [see (1); x, filtered samples from one channel; N, number of samples in the time interval] were calculated for every stimulation frequency at one finger and also for its related reference intervals. Afterwards mean, standard deviation and 95 % confidence intervals (computed using bootstrapping [5]) for the mean were determined.

Because of the long duration of the measurements, two different methods to compute the relative BP increase were used. The first method, named "common weighting", similar to [17], does not take the measurement duration into account. A second method, named as "trial based weighting", considers EEG changes over time.

2.3.1.1 Common weighting BP values during stimulation for one frequency and one finger are summed up and averaged. The same step is also done to obtain reference BP values per finger and frequency. A certain reference period is used to calculate a BP value, if the respective finger was stimulated with the respective frequency in the trial related to the reference period. Thus, a common mean stimulation BP per frequency and finger and a common reference BP related to the respective finger and frequency are calculated. The mean BP during stimulation is related to the respective BP during reference and scaled to zero to get a common relative bandpower (crBP) increase or decrease.

$$\mathrm{crBP}_{\mathrm{Fi,Freq}} = \left(\frac{\sum_{n=1}^{N} \mathrm{BP}_{\mathrm{n,Fi,Freq}}}{\sum_{n=1}^{N} \mathrm{BP}_{n,\mathrm{Fi,Ref\_freq}}} - 1 \right) \cdot 100\,\% \tag{2}$$

The variables within the equation have following meaning: BP, bandpower based on (1); N, repetitions of one frequency at one finger; Fi, the respective finger; Freq, the applied stimulation frequency; Ref_freq, the respective reference period when the finger 'Fi' was stimulated with the frequency 'Freq'.

2.3.1.2 Trial-based weighting Within this method, the BP during stimulation is related to the reference period of the respective trial. Thus trial based BP values are obtained, considering EEG changes over time this way. The BP values per trial are again summed up and averaged to get an overall BP alternation value named trial-based relative bandpower (tbrBP).

$$\mathrm{tbrBP}_{\mathrm{Fi,Freq}} = \frac{1}{N} \cdot \sum_{n=1}^{N} \left(\frac{\mathrm{BP}_{\mathrm{n,Fi,Freq}}}{\mathrm{BP}_{n,\mathrm{Fi,Ref\_freq}}} - 1 \right) \cdot 100\,\% \tag{3}$$

The evaluation of the existence of individual tuning curves was performed in two steps. In a first step, a t-test for single samples was performed to check if the BP values differ significantly from zero. In a second step, the appearance of the tuning curves was evaluated by a 2 × 5 × 10 ANOVA for repeated measures, conducted for every single participant. The independent variables were "SESSION" (session 1 vs. session 2), "FINGER" (finger 1–finger 5) and "FREQUENCY" (frequency 1–10) and the dependent variable was the BP value of C3.

For statistical testing over all participants, a 2 × 2 × 5 × 3 ANOVA for repeated measures was applied to the (1) obtained BP values of the resonance-like frequency between the sessions, (2) the common and trial-based weighting method, (3) the different fingers and (4) the three electrode positions. The independet variables were "METHOD" (common vs. trial-based), "SESSION" (session 1 vs. session 2), "FINGER" (finger 1 to finger 5) and "CHANNEL" (C3, Cz, and C4). The dependent variable was the BP value of the resonance-like frequency. This frequency was obtained, calculating a score by dividing the respective trial-based relative BP by it's confidence interval. The frequency with the highest similar score on all five fingers was used for statistics. The resonance-like frequency was selected individually for every participant and was validated by the results of the individual statistical analysis of the tuning curves (see Table 1). In case of significant effects Newman–Keuls post-tests were used. Furthermore the trial-based relative band power values from the first session for all channels and fingers were correlated with the second session using the Pearson product-moment correlation coefficient (PPMCC). Statistical analysis was performed with the data analysis software system STATISTICA 7.0 (StatSoft. Inc., Tulsa, USA).

2.3.2 Classification of SSSEP

A classifier was trained with data from the first session. This classifier was afterwards applied to the data from the

Table 1 Selected resonance-like frequencies for all participants used for statistical group analysis and frequencies used for classification

Participants	s1	s2	s3	s4	s5	s6	s7	s8	s9
Frequencies [Hz] used for statistics:									
	27	29	31	27	25	19	27	25	17
Frequencies [Hz] used for classification:									
Thumb	23	29	25	23	25	19	25	25	31
Index finger	25	27	31	27	33	17	19	29	17
Middle finger	33	31	27	31	21	21	27	17	19
Ring finger	27	35	17	29	23	25	33	33	27
Little finger	29	25	23	25	17	27	21	35	29

second session. Thus it was investigated if a classification of the recorded SSSEPs with a classifier trained with data from another session is possible. Fisher's LDA (linear discriminant analysis) was chosen as a classifier. Features were selected using the same method as for selecting the resonance-like frequency used for statistical analysis. Five frequencies with a high and also possibly equal score on all fingers were selected as target frequencies for the five fingers. The same score was used here as the one to select frequencies for statistical testing. One frequency was manually assigned to each finger. For this purpose five different classifiers were calculated. Initially, the raw EEG of the first session was bandpass filtered with five fifth-order butterworth filters with their center frequencies according to the five selected frequencies to obtain five frequency bands. The width of the bandpass was set to 2 Hz, the filtered signals were smoothed using a moving average filter with a duration of 1 s. For training the classifiers, one frequency out of the five available frequencies, was selected as target for one classifier, the others as non-target. All classifiers were 10 x 10 cross validated. Data from the second session was also preprocessed as mentioned before. The classifiers trained with data from the first session were applied to the preprocessed data from the second session. The hit rate of the classifier during stimulation with the respective target frequency was analyzed.

3 Results

3.1 Determination of resonance-like frequencies

In Fig. 3, the emergence of a tuning curve (participant s2) is visible with its maximum of relative BP increase at 29 Hz for channel C3. Similarities between common and trial-based method are visible. For participant s2, the time between first and second session amounted to 14 days. Channel Cz showed a similar trend as channel C3, but with an additional attenuation, channel C4 showed no increase.

No BP increase was visible during the validation measurements, where participants were not touching the stimulator or running the stimulation without any person attached to the EEG amplifier. Furthermore, as visible within the online supplementary material, an amplitude increase during stimulation compared to the reference is visible as a peak in the FFT spectra, mainly at channel C3.

An overview on the distribution and the overall stability of the SSSEPs for all participants can be seen in Fig. 4. All participants responded to the stimulation in a different but stable way. Four participants (s1, s5, s8, and s9) showed only a small BP increase (lower than 100 %) with a confidence interval encompassing a large region and values below 0.

The statistical analysis of the BP values of the resonance-like frequencies (see Table 1) resulted in significant main effects for "METHOD" [$F_{(1,8)} = 86.29$; $p < 0.001$] and "CHANNEL" [$F_{(2,16)} = 10.26$; $p < 0.01$]. The trial-based method (tbrBP) ($M = 0.67$; SD = 0.49) was significantly higher than the common method (crBP) ($M = 0.22$; SD = 0.37). The difference between the three channels showed that the BP of the resonance-like frequency was significantly higher at C3 ($M = 0.89$; SD = 0.82) compared to Cz ($M = 0.39$; SD = 0.98) and C4 ($M = 0.05$; SD = 0.15).

These resonance-like frequencies were also statistically validated individually for every participant. As also visible in Fig. 4, the participants s2, and s6 showed a significant resonance peak [s2: $F_{(9,351)} = 100.86$; $p < 0.0001$, s6: $F_{(9,351)} = 92.20$; $p < 0.0001$], whereas s3, s4, and s7 showed a resonance 'plateau' with at least two frequencies [s3: $F_{(9,351)} = 9.47$; $p < 0.0001$, s4: $F_{(9,351)} = 36.06$; $p < 0.0001$, s7: $F_{(9,351)} = 4.10$; $p < 0.0001$]. The participants s1, s5, and s8 did not show significant relative BP increases from zero in both sessions for a single stimulation frequency on all fingers. Participant s9 showed a significant rel. BP increase from zero, but no resonance frequency or plateau could be identified.

Considering the stability of SSSEP responses, five participants showed no significant differences between the two

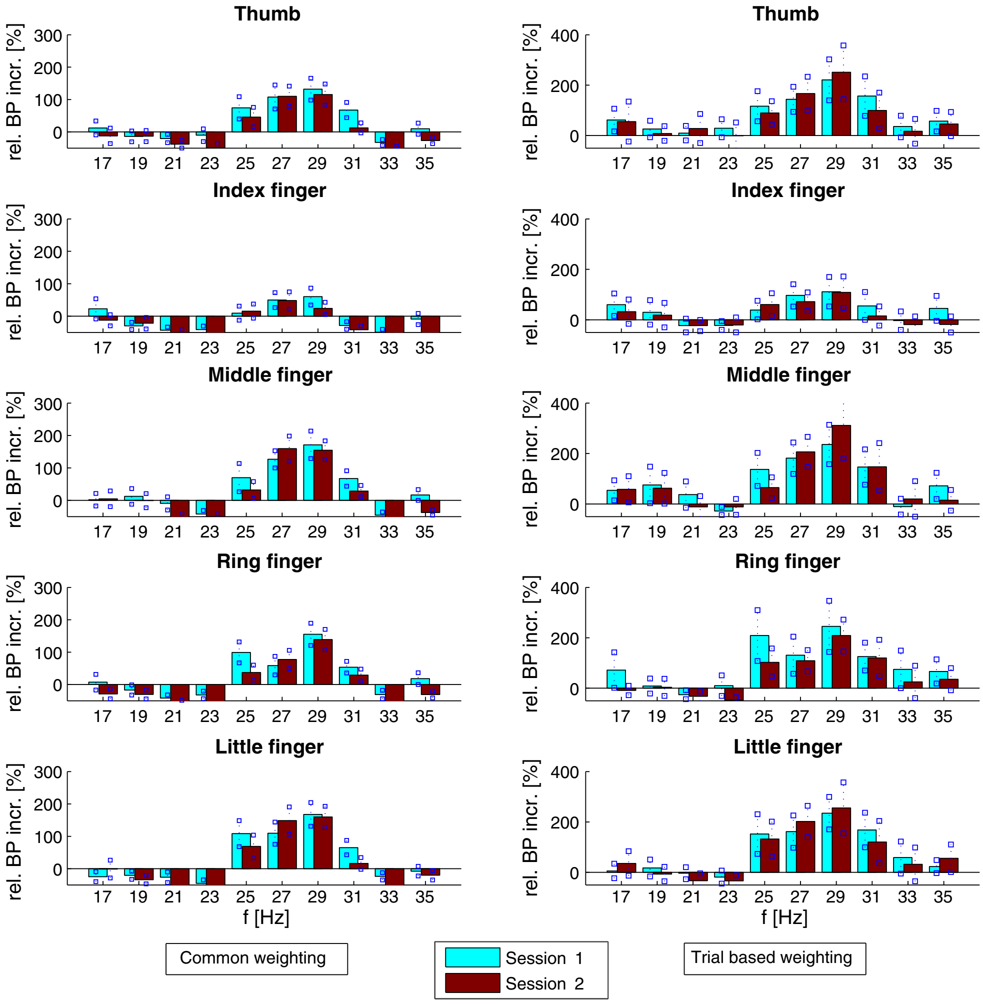


Fig. 3 Relative BP increase of participant s2 from channel C3. The *left column* shows the results using the common method, the *right column* the results using the trial based method. Every row represents one finger. The respective stimulation frequency is plotted on the *x* axis, the *y* axis represents the relative BP increase in [%] (different scaling between *left* and *right column*). For every stimulation frequency a bar for the first and the second session are shown. *Rectangles* indicate the particular 95% confidence intervals for every frequency and session

sessions as a main effect. The participants s6 and s9 showed a lower rel. BP increases during the first session [s6: $F_{(1,39)} = 50.61$; $p < 0.0001$, s9: $F_{(1,39)} = 9.49$; $p < 0.001$]. However, considering the interaction between session and finger, again no significant difference was found. The participants s7 and s8 also showed a lower rel. BP increase during the first session. However, this effect was only observable for finger four at s7 and fingers three and five for s8 [s7: $F_{(4,156)} = 4.32$; $p < 0.01$, s8: $F_{(4,156)} = 3.53$; $p < 0.01$].

Only s8 showed no significant difference for the finger as a main effect. Taking the interaction of frequency and finger into account, all participants with a rel. BP increase above zero showed no significant differences between the respective resonance frequencies and the individual fingers. The resonance frequencies always showed the highest rel. BP increase compared to other frequencies. The statistical analysis across all participants showed that the relative BP increase did not change significantly during session one and session two [$F_{(1,8)} = 0.001$; n.s.] or the stimulated fingers [$F_{(4,32)} = 1.59$; n.s.]. The PPMCC showed significant results for all five fingers and channel C3 ($p < .05$, min. $r = 0.76$, max. $r = 0.93$), four significant results for channel Cz ($p < .05$, min. $r = 0.64$, n.s.; max. $r = 0.91$) and no significant results for channel C4.

3.2 Classification of SSSEP

The classification results (hit rate) for all participants for every finger, classifying the second session with a classifier trained with data from the first session are presented in Table 2. Figure 5 shows the hit rate curves from five selected participants, marked bold in Table 2. An increase of the common classification result (bold black dashed line)

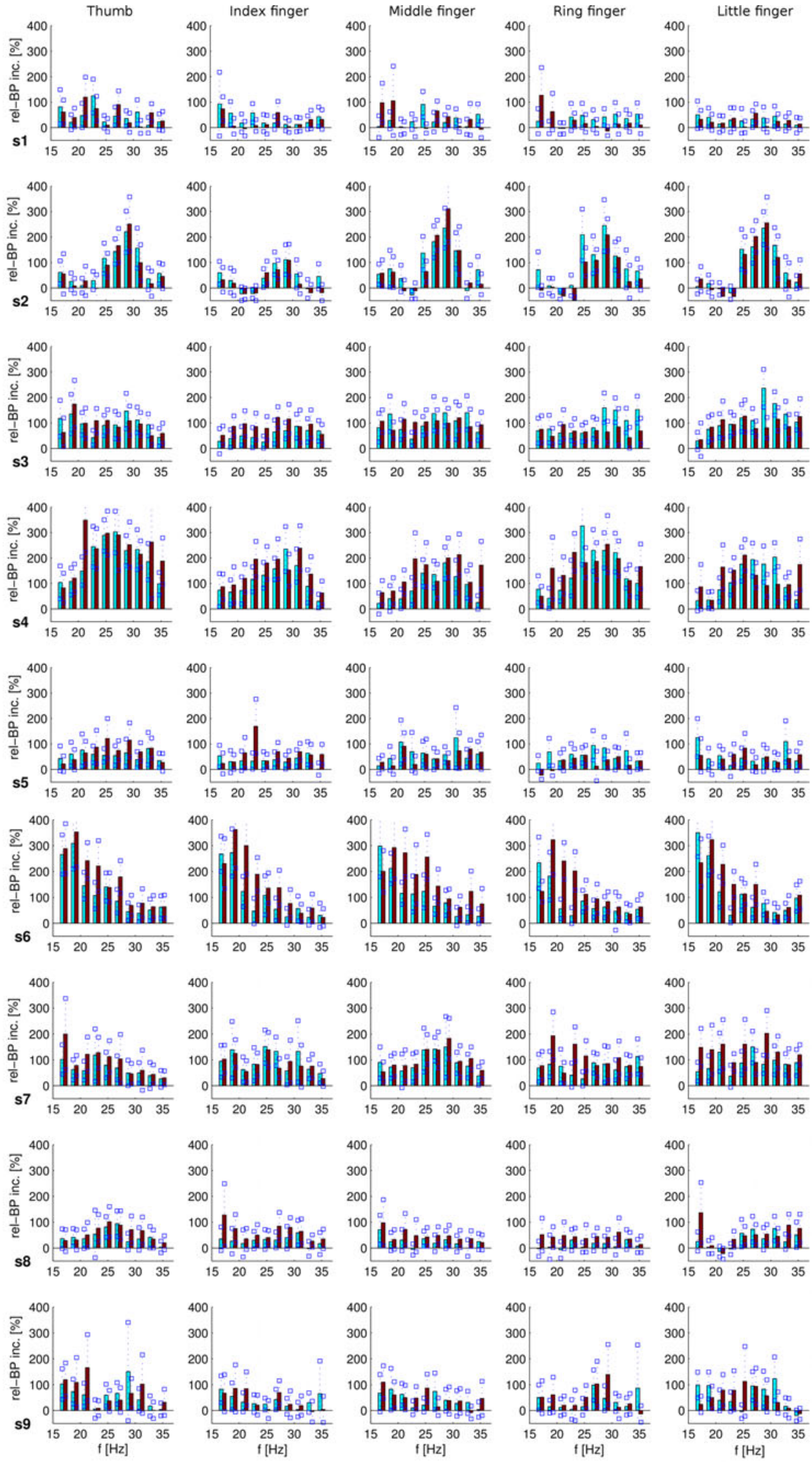


Fig. 4 Comparison over all participants of all five fingers with trial-based weighting for session 1 and session 2 with 95% confidence intervals (indicated with *rectangles*)

is visible after about 1 s. The delay is caused by the moving average filter. After the stimulation the classification result drops again, delayed by the moving average effect.

4 Discussion

In this study the effects of vibro-tactile stimulation of all five fingers of the right hand were investigated. The emergence of a person-dependent tuning curve with person-specific maxima in a range between 19 and 29 Hz was shown.

These findings are similar to the results presented in [17] where participants also showed narrow tuning curves with maxima between 17 and 31 Hz. The results from [28] with a person-independent resonance peak at 21 Hz could not be reproduced. A possible explanation for this differences could be the different setup used in [28], where the palm was stimulated with a 128-Hz sine carrier frequency, modulated with a sinusoidal signal within a range from 5 to 30 Hz.

As described in [14], the firing rate of neurons is also related to the size and the shape of a surface touching the skin, mainly encoded by populations of Merkel cells. In addition the density of mechanoreceptors is different between the palm and the individual fingers. This might be a possible explanation for the different findings in [17] and [28]. Furthermore, this is a potential explanation why the statistical analysis showed differences for some participants with the finger as a main effect. Comparing results from [17] and our findings, also slight differences are observable like different relative BP increase values. This could be caused by the fact that Müller et al. used a stimulation surface of 3 mm^2, whereas 50 mm^2 was used in the actual study. According to [14], the shape of a surface is mainly perceived by Merkel corpuscles. But also Meissner corpuscles are involved in surface perception, although they have a bigger perceptive field. However, Merkel corpuscles are most sensitive for vibratory stimulation in a range between 5 and 15 Hz and Meissner corpuscles between 20 and 50 Hz [14]. The frequency of tactile stimulation applied within this work and also in [17] and [28] was mainly stimulating Meissner and Pacinian corpuscles. But Merkel corpuscles might also be influenced as well, as their frequency perception does not end at 15 Hz. Because of this, the size and shape of the stimulation surface might be influencing the distribution of SSSEP resonance-like frequencies. Furthermore, Merkel corpuscles can evoke neuron firing rates in the range of SSSEP resonance-like frequencies, if very small stimulation surfaces are used [14]. However, this firing rates decrease continuously after the first skin contact, but might also influence the distribution of SSSEP tuning curves. Therefore, effects related to the size of the stimulation surface and SSSEP, especially during stimulation onset and also in combination with focused attention should be investigated in more detail.

An interesting effect was the emergence of similar tuning curves on all fingers. This finding suggests that the neuronal networks involved in processing vibratory tactile stimulation are similar for all fingers, despite being spatially separable. However, as mentioned in [13], Pacinian corpuscles have a very big receptive field: “The receptive field of a PC receptor may include the entire hand”. This could be another explanation, why the BP tuning curves had similar shapes, also for different fingers.

As visible in Fig. 4, all participants showed different tuning curve distributions but they were similar over both measurements. Considering the results of the ANOVA and the PPMCC, a stability of SSSEP over time is given. However, only nine subjects participated within this study, which is a low number to calculate the PPMCC.

Not all participants responded in a similar way to the tactile stimulation. Five actually showed a relative BP increase lower than 100 %. As presented in [1–3, 8, 14],

Table 2 Hit rate [%] for all participants

	Thumb	Index fi.	Middle fi.	Ring fi.	Little fi.	Mean	±SD
s1	61.5	92.5	82.5	65.0	80.0	76.3	11.5
s2	85.0	65.0	85.0	75.0	82.5	78.5	8.6
s3	75.0	75.0	70.0	67.5	62.5	70.0	5.3
s4	100	97.5	95.0	100	90.0	96.5	4.2
s5	82.5	47.5	45.0	52.5	60.0	57.5	13.5
s6	85.0	65.0	70.0	67.5	60.0	69.5	9.4
s7	69.4	65.7	62.9	68.6	75.0	68.3	4.5
s8	20.0	94.9	25.0	32.5	95.0	53.4	34.1
s9	69.2	47.4	47.4	46.2	47.4	51.5	8.9
Mean	72.0	72.3	64.8	63.9	72.5	69.1	
±SD	22.6	19.2	22.3	19.1	15.9	14.1	

Those who showed a relative BP increase with the mean bigger than 60 % and the standard deviation smaller than 10 % in the first session are printed bold

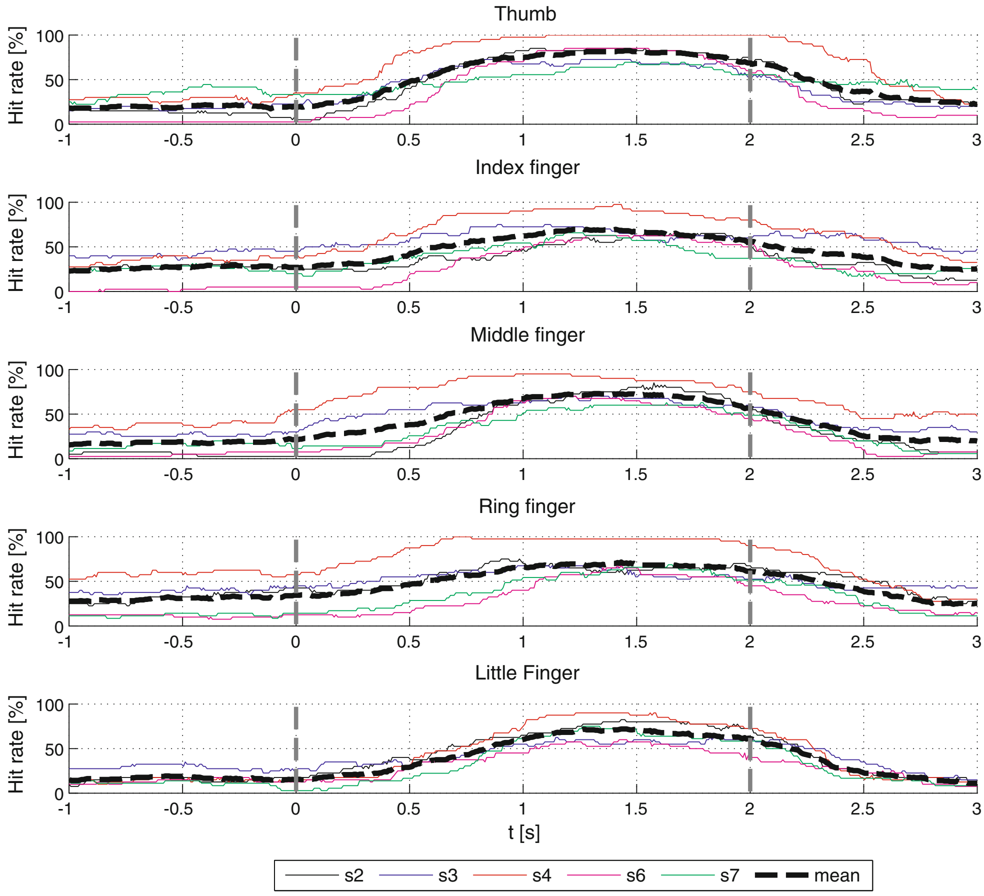


Fig. 5 Hit rate for selected participants for all five fingers. *Vertical bold dashed black lines* indicate the stimulation start and stop. The x axis shows the time from stimulation start in seconds, the y axis the hit rate

cortical response can be modulated based on attention shifting. This effect has been shown in fMRI as well as in EEG-based studies. To eliminate influences based on attention shifting, participants were distracted with the presented counting task. In addition, the applied force of vibratory stimulation affects cortical responses as shown in [28]. As reported by all participants, the tactile stimulation was near the perception boarder. Thus, the effect of neural inhibition and the gating functionality of the thalamus [14] together with a stimulation at the perception limit could potentially completely inhibit ascending signals caused by the tactile stimulation. This could be a reason why some participants showed a much higher relative BP increase with the emergence of a tuning curve, whereas others did not respond to the stimulation at all. Therefore, the possibility for a participant to have control over the pressure applied to the stimulation unit should be avoided, as this might further influence the results. Otherwise, stimulators still providing a sufficient and constant displacement by varying finger pressure should be used.

Considering the two different analysis methods, the trial-based method showed higher values with a only slightly increased standard deviation compared to the common method. Considering the work presented in, e.g., [15, 25, 27, 30], methods similar to the common weighting are used. Roughly speaking, all trials and reference periods are equally treated, averaged and analyzed in an ongoing process. Such methods are commonly used within the neuroscience community and are well established. However, during longtime and more demanding measurements, in the case of the presented study: >2 h with a mathematical task, the EEG signal might change, e.g., as a result of tiredness. Furthermore, the EEG signal is known to be highly non-stationary [29]. Therefore, treating time epochs recorded over a longer time period the same way does not take such effects into account. Using a trial-based method as shown in this paper is a potential way to cope with such issues, where every trial is related to the respective reference period. However, a slightly more complex analysis structure is required, as every trial has to be considered together with the respective reference period. Having, e.g., artifacts within the reference would also affect calculations on the data within the trial, because the trial is related to exactly this one reference. Therefore, an increased number of trials is required.

The electrode positions C3, Cz, and C4 showed significant differences. However, cortical activity elicited with vibratory stimulation also affects regions beyond the primary cortex, which is mainly covered with the bipolar electrode placement used in this study. E.g., in Severens et al. [25] a fronto-central and central-parietal activation is visible. Other studies also showed activity in other regions beyond the primary somatosensory cortex [2, 3, 21]. Thus, the activity picked up with the bipolar electrode placement is also affected by cortical processes in other regions, e.g., from the secondary somatosensory cortex. Regrading further studies, an electrode placement also covering parietal regions on both hemispheres [2, 3] and fronto-central regions [25, 27], is suggested. However, mainly for BCI usage, a low number of channels is still a desired goal.

Unfortunately the chosen electrode placement might also be a reason why some participants did not show a significant relative BP increase.

Regarding the classification results, it could be shown that tactile stimulation can also be automatically detected with rates up to more than 90 %. Classifiers were trained and applied automatically without further manual modifications (e.g., bias). Considering the classification results of s1 and s8 in more detail, heavily biased classifiers to two or three classes could be observed, resulting in high results for the respective classes. As presented in [4], SEPs (somatosensory evoked potentials) are already applied in clinical practice. SEPs are as an example used to detect spinal cord damages as already mentioned in [22] or used as a tool to monitor potential injuries during spinal cord surgery [12]. However, SEP methods are mainly based on signal averaging and take therefore a longer recording time (1–2 min) to reach a sufficient signal-to-noise ratio (SNR) as claimed in [22]. SSSEPs might be an alternative concerning this issue, as mentioned in [22]. Applying a classification method as done within this studies could be a potential alternative to the SEP-based methods.

In terms of BCI research, applying SSSEPs elicited in different fingers for BCI control, the tuning curve similarities between different fingers might reduce screening procedures, as determining the tuning curve of one finger is enough to imply the tuning curves of the other fingers. Up to now a direct relation between BCI performance and an optimal stimulation frequency selection has not been investigated. But it is indicated that using a frequency below or above the frequency range, covered by the persons tuning curve might not be suitable to gain control through a BCI. Therefore, it is suggested to use stimulation frequencies between 19 and 29 Hz for SSSEP BCI purposes, if the fingertips are stimulated and no screening session is conducted and to prefer frequencies closer to 25 than 21 Hz as also used, e.g., in [30]. However, a mental strategy to control a BCI via SSSEP, as shown in [19] is needed what has not been done within this study.

Summarizing the results obtained within this study, a different response to tactile stimulation for different persons could be shown. Furthermore, this response seems to be stable over time and all fingers seem to respond in a similar way. However, it is unclear if this similar response is caused by cortical processes or the stimulus perception directly at the mechanoreceptors.

References

1. Adler J, Giabbiconi CM, Müller MM (2009) Shift of attention to the body location of distracters is mediated by perceptual load in sustained somatosensory attention. Biol Psychol 81:77–85
2. Burton H, Sinclair RJ, McLaren DG (2004) Cortical activity to vibrotactile stimulation: an fMRI study in blind and sighted individuals. Hum Brain Mapp 23:210–228
3. Burton H, Sinclair RJ, McLaren DG (2008) Cortical network for vibrotactile attention: a fMRI study. Hum Brain Mapp 29:207–221
4. Cruccu G, Aminoff MJ, Curio G, Guerit JM, Kakigi R, Mauguiere F, Rossini PM, Treede RD, Garcia-Larrea L (2008) Recommendations for the clinical use of somatosensory-evoked potentials. Clin Neurophysiol 119:1705–1719
5. DiCiccio TJ, Efron B (1996) Bootstrap confidence intervals. Stat Sci 11:189–212
6. Farwell LA, Donchin E (1988) Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr Clin Neurophysiol 70:510–523
7. Georgesco M, Salerno M, Camu W (1997) Somatosensory evoked potentials elicited by stimulation of lower-limb nerves in amyotrophic lateral sclerosis. Electroencephalogr Clin Neurophysiol 104:333–342
8. Giabbiconi CM, Dancer C, Zopf R, Gruber T, Müller MM (2004) Selective spatial attention to left or right hand flutter sensation modulates the steady-state somatosensory evoked potential. Brain Res Cogn Brain Res 20:58–66
9. Giabbiconi CM, Trujillo-Barreto NJ, Gruber T, Müller MM (2007) Sustained spatial attention to vibration is mediated in primary somatosensory cortex. Neuroimage 35:255–262
10. Hamada M, Hanajima R, Terao Y, Sato F, Okano T, Yuasa K, Furubayashi T, Okabe S, Arai N, Ugawa Y (2007) Median nerve somatosensory evoked potentials and their high-frequency oscillations in amyotrophic lateral sclerosis. Clin Neurophysiol 118:877–886
11. Hinterberger T, Neumann N, Pham M, Kübler A, Grether A, Hofmayer N, Wilhelm B, Flor H, Birbaumer N (2004) A multimodal brain-based feedback and communication system. Exp Brain Res 154:521–526
12. Hu Y, Luk K, Lu W, Leong J (2003) Application of time-frequency analysis to somatosensory evoked potential for intraoperative spinal cord monitoring. J Neurol Neurosurg Psychiatry 74:82–87
13. Johnson KO (2001) The roles and functions of cutaneous mechanoreceptors. Curr Opin Neurobiol 11:455–461
14. Kandel ER, Schwartz JH, Jessell TM (2000) Principles of neural science, 4th ed. McGraw-Hill Medical, New York
15. Kourtis D, Seiss E, Praamstra P (2008) Movement-related changes in cortical excitability: a steady-state SEP approach. Brain Res 1244:113–120
16. Kübler A, Birbaumer N (2008) Brain–computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients?. Clin Neurophysiol 119:2658–2666
17. Müller GR, Neuper C, Pfurtscheller G (2001) Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation. Biomed Tech (Berl) 46:186–190

18. Müller-Putz GR, Neuper C, Pfurtscheller G (2002) Do various stimulation characters cause different steady-state evoked potentials in man? In: Hutten H, Krösl P (eds) Proceedings of 2nd European medical and biological engineering conference EMBEC'02, Graz University of Technology, Vienna, pp 1312–1313
19. Müller-Putz GR, Scherer R, Neuper C, Pfurtscheller G (2006) Steady-state somatosensory evoked potentials: suitable brain signals for brain–computer interfaces?. IEEE Trans Neural Syst Rehabil Eng 14:30–37
20. Müller-Putz GR, Pfurtscheller G (2008) Control of an electrical prosthesis with an SSVEP-based BCI. IEEE Trans Biomed Eng 55:361–364
21. Nangini C, Ross B, Tam F, Graham SJ (2006) Magnetoencephalographic study of vibrotactile evoked transient and steady-state responses in human somatosensory cortex. Neuroimage 33:252–262
22. Noss RS, Boles CD, Yingling CD (1996) Steady-state analysis of somatosensory evoked potentials. Electroencephalogr Clin Neurophysiol 100:453–461
23. Pfurtscheller G, Neuper C (2006) Future prospects of ERD/ERS in the context of brain–computer interface (BCI) developments. In: Neuper C, Klimesch W (eds) Event-related dynamics of brain oscillations. Progress in brain research, vol. 159. Elsevier, Amsterdam, pp 433–437
24. Regan D (1989) Human brain electrophysiology: evoked potentials and evoked magnetic fields in science and medicine. Elsevier Science, New York
25. Severens M, Farquhar J, Desain P, Duysens J, Gielen C (2010) Transient and steady-state responses to mechanical stimulation of different fingers reveal interactions based on lateral inhibition. Clin Neurophysiol 121:2090–2096
26. Snyder AZ (1992) Steady-state vibration evoked potentials: descriptions of technique and characterization of responses. Electroencephalogr Clin Neurophysiol 84:257–268
27. Spitzer B, Wacker E, Blankenburg F (2010) Oscillatory correlates of vibrotactile frequency processing in human working memory. J Neurosci 30:4496–4502
28. Tobimatsu S, Zhang YM, Kato M (1999) Steady-state vibration somatosensory evoked potentials: physiological characteristics and tuning function. Clin Neurophysiol 110:1953–1958
29. Vidaurre C, Schlögl A, Cabeza R, Scherer R, Pfurtscheller G (2007) Study of on-line adaptive discriminant analysis for EEG-based brain computer interfaces. IEEE Trans Biomed Eng 54:550–556
30. Voisin JI, Rodrigues EC, Hétu S, Jackson PL, Vargas CD, Malouin F, Chapman CE, Mercier C (2011) Modulation of the response to a somatosensory stimulation of the hand during the observation of manual actions. Exp Brain Res 208:11–9
31. Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM (2002) Brain–computer interfaces for communication and control. Clin Neurophysiol 113:767–791

A.5. Somatosensory Evoked Potentials Elicited by Stimulating Two Fingers from One Hand–Usable for BCI?

C. Breitwieser, C. Pokorny, C. Neuper, and G. R. Müller-Putz. "Somatosensory evoked potentials elicited by stimulating two fingers from one hand - Usable for BCI?" In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2011, pp. 6373–6376. DOI: 10.1109/IEMBS.2011.6091573 [194]

Distribution of dedicated work:

- **Christian Breitwieser**: 65
- Christoph Pokorny: 20 %
- Christa Neuper: 2 %
- Gernot R. Müller-Putz: 13 %

33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Somatosensory Evoked Potentials Elicited by Stimulating Two Fingers from One Hand - Usable for BCI?

Christian Breitwieser, Christoph Pokorny, Christa Neuper, Gernot R. Müller-Putz

***Abstract*— Steady-state somatosensory evoked potentials (SSSEPs) have been elicited using vibro-tactile stimulation on two fingers of the right hand. Fourteen healthy subjects participated in this study. A screening session, stimulating each participant's thumb, was conducted to determine individual optimal resonance-like frequencies. After this screening session, two stimulation frequencies per subject were selected. Stimulation was then applied simultaneously on the participant's thumbs and middle finger. It was investigated whether it is possible to classify SSSEP changes based on an attention modulation task to determine possible BCI applications. A cue indicated the participants to shift their attention to either the thumb or the middle finger. Offline classification with a lock-in analyzer system (LAS) and a linear discriminant analysis (LDA) classifier was performed. One bipolar channel and no further optimization methods were used. All participants except one reached classification results above chance level classifying a reference period without focused attention against focused attention either to the thumb or the middle finger. Only two subjects reached accuracies above chance, classifying focused attention to the thumb vs. attention to the middle finger.**

I. Introduction

Different strategies are used nowadays for Brain-Computer Interfaces (BCIs). Prominent examples are BCIs controlled via sensorimotor rhythms [1] or evoked potentials (EPs) [2]. Visual evoked potentials (VEPs) can occur after row and column flashes from a P300 speller [3]. In [3], the occurrence and usability of, for example, the P300 component [4] was analyzed. EPs can also be utilized for BCI control using amplitude modulation of steady-state EPs (SSEPs) through shifting attention [5], [6]. A major drawback of VEP-based BCI systems is the requirement of a functional visual system. Patients suffering from a locked-in syndrome or amyotrophic lateral sclerosis (ALS) can lose control over their eyes and the ability to lift their eyelids [7], but their somatosensory system seems to remain functional. As an alternative, SSEPs could also be elicited using tactile stimulation, producing steady-state somatosensory evoked potentials (SSSEPs) [8]. These potentials have already been successfully applied for BCI control, stimulating the index fingers of both hands [9]. Control was gained by shifting attention to a target finger. Person dependent stimulation frequencies were obtained via a simple screening process. Classificaion accuracies of up to 80 % could be reached by classifying focused attention on the left or the right index finger during tactile stimulation. Applying vibratory stimulation also produces cortical activity beyond the primary somatosensory system, especially when focusing on a target stimulus [10]–[12]. Therefore channels not just covering the primary somatosensory cortex could lead to an increased BCI performance.

The goal of this work was to investigate whether users could gain control through a BCI based on attention modulation by just stimulating fingers of one hand using a person specific stimulation frequency selection. If it is possible to distinguish attention modulation within one hand, it could become feasible to build a BCI with more than two classes by stimulating multiple fingers on both hands.

This work is supported by the European ICT Programme Project FP7-247919. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.

C. Breitwieser, C. Pokorny, C. Neuper and G.R. Müller-Putz are with the Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria, 8010 Graz, Krenngasse 37, e-mail: c.breitwieser@tugraz.at, christoph.pokorny@tugraz.at, gernot.mueller@tugraz.at

C. Neuper is also with the Department of Psychology, University of Graz, Austria, 8010 Graz, Universitätsplatz 2/III, e-mail: neuper@tugraz.at

II. Methods

A. Measurment Setup and Participants

Tactile stimulation was applied to the finger tips of the thumb and the middle finger of the right hand using C2 tactors [Engineering Acoustics, Inc., Casselberry, FL, USA]. The stimulation signal was produced via a custom-built signal generator generating a 200 Hz sine, modulated with a rectangular signal for stimulation as suggested by Müller-Putz et al. [9]. The resulting stimulation signals were short 200 Hz pulses with a given frequency. The measurement was divided into the parts: (i) screening and (ii) focused attention. Electrode coordinates were gathered using ELPOS from zebris [zebris Medical GmbH, Isny, Germany]. Fourteen paid subjects participated in the studies (50 % male, 50 % female, mean age: 25.64 $\pm$ 2.6 years).

B. EEG Recording

Forty-eight Ag/AgCl electrodes were used for EEG recording with linked references as shown in Fig 1. Three g.USBamps [Guger Technologies OG, Graz, Austria] were used for EEG recording with a sampling rate of 2.4 kHz. Impedances were kept below 5 kΩ. All EEG measurements were done in a shielded room.

C. Measurement Procedure

1) Screening: According to [13], every person reacts in a different way to tactile stimulation with an individual resonance-like frequency. To determine person specific tuning curves, a screening measurement was conducted by stimulating the participant's thumb with stimulation frequencies

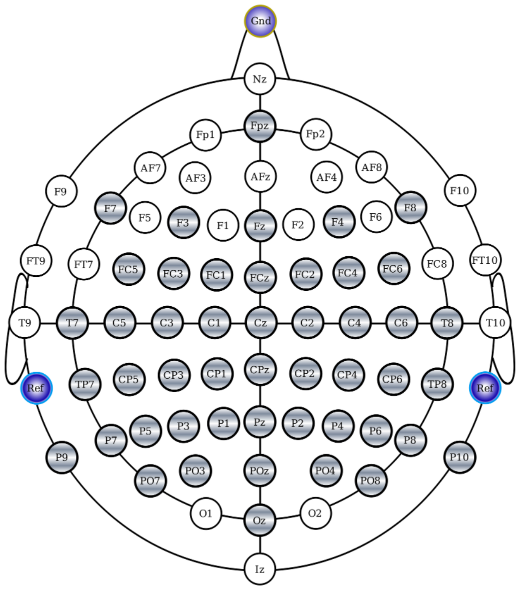
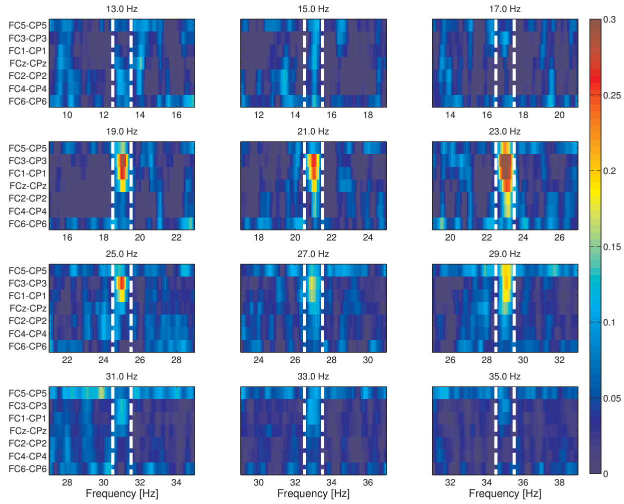


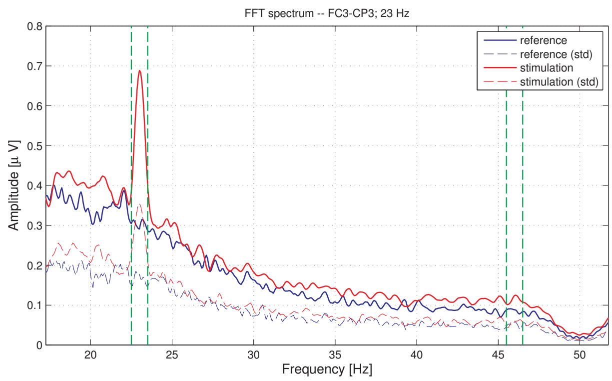
Fig. 1. International 10–20 system electrode setup used for measurement. Recorded electrode positions are highlighted in gray, reference electrodes were placed at left and right mastoids, and a ground electrode was mounted on the participant's nose.

from 13 Hz to 35 Hz, in 2 Hz steps. Only the thumb was stimulated as the tuning curve is assumed to be similar on all fingers [14]. Every frequency was stimulated randomly 60 times for 2 s. Reference periods without tactile stimulation were placed in the screening paradigm. The screening was divided into 6 runs, every run lasting about 8 min. Participants were distracted to avoid concentrating on the stimulated finger. They had to perform a mathematical task during the screening: add or subtract randomly appearing numbers on a screen. After the screening, FFT difference maps (fast fourier transform) were calculated based on the screening data to show power changes during stimulation. An example is presented in Fig. 2(a). This maps outline the difference between the FFT spectra during reference and during stimulation. FFT spectra from the bipolar channel FC3-CP3 from time-intervals during stimulation were plotted as shown in Fig. 2(b). Two frequencies with the highest amplitudes during stimulation were selected as stimulation frequencies for the following paradigm.

2) Focused Attention: This paradigm was divided into single trials. Every trial consisted of a 3 – 3,5 s reference followed by a 4 – 4,5 s focused attention period. During the reference period, participants were instructed to merely look at the blank screen. Tactile stimulation was applied during both periods with the frequencies selected from the screening. Randomly appearing amplitude changes, called "twitch" [9], were mixed into the stimulation to facilitate focusing on a finger by counting the twitches. A fading text indicated the respective target finger. Every class (target finger to focus on) was repeated 80 times.



(a) FFT difference maps used to determine stimulation frequencies with the highest SSSEP response. Every plot belongs to the time window of one stimulation frequency, the x-axis shows the frequency, and the y-axis shows seven bipolar channels over the primary sensory and motor regions. Blue colored regions indicate a low amplitude, while red and yellow colored sections show an increased amplitude. Applied stimulation frequencies are highlighted with white dashed lines.



(b) FFT spectrum of bipolar channel FC3–CP3 during stimulation with 23 Hz used for manual inspection. The red lines represent the mean frequency response and its standard deviation during stimulation, and blue lines during reference period. The range of the stimulation frequency and its 2^{nd} harmonic are highlighted with green dashed lines.

Fig. 2. FFT maps and FFT spectra used to determine optimal stimulation frequencies for further measurements from participant s1.

D. Analysis

All data were visually inspected before analysis. EOG (electrooculogram) and EMG (electromyogram) artifacts were manually marked; trials containing EMG artifacts were discarded from further calculations.

1) Band Power Tuning Curves: Tuning curves, based on relative band power (BP) increase [13], were calculated for comparison with the FFT maps. To obtain relative BP values, the BP during stimulation with a single frequency was related to the respective reference interval. For all relative BP values, 95 % confidence intervals using a bootstrap algorithm [15] provided by Matlab [The MathWorks Inc., Natick, USA] were computed with 1000 bootstrap samples and the mean as the bootstrapping function.

2) Classification: The amplitude output of a lock-in analyzer system (LAS) [9] and an LDA (linear discriminant analysis) classifier (Fishers LDA) were utilized for classification. As a first attempt, the bipolar channel FC3–CP3, which showed the highest amplitudes in the stimulation frequency range inside the FFT maps, was used for classification. This channel selection was also used to obtain comparable results with [9]. The LAS output was smoothed using a moving average filter (length 1 s) before classification. A classifier was trained using 10 x 10 cross validation. The classes attention on thumb or middle finger were classified against the reference period and against each other.

III. Results

All figures presented were obtained from participant s1, who was randomly selected.

A. Band Power Tuning Curves

Fig. 3 shows relative BP values for different bipolar channels of one participant. An emergence of a tuning curve is visible at bipolar channels over the left hemisphere. Channels covering the right hemisphere show merely a slight or no increase. A maximum relative BP increase can be seen at FC3–CP3 around 23 and 25 Hz.

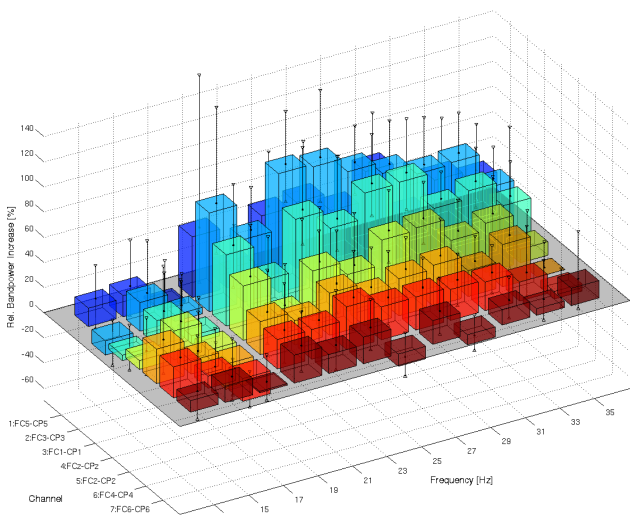


Fig. 3. Relative BP increase tuning curves during stimulation for seven bipolar channels over the primary sensory and motor cortex for participant s1. The respective stimulation frequency is shown on the x-axis, channels are displayed on the y-axis and the relative BP increase is shown on the z-axis. Every channel is plotted using the same color. Vertical lines show the 95 % confidence interval (computed using bootstrapping [15]).

B. Classification

Classification results for participant s1 can be seen in Fig. 4. The results shown in this figure were 10x10 cross validated with 79 trials per class. Maximum accuracies of 74 % and 73 % for the respective classes vs. reference and 56.7 % for thumb vs. middle finger were reached by this participant. In both cases, classifying against reference, the classification accuracy was above chance level [16]. Tab. I shows the classification accuracies, their resonance-like frequency and the selected frequencies for stimulation for all participants. Thirteen of them reached accuracies above chance for at least one class against reference. However, only two participants reached a classification accuracy slightly above chance, classifying attention on the thumb vs. attention on the middle finger. The mean accuracy for all participants was 66.8 % (± 5,7) for thumb vs. reference, 66.6 % (± 5.1) for middle finger vs. reference and 58.6 % (± 2.0) for thumb vs. middle finger.

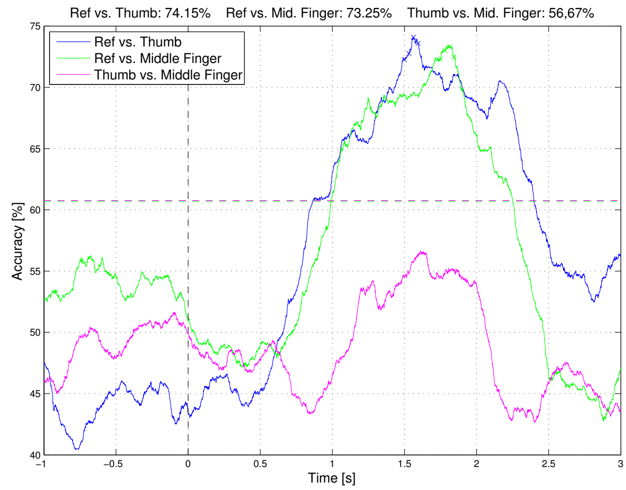


Fig. 4. Classification accuracies for attention on thumb or middle finger against the reference period and thumb vs. middle finger for participant s1. The blue line represents switching attention to the thumb classified against reference and the green line the attention to the middle finger against reference. The magenta colored line shows the classification accuracy of thumb vs. middle finger. The horizontal dashed line indicates the chance level at 61 % for a significance level of 5 % with 79 trials per class [16]. A vertical dashed line indicates the trial start, when the participants started shifting their attention to a single finger.

IV. Discussion

This study assessed the possibility of successfully classifying steady-state somatosensory evoked potentials on two fingers from the same hand using attention modulation. FFT calculations and relative BP tuning curves were utilized to determine optimal stimulation frequencies.

A. Band Power Tuning Curves

Similar effects as in Müller et al. [13] could be observed. Participants showed an individual emergence of a broad tuning curve with maxima in a range from 21 to 35 Hz, as visible in Table I. This is contrary to the findings by Tobimatsu et al. [17], who reported a narrow tuning curve with a person independent maximum at 21 Hz. The reasons for these different findings are still an open question, as Tobimatsu et al. used a different stimulator placement and a different tactile stimulation paradigm (stimulation applied to the palm, a bigger stimulation surface, and a sine modulated 128 Hz sinusoidal stimulation signal).

TABLE I

RESONANCE LIKE FREQUENCIES (F_{res}, STIMULATION FREQUENCIES AND MAXIMUM CLASSIFICATION ACCURACIES IN [%] FOR ALL PARTICIPANTS. THE STIMULATION FREQUENCY FOR THE THUMB IS F_1, THE FREQUENCY FOR THE MIDDLE FINGER F_2. THUMB AND MID. FI. (MIDDLE FINGER) REPRESENT THE ACCURACIES OF THE REFERENCE AGAINST THE RESPECTIVE CLASS. THE LAST ROW SHOWS THE ACCURACIES CLASSIFYING ATTENTION ON THE THUMB VS. ATTENTION ON THE MIDDLE FINGER (* INDICATES A VALUE ABOVE CHANCE LEVEL).

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	mean ± std
f_{res}	23	31	27	25	29	23	31	23	21	35	21	23	29	21	
f_1 / f_2	23/29	19/29	25/29	21/27	23/27	23/29	19/23	23/27	19/25	19/35	21/31	19/27	19/23	21/27	
thumb	74*	72*	64	76*	69*	70*	59	73*	64*	67*	63*	61*	65*	58	66.8 ± 5,7
mid fi	73*	64*	65*	78*	64*	69*	66*	72*	65*	66*	58	68*	64*	61	66.6 ± 5.1
th/mf	57	56	57	59	58	62*	62 *	60	61	60	58	56	60	59	58.6 ± 2.0

B. Classification

All participants except one performed above chance chance in at least one class vs. reference. However only two participants slightly exceeded the chance level, classifying focused attention on thumb vs. focused attention on the middle finger. This was achieved using merely a single bipolar channel over the primary sensor and motor regions of the cortex. No further optimizations like individual channel selection and channel combinations have been performed. According to [10], [11] and [12], other cortical regions are also involved in processing vibro-tactile stimulation. Therefore, different channel combinations might further increase classification accuracy, especially classifying thumb vs. middle finger. Measured electrode positions have also not been taken into account yet and could be used for source localization and electrode placement. Participants reported problems switching their attention to a specific finger. The twitches should help the participants focus on a specific finger. The importance of such twitches has to be investigated in more detail, to clarify whether twitches are useful or not. In addition, using higher harmonics for classification already significantly increased classification accuracy in SSVEP BCIs [18]. This principle could also be applied to a BCI based on SSSEP.
To sum up, the results indicate that focusing attention to some tactile stimulation on one hand can be modulated quite well, but shifting attention to a specific finger during parallel stimulation is a much more demanding task.

C. Future Works

To further increase classification accuracy, investigations regarding optimal channel selection, perhaps person specific, will be done. Including higher harmonics into the classification procedure will also be investigated, as well as the effect of twitches or modifications in the stimulation signal (e.g. amplitude).

ACKNOWLEDGMENT

Special thanks to Ian Daly for proofreading.

REFERENCES

[1] G. Pfurtscheller and C. Neuper, "Future prospects of ERD/ERS in the context of brain-computer interface (BCI) developments," in *Event-Related Dynamics of Brain Oscillations*, ser. Progress in Brain Research, C. Neuper and W. Klimesch, Eds. Elsevier, 2006, vol. 159, pp. 433 – 437.

[2] D. Regan, *Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine*. Elsevier, 1989.

[3] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials." *Electroencephalogr Clin Neurophysiol*, vol. 70, no. 6, pp. 510–523, Dec 1988.

[4] W. S. Pritchard, "Psychophysiology of P300." *Psychol Bull*, vol. 89, no. 3, pp. 506–540, May 1981.

[5] M. Middendorf, G. McMillan, G. Calhoun, and K. S. Jones, "Brain-computer interfaces based on the steady-state visual-evoked response," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 211–214, 2000.

[6] G. R. Müller-Putz and G. Pfurtscheller, "Control of an electrical prosthesis with an SSVEP-based BCI." *IEEE Trans Biomed Eng*, vol. 55, no. 1, pp. 361–364, Jan 2008.

[7] T. Hinterberger, N. Neumann, M. Pham, A. Kübler, A. Grether, N. Hofmayer, B. Wilhelm, H. Flor, and N. Birbaumer, "A multimodal brain-based feedback and communication system," *Experimental Brain Research*, vol. 154, pp. 521–526, 2004, 10.1007/s00221-003-1690-3.

[8] A. Snyder, "Steady-state vibration evoked potentials: descriptions of technique and characterization of responses." *Electroencephalography and clinical neurophysiology*, vol. 84, no. 3, pp. 257–268, 1992.

[9] G. Müller-Putz, R. Scherer, C. Neuper, and G. Pfurtscheller, "Steady-state somatosensory evoked potentials: suitable brain signals for brain-computer interfaces?" *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 14, no. 1, pp. 30–37, March 2006.

[10] H. Burton, R. J. Sinclair, and D. G. McLaren, "Cortical activity to vibrotactile stimulation: An fMRI study in blind and sighted individuals," *Human Brain Mapping*, vol. 23, no. 4, pp. 210–228, 2004.

[11] ——, "Cortical network for vibrotactile attention: a fMRI study." *Hum Brain Mapp*, vol. 29, no. 2, pp. 207–221, Feb 2008.

[12] M. Severens, J. Farquhar, P. Desain, J. Duysens, and C. Gielen, "Transient and steady-state responses to mechanical stimulation of different fingers reveal interactions based on lateral inhibition," *Clinical Neurophysiology*, vol. In Press, Corrected Proof, pp. –, 2010.

[13] G. R. Müller, C. Neuper, and G. Pfurtscheller, "Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation." *Biomed Tech (Berl)*, vol. 46, no. 7-8, pp. 186–190, 2001.

[14] C. Breitwieser, "Are steady-state somatosensory evoked potentials suitable for biometric use?" Master's thesis, Graz University of Technology, 2009.

[15] T. J. DiCiccio and B. Efron, "Bootstrap confidence intervals," *Statistical Science*, vol. 11, no. 3, pp. pp. 189–212, 1996.

[16] G. R. Müller-Putz, R. Scherer, C. Brunner, R. Leeb, and G. Pfurtscheller, "Better than random? A closer look on BCI results," *International Journal of Bioelectromagnetism*, vol. 10, pp. 52–55, 2008.

[17] S. Tobimatsu, Y. Zhang, and M. Kato, "Steady-state vibration somatosensory evoked potentials: physiological characteristics and tuning function," *Clinical Neurophysiology*, vol. 110, pp. 1953–1958, 1999.

[18] G. R. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller, "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *Journal of Neural Engineering*, vol. 2, pp. 1–8, 2005.

A.6. A Hybrid Three-Class Brain-Computer Interface System Utilizing SSSEPs and Transient ERPs

C. Breitwieser, C. Pokorny, and G. R. Müller-Putz. "A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERPs." In: *Journal of Neural Engineering* 13.6 [2016]. DOI: 10.1088/1741-2560/13/6/066015 [197]

Distribution of dedicated work:

- **Christian Breitwieser**: 55
- Christoph Pokorny: 35 %
- Gernot R. Müller-Putz: 10 %

IOP Publishing Journal of Neural Engineering

J. Neural Eng. **13** (2016) 066015 (13pp) doi:10.1088/1741-2560/13/6/066015

A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERPs

Christian Breitwieser, Christoph Pokorny and Gernot R Müller-Putz[1]

Institute of Neural Engineering, Laboratory of Brain–Computer Interfaces, Graz University of Technology, Stremayrgasse 16, A-8010 Graz, Austria

E-mail: c.breitwieser@tugraz.at, christoph.pokorny@tugraz.at and gernot.mueller@tugraz.at

Received 14 June 2016, revised 5 October 2016
Accepted for publication 10 October 2016
Published 27 October 2016

Abstract

Objective. This paper investigates the fusion of steady-state somatosensory evoked potentials (SSSEPs) and transient event-related potentials (tERPs), evoked through tactile simulation on the left and right-hand fingertips, in a three-class EEG based hybrid brain–computer interface. It was hypothesized, that fusing the input signals leads to higher classification rates than classifying tERP and SSSEP individually. *Approach.* Fourteen subjects participated in the studies, consisting of a screening paradigm to determine person dependent resonance-like frequencies and a subsequent online paradigm. The whole setup of the BCI system was based on open interfaces, following suggestions for a common implementation platform. During the online experiment, subjects were instructed to focus their attention on the stimulated fingertips as indicated by a visual cue. The recorded data were classified during runtime using a multi-class shrinkage LDA classifier and the outputs were fused together applying a posterior probability based fusion. Data were further analyzed offline, involving a combined classification of SSSEP and tERP features as a second fusion principle. The final results were tested for statistical significance applying a repeated measures ANOVA. *Main results.* A significant classification increase was achieved when fusing the results with a combined classification compared to performing an individual classification. Furthermore, the SSSEP classifier was significantly better in detecting a non-control state, whereas the tERP classifier was significantly better in detecting control states. Subjects who had a higher relative band power increase during the screening session also achieved significantly higher classification results than subjects with lower relative band power increase. *Significance.* It could be shown that utilizing SSSEP and tERP for hBCIs increases the classification accuracy and also that tERP and SSSEP are not classifying control- and non-control states with the same level of accuracy.

S Online supplementary data available from stacks.iop.org/jne/13/066015/mmedia

Keywords: brain–computer interface, BCI, steady-state somatosensory evoked potential, SSSEP, P300, tERP, hybrid

(Some figures may appear in colour only in the online journal)

1. Introduction

A traumatic brain injury, a severe neurological disease or something similar can happen to anyone. Such an incident, like the neurodegenerative disease amyotrophic lateral sclerosis, is a serious impediment for a person and can also inhibit all voluntary motor functions. Those people affected may no longer be capable of interacting with their environment and become locked in their own bodies, ending up in whats is known as a ‘locked-in’ state.

[1] Author to whom any correspondence should be addressed

Utilizing brain–computer interfaces (BCIs) [1], a new communication channel has become available. A BCI provides the possibility to directly communicate by measuring the brain activity and translating this activity into an output signal, with the result that muscular activity will no longer be essential for communication. During the last few years, different forms of BCIs have been developed, which can control spelling devices, neuroprosthesis, robotic devices and much more. Different mental strategies are utilized to setup such BCI systems. Prominent examples for such strategies make use of dynamic motor rhythms like the ERD/S effect [2], transient event related potentials (tERPs) such as P300, or steady-state evoked potentials (SSEPs) [3].

The selection of the respective BCI system and its strategy for a potential person also depends on the nature of the impairment. BCIs relying on a functional visual system (like a visual P300 speller) are not applicable for persons without a functional visual system, which provides voluntary eye control to focus the view. In such cases other strategies are often used. A popular and thoroughly investigated strategy relies in the already mentioned ERD/S effect. To induce ERD/S, strategies such as motor movement imagination [2] or other mental tasks are used. Another approach, which was rarely investigated in the past, utilizes the tactile system, which often stays fully functional in case of a neural impairment. Therefore, tactile BCIs are a reasonable alternative to e.g., steady-state visual evoked potentials (SSVEPs), P300, or motor imagery based systems.

Such tactile BCI systems rely on either steady-state somatosensory evoked potentials (SSSEPs) [4, 5] or tERPs [6] (for example P300 [7]). SSSEPs are induced by continuous and periodic sensory stimulation, reflecting a persistent cortical response while tERPs are triggered by a concise stimulus and reflect a phasic cortical response to this stimulus. SSSEP based BCIs [8] as well as P300 based BCIs [7] have already been investigated and reasonable results have been achieved. To evoke such potentials, tactile stimulation is applied to the body. Due to the variety in human nature, different people respond in different ways to a stimulation of this kind. For example, vibratory stimulation evokes different 'resonance-like' frequencies [9], which differ from person to person [10]. Moreover, when tactile stimulation is applied in parallel to different fingers, certain interaction effect types become visible [6]. Thus different factors, whether person dependent or otherwise, have an influence on the setup of a BCI. For example, in the studies performed by Müller-Putz *et al* [8], classification results of up to 80% could be reached for one subject, while other subjects hardly reached 60% and stayed below the chance level. Due to a cause that is still unknown, the tactile BCI only worked in an excellent manner in the case of one single subject. The precise reasons why the others have not been able to equal this optimum performance have not yet been established.

In order to combine the advantages of different BCI strategies, hybrid BCI (hBCI) systems were introduced [11]. Such hBCIs are capable of combining different kinds of brain signals as well as external signals to enhance the performance of common BCIs [11, 12]. As shown e.g., by Allison *et al* [13], an hBCI utilizing SSVEP and motor imagery delivers better classification results than those achieved by classifying the individual strategy alone. The combining of different BCI approaches in a hybrid system is thus a reasonable step; for example, combining tERPs and SSEPs, e.g. in the visual [14] or the tactile [15] field.

As stated above the classification results for tactile BCIs can vary from below to significantly above chance [8]. Taking into consideration the hBCI approach as presented by Severens *et al* [15], the SSSEP component performance was inferior to that of the tERP component. On the other hand, as mentioned above, Müller-Putz *et al* [8] were able to achieve classification results up to 80%. Furthermore, Giabbiconi *et al* [16, 17] demonstrated the possibility for modifying the SSSEP amplitudes using focused attention. The possibility of performing an amplitude modulation of this kind is the underlying principle of many SSSEP related BCIs [8, 18]. As stated by Severens *et al* [15] in their discussion, the usage of standard stimulation frequencies instead of individual ones, might have had an influence on their SSSEP classification results. Additionally, as shown by Pinegger *et al* [19], transient signals might be a more suitable option for control states, while steady-state signals might be better for detecting a non-control state.

This paper introduces an hBCI utilizing tactile stimulation to evoke SSSEPs and tERPs together. Person dependent stimulation frequencies, determined in an initial screening session as discussed by Severens *et al* [15], are used for evoking SSSEPs. Three classes are introduced with two control states and one dedicated non-control state. The setup follows the insights of Pinegger *et al* [19], because investigating non-control states more deeply is a crucial step towards asynchronous BCIs [20]. The subjects performed a tactile focused attention task, either focusing on the target classes or residing in the non-control state. The BCI described in this paper is set up using a common implementation platform and fusion strategies as suggested by Müller-Putz *et al* [11]. The open interfaces TiA [21] and TiD [25] are utilized for inter-process and inter-machine communication to facilitate module exchangeability and follow the suggestions made by Müller-Putz *et al* [11]. The question of whether fusing the output of SSSEP and tERP classification might extend beyond the individual classification results is investigated here. Different fusion strategies, e.g. inspired by Leeb *et al* [22] are utilized to combine the individual input signals. It is hypothesized that fusing tERP and SSSEP classification also increases the overall classification rate [22].

2. Methods

2.1. Measurement setup

2.1.1. Subjects, EEG recording and tactile stimulation. Fourteen paid subjects participated in the studies. All the subjects were healthy; none of them was ever diagnosed with any neurological disease. The resulting fourteen subjects were 50% male/female and had a mean age of 26.3 (SD: 6.2)

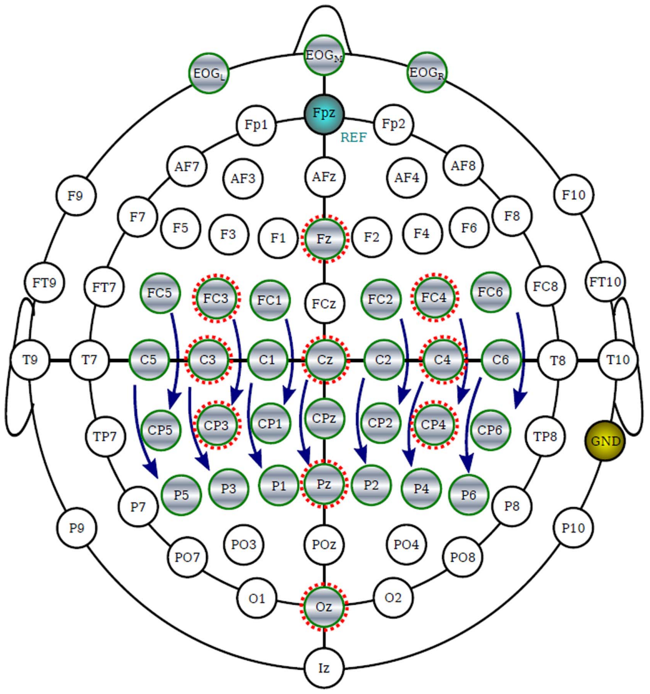


Figure 1. Electrode setup according to the international 10–20 system (29 EEG + 3 EOG channels—green colored). 10 monopolar channels (red dashed circles) are used for tERP classification, 13 bipolar channels (solid arrows) for SSSEP classification.

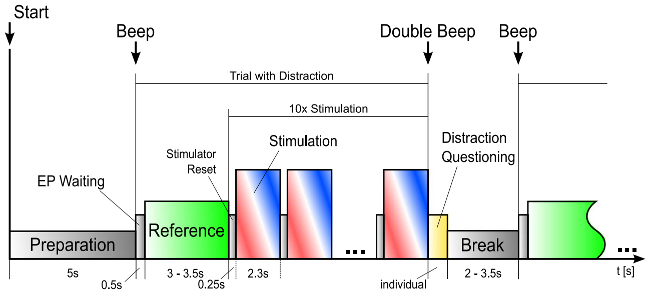


Figure 2. Screening paradigm to obtain person-dependent resonance-like frequencies. The measurement started with a 5 s preparation phase. Every trial started with an acoustic beep beep and ended with a double beep. The trial consisted of a 3–3.5 s reference period with 0.5 s waiting time for evoked potentials. The fingers were stimulated ten times with random frequencies for 2.3 s (only last 2 s were used for analysis). A 0.2 s period for a stimulator reset without stimulation was inserted for every stimulation. A visual calculation paradigm was running during the entire trial. The subjects were asked for the calculation result after the trial. A break of 2–3.5 s was inserted between trials.

years. The experiment was conducted in accordance with local ethics regulations and the Declaration of Helsinki. All the subjects gave their written informed consent prior to the experiment. Two EEG amplifiers (g.tec medical engineering GmbH, Graz, Austria) with a sampling rate of 600 Hz using active electrodes were used for data recording. Twenty-nine electroencephalogram (EEG) channels and three EOG channels were recorded; channel positions are shown in figure 1. The reference electrode was placed at position Fpz to avoid an uneven amplitude distribution across the skull. The ground electrode was placed at the right mastoid. The amplifiers' notch filter was applied at 50 Hz; high-pass/low-pass filtering was applied at 0.5 Hz/200 Hz. The EEG signal was visually inspected before starting any recording. All measurements were done in an electrically shielded room. The subjects were seated in comfortable armchairs.

Tactile stimulation was applied to the fingertips of the index fingers of both hands using C2 tactors (Engineering Acoustics Inc., Casselberry, FL, USA). The stimulation signal was created by a custom-made tactile stimulation device [23], creating a 237 Hz sinusoidal carrier signal. This carrier signal was amplitude modulated with a rectangular signal with the respective stimulation signal (duty cycle close to 50%, matching integer multiples of the carrier cycles) [9].

2.2. Paradigm

The measurement was divided into three dedicated parts: (i) eye artifact recording, (ii) screening to obtain subject-dependent resonance-like frequencies and (iii) cue-based focused attention with real-time signal classification and feedback.

2.2.1. Eye artifact recording. An automated correction method for EOG, as described in [24], was used to automatically remove EOG artifacts from the recorded data. To estimate the regression coefficients, two minutes of EOG artifacts were recorded. The subjects were instructed to blink for one minute and then to roll the eyes for another minute.

2.2.2. Screening paradigm. As shown previously [10], the response to tactile stimulation is person dependent; meaning that everyone reacts with different resonance-like frequencies [9, 10]. To determine these resonance-like frequencies, a screening measurement was conducted. The fingertips of both index fingers were randomly stimulated with frequencies from 17 to 35 Hz in 2 Hz steps. The tuning curve over all fingers on one hand can be assumed to be similar in the case of one single subject [10]. It is not known, however, if this assumption also applies to both hands. Therefore, both hands were stimulated during the screening to obtain dedicated tuning-curves.

A graphical illustration of the screening paradigm is available in figure 2. Every finger was stimulated with each frequency 40 times. Subsequent stimulation of one finger with the same frequency was avoided. One single finger could be stimulated subsequently, however, using two different frequencies. Reference periods without stimulation were placed at the beginning of the trial and short stimulation pauses were inserted between the stimulation. The screening was divided into eight runs; every run took about 8 min. Short breaks were made between the runs according to the subjects' wishes. Participants performed a mathematical task during the stimulation period, adding and subtracting randomly appearing numbers on a monitor. This was done to avoid shifting their attention to one finger and as a result influencing the tuning curve. Subjects were asked for the calculation result after each trial.

Band power tuning curves were used to determine the maximum frequency response per finger [21]. Two

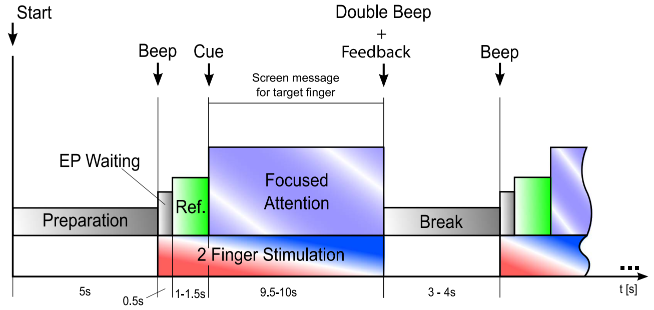


Figure 3. Cue-based BCI paradigm with focused attention. The measurement started with 5 s of preparation. An acoustic beep/double beep indicated the start/end of a trial together with the appearance of a red cross. The trial began with a 0.5 s waiting period for evoked potentials followed by a 1–1.5 s reference period. A cue in form of a left/right arrow on the screen indicated the target finger. The subjects had to either focus their attention on this finger for 9.5–10 s or simply look at the red cross. A break of 3–4 s was inserted between trials.

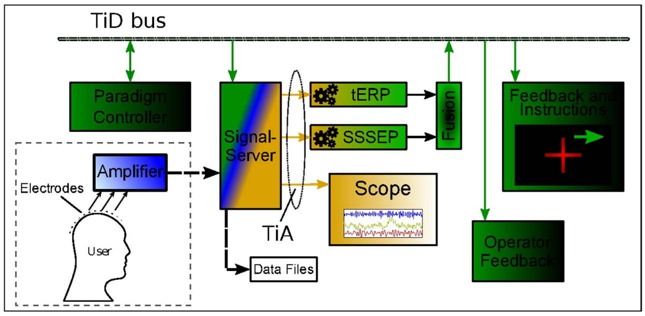


Figure 4. Architecture of the hBCI system. TiA channels are displayed in orange; the TiD bus and the connections to it are displayed in green. The black arrows indicate proprietary connections (driver specific outgoing from the amplifier; Matlab/Simulink specific as input for fusion). Three different computers were used for this setup. A Windows machine was running the SignalServer for data acquisition and for saving acquired data and incoming events. Another machine was running a scope for real-time signal visualization and inspection. The third machine was running Matlab/Simulink for calculations and dedicated user feedback software. EEG and EOG data were acquired by an amplifier and forwarded with TiA using the SignalServer. This data was subsequently processed by the SSSEP and tERP modules. The results obtained were fused and sent as a final result using TiD. The measurement procedure and timing was controlled by the paradigm controller. The user's feedback as well as monitoring information was display to the operator through the 'operator feedback'.

stimulation frequencies with the highest responses were selected for the following paradigm. The selected frequencies had to be separated by at least one stimulation frequency. If both fingers showed the maximum response for close frequencies, the second-highest frequency was selected.

2.2.3. Cue-based BCI paradigm. To investigate the classification of SSSEP as well as tactile tERP, the fingertips of both index fingers were stimulated with the two selected frequencies. To induce tERP (mainly P300) patterns, seven semi-random twitches occurred while stimulating each finger. A twitch [8] is a short change in the stimulation signal. During a twitch, the stimulation amplitude was decreased to zero. One of three twitch patterns with defined time intervals between the twitches was randomly used in each trial. These patterns were generated in such a manner that twitches did not occur simultaneously on both fingers or were too close together. A twitch lasted exactly one cycle of the stimulation frequency.

The entire paradigm was split into eight runs (short breaks between runs) with thirty trials each. A graphical illustration of the paradigm and its explanation is presented in figure 3. The subjects had to focus their attention on the given target finger. In the event of the absence of a target cue, the subjects were instructed to avoid focusing on their fingers and look at the red cross until the end of the trial. The resulting classes are thus: 'Left/Right/Idle' (L/R/I). Stimulation was applied during the entire trial. Twitches were only applied during the focused attention period. Every run consisted of ten trials per class.

After two runs, an SSSEP and a tERP classifier were trained with all data from the first two runs. The subjects received feedback in succession according to the classification: correct/wrong/no decision made. The classification result was shown by a green, a red, or a yellow circle on the screen at the end of each trial. After four runs, the classifiers were updated with all recorded data. The resulting classifier was used for the remaining four runs. Performing data analysis during the recording is designated as 'online analysis' while data analysis after the measurement is designated as 'offline analysis'.

2.2.4. Measurement architecture. The setup of the individual software components is visible in figure 4. The design of this experiment followed the suggestions proposed in [11] using open interfaces such as TiA [21] and TiD [25]. The same back-end structure was used for the screening paradigm and the cue-based BCI paradigm. The only changes were a different feedback algorithm and a different controller sequence used during screening while the processing modules were disabled.

2.2.5. Artifact treatment. In order to eliminate EOG artifacts, autoregressive parameters were calculated based on the data obtained from the eye artifact run [24]. This autoregressive parameter based removal was applied during the online and the offline analysis.

To reject trials with severe artifacts, mainly based on EMG activity, a threshold-based detection was applied to the EOG corrected data, achieving reasonable results especially for muscular activity [26]. The thresholds were set to 90 μV for monopolar channels and to 60 μV for bipolar channels.

2.3. Online analysis—feature extraction and classification

2.3.1. Classification of SSSEP. A lock-in amplifier system (LAS) was used to classify SSSEP activity [8, 18]. An LAS is a system able to extract signals with a known carrier frequency from noisy environments. The filter bandwidth was set to ±1 Hz around the stimulation frequencies with a

5th order butterworth bandpass filter. The moving average window was set to 1 s. LAS features were calculated and logarithmized for the bipolar channels, shown in figure 1. LAS features were averaged within the time window from 1 s to 8.5 s after cue onset in order to obtain a stable estimate of the mean SSSEP over a whole trial. The resulting 26 features (13 bipolar channels × 2 stimulation frequencies) were classified with a shrinkage LDA classifier from BCILAB https://sccn.ucsd.edu/wiki/BCILAB. To classify the L/R/I classes, three classifiers were trained using the one-versus-rest strategy. These classifiers returned the predicted class label together with the respective linear scores (which can be interpreted as distance values to the classifiers hyperplane).

2.3.2. Classification of tERP. The tERP activity, evoked by seven twitches, was classified using an averaged time domain signal. First, time domain signals were low-pass filtered at 10 Hz with a 3rd order butterworth filter. The time segments of 0.8 s starting with the individual twitch onsets were then extracted, linearly detrended, averaged, and downsampled by a factor of ten. The utilized channels for classification are shown in figure 1. The resulting 960 features (10 bipolar channels $\times$ 0.8 s $\times$ $\frac{600\text{ Hz}}{10(\text{downsampling factor})}$ $\times$ 2 classes) were classified using another multi-class shrinkage LDA classifier, as described in the SSSEP classification section.

2.3.3. Threshold-based fusion (thFusion). At the end of each trial, the SSSEP as well as the tERP classifier returned class decisions and related linear scores for the classes, which were then fused together to a final result. Each classifier can be described by a probabilistic generative model [27]. Using Bayes' theorem, the posterior probability for the class C_k, that is the probability of class C_k given some evidence x, can be written as

$$p(C_k|x) = \frac{p(x|C_k)p(C_k)}{\sum_j p(x|C_j)p(C_j)}, \tag{1}$$

where $p(x|C_k)$ are the class-conditional densities (likelihoods), and $p(C_k)$ the class priors. This posterior probability can be rewritten as

$$p(C_k|x) = \frac{\exp(a_k)}{\sum_j \exp(a_j)}, \tag{2}$$

with $a_k = \ln p(x|C_k)p(C_k)$, which is the multi-class generalization of the logistic sigmoid function (softmax function).

Using K linear discriminant functions $w_k^T x + w_{k0}$ for $K = 3$ classes with weight vectors w_k and biases w_{k0}, and under the assumptions that the class-conditional densities (likelihoods) are Gaussian and that all classes share the same covariance matrix, the term $a_k(x)$ can be computed as

$$a_k(x) = w_k^T x + w_{k0}, \tag{3}$$

which is referred to as linear score and corresponds to a measure of perpendicular distance of a data point x from the decision surface. Class decisions of the SSSEP and tERP classifiers respectively are independently made by each of them, returning the class with the highest posterior probability, i.e.

$$\text{class}_i = \arg\max_k\,(p_i(C_k|x)), \quad i = \begin{cases} 1 \text{ for SSSEP classifier} \\ 2 \text{ for tERP classifier.} \end{cases} \tag{4}$$

As the final result, the classifier with the highest class probability was chosen as fusion output. A minimum probability of 0.5 was set as the threshold Θ. If no classifier reached this threshold, the result was interpreted as 'non-conclusive'. Therefore, this thFusion can be written as:

$$\text{fusion output} = \begin{cases} \text{class}_i \text{ if } \max_{i,k}\,(p_i(C_k|x)) > \Theta \\ \text{'non-conclusive otherwise'.} \end{cases} \tag{5}$$

A green circle was presented to the subject if the chosen classifier's result was correct. A red circle was presented if it was wrong and a yellow circle was shown if no classifier reached the threshold. The assumption was that the best and correct classifier returns the highest class probability.

2.4. Offline analysis—threshold analysis and combined fusion

After the measurements, further data analysis was conducted on the recorded data. All calculations were again performed with the aforementioned EOG correction and threshold-based trial rejection.

In later analysis, a classifier based on all data from runs 1–8 was trained with 10 × 10 cross-validation to get an overall performance estimate of the whole measurement. The classification parameters were kept the same as during the online analysis to obtain comparable results. For 80 trials per class (offline analysis) the 5% chance level was 38.6% and the 1% chance level was 40.6% [28].

2.4.1. Influence of fusion threshold. Simulations with different threshold values were carried out to investigate the influence of the fusion threshold, which was set to 0.5 during the online measurement. The threshold was increased from 0 to 1 with a step size of 1/1000. This threshold increase simulation was done, as an abstention was interpreted as a better decision than a false classification of the trial. The intention was to visualize the relationship between the abstention rate, the false classification rate and the correct classification rate. As there is no standard procedure for visualizing multi-class classification results [29], the results were presented graphically in figure 8. The average accuracy, the mean error rate, and the mean rejection rate were thus calculated and plotted against the respective fusion threshold value. This was done for the SSSEP and the tERP classifier as also for the fused result. To fuse the values, the class with the highest probability value was chosen if the probability was above the threshold. Otherwise fusion rejected the results.

2.4.2. Combined fusion and feature balancing. As shown in [22], the combined classification of different input signals (in this case, EEG and muscular activity) increased the classification results. For this reason combining SSSEP and tERP is a reasonable step. The combined features were classified in the same manner using a shrinkage LDA classifier, as mentioned above, with a 10 × 10 cross-validation.

Based on the parameter set from the online analysis for the SSSEP and the tERP classifiers, the number of features were different (SSSEP: 26; tERP: 960). This occurred because a different number of channels were used for feature extraction and the SSSEP features were not split into time segments. This leads to different probability mappings, affecting especially the thFusion, because a higher dimensional feature space leads to larger distances from the classification hyperplane. These differences were not handled during the real-time classification and therefore, a non-optimal thFusion was performed. Thus, in the offline analysis the number of features were balanced. The time span of the SSSEP features was sliced, and the resulting features were treated as additional features. By this means the classifier could also select a dedicated timeframe which was better separable than the SSSEP timeframe as a whole. As shown in our prior work [18] the maximum classification accuracy might not be reached at the end of the trial. Thus, a classification of sub time windows is a reasonable step. This increases the number of SSSEP features with the result that the probability values will become equal to the tERP probability values.

2.4.3. Statistical analysis. Two repeated measures ANOVAs were made to identify potential effects of thFusion, combined fusion or feature balancing on the classification accuracies or if a certain classifiers has a predominance for a specific class label. As an initial step, a t-test for single samples was performed to check if the obtained classification accuracies significantly differ from zero. To identify whether a combined classification increases the classification accuracy and whether feature balancing causes an effect on the classification results, a 4 × 3 ANOVA for repeated measures was used. The independent variables were 'METHOD' (tERP, SSSEP, thFfusion, and combined fusion) and 'TYPE' (online, offline, and offline with feature balancing); the dependent variable was the classification accuracy. As no combined fusion was calculated during the online measurement and in order to compute the ANOVA for repeated measures, this kind of classification was also performed offline, applying the same settings and conditions as during the online run (e.g., updating the classifier and using a dedicated training set). Another 3 × 2 × 3 ANOVA for repeated measures with the independent variables TYPE (see above), METHOD (SSSEP, tERP) and CLASS (left, right, idle) was conducted to investigate whether a certain classifier or measurement type caused an effect. The classification accuracy was again the dependent variable. In case of significant effects, Tukey HSD tests were carried out.

To identify whether higher band power values are also leading to higher classification results, the Pearson product-moment correlation coefficient between the band power increases and the individual classification results was investigated. All Statistical analyses were carried out using Statistica 12 (Dell Inc, Round Rock, TX, USA).

3. Results

The subjects reacted with different resonance-like frequencies and different relative band power increases as shown in table 1. The results from different analysis methods (online, offline), classification, and fusion types (SSSEP, tERP, thFusion, and combined fusion) including the trial rejection rate for SSSEP due to artifacts are available in table 1. In order to obtain unified estimates for the chance level, rejected trials due to artifacts or a classifier/fusion abstention, were treated as false classifications. As a result, for 60 trials per class (online analysis), the 5% chance level was 39.8% and the 1% chance level was 41.8%. The chance level was computed according to Billinger *et al* [28] The tERP trial rejection rate is not shown as it was 0.0% for all subjects. Individual tERP time segments were rejected on occurrence of artifacts. The averaged overall remaining number of tERP time segments for all subjects was 6.997 (SD = 0.07). Thus, merely a few single tERP segments were rejected. As can be seen in the table the classification results varied greatly. Fusion sometimes increased the classification result, but not in all cases. After a more detailed inspection of the raw data from subject s10, high alpha wave EEG activity could be observed. This led to the rejection of more than two thirds of all trials and effected the further classification. For this reason subject s10 was excluded from statistical analysis together with the overall mean shown in the figures and table 1.

Figure 5 shows an averaged time domain signal of channel Pz after a twitch of subject s05. An event-related response very similar to a P300 potential is visible. This response is also in line with the findings present by van der Waal *et al* [30]. In case of a left twitch, when the target was also left, an amplitude increase is visible at around 400 ms after the twitch. A similar effect also occurred for right-hand twitches in case of a right-cue. In case of the Idle class, no increase is visible either for right or left-hand twitches.

A time/frequency map (similar to an ERD/S map [2]) for bipolar channels FC3-PC4 and FC4-PC4 from subject s05 is presented in figure 6. The stimulation frequencies, as also listed in table 1, were 25 Hz (left) and 29 Hz (right). A synchronization (blue colored) is clearly visible at the respective frequencies. This indicates that the stimulation was perceived by the subject.

3.1. Influence of fusion threshold

Figure 8 shows the grand averaged influence of the thFusion when adjusting the threshold from 0 to 1. As visible, the threshold affects the error rate in a stronger manner than the precision (precision = tp /(tp + fp); tp/fp ...true/false positives [29]). Thus, more false decisions are rejected than true decisions. Additionally, the threshold affects SSSEP earlier

Table 1. The selected frequencies of left and right index fingers for each subject are listed in columns two and three.

	Frequ (Hz)		rel. BP incr. (%)		Rej-R. (%)	Online accuracy (%)		
Subj	L	R	L	R	SSSEP	tERP	SSSEP	thF
s01	25	21	536.2	474.9	14.2	37.2	43.9	39.4
s02	23	27	356.5	481.5	1.7	45.6	50.0	**51.7**
s03	33	27	113.8	133.3	0.4	50.0	43.9	**52.8**
s04	31	35	290.5	287.6	2.1	36.1	39.4	**40.6**
s05	25	29	190.5	200.5	2.9	37.8	41.7	41.7
s06	27	23	291.2	314.9	4.6	36.1	36.7	**40.0**
s07	23	27	161.2	418.5	13.3	37.2	35.0	**43.3**
s08	33	27	376.0	291.0	5.0	30.0	46.7	32.8
s09	25	29	154.7	164.6	31.7	37.2	26.1	**40.0**
~~s10~~	~~29~~	~~25~~	~~52.7~~	~~100.7~~	~~67.1~~	~~35.0~~	~~5.6~~	~~34.4~~
s11	23	27	234.3	294.1	7.1	48.9	38.9	**54.4**
s12	23	27	120.2	123.2	1.6	47.2	47.2	**50.0**
s13	27	21	310.5	307.9	1.3	46.7	60.0	52.2
s14	21	25	101.3	164.6	5.0	34.4	37.2	**39.4**
M.	26.1	26.5	249.0	289.0	7.0	40.3	42.1	44.5
Sig-M.						47.7	48.6	50.7

	Offline accuracy (%)				Offline balanced accuracy (%)			
Subj	tERP	SSSEP	thF	CF	tERP	SSSEP	thF	CF
s01	47.9	55.3	50.4	49.6	46.2	49.0	**49.8**	**55.5**
s02	52.4	57.5	54.5	54.0	52.1	56.4	**58.3**	**58.4**
s03	58.3	46.2	**58.8**	**60.5**	65.4	39.9	61.3	61.6
s04	42.4	40.1	42.0	**43.4**	46.3	38.5	42.9	44.8
s05	46.4	36.8	46.0	**47.1**	49.7	34.4	42.8	48.2
s06	44.5	45.7	**46.2**	**48.7**	46.6	44.8	**47.1**	**52.6**
s07	42.4	54.6	44.1	44.2	48.5	51.7	51.4	**57.1**
s08	39.2	48.4	41.4	43.7	46.1	55.0	**55.9**	**55.9**
s09	42.0	45.3	42.9	44.2	49.5	42.3	47.0	47.7
~~s10~~	~~35.5~~	~~25.5~~	~~34.5~~	~~41.3~~	~~37.3~~	~~28.4~~	~~24.5~~	~~38.8~~
s11	62.8	44.4	**62.9**	62.2	66.5	47.1	63.9	63.8
s12	64.4	49.0	**65.2**	**70.1**	73.9	46.3	70.8	72.2
s13	56.8	62.2	**62.9**	**69.5**	61.7	63.3	**67.1**	**66.7**
s14	47.6	41.4	**47.7**	**51.4**	46.7	42.8	42.1	43.9
M.	49.8	48.2	51.2	53.0	53.8	47.0	53.9	56.0
Sig-M.	50.7	50.0	51.2	53.0	53.8	49.9	53.9	56.0

Note. Columns four and five show the relative band power increase over channels FC4–CP4 for the left-hand, and FC3–CP3 for the right-hand. The trial rejection rate for SSSEP is listed in column six. The multi-column 'online accuracy' shows the 3-class classification accuracies for tERP and SSSEP classification and the result of the thFusion (thF ...thFusion). The multi-column 'offline accuracy' shows the classification accuracies for offline analysis (CF ... combined fusion); the multi-column 'offline balanced accuracy' the ones for the offline analysis with feature balancing. Fusion results which were higher than the related classification results are marked in bold. The mean for each column (s10* was excluded) is shown in the second to the last row. The mean considering significant results only is shown in the last row. The 5% chance level was 38.6% and the 1% chance level was 40.6% [28] (see above).

than tERP. This occurred because of different probability values due to a different number of features compared to tERP. However this led to a biased fusion, as the same threshold level was applied for both classifiers.

3.2. Hybrid classification and feature balancing

Figure 9(a) shows the classification results of the offline analysis using the same parameters as in the online analysis. Results were obtained within a 10×10 cross-validation. Comparing figures 7 and 9(a), an accuracy increase for various subjects is visible. The overall classification accuracy increased from around 40%–50%. This effect could have occurred due to some kind of training effect where the subjects learned to focus their attention better during the measurement. Otherwise, the fact, that more trials were available to the classifier might also have caused an effect.

Considering figure 9(b), a classification accuracy increase is again visible. Thus, feature balancing also generally caused a positive effect. Taking a look at the overall results, the accuracies from thFusion and combined fusion were close to each other, although a sub-optimal thFusion was used due to unbalanced probability values. Taking the individual classification results into consideration, fusion seemed

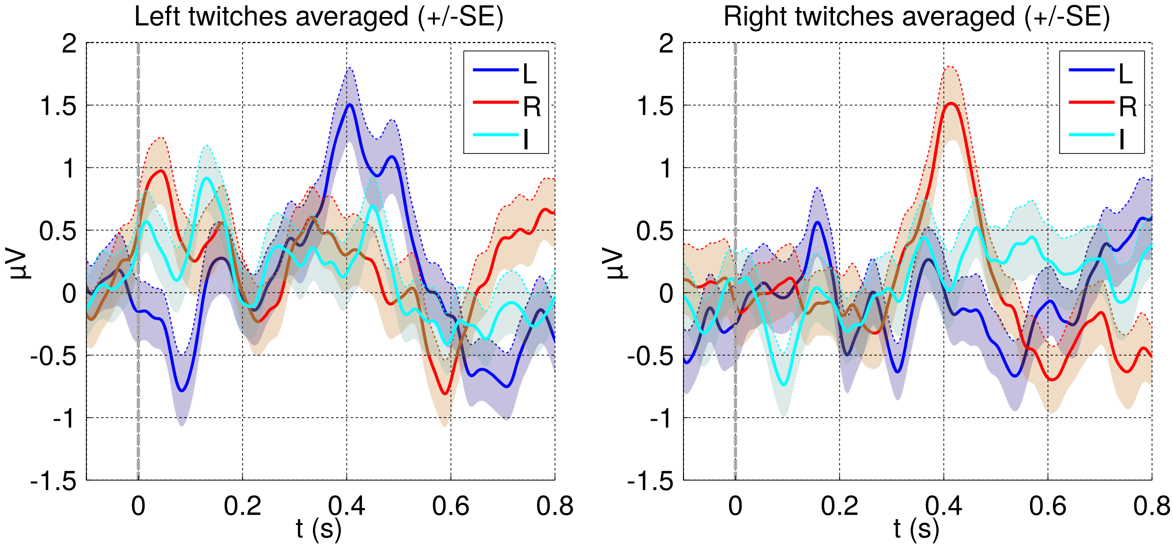


Figure 5. The ERP response (for the time period $-0.1 - 0.8$ s after a twitch of channel Pz) to a target class and a non-target class for subject s05 averaged over trials. The left image shows the response for left-hand twitches, the right image for right-hand twitches. The shaded areas indicate the respective standard error.

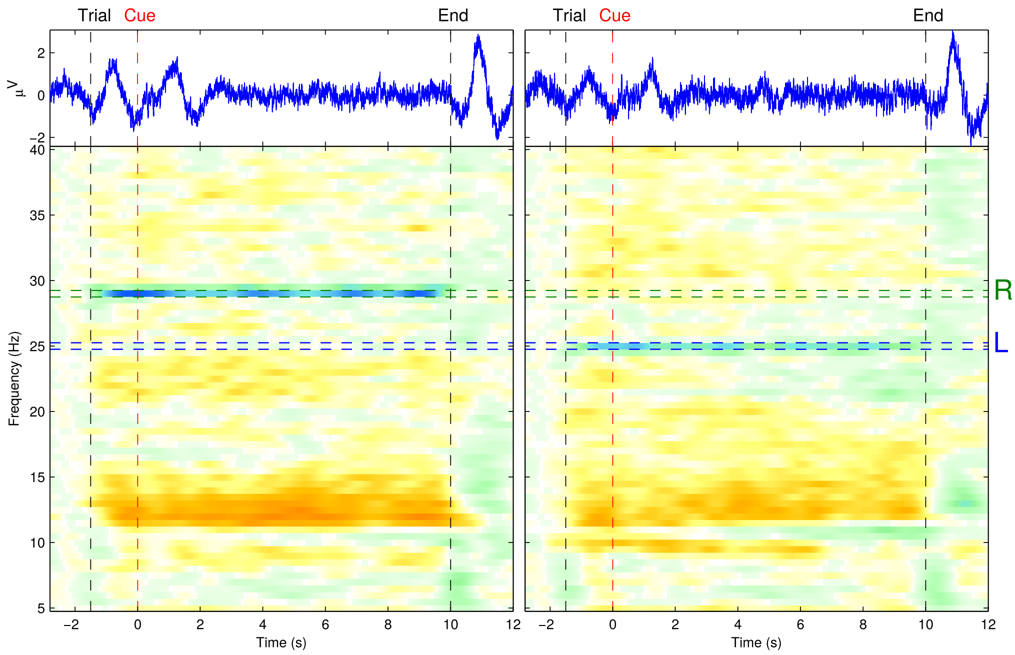


Figure 6. Averaged time/frequency map over all trials of channels FC3–CP3 (left) and FC4–CP4 (right) from subject s05. The blue signal at the top represents the averaged time domain signal. Event-related potentials, due to the trial start, the cue, and the trial end, are clearly visible. The green and blue dashed lines indicate the stimulation frequencies.

to mostly make sense when both classifiers delivered comparable results. However, fusion did not always result in a better classification, especially when one classifier outperformed the other one (e.g. visible in figure 9(b) for subject s03).

3.3. Statistical interpretation

The statistical analysis of classification accuracies for the offline measurement with and without feature balancing resulted in a significant main effect for 'METHOD' ($F_{3,48} = 4.79$; $p < 0.001$). The classification results using a combined classifier ($M = 56.4$; SD $= 7.5$) were significantly higher than the ones obtained by the SSSEP classifier ($M = 45.8$; SD $= 8.12$) and the tERP classifier ($M = 48.0$; SD $= 9.84$).

Statistical tests comparing the online versus the two offline analysis methods revealed a highly significant main effect for 'TYPE' ($F_{2,96} = 30.8$; $p < 0.00001$). Tests revealed that the offline classification accuracy ($M = 50.5$; SD $= 8.5$) and the offline balanced accuracy ($M = 52.7$; SD $= 9.4$) were higher than the online accuracy ($M = 46.8$; SD $= 10.4$).

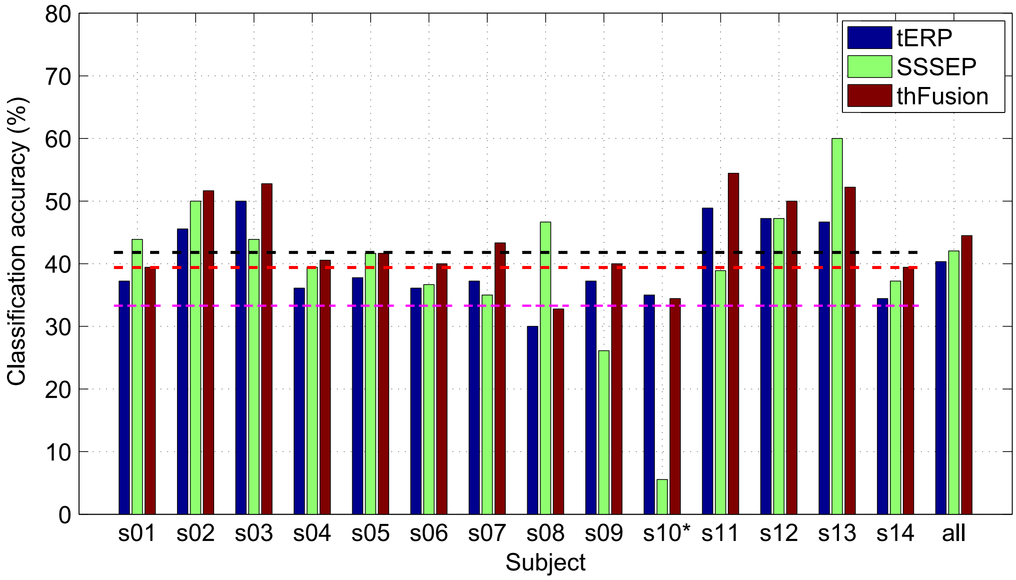


Figure 7. Mean classification accuracies of all subjects and across all subjects (except s10) for the online analysis. The red dotted lines represent the 5% chance level for three classes, the back dotted line the 1% chance level and the purple dotted line the theoretical 33.3% chance border.

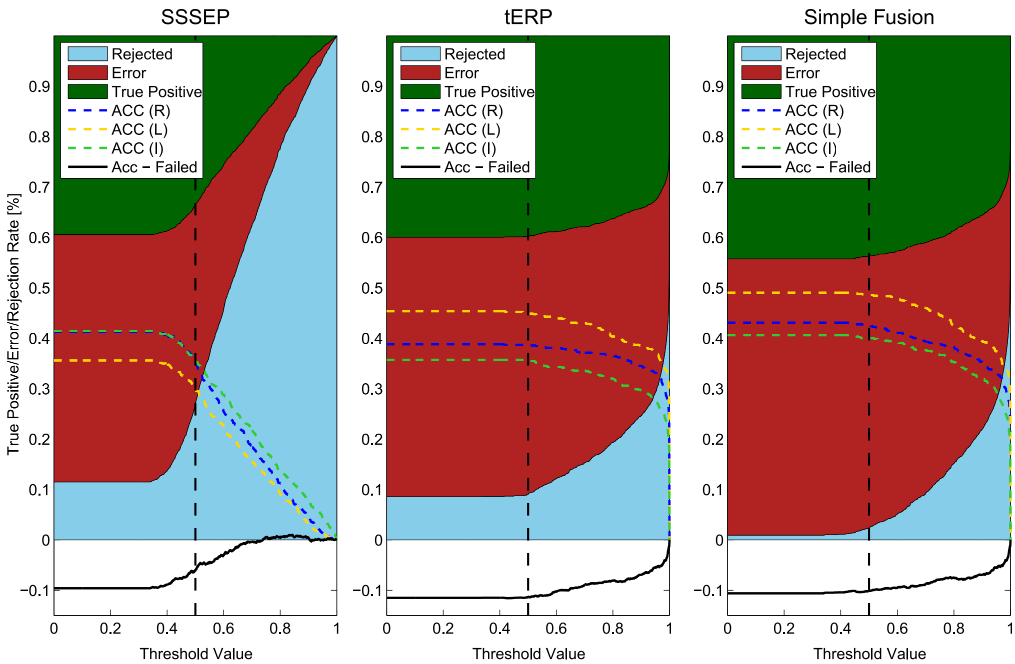
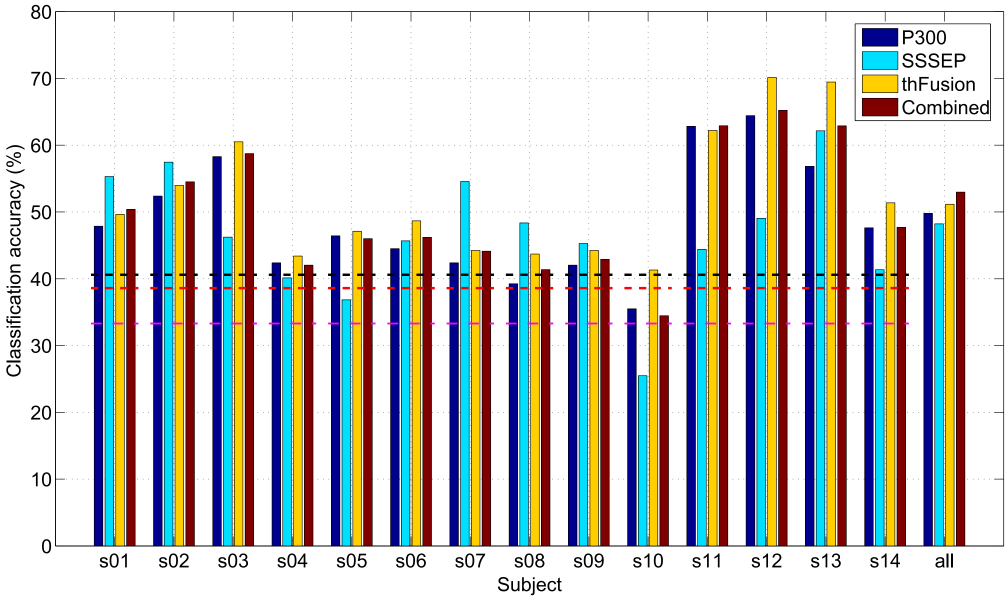
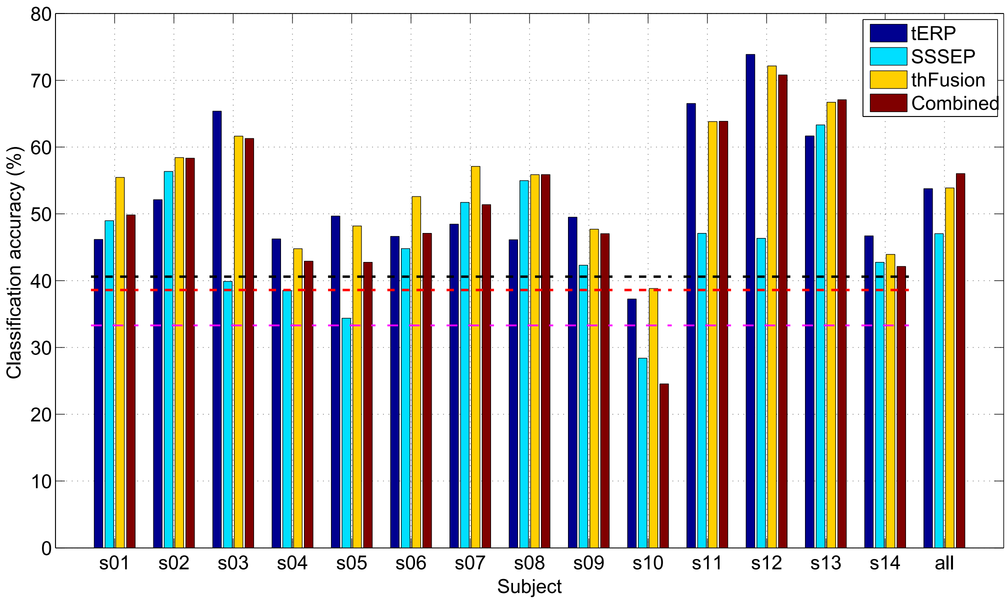


Figure 8. Grand average threshold influence for the threshold being applied to the SSSEP classifier, tERP classifier and the final fusion. The green colored region shows the correct classified trials against an increased threshold; the red colored region false classified trials and the light-blue region the rejected ones. The black dotted line indicates the threshold of 0.5, applied during the online experiment. The blue/yellow/green dashed lines show the respective classification accuracies for the Right/Left/Idle classes. The black solid line at the bottom shows the difference between the correct and the wrong classifications, dependent on the threshold. As visible, the threshold appliance was most effective at the SSSEP classifier.

The analysis, taking a closer look at the classification of individual classes within the second ANOVA, clearly showed the same effect for 'TYPE' as described above. Furthermore, two other significant effects were identified. The first one was significant for the interaction 'TYPE*METHOD' ($F_{2,216} = 3.23$; $p < 0.05$). Post-hoc tests showed that online tERP classification ($M = 40.3$; SD = 9.8) was lower than offline tERP ($M = 49.8$; SD = 9.9), offline SSSEP ($M = 48.2$; SD = 9.6) and offline balanced tERP ($M = 53.8$; SD = 11.8). Another highly significant effect could be found for the interaction 'METHOD*CLASS' ($F_{2,216} = 12.3$; $p < 0.00001$). The classification accuracy for tERP 'Idle' ($M = 41.8$; SD = 9.6) was significantly lower than the accuracies for tERP 'Left' ($M = 50.0$; SD = 11.7), tERP 'Right' ($M = 52.2$; SD = 11.8), and SSSEP 'Idle' ($M = 48.6$; SD = 14.0). Additionally, the SSSEP 'Right'



(a) Same configuration as in online analysis.



(b) With feature balancing. tERP 100 features; SSSEP 96 features.

Figure 9. Cross-validated mean classification accuracy of all subjects across all runs. Subject s10 was excluded from the overall mean. The red dotted lines represent the 5% chance level for three classes, the back dotted line the 1% chance level and the purple dotted line the theoretical 33.3% chance border. (a) Same configuration as in online analysis. (b) With feature balancing. tERP 100 features; SSSEP 96 features.

($M = 42.7$; $\mathrm{SD} = 9.4$) classification accuracy was significantly lower than tERP 'Left' and tERP 'Right' (both values see above).

Moreover, significant correlations between left BP increase with offline SSSEP ($r = 0.572$, $p < 0.05$) and with balanced SSSEP ($r = 0.567$, $p < 0.05$); between right BP increase with offline SSSEP ($r = 0.672$, $p < 0.01$) and with balanced SSSEP ($r = 0.637$, $p < 0.05$); and between left BP and right BP increase ($r = 0.8$, $p < 0.001$).

4. Discussion

In this paper the successful setup of a tactile stimulation based hBCI for three-classes with two target classes and one non-control class could be shown. The system architecture of this BCI followed the suggestions towards a common implementation platform [11, 12]. This approach, setting up a BCI system with open and well-known interfaces, has the advantage that individual parts within the system become easily replace-, interchange-, or expandable. Another benefit was a rapid prototype system creation, as the individual components could be added and tested one by one. Following the standardization approaches [11, 12, 21], the individual components can also be shared with other institutions. The usage of this approach can be seen as another step towards a standardization in the BCI field.

Analyzing the online experiment, only six subjects performed above chance, even using a fusion approach. When considering all recorded trials within the cross-validated offline analysis and considering the feature balancing approach too, all subjects (except the excluded one) have reached the 1% chance level for at least one classification method, which was at 40.6% for 80 trials per class (three classes). Thus, the combination of SSSEP and ERP features is a reasonable approach to set up a hBCI. Subjects responded with person-dependent resonance-like frequencies, which is in line with our prior findings [10]. In contrast to the findings from Severens *et al* [15], subjects were also able to perform above chance for SSSEP classification alone; only the subjects s03, s04, and s05 stayed below 40.6%. As already discussed by Severens *et al* [31], the usage of subject-dependent stimulation frequencies might be a potential explanation for this difference. As revealed by the statistics, subjects who responded with a high band power increase also achieved higher classification results. It is currently not known if such results could also have been achieved with standard stimulation frequencies. In order to investigate this influence, a direct comparison between the classification of standard stimulation frequencies and person-dependent ones would be needed. However, it is hypothesized that using person-dependent frequencies might have had a positive influence on the classification accuracy.

Another effect on classification accuracies might be related to the tactors used. In case of Severens *et al* [31], braille stimulators have been used, or Giabbiconi *et al* [17] used a 'V101' mechanical stimulator, compared with the C2 tactors in this study. Furthermore, only one finger per hand was stimulated in this study, whereby three fingers were stimulated in case of the work from Severens *et al* Thus, investigating a potential tactor type/positioning influence or the number of fingers being stimulated (maybe causing some lateral inhibition) would be another reasonable follow-up step, as the body posture can also effect tactile discrimination [32].

Adler *et al* [33] provided an interesting insight, related to the complexity of a given target stimulus. They could show that the SSSEP amplitude significantly increases under conditions of high perceptual load, e.g., by providing a target stimulus which is perceived more difficultly. This might be another option to improve the classification of both, SSSEP and tERP based features.

As revealed by the statistical analysis, classification accuracies became significantly better within the offline analysis and after applying a feature balancing. Two factors might have had an influence on this effect. Firstly, subjects may have learned to focus their attention in a better way or detect target twitches more accurately. However, the classifier used in the online experiment was not updated anymore after the fourth run. Secondly, the number of trials for training the classifier might have been too low in the online experiment to properly distinguish between the three classes. Another interesting finding was that the 'idle' class (equivalent to the non-control state) was detected more accurately by the SSSEP classifier and that the tERP classifier detected either the 'right' or 'left' class better than the 'idle' class. Thus, SSSEP would appear to be the better alternative to provide the important non-control state [20]. Similar findings were also achieved in the visual domain, where frequency domain signals were used to detect non-control states and time domain signals were used to detect control states [19]. Subjects reported that it was difficult for them to ignore twitches during the non-control state. This might explain the class preference for the two feature types. Additionally, the attenuation of the twitches was 100% for a short period of time, making the twitches very prominent and hard to blank out.

Considering the different results from the thFusion and the combined fusion (as also visible in figure 9(a)), it can be seen that fusion generally increases classification accuracy. As revealed by the statistical analysis, the usage of the combined fusion reached significantly higher accuracies than either SSSEP or tERP classification alone. Fusion of different kinds of input signals can significantly increase classification accuracy, as presented by Leeb *et al*, fusing muscular and EEG signals [22]. As the thFusion in the online experiment was based on sub-optimal numbers of features, no significant increase in classification accuracy could be achieved. However, the usage of a combined classification achieved significantly better results, which contrasts the findings of Severens *et al* [15], where no classification improvement was achieved when combining features. However, the usage of a combined fusion did not increase the classification accuracy for every subject; especially if either the SSSEP classification or the tERP classification has already reached a much higher accuracy than the other classifier.

Twitches were once introduced by Müller *et al* [9] with the intention of assisting subjects to focus their attention on a specific finger. Unfortunately each twitch interrupts the repetitive stimulation which induces the SSSEP pattern. Thus, twitches might have negative effects on the evolvement of SSSEP. The highest classification of SSSEP is possible later in the trial [18]. Due to a potential 'interfering' effect of the twitches, it is possible that the evolvement of a 'stable' SSSEP oscillation could have never happened for some subjects. Twitches might have even had a negative effect in terms of SSSEP classification [34]. This potential effect could have had an influence on the SSSEP classification results, presented by Severens *et al* [15], explaining the fact that a classification above chance was scarcely achieved at all for SSSEP. The introduction of more specific and complex twitch patterns may be an option as a means of reducing this eventual effect. Using specific target and no-target stimuli, the number of necessary twitches can get further reduced, especially when applying more complex twitches, which increase the workload for the subject [33]. However, utilizing twitches could also have other effects to SSSEP classification or might even decrease the classification rate [34].

Xu *et al* [35] presents a very interesting phenomenon, showing the effect when target stimuli (to evoke e.g., a P300) are added to an SSVEP paradigm. This effect was called 'blocking feature' and can be interpreted as SSVEP amplitude attenuation during and after the target stimulus. These blocking features might hamper the creation of a stable SSSEP oscillation and reduce the classification of SSSEP features [34]. However, classifying such blocking effects as additional features might again bring an increased classification performance, especially within a hBCI approach.

As stated by Erp *et al* [36], the field of tactile BCI systems still remains relatively unexplored and there are many open questions and possibilities to improve tactile BCIs. An interesting approach for hybridization based on tactile stimulation was shown by Yao *et al* [37], using and classifying ERD-like patterns, which evolve during tactile stimulation. Such a phenomenon was also presented by Spitzer *et al* [38] in the context of tactile working memory. Within the present work, only a narrow frequency band around the stimulation frequency was used for classification. Utilizing the aforementioned effect should thus further improve classification accuracy.

All the aforementioned systems were either based on techniques similar to time division multiple access or frequency division multiple acces. However, some kind of code division multiple access approach has not yet been used for tactile BCI systems. It could already be shown that applying an m-sequence technique to the visual domain achieved reasonable classification results [39]. These techniques were already used in BCIs and compared with a common SSVEP based BCI [40, 41], outreaching this BCI in terms of classification performance. Thus, considering such a code modulated stimulation approach for the tactile modality might be another reasonable step towards an improved classification performance.

4.1. Conclusion

The results presented in this paper show the successful fusion of SSSEP as also tactile tERP. Fusing both kinds of input signals can improve the overall classification rate. Additionally, the SSSEP component produced better results than the tERP component for non-control states. Thus, fusion could also be treated in a different manner, as described in the presented work. Here, tERP and SSSEP were treated the same way for all target classes. However, utilizing, e.g., the tERP component in particular for control states and the SSSEP component for non-control states already during an online experiment might further boost the classification performance.

Furthermore, as the classification of the SSSEP also achieved results above chance, the usage of subject specific stimulation frequencies is suggested. This suggestion is confirmed by the result, that subjects with higher relative band power increase upon tactile stimulation also achieved higher classification results.

Acknowledgments

This work was supported by the European ICT Program Project FP7-224631. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein. Special thanks to Christina Reisinger for proofreading.

Appendix

To guarantee error free calculations, synthetic data were created for system integrity and regression testing. To validate the SSSEP calculations functionality, sinusoidal signals with defined frequency and amplitude were added to random noise data. Events and triggers as produced by the real-time system were added to the data. Test data files with different signal to noise ratio (SNR) values were created and classified. The classification results implicitly validated the offline as well as the online analysis, as the same back end code was used in both cases.

The ERP calculations code was validated by a representative P300 curve which was extracted from real data. Events and triggers were inserted as described before and the tERP curve was added at the respective positions after a twitch. The SNR ratio was increased for different files and a classification of this artificial data was carried out similar to the SSSEP system validation.

The system validation checks showed a classification rate of 100% for SSSEP and tERP when classifying artificially generated data with a SNR higher than 0 dB. In contrast, reducing the SNR below –30 dB resulted in random classification at chance level. Classifying random noise also resulted in a classification accuracy at chance level. The same code was used for all online as well as offline analysis. The functionality of both systems was thus proved. Feature segmentation and visualization tests also proved proper functionality. Detailed plots showing the system validation results are available below.

References

[1] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91

[2] Pfurtscheller G, Brunner C, Schlögl A and Lopes da Silva F H 2006 Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks *NeuroImage* **31** 153–9

[3] Pfurtscheller G, Solis-Escalante T, Ortner R, Linortner P and Müller-Putz G R 2010 Self-paced operation of an SSVEP-based orthosis with and without an imagery-based 'brain switch:' a feasibility study towards a hybrid BCI *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 409–14

[4] Snyder A Z 1992 Steady-state vibration evoked potentials: descriptions of technique and characterization of responses *Electroencephalogr. Clin. Neurophysiol.* **84** 257–68

[5] Tobimatsu S, Zhang Y M and Kato M 1999 Steady-state vibration somatosensory evoked potentials: physiological

characteristics and tuning function *Clin. Neurophysiol.* **110** 1953–8

[6] Severens M, Farquhar J, Desain P, Duysens J and Gielen C 2010 Transient and steady-state responses to mechanical stimulation of different fingers reveal interactions based on lateral inhibition *Clin. Neurophysiol.* **121** 2090–6

[7] Brouwer A-M and Van Erp J B F 2010 A tactile P300 brain–computer interface *Front. Neurosci.* **4** 19

[8] Müller-Putz G R, Scherer R, Neuper C and Pfurtscheller G 2006 Steady-state somatosensory evoked potentials: suitable brain signals for brain–computer interfaces? *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 30–7

[9] Müller G R, Neuper C and Pfurtscheller G 2001 Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation *Biomed. Tech.* **46** 186–90

[10] Breitwieser C, Kaiser V, Neuper C and Müller-Putz G R 2012 Stability and distribution of steady-state somatosensory evoked potentials elicited by vibro-tactile stimulation *Med. Biol. Eng. Comput.* **50** 347–57

[11] Müller-Putz G R *et al* 2011 Tools for brain–computer interaction: a general concept for a hybrid BCI. *Front. Neuroinform.* **5** 30

[12] Müller-Putz G R, Leeb R, Tangermann M, Höhne J, Kübler A, Cincotti F, Mattia D, Rupp R, Müller K-R and Millán J D R 2015 Towards noninvasive hybrid brain–computer interfaces: framework, practice, clinical application, and beyond *Proc. IEEE* **103** 926–43

[13] Allison B Z, Brunner C, Kaiser V, Müller-Putz G R, Neuper C and Pfurtscheller G 2010 Toward a hybrid brain–computer interface based on imagined movement and visual attention *J. Neural Eng.* **7** 026007

[14] Yin E, Zhou Z, Jiang J, Chen F, Liu Y and Hu D 2013 A novel hybrid BCI speller based on the incorporation of SSVEP into the P300 paradigm *J. Neural Eng.* **10** 026012

[15] Severens M, Farquhar J, Duysens J and Desain P 2013 A multi-signature brain–computer interface: use of transient and steady-state responses *J. Neural Eng.* **10** 026005

[16] Giabbiconi C-M, Dancer C, Zopf R, Gruber T and Müller M M 2004 Selective spatial attention to left or right hand flutter sensation modulates the steady-state somatosensory evoked potential *Cogn. Brain Res.* **20** 58–66

[17] Giabbiconi C-M, Trujillo-Barreto N J, Gruber T and Müller M M 2007 Sustained spatial attention to vibration is mediated in primary somatosensory cortex *NeuroImage* **35** 255–62

[18] Breitwieser C, Pokorny C, Neuper C and Müller-Putz G R 2011 Somatosensory evoked potentials elicited by stimulating two fingers from one hand-usable for BCI? *Conf. Proc. IEEE Eng. Med. Biol. Soc.* pp 6373–6

[19] Pinegger A, Faller J, Halder S, Wriessnegger S C and Müller-Putz G R 2015 Control or non-control state: that is the question! an asynchronous visual p300-based bci approach *J. Neural Eng.* **12** 014001

[20] Leeb R, Perdikis S, Tonin L, Biasiucci A, Tavella M, Creatura M, Molina A, Al-Khodairy A, Carlson T and Millán J d R 2013 Transferring brain–computer interfaces beyond the laboratory: successful application control for motor-disabled users *Artif. Intell. Med.* **59** 121–32

[21] Breitwieser C, Daly I, Neuper C and Müller-Putz G R 2012 Proposing a standardized protocol for raw biosignal transmission *IEEE Trans. Biomed. Eng.* **59** 852–9

[22] Leeb R, Sagha H, Chavarriaga R and Millán J D R 2011 A hybrid brain–computer interface based on the fusion of electroencephalographic and electromyographic activities *J. Neural Eng.* **8** 025011

[23] Pokorny C, Breitwieser C and Müller-Putz G R 2014 A tactile stimulation device for EEG measurements in clinical use *IEEE Trans. Biomed. Circuits Syst.* **8** 305–12

[24] Schlögl A, Keinrath C, Zimmermann D, Scherer R, Leeb R and Pfurtscheller G 2007 A fully automated correction method of EOG artifacts in EEG recordings *Clin. Neurophysiol.* **118** 98–104

[25] Breitwieser C, Tavella M, Schreuder M, Cincotti F, Leeb R and Müller-Putz G R 2016 TiD - Documentation of TOBI interface D *CoRR* http://arxiv.org/abs/1507.01313 in preparation

[26] Delorme A, Sejnowski T and Makeig S 2007 Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis *NeuroImage* **34** 1443–9

[27] Bishop C M 2006 *Pattern Recognition and Machine Learning* (New York: Springer)

[28] Billinger M, Daly I, Kaiser V, Jin J, Allison B Z, Müller-Putz G R and Brunner C 2013 Is it significant? Guidelines for reporting BCI performance *Towards Practical Brain–Computer Interfaces: Bridging the Gap from Research to Real-World Applications* (*Biological and Medical Physics, Biomedical Engineering*) ed B Z Allison *et al* (Berlin: Springer) pp 333–54

[29] Sokolova M and Lapalme G 2009 A systematic analysis of performance measures for classification tasks *Inf. Process. Manage.* **45** 427–37

[30] der Waal M V, Severens M, Geuze J and Desain P 2012 Introducing the tactile speller: an ERP-based brain–computer interface for communication *J. Neural Eng.* **9** 045002

[31] Severens M, Der Waal M V, Farquhar J and Desain P 2014 Comparing tactile and visual gaze-independent brain–computer interfaces in patients with amyotrophic lateral sclerosis and healthy users *Clin. Neurophysiol.* **125** 2297–304

[32] Riemer M, Trojan J, Kleinbühl D and Hölzl R 2010 Body posture affects tactile discrimination and identification of fingers and hands *Exp. Brain Res.* **206** 47–57

[33] Adler J, Giabbiconi C-M and Müller M M 2009 Shift of attention to the body location of distracters is mediated by perceptual load in sustained somatosensory attention *Biol. Psychol.* **81** 77–85

[34] Pokorny C, Breitwieser C and Müller-Putz G R 2016 The role of transient target stimuli in a steady-state somatosensory evoked potential-based brain–computer interface setup *Front. Neurosci.* **10** 34

[35] Xu M, Qi H, Wan B, Yin T, Liu Z and Ming D 2013 A hybrid BCI speller paradigm combining P300 potential and the SSVEP blocking feature *J. Neural. Eng.* **10** 026001

[36] Van Erp J B F and Brouwer A-M 2014 Touch-based brain computer interfaces: state of the art *2014 IEEE, Haptics Symp. (HAPTICS)* pp 397–401

[37] Yao L, Meng J, Zhang D, Sheng X and Zhu X 2013 Selective sensation based brain–computer interface via mechanical vibrotactile stimulation *PLoS One* **8** 1–9

[38] Spitzer B, Wacker E and Blankenburg F 2010 Oscillatory correlates of vibrotactile frequency processing in human working memory *J. Neurosci.* **30** 4496–502

[39] Sutter E E 2001 Imaging visual function with the multifocal m-sequence technique *Vis. Res.* **41** 1241–55

[40] Bin G, Gao X, Wang Y, Hong B and Gao S 2009 VEP-based brain–computer interfaces: time, frequency, and code modulations *IEEE Comput. Intell. Mag.* **4** 22–6

[41] Bin G, Gao X, Wang Y, Li Y, Hong B and Gao S 2011 A high-speed BCI based on code modulation VEP *J. Neural Eng.* **8** 025015

A.7. Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI

G. R. Müller-Putz, C. Breitwieser, F. Cincotti, R. Leeb, M. Schreuder, F. Leotta, M. Tavella, L. Bianchi, A. Kreilinger, A. Ramsay, M. Rohm, M. Sagebaum, L. Tonin, C. Neuper, and J. d. R. Millán. "Tools for Brain-Computer Interaction: A General Concept for a Hybrid BCI." In: *Frontiers in Neuroinformatics* 5.November [2011], p. 30. DOI: 10.3389/fninf.2011.00030 [165]

Distribution of dedicated work:

- Gernot R. Müller-Putz: 40 %
- **Christian Breitwieser**: 15 %
- Febo Cincotti: 10 %
- Robert Leeb: 10 %
- Martijn Schreuder: 5 %
- Francesco Leotta: 2 %
- Michele Tavella: 2 %
- Luigi Bianchi: 2 %
- Alex Kreilinger: 2 %
- Andrew Ramsay: 2 %
- Martin Rohm: 2 %
- Max Sagebaum: 2 %
- Luca Tonin: 2 %
- Christa Neuper: 2 %
- José del. R. Millán: 2 %

A.8. BCI Software Platforms

A.8.1. BCI Software Platforms

C. Brunner, G. Andreoni, L. Bianchi, B. Blankertz, C. Breitwieser, S. Kanoh, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, G. R. Müller-Putz, C. A. Kothe, A. Lécuyer, S. Makeig, J. Mellinger, P. Perego, Y. Renard, G. Schalk, I. P. Susila, B. Venthur, and G. R. Müller-Putz. "BCI Software Platforms." In: *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*. Ed. by B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millán, and A. Nijholt. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. Chap. BCI Softwa, pp. 303–331. DOI: 10.1007/978-3-642-29746-5_16 [198]

Distribution of dedicated work:

- Brunner Clemens: 25 %
- Guiseppe Andreoni: 5 %
- Luigi Bianchi: 5 %
- Benjamin Blankertz: 5 %
- **Christian Breitwieser**: 5 %
- Shin'ichiro Kanoh: 5 %
- Christian A. Kothe: 5 %
- Anatole Lécuyer: 5 %
- Scott Makeig: 5 %
- Jürgen Mellinger: 5 %
- Paolo Perego: 5 %
- Yann Renard: 5 %
- Gerwin Schalk: 5 %
- I Putu Susila: 5 %
- Bastian Venthur: 5 %
- Gernot R. Müller-Putz: 5 %