



Karina Statthaler, BSc.

Opening a Parachute - Usability of a Brain-Computer Interface in a Stressful Situation

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Supervisor

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

Institute of Neural Engineering

AFFIDAVIT

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Abstract

A Brain-Computer Interface (BCI) is a system, that enables the communication between severely impaired users and their environment via motor imagery (MI), e.g., hand and foot movement or P300 for example. BCIs are closed loop systems and thus the users can learn how to control the device with the help of the feedback they get. Present-day studies with BCIs are normally performed in a laboratory environment. There, the participants sit in a quiet measurement box to ensure that they can focus completely on the task. In real-life BCI applications are used in noisy environments, for instance at home while other family members are around. In the future BCIs may for example be used to control prosthesis or play computer games and thus it is necessary that users are able to control a BCI when they are stressed. The aim of this work was to investigate whether people are able to reliably control a BCI outside of a laboratory environment while under acute stress.

For this thesis, the idea was to open a parachute using a BCI. For this a post-movement beta event related synchronization was used which is found in nearly every person and appears approximately one second after a movement or the imagination of such is stopped and the signal to noise ratio is very high compared to other brain signals. A parachute fell down within five seconds and thus the participants had just one chance to do the imagination and open the parachute. To increase the motivation and the level of stress even further there was a competition within the participants who is able to open the parachute most often. To measure the stress level of the volunteers in this study everyone had to answer a questionnaire and the ECG was recorded. The ECG was later used to calculate the heart rate and the heart rate variability. Results show that the participants were able to open the parachute while feeling stressed and thus the hypothesis, that users are able to control a BCI reliably in an acute stress situation, can be accepted.

In the future, the results of the study can be used to investigate if it is also possible to control a BCI with more than one class under stress or if BCIs can also be controlled in other stressful situations.

Kurzfassung

Ein Brain-Computer Interface (BCI) ermöglicht es Personen, die in ihrer Kommunikation stark eingeschränkt sind, über Bewegungsvorstellungen, zum Beispiel der Vorstellung von Hand- und Fußbewegungen, mit ihrer Umgebung zu interagieren. Durch Feedback aufgrund des geschlossenen Lernkreislaufes können Nutzer lernen, ein solches System zu kontrollieren. Heutige Studien die ein BCI verwenden, werden in wissenschaftlichen Laborumgebungen durchgeführt. Während eines Experiments sitzen die Studienteilnehmer in einer ruhigen Messbox, um sicherzustellen, dass sie sich bestmöglich auf die Durchführung der Aufgaben konzentrieren können. Im Alltag werden solche Systeme aber in lauterer Umgebung, zum Beispiel zuhause während weitere Familienmitglieder anwesend sind, verwendet. In Zukunft könnten BCIs dazu verwendet werden um Prothesen zu kontrollieren oder Computerspiele zu steuern. Dafür ist es wichtig, ein solches System auch unter Stress verlässlich bedienen zu können. Das Ziel dieser Arbeit war es, zu zeigen, dass Brain-Computer-Interfaces auch außerhalb von Laborumgebungen in stressigen Situationen verlässlich bedient werden können.

Die Idee dieser Studie war es, einen Fallschirm mit Hilfe eines BCIs zu öffnen. Zum Öffnen des Fallschirms wurde eine post-movement beta event related synchronization verwendet. Diese tritt bei den meisten Menschen circa eine Sekunde nach einer Bewegung, beziehungsweise deren Vorstellung, auf. Außerdem weist dieses Gehirnsignal, im Gegensatz zu anderen, ein sehr gutes Signal-Rausch-Verhältnis auf. Die Fallzeit des Fallschirms betrug fünf Sekunden, dadurch hatten die Versuchsteilnehmer nur einen Versuch die Bewegungsvorstellung durchzuführen um damit den Fallschirm zu öffnen. Um die Motivation und damit das Stresslevel der Freiwilligen weiter zu erhöhen, wurde ein Wettkampf zwischen den Teilnehmern veranstaltet. Um festzustellen ob die Studienteilnehmer gestresst waren musste jeder von ihnen einen Fragebogen ausfüllen und das EKG wurde aufgezeichnet. Mithilfe des EKGs wurde sowohl die Pulsfrequenz berechnet als auch die Herzratenvariabilität analysiert.

Die Ergebnisse zeigen, dass die Teilnehmer in der Lage waren das BCI zu kontrollieren obwohl sie unter stress standen.

In Zukunft können die Ergebnisse dieser Studie dazu verwendet werden, um herauszufinden, ob auch ein BCI mit mehreren Klassen unter Stress verwendet werden kann, beziehungsweise ob es auch in anderen stressigen Situationen eingesetzt werden kann.

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1

Introduction

A Brain-Computer Interface (BCI) is a device that enables communication between a human brain and an external device, e.g., a computer, without using the normal muscular pathways or peripheral nerves. The communication between the brain and the neuromuscular pathways can be disabled by different diseases but also by traumas or injuries. If no motor functions are left, a BCI can be used to provide new communication channels to enable people to interact with their environment again [1, 2]. The first BCI was implemented in 1973 by Vidal J. [1] and since then numerous different approaches about how to measure and classify brain signals were developed. There are two ways to record the signals of the brain: invasive and non-invasive methods. To use invasive BCIs patients need to undergo surgery to implant the electrodes in the cortex. The electrodes can either be placed in the cortex [3] or an array of electrodes is placed on the surface of the cortex to record the electrocorticogram (ECoG). There is a number of methods to record brain signals in a non invasive way; nonetheless, the electroencephalogram (EEG) is the most common used for BCIs.

To measure EEG, electrodes are placed on the scalp and cortical potentials of the brain are recorded. Activated brain cells generate action potentials which lead to postsynaptic potentials (PSP). The excitatory and inhibitory postsynaptic potentials of a group of brain cells are added spatially and temporally and the resulting signal can be measured using surface electrodes [3, 4]. There are different advantages using EEG for BCIs: it is a non-invasive method, which means that users do not need complicated surgeries as all electrodes are placed on the scalp and thus the setup can be done within minutes. The temporal resolution of the EEG is in range of milliseconds and it can be used in different environments since the equipment is mobile and also cheap compared to other methods. The main disadvantages of non-invasive EEG are the poor signal-to-noise ratio as the measured signals are in range of μV and the poor spatial resolution since one electrode records the signals of millions of neurons due to volume conduction [5].

To control a BCI, different electrophysiological signals can be used: visual evoked potentials (VEPs), slow cortical potentials, P300 evoked potentials, mu and beta rhythms and cortical neuronal action potentials [6]. To control a BCI using mu and beta rhythms, which are used for the Graz BCI system, it is necessary that users are able to modulate their brain signals voluntarily. One possibility to cause oscillatory changes and thus modulate brain signals is the imagery of simple movements, e.g., right/left hand or feet movement. Due to the motor imageries (MI) the power in certain frequency bands, especially in the α (8 - 12Hz) and in β -band (13 - 30Hz) either increases or decreases. During MI the activity of the neural networks is desynchronized which leads to a decrease of power in a certain frequency band whereas in rest conditions the activity of the neurons is synchronized which leads to an increase of power in certain frequency bands. The former phenomenon is called event-related desynchronization (ERD) and the latter is called event-related synchronization (ERS). Depending on the type of imagery different regions in the brain are activated and thus this signals can be used to control BCIs. After stopping a movement or the imagination of a movement a post-movement beta ERS (PMBERS) appears. This signal has a relatively good signal-to-noise ratio compared to other brain signals. It appears in the β -band approximately one second after the movement is stopped. The so called PMBERS is found in nearly every person and appears after finger, hand, arm and foot movement but the

frequency bands differ from person to person [7].

ERD/S is time-locked but not phase-locked to an event which means that it cannot be extracted by linear methods. To compute ERD/S, all trials are band-pass filtered in the respective frequency range. To retrieve the signal power the amplitude samples are squared. The averaged reference signal power before the event is subtracted from the result and divided to obtain the relative changes in brain activity [7].

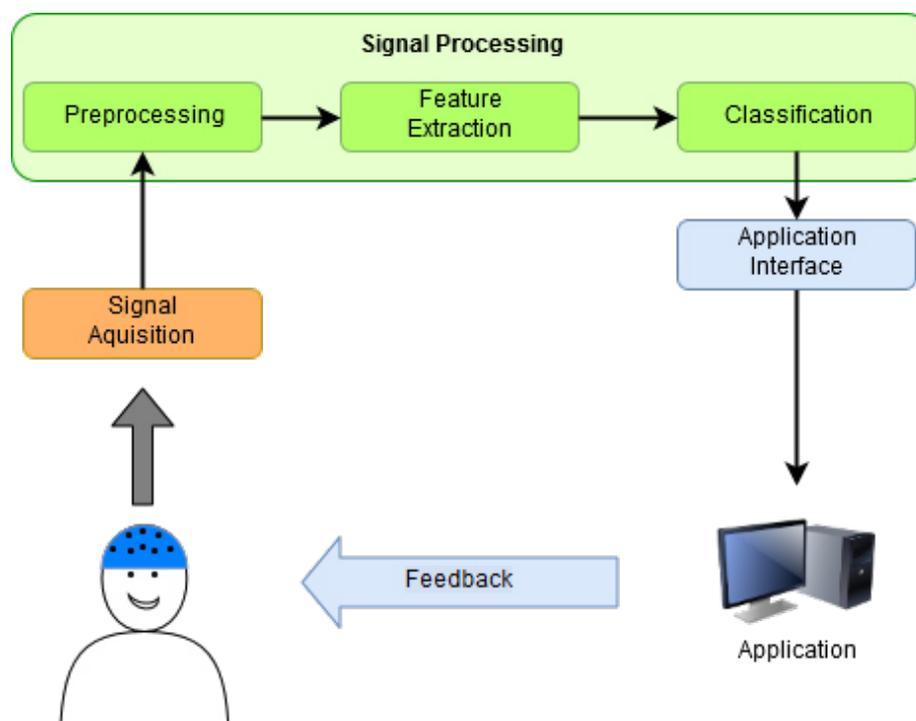


Figure 1.1: Overview of a standard BCI model.

To control an online BCI an offline training phase to calibrate the system is necessary in most cases. The online system consists of different parts. Normally, it is a closed-loop system which provides feedback to the users so that they know if a mental command was classified correctly or not, which can be seen in Figure 1.1. The first part consists of recording the EEG. Therefore, electrodes, which are placed on the scalp, are used. Before the signal gets digitized it needs to be amplified, which is done by the appropriate hardware. The second part contains the signal processing chain. First, in the preprocessing block, artifacts and noise are removed and the signal is filtered to prepare it for the feature extraction block. To differentiate mental tasks, it is necessary to find features which maximize the differences between them. A common approach is to use the power information of the brain signals in the frequency ranges which are of interest. For a classifier training, a lot of training data is necessary to get good classification results. Since a user cannot reproduce the same mental tasks several hundred times, there are different classifiers, e.g., shrinkage LDA, random forest or Riemannian classifiers; these are able to classify data after 20-100 trials per class. The classifier also needs to be trained for every individual subject since brain patterns differ from person to person. The output of the classifier is used as a control signal to operate with the application and thus feedback is provided to the user [6, 8].

Stress describes the physical and psychic reaction of living beings on external stressors, e.g., threat or challenges, to cope with special demands and the physical and mental loading result-

ing from them. The autonomic nervous system (ANS) is one of the major systems reacting to stress, whereby the sympathetic part is activated while the parasympathetic part is suppressed. Stress has an influence on memory, immune and cognitive functions and chronic stress can cause certain diseases [9, 10]. There are many different types of stress such as eustress and distress, whereby the latter can be further divided into acute and chronic stress. Not all types of stress have a negative impact on people. Eustress for example helps to motivate people and thus achieve better performances, e.g., in their jobs or during challenges [11]. Stress can be monitored using different methods, e.g., measure the level of cortisol (in blood, urine or saliva), the heart rate variability (HRV) and the skin conductance. HRV is a feasible and reliable method and another advantage of it is that it is non-invasive and no special equipment is required. HRV is the ability of human beings to change the frequency of the heart beat according to physical or psychical loads. During physical training or mental stress the heart rate increases and afterwards it decreases. Often, ECG is used to measure HRV since it provides a clear waveform and heartbeats can easily be detected. The research of heart rate variability moved into three main directions. First, understanding of the physiological mechanisms which regulate the heart rhythms, second, understanding the relationships between HRV and medical conditions and third, understanding the relationship between physiological processes and HRV [12, 13]. The heart rhythm is influenced by the sympathetic and parasympathetic parts of the autonomic nervous (ANS) system. Both parts of the ANS influence the rate of depolarization and discharge the cardiac sinoatrial node. The parasympathetic terminals release acetylcholine which slows down the heart rate whereas the sympathetic terminals release norepinephrine which raises the heart rate. Besides those two neurotransmitters, there are also different neuropeptides which influence the heart rate variability [14]. In 1996, the European Society of Cardiology and the North American Society of Pacing and Electrophysiology constituted a task force to standardize the nomenclature, develop definitions of terms and specify standard methods of measurement among other important aspects which are important in clinical use [15]. There are time domain methods, frequency domain methods, rhythm pattern based methods and non-linear methods to evaluate the variations in heart rate variability. In this work, time domain as well as frequency domain methods were used. It can also be recorded in long-term (24h), short-term (5min) and ultra-short term (≤ 5 min) recordings. To investigate ultra short time recordings methods in the frequency domain should be preferred. Castaldo et al. presented a systematic review which shows the correlation between acute stress and HRV measurements to reliably detect stress in seven different parameters [16].

1.1 Motivation and Aim

Present-day standard BCI experiments are usually tested in a laboratory environment. Participants sit in a comfortable chair in front of a monitor in an shielded cabin. They are alone in the cabin and there is no distraction so they can focus on the task. During the experiments the participants are relaxed and they have enough time for their tasks. Even if they participate the first time and are nervous because of that, after some runs they get used to the situation, relax and do not feel stressed anymore.

The idea of this work was to design an experiment in which users need to focus on a mental task even though they have to perform it in an acute stress situation. On the one hand they are stressed because the experiment takes place outside the laboratory environment in the foyer of the Biomedical Engineering Building at the Graz University of Technology. Due to this unusual location, people were walking by in irregular intervals and some were asking what we were doing and if they were allowed to watch. On the other hand, there was time pressure because the participants had to open a parachute falling from the ceiling within five seconds. An additional

factor was a competition between the participants to see who is able to open the parachute the most and the winner was promised to receive a bottle of wine.

The hypothesis of this study was to show that users are able to control a BCI reliably even though they are performing in an acute stress situation.

Chapter 2 provides an overview of the concept and the methods which were used are described in more detail. Chapter 3 shows the results of this work and in Chapter 4 the results are discussed in various aspects. The conclusion of this thesis can be found in Chapter 5. The questionnaires which were filled out by each of the participants can be found in the appendix.

2

Methods

2.1 Overview

The goal of this work was to find out if it is possible to control a BCI under acute stress. The idea was to plan an experiment in which participants have only one chance to open a parachute. In order to do so, a mental task had to be found that can be imagined just once while the parachute falls so that there is just one possibility to open it. Mental tasks normally used in BCI experiments are imagined for around five seconds which makes them unusable for this study. Hence, the idea was to use a PMBERS to open the parachute. A PMBERS is a strong activity in the beta band which appears 1 to 2 seconds the imagination of a movement stops. Since it is more prominent after moving the feet, the motor imagery of one brisk feet movement was chosen to be the mental task for this study. Since it is not possible to let a parachute fall down in a laboratory, the experiment was planned to be outside. Therefore, an experimental setup was necessary that allows the parachute to fall down from the ceiling. To ensure a straight fall, a steel cable was used as a lead. For the experiment an umbrella was used instead of a parachute. This turned out to be very handy since the steel cable could be put through the handle of it and thus ensure that it falls down straight.

To be sure that the experiment worked as it was planned a pilot experiment was planned at the 7th Graz BCI Conference.

A schematic overview of the online BCI can be seen in Figure 2.1. The 16 EEG channels were first filtered using a combination of filter bank and common spatial pattern; second, the logarithmic bandpower was calculated; third, a random forest was used to classify the data and then feedback was shown to the users.

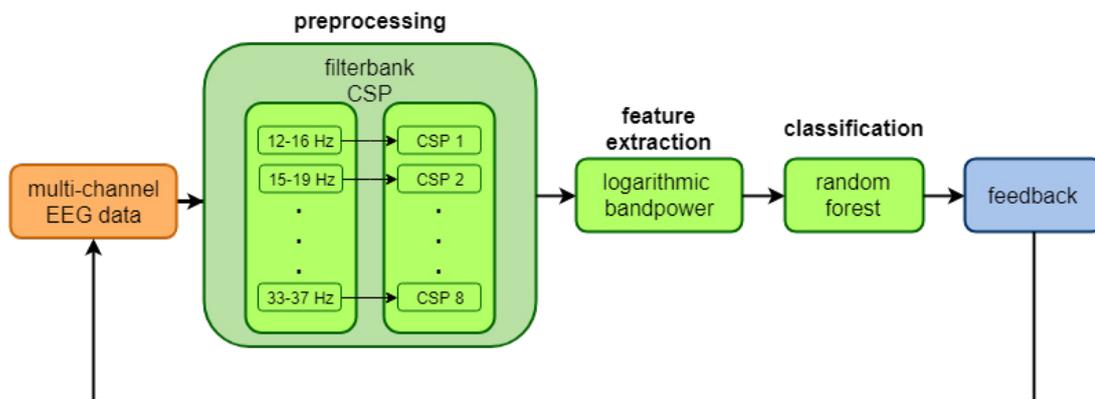


Figure 2.1: Schematic overview of the online system which was used in this study.

2.2 Experimental Setup and Paradigm

This experiment was divided into three parts. In the first one, the classifier was trained, in the second one the participants were able to practice the opening of the parachute in an online simulation and in the third part they tried to open the real parachute. Before the actual experiment a rest recording was performed, to compare the ECG of the different parts to a rest condition.

In the first part, 60 trials of the motor imagery of a brisk foot movement of each of the subjects were recorded. It was divided into 3 runs consisting of 20 trials each and took approximately 10 minutes. Thereafter, ERD/S maps were plotted not only to check if the participants showed a PMBERS but also to find the best time point to train the classifier [7].

In the second part, the participants saw a grey rectangle, which simulated the parachute, falling down the screen of the monitor. With the same motor imagery as in the first part, they were able to color it green which indicated that they were able to open the parachute.

In the third part, a real parachute, i.e., an umbrella, fell down from the 5th floor and by imagining the same motor task as before the participants had to open it. To realize the third part it was necessary to find a way to let the parachute fall down without endangering any people. Therefore, an umbrella was used as a parachute since the inner part of the tube is hollow when the top and the handle are removed. This way it could be fixed on a steel cable which is fixated on both ends so that the umbrella cannot change direction when opened. One end of the steel cable was fixated on a wooden brick, which was attached to the handrail of the stairs at the 5th floor (Figure 2.2 left part). The other end was fixated with the help of a box filled with stones on the bottom of the ground floor, which can be seen on the right part of Figure 2.2.



Figure 2.2: (left) Wooden brick which is attached to the handrail at the 5th floor. The steel cable is fixated on the right part of it. (right) steel cable fixated with the help of a box filled with stones and the umbrella which was used as parachute.

To automatically open the umbrella a servo motor was used. Since it is not possible to press the button which opens the umbrella with a servo motor, the spring that keeps the umbrella closed was removed. Thereby, the umbrella opened automatically. To keep the umbrella closed in the beginning, a string was wrapped around the stretchers of it and attached to the servo motor.

The servo motor was screwed to the shaft to keep the umbrella closed. To interact with the servo, a Raspberry Pi Zero W was used for two reasons. First, it is very small and can connect to the internet via WiFi and second, there is a Matlab toolbox which means that commands can easily be sent to the Raspberry Pi. As the space on the umbrella is very limited and the Raspberry Pi also needs a power supply, a soft toy was bent to the umbrella. The Raspberry Pi and the power bank were placed in the head of the stuffed toy rabbit. The modified umbrella with the attached rabbit can be seen on the left side of Figure 2.3. To open the umbrella, the servo motor turned 180° to release the string and afterwards turned back into its initial position. The umbrella was not closed completely because it would fall down too fast and the users would not have a chance to open it. Thus, it was opened a bit so that the duration of the fall was 5 seconds.

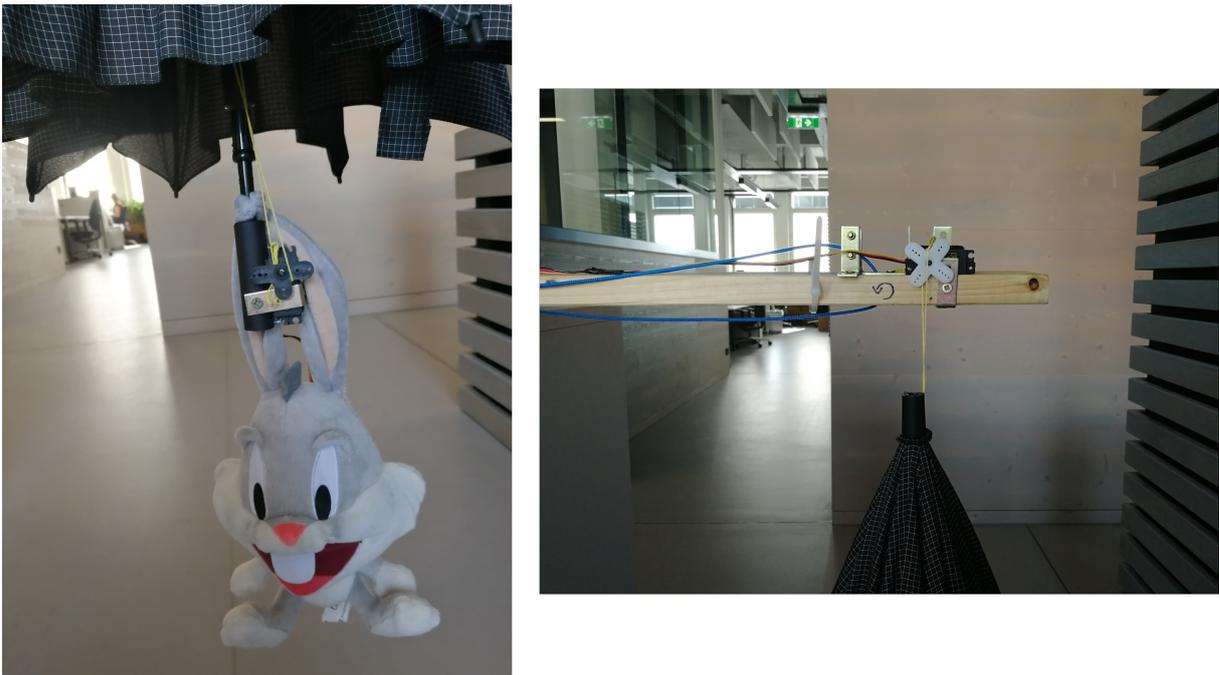


Figure 2.3: The left side shows the modified umbrella with the attached stuffed toy rabbit. On the right side the servo which releases the umbrella can be seen.

To release the umbrella on top of the rope, a second servo motor was used. It was screwed to the right end of the wooden brick, which was mounted on the hand rail. The brick was fixated using two screw clamps. To be sure that it cannot fall down, the brick was additionally fixated with a steel rope. The rope was lead through a hole in the wood and around the handrail and bound together using a rope clamp. To interact with this servo, a second Raspberry Pi Zero W was used. The Raspberry Pi was fixated on the wooden brick using cable ties. When the command to release the umbrella was sent, the servo turned 180° for the umbrella to fall down and afterwards it turned back into the initial position. This setup can be seen on the right side of Figure 2.3.

At the end of each trial, the umbrella needed to be lifted up again. Therefore, a second person assisted during the experiment. A long rope, which was mounted on the brick, was let down after each trial and the umbrella was attached to it via a carabine. The rope had a diameter of 3mm and can be seen on the right side of Figure 2.3. Since the umbrella was very lightweight, it could be lifted up by hand. At the top, the umbrella needed to be hooked to the servo motor again and after that the next trial could start.

2.2.1 Paradigm and Feedback

To test this study, three different paradigms were used. The first one to train the classifier, the second one to simulate the fall of the parachute on the PC and thus train the participants for the third part, which was the actual falling of the parachute.

First Paradigm

As a first paradigm, the standard Graz-BCI paradigm [17] was used. An overview of it can be seen in Figure 2.4. It contained three runs, each run contained 20 trials which made 60 trials in total and each trial took 10s. At second 0, a green cross appeared on the black screen and the participants were instructed to focus on the middle of it. At second 2, there was a beep to get the user's attention and at second 3, a visual cue in form of a foot appeared. The volunteers were instructed to imagine just one brisk foot movement (plantar flexion and extension of their feet) as soon as they saw the foot and stay focused until the green cross disappeared at second 8. After that, there was a short pause of 2 to 3 seconds and then the next trial started. To reduce artifacts to a minimum the participants were instructed to avoid blinking, eye movements and swallowing during the trials.

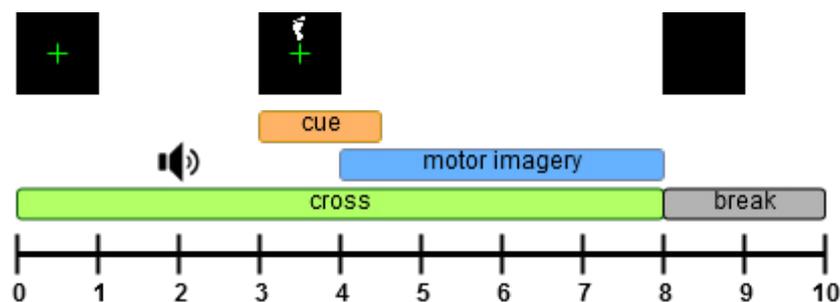


Figure 2.4: Standard Graz BCI paradigm.

Second Paradigm

The second paradigm was used to simulate the falling of the parachute to give the participants an opportunity to practice and also compare if the participants are more stressed within the real fall compared to the simulation. It consisted of 2 runs of 20 trials each and each trial took 10s. Figure 2.5. shows what the paradigm looked like. At the beginning of the trial, there was a small gray rectangle on top of the screen, similar to the cross in the first paradigm. After 2 to 3 seconds, the rectangle started to fall down and the participants were instructed to imagine the same movement as in the first part as soon as they recognize that the rectangles falls. During this part of the experiment, feedback was given to the participants. When the classifier was able to detect a PMBERS, the rectangle became green to show the participant that they would have been able to open the parachute. This can be seen in the upper part of the right side of Figure 2.5. If the classifier was not able to detect the PMBERS, the rectangle stayed gray. The participants were instructed to stay focused until the rectangle reached the ground and to not repeat the imagination of the movement, even if the PMBERS was not detected. To avoid eye

movements during the trial, the participants were instructed to focus on the logo centered at the bottom of the screen instead of following the rectangle with their eyes.

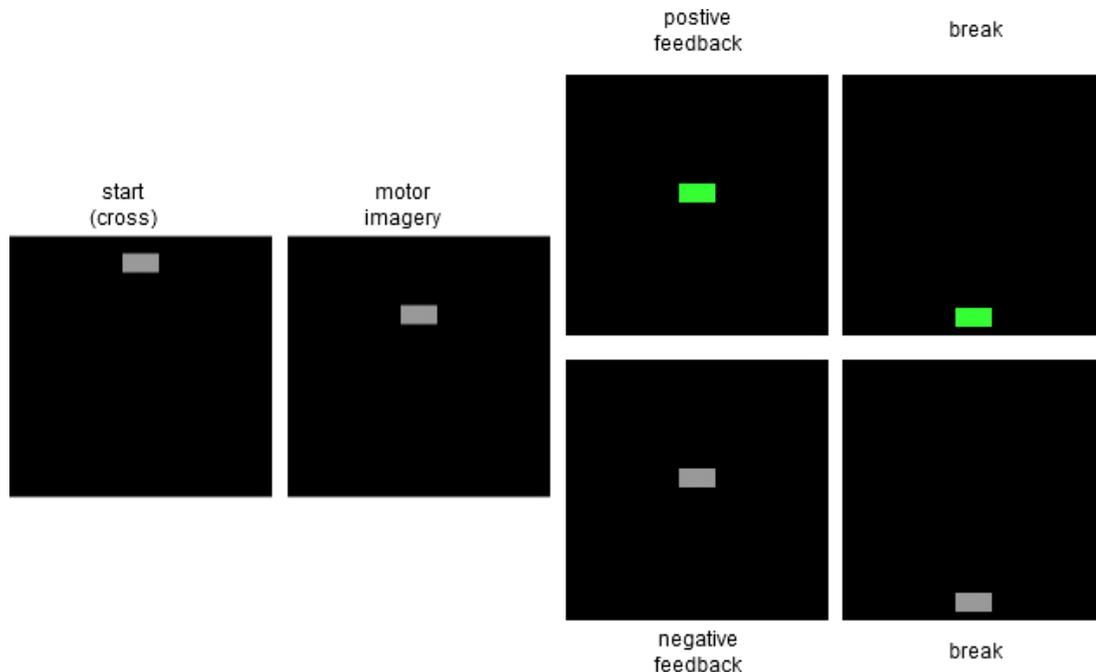


Figure 2.5: Paradigm with feedback for the second part of the experiment.

Third Paradigm

In the third part of the experiment, the participants had to open the falling parachute. Thus, the screen was black during each trial. As the breaks between two trials were around 1 minute because the umbrella had to be lifted up and hooked on the servo motor again each time, the black screen was shown between 11 and 13 seconds before the umbrella fall to give the participants the possibility to focus and concentrate again after the long break. The volunteers were instructed to imagine the same movement as before as soon as they heard that the parachute was released.

2.2.2 Mental Task

There are two reasons why a PMBERS was chosen as a mental task for this experiment. First, it is very prominent after motor imagery, i.e., motor imagery of feet movement. Second, it appears approximately one second after the motor imagery which means that a participant had just one chance to induce a PMBERS and open the parachute. It was shown before that a PMBERS can be used to implement a brain switch [18][19] and that this brain switch also works in combination with a neuroprosthesis [20].

2.2.3 Participants

Ten healthy volunteers (five females, five males) participated in this study. They were aged between 24 to 28 and were informed about the aim of the study. Nine of them were non-naive users.

2.2.4 EEG and ECG Recording

All experiments took place in the foyer of the Biomedical Engineering Building (Stremayrgasse 16) at Graz University of Technology. The participants sat on a chair in front of a laptop, approximately 1.5 meter distance. They were able to see the parachute reaching the ground but they could not see where it was placed on the 5th floor. The first and second paradigm were presented on the screen of the laptop and a black screen was shown as a third paradigm. The experiments were performed on weekends so that the normal University processes were not disturbed. The experimental setup on the ground floor can be seen on Figure 2.6.



Figure 2.6: Experimental setup at the ground floor of the Biomedical Engineering Building at the Graz University of Technology.

EEG was recorded using 16 active electrodes placed in an equidistant manner over the motor cortex using one biosignal amplifier (g.USBamp, g.GAMMAsys, g.tec OG, Austria). The positions of the electrodes were: FCzb, FC3a, FCza, FC4a, C5a, C3, C1b, C1a, Cz, C2a, C2b, C4,

C6a, CP3a, CPza and CP4a. The ground electrode was placed at AFzb and the reference clip at the ear. Data was sampled with 512Hz and filtered using a filter-bank. The electrode setup can be seen on the left side of Figure 2.7. To record the ECG one Kendall™ ECG electrode was placed at the left anterior axillary line at the 5th intercostal space. The position of this electrode is represented as a red circle on the right side of Figure 2.7. To measure ECG according to Goldberger, the ground and reference electrode of the EEG setup were used. Therefore, a second g.USBamp which was connected to the first one was used to record the ECG data.

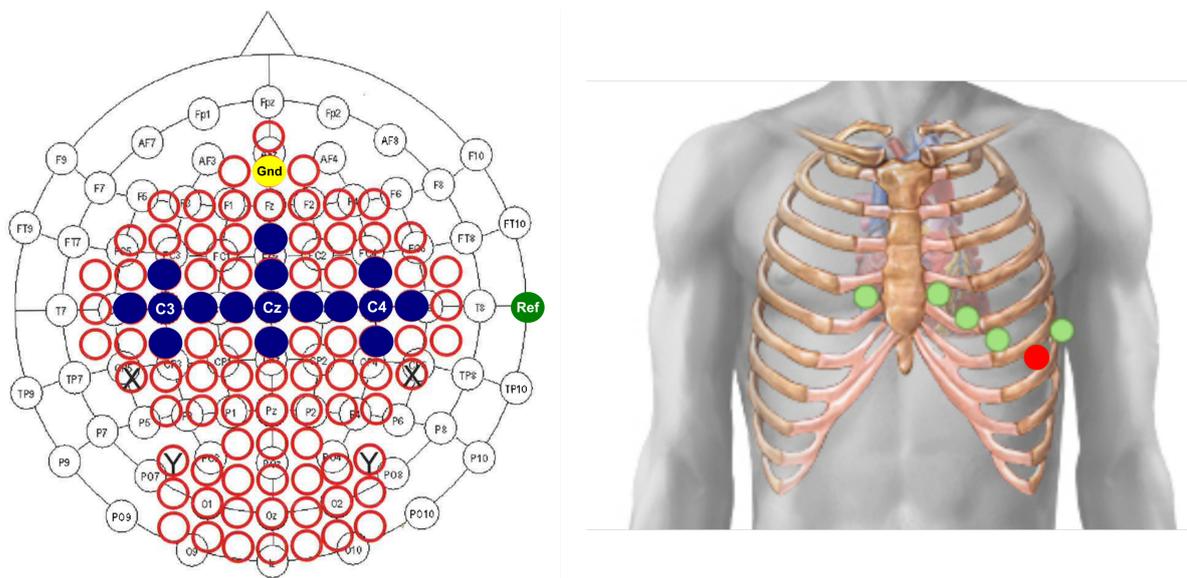


Figure 2.7: (left) Electrode positions of the experiment. The blue circles show the electrode positions, the yellow circle the position of the ground electrode and the green circle represents the reference electrode which was placed on the right ear lobe. (right) The red circle represents the position of the ECG electrode.

2.2.5 Pilot Experiment

To be sure that the experimental setup worked as planned, a pilot study was executed. The 7th Graz BCI conference was used as an opportunity to on the one hand show the conference participants that it is possible to open a parachute using a BCI and on the other hand to see if a participant is able to concentrate on a mental task even though several people are watching. The experimental setup was done as described above. The participant sat on the ground floor of the Biomedical Engineering Building in front of a laptop and was able to see the landing of the parachute but not the start of the fall. The paradigms were slightly different in the pilot study. To train the classifier, the same paradigm as described in chapter 2.6.5.1 was used. Therefore, 60 trials of the imagination of a brisk foot movement were recorded and thereafter ERD/S maps were calculated to find the best time point to train the classifier. In the second paradigm, a countdown was shown so that the participant knew when the rectangle starts to fall. After simulating the fall 40 times, the demonstration of the real fall started. In the third paradigm again a countdown was displayed so that the user knew when the parachute falls down. Since the time at the conference was limited, the last part of the experiment was just performed five times. In the pilot experiment, ECG was not recorded because it was just performed to see if the setup works.

2.3 System Setup

2.3.1 Software and Toolboxes

The following software and toolboxes were used in this work:

- Matlab 2016b (Mathworks Inc., Natick, USA) for implementing the system and data analysis
- TCP/UDP/IP Toolbox 2.0.6 [21]
- TOBI SignalServer + Client [22]
- Random Forest mex implementation [23]
- GRAZ-BCI libraries [24]
- BioSig toolbox [24, 25]
- MATLAB Support Package for Raspberry Pi Hardware [26]

2.3.2 Online System

The online system for this work was implemented in Matlab and Simulink and the TOBI SignalServer was used to feed raw EEG data recorded from 16 electrode channels into the system. The EEG data was filtered by 8 parallel bandpass filters and each output was multiplied by a CSP filter. Thereafter, the logarithmic bandpower features were calculated. Afterwards, the signal was fed into the random forest classifier. Since the EEG signal was recorded with 512Hz, there were 512 class labels predicted each second which is computationally expensive. To avoid that the system gets too slow, the signal is downsampled to 16Hz before being classified by the random forest. Finally, feedback is given according to the classifier output. After each run, a mat file including the processed EEG, the raw ECG, the true classlabels and the predicted classlabels were saved to analyse the data after the experiment. The Simulink model of the online system can be seen in Figure 2.8.

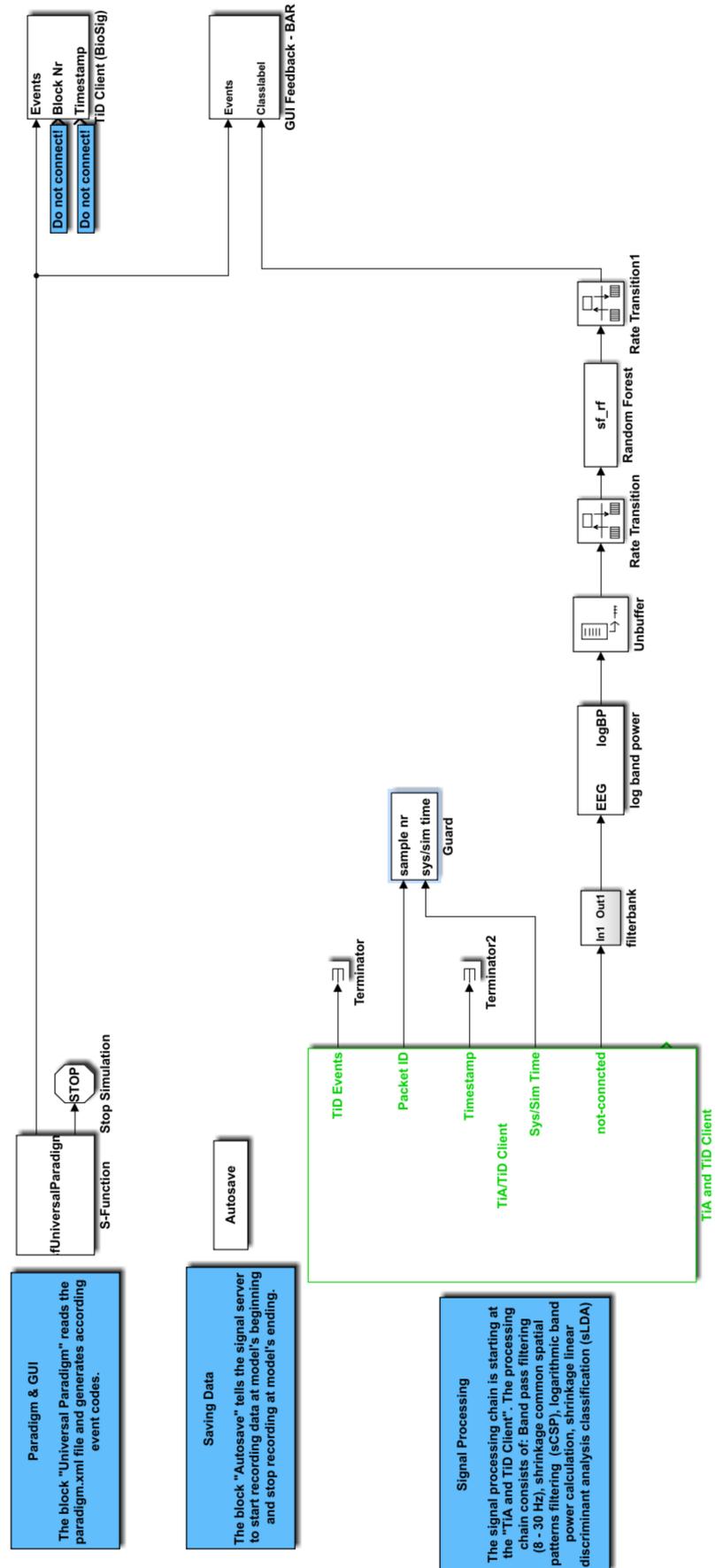


Figure 2.8: Simulink model of the online system which was used in this work.

The online system was also used in the third part of the experiment to send a command to the two Raspberry Pi Zero W which were needed to control the two servo motors. The first released the umbrella so it could fall down automatically and the second one opened the parachute. When a command with Matlab was sent via WiFi to one of the Raspberry Pis a servo motor started to rotate and the umbrella was either released or opened.

2.4 Preprocessing and Feature Extraction

2.4.1 Common Spatial Pattern

Since the spatial resolution of EEG signals is very poor because the scalp and the skull cause spatial smearing of the cortical signals it is necessary to preprocess the signal to improve the classification results. By decompensation of raw EEG signals into spatial patterns using a method called common spatial pattern (CSP) the separability of two different classes can be maximized [16,17]. CSP was first used in 1990 to classify normal vs. abnormal EEG [16–18] and was then applied to classify movement related EEG.

In brief, multi-channel EEG data is projected into a low-dimensional spatial subspace using a projection matrix. The rows of this matrix consists of the weights for each of the channels. For both classes the covariance matrices are diagonalized simultaneously [19].

More detailed, the matrices containing preprocessed EEG data from two different conditions, e.g., feet and rest, are called X_F and X_R . Both matrices have dimensions $N \times T$, where N is the number of channels and T is the number of samples per channel. With this, the normalized spatial covariance matrices of the EEG can be calculated as:

$$R_F = \frac{(X_F X_F^T)}{\text{trace}(X_F X_F^T)} \text{ and } R_R = \frac{(X_R X_R^T)}{\text{trace}(X_R X_R^T)} \quad (2.1)$$

By averaging the normalized covariance $\overline{R_F}$ and $\overline{R_R}$ over all trials of each group, the composite spatial covariance can be factorized as follows:

$$R = \overline{R_F} + \overline{R_R} = U_0 \cdot \Sigma \cdot U_0^T \quad (2.2)$$

With U_0 as matrix of eigenvectors and Σ diagonal matrix of eigenvalues. A whitening transformation matrix equalizes the variances in the space extended by U_0^T

$$P = \Sigma^{-1/2} \cdot U_0^T \quad (2.3)$$

and can be used to transform the average covariance matrices:

$$S_F = P \overline{R_F} P^T \text{ and } S_R = P \overline{R_R} P^T. \quad (2.4)$$

Since S_F and S_R share their eigenvectors, the sum of their corresponding eigenvalues will always be one:

$$S_F = U\Sigma_F U^T, S_R = U\Sigma_R U^T \text{ and } \Sigma_F + \Sigma_R = I \quad (2.5)$$

Because of that, the eigenvector with the largest eigenvalues for S_F has the smallest eigenvalues for S_R and vice versa. Thus, the eigenvectors U can be used to classify the two different classes. To get feature vectors which can be used to achieve the highest discriminability between two populations, the whitened EEG has to be projected onto the first and last eigenvectors of U . The projection matrix can be calculated as follows:

$$W = U^T P \quad (2.6)$$

Using W , the original EEG can be transformed into uncorrelated components:

$$Z = WX. \quad (2.7)$$

The matrix Z consists of source components of the EEG and also specific components of the different tasks.

By using W^{-1} which can be seen as EEG source distribution vector one can reconstruct the original EEG X . Since the first and the last columns of W^{-1} contain the spatial pattern they explain the largest variance of one task and the smallest one of the other task [27, 28].

2.4.2 Filter Bank CSP

The performance of the CSP depends on the selected frequency range of the EEG and also differs between subjects. To achieve a high performance either a broad frequency range is used or the frequency bands are chosen manually for each of the subjects. There are several algorithms to select the individual frequency bands, e.g., Common Spatio-Spectral Pattern (CSSP) [29], Common Sparse Spectral Spatial Pattern (CSSSP) [30], Sub-band Common Spatial Pattern (SBCSP) [31] or Filter Bank Common Spatial Pattern (FBCSP) [32].

For this work, a filter bank CSP was chosen. Therefore, the measured EEG was bandpass-filtered into multiple frequency bands, CSP filters were applied to each of those bands, the discriminative CSP features of the filter bank were chosen and lastly the CSP features were classified [32]. To detect a beta rebound the frequency range from 12 - 37Hz was divided into eight overlapping frequency bands of 4Hz bandwidth. The overlapping of the filters was necessary to compensate the slopes of the filters. For the filterbank eight IIR bandpass filters of order 4 were used.

2.4.3 Logarithmic Bandpower Features

2.4.3 Logarithmic Bandpower Features As a last step before classifying the data, features have to be extracted from the CSP-filtered signals. Imagination of a movement induces oscillatory changes in frequency as well as in the amplitude of the EEG signals. For these features to be

extracted, the logarithmic bandpower is applied to the signal. Therefore, the samples of the EEG are squared, a sliding window of one second is used to calculate the bandpower of the features and afterwards the samples are logarithmized.

2.5 Classification: Random Forest

Random forest (RF) is a classification method which is based on several uncorrelated decision trees. It was developed by Leo Breiman and first published in 2001 [33]. Breiman et al. defined it as a classifier consisting of a collection of tree-structured classifiers $\{h(x, k), k = 1, \dots\}$ where the $\{k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x [33].

Decision trees build the basis of a random forest but they are often combined with a method called bagging which leads to higher classification accuracies. Classification trees divide the feature space into non-overlapping rectangular regions and for every observation which falls into the same region, the same decision is made. This process is called growing of a tree and is performed as follows: each tree starts at the root, where the entire feature space is available. To classify the data, each node of the tree represents a criterion and splits the data into two different regions depending on the condition of the node. At each node, the data is further splitted and the trees grow iteratively until either a stopping criterion is reached or there is only one observation left at each node. The Gini index or cross-entropy are used to decide if the tree should split up further because these approaches are sensitive to node purity. In the end, all leaves or terminal nodes represent a set of training data of the same class. Training the tree as described above leads to very high accuracies for the training data but may lead to overfitting since the trees are very complex. Therefore, using a smaller tree with fewer splits would be beneficial. To find such a tree a very complex one is grown and then pruned back to obtain a subtree. To prune the tree the classification error rate should be used when the prediction accuracy of the final pruned tree is the goal otherwise the Gini index or cross-entropy can be used.

Decision trees show a high variance which means that if training data is split up into two parts and each of the parts is used to train a decision tree, both trees would be very different. To reduce the variance of trees a method called bagging, or bootstrap aggregation, is used. Bootstrapping is used to generate B different training sets and each of this sets is used to build a prediction model. Each of the trees has a high variance but a low bias and by averaging the B trees the variance can be reduced. For classification problems a majority vote is used to predict the class label.

Random forests can further decrease the variance by reducing the correlation between the singular trees. Before each split during the tree growing process, a random set of input variables ($m \leq p$) is chosen to split the tree. In classification problems, m is typically p and the minimum node size is 1. To classify data, a majority voting is again used to predict the class label.

Summed up, the following algorithm can be used as classifier for this work:

1. for $b = 1$ to B :
 - (a) bootstrapping: drawing a bootstrap sample (size N) from the training data
 - (b) grow a random forest tree T_b for each bootstrapped data using the following steps for each terminal node repeatedly until the stop criterion is reached:
 - (i) select m random variables from p
 - (ii) pick the best splitting point among m
 - (iii) split node into two nodes
2. output: ensemble of trees $\{T_b\}_1^B$

For classification problems let $\hat{C}_b(x)$ be the class prediction of the b^{th} random forest tree. Then, $\hat{C}_{rf}^B(x)$ equals the majority vote $\{\hat{C}_b(x)\}_1^B$ [34][35][36].

The accuracy of random forests is mainly influenced by two parameters, namely the number of tree classifiers and the number of randomly chosen data dimensions per node. On the one hand a certain number of trees is necessary to reduce the variance but on the other hand the computational expenses rise with the number of trees. Steyrl et al. [36] concluded that a number of 1000 trees and $\sqrt{\#numberof\ features}$ should be used which was followed in this work.

2.6 Artifact Removal

Since the amplitudes of the EEG signals are very small (μV), artifacts have a very high impact on them. These can be divided into biological artifacts, e.g., blinking, sweating, swallowing, and non-biological artifacts, e.g., power-line noise or moving electrodes. Non-biological artifacts can be reduced to a minimum by a careful preparation of the experimental setup, but biological artifacts are hard to avoid. Since artifacts have a wide influence on the EEG and can, in worst case, control the BCI, it is crucial to deal with them.

In this work, a statistical outlier rejection was applied and thus every trial, which showed artifacts, was excluded. The outlier rejection is based on the work of Delorme et al. [37]. Four statistical methods were used to detect artifacts:

- rejection by amplitude threshold: each trial that includes at least one data point, which exceeds a threshold is excluded. The threshold is set to $\pm 100\mu V$
- rejection by channel variance: each trial that has a standard variance, which is higher than 5 times the standard variance, is excluded
- rejection by probability: trials which show a unusual behavior over time are excluded. Therefore, the joint probability of one column of a trial are compared to the probability distribution of all columns
- rejection by kurtosis: each trial, which shows an unusual probability behavior of the kurtosis compared to a threshold, is excluded

2.7 Event-Related Desynchronization/Synchronization

During motor imagery, the brain changes from a synchronized mode into an desynchronized one and changes back in resting phases. These changes could be either time- and phase locked (ERP) or time- but not phase-locked which is known as event-related synchronization or desynchronization. To control applications which are based on ERD/S, it is necessary to find the frequency band which is the most reactive at different electrode positions. Thus, processing and visualization of multichannel EEG is very important. Therefore, a bootstrap based method is used which calculates a time-frequency map for the significant changes of power increase (ERS) or decrease (ERD) of each electrode. All maps can be combined in a topographic plot to receive an overview of the significant ERD/S patterns in EEG recordings. To calculate ERD/S maps, at least 30 trials of several seconds per class are necessary and between two trials there should be a pause of some seconds. ERD/S is defined as the proportional power decrease or power increase in relation to a specific reference interval. To calculate ERD/S maps each trial is bandpass filtered, the samples are squared and there is a subsequent averaging over the trials and sample points.

2.8 Questionnaire

To find out if the participants felt stressed during the experiment, each of them had to fill out a questionnaire. They were asked how stressed/nervous they are in their daily lives, how stressed/nervous they are because of the experiment and before each part of the experiment, they were asked how stressed they are compared to the part before. For the answers a visual analogue scale [38] was used and the answers were between “not at all” on the left side to “very much” on the right site. The questionnaire can be seen on Figure 2.9.

2.9.1 R-Peak-Detection

As a R-peak detection a second order derivatives algorithm was used. It was implemented according to the practical course of the lecture Biosignal Processing at Graz University of Technology [39]. An overview of this algorithm can be seen in Figure 2.10. First, the drift was removed by subtracting the mean of the ECG of the ECG. Then the signal was zero-phase filtered with a second order bandpass butterworth filter between 10 and 30Hz. Next step, the signal was differentiated and low pass filtered using a second order butterworth filter with a cutoff frequency of 15Hz. Thereafter, the signal was normalized between \pm and every sample point between ± 0.5 was set to zero. Afterwards, the signal was differentiated again and then all samples which were not zero were marked. Then, the QRS complexes were marked. If the distance between two marked points was higher than 0.6 seconds, two QRS complexes were separated. Finally, the R peak was detected as the maximum of each QRS complex.

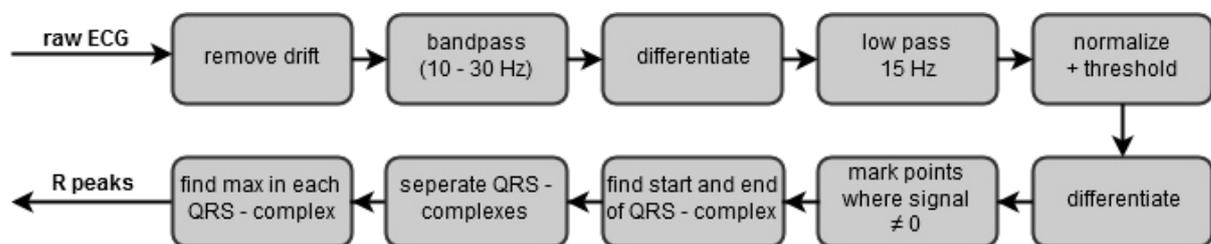


Figure 2.10: Overview of the R-peak detection.

2.9.2 Heart Rate Variability

In this work, the length of ECG recording varied between 20s in the last parts of the experiment and 200s in the first parts. Since only ultra-short term recordings were investigated, frequency domain methods should be preferred but also some time domain methods can be used. It is necessary that the recorded ECGs have the same length to calculate HRV and compare them afterwards. Therefore, the HRV parameter were calculated for each of the three recording and the two simulation runs and afterwards the mean was calculated. The trials of the last part were merged at the R-peaks [15][40]. The following time domain and frequency domain methods were used in this thesis to analyse the HRV.

• Time Domain Methods

The calculation of HRV using time domain methods is very simple. Using this methods one can measure the heart rate or the intervals between sequential QRS complexes. Time domain methods are separated in statistical and geometrical methods but just statistical methods were used in this work since they can also be used for ultra-short term recordings [15]. There are several variables which can be calculated:

- meanRR in ms: mean of RR intervals
- SDNN in ms: standard deviation of RR intervals
- RMSSD in ms: square root of the mean squared differences of successive RR intervals
- NN50: number of pairs of adjacent RR intervals which differ by more than 50 seconds

- pNN50 in %: dividing the total number of RR intervals by the number of interval differences of successive RR intervals greater than 50ms

Frequency Domain Methods

Using frequency domain methods, the ECG data is decomposed into its frequency components, which can be expressed as spectral density function (PSD) which describes the spectral power as a function of frequency. There are two common approaches to do a spectral analysis of the HRV: fast Fourier transformation (FFT) and autoregressive (AR) modeling but the latter was not used in this work [14]. To analyze short-term recordings three main spectral components can be distinguished: very low frequency (VLF, $\nu=0.04\text{Hz}$), low frequency (LF, 0.04-0.15Hz) and high frequency (HF, 0.15-0.4Hz) components. All three components are absolute values of power (ms^2) but they can also be presented in normalized units (nu) [15].

3

Results

The following section shows the results of this thesis. It begins with the results from the offline analysis and the pilot study and thereafter the online results can be seen.

3.1 Offline Analysis

Before starting the experiment, it was tested if a CSP before the random forest has an positive impact on the classification accuracy.

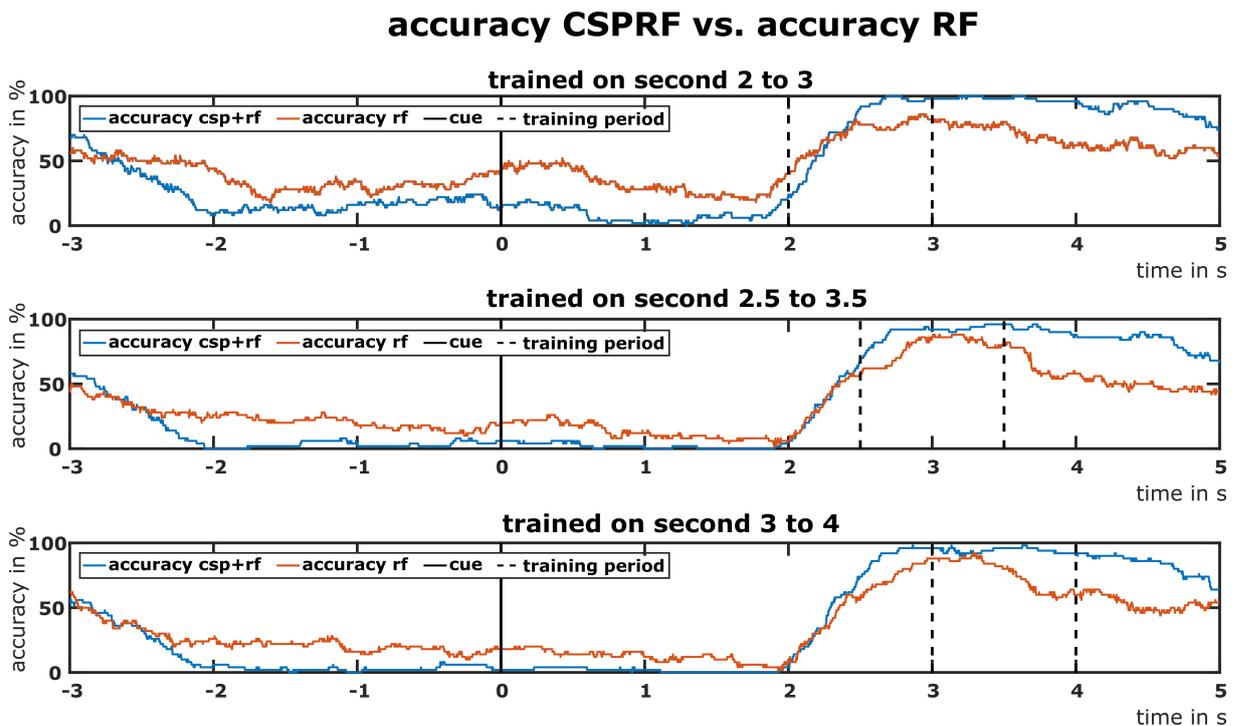


Figure 3.1: Classifier output of the the system. The orange line represents the accuracy of the random forest and the blue line shows the accuracy of csp and a random forest.

Figure 3.1 shows the accuracy curves of the system whereby two different classifiers were used. The orange curve shows the accuracy of a random forest as classifier and the blue line shows the combination of a CSP and a RF. The accuracy was calculated using a five times five cross validation and 60 trials in total were recorded. To find the second in which the PMBERS was the most prominent the classifier was trained on three different seconds. In the plot on top, the classifiers were trained on second 2 to 3, in the middle plot the classifiers where trained on

second 2.5 to 3.5 and on the bottom, the classifier was trained on second 3 to 4. The x-axis shows the time in seconds. At second -3 the cross appeared, at second 0 the cue was shown and the dotted line shows in which second the classifiers were trained. The accuracies were statistically tested using a Wilcoxon rank-sum test at a significance level of $\alpha = 0.05$. The accuracies of the CSPRF classifier are significantly higher than the accuracies of the RF classifier. The means of the three accuracies classified by CSPRF are not significantly different. The peak accuracies are 86%, 88% and 92% for the RF from top to bottom and 100%, 96% and 98% for the CSPRF.

3.2 ERD/S Maps

The time-frequency maps of all subjects of the laplace-deviations of channels C3, Cz and C4 were calculated and can be seen in Figures 3.2 to 3.12. The colors yellow to red indicate weak to strong event-related desynchronization, the colors green to blue indicate weak to strong event-related synchronization. The y-axis shows the frequency in Hz and the x-axis shows the time in s. At second 0 the motor imagery period starts. The sampling frequency of all ERD/S maps was 512Hz, as a reference period second -2.5 to -1.5 was used and the bootstrap significance test was $\alpha = 0.05$.

3.2.1 Pilot Study

Figure 3.2 shows the ERD/S maps of the participant of the pilot study over the electrodes C3, Cz and C4. In the reference period no clear ERD/S can be seen. On channel Cz a clear event-related desynchronization in the β -band between 16 and 22Hz can be seen. Since the channel Cz represents the cortical area which is correlated with the motor imagery of the feet the desynchronization indicates the imagination of the brisk foot movement. Directly after the desynchronization there is a synchronization, in the same frequency range which represents the PMBERS. Electrodes C3 and C4 do not show clear ERD/S in the β -band.

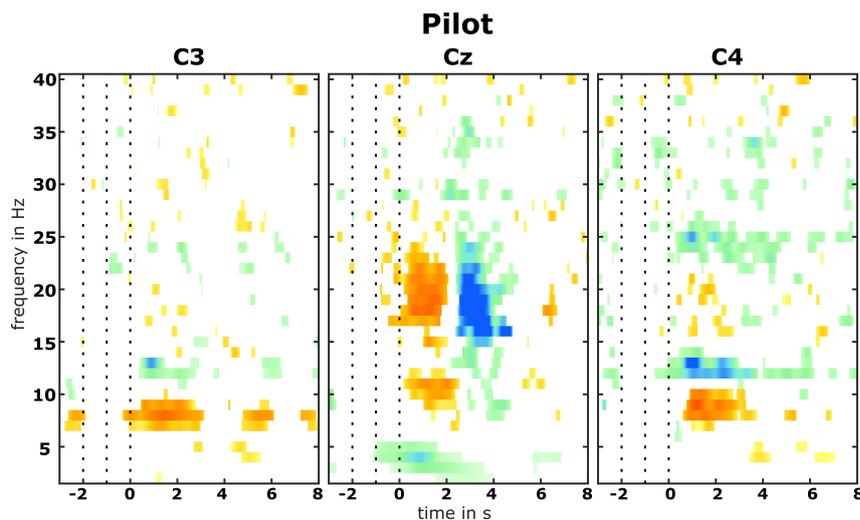


Figure 3.2: ERD/S map of the participant in the pilot study.

3.2.2 Online Study

The Figures 3.3 to 3.12 show the ERD/S maps of the 10 participants of this study. In the time-frequency maps of S1, S4 and S6 (Figure 3.3, 3.6 and 3.10) no distinct patterns are evident. The ERD/S maps of the other seven participants show distinct synchronization in the channel Cz in the β -band around two seconds after the cue. The PMBERS of S7 is the most prominent one. The synchronization in Cz of S10 appears already 1 second after the cue. There are no distinct patterns in the channels C3 and C4 for all but one subject. The ERD/S maps of S3 show distinct desynchronization at C3 from second 0 to 2. In Figure 3.11 artifacts on C4 are apparent.

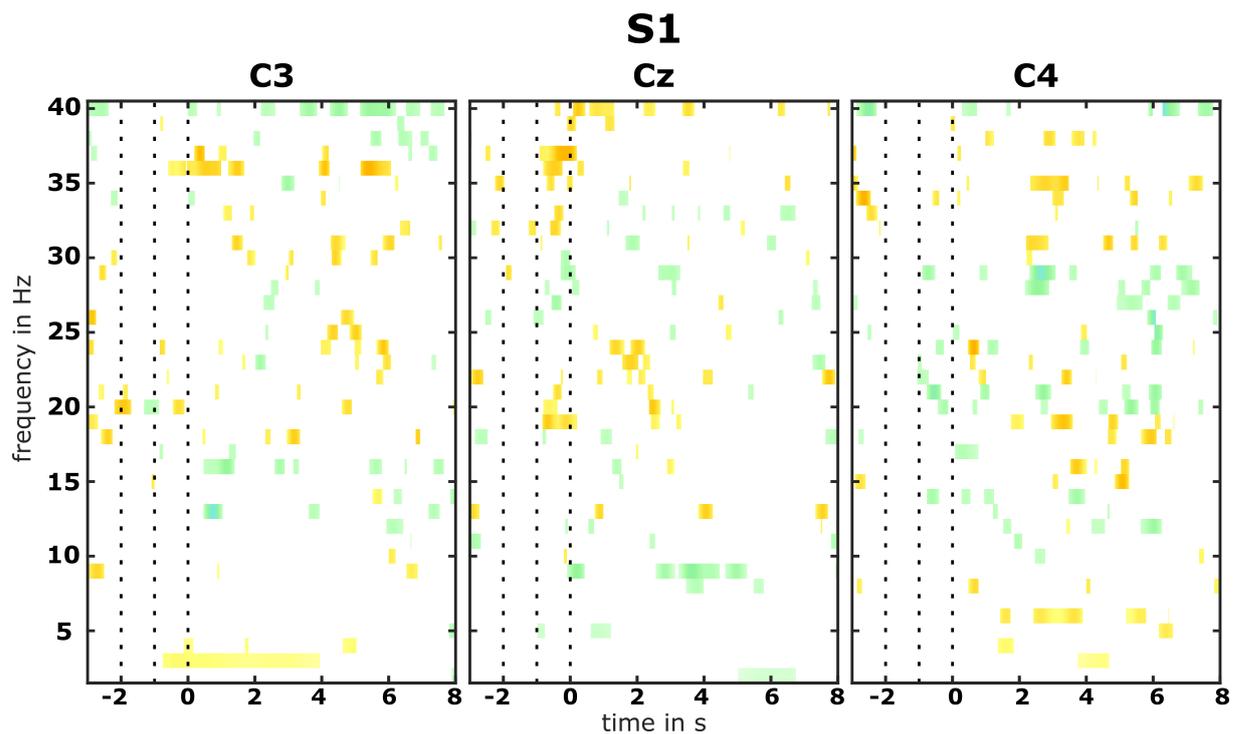


Figure 3.3: ERD/S maps of participant S1.

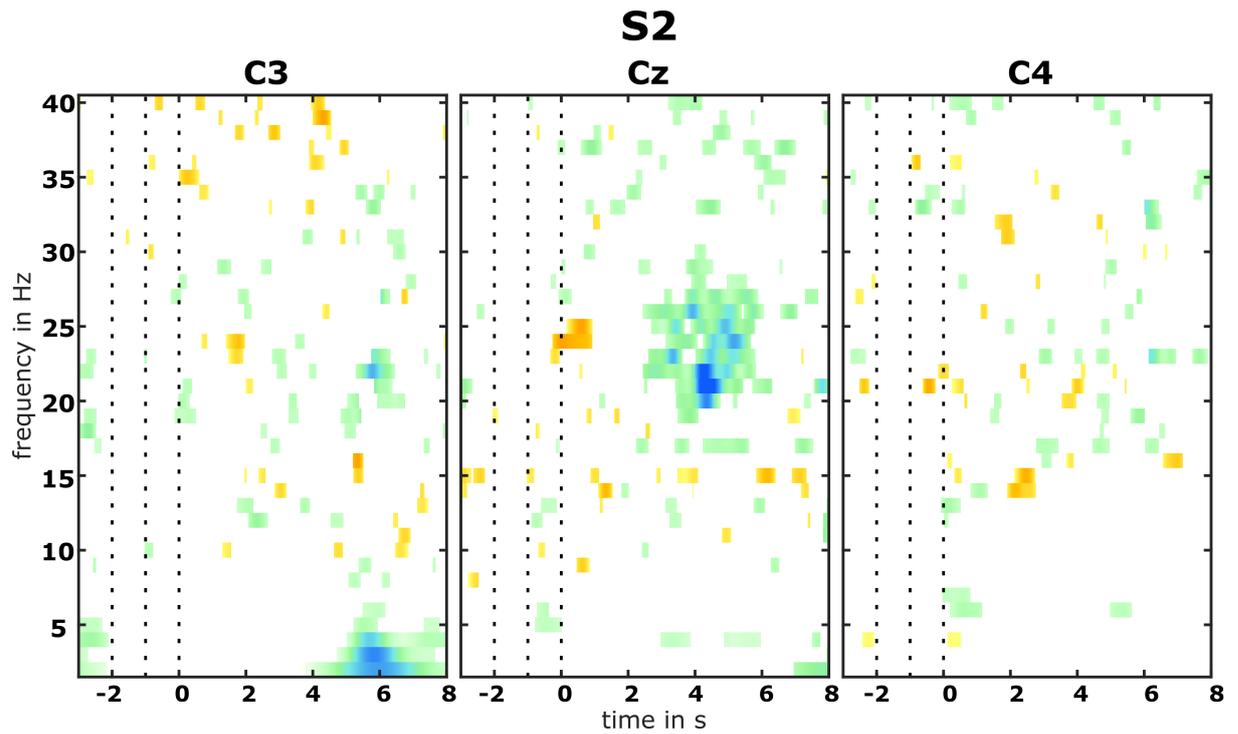


Figure 3.4: ERD/S maps of participant S2.

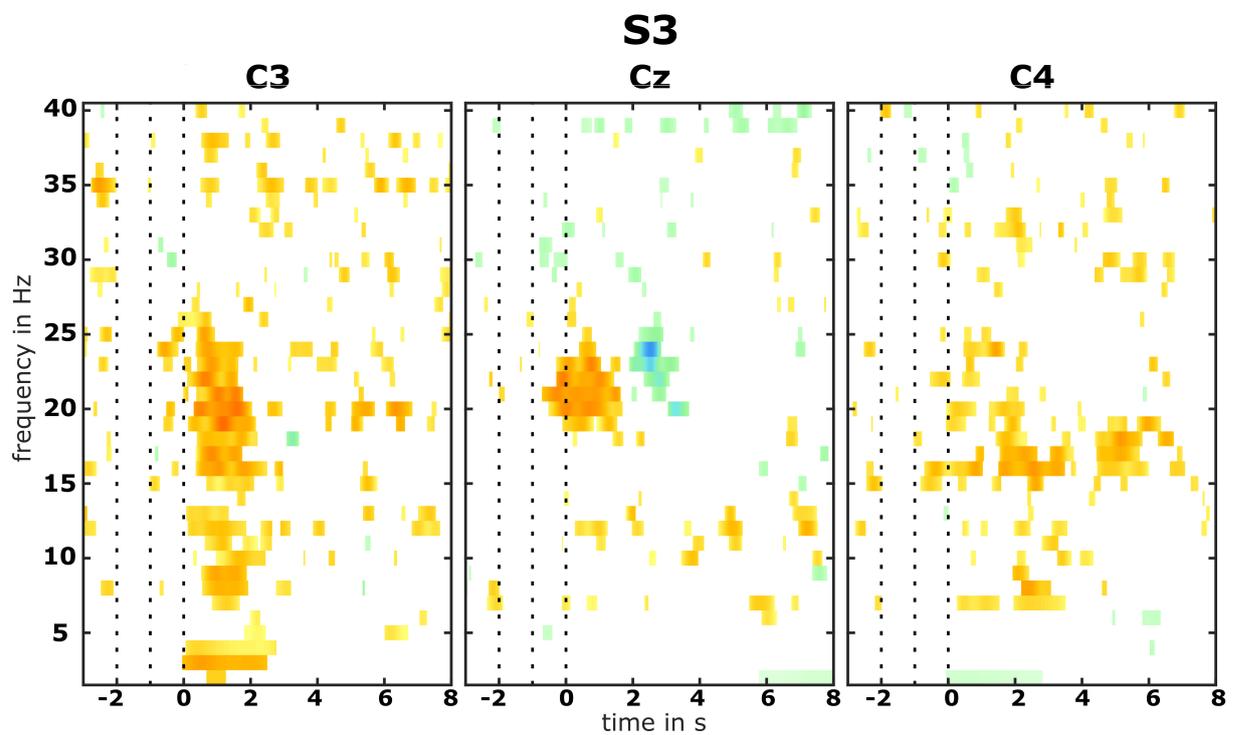


Figure 3.5: ERD/S maps of participant S3.

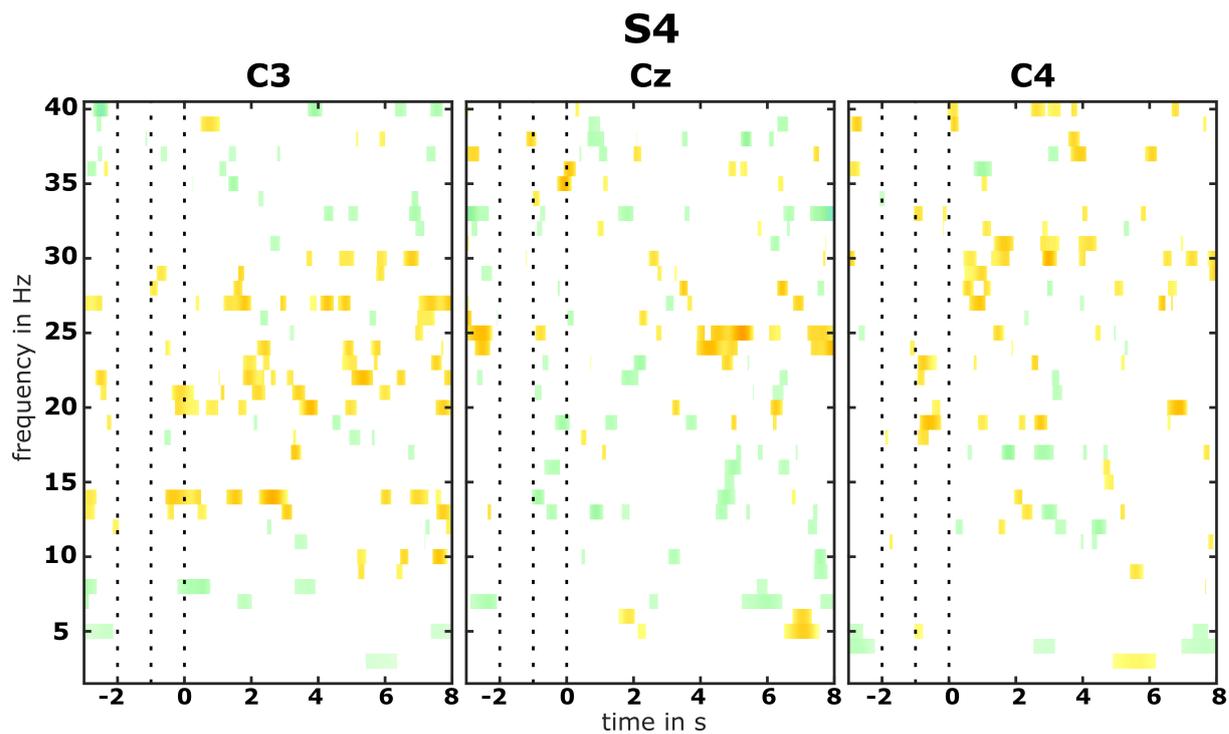


Figure 3.6: ERD/S maps of participant S4.

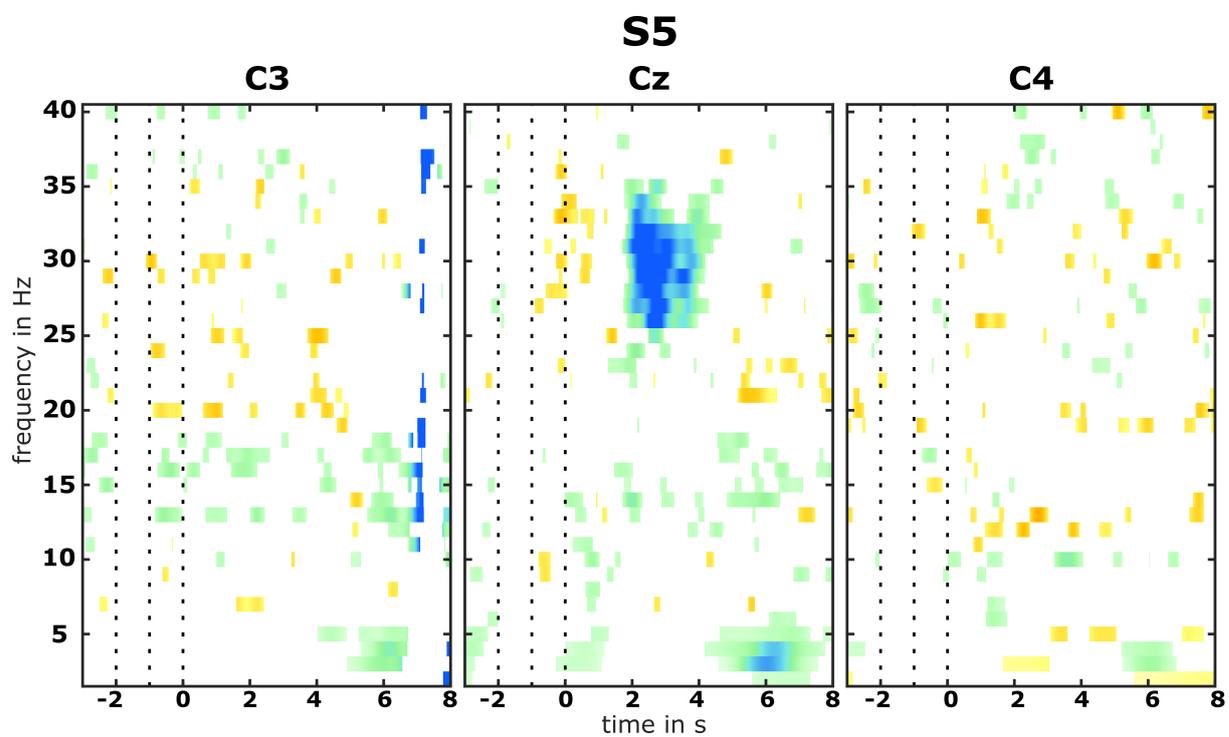


Figure 3.7: ERD/S maps of participant S5.

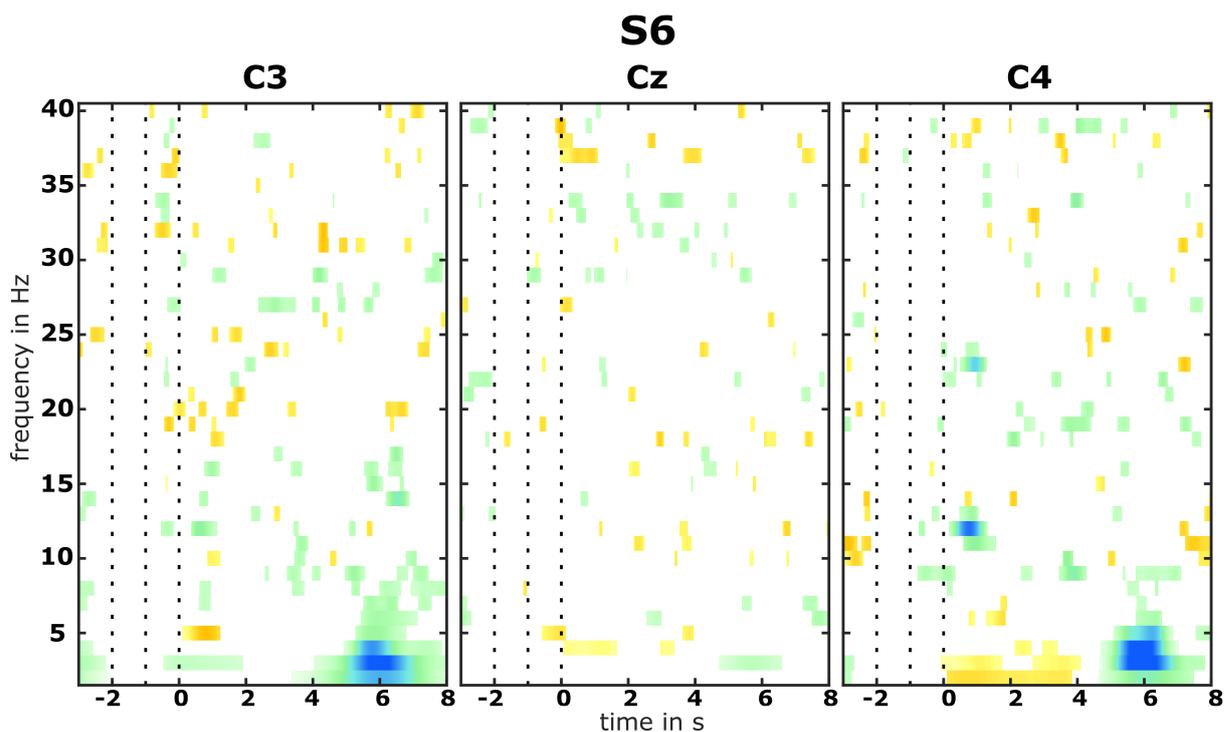


Figure 3.8: ERD/S maps of participant S6.

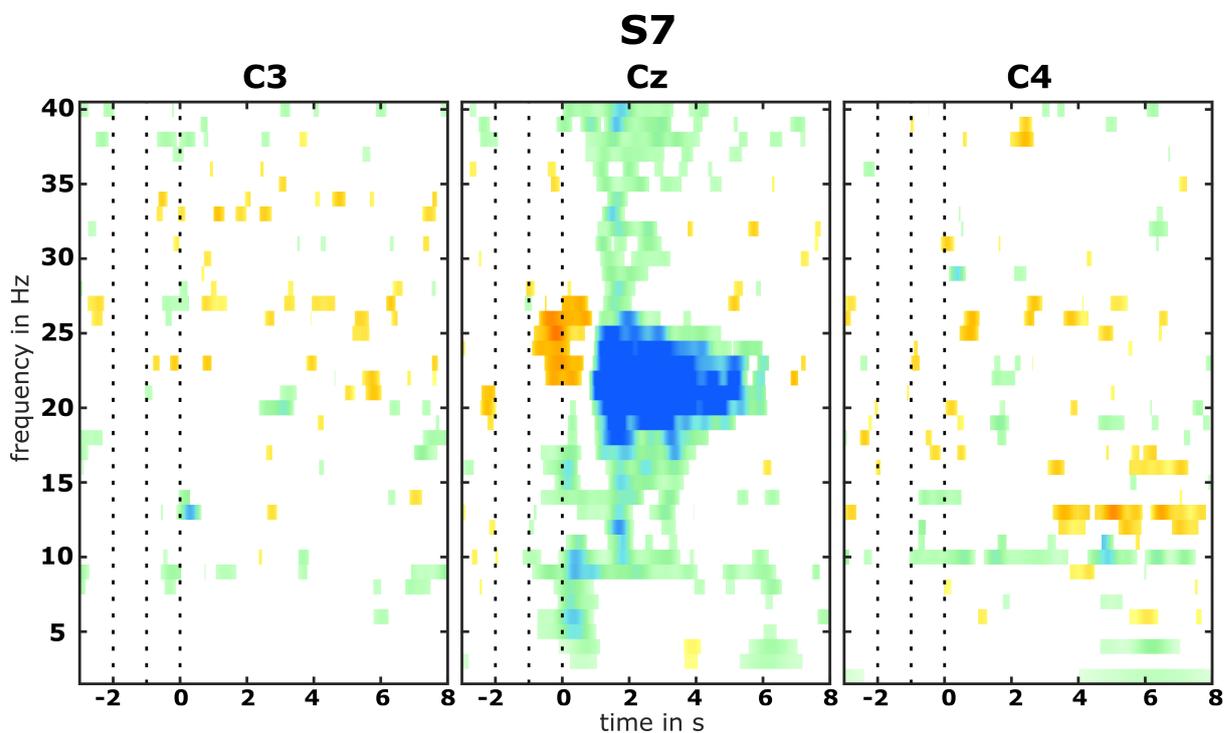


Figure 3.9: ERD/S maps of participant S7.

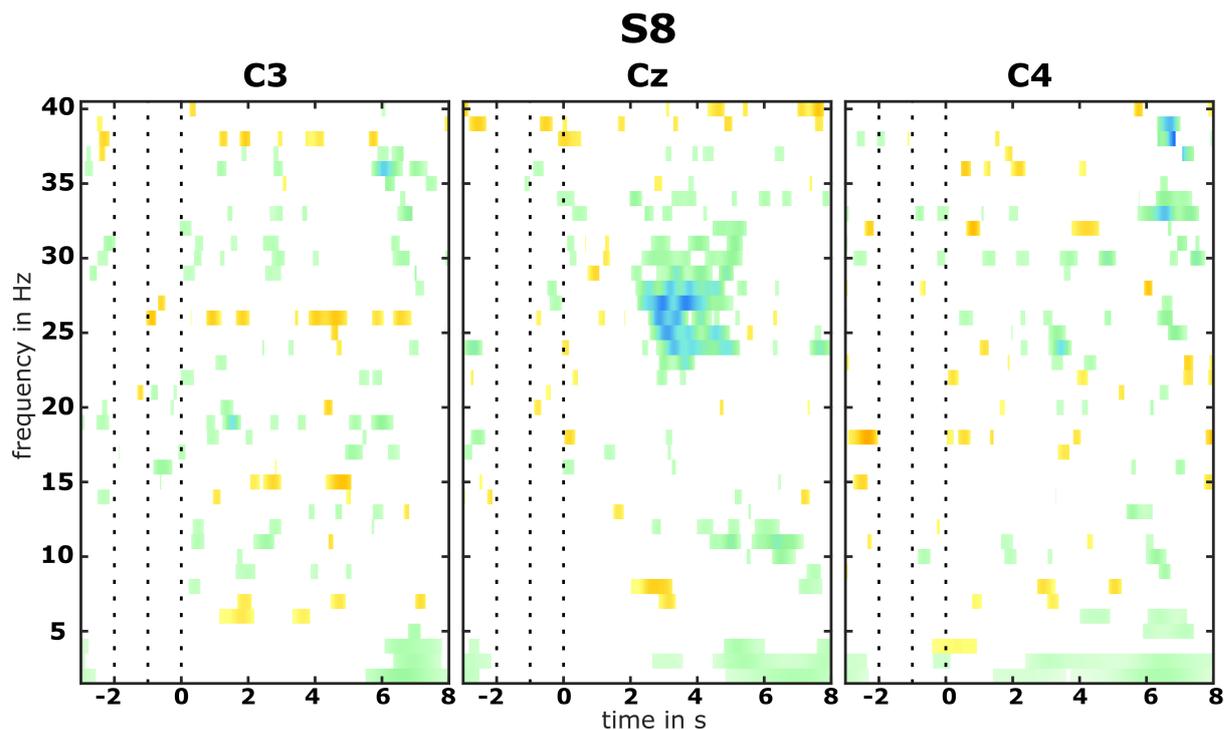


Figure 3.10: ERD/S maps of participant S8.

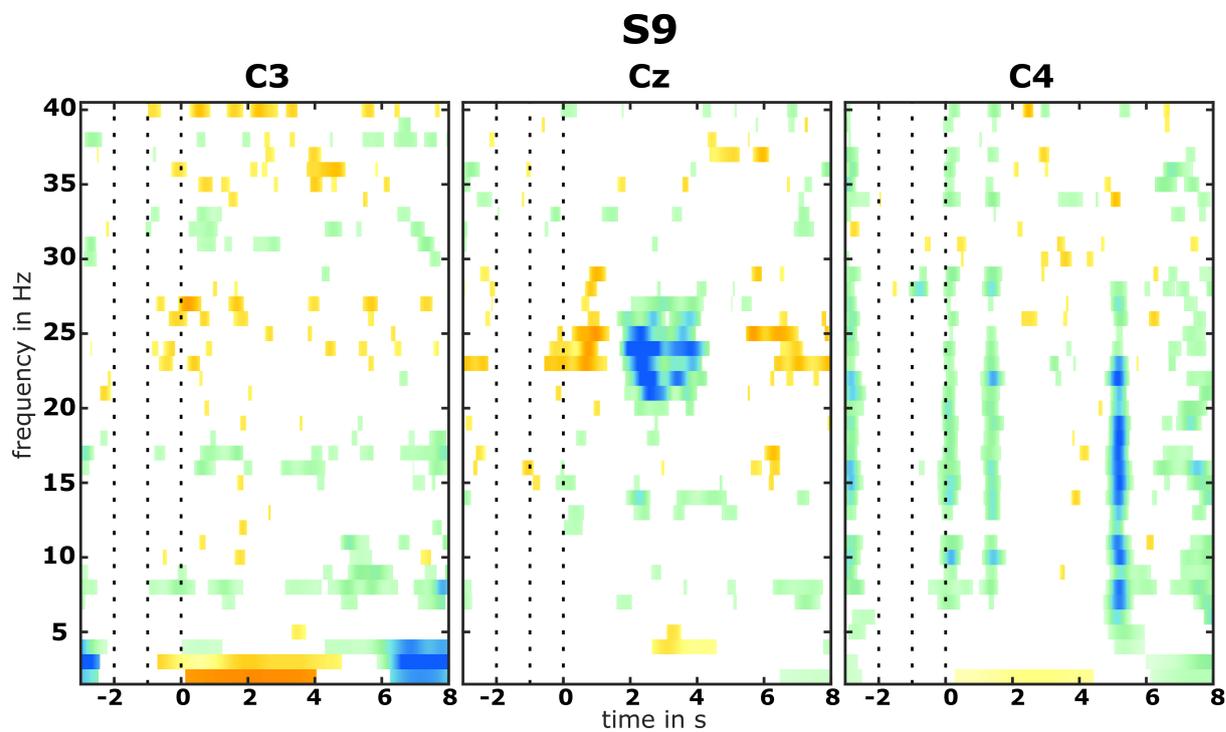


Figure 3.11: ERD/S maps of participant S9.

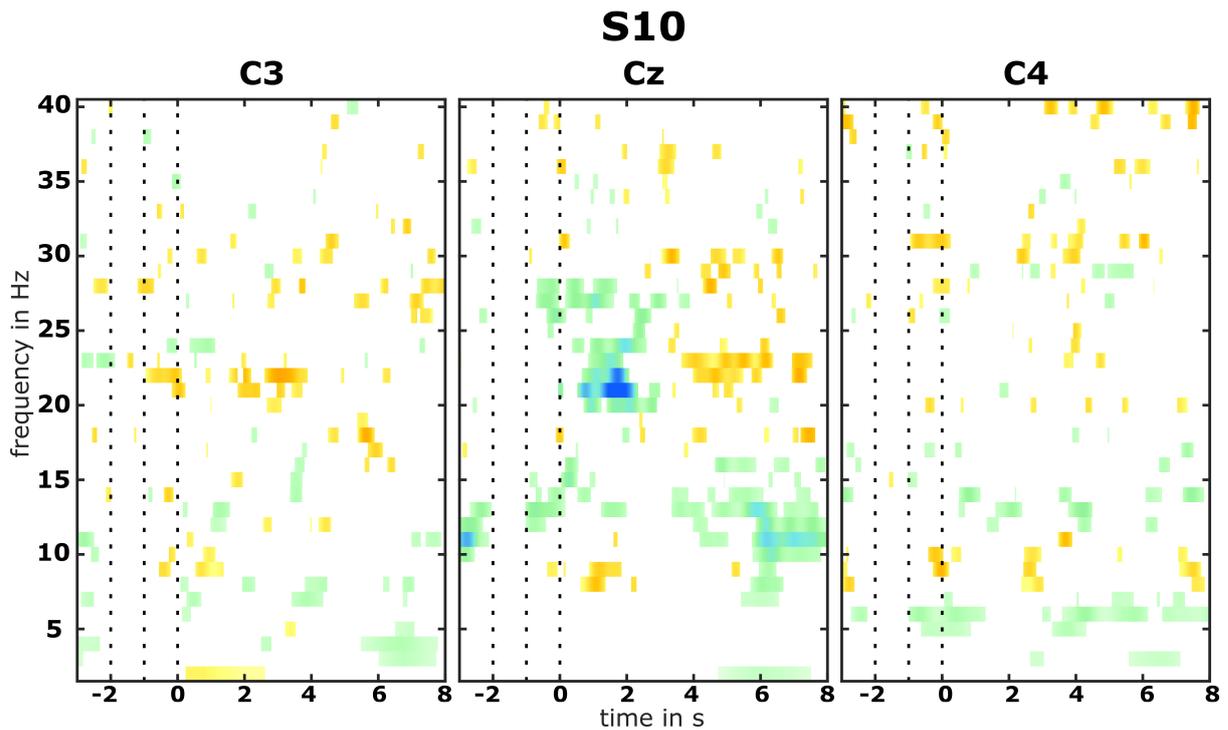


Figure 3.12: ERD/S maps of participant S10.

3.3 High Score List

Table 3.1: Number of opened parachutes of each of the subjects.

subject	number of opened parachutes
S3*	20
S1	20
S8*	19
S9*	19
S10*	17
S7*	16
S4	15
S5*	15
S6	15
S2*	14

Table 3.1 shows how often each of the participants was able to open the parachute. All subjects were able to open the parachute at least 14 times. Participants marked with a * showed a PMBERS.

3.4 Accuracy Plots

Figures 3.13 to 3.22 show the accuracy of detected motor imagery after the brisk feet movement for all subjects. On the x-axis the time in seconds is represented and the y-axis shows the accuracy in %. At second zero the cue was presented to the subject, the dashed line shows the chance level. The the top plot of each Figure shows the accuracy while simulating the fall of the parachute and the bottom plot shows the accuracy while the parachute fell down. During the simulation, 40 trials were recorded, whereas the parachute fell down only 20 times. For the three subjects who did not showed a PMBERS no increase in the accuracy after the motor imagery is recognizable. Even though S2 and S10 show an ERS in the ERD/S maps their accuracy curves do not show an increase in the accuracy after the motor imagery. In all other Figures an increase in the accuracy is visibel. Three of the subjects, namely S3, S7 and S8, were able to achieve accuracies higher than the chance level, which was 62.5% in the simulation and 70% in the fall experiment.

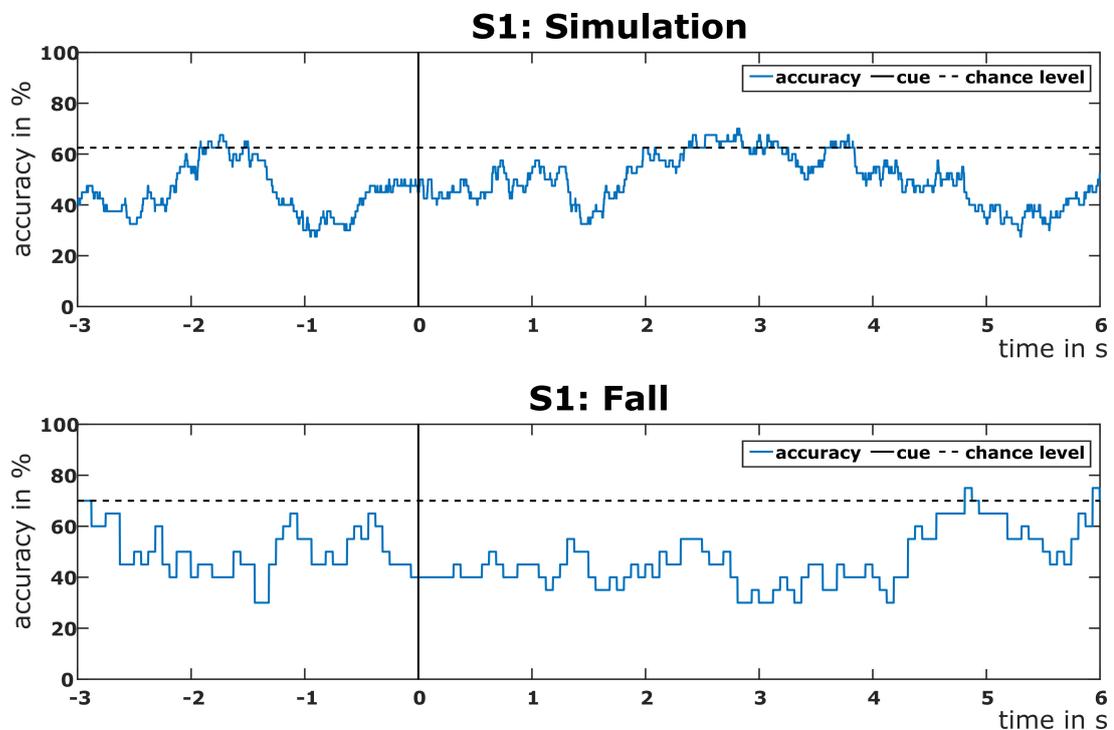


Figure 3.13: Accuracy plots of S1. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

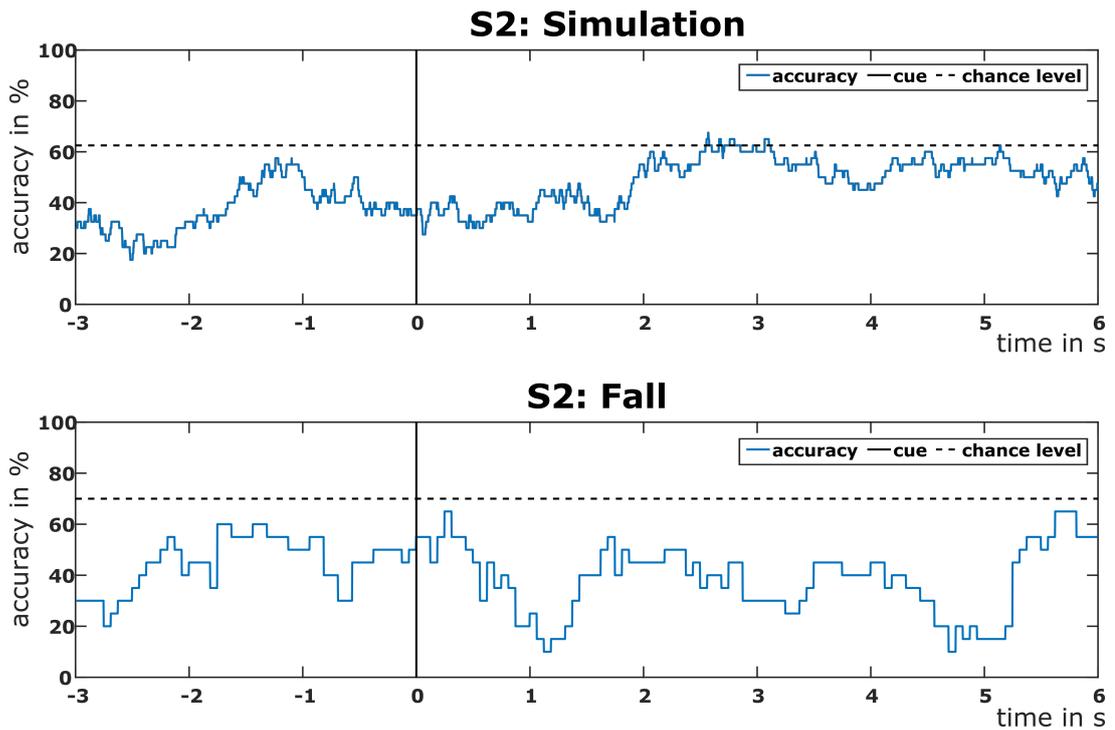


Figure 3.14: Accuracy plots of S2. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

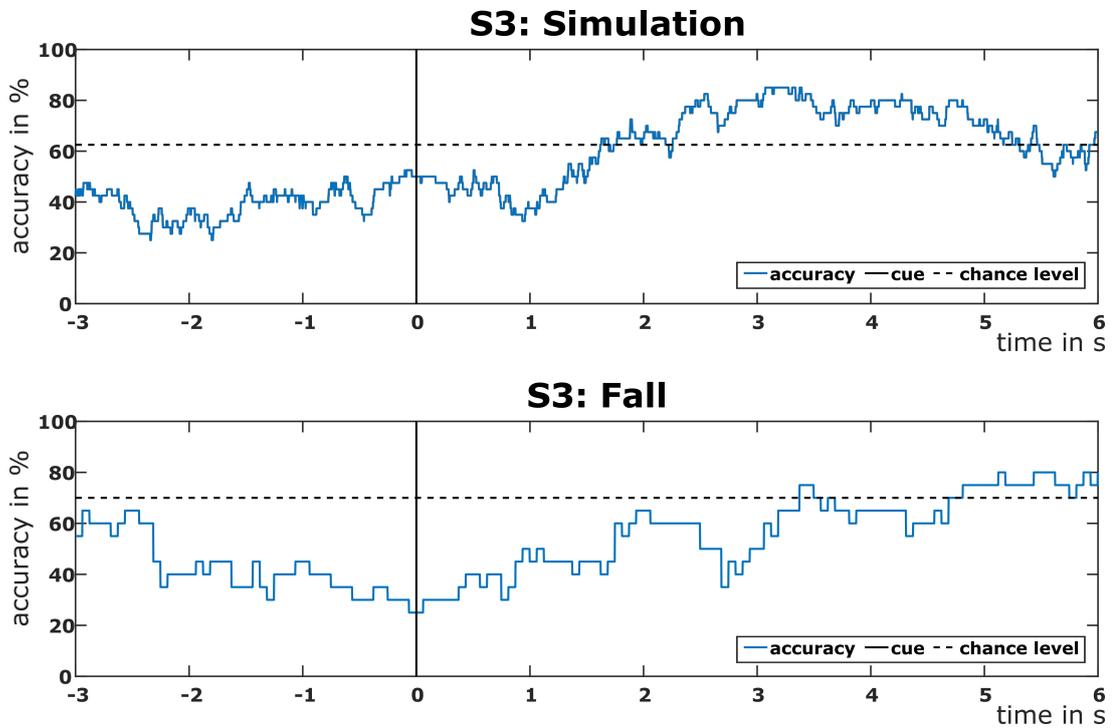


Figure 3.15: Accuracy plots of S3. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

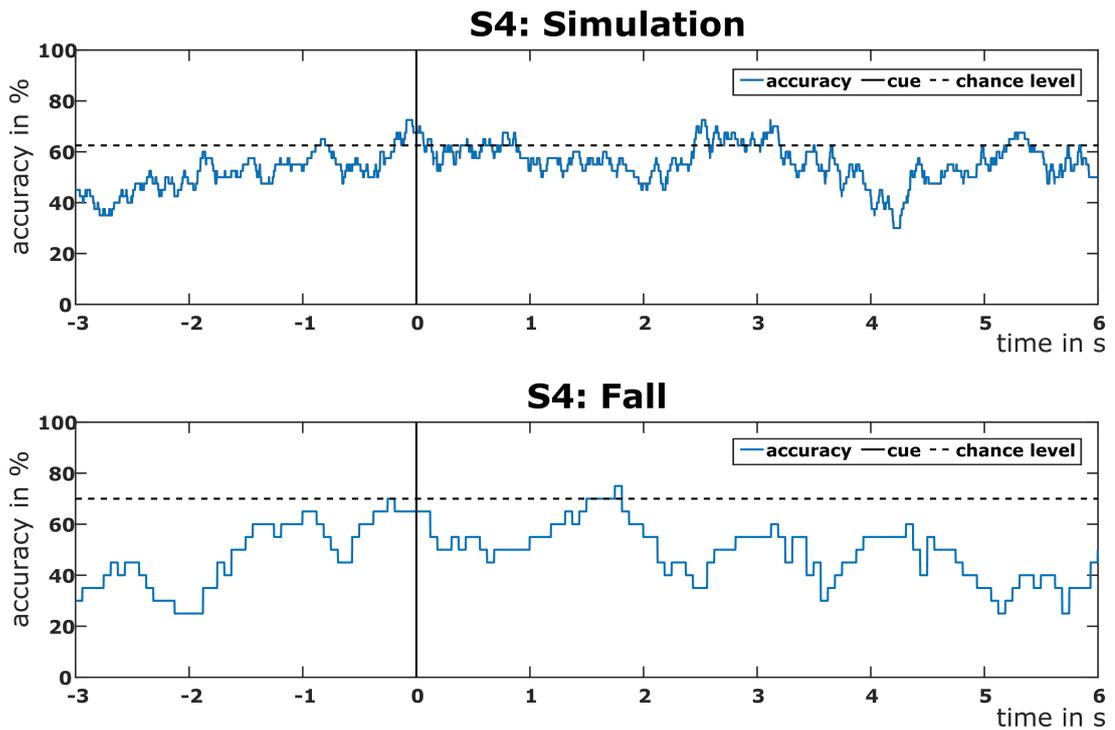


Figure 3.16: Accuracy plots of S_4 . The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

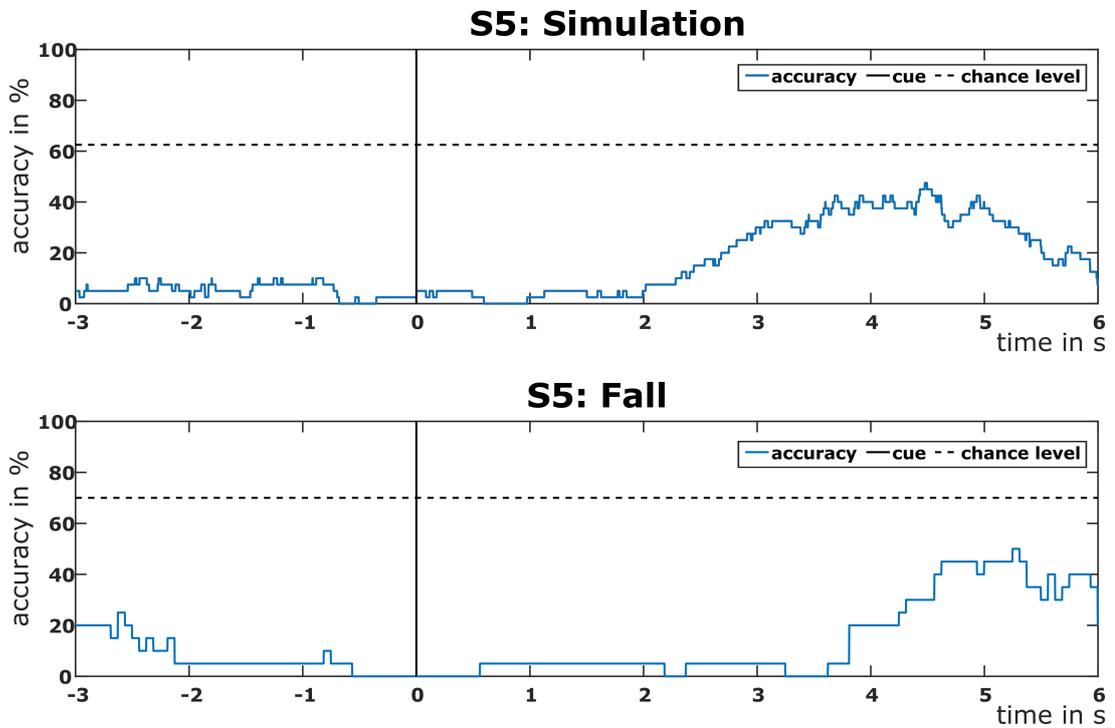


Figure 3.17: Accuracy plots of S_5 . The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

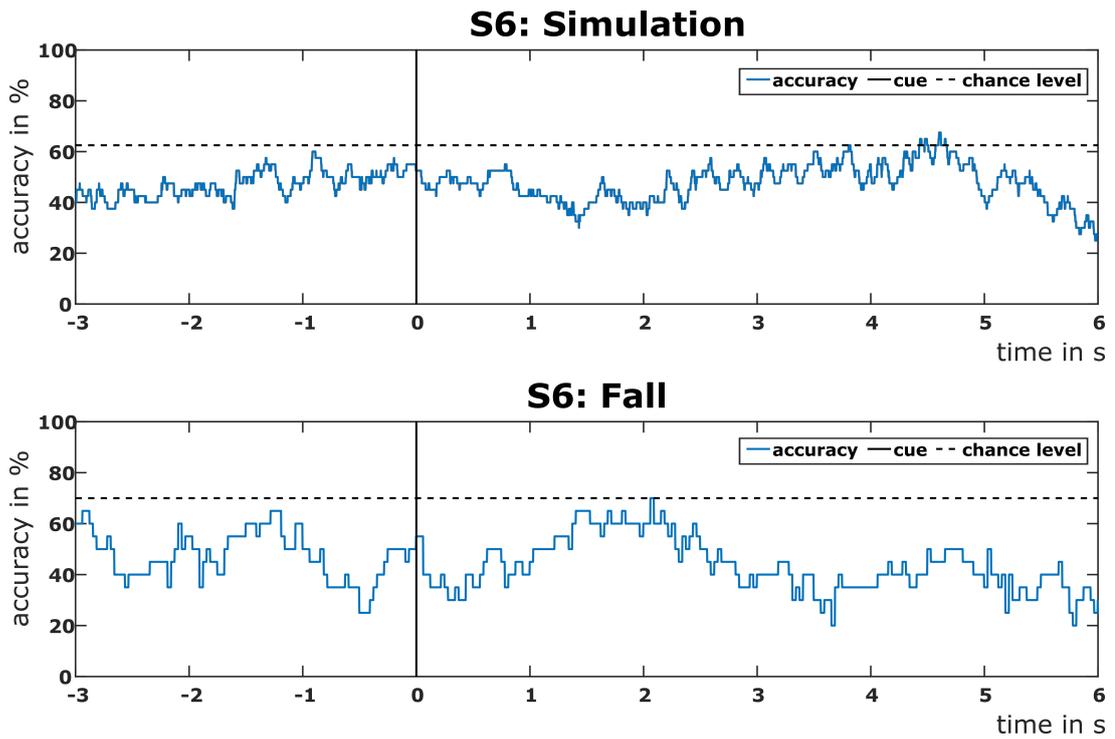


Figure 3.18: Accuracy plots of S6. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

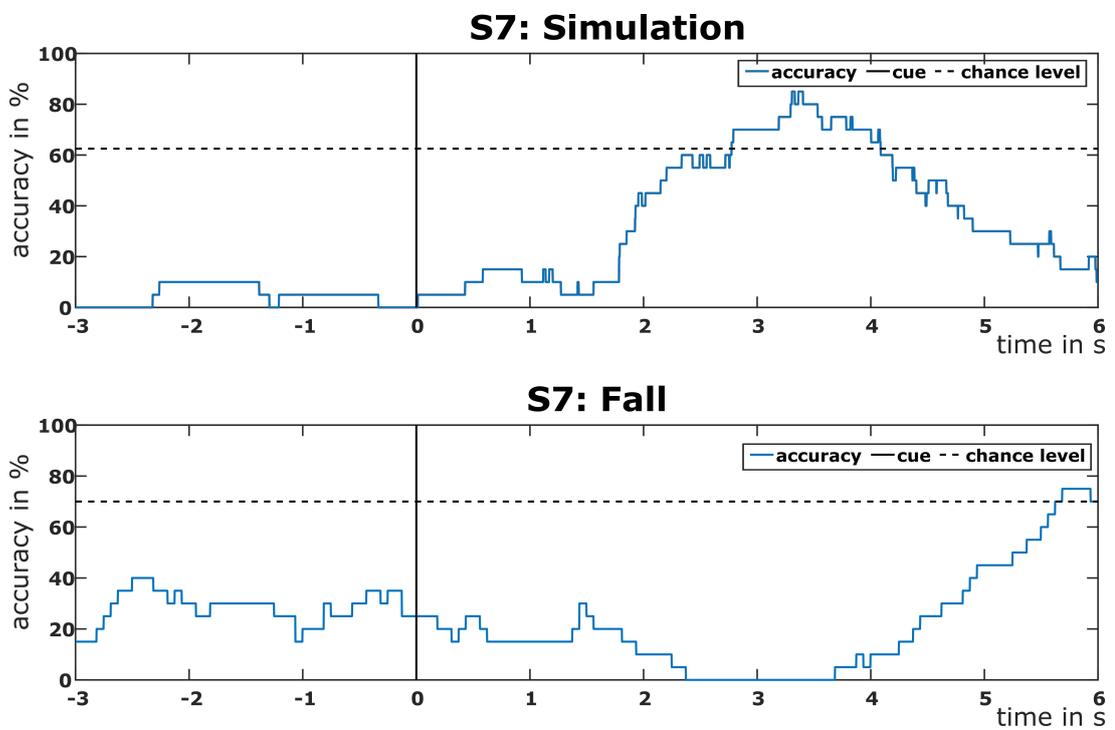


Figure 3.19: Accuracy plots of S7. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

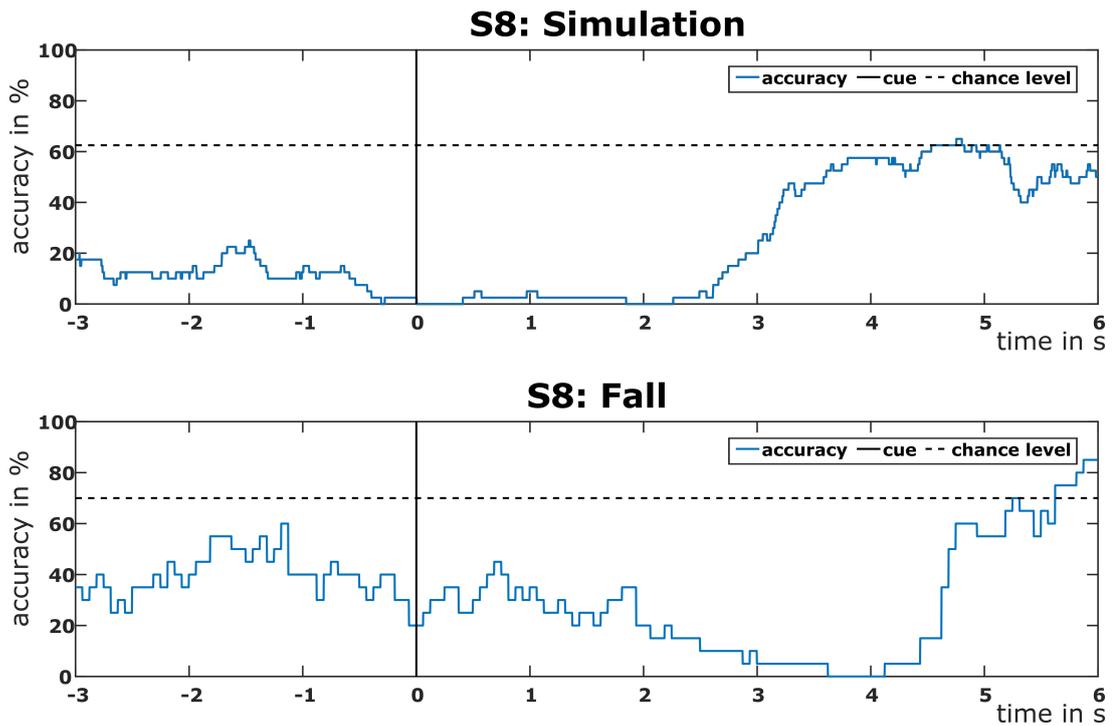


Figure 3.20: Accuracy plots of S8. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall..

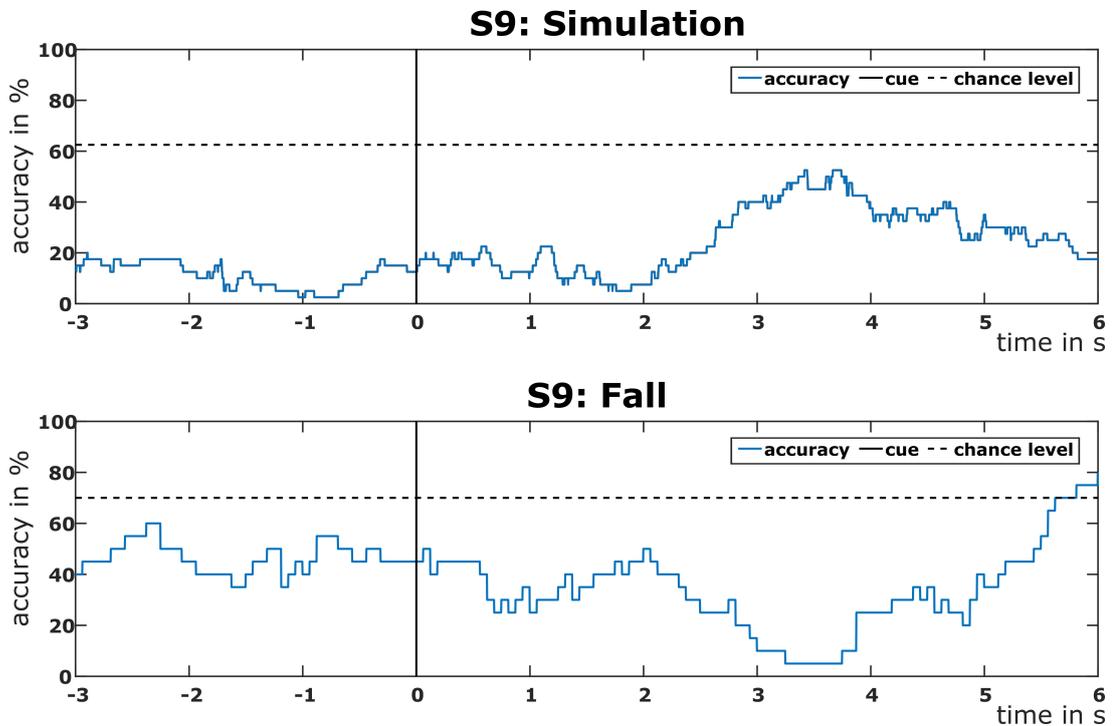


Figure 3.21: Accuracy plots of S9. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

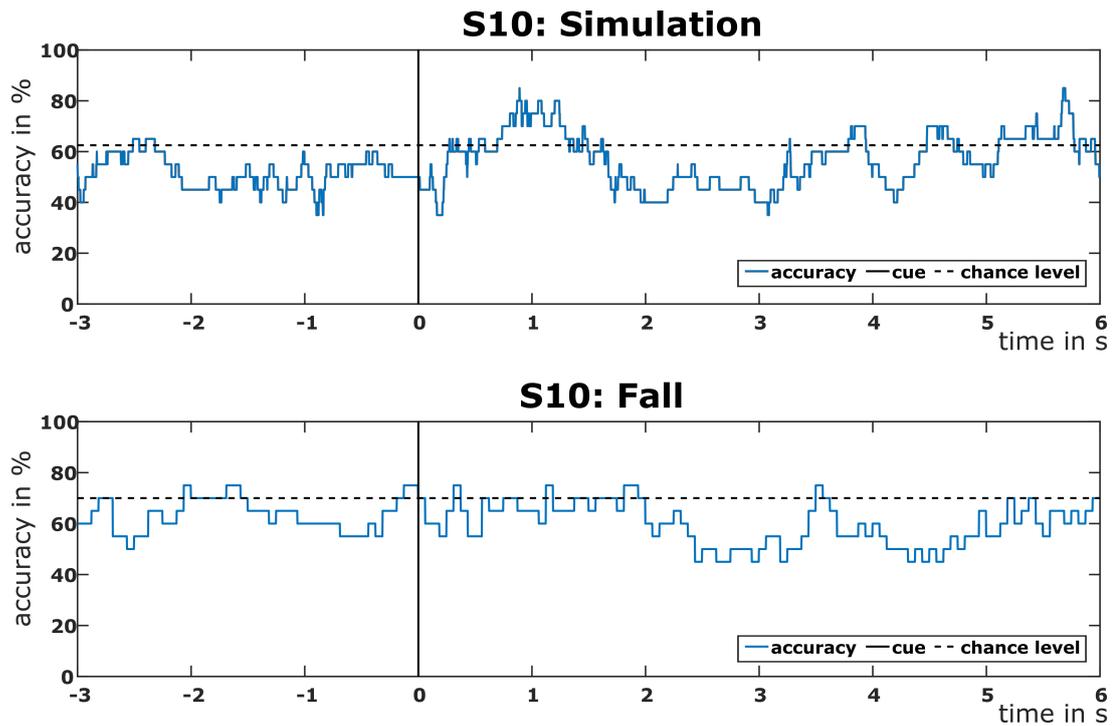


Figure 3.22: Accuracy plots of S10. The plot on top shows the accuracy of the simulation and the plot on the bottom the accuracy of the fall.

3.5 Questionnaire

Table 3.2 shows the stress level of the participants according to their answers in the questionnaire. It shows how stressed they are in general, how stressed they are because of the experiment, if they are more stressed before the second part of the experiment than before the first part, if they are more stressed before the third part than before the second part and if they are stressed because of the competition. The last row displays the mean of all participants. The values in the table are between 0 and 100 on VAS.

Table 3.2: Subjective stress response of each participant.

subject	stress general	stress experiment	more stressed (2nd part)	more stressed (3rd part)	stressed competition
S1	5	31	60	18	19
S3	13	0	13	0	10
S8	3	13	36	27	71
S9	57	0	85	28	0
S10	55	33	64	70	59
S7	21	26	38	61	73
S4	4	4	29	25	28
S5	0	15	26	39	55
S6	5	4	17	50	80
S2	60	30	47	66	65
mean	22,3	15,6	41,5	38,4	46

Table 3.3 shows how nervous the participants felt according to their answers in the questionnaire. It shows how nervous they are in general, how nervous they are because of the experiment, if they are more nervous because of the second part than the first part and if they are more nervous because of the third part than the second part. The last row displays the mean of all participants. The values in the table are between 0 and 100 on VAS.

Table 3.3: Subjective nervousness of each participant.

subject	nervous general	nervous experiment	more nervous (2nd part)	more nervous (3rd part)
S1	5	32	41	10
S3	0	0	0	18
S8	3	10	34	47
S9	72	0	86	30
S10	39	51	57	76
S7	27	27	40	63
S4	10	10	32	24
S5	0	16	36	52
S6	6	9	18	49
S2	34	22	59	65
mean	19,6	17,7	40,3	43,4

3.6 Electrocardiogram

3.6.1 Heart Rate

In Figure 3.23, the heart rate during the different parts of the experiments of all the subjects can be seen. On the x-axis, the different parts of the experiment are displayed, the y-axis indicates the corresponding heart rate in beats per minute. The red line represents the mean of all participants. During the experiment, the heart rate of all participants decreased. To check if the heart rate decreased within the second and the third part, the heart rate was separately calculated for the first 20 trials of the simulation and the first five trials of the falling part. The ECG electrode of S2 and S4 stopped working in the last part of the experiment so that it was not possible to calculate the heart rate for the fall. Since it stopped working at the end, it was possible to calculate it for the first five trials.

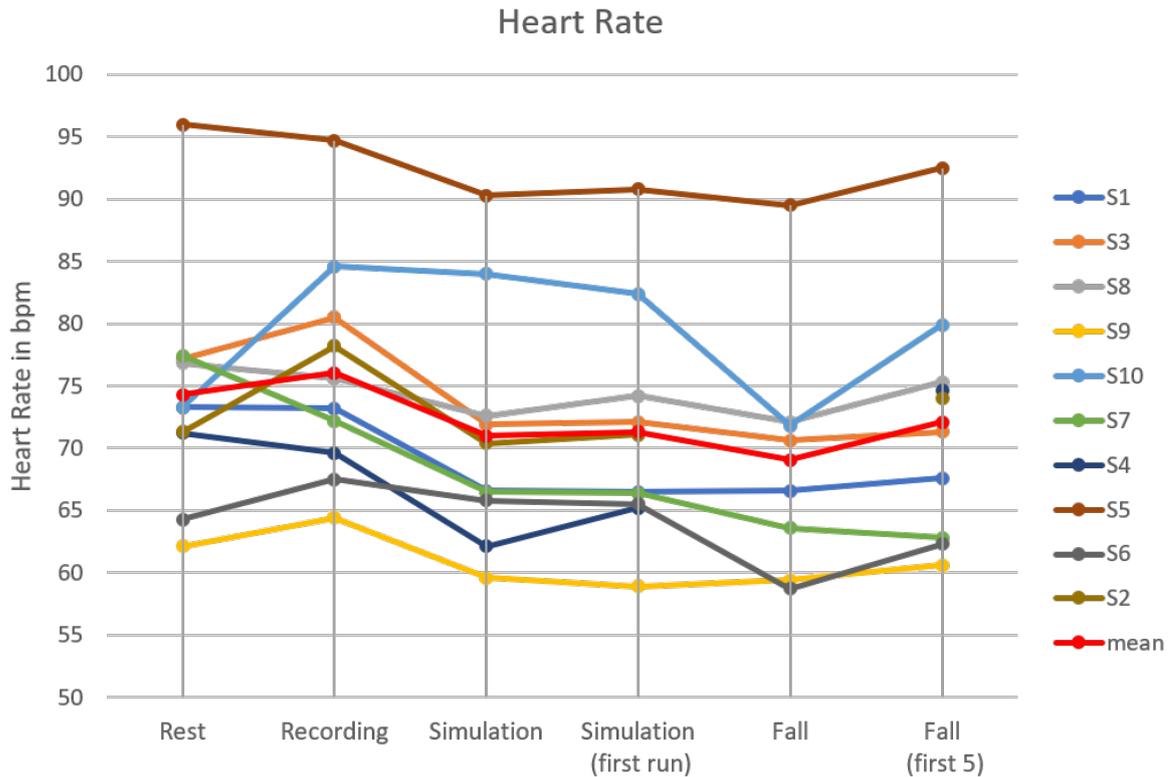


Figure 3.23: Heart rate of each of the participants.

3.6.2 Heart Rate Variability

Table 3.4 shows the mean of the different parameters of the heart rate variability for all subjects. MeanRR, RMSSD and LF increases in the different parts of the experiment whereas HF decreases from the rest to simulation but increases in the last part again. The ratio of HF to LF increases from the rest to simulation but since HF increases in the last part, the LF it decreases in the last part. Because the ECG electrodes of two participants stopped working during the fall experiment, they are excluded in the calculation of the mean.

Table 3.4: Mean heart rate variability of all subjects for each part of the experiment.

experiment	meanRR ms	SDRR ms	pRR50 %	RMSSD ms	LF ms ²	HF ms ²	LF/HF
rest	810,77	52,01	0,19	37,28	494,43	482,47	1,45
recording	799,25	48,53	0,11	30,64	669,18	217,06	4,35
simulation	809,98	48,79	0,1	30,15	664,18	195,09	4,43
fall	881,74	63,51	0,26	55,16	725,71	579,63	1,54

In Table 3.5, the different parameters of the heart rate variability of each of the subjects during the rest recording can be seen.

Table 3.5: Heart rate variability of each subject during rest recording.

subject	meanRR ms	SDRR ms	pRR50 %	RMSSD ms	LF ms ²	HF ms ²	LF/HF
S1	817,3	47,52	0,04	23,64	294,36	128,06	2,3
S3	774,73	52,54	0,07	27,95	596,13	235,3	2,53
S8	777,99	51,95	0,1	29,81	594,38	331,05	1,8
S9	967,93	64,84	0,5	58,52	771,01	891,06	0,87
S10	816,81	67,96	0,45	59,77	445,36	1.307,56	0,34
S7	774,27	55,16	0,28	44,04	702,84	494,47	1,42
S4	843,39	50,5	0,05	73,48	132,16	441,22	0,3
S5	627,19	39,06	0,03	24,31	284,53	238,01	1,2
S6	929,91	37,09	0,07	30,22	266,82	234,26	1,14
S2	839,89	58,88	0,22	46,24	815,66	443,78	1,84

Table 3.6 represents the parameters of the heart rate variability for each participant during the recording part of the study. Three sessions of 200 seconds were recorded. Since the length of the recorded ECG data needed to be the same to make the HRV parameters comparable, the mean of the three sessions was calculated.

Table 3.6: Mean heart rate variability of each subject during classifier training.

subject	meanRR ms	SDRR ms	pRR50 %	RMSSD ms	LF ms ²	HF ms ²	LF/HF
S1	819,8	47,52	0,07	26,39	576,17	127,45	4,67
S3	782,67	44,01	0,05	24,18	505,83	110,85	4,65
S8	785,92	50,03	0,07	27,45	836,03	130,12	6,14
S9	823,41	50,71	0,12	32,42	790,54	223,45	4,95
S10	800,98	49,63	0,12	32,63	713,87	258,6	4,17
S7	805,78	50,67	0,16	35,51	698,38	314,49	3,65
S4	813,46	50,27	0,15	34,54	673,24	287,7	3,71
S5	790,86	48,55	0,13	33,08	623,66	273,15	3,45
S6	801,61	47,13	0,12	32,36	586,51	260,74	3,28
S2	798,25	48,84	0,13	32,81	683,74	253,36	3,87

Table 3.7 represents the parameters of the heart rate variability for each participant during the simulation. Two sessions of 200 seconds were recorded. Since the length of the recorded ECG data needed to be the same to make the HRV parameters comparable, the mean of the three sessions was calculated.

Table 3.7: Mean heart rate variability of each subject during simulation.

subject	meanRR ms	SDRR ms	pRR50 %	RMSSD ms	LF ms ²	HF ms ²	LF/HF
S1	839,75	48,01	0,1	28,86	544,68	153,02	4
S3	808,19	46,06	0,07	26,61	537,23	135,69	4,28
S8	799,51	48,4	0,08	27,33	699,51	136,32	5,17
S9	814,04	49,6	0,1	29,83	733,15	177,3	4,99
S10	808,14	49,69	0,11	30,85	724,46	207,72	4,67
S7	808,88	50,01	0,13	32,4	714,86	240,24	4,35
S4	810,57	50,09	0,13	32,83	700,12	250,09	4,17
S5	805,23	49,71	0,13	32,84	680,16	255,17	4,00
S6	805,28	49,13	0,13	32,71	659,67	255,44	3,85
S2	804,33	49,22	0,13	32,81	668,71	255,85	3,85

Table 3.8 represents the parameters of the heart rate variability for each participant during the last part of the experiment. 20 trials of 20 seconds were recorded. Since the length of the recorded ECG needed to be same for each of the different parts to make the HRV parameters comparable, the different trials were merged together at the R-peaks. The ECG electrodes of S2 and S4 stopped working during this part of the study and thus the HRV parameters could not be calculated correctly.

Table 3.8: Mean heart rate variability of each subject during simulation.

subject	meanRR ms	SDRR ms	pRR50 %	RMSSD ms	LF ms ²	HF ms ²	LF/HF
S1	901,79	53,95	0,23	51,82	710,52	433,26	1,64
S3	855,31	54,33	0,24	41,53	553,62	234,73	2,36
S8	837,14	74,29	0,18	47,45	1398,61	349,46	4
S9	1007,04	47,39	0,31	48,57	310,46	399,53	0,78
S10	839,07	89,57	0,37	60,88	855,08	795,35	1,08
S7	950,39	53,92	0,45	58,83	402,63	637,39	0,63
S4	#	#	#	#	#	#	#
S5	675,3	35,86	0,04	24,16	168,37	170,54	0,99
S6	987,93	98,76	0,31	108,09	1406,38	1616,79	0,87
S2	#	#	#	#	#	#	#

4

Discussion

In this thesis, we could show that a BCI can be controlled in acute stress situations using a brisk foot movement as a motor imagery. Seven out of the ten subjects showed a PMBERS. All of them were able to fulfill the mental task at least 14 out of 20 times. Besides the performance of the subjects, the increase of their stress level was also analyzed. Therefore, a questionnaire was evaluated and the heart rate variability was investigated.

4.1 Random Forest vs. Common Spatial Pattern + Random Forest

The combination of a CSP and a RF significantly increases the classification accuracy compared to only the RF classifier, which agrees with the study of Steyrl et al. [36]. The mean of the classification accuracy of the CSPRF classifier trained on the different seconds is statistically not different. Hence, for the later study the second on which the classifier was trained was chosen based on the ERD/S maps instead of calculating a five times five cross validation each time.

4.2 Hardware

To perform the experiment, a notebook with Windows 10 as an operating system, an Intel Core i7 and 6GB of RAM was used. To control the two servo motors, two Raspberry Pis which were connected to the laptop via WiFi were used. The communication between the computer and the Raspberry Pis worked without time loss, so the servo motors could be controlled in real time. With this setup no performance issues occurred during the experiment. Since the BCI system did not need any special equipment, it could be easily performed in the foyer of the Biomedical Engineering Building at the Graz University of Technology.

4.3 Experimental Setup

To perform this experiment it was necessary to build a setup so it could be performed outside the laboratory. The umbrella fell down along a steel rope which was fixated on a wooden brick in the fifth floor and the brick was mounted on the handrail. The umbrella was released by a servo motor which was controlled by a Raspberry Pi. The same mechanism was used to open the umbrella while falling. WiFi was used to send commands from the laptop to the user. The setup and the system were tested before starting the experiment and proved to be very robust and reliable.

4.4 Pilot Experiment

The pilot experiment at the 7th Graz BCI Conference 2017 showed that it is possible to perform the experiment as planned. The pilot was able to open the umbrella in each of the five repetitions. This showed that people are able to focus in a noisy environment, compared to the measurement box. The pilot was able to concentrate and perform very well, even though there were people around watching and talking to each other. The countdown, which indicated when the parachute started to fall, was removed for two reasons. First, the participants were not able to start the MI too early since they did not know when it would fall. Second, the stress level increased because of this uncertainty and thus they had to focus more on the task so they would not miss when the parachute starts to fall.

4.5 Performance

Time-frequency maps were calculated for each participant. Based on those maps, the second in which the classifier should be trained was chosen. As seen in Figures 3.3 to 3.12, seven out of the ten subjects showed an event-related synchronization in the β -band at channel Cz. This is conform with the studies concerning ERS of the PMBERS Pfurtscheller et al. [41]. The second in which the event-related synchronization was the strongest was chosen to train the classifier. For the three subjects who did not show any significant event-related synchronization, second 2.5 to 3.5 after the cue are chosen to train the random forest. Artifacts in the μ -band, as can be seen in Figures 3.4, 3.7, 3.8 and 3.11, did not influence the training of the classifier because it was only trained on the β -band.

Table 3.1 shows the high score list of this experiment. Nine of the subjects were able to open the parachute at least 14 times, which means that they performed at least as good as chance level (70%). One of the subjects who did not show a PMBERS was able to open the parachute 20 times. The reason for that could be that the classifier was not able to differentiate between “rest” and MI since there was no clear PMBERS. The subject who performed worst was able to open the umbrella 14 times even though PMBERS could be seen in the ERD/S maps (Figure 3.4). The poor performance might be attributed to an increase of the stress level or less concentration than in the beginning of the measurement.

When looking at accuracy plots (Figure 3.13 to 3.21), it can be seen that five out of the ten subjects showed a clear increase in the detection of the brisk foot movement after the rectangle or the parachute started to fall. The classifier output for the subjects who did not show a PMBERS is around chance level which means that the classifier was not able to distinguish between “rest” and motor imagery. Despite the fact that two subjects showed clear PMBERS in ERD/S maps high classification accuracy could not be achieved. This might be the case because of changes in performing the mental strategy or timing changes. By comparing the accuracies of the second and third part, it can be seen that the detection of motor imagery increases around two seconds later in the third part. The reason for this might be a difference in the processing of visual and auditory cues. Furthermore, three of the five participants were not able to perform better than chance level, even though their accuracy plots indicate that they were able to control the BCI. There are two possible reasons for this: first, the chance level for this experiment was very high, namely 62.5% for the simulation and 70% for the part in which the parachute fell down. Due to the small number of trials in the two parts of the experiment. Second, the timing of imagining the brisk foot movement was not same within the runs, so in one trial the PMBERS

appears earlier than in others. Since the PMBERS lasts for approximately two seconds the classifier output can be blurred if the timing varies within the trials. S7 achieved the highest accuracy in the simulation as well as in the last part of the experiment. Also, the PMBERS of this participant is very prominent and it lasted for four seconds. Hence, timing differences within the trials did not have a large influence on the classifier output.

Looking at the analysis of the questionnaire in Tables 3.2 and 3.3, one can see that the subjective level of stress as well as the level of nervousness increased during the different parts of the experiment. All of the subjects felt more stressed before the second part compared to the first part and all except one felt more stressed before the third part compared to the second part. The same is true for the nervousness of the participants.

The heart rate of the participants was higher in the beginning of the experiment than during the simulation or the part where the umbrella fell down. The heart rate of four participants was higher during the first run of the simulation. In the first five trials of the fall experiment however, nine out of the ten subjects had a higher heart rate. One possible reason for this could be that the participants were more stressed because of the unfamiliar situation. After the first trials, they knew what was happening and they were more confident about their performance because they were able to control the parachute during the first trials.

According to Castaldo et al. RMSSD, meanRR, pRR50, SDRR and HF decrease during stress whereas LF and the ratio from LF to HF increase in stressful situations [16]. When looking at Table 3.4, it can be seen that our findings agree with this if the rest is compared to recording and to the simulation. However, if the rest is compared to the fall, our results agree just partially. A possible reason for this could be that according to the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology HRV parameters which are compared to each other must have the same length [15]. Thus, the trials of the last part of the experiment had to be merged to get one ECG stream of 200s. This could have influenced the calculation of the HRV parameters. Another possible reason could be that the pauses between the trials were relatively long compared to the length of the trials. Also, the parasympathetic and the sympathetic nervous systems needed some time to adapt to new situations and thus it is possible that the length of one trial was too short for their adaptation. Although, it would be interesting to compare the stress level of the simulation to the stress level of the last part of the experiment this is not possible because of the reasons mentioned before. The comparison of the individual HRV parameters, which are displayed in Table 3.5, 3.6 and 3.7 of the rest compared to recording and the rest compared to the simulation based on LF shows that the parameters of eight out of the ten participants agree with the findings of Castaldo et al. [16]. A comparison between the individual HRV parameters of the rest recording compared to the last experiment shows that five of the participants showed an increase of the LF.

4.6 Further Improvements

Several points for further improvements for pursuing experiments can be addressed.

First of all, the pause within the different trials of the last part of the experiment was very long compared to the length of the trial. It could be possible to combine the releasing mechanism with a rope winch. This way, the experiment can be executed by only one person because there is no need to attach it to servo motor again. Also other experiments which are performed under stress can be executed.

Second, there are more possibilities to measure if participants are stressed. Apart from the heart rate and the HRV also the skin conductance, the cortisol level in salivary or blood and the size

of the pupils can assess stress levels. The skin conductance can be measured by devices which can be combined to the EEG system. To measure the level of cortisol it is necessary that saliva or blood samples are analyzed by a laboratory. The change of size of the pupil can be measured using a camera.

Another interesting aspect for further experiments would be to find out if people are also able to control a BCI with more than one class. For example, experiments in which participants have to control an robot arm or a prosthesis under time pressure could be performed.

5

Conclusion

The goal of this thesis was to show that users are able to reliably control a brain-computer interface under acute stress. Therefore, an experiment in which participants feel stressed needed to be planned. The idea was to open a parachute while it fell down from the fifth floor of the Biomedical Engineering Building of the University of Technology. A PMBERS was chosen as mental task because it appears approximately one second after a motor imagery and thus the participants had just one chance to open the parachute. To be sure that the experiment works as it was planned, a pilot study at the 7th Graz BCI conference was performed. In the study nine out of ten participants were able to open the parachute 15 times. According to the questionnaire all of them felt more nervous and nine of them felt more stressed in the last part of the experiment. The calculated parameter also showed that the stress level increased from the rest recording to the simulation but they do not indicate that the stress level was higher during the last part of the experiment.

All in all, the results of this study show that a BCI can be controlled by users in acute stress situations and the findings can be used to proceed the research in this direction.

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6

Appendix

In this Chapter, the questionnaires which were filled out by each of the participants can be found.

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
 not at all very much

How stressed are you because of the experiment?
 not at all very much

How nervous are you in general?
 not at all very much

How nervous are you because of the experiment?
 not at all very much

Part II

Are you more stressed now than before the first part?
 not at all very much

Are you more nervous now than before the first part?
 not at all very much

Part III

Are you more stressed now than before the second part?



Are you more nervous now than before the second part?



Do you want to perform better than the other participants?



How stressed are you because of the competition?



Part IV

Did you like the experiment?

yes

no

Did you try to perform better because of the competition?

yes

no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?

not at all  very much

How stressed are you because of the experiment?

not at all  very much

How nervous are you in general?

not at all  very much

How nervous are you because of the experiment?

not at all  very much

Part II

Are you more stressed now than before the first part?

not at all  very much

Are you more nervous now than before the first part?

not at all  very much

Part III

Are you more stressed now than before the second part?

_____ not at all very much

Are you more nervous now than before the second part?

_____ not at all very much

Do you want to perform better than the other participants?

_____ not at all very much

How stressed are you because of the competition?

_____ not at all very much

Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?

not at all very much

How stressed are you because of the experiment?

not at all very much

How nervous are you in general?

not at all very much

How nervous are you because of the experiment?

not at all very much

Part II

Are you more stressed now than before the first part?

not at all very much

Are you more nervous now than before the first part?

not at all very much

Part III

Are you more stressed now than before the second part?



Are you more nervous now than before the second part?



Do you want to perform better than the other participants?



How stressed are you because of the competition?



Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?

not at all _____ very much

How stressed are you because of the experiment?

not at all _____ very much

How nervous are you in general?

not at all _____ very much

How nervous are you because of the experiment?

not at all _____ very much

Part II

Are you more stressed now than before the first part?

not at all _____ very much

Are you more nervous now than before the first part?

not at all _____ very much

Part III

Are you more stressed now than before the second part?

_____ X
not at all very much

Are you more nervous now than before the second part?

_____ X
not at all very much

Do you want to perform better than the other participants?

_____ X
not at all very much

How stressed are you because of the competition?

_____ X
not at all very much

Part IV

Did you like the experiment?

yes

no

Did you try to perform better because of the competition?

yes

no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
not at all _____ very much

How stressed are you because of the experiment?
not at all _____ very much

How nervous are you in general?
not at all _____ very much

How nervous are you because of the experiment?
not at all _____ very much

Part II

Are you more stressed now than before the first part?
_____ very much
not at all

Are you more nervous now than before the first part?
_____ very much
not at all

Part III

Are you more stressed now than before the second part?

_____ very much
not at all

Are you more nervous now than before the second part?

_____ very much
not at all

Do you want to perform better than the other participants?

_____ very much
not at all

How stressed are you because of the competition?

_____ very much
not at all

Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?

 not at all very much

How stressed are you because of the experiment?

 not at all very much

How nervous are you in general?

 not at all very much

How nervous are you because of the experiment?

 not at all very much

Part II

Are you more stressed now than before the first part?

 not at all very much

Are you more nervous now than before the first part?

 not at all very much

Part III

Are you more stressed now than before the second part?

not at all  very much

Are you more nervous now than before the second part?

not at all  very much

Do you want to perform better than the other participants?

not at all  very much

How stressed are you because of the competition?

not at all  very much

Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
_____ not at all very much

How stressed are you because of the experiment?
_____ not at all very much

How nervous are you in general?
_____ not at all very much

How nervous are you because of the experiment?
_____ not at all very much

Part II

Are you more stressed now than before the first part?
_____ not at all very much

Are you more nervous now than before the first part?
_____ not at all very much

Part III

Are you more stressed now than before the second part?



Are you more nervous now than before the second part?



Do you want to perform better than the other participants?



How stressed are you because of the competition?



Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
~~X~~ _____ very much
not at all

How stressed are you because of the experiment?
_____ very much
not at all

How nervous are you in general?
~~X~~ _____ very much
not at all

How nervous are you because of the experiment?
~~X~~ _____ very much
not at all

Part II

Are you more stressed now than before the first part?
_____ very much
not at all

Are you more nervous now than before the first part?
_____ very much
not at all

Part III

Are you more stressed now than before the second part?

not at all  very much

Are you more nervous now than before the second part?

not at all  very much

Do you want to perform better than the other participants?

not at all  very much

How stressed are you because of the competition?

not at all  very much

Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

SA

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
_____ not at all very much

How stressed are you because of the experiment?
_____ not at all very much

How nervous are you in general?
_____ not at all very much

How nervous are you because of the experiment?
_____ not at all very much

Part II

Are you more stressed now than before the first part?
_____ not at all very much

Are you more nervous now than before the first part?
_____ not at all very much

SA-1

SA-2

Part III

Are you more stressed now than before the second part?



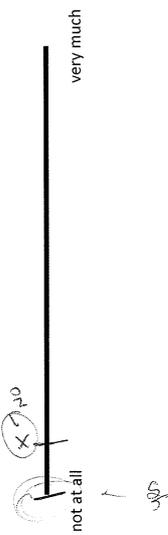
Are you more nervous now than before the second part?



Do you want to perform better than the other participants?



How stressed are you because of the competition?



Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no

Master Thesis's Questionnaire

Have you participated in a BCI experiment before? yes no

How stressed are you in general?
_____ not at all very much

How stressed are you because of the experiment?
_____ not at all very much

How nervous are you in general?
_____ not at all very much

How nervous are you because of the experiment?
_____ not at all very much

Part II

Are you more stressed now than before the first part?
_____ not at all very much

Are you more nervous now than before the first part?
_____ not at all very much

Part III

Are you more stressed now than before the second part?

not at all  very much

Are you more nervous now than before the second part?

not at all  very much

Do you want to perform better than the other participants?

not at all  very much

How stressed are you because of the competition?

not at all  very much

Part IV

Did you like the experiment?

yes no

Did you try to perform better because of the competition?

yes no