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Development of an event-related potential based brain-computer interface following user-centered design principles

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Abstract

A brain-computer interface (BCI) provides a direct connection between a brain and a computer. As a result, BCI allows user to control a computer and connected devices without muscle activity. A standard method to create a BCI is to use event-related potentials (ERP). Since the initial publication of an ERP-based BCI, it has evolved significantly in many areas. Currently on its way out of the laboratories to the end users, user-centered design (UCD) principles are becoming increasingly important. The central aim of this thesis is to develop an ERP-based BCI based on the findings of 30 years of research, while considering UCD principles. User requirements from previous publications such as ease of use, functionality, robustness, and wearing comfort should be incorporated.
In the first step, an ERP-based BCI with a universal interface to EEG acquisition devices was implemented, i.e., with little effort, many different acquisition devices can be used, and only a single graphical user interface is needed to start the EEG acquisition, the automatic calibration, or a free spelling mode.
In the second step, interfaces to control other applications were implemented and evaluated among a group of ten healthy and three disabled users according to UCD criteria. Users were able to spell and control applications effectively and efficiently. The satisfaction with the system was high. However, users also suggested considerable number recommendations for further improvements.
Consequently, to satisfactorily control applications, a novel method for an asynchronous ERP-based BCI was developed and successfully tested. In addition, different EEG acquisition systems were evaluated and their suitability for building an ERP-based BCI was shown.
Finally, a novel method for users' self-expression was integrated by connecting a music composing software to the BCI. This system, known as Brain Composer, was evaluated among a group of seventeen musical users and one professional composer. The main result was that all the users enjoyed composing a provided melody as well as a melody they have in their mind.

In conclusion, an easy to use and set up as well as functional and universal BCI was developed and evaluated. In addition, different EEG acquisition systems were evaluated, and more comfortable alternatives to the gel-based standard were presented. The BCI developed within this thesis, therefore, contributes to bringing the ERP-based BCI out of the laboratories to the end users.

Kurzfassung

Eine Gehirn-Computer Schnittstelle (engl. brain-computer interface; BCI) stellt eine direkte Verbindung zwischen dem Gehirn und einem Computer her, um ihn und angeschlossene Geräte ohne Muskelaktivität zu steuern. Eine gängige Methode zur Erzeugung eines BCIs ist die Verwendung von ereigniskorrelierten Potenzialen (engl. event-related potentials; ERP). Seit der ersten Veröffentlichung eines ERP basierenden BCIs hat sich diese Art von BCI auf vielen Gebieten weiterentwickelt. Auf dem Weg aus den Labors zu den Endanwendern ist die nutzerorientierte Gestaltung (engl. user-centered design; UCD) sehr wichtig. Im Rahmen dieser Dissertation wurde ein ERP basierendes BCI entwickelt, das auf den Ergebnissen von 30 Jahren Forschung aufbaut. UCD Vorgaben wurden soweit wie möglich berücksichtigt. In aktuellen Publikationen sind folgende Benutzeranforderungen an ein BCI genannt: Das System soll einfach zu bedienen, funktional, robust und komfortabel sein.

Als Basis wurde ein ERP basierendes BCI implementiert, das eine universelle Schnittstelle zu EEG Verstärkern hat, d.h. mit wenig Aufwand können verschiedene EEG Verstärker verwendet werden. Weiters gibt es nur eine einzige grafische Benutzeroberfläche, um den EEG Verstärker, die automatische Kalibrierung oder den Buchstabiermodus zu starten.

In einem zweiten Schritt wurden weitere Schnittstellen zur Steuerung anderer Anwendungen implementiert und an einer Gruppe von zehn gesunden und drei motorisch eingeschränkten Nutzern nach UCD Kriterien evaluiert. Die Studienteilnehmer waren in der Lage effektiv und effizient zu buchstabieren und Anwendungen zu kontrollieren. Die Zufriedenheit mit dem System war hoch, es wurden jedoch auch einige Verbesserungsvorschläge abgegeben.

Um Anwendungen zufriedenstellend zu steuern, wurde eine neuartige Methode für ein asynchrones ERP basierendes BCI entwickelt und erfolgreich getestet. Ebenfalls wurden verschiedene EEG Verstärkersysteme evaluiert und ihre unterschiedlichen Verwendungszwecke hinsichtlich eines ERP basierenden BCIs gezeigt.

Schließlich wurde das BCI mit einer Musikkompositionssoftware verbunden. Dieses System namens Brain Composer wurde mit einer Gruppe von 17 Musikern und einem professionellen Komponisten evaluiert. Alle Benutzer des Systems waren in der Lage sowohl vorgegebene als auch frei komponierte Musik zu erzeugen.

Zusammenfassend kann gesagt werden, dass ein BCI entwickelt und evaluiert wurde, das einfach zu bedienen und einzurichten, funktional und universell ist. Das im Rahmen dieser Arbeit entwickelte BCI trägt dazu bei das ERP basierende BCI aus den Labors in Richtung Endanwender zu bringen.

Danksagung (Acknowledgment)

Diese hier vorliegende Dissertationsschrift habe ich am Institut für Neurotechnologie der technischen Universität Graz angefertigt. Ohne die Unterstützung zahlreicher Personen und Institutionen hätte sie in dieser Form nicht realisiert werden können. Für die vielfältig erfahrene Hilfe möchte ich mich an dieser Stelle sehr herzlich bedanken.

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Neben der Unterstützung im Arbeitsumfeld habe ich auch von privater Seite viel Unterstützung erfahren:
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Von tiefstem Herzen danke ich auch meiner Partnerin Michaela, für ihre Geduld und Verständnis während des Entstehens dieser Arbeit.

List of Abbreviations

Ag/AgCl	silver/silver chloride
BCI	brain-computer interface
CNS	central nervous system
ECoG	electrocorticogram
EEG	electroencephalogram
EMG	electromyogram
eQUEST 2.0	extended QUEST 2.0
ERD/S	event-related de-/synchronization
ERP	event-related potential
fMRI	functional magnetic resonance imaging
fNIRS	functional near infrared spectroscopy
GUI	graphical user interface
ISI	inter stimulus interval
ITR	information transfer rate
JSON	javascript object notation
LFP	low field potential
MEG	magnetoencephalography
NASA-TLX	national aeronautics and space administration - task load index
QUEST 2.0	quebec evaluation of satisfaction with assistive technology

SCP slow cortical potential

SI stimulus interval

sLDA shrinkage regularized linear discriminant analysis

SMR sensorimotor rhythm

SSAEP steady-state auditory evoked potential

SSEP steady-state evoked potential

SSSEP steady-state somatosensory evoked potential

SSVEP steady-state visual evoked potential

SWLDA stepwise linear discriminant analysis

UCD user-centered design

UEQ user experience questionnaire

VAS visual analog scale

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1. Introduction

1.1. The Brain-Computer Interface

A brain-computer interface (BCI) is a communication system that does not require any natural neuromuscular central nervous system (CNS) output [1]. Measured patterns of the brain activity are translated into control signals in real-time ("online"). Therefore, a BCI establishes a direct connection between the human brain and a computer [1–4]. According to the BNCI Horizon 2020 roadmap [5], a BCI can be used in five application scenarios: (i) To provide a communication channel for people suffering from severe neurological disease or injury and without their motor functions. Subsequently, the BCI *replaces* the natural CNS output. (ii) The natural CNS output can be *restored*, for example, with BCI-controlled functional electrical stimulation of muscles in a paralyzed person. (iii) Natural CNS output can be *enhanced*, for example, by passively monitoring the brain activity and informing the user about abnormal behavior. (iv) To *improve* the motor output of the CNS during rehabilitation, e.g., after a stroke. (v) As a *research tool* to study CNS functions during basic studies. In this thesis, the BCI is used to replace the only limited functioning natural CNS output.

Typically, a BCI works as a closed loop system. Signals from the brain are acquired and processed (amplified, digitized, filtered). Eventually, features are extracted, classified, and translated into commands for the previously mentioned BCI application scenarios, see Figure 1.1. In the following sections, the four stages of BCIs are explained in detail.

1.1.1. Acquisition of Brain Signals

Different methods exist for recording the brain activity. Based on the invasiveness of the recording, these methods can be split into two different groups: non-invasive and invasive methods, see Figure 1.2. The most common and oldest method to record brain activity non-invasively is to use the electroencephalogram (EEG) measured on the scalp. Other existing non-invasive methods with minor importance for BCIs are magnetoencephalography (MEG) [7, 8], functional magnetic resonance imaging (fMRI) [9, 10], and functional near infrared spectroscopy (fNIRS) [11, 12].

A surgical intervention enables measuring the brain activity invasively. To record the electrocorticogram (ECoG), electrodes are implanted on the surface

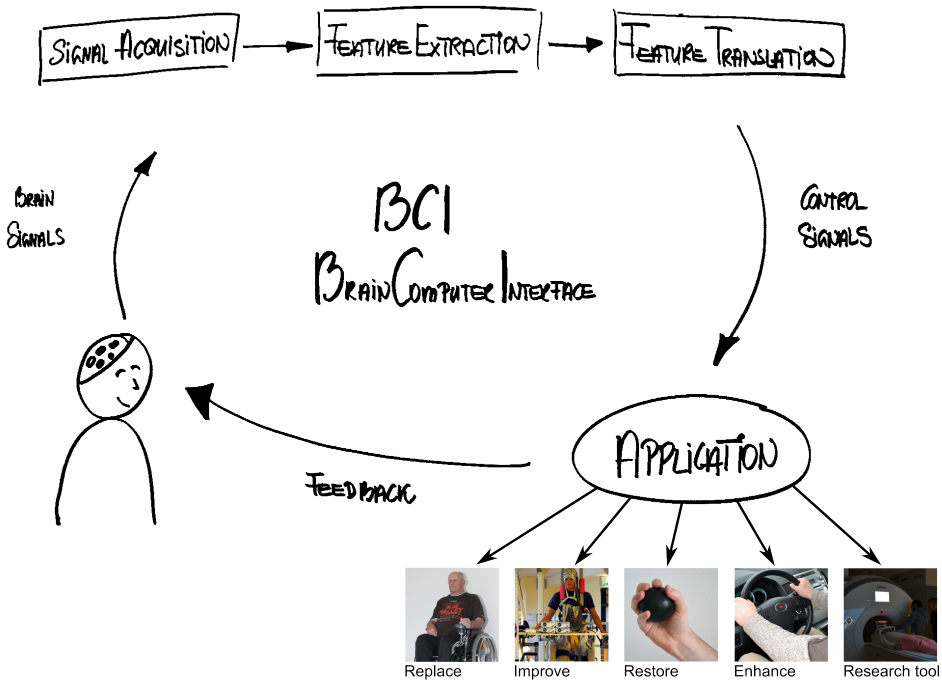


Figure 1.1.: Closed feedback loop of a brain-computer interface. Signals from the user's brain are acquired, processed, and translated into a control signal. This control signal can be used for, e.g., control an application. Finally, the effect of the control signal is fed back to the user. Photographs are taken from [6].

of the brain [13, 14]. The location can be epidural (between the skull and the dura mater) or subdural (between the dura mater and the arachnoid mater). An even more invasive method is to implant intracortical microelectrodes, where microelectrodes are inserted into the cortex to measure spiking activity [15, 16] or low field potentials (LFPs) [17]. Advantages of invasive methods are potentially better quality of signal as well as the higher spatial resolution compared to non-invasively measured signals, see Figure 1.2. On the other hand, invasive electrodes bear the risk of short durability and bacterial infections [17].

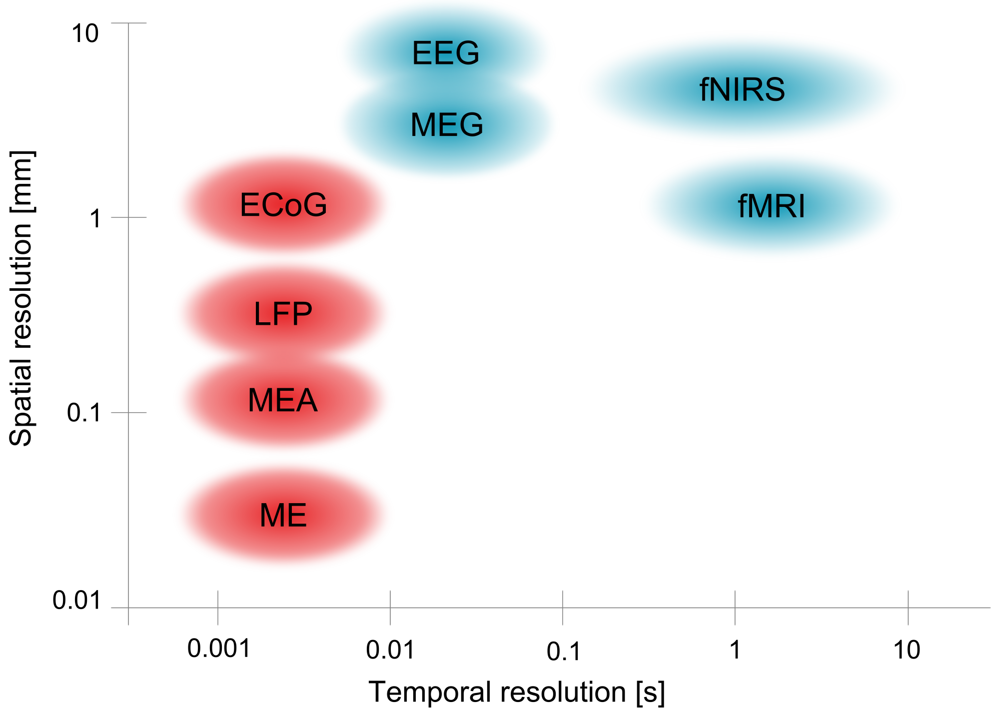


Figure 1.2.: Brain signal measurement methods in relation to spatial and temporal resolution. Please note that this figure is an illustration for relative comparison only. Non-invasive methods are shown in blue, and invasive methods are shown in red. The values for the spatial and temporal resolution are taken from [18].

All the introduced BCIs in this thesis are based on recording the EEG. This is because measuring the EEG is relatively inexpensive, portable, and convenient compared to the other presented non-invasive methods [19]. The flow of electric currents during synaptic excitations of the dendrites in the neurons incites the signal measured with the EEG electrodes [20]. Through volume conduction, this imbalance of ions is represented as a voltage potential on the skull. The cranial bone is a substantially poor conductor and attenuates the potential from the brain [21, 22]. Therefore, thousands to millions of neurons have to fire synchronously to get a useable EEG signal, i.e., a signal above the noise level. The first recording of human EEG was documented by the German scientist Hans Berger in 1924. He put steel needles into the subcutaneous tissue of the scalp and used galvanometers to visualize and interpret the recorded signals [23]. Later, vacuum tubes were used and currently, transistor technology is standard for amplifying the very small signals. These new technologies significantly improved the quality and the interpretability of the recorded signals. Silver/silver chloride (Ag/AgCl) electrodes, nowadays standard, were also introduced by Berger in the early 1930s [24]. The first documented EEG-based BCI was presented by Jacques Vidal in the 1970s [25, 26]. This first BCI approach enabled the user to control a computer by focusing attention on visual stimuli.

1.1.2. Brain Signals, Feature Extraction, and Classification

Time-domain, frequency-domain, or both features may be extracted depending on the neuroelectrical phenomenon used to operate the BCI. Four different phenomena are mainly used. In the following, a brief overview of three BCI methods that are not directly in the scope of this thesis will be provided followed by sections about event-related potential based BCIs and hybrid BCIs.

Slow cortical potentials (SCPs) are slow potential shifts in the EEG that can be voluntarily induced by the user [27–29]. These potentials are the response to imagination (e.g., imaginary movement) or cognitive tasks (e.g., waiting for a go cue). Compared to a baseline condition from the beginning of each trial, the SCP can be negative, providing basis for association with increased neuronal activation or positive, representing a decreased cortical activation. As the name implies, SCP-based BCIs work slowly and additionally require long training by the user with moderate accuracy, (around 70–85% control [30]). However, it has been demonstrated that severely disabled locked-in patients were able to communicate with an SCP-based BCI [30, 31].

Event-related de-/synchronization (ERD/S) -based BCIs are another approach that also does not require external stimulation. Originally, this kind of BCI utilized movement-evoked EEG patterns. A voluntary movement execution or imagination induced a relative power increase (ERS) or decrease (ERD) compared to a reference period in the ongoing human EEG. Nowadays, this method is also referred as sensorimotor rhythm (SMR)-based BCI. However, other tasks such as mental arithmetic, word association, spatial navigation, geometric figure rotation, or auditory imagery induce these phenomena [32–35]. ERD/S-based BCIs are used for communication [36–38], control of neuroprostheses [39–42] or wheelchairs [43, 44], and as a tool for stroke rehabilitation [45–48].

The so-called BCI illiteracy or BCI inefficiency [49] is high. The meaning of these two phrases is that up to 30% of the people are unable to control a BCI with this method, cf. [50]. According to a study by Guger et al. [51], only 54 of 100 tested people achieved sufficient ERD/S-based BCI control with an accuracy above 70%.

Steady-state evoked potential (SSEP) -based BCIs take advantage of the fact that frequently presented external stimuli evoke oscillatory potential fluctuations in the EEG. Typically, the driving stimulation and the SSEP have the same frequency. Depending on the stimuli presentation, the SSEP can be divided into steady-state visual evoked potential (SSVEP) [52], steady-state somatosensory evoked potential (SSSEP) [53], and steady-state auditory evoked potential (SSAEP) [54]. For review, see [55].

An SSEP-based BCI can be implemented by simultaneously presenting stimuli with varying frequencies to the user. The user has to focus on a desired stimulus to select it as the target. The stimulation frequency of the target is dominantly represented within the EEG and can be used to select the its represented functionality. The targets can be flickering virtual buttons (SSVEP-based BCI), modulated tone streams (SSAEP-based BCI), or repetitive tactile stimuli applied to different body parts (SSSEP-based BCI). Applications of SSVEP-based BCIs are, e.g.: two-dimensional control of a virtual car [56] or a cursor [57], environmental control [58], spelling [59], and prosthesis or orthosis control [60, 61].

Examples for SSAEP-based BCIs are [62–64] and for SSSEP-based BCIs are [53, 65].

1.1.3. BCIs Based on Event-Related Potentials

Event-related potentials (ERPs) are deflections of the EEG, which occur time-locked to an event. This event can be a sensory stimulus or a motor act [66]. In general, ERPs induced by a sensory stimulus show a high level of activation just after the stimulus, whereas ERPs induced by a motor act show such high level of activation before and during the motor actions [67]. This second type of ERPs belong to the group of movement-related cortical potentials (MRCPs). A prominent part of the MRCP is the Bereitschaftspotential, which is a slow rising negativity with its negative peak just before the movement onset [68]. Recently, scientists have aimed to use these potentials for rehabilitation and controlling (neuro)prosthesis [69–72]. The focus of the following explanations is on ERPs induced by a sensory stimulus. This method was used for the implemented and investigated BCIs of this thesis.
Depending on the latency between the stimulus and the deflection, ERPs can have different names. They are named after the direction of the deflection, either a "P" for a positive or an "N" for a negative deflection, followed by the time in milliseconds they occur on average after the stimulus. Sometimes, the zeros are omitted, and the number indicates the ordinal position in the waveform [73]. Very prominent ERPs are the N2(00), P3(00), or N400. A cascade of ERPs are elicited by focusing attention on rare target stimuli in a stream of target and non-target stimuli, see Figure 1.3. The number of irrelevant (non-target) stimuli should be at least four times higher to evoke pronounced ERPs. This method is called the "oddball paradigm" [74, 75].
The fact that the ERPs in an oddball paradigm are time-locked can be used to determine the causative stimulus in a stream of stimuli. Therefore, it is possible to determine the stimulus on which the user concentrates from a set of stimuli. This kind of BCI is also often referred to as P300 or P300-based BCI, since it mainly relies on a positive deflection of the EEG approximately 300 milliseconds after the target stimulus. In the year 1988, Farwell and Donchin published the first version of an ERP- or P300-based BCI [76]. Given that some of the methods and techniques they used are still the same, the main ideas of their publication are described below, supplemented by the state of the art of ERP-based BCIs.
The original P300-based BCI of Farwell and Donchin was designed to communicate by spelling Latin letters and numbers. These items were the elements of a visually displayed matrix, see Figure 1.4. Different methods exist to realize an oddball paradigm with this matrix. One method is to randomly highlight single characters [77, 78], see Figure 1.4 red diamond. Users are introduced to

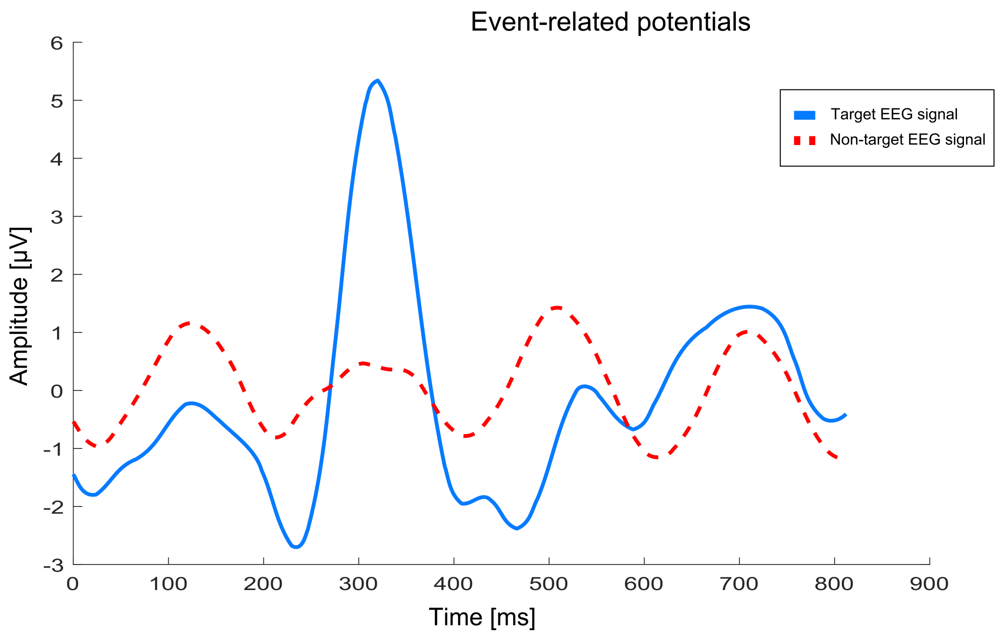


Figure 1.3.: Plot of the averaged EEG signals after target (blue curve) and non-target (red curve) stimuli at electrode position Cz.

focus visual attention on a specific character (target) and count the number of target intensifications mentally, while ignoring the highlighting flashes of the other characters. Target stimuli will elicit distinct ERPs in the recorded EEG, and with the knowledge of the stimulus timing, the desired characters can be determined. Highlighting every single character is time-consuming. Therefore, groups of characters are normally highlighted at the same time. One prevalent method is to highlight rows and columns of the matrix randomly, see Figure 1.4 yellow rectangles. The row and column containing the target elicit distinct ERPs and the intersection of the detected row and column yields the target element, see Figure 1.5 for demonstration. In addition, other methods exist to highlight the elements of the matrix in a different way [79, 80], see Figure 1.4 blue circles. These methods target to avoid ”adjacency-distraction errors”, i.e., the user being distracted by the intensification of an adjacent element, and this erroneously evokes ERPs. Also, the problem of flashing the target twice in a row could be avoided with these methods. An additional aim of the Jin et al. approach is to fasten the BCI by simultaneously highlighting the optimal number of matrix elements [80].
All the ERP-based BCIs in this thesis are based on the row/column method.

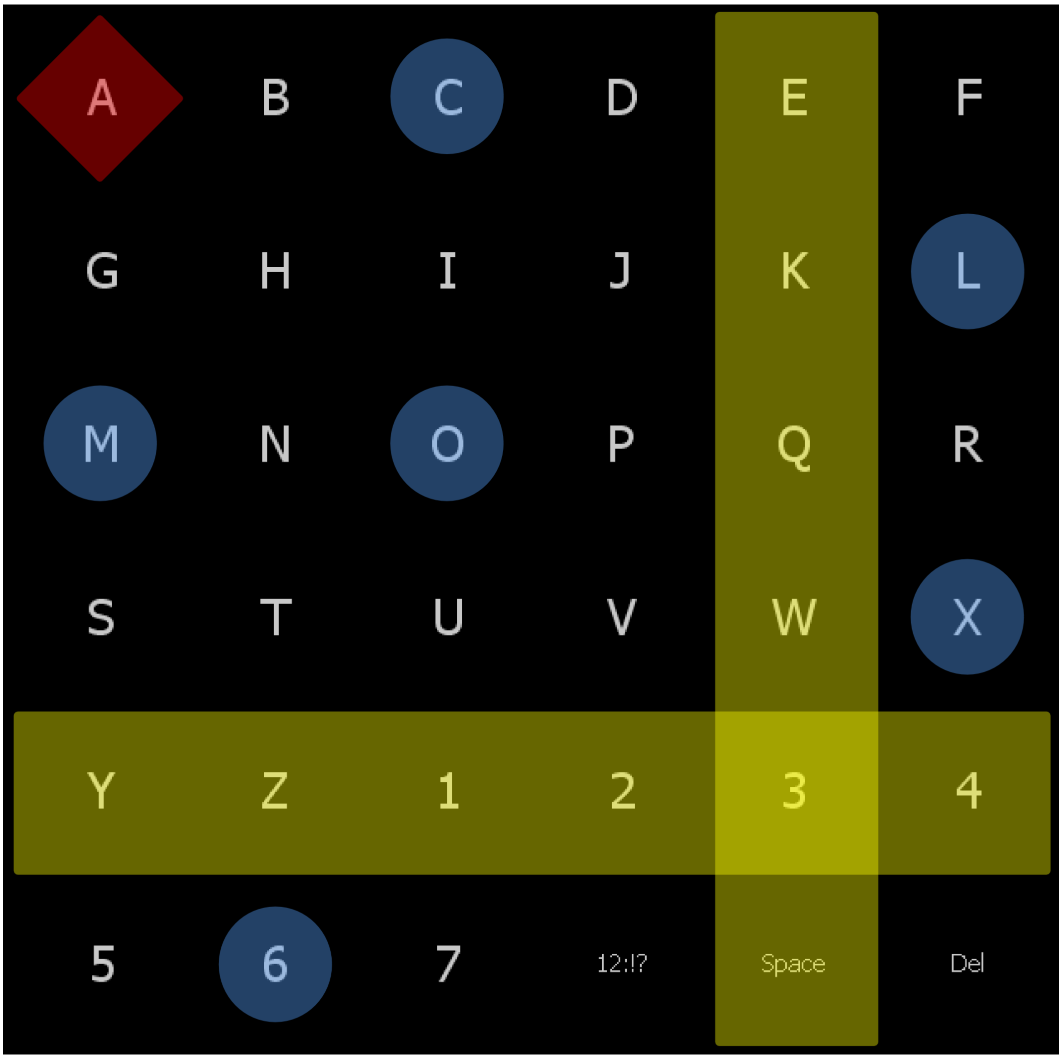


Figure 1.4.: Example for a visually displayed matrix that can be used to build an ERP-based BCI. Highlighting methods are: Single character (red diamond), multiple, random characters (blue circles), and row and column highlighting (yellow rectangles).

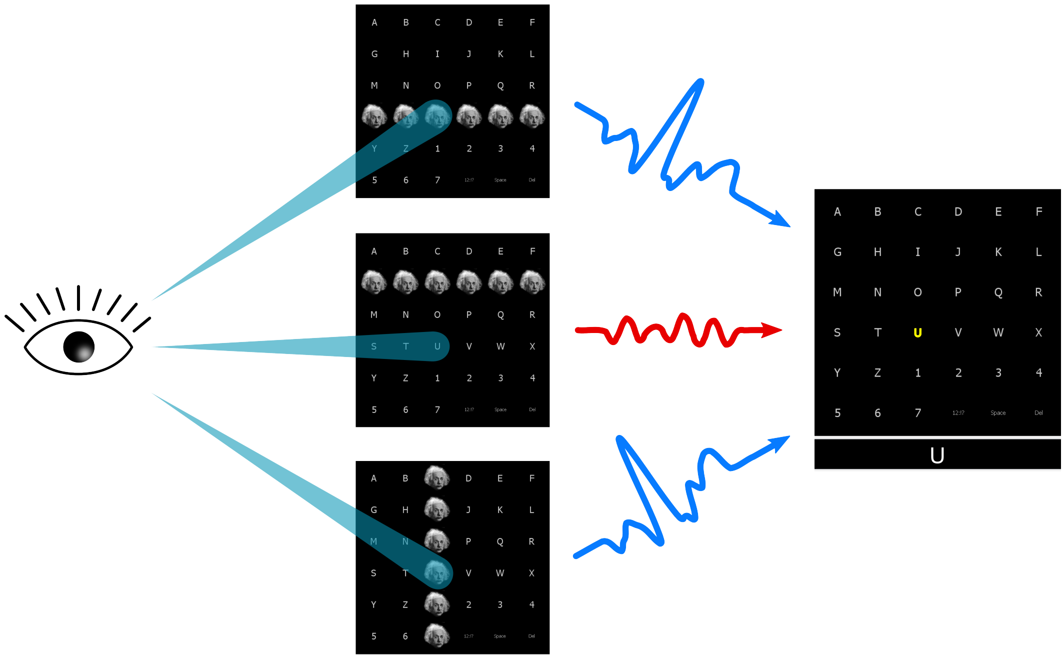


Figure 1.5.: Demonstration of the row/column paradigm. Users focus their visual attention on the letter "U" and count the number of target character highlighting flashes. Top and bottom matrices in the middle of the figure show a target highlighting; the central matrix a non-target highlighting. The EEG signal of the target row and column differs significantly from the non-target signal–indicated by the blue and red arrows. The intersection of the target row and column is the desired character, in this example "U".

Therefore, features of this method are described in detail in the following paragraphs.
Not only approaches to optimize the pattern of stimulation exist, but also the kind of intensification was investigated. Kaufmann et al. reported in [81] changing the intensification from simple contrast changes to overlays of famous faces boosts the speed and accuracy of ERP-based BCIs significantly. Recognizing familiar faces evoke additional ERPs (N170, N400f – 'f' for face) and they are responsible for this boost. Other scientists use emoticons [82], move characters [83], or change the emotion of the shown face [84] as overlays.
Typically, it is necessary to calibrate the ERP-based BCI prior to using it. A few approaches exist to avoid this step with the help of unsupervised learning algorithms [85, 86]. However, copy-spelling 5–10 characters with 20–30 intensification per character is sufficient to calibrate a classifier. The time required for the calibration is three to thirteen minutes. During this time, users have to spell predefined characters of the stimulation matrix. The EEG of the calibration is recorded and used to calculate a personalized classifier. In general, the feature extraction and classification of ERP-based BCIs work as follows: Depending on the sampling frequency, the EEG signal is downsampled to reduce the number of features. Subsequently, the EEG signal of every electrode is divided into epochs of approximately 800 ms post stimulus. Epochs, which belong to the same stimulus and electrode are averaged to improve the signal-to-noise ratio. Finally, the averaged epochs of all electrodes are concatenated to receive a single feature vector that is classified. More complex feature extraction methods (e.g., xDAWN [87]) have been proposed and evaluated in the literature.
Using stepwise linear discriminant analysis (SWLDA)-based classifiers for ERP-based BCIs was found superior for a long time [76, 88, 89]. However, recently, it was reported that for a low number of training samples a shrinkage regularized linear discriminant analysis (sLDA)-based classifier outperforms the SWLDA-based classifier and at worst, the sLDA-based works as well as the SWLDA-based classifier [90, 91].
Different methods exist to determine the number of stimulation sequences used for the free-spelling mode. Since the row/column paradigm is used for the implemented ERP-based BCIs in this thesis, methods for this paradigm are described in the following. Initially, a fixed number of stimulation sequences are used, e.g., fifteen sequences. Second, the number of stimulations for the free-spelling mode is calculated from the data of the calibration. Performing a cross-validation allows determining the optimal number of stimulations as a trade-off between speed and accuracy. Third, algorithms (e.g., [83, 92–96]) that define different thresholds or rules to perform an "early" or "dynamic stop-

ping", i.e., if the threshold is reached or the rule is true, the stimulation stops and the classification result is presented to the user. Schreuder et al. performed comparative analysis of the different methods in [97].
ERP-based BCIs have been intensively used for spelling applications for both healthy and severely disabled users [78, 98–100]. In addition to pure communication applications, the control of various other applications has been reported. The scope of these applications includes environmental control [101, 102], painting application [103, 104], web browsing [105, 106], wheelchair control [107–109], and music player control [110] among others.

All the above described ERP-based BCIs work in the visual modality. When people are unable to perceive visual stimulation or for settings, where visual stimulation is not viable, other sensory inputs can be used to realize an ERP-based BCI. Using auditory or tactile stimuli is a common alternative. Like the visual ERP-based BCIs they also use the oddball paradigm to evoke ERPs. Examples for auditory ERP-based BCIs are [111–116] and for tactile are [117–119]. However, a comparative study [117] between the different ERP-based BCI methods revealed a strong superiority of the visual modality regarding the achieved classification accuracies.

1.1.4. Hybrid BCIs

A hybrid BCI is the advantageous combination of different approaches within one BCI system [120–122]. According to Pfurtscheller et al. [122], a BCI is called hybrid BCI if: (i) Different types of brain signals are combined (e.g., EEG and fNIRS [123]); (ii) One type of brain signal is used for various mental tasks, like ERPs and SSVEP [124]); (iii) A brain signal is combined with external or physiological signals (e.g., eye tracker [125] or electromyogram (EMG) [126]).
The input signals can either be processed in parallel [127] or serially [128], i.e., one input triggers the processing of the second one.

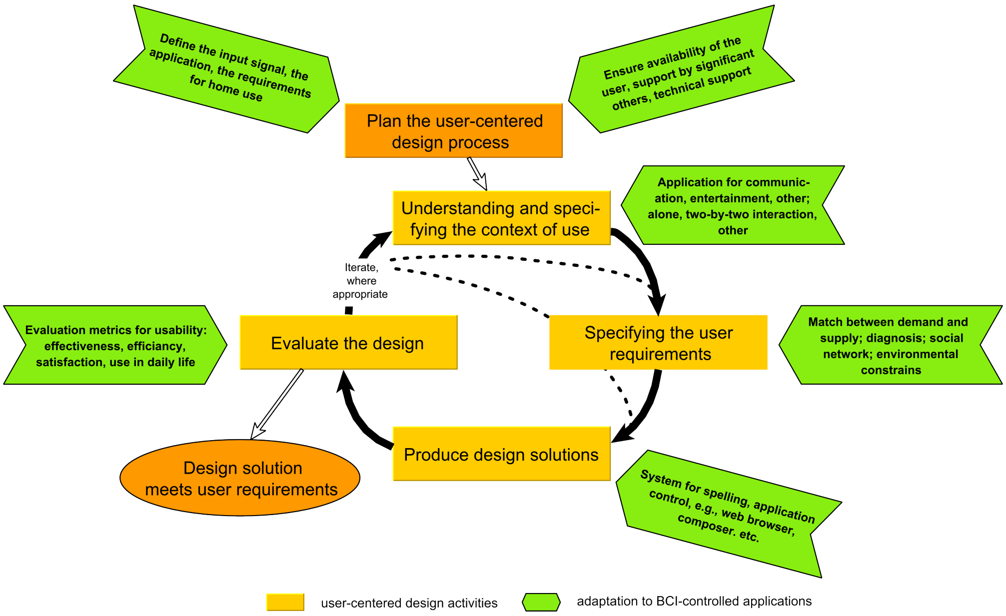


Figure 1.6.: User-centered design activities adapted to BCI-controlled applications. Adapted from [129, 130].

1.2. User-centered Design in BCI Research

Human- or user-centered design (UCD) in general is an approach for the realization of usability and usefulness of systems by focusing on the users' needs and requirements. Human factors and usability knowledge and techniques shall be taken into account. The aim is to enhance effectiveness and efficiency, user satisfaction, accessibility and sustainability, and to avoid any possible adverse effects of use on humans [129]. This design approach was standardized in the ISO 9241-210 (Ergonomics of human-system interaction-Part 210: Human-centred design for interactive systems) [129].

Since the BCI technology is now on the way out of the laboratories to the end users, it is substantial to consider this design approach. The ISO 9241-210 defines six principles and four activities of the user-centered design and development process. The principles include properties such as user involvement, explicit understanding of the user, tasks and environment, while the process remains iterative. The four activities specify the iterative development process, see Figure 1.6 yellow boxes. When producing a design solution, three aspects of usability are especially important: user satisfaction (emotional and aesthetic), effectiveness, and efficiency. The overall evaluation of the designed system is based on evaluating these aspects. Therefore, they must be assessed appropriately.

Kübler et al. described in [130] the UCD of the Brain Painting [103] application. Brain Painting is a fully BCI-controlled painting application. In [130] evaluation metrics and BCI-specific activities, see Figure 1.6 green boxes, for the UCD of BCIs are presented. Previously mentioned usability aspects for BCI systems are defined as follows: *Effectiveness* corresponds to the accuracy achieved by the user when using a BCI-controlled application. It relates successful selections to the total number of attempted selections. *Efficiency* relates the costs, i.e., effort and time invested by the user, to the effectiveness. The information transfer rate (ITR) [131] is often used as an objective measure of efficiency. It is calculated from the available number of possible selections, the time needed for a single selection and the accuracy [132]. It is expressed in bits per minute. The problem of the original ITR definition by Wolpaw et al. [132] is that it is based on two occasionally invalid assumptions. These two assumptions are that all possible selections are equally probable and systems are memoryless [133]. Other definitions aim to minimize the negative effects of these two assumptions [79, 133–135]. In addition, the Utility Metric was introduced setting the ITR to 0 bits per minute when the accuracy is below the chance level [136]. The reason is that for accuracies below the chance level, no useful communication is possible.

The workload as a measure of efficiency can be assessed with the national aeronautics and space administration - task load index (NASA-TLX) [137, 138]. With the NASA-TLX, it is also possible to assess the overall workload experience during a task and to identify the main sources of workload in six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. In a two-step procedure, the workload is determined. First, all six dimensions need to be rated on twenty step bipolar scales with scores from 0 to 100. Second, a weight for every dimension must be determined with pairwise comparisons. Finally, the global workload score is calculated from the weighted scores of the dimensions. A high score indicates a high workload.

Several measures can be used to assess the *satisfaction* with the device. The methods range from simple visual analog scales (VASs) to complex questionnaires. Typically, simple VASs are used to easily and quickly assess the overall satisfaction. Therefore, users are asked to report their overall satisfaction by indicating a position along a continuous line between two endpoints. This VAS ranges from 0 (not satisfied at all) on the left endpoint to 10 (absolutely satisfied) on the right endpoint. The assessment can be carried out after every BCI session, whereas complex questionnaires are intended to assess more facets of satisfaction after an entire session of BCI system uses. An example for a complex

questionnaire is the quebec evaluation of satisfaction with assistive technology (QUEST 2.0) [139]. This is a tool to quantify satisfaction with general aspects of an assistive technology product. This questionnaire covers twelve different aspects. Users are asked to rate the items on a Likert-type scale from 1 (not satisfied at all) to 5 (very satisfied). Whenever users are not "very satisfied" they are asked to comment the reasons. The total satisfaction score is the arithmetic mean across all items. In addition, users are asked to indicate the three most important items.
Some items of the original questionnaire are irrelevant for assessing BCI applications. Therefore, Zickler et al. [106] suggested, and this is absolutely in the sense of the creators of the questionnaire [139], to change some of the items to make the questionnaire more suitable for evaluation of BCI controlled assistive technology. They replaced the items "durability", "service delivery", "repairs/servicing", and "follow-up service" with "reliability", "speed", "learnability", and "aesthetic design". This BCI adapted QUEST 2.0 is referred to as extended QUEST 2.0 (eQUEST 2.0) [106].

One possibility to evaluate the user experience of BCI systems is the user experience questionnaire (UEQ) [140]. This tool has been used to assess user experience for many software products (e.g., [141, 142]) and was also used in a recent BCI study [143]. The UEQ consists of 26 bipolar items rated on a 7-point semantic differential scale. Single items are transformed to the range from -3 to $+3$ and assigned to six subscales: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. The average values of each subscale can be further grouped into three categories: attractiveness, use quality, and design quality. Attractiveness describes a person's general attitude towards a product. Use quality reflects practical quality aspects and is the average of the subscales efficiency, perspicuity, and dependability. Design quality represents hedonic quality aspects and is the average of the subscales novelty and stimulation. Results are interpreted so that values below -0.8 represent a negative impression, values between -0.8 and $+0.8$ a neutral impression, and above $+0.8$ a positive impression.

1.3. Limitations of Previous Work

Since the initial publication of a working P300- or ERP-BCI [76], scientists have focused on many different aspects of improving that kind of BCI. The optimization of aspects such as signal processing and classification, for reviews see [144, 145], and stimulus presentation, e.g., [79, 81, 135, 146, 147], was already mentioned in Section 1.1.3. However, according to [148] assistive device users wish for an easy-to-use, functional, and robust system. Taking into account known publications, the main focus of research was on improving the speed and accuracy of ERP-BCI systems. Ease of use and functionality have not been taken into account so far.

Another study [106] investigated the satisfaction of BCI end users. End users were very dissatisfied with the EEG acquisition hardware. They criticized the comfort, the time-consuming setup, and the aesthetic design of the system [106]. So far, EEG acquisition hardware has only been evaluated regarding efficiency and effectiveness, e.g., [149, 150]. Investigating all aspects of usability, see Section 1.2, of different EEG hardware is a blind spot in research.

Having complex BCI-controlled applications such as a web browser or media player require other control concepts than a simple BCI-controlled speller. Reading content, listening to music, or watching videos require asynchronous control, i.e., the users decide whether they want to select something with the BCI. Typically, ERP-BCIs work in synchronous mode, i.e., after every stimulation sequence, something is selected, intentionally or not. Approaches for asynchronous ERP-BCIs exist [101, 151–153], but the achieved accuracies are not convincing regarding reliability and accuracy.

1.4. Aims of this Thesis

To overcome these limitations, the primary aim of this thesis is to develop and evaluate an ERP-based BCI system for communication and control based on the requirements found by [106, 148] incorporating all recently published improvements. The main requirements are to be **easy to use, functional and robust, comfortable,** and **universal**. Universal, in terms of working with different EEG acquisition systems, and the possibility to control different applications with the ERP-based BCI.

Easy-to-use system for the users and the caregivers should be developed. Since severely disabled users are normally dependent on the help of caregivers, the system must be easy to use for both. Typically, caregivers are not experts on technically complex systems. Therefore, the caregivers' user interface must be intuitively and clearly designed. In addition, EEG hardware must be easy to use even for non-experts.

Functional and robust algorithms for signal processing and EEG classification are necessary to meet the expectations of the potential users. These two terms also imply that the software works stably and provides easy access to desired functions. End users also mentioned speed as a major aspect [106]. Another crucial factor is finding a compromise between speed and reliability. Therefore, it applies that the speed of selections should be increased as long as the reliability, synonymous with accuracy, is not significantly decreased.

Comfortable EEG hardware is mandatory. This includes the cap, wiring, and the cleaning of the EEG hardware. The cap should be as inconspicuous as possible. The use of electrode gel makes it necessary to clean the hairs and the equipment after each BCI use and this cannot be in the users' interest. Moreover, wireless solutions should be considered to avoid distracting and annoying wires. Therefore, possible alternatives to gel-based, wired EEG acquisition system must be found and evaluated.

Universal interfaces to EEG acquisition systems and applications should be provided. Since different EEG acquisition system should be evaluated to find a comfortable and reliable system, an interface to different acquisition devices should be integrated allowing easy switching between the systems. On the other hand, application interfaces must provide the possibility to control other applications such as a web browser or a music player with the developed ERP-based BCI.

Since one aim of this thesis is to provide an interface to applications such as a web browser or music player, derived additional aim is to provide asynchronous BCI control. Therefore, methods have to be found to decide whether a user wants to use the ERP-based BCI intentionally or the BCI classifies random signals and selects items unintentionally.

In order to meet the requirements in the best possible way, it is necessary to apply UCD principles [129, 130]. The feedback of users during different stages of the development process is useful to improve the future versions of the system. Here, the aim of this thesis is to improve the BCI system based on comprehensive and meaningful evaluation data. This is guaranteed by using different questionnaires and other evaluation metrics. As a consequence, useful improvements shall be determined or derived out of these results. Finally, the improvements must be iteratively incorporated.

1.5. Organization of this Thesis

Chapter 1, Introduction, gives an overview of the most important types of BCIs and signal processing techniques, reviews the state of the art, and indicates limitations of relevant previous work in the field of ERP-based BCIs. User-centered design is becoming increasingly important in this area and will be introduced accordingly. Finally, this chapter points out overall and specific objectives of this thesis.

Chapter 2, Methods and Results, summarizes the aim, methods, main results, and significance of the core papers for this thesis.

Chapter 3, Discussion, Conclusion, and Prospects, explains how the findings reported in the core papers contribute to accomplishing the aim of the thesis. This section further relates the outcome of the studies to other work in literature and discusses possible limitations of this work. Finally, the main achievements of this thesis are summarized, and possible future research directions are pointed out.

2. Methods and Results

2.1. Development and Implementation of a Universal ERP-based BCI system

A. Pinegger, S.C. Wriessnegger, and G.R. Müller-Putz. Introduction of a Universal P300 Brain-Computer Interface Communication System. *Biomedical Engineering/Biomedizinische Technik*, 58 (Suppl. 1), 2013. Doi: 10.1515/bmt-2013-4445. [154]

The first version of a universal and practical ERP-based BCI communication system was developed. We defined interfaces between the different parts of the system, see Figure 2.1.
The SignalServer application [155], see Figure 2.1 (a), was chosen for signal acquisition. By using the SignalServer software, it is easily possible to connect different EEG acquisition devices to the developed ERP-based BCI. The data from the SignalServer is sent via a TCP/IP network connection to Matlab/Simulink, see Figure 2.1 (b). A Simulink model records and processes the EEG data and also communicates via a TCP/IP network connection with a graphical user interface (GUI), see Figure 2.1 (c) and Figure 2.2.
The GUI is an application written in C++. Additionally, other applications, such as a web browser or media player, can be controlled with this system. Images of famous faces are used to highlight elements of the stimulation matrix instead of just changing the contrast. Using famous faces has the advantage that additional ERPs are elicit and can be additionally used for classification [81]. SWLDA is used for EEG classification [89]. The developed system is straightforward to use and set up. Therefore, the entire system can be controlled via the GUI, see Figure 2.2. The signal acquisition, the Simulink model as well as a signal viewer can be started with simple mouse clicks inside the GUI. Moreover, the calibration of the system is performed with a single mouse click. After the data acquisition of the calibration, an algorithm automatically calculates the best number of stimulation sequences, and the free-spelling can start immediately.

Contribution to this thesis: This conference submission describes for the first time the developed universal ERP-based BCI system with its principal functions and signal paths. The system was implemented by incorporating state-of-the-art findings of recent publications.

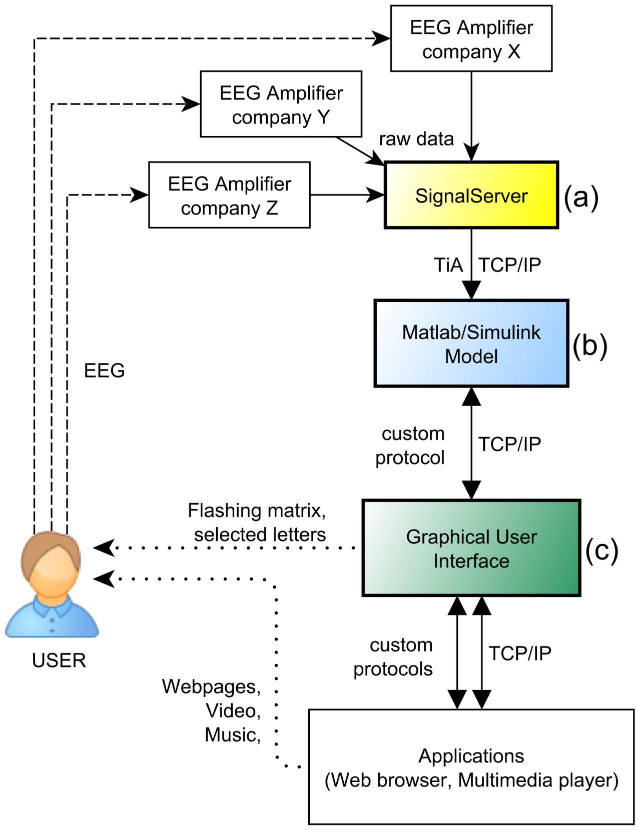


Figure 2.1.: Design sketch of the universal ERP-based BCI communication system. EEG can be recorded with varying amplifier systems. Data of the amplifiers is sent to Matlab using the SignalServer software. In Matlab, data is filtered, downsampled, averaged, and classified. A graphical user interface (GUI) shows the stimulation to the user and sends the actual stimulation to the Matlab part. The classification result is sent back to the GUI and presented to the user.

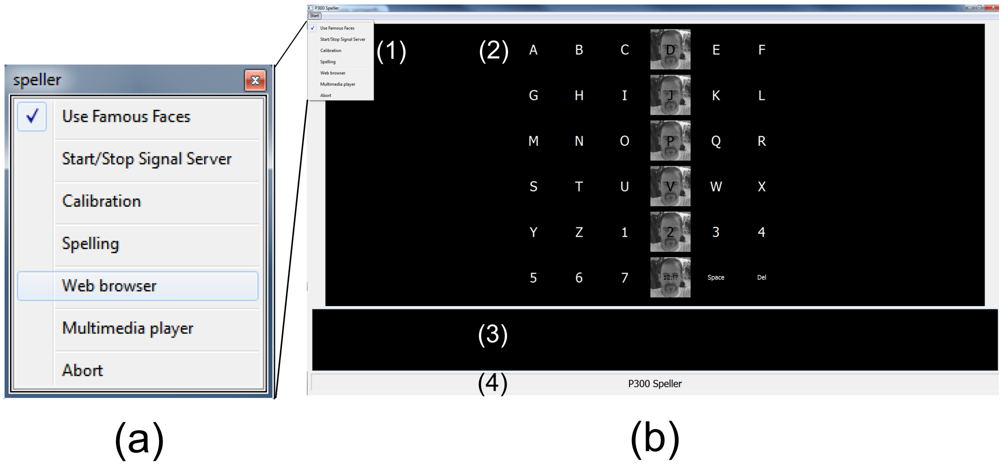


Figure 2.2.: Screenshot of (a) the user menu and (b) the user interface. The different areas are (1) the menu, (2) the stimulation matrix, (3) the text field, and (4) the status bar. Normally, the face of Albert Einstein showing his tongue is used which is not shown in this figure due to print license.

2.2. Brain-controlled Applications Using Dynamic Stimulation Matrices

S. Halder, A. Pinegger, I. Käthner, S.C. Wriessnegger, J. Faller, J. Antunes, G.R. Müller-Putz, and A. Kübler. Brain-controlled applications using dynamic P300 speller matrices. *Artificial Intelligence in Medicine*, 63(1): pp. 7–17, 2015. Doi: 10.1016/j.artmed.2014.12.001. [156]

In order to control other applications with the universal ERP-based BCI controller, described in the last section, different content must be selectable. We decided to implement this feature in two different ways. To control a web browser, it actively sends codes for selectable items, e.g., links, text fields, and buttons, to the BCI controller, see Figure 2.3 left. The number of items is not constant, since it depends on the selectable items displayed on the web page. Consequently, the number of elements of the stimulation matrix is also not constant and dynamically adapted to the number of received elements. The size of the display limits the space for the matrix. Therefore, we set the number

of rows to six and also limited the maximum number of columns to fourteen. If the number of selectable items of a web page is higher than the maximum number of items that can be displayed, the user can scroll to select an unmarked element, since only the visible elements are sent to the BCI controller.
The second application which is controllable with the ERP-based BCI is a media player. To control this application, a 3×6 matrix with dedicated elements is used, see Figure 2.3 right. Both applications are connected to the ERP-based BCI via a TCP/IP network connection. A study with ten healthy participants as well as three participants with motor disabilities was performed. The aim was to generate the operating principal and to evaluate the system. First, the participants had to calibrate the system by copy-spelling the word "BRAIN". The second task was to spell the words "SONNE" (Engl. "SUN") and "BLUME" (Engl. "FLOWER").
The third task was to navigate through the media player (min. 10 selections). The fourth task was a web browsing task: The participants had to look for the word "BCI" in Google and select and read the Wikipedia article about BCI (min. 12 selections). The last task was to copy-spell two words ("TRAUM", Engl. "DREAM" and "KRAFT", Engl. "STRENGTH"). The averaged signals of the target and non-target epochs are shown in Figure 2.4. Nine out of the ten healthy participants achieved control accuracies above 70%, and one of the disabled participants achieved accuracy above 75%.

Contribution to this thesis: We introduced the connection of the developed ERP-based BCI controller, see Section 2.1, to two different applications, namely a web browser and a media player. The control methods and the protocols of the connections were presented. The size of the stimulation matrix is automatically adapted to the used application. Finally, the initial study showed that both healthy and disabled people are able to control these applications with high accuracies.

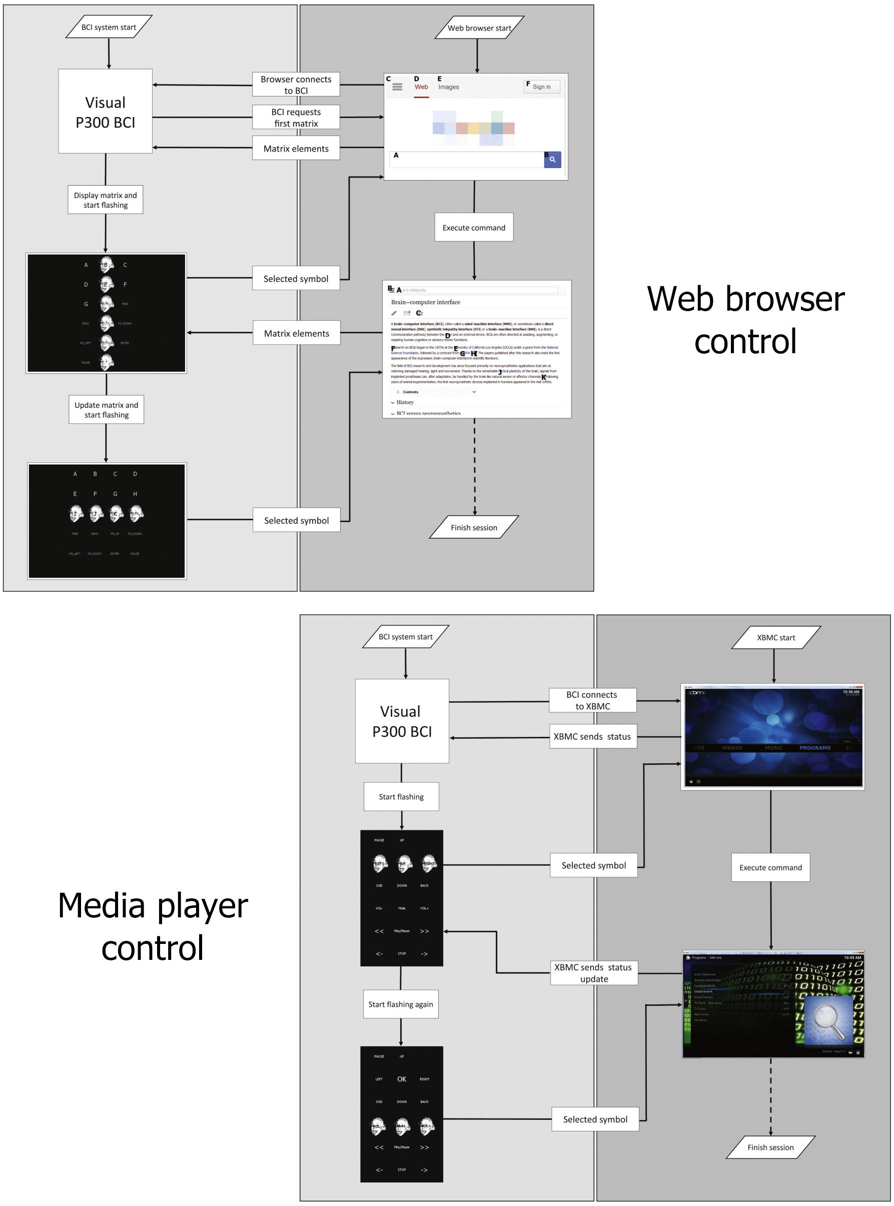


Figure 2.3.: **Top:** Sketch of the bidirectional communication between browser and brain-computer interface (BCI). First, the BCI establishes a connection to the browser. After loading a new page or selecting a new element on the current page, the browser sends the list of appropriate commands to the BCI. The BCI, in turn, displays a stimulation matrix with these commands to the user.
Bottom: Sketch of the bidirectional communication between the media player and the BCI. The BCI sends the selected commands to the player. The player reacts accordingly and sends status updates or error messages back to the BCI.

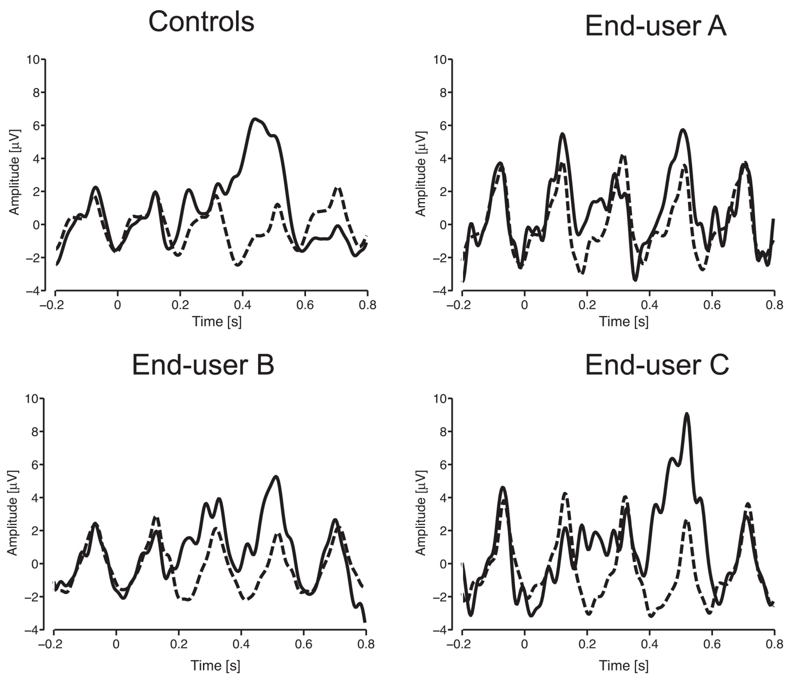


Figure 2.4.: Averaged ERPs of the calibration run. The grand average signal of all healthy participants (top left) and individually for each of the three end users is shown. Signals were recorded from electrode Pz. The continuous lines show the target response and the dashed lines the non-target response.

2.2.1. Write, Read and Answer Emails with a Dry 'n' Wireless BCI System

A. Pinegger, L. Deckert, S. Halder, N. Barry, J. Faller, I. Käthner, Ch. Hintermüller, S.C. Wriessnegger, A. Kübler, and G.R. Müller-Putz. Write, read and answer emails with a dry 'n' wireless brain-computer interface system. *Proceedings of the 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2014, pp. 1286–1289. Doi: 10.1109/EMBC.2014.6943833. [157]

With this study, the question was answered whether the developed ERP-based BCI controller enables users to write and read emails in a comfortable way. We connected a dry electrode-based wireless EEG amplifier to our controller and asked ten participants to write, read, and answer emails using the web browser introduced in Section 2.2, see Figure 2.5.
A minimum of 52 selections were necessary to complete the task. Usability was

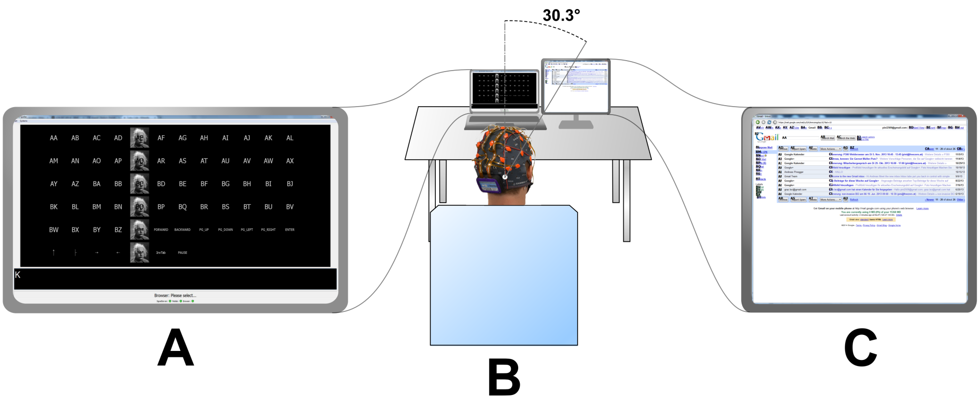


Figure 2.5.: (A) Screen displaying the GUI for feedback and stimulation. (B) Sketch of the experimental design. (C) Screen displaying the webmail client.

evaluated regarding effectiveness, efficiency, and satisfaction. Satisfaction was assessed using a VAS, the eQUEST 2.0, and a self-compiled usability questionnaire. Accuracies were high for nine out of ten participants, see Figure 2.6. One participant could not finish the task because the accuracy stayed below 70%, see "S2" in Figure 2.6. The average time needed to complete the task was 58 minutes. Satisfaction, in general, was high. However, the participants criticized the aesthetic design and comfort of the EEG amplifier as well as the effectiveness of the system.

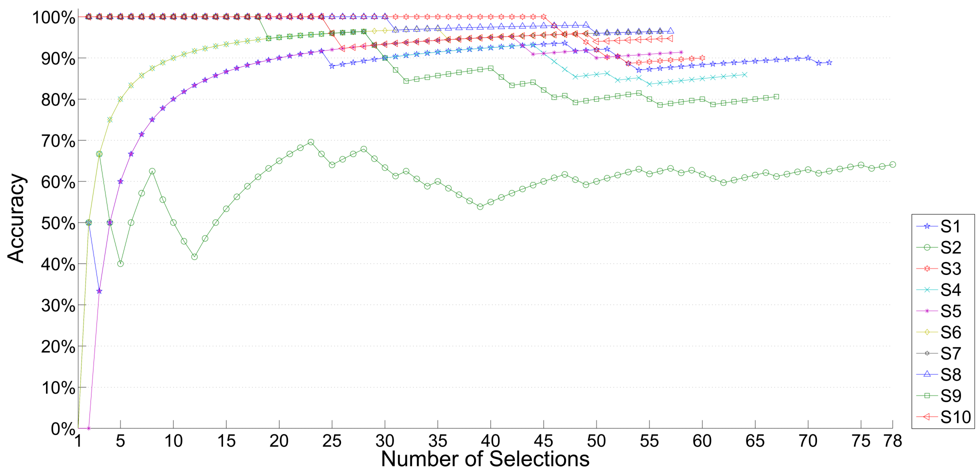


Figure 2.6.: Comparison of accuracies from different participants over number of selections. The minimal number of selections was 52.

Contribution to this thesis: Results of this study indicate that users can effectively read and write emails with the developed ERP-based BCI. However, apart from the high, general satisfaction ratings, the used dry electrodes for EEG acquisition were described as uncomfortable by eight out of the ten study participants.

2.3. Asynchronous Visual ERP-based BCI Approaches

A. Pinegger, J. Faller, S. Halder, S.C. Wriessnegger, and G.R. Müller-Putz. Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach. *Journal of Neural Engineering*, 12(1). 2015. Doi: 10.1088/1741-2560/12/1/014001. [158]

The main disadvantage of current ERP-based BCIs is that they normally work synchronously, i.e., after every stimulation sequence something is selected, intentionally or not. This behavior is not a fundamental problem when an ERP-based BCI is simply used as a spelling device. However, when the BCI is used as a web browser or media player controller, it needs to work asynchronously. In this paper, we present two different ways and the hybridization of both as control state detectors. One technique takes advantage of the fact that the stimulation with a defined frequency is represented as SSVEP in the EEG, see Figure 2.7. Consequently, the SSVEP is only detectable when the user is looking at the stimulation screen. However, it is also detectable when the user has the stimulation screen in his field of view, e.g., when the user wants to read something close to the stimulation matrix. The second technique utilizes features of the classifier output. The idea is that the distance between the two classes (target–non-target) is larger when the user wants to select something. However, artifacts in the EEG can easily transform this detection method of the control state unreliable. Hence, we hybridized the two methods to combine the advantages of both techniques. We tested the capabilities of these three methods for state detection in different control scenarios on offline data from 21 healthy volunteers, see Figure 2.8. With the hybridization of the methods, we achieved an average correct state detection accuracy of over 95%.

Contribution to this thesis: We introduced and evaluated a new method to make a visual ERP-based BCI work asynchronously. The developed hybrid method is the most effective approach, and we could show that a correct state detection accuracy of more than 95% is feasible.

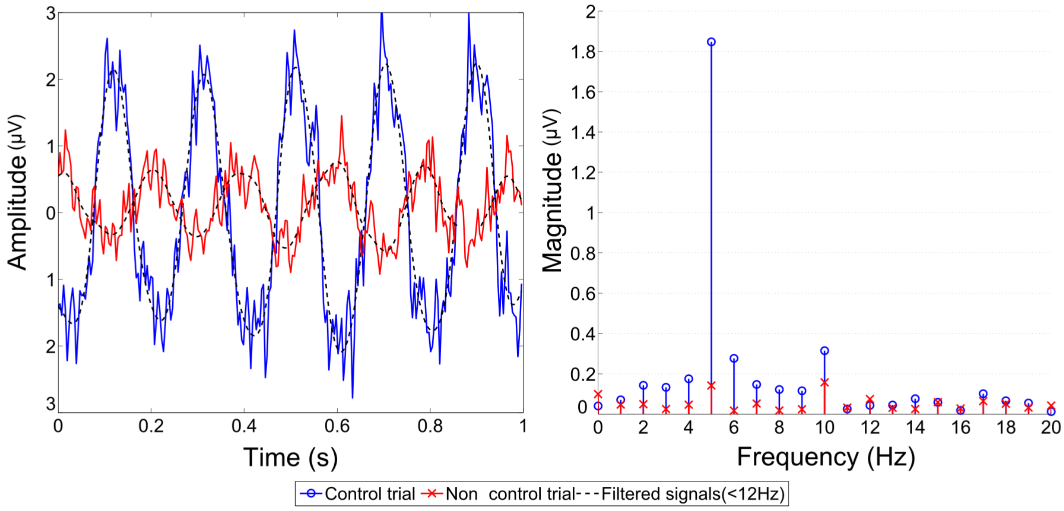


Figure 2.7.: Comparison of the spatial and temporal averaged signal of an ERP-based spelling trial (blue line) and a non-control trial (red line). On the left, the time-domain and on the right, the frequency domain plot of the signal. The black dashed lines represent the same signals after 12 Hz low pass filtering.

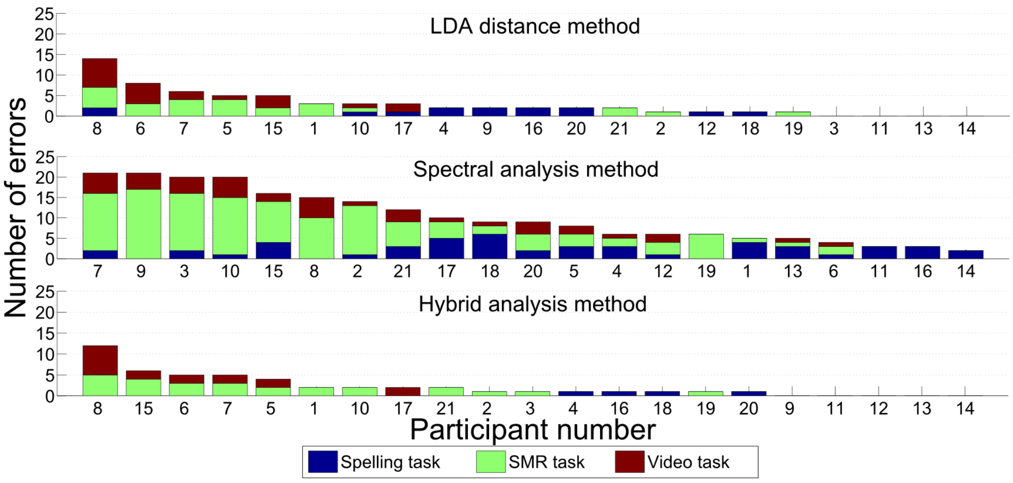


Figure 2.8.: Graphical comparison of different state detection errors per method and participant. The data was sorted with decreasing number of errors from left to right. The total number of trials per participant was 50.

2.3.1. Automatic Pause Detection During BCI Web Browsing

A. Pinegger, L. Deckert, S. Halder, J. Faller, I. Käthner, S.C. Wriessnegger, A. Kübler, and G.R. Müller-Putz. Automatic pause detection during P300 web browsing. *Proceedings of the 6th International Brain-Computer Interface Conference,* 2014. Doi: 10.3217/978-3-85125-378-8-76. [159]

Analyzing the data of the study presented in Section 2.2.1 inspired us to test a further, new state detection approach. We hypothesized that during the control trials, the user produces fewer artifacts in the EEG than during non-control trials. There are two reasons for this hypothesis: First, we used a dry electrode-based system prone to movement artifacts and second, by observations made during the study, we determined that the users move more when they do not want to spell with the BCI. This knowledge can be used to detect non-control periods during BCI spelling or control tasks. We used the offline data of the mentioned study to test this approach. An inverse filter was trained on the calibration data of each participant. This filter was used to classify the trials of the email writing and reading tasks. Results indicated the possibility of detecting the correct state in eight out of the ten users with 100% accuracy. Furthermore, misclassifications due to movement artifacts could be effectively suppressed.

Contribution to this thesis: We introduced and tested a further method to make a visual ERP-based BCI work asynchronously. The used setup allows detection of non-control states with an accuracy of up to 100%.

2.4. Evaluation of Different EEG Acquisition Systems Concerning their Suitability for Building a BCI

A. Pinegger, S.C. Wriessnegger, J. Faller, and G.R. Müller-Putz. Evaluation of different EEG acquisition systems concerning their suitability for building a brain-computer interface: Case Studies. *Frontiers in Neuroscience*, 10, 2016. doi: 10.3389/fnins.2016.00441. [160]

As indicated in the last section, different EEG amplifier systems have different characteristics. Therefore, the system fitting best for the usability requirements for building an ERP-based BCI needs to be examined. We tested and evaluated three different biosignal acquisition systems. The systems had dry , gel-, and tap water-based electrodes, see Figure 2.9. One of them also had a wireless data transmission. First, we tested the short circuit noise as a technical feature of

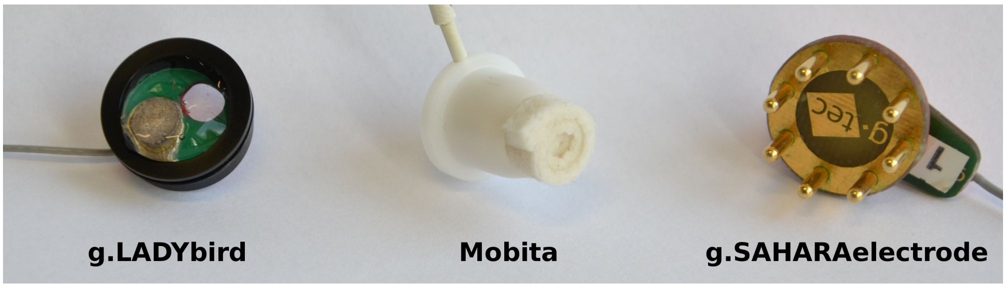


Figure 2.9.: From left to right: the g.LADYbird hydrogel-based electrode (Guger Technologies OG, Graz, Austria), the tap water-based electrode of the Mobita system (Twente Medical Systems International B.V., Oldenzaal, the Netherlands), and the dry electrode of the g.Sahara system (Guger Technologies OG, Graz, Austria).

each system, see Figure 2.10. Second, usability characteristics such as accuracy and comfort of the system were evaluated in a study with nine participants. The spelling and control tasks were identical with the tasks already introduced in Section 2.2. Moreover, the users had to answer various questionnaires to evaluate satisfaction and comfort.
Results were that small, but important differences between the systems are detectable, see Figures 2.10 and 2.11. These differences deliver arguments to define special areas of application for each system. The gel electrode-based system has the advantage that the signal quality is high and stable, and as a result, the

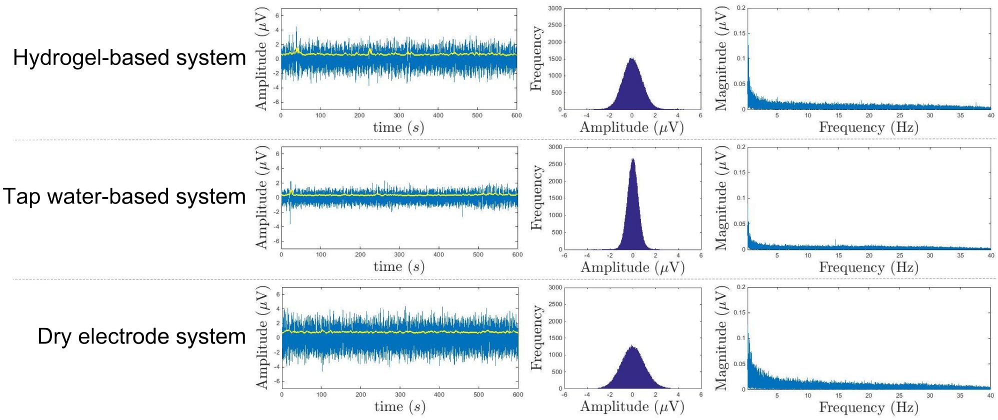


Figure 2.10.: Comparison of the short circuit noise measurement results. A raw signal plot (left), histogram (middle), and amplitude spectrum (right) after 0.1–40 Hz band-pass filtering is shown. A yellow line indicates the RMS of the signals in the left plots.

efficiency and effectiveness are also high. One disadvantage may be that hair must be cleaned after the use because of the gel. The tap water electrode-based system delivers a comparable signal quality without the problem of cleaning the hair after every use. However, it is tricky to set up the system when the user has long hair, because the hairs under each electrode have to be pushed to the side to achieve a high signal quality. The signal quality of the dry electrode-based system is worse than the others with all its consequences. However, the setup is the easiest because the user has to wear only the electrode cap, and cleaning the hair is not necessary.

Contribution to this thesis: The question we wanted to answer here was whether an EEG acquisition system exists that perfectly suits for building an ERP-based BCI. We evaluated technical as well as UCD characteristics. The result and consequently the answer to the initial question is that none of the tested systems, in general, suit perfectly. According to usability requirements, every tested system has weaknesses. As a consequence, further research and development in user-friendly EEG acquisition hardware is necessary.

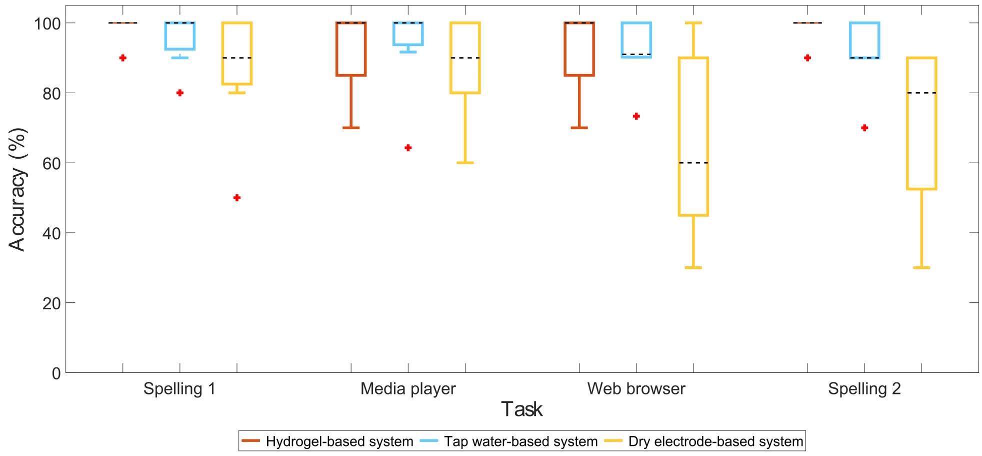


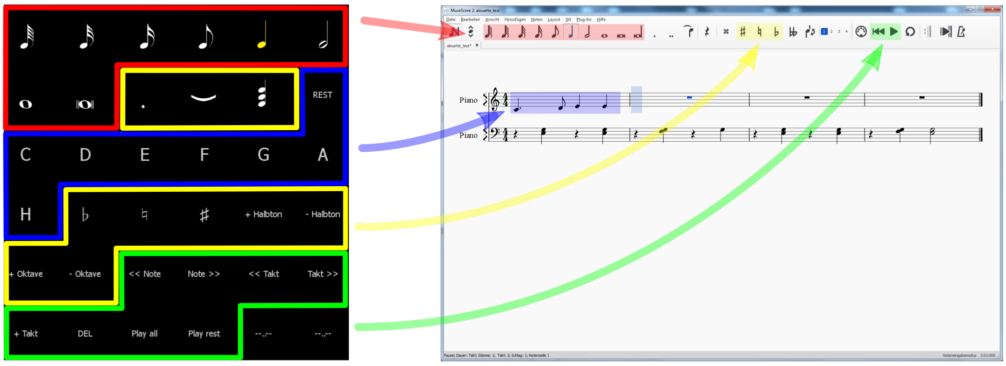
Figure 2.11.: Boxplots of the averaged accuracies per task and system. The central mark (dashed line) of each box is the median, the edges of the box are the 25th and 75th percentiles; the whiskers extend to the most extreme data points (1.5× interquartile range). Outliers are marked with red crosses.

2.5. Composing only by Thought: Novel Application of the ERP-based BCI

A. Pinegger, H. Hiebel, S. Wriessnegger, and G. Müller-Putz. Composing only by thought: Novel application of the P300 brain-computer interface. *Public Library of Science (PLoS) One*, 12(9), 2017. Doi: 10.1371/journal.pone.0181584. [161]

Various applications are controllable via an ERP-based BCI. So far, users can control a media player, a web browser, and a spelling application with the implemented BCI. Here, we introduce the control of a music composing software. This is an application which was not controllable via a BCI before, and in addition to the already existing Brain Painting [103, 104, 162] application, this is a further method for users to express themselves creatively. We adapted our ERP-based BCI controller in a way that the elements shown inside the matrix are easily and flexible exchangeable by the operator. Therefore, we implemented a javascript object notation (JSON) interface so that the controller can read the content of the stimulation matrix out of a JSON file. Controlling such a complex application makes it necessary to add additional parameters to each element of the stimulation matrix. We added a parameter to mark whether the element is a jump element, i.e., when the user selects this element the matrix changes to a different matrix by "jumping" to a different matrix object inside the JSON file. Furthermore, what is shown inside the matrix and what is sent to the application can be defined separately for each element. Finally, an element can stay selected until the user selects it again. With these additional features, it is possible to control applications by sending keyboard shortcuts. We decided to use MuseScore (https://musescore.org) as composing software because this application is fully controllable via keyboard shortcuts. In Figure 2.12, the stimulation matrix for composing and the corresponding MuseScore functionality are shown.

We performed a study with seventeen musical participants and one professional



a b

Figure 2.12.: Sketch of the stimulation matrix and the corresponding commands in MuseScore. Red elements inside the red rectangle change the note length; elements inside the yellow rectangles provide extra features per note such as dot or slur; the pitch is selected with the elements in the blue rectangle; finally to play the composition, the elements in the green rectangle can be used.

composer to evaluate our implemented ERP-based music composing system – we called it Brain Composer. The participants had to fulfill four different tasks using the Brain Composer system, see Figure 2.13. Once they completed all tasks, additional UCD aspects were evaluated using questionnaires and VASs. The results of the effectiveness and efficiency assessment showed that fourteen participants were able to copy-compose the presented melody within the given time frame and only two of the eighteen participants were more than ten selections away from finishing when the task was aborted. All participants used the opportunity to compose their own melody with the Brain Composer. Thirteen participants composed the maximum length of 30 minutes.

Results of the workload evaluation with the NASA-TLX indicate a moderate

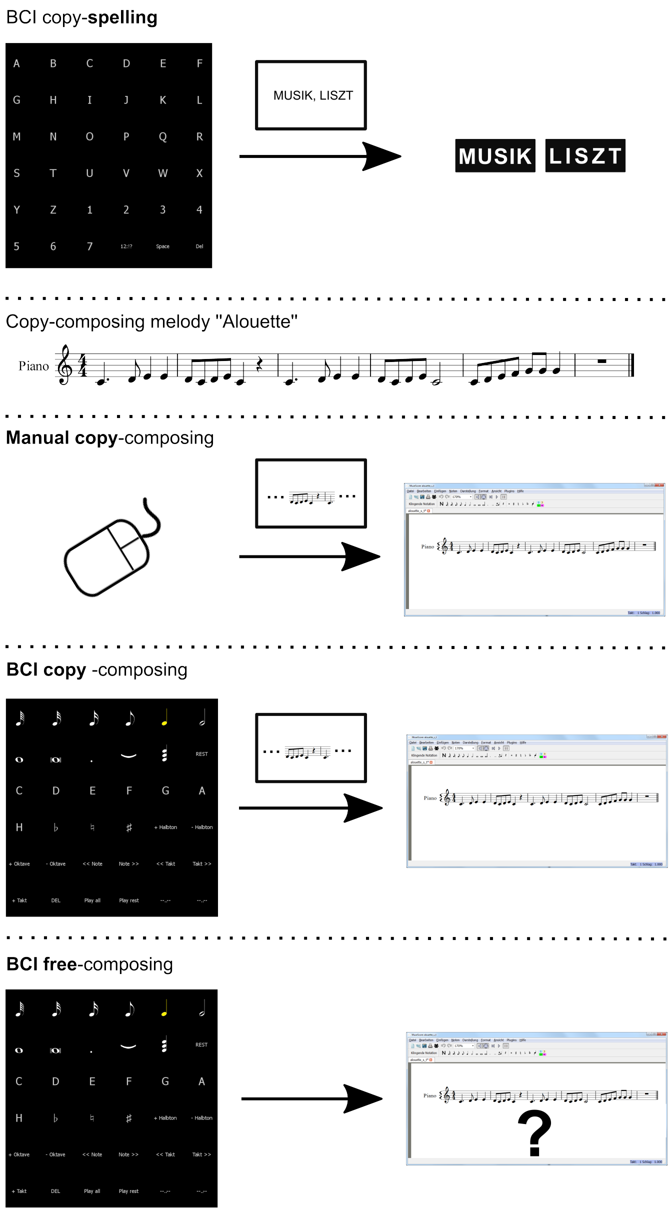


Figure 2.13.: Every row shows one task the participants had to fulfill. Task 1 was to copy-spell "musik" and "liszt" with the ERP-based BCI. The second row shows the first six bars of the well-known French Canadian children's song Alouette. Task 2 was to manually copy-compose the melody of Alouette. Task 3 was to copy-compose the melody of Alouette with the ERP-based BCI. Finally, task 4 was to compose free for 30 minutes.

workload. Even more importantly, however, satisfaction needed to be evaluated. All non-professional participants enjoyed using of the Brain Composer system, felt good control, and were satisfied with the system, see Figure 2.14. The professional composer was not as satisfied as the other participants. He argued that the method of making selections restricts his composing process. According to the UEQ, the participants had a positive impression of all the asked items, except for efficiency, which was rated as neutral. The participants also had the opportunity to provide direct written feedback. Many participants suggested a "pause" button to have flexible time between selections. Some of the reported problems and suggestions to improve the system are already solved and integrated into the upcoming version of the MuseScore software, as initial tests with the new version indicate.

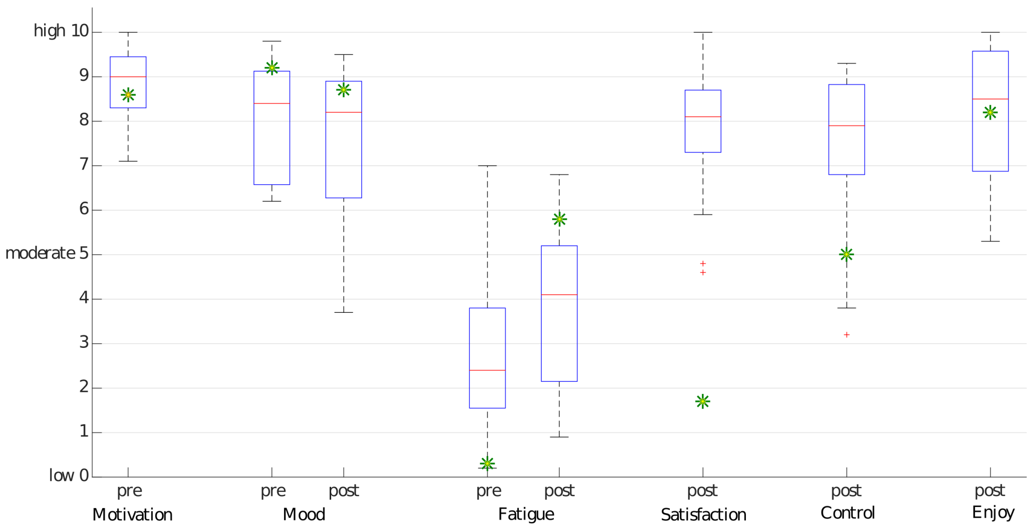


Figure 2.14.: Boxplots of the non-professional participants' VAS scores. The professional composer's scores are shown as green asterisks.

Contribution to this thesis: We introduced and evaluated a new application that is fully controllable with the ERP-based BCI. This so-called Brain Composer enables users to compose music with different instruments via BCI. Therefore, we fundamentally changed the source code of the ERP-based BCI controller. Now, the content of the matrix can be easily changed, and single items are more powerful than before. In addition, a dynamic stopping algorithm [97] was integrated, which increased the speed of the ERP-based BCI. Furthermore, the classification method was changed. Now the sLDA [90] was used for classification instead of the SWLDA. We showed that users are able to copy-compose a given melody very quickly and composing a new melody is easy and amusing.

2.6. A Generic ERP Classifier Approach

A. Pinegger and G.R. Müller-Putz. No training, same performance!? - A generic P300 classifier approach. *Proceedings of the 7th International BCI Conference*, 2017. Doi: 10.3217/978-3-85125-533-1-77. [163]

Thinking about the timing and the stability of ERPs leads us to our next work. Should not it be possible to calculate a working generic classifier out of the calibration data from recent studies? We used the data of the Brain Composer study, see Section 2.5, to train a generic classifier and tested it with the data of the EEG acquisition devices study, see Section 2.4. A graphical comparison of parts of the results can be seen in Figure 2.15.
In brief, the simulated results were comparable, whereby at a lower number of flashing sequences, the personalized classifier outperformed the generic classifier.

Contribution to this thesis: This work was the proof of the idea that a generic classifier made out of a big user dataset works comparable to a personalized classifier, calibrated on the data of a single user. This work provides many further opportunities for future research in this field.

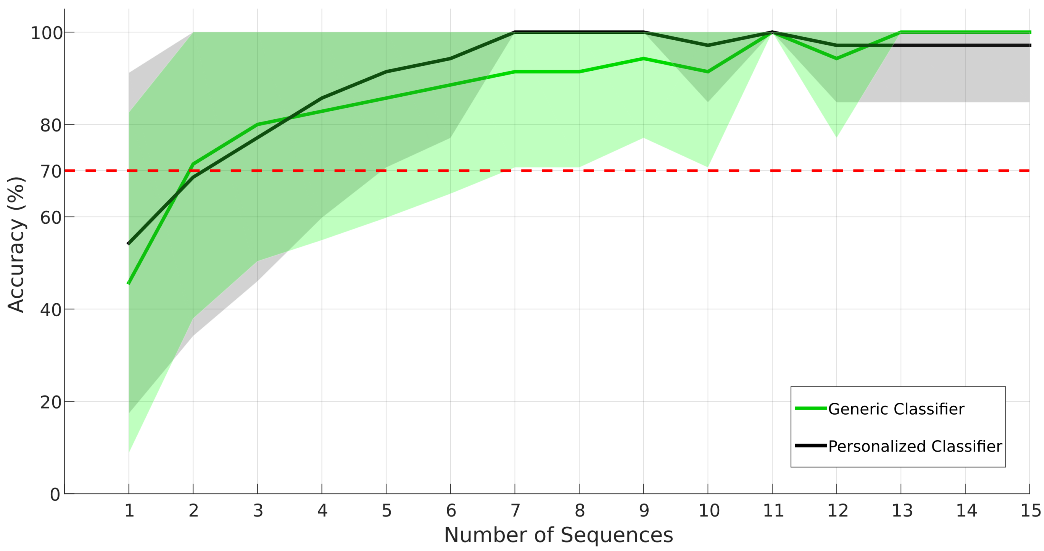


Figure 2.15.: Comparison of the results achieved using the generic and the personalized classifier. Gray and green areas indicate the confidence intervals for proportions. The red dashed line indicates the minimal level of sufficient accuracy according to recent publications.

3. Discussion

The central aim of this thesis was to implement and evaluate an easy-to-use, visual ERP-based BCI using UCD principles. Therefore, a BCI was designed based on the outcome of recent research. This ERP-based BCI can control various applications not only for communication (speller), but also for fun and social interaction (media player and web browser), as well as creative self-expression (Brain Composer). Suitable EEG acquisition systems and asynchronous control methods were investigated to make the developed ERP-based BCI system more comfortable and user-friendly. In the following, the achievements of this thesis towards building a practical and user-friendly ERP-based BCI system are discussed.

3.1. Towards a Practical ERP-based BCI

The first paper regarding a working, visual ERP-based BCI was published more than thirty years ago [76]. Since then, significant amount of research in this field has been conducted. However, only beginnings to make the visual ERP-based BCI have become a practical, universal, and easy-to-use assistive device, which can be used outside the laboratories are recognizable [102, 106, 164]. To the knowledge of the author, only one commercial visual ERP-based BCI is available by the company g.tec (Guger Technologies OG, Graz, Austria)

In the first publication (Pinegger et al. [154]), an innovative visual ERP-based BCI system was introduced. The SignalServer software is used for signal acquisition. This software has been developed during the EC FP7 project TOBI (2008–2013) as a universal interface for signal acquisition [155]. A major advantage of this software is its ability to connect different signal acquisition devices to the BCI only by changing the configuration. Meanwhile, other implementations exist also targeting the abstraction of the interface between the signal acquisition on hardware level and signal distribution on software level, e.g., the Lab Streaming Layer framework (https://github.com/sccn/labstreaminglayer).

The core unit of the BCI was split into two parts: The GUI which displays the stimulation matrix and handles the manual user inputs, and a Simulink model, which performs the signal processing and classification. A visual ERP-based BCI requires an exact timing of the stimulation events [73]. The graphical representation capabilities of Matlab/Simulink are limited and an accurate timing could not be guaranteed. Therefore, a design decision was to implement the

GUI using the QT framework and C++ code. Additionally, designing and implementing the user interface to start, calibrate, and use the BCI as well as select an application to be controlled was also simpler and more appealing using the mentioned framework. Another design decision was that the whole signal acquisition and processing should run in the background and not be visible to the user. This means that the operator controls the whole system via clickable menu items of the GUI. The operator is also able to check the EEG signals by clicking a menu item and without manually starting another application.
The famous faces paradigm was chosen to highlight the rows and columns of the stimulation matrix. According to [81], this paradigm guarantees a higher spelling speed and accuracy compared to simple contrast changes as stimulation event. An additional benefit of using famous faces is that it is also more attractive and by changing the picture of the face, less monotonous. Signal processing and classification were performed according to the findings of Krusienski et al. [89]. In [89], different classifiers are compared for their suitability classifying ERPs. The main result was that the SWLDA classifier suites the most. Therefore, we decided to use an SWLDA classifier in this first version of the BCI.
The calibration of the BCI was performed automatically, cf. [164]. Automatically, in the meaning of that the operator manually starts the calibration, the calibration procedure takes places including classifier calculation without any further manual inputs, and finally, the system generates feedback whether the calibration was successful. In this case, it was successful, the user could immediately start with the free spelling. This initial version of the system was a simple visual ERP-based speller.
However, users do not only want to spell letters [148], they also want to control other applications with an ERP-based BCI. Therefore, methods were developed to control other applications with this BCI (Halder and Pinegger et al. [156], Pinegger et al. [157]). Interfaces to a web browser and a media player were defined and implemented. The web browser has an active interface, i.e., the browser sends the elements of the stimulation matrix actively to the ERP-based BCI controller and the size of the matrix changes accordingly. Compared to previously developed visual ERP-based BCI controlled web browser approaches [105, 165, 166], this implementation differs in two points: (i) The developed system automatically switches between control and spelling matrices, and (ii) the size of the matrix is automatically adapted to the number of visible links inside the browser window. These two features allow fast and convenient web browsing. The implemented system still requires two screens, but an intuitive control would be displaying the stimuli directly on the screen overlaying the links of the website. This implementation already exists [106], but it has the

shortcoming of being able to be used only with specially prepared websites due to the clustering of the links. Consequently, the stimuli of different links may be challenging to fixate individually.
The interface to the media player is passive, which means that the size and the elements of the stimulation matrix are fixed. This interface enables the user to control a fancy, freely available media player. All prior approaches consisted of custom-made media players which had the focus on functionality rather than an appealing GUI [110, 167, 168]. The results of the in [156] performed study confirmed that the users, even one out of three disabled users, can control various applications with high accuracies. The accuracies were all above the – in the literature – suggested minimum level of sufficient control of 70% [169].

In addition to evaluating the system in means of accuracy and information transfer rate, we also assessed the usability of the system with questionnaires. Users were, in general, satisfied with the system, but rated the speed and comfort low. Moreover, the synchronous mode of the system, i.e., the system selects an item of the matrix even when the user wants to make a pause, was criticized. The latter problem is discussed in more detail within the next section.
Speed and comfort of a BCI are, among others, correlated with the used EEG acquisition system. In Pinegger et al. [160], three different biosignal acquisition systems were investigated regarding their suitability of building an ERP-based BCI. Similar to the [156] objective, e.g., accuracy, and subjective, e.g., the satisfaction of the user, parameters were determined to evaluate the systems. Additionally, a technical parameter, namely the short circuit noise, as an additional signal quality parameter was measured. To our knowledge, this was the first time that EEG acquisition systems were evaluated regarding all usability aspects. Previous publications in this area have mainly focused on the achieved accuracy and used it as a benchmark for systems [149, 150, 170]. Our results indicate that more comfortable systems (in terms of hair treatment after the usage) have the problem of obtaining a good signal quality. This is due to the gap between the electrode and the skull surface, which can be perfectly bridged with conductive gel. However, when using a small water-soaked cotton piece or gold alloy pins, such as the tested tap water electrode-based and dry electrode-based systems, this conductive connection works only under perfect conditions satisfactorily. The knowledge of the way of creating perfect conditions enables the user to obtain a comfortable and efficient ERP-based BCI without the necessity of gel. This study indicates the way of treating these more comfortable systems to achieve a sufficient signal quality. However, in contrast

to the reported results in Zander et al. [149] and Guger et al. [150], we achieved significantly lower accuracies of the dry electrode-based system compared to the ”wet” systems. One reason might be that our participants used the system over a longer period than the participants of [149, 150]. It seems that the signal quality of the ”dry” system is not as stable over time as the ones using ”wet” electrodes. The reported decreasing comfort over time for the dry electrode-based system might distract the participants and is probably also a reason for the achieved lower accuracies of this system.

In Pinegger et al. [161] healthy participants control a music composing software using the previously introduced and evaluated ERP-based BCI [154, 156]. A music composing software is a very complex application with a wealth of input options. We decided to use a composing software that can be controlled entirely by keyboard shortcuts. Consequently, the developed ERP-based BCI controller was modified in a way that it could send keystroke codes to a defined application. Additionally, a dynamic stopping algorithm was implemented allowing the ERP-based BCI to be faster. Many different dynamic stopping algorithms have been implemented so far. For review, see [97]. For this thesis, a simple but robust dynamic stopping algorithm was used: After every sequence, the data is classified, and three identical classifications of the same element in a row result in the selected element, cf. [96]. The classification method was also changed. According to the suggestions of [90], an sLDA classifier was used instead of the previously used SWLDA classifier. However, the performance of the sLDA classifier could not be compared with earlier studies, due to the also newly used dynamic stopping method.
This system, the so-called Brain Composer, was evaluated among eighteen participants. In addition to regular musical participants, one professional composer took part. The participants were asked to use the Brain Composer for copy-composing a given melody as well as for free-composing a melody they had in mind. As in [156, 160], usability parameters were assessed. The results indicate that the participants enjoyed using the Brain Composer. Thanks to the dynamic stopping method, selections are possible within twelve seconds. This algorithm makes the system significantly faster than previous versions of the introduced ERP-based BCI. Results from the questionnaires and the VASs indicate that the participants, in general, were highly satisfied with the system. However, the professional composer was not satisfied. He reported two reasons. First, when he heard about the study, he had a different composing method in his mind. He thought that he would have to think of notes and the system

would detect the correct note. Second, normally he uses a musical keyboard in combination with a composing software to compose, and the way he had to compose with the Brain Composer restricted his creative process.

Finally, a generalized classifier approach was tested in Pinegger et al. [163]. Calibration data of the Brain Composer study [161] was used to calculate a general classifier. This classifier was evaluated offline performing cross-validation on the same data (leave-one-participant-out method) and with an offline re-classification of the data of a previous study [160]. Results indicated that the calculated classifier can be used instead of a personally calibrated classifier. Sufficient accuracies were also reported by other scientists when using a generic classifier approach [85, 86]. However, our main result indicated that comparable accuracies can only be achieved with a higher number of flashing sequences. Therefore, this general classifier suits perfectly as a basis for online adaption during the ERP-based BCI controller usage.

3.1.1. The Asynchronous ERP-based BCI Controller

Compared to using an ERP-based BCI for continuous spelling, controlling a web browser or media player is significantly more challenging. The user often has to wait until the content is loaded or wants to read or watch something and the ERP-based BCI controller should pause in the meantime. This functionality was not intended in the implementation of simple ERP-based spelling BCIs of the past, e.g., [88, 171, 172]. A few seconds after the last selection, the stimulation starts again and a new selection is eventually made, intentionally or not. This problem can be neglected when the user wants to spell letters because superfluous letters can be deleted afterwards. However, when the user wants to watch a movie or read the content of a web page, this behavior is a serious problem. Therefore, two different states were defined [151]: (i) The control state, i.e., the user wishes to actively use the ERP-based BCI, and (ii) the non-control state, i.e., the user wants to put the ERP-based BCI into standby mode to watch, for example, a movie. In Pinegger et al. [158] a novel method to detect the control state was developed. This is a hybrid method utilizing two different parameters of the ERP-based BCI. On one side, the distances of the classifier outputs and on the other side, frequency components of the EEG, which are evoked by the stimulation frequency. The combination of these two parameters delivers an accurate indicator of whether the user is in control or non-control state. A

direct comparison of the results from this study and the studies performed by different other groups [101, 151–153] is difficult due to varying classification approaches, stimulation modalities, and especially, performance evaluations. However, comparable existing methods [173, 174] show lower accuracies than the suggested hybrid approach without using another BCI methodology as in [124].
The second method utilizes a weakness of a specific EEG acquisition device to decide between control and non-control state in Pinegger et al. [159]. Dry electrode-based EEG acquisition devices are normally prone to movement artifacts, which evoke high amplitudes inside the EEG. Using an inverse filter [175] created out of the almost artifact free calibration data allows detecting artifacts during the online control task. The hypothesis behind this is that a user in control state produces fewer artifacts than a user in the non-control state. This work indicated that this method works accurately as state detector (accuracies between 83.64% and 100%), and additionally misclassifications based on artifacts can be avoided.

3.2. Limitations and Outlook

The results of this thesis are mainly based on testing and evaluating the developed ERP-based BCI with healthy individuals. However, according to the BNCI Horizon 2020 roadmap [5], BCIs are mainly tools for disabled people and the results do not readily apply to disabled people. The results of the three disabled users who used the developed system in Halder and Pinegger et al. [156] were inconclusive. One had excellent control, one moderate, and for one disabled user the system did not work. However, many studies exist, showing that ERP-based BCIs can be used satisfactorily by disabled people, e.g., [98–100]. Moreover, it is quite easy to change the settings of the developed system and customize it to the user. With the GUI the inter stimulus interval (ISI), the stimulus interval (SI), the length of the break after every spelled symbol, the stimulus picture, as well as other calibration settings can be adapted to the users' needs.

An important feature of a state-of-the-art BCI systems is the ability to be controlled asynchronously. In this thesis, two methods for asynchronous control are introduced [158, 159]. However, these methods were evaluated based on offline data. No online study has been performed to evaluate the findings of these two publications. The users of the Brain Composer study [161] asked for such an asynchronous mode. Therefore, the next step should be to integrate the asynchronous methods into the well-working Brain Composer.

Speed is still the parameter that makes the visual ERP-based BCI uncompetitive compared to hands-free control methods like eye-tracking. However, the results of recent publications indicate that speed boosts for ERP-based BCIs are possible [176–179]. In particular, Townsend and Platsko [178] introduced a method to significantly speed up visual ERP-based BCIs. They report that the users of their BCI can select on average 17.5 elements per minute from an 8×9 matrix. Compared to the word copy-spelling results of the Brain Composer study [161] in this thesis, this is more than three times faster without taking the slightly bigger matrix into account. The high spelling rates are almost comparable to the reported spelling rates (18.7 selections per minute) of an eye-tracking system [180]. The latest publication in that area from Nagel and Spüler [179] introduced an asynchronous working BCI based on visual evoked potentials. They reported that participants wrote on average 16.1 correct case-sensitive letters per minute.

A vision for the future of BCIs is that they may be used by healthy people as well. The introduced training-free approach [163] in combination with an asynchronous control method, e.g. the introduced approaches [158, 159], point a way in this direction. Moreover, in the year 2013, the introduced system was part of an art project [181] in Graz, Austria. Within the scope of the "Steirischer Herbst" the life and environment of patients in vegetative state and people living with a mental or physical impairment were shown. There, inter alia, the possible applications of ERP-based BCIs in this field were demonstrated. At the same time, many visitors – mainly artists – were enthusiastic about the BCI technology and its possible application in art projects. Furthermore, the German artist Adi Hoesle [182] uses the BCI-based Brain Painting system [103, 183] to create pictures.

3.3. Conclusion

Within this thesis, significant steps towards an easy to set up and operate, functional, and robust visual ERP-based BCI controller were made. Developing a single application, which allows the operator to start the signal acquisition, check the signals, start the automatic calibration of the classifier, and finally enables the user to spell letters or control other applications are significant achievements. Evaluating biosignal acquisition systems regarding their suitability building an ERP-based BCI and developing a new asynchronous method for visual ERP-based BCI control further contribute to the main aim of this thesis of bringing the ERP-based BCI out of the laboratories to the end users.

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 (2002), pp. 767–791. DOI: 10.1016/S1388-2457(02)00057-3 (cit. on p. 1).

[2] A. Kübler, B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer. "Brain-computer communication: unlocking the locked in." In: *Psychological Bulletin* 127 (2001), pp. 358–375. DOI: 10.1037/0033-2909.127.3.358 (cit. on p. 1).

[3] J. Millán, R. Rupp, et al. "Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges." In: *Frontier in Neuroscience* 4.161 (2010). DOI: 10.3389/fnins.2010.00161 (cit. on p. 1).

[4] J. Wolpaw and E. W. Wolpaw. *Brain-Computer Interfaces: Principles and Practice*. 1st ed. Oxford University Press, Jan. 11, 2012. ISBN: 0195388852 (cit. on p. 1).

[5] C. Brunner, N. Birbaumer, et al. "BNCI Horizon 2020: towards a roadmap for the BCI community." In: *Brain-Computer Interfaces* 2.1 (2015), pp. 1–10. DOI: 10.1080/2326263X.2015.1008956 (cit. on pp. 1, 43).

[6] C. Brunner, N. Birbaumer, et al. *Roadmap – The future in brain/neural-computer interaction: Horizon 2020*. 2015. DOI: 10.3217/978-3-85125-379-5 (cit. on p. 2).

[7] E. Buch, C. Weber, et al. "Think to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke." In: *Stroke* 39 (2008), pp. 910–917. DOI: 10.1161/STROKEAHA.107.505313 (cit. on p. 1).

[8] J. Mellinger, G. Schalk, et al. "An MEG-based brain-computer interface (BCI)." In: *NeuroImage* 36.3 (July 2007), pp. 581–593. DOI: 10.1016/j.neuroimage.2007.03.019 (cit. on p. 1).

[9] R. Sitaram, N. Weiskopf, A. Caria, R. Veit, M. Erb, and N. Birbaumer. "fMRI brain-computer interfaces." In: *IEEE Signal Processing Magazine* 25 (2008), pp. 95–106. DOI: 10.1109/MSP.2008.4408446 (cit. on p. 1).

[10] N. Weiskopf, K. Mathiak, et al. "Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI)." In: *IEEE Transactions on Biomedical Engineering* 51 (2004), pp. 966–970. DOI: 10.1109/TBME.2004.827063 (cit. on p. 1).

[11] G. Bauernfeind, R. Leeb, S. Wriessnegger, and G. Pfurtscheller. "Development, set-up and first results of a one-channel near-infrared spectroscopy system." In: *Biomedizinische Technik* 53 (2008), pp. 36–43. DOI: 10.1515/BMT.2008.005 (cit. on p. 1).

[12] R. Sitaram, H. Zhang, et al. "Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface." In: *NeuroImage* 34 (2007), pp. 1416–1427. DOI: 10.1016/j.neuroimage.2006.11.005 (cit. on p. 1).

[13] 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 (2004), pp. 63–71. DOI: 10.1088/1741-2560/1/2/001 (cit. on p. 3).

[14] G. Schalk and E. C. Leuthardt. "Brain-Computer Interfaces Using Electrocorticographic Signals." In: *IEEE Reviews in Biomedical Engineering* 4 (2011), pp. 140–154. DOI: 10.1109/rbme.2011.2172408 (cit. on p. 3).

[15] E. Fetz. "Operand conditioning of cortical unit activity." In: *Science* 163.3870 (1969), pp. 955–958. DOI: 10.1126/science.163.3870.955 (cit. on p. 3).

[16] L. R. Hochberg, M. D. Serruya, et al. "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).

[17] K. J. Otto, K. A. Ludwig, and D. R. Kipke. "Acquiring Brain Signals from within the Brain." In: *Brain–Computer InterfacesPrinciples and Practice*. Jan. 2012, pp. 81–103. DOI: 10.1093/acprof:oso/9780195388855.003.0005 (cit. on p. 3).

[18] M. van Gerven, J. Farquhar, et al. "The brain-computer interface cycle." In: *Journal of Neural Engineering* 6, 041001 (2009). DOI: 10.1088/1741-2560/6/4/041001 (cit. on p. 3).

[19] *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Oxford University Press, Jan. 4, 2018. ISBN: 0190228482 (cit. on p. 3).

[20] E. R. Kandel, J. H. Schwartz, T. M. Jessell, S. A. Siegelbaum, and A. J. Hudspeth. *Principles of Neural Science*. McGraw-Hill Education Ltd, Nov. 14, 2012. ISBN: 0071390111 (cit. on p. 3).

[21] S. Rush and D. A. Driscoll. "EEG Electrode Sensitivity—An Application of Reciprocity." In: *IEEE Transactions on Biomedical Engineering* BME-16.1 (Jan. 1969), pp. 15–22. DOI: 10.1109/tbme.1969.4502598 (cit. on p. 4).

[22] T. Oostendorp, J. Delbeke, and D. Stegeman. "The conductivity of the human skull: results of in vivo and in vitro measurements." In: *IEEE Transactions on Biomedical Engineering* 47.11 (Nov. 2000), pp. 1487–1492. DOI: 10.1109/tbme.2000.880100 (cit. on p. 4).

[23] H. Berger. "Über das Elektrenkephalogramm des Menschen." In: *Archiv für Psychiatrie und Nervenkrankheiten* 87 (1929), pp. 527–570. DOI: 10.1007/BF01797193 (cit. on p. 4).

[24] T. F. Collura. "History and Evolution of Electroencephalographic Instruments and Techniques." In: *Journal of Clinical Neurophysiology* 10.4 (1993), pp. 476–504. DOI: 10.1097/00004691-199310000-00007 (cit. on p. 4).

[25] J. J. Vidal. "Toward direct brain-computer communication." In: *Annual Review of Biophysics and Bioengineering* 2 (1973), pp. 157–180. DOI: 10.1146/annurev.bb.02.060173.001105 (cit. on p. 4).

[26] J. Vidal. "Real-time detection of brain events in EEG." In: *Proceedings of the IEEE* 65.5 (1977), pp. 633–641. DOI: 10.1109/proc.1977.10542 (cit. on p. 4).

[27] N. Birbaumer, T. Elbert, A. G. M. Canavan, and B. Rockstroh. "Slow potentials of the cerebral cortex and behavior." In: *Physiological Reviews* 70.1 (1990), pp. 1–41 (cit. on p. 4).

[28] 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: *International Journal of Neuroscience* 9.3 (1979), pp. 175–183. DOI: 10.3109/00207457909147670 (cit. on p. 4).

[29] T. Hinterberger, S. Schmidt, et al. "Brain-Computer Communication and Slow Cortical Potentials." In: *IEEE Transactions on Biomedical Engineering* 51.6 (2004), pp. 1011–1018. DOI: 10.1109/TBME.2004.827067 (cit. on p. 4).

[30] A. Kübler, B. Kotchoubey, et al. "The thought translation device: a nerurophysiological approach to communication in total motor paralysis." In: *Experimental Brain Research* 124 (1999), pp. 223–232. DOI: 10.1007/s002210050617 (cit. on p. 4).

[31] N. Birbaumer, N. Ghanayim, et al. "A spelling device for the paralysed." In: *Nature* 398 (1999), pp. 297–298. DOI: 10.1038/18581 (cit. on p. 4).

[32] B. Obermaier, C. Neuper, C. Guger, and G. Pfurtscheller. "Information transfer rate in a five-classes brain-computer interface." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 9 (2001), pp. 283–288. DOI: 10.1109/7333.948456 (cit. on p. 5).

[33] E. Curran, P. Sykacek, et al. "Cognitive tasks for driving a brain-computer interfacing system: a pilot study." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12 (2003), pp. 48–54. DOI: 10.1109/TNSRE.2003.821372 (cit. on p. 5).

[34] E. V. 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 (Apr. 2012), pp. 86–94. DOI: 10.1016/j.ijpsycho.2012.01.014 (cit. on p. 5).

[35] J. Faller, R. Scherer, et al. "Non motor tasks improve adaptive brain-computer interface performance in users with severe motor impairment." In: *Frontiers in Neuroscience* 8.320 (Oct. 2014). DOI: 10.3389/fnins.2014.00320 (cit. on p. 5).

[36] J. Millán and J. Mouriño. "Asynchronous BCI and local neural classifiers: an overview of the adaptive brain interface project." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11 (2003), pp. 159–161. DOI: 10.1109/TNSRE.2003.814435 (cit. on p. 5).

[37] C. Neuper, G. R. Müller, A. Kübler, N. Birbaumer, and G. Pfurtscheller. "Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment." In: *Clinical Neurophysiology* 114 (2003), pp. 399–409. DOI: 10.1016/S1388-2457(02)00387-5 (cit. on p. 5).

[38] A. Kübler, F. Nijboer, et al. "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface." In: *Neurology* 64.10 (May 2005), pp. 1775–1777. DOI: 10.1212/01.wnl.0000158616.43002.6d (cit. on p. 5).

[39] G. Pfurtscheller, C. Guger, G. Müller, G. Krausz, and C. Neuper. "Brain oscillations control hand orthosis in a tetraplegic." In: *Neuroscience Letters* 292 (2000), pp. 211–214. DOI: 10.1016/S0304-3940(00)01471-3 (cit. on p. 5).

[40] G. Pfurtscheller, G. R. Müller, J. Pfurtscheller, H. J. Gerner, and R. Rupp. ""Thought"-control of functional electrical stimulation to restore handgrasp in a patient with tetraplegia." In: *Neuroscience Letters* 351 (2003), pp. 33–36. DOI: 10.1016/S0304-3940(03)00947-9 (cit. on p. 5).

[41] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp. "EEG-based neuroprosthesis control: a step towards clinical practice." In: *Neuroscience Letters* 382 (2005), pp. 169–174. DOI: 10.1016/j.neulet.2005.03.021 (cit. on p. 5).

[42] M. Rohm, M. Schneiders, et al. "Hybrid brain–computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury." In: *Artificial Intelligence in Medicine* 59.2 (Oct. 2013), pp. 133–142. DOI: 10.1016/j.artmed.2013.07.004 (cit. on p. 5).

[43] R. Leeb, D. Friedman, G. R. Müller-Putz, R. Scherer, M. Slater, and G. Pfurtscheller. "Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegics." In: *Computational Intelligence and Neuroscience* 2007, 79642 (2007). DOI: 10.1155/2007/79642 (cit. on p. 5).

[44] F. Galán, M. Nuttin, et al. "A brain-actuated wheelchair: asynchronous and non-invasive brain-computer interfaces for continuous control of robots." In: *Clinical Neurophysiology* 119 (2008), pp. 2159–2169. DOI: 10.1016/j.clinph.2008.06.001 (cit. on p. 5).

[45] F. Pichiorri, F. D. V. Fallani, et al. "Sensorimotor rhythm-based brain-computer interface training: the impact on motor cortical responsiveness." In: *Journal of Neural Engineering* 8, 025020 (2011). DOI: 10.1088/1741-2560/8/2/025020 (cit. on p. 5).

[46] M. Grosse-Wentrup, D. Mattia, and K. Oweiss. "Using brain-computer interfaces to induce neural plasticity and restore function." In: *Journal of Neural Engineering* 8, 025004 (2011). DOI: 10.1088/1741-2560/8/2/025004 (cit. on p. 5).

[47] K. K. Ang and C. Guan. "Brain-Computer Interface in stroke rehabilitation." In: *Journal of Computing Science and Engineering* 7.2 (2013), pp. 139–146. DOI: 10.1016/j.patcog.2011.04.018 (cit. on p. 5).

[48] A. Biasiucci, R. Leeb, et al. "Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke." In: *Nature Communications* 9.1 (June 2018). DOI: 10.1038/s41467-018-04673-z (cit. on p. 5).

[49] A. Kübler, B. Blankertz, K. R. Müller, and C. Neuper. "A Model of BCI-Control." In: *Proceedings of the 5th International Brain-Computer Interface Conference 2011*. 2011, pp. 100–103. DOI: 10.3217/978-3-85125-140-1 (cit. on p. 5).

[50] T. Dickhaus, C. Sannelli, K.-R. Müller, G. Curio, and B. Blankertz. "Predicting BCI performance to study BCI illiteracy." In: *BMC Neuroscience* 10.Suppl 1 (2009), P84. DOI: 10.1186/1471-2202-10-s1-p84 (cit. on p. 5).

[51] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller. "How many people are able to operate an EEG-based brain-computer interface (BCI)?" In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11 (2003), pp. 145–147. DOI: 10.1109/TNSRE.2003.814481 (cit. on p. 5).

[52] M. Middendorf, G. McMillan, G. Calhoun, and K. S. Jones. "Brain-computer interfaces based on the steady-state visual-evoked response." In: *IEEE Transactions on Rehabilitation Engineering* 8 (2000), pp. 211–214. DOI: 10.1109/86.847819 (cit. on p. 5).

[53] 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 (2006), pp. 30–37. DOI: 10.1109/TNSRE.2005.863842 (cit. on p. 5).

[54] T. Picton, M. John, D. Purcell, and G. Plourde. "Human auditory steady-state responses: The effects of recording technique and state of arousal." In: *Anesthesia and Analgesia* 97.5 (Nov. 2003), pp. 1396–1402. DOI: 10.1213/01.ANE.0000082994.22466.DD (cit. on p. 5).

[55] B. Z. Allison, J. Faller, and C. Neuper. "BCIs That Use Steady-State Visual Evoked Potentials or Slow Cortical Potentials." In: *Brain-Computer Interfaces Principles and Practice*. Jan. 2012, pp. 242–249. DOI: 10.1093/acprof:oso/9780195388855.003.0014 (cit. on p. 5).

[56] P. Martinez, H. Bakardjian, and A. Cichocki. "Fully Online Multicommand Brain-Computer Interface with Visual Neurofeedback Using SSVEP Paradigm." In: *Computational Intelligence and Neuroscience* 2007 (2007), pp. 1–9. DOI: 10.1155/2007/94561 (cit. on p. 5).

[57] M. Cheng and S. Gao. "An EEG-based cursor control system." In: *Proceedings of the First Joint BMES/EMBS Conference. 1999 IEEE Engineering in Medicine and Biology 21st Annual Conference and the 1999 Annual Fall Meeting of the Biomedical Engineering Society*. IEEE, Oct. 1999. DOI: 10.1109/iembs.1999.802747 (cit. on p. 5).

[58] X. Gao, D. Xu, M. Cheng, and S. Gao. "A BCI-based environmental controller for the motion-disabled." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11 (2003), pp. 137–140. DOI: 10.1109/TNSRE.2003.814449 (cit. on p. 5).

[59] X. Chen, Y. Wang, M. Nakanishi, X. Gao, T.-P. Jung, and S. Gao. "High-speed spelling with a noninvasive brain-computer interface." In: *Proceedings of the National Academy of Sciences* 112.44 (Oct. 2015). DOI: 10.1073/pnas.1508080112 (cit. on p. 5).

[60] G. R. Müller-Putz and G. Pfurtscheller. "Control of an electrical prosthesis with an SSVEP-based BCI." In: *IEEE Transactions on Biomedical Engineering* 55 (2008), pp. 361–364. DOI: 10.1109/TBME.2007.897815 (cit. on p. 5).

[61] R. Ortner, B. Z. Allison, G. Korisek, H. Gaggl, and G. Pfurtscheller. "An SSVEP BCI to control a hand orthosis for persons with tetraplegia." In: *IEEE Transactions on Neural Systems Rehabilitation Engineering* 19.1 (Feb. 2011), pp. 1–5. DOI: 10.1109/TNSRE.2010.2076364 (cit. on p. 5).

[62] H. Higashi, T. M. Rutkowski, Y. Washizawa, A. Cichocki, and T. Tanaka. "EEG auditory steady state responses classification for the novel BCI." In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, Aug. 2011. DOI: 10.1109/iembs.2011.6091133 (cit. on p. 5).

[63] D.-W. Kim, H.-J. Hwang, J.-H. Lim, Y.-H. Lee, K.-Y. Jung, and C.-H. Im. "Classification of selective attention to auditory stimuli: Toward vision-free brain-computer interfacing." In: *Journal of Neuroscience Methods* 197.1 (Apr. 2011), pp. 180–185. DOI: 10.1016/j.jneumeth.2011.02.007 (cit. on p. 5).

[64] M.-A. Lopez, H. Pomares, F. Pelayo, J. Urquiza, and J. Perez. "Evidences of cognitive effects over auditory steady-state responses by means of artificial neural networks and its use in brain-computer interfaces." In: *Neurocomputing* 72 (2009), pp. 3617–3623. DOI: 10.1016/j.neucom.2009.04.021 (cit. on p. 5).

[65] C. Pokorny, C. Breitwieser, C. Neuper, and G. Müller-Putz. "Towards a Single-Switch BCI Based on Steady-State Somatosensory Evoked Potentials." In: *Proceedings of the 5th International Brain-Computer Interface Conference 2011*. 2011, pp. 200–204. DOI: 10.3217/978-3-85125-140-1 (cit. on p. 5).

[66] M. Rugg. "Event-related/Evoked Potentials." In: *International Encyclopedia of the Social & Behavioral Sciences*. Elsevier, 2001, pp. 4962–4966. DOI: 10.1016/b0-08-043076-7/03410-0 (cit. on p. 6).

[67] J. D. Kropotov. "Event-Related Potentials." In: *Functional Neuromarkers for Psychiatry*. Elsevier, 2016, pp. 59–78. DOI: 10.1016/b978-0-12-410513-3.00006-1 (cit. on p. 6).

[68] H. Shibasaki and M. Hallett. "What is the Bereitschaftspotential?" In: *Clinical Neurophysiology* 117.11 (Nov. 2006), pp. 2341–2356. DOI: 10.1016/j.clinph.2006.04.025 (cit. on p. 6).

[69] M. Jochumsen, I. K. Niazi, N. Mrachacz-Kersting, D. Farina, and K. Dremstrup. "Detection and classification of movement-related cortical potentials associated with task force and speed." In: *Journal of Neural Engineering* 10.5, 056015 (Aug. 2013). DOI: 10.1088/1741-2560/10/5/056015 (cit. on p. 6).

[70] M. Jochumsen, I. K. Niazi, K. Dremstrup, and E. N. Kamavuako. "Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation." In: *Medical & Biological Engineering & Computing* 54.10 (Dec. 2015), pp. 1491–1501. DOI: 10.1007/s11517-015-1421-5 (cit. on p. 6).

[71] P. Ofner, A. Schwarz, J. Pereira, and G. R. Müller-Putz. "Upper limb movements can be decoded from the time-domain of low-frequency EEG." In: *PLoS ONE* 12.8, e0182578 (Aug. 2017). DOI: 10.1371/journal.pone.0182578 (cit. on p. 6).

[72] A. Schwarz, P. Ofner, J. Pereira, A. I. Sburlea, and G. R. Müller-Putz. "Decoding natural reach-and-grasp actions from human EEG." In: *Journal of Neural Engineering* 15.1, 016005 (Dec. 2017). DOI: 10.1088/1741-2552/aa8911 (cit. on p. 6).

[73] S. J. Luck. *An Introduction to the Event-Related Potential Technique*. The MIT Press, 2005. ISBN: 9780262122771 (cit. on pp. 6, 38).

[74] N. K. Squires, K. C. Squires, and S. A. Hillyard. "Two varieties of long-latency positive waves evoked by unpredictable auditory stimuli in man." In: *Electroencephalography and Clinical Neurophysiology* 38.4 (Apr. 1975), pp. 387–401. DOI: 10.1016/0013-4694(75)90263-1 (cit. on p. 6).

[75] 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. 6).

[76] 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 (1988), pp. 510–523. DOI: 10.1016/0013-4694(88)90149-6 (cit. on pp. 6, 10, 15, 38).

[77] C. Guan, M. Thulasidas, and J. Wu. "High performance p300 speller for brain-computer interface." In: *IEEE International Workshop on Biomedical Circuits and Systems*. IEEE, 2004. DOI: 10.1109/biocas.2004.1454155 (cit. on p. 6).

[78] C. Guger, S. Daban, et al. "How many people are able to control a P300-based brain-computer interface (BCI)?" In: *Neuroscience Letters* 462 (2009), pp. 94–98. DOI: 10.1016/j.neulet.2009.06.045 (cit. on pp. 6, 11).

[79] G. Townsend, B. K. LaPallo, et al. "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 pp. 7, 13, 15).

[80] J. Jin, B. Allison, et al. "Optimized stimulus presentation patterns for an event-related potential EEG-based brain-computer interface." In: *Medical and Biological Engineering and Computing* 49.2 (2011), pp. 181–191. DOI: 10.1007/s11517-010-0689-8 (cit. on p. 7).

[81] 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, 056016 (2011). DOI: 10.1088/1741-2560/8/5/056016 (cit. on pp. 10, 15, 19, 39).

[82] I. Käthner, A. Kübler, and S. Halder. "Rapid P300 brain-computer interface communication with a head-mounted display." In: *Frontiers in Neuroscience* 9.207 (June 2015). DOI: 10.3389/fnins.2015.00207 (cit. on p. 10).

[83] T. Liu, L. Goldberg, S. Gao, and B. Hong. "An online brain-computer interface using non-flashing visual evoked potentials." In: *Journal of Neural Engineering* 7, 036003 (2010). DOI: 10.1088/1741-2560/7/3/036003 (cit. on p. 10).

[84] J. Jin, B. Z. Allison, et al. "The Changing Face of P300 BCIs: A Comparison of Stimulus Changes in a P300 BCI Involving Faces, Emotion, and Movement." In: *PLoS ONE* 7.11, e49688 (Nov. 2012). DOI: 10.1371/journal.pone.0049688 (cit. on p. 10).

[85] S. Lu, C. Guan, and H. Zhang. "Unsupervised brain computer interface based on intersubject information and online adaptation." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 17.2 (2009), pp. 135–145. DOI: 10.1109/TNSRE.2009.2015197 (cit. on pp. 10, 42).

[86] P.-J. Kindermans, M. Tangermann, K.-R. Müller, and B. Schrauwen. "Integrating dynamic stopping, transfer learning and language models in an adaptive zero-training ERP speller." In: *Journal of Neural Engineering* 11.3, 035005 (May 2014). DOI: 10.1088/1741-2560/11/3/035005 (cit. on pp. 10, 42).

[87] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert. "xDAWN Algorithm to Enhance Evoked Potentials: Application to Brain-Computer Interface." In: *IEEE Transactions on Biomedical Engineering* 56.8 (Aug. 2009), pp. 2035–2043. DOI: 10.1109/tbme.2009.2012869 (cit. on p. 10).

[88] 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 Neural Systems and Rehabilitation Engineering* 8 (2000), pp. 174–179. DOI: 10.1109/86.847808 (cit. on pp. 10, 42).

[89] D. J. Krusienski, E. W. Sellers, et al. "A comparison of classification techniques for the P300 speller." In: *Journal of Neural Engineering* 3.4 (2006), pp. 299–305. DOI: 10.1088/1741-2560/3/4/007 (cit. on pp. 10, 19, 39).

[90] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Müller. "Single-trial analysis and classification of ERP components – a tutorial." In: *NeuroImage* 56 (2011), pp. 814–825. DOI: 10.1016/j.neuroimage.2010.06.048 (cit. on pp. 10, 36, 41).

[91] J. Farquhar and N. J. Hill. "Interactions Between Pre-Processing and Classification Methods for Event-Related-Potential Classification." In: *Neuroinformatics* 11.2 (Dec. 2012), pp. 175–192. DOI: 10.1007/s12021-012-9171-0 (cit. on p. 10).

[92] A. Lenhardt, M. Kaper, and H. J. Ritter. "An adaptive P300-based online brain-computer interface." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 16 (2008), pp. 121–130. DOI: 10.1109/TNSRE.2007.912816 (cit. on p. 10).

[93] J. Höhne, M. Schreuder, B. Blankertz, and M. Tangermann. "Two- dimensional auditory P300 speller with predictive text system." In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. IEEE, Aug. 2010. DOI: 10.1109/iembs.2010.5627379 (cit. on p. 10).

[94] J. Jin, B. Z. Allison, et al. "An adaptive P300-based control system." In: *Journal of Neural Engineering* 8.3, 036006 (Apr. 2011). DOI: 10.1088/1741-2560/8/3/036006 (cit. on p. 10).

[95] M. Schreuder, T. Rost, and M. Tangermann. "Listen, You are Writing! Speeding up Online Spelling with a Dynamic Auditory BCI." In: *Frontiers in Neuroscience* 5.112 (2011). DOI: 10.3389/fnins.2011.00112 (cit. on p. 10).

[96] T. Kaufmann, A. Herweg, and A. Kübler. "Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials." In: *Journal of NeuroEngineering and Rehabilitation* 11.1 (2014). DOI: 10.1186/1743-0003-11-7 (cit. on pp. 10, 41).

[97] M. Schreuder, J. Höhne, B. Blankertz, S. Haufe, T. Dickhaus, and M. Tangermann. "Optimizing event-related potential based brain–computer interfaces: a systematic evaluation of dynamic stopping methods." In: *Journal of Neural Engineering* 10.3, 036025 (2013). DOI: 10.1088/1741-2560/10/3/036025 (cit. on pp. 11, 35, 41).

[98] J. N. Mak, Y. Arbel, et al. "Optimizing the P300-based brain-computer interface: current status, limitations and future directions." In: *Journal of Neural Engineering* 8.2, 025003 (Mar. 2011). DOI: 10.1088/1741-2560/8/2/025003 (cit. on pp. 11, 43).

[99] L. M. McCane, S. M. Heckman, et al. “P300-based brain-computer interface (BCI) event-related potentials (ERPs): People with amyotrophic lateral sclerosis (ALS) vs. age-matched controls.” In: *Clinical Neurophysiology* 126.11 (Nov. 2015), pp. 2124–2131. DOI: 10.1016/j.clinph.2015.01.013 (cit. on pp. 11, 43).

[100] L. L. Neto, A. C. Constantini, and R. Y. S. Chun. “Communication vulnerable in patients with Amyotrophic Lateral Sclerosis: A systematic review.” In: *NeuroRehabilitation* 40.4 (June 2017), pp. 561–568. DOI: 10.3233/NRE-171443 (cit. on pp. 11, 43).

[101] F. Aloise, F. Schettini, et al. “P300-based brain-computer interface for environmental control: an asynchronous approach.” In: *Journal of Neural Engineering* 8.2, 025025 (2011). DOI: 10.1088/1741-2560/8/2/025025 (cit. on pp. 11, 15, 43).

[102] F. Miralles, E. Vargiu, et al. “Brain-Computer Interfaces on Track to Home: Results of the Evaluation at Disabled End-Users’ Homes and Lessons Learnt.” In: *Frontiers in ICT* 2.25 (Nov. 2015). DOI: 10.3389/fict.2015.00025 (cit. on pp. 11, 38).

[103] J. Münßinger, S. Halder, et al. “Brain painting: first evaluation of a new brain-computer interface application with ALS-patients and healthy volunteers.” In: *Frontiers in Neuroprosthetics* 4.182 (2010). DOI: 10.3389/fnins.2010.00182 (cit. on pp. 11, 13, 32, 44).

[104] E. M. Holz, L. Botrel, T. Kaufmann, and A. Kübler. “Long-Term Independent Brain-Computer Interface Home Use Improves Quality of Life of a Patient in the Locked-In State: A Case Study.” In: *Archives of Physical Medicine and Rehabilitation* 96.3 (2015), S16–S26. DOI: 10.1016/j.apmr.2014.03.035 (cit. on pp. 11, 32).

[105] E. M. Mugler, C. A. Ruf, S. Halder, M. Bensch, and A. Kubler. “Design and Implementation of a P300-Based Brain-Computer Interface for Controlling an Internet Browser.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 18.6 (Dec. 2010), pp. 599–609. DOI: 10.1109/TNSRE.2010.2068059 (cit. on pp. 11, 39).

[106] C. Zickler, A. Riccio, et al. “A Brain-Computer Interface as Input Channel for a Standard Assistive Technology Software.” In: *Clinical EEG and Neuroscience* 42.4 (2011), pp. 236–244. DOI: 10.1177/155005941104200409 (cit. on pp. 11, 14–16, 38, 39).

[107] G. Pires, M. Castelo-Branco, and U. Nunes. "Visual P300-based BCI to steer a wheelchair: A Bayesian approach." In: *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, Aug. 2008. DOI: 10.1109/iembs.2008.4649238 (cit. on p. 11).

[108] I. Iturrate, J. Antelis, A. Kubler, and J. Minguez. "A Noninvasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation." In: *IEEE Transactions on Robotics* 25.3 (June 2009), pp. 614–627. DOI: 10.1109/tro.2009.2020347 (cit. on p. 11).

[109] B. Rebsamen, C. Guan, et al. "A Brain Controlled Wheelchair to Navigate in Familiar Environments." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 18.6 (Dec. 2010), pp. 590–598. DOI: 10.1109/tnsre.2010.2049862 (cit. on p. 11).

[110] E. Teo, A. Huang, Y. Lian, C. Guan, Y. Li, and H. Zhang. "Media Communication Center Using Brain Computer Interface." In: *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*. Aug. 2006, pp. 2954–2957. DOI: 10.1109/IEMBS.2006.260092 (cit. on pp. 11, 40).

[111] N. J. Hill, T. N. Lal, K. Bierig, N. Birbaumer, and B. Schölkopf. "An Auditory Paradigm for Brain-Computer Interfaces." In: *Advances in Neural Information Processing Systems 17*. 2005, pp. 569–576. URL: http://papers.nips.cc/paper/2551-an-auditory-paradigm-for-brain-computer-interfaces.pdf (cit. on p. 11).

[112] 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. 11).

[113] D. S. Klobassa, T. M. Vaughan, et al. "Toward a high-throughput auditory P300-based brain-computer interface." In: *Clinical Neurophysiology* 120 (2009), pp. 1252–1261. DOI: 10.1016/j.clinph.2009.04.019 (cit. on p. 11).

[114] A. Kübler, A. Furdea, S. Halder, E. M. Hammer, F. Nijboer, and B. Kotchoubey. "A brain-computer interface controlled auditory event-related potential (P300) spelling system for locked-in patients." In: *Annals of the New York Acadamy of Sciences* 1157 (2009), pp. 90–100. DOI: 10.1111/j.1749-6632.2008.04122.x (cit. on p. 11).

[115] I. Käthner, C. A. Ruf, E. Pasqualotto, C. Braun, N. Birbaumer, and S. Halder. "A portable auditory P300 brain-computer interface with directional cues." In: *Clinical Neurophysiology* 124.2 (2013), pp. 327–338. DOI: 10.1016/j.clinph.2012.08.006 (cit. on p. 11).

[116] C. Pokorny, D. S. Klobassa, et al. "The auditory P300-based single-switch BCI: Paradigm transition from healthy subjects to minimally conscious patients." In: *Artif Intell Med* 59.2 (2013), pp. 81–90. DOI: 10.1016/j.artmed.2013.07.003 (cit. on p. 11).

[117] F. Aloise, I. Lasorsa, et al. "Multimodal stimulation for a P300-based BCI." In: *International Journal of Bioelectromagnetism* 9 (2007), pp. 128–130 (cit. on p. 11).

[118] A. M. Brouwer and J. B. van Erp. "A tactile P300 brain-computer interface." In: *Frontiers in Neuroscience* 4.19 (2010). DOI: 10.3389/fnins.2010.00019 (cit. on p. 11).

[119] 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, 045002 (July 2012). DOI: 10.1088/1741-2560/9/4/045002 (cit. on p. 11).

[120] S. Amiri, R. Fazel-Rezai, and V. Asadpour. "A Review of Hybrid Brain-Computer Interface Systems." In: *Advances in Human-Computer Interaction* (2013), pp. 1–8. DOI: 10.1155/2013/187024 (cit. on p. 11).

[121] G. R. Müller-Putz, C. Breitwieser, et al. "Tools for brain-computer interaction: a general concept for a hybrid BCI." In: *Frontiers in Neuroinformatics* 5.30 (2011). DOI: 10.3389/fninf.2011.00030 (cit. on p. 11).

[122] G. Pfurtscheller, B. Z. Allison, et al. "The hybrid BCI." In: *Frontiers in Neuroscience* 4.30 (2010). DOI: 10.3389/fnpro.2010.00003 (cit. on p. 11).

[123] S. Fazli, J. Mehnert, et al. "Enhanced performance by a hybrid NIRS-EEG brain computer interface." In: *Neuroimage* 59 (2012), pp. 519–529. DOI: 10.1016/j.neuroimage.2011.07.084 (cit. on p. 11).

[124] R. Panicker, S. Puthusserypady, and Y. Sun. "An Asynchronous P300 BCI with SSVEP-Based Control State Detection." In: *IEEE Transactions on Biomedical Engineering* 58.6 (2011), pp. 1781–1788. DOI: 10.1109/TBME.2011.2116018 (cit. on pp. 11, 43).

[125] T. O. Zander, M. Gaertner, C. Kothe, and R. Vilimak. "Combining eye gaze input with a brain-computer interface for touchless human-computer interaction." In: *International Journal of Human-Computer Interaction* 27 (2011), pp. 38–51. DOI: 10.1080/10447318.2011.535752 (cit. on p. 11).

[126] 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, 025011 (2011). DOI: 10.1088/1741-2560/8/2/025011 (cit. on p. 11).

[127] 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, 026007 (2010). DOI: 10.1088/1741-2560/7/2/026007 (cit. on p. 11).

[128] 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." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 18 (2010), pp. 409–414. DOI: 10.1109/TNSRE.2010.2040837 (cit. on p. 11).

[129] ISO 9241–210: 2010. *Ergonomics of human system interaction-Part 210: Human-centred design for interactive systems*. 2009 (cit. on pp. 12, 17).

[130] A. Kübler, E. M. Holz, et al. "The User-Centered Design as Novel Perspective for Evaluating the Usability of BCI-Controlled Applications." In: *PLoS ONE* 9.12, e112392 (Dec. 2014). DOI: 10.1371/journal.pone.0112392 (cit. on pp. 12, 13, 17).

[131] J. R. Pierce. *Introduction to Information Theory, Symbols, Signals and Noi*. Dover Publications, Jan. 11, 1980. ISBN: 0486240614 (cit. on p. 13).

[132] J. R. Wolpaw, H. Ramoser, D. J. McFarland, and G. Pfurtscheller. "EEG-based communication: improved accuracy by response verification." In: *IEEE Transactions on Rehabilitation Engineering* 6 (1998), pp. 326–333. DOI: 10.1109/86.712231 (cit. on p. 13).

[133] W. Speier, C. Arnold, and N. Pouratian. "Evaluating True BCI Communication Rate through Mutual Information and Language Models." In: *PLoS ONE* 8.10, e78432 (Oct. 2013). DOI: 10.1371/journal.pone.0078432 (cit. on p. 13).

[134] A. Furdea, S. Halder, et al. “An auditory oddball (P300) spelling system for brain-computer interfaces.” In: *Psychophysiology* 46 (2009), pp. 1–9. DOI: 10.1111/j.1469-8986.2008.00783.x (cit. on p. 13).

[135] D. J. McFarland, W. A. Sarnacki, G. Townsend, T. Vaughan, and J. R. Wolpaw. “The P300-based brain-computer interface (BCI): Effects of stimulus rate.” In: *Clinical Neurophysiology* 122.4 (Apr. 2011), pp. 731–737. DOI: 10.1016/j.clinph.2010.10.029 (cit. on pp. 13, 15).

[136] B. D. Seno, M. Matteucci, and L. Mainardi. “The Utility Metric: A Novel Method to Assess the Overall Performance of Discrete Brain-Computer Interfaces.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 18.1 (Feb. 2010), pp. 20–28. DOI: 10.1109/tnsre.2009.2032642 (cit. on p. 13).

[137] S. G. Hart and L. E. Staveland. “Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research.” In: *Advances in Psychology*. 1988, pp. 139–183. DOI: 10.1016/s0166-4115(08)62386-9 (cit. on p. 13).

[138] S. G. Hart. “Nasa-Task Load Index (NASA-TLX); 20 Years Later.” In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 50.9 (2006), pp. 904–908. DOI: 10.1177/154193120605000909 (cit. on p. 13).

[139] L. Demers, R. Weiss-Lambrou, and B. Ska. “The Quebec User Evaluation of Satisfaction with Assistive Technology (QUEST 2.0): An overview and recent progress.” In: *The Assessment of Assistive Technology Outcomes, Effects and Costs* 14.3 (2002) (cit. on p. 14).

[140] B. Laugwitz, T. Held, and M. Schrepp. “Construction and Evaluation of a User Experience Questionnaire.” In: *HCI and Usability for Education and Work, Proceedings*. Vol. 5298. Lecture Notes in Computer Science. 2008, pp. 63–76. DOI: 10.1007/978-3-540-89350-9_6 (cit. on p. 14).

[141] A. Newe, L. Becker, and A. Schenk. “Application and Evaluation of Interactive 3D PDF for Presenting and Sharing Planning Results for Liver Surgery in Clinical Routine.” In: *PLoS ONE* 9.12, e115697 (Dec. 2014). DOI: 10.1371/journal.pone.0115697 (cit. on p. 14).

[142] A. M. Bernardos, J. M. Sánchez, J. I. Portillo, X. Wang, J. A. Besada, and J. R. Casar. “Design and deployment of a contactless hand-shape identification system for smart spaces.” In: *Journal of Ambient Intelligence*

and Humanized Computing 7.3 (2016), pp. 357–370. DOI: 10.1007/s12652-016-0363-6 (cit. on p. 14).

[143] R. Lorenz, J. Pascual, B. Blankertz, and C. Vidaurre. "Towards a holistic assessment of the user experience with hybrid BCIs." In: *Journal of Neural Engineering* 11.3, 035007 (2014). DOI: 10.1088/1741-2560/11/3/035007 (cit. on p. 14).

[144] 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 (Jan. 2007), R1–R13. DOI: 10.1088/1741-2560/4/2/r01 (cit. on p. 15).

[145] S. C. Kleih, T. Kaufmann, et al. "Out of the frying pan into the fire—the P300-based BCI faces real-world challenges." In: *Brain Machine Interfaces: Implications for Science, Clinical Practice and Society*. 2011, pp. 27–46. DOI: 10.1016/b978-0-444-53815-4.00019-4 (cit. on p. 15).

[146] E. W. Sellers, A. Kübler, and E. Donchin. "Brain-computer interface research at the University of South Florida Cognitive Psychophysiology Laboratory: the P300 speller." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14 (2006), pp. 221–224. DOI: 10.1109/TNSRE.2006.875580 (cit. on p. 15).

[147] J. Jin, P. Horki, C. Brunner, X. Wang, C. Neuper, and G. Pfurtscheller. "A new P300 stimulus presentation pattern for EEG-based spelling systems." In: *Biomedical Engineering* 55 (2010), pp. 203–210. DOI: 10.1515/BMT.2010.029 (cit. on p. 15).

[148] C. Zickler, V. D. Donna, et al. "BCI applications for people with disabilities: Defining user needs and user requirements." In: *Assistive Technology from Adapted Equipment to Inclusive Environments* (2009), pp. 185–189. DOI: 10.3233/978-1-60750-042-1-185 (cit. on pp. 15, 39).

[149] T. O. Zander, M. Lehne, et al. "A Dry EEG-System for Scientific Research and Brain-Computer Interfaces." In: *Frontiers in Neuroscience* 5.53 (2011). DOI: 10.3389/fnins.2011.00053 (cit. on pp. 15, 40, 41).

[150] C. Guger, G. Krausz, B. Z. Allison, and G. Edlinger. "Comparison of dry and gel based electrodes for P300 brain-computer interfaces." In: *Frontiers in Neuroscience* 6.60 (2012). DOI: 10.3389/fnins.2012.00060 (cit. on pp. 15, 40, 41).

[151] H. Zhang, C. Guan, and C. Wang. "Asynchronous P300-based brain-computer interfaces: a computational approach with statistical models." In: *IEEE Transactions on Biomedical Engineering* 55 (2008), pp. 1754–1763. DOI: 10.1109/TBME.2008.919128 (cit. on pp. 15, 42, 43).

[152] A. Lenhardt and H. Ritter. "An Augmented-Reality Based Brain-Computer Interface for Robot Control." In: *Neural Information Processing. Models and Applications*. Vol. 6444. Lecture Notes in Computer Science. 2010, pp. 58–65. DOI: 10.1007/978-3-642-17534-3_8 (cit. on pp. 15, 43).

[153] H. Riechmann, N. Hachmeister, H. Ritter, and A. Finke. "Asynchronous, parallel on-line classification of P300 and ERD for an efficient hybrid BCI." In: *5th International IEEE/EMBS Conference on Neural Engineering*. 2011, pp. 412–415. DOI: 10.1109/NER.2011.5910574 (cit. on pp. 15, 43).

[154] A. Pinegger, S. Wriessnegger, and G. Müller-Putz. "Introduction of a Universal P300 Brain-Computer Interface Communication System." In: *Biomedical Engineering / Biomedizinische Technik*. Vol. 58. Suppl. 1. 2013. DOI: 10.1515/bmt-2013-4445 (cit. on pp. 19, 38, 41).

[155] 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, 38).

[156] S. Halder, A. Pinegger, et al. "Brain-controlled applications using dynamic P300 speller matrices." In: *Artificial Intelligence in Medicine* 63.1 (2015), pp. 7–17. DOI: 10.1016/j.artmed.2014.12.001 (cit. on pp. 21, 39–41, 43).

[157] A. Pinegger, L. Deckert, et al. "Write, read and answer emails with a dry 'n' wireless brain-computer interface system." In: *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*. Aug. 2014, pp. 1286–1289. DOI: 10.1109/EMBC.2014.6943833 (cit. on pp. 25, 39).

[158] A. Pinegger, J. Faller, S. Halder, S. C. Wriessnegger, and G. R. Müller-Putz. "Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach." In: *Journal of Neural Engineering* 12.1, 014001 (Jan. 2015). DOI: 10.1088/1741-2560/12/1/014001 (cit. on pp. 27, 42–44).

[159] A. Pinegger, L. Deckert, et al. "Automatic pause detection during P300 web browsing." In: *6th International Brain-Computer Interface Conference 2014*. Sept. 2014. DOI: 10.3217/978-3-85125-378-8-76 (cit. on pp. 29, 43, 44).

[160] A. Pinegger, S. C. Wriessnegger, J. Faller, and G. R. Müller-Putz. "Evaluation of Different EEG Acquisition Systems Concerning Their Suitability for Building a Brain–Computer Interface: Case Studies." In: *Frontiers in Neuroscience* 10.441 (Sept. 2016). DOI: 10.3389/fnins.2016.00441 (cit. on pp. 30, 40–42).

[161] A. Pinegger, H. Hiebel, S. C. Wriessnegger, and G. R. Müller-Putz. "Composing only by thought: Novel application of the P300 brain-computer interface." In: *PLoS ONE* 12.9, e0181584 (Sept. 2017). DOI: 10.1371/journal.pone.0181584 (cit. on pp. 32, 41, 42, 44).

[162] E. Holz, L. Botrel, T. Kaufmann, and A. Kübler. "Long-Term Independent BCI Home-Use by a Locked-In End-User: An Evaluation Study." In: *Proceedings of the 5th International Brain-Computer Interface Meeting*. 2013. DOI: 10.3217/978-3-85125-260-6-181 (cit. on p. 32).

[163] A. Pinegger and G. R. Müller-Putz. "No training, same performance!? - A generic P300 classifier approach." In: *Proceedings of the 7th International BCI Conference Graz 2017*. Sept. 2017. DOI: 10.3217/978-3-85125-533-1-77 (cit. on pp. 36, 42, 44).

[164] T. Kaufmann, S. Völker, L. Gunesch, and A. Kübler. "Spelling is just a click away - a user-centered brain-computer interface including auto-calibration and predictive text entry." In: *Frontiers in Neuroscience* 6.72 (2012). DOI: 10.3389/fnins.2012.00072 (cit. on pp. 38, 39).

[165] T. Yu, Y. Li, J. Long, and Z. Gu. "Surfing the internet with a BCI mouse." In: *Journal of Neural Engineering* 9.3, 036012 (2012). DOI: 10.1088/1741-2560/9/3/036012 (cit. on p. 39).

[166] J. L. Sirvent, J. M. Azorín, E. Iáñez, A. Úbeda, and E. Fernández. "P300-Based Brain-Computer Interface for Internet Browsing." In: *Trends in Practical Applications of Agents and Multiagent Systems*. Berlin, Heidelberg, 2010, pp. 615–622. DOI: 10.1007/978-3-642-12433-4_72 (cit. on p. 39).

[167] B. Wei, X. Wu, and D. Zhang. "Design and Implementation of an Improved BCI System Based on Alpha Rhythm." In: *2009 3rd International Conference on Bioinformatics and Biomedical Engineering*. June 2009, pp. 1–4. DOI: 10.1109/ICBBE.2009.5162588 (cit. on p. 40).

[168] L. Zhang, X.-j. Guo, and X.-p. Wu. "Design and Implementation of a BCI System Based on Steady-State Visual Evoked Potentials." In: *2010 4th International Conference on Bioinformatics and Biomedical Engineering*. IEEE, June 2010. DOI: 10.1109/icbbe.2010.5516395 (cit. on p. 40).

[169] A. Kübler, N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N. Birbaumer. "Brain-computer communication: self-regulation of slow cortical potentials for verbal communication." In: *Archives of Physical Medicine and Rehabilitation* 82 (2001), pp. 1533–1539. DOI: 10.1053/apmr.2001.26621 (cit. on p. 40).

[170] I. Volosyak, D. Valbuena, T. Malechka, J. Peuscher, and A. Gräser. "Brain-computer interface using water-based electrodes." In: *Journal of Neural Engineering* 7.6, 066007 (2010). DOI: 10.1088/1741-2560/7/6/066007 (cit. on p. 40).

[171] F. Nijboer, E. W. Sellers, et al. "A P300-based brain-computer interface for people with amyotrophic lateral sclerosis." In: *Clinical Neurophysiology* 119.10 (2008), pp. 1909–1916. DOI: 10.1016/j.clinph.2008.03.034 (cit. on p. 42).

[172] F. Piccione, F. Giorgi, et al. "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. 42).

[173] Y. Liu, H. Ayaz, A. Curtin, P. Shewokis, and B. Onaral. "Detection of attention shift for asynchronous P300-based BCI." In: *Engineering in Medicine and Biology Society (EMBC), Annual International Conference of the IEEE*. 2012, pp. 3850–3853. DOI: 10.1109/EMBC.2012.6346807 (cit. on p. 43).

[174] Y. Liu, H. Ayaz, B. Onaral, and P. A. Shewokis. "EEG band powers for characterizing user engagement in P300-BCI." In: *6th International IEEE/EMBS Conference on Neural Engineering*. 2013, pp. 1066–1069. DOI: 10.1109/NER.2013.6696121 (cit. on p. 43).

[175] R. Scherer, A. Schlögl, F. Lee, H. Bischof, J. Janša, and G. Pfurtscheller. "The Self-Paced Graz Brain-Computer Interface: Methods and Applications." In: *Computational Intelligence and Neuroscience* 2007 (2007), pp. 1–9. DOI: 10.1155/2007/79826 (cit. on p. 43).

[176] 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, e51077 (Dec. 2012). DOI: 10.1371/journal.pone.0051077 (cit. on p. 44).

[177] T. Kaufmann and A. Kübler. "Beyond maximum speed—a novel two-stimulus paradigm for brain-computer interfaces based on event-related potentials (P300-BCI)." In: *Journal of Neural Engineering* 11.5, 056004 (July 2014). DOI: 10.1088/1741-2560/11/5/056004 (cit. on p. 44).

[178] G. Townsend and V. Platsko. "Pushing the P300-based brain-computer interface beyond 100 bpm: extending performance guided constraints into the temporal domain." In: *Journal of Neural Engineering* 13.2, 026024 (Feb. 2016). DOI: 10.1088/1741-2560/13/2/026024 (cit. on p. 44).

[179] S. Nagel and M. Spüler. "Asynchronous non-invasive high-speed BCI speller with robust non-control state detection." In: *Scientific Reports* 9.1 (June 2019). DOI: 10.1038/s41598-019-44645-x (cit. on p. 44).

[180] P. Stawicki, F. Gembler, A. Rezeika, and I. Volosyak. "A Novel Hybrid Mental Spelling Application Based on Eye Tracking and SSVEP-Based BCI." In: *Brain Sciences* 7.12 (Apr. 2017), p. 35. DOI: 10.3390/brainsci7040035 (cit. on p. 44).

[181] B. Hölbling and M. Höber. *Close Link – Performance Julius Deutschbauer*. 2013. URL: http://2013.steirischerherbst.at/editions.steirischerherbst.at/2013/english/calendar/calendar264f.html?eid=96 (visited on 06/15/2019) (cit. on p. 44).

[182] A. Hoesle. *Adi Hoesle, Retrogradist undKünstler*. Ed. by A. Hoesle. 2019. URL: http://retrogradist.com/ (visited on 06/15/2019) (cit. on p. 44).

[183] L. Botrel, E. M. Holz, and A. Kübler. "Brain Painting V2: long-term evaluation by an end-user at home - an update." In: *Proceedings of the 6th International BCI Meeting*. 2016, p. 232. DOI: 10.3217/978-3-85125-467-9-232 (cit. on p. 44).

Appendix

Appendix A.

Core Publications

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INTRODUCTION OF A UNIVERSAL P300 BRAIN-COMPUTER INTERFACE COMMUNICATION SYSTEM

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Abstract: *We developed a new P300-based BCI communication system. The design is tripartite: One part operates as a universal data acquisition unit, which allows to easily use different data acquisition devices. The second part is a rapid prototyping platform based on Matlab/Simulink® for data processing, which can be modified in an easy way. The last part is a graphical user interface, which also acts as main controller. Every single part is state-of-the-art designed and implemented. Connected together they are a very powerful tool not only for scientists and research issues, but also for non-expert users.*

Keywords: *P300, BCI, user-centered-design, famous faces*

Introduction

A brain-computer interface (BCI) is an interface that connects a human brain directly with a computer. It recognizes mentally induced changes of brain signals, in our case the electroencephalogram (EEG) and forms a control signal.
There are different kinds of brain activity patterns which can be used for a BCI. One of them, the P300 phenomenon, is an event-related potential (ERP), triggered by unexpected, rare, or particularly informative stimuli. It is described as a positive peak visible in the EEG approximately 300 ms after the stimuli.
Donchin and colleagues presented in [1] the first P300-based BCI, also called P300 speller, which permits to spell words. A 6×6 matrix filled with letters and symbols is presented to the user, and entire columns or rows are flashed one after the other in random order. When the column/row containing the desired letter is flashed, a P300 is elicited.
If the stimulus is more complex than just a flash, other ERPs are generated too. Kaufmann and colleges showed in [2] that the use of famous face images as stimuli cause two further negative deflections, the N170 and N400f, and that these can be additionally used for classification. This modification improves the classification rates significantly.

In this work we present our newly developed universal P300-famous faces speller, see Fig.1, based on the ideas of Donchin and Kaufmann. With this BCI the user is able to spell, to control a multimedia player, or to browse the Internet.

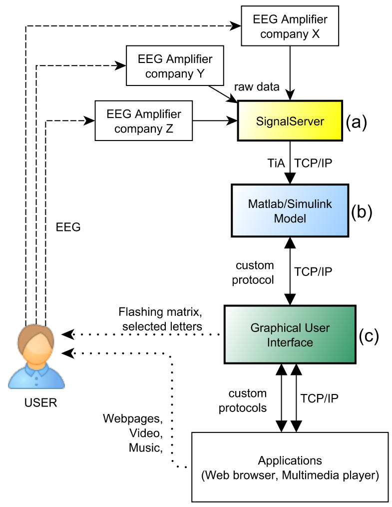

Figure 1: Design sketch of the universal P300 BCI communication system.

Methods

Data acquisition:
For data acquisition the TOBI SignalServer software [3] is used, see Fig. 1a). The big advantage of this software is that it can handle many different data acquisition devices [4].
Paradigm:
The paradigm is inspired by the work of Donchin [1] which has been described before. The only differences are (i) the matrix has a fixed size of 6×6 just during the calibration and can have an $n \times 6$ $(with\ n = 6...14)$ size afterwards, and (ii) the intensification of the rows /columns is done with famous faces instead of flashing them.
Data processing:
Matlab/Simulink® (*The MathWorks, USA*) is used for data processing, see Fig. 1b). The processing itself is mainly based on results found in [5] with some deviations.
For each channel, 800 ms segments of data following each intensification are extracted. Afterwards a baseline correction with 200 ms pre-stimulus data is performed. The segments are then moving average filtered and decimated by equivalent values. The resulting data segments are concatenated by channel for each intensification (highlighting

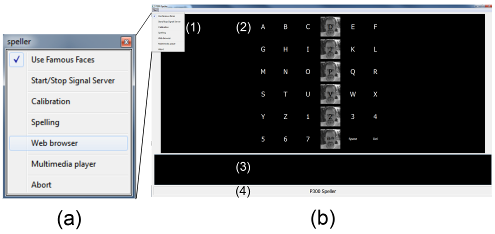

Figure 2: Screen-shot of a) the user menu and b) the P300 user interface. The different areas are (1) the menu, (2) the P300 matrix, (3) the text field, and (4) the status bar. Normally famous faces are used which are not shown in this figure due to print license.

of a row or column), creating a single feature vector. For each stimulus one feature vector per sequence (all rows and columns highlighted once) is generated and averaged over all sequences (maximum 15 per selection).

In training mode this is done for ten letters and afterwards a classifier is trained using stepwise linear discriminant analysis (SWLDA) [6]. To get the best trade-off between speed and accuracy the lowest number of sequences is calculated with a leave-one-out cross-validation (LOOCV) and successive adding of sequences to the test set. However, the practically best number of sequences is determined afterwards as described in [7].

In spelling mode the calculated classifier and the determined best number of sequences will automatically be used.

Results

We developed a P300 BCI system which is based on three main components: The TOBI SignalServer for data acquisition and distribution, a Matlab/Simulink ® model for data processing and an in C++ implemented graphical user interface and paradigm control, see Fig. 2. Within the application it is possible to start and stop the data acquisition software (SignalServer). Once the Matlab/Simulink ® model is running in the background the training or spelling session can be started just by one click. Also the image (preferred famous face) for highlighting can be selected freely just by three mouse clicks.

The communication with Matlab/Simulink ® is done via a network (TCP/IP) connection. Two further TCP/IP connections to control other applications are already implemented: One to control a web browser and one to control a multimedia player. To fulfill the needs of these two applications the size of the matrix adapts automatically, as described before.

Discussion

This work introduces a state-of-the-art P300 BCI system based on famous faces. It was designed and developed for the EC founded project BackHome (www.backhome-fp7.eu). It should be easy and intuitive in use with simultaneous consideration of the latest research results. To achieve this, it combines the universal data acquisition interface idea from [4] with the improvements of Kaufmann and colleges [2] and [7] showing letters highlight as famous faces and a user-centered, easy-to-use graphical user interface design. Regarding the data processing part the design is focused on best on-line performance as it is described in [5] and [7].

From a scientific perspective the use of Matlab/Simulink ® as data processing and partly control software allows scientific users to easily implement and test new algorithms or paradigm control structures to address research questions.

The two implemented interfaces to external applications (multimedia player and web browser),which are still under development, round off the universal applicability of this system.

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Bibliography

[1] E. Donchin, K. Spencer, and R. Wijesinghe, "The mental prosthesis: Assessing the speed of a p300-based brain- computer interface," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 174–179, 2000.

[2] T. Kaufmann *et al.*, "Flashing characters with famous faces improves erp-based brain-computer interface performance," *Journal of Neural Engineering*, vol. 8, no. 5, 2011.

[3] C. Breitwieser *et al.*, "Proposing a standardized protocol for raw biosignal transmission," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 3, pp. 852–859, 2012.

[4] G. R. Müller-Putz *et al.*, "Tools for brain-computer interaction: a general concept for a hybrid bci (hbci)," *Frontiers in Neuroinformatics*, vol. 5, no. 30, 2011.

[5] D. Krusienski *et al.*, "Toward enhanced p300 speller performance," *Journal of Neuroscience Methods*, vol. 167, no. 1, pp. 15 – 21, 2008.

[6] D. J. Krusienski *et al.*, "A comparison of classification techniques for the p300 speller," *Journal of Neural Engineering*, vol. 3, no. 4, p. 299, 2006.

[7] T. Kaufmann *et al.*, "Spelling is just a click away – a user-centered brain-computer interface including autocalibration and predictive text entry," *Frontiers in Neuroscience*, vol. 6, no. 72, 2012.

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Brain-controlled applications using dynamic P300 speller matrices

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ABSTRACT

Objectives: Access to the world wide web and multimedia content is an important aspect of life. We present a web browser and a multimedia user interface adapted for control with a brain-computer interface (BCI) which can be used by severely motor impaired persons.
Methods: The web browser dynamically determines the most efficient P300 BCI matrix size to select the links on the current website. This enables control of the web browser with fewer commands and smaller matrices. The multimedia player was based on an existing software. Both applications were evaluated with a sample of ten healthy participants and three end-users. All participants used a visual P300 BCI with face-stimuli for control.
Results: The healthy participants completed the multimedia player task with 90% accuracy and the web browsing task with 85% accuracy. The end-users completed the tasks with 62% and 58% accuracy. All healthy participants and two out of three end-users reported that they felt to be in control of the system.
Conclusions: In this study we presented a multimedia application and an efficient web browser implemented for control with a BCI.
Significance: Both applications provide access to important areas of modern information retrieval and entertainment.

1. Introduction

The idea that brain signals can be used to control external devices or computers was proposed in [1]. As most brain-computer interface (BCI) systems today, the design was based on fluctuations of electrical potential recorded using electroencephalogram (EEG) [2]. Various phenomena can be used to control BCIs such as slow cortical potentials (SCPs), the sensorimotor-rhythm (SMR) and event-related potentials (ERPs) [3–5]. Many applications have been developed for BCIs. For instance the SMR can be used to control prosthetic devices for rehabilitative or restorative purposes [6]. BCIs used for communication are continuously being adapted to improve usability and communication speed for people with motor or even visual impairments by using different stimulation techniques or improving the software used for communication [7–11]. Additionally, new insights contribute to the models behind BCI control and how usage and training can be improved [12–16].

Ultimately, much of the research conducted with BCIs is focused on providing communication methods for people with severe motor impairments preventing the use of assistive devices that require control of muscles [17]. Much of this research has focused on the BCI paradigm that uses visually elicited P300 ERPs [5]. In this paradigm the possible commands (usually letters for communication) are displayed in a matrix on a screen in front of the user. The rows and columns are then highlighted using an unpredictable sequence. When the user focuses on an element of the matrix a P300 and other ERPs components are elicited whenever this row or column is highlighted. This response can be detected online and is used for selection. Several repetitions are needed to achieve a sufficient signal to noise ratio. Highlighting was up until recently performed by increasing the brightness of the row or column but it has now been shown that stimuli such as faces are much more efficient at eliciting ERPs due to their higher psychological salience [18]. The pattern with which the stimulation is performed can also be improved by lifting the row and column restriction [19] or using different colours for stimulation [20].

Various neurodegenerative diseases and injuries can lead to degrees of motor impairment at which the use of a BCI can provide an improvement in quality of life by restoring communication.

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These degrees of impairment are termed the locked-in state (LIS), in which only rudimentary muscle control (over e.g. the eye muscles) remains, and the complete locked-in state (CLIS) in which no control and thus no communication or control possibilities remain [21]. People with such severe disabilities would benefit from improvement in areas of manipulation, communication, computer access/entertainment, and environmental control [22,23]. BCIs have been proposed for many of these areas. Mostly SMR based BCIs have been used to control robotic arms or neuroprostheses [24–27]. Communication applications have been implemented using visual and auditory ERPs and motor potentials [28–32]. For a review see [33]. In the area of entertainment BCIs can provide methods of artistic expression and gaming [34–38]. Finally, BCIs can also be adapted to control smart homes [39,40].

In this paper we focused on a particular aspect of modern communication, namely the use of information technology such as web browsing [41]. The first BCI controlled web browsers were operated using SCPs. Initial versions of this browser were restricted to fixed links that were selected from a list but the browser was later extended to enable free navigation [42,43]. Besides needing a substantial amount of training SCP BCIs can be used for binary choices only. Thus with many links on the website a large number of selections is needed for a single link. Due to the higher efficiency of selecting one of multiple commands a P300 controlled web browser was created [44]. Each link on a webpage was assigned a letter (termed a "hint") or several letters (if more than 26 links were on the page). This resulted in the requirement of very large matrices (8 rows and columns) and thus increased selection times (because each row and column needed to be flashed). Additionally, when filling out forms or writing text in general the matrix needed to be changed by the user requiring an additional selection. An alternative implementation of a P300 web browser displayed the flashes directly over the link on the web page [45]. This reduces the necessity of shifting the gaze from the screen displaying the matrix to the screen displaying the browser. Displaying the stimuli on the links does not resolve the need for an additional matrix for text entry and also introduces other visibility issues if links cluster together. It is also more complicated to use alternative visual stimuli such as faces. An alternative utilises a P300 BCI controlled mouse that automatically snaps to possible selections on websites [46].

In addition to accessing information it can be desirable to be able to manage and view local media files such as videos and photographs using multimedia applications. Control of media players is often mentioned or used with small samples in BCI studies [47–49]. But an extensive evaluation of a media player system is missing from the literature. Displaying photographs, watching movies and listening to music is an important part of modern entertainment and general media consumption.

In this publication it was our goal to address the shortcoming of current P300 BCI browsers of displaying superfluous elements in the P300 matrix used for control. We thus implemented a dynamic protocol that generated the P300 matrix from the relevant elements on the website online. Thus only the options needed by the user were included in the P300 matrix. In this paper we present the evaluation of the dynamic matrix generation with healthy participants and participants with motor disabilities. In addition to information retrieval, we wanted to enable users to independently consume media content. Thus, we also integrated control of a multimedia software.

2. Methods

We evaluated the new BCI web browser and media player with ten healthy participants and three persons with motor disabilities in terms of efficiency, effectiveness and satisfaction [37]. The BCI system was based on the design presented in [50]. Stimulation was performed using the famous faces paradigm described by [18].

2.1. Participants

The healthy participants were university students ($N = 10$, 5 female, mean age 23.8 years). They were compensated for their participation with €8 per hour. Three users with motor impairments participated. User A was female, 57 years old and diagnosed with cerebral palsy (tetraplegia, speech disturbance, ALS functional rating scale revised (ALS FRS-R) 24, no BCI experience). User B was male, 48 years old and diagnosed with cerebral aneurysm (hemiplegia right, no speech, ALS FRS-R 21, BCI experience). Finally, User C was also 48 years old, male and diagnosed with stroke (tetraplegia, speech disturbance, ALS FRS-R 30, BCI experience).

2.2. Data acquisition

Stimulation was performed with an external 22 in. TFT display. The data was recorded using a g.USBamp amplifier set to a sampling rate of 256 Hz and g.Gamma active electrodes. The amplifier filtered the raw data with a 0.1–60 Hz bandpass and a 50 Hz notch filter. Recording and stimulation was performed using the TOBI SignalServer software [51] in combination with Matlab and C++ software written specifically for the BackHome project (http://www.backhome-fp7.eu). The reference electrode was attached to the right earlobe, ground was positioned at FPz. The following six positions were recorded: Fz, Cz, Pz, Po7, Oz, Po8. We used a Hewlett-Packard ProBook 6460b with a dual-core CPU, 4 GB of RAM and a 64-bit Windows 7 for recording, running the BCI system and displaying the two applications (web browser and multimedia player).

2.3. Signal processing

Signal processing was performed with Matlab. Epochs consisting of 204 post-stimulus samples (approx. 800 ms) which were baseline corrected with the average amplitude of 51 pre-stimulus samples (approx. 200 ms) were used for classification. The channel by sample matrix of each epoch was smoothed along the temporal dimension with a moving average filter with a width of 17 samples, and decimated by a factor of 12 prior to averaging and feature selection. Data segments were concatenated by channel, creating a single feature vector of length 102. We trained a stepwise linear discriminant analysis (SWLDA) classifier on the features of five copy-spelled letters. Considering the used stimulation matrix size (6×6) 10 target and 50 non-target feature vectors were available. The entry criteria for the SWLDA was $p < 0.1$ and the removal criteria was $p > 0.15$ with 100 as maximum number of features. We determined the number of sequences based on leave-one-letter-out cross-validation of the training data. A graphical visualisation of how SWLDA functions can be found in [32].

2.4. Web browser design

The new web browser supports bidirectional communication with the BCI and was developed using the Qt software framework. To minimise matrix size the browser determines the minimal amount of commands needed on the current website. For example if only a small number of links is visible (e.g. on the websites of some search engines) only a small number of hints can be selected using the P300 matrix (see Fig. 1 for an example). Or if a text entry field is selected, the alphabet and numerals are displayed. Conversely, if a site with a large number of links is opened, matrices with up to 84 (14×6) elements can be displayed. A minimum of eight commands (plus one "pause command") was reserved for navigation

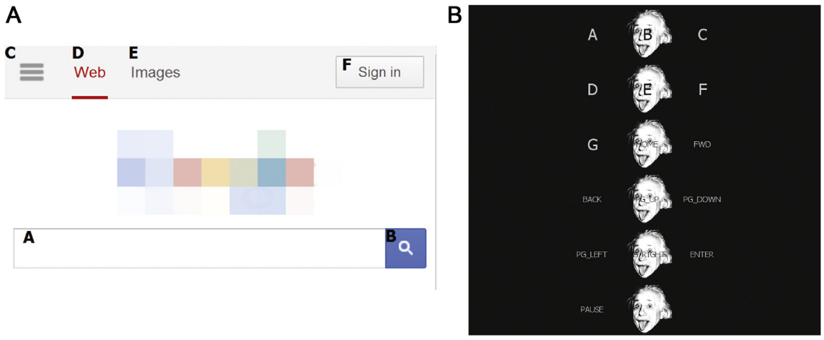

Fig. 1. User interfaces of the web browser (A) and one of the possible matrix configurations (B).

and other purposes. Thus each matrix had a minimum of nine elements. It is difficult to estimate what the average matrix size is when surfing the web. Using the settings for the BCI described in Section 2.7 a selection with a matrix with 64 elements would need 26 s, a selection with 36 elements 20 s. This is a reduction in selection time of 25%. Additionally, changing the matrix manually for text entry becomes unnecessary because the browser automatically recognises text fields. See Fig. 2 for a visualisation of this concept.

2.5. Dynamic matrix design

The principle of dynamic P300 matrices is illustrated in Fig. 2. After the BCI and web browser are started the start web page is loaded, in this case a search engine. The web page has seven links (only six are visible). These seven links are assigned the letters A to G. In addition the navigation commands HOME, FORWARD, BACK, PAGE UP, PAGE DOWN, PAGE LEFT, PAGE RIGHT and ENTER are added to the matrix. Finally, a PAUSE button is offered to the user.

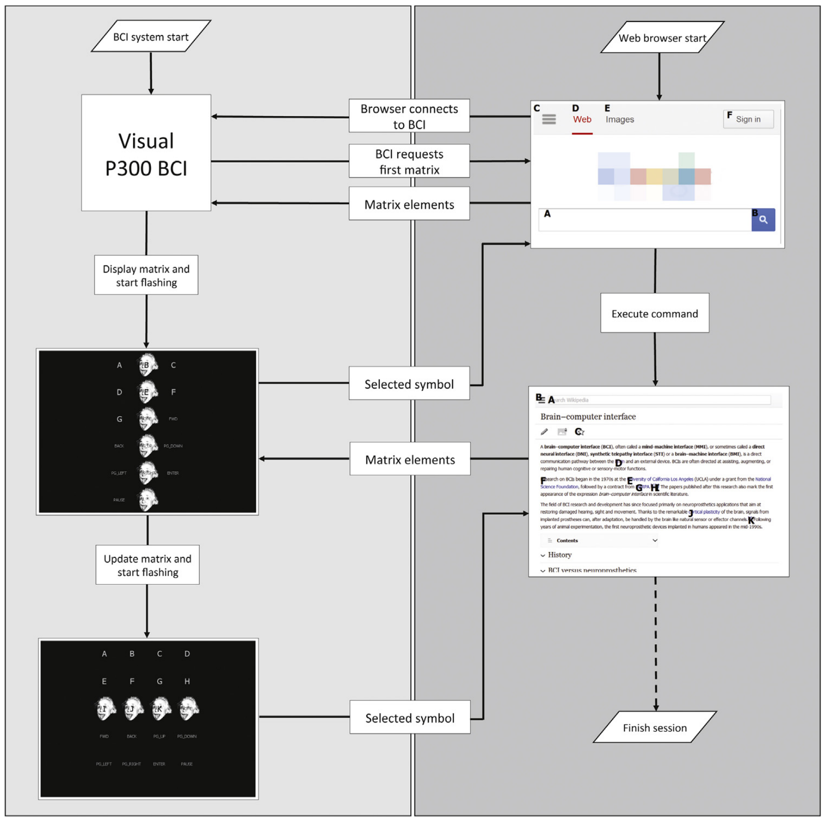

Fig. 2. Bidirectional communication between browser and brain-computer interface (BCI). The BCI sends the selected commands to the browser. The browser reacts accordingly and after loading the new page or selecting a new element on the current page sends the list of appropriate commands back to the BCI. The BCI in turn displays a matrix with these commands to the user. Each matrix includes the letters or combinations of letters necessary for hint selection and some additional commands useful for the current element. These can be commands such as "FORWARD", "BACKWARD" or "PAUSE".

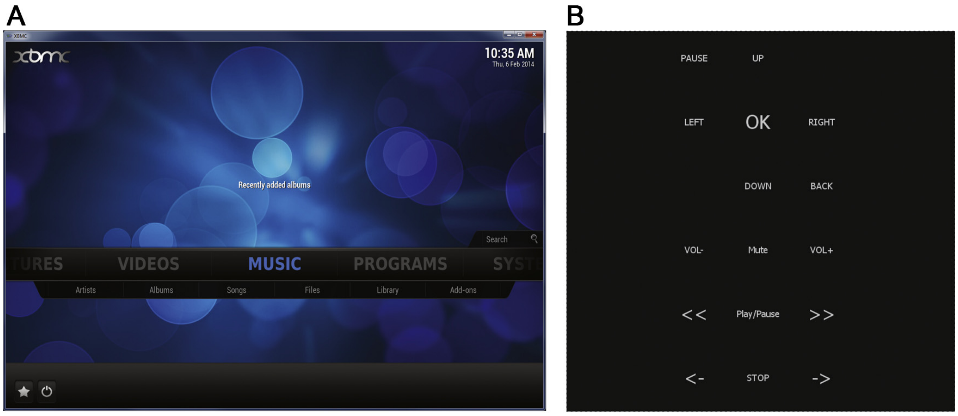

Fig. 3. User interface of the Xbox media center application (A) and the corresponding P300 matrix of the brain-computer interface system (B).

This results in a matrix with six rows and three columns. When the user opens a new web page the list of links is updated. In the example the new page has eleven links. With the eight navigation commands and the pause command this results in twenty commands and thus requires five rows and four columns. This regularly updated matrix we refer to as dynamic matrix in this paper.

2.6. Multimedia player

Many different multimedia players are available on the Internet. However, only few are suitable for our purpose and just one exactly meets our requirements: the Xbox media center (XBMC) is a free and open source media player application, which is designed to be controlled with a remote control or game controller. It fulfils our two main requirements: controllable with (1) few commands and (2) via a network connection.

A comparatively small P300 matrix (3×6 elements) is sufficient to control the application. Available commands are: UP, DOWN, LEFT, RIGHT, OK, VOLUME+, VOLUME-, MUTE, BACK, PLAY/PAUSE, STOP, FAST FORWARD, REWIND, LAST, NEXT, and a PAUSE/RUN toggle element. The PAUSE/RUN element serves as a break button. If this element is selected once, no command will be sent to the XBMC until the same element has been selected again. Fig. 3 shows the two corresponding user interfaces.

The built-in raw TCP socket based interface together with a JSON-RPC protocol is used to communicate with the BCI system, see Fig. 4. The JSON-RPC is a very simple protocol, defining only a handful of data types and commands.

2.7. Procedure

Each participant performed a calibration session consisting of selecting five symbols. The data from this session was then used to train the classifier described in Section 2.3.

Calibration was performed with fifteen flashes per row and column. Each flash had a duration of 60 ms and the time between flashes was set to 125 ms. The word used for calibration was "BRAIN". A 6×6 letter matrix was used for calibration. After the calibration the optimal number of flashes for feedback was calculated (number of flashes to achieve one hundred percent plus two; minimum eight). The pause between selections was set to two seconds. Assuming the user's calibration data resulted in an optimal number of flashes of eight, one selection would need 20 s. The user then performed two copy spelling runs with these settings. The words used for copy spelling were "SONNE" (engl. "SUN") and "BLUME" (engl. "FLOWER"). This first copy spelling task we will refer to as "spelling task one". Then a task involving the multimedia player and afterwards a task with the web browser had to be completed. The multimedia task needed a minimum of ten selections with a 3×6 matrix. The task was to navigate to a particular folder with pictures and to start a slideshow. Specifically, the required selections were: LEFT, OK, OK, RIGHT, OK, RIGHT, RIGHT, PAUSE, RUN, BACKWARD. The web browsing task needed a minimum of twelve selections with matrix sizes between 3×6 and 14×6. The goal of the task was to search for the word "BCI" and then open the corresponding Wikipedia article. In the optimal case, starting with the page of a popular web search engine, the following selections had to be made: A, B, C, I, ENTER, PG_DOWN, PAUSE, RUN, choose the hint corresponding to the Wikipedia article, PAUSE, RUN, PG_DOWN. The minimum instead of the actual numbers is given because the user was asked to correct mistakes and thus the actual number of selections was unknown before the completion of the task. The session closed with spelling two words of five letters each. The words used for this copy spelling task were "TRAUM" (engl. "DREAM") and "KRAFT" (engl. "STRENGTH"). This second copy spelling task we will refer to as "spelling task two". We performed two copy-spelling tasks to investigate for possible fatigue effects.

2.8. Offline analysis

The data was segmented around the stimulus markers indicating target and non-target flashes of the matrix. ERP segments (0–800 ms) were extracted from the raw data using EEGLAB and the BIOSIG toolbox [52,53]. All amplitudes and latencies were calculated using the target–non-target difference. We defined the P300 as the maximum amplitude between 200 and 700 ms on Pz, the vertex positive potential (VPP) as the maximum amplitude between 130 and 250 ms on Fz, the N170 as the minimum amplitude between 130 and 200 ms on Pz, the N400f as the minimum between 300 and 400 ms on Pz (all relative to stimulus presentation stimulation) and extracted amplitude and time point relative to the preceding stimulus of this maximum for each participant from the screening data. VPP, N170 and N400f are face specific ERP components [18,54,55]. Before segmentation the data was bandpass filtered between 0.1 and 30 Hz. A trial-wise baseline correction was performed by subtracting the mean of the 200 ms before each stimulus from the 800 ms following each stimulus. Amplitude and latency values, for healthy participants and end-users, were

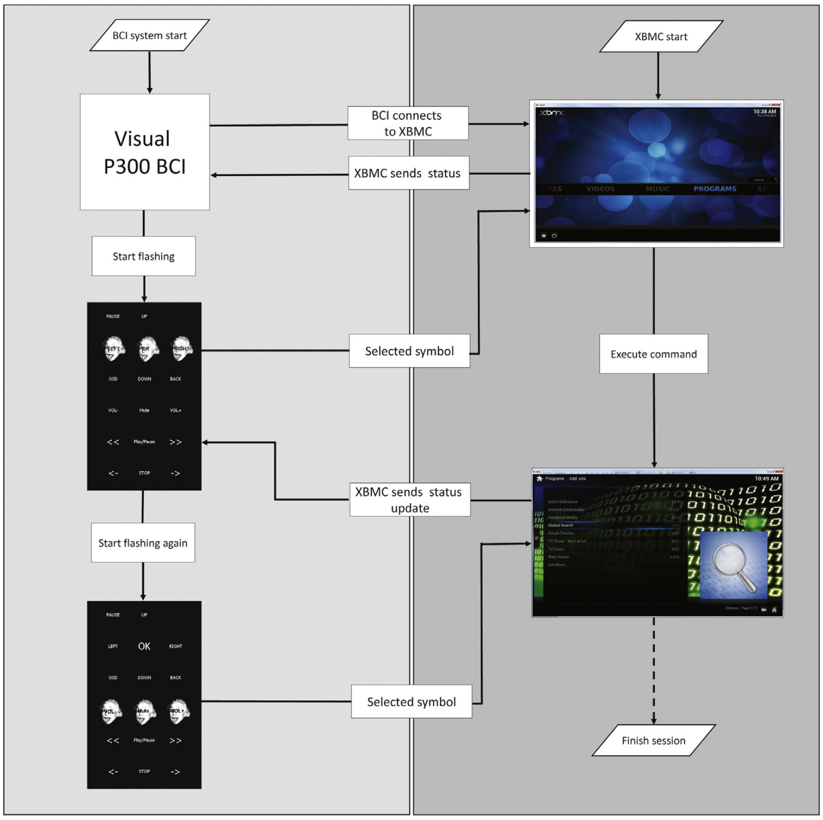

Fig. 4. Bidirectional communication between Xbox media center (XBMC) application and brain-computer interface (BCI). The BCI sends the selected commands to the XBMC. The XBMC reacts accordingly and sends status updates or error messages back to the BCI.

calculated using data from electrode Pz. Latencies were calculated in relation to the occurrence of target flashes of either a row or a column. All calculations were performed under Matlab R2012a on a personal computer running a 64-bit Linux operating system.

2.9. Evaluation metrics

After completing the BCI tasks all participants (healthy participants and end-users) completed several questionnaires. Satisfaction was evaluated using a visual-analogue scale (VAS), the extended version of the Quebec Evaluation of Satisfaction with Assistive Technology (QUEST) version 2.0 (see [45,56] for extended version) and a custom usability questionnaire. The extended QUEST does not contain four of the twelve initial items (durability, service delivery, repairs/servicing, follow-up services) which are replaced with (reliability, speed, learnability, aesthetic design). All of these items can be rated from 1 (not satisfied at all) to 5 (very satisfied) by the users. The custom questionnaire was used to assess aspects of system design (quality of the interface: symbols, feedback, simplicity of use) that are important for user satisfaction with yes/no questions.

The spelling tasks were evaluated on basis of the selection accuracy and information transfer rate (ITR) [57], the former termed effectiveness and the latter efficiency. Web browsing and multimedia player tasks were evaluated on basis of the percent correct selections of all selections. The total number of selections varied between participants due to the necessity to correct mistakes.

3. Results

3.1. Physiological data

The P300 of the control participants had a mean peak amplitude of 8.7 μV (SD 4.7, range 3.5–20.9). Peak latencies of the P300 were at 493 ms (SD 99, range 308–601).

End-user A had a P300 amplitude of 3.1 μV, end-user B of 4.5 μV and end-user C of 8 μV. The corresponding peak latencies were at 597 ms, 585 ms and 570 ms. See Fig. 5 for a visualisation of the ERPs.

A comparison of P300, VPP, N170 and N400f amplitudes and latencies can be found in Table 1.

3.2. Effectiveness and efficiency

After calibrating the classifier the metric described in Section 2 resulted in an average of 9.5 repetitions for the healthy participants (SD 2.4, range 8–15) and 12 repetitions for end-user A, 12 for end-user B and 9 for end-user C. The healthy participants completed the spelling task one with an average of 94% (SD 10, range 80–100) and the spelling task two with an average of 87% (SD 20, range 40–100; the difference was not significant, $t_9 = 1.35$, $p = 0.21$). The motor impaired participants achieved an accuracy of 20% (end-user A), 80% (end-user B) and 90% (end-user C) before the internet task. The average for spelling the two words after the internet tasks cannot be compared to this because end-user A did not complete the second two words. The other two participants achieved 80% (end-user B) and 100% (end-user C).

During the multimedia player task the users had to select a sequence of ten commands that required mistakes to be corrected. Thus we counted the total number of correct commands (including correctly selected revisions of mistakes). On average 90% (SD 20, range 33–100) of all selections by the control group were correct. The end-users made 27% (end-user A), 60% (end-user B) and 100% (end-user C) correct selections.

The web browsing task consisted of a sequence of twelve commands. This resulted in an average accuracy of 85% (SD 22, range 27–100). The end-users made 57% (end-user A), 44% (end-user B) and 75% (end-user C) correct selections.

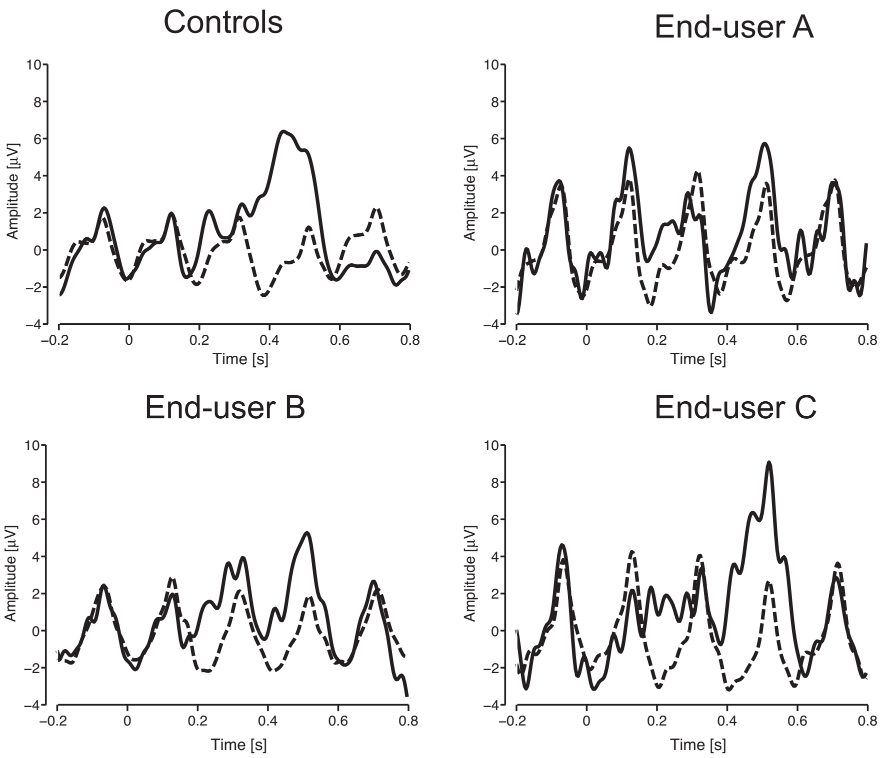

Fig. 5. Averaged event-related potentials (ERPs) of the screening session (the word 'BRAIN'). Shown averaged across all healthy participants (top left) and individually for each of the three end-users. All ERPs shown above were recorded from electrode Pz. The continuous lines show the target response, the dashed lines the non-target response.

Table 1
Overview of amplitude and latency for P300, vertex positive potential (VPP), N170 and N400f averaged across all for the healthy participants and individually for the end-users. All values were calculated using target–non-target differences.

User	P300		VPP		N170		N400f	
	Amplitude (µV)	Latency (ms)	Amplitude (µV)	Latency (ms)	Amplitude (µV)	Latency (ms)	Amplitude (µV)	Latency (ms)
Healthy	8.7	493	3.9	202	−1.5	159	0.2	329
A	3.1	597	2.7	251	1.9	169	−2.5	316
B	4.5	585	1.4	236	−1.5	161	0.7	382
C	8	570	3	243	−2	134	−1.7	316

Table 2
Performance of the healthy participants. For each user the number of iterations determined from the calibration data is given in the second column. For each of the three tasks the accuracy in percent (acc.) and the number of correct selections is given. For the two tasks involving the multimedia player and web browser we additionally give the total number of commands because this varied from participant to participant.

Healthy participants	Num. iterations	Spelling		Multimedia player			Web browser		
		One acc.	Two acc.	Num. correct	Num. commands	acc.	Num. correct	Num. commands	acc.
1	8	100	100	10	10	100	13	13	100
2	11	100	80	10	10	100	13	16	81
3	8	100	100	10	11	91	12	13	92
4	8	100	100	10	10	100	12	13	92
5	8	80	40	5	15	33	4	15	27
6	9	100	80	11	12	92	13	13	100
7	15	100	100	10	10	100	12	12	100
8	12	80	70	11	12	92	12	15	80
9	8	100	100	10	10	100	12	12	100
10	8	80	100	10	11	91	13	17	76
Average	10	94	87	10	11	90	12	14	85

Table 3
Performance of the participants with motor impairments. For each user the number of iterations determined from the calibration data is given in the second column. For each of the three tasks the accuracy in percent (acc.) and the number of correct selections is given. For the two tasks involving the multimedia player and web browser we additionally give the total number of commands because this varied from participant to participant.

End-user	Num. iterations	Spelling		Multimedia player			Web browser		
		One acc.	Two acc.	Num. correct	Num. commands	acc.	Num. correct	Num. commands	acc.
A	12	20	–	4	15	27	8	14	57
B	12	80	80	9	15	60	8	18	44
C	9	90	100	10	10	100	12	16	75
Average	11	63	90	8	13	62	9	16	59

All tasks were performed equally well by the control participants. An analysis of variance (ANOVA) on all four tasks (spelling task one, spelling task two, multimedia player, web browser) also revealed no main effect of task on spelling accuracy ($F_{3,36} = 0.44$, $p = 0.73$). See Tables 2 and 3 for an overview.

ITRs for the copy spelling task (based on the mean values in Table 2) one was 11.8 bits/min for the healthy users and 5.3 bits/min for the end-users. This decreased to 10.3 bits/min in the copy spelling task two. The values of the end-users were not comparable because one end-user did not complete the copy spelling task two.

3.3. Satisfaction

Overall device satisfaction (VAS scores) and results of the extended QUEST 2.0 and the usability questionnaire concerning the system design are listed in Table 4. For healthy participants, the item that received the lowest score in the extended QUEST 2.0 was "speed" (3.67). It is the only item that received an average score below 4 (quite satisfied). The items that were rated as most important by the study participants were "ease of use" ($n = 8$), "effectiveness" ($n = 5$) and "speed" ($n = 4$). Participants negatively remarked on the necessity of gel, the "clinical design of the cap", the many cables that "restrict movements of the head", the low speed and suggested that the cap "should be made less eye-catching". Using the system design questionnaire, one user suggested that it would be better if the users could decide when to choose the next symbol in order to feel less pressured.

For potential end-users, the items of the extended QUEST 2.0 with the lowest average scores were "speed" (2.33), "effectiveness" (2.66) and "ease of use" (3). The items that were rated as most important by the potential end-users were "effectiveness" (3), "reliability" (3) and "learnability" (2). The potential end-users remarked that selection speed could be "quicker" and the wearing comfort of the cap better. Under "Suggestions to improve the system" in the system design questionnaire, end-user A asked for more functions and in particular an application that would allow her to paint, end-user B suggested wireless transmission of the signals from the cap to the computer and would like to use no or a less conspicuous cap and end-user C only noted that the system was already "pretty simple to control".

4. Discussion

We presented the evaluation of a visual P300 BCI system using face stimuli that provides control over a web browser and multimedia player interface. The web browser has a unique new feature in the sense that it sends the minimal number of symbols needed for control of the current page to the BCI. This reduces the time needed to make a single selection.

4.1. Effectiveness and efficiency

The data of the healthy participants was used to determine if any differences in accuracy could be found between the different tasks. Even though the means were slightly lower for the application tasks (multimedia, web browser) there was no statistical difference to the spelling tasks. Similar observations have been made in other publications that compared spelling with more complex applications that have higher attentional demands. Mugler et al. [44] stated that participants with the ability to control a P300 speller also obtained control over the web browser. In [36] accuracies when controlling a painting application were initially lower. The accuracy was identical after switching from a coloured version of the painting matrix to a black and white version. Also in samples consisting of end-users similar levels of performance were found between speller and application [37].

The healthy participants achieved ITRs of 11.78 bits/min in the first spelling condition. This is comparable to other studies with similar stimulus repetition rates [58–60]. The ITRs of the end-users is below what has been demonstrated in other publications, with classical and face stimuli [18,29] but similar to other studies also investigating the control over a complex application [37].

Albeit not significant there were trends in the data showing a decrease in performance towards the end of the session. In part this may be attributed to increasing task complexity (speller, multimedia player, web browser). Most likely fatigue also contributes due to the decrease in performance since the spelling task two accuracy (87%) is lower than the spelling task one accuracy (94%). This difference however, was also not significant.

4.2. End-user performance

On average the performance of the end-users participating in this study was lower than that of the healthy participants. The lowest performance was achieved by end-user A. The performance of end-users B and C was comparable to that of the healthy participants. When considering only the performance when controlling the web browser it was clearly lower, however. This could in part be due to the smaller sample, since several healthy participants also exhibited decreased performance when controlling the web browser. Part of this decrease in performance may be due to the complexity of the browsing tasks which involves switching attention between screens. The same classifier was used throughout the experiment and the spelling task and multimedia player task covered a large range of matrix sizes, making it improbable that the decrease in performance was due to either large or small matrices. In future studies it may be worth allocating more time or even additional sessions for evaluation of the web browsers to give end-users more time to adapt to the interface.

Generally reasons for performance variations are vast and have been subject to a number of studies themselves [13,61–64]. That a single reason for low performance will be found is improbable. Besides training a viable approach to increase performance is to apply one of the aforementioned methods to determine if another BCI paradigm is more suitable for a particular end-user. Using hierarchical menus most applications designed for P300 BCIs can also be controlled with SMRs [65]. Visually evoked potential (VEP) based BCIs allow retaining the matrix based control scheme [66].

4.3. Possible influences of matrix size on classification performance

P300 amplitude can be influenced by various factors such as stimulus modality and intensity or how easily target and non-target can be discriminated. Another factor is the so called target-to-target interval (TTI) which depends on the target probability, the number of non-targets preceding each target and the inter-stimulus interval [67]. In the context of a P300 BCI the TTI is influenced strongly by the matrix size. A reduction in matrix sizes increases target probability (number of targets is constant whereas the number of

Table 4
Satisfaction ratings and results of the usability questionnaires for healthy participants and end-users. Total score of Quebec Evaluation of Satisfaction with Assistive Technology (QUEST) 2.0 consisted of an average of the items: dimensions, weight, adjustment, safety, comfort, ease of use, effectiveness, professional services. Total score of extended QUEST 2.0 items consisted of an average of the items: reliability, speed, learnability, aesthetic design.

Participants	Overall satisfaction	Extended QUEST 2.0 (1 = not satisfied at all to 5 = very satisfied)		Usability questionnaire – system design (selected items)				
	(VAS 0–10)	Total score	Total score of added items	Did you feel in control, while using the system?	Operating the interface was...	Would you describe the system as intuitive?	Did you like the symbols/icons of the interface?	Did you like the colors of the interface?
Healthy participants ($n = 10$)	$M = 8.5 \pm 1.5$	$M = 4.7 \pm 0.2$	$M = 4.7 \pm 0.5$	Yes (10)	Easy/ok (9)	Yes (10)	Yes (7)	Yes (8)
A	4.4	3.1	2.9	No	Ok	Yes	Yes	Yes
B	2.8	3.1	2.8	Yes	Ok	Yes	Yes	Yes
C	8.0	4.2	3.7	Yes	Easy	Yes	Yes	Yes

non-targets is reduced) and decreases the number of non-targets preceding each target. Due to the fact that matrix sizes vary considerably in our study between applications and also dynamically within applications this should be discussed. Studies investigating this issue in the context of P300 BCIs have found there to be reductions in P300 amplitude when 4×4 matrices (7.7 μV) were used as opposed to 12×12 matrices (9.2 μV, see [68]). This study did not show whether this influenced classification performance, however. In a later study 6×6 matrices were compared with 3×3 matrices [69]. And contrary to what should be expected based on the reduction in amplitude caused by the smaller matrices, selection accuracies were improved in case of the smaller matrices. This may be partially due to the increased probability to select the target by chance. The authors concluded that it is feasible to present matrices with different sizes to the user depending on the function that is being used or the application that is being controlled. Considering the fact that the smallest matrices used in our experiment (e.g. 6×3 for controlling the multimedia player) differed substantially from the largest matrix (e.g. 14×6 as the largest size when controlling the internet browser) and that we found no significant difference in performance between the applications we believe that matrix size has little influence on classification performance. In fact contrary to the hypothesis that decreased matrix size would lead to decreased P300 amplitude and thus accuracy, classification performance is higher when controlling the multimedia player compared to the web browser. Thus, we conclude the influence of matrix size to be negligible. The reason for this may be due to the moving average window and subsampling that is applied before classification, which decreases the differences between the ERPs elicited by different matrix sizes.

The reduced ERP amplitudes caused by smaller matrices may have no effect if conservative values are used for the number of stimulus repetitions. An effect on performance may become visible if speed is optimised to a minimum number of repetitions e.g. by using dynamic stopping methods [10].

4.4. Evaluation

The high average accuracy achieved by the healthy participants is also reflected in a high overall satisfaction with the device as indicated by the mean VAS score of 8.53 and total scores of the extended QUEST 2.0, which indicate that participants were “very satisfied” with the BCI system. Of the three end-users, however, only end-user C rated overall satisfaction with the system as high and the QUEST 2.0 scores indicated that he was quite satisfied with the device. The QUEST 2.0 scores of end-users A and B indicated that they were only “more or less satisfied” and their overall satisfaction with the BCI was low. These users also achieved substantially lower selection accuracies than end-user C. Nevertheless, all users regarded the system as either “ok” or “easy” to operate and intuitive to use and only end-user A did not feel in control while using the system.

The aspects of the BCI systems that received the lowest scores by the potential end-users in the QUEST 2.0 were “effectiveness”, “ease of use” and “speed”. These were the exact items that were rated as most important by the healthy participants. However, of these items, only “effectiveness” was also rated as most important by the potential end-users. The other two items that were rated as most important were “reliability” and “learnability”. These results demonstrate that for end-users it is more important to have a system that they can reliably control than to have a system that is easy to use and quick, but not reliable. The evaluation results reveal two main factors to improve the system and ultimately usability of the BCI system. It needs to work effectively (high selection accuracies) and also reliably, not only for healthy participants, but also for potential end-users. A less conspicuous electrode cap (or another inconspicuous fixation of electrodes) and wireless transmission of the EEG signals would increase the likelihood that the BCI system can be used as assistive technology in daily life.

In most studies concerned with the evaluation of BCIs, only objective metrics, such as accuracy and information transfer rates were assessed to estimate the effectiveness and efficiency of the BCI system, thereby neglecting the user. Now that BCIs are on the verge of being used as assistive technology in a home environment, a user centred approach gains importance. Therefore, a framework for evaluation was introduced by [45] that takes into account the opinions of the user in the evaluation of effectiveness, efficiency and satisfaction with the BCI. It has since proven useful in several studies to reveal areas in need of further improvement [37,38,70]. In these studies, as in our study, low speed and the conspicuous electrode cap and necessity of gel were identified as obstacles to the use in daily life. This study shows that satisfaction with the BCI, although largely influenced by the level of control achieved with the BCI, depends on a variety of factors that can only be identified with a user centred approach. Therefore, the opinions of end-users must be considered in the evaluation process to ensure that BCIs meet end-users' needs.

4.5. Comparison to other web browsers

Several different BCI browser implementations exist [43–46,71]. The first characteristic that distinguishes the different implementations are the control signals they are designed for. Most current implementations are designed to be used with a visual P300 BCI. P300 BCIs have inherent advantages over other BCI control signals, e.g. that they require no training (only calibration) and offer a large number of possible selections. Other signals such as SCPs require large amounts of training and allow for binary choices only [42,43]. One of the main disadvantages of visual P300 BCIs is their reliance on gaze control. When controlling a web browser this is alleviated by the fact that gaze control is needed to view websites in general. Thus, the visual P300, in particular after considering recent improvements to the paradigm (see [18]), remains the most suitable BCI control signal for web browsing. Considering only P300 BCI web browsers three different designs have been established. The first using hints for each link as initially shown in [44]. This is the design the browser that was presented in this paper built upon. Compared to this design the browser presented in this paper features automatic switching of the matrix and a minimisation of the rows and columns presented in each matrix. Both features decrease the number of selections but also the time needed per selection. For example [44] used an 8×8 matrix. With the stimulation parameters used in this paper (185 ms stimulus duration plus inter stimulus interval (ISI), ten repetitions per stimulus, two second pause between selections) 1.90 selections/min can be performed and an 8×8 matrix. A 6×6 matrix allows for 2.48 selections/min. The example showing a search engine in Fig. 2 only requires a 6×3 matrix which almost doubles the speed of the system to 3.22 selections per minute. Additionally, if the number of links in the browser exceeds the number of letters in the alphabet two letters are required to code the links. In [44] this still required two selections, with the browser described in this paper only one selection is required because the matrix is created with two letter entries. The second type of browser also uses a conventional P300 matrix on a separate screen or region of the screen but no hints. Thus, the user sequentially navigates from link to link always using the same matrix [46,71]. In this design many selections may be needed until the desired link is reached. Also the browser has to incorporate a mechanism for text entry. Thus, many of the tasks that would require many selections with this type of browser (e.g. navigating through the six links in the search engine example) can be performed with one selection in the design we propose. Finally, there are browser designs that are based on displaying the stimuli directly on the links of the website [45]. This design has many advantages. For example only one screen is required. Additionally, the method of control is very intuitive ("look at the link that you want to open"). The disadvantages of this system are that links tend to cluster on websites (e.g. on navigation bars). These may be difficult to fixate individually. Generally, control over the arrangement of the BCI matrix is lost. Also, state-of-the-art stimuli such as faces are difficult to utilise since the stimuli are by nature smaller in this design. Many of these disadvantages may be alleviated by redesigning the browser itself to allow for larger stimuli by preventing link clustering. Then displaying the BCI stimuli on top of the web browsing window would be the preferential method. Another approach to making the link selection process more intuitive is to display the stimuli on the margin around the websites and associating them with links by thin lines. The visual stimuli in P300 BCI can even be moving during the selection process, as shown in [72]. This implies that there are few restrictions in the spatial arrangement of the stimuli.

4.6. Comparison of multimedia software

Wei et al. [48] turned a multimedia player on and off by detecting alpha waves in the EEG. Lei et al. [49] demonstrated control of a multimedia player based on a steady state visually evoked potential (SSVEP)-based BCI. The control possibilities with both of these initial approaches were rather limited, though. The work of [47] on the other hand allowed for slightly more elaborate control. The system in [47] is also more similar to our approach as it also uses a visual P300 BCI. Unfortunately, Teo et al. [47] do not report any results concerning the accuracy, ITR, or number of flashing elements in their paper. However, one main difference is obvious: They used a single screen to show the P300 stimulation as well as the multimedia player user interface in contrast to our dual-screen approach. A single screen approach has the advantage that the user does not have to move her/his head between the control and the media player screen. On the other hand, the size of the pictures and videos is very small using only one screen to show both. We believe the best solution would be to integrate the P300 control elements into the multimedia player user interface which we are currently developing.

5. Conclusion

In this paper we presented the evaluation of two BCI applications: a web browser and a multimedia player. Both applications can reduce or prevent the social exclusion of end-users. Our results indicate that the simplicity and efficiency due to the use of dynamic matrices of both applications make them possible candidates for independent home use. Together with other important developments such as easy-to-use electrodes, wireless amplifiers [73] and remote support of BCI systems the presented applications will provide further momentum to moving BCIs from the laboratory to end-users' homes.

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References

[1] Vidal JJ. Toward direct brain-computer communication. Annu Rev Biophys Bioeng 1973;2:157–80, http://dx.doi.org/10.1146/annurev.bb.02.060173.001105.

[2] Berger H. Über das Elektrenkephalogramm des Menschen. Arch Psychiatr Nervenkr 1929;87:527–70.
[3] Birbaumer N, Ghanayim N, Hinterberger T, Iversen I, Kotchoubey B, Kübler A, et al. A spelling device for the paralysed. Nature 1999;398(6725):297–8, http://dx.doi.org/10.1038/18581.
[4] Pfurtscheller G, Neuper C, Krausz G. Functional dissociation of lower and upper frequency mu rhythms in relation to voluntary limb movement. Clin Neurophysiol 2000;111(10):1873–9.
[5] Farwell L, Donchin E. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr Clin Neurophysiol 1988;70:510–23.
[6] Ramos-Murguialday A, Broetz D, Rea M, Läer L, Yilmaz O, Brasil FL, et al. Brain-machine interface in chronic stroke rehabilitation: a controlled study. Ann Neurol 2013;74(1):100–8, http://dx.doi.org/10.1002/ana.23879.
[7] Jin J, Allison BZ, Kaufmann T, Kübler A, Zhang Y, Wang X, et al. The changing face of p300 BCIs: a comparison of stimulus changes in a p300 BCI involving faces, emotion, and movement. PLoS One 2012;7(11):e49688, http://dx.doi.org/10.1371/journal.pone.0049688.
[8] Lim J-H, Hwang H-J, Han C-H, Jung K-Y, Im C-H. Classification of binary intentions for individuals with impaired oculomotor function: 'eyes-closed' SSVEP-based brain-computer interface (BCI). J Neural Eng 2013;10(2):026021, http://dx.doi.org/10.1088/1741-2560/10/2/026021.
[9] Kaufmann T, Holz EM, Kübler A. Comparison of tactile, auditory and visual modality for brain-computer interface use: a case study with a patient in the locked-in state. Front Neurosci 2013;7(129), http://dx.doi.org/10.3389/fnins.2013.00129.
[10] Schreuder M, Höhne J, Blankertz B, Haufe S, Dickhaus T, Tangermann M. Optimizing event-related potential based brain-computer interfaces: a systematic evaluation of dynamic stopping methods. J Neural Eng 2013;10(3):036025.
[11] Jin J, Daly I, Zhang Y, Wang X, Cichocki A. An optimized ERP brain-computer interface based on facial expression changes. J Neural Eng 2014;11(3):036004, http://dx.doi.org/10.1088/1741-2560/11/3/036004.
[12] Friedrich EVC, Scherer R, Neuper C. Long-term evaluation of a 4-class imagery-based brain-computer interface. Clin Neurophysiol 2013;124(5):916–27, http://dx.doi.org/10.1016/j.clinph.2012.11.010.
[13] Halder S, Ruf CA, Furdea A, Pasqualotto E, De Massari D, van der Heiden L, et al. Prediction of P300 BCI aptitude in severe motor impairment. PLoS One 2013;8(10):e76148, http://dx.doi.org/10.1371/journal.pone.0076148.
[14] Kaiser V, Bauernfeind G, Kreilinger A, Kaufmann T, Kübler A, Neuper C, et al. Cortical effects of user training in a motor imagery based brain-computer interface measured by fNIRS and EEG. Neuroimage 2014;85(Pt 1):432–44, http://dx.doi.org/10.1016/j.neuroimage.2013.04.097.
[15] Wander JD, Blakely T, Miller KJ, Weaver KE, Johnson LA, Olson JD, et al. Distributed cortical adaptation during learning of a brain-computer interface task. Proc Natl Acad Sci USA 2013;110(26):10818–23, http://dx.doi.org/10.1073/pnas.1221127110.
[16] Wriessnegger SC, Leeb R, Kaiser V, Neuper C, Müller-Putz GR. Watching object related movements modulates mirror-like activity in parietal brain regions. Clin Neurophysiol 2013;124(8):1596–604, http://dx.doi.org/10.1016/j.clinph.2013.02.019.
[17] Silvoni S, Cavinato M, Volpato C, Ruf CA, Birbaumer N, Piccione F. Amyotrophic lateral sclerosis progression and stability of brain-computer interface communication. Amyotroph Lateral Scler Frontotemporal Degener 2013;14(5–6):390–6, http://dx.doi.org/10.3109/21678421.2013.770029.
[18] Kaufmann T, Schulz SM, Köblitz A, Renner G, Wessig C, Kübler A. Face stimuli effectively prevent brain-computer interface inefficiency in patients with neurodegenerative disease. Clin Neurophysiol 2013;124(5):893–900, http://dx.doi.org/10.1016/j.clinph.2012.11.006.
[19] Townsend G, LaPallo BK, Boulay CB, Krusienski DJ, Frye GE, Hauser CK, et al. A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. Clin Neurophysiol 2010;121(7):1109–20, http://dx.doi.org/10.1016/j.clinph.2010.01.030.
[20] Takano K, Komatsu T, Hata N, Nakajima Y, Kansaku K. Visual stimuli for the P300 brain-computer interface: a comparison of white/gray and green/blue flicker matrices. Clin Neurophysiol 2009;120(8):1562–6, http://dx.doi.org/10.1016/j.clinph.2009.06.002.
[21] Kübler A, Birbaumer N. Brain-computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? Clin Neurophysiol 2008;119(11):2658–66, http://dx.doi.org/10.1016/j.clinph.2008.06.019.
[22] Zickler C, Di Donna V, Kaiser V, Al-Khodairy A, Kleih S, Kübler A, et al. BCI applications for people with disabilities: defining user needs and user requirements. In: Assistive technology from adapted equipment to inclusive environments, AAATE. 25 Assistive Technology Research Series; 2009. p. 185–9.
[23] Kübler A, Mattia D, Rupp R, Tangermann M. Facing the challenge: bringing brain-computer interfaces to end-users. Artif Intell Med 2013;59(2):55–60, http://dx.doi.org/10.1016/j.artmed.2013.08.002.
[24] Müller-Putz GR, Scherer R, Pfurtscheller G, Rupp R. EEG-based neuroprosthesis control: a step towards clinical practice. Neurosci Lett 2005;382(1–2):169–74, http://dx.doi.org/10.1016/j.neulet.2005.03.021.
[25] McFarland DJ, Wolpaw JR. Brain-computer interface operation of robotic and prosthetic devices. Computer 2008;41(10):52–6.
[26] Rohm M, Schneiders M, Müller C, Kreilinger A, Kaiser V, Müller-Putz GR, et al. Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury. Artif Intell Med 2013;59(2):133–42, http://dx.doi.org/10.1016/j.artmed.2013.07.004.
[27] Kreilinger A, Kaiser V, Rohm M, Rupp R, Müller-Putz GR. BCI and FES training of a spinal cord injured end-user to control a neuroprosthesis. Biomed Tech (Berl). http://dx.doi.org/10.1515/bmt-2013-4443
[28] Blankertz B, Krauledat M, Dornhege G, Williamson J, Murray-Smith R, Müller K-R. A note on brain actuated spelling with the Berlin brain-computer interface. In: Stephanidis C, editor. Universal access in human–computer interaction. Ambient interaction. Berlin, Heidelberg: Springer; 2007. p. 759–68.
[29] Nijboer F, Sellers EW, Mellinger J, Jordan MA, Matuz T, Furdea A, et al. A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. Clin Neurophysiol 2008;119(8):1909–16, http://dx.doi.org/10.1016/j.clinph.2008.03.034.
[30] Schreuder M, Blankertz B, Tangermann M. A new auditory multi-class brain-computer interface paradigm: spatial hearing as an informative cue. PLoS One 2010;5(4):e9813, http://dx.doi.org/10.1371/journal.pone.0009813.
[31] Pokorny C, Klobassa DS, Pichler G, Erlbeck H, Real RGL, Kübler A, et al. The auditory P300-based single-switch brain-computer interface: paradigm transition from healthy subjects to minimally conscious patients. Artif Intell Med 2013;59(2):81–90, http://dx.doi.org/10.1016/j.artmed.2013.07.003.
[32] Halder S, Rea M, Andreoni R, Nijboer F, Hammer EM, Kleih SC, et al. An auditory oddball brain-computer interface for binary choices. Clin Neurophysiol 2010;121(4):516–23, http://dx.doi.org/10.1016/j.clinph.2009.11.087.
[33] Riccio A, Mattia D, Simione L, Olivetti M, Cincotti F. Eye-gaze independent EEG-based brain-computer interfaces for communication. J Neural Eng 2012;9(4):045001, http://dx.doi.org/10.1088/1741-2560/9/4/045001.
[34] Lalor EC, Kelly SP, Finucane C, Burke R, Smith R, Reilly RB, et al. Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment. EURASIP J Appl Signal Process 2005;2005:3156–64.
[35] Nijholt A, Bos DP-O, Reuderink B. Turning shortcomings into challenges: brain-computer interfaces for games. Entertain Comput 2009;1(2):85–94.
[36] Münßinger JI, Halder S, Kleih SC, Furdea A, Raco V, Hösle A, et al. Brain painting: first evaluation of a new brain-computer interface application with ALS-patients and healthy volunteers. Front Neurosci 2010;4:182, http://dx.doi.org/10.3389/fnins.2010.00182.
[37] Zickler C, Halder S, Kleih SC, Herbert C, Kübler A. Brain painting: usability testing according to the user-centered design in end users with severe motor paralysis. Artif Intell Med 2013;59(2):99–110, http://dx.doi.org/10.1016/jartmed.2013.08.003.
[38] Holz EM, Höhne J, Staiger-Sälzer P, Tangermann M, Kübler A. Brain-computer interface controlled gaming: evaluation of usability by severely motor restricted end-users. Artif Intell Med 2013;59(2):111–20, http://dx.doi.org/10.1016/j.artmed.2013.08.001.
[39] Holzner C, Guger C, Grönegress C, Edlinger G, Slater M. Using a P300 brain computer interface for smart home control. In: Dössel O, Schlegel WC, editors. World congress on medical physics and biomedical engineering. Berlin, Heidelberg: Springer; 2009. p. 174–7.
[40] Edlinger G, Holzner C, Guger C. A hybrid brain-computer interface for smart home control. In: Jacko JA, editor. Human–computer interaction. Interaction techniques and environments. Berlin, Heidelberg: Springer; 2011. p. 417–26.
[41] Hendriks A. UN convention on the rights of persons with disabilities. Eur J Health Law 2007;14(3):273–80.
[42] Karim AA, Hinterberger T, Richter J, Mellinger J, Neumann N, Flor H, et al. Neural internet: web surfing with brain potentials for the completely paralyzed. Neurorehabil Neural Repair 2006;20(4):508–15, http://dx.doi.org/10.1177/1545968306290661.
[43] Bensch M, Karim AA, Mellinger J, Hinterberger T, Tangermann M, Bogdan M, et al. Nessi: an EEG-controlled web browser for severely paralyzed patients. Comput Intell Neurosci 2007:71863, http://dx.doi.org/10.1155/2007/71863.
[44] Mugler EM, Ruf CA, Halder S, Bensch M, Kübler A. Design and implementation of a P300-based brain-computer interface for controlling an internet browser. IEEE Trans Neural Syst Rehabil Eng 2010;18(6):599–609, http://dx.doi.org/10.1109/TNSRE.2010.2068059.
[45] Zickler C, Riccio A, Leotta F, Hillian-Tress S, Halder S, Holz E, et al. A brain-computer interface as input channel for a standard assistive technology software. Clin EEG Neurosci 2011;42(4):236–44.
[46] Yu T, Li Y, Long J, Gu Z. Surfing the internet with a BCI mouse. J Neural Eng 2012;9(3):036012.
[47] Teo E, Huang A, Lian Y, Guan C, Li Y, Zhang H. Media communication center using brain computer interface. In: Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual international conference of the IEEE. 2006. p. 2954–7.
[48] Wei B, Wu X, Zhang D. Design and implementation of an improved BCI system based on alpha rhythm. In: Bioinformatics and biomedical engineering, 2009. ICBBE 2009. 3rd international conference on IEEE. 2009. p. 1–4.
[49] Lei Z, Xiao-jing G, Xiao-pei W. Design and implementation of a BCI system based on steady-state visual evoked potentials. In: Bioinformatics and biomedical engineering, 2010. ICBBE 2010. 4th international conference on IEEE. 2010. p. 1–4.

[50] Pinegger A, Wriessnegger S, Müller-Putz G. Introduction of a universal P300 brain-computer interface communication system. Biomed Tech (Berl), http://dx.doi.org/10.1515/bmt-2013-4445

[51] Breitwieser C, Daly I, Neuper C, Müller-Putz GR. Proposing a standardized protocol for raw biosignal transmission. IEEE Trans Biomed Eng 2012;59(3):852–9, http://dx.doi.org/10.1109/TBME.2011.2174637.

[52] Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J Neurosci Methods 2004;134(1):9–21, http://dx.doi.org/10.1016/j.jneumeth.2003.10.009.

[53] Vidaurre C, Sander TH, Schlögl A. Biosig: the free and open source software library for biomedical signal processing. Comput Intell Neurosci 2011;2011:935364, http://dx.doi.org/10.1155/2011/935364.

[54] Kaufmann T, Schulz S, Grünzinger C, Kübler A. Flashing characters with famous faces improves ERP-based brain-computer interface performance. J Neural Eng 2011;8(5):056016.

[55] Zhang Y, Zhao Q, Jin J, Wang X, Cichocki A. A novel BCI based on ERP components sensitive to configural processing of human faces. J Neural Eng 2012;9(2):026018, http://dx.doi.org/10.1088/1741-2560/9/2/026018.

[56] Demers L, Weiss-Lambrou R, Ska B. Item analysis of the Quebec user evaluation of satisfaction with assistive technology (QUEST). Assist Technol 2000;12(2):96–105, http://dx.doi.org/10.1080/10400435.2000.10132015.

[57] Pierce J. An introduction to information theory: symbols, signals & noise. 2nd ed. New York: Dover Publications; 1980.

[58] Furdea A, Halder S, Krusienski DJ, Bross D, Nijboer F, Birbaumer N, et al. An auditory oddball (P300) spelling system for brain-computer interfaces. Psychophysiology 2009;46(3):617–25, http://dx.doi.org/10.1111/j. 1469-8986.2008.00783.x.

[59] Kleih SC, Nijboer F, Halder S, Kübler A. Motivation modulates the P300 amplitude during brain-computer interface use. Clin Neurophysiol 2010;121(7):1023–31, http://dx.doi.org/10.1016/j.clinph.2010.01.034.

[60] Halder S, Hammer EM, Kleih SC, Bogdan M, Rosenstiel W, Birbaumer N, et al. Prediction of auditory and visual P300 brain-computer interface aptitude. PLoS ONE 2013;8(2):e53513, http://dx.doi.org/10.1371/journal.pone.0053513.

[61] Halder S, Agorastos D, Veit R, Hammer EM, Lee S, Varkuti B, et al. Neural mechanisms of brain-computer interface control. Neuroimage 2011;55(4):1779–90, http://dx.doi.org/10.1016/j.neuroimage.2011.01.021.

[62] Hammer EM, Halder S, Blankertz B, Sannelli C, Dickhaus T, Kleih S, et al. Psychological predictors of SMR-BCI performance. Biol Psychol 2012;89(1):80–6, http://dx.doi.org/10.1016/j.biopsycho.2011.09.006.

[63] Mak JN, McFarland DJ, Vaughan TM, McCane LM, Tsui PZ, Zeitlin DJ, et al. EEG correlates of P300-based brain-computer interface (BCI) performance in people with amyotrophic lateral sclerosis. J Neural Eng 2012;9(2):026014, http://dx.doi.org/10.1088/1741-2560/9/2/026014.

[64] Grosse-Wentrup M, Schölkopf B, Hill J. Causal influence of gamma oscillations on the sensorimotor rhythm. Neuroimage 2011;56(2):837–42, http://dx.doi.org/10.1016/j.neuroimage.2010.04.265.

[65] Halder S, Lukito S, Pasqualotto E, Ruf C, Matuz T, Birbaumer N, et al. Universal menu design for BCI applications. In: Neuroscience 2010. 2010.

[66] Spüler M, Rosenstiel W, Bogdan M. Online adaptation of a c-VEP brain-computer interface (BCI) based on error-related potentials and unsupervised learning. PLoS One 2012;7(12):e51077, http://dx.doi.org/10.1371/journal.pone.0051077.

[67] Gonsalvez CL, Polich J. P300 amplitude is determined by target-to-target interval. Psychophysiology 2002;39(3):388–96.

[68] Allison BZ, Pineda JA. ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system. IEEE Trans Neural Syst Rehabil Eng 2003;11(2):110–3, http://dx.doi.org/10.1109/TNSRE.2003.814448.

[69] Sellers EW, Krusienski DJ, McFarland DJ, Vaughan TM, Wolpaw JR. A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance. Biol Psychol 2006;73(3):242–52, http://dx.doi.org/10.1016/j.biopsycho.2006.04.007.

[70] Schreuder M, Riccio A, Risetti M, Dähne S, Ramsay A, Williamson J, et al. User-centered design in brain-computer interfaces – a case study. Artif Intell Med 2013;59(2):71–80, http://dx.doi.org/10.1016/j.artmed.2013.07.005.

[71] Sirvent JL, Azorín JM, Iáñez E, Úbeda A, Fernández E. P300-based brain-computer interface for internet browsing. In: Pawlewski P, editor. Trends in practical applications of agents and multiagent systems. Berlin, Heidelberg: Springer; 2010. p. 615–22.

[72] Ganin IP, Shishkin SL, Kaplan AY. A P300-based brain-computer interface with stimuli on moving objects: four-session single-trial and triple-trial tests with a game-like task design. PLoS One 2013;8(10):e77755, http://dx.doi.org/10.1371/journal.pone.0077755.

[73] De Vos M, Gandras K, Debener S. Towards a truly mobile auditory brain-computer interface: exploring the P300 to take away. Int J Psychophysiol 2014;91(1):46–53, http://dx.doi.org/10.1016/j.ijpsycho.2013.08.010.

Write, Read and Answer Emails with a Dry 'n' Wireless Brain-Computer Interface System*

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Abstract— **Brain-computer interface (BCI) users can control very complex applications such as multimedia players or even web browsers. Therefore, different biosignal acquisition systems are available to noninvasively measure the electrical activity of the brain, the electroencephalogram (EEG). To make BCIs more practical, hardware and software are nowadays designed more user centered and user friendly. In this paper we evaluated one of the latest innovations in the area of BCI: A wireless EEG amplifier with dry electrode technology combined with a web browser which enables BCI users to use standard webmail. With this system ten volunteers performed a daily life task: Write, read and answer an email. Experimental results of this study demonstrate the power of the introduced BCI system.**

I. INTRODUCTION

First experiments to measure the electrical activity of the human brain were started in the year 1924 by Hans Berger. In the year 1929 he reported the measurement of the electroencephalogram (EEG) from several patients [1]. However, he had great problems to visualize the signals because of primitive electrodes and signal plotting devices. More than 40 years later the idea emerged to use the EEG to control computers [2], nowadays well known as brain-computer interface (BCI). Unfortunately, the signal acquisition and the performance of the used computers were still a bottleneck. It took another 15 years to develop a practically usable BCI [3]. With this approach it was possible to spell words just by concentrating on randomly highlighted elements of a letter matrix. A prominent positive potential in the EEG approximately 250-500 ms post target stimulus [4] is the main control signal for this so-called P300-based BCI. Such a system enables healthy as well as users with motor impairment to communicate [5], [6], [7], [8], [9], [10]. Many software improvements have been introduced concerning: the signal processing (e.g., different classification methods [11], [12]) and the paradigm presentation (e.g., checkerboard flashing pattern [13], binomial flashing pattern [14], and famous faces highlighting [15]). On the signal acquisition side there was an evolution from passive gel-based electrodes, i.e., they require the application of abrasive, conductive gel between electrode and skin, to active gel-based electrodes, without the necessity to abrade the skin because the signal is pre-amplified at the electrode. Finally, in the last years dry electrodes were developed [16], [17].

Within the project BackHome we tested and evaluated one of the latest hardware developments. Namely the g.Nautilus, a wireless EEG signal amplifier with dry electrodes from Guger Technologies OG, Graz, Austria (http://www.gtec.at). Participants had to write, read and answer emails using a very popular webmail client with this device.

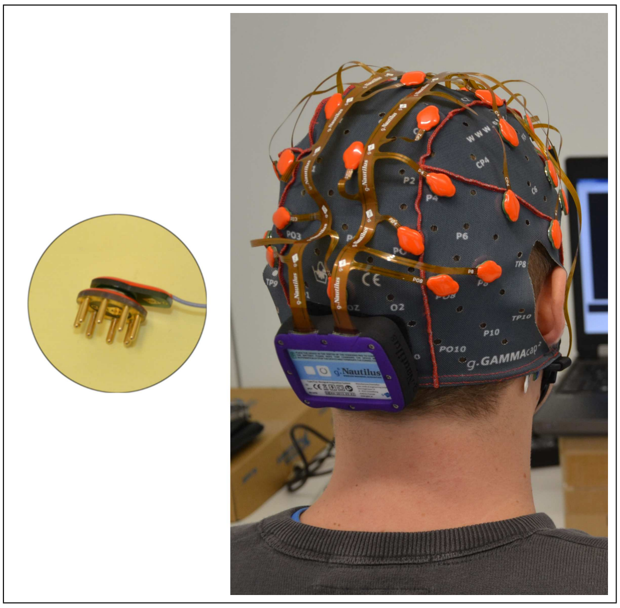

Fig. 1. A participant wearing the g.Nautilus system with dry electrodes. A close-up of the 7mm dry electrode is shown in the yellow circle.

II. MATERIALS AND METHODS

A. Participants

Ten volunteers (3 female; mean age 23.9 ± 1.2 years) participated in this study. All stated that they have no history of neurological or psychiatric disorders. The study protocol was approved by the ethics committee of the Medical University of Graz and the subjects gave written, informed consent before the experiment. Eight of the participants had no prior experience with BCIs.

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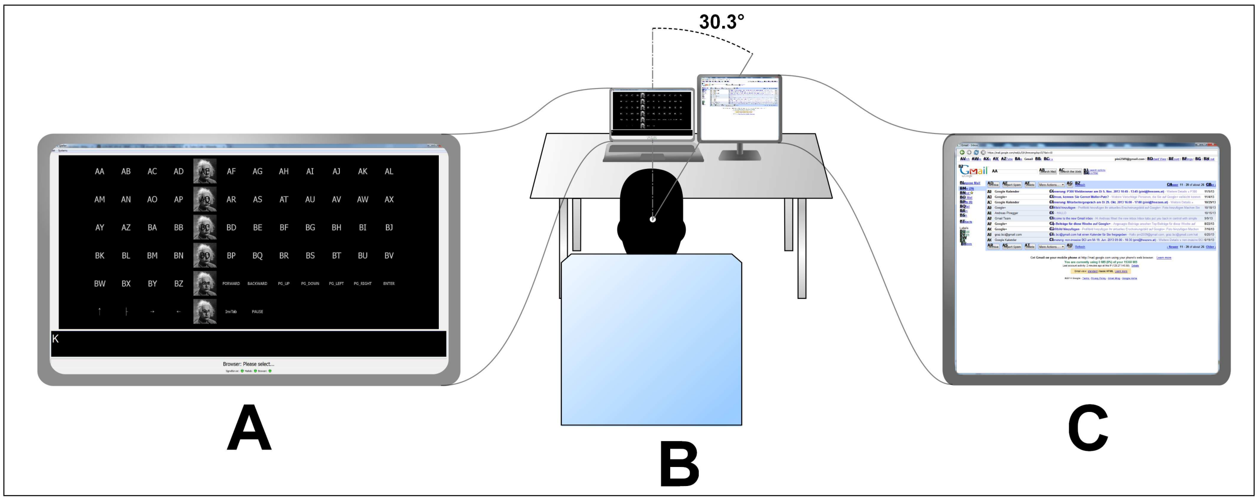

Fig. 2. (A) Screen displaying the user interface for feedback and P300 stimulation. (B) Sketch of the experimental design. The angle between the participant, the laptop, and the monitor was 30.3^o. (C) Screen for the web browser.

B. Data Acquisition

The g.Nautilus biosignal amplifier uses the ZigBee wireless technology to transmit the EEG signals with 24 bit resolution. Thirty-four electrodes, a reference channel, ground and 32 electrodes at pre-configured positions, are connected to the amplifier, see Fig. 1. Dry electrodes with two different pin lengths (7 and 16 mm) are available to adapt them to different hair lengths and shapes of users' heads. The operator has to find the optimal type of electrodes for each participant to get the best signal quality. The signal of each EEG channel is highly oversampled in order to keep the signal to noise ratio (SNR) high at the offered sampling rates of 250 Hz and 500 Hz.
In the presented study the signals from Fz, Cz, Pz, PO7, PO8, and Oz were sampled at 250 Hz and bandpass filtered between 0.5 and 30 Hz.
The whole g.Nautilus system consists of a headset with dry EEG electrodes (Fig. 1 yellow circle), a medium size EEG cap, and a base station for connecting it to the host computer. The device is charged with a Qi charging station. Qi is a wireless power transmission standard (http://www.wirelesspowerconsortium.com). This has the advantage that the device just has to be placed on the power transmission pad without the need to connect any wires.

C. Experimental Design

The participants were seated in a comfortable chair approximately 65 cm away from two computer screens (39.5 cm and 43 cm diameter), see Fig. 2 (B). One screen was centered in front of the participants. At this screen a P300 matrix was displayed to control a web browser (see Halder et al., under review), which was shown on a second screen placed right beside the first one, see Fig. 2 (A) and (C). The web browser automatically detects all possible links, buttons, and text fields of the currently shown website and marks them with letters. These letters were sent to the BCI for selection with a P300 spelling device. By sending back the desired element to the web browser the corresponding link, button, or text field was selected. In case the element was a text field the matrix automatically changed to a matrix with letters from the Latin alphabet, text manipulation, and control entries.
The P300 user interface and the signal processing in Matlab (MathWorks, Natick, USA) were presented in [18]. Elements of the matrix were highlighted with famous faces [15]. The aforementioned best electrode length selection was done by visual inspection of the measured EEG.
Calibration was performed with fifteen highlightings per row and column. Each flash had a duration of 50 ms and the time between flashes was set to 175 ms. The participants were asked to copy-spell ten letters. After the last letter the optimal number of sequences (each row and column flashed once) for feedback was calculated (number of sequences to achieve one hundred percent accuracy plus two; minimum eight, maximum fifteen sequences).
The task for the participants was to write an email to a given address and to reply to an automatically generated email from that address afterwards. First, they had to choose an address and spell "EINKAUFEN" (engl. "SHOPPING") into the subject field. Then, write "GEH BITTE HEUTE EINKAUFEN." (engl. "PLEASE GO SHOPPING TODAY.") into the message field and finally, send the message. At the end of this first part they had to select a "PAUSE" element to pause the system and wait for the reply. If the user selected this element, no further selections were sent to the web browser until the same element was selected again. The text of the answer mail was "MILCH AUCH?" (engl. "MILK TOO?"). After reading the mail the participants had to leave the pause mode and answer the new mail with the word "JA" (engl. "YES").
The whole email task needed a minimum of 52 selections and was aborted if the goal was not reached within 78 selections. The minimum instead of the actual number is given because

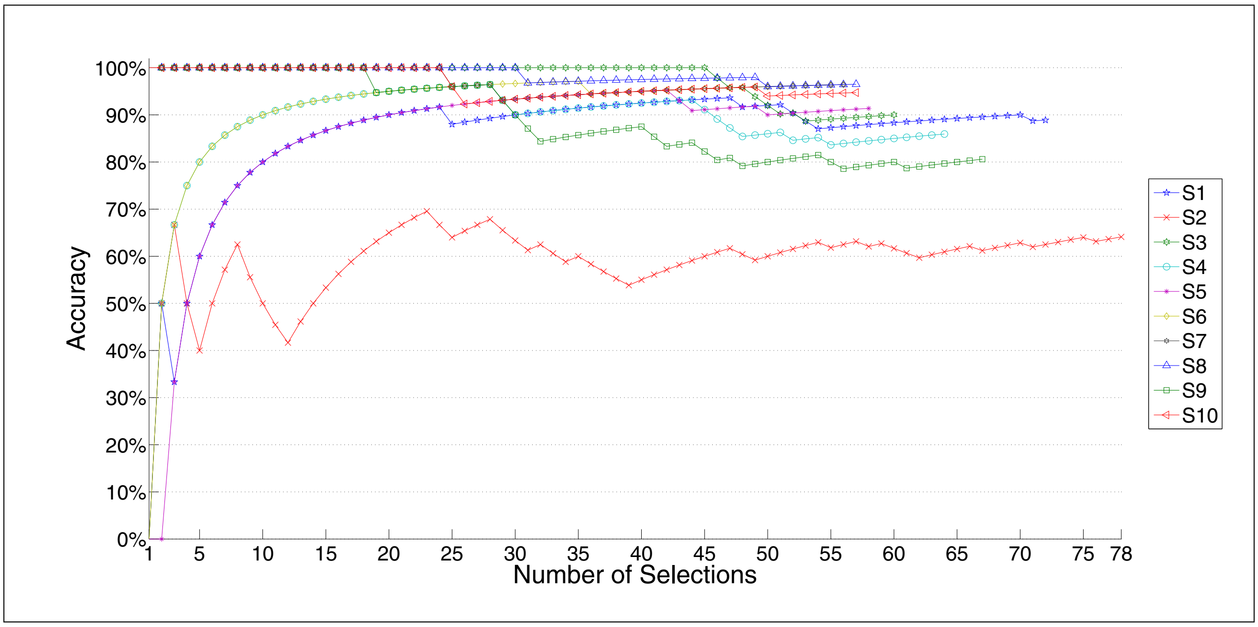

Fig. 3. Comparison of spelling accuracies from different participants over number of selections. The minimal number of selections was 52.

the user was asked to correct mistakes and thus the actual number of selections was unknown before the completion of the task.

D. Evaluation Metrics

After completing the BCI tasks all participants were asked to complete several questionnaires. Satisfaction was evaluated using a visual analog scale (VAS). The extended Quebec Evaluation of Satisfaction with Assistive Technology (eQUEST) version 2.0 [19] and a custom usability questionnaire were used to evaluate the usability of the soft- and hardware.

III. Results

Different electrode pin lengths were used for the participants. Only the six used electrodes of all 32 were adapted to the participants needs. Two participants needed just short electrodes, five only long electrodes, and three needed a mixture of both electrode types. The time between the instruction of the participant and the start of the calibration was on average 14 (SD 5) minutes.

A. Efficiency and Effectiveness

After calibrating the classifier the number of highlighting sequences for the online session was calculated for every participant. The participants needed on average 12 (SD 3, range 8–15) highlighting sequences.

A comparison of the accuracies after a certain number of selections is shown in Fig. 3. Nine participants completed the online task within the maximum allowed value of 78 selections. They had an average accuracy of 92.1% (SD 4.8). The time to complete the task including pauses varied between 38 minutes (S6) and 79 minutes (S1) with an average time of 58 (SD 16) minutes to complete the task. The accuracy of the participant S2 who did not complete the task was 66.7% after 95 minutes. Five participants started the online session with one or two errors. However, later on four of them (S1, S4, S5, S6) had very few errors. Only the accuracy of participant S2, who did not complete the task, stayed continuously below 70%, see Fig. 3. The participant with the longest period without making any error was S3 with 45 correct selections in a row from the beginning.

The average accuracy of all participants was 89.5% (SD 9.2).

B. Satisfaction

Overall device satisfaction (VAS score) was 7.5 (SD 2.3; not at all satisfied: 0, absolutely satisfied: 10).

The items which received scores below 4 (quite satisfied) in the eQuest were “aesthetic design” (3.4), “comfort” (3.8), and “effectiveness” (3.9). Highest rated items were the “adjustment of the hardware” (5.0) and the “reliability” (5.0). The items that were rated as most important by the study participants were “effectiveness” (n=5), “comfort” (n=5), and “learnability” (n=5). Most participants negatively remarked that the electrodes hurt after a while and criticized the low speed of the system.

Using the system design questionnaire, three users remarked that their eyes hurt after a while.

IV. Discussion

In this study, the performance of a new wireless EEG amplifier system with dry electrodes was evaluated and tested with an actual web browsing task.

The reached accuracies of the participants who completed the online task were between 84.9 % and 96.5 %. This performance is comparably high. Only one participant (S2) did not finish the task within 78 selections. A possible reason could be that the used short electrodes did not fit well enough which resulted in the signal to noise ratio being too low. Another interesting issue to be noted was that one participant (S8) paused the system and had to go urgently to the restroom after 47 selections. Afterwards the user selected the pause-leave element and finished the task with only one error. This would absolutely be impossible with a wired EEG amplifier system.

The needed highlighting sequences calculated after the calibration were nearly evenly distributed over the possible range (8–15). This result indicates that there is space to further improve the signal processing pipeline to better fit the requirements of a wireless dry electrode system. Originally, the software was designed for EEG amplifiers with active gel-based electrodes and was just slightly adapted. Other filter parameters and classification methods [12] could result in a decrease of needed highlighting sequences and consequently a reduction of needed time to spell a symbol.

According to the VAS the participants were very satisfied with the system. Only two participants rated the system below 7 and one of them did not finish the task.

The evaluation of the eQUEST showed that the users find the headset very conspicuous and they criticize the aesthetic design. Another low rated point in the eQUEST was the comfort of the headset. Nearly all the participants remarked that they felt the pressure of the dry electrode pins after a while and they had pressure marks on the forehead after the measurement. Another low rated point was the effectiveness. However, healthy people tend to compare assistive device systems with their normal communication and control devices. Compared to these systems the speed of current BCIs will always be low. All participants rated the "adjustment of the hardware" with the highest possible value. Compared to passive systems with abrasive electrode gel the development of dry electrodes is a huge improvement. However, there are still problems to be solved. It would be almost impossible to use such a system in a room where people are moving around, the induced artifacts would be dominant and would cover the EEG.

The participants rated "effectiveness" and "comfort" among the three most important as well as unsatisfied items. Consequently, the further development of the system should go in that direction.

In conclusion, this study shows that the introduced wireless EEG amplifier system with dry electrodes in combination with the BCI system and the BCI web browser works with very high accuracy. Despite the moderate speed of the system, the healthy users reported a very high overall satisfaction.

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REFERENCES

[1] H. Berger, "Über das Elektrenkephalogramm des Menschen," *Archiv fr Psychiatrie und Nervenkrankheiten*, vol. 87, pp. 527–570, 1929.

[2] J. J. Vidal, "Toward direct brain-computer communication," *Annual Review of Biophysics and Bioengineering*, vol. 2, pp. 157–180, 1973.

[3] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and Clinical Neurophysiology*, vol. 70, pp. 510–523, 1988.

[4] J. Polich, "Updating P300: an integrative theory of P3a and P3b." *Clinical Neurophysiology*, vol. 118, no. 10, pp. 2128–2148, 2007.

[5] E. Donchin, K. M. Spencer, and R. Wijesinghe, "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 8, pp. 174–179, 2000.

[6] 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," *Clinical Neurophysiology*, vol. 117, no. 3, pp. 531–537, 2006.

[7] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, "An efficient P300-based brain-computer interface for disabled subjects," *Journal of Neuroscience Methods*, vol. 167, pp. 115–125, 2008.

[8] 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," *Clinical Neurophysiology*, vol. 119, no. 10, pp. 1909–1916, 2008.

[9] 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 BCI: Paradigm transition from healthy subjects to minimally conscious patients," *Artif Intell Med*, vol. 59, no. 2, pp. 81–90, 2013.

[10] T. Kaufmann, S. M. Schulz, A. Köblitz, G. Renner, C. Wessig, and A. Kübler, "Face stimuli effectively prevent brain-computer interface inefficiency in patients with neurodegenerative disease," *Clinical Neurophysiology*, vol. 124, no. 5, pp. 893 – 900, 2013.

[11] 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," *Journal of Neural Engineering*, vol. 3, no. 4, pp. 299–305, 2006.

[12] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Müller, "Single-trial analysis and classification of ERP components – a tutorial," *NeuroImage*, vol. 56, pp. 814–825, 2011.

[13] 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," *Clinical Neurophysiology*, vol. 121, no. 7, pp. 1109–1120, 2010.

[14] J. Jin, P. Horki, C. Brunner, X. Wang, C. Neuper, and G. Pfurtscheller, "A new P300 stimulus presentation pattern for EEG-based spelling systems," *Biomedical Engineering*, vol. 55, pp. 203–210, 2010.

[15] T. Kaufmann, S. M. Schulz, C. Gruenzinger, and A. Kübler, "Flashing characters with famous faces improves ERP-based brain-computer interface performance," *Journal of Neural Engineering*, vol. 8, no. 5, 2011.

[16] C. Guger, G. Krausz, B. Z. Allison, and G. Edlinger, "Comparison of dry and gel based electrodes for P300 brain-computer interfaces," *Frontiers in Neuroscience*, vol. 6, no. 60, 2012.

[17] A. Mota, L. Duarte, D. Rodrigues, A. Martins, A. Machado, F. Vaz, P. Fiedler, J. Haueisen, J. Nbrega, and C. Fonseca, "Development of a quasi-dry electrode for EEG recording," *Sensors and Actuators A: Physical*, vol. 199, pp. 310 – 317, 2013.

[18] A. Pinegger, S. Wriessnegger, and G. Müller-Putz, "Introduction of a universal P300 brain-computer interface communication system," in *Biomedical Engineering*, vol. 58, 2013.

[19] C. Zickler, A. Riccio, F. Leotta, S. Hillian-Tress, S. Halder, E. Holz, P. Staiger-Sälzer, E. Hoogerwerf, L. Desideri, D. Mattia, and A. Kübler, "A brain-computer interface as input channel for a standard assistive technology software," *Clinical EEG and Neuroscience*, vol. 42, no. 4, pp. 236–244, 2011.

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Note

Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach

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Abstract

Objective. Brain–computer interfaces (BCI) based on event-related potentials (ERP) were proven to be a reliable synchronous communication method. For everyday life situations, however, this synchronous mode is impractical because the system will deliver a selection even if the user is not paying attention to the stimulation. So far, research into attention-aware visual ERP–BCIs (i.e., asynchronous ERP–BCIs) has led to variable success. In this study, we investigate new approaches for detection of user engagement. *Approach.* Classifier output and frequency-domain features of electroencephalogram signals as well as the hybridization of them were used to detect the user's state. We tested their capabilities for state detection in different control scenarios on offline data from 21 healthy volunteers. *Main results.* The hybridization of classifier output and frequency-domain features outperformed the results of the single methods, and allowed building an asynchronous P300-based BCI with an average correct state detection accuracy of more than 95%. *Significance.* Our results show that all introduced approaches for state detection in an asynchronous P300-based BCI can effectively avoid involuntary selections, and that the hybrid method is the most effective approach.

Keywords: brain–computer interface, BCI, P300, asynchronous, control state

(Some figures may appear in colour only in the online journal)

1. Introduction

The human electroencephalogram (EEG) consists of various components, oscillatory as well as event-related potentials (ERP). ERPs are a result of external stimulation. They are the response to stimuli, which can be given via any sensory perception. The P300 potential is a prominent positive ERP in the EEG approximately 250–500 ms post stimulus [1]. It is elicited in a so-called 'oddball' paradigm: many stimuli are given to users but just some of them are relevant (target stimuli)—users have to focus their attention on them—and many others are irrelevant (non-target stimuli) [2]. Using visually evoked signals for brain–computer interface (BCI) based communication was first suggested by Farwell and Donchin in 1988 [3].

A traditional application for a P300-based BCI is the so-called P300 speller. Letters, numbers, and/or symbols are presented to users within a visual P300 speller on a computer screen. These characters will be highlighted randomly and users have to mentally count the highlighting of the character they intend to select, while ignoring all the other flashing items. After a number of sequences (all characters flashed

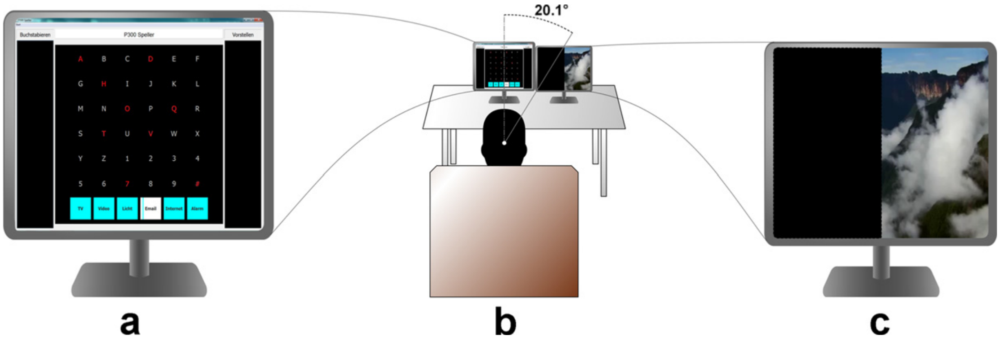

Figure 1. (a) Monitor displaying the user interface for feedback and P300 stimulation. (b) Sketch of the experimental design. The angle between the participant, the a-, and the c monitor was 20.1°. (c) During the video tasks a video was shown on this monitor otherwise the screen was black.

once) a classification algorithm detects the P300 in the recorded EEG and determines the intended character. This system enables healthy as well as motor impaired users to communicate [4–9]. Many improvements have been introduced since 1988 concerning: the data acquisition (e.g., dry electrodes [10, 11]), the signal processing (e.g., different classification methods [12, 13]), and the paradigm presentation (e.g., checkerboard flashing pattern [14], binomial flashing pattern [15], and famous faces highlighting [16]).

It has been proven that a P300-speller works very well with tasks which need input periodically (e.g., to spell characters and sentences). Consequently, the user has to be constantly engaged in the task. Whereas performing tasks which need aperiodic or asynchronous input (e.g., to control a web browser or a multimedia player) is not possible in a practical way. In that case, it is substantial that users have time to read or look at the content.

Zhang *et al* [17] proposed a first approach for an asynchronous P300-based BCI using statistical and probabilistic methods to model the user's mental state in control and non-control condition. Some following approaches were based on statistical P300 amplitude features as well [18–20]. Others used a steady-state visually evoked potentials (SSVEP) paradigm together with a standard P300 paradigm to run the system asynchronously [21], or the band power of the EEG as additional source of information [22].

In this work, we investigated different methods for control and non-control state detection. Similarly to Zhang *et al* in [17], we call a P300 selection task a *control* task and all other tasks *non-control* tasks.

Our first method is based on statistical analysis of the classifier output (see [17–20]). This method takes advantage of the fact that if the user is not concentrating on a specific symbol of the matrix the output of the classifier is statistically significantly different than when she/he is engaged with the flashing matrix.

Our second method is based on the hypothesis that when a person is looking at the flashing matrix the flashing frequency is represented more or less pronounced in the averaged signal from the occipital electrodes. The shape of this signal is comparable to an SSVEP signal without focusing on a defined target. Using this frequency-domain feature of the EEG for correct state detection is a completely novel approach and our second method.

Our third method is based on the hypothesis that combining these aforementioned two independent detection methods (classifier output—and frequency analysis) increases the correct state detection accuracy.

2. Methods

2.1. Participants

Twenty-one healthy volunteers (eight female, mean age 25.8 ± 3.9, range 21–34 years) participated in this study. All participants stated that they have no history of neurological or psychiatric disorders. The study protocol was approved by the ethics committee of the Medical University of Graz and the participants gave informed written consent before the experiment. Twelve participants had no prior experience with P300-based BCIs.

2.2. Data acquisition

We recorded EEG from 40 scalp locations using active Ag/AgCl electrodes (g.LADYbirds by Guger Technologies OEG, Graz, Austria). The locations of the electrodes were based on the extended international 10–20 system for electrode placement. Only eight EEG channels (Fz, Cz, Pz, PO3, POz, PO4, O1, Oz, O2) were used in this study and the other electrodes retained for future analyses. The channels were referenced to the left earlobe and grounded at position FPz. In addition to the EEG, we also recorded three orthogonal EOG channels, ECG, and EMG (tibialis anterior of both legs). We recorded all signals with a sampling rate of 256 Hz with three synchronized amplifiers (g.USBamps by Guger Technologies OEG, Graz, Austria). The amplifiers filtered the raw data with a 0.5–100 Hz bandpass and a 50 Hz notch filter.

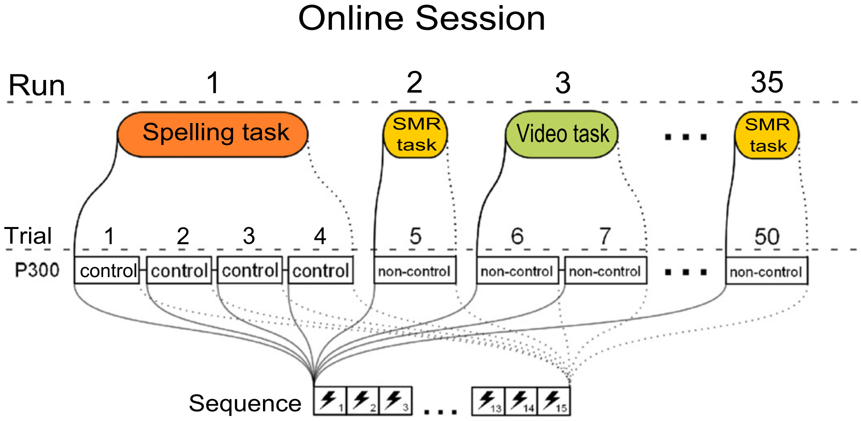

Figure 2. Online session scheme. Different runs consisted of different numbers of trials. One trial (control as well as non-control) always consisted of 15 flashing sequences.

2.3. Experimental design

The participants were seated in a comfortable chair 1 m away from two computer screens (43 and 37 cm diameter), see figure 1. One screen was centered in front of the participants. At this screen a 6 × 6 P300 matrix was presented containing the letters of the Latin alphabet and numbers from 0–9. The screen also contained areas where instructions were shown and feedback was given, see figure 1(a). Additionally, there was a row with six elements arranged below the P300 matrix. These elements were selected with a sensorimotor rhythm (SMR)-based BCI [23, 24]. The second screen was placed right beside the first one. During defined tasks a video was shown on this monitor otherwise the screen was black, see figure 1(c).

One P300 selection *sequence* comprised 12 flashes (one for each row and column) of 50 ms duration and a 125 ms inter-stimulus interval. The highlighting (flashing) was realized by showing the face of the scientist Albert Einstein as Kaufmann *et al* proposed in [16]. A *trial* consisted of 15 sequences followed by an 8 s break. Furthermore, a trial was either a control trial (i.e., the user had to focus on an specific item of the matrix) or a non-control trial (i.e., the users should ignore the flashing of the matrix).

In the calibration phase the participants had to spell ten predefined symbols (red marked letters in figure 1(a)) to train the P300 classifier. During the online session the participants had to perform 35 *runs*:

(i) Five control runs: spelling five words with four letters each (5 control runs × 4 trials (letters) = 20 control trials).
(ii) Twenty-five non-control runs:
  (a) Selecting elements of the aforementioned SMR row (20 non-control runs × 1 trial = 20 non-control trials).
  (b) Watching a video on the second screen (5 non-control runs × 2 trials = 10 non-control trials).
(iii) Five rest runs: looking at the frozen screen (no changes) for 1 min.

Figure 2 illustrates the scheme for the online session. In total the participants had to perform 50 trials (20 control trials and 30 non-control trials). During the non-control trials the matrix was flashing without presenting the classification result. However, the participants were instructed to ignore the highlighting of the P300 matrix and to concentrate just on the elements below the matrix, or the video. An SMR selection run lasted as long as one letter selection trial (approximately 44 s) and a video-watching run lasted as long as two letter selection trials (approximately 88 s).

2.4. P300 classification

We used stepwise linear discriminant analysis (SWLDA) for classification of the P300 related tasks. This method, an extension of Fisher's linear discriminant analysis, is an established classification method for visual P300 BCIs [8, 9, 12]. The chosen epoch length was 204 samples or approximately 800 ms long. The channel by sample matrix of each trial was smoothed with a moving average filter with a width of 17 samples, and then decimated by a factor of 12 prior to averaging and feature selection.

For online classification the SWLDA classifier model was separately applied on all rows and columns. The row and the column which yielded the highest LDA distances were selected by the classifier.

2.5. Control state detection

2.5.1. LDA distance method (LDM). For this method the output of the described P300 SWLDA classifier was used to distinguish between control and non-control state. The difference between the mean $\bar{d}_{\mathrm{all}}$ and the sum of the maximum values for rows d_{row} and columns d_{col} of the classifier output was

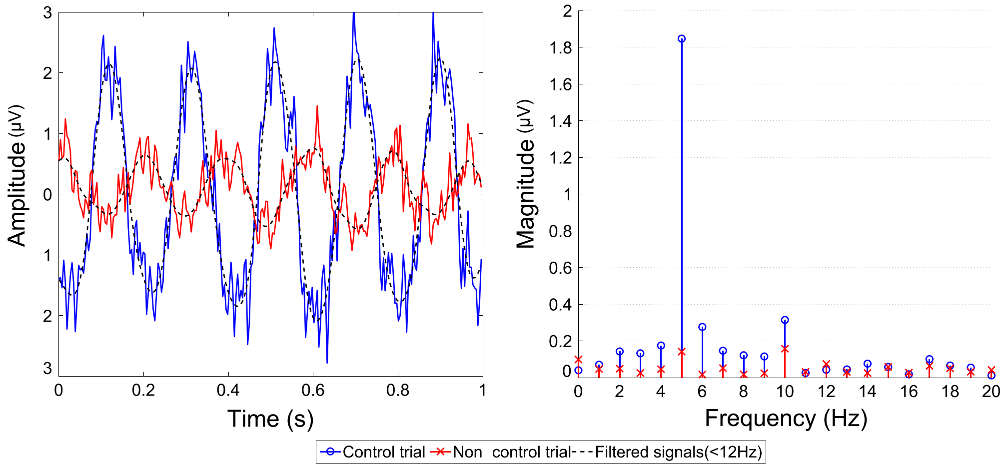

Figure 3. Comparison of the spatial (six channels) and temporal (1 s post stimulus) averaged signal of a P300 spelling trial (blue line) and a video-watching trial (red line) of participant 1. On the left the time-domain plot. The black dashed lines represent the same signals after 12 Hz low pass filtering. On the right the frequency domain plot of the signal.

calculated for every trial i:

$$d_i = [\max (d_{\text{row}}) + \max (d_{\text{col}})] - \bar{d}_{\text{all}}. \tag{1}$$

Results from the P300 speller training $d_{1-10}^{\,t}$ were used to get the threshold d_0 for the detection by averaging the ten results from the training $\bar{d}^{\,t}$ minus their standard deviation multiplied with a factor k_L:

$$d_0 = \bar{d}^{\,t} - k_L \cdot \text{stdev}\left[d_1^{\,t}\ d_2^{\,t}\ \ldots\ d_{10}^{\,t}\right] \tag{2}$$

k_L was set to a value between 0 and 2 with a leave-one-participant-out cross-validation (LOPOCV) of the online data. The factor was set to the value which resulted in the lowest error rate in total.

To detect whether the participant was focusing on the flashing matrix the actual calculated LDA max–mean distance difference d_i was compared with the threshold. Results higher than or equal to the threshold were classified as control state related:

$$s_{i,(\text{LDM})} = \begin{cases} \text{control state} & \text{if } d_i \geqslant d_0, \\ \text{non-control state} & \text{if } d_i < d_0, \end{cases} \quad i = 1, 2, \ldots 50. \tag{3}$$

2.5.2. Spectral analysis method (SAM). The SSVEP phenomenon, that was described in the introduction, was used to distinguish between control and non-control state. The used stimulus interval of 175 ms is reflected in an EEG frequency of 5.71 Hz. However, to see this phenomenon a spatial and temporal averaging of the parietal-occipital (PO3, POz, PO4, O1, Oz, and O2) EEG signals is necessary. The temporal averaging was performed by calculating the mean of 1 s long post stimulus (i.e., highlighting of a row/column) epochs per trial. The epoch length was set to 1 s to receive a frequency resolution of 1 Hz. Figure 3 demonstrates the difference between the resulting signals when the user either was performing a P300 selection task (control task) or was watching a video (non-control task) while the matrix was flashing.

An FFT was performed on this averaged signal and the magnitudes of the first harmonic (5 and 6 Hz), the second harmonic (10 and 11 Hz), and the third harmonic (15 and 16 Hz) were calculated. The magnitudes were added up to receive one value for every trial:

$$m_i = \sum_{n=1}^{3} \left(m_{(5\cdot n)\text{Hz}} + m_{(5\cdot n+1)\text{Hz}}\right). \tag{4}$$

Different methods were tested to calculate (4) including normalization by the total frequency spectrum and by defined frequencies. However, the suggested method worked best for all participants and trials.

The threshold for the detection was calculated with the ten magnitudes, which were calculated with (4) from the P300 training. The mean of these ten magnitudes $\bar{m}^{\,t}$ minus their standard deviation multiplied with a factor k_S represented the threshold for the online-data detection algorithm:

$$m_0 = \bar{m}^{\,t} - k_S \cdot \text{stdev}\left[m_1^{\,t}\ m_2^{\,t}\ \ldots\ m_{10}^{\,t}\right]. \tag{5}$$

Similarly to the LDM, k_S was set to a value between 0 and 2 with an LOPOCV of the online data.

During the online phase the calculated magnitude m_i of one trial was compared with the threshold m_0 to detect whether the participant was focusing on the flashing matrix:

$$s_{i,(\text{SAM})} = \begin{cases} \text{control state} & \text{if } m_i \geqslant m_0, \\ \text{non-control state} & \text{if } m_i < m_0, \end{cases} \quad i = 1, 2, \ldots 50. \tag{6}$$

2.5.3. Hybrid analysis method (HAM). This method is a combination of the LDM and the SAM. We divided the actual LDA distance (d_i) and spectral analysis result (m_i) by their thresholds (d_0, m_0) and weighted them with w_L and w_S, with $w_L + w_S = 1$. The sum of these results was calculated and values higher than or equal to 1 were classified as control state belonging:

$$s_{i,(\mathrm{HAM})} = \begin{cases} \text{control state} & \text{if } \left(w_L \cdot \dfrac{d_i}{d_0} + w_S \cdot \dfrac{m_i}{m_0}\right) \geqslant 1, \\ \text{non-control state} & \text{if } \left(w_L \cdot \dfrac{d_i}{d_0} + w_S \cdot \dfrac{m_i}{m_0}\right) < 1, \end{cases} \quad i = 1, 2, \ldots 50. \tag{7}$$

Weights (w_L, w_S) for the LDA distance result and the spectral analysis result were determined by simulating different weight combinations and performing a nested cross-validation.

2.6. Data analysis

To determine k_L, k_S, w_L, and w_S normal and nested LOPOCVs of the online data were used. The inter participant cross-validation was chosen to demonstrate how well the approaches generalize. Only 40 trials (20 control and 20 non-control trials) out of the 50 were used to perform the LOPOCVs to have equally sized class sets. However, we used all available 50 trials to determine the performance of the different methods.

Due to the facts that we had unbalanced trials per class and in total 50 trials per participant the practical chance level for correct state detections had to be calculated [25]. The conservatively calculated chance level for our study was 68% ($p = 0.01$).

Statistically significant differences between the methods were investigated with Bonferroni corrected paired Wilcoxon signed-rank tests. Due to the Bonferroni correction the significance criterion α was set at 0.0167 (0.05/3).

3. Results

The results of the three state detection methods were calculated offline after all measurements have been completed. The *standard error of the mean* is given in parenthesis after every accuracy result.

3.1. Spelling accuracy

After the training session the 21 participants showed a mean P300 spelling accuracy of 94.3%(2.1), range: 70–100%. In the online session each participant spelled 20 letters with a mean accuracy of 96.2% (1.6), range: 70–100%.

Table 1. Comparison between the different methods and their correct detection rates (TPR…true positive rate, TNR…true negative rate) and accuracy. The standard error of the mean is given in parenthesis.

Method	Control runs TPR(%)	Non-control runs TNR(%)	All runs Accuracy(%)
LDM[a]	96.7 (0.9)	92.5 (2.4)	94.2 (1.4)
SAM[b]	88.3 (1.8)	73.7 (5.1)	79.5 (2.8)
HAM[c]	99.0 (0.4)	93.2 (2.2)	95.5 (1.2)

[a] LDM = LDA distance method.
[b] SAM = spectral analysis method.
[c] HAM = hybridization of LDM and SAM.

3.2. Detection methods evaluation

An overview of the calculated results is shown in table 1. A graphical overview of all false detections per participant can be seen in figure 4. In figure 4 the number of errors decrease from left to right. Detailed results for every participant are shown in table 2.

3.2.1. LDA distance method. The determined factors k_L for every participant after the LOPOCV are presented in figure 5 with blue plus signs.

The mean correct detection accuracy for control states was 96.7%(0.9) and for non-control states was 92.5% (2.4).

3.2.2. Spectral analysis method. Red asterisks in figure 5 present the participant specific parameters k_S.

Control states were detected correctly with an accuracy of 88.3%(1.8) and non-control states with an accuracy of 73,7%(5.1). This method showed a significantly lower performance for the control tasks ($Z = -2.98$, $p = 0.003$, $r = 0.46$) as well as for the non-control tasks ($Z = -3.18$, $p = 0.002$, $r = 0.49$) compared with the LDM.

3.2.3. Hybrid analysis method. Best weights (w_L, w_S) for the combination of the LDM and the SAM results were found by simulating different rates with a nested LOPOCV to avoid over-fitting. The values for w_L are plotted as green crosses and the values for w_S as cyan dots in figure 5.

The hybrid method yielded a mean correct control state detection accuracy of 99.0% (0.4) and a mean correct non-control state detection accuracy of 93.2% (2.2).

The control state detection accuracy of this hybrid method was significantly better than the LDM ($Z = -2.64$, $p = 0.008$, $r = 0.41$) and the SAM ($Z = -3.75$, $p < 0.001$, $r = 0.58$). Between the non-control state detection accuracy of this method and the LDM was a slight difference of +0.7% in accuracy. However, the HAM was significantly better than the SAM ($Z = -3.51$, $p < 0.001$, $r = 0.54$). The overall correct detection accuracy (4th column in table 1) of the hybrid method was significantly better than the LDM ($Z = -2.69$, $p = 0.007$, $r = 0.42$) and the SAM ($Z = -3.98$, $p < 0.001$, $r = 0.61$).

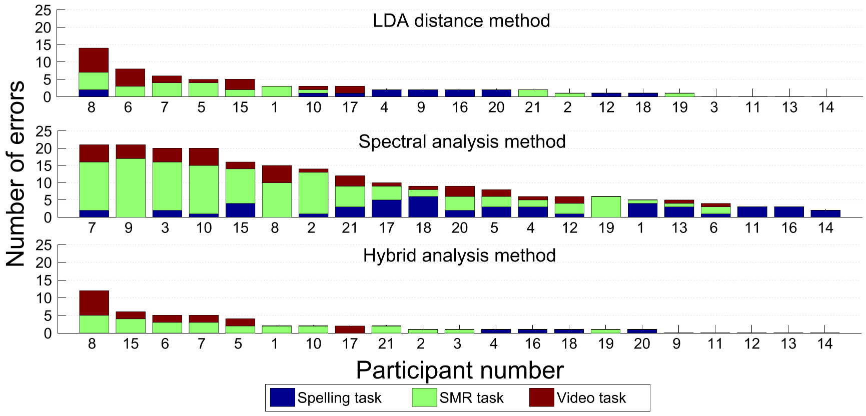

Figure 4. Graphical comparison of different state detection errors per method and participant. The data was sorted with decreasing number of errors from left to right.

Table 2. Comparison of the (non-)control state detection rates of all methods (*L*…LDA distance method, *S*…spectral analysis method, *H*…hybrid analysis method) and participants.

Participant	Word task *L*/*S*/*H*(TPR[a] (%))	SMR task *L*/*S*/*H*(TNR[b] (%))	Video task *L*/*S*/*H*(TNR[b] (%))
1	100/ 80/100	85/95/90	100/100/100
2	100/ 95/100	95/ 40/ 95	100/ 90/100
3	100/ 90/100	100/ 30/ 95	100/ 60/100
4	90/ 85/ 95	100/ 90/100	100/ 90/100
5	100/ 85/100	80/ 85/ 90	90/ 80/ 80
6	100/ 95/100	85/ 90/ 85	50/ 90/ 80
7	100/ 90/100	80/ 30/ 85	80/ 50/ 80
8	90/100/100	75/ 50/ 75	30/ 50/ 30
9	90/100/100	100/ 15/100	100/ 60/100
10	95/ 95/100	95/ 30/ 90	90/ 50/100
11	100/ 85/100	100/100/100	100/100/100
12	95/ 95/100	100/ 85/100	100/ 80/100
13	100/ 85/100	100/ 95/100	100/ 90/100
14	100/ 90/100	100/100/100	100/100/100
15	100/ 80/100	90/ 50/ 80	70/ 80/ 80
16	90/ 85/ 95	100/100/100	100/100/100
17	95/ 75/100	100/ 80/100	80/ 90/ 80
18	95/ 75/ 95	100/ 90/100	100/ 90/100
19	100/100/100	95/ 70/ 95	100/100/100
20	90/ 90/ 95	100/ 80/100	100/ 70/100
21	100/ 80/100	90/ 70/ 90	100/ 70/100
Mean	96.7/88.3/99.0	93.8/70.2/93.8	90.0/80.5/91.9
SEM[c]	0.9/ 1.8/ 0.4	1.8/ 6.0/ 1.7	4.1/ 3.9/ 3.6

[a] True positive rate.
[b] True negative rate.
[c] Standard error of the mean.

4. Discussion

In this study, we provide evidence that the P300 flashing frequency in the EEG detection is a powerful user's state detection method and that the hybridization of this method with the LDM outperforms the results of the single methods.

4.1. Effectiveness

All applied methods were very effective in detecting the correct user's state. Our hybrid approach was the most effective, see table 1. With this approach 17 out of 21 participants reached a correct control state detection rate of 100% and no participant had a lower rate than 95% (see table 2, 2nd column). For 16 participants the non-control states were detected correctly with equal or more than 90% accuracy (see table 2, 3rd and 4th column). Taking into account the probability that some of the participants may have looked at the flashing matrix, when they should perform another task, this was a quite high result. We showed that for 11 participants the hybrid method was the best method to detect their correct state and for further seven participants it worked as well as one of the other methods. Additionally, all the results of the hybrid method (excluding participant 8) were between 80–100% and thus far above the practical chance level of 68% [25].

4.2. Robustness

To demonstrate the generality of our methods we used LOPOCV to determine the classification parameters (k_L, k_S, w_L, w_S) for every participant. It is obvious that these parameters were determined as person unspecific as possible. Additionally, figure 5 indicates that the parameter values do not vary much between the participants. As a result the mean values of those parameters can be used as a start configuration for further online usage. Then a new user has to perform only a normal P300 BCI calibration to use the introduced control state detection method without the necessity of any additional calibration.

Based on the findings of Zickler *et al* in [26] it can be argued that the calculated P300 classifier and state detection

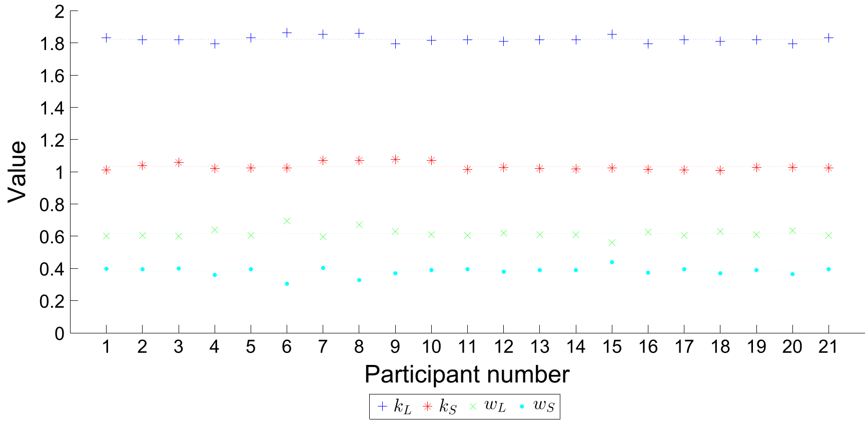

Figure 5. Graphical representation of the values k_L, k_S, w_L, and w_S from equations (2), (5), and (7) determined with LOPOCVs. The dotted lines represent the respective mean values.

thresholds should work for several sessions with acceptable (>80%) accuracies.

4.3. Limitations

The introduced SAM is limited in its effectiveness by the fact that it requires sufficient gaze control. Otherwise, the SAM as well as the hybrid method will not work properly. However, the LDM with its acceptable accuracies should work even for users with insufficient gaze control (see, [19]). Furthermore, the SAM could work as a simple eyes open detector: the flashing frequency will not be detectable in the EEG, if the eyes are closed. Consequently the method can be used for example to call a carer or to switch off the BCI.

4.4. Comparison to other approaches

A direct comparison of the results from this study and the studies performed by different groups [17–21] mentioned in the introduction is difficult due to different classification approaches, stimulation modalities, and especially performance evaluations. However, Liu *et al* investigated in [22, 27] comparable features (classifier output and frequency domain) and the hybridization of them. In contrast to our approach, they use the band power of dedicated EEG frequency bands instead of the magnitude of the stimulation frequency to distinguish between control and non-control state. In [27] they performed a comparable experiment and reported a mean area under the receiver operating characteristic curve (AUC) value of 0.86 (SD: 0.06) (hybrid method and control versus all non-control trials). If we use the same calculation method our hybrid method would reach a mean AUC value of 0.95 (SD: 0.06).

Another interesting approach already mentioned by Zhang *et al* in [17] is to add a 'PAUSE/RUN' element into the matrix. If the user selects this element, the system switches into pause mode and no other selections except this element will be possible. Consequently, the system stays in this mode until the same element is selected again. Two selections are necessary to go manually into pause mode and leave the pause mode. The time the participants would need to perform these two selections with our system is 100 s. However, the probability that the pause mode is left by chance is $1/N$ with N being the number of matrix elements. The probability for our spelling system with $N = 36$ that the system will stay in pause mode is 97.2%. This value is just slightly higher than our non-control state detection value of 93.2%. Furthermore, a disadvantage of this method is that two selections are necessary to switch on and off the pause mode even if the user just wants e.g., to read one or two sentences of a homepage.

A useful combination of the idea from Zhang *et al* and our approach would be to switch into the suggested pause mode after a variable number (e.g., two in a row) non-control state detections by our system. To leave the pause mode the user would have to select the 'RUN' element twice in a row. This double selection decreases the probability that the non-control state is left by chance from $p = 0.03$ to $p < 0.001$. Then the short time non-control state detection would be realized by our system and the long time pause by the approach from Zhang *et al*. Due to the fact that our state detection system creates about four wrong state detections (mainly non-control, cf table 2) per hour this proposed combination would considerably improve the usability of the system.

Comparable functionality could also be realized with a simple assistive device (e.g., a switch). This device could be used to switch on and off the P300 BCI. However, this approach requires that the user has sufficient motor control of at least the neck muscles to use the assistive device. Additionally, if the user doze off without switching off the P300 BCI, selections would be made unintentionally. Our suggested system would prevent such unintended selections.

5. Conclusion

In this study, we investigated the possibility of making a P300-based BCI system asynchronous. Our results showed that it is possible to detect the state of a P300-based BCI user with very high (⩾90%) accuracy for 19 out of 21 participants during different tasks. This work might be the basis for complex BCI controlled applications (e.g., web browser, multimedia player), for whom an asynchronous P300 control modality is indispensable.

Acknowledgments

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References

[1] Polich J 2007 Updating P300: an integrative theory of P3a and P3b *Clin. Neurophysiol.* **118** 2128–48

[2] Pritchard W S 1981 Psychophysiology of P300 *Psychological Bull.* **89** 506–40

[3] Farwell L A and Donchin E 1988 Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials *Electroencephalogr. Clin. Neurophysiol.* **70** 510–23

[4] Donchin E, Spencer K M and Wijesinghe R 2000 The mental prosthesis: assessing the speed of a P300-based brain–computer interface *IEEE Trans. Neural Syst. Rehabil. Eng.* **8** 174–9

[5] Piccione F, Giorgi F, Tonin P, Priftis K, Giove S, Silvoni S, Palmas G and Beverina F 2006 P300-based brain–computer interface: reliability and performance in healthy and paralysed participants *Clin. Neurophysiol.* **117** 531–7

[6] Sellers E W and Donchin E 2006 A P300-based brain–computer interface: initial tests by ALS patients *Clin. Neurophysiol.* **117** 538–48

[7] Hoffmann U, Vesin J-M, Ebrahimi T and Diserens K 2008 An efficient P300-based brain–computer interface for disabled subjects *J. Neurosci. Methods* **167** 115–25

[8] Nijboer F *et al* 2008 A P300-based brain–computer interface for people with amyotrophic lateral sclerosis *Clin. Neurophysiol.* **119** 1909–16

[9] Kaufmann T, Schulz St M, Köblitz A, Renner G, Wessig C and Kübler A 2013 Face stimuli effectively prevent brain–computer interface inefficiency in patients with neurodegenerative disease *Clin. Neurophysiol.* **124** 893–900

[10] Guger C, Krausz G, Allison B Z and Edlinger G 2012 Comparison of dry and gel based electrodes for P300 brain–computer interfaces *Frontiers Neurosci.* **6**

[11] Mota A R, Duarte L, Rodrigues D, Martins A C, Machado A V, Vaz F, Fiedler P, Haueisen J, Nóbrega J M and Fonseca C 2013 Development of a quasi-dry electrode for EEG recording *Sensors Actuators* A **199** 310–7

[12] Krusienski D J, Sellers E W, Cabestaing F, Bayoudh S, McFarland D J, Vaughan T M and Wolpaw J R 2006 A comparison of classification techniques for the P300 speller *J. Neural Eng.* **3** 299–305

[13] Blankertz B, Lemm S, Treder M, Haufe S and Müller K-R 2011 Single-trial analysis and classification of ERP components—a tutorial *NeuroImage* **56** 814–25

[14] Townsend G, LaPallo B K, Boulay C B, Krusienski D J, Frye G E, Hauser C K, Schwartz N E, Vaughan T M, Wolpaw J R and Sellers E W 2010 A novel P300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns *Clin. Neurophysiol.* **121** 1109–20

[15] Jin J, Horki P, Brunner C, Wang X, Neuper C and Pfurtscheller G 2010 A new P300 stimulus presentation pattern for EEG-based spelling systems *Biomed. Eng. Appl. Basis Commun.* **55** 203–10

[16] Kaufmann T, Schulz S M, Gruenzinger C and Kübler A 2011 Flashing characters with famous faces improves ERP-based brain–computer interface performance *J. Neural Eng.* **8** 056016

[17] Zhang H, Guan C and Wang C 2008 Asynchronous P300-based brain–computer interfaces: a computational approach with statistical models *IEEE Trans. Biomed. Eng.* **55** 1754–63

[18] Lenhardt A and Ritter H 2010 An augmented-reality based brain-computer interface for robot control *Neural Information Processing. Models and Applications* (*Lecture Notes in Computer Science* vol 6444) ed K W Wong, B Mendis, U Sumudu and A Bouzerdoum (Berlin: Springer) pp 58–65

[19] Aloise F, Schettini F, Aricó P, Leotta F, Salinari S, Mattia D, Babiloni F and Cincotti F 2011 P300-based brain–computer interface for environmental control: an asynchronous approach *J. Neural Eng.* **8** 025025

[20] Riechmann H, Hachmeister N, Ritter H and Finke A 2011 Asynchronous, parallel on-line classification of P300 and ERD for an efficient hybrid BCI *5th Int. IEEE/EMBS Conf. on Neural Engineering* pp 412–415

[21] Panicker R, Puthusserypady S and Sun Y 2011 An asynchronous P300 BCI with SSVEP-based control state detection *IEEE Trans. Biomed. Eng.* **58** 1781–8

[22] Liu Y, Ayaz H, Curtin A, Shewokis P A and Onaral B 2012 Detection of attention shift for asynchronous P300-based BCI *Engineering in Medicine and Biology Society (EMBC) Annual Int. Conf. IEEE* pp 3850–3853

[23] Müller-Putz G R, Kaiser V, Solis-Escalante T and Pfurtscheller G 2010 Fast set-up asynchronous brain-switch based on detection of foot motor imagery in 1-channel EEG *Med. Biol. Eng. Comput.* **48** 229–33

[24] Faller J, Vidaurre C, Solis-Escalante T, Neuper C and Scherer R 2012 Autocalibration and recurrent adaptation: towards a plug and play online ERD-BCI *IEEE Trans. Neural Syst. Rehabil. Eng.* **20** 313–9

[25] 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* (*Biological and Medical Physics, Biomedical Engineering*) ed B Z Allison, S Dunne, R Leeb, J Del, R Millán and A Nijholt (Berlin: Springer) pp 333–354

[26] Zickler C, Halder S, Kleih S C, Herbert C and Kübler A 2013 Brain painting: usability testing according to the user-centered design in end users with severe motor paralysis *Artif. Intell. Med.* **59** 99–110 special issue: brain–computer interfacing

[27] Liu Y, Ayaz H, Onaral B and Shewokis P A 2013 EEG band powers for characterizing user engagement in p300-BCI *6th Int. IEEE/EMBS Conf. on Neural Engineering* pp 1066–1069

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Automatic Pause Detection during P300 Web Browsing

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Abstract

Brain-computer interfaces (BCI) have been investigated for more than 40 years. P300-based BCIs can nowadays control very complex applications such as spelling applications and even web browsers. To do this in a practical way, it is essential to have the possibility to pause the command selection of the BCI. We implemented and evaluated an automatic pause detection system for P300-based BCIs based on artifact detection with an inverse filtering method. Experimental results of an offline study (9 healthy participants) demonstrate the feasibility of the proposed approach and its high performance.

1 Introduction

The electroencephalogram (EEG) can be used to establish a noninvasive communication/control channel between the human brain and a computer, a so-called brain-computer interface (BCI). A very prominent BCI application is the P300 speller [1]. This system enables healthy as well as severely impaired users to communicate [2, 4]. However, a standard P300 speller is designed to work in synchronous mode, i.e., after defined stimulation sequences one item of all selectable items will be selected. This is not an issue as long as the user just wants to write a text without making a pause. However, if the user wants to make a pause during spelling a text or because she/he wants to look at the content of a web page it becomes a substantial problem. A very simple approach to avoid unintended selections is to include a pause element into the spelling matrix. This approach has two main disadvantages: First, you have to select two correct elements to go into and leave the pause mode and second, there is a certain probability that the pause-end element is selected by chance.
In this study, we introduce an automatic pause detection method on the basis of artifact detection with inverse filtering. Originally, the inverse filtering method was introduced in [5] to detect muscle and movement artifacts in the EEG of a sensorimotor rhythm (SMR)-based BCI. The main idea behind our approach is that a user produces more EEG artifacts during a pause than when she/he is actively engaged with the BCI. We use this difference to distinguish between the pause and the control state, i.e., when the user wants to select something.

2 Methods

2.1 Participants, Data Acquisition, and Experimental Design

Ten volunteers participated in this study. All participants stated that they have no history of neurological or psychiatric disorders. Due to a technical problem the data of one participant was not useable for this study. The final sample comprised 9 participants (3 female; mean age

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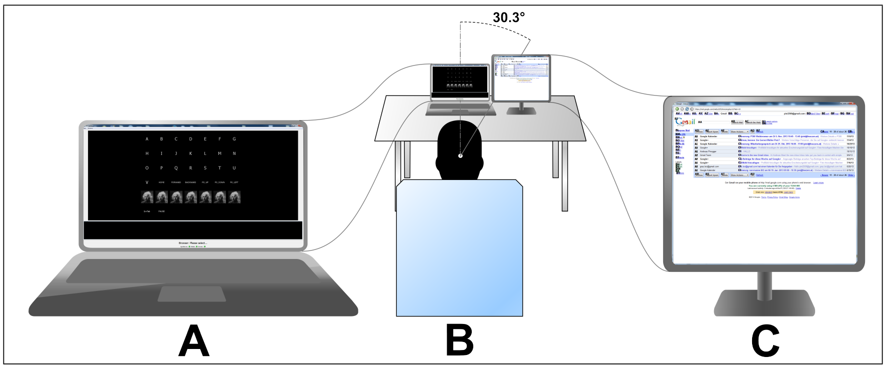

Figure 1: (A) Laptop displaying the user interface for feedback and P300 stimulation. (B) Sketch of the experimental design. The angle between the participant, the laptop, and the monitor was 30.3^o. (C) Monitor for the web browser.

23.9 ± 1.3 years).
EEG was acquired with a wireless EEG amplifier with dry electrodes (g.Nautilus, Guger Technologies OG, Graz, Austria). Signals from Fz, Cz, Pz, PO7, PO8, and Oz were used in this study with a sampling rate of 250 Hz. The channels were referenced to the right mastoid and grounded at the left mastoid. The raw signal of the Wi-Fi headset was filtered with a 0.5–30 Hz bandpass.
The participants were seated in a comfortable chair approximately 65 cm away from two screens (39.5 cm and 43 cm diameter), see Figure 1 (B). One screen was centered in front of the participants. At this screen a P300 matrix was displayed to control a special web browser (see Halder et al., in preparation), which was shown on a second screen placed right beside the first one, see Figure 1 (A) and (C).
The P300 user interface and signal processing in Matlab (MathWorks, Natick, USA) was presented in [3].
Calibration was performed with fifteen highlightings per row and column and ten letters as described in [3]. The online task for the participants was to write an email to a given address and reply to an automatically generated email. The whole task needed a minimum of 52 selections and was aborted if the goal was not reached within 78 regular selections.

2.2 Manual Pause

A “PAUSE/RUN” element was selectable with the matrix. If the user selected this element, no further selections were sent to the web browser until the same element was selected again. The participants had to select the “PAUSE/RUN” element in the study when they were waiting for the reply of the first email and they could select it whenever they needed a pause.

2.3 Automatic Pause Detection

The automatic pause detection was performed on the offline data by detecting artifacts in the EEG during the flashing time periods. The principle of inverse filtering was applied to detect the artifacts, cf. [5]. For this method autoregressive filter model parameters have to be estimated

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out of clean (i.e., artifact free) EEG data. Our assumption was that the participants generated few artifacts during the P300 calibration period. Consequently, we used the data of the P300 calibration to estimate autoregressive filter model parameters (model order $p = 10$) by using the Burg method.
The created filter model was applied inversely to the EEG data of every online task selection. An artifact detection threshold was set to three times the standard deviation of values calculated with this inverse filter from the calibration EEG data. If in more than 1 percent of the online task data artifacts were detected, the selection was marked as pause state related.

3 Results

The participants needed on average 11.8 (SD 2.9) highlighting sequences to select a command. Eight participants completed the task within the maximum allowed value of 78 selections. Only participant S7 did not complete the task. They had an average selection accuracy of 88.7% (SD 9.4) and needed an average time of 63.1 (SD 16.4) minutes including pauses to complete the whole task.

3.1 Manual Pause

Two selections were necessary to go manually into pause mode and leave the pause mode. The time the participants needed to perform these two selections was between 58 and 100 seconds depending on the number of highlighting sequences and the actual number of rows and columns. Seven participants had no problem to switch between pause and control mode. Two participants (S6, S7) needed more than one attempt to leave the pause mode. The probability that the pause mode was left by chance was $1/N$ with N being the actual number of matrix elements. This occurred once (S7) in this study.

3.2 Automatic Pause Detection

Participant	All	Pause Detection						Cohen's
	Selections[a]	TP	TN	FP	FN	TPR	TNR	κ
S1	61	5 (6)	52	4 (3)	0	100.0%	92.9%	0.68
S2	62	7 (7)	46	9 (9)	0	100.0%	83.6%	0.54
S3	61	3 (5)	56	2 (0)	0	100.0%	96.6%	0.73
S4	66	2 (2)	63	1 (1)	0	100.0%	98.4%	0.79
S5	93	26 (29)	63	4 (1)	0	100.0%	94.0%	0.90
S6	101	8 (9)	92	1 (0)	0	100.0%	98.9%	0.94
S7	94	9 (12)	74	6 (3)	5	64.3%	92.5%	0.55
S8	73	10 (12)	60	3 (1)	0	100.0%	95.2%	0.85
S9	64	6 (6)	64	0 (0)	0	100.0%	100.0%	1.00

[a] incl. selections during pause.

Table 1: Automatic pause state detection results. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) detections as well as the true positive rate (TPR) and the true negative rate (TNR) are presented for every subject. Values in parentheses indicate prevented wrong item selections during the control state. Cohen's Kappa was calculated to give a measure of agreement.

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In Table 1 the offline simulation results of the automatic pause detection are shown. The number of selections of some participants was higher than 78 because selections during the pause were also counted for evaluation. The sensitivity (TPR) of the automatic pause detection was 100 % for eight participants and 64.3 % for one participant. Consequently, the overall mean TPR was 96.0% (SD: 11.9). The specificity (TNR) was between 83.6 % and 100% with a mean of 94.7 % (SD: 4.9). At eight participants no false negative (FN) detections were made, see 6^{th} column in Table 1. This is very important because false negative detections would result in unintended, random selections. The measured Cohen's Kappas for our results were between 0.54 and 1.00, indicating moderate to strong agreement.

4 Discussion

In this study we provide evidence that our suggested automatic pause detection method works comparable to the manual pause selection method without its disadvantages.
The introduced automatic pause detection method detected the pause state with 100% accuracy at eight participants and the control state with an accuracy between 83.64% and 100%. Unintended selections in the pause state are almost non-existent and the number of prevented selections in the control state is low and acceptable. Considering the prevented wrong selections during the voluntary control periods by the automatic pause detection the number of wrong classifications would be even lower (numbers in parentheses beside the TPs and FPs in Table 1).
In conclusion, this study shows that detecting artifacts in a P300-based BCI can be used as a very reliable and effective automatic P300 pause state detection method.

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References

[1] L. A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology*, 70:510–523, 1988.

[2] 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. *Clinical Neurophysiology*, 117(3):531–537, 2006.

[3] A. Pinegger, S. Wriessnegger, and G. Müller-Putz. Introduction of a universal P300 brain-computer interface communication system. In *Biomedical Engineering*, volume 58, 2013.

[4] 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 BCI: Paradigm transition from healthy subjects to minimally conscious patients. *Artif Intell Med*, 59(2):81–90, 2013.

[5] R. Scherer, A. Schlögl, F. Lee, H. Bischof, J. Jansa, and G. Pfurtscheller. The self-paced Graz brain-computer interface: methods and applications. *Computational Intelligence and Neuroscience*, 2007.

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Evaluation of Different EEG Acquisition Systems Concerning Their Suitability for Building a Brain–Computer Interface: Case Studies

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One important aspect in non-invasive brain–computer interface (BCI) research is to acquire the electroencephalogram (EEG) in a proper way. From an end-user perspective, it means with maximum comfort and without any extra inconveniences (e.g., washing the hair), whereas from a technical perspective, the signal quality has to be optimal to make the BCI work effectively and efficiently. In this work, we evaluated three different commercially available EEG acquisition systems that differ in the type of electrodes (gel-, water-, and dry-based), the amplifier technique, and the data transmission method. Every system was tested regarding three different aspects, namely, technical, BCI effectiveness and efficiency (P300 communication and control), and user satisfaction (comfort). We found that water-based system had the lowest short circuit noise level, the hydrogel-based system had the highest P300 spelling accuracies, and the dry electrode-based system caused the least inconveniences. Therefore, building a reliable BCI is possible with all the evaluated systems, and it is on the user to decide which system meets the given requirements best.

Keywords: brain–computer interface, practical electrodes, dry electrodes, water-based electrodes, gel electrodes, P300, electrode test

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1. INTRODUCTION

Measuring electrical activity of the human brain and utilizing this data to bypass the traditional motor output pathways of the nervous system is one of the main purposes of brain–computer interface (BCI) systems. One way to collect these signals non-invasively is by using electroencephalography (EEG). Nowadays, two main factors that impede the widespread use of BCIs for healthy as well as for severely impaired people are the BCI control method (i.e., how measurable brain signals are generated) and the EEG signal acquisition system (i.e., the used hardware) to measure the signals.

We consider three control methods based on different brain signals: (i) neural oscillations, (ii) event-related potentials (ERP), and (iii) steady-state evoked potentials (SSEP).

A typical BCI based on neural oscillations, for example, utilizes the fact that defined frequency components of the EEG signal create a typical pattern briefly before, during, and after movement execution and less pronounced at movement imagination (e.g., Pfurtscheller et al., 2000; Faller et al., 2014; Schwarz et al., 2015). Tasks that also show detectable oscillations are word association, mental subtraction, mental rotation, auditory imagery, or spatial navigation (Friedrich et al., 2013). This phenomenon can be used to create a so-called self-paced BCI (i.e., no external trigger is needed). However, the illiteracy rate and also the effort on training the system are very high (cf. Blankertz et al., 2010).

The other two BCI control methods need stimulation to evoke a defined pattern in the EEG. A very prominent representative of this group relies on the P300 EEG-wave complex. This positive amplitude approx. 250–500 ms after an event can be elicited by an odd-ball paradigm (Pritchard, 1981; Polich, 2007). Due to the fact that the difference between the P300 amplitude and the spontaneous EEG is small, the stimulation has to be repeated, and the signals averaged until the signal to noise ratio (SNR) is high enough for classification. One of the first implemented BCIs (Farwell and Donchin, 1988) was based on this method. Many studies were conducted to show that P300-based BCIs enable healthy as well as motor impaired users to communicate or to control their environment (Donchin et al., 2000; Piccione et al., 2006; Hoffmann et al., 2008; Nijboer et al., 2008; Kaufmann et al., 2013; Pokorny et al., 2013).

SSEP-based BCIs, as another type, also require stimulation. The stimuli are periodically presented at a repetition rate higher than approx. 6 Hz. SSEP BCIs are based on the fact that the stimulation rate is represented as SSEP (i.e., a periodically repeated pattern) in the EEG when the user shifts their attention to these stimuli. Stimuli can be visual (SSVEP, Bagolini et al., 1988; Müller-Putz et al., 2005; Vialatte et al., 2009), auditory (Stapells et al., 1984; Picton et al., 2003; Lopez et al., 2009), or somatosensory (Müller-Putz et al., 2001, 2006; Pokorny et al., 2011).

The second important part of each BCI is how brain signals are measured. At the very beginning, in 1924, scientists inserted steal needles into the subcutaneous tissue of the scalp and had galvanometers to visualize and interpret the recorded signals (Berger, 1929). The quality and the interpretability of the signals improved with the usage of vacuum tubes, and later, transistor technology was used to amplify the very small signals. Silver chloride (AgCl) covered electrodes, which are standard nowadays, were introduced by Berger in 1931 (Collura, 1993). Today, Bergers' method would not be called non-invasive but it is called minimal invasive EEG acquisition, because he penetrated the skin of the scalp. More invasive brain signal acquisition techniques are the electrocorticogram (ECoG), subdurally/epidurally measured on the brain surface (Leuthardt et al., 2004), and multi/single unit activity derived with needle electrodes directly from the cortex (Hochberg et al., 2006). However, these methods are more common in clinical settings and not yet envisaged for everyday use in practical BCI systems.

One major issue concerning the EEG measurement is noise. According to Bressler and Ding (2006), the following sources of noise in brain activity recordings exist: (1) potentials from the brain (cephalic noise), (2) potentials from the head muscles and skin, eyes, and tongue (extracephalic cranial noise), (3) potentials from parts of the body other than the head, such as the heart (extracranial physiological noise), (4) random microscopic fluctuations at the electrodes (thermal noise), (5) noise from movement of the person or animal (movement artifact), (6) fluctuations introduced by electronic recording components (electronic noise), (7) radiated contamination from other electrical equipment (environmental noise), and even (8) fluctuations due to imprecision in the discrete digitization of the continuously varying voltage from the electrode for storage in a digital computer (quantization noise) (Bressler and Ding, 2006). According to points 4–8, the recorded amount of noise strongly depends on the characteristics of the EEG acquisition system being used.

To measure EEG, a way has to be found to bridge the gap between the electrode and skin surface. Currently, there are three common types of electrodes that differ based on whether the conductive connection is established based on gel, water, or no additional conductive substance ("dry").

The gel-based type can be subdivided based on the usage of abrasive gel and hydrogel, respectively. Abrasive gel is mainly used in combination with passive electrodes (i.e., no amplification happens directly at the electrode). In contrast, the hydrogel is mainly used for active electrodes (i.e., the signal is pre-amplified directly at the electrode). The main difference between these two types of gels is that with the abrasive gel, the topmost layer of the skin, consisting of dead cells, is removed in a time-consuming procedure to decrease the impedance. This can lead to skin irritation, infection, or inflammation. For both types of gel-based electrodes, gel has to be filled between the electrode and the scalp, which then typically makes it necessary for the user to wash their hair, after the measurement. Water-based electrodes use a water or saline solution soaked felt or fabric to connect the metal part of the electrode with the skin. Using tap water-soaked fabric to connect the two surfaces is a new and practical method. This type of electrodes should deliver a very good signal quality, and no hair wash is needed after the measurement (Volosyak et al., 2010).

Dry electrodes, work without any conductive substance. Pins made of metal alloy or conductive rubber are pressed directly onto the skin, and rely on small amounts of existing perspiration to get connected to the skin. Several studies were conducted highlighting the advantages of different dry electrode-based systems (e.g., Zander et al., 2011; Guger et al., 2012; Mota et al., 2013). However, experience shows that one main disadvantage of this type of electrodes is their sensitivity to movement artifacts.

Several papers deal with user-centered BCI approaches (e.g., Zickler et al., 2011; Kübler et al., 2014; Scherer et al., 2015). Concerning data acquisition, these papers find similar results: Users want to have an easy to handle data acquisition system, which should not require the subject to wash their hair after acquisition. At the same time, the signal quality should allow for BCI accuracies comparable to gel-based systems. The dry electrode-based systems can only fulfill the first part as the BCI accuracies of gel-based systems are not fully achieved yet. For example, Zander et al. (2011) reported a mean BCI classification accuracy of 94.0% for gel-based and 90.7% for dry electrode-based systems, respectively, and Guger et al. (2012) reported a mean P300 BCI accuracy of 91.0% for gel-based and 90.4% for dry based-electrode systems, respectively.

Existing literature only compared one new EEG acquisition system (i.e., the dry electrode-based or the tap water-based electrode system) with one gel-based system, aiming to show that the new system works comparably well (cf. Volosyak et al., 2010; Zander et al., 2011; Guger et al., 2012; Mota et al., 2013).

The aim of this study is to evaluate three different EEG acquisition systems with regard to their suitability for building a BCI, meeting technical requirements and requirements for user-centered design specifications. Therefore, we tested and evaluated a hydrogel-based, a tap water-based, and a dry electrode-based systems with their corresponding amplifiers under controlled conditions. Technical tests and real BCI tasks with healthy volunteers were performed. Subsequently, we compared our findings with the findings of existing literature.

2. MATERIALS AND METHODS

2.1. Systems and Data Acquisition Methods

Three different EEG acquisition systems were tested. The systems differ in electrode design, amplifier technique, and data transmission (see **Table 1**).

2.1.1. The Hydrogel-Based Electrode System

We tested the g.GAMMAsys from g.tec (Guger Technologies OG, Graz, Austria) in combination with active, hydrogel-based, silver/silver chloride (Ag/AgCl) electrodes (g.LadyBirds) (see **Figure 1**). The system allows the acquisition of up to 64 biosignals such as EEG, electrooculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG) simultaneously in combination with up to four g.USBamps to amplify and transmit the signals via universal serial bus (USB) to a personal computer (PC) or laptop. Main technical specifications are listed in **Table 1**. In addition, different filter settings are available. After every usage, the electrodes as well as the cap have to be washed under running water using a brush.

TABLE 1 | Comparison of the used EEG amplifier systems.

	g.GAMMAsys	Mobita	g.Sahara
Electrode technique	Hydrogel-based	Tap water-based	Dry
ADC resolution	24 bit	24 bit	24 bit
Voltage input range	$\pm 250.0\,mV$	$\pm 204.8\,mV$	$\pm 250.0\,mV$
Notch filter	50 and 60 Hz	n/a (active cable shielding)	50 and 60 Hz
Sampling frequencies	64–38 400 Hz	250–2000 Hz	64–38 400 Hz
Data transmission technique	USB	WiFi (802.11b/g)	USB

2.1.2. The Water-Based Electrode System

The Mobita is a wireless system of the company TMSi (Twente Medical Systems International B.V., Oldenzaal, the Netherlands). It acquires a maximum of 32 channels of EEG plus three channels for the built-in accelerometer. We tested its capability to measure EEG with passive, water-based electrodes (see **Figure 1**). The special characteristics of these water-based electrodes are rolled-in, tap water-soaked cotton pieces attached to small AgCl pellets as electrodes. These cotton pieces are disposable. Therefore, for regular cleaning, it is sufficient to dry the cap and the wristband. Another main feature is the actively shielded cable connection between the electrodes and the amplifier. This active shielding should strongly reduce the mains interference and cable movement artifacts. These techniques should provide high signal quality without the necessity of washing the hair after the measurement.

Technical specifications are listed in **Table 1**. The channel bandwidth is limited between direct current (DC) and $0.2 \times$ sampling frequency (i.e., the average number of samples obtained in 1 s). The system uses the WLAN IEEE standard 802.11 b/g to transmit the amplified signals wirelessly to a PC or laptop.

2.1.3. The Dry Electrode-Based System

The g.Sahara is also produced by g.tec (Guger Technologies OG, Graz, Austria). The acquisition of the EEG with up to 16 dry electrodes in combination with the g.USBamp (also from g.tec) is possible. The electrodes consist of 8 pins made of a special gold alloy (see **Figure 1**). Two different pin lengths (7 and 16 mm) and three different cap sizes are available to adapt the system to different hair lengths and shapes of users' heads. The operator has to find the optimal type of electrodes and cap size for each participant to get the best signal quality. Disposable Ag/AgCl mastoid electrodes are used for reference and ground. The other electrodes have to be cleaned with a smooth cotton cloth and alcohol (70%). Since we used the g.USBamp to amplify the signals, the same technical amplifier specifications for the g.GAMMAsys are valid.

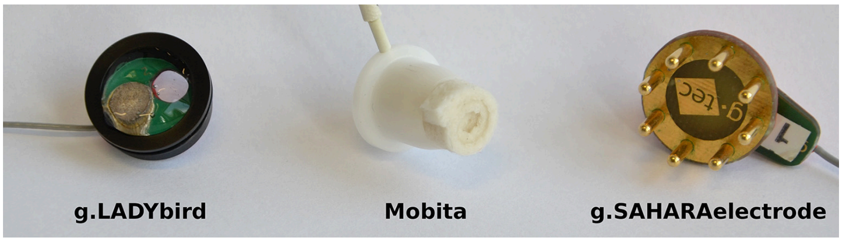

FIGURE 1 | From left to right: the g.LADYbird hydrogel-based electrode, the tap water-based electrode of the Mobita system, and the dry electrode of the g.Sahara system.

2.2. Technical Test

The short circuit noise of the EEG acquisition systems (electrodes and amplifier) was determined by acquiring the signal of the electrodes that were attached to a polished copper plate (10 × 10 cm) (see **Figure 2**). The copper plate was polished with an abrasive cleaner and residues were removed with ethyl alcohol shortly before each measurement. The measurement was conducted at normal room temperature (approx. 21°C). Since the electrode systems were purchased nearly at the same time, the influence of aging should be the same for all electrodes.

Sampling frequencies (fs) were 500 Hz for the tap water-based system and 512 Hz for the hydrogel-based and dry electrode-based systems. Signal processing was performed with Matlab (2014b, The MathWorks, Natick, USA). The data of the different electrode systems was streamed to Matlab with the TOBI SignalServer software (Breitwieser et al., 2012). Signal filters were disabled as far as possible to get the full spectrum of the signal. As recommended by the manufacturer, proper grounding was performed for the dry electrode-based system.

Twelve minutes of short circuit noise was recorded with all systems. The first and the last minute were excluded from analysis to avoid any movement artifacts from the operator. Consequently, 10 min of noise were available from all systems for analysis.

The noise was evaluated for a frequency range of 0.1–40 Hz, which is typical for BCI systems. Therefore, the signals were 8th order band-pass filtered (Butterworth) between 0.1 and 40 Hz. The histogram and the amplitude spectrum were calculated with Matlab to compare the different systems. In addition, the root mean square (RMS) was calculated and smoothed with a Gaussian filter (3-dB bandwidth-symbol time = 0.1 s, periods to the filters peak = 4, oversampling factor = 250/256).

2.3. User-Centered Test

BCI effectiveness and efficiency were evaluated with P300 communication and control tasks. Participants had to spell several words and then had to control a multimedia player and a web browser with a P300 BCI. Afterwards, the participants were asked to complete several questionnaires.

It was not possible to randomize the sequence of the tests, because the EEG acquisition systems were not available at the same time. Therefore, the participants tested the dry system first, then the gel-based system, and finally the tap water-based system. However, between the user-centered tests of the different EEG acquisition systems were always more than 1 month, and therefore, one can assume that adaptation or learning effects did not occur.

2.3.1. Participants

Eight healthy volunteers (1 female, mean age 25 ± 2.3, range 22–30 years) participated in this study. All participants stated that they had no history of neurological or psychiatric disorders. The study protocol was approved by the ethics committee of the Medical University of Graz, and the participants gave informed written consent before the experiment. Out of the eight study participants, seven performed the user-centered test per EEG aquisition system.

2.3.2. Signal Acquisition and Processing

Six channels per system were recorded at a sampling rate of 250 Hz (tap water-based system) and 256 Hz (hydrogel-based and dry system), respectively. The locations of the electrodes (Fz, Cz, Pz, PO7, PO8, and Oz) were based on the extended international 10–20 system for electrode placement. The channels were referenced to the left and grounded to the right earlobe when using the gel-based and dry electrode-based systems. The ground of the tap water-based system was attached to the participant's wrist. In addition, as recommended by the manufacturer, a grounding of the user and operator was performed for the dry electrode-based system. The data acquisition was started only once before each session.

Due to the fact that different data acquisition systems (see Section 2.1) were used, the signal processing differed slightly between the systems (see **Table 1**). We used the integrated 0.1–60 Hz band-pass filter for the hydrogel-based electrode signal and the 0.5–30 Hz filter for the dry electrode-based signal. The dry electrode is more sensitive to person and cable movement artifacts. Therefore, the signals from that electrodes

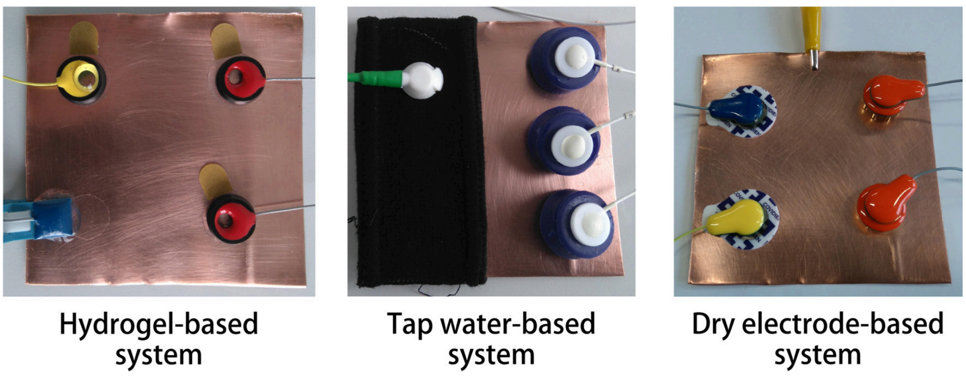

FIGURE 2 | Setup of the noise test. All three systems were attached to a polished copper plate to simulate a short circuit of the electrodes.

were band-pass filtered between 0.5 and 30 Hz. Further signal processing was performed with Matlab. The data of the systems were streamed to Matlab, see Section 2.2. No band-pass filter is integrated into the tap water-based system. Consequently, we implemented a filter in Matlab. We used a fourth order Butterworth band-pass filter with cut-off frequencies of 0.1 and 60 Hz. The rest of the signal processing and classification was identical between the tested systems.

2.3.3. P300 Classification

A stepwise linear discriminant analysis (SWLDA) classifier was trained with the training data and used for the online runs. The number of flashing sequences (one sequence means that all characters of the stimulation matrix flashed once) was automatically set between 8 and 15 according to Pinegger et al. (2013). The algorithm classifies the training letters with a leave one letter out cross-validation and calculates the reached total accuracy for every flashing sequence. The number of sequences, where 100% accuracy is reached, plus two sequences is chosen as number of flashing sequences for the online run. Whenever 100% accuracy is not reached, but the highest value for the accuracy is higher than 75% , 15 sequences are chosen. Otherwise, the calibration fails and must be performed again.

2.3.4. Experimental Design

The participants were seated in a comfortable chair approx. 65 cm away from two computer screens (39.5 and 43 cm diameter). One screen was centered in front of the participants. On this screen, a P300 matrix was displayed to select letters or commands; a second screen was placed right beside the first and was used to show a multimedia player or a web browser. The multimedia player was controlled via network commands (see Halder et al., 2015 for details). The custom-made web browser automatically detects all possible links, buttons, and text fields of the currently shown website and marks them with letters. These letters were sent to the BCI for selection with the P300 matrix. By sending back the desired element to the web browser, the corresponding link, button, or text field was selected (see Halder et al., 2015 for details).

The P300 user interface and the signal processing in Matlab were presented in Pinegger et al. (2013). Elements of the matrix were highlighted with famous faces (Kaufmann et al., 2011).

Every participant performed one session per day and system. The experimenter was trained once on every system by an experienced supervisor. In addition, the supervisor supported the experimenter and was available during the whole length of every measurement. A graphical sketch of the user-centered test can be seen in **Figure 3**. One session comprised the following tasks:

- **P300 classifier training**
  The word "BRAIN" was used for P300 classifier calibration. The speller matrix consisted of six rows and six columns, and every target letter was highlighted 30 times. The collected data was used to train an SWLDA classifier and to calculate an optimal number of flashing sequences.
- **Task 1: First copy spelling**

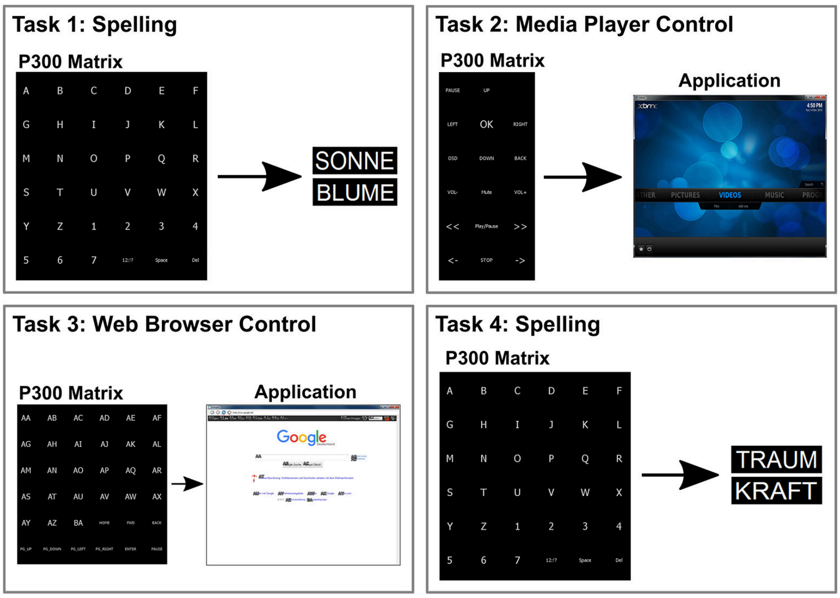

FIGURE 3 | The participants had to perform four tasks for the user-centered test. The basis was a P300 BCI system. The first task was to spell two words (ten letters), the second task was to control a media player, the third task was to look for a certain web page in a special web browser, and the fourth task was to spell two words (10 letters) again.

The participants had to spell the German words "SONNE" (English "sun") and "BLUME" (English "flower") consecutively. Each word was presented to them shortly before they started spelling. The users were instructed not to correct wrongly spelled letters. After a short break, the second word was spelled. The matrix for training and copy spelling was the same.

- **Task 2: Multimedia player**
  Within this task, the participants had to start a slideshow and to look at certain pictures within the Xbox media center (XBMC), a powerful multimedia player. Instructions as to which commands to execute were provided by the experimenter in spoken form. The task could be completed at best with 10 correct selections. To correct wrong selections, the investigator indicated a correct alternative or the way back to the last correct selection. If the goal could not be reached within 15 selections, the task was aborted. The matrix for this task consisted of six rows and three columns.
- **Task 3: Web browser**
  The goal of this task was to navigate to the Wikipedia article about BCI and look over the whole article. The start page was "www.google.de". Instructions as to which commands to execute were provided by the experimenter in spoken form. The task could be finished within 10–12 correct selections. The ideal number of selections varies because Google has very dynamic web pages, and therefore, the number of links vary considerably over time on these pages. Wrong selections were corrected in the same manner as during the media player run. If the goal could not be reached within 18 selections, the task was aborted. The matrix for this task consisted of six rows and a variable number of columns depending on the number of links on the actual web page. However, the maximum number of columns was seven.
- **Task 4: Second copy spelling**
  This task was performed in the same way as the first copy spelling task. The only difference was that two other words—"TRAUM" (English "dream") and "KRAFT" (English "force")—have to be spelled.

Overall, every participant had to perform a minimum of 40 and a maximum of 53 selections per system.

2.3.5. Questionnaires

After the last run of every session, the participants were asked to fill out several questionnaires concerning the satisfaction with the system and the system design.

- VAS: The level of satisfaction of the users was assessed with a visual analog scale (VAS), ranging from 0 (not at all satisfied) to 10 (absolutely satisfied).
- eQUEST 2.0: A usability test was adapted for BCI usage by Zickler et al. (2011). This test evaluates 12 categories (dimension, weight, adjustability, safety, ease of usage, well-being, effectiveness, service features, reliability/robustness, speed, learnability, and aesthetic of design) on a scale from one to five where one stands for not satisfied and five stands for very satisfied. In addition, the three most important categories must be indicated.

2.3.6. Evaluation Metrics

The effectiveness was determined by calculating the percentage of correct selections of all selections (accuracy). The efficiency of a system was determined with the amount of flashing repetitions participants needed to make selections with the P300 speller. Results of the questionnaires were evaluated by calculating the averaged values.

3. RESULTS

3.1. Technical Results

The noise of the different systems was recorded and evaluated. A graphical comparison of the signals from the systems can be seen in **Figure 4**. The tap water-based system with a mean RMS (yellow line in **Figure 4**) of 0.37 μV had the lowest measured value followed by the hydrogel-based (0.68 μV) and the dry electrode-based system (0.82 μV) within the frequency range of 0.1–40 Hz. Moderate pressure on the electrodes was necessary to obtain a good signal from the tap water-based and the dry electrode-based system.

3.2. User-Centered Results

3.2.1. Effectiveness and Efficiency

The hydrogel-based system was the most effective with a mean BCI accuracy of 96 % (SD: 3.5) followed by the tap water-based system with 93 % (SD: 4.5) and the dry electrode-based system with 77 % (SD: 11.8). On average, the accuracies of the hydrogel-based (between 93 and 99 %) and the tap water-based system (between 91 and 96 %) stayed stable above 90 % over the four tasks, whereas the dry electrode-based system showed decreasing accuracies over time from 87 % for the first spelling task to 70 % for the second spelling task (see **Table 2** and **Figure 5**).

The inter-participant variance (cf. SD in **Table 2**) was low for the hydrogel-based system, moderate for the tap water-based system, and high for the dry electrode-based system.

The tap water-based and gel-based systems showed on average the same number of needed sequences followed by the dry electrode-based system (see **Table 3**). The overall result of the training cross-validation can be seen in **Figure 6**. The hydrogel-based and tap water-based systems showed comparable results; the accuracies of the dry electrode-based system, however, were slightly lower at the same number of sequences.

3.2.2. Satisfaction

Overall device satisfaction per system and results of the eQUEST 2.0 are listed in **Table 4**. Scores from the VAS were between 6.64 (dry electrode) and 8.76 (tap water-based) on average and indicate a high general satisfaction.

In the eQUEST 2.0, only "speed" received scores below 4 (quite satisfied) for all three systems. The items that were rated as most important by the study participants were "effectiveness" ($n = 6$), "reliability" ($n = 3$), and "speed" ($n = 3$) for the

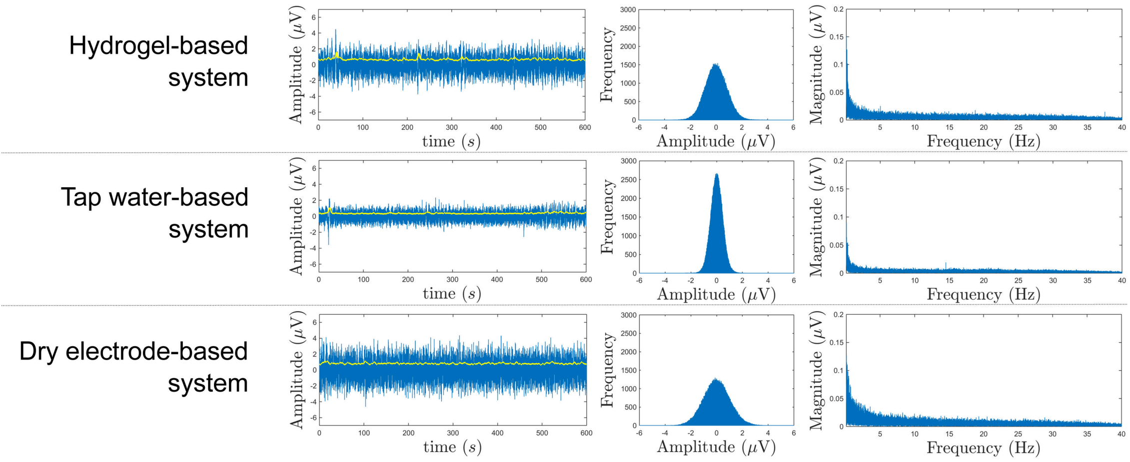

FIGURE 4 | Signal plot (left), histogram (middle), and amplitude spectrum (right) of the short circuit noise measurement after 0.1–40 Hz band-pass filtering. The yellow line in the left plots represents the RMS of the signal.

TABLE 2 | Accuracies of the systems in percent (%).

Participant	Hydrogel-based system				Tap water-based system				Dry electrode system			
	Sp1	**MmP**	**WeB**	**Sp2**	**Sp1**	**MmP**	**WeB**	**Sp2**	**Sp1**	**MmP**	**WeB**	**Sp2**
P1	100	100	70	100	100	100	91	90	80	90	60	50
P2	100	100	100	100	90	100	90	100	90	80	60	90
P3	90	80	100	90	100	100	100	100	50	80	40	60
P4	100	70	80	100	80	64	73	70	90	60	30	30
P5	100	100	100	100	*	*	*	*	100	100	100	80
P6	100	100	100	100	100	100	91	100	100	100	100	90
P7	100	100	100	100	100	100	100	90	100	100	60	90
P8	*	*	*	*	100	92	100	90	*	*	*	*
Mean	99	93	93	99	96	94	92	91	87	87	64	70
SD	4	13	1	4	8	13	10	11	18	15	27	24

Sp1, Sp2. . . Spelling run 1, 2; MmP. . .Multimedia player; WeB. . .Web browser.
Data not available for this system.

hydrogel-based system; "speed" ($n = 6$), "effectiveness" ($n = 4$), and "learnability" ($n = 4$) for the tap water-based system; "speed" ($n = 6$), "effectiveness" ($n = 5$), and "easy of use," "reliability" and "learnability" (all three: $n = 3$) for the dry electrode-based system.

Participants commented negatively on the unaesthetic and tight design of the caps and the low speed. On the other hand, most of the participants were positively surprised that it worked at all.

4. DISCUSSION

Building a reliable BCI is possible with all the introduced EEG amplifier systems. However, small but important differences between the systems are detectable and deliver arguments to define special areas of application for each system.

4.1. Technical Evaluation

For EEG measurements, it is crucial to have minimal noise resulting in a maximum signal-to-noise ratio. Having in mind that all short circuit RMS noise levels stayed below 1 μV, our measurements indicate that the short circuit RMS noise level of the tap water-based system is almost half the level of the hydrogel-based and less than half of the dry electrode-based system. It is obvious that the histogram of the tap water-based system is very narrow compared to the others, which means that the noise amplitude is low (see **Figure 4**). This is not surprising with the knowledge that the other electrodes are active electrodes, i.e., powered electronics are contained within

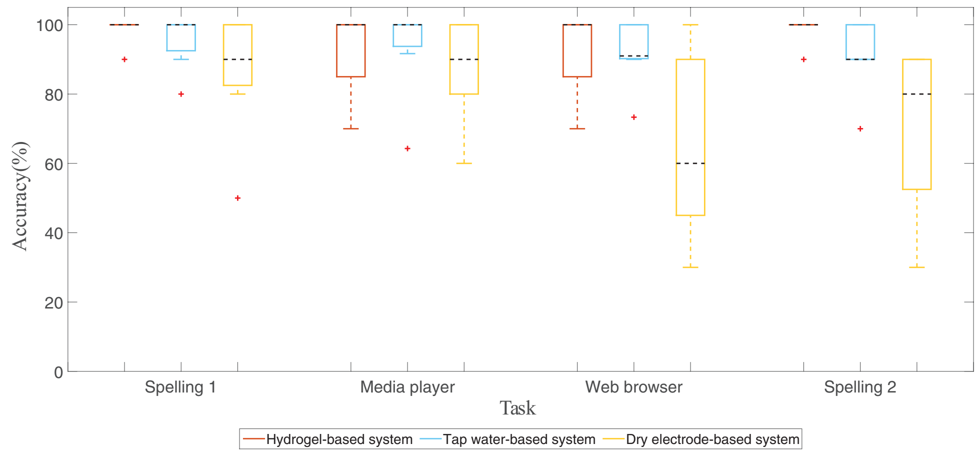

FIGURE 5 | Boxplots showing the BCI accuracies of each task for every system. The central mark (dashed line) of each box is the median, the edges of the box are the 25th and 75th percentiles; the whiskers extend to the most extreme data points (1.5× interquartile range). Outliers are marked with red crosses.

TABLE 3 | Sequences needed after training.

Participant	Hydrogel-based system	Tap water-based system	Dry electrode system
P1	8	8	8
P2	15	13	13
P3	14	9	15
P4	13	11	15
P5	8	*	8
P6	8	8	15
P7	8	14	15
P8	*	10	*
Mean	10.6	10.4	12.7
SD	3.3	2.4	3.3

Minimum possible value is eight.
**Data not available for this system.*

the electrode, and this feature is probably the source of the additional short circuit noise. The active electronic parts (dry electrode-based and gel-based systems) and the active shielding technique (tap water-based system) are used to reduce noise pickup from cables. From our results, we cannot determine which technique works better regarding suppressing cable movement artifacts, because all the cables were fixed and not moving like they could in real-world usage. To determine the real-world behavior of the systems, we performed the user-centered evaluation.

4.2. User-Centered Evaluation

4.2.1. Effectiveness and Efficiency

Both "wet" systems, the hydrogel-based and the tap water-based, showed comparable averaged accuracies and seemed to be equally effective (see **Figure 5**). In addition, the increase of accuracy with increased number of sequences is also comparable (see **Figure 6**). However, the tap water-based as well as the dry electrode-based system showed a higher standard deviation of the accuracies (see **Table 2**). One possible explanation for this is that the connection between the electrode and the skin of the head is also a crucial factor. The shape of the human head is neither a sphere nor identical for all people. Therefore, the connection between the electrode and the head has to be very flexible. The tap water-based system as well as the dry electrode-based system has a more or less rigid connection. The dry electrode-based system with its gold alloy pins is delivered with two different pin lengths and three different cap sizes to be adaptable to different head shapes and hair lengths. It is time consuming to find a tradeoff between too much pressure of the pins against the skin (good signal quality, but less wearing comfort) and too little pressure (moderate signal quality, but comfortable). Since the time of our participants was limited and every participant used the system only once, we might have not found the optimal pin length and cap size solution for all of our participants. However, a visual inspection of the recorded signal before the measurement guaranteed that at least the alpha wave (i.e., an oscillation of approx. 8–13 Hz) was visible within the EEG, when the participants were instructed to close their eyes and relax.

The cotton pieces that connect the electrode of the tap water-based system with the skin are soft and flexible. However, they are rolled up and put into a housing where just 3 mm of the material is outside. Only these 3 mm of the material are available to fit the electrode to the head shape (see **Figure 1**). Consequently, the hair under each electrode has to be carefully pushed to the side (i.e., under the electrode housing of the cap) to reach a high real-world signal quality.

These problems will not occur with hydrogel-based electrodes, because the electrodes and the skin are connected with gel. Gel perfectly bridges the gap between the electrode and the skin.

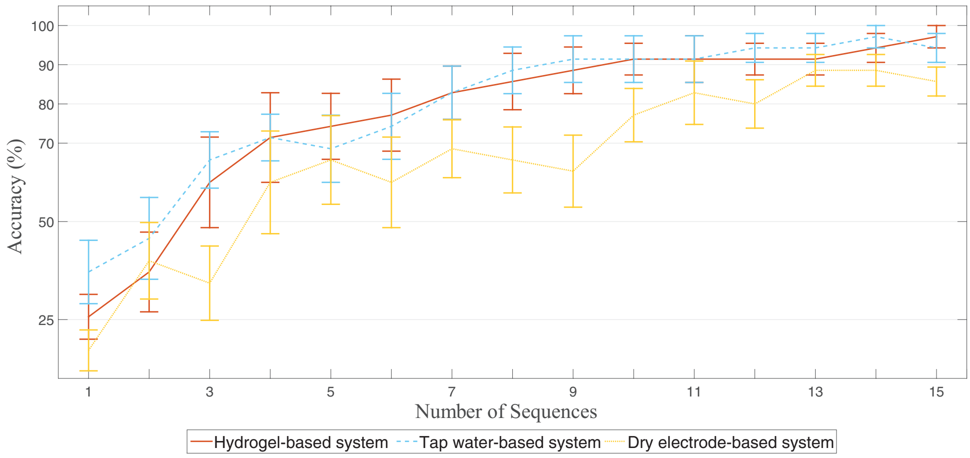

FIGURE 6 | Result of the leave one letter out cross-validation of the training data. Error bars indicate the standard error of the mean. The dry electrode-based system showed in general lower accuracies at the same number of sequences compared to the hydrogel-based and the tap water-based systems.

TABLE 4 | Results of the eQUEST 2.0 and VAS for all systems.

	Category	Hydrogel-based system	Tap water-based system	Dry electrode system
eQUEST 2.0	Dimensions	4.6 (0.8)	4.6 (0.8)	4.1 (0.7)
	Weight	4.4 (1.0)	4.6 (0.5)	4.4 (0.8)
	Adjustment: EEG cap	4.4 (0.8)	4.7 (0.8)	4.7 (0.8)
	Adjustment: Amplifier	4.8 (0.4)	4.8 (0.4)	4.8 (0.4)
	Safety	5.0 (0.0)	5.0 (0.0)	5.0 (0.0)
	Comfort: physical	4.1 (0.9)	4.0 (0.8)	4.1 (0.9)
	Comfort: emotional	4.3 (1.0)	4.4 (0.8)	4.3 (1.0)
	Easy of use	4.4 (0.5)	4.6 (0.8)	**3.7 (1.3)**
	Effectiveness	**4.4 (0.5)**	**4.4 (0.8)**	**3.3 (1.5)**
	Reliability: EEG cap	**4.7 (0.8)**	**5.0 (0.0)**	**5.0 (0.0)**
	Reliability: Amplifier	**5.0 (0.0)**	**5.0 (0.0)**	**4.7 (0.8)**
	Speed	**3.4 (1.3)**	**3.7 (1.0)**	**3.6 (1.0)**
	Learnability	4.7 (0.5)	4.9 (0.4)	**4.9 (0.4)**
	Aesthetic design: EEG cap	3.9 (0.9)	4.1 (1.1)	4.0 (1.3)
	Aesthetic design: Amplifier	4.4 (0.8)	4.6 (0.5)	3.7 (1.3)
	Mean	4.44 (0.40)	4.58 (0.39)	4.33 (0.50)
VAS	*Mean*	8.00 (1.75)	8.76 (2.00)	6.64 (1.41)

The eQUEST 2.0 scores range from 1 (not satisfied at all) to 5 (very satisfied), and the VAS scores range from 0 (not at all satisfied) to 10 (absolutely satisfied). The standard deviation (SD) is given in parenthesis. Results of the most important features per system are printed in bold.

In addition, this connection is flexible, which means that the connection will not be lost if the head is slightly moved.

The described electrode fitting problem might also be an explanation for the higher inter-individual variances (i.e., higher standard deviations) of the tap water-based and the dry electrode-based systems (see **Table 2**).

Another shortcoming of the tap water-based system is that all 32 available electrodes are permanently connected to the amplifier in contrast to the two other systems where only the used number of electrodes are connected. However, it is possible to order the tap water-based system with fewer permanently connected electrodes. Nevertheless, the problem is that unused electrodes could swing around, when the user moves the head, and the weight of the cable bundle might pull the used electrodes down causing EEG artifacts. Therefore, we fastened the cable bundle and the unused electrodes to the cap to minimize those ar tifacts.

4.2.2. Satisfaction

The high average accuracies achieved with the hydrogel-based and the tap water-based systems are also reflected in the results of the VAS and eQUEST 2.0. A mean VAS score of

8.00 (hydrogel-based) and 8.76 (tap water-based) and a mean eQUEST 2.0 score close to the maximum indicate that the participants were "very satisfied" with these two systems.

Although the mean eQUEST 2.0 score of the dry electrode-based system is not considerably lower than the scores of the two other systems, the negative difference of the VAS score is 2.12 to the tap water-based and 1.36 to the hydrogel-based systems (see **Table 4**). The main reason for that is probably the dissatisfaction of the users with the speed and effectiveness of the dry electrode-based system. Both criteria are rated low (below 4.0), whereas at the same time, they are listed as the most important features by most of the users.

However, the participants tested every system only once. Therefore, one can assume that the questionnaire scores may change when they are using the systems more often. Consequently, the results can only indicate a trend not absolute values.

One statement of the participants is consistent for all EEG amplifier systems: The users disliked the electrode cap. They felt that the cap was unaesthetic and conspicuous.

4.3. Comparison to Existing Literature

Volosyak et al. (2010) compared a prototype of the used water-based electrode system with passive Ag/AgCl electrodes. The major statements and conclusions out of this paper are "EEG activity can be measured with the novel water-based electrodes" and no significant differences between the two sensor modalities concerning the BCI classification accuracy (SSVEP spelling task) could be found. Both the points are also supported by our findings.

In Zander et al. (2011), the prototype of a dry electrode-based system was compared to an active Ag/AgCl electrode system. The electrodes were tested in two scenarios: ERPs were investigated and occipital alpha was measured. In addition, BCI classification accuracies were evaluated. The outcomes were, that no significant differences in the amplitude and the temporal structure of ERPs and no significant classification accuracy differences between the dry electrode-based and gel-based systems were detectable. However, the dry electrode-based system has a slightly lower ERP classification accuracy. Our findings indicate that the dry electrode-based system has a considerably lower ERP classification accuracy.

Guger et al. (2012) tested dry electrodes that were identical with the electrodes tested in this manuscript. Participants performed a simple P300 spelling task. The results were compared with the results gathered from standard passive and active electrodes. In addition, the dry electrodes were evaluated concerning the wearing comfort. Our results support their findings that the dry electrodes have a lower ERP classification accuracy. However, our assessed classification accuracy of the dry electrodes is on average more than 15% (cf. Guger et al.: 0.6%) lower and some participants reported discomfort after some time of usage. This is hardly surprising, considering that the participants of Guger et al. just had to copy spell five characters. In contrast, our participants had to copy spell at least 40 characters.

5. CONCLUSION

On the basis of the findings, the gel- and tap water-based systems are comparably suitable to build a very effective and efficient BCI. However, many users do not want to have gelled or wet hair and may accept a possibly lower effectiveness or efficiency to avoid inconveniences. Therefore, the dry based-electrode system is perfectly suitable.

Taking into account the outcome of a recent user-centered BCI evaluation (Kübler et al., 2014) and the recommendations of the BNCI roadmap (Brunner et al., 2015), the further development of BCI-suitable EEG acquisition systems should focus on the integration of the hardware into a single unit, wireless data transmission, and especially an appealing solution for placing gel-free electrodes on the head. The realization of these recommendations would strongly increase the user acceptance of BCIs outside the laboratory.

AUTHOR CONTRIBUTIONS

AP and SW conceived the experiments. AP and JF implemented the data acquisition system. AP collected the data and performed all data analysis. AP, SW, JF, and GM wrote the manuscript.

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REFERENCES

Bagolini, B., Porciatti, V., and Falsini, B. (1988). Binocular interaction and steady-state visual evoked potentials. *Graefe's Arch. Clin. Exp. Ophthalmol.* 226, 401–406. doi: 10.1007/BF02169996

Berger, H. (1929). Über das Elektrenkephalogramm des Menschen. *Arch. Psychiatr. Nervenkr.* 87, 527–570. doi: 10.1007/BF01797193

Blankertz, B., Sanelli, C., Halder, S., Hammer, E. M., Kübler, A., Müller, K.-R., et al. (2010). Neurophysiological predictor of SMR-based BCI performance. *Neuroimage* 51, 1303–1309. doi: 10.1016/j.neuroimage.2010.03.022

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, 852–859. doi: 10.1109/TBME.2011.2174637

Bressler, S. L., and Ding, M. (2006). *Event-Related Potentials*. Wiley Encyclopedia of Biomedical Engineering.

Brunner, C., Birbaumer, N., Blankertz, B., Guger, C., Kübler, A., Mattia, D., et al. (2015). BNCI Horizon 2020: towards a roadmap for the BCI community. *Brain Comput. Interfaces* 2, 1–10. doi: 10.1080/2326263X.2015.1008956

Collura, T. F. (1993). History and evolution of electroencephalographic instruments and techniques. *J. Clin. Neurophysiol.* 10, 476–504. doi: 10.1097/00004691-199310000-00007

Donchin, E., Spencer, K. M., and Wijesinghe, R. (2000). The mental prosthesis: assessing the speed of a P300-based brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.* 8, 174–179. doi: 10.1109/86.847808

Faller, J., Scherer, R., Costa, U., Opisso, E., Medina, J., and Müller-Putz, G. R. (2014). A co-adaptive brain-computer interface for end users with severe motor impairment. *PLoS ONE* 9:e101168. doi: 10.1371/journal.pone.0101168

Farwell, L. A., and 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. doi: 10.1016/0013-4694(88)90149-6

Friedrich, E. V. C., Scherer, R., and Neuper, C. (2013). Whatever works: a systematic user-centered training protocol to optimize brain-computer interfacing individually. *PLoS ONE* 8:e76214. doi: 10.1371/journal.pone.0076214

Guger, C., Krausz, G., Allison, B. Z., and Edlinger, G. (2012). Comparison of dry and gel based electrodes for P300 brain-computer interfaces. *Front. Neurosci.* 6:60. doi: 10.3389/fnins.2012.00060

Halder, S., Pinegger, A., Käthner, I., Wriessnegger, S. C., Faller, J., Antunes, J. B. P., et al. (2015). Brain-controlled applications using dynamic P300 speller matrices. *Artif. Intell. Med.* 63, 7–17. doi: 10.1016/j.artmed.2014.12.001

Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature* 442, 164–171. doi: 10.1038/nature04970

Hoffmann, U., Vesin, J.-M., Ebrahimi, T., and Diserens, K. (2008). An efficient P300-based brain-computer interface for disabled subjects. *J. Neurosci. Methods* 167, 115–125. doi: 10.1016/j.jneumeth.2007.03.005

Kaufmann, T., Schulz, S. M., Grünzinger, C., and Kübler, A. (2011). Flashing characters with famous faces improves ERP-based brain-computer interface performance. *J. Neural Eng.* 8:056016. doi: 10.1088/1741-2560/8/5/056016

Kaufmann, T., Schulz, S. M., Köblitz, A., Renner, G., Wessig, C., and Kübler, A. (2013). Face stimuli effectively prevent brain-computer interface inefficiency in patients with neurodegenerative disease. *Clin. Neurophysiol.* 124, 893–900. doi: 10.1016/j.clinph.2012.11.006

Kübler, A., Holz, E. M., Riccio, A., Zickler, C., Kaufmann, T., Kleih, S. C., et al. (2014). The user-centered design as novel perspective for evaluating the usability of bci-controlled applications. *PLoS ONE* 9:e112392. doi: 10.1371/journal.pone.0112392

Leuthardt, E. C., Schalk, G., Wolpaw, J. R., Ojemann, J. G., and Moran, D. W. (2004). A brain-computer interface using electrocorticographic signals in humans. *J. Neural Eng.* 1, 63–71. doi: 10.1088/1741-2560/1/2/001

Lopez, M.-A., Pomares, H., Pelayo, F., Urquiza, J., and Perez, J. (2009). Evidences of cognitive effects over auditory steady-state responses by means of artificial neural networks and its use in brain-computer interfaces. *Neurocomputing* 72, 3617–3623. doi: 10.1016/j.neucom.2009.04.021

Mota, A., Duarte, L., Rodrigues, D., Martins, A., Machado, A., Vaz, F., et al. (2013). Development of a quasi-dry electrode for EEG recording. *Sens. Actuators A Phys.* 199, 310 – 317. doi: 10.1016/j.sna.2013.06.013

Müller-Putz, G. R., Neuper, C., and Pfurtscheller, G. (2001). Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation. *Biomed. Tech.* 46, 186–190. doi: 10.1515/bmte.2001.46.7-8.186

Müller-Putz, G. R., Scherer, R., Brauneis, C., and Pfurtscheller, G. (2005). Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components. *J. Neural Eng.* 2, 1–8. doi: 10.1088/1741-2560/2/4/008

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, 30–37. doi: 10.1109/TNSRE.2005.863842

Nijboer, F., Sellers, E. W., Mellinger, J., Jordan, M. A., Matuz, T., Furdea, A., et al. (2008). A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. *Clin. Neurophysiol.* 119, 1909–1916. doi: 10.1016/j.clinph.2008.03.034

Pfurtscheller, G., Guger, C., Müller, G., Krausz, G., and Neuper, C. (2000). Brain oscillations control hand orthosis in a tetraplegic. *Neurosci. Lett.* 292, 211–214. doi: 10.1016/S0304-3940(00)01471-3

Piccione, F., Giorgi, F., Tonin, P., Priftis, K., Giove, S., Silvoni, S., et al. (2006). P300-based brain computer interface: reliability and performance in healthy and paralysed participants. *Clin. Neurophysiol.* 117, 531–537. doi: 10.1016/j.clinph.2005.07.024

Picton, T., John, M., Purcell, D., and Plourde, G. (2003). Human auditory steady-state responses: The effects of recording technique and state of arousal. *Anesth. Analg.* 97, 1396–1402. doi: 10.1213/01.ANE.0000082994.22466.DD

Pinegger, A., Wriessnegger, S., and Müller-Putz, G. (2013). Introduction of a universal P300 brain-computer interface communication system. *Biomed. Tech. (Berl).* doi: 10.1515/bmt-2013-4445. [Epub ahead of print].

Pokorny, C., Breitwieser, C., Neuper, C., and Müller-Putz, G. (2011). "Towards a single-switch bci based on steady-state somatosensory evoked potentials," in *Proceedings of the 5th International Brain-Computer Interface Conference 2011* (Graz), 200–204.

Pokorny, C., Klobassa, D. S., Pichler, G., Erlbeck, H., Real, R. G. L., Kübler, A., et al. (2013). The auditory P300-based single-switch BCI: Paradigm transition from healthy subjects to minimally conscious patients. *Artif. Intell. Med.* 59, 81–90. doi: 10.1016/j.artmed.2013.07.003

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin. Neurophysiol.* 118, 2128–2148. doi: 10.1016/j.clinph.2007.04.019

Pritchard, W. S. (1981). Psychophysiology of P300. *Psychol. Bull.* 89, 506–540. doi: 10.1037/0033-2909.89.3.506

Scherer, R., Billinger, M., Wagner, J., Schwarz, A., Hettich, D. T., Bolinger, E., et al. (2015). Thought-based row-column scanning communication board for individuals with cerebral palsy. *Ann. Phys. Rehabil. Med.* 58, 14–22. doi: 10.1016/j.rehab.2014.11.005

Schwarz, A., Scherer, R., Steyrl, D., Faller, J., and Müller-Putz, G. (2015). "A co-adaptive sensory motor rhythms brain-computer interface based on common spatial patterns and random forest," in *Engineering in Medicine and Biology Society (EMBC),2015 37th Annual International Conference of the IEEE* (Milan), 1049–1052.

Stapells, D., Linden, D., Suffield, J., Hamel, G., and Picton, T. (1984). Electrophysiologic techniques in audiology and otology - human auditory steady-state potentials. *Ear Hear.* 5, 105–113. doi: 10.1097/00003446-198403000-00009

Vialatte, F.-B., Maurice, M., Dauwels, J., and Cichocki, A. (2009). Steady-state visually evoked potentials: focus on essential paradigms and future perspectives. *Progr. Neurobiol.* 90, 418–138. doi: 10.1016/j.pneurobio.2009.11.005

Volosyak, I., Valbuena, D., Malechka, T., Peuscher, J., and Gräser, A. (2010). Brain-computer interface using water-based electrodes. *J. Neural Eng.* 7:066007. doi: 10.1088/1741-2560/7/6/066007

Zander, T. O., Lehne, M., Ihme, K., Jatzev, S., Correia, J., Kothe, C., et al. (2011). A dry eeg-system for scientific research and brain-computer interfaces. *Front. Neurosci.* 5:53. doi: 10.3389/fnins.2011.00053

Zickler, C., Riccio, A., Leotta, F., Hillian-Tress, S., Halder, S., Holz, E., et al. (2011). A brain-computer interface as input channel for a standard assistive technology software. *Clin. EEG Neurosci.* 42, 236–244. doi: 10.1177/155005941104200409

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PLOS ONE

RESEARCH ARTICLE

Composing only by thought: Novel application of the P300 brain-computer interface

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Abstract

The P300 event-related potential is a well-known pattern in the electroencephalogram (EEG). This kind of brain signal is used for many different brain-computer interface (BCI) applications, e.g., spellers, environmental controllers, web browsers, or for painting. In recent times, BCI systems are mature enough to leave the laboratories to be used by the end-users, namely severely disabled people. Therefore, new challenges arise and the systems should be implemented and evaluated according to user-centered design (USD) guidelines. We developed and implemented a new system that utilizes the P300 pattern to compose music. Our Brain Composing system consists of three parts: the EEG acquisition device, the P300-based BCI, and the music composing software. Seventeen musical participants and one professional composer performed a copy-spelling, a copy-composing, and a free-composing task with the system. According to the USD guidelines, we investigated the efficiency, the effectiveness and subjective criteria in terms of satisfaction, enjoyment, frustration, and attractiveness. The musical participants group achieved high average accuracies: 88.24% (copy-spelling), 88.58% (copy-composing), and 76.51% (free-composing). The professional composer achieved also high accuracies: 100% (copy-spelling), 93.62% (copy-composing), and 98.20% (free-composing). General results regarding the subjective criteria evaluation were that the participants enjoyed the usage of the Brain Composing system and were highly satisfied with the system. Showing very positive results with healthy people in this study, this was the first step towards a music composing system for severely disabled people.

Introduction

Brain-computer interfaces (BCIs) are useful tools to provide communication without the need of any voluntary muscular control. A BCI can be an assistive device for people who are suffering from severe disabilities, i.e., who cannot communicate via the normally available channels due to motor degeneration or brain damage [1]. The so-called P300 event-related potential (ERP) is a prominent brain signal for BCI-control and is often assessed non-invasively by measuring the electroencephalogram (EEG). Farwell and Donchin [2] developed the first P300-based BCI application utilizing the so-called oddball paradigm where approx. 300ms after the presentation of a rare stimulus between frequently presented standard stimuli a positive deflection in the EEG occurs [3]. The P300 was elicited by randomly flashing the rows and columns of a 6×6 matrix containing the letters of the alphabet and numbers between 0–9. Volunteers were asked to count the flashings of the symbol to be selected and to ignore the highlighting of the other characters. Almost all existing BCIs attempting to evoke the P300 pattern visually are using this method. This type of BCI allows writing characters and letters or selecting commands on a computer screen. Based on the oddball principle, also auditory [4] and tactile [5] P300-based BCIs were developed and evaluated with healthy as well as severely disabled people, e.g., [6–9]. It has been shown that with a P300 BCI it is possible to spell, browse the internet, control a smart home, and drive a wheelchair [10–12]. Also applications for entertainment have been developed [13, 14].

One example for an application which allows the users to paint pictures and thereby express their creativity is the so-called Brain Painting application. This application was designed by the German artist Adi Hösele in cooperation with the Institute of Medical Psychology and Behavioural Neurobiology at the University of Tübingen [15]. A P300-based BCI is the basis of the Brain Painting system. With a special P300 matrix, it is possible to select the color, grid size, object size, transparency, and other features which allow painting pictures on a virtual canvas. Various studies have been conducted with the Brain Painting application demonstrating that it is possible for healthy people as well as for severely disabled people to paint pictures [16–18]. Furthermore, the Brain Painting system was used by several severely disabled painters in their homes over a long time period and these painters had several exhibitions in different countries [17]. The development of the Brain Painting application was based on a user-centered design (USD) approach according to the ISO 9241–210 norm. UCD is becoming more and more important in BCI research. Many studies have already been published regarding this topic [19–22]. According to Kübler et al. [23] a BCI system for communication and control developed by UCD standards is evaluated and improved by three main factors, namely effectiveness, efficiency and satisfaction.

Besides painting pictures, another possibility for creative expression is to make music. Utilizing the EEG to make music was first introduced by Adrian and Matthews in 1934 [24]. They implemented a sonification of the EEG signals. The first attempt to really compose a musical piece using EEG was performed by Lucier et al. [25] in 1965. Other composers, like Rosenboom [26] and Teitelbaum [27], followed. All these early so-called brain-to-music interfaces are based on sonification of the EEG signals. The first attempt to assess the performer's attention with the EEG and make parameter-driven music by detecting selective attention was introduced by Rosenboom in 1990 [28]. Fifteen years later Miranda and Boskamp introduced the brain-controlled piano [29]. They gave generative rules to the most prominent frequency bands in the spectrum of the EEG. Additionally, the system measured the complexity of the EEG signals to modulate the tempo and dynamics of the music. Wu et al. proposed a direct parameter mapping method to translate characters of the EEG into musical notes which is based on the power law of brain activities and music [30]. Later this method was extended for deriving a quartet from multichannel EEG [31]. Daly et al. developed and evaluated an affective brain-computer music interface for modulating the affective states of its users [32]. Their system attempts to modulate the users current affective state by playing music which is generated by an algorithmic music composition system and a case-based reasoning system. An overview about brain-to-music interfaces is given in the book: "Guide to Brain-Computer Music Interfacing" [25].

Utilizing the P300 component of the EEG to compose music was introduced by Grierson et al. [33]. They arranged different tone pitches, between A1 and G5, on a P300 spelling matrix. In a pilot study, five users were asked to select the C major notes, i.e., *c'''*, *d*, *e*, *f*, *g*, *a*, *b*, *c''''*. Four of the tested five subjects could finish the task with an accuracy rate of 75% or above.

Our Brain Composing system is based on the hypothesis that it is possible to effectively compose music via BCI without constraints. Therefore, we combined two powerful systems, a P300-based BCI with a music composing software. The BCI allows the user to control the composing software completely by concentrating on the elements of the P300 matrix. In addition to the suggested USD approach, in our opinion, a BCI system for disabled people has to be developed in two steps: first, the system has to be tested and evaluated with healthy subjects and improved according to the suggestions of that user group. In a second step, the system has to be evaluated with the disabled users and adapted according to their feedback. This two-step method allows solving error and usability problems of the system before the intended end-users work with it for the first time. The objective of this strategy is to avoid that severely disabled people become demotivated by initial problems.

A pilot study, addressing the usability of the Brain Composing system, showed positive results [34]. Five healthy participants took part in the pilot study. Their task was to copy-compose a given melody with the Brain Composing system. A minimum of 42 selections were necessary to finish the task. Three participants completed the task with accuracies between 77.8 and 95.7% and two participants were able to copy-compose more than half of the melody correctly.

The aim of the current study is to test our hypothesis and therefore, to investigate accuracy and user-acceptance of the Brain Composing system. User acceptance was determined with visual analogue scales, user experience questionnaires, and workload assessments. We evaluated the Brain Composing system with 17 healthy volunteers with musical background and one professional composer with at least 40 years experience in composing. They were asked to perform several tasks with the system and answer several questionnaires before and after the usage of the Brain Composing system. Tasks were a copy-spelling task, two copy-composing tasks and a free-composing task. This study was the proof of concept before testing the system with disabled people.

Materials and methods

The designed Brain Composing system consists of three parts: the EEG acquisition system, the P300 control software, and the music composing software. For signal acquisition, we used a gel-less biosignal acquisition system. Additionally, a universal P300-based BCI control system [11] was connected to a powerful, open-source music composing software (MuseScore 1.3, https://musescore.org).

Data acquisition

EEG signals were recorded with the Mobita (Twente Medical Systems International B.V., Oldenzaal, the Netherlands) biosignal amplifier, which transmits signals with 24 bit resolution via Wi-Fi wireless technology. The electrodes consist of small cotton pieces, connected to silver chloride pellets. The cotton is soaked in tap water prior to the measurement. The ground electrode is connected to a tap water soaked, conductive wrist band. The amplifier internally creates an average reference out of all used electrodes. Therefore, a real reference electrode is not required. This system ensures high usability [35]. EEG was recorded from six scalp electrodes (Fz, Cz, Pz, PO7, PO8, Oz) placed according to the extended international 10–20 system, with a sampling rate of 250 Hz.

P300-based BCI control system

The used P300-based BCI control system is a further development of a system which was introduced in [36] and has been used for various studies, e.g., [11, 35, 37]. One of the main features is that it is a distributed system, i.e., a C-code written part is used for the stimulation, Matlab (The MathWorks, Natick, USA) is responsible for the signal processing, and another C-coded program handles the signal acquisition [38]. All the different parts are connected via a TCP network. The used data acquisition system delivers raw signals. Therefore, we used a 4^{th} order Butterworth band-pass filter with cut-off frequencies of 1 and 15 Hz. As described in [11], different stimulation matrices are possible. In addition to the described method in [11], new ways to change the content of the P300 matrix and to control an external application were implemented. The content of the P300 matrix is stored in a JSON (javascript object notation) file. JSON is a lightweight data-interchange format. A JSON file can include the information for multiple matrices. The transition between different matrices is implemented by means of cross-links, i.e., every matrix has a unique name and can be called by an element of another matrix. In sum, every JSON matrix item consists of four parts: a symbol that is shown in the matrix, a value that is sent to the external application by key-press simulations, a cross-link element that can contain the name of another matrix, and finally a selectable element that indicates whether the symbol should change the color when it was selected. This implementation enables the user to control entire programs with the P300-based BCI.

Additionally, we implemented a dynamic stopping strategy that classifies the data after every flashing sequence, i.e., all rows and columns flashed once. If the classification result had been identical three times in a row, the corresponding element was marked yellow in the matrix, printed out in the bottom line, and sent to the controlled application. Therefore, the minimal number of highlighting sequences was three, cf. [12]. If the defined maximum number of flashing sequences was reached without having a final result, the stimulation was reset and started again.

Music composing software

For the Brain Composing system, we connected the P300-based BCI control system with the music composing software MuseScore (https://musescore.org) version 1.3. This open-source music composing software provides an easily and commonly used environment to create high-quality western musical scores. Music can be composed for many different instruments, e.g., string instruments, piano, or brass instruments, by combining note lengths and note pitches. Additional features like rests, slurs, accords, and many more are also available. Sheets of music can be saved and exported in different media file formats, like MP3 or MIDI. However, the main reason why we decided to use this composing software is that an integrated shortcut manager allows creating shortcuts with different key combinations for nearly every possible command. In this way, all important control functions of the MuseScore software can be directly called via keyboard shortcuts.

The composer control method

By selecting the MuseScore item in the menu bar of the P300-based BCI control application, the MuseScore application is started. At the same time, the P300-based BCI control application displays the main Brain Composing matrix consisting of four cross-link elements: “New”, “Open”, “Save”, and “Compose”. By selecting one of these first three elements, the MuseScore program opens the new, open, or save dialog window and the matrix changes to a matrix filled with Latin letters and control elements to create, open, or save a sheet of music. By selecting the “Compose” element, the user can directly start to compose music. Composing elements are displayed in the matrix and the last used sheet of music is shown in the MuseScore window.

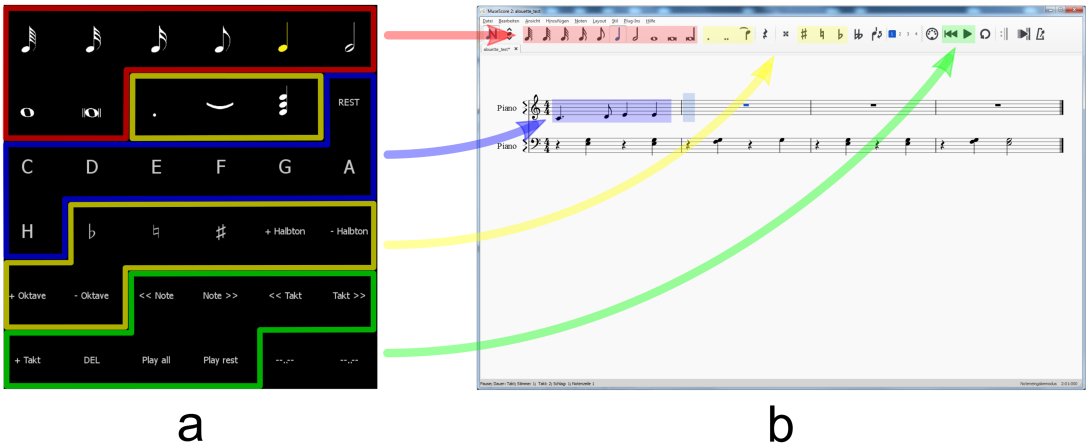

Fig 1. Brain Composing P300 matrix. Sketch of the P300 matrix and the corresponding commands in MuseScore. (a) Screenshot of the black and white P300 stimulation matrix; (b) Screenshot of the MuseScore window. All colored areas are inserted to visualize the different commands for the reader and were not shown during the study.

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To insert a note into a given sheet of music, first the note length has to be selected, see Fig 1 red arrow. The currently selected value is indicated by yellow color in the P300 matrix, see Fig 1(a). Extra features for the note, like accidentals, dot, slur or chord, can be selected, see Fig 1 yellow arrow. Accidentals and dots are just applied to the note pitch that is selected subsequently, whereas the slur and chord function remain activated, marked with yellow color until selected again. Finally, to add a note, a pitch has to be selected, see Fig 1 blue arrow. Afterwards, the selected note is played and the user sees the note on the sheet of music. Errors can be corrected by deleting the note. Two elements ("play all", "play rest") are available to play the composed melody, see Fig 1 green arrow. Various other elements are available, e.g., to navigate back and forth between notes or bars and to change the pitch in steps of one octave.

Study design and procedure

We evaluated the new Brain Composing system with eighteen participants in terms of efficiency, effeciveness and satisfaction. During the performed experiment, participants were seated in a comfortable chair approximately 70 cm away from two computer screens centered in front of them, see Fig 2. The upper screen displayed the P300 matrix used to control the music composing software, which was shown on the bottom screen when activated. The bottom screen remained black during the calibration and copy-spelling tasks.

Participants. Seventeen healthy, non-professional musicians, hereinafter called non-professional participants, (5 female, mean age: 27.12, SD:8.54 years) took part in the study (16 right-handers, 1 left-hander). Twelve participants were naive to BCI, four had experience with BCI (not P300-based), and one had taken part in the Brain Composing pilot study. All participants disavowed any history of neurological or psychiatric disease and hearing impairment, and had normal or corrected-to-normal vision. They gave written, informed consent before the experiment. The study was approved by the Ethic Committee of the Medical University of Graz, Austria.

Before the main experiment participants had to fill out a questionnaire covering different aspects of musical training, instruments and demographic information. All participants had

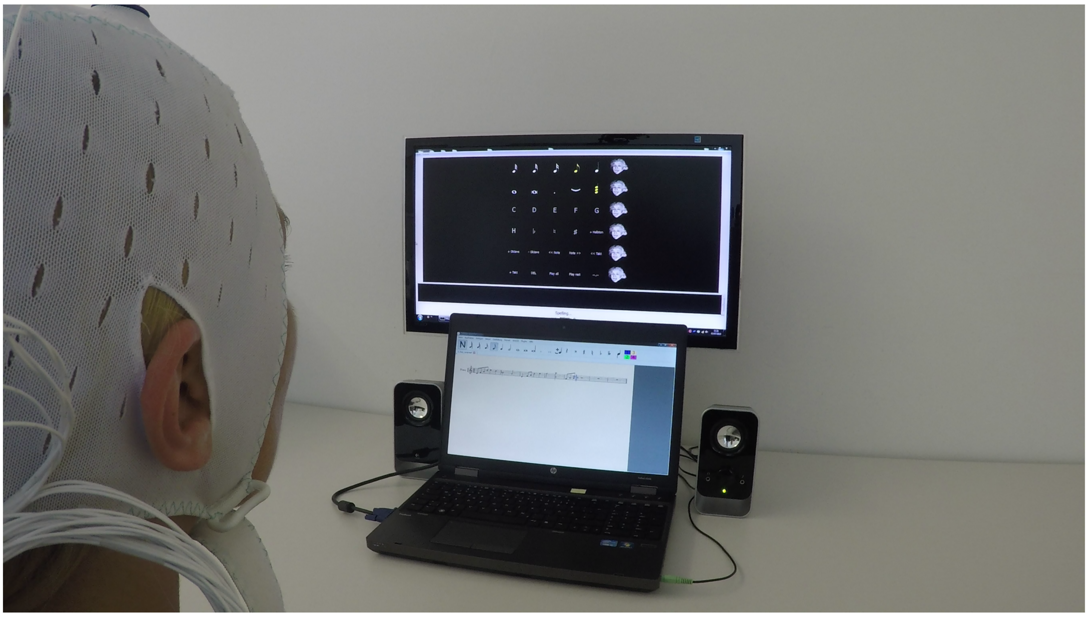

Fig 2. Brain Composing setup. The upper screen shows the P300 stimulation matrix and the bottom screen shows the music composing software.

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played at least one instrument and/or sang (mean duration: 15.18, SD:5.83 years), and had received instrumental or vocal training in the past (mean duration: 10.74, SD:5.83 years). Four participants were still taking instrumental lessons. Twelve participants were playing their instrument/singing regularly (mean 5.25, SD:3.79 hours/week), five did currently not play/sing. Six participants had been playing/singing exclusively solo, eleven had additional experience in playing/singing in a band, orchestra or choir. All participants were able to read music notes. Apart from instrumental or vocal lessons, they had received musical training to a varying degree. However, none of them worked as a professional musician or composer. Nine participants stated that they did not compose music, eight composed music. Six participants reported to use composing software, three of them had used MuseScore before. The participants considered themselves as moderately to highly musical (M:7.55, SD:1.65), indicated by a score between 0 and 10 (0 = "not musical at all", 10 = "highly musical").

One professional musician and composer, hereinafter called professional composer, (68 years old, right-hander, BCI naive) took part in the study. He has played clarinet for 58 years and had received instrumental training for 20 years. He had studied clarinet, composition and orchestral training at the University and had been teaching music as a professor for many years. He has been working as a free-lance composer for more than 10 years and has created numerous compositions. He composed up to 10 hours/day and played clarinet 2 hours/day. He worked with professional computer software but had not used MuseScore before.

We performed the evaluation of the Brain Composing system separately for the non-professional participants and the professional composer to investigate related differences.

Calibration. For calibration, a 6 × 6 matrix, consisting of the letters of the German alphabet, the numerals 1–7, and three other commands, was used. Calibration was performed with

15 highlighting flashes per row and column, with a flash duration of 50 ms and an inter-stimulus interval (ISI) of 125 ms. Elements of the matrix were highlighted with famous faces [39]. Each block of sequences was followed by a four seconds pause. Participants were asked to copy-spell six symbols ("H3P5FU"), which were equally distributed over the matrix. At the beginning of each block, the target element was marked yellow in the matrix for two seconds. Participants were asked to focus their attention on the target and to mentally count the number of times the symbol was highlighted. Accuracy was calculated for every flashing sequence with a leave-one-letter-out cross validation. The calibration was successful when the accuracy was higher than 70% at any number of sequences.

Main experiment. After the calibration, participants had to fulfill four different tasks: a copy-spelling, a manual copy-composing, a P300-based BCI copy-composing, and a free-composing task, see Fig 3.

The copy-spelling task consisted of copy-spelling the words “MUSIK” (Eng. “MUSIC”) and “LISZT” (the name of a famous Austrian composer), see Fig 3, first row. The word to spell was inserted in the bottom line of the computer screen, below the P300 matrix. Stimulation parameters were equal to the calibration except the number of flashing repetitions, which were dynamically stopped. In case of an error, participants were instructed not to correct it but to proceed with the next selection. In the copy-composing task, participants were asked to copy-compose the first six bars of the well-known French Canadian children’s song “Alouette”, see Fig 3, second row. The melody was printed on a sheet of paper and placed at the top of the bottom monitor, thus located in the middle of the two screens. First, participants were given a verbal instruction how to control the composing software, insert music notes via the P300 matrix by mouse clicks, and get familiar with the application. Afterwards, they were asked to copy-compose the given melody via the P300 matrix by mouse clicks, see Fig 3, third row. In case of mistakes, further explanations were given how to control the music composing system.

For the P300-based BCI controlled copy-composing task, see Fig 3, fourth row, the pause after each block of sequences was set to 10 seconds in order to give the participants sufficient time to prepare for the next selection. Additionally, the participants were instructed to briefly state each element they intended to select before the next block of flashes started. Errors and false intentions were corrected via spoken commands of the experimenter. Intended and actual selections were noted in a protocol. The task included first selecting the “Compose” element in a 3×6 matrix with the elements “New”, “Open”, “Save”, and “Compose”. All other fourteen elements were filled with a meaningless symbol ("–„–"). When the “Compose” element was selected, the matrix switched automatically to the 6×6 “composing” matrix and the music composing software was opened on the bottom screen with a prepared empty music sheet. After inserting all notes correctly, participants were asked to select the element “play all”. In total, 41 selections were required to complete the task. The task was aborted when the participants reached a number between 62 and 70 selections. This number varies because the task was aborted in this range when the user had no chance to finish.

After copy-spelling and copy-composing, participants could compose an individual melody (free-composing task), see Fig 3, fifth row. They were given a maximum of 30 minutes but they were also able to stop earlier. The stimulation parameters were identical to the copy-composing task. The participants again had 10 seconds time between each block of sequences to think about the next step, i.e., the next note length, pitch, feature. During this part of the experiment, they were no longer instructed to verbally state the symbols they intended to select but to say “false” in case of a misclassification, i.e., if the symbol they had focused on was not selected. Misclassifications were again noted in a protocol to calculate accuracies for the different tasks afterwards. Accuracies are defined as the ratio of the sum of correct selections to the sum of made selections for the copy-spelling, the copy-composing, and the free-composing tasks.

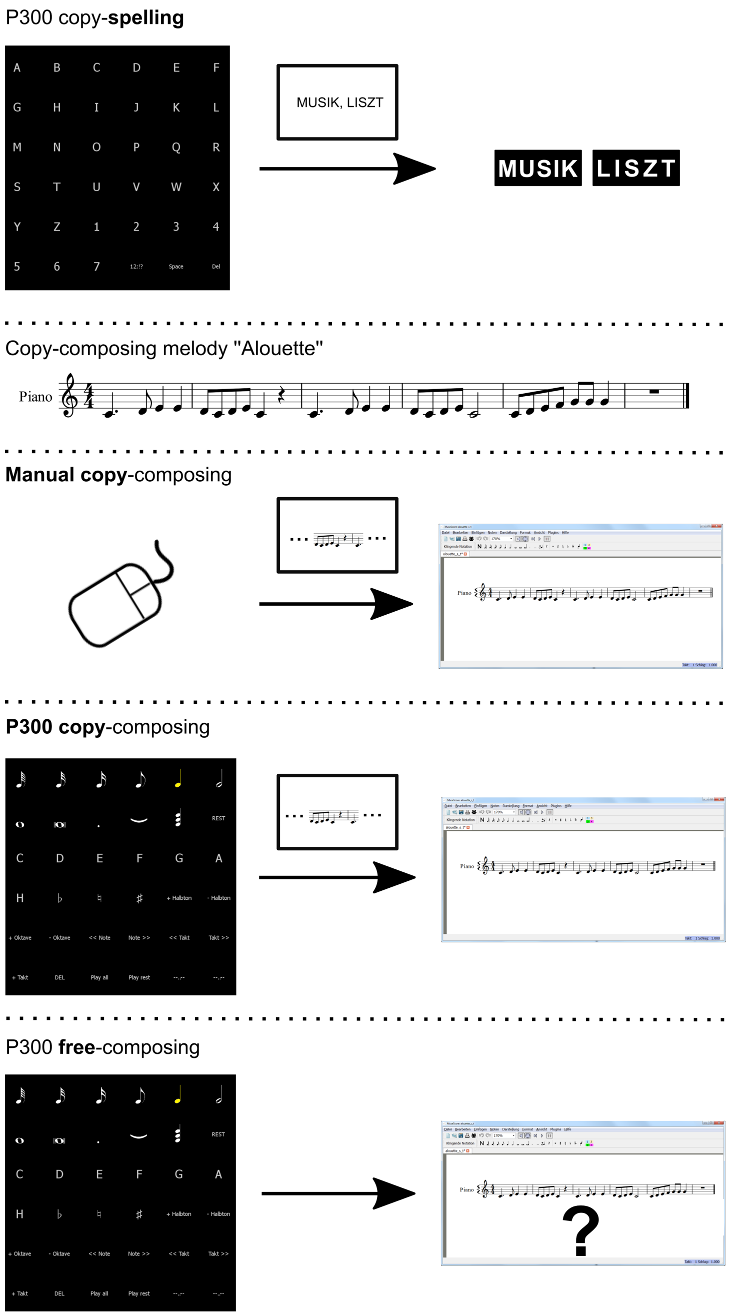

Fig 3. Sketch of the tasks. First row: Task 1 was to copy-spell "musik" and "liszt" with the P300-based BCI. Second row: The participants had to copy-compose the first six bars of the well-known French Canadian children's song "Alouette". Third row: Task 2 was to manually, i.e., by mouse-clicks, copy-compose the melody of Alouette. Fourth row: Task 3 was to copy-compose the melody of Alouette with the P300-based BCI. Fifth row: Task 4 was to compose free for 30 minutes.

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Acquisition of behavioral data

In the present study, participants had to fill out several questionnaires covering their motivation, mood, fatigue, workload and user experience. In the following section, the used questionnaires are introduced in detail.

Motivation, mood, fatigue. Visual analogue scales have been used in many BCI studies, e.g., [20, 22, 40], and have been shown to be reliable and valid in measuring emotions or attitudes. The participants were asked to indicate their motivation, mood and fatigue on a VAS. Each VAS consists of a 10 cm long horizontal line with the anchor points 0 and 10 (0 = "not at all motivated"/ "bad mood"/ "not at all tired", 10 = "highly motivated"/ "very good mood"/ "very tired"). Participants were asked to mark the position on the line which best represented their motivation, mood, or fatigue. Motivation was assessed before the experiment, mood and fatigue before and after the experiment. Pre- and post-values of mood and fatigue were compared with a paired sample t-test, respectively.

Workload. To assess subjective workload an electronic version of the NASA Task Load Index (NASA-TLX) [41] was administered. The NASA-TLX is a well validated instrument for workload assessment [42] also used in BCI research [21, 23, 43]. The NASA-TLX is a multidimensional scale used to estimate subjective workload on six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. Each of these factors is rated on a 20-step bipolar rating scale with a score ranging from 0 to 100 and anchor descriptors such as "high/low". In a second step, participants indicate in 15 pairwise comparisons which factor contributed more to their subjective workload. The number of times a factor is chosen as more relevant is the weighting of the factor for the given task. By this weighting procedure, a global workload score is yielded (ranging from 0 to 100, a high score indicating a high workload), and the relative contribution of each factor to the total workload is identified (the highest possible score for each factor is 33.3).

User experience. To evaluate user experience (UX), the user experience questionnaire (UEQ) was administered [44]. The UEQ was developed to assess UX in an easy and immediate way, covering both pragmatic and hedonic aspects. It has been used to assess UX for a variety of software products, e.g., [45, 46] and was used in a recent BCI study [21]. The UEQ consists of 26 bipolar items rated on a 7-point semantic differential scale. The single items are transformed to the range from −3 to +3 and are assigned to six subscales: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. Values above 0.8 indicate a positive impression, values below −0.8 a negative impression and values between −0.8 and 0.8 a neutral impression. The score of each subscale is calculated by averaging the rating of the corresponding items. The obtained subscales can further be grouped into three categories: attractiveness, use quality, and design quality. Attractiveness is a pure valence dimension, describing a person's general attitude towards a product. Use quality reflects pragmatic quality aspects (average over the subscales efficiency, perspicuity and dependability) and design quality describes hedonic quality aspects (average over the scales novelty and stimulation).

In addition, participants completed a custom-made usability questionnaire (UQ) gathering further information about user satisfaction with the Brain Composing system, and rated their overall satisfaction, enjoyment and level of control on VAS (ranging from 0 and 10) after the experiment (0 = "not at all satisfied"/ "no enjoyment at all"/ "no control", 10 = "absolutely satisfied"/ "absolute enjoyment"/ "absolute control").

Results

A video that demonstrates how the Brain Composing system works is available: S1 Video.

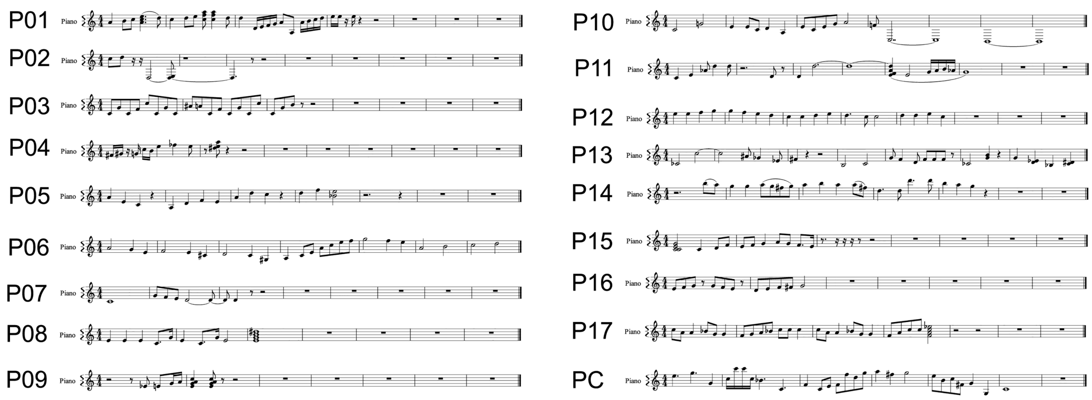

Fig 4. Accuracies of the different tasks. The accuracies of the copy-spelling, copy-composing, and the free-composing tasks are shown. P1-17 represent the non-professional participants and PC is the professional composer. Asterisks indicate that the participant did not finish the copy-composing task. The red dotted line indicates the 70% accuracy limit. Below that limit a BCI could not be used satisfactorily.

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BCI effectiveness and efficiency

A comparison of the different accuracies per participant and task is shown in Fig 4. The accuracy has to be higher than 70% to be sufficient, cf. [47–50]. This threshold value is marked by a red dotted line in Fig 4. The non-professional participants' (N = 17) average copy-spelling accuracy was 88.2 (SD:16.3)% in a range between 60 and 100%. The average time to spell one word (5 letters) was 77 (SD:6.8) seconds with a break of 6 seconds between the letters. For two participants, the task was unclear at the beginning. Their accuracy increased from 20% for the first word to 100% for the second word. Calculating the accuracy without these two participants (N = 15), the average accuracy would be 92.0 (SD:13.2)% instead.

The professional composer needed 73 seconds and 66 seconds to spell the two words with an accuracy of 100%.

Thirteen non-professional participants finished the copy-composing task with an average accuracy of 88.6 (SD:8.2)%. On average, they needed 54 (SD:9) selections to finish the task. With a pause of 11.5 seconds between the selections, the average time was 21:23 (SD:3:38) minutes. Four participants did not finish the task, because the task was aborted between 62 and 70 selections when the participants had no chance to finish it within 70 selections. However, at the end of the task only two participants were more than 10 steps away from finishing the composition. One participant copy-composed the given melody without any error. Six out of 17 participants composed the given melody with fewer than four errors. The professional composer composed the given melody with an accuracy of 93.6% in 20 minutes. He needed 47 selections.

Thirteen non-professional participants used the full length of 30 minutes to compose their own melody. The four participants who did not used the whole 30 minutes, stated that they composed what they wanted to achieve. All the composed pieces of music are shown in Fig 5. To hear the compositions please use S1 Music. The average classification accuracy of the non-professional participants was 76.5 (SD:17.2)%. If the participants that could not finish the copy-composing task were excluded, the average accuracy would increase to 84.3 (SD:9.6)%.

The non-professional participants composed, on average, 17.9 (SD:6.9, range: 6–31) notes during the free-composing run. For this, they needed, on average, 4.3 (SD:2.3, range 2.4–10.7)

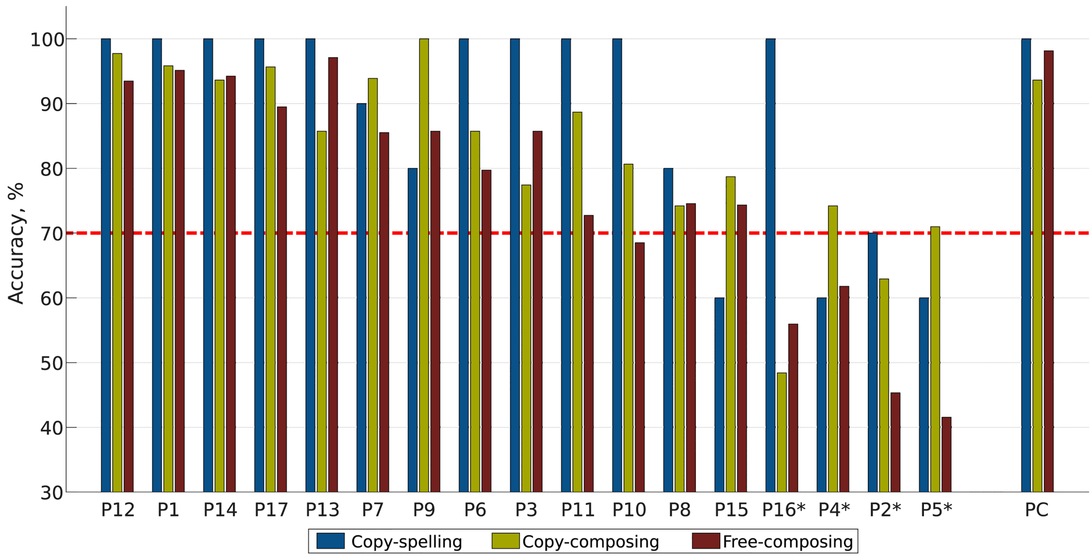

Fig 5. Participants' free compositions. The non-professional participants' (P1-17) and the professional composer's (PC) musical pieces.

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selections per note. Consequently, the participants made 2.4 selections per minute (SD:0.21) with an inter-selection pause of 11.5 seconds. On average, they needed 1 hour and 32 minutes to fulfil all tasks plus the calibration with a standard deviation of 13 minutes. This period also includes pauses between the tasks. During that time the participants made, on average, 132 (SD:18) selections with the BCI.

The professional composer composed only fourteen minutes freely. However, he had an accuracy of 98.1%, composed 26 notes, needed 2.1 selections per note, and made 3.9 selections per minute.

Behavioral data

Visual analogue scales. All non-professional participants were highly motivated (M:8.85, SD:0.83). During the study, mood did not change significantly ($t(16) = 1.08$, $p = 0.30$, Cohen's $d = 0.26$) from M:8.04 (SD:1.31) to M:7.55 (SD:1.66) and fatigue increased significantly from M:2.74 (SD:1.8) to M:3.73 (SD:1.89) ($t(16) = 2.52$, $p = 0.02$, Cohen's $d = 0.61$). Satisfaction was rated high (M:7.85, SD:1.60). All non-professional participants enjoyed the usage of the brain composing system (M:8.11, SD:1.49) and felt to have good control (M:7.39, SD:1.89). Box plots of the results can be seen in Fig 6.

Ratings of the professional composer are shown as green asterisks in Fig 6. In the satisfaction box plot, the value of the professional composer is an outlier. He argued that the method to make selections restricted his composing process.

NASA-TLX. Fig 7 shows the stacked bar plot of the NASA-TLX workload score for all participants. The non-professional participants' mean global workload score was 62.92 (SD:13.75, range:25.33–83.33). Four participants reached workloads higher than 70. Factors contributing to the global workload score were mental demand (M:19.82, SD:7.07), effort (M:15.06, SD:8.69), performance (M:11.33, SD:7.32), temporal demand (M:9.76, SD:8.14), frustration (M:4.92, SD:5.29), and physical demand (M:2.02, SD:6.48).

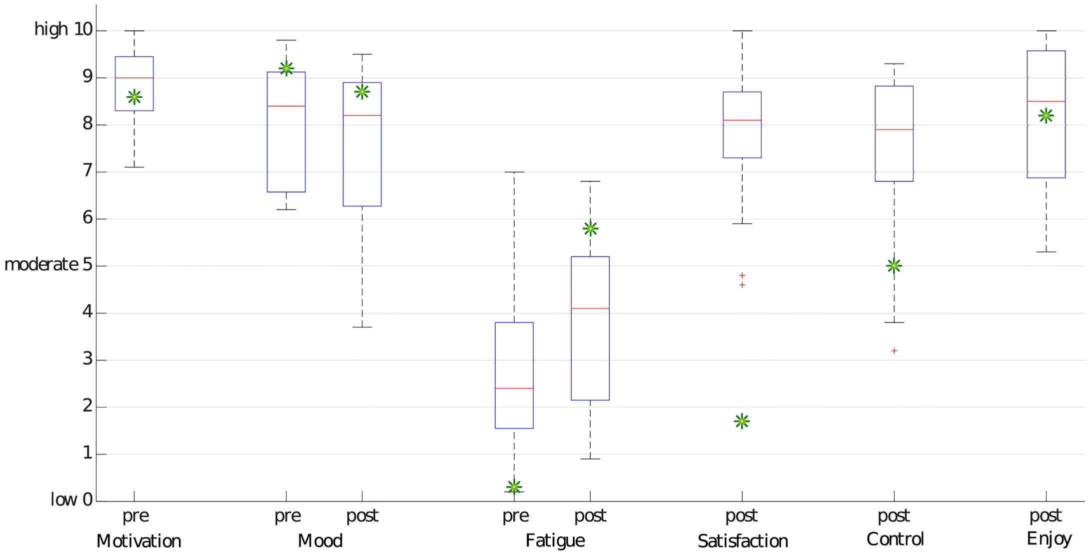

Fig 6. VAS scores. The non-professional participants' VAS scores are presented as box plots. The professional composer's scores are shown as green asterisks.

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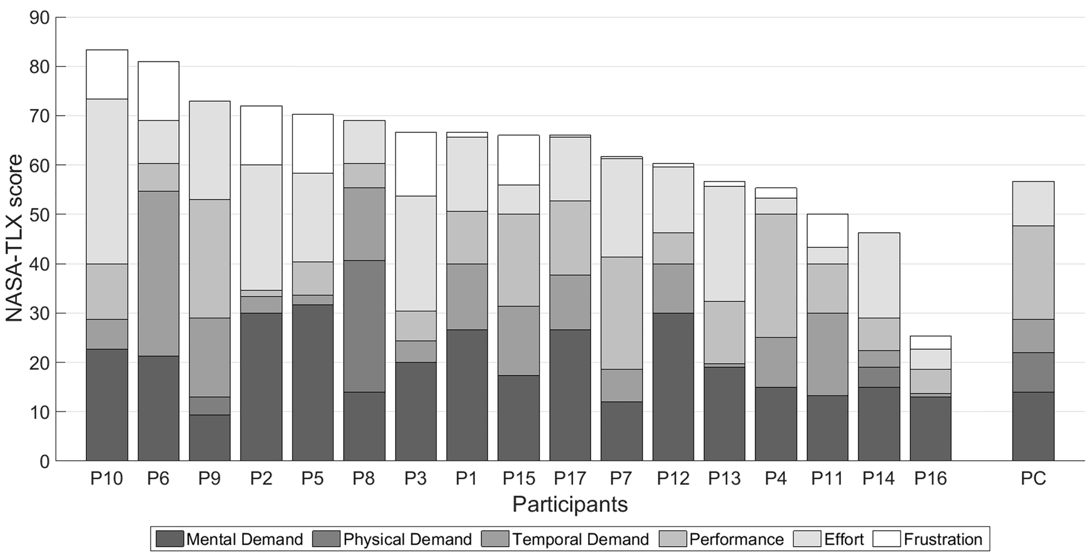

Fig 7. NASA-TLX scores. The non-professional participants' (P1-17) and the professional composer's (PC) NASA-TLX scores.

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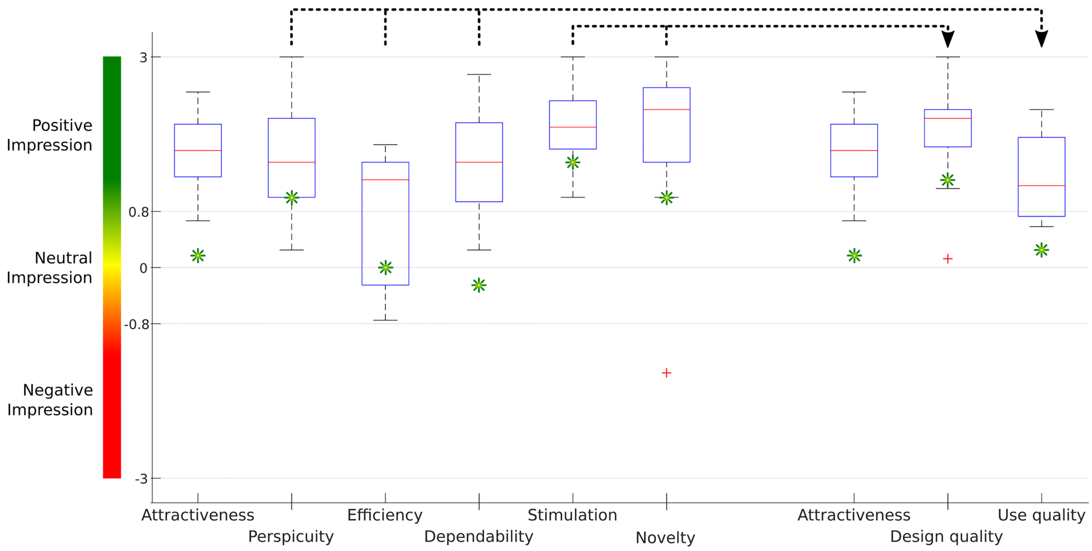

Fig 8. UEQ scores. The non-professional participants' UEQ scores are presented as box plots. The professional composer's UEQ scores are shown as green asterisks.

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The global NASA-TLX workload score of the professional composer was 56.67 (performance: 19.00, mental demand: 14.00, effort: 9.00, physical demand: 8.00, temporal demand: 6.67, and frustration: 0.00).

User experience questionnaire. According to the six subscales, the non-professional participants gave the system high average ratings for stimulation (M:2.02, SD:0.58) and novelty (M:1.93, SD:1.09) and a moderate rating for attractiveness (M:1.62, SD:0.50), perspicuity (M:1.60, SD:0.81), efficiency (M:0.84, SD:0.90), and dependability (M:1.49, SD:0.74), see Fig 8. Consequently, the averaged value for the design quality was higher (M:1.97, SD:0.67) than for the user quality (M:1.31, SD:0.60). However, the impression of all parameters was positive except for the efficiency, which was neutral.

The professional composer rated the system lower compared to the other participants' values, see green asterisks in Fig 8. Participant four rated the "novelty" with a low value (−1.5), see outlier in Fig 8, without giving reasons.

Usability questionnaire. Two participants stated that sometimes it was unclear to them where the next note will be set. Normally, the position was indicated by a grey line in the MuseScore software. However, sometimes the note was set before or after this grey line depending on the previous selections. Eight users remarked that they want to have something like a pause button to have time to think about the next step (note) or that the system should detect when they think about the next note and pause automatically. Eight users negatively remarked that the correction of an error can be difficult and often requires more than one selection. The professional composer negatively remarked that it is complicate to select one note and this disturbs his creative process of composing. He suggested that commonly used notes (the combination of note length and pitch) should be selectable with a single selection step to fasten the system.

Discussion

We presented the implementation and evaluation of the first BCI controlled music composing system. Furthermore, the results indicate that the system works efficiently and effectively and the users enjoyed using it. However, there is still potential to improve the whole system according to the participants' recommendations. Additionally, a new version of the MuseScore software is available, which solves some arising problems and can be used without substantial changes in the system.

Composer control method

The communication between the P300-based BCI system and the composing software works only in one direction: from the BCI to the composer. Therefore, if a command from the P300-based BCI does not reach the composing software, an asynchrony between the two systems can occure. For example, if the selection of a different note length is lost between the speller and the composing software, a wrong note length will be displayed in the P300 matrix. This problem can only be solved by a two-way communication between the P300-based BCI and the music composing software. Then the composing software can acknowledge the received commands. The implementation would require a network connection between the applications. Due to the open-source-feature of MuseScore, this implementation would be possible, but with much more implementation effort.

Evaluation of the BCI efficiency and effectiveness

The used tap water-based EEG amplifier system worked satisfactorily and had the advantage that hair wash was not necessary after the measurements. Excluding the two participants who did not know how to spell at the beginning, the accuracy of the copy-spelling task was above 90%. This high value could not be reached again at the copy-composing or the free-composing task. The copy-composing tasks were more complex and thus cognitively more demanding than the simple spelling tasks. As opposed to copy-spelling, during composing sometimes a combination of subsequent selections was necessary to insert a specific note, i.e., specifying according features such as accidentals or dots. Moreover, in free-composing one needs to focus their attention on the to-be-selected element in the matrix while still creating a composition/melody. For the non-professional participants, this is even more challenging and demanding than copy-composing a given melody. On the other side, it seems that this fact did not influence the performance of the professional composer: his accuracies were at all three P300-based BCI tasks above 93%, see Fig 4. Therefore, one can assume that he had the melody in his mind and just concentrated on the transposition of it. Interestingly, he had lower accuracies when he had to copy-compose a melody than when he composed his own melody.

The pause between the blocks of P300 stimulation sequences was 10 seconds. The professional composer and one non-professional participant told us that 10 seconds were too long. According to their recommendation, the breaks between the P300 stimulation periods could be adapted to the users to increase the efficiency of the system.

Another reason for decreasing accuracies might be the time the participants had to spell in a row. During the spelling task, the participants had a break after five selections. No regular breaks were planned during the composing tasks. Eight of the seventeen non-professional participants recommended that a "pause" element should be included into the P300 matrix to pause the system, cf. [11]. This functionality should definitely be integrated in the next version of the Brain Composing system.

A third reason for the lower composing accuracies could be that nine of the seventeen non-professional participants did not compose music at all and only six of the remaining participants reported to use composing software. Out of this six only one participant solely uses composing software. All the other non-professional participants stated that they first use their favorite instrument to compose and afterwards they transfer the composition to a computer using composing software. Therefore, they are not used to compose directly on the computer like the professional composer.

Evaluation of behavioral data

The motivation of the users is a crucial factor for P300-based BCIs [51]. The average result of the motivation VAS indicates that all participants were highly motivated. This fact is reflected in the averaged high accuracies. In line with these high accuracies, the participants felt to have good control over the system which, in turn, likely contributed to the high enjoyment and satisfaction they reported. After approximately one hour and 31 minutes of using the system, the fatigue score had increased only slightly from 2.6 to 3.84. This result indicates that the duration of our measurement is not the upper limit of usage and can be extended. One important outlier of the satisfaction values was the score of the professional composer. The way he had to compose music with the Brain Composing system was very different to his normally used method, namely, a musical keyboard in combination with a music composing software (not MuseScore). This combination allows him to give complex commands with low effort. Compared to the Brain Composing method, his method is of course faster and more efficient.

According to the UEQ, the participants had a positive impression of all the asked items, except for efficiency, which was rated as neutral. This is not very surprising, because compared to the normally used healthy participants' input modalities a BCI works much slower and therefore less efficient. However, one has to keep in mind that the introduced Brain Composing system is not designed for healthy people. It is designed for disabled people, who are not able to use the normal computer input modalities. The design quality factor is very high, which means that the users had a very positive impression about the design of the Brain Composing system. The use quality, which is calculated out of perspicuity, efficiency, and dependability, delivers also a mostly positive impression, albeit with a trend to be neutral. The professional composer rated the attractiveness and dependability significant lower than the other participants, but not negative. The reasons might be the same as for the already described VAS satisfaction item.

Although the given tasks were complex and cognitively demanding, the non-professional participants' averaged NASA-TLX scores were moderate ranging from 25.33 to 83.33. Mainly three factors contributed to the workload: mental demand, effort, and performance. These three elements have also contributed most to the professional composer's result. The low values for frustration indicate that the partly low accuracies did not seriously frustrate the participants. The overall rating of the professional composer was lower compared to the mean value of the others. Interestingly, temporal demands did not contribute much to the total score, although eight of the seventeen non-professional participants asked for a "pause" button inside the matrix.

Summarizing the answers from the UQ, many participants recognize that it is very important to avoid errors, because it costs a lot of effort to correct wrong selections. As already mentioned, many users suggest to implement a "pause" button to have flexible time between selections to think or make a break. The most important reported weakness, namely that it was sometimes unclear to the users where the selected note will be set, is already solved and/or integrated in the next version of the MuseScore software as first tests with the new version indicated. There the actual position in the sheet of music is better highlighted with a half transparent grey box instead of a line. Therefore, any uncertainty about the actual composing position should be a problem of the past. Apart from minor remarks, fifteen of the seventeen non-professional participants stated that they enjoyed using the Brain Composing system.

Conclusion

We could show that it is possible to compose complex music pieces with the introduced Brain Composing system in a fast and comfortable way. The average accuracies of the P300-based BCI tasks were very high even though the participants reported a moderate to high workload. Furthermore, the participants reported that they enjoyed composing with the system.

This was the first step towards establishing a Brain Composing system as a tool for entertainment and, even more important, self-expression for severely disabled people.

Supporting information

S1 Music. Composed music. This mp3 file contains the study participants' compositions.
(MP3)

S1 Video. Brain Composing video. This video shows how the Brain Composing system is used.
(MP4)

S1 File. Original raw data of the tasks and the questionnaires. XLSX file containing the original raw data of the tasks and the questionnaires.
(XLSX)

Acknowledgments

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. At last, we would like to express our deepest condolences to the family of the professional composer—A few months after his participation in this study he died unexpectedly. He will live on forever through his compositions.

Author Contributions

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References

1. Millán J, Rupp R, Müller-Putz GR, Murray-Smith R, Giugliemma C, Tangermann M, et al. Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges. Frontier in Neuroscience. 2010; 4:12.
2. Farwell LA, Donchin E. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalography and Clinical Neurophysiology. 1988; 70:510–523. https://doi.org/10.1016/0013-4694(88)90149-6 PMID: 2461285
3. Polich J. Updating P300: an integrative theory of P3a and P3b. Clinical Neurophysiology. 2007; 118(10):2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019 PMID: 17573239
4. Käthner I, Ruf CA, Pasqualotto E, Braun C, Birbaumer N, Halder S. A portable auditory P300 brain-computer interface with directional cues. Clinical Neurophysiology. 2013; 124(2):327–338. https://doi.org/10.1016/j.clinph.2012.08.006 PMID: 22959257
5. Brouwer AM, van Erp JB. A tactile P300 brain-computer interface. Frontiers in Neuroscience. 2010; 4:19. https://doi.org/10.3389/fnins.2010.00019 PMID: 20582261
6. Piccione F, Giorgi F, Tonin P, Priftis K, Giove S, Silvoni S, et al. P300-based brain computer interface: reliability and performance in healthy and paralysed participants. Clinical Neurophysiology. 2006; 117(3):531–537. https://doi.org/10.1016/j.clinph.2005.07.024 PMID: 16458069
7. Sellers EW, Kübler A, Donchin E. Brain-computer interface research at the University of South Florida Cognitive Psychophysiology Laboratory: the P300 speller. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2006; 14:221–224. https://doi.org/10.1109/TNSRE.2006.875580 PMID: 16792299
8. Pokorny C, Klobassa DS, Pichler G, Erlbeck H, Real RGL, Kübler A, et al. The auditory P300-based single-switch BCI: Paradigm transition from healthy subjects to minimally conscious patients. Artif Intell Med. 2013; 59(2):81–90. https://doi.org/10.1016/j.artmed.2013.07.003 PMID: 24076342
9. Kaufmann T, Holz E, Kübler A. Comparison of tactile, auditory, and visual modality for brain-computer interface use: a case study with a patient in the locked-in state. Frontiers in Neuroscience. 2013; 7:129. https://doi.org/10.3389/fnins.2013.00129 PMID: 23898236
10. Donchin E, Spencer KM, Wijesinghe R. The mental prosthesis: assessing the speed of a P300-based brain-computer interface. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2000; 8:174–179. https://doi.org/10.1109/86.847808
11. Halder S, Pinegger A, Käthner I, Wriessnegger SC, Faller J, Antunes JBP, et al. Brain-controlled applications using dynamic P300 speller matrices. Artificial Intelligence in Medicine. 2015; 63(1):7–17. https://doi.org/10.1016/j.artmed.2014.12.001 PMID: 25533310
12. Kaufmann T, Herweg A, Kübler A. Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials. Journal of NeuroEngineering and Rehabilitation. 2014; 11(1):7. https://doi.org/10.1186/1743-0003-11-7 PMID: 24428900
13. Finkea A, Lenhardt A, Ritter H. The MindGame: a P300-based brain-computer interface game. Neural Networks. 2009; 22:1329–1333. https://doi.org/10.1016/j.neunet.2009.07.003
14. Andreev A, Barachant A, Lotte F, Congedo M. In: Recreational Applications of OpenViBE: Brain Invaders and Use-the-Force. John Wiley & Sons, Inc.; 2016. p. 241–258.
15. Münßinger J, Halder S, Kleih S, Furdea A, Raco V, Hösle A, et al. Brain painting: first evaluation of a new brain-computer interface application with ALS-patients and healthy volunteers. Frontiers in Neuroprosthetics. 2010; 4:182.
16. Holz EM, Botrel L, Kaufmann T, Kübler A. Long-Term Independent BCI Home-Use by a Locked-In End-User: An Evaluation Study. In: Proceedings of the 5th International Brain-Computer Interface Meeting; 2013. p. 181.
17. Holz EM, Botrel L, Kaufmann T, Kübler A. Long-Term Independent Brain-Computer Interface Home Use Improves Quality of Life of a Patient in the Locked-In State: A Case Study. Archives of Physical Medicine and Rehabilitation. 2015; 96(3):S16–S26. https://doi.org/10.1016/j.apmr.2014.03.035 PMID: 25721543
18. Botrel L, Holz EM, Kübler A. Brain Painting V2: long-term evaluation by an end-user at home—an update. In: Proceedings of the 6th International BCI Meeting; 2016. p. 232.

19. Laar B, Nijboer F, Gürkök H, Plass-Oude Bos D, Nijholt A. User Experience Evaluation in BCI: Bridge the Gap. International Journal of Bioelectromagnetism. 2011; 13(3):157–158.
20. Zickler C, Halder S, Kleih SC, Herbert C, Kübler A. Brain painting: usability testing according to the user-centered design in end users with severe motor paralysis. Artificial intelligence in medicine. 2013; 59(2):99–110. https://doi.org/10.1016/j.artmed.2013.08.003 PMID: 24080077
21. Lorenz R, Pascual J, Blankertz B, Vidaurre C. Towards a holistic assessment of the user experience with hybrid BCIs. Journal of Neural Engineering. 2014; 11(3):035007. https://doi.org/10.1088/1741-2560/11/3/035007 PMID: 24835132
22. Daly Lynn JM, Armstrong E, Martin S. User centred design and validation during the development of domestic brain computer interface applications for people with acquired brain injury and therapists: a multi-stakeholder approach. Journal of Assistive Technologies. 2016; 10(2):67–78. https://doi.org/10.1108/JAT-01-2016-0002
23. Kübler A, Holz EM, Riccio A, Zickler C, Kaufmann T, Kleih SC, et al. The User-Centered Design as Novel Perspective for Evaluating the Usability of BCI-Controlled Applications. PLoS ONE. 2014; 9(12): e112392. https://doi.org/10.1371/journal.pone.0112392 PMID: 25469774
24. Adrian ED, Matthews BH. The Berger rhythm: potential changes from the occipital lobes in man. Brain. 1934; 57:355–385. https://doi.org/10.1093/brain/57.4.355
25. Miranda ER, Castet J. Guide to Brain-Computer Music Interfacing. 1st ed. Springer London; 2014.
26. Rosenboom D. A Model for Detection and Analysis of Information Processing Modalities in the Nervous System Through an Adaptive, Interactive, Computerized, Electronic Music Instrument. In: Proceedings of the International Computer Music Conference; 1975. Available from: http://hdl.handle.net/2027/spo.bbp2372.1975.021.
27. Teitelbaum R. In Tune: Some Early Experiments in Biofeedback Music. In: Rosenboom D, editor. Biofeedback and the arts, results of early experiments. Aesthetic Research Center of Canada Publications; 1976.
28. Rosenboom D. Extended musical interface with the human nervous system, assessment and prospectus(Reprint from 1990); 1997. Available from: http://davidrosenboom.com/sites/default/files/media/downloads/MusInter.LEO_.97.final_.w_figs.pdf.
29. Miranda ER, Boskamp B. Steering generative rules with the EEG: An approach to brain-computer music interfacing. In: Proceedings of the SMC Conference 2005; 2005. Available from: http://smcnetwork.org/files/proceedings/2005/MirandaBoskamp.pdf.
30. Wu D, Li CY, Yao DZ. Scale-Free Music of the Brain. PLoS ONE. 2009; 4(6):e5915. https://doi.org/10.1371/journal.pone.0005915 PMID: 19526057
31. Wu D, Li C, Yao D. Scale-Free Brain Quartet: Artistic Filtering of Multi-Channel Brainwave Music. PLoS ONE. 2013; 8(5):e64046. https://doi.org/10.1371/journal.pone.0064046 PMID: 23717527
32. Daly I, Williams D, Kirke A, Weaver J, Malik A, Hwang F, et al. Affective brain—computer music interfacing. Journal of Neural Engineering. 2016; 13(4):046022. https://doi.org/10.1088/1741-2560/13/4/046022 PMID: 27396478
33. Grierson M, Kiefer C. Contemporary Approaches to Music BCI Using P300 Event Related Potentials. In: Miranda E, Castet J, editors. Guide to Brain-Computer Music Interfacing. Springer London; 2014. p. 43–59.
34. Pinegger A, Wriessnegger SC, Müller-Putz GR. Sheet music by mind: Towards a brain-computer interface for composing. In: Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE; 2015. p. 1053–1056.
35. Pinegger A, Wriessnegger SC, Faller J, Müller-Putz GR. Evaluation of different EEG acquisition systems concerning their suitability for building a brain-computer interface: case studies. Frontiers in Neuroscience. 2016;.
36. Pinegger A, Wriessnegger S, Müller-Putz G. Introduction of a Universal P300 Brain-Computer Interface Communication System. In: Biomedical Engineering. vol. 58; 2013.
37. Pinegger A, Faller J, Halder S, Wriessnegger SC, Müller-Putz GR. Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach. Journal of Neural Engineering. 2015; 12(1):014001. https://doi.org/10.1088/1741-2560/12/1/014001 PMID: 25587889
38. Breitwieser C, Daly I, Neuper C, Müller-Putz GR. Proposing a standardized protocol for raw biosignal transmission. IEEE Transactions on Biomedical Engineering. 2012; 59(3):852–859. https://doi.org/10.1109/TBME.2011.2174637 PMID: 22194230
39. Kaufmann T, Schulz SM, Grünzinger C, Kübler A. Flashing characters with famous faces improves ERP-based brain-computer interface performance. Journal of Neural Engineering. 2011; 8(5). https://doi.org/10.1088/1741-2560/8/5/056016 PMID: 21934188

40. Kleih S, Kübler A. Empathy, motivation, and P300 BCI performance. Frontiers in Human Neuroscience. 2013; 7:642. https://doi.org/10.3389/fnhum.2013.00642 PMID: 24146640

41. Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in psychology. 1988; 52:139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

42. Hart SG. Nasa-Task Load Index (NASA-TLX); 20 Years Later. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2006; 50(9):904–908. https://doi.org/10.1177/154193120605000909

43. Pasqualotto E, Matuz T, Federici S, Ruf CA, Bartl M, Olivetti Belardinelli M, et al. Usability and Workload of Access Technology for People With Severe Motor Impairment: A Comparison of Brain-Computer Interfacing and Eye Tracking. Neurorehabilitation and Neural Repair. 2015; 29(10):950–957. https://doi.org/10.1177/1545968315575611 PMID: 25753951

44. Laugwitz B, Held T, Schrepp M. Construction and Evaluation of a User Experience Questionnaire. In: Holzinger A, editor. HCI and Usability for Education and Work, Proceedings. vol. 5298 of Lecture Notes in Computer Science; 2008. p. 63–76.

45. Newe A, Becker L, Schenk A. Application and Evaluation of Interactive 3D PDF for Presenting and Sharing Planning Results for Liver Surgery in Clinical Routine. PLOS ONE. 2015; 9(12):1–28.

46. Bernardos AM, Sánchez JM, Portillo JI, Wang X, Besada JA, Casar JR. Design and deployment of a contactless hand-shape identification system for smart spaces. Journal of Ambient Intelligence and Humanized Computing. 2016; 7(3):357–370. https://doi.org/10.1007/s12652-016-0363-6

47. Perelmouter J, Birbaumer N. A binary spelling interface with random errors. IEEE Transactions on Rehabilitation Engineering. 2000; 8:227–232. https://doi.org/10.1109/86.847824 PMID: 10896195

48. Kübler A, Kotchoubey B, Kaiser J, Wolpaw JR, Birbaumer N. Brain-computer communication: unlocking the locked in. Psychological Bulletin. 2001; 127:358–375. https://doi.org/10.1037/0033-2909.127.3.358 PMID: 11393301

49. Nijboer F, Furdea A, Gunst I, Mellinger J, McFarland DJ, Birbaumer N, et al. An auditory brain-computer interface (BCI). Journal of Neuroscience Methods. 2008; 167(1):43–50. https://doi.org/10.1016/j.jneumeth.2007.02.009 PMID: 17399797

50. Furdea A, Halder S, Krusienski DJ, Bross D, Nijboer F, Birbaumer N, et al. An auditory oddball (P300) spelling system for brain-computer interfaces. Psychophysiology. 2009; 46:1–9. https://doi.org/10.1111/j.1469-8986.2008.00783.x

51. Kleih SC, Nijboer F, Halder S, Kübler A. Motivation modulates the P300 amplitude during brain-computer interface use. Clinical Neurophysiology. 2010; 121:1023–1031. https://doi.org/10.1016/j.clinph.2010.01.034 PMID: 20188627

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NO TRAINING, SAME PERFORMANCE!? – A GENERIC P300 CLASSIFIER APPROACH

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ABSTRACT: One of the main goals of modern brain-computer interfaces (BCIs) is that they should be simple and intuitive to use. Long-lasting training and learning periods are demotivating for the intended user. Therefore, the training should be reduced to a minimum. This particularly applies to P300-based BCIs, which are known as highly accurate and robust.

In this paper, we evaluated an approach that uses a generic classifier for P300 spelling instead of the usual personalized classifier, which users have to train before they can use the P300-based BCI. The generic classifier was calculated using the training data of 18 persons and evaluated with the data of 7 persons. Results were compared to the results achieved with personalized classifiers. We found that the generic classifier achieved comparable results regarding the effectiveness and efficiency. Therefore, our approach seems to be an appropriate, zero training alternative to personalized classifiers.

INTRODUCTION

The electroencephalogram (EEG) can be used to establish a noninvasive communication or control channel between the human brain and a computer, a so-called brain-computer interface (BCI) [1].

A very prominent BCI application is the P300 speller [2]. This type of BCI is mainly based on the positive component of an event-related potential (ERP) that appears approximately 300ms after a rare stimulus occurred among frequently occurring stimuli.

P300-based BCI provide high accuracies in combination with low illiteracy rates. Therefore, they are often used for communication and control systems. Various applications (e.g., speller [3], Brain Painting [4], music composer [5], and web browser [6]) are implemented.

Prior using such an application, training of a classifier is required. Normally, the training is performed by copy-spelling 5-10 predefined symbols and takes between 5 and 10 minutes. However, the question is, whether this training is really necessary.

Different approaches are proposed to avoid or reduce the training of the classifier. Kindermans et al. introduced a probabilistic zero training framework for ERPs [7]. They report high accuracies after a certain number of sequences. A sequence is defined as all rows and columns of the P300 matrix flashed once. However, the accuracy is still poor, when the number of sequences is limited to 3 or 4.

Lu et al. introduced a subject-independent model, learned offline from EEG of a pool of subjects, to capture common P300 characteristics [8]. They compared the learned model with a subject-specific classification model and a cross-subject model. Results indicate that this approach delivers high classification accuracies (on average approx. 84%) in combination with zero training. The number of sequences was defined with ten. No statement was given regarding the accuracies achieved with a lower number of sequences.

We asked whether the measured ERP during a P300 spelling task is stable enough to use a generic classifier. Consequently, the aim of this paper is to evaluate the power of a generic classifier (GC). The GC was calculated with the training data of eighteen P300 BCI users. The shrinkage regularized linear discriminant analysis (sLDA) was used for classification. Blankertz et al. suggested to use this method as a new standard for classifying ERPs [9]. The GC was evaluated with the data of seven users regarding the efficiency, in terms of highlighting sequences that are needed to reach certain accuracy. Effectiveness was investigated by recalculating the results of a prior study [10] with the GC: seven users had to spell four words and to control a multimedia player and a web browser with the P300 BCI. The accuracies of the online measurements and the offline simulations were compared.

MATERALS AND METHODS

Data acquisition:

The EEG data were acquired with a tap water-based biosignal amplifier (Mobita, TMSi, Oldenzaal, the Netherlands). Data were taken from six scalp electrodes (Fz, Cz, Pz, PO7, PO8, Oz) placed according to the extended international 10-20 system. A sampling rate of 250 Hz was used. The signal processing was performed in Matlab (MathWorks, Natick, USA). The EEG signal was filtered between 0.1 and 60 Hz with a 4^{th} order Butterworth band pass filter. These filter settings were chosen to compare the results of this evaluation to the results of a prior study [10].

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Generic training data generation:
Eighteen healthy volunteers (5 female, mean age: 29.39, SD:12.71 years) performed a standard P300 classifier training procedure: the participants were seated in a comfortable chair approximately 60 cm away from a computer screen showing the P300 stimulation matrix, see Fig. 1. The training was performed with fifteen highlighting flashes per row and column. Each highlighting had a duration of 50 ms and the time between flashes was set to 125 ms. The task of the participants was to copy-spell five characters out of a 6 x 6 matrix filled with letters and numbers. The characters were "H3P5FU", which were equally distributed over the matrix. Elements of the matrix were highlighted with famous faces [11].

Figure 1 – P300 stimulation matrix with letters and numbers. Rows and columns were highlighted with the face of Albert Einstein.

Test data generation:
Data from the study presented in [10] were used as test data. Seven participants (1 female, mean age 25.29, SD:2.75) performed a training, hereinafter called personal training, two copy-spelling tasks, a multimedia player, and a web browser control task with the same data acquisition system, which we used to gather the training data. None of the seven participants participated in the generic training data generation measurements and the data were acquired at least half a year later than the training data. In [10] the personal training setup and signal processing were the same as described for the generic training data generation, except the word ‘’BRAIN’’ was spelled.
The copy-spelling tasks consisted of spelling 4 words with 5 letters each. The participants were advised to spell the German words ‘’SONNE’’ (engl. ‘’sun’’), ‘’BLUME’’ (engl. ‘’flower‘‘), ‘’TRAUM‘‘ (engl. ‘’dream’’), and ‘’KRAFT’’ (engl. ‘’force’’). Between the second and the third word additional tasks, see below, were performed. The users were instructed not to correct wrongly spelled letters. The matrix was the same for training and copy-spelling.
The multimedia player task was to control a multimedia player to look at pictures. The minimal number of selections was 10 and the maximum number was 15. The participants were advised to correct misclassifications. The web browser task was to look for ‘’BCI’’ in Google and to select and read the Wikipedia webpage about BCI. The minimal number of selections was 9 and the maximum number was 18. The participants were advised to correct misclassifications. The P300 matrices for the multimedia player and the web browser task were different, cf. [6].

Generic classifier creation:
The generic training data of the eighteen volunteers were divided into epochs of approximately 800 ms (204 samples) after stimulus onset. The epochs were averaged per channel and row or column. Afterwards, the data were downsampled by the factor of 12 to reduce the number of features per channel. The data of each channel were concatenated to receive one feature vector per row and column. Thus, ten target feature vectors (2 vectors * 5 characters) and fifty non-target feature vectors (10 vectors * 5 characters) were available per volunteer.
In sum, 180 target feature vectors and 900 non-target feature vectors were used to train a generic sLDA classifier.

Generic classifier evaluation:
The GC was evaluated with the test data described before. We compared the accuracies calculated with the personalized classifier (PC), i.e., the classifier trained with data from the personal training, and the GC, respectively. PC accuracies for every flashing sequence were calculated per participant by a leave-one-letter-out cross validation of the personal training data. The same personal training data were classified with the GC. Accuracies per sequence and participant were calculated to evaluate the efficiency of the GC. The efficiency is high when a small number of sequences suffice to achieve high accuracy, i.e. above 70%. This is the proposed minimal level of sufficient accuracy for BCIs, cf. [12-15].
Additionally, we compared the online accuracies of the different tasks with simulated accuracies calculated with the GC to investigate the effectiveness of the GC.

RESULTS

The spatial GC weight distribution is shown in Fig. 2. To highlight only important weights, absolute values below 0.2 are not shown.
Fig. 3 shows the average accuracies and confidence intervals of the GC and the PC using the training data of [10]. The confidence intervals show no significant differences. Interestingly, the GC on average showed better classification accuracies after sequence 13: the accuracies of the GC stayed stable at 100% or 2.9% above the PC accuracies. The proposed minimal level of

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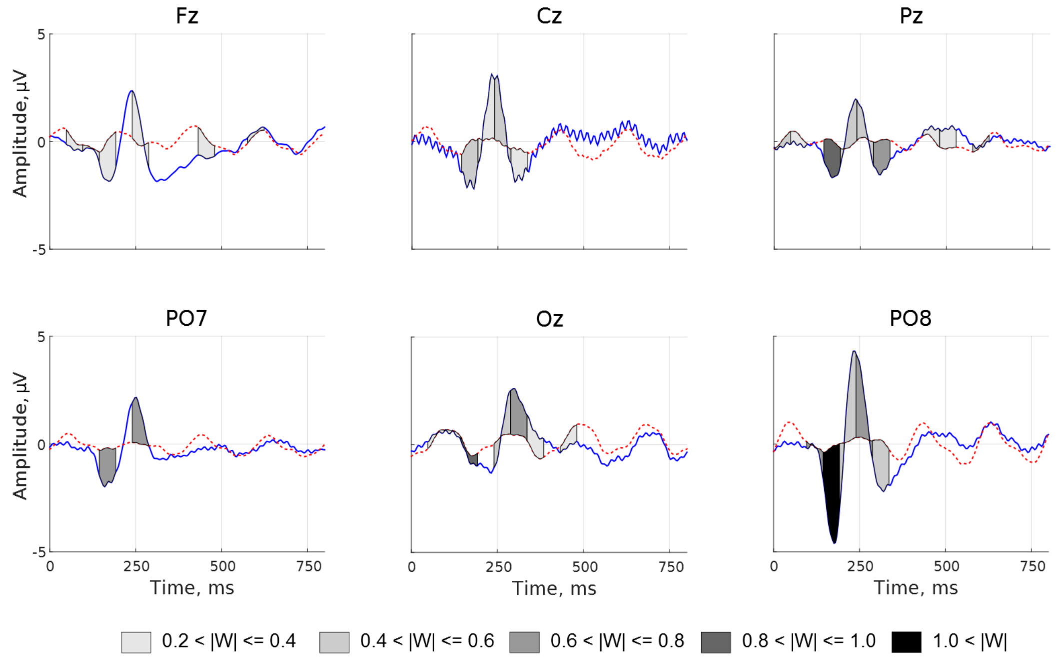

Figure 2 – The graphs show the averaged EEG data of 18 participants after targets stimulations (blue solid lines) and non-target stimulations (red dashed lines). Additionally, the weights of the GC are represented by different gray tone areas. Due to the downsampling of the signals, weights are shown as areas.

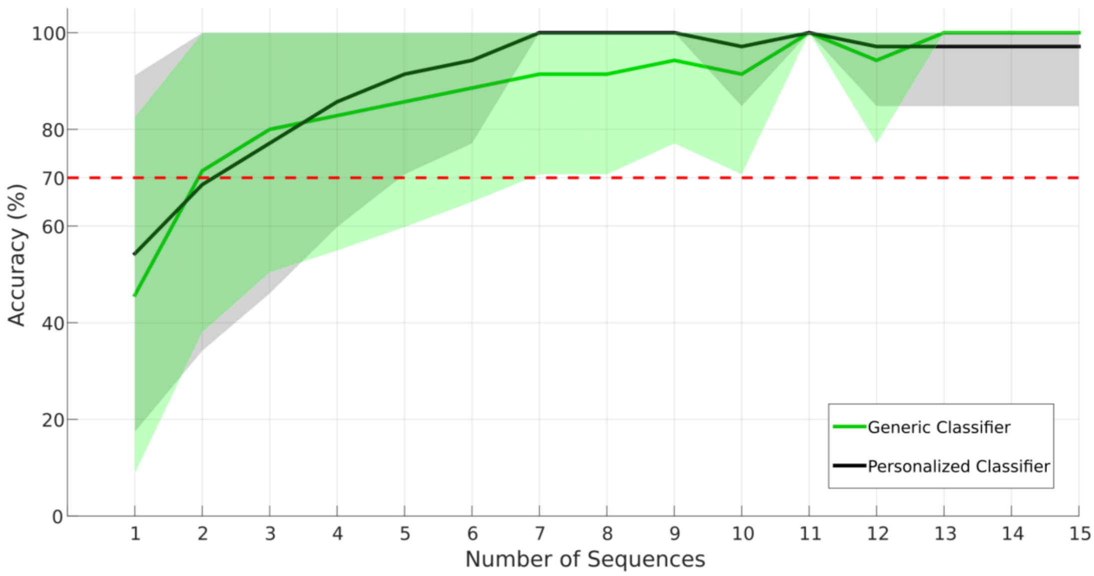

Figure 3 – Average (N=7) accuracies achieved with a certain number of sequences. The accuracies for the personal classifier were calculated with a leave-one-letter-out cross validation. Gray and green areas indicate the confidence intervals (CI) for proportions. The red dashed line indicates the minimal level of sufficient accuracy.

Table 1 – Offline (simulated) accuracies of the copy-spelling tasks using the generic classifier (GC) and the personalized classifier (PC). Different results are marked in bold. Sp1, Sp2…Spelling run 1, 2; MMP…Multimedia player; WB…Web browser.

Part.	Sequ.	GC accuracies in %						PC accuracies in %					
		Sp1	MMP	WB	Sp2	Av.	SEM	Sp1	MMP	WB	Sp2	Av.	SEM
1	8	100	100	81.8	**100**	**95.5**	10.4	100	100	**90.9**	90	95.2	10.7
2	8	100	90	**100**	80	92.5	13.2	100	**100**	90.9	**100**	**97.7**	7.5
3	9	100	100	100	100	100	0.0	100	100	100	100	100	0.0
4	10	80	91.7	88.9	80	83.9	18.4	**100**	91.7	**100**	**90**	**95.4**	10.4
5	11	70	**100**	66.7	**80**	**79.2**	20.3	**80**	64.3	**73.3**	70	71.9	22.5
6	13	100	100	**100**	100	**100**	0,0	90	100	90	100	95.0	10.9
7	14	100	100	100	**100**	**100**	0.0	100	100	100	90	97.5	7.8

sufficient accuracy (70%) was reached by the GC on average after 2 (71.4%) and by the PC after 3 (77.1%) sequences. However, the lower limits of the confidence intervals exceeded this level after 5 sequences (PC) and 7 sequences (GC), respectively, see Fig. 3.

The GC evaluation showed comparable results between the PC and GC, see Tab. 1. Differences are marked in bold. On average the GC outperformed the PC four times (range 0.3 – 7.3%) and the PC outperformed the GC two times (5.2% and 11.5%, respectively).
The average accuracies are far above the level of sufficient accuracy (70%).

DISCUSSION AND CONCLUSION

We showed that it is possible to use a P300-based BCI with zero training and high accuracies using a generic classifier. The results indicate that in terms of efficiency and effectiveness both classifiers are about equal. Moreover, the simulated GC spelling results partly outperformed the PC results.
The comparison of the accuracies for a defined number of sequences, see Fig. 3, shows that in case of a small number (between 1 and 4) no differences were detectable. For a medium number (between 5 and 10), the PC achieved better results than the GC. Finally for a large number (above 12), the GC outperformed the PC. However, the confidence intervals overlap most of the time and to make a more accurate statement more data must be taken into account.
During the spelling and control tasks the participants used a defined number of flashing sequences, see Tab. 1 second column. Comparing the averaged results indicates that participants (P2, P4) who used a medium number of sequences (between 8 and 10) would achieve better results with the PC. On the other hand, participants (P5, P6, and P7) who used a large number of sequences (above 10) would achieve higher accuracies with the GC.

One limitation of this comparison is that the presented online results were achieved with an SWLDA classifier and the simulated results were achieved with an sLDA classifier. Another limitation is that the GC was evaluated with data obtained by the same setup regarding the biosignal acquisition system, the signal processing etc. as the training data. It might be reasonably assumed that using a different biosignal acquisition system requires an adapted generic classifier.

Lu et al. also reported high P300 spelling accuracies using a generic classifier [8]. However, they performed two similar sessions with ten participants spelling the same 41 characters twice and performed a two-fold cross validation. No information was given regarding the time between the sessions and they did not evaluate the efficiency of their subject-independent model. We trained the GC with the data from different users and tasks than we evaluated it. In addition, we used different matrix sizes, cf. [6]. Finally, we used only six electrodes instead of eight in [8].

The next step would be to test the GC online with a representative number of people. In addition, it is conceivable to adapt the GC to a person by recalculating the GC with data of the actual user. Our results indicate that it should be sufficient to use a high number of sequences at the beginning to achieve almost 100% accuracy with the GC. This data can be used to recalculate the GC and adapt it to a person. Subsequently, the number of stimulation sequences can be reduced afterwards.

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Appendix B.

Author Contributions

A. Pinegger, S.C. Wriessnegger, and G.R. Müller-Putz. "Introduction of a Universal P300 Brain-Computer Interface Communication System." *Biomedical Engineering / Biomedizinische Technik.*, 58 (Suppl. 1), 2013. doi: 10.1515/bmt-2013-4445

Distribution of work: AP (80%); SW (10%); GM (10%)

S. Halder, A. Pinegger, I. Käthner, S.C. Wriessnegger, J. Faller, J. Antunes, G.R. Müller-Putz, and A. Kübler. "Brain-controlled applications using dynamic P300 speller matrices." *Artificial Intelligence in Medicine.*, 63 (1): pp. 7–17, 2014. doi: 10.1016/j.artmed.2014.12.001

Distribution of work: SH (35%); AP (35%); IK, SW, JF, JA, GM (20%); AK (10%)

A. Pinegger, L. Deckert, S. Halder, N. Barry, J. Faller, I. Käthner, Ch. Hintermüller, S.C. Wriessnegger, A. Kübler, and G.R. Müller-Putz. "Write, read and answer emails with a dry 'n' wireless brain-computer interface system." In *Proc. Engineering in Medicine and Biology Society (EMBC), 36th Annual International Conference of the IEEE.*, Aug. 2014, pp. 1286–1289. doi: 10.1109/EMBC.2014.6943833

Distribution of work: AP (40%); LD (30%); SH, NB, JF, IK, CH, SW, AK (20%); GM (10%)

A. Pinegger, J. Faller, S. Halder, S.C. Wriessnegger, and G.R. Müller-Putz. "Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach." *Journal of Neural Engineering.*, 12 (1). 2015. doi:

10.1088/1741-2560/12/1/014001

Distribution of work: AP (60%); JF, (20%); SH (5%); SW (5%); GM (10%)

A. Pinegger, L. Deckert, S. Halder, J. Faller, I. Käthner, S.C. Wriessnegger, A. Kübler, and G.R. Müller-Putz. "Automatic pause detection during P300 web browsing." In *Proc. 6th International Brain-Computer Interface Conference.*, Sept. 2014. doi: 10.3217/978-3-85125-378-8-76

Distribution of work: AP (60%); LD (20%); SH, JF, IK, SW, AK (10%); GM (10%)

A. Pinegger, S.C. Wriessnegger, J. Faller, and G.R. Müller-Putz. "Evaluation of different EEG acquisition systems concerning their suitability for building a brain-computer interface: Case Studies." *Frontiers in Neurosci.*, 10, 2016. doi: 10.3389/fnins.2016.00441

Distribution of work: AP (65%); JF (15%); SW (10%); GM (10%)

A. Pinegger, H. Hiebel, S. Wriessnegger, and G. Müller-Putz. "Composing only by thought: Novel application of the P300 brain-computer interface." *PLoS ONE*, Sept. 2017. doi: 10.1371/journal.pone.0181584

Distribution of work: AP (45%); HH (35%); SW (10%); GM (10%)

A. Pinegger and G.R. Müller-Putz. "No training, same performance!? - A generic P300 classifier approach." In *Proc. of the 7th International BCI Conference.*, Sept. 2017. doi: 10.3217/978-3-85125-533-1-77

Distribution of work: AP (90%); GM (10%)