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EEG BIOFEEDBACK APPLICATION

APLIKACE PRO EEG BIOFEEDBACK

MASTER'S THESIS

DIPLOMOVÁ PRÁCE

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Master's Thesis Specification



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Assignment:

1. Get acquainted with the topic of electroencephalogram (EEG) analysis for the purposes of biofeedback in the area of stress, focus, anxiety or depression and study machine learning methods for EEG signal recognition.
2. Design your own implementation of EEG signal recognition and an application, which will allow users to train stress reduction, anxiety reduction, focus, detect depression etc. It is sufficient to focus on a single variant. Design a case study inspired by case studies in relevant psychological literature and consider it in your implementation design.
3. Implement the designed solution and conduct the case study including experiments in various situations, if the epidemiological situation allows for it.
4. Review achieved results, discuss them, suggest possible continuations of your work and present main features of your work with a short video and a poster.

Recommended literature:

- Wolpaw, J. and Wolpaw, E. W., eds. Brain-computer interfaces: principles and practice. Oxford University Press, 2012. ISBN 978-0-19-538885-5.
- Siuly, S., Li, Y. and Zhang, Y. EEG Signal Analysis and Classification. Springer International Publishing, 2016. Health Information Science. ISBN 978-3-319-47652-0. Available from: <http://link.springer.com/10.1007/978-3-319-47653-7>.
- Cohen, M. X. Analyzing neural time series data: theory and practice. The MIT Press, 2014. Issues in clinical and cognitive neuropsychology. ISBN 978-0-262-01987-3.
- Luck, S. J. An introduction to the event-related potential technique. Second edition. The MIT Press, 2014. ISBN 978-0-262-52585-5.

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Abstract

This work is a summary of current approaches to EEG signal processing for EEG biofeedback purposes and contains a design and implementation details of a custom EEG biofeedback application for attention training. It is accompanied by a case study, which evaluates the effects of the application on measured EEG signals of a neurotypical student and a student with ADHD.

Abstrakt

Tato práce je shrnutím existujících přístupů pro zpracování EEG signálu za účelem EEG biofeedbacku a dále popisuje návrh a implementaci vlastní aplikace pro EEG biofeedback se zaměřením na trénink pozornosti. Dále obsahuje případovou studii provedenou na neurotypickém studentovi a studentovi s ADHD, která zkoumá vliv implementované aplikace na měřený EEG signál subjektů.

Keywords

EEG, Biofeedback, Neurofeedback, Attention Training, ADHD

Klíčová slova

EEG, Biofeedback, Neurofeedback, Trénink pozornosti, ADHD

Reference

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Rozšířený abstrakt

Tato práce se zabývá návrhem a tvorbou neurofeedbackové aplikace pro trénování pozornosti. Neurofeedback je proces, během něž uživatel provádí nějakou činnost, která může být jak mentálně náročná, tak i třeba meditativní, při níž je napojen na EEG snímací zařízení. Mozková aktivita tohoto uživatele je v průběhu činnosti monitorována a analyzována za účelem rozlišení mentálního stavu uživatele. Ten dostává zpětnou vazbu ve vizuální či zvukové podobě na základě toho, zdali jeho mentálně stav splňuje nějaké nastavené požadavky — třeba že je ve stavu aktivního soustředění. Tato zpětná vazba slouží k tomu, aby se uživatel naučil svůj mentální stav identifikovat, či ovládat. Neurofeedback se obvykle zaměřuje na trénování či odhalení nějakého specifického mentálního stavu, kupříkladu pozornosti či deprese. Obvykle se dělí na aktivní a pasivní. Při aktivním uživateli svou mozkovou aktivitou přímo ovládá nějakou aplikaci a při pasivním je pouze monitorován zatímco provádí nějakou činnost. Neurofeedback je obvykle prováděn po delší dobu, přes mnoho sezení, která trvají různou dobu podle toho, co je cílem daného tréninku. Při tréninku obvykle bývá cíleno na posílení či potlačení nějakého specifického frekvenčního pásma mozkové aktivity. Tato pásma jsou:

- Delta(0.5-4Hz) — Indikuje NREM spánek.
- Théta(4-8Hz) — Indikuje zasnění, hlubokou relaxaci, meditaci
- Alfa(8-14Hz) — Indikuje klidné soustředění, relaxaci
- Sensorimotorický rytmus(12—16Hz) — Indikuje soustředění, fyzickou relaxaci
- Beta(16-30Hz) — Indikuje silné soustředění, neklid, úzkost, stres
- Gamma(>30Hz) — Indikuje stres, úzkost, vzrušení, paměťovou retenci

Implementovaná aplikace se zaměřuje na trénink pozornosti a snaží se tedy u uživatelů posilovat výkon sensorimotorického rytmu(SMR). Pro měření EEG signálu je využito 16-ti kanálové zařízení Cython s rozšířením Daisy, od společnosti OpenBCI. Ke snímání je využito headsetu Ultracortex Mark IV se suchými špičatými elektrodami od téže společnosti. Zpracování signálu je dosaženo pomocí open source knihovny brainflow. Signál je nejprve zbaven síťového šumu na 50Hz, následně pomocí pásmové propusti ořezán na interval 1-30Hz. Nakonec jsou z něj odděleny výkony jednotlivých frekvenčních pásem. Aplikace následně převádí výkon SMR pásma na feedback pomocí jednoduchého prahového klasifikátoru. Hodnota výkonu je porovnávána vůči vnitřnímu prahu, který je v čase automaticky modifikován tak, aby reagoval na úspěšnost uživatele buď svým snížením nebo zvýšením. Pokud je práh překonán, uživateli je poskytnuta pozitivní zpětná vazba. Aplikace poskytuje vizuální zpětnou vazbu v podobě jednoduché hry. Uživatel hraje roli čarodějova učně, který se učí nová kouzla. Každé trénovací sezení sestává z odehrání jedné scény hry, která trvá v průměru 4 minuty. Každá scéna je rozdělena na 3 části. V první části uživatel "kreslí" symbol kouzla — na obrazovce je kurzor v podobě ruky s tužkou, který odkrývá obrázek jako pozitivní zpětnou vazbu. Druhá část zpočívá v učení kouzla, kdy je uživateli zobrazen nakreslený symbol a jako zpětná vazba se rozsvěcuje a vysílá částice. Po udržení pozornosti po stanovenou dobu se přejde do poslední části. Zde je uživatel postaven před nějaký objekt na který má kouzlo seslat, přičemž jako pozitivní efekt zde slouží postupné aplikování efektu kouzla. Jakmile uživatel dokončí třetí část, sezení končí.

Součástí této práce byla také případová studie, která měla za úkol zhodnotit efekt aplikace na uživatele. byla provedena na dvou studentech, z nichž jeden trpí ADHD a druhý je neurotypický. Tato studie analyzovala hodnoty výkonu SMR pásma, hodnotu prahu aplikace, poměr pásem SMR a Théta a pásma SMR a vyšší frekvenční části Bety. Výsledky studie neprokázaly žádné jednoznačné změny v mozkové aktivitě ani jednoho z uživatelů.

EEG Biofeedback Application

Declaration

I hereby declare, that I worked on this project alone under the supervision of Ing. Jan Tinka. I have disclosed all the literary sources, publications and other sources used.

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Jakub Zapletal

July 27, 2021

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Chapter 1

Introduction

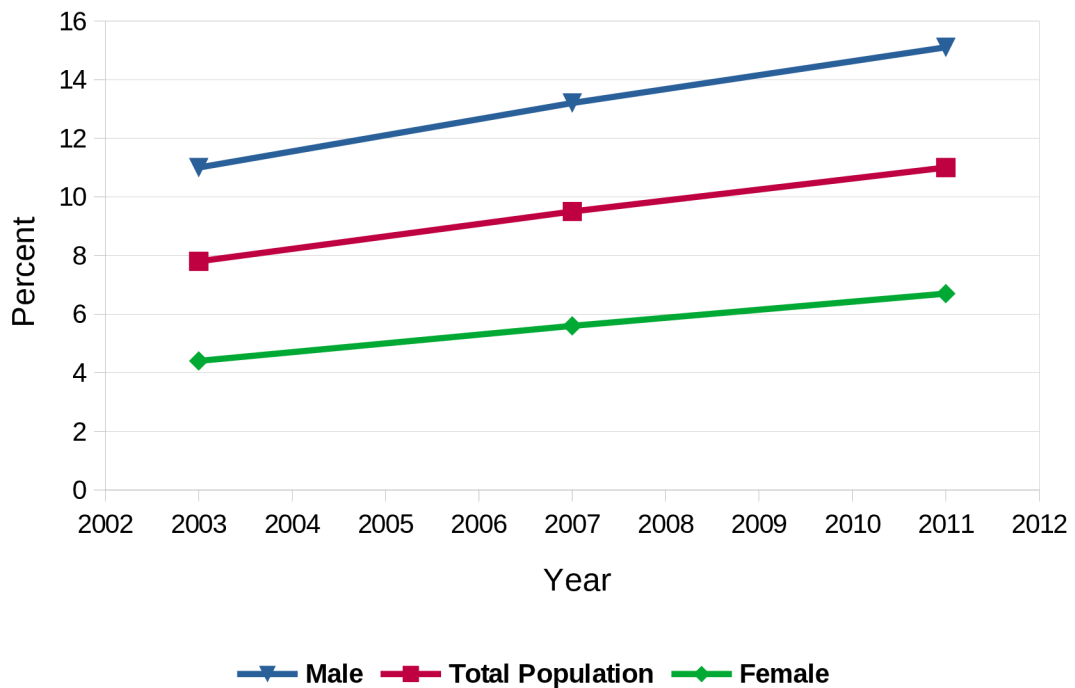


Figure 1.1: Trend of ADHD diagnoses in American children, aged 4-17. (American national institute of mental health)[30]

Attention Deficit Hyperactivity Disorder (ADHD)[1] and ADHD-like problems are a fairly common occurrence among the population. This attention deficit disorder causes serious problems in day-to-day life of affected individuals, often without the person ever being properly diagnosed. Formerly, ADHD was only diagnosed in children and was thought to dissipate, coming adulthood. While that can happen, as much as third of affected children retain their ADHD through adulthood, often with other comorbid diagnoses¹[5]. In recent years, statistics of ADHD-impaired children are rising as can be seen illustrated on figure 1.1. Traditionally, attention deficit disorders are treated using medications such as Strattera or Adderall, which are unfortunately sometimes accompanied by side effects ranging from

¹Comorbidities are additional conditions appearing alongside a primary condition. In the case of ADHD, common comorbidities can be anxiety or depression.

annoying to severely impairing the individual. Some people may never find an appropriate prescription to help them, resulting in them having to cope with ADHD symptoms only using therapy. However, research suggests that a non-invasive treatment of ADHD could be performed via electroencephalography (EEG) biofeedback training, commonly referred to as neurofeedback[3]. This method has the patient be monitored via EEG equipment while performing a specific mental task during a training session. During the task, measured brain activity can show when the patient is in a state of distraction, inattention or anxiety. They can then be alerted of the fact, so that they can correct themselves. This feedback can be given in a variety of ways, from simple audio blips to gamified audio-visual applications. Thus, the patient can be trained to recognize when they are in such a state and how to counter it.

This work documents the underlying approaches and technology behind electroencephalography and attention-focused neurofeedback training and maps the design and implementation of a neurofeedback training application using gamification. The application is developed in the Unity3D game engine and utilizes SMR power band enhancement training[12]. A case study involving one ADHD-diagnosed university student and one neurotypical university student has been performed to evaluate the effectiveness of the application in attention training. The recorded data and their analysis are also contained in this work.

Chapter 2

Neurofeedback for Attention Training

Electroencephalography (EEG) serves as a method of reading signals from the brain. This technology sees broad use not only in neurological sciences, medicine or psychiatry but also in the field of brain-computer interfaces (BCIs) which develops methods for controlling the computer via brain signals.

One of the applications of EEG is that of neurofeedback training. Neurofeedback training is a process, during which a user, monitored via EEG monitoring device, performs a specifically designed task. During this task, the user's brain activity is monitored and analyzed in order to decipher the user's current mental state. The ultimate goal of neurofeedback training is to teach the user to identify when they are in a specific mental state and how to control their brain activity in order to attain this state or to get out of it. Ideally, the user should then be able to do this instinctively, leading to long-term normalization of their anomalous brain activity. Neurofeedback training regimens employ a variety of possible training protocols, targeting different frequency bands, depending on what mental state should the user be trained to better control. Most common applications of neurofeedback nowadays are neurofeedback protocols for attention training[11], stress control[15] and anxiety control[7]. Other notable applications are neurofeedback regimens for epilepsy patients[20], schizophrenia patients[21] or a method of training paralyzed patients in using BCIs. The users are taught to control their brains with the help of provided feedback. This feedback can be in a variety of audio, visual or audio-visual forms.

This chapter explores the different main brain wave frequency bands, along with their significance for neurofeedback training in general. Then, common attention training neurofeedback protocols, targeting specific frequency bands, are presented. Lastly, the types of possible feedback that neurofeedback applications can provide is summarized.

2.1 Brain Wave Frequency Bands and Their Relation to Neurofeedback Training

Depending on what is the focus of neurofeedback training, different brain wave frequency bands are targeted. What follows are summaries of the main frequency bands, their significance for neurofeedback in general and their role in attention training regimens. Also listed for bands focused during biofeedback regimens are the usual scalp regions as seen on figure 2.1 where electrodes are placed when said frequencies are recorded.

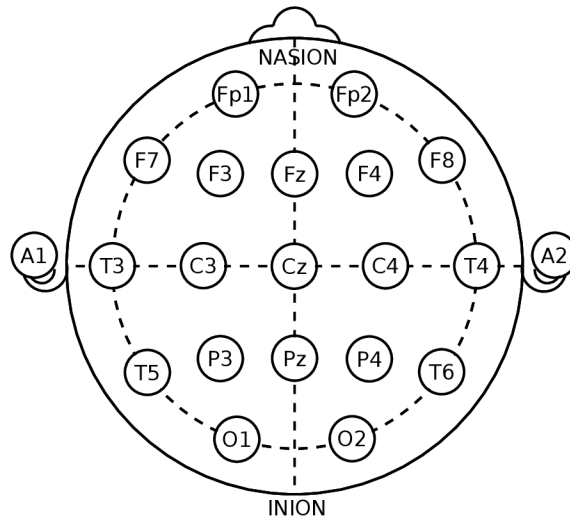


Figure 2.1: The 10-20 electrode placement system.

Delta

- **Frequency Range:** 0.5-4Hz
- **General Characteristics:** NREM sleep, waking up

Delta waves appear during NREM sleep and are indicative of the specific stage of NREM sleep subject is currently in depending on how much of brain activity as a whole is composed of them. It is also an important indicator of a range of disorders, with the occurrence of specific waveforms in the Delta frequency acting as the indication. E.g., K-complex waveforms¹ occurring at the start of a seizure. Delta waves are not used when training for attention.

Theta

- **Frequency Range:** 4-8Hz
- **General Characteristics:** daydreaming, deep relaxation, meditation, sleepiness, arousal in adults
- **Scalp Regions:** O1, O2, Pz

Theta waves are generally observed when one is in a state of sleepiness or tiredness and about to fall asleep or when daydreaming. During training, it can be desirable to either enforce it, when the goal is stress or anxiety management, or suppress it, when training for attention.

Alpha

- **Frequency Range:** 8-14Hz
- **General Characteristics:** passive attention, peacefulness, meditation, deep relaxation, most prominent when eyes are closed

¹A waveform normally occurring during stage 2 of NREM sleep.

- **Scalp Regions:** F3, F4, P3, P4, O1, O3, O2, Fz, Pz, Oz

Alpha waves are mostly targeted in biofeedback regimens with the goal of stress or pain control. For attention purposes, alpha can indicate passive attention without specific focus.

Sensorimotor Rhythm / Mu Rhythm / Low-Beta

- **Frequency Range:** 12-16Hz
- **General Characteristics:** mental alertness, physical relaxation, inhibited by motor activity
- **Scalp Regions:** C3, C4

Sensorimotor rhythm(SMR) a.k.a. Mu rhythm is a frequency band located in the frequencies of Low-Beta. This band indicates a state of calm concentration and as such is in some attention training regimens enforced. SMR is also naturally suppressed during motor activity, whether it is actually performed or even imagined. Because of this suppression, SMR is used in biofeedback applications as a control scheme of an application via imaginary movement, often in addition to VR[36]. This application control method is called Motor Imagery and will be discussed in later parts of the project. SMR enforcement is generally desirable for both attention training and stress and anxiety management training.

Beta

- **Frequency Range:** 16-30Hz
- **General Characteristics:** strong concentration, high energy, stress, anxiety
- **Scalp Regions:** Pz, C4, C3, Cz

Beta, in some works separated into Beta(16-20Hz) and High-Beta(20-30Hz), waves are the go-to indicator of focus and alertness and as such are generally the focus of attention training. They are, however, also an important indicator of stress and anxiety and thus are inhibited during stress management training. In attention training regimens, the Beta waves are enforced in order to achieve a state of focus.

Gamma

- **Frequency Range:** >30Hz
- **General Characteristics:** memory retention, focus, attention, learning, stress, anxiety, high arousal
- **Scalp Regions:** Oz

Gamma waves have demonstrated relevance for several cognitive processes, such as perception, learning and memory. Studies have been done, exploring, whether gamma training can enhance intelligence[17] or perceptual processing[26] with some promising results. Biofeedback training of the Gamma frequency band is not as common as stress or attention regimens, however. This is in part due to difficulties in separating the Gamma waves from muscle-activity interference(20-300Hz), which it is entirely overlapped by. This strong interference needs to be resolved before any actual research conclusions into Gamma biofeedback training can be made.

2.2 Attention Training Protocols

In general, neurofeedback attention training protocols consist of a number of sessions, usually in the tens, with frequency of one or two per week. The length of each session can also vary, depending on the neurofeedback application used and on the user. Common lengths are between 30 minutes and an hour. Different approaches need to be taken for example when working with children because of their shorter attention span and the fact that they often undertake neurofeedback training not of their own volition.

Typical session starts with a pre-training EEG screening to determine baseline threshold values of the monitored brain frequency bands. This is absolutely necessary to do, as these values depend on many changing factors such as the user's mood, how tired they are, if they are in any stress, etc. The session itself then consists of the user controlling the neurofeedback training application. During the training, supervising person monitors brain activity of the user. Some applications, for example at the VUT's Alfons student help center², allow the supervising person to modify the target thresholds on the fly. This is done, so the user is not discouraged if they are not very successful during the session, as their willingness to participate is an important factor in the effectivity of neurofeedback training. If the training session is long, or when working with children, breaks can be made during. After the training session, the supervisor finishes with a short evaluation of the user's performance.

There are three common attention training protocols:

- **Theta/Beta** — Protocol aiming to suppress Theta level and enhance Beta. Probably the most common attention training protocol. In some cases, Low-Beta is targeted instead of Beta.
- **Theta/SMR** — Protocol aiming to suppress Theta level and enhance SMR. This training protocol tries to improve calm focus without increasing anxiety and stress, which are indicated by higher Beta frequencies. Can be used alongside Theta/Beta protocol.
- **Alpha/Beta** — Protocol aiming to enhance Alpha frequency band and regulate Beta. This is usually done when the goal is anxiety treatment. It can, however have positive impact for attention also. Mainly because anxiety is a very common comorbidity to ADHD, with intrusive thought as a common symptom affecting both disorders[1].

2.3 Approaches and Methods in Attention-Focused Neurofeedback Training Applications

Neurofeedback for improving user's attention generally falls under the so-called high-frequency neurofeedback. This means that it focuses on amplifying higher-frequency bands — Low-Beta, Beta, governing alertness and focus, while impeding or regulating lower ones — Theta, sometimes Alpha, governing relaxation and distraction. Neurofeedback then usually follows one of two primary approaches, those being **biofeedback monitoring** (a.k.a. passive biofeedback) and **biofeedback training** (a.k.a. active biofeedback), which differ in the way the user interacts with the feedback application.

²VUT's Alfons student help center — <https://alfons.vutbr.cz>

Passive Biofeedback

Passive biofeedback has the user performing a mental task, such as studying educational materials, while they are monitored by EEG equipment. During this task, feedback is provided to them in the forms of audio feedback, visual feedback, tactile feedback or a combination thereof. As the feedback's effect is only informative, the user needs to be taught how to interpret the feedback given, so that they can adequately react to it.

Passive visual feedback usually consists of a variety of dynamic graphs on a screen, displayed in such a way, that the user can at a glance evaluate their current state. Audio feedback works off of a threshold, set at the beginning of a training session, derived from the user's overall mental state at that particular time. When the values of monitored frequency bands are below or above the threshold, a repeated auditory cue is played as a form of negative or positive feedback respectively. This cue informs the user of their current attention state. The feedback can either be simple, just playing a sound when threshold is or is not met, or more complex, with different sounds for specific frequency bands or multiple thresholds. Audio and visual feedback are often combined. Tactile feedback affects an instrument the user is using to perform their task. For example, [2] uses a modified game controller to provide feedback. The user plays an unmodified commercial video game, while the biofeedback application modifies the responsiveness(vibrations, precision of controls) of the game controller depending on the user's attention level. The overall goal of passive biofeedback applications is to incite in the user a feeling of relaxed attention.

Active Biofeedback

In active biofeedback training, the user, instead of simply being monitored while accomplishing a task, actively controls the application through their brain. The tasks of one or more objects on screen, that change position, shape, color or other characteristics based on user's brain activity. This approach often utilizes gamification³ to make the tasks the application throws at the user as appealing as possible. Motor imagery(MI) is a specific form of control scheme utilized for active biofeedback. MI uses the fact, that imaginary motor movement has a noticeable effect on the SMR frequency band in the form of its suppression. This is a useful thing for gamified applications, because it increases the user's level of immersion into the game, thus making focus on it easier. MI games can be paired with virtual reality(VR) headsets to further improve immersion and filter out the environment. This can for example produce a simple flight simulator game[36], where the user is in a cockpit and through imagining simple arm movement controls the plane or spaceship. The disadvantage of MI is that it can be very difficult to get the user to a point where they can actually imagine the movement in such way that the changes in SMR are usable for this control scheme, because active imagination of motor movement is not something a person is used to. Active biofeedback sessions tend to be shorter than passive feedback ones, mostly because of the higher mental demand for active focus. At the end of the session, the user should be feeling alert and energized.

³Gamification is the application of game-design elements and principles in non-game contexts.

Chapter 3

Electroencephalography Signal Processing for Neurofeedback Purposes

This chapter explores the underlying technology behind neurofeedback, specifically EEG signal, its acquisition from the user and the processing necessary for it to be usable for neurofeedback training. It also discusses the role machine learning can play in EEG signal processing and its possible use for neurofeedback purposes. This chapter draws heavily from the books *Brain-Computer Interfaces: Principles and Practice* by J. Wolpaw and E. W. Wolpaw[34] and *Analyzing Neural Time Series Data: Theory and Practice* by M. X. Cohen[9], which focus on EEG signal processing and brain-computer interfaces.

3.1 Basics of Electroencephalography

Electroencephalography(EEG) is typically a non-invasive method of measuring electrical activity in the brain of a person at a given time through the use of electrodes placed along the person's scalp. While intracranial¹ EEG methods exist, as this work focuses on the use of EEG in neurofeedback training, only scalp electrode-based methods will be considered. Each of the electrodes is connected to an amplifier, which in turn is connected to a EEG recording machine. The number of electrodes can vary. Two electrodes, usually adjacent ones or one at measured site and second on some reference site common to all electrodes, form an EEG channel. The potential of this channel is calculated as the difference between the potentials of the two electrodes. This then produces a continuous chart with the amplified electric charge of the channel, like the one that can be seen on figure 3.2 with example of multi-channel eeg.

Placement of the reading electrodes is an extremely important part of EEG recording and is highly dependent on what exactly are the EEG data going to be used for. As different regions of the brain serve different function, corresponding regions of the scalp can provide readings related to the corresponding function. The placement of electrodes usually follows the international 10-20 system[18] or the higher-resolution 10-10[22](on the figure 3.1) system, which specify these different region with relation to the size of the head. The digits in the system name represent actual distances between electrodes which are 10%

¹Invasive method, which has electrodes surgically implanted directly into the brain.

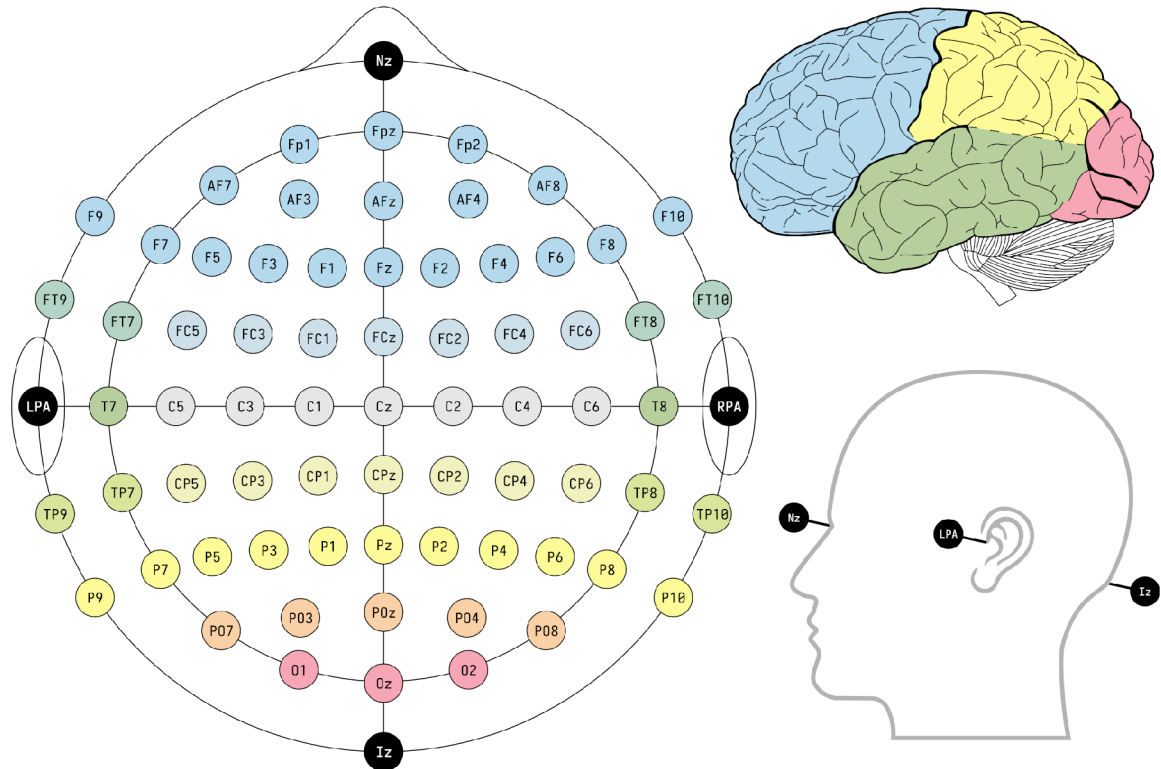


Figure 3.1: The international 10-10 electrode placement system. Colors of locations represent corresponding brain regions as seen on the brain image in the top right.

or 20% (or 10%, 10% etc. for more precise systems) of front to back or right to left scalp distance.

Electrode placement locations use naming convention consisting of a letter and a number. The letter specifies lobe — F - Frontal, O - Occipital, C - Central, P - Parietal and T - Temporal. The number specifies hemisphere location, with odd numbers for left hemisphere and even ones for right hemisphere. In place of the number, z can be found, which refers to an electrode placed on the midline.

When used for neurofeedback attention training, EEG signal from the sensorimotor cortex, cingulate gyrus and frontal lobes, specifically locations C3, C4, Cz, FCz, CPz are of interest as usual locations for measuring Beta, SMR and Theta bands[19].

EEG Signal Artifacts

In the process of EEG monitoring, undesirable artifacts have to be taken into account. These artifacts are signals not originating from the brain, that contaminate the measured EEG signal. Prevention and removal of artifacts is a very important part of the process whenever EEG is used. Generally artifacts can be classified into two main groups, physiological and non-physiological. 3.3 shows an example of the effect different artifacts can have on the EEG reading.



Figure 3.2: Example of multi-channel EEG recording[33].

Physiological Artifacts

Physiological artifacts are signals caused by non-brain body activity. Some of the most common ones are:

- **Ocular activity** — Caused by blinking and eye movements. This artifact cannot be fully prevented, as blinking is involuntary, as are micro eye movements. Ocular activity contaminate EEG signals in the lower frequencies(delta, theta, alpha), specific frequencies depending on the type of activity, e.g., kappa rhythm(eyelid fluttering) showing up in the alpha frequency range.
- **Cardiac activity** — Caused by the heartbeat. Shows up as periodic artifacts, depending on the specific electrode location. Filtering it can be aided by including single referential electrocardiography electrode.
- **Muscle activity** — Caused by moving muscles in the head, neck and shoulder areas. Causes very noticeable artifacts in higher frequencies(beta, gamma and above). Is very disrupting when staying still is not a possibility for a user. As it overlaps beta frequencies, care should be taken to try and remove this artifact or prevent it when any beta-focus neurofeedback regimen is implemented.
- **Respiratory activity** — Caused by breathing while the user is laying down, which may change skin-electrode contacts with chest movements. Generally not a problem apart from EEG monitoring concerning sleep. Causes periodic interference in lower frequencies.

Non-Physiological Artifacts

Non-physiological artifacts are caused by environmental or technical interference. Sources of this can be for example poor grounding, power network noise, bad electrode contact with

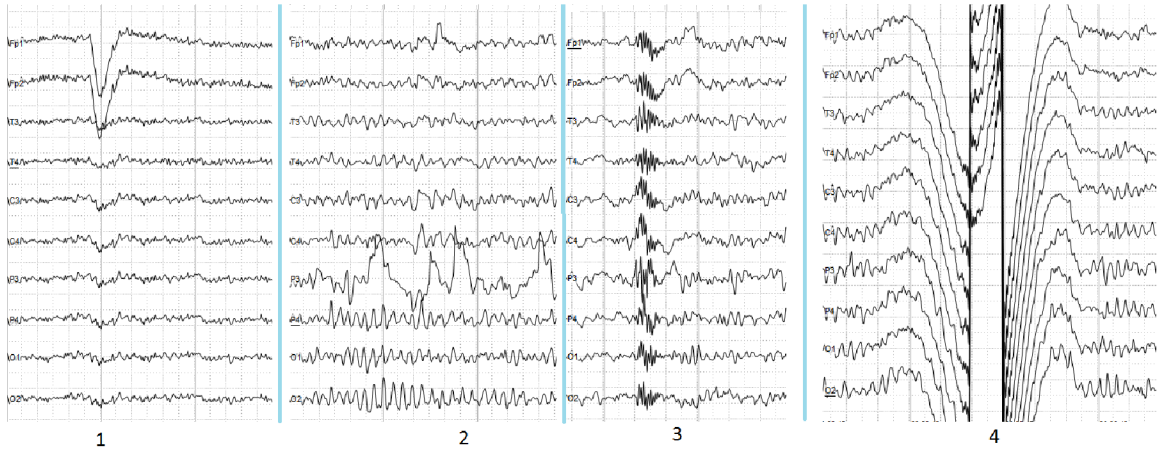


Figure 3.3: Example of the effects that different artifacts can have on an EEG reading. From the left, these artifacts are: blinking, bad contact between fourth electrode from the bottom and skin, swallowing and bad contact between shared reference electrode and skin[8].

skin or cable interference. These can usually be prevented by proper practice or filtered out in case of some that are expected, like the Czech power network noise around 50Hz.

3.2 Acquiring the EEG Signal

The EEG signal represents changes in electrical potential coming from the activity of cerebral neurons, measured on the skin surface by scalp-placed electrodes during a time-frame and amplified. This change in potential is measured in specific channels. A channel represents a pair of EEG electrodes, one located on the specific region the measurement requires and one reference electrode, which is usually either adjacent to the first or one that is shared by all electrodes as a referential electrode. More common of the two approaches is the common referential electrode approach. A collective placement of electrodes and the resulting set of channels is called a montage. The output voltage of a specific channel at time t is then given, in respect to an external ground and used amplifiers, as follows[34]:

$$E(t) = A[V_1(t) - V_2(t)], \quad (3.1)$$

where $E(t)$ is the channel output voltage, A is the total system *gain* due to the several amplifier stages and V_1 and V_2 are electric potentials of the two EEG electrodes. Example of signal acquisition pipeline feeding into a brain-computer system can be seen on figure 3.4. The raw potentials from the EEG electrodes are first ran through a differential amplifier. This step removes a significant amount of noise shared between the two electrodes. Then, usually a series of analog filters is applied, most commonly, following are employed:

- A low-pass filter[27] to remove higher frequencies (e.g., 100+Hz), which correlate to brain frequencies that are not interesting for a specific analysis and higher-frequency muscle movement artifacts which are present in most of EEG readings.
- A high-pass filter[27] to remove lower frequencies (e.g., <1Hz), again, to remove uninteresting frequencies.

- A notch filter[27] to remove specific frequency correlating to power network noise. In the Czech Republic, that would be about 50Hz.

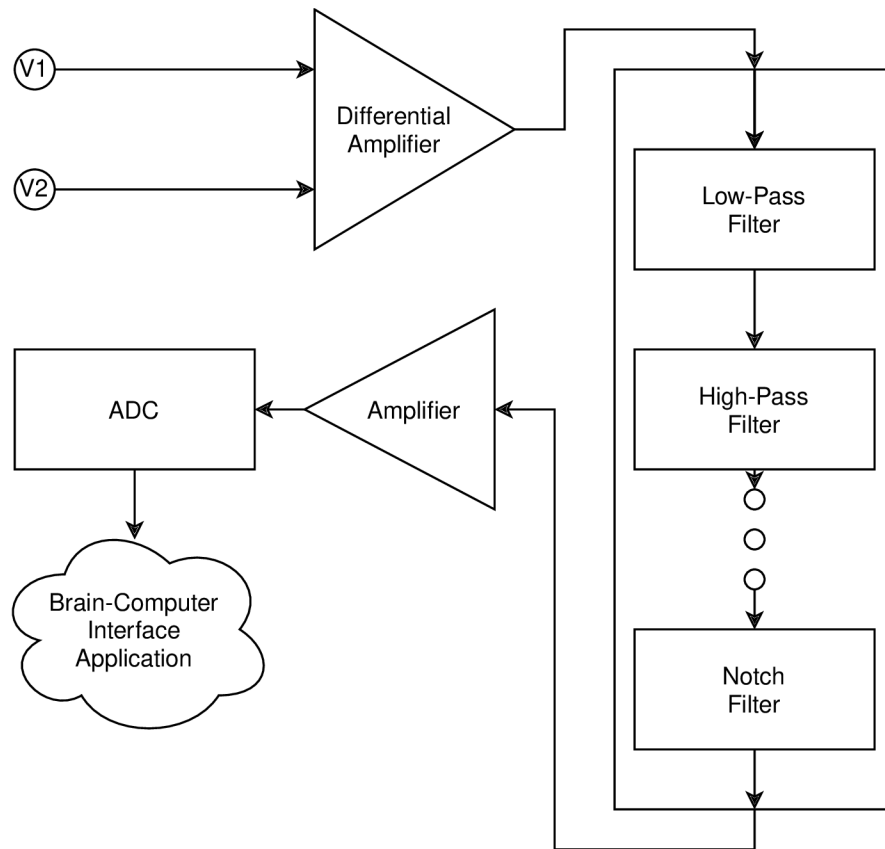


Figure 3.4: A diagram example of signal acquisition pipeline. V_1 and V_2 represent scalp-placed EEG electrodes, with V_2 being referential. The difference between the raw measured potentials is fed through a differential amplifier. What follows is a series of filters to remove common artifacts. This filtered signal is then amplified significantly, sampled and digitized. The digital signal is then processed and used by a BCI system.

As the signal from the EEG electrodes is very weak (units to tens of μV), it is then significantly (e.g., 20000 times) amplified, following the filters[34]. The amplified signal is then sampled and digitized using an analog-digital converter. This digital result can then be projected onto a display or further processed for other purposes, like for a BCI application.

3.3 Extracting and Translating EEG Signal Features for Neurofeedback

Having an amplified digital EEG signal is not enough for a neurofeedback application to work with. A further processing must be done on the signal. Feature extraction is a process during which signal is analyzed in a way that allows it to be represented by its features — specific characteristics of the signal, in form understandable for the human or application and free from extraneous content. Complex BCI applications, which are controlled by translating user’s mental commands to application commands, generally require these features

to fulfill a number of conditions. Traditional neurofeedback applications however usually work by monitoring current power of a specific frequency band in order to control the feedback given to the user. Most commonly, neurofeedback applications are controlled with just modulations of targeted frequency bands — e.g., application for attention training, which moves a cube when Beta is above set threshold and Theta below a set threshold. Thus, the features to be extracted from EEG signal when performing neurofeedback training are the base frequency bands — Delta, Theta, SMR, Beta and Gamma. For attention, Theta, SMR and Beta should be sufficient, maybe in addition to Alpha, if monitoring stress level is desirable. A set of multiple extracted features is referred to as feature vector. This feature vector is then converted to application commands in a process called feature translation. In some solutions, a single transformation can produce these commands right from the digital signal, making no distinction between the feature extraction and translation stages. The feature extraction process can be seen as three consecutive steps[34]:

- Signal preprocessing in order to minimize noise and enhance relevant aspects of the signal.
- Extraction of the target features.
- Preparation of feature vector for translation stage such as normalization.

Preprocessing

The preprocessing step when extracting features for neurofeedback usually starts by filtering the uninteresting frequencies from EEG signal. This can be done using a band pass filter[27], which passes a selected frequency band. For attention training neurofeedback, such a band could be 4—30Hz, which would allow extraction of Theta, Alpha, SMR and Beta. Generally, it is wise to choose this frequency interval prudently, as even though higher frequencies are not monitored during attention training, they could be useful for identifying muscle artifacts in the EEG signal [34]. Resulting signal is then sometimes normalized in order to simplify further processing. This, however should be done with caution, as it may lead to loss of important information, especially for neurofeedback. Normalization is more useful when signal dynamics are monitored rather than amplitudes. Neurofeedback is generally interested in amplitudes, hence normalization is not as useful there.

The last preprocessing step is the removal of noise and artifacts. As discussed before, artifacts are an undesirable contamination of the EEG signal, originating from somewhere else than the brain. Noise on the other hand is a signal contamination originating from unrelated brain functions. A common way to remove noise and some artifacts are spatial filters[9]. Spatial filters take advantage of the fact, that recorded EEG channels often have a common referential electrode. This allows for reconstruction of any alternative set of channels by weighting and combining the channels after digitization. The use of a spatial filter can enhance sensitivity to specific brain signals — which is crucial for a neurofeedback application — or suppress certain artifacts and noise common to more electrodes[34]. Usually, spatial filters are selected as weighted sums of respective channels, e.g., in matrix form and matrix notation:

$$\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1P} \\ x_{21} & x_{22} & \dots & x_{1P} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \dots & x_{NP} \end{bmatrix} \begin{bmatrix} for: & \vdots & \ddots & \vdots \\ w_{M1} & w_{M2} & \dots & w_{MN} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1P} \\ y_{21} & y_{22} & \dots & y_{1P} \\ \vdots & \vdots & \ddots & \vdots \\ y_{M1} & y_{M2} & \dots & y_{MP} \end{bmatrix}, \quad (3.2a)$$

$$Y = XW, \quad (3.2b)$$

where X is a matrix of consecutive signals in channels, with P being the number of consecutive signals and N number of channels. W is the weight matrix with each of M rows representing a set of N channel weights. Each row of Y then constitutes a resulting spatially filtered channel — M channels with P samples.

There are 2 main categories of spatial filters, depending on how they acquire the weights W , these being data-independent spatial filters and data-dependent spacial filters. Data-independent spatial filters, as the name suggests, rely solely on fixed geometrical relationships with no regards for the specific data. Three common filters in this category are small and large Laplacian spacial filters and common-average reference filters[34]. The common-average reference filters are realized by recording all channels with a common reference electrode, computing the global mean of all the channels and subtracting it from each and every channel. This operation helps mitigate the effect of noise and artifacts shared by all electrodes, like the power line interference. The surface Laplacian spatial filters on the other hand do not use the average of all the electrodes, but instead only taking into account a number of electrodes around a specific one in some radial distance. Again, a mean of these is computed and subtracted from the specific electrode channel. This removes the commonalities between spatially close channels, resulting in emphasized local activity.

Data-dependent spatial filters are derived from each individual person's data. With increased complexity, these filters allow for results that are more tailored to the specific user, which can be highly beneficial for BCI applications utilizing a more complex control scheme. They are also useful where exact characteristics of the monitored brain activity are not fully known. Some common methods for deriving these filters are principal component analysis, independent component analysis and common spatial patterns[34]. As the characteristics relevant for attention training neurofeedback are fairly well known and the control scheme of these applications not overly complex, data-dependent spatial filters are not as common.

Target Feature Extraction

When developing a neurofeedback application, the sort of signal features of interest are the frequency features. Usually, neurofeedback applications are controlled by the power of specific frequencies being over or under a set threshold for a period of time. Therefore, computing the power of monitored frequencies is the goal of feature extraction for neurofeedback training application. The most common method of converting a signal from time domain to frequency domain is the discrete Fourier transform[9] (DFT), usually computed with fast Fourier transform[9] (FFT). There are, however some alternatives to FFT, notably simply computing band powers and autoregressive (AR) modelling[34].

Band power calculation is a very simple and straightforward method for tracking specific frequency amplitudes. It consists of first isolating said frequency using a band pass filter, producing a largely sinusoidal signal. This signal is then either squared or converted to its absolute value, in order to receive only positive numbers. Lastly, the whole signal is

smoothed using either a low-pass filter or integration. This resulting smoothed signal then represents the respective band power. While yielding good results, FFT or AR modelling is preferred to this simple method when tracking multiple different frequency bands at once because of the need for multiple band pass filters. As neurofeedback generally does monitor multiple frequency bands, other methods are preferred.

The primary method behind AR modelling is representing the signal to be analyzed as white noise passing through an infinite impulse response (IIR) filter[27]. The signal's spectrum is then defined by the weights of such a filter. This method is able to perform spectral analysis on shorter signal blocks than FFT, which is a boon for BCI applications, that require to be highly responsive — e.g., cursor movement on the screen or wheelchair controls. AR modelling however has some problems with accounting for spectrally adjacent or outright overlapping signals (e.g., SMR, which overlaps lower Beta) or distinguishing artifacts.

DFT and its efficient implementation — the FFT — is probably the most common method for converting signal from the time domain to the frequency domain. It often serves as a baseline method for comparison between spectral analysis methods due to its relative simplicity and effectiveness. Fundamentally, the Fourier transform works by representing the signal as a sum of a number of sinusoids. Formally, Fourier transformation of variable x at frequency f can be defined as[9]:

$$X_f = \sum_{k=1}^N x_k e^{\frac{-i2\pi f(k-1)}{N}}, \quad (3.3)$$

where N is the number of discrete points in the sampled signal and X_f is the Fourier coefficient of x on f . This coefficient is a complex number representing magnitude and phase. With that, the magnitude is computed as such:

$$|X_f| = \sqrt{a^2 + b^2}, \quad (3.4)$$

where a and b are the real and imaginary components of the complex number X_f respectively. Power, which is to be used as the final extracted feature, is then computed as magnitude squared.

Feature Translation

Simply put, feature translation is the process of translating some feature vector X into some application command C . This process is done by a model, which can be either some mathematical equation, a set of them or some mapping mechanism. For a theoretical neurofeedback attention training application, with feature vector x , a model comparing the powers of individual brain frequencies to set threshold could have this form:

$$C = \begin{cases} \text{positive} & \text{for } x_i \geq \theta \quad \forall x_i \in X \\ \text{negative} & \text{for } x_i < \theta \quad \forall x_i \in X \end{cases}, \quad (3.5)$$

where C is command given to an application, *positive* meaning "give positive feedback" and *negative* meaning "give negative feedback", x_i is the power of brain frequency ' i ' and θ is the set threshold. Some variations on this simple threshold model are the basis of many typical neurofeedback training applications. Other example of a simple model could be one described by a linear function:

$$C = bX + a, \tag{3.6}$$

where again, C again represents an application command vector and X represents a feature vector. a and b are then parameters of this model. Some more sophisticated models, such as those using machine learning, can even encompass both feature extraction and translation, as they take digitized EEG signal as input and output application command outright. Generally, these models are highly dependent on the specific BCI application.

Machine Learning for EEG Processing

Machine learning, especially deep learning(DL)[14], can be a valuable tool in all stages of EEG signal processing[16][29], from artifact filtering to feature translation[35]. It can help mitigate some problems inherent to the nature of EEG signal, such as its low signal to noise ratio due to multitude of possible artifacts, its strong variability in time and high inter-subject variability due to physiological differences between individuals. When taking other domains as examples, such as natural language processing and image processing, DL could alleviate the need for rigorous preprocessing of data, as it potentially could extract features from raw data. It could also help with generalization of used models to help with the inter-subject variability. There are, however, still many problems present with the usage of DL for EEG signal processing purposes. The field of DL EEG processing is still fairly new and certainly more niche than natural language or computer vision. The professional extraction of EEG signal is also time and money intensive process, with large privacy concerns, which leads to a problem of not enough data available for creating large open datasets such as those available for other domains. EEG signal is also very different from visual or language data in its signal to noise ratio and it has not been sufficiently explored whether existing DL techniques are sufficient for this. There is also a problem of training the neural networks present when employing supervised learning. This requires a sufficient training dataset, where an EEG professional is needed for annotation, as it is very difficult to distinguish between a clean signal and a noisy one. As far as unsupervised learning goes, there has been some reports of succesful applications, however it is still a very unexplored field.

Chapter 4

Attention Neurofeedback Application

The main focus of this project was the development of neurofeedback training application. Specifically, this application targets users with attention deficit hyperactivity disorder (ADHD) or other attention-affecting problems. The feedback is provided in the form of a simple interactive game, where the results of the player character's action are decided by whether the user's attention level is sufficient. This gamified approach to neurofeedback aims to provide to a user an actual enjoyable experience, not only training. The application is developed using the OpenBCI platform¹, which is a community platform, providing open hardware and open source software solutions for BCI technology. For EEG signal acquisition, the Ultracortex "Mark IV" EEG Headset² with dry electrodes is used. The headset is designed with 10-20 electrode placement system in mind. The 16-channel Cyton Board with the Daisy extension board³ will then be used for signal acquisition. For the application development, the Unity game engine will be used⁴, utilizing the open source brainflow library⁵ to process raw EEG data.

This chapter will discuss design philosophy and implementation of this neurofeedback training game (further addressed as "neurogame").

4.1 EEG Signal Processing Pipeline

The neurogame is controlled by measuring the value of SMR frequency band power and comparing it to automatically adjusted threshold value. The goal of the EEG processing pipeline is to filter the incoming raw EEG signal, isolate the SMR frequency band and calculate its power value. The whole process is illustrated on figure 4.1, with figure 4.2 showing the scalp electrode placements chosen. The digitized EEG signal, acquired from the Daisy board is further filtered, first by using a 50Hz notch filter to get rid of the electrical network interference and second by using a band filter to acquire only the range of 1–30Hz, in order to remove the inherent DC offset[23] of the device. Then, all samples with values over $100\mu V$ or under $-100\mu V$ are removed, as these are most likely artifacts. Data is further detrended to remove any potential linear trends [10]. The power of these

¹OpenBCI website

²Open BCI e-shop link for the headset

³Open BCI e-shop link for the board

⁴Unity3D engine

⁵The Brainflow library

frequency bands is extracted by computing the Fast Fourier Transform, which is used to compute the power spectral density[28], which will in turn is fed into the brainflow library to extract the power of the SMR band. This power value is then translated into input using a threshold model as seen in 3.5.

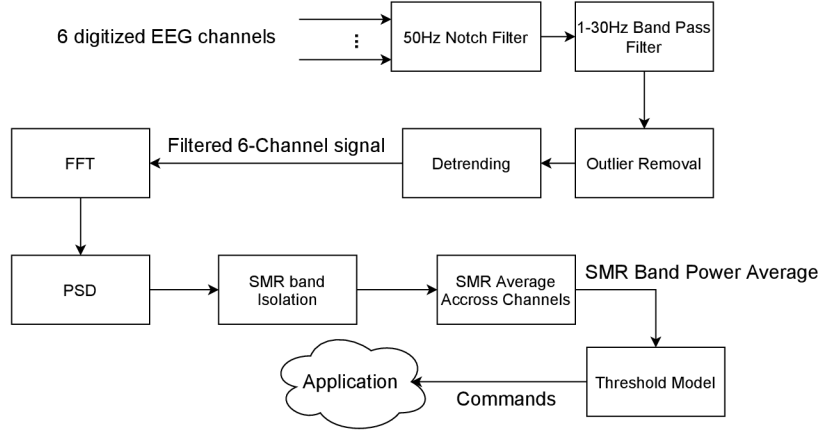


Figure 4.1: The diagram of EEG processing pipeline to be used. The EEG signal is filtered by a 50Hz notch filter, followed by band pass filter to acquire only frequencies 1—30Hz. Outliers with amplitudes lower than $-100\mu V$ and higher than $100\mu V$ are removed. De-trending is applied to filtered data. Features in the form of frequency band powers are extracted using fast Fourier transform and PSD, averaged accross channels and then translated using a threshold model.

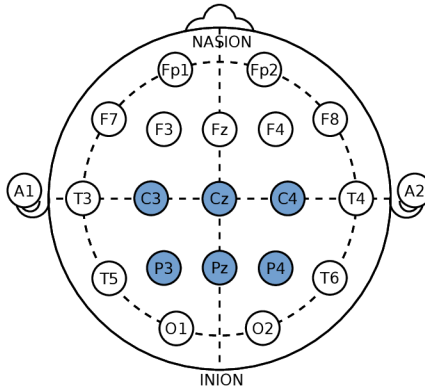


Figure 4.2: The chosen electrode placements according to the 10-20 model.

Using Machine Learning

This work has decided not to employ machine learning in its implementation. While it could provide some help with mitigating the expected high levels of noise, natural for dry-electrode recordings, the potential problems still overweight the benefits. The unavailability of useable public datasets would make training the neural network difficult, along with

the fact that any custom dataset would have to be made without supervision of an EEG professional, which would make its value questionable. The more common approach of an EEG processing pipeline is employed as it time-tested and can be used without the need of consulting an EEG professional in order to confirm correctness of recorded data.

4.2 Design of the Neurogame

The primary goal of the neurogame is to train the user in taking control of their mental state. This is usually done by utilizing a simple feedback loop — the user is instructed to try and get into and stay in some mental state (in this case attention); the application decides whether this state is attained by monitoring user’s brain activity based on some thresholds, which are usually modifiable by the training supervisor on the run; the application provides either positive or negative feedback; the user tries to stay in their current mental state or modify it based on the feedback given; repeat ad infinitum. Graphically, such a loop is shown on figure 4.3. This process can feel tedious to the user, as these applications tend to be very simple in terms of user-application interaction and their feedback often consists of the movement of an object when mental activity criteria are met. The developed neurogame tries to create a more immersive and engaging experience for the player. To attain this goal, following is important:

- A fitting theme for the game — so that it makes sense that the user is affecting the game just by using their mind.
- Mixing up the training tasks to try and break the tedium — instead of just moving some arbitrary object, change the object of focus during the training sessions and along with it change how the object reacts to user input.
- Creating some idea of progress — an end goal for the session. Instead of the session ending when some time limit is met, have an actual goal the user is trying to achieve.

But even with these criteria, this game still followss the basic neurofeedback training loop 4.3, in order to properly work at improving attention. The goal is to not make the user feel that they are exercising while that is exactly what they are doing. They should at least partially enjoy the experience.

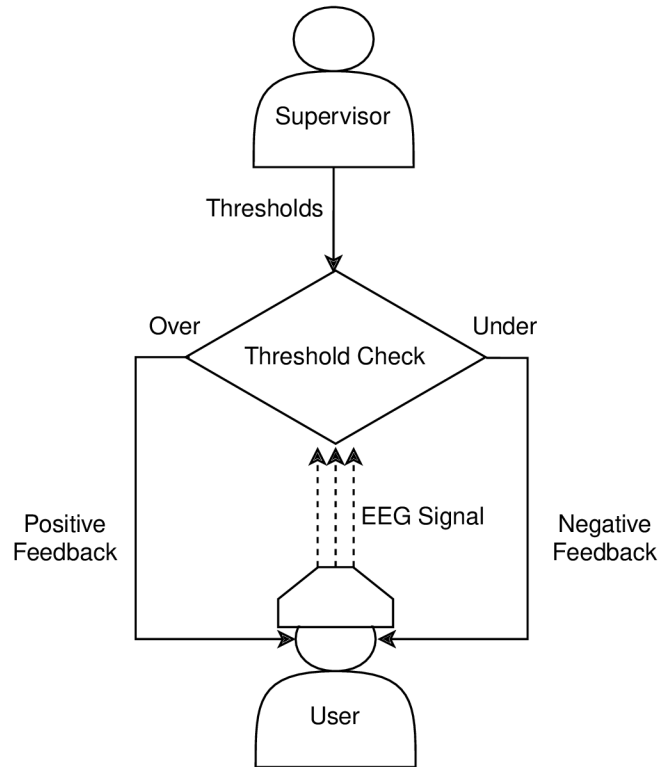


Figure 4.3: Diagram of a typical neurofeedback application feedback loop.

More formally, the game implements an SMR-enhancement training regimen using visual feedback.

Thematic Design and Gameplay Loop

An immersive neurogame should have a reason as to why the player is affecting his environment with his mind. This neurogame makes the player a wizard’s apprentice. In such an environment, it makes sense that the user is using their mind to change it — they are casting spells, which as one would expect, requires focus and attention. A theme such as this provides an immersive link between the technology used and the feedback given.

The gameplay loop consists of the user learning a specific spell. This process has three stages. **Drawing a spell glyph** 4.4 — Here, the user is faced with a task of drawing a symbol. The screen displays the symbol, which is automatically traced by a cursor. The speed of the cursor is changed by whether the user’s attention is sufficient or not, slowing down on negative evaluation and speeding up on positive. This stage is finished when the cursor traces the whole symbol.

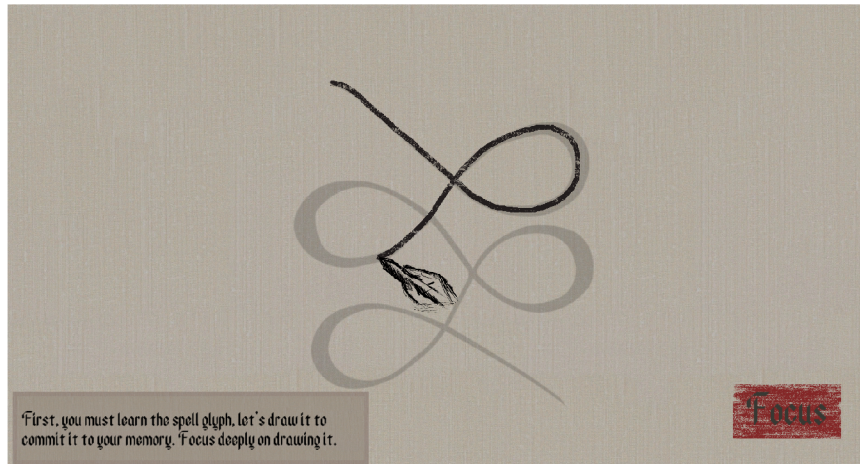


Figure 4.4: Spell glyph drawing stage.

Learning the spell 4.5 — The cursor disappears and only the spell symbol remains. The user is instructed to focus on lighting up the symbol. When the user is sufficiently focused, the symbol's color changes and particles are emitted from it. When focus is not sufficient, the symbol starts reverting its color to faded black at a much slower pace and stops emitting particles. When the symbol is completely lit up, this stage ends and the symbol moves to a side part of the screen and last stage begins.

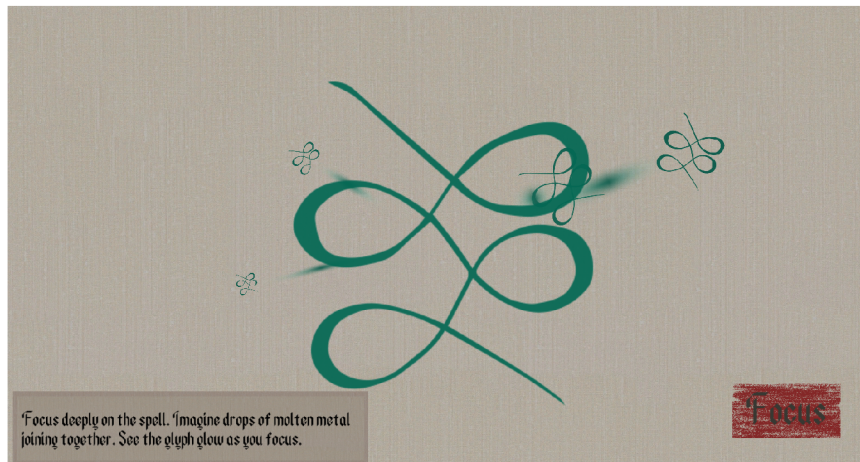


Figure 4.5: Spell learning stage.

Trying out the spell 4.6 — Now, the user is met with a task to complete. A spell target is shown and the user is briefed on what the spell effect should do. This is for example lighting up an extinguished campfire. When the user's focus is sufficient the spell effect starts to manifest — a fire starts to appear etc. and particles are emitted by the spell target. When focus is insufficient, the spell starts to revert at slower rate and particles are no longer emitted. Upon successfully casting the spell, the session ends.



Figure 4.6: Spell casting stage.

User Interface and App Flow

The game consists of two main scenes — the main menu scene and the feedback scene. **Main menu scene 4.7** is used to connect to the EEG headset and select a specific training scene. The UI consists of:

1. **Settings Button** — When pressed, the configuration dialogue pops up, where the user can change some default training parameters.
2. **Connect to headset button** — When the headset dongle is connected to USB and the headset is powered on, this button established connection between the app and the headset.
3. **Start stream button** — This button is enabled upon connecting to the headset and starts the stream off raw EEG data from the headset to the app and also starts the signal processing on the app side. Upon hitting this button, the application starts the logging of raw data.
4. **Game Scene Selection** — This area consists of buttons which are enabled after stream start. Upon clicking a specific button, representing a training scene, the app switches to the screen selected and BF training begins.



Figure 4.7: Main menu screen.

Feedback scene 4.8 is where the actual BF training and the gameplay loop take place. The UI consists of:

1. **Focus indicator** — This box changes colour based on the level of users focus on gradient from red to green. Fully green represents the user's SMR band power being at or above the current set threshold and fully red representing being $2\mu V^2/Hz$ or more under the set threshold. It serves as another form of visual feedback to the player.
2. **Text box** — Here, the user is provided encouragement and flavour text about the current spell.
3. **Play area** — Here, all the game components — drawing, symbol and spell targets are displayed during the training session.
4. **Pause screen** — pressing the Escape keyboard button stops the app (the raw eeg is still being logged) until it is pressed again.

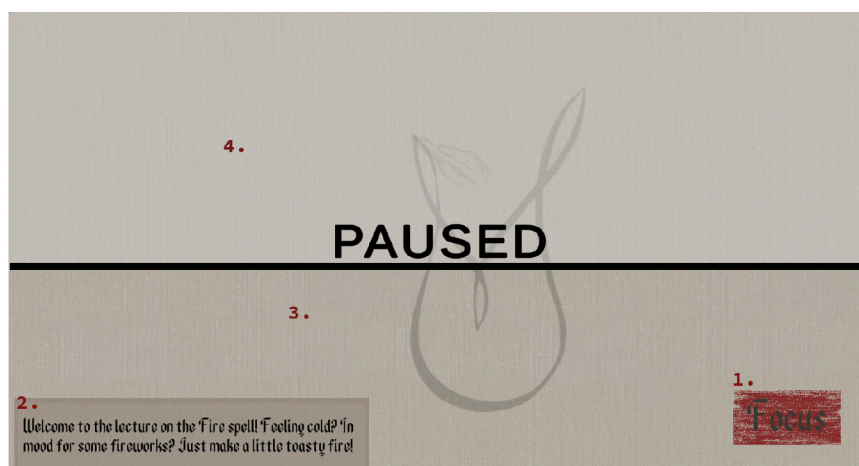


Figure 4.8: Feedback scene. Pause screen usually covers whole scene.

The training session generally starts by connecting the headset, starting streaming and selecting a specific training scene. Then, the control is in the hands of the training user and no intervention is generally necessary.

Data Gathering and Analysis tools

After pressing the **Start stream button**, logging starts. All logs are located in folder *Recordings* and the filenames are in the form of *timestamp_logtype.csv*. The application logs all raw EEG data received so it can later be accessed for analysis, as seen on 4.9. Apart from raw EEG log, second log file is created, to which all changes to SMR band power threshold, used in the threshold classifier, are recorded, as seen on 4.10.

2.000000	-187500.022352	-187500.022352	17372.781619	...	0.147000	192.000000	...	1627127003.234021	0.000000
4.000000	-187500.022352	-187500.022352	18320.227363	...	0.147000	192.000000	...	1627127003.242023	0.000000
6.000000	-187500.022352	-187500.022352	17319.003322	...	0.223500	192.000000	...	1627127003.249028	0.000000
8.000000	-187500.022352	-187500.022352	18017.785909	...	0.223500	192.000000	...	1627127003.258020	0.000000
10.000000	-187500.022352	-187500.022352	17953.815216	...	0.223500	192.000000	...	1627127003.266030	0.000000

Figure 4.9: Raw EEG log example. First column is sample index. Columns 2—17 are raw values recorded in channels 1—16 (value of ± 187500 means channel is not recording anything). What follows is a number of columns with other values (depending on used board). 31th column contains a UNIX timestamp and the last column is again some other value (used only is some boards).

Timestamp	Event	Value
1627057957	TNEGAUTO	3.46487084504759
1627057958	TPOSAUTO	4.46487084504759
1627057959	TPOSAUTO	5.24924394206433
1627057960	TPOSAUTO	5.24924394206433
1627057961	TPOSAUTO	6.71505900128202
1627057962	TPOSAUTO	6.71505900128202
1627057963	TPOSAUTO	6.71505900128202
1627057964	TPOSAUTO	7.96046226083725
1627057966	TNEGAUTO	7.30450092578258
1627057967	TNEGAUTO	7.30450092578258
1627057968	TNEGAUTO	6.35954535754115
1627057969	TNEGAUTO	6.35954535754115

Figure 4.10: Threshold change log example. First column is a UNIX timestamp, second is type of change — TNEGAUTO is lowering the threshold, TPOSAUTO is increasing the threshold. Last column in the value the threshold has been changed to.

For data analysis, a python jupyter notebook⁶ *Analysis.ipynb* is used. This notebook loads specified csv files with raw eeg data and threshold change data. The eeg data undergoes the same preprocessing as in the app itself — notch filter, bandpass filter, detrending. the notebook then provides methods for plotting data samples in relation to time, with the ability to plot multiple files at once for comparison purposes. The data plotted can be raw EEG samples, processed EEG samples, SMR band power in time, changes to threshold in time. Other than plotting, the notebook provides methods for scoring session data based on either the average SMR band power achieved, median SMR band power, ratio of threshold increases to threshold decreases, highest maximum threshold achieved, highest

⁶Project Jupyter

minimum threshold achieved. The notebook utilizes the brainflow and numpy libraries for data processing and the matplotlib library for data plotting.

4.3 Implementation and Usage

The application as a whole, including the EEG processing has been implemented using the Unity3D game engine in the C# programming language. The analytic tools were written in Python.

EEG Recording

The recordings are taken using the **Ultracortex "Mark IV" EEG Headset** with dry electrodes and the **OpenBCI Cython board with the Daisy extension**. 6 of the 16 available channels are used, with electrodes placed on the locations C3, Cz, C4, P3, Pz and P4 according to the 10-20 system. Before each session, proper placement of the headset on the head of the user must be ensured. For this purpose, the OpenBCI GUI application (4.11) is ideal⁷. First, place the headset on the subject's head and turn on the usb dongle and the cyton board in this order. Next, in the OpenBCI GUI app, select live streaming from Cython board with 16 channels and let it autoconnect to the headset. Afterwards, start the stream and check impedances on the used electrode channels (available by clicking the omega icon next to each channel), this value should not pass 70 k Ω . If the impedance value is too high, adjust the headset and electrode positions, until it registers under 70k Ω . Next, have the user blink repeatedly and check on the FFT plot if there are visible significant artifacts in the <10Hz range. If so, all should be ready, otherwise try restarting the OpenBCI GUI and try again. If there is still no visible blink artifacting, there may be a problem with the device. Another possible test of measurement can be the closed eyes Alpha response[6]. When the user closes their eyes for a few seconds, their FFT values at around 10Hz should noticeably spike. This does not however work for all people, some people may not produce this increase in Alpha. If everything seems fine with the OpenBCI GUI application, close it and proceed with the BF session, as only one application can be connected to the board at a time, unless restreaming is set up in the OpenBCI GUI application. The board can now produce raw EEG recordings of the user with 125Hz sampling rate.

⁷OpenBCI GUI



Figure 4.11: The OpenBCI GUI.

EEG Processing

The EEG signal was processed with the open source **Brainflow** library. This library provides an interface for connecting to various EEG recording devices and a large variety of EEG signal processing methods. The preprocessing steps are all implemented in the C# script *NeuroinputHandler.cs*. This script handles both connecting to the board and reception and processing of data. The board object employs a ring buffer of size 45000 to buffer incoming raw EEG samples, which equates to 6m of streaming (sampling frequency of 125Hz). After starting the stream, the script waits 10s for the buffer to be sufficiently filled with data. Then, a processing method, which handles all the data manipulation and sets the current value of SMR band power, is set to be invoked every 200ms. The processing starts by applying a 50Hz notch filter to get rid of the ambient electrical network noise. Next, a bandpass filter with a band of 1-30Hz is applied, specifically using a fourth order Butterworth filter[25]. This specific band was selected to fully encompass the SMR band. The lower frequency end should not be set higher than 1Hz due to high pass filters creating further distortions when the pass value is higher than 1Hz and 1Hz is enough to remove the present DC offset in raw data[23]. The reason for using both a 1-30Hz band pass and a 50Hz notch filter is that if only the band pass was used, there could still be some network interference left across the recording if it is particularly strong[13]. Hence, to be sure, both a notch filter and a band pass filter are applied. After the band pass is applied, outlier filtering is performed. This removes all samples with voltage higher/lower than $100\mu\text{V}/-$

100 μ V, as those are most likely artifacts. As dry electrodes specifically have problem with signal drift, the data is then detrended using the provided Brainflow method. Then, power spectral density is calculated using the Welch method[32] using FFT with 256 point hanning window. Lastly, using the provided brainflow method, the SMR band power is extracted. All of these operations are done for each separate channel. At the end, the band powers are averaged to get the final value to be used. The script also computes and provides a 2s average of the SMR band power to be used in threshold classifier modification.

Classification

Classification of the extracted SMR band power is implemented in the C# script *Input-Classifier.cs*. The classifier can on demand evaluate the user's current SMR band power against a set threshold and returns a boolean value referring to the result — true value if at or above threshold, false if below. The classifier is self-setting in the way, that it changes the threshold value based on the ratio of successful evaluations against the unsuccessful ones. Every second, a ratio of success/failure evaluations is checked. If it is at or above 1.2, the classifier threshold is changed to the 2s average of user's SMR band power increased by $2\mu V^2/Hz$ to increase difficulty and encourage SMR band power enhancement in the long run. Similarly if at or below 0.7, the threshold is set to the 2s average decreased by $2\mu V^2/Hz$ to reduce the difficulty and prevent frustration from prolonged failure.

Application

The application is developed using the Unity3D game engine and written in the C# language. Apart from Unity itself, one free addon to it was used in the implementation of this application. The addon is the DOTween animation engine⁸. The free font *Ancient Modern Tales*⁹ was also used. Then, the Brainflow library was added to the Unity engine for EEG signal processing. The application consists of a Main Menu scene and then 10 other scenes, which house the BF scenarios. The Main Menu provides means to connect to the EEG headset, start data stream and a setup dialog. The setup dialog allows the user to change the default values of following training parameters:

- List of 6 channels to be used for EEG signal. Have to correspond to the same channel numbers as in the OpenBCI GUI application. (Defaults: 3, 4, 11, 12, 15, 16)
- Frequency of threshold modification check in seconds. (Default: 2)
- Amounts by which threshold is increased/decreased in relation to average, when the user is too succesfull/unsuccessful in $\mu V^2/Hz$. (Default: 2/2)
- Min/Max speed of symbol drawing cursor, modifying the length of drawing stage. (Default: 0.2, 2)
- Success/Failure evaluation ratios needed for changing the threshold. (Default: 1.2/0.7)
- Length of symbol glowing animation in seconds, modifying the length of spell learning stage. (Default: 15)

⁸Dotween animation engine — <http://dotween.demigiant.com>

⁹Ancient Modern Tales font — <https://www.dafont.com/ancient-modern-tales.font>

- Length of casting animation in seconds, modifying the length of spell casting stage. (Default: 20)

These values are saved in the public class *settings* and accessed by the relevant objects at runtime and have to be set before starting the EEG stream. The input reception and classification is handled by the *InputHandler* object, which houses the *NeuroinputHandler.cs* and *InputClassifier.cs* scripts. This object is set to be persistent across game scenes.

The application uses a simple event messaging system object^[31] to allow game object scripts to monitor game events without having to couple them using direct references. This message system uses very simple Listen/Trigger paradigm. There is one *EventManager* object housing a *EventManager.cs* script that provides the interface for listening to/trigging events. All of the possible events are listed in the *Enums.Message* enum. The event manager keeps a dictionary of messages and methods that should be invoked provided the message is supplied using the *TriggerEvent* method. Any object can add its methods to the dictionary by calling the *StartListening* method or remove it from the dictionary using the *StopListening* method. An example of event messaging is depicted on diagram ¹⁰

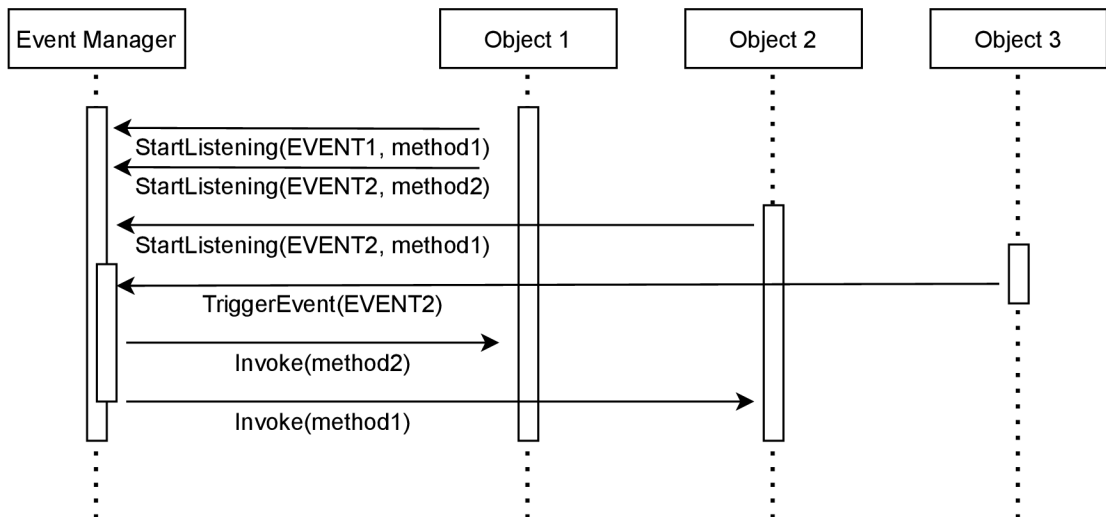


Figure 4.12: Example of two objects subscribing their methods to specific messages and then them getting triggered by third object.

Upon successfully connecting to the headset, starting the EEG stream and selecting the BF scenario, the relevant game scene is loaded and the game starts. The *FlowManager* object triggers some game events which are not dependent on the user input. Such an event can be progressing to next game stage after the congratulatory message for completing the current stage has been displayed for long enough amount of time. This is done simple by delayed invoking of methods, and is done in the *FlowManagerTraining.cs* script attached to the object. The game scenes contain a *FocusIndicator* UI object, which is a colored and textured rectangle sprite that changes color on a gradient from red to green based on user's neuroinput. This is done simply by accessing the *NeuroinputHandler* SMR band power values and comparing the input to an interval of $< threshold - 2, threshold >$ and

¹⁰fig:eventdiag

changing the gradient according to that. Another prominent object in the game scenes is the *TextBox* object, which displays messages to the user. These generally inform the user of what the visual feedback of the current stage will look like, e.g. that the symbol will start glowing with input in the spell learning stage. It also displays some lighthearted fluff messages to break the monotony of the BF training and provides words of encouragement to the user.

The game scenes are broken down into three distinct stages which differ by the goal of the user and provided visual feedback. First stage consists of the drawing of spell symbol. For this stage, the centerpiece is the symbol to be drawn and cursor, which follows a path and "draws" the symbol. The path of the cursor is hardcoded in the way that its path is constructed of invisible *Node* objects. The cursor slowly travels along the path and as it travels, circles are drawn onto a blank mask texture on the corresponding location. Under this mask, an object with a texture of charcoal drawing is located which is set to only be visible when under a mask. This process is done in the *Rail.cs* script. The speed of the cursor is dependent on the threshold evaluation. If it is negative, it travels with minimum speed, if positive, with maximum. This ensures that this stage is always completed, even without any user input. After the cursor "draws" the whole symbol, the game proceeds to the next stage.

The second stage is spell training. Here, the cursor and drawn symbol disappear completely and only a faded pre-drawn symbol image is left. Now, with the user's input, the symbol's color and opacity change. Positive input is further indicated by enabling the symbol's particle system. Now, in contrast to first stage, when the input threshold is not met, the image starts reverting to its faded state at approximately the rate of 1/5 of positive change. This means that now the user input is necessary for the progress to next stage, meaning a slight increase in difficulty. This stage ends when the symbol is fully colored and opaque. On stage end, the symbol is moved to the side and the last stage starts.

In the last stage, the main objects of attention is some spell target. The user is instructed to "cast" the spell on the target. As the user meets the set threshold, the target object starts to emit particles and change in accordance to the current spell effect, e.g. fire starting to appear in a cold campfire. Again, if the user does not meet the threshold, the object starts reverting and stops emitting particles, now reverting at the rate of 1/4 of positive change, in order to increase difficulty.

After the user succeeds in casting the spell, the game session ends, EEG stream stops and the application closes.

Chapter 5

Case Study: Effects of Neurofeedback Application on a User with ADHD and on a Neurotypical User

As Part of this master's thesis a case study of the effectivity of the resulting application has been conducted. Most case studies regarding attention-focused biofeedback training are conducted on children or young adolescents, such as [4] or [24]. They also tend to only focus on neurotypical subjects as controls. This study aims, apart from evaluating the effectivity of biofeedback training on an ADHD individual, to also explore the effects of such training on a neurotypical student. This study looks at data recorded during training sessions. It analyses the recorded data to find any possible trends in the data or correlations present.

5.1 Study Variables

Participants

This study will be performed on two participants, which are as follows:

- Person A is a 25year-old male university student diagnosed with ADHD, with OCD, anxiety and depression comorbidities and experiences difficulties in his studies. Subject was treated with atomoxetine medication for his ADHD in the past. The goal with person A is to improve self-reported attention level and improve ADHD symptoms.
- Person B is a 23year-old neurotypical male university student with no reported psychiatric or neurological problems. The subject will both act as a control for this study and will be used to explore the possibility for improving the ability to sustain attention in healthy individuals.

Equipment and Setup

For recording, the OpenBCI Ultracortex Mark IV headset with dry spikey electrodes and the Cython board with Daisy extension was used. Out of the 16 available channels, 6 were used in the following configuration according to the 10-20 system:

- Ch3 — C3
- Ch4 — C4
- CH11 — Pz
- CH12 — Cz
- Ch15 — P3
- Ch16 — P4

In the locations O1 and O2, stabilization pins were placed instead of electrodes to ensure higher stability of headset on subject’s head. The subjects were seated in office chairs without head support to be able to fully lean back on it and relax without putting pressure on the headset. Application was ran on a Windows 10 dektop PC with 32” monitor. Application settings were set to default values.

Limitations

There are several problems with the reliability of measured data that stem from the limitations of employed hardware. The biggest problems come with the usage of spikey dry electrodes. While they theoretically allow faster setup due to no need of any preparation of subject’s scalp area, this comes at a cost. During the study, it became apparent, that the dry electrodes are less than ideal for users with thick and long hair, which was the case for person A. Each session was preceeded with difficulties trying to provide sufficient skin connection for the dry electrodes and even then, the results were quite inconsistent. The electrodes were also uncomfortable and caused light pain during sessions. They are also less sensitive than wet electrodes and more prone to artifacts.

Training Regimen

Recording sessions consist first of equipment setup and user instruction. A scene in the BF training application is selected. The subject goes through the scene, which consists of three sections of BF with short pauses (tens of seconds) inbetween. After the last section is completed, the session ends. The BF controls are set to evaluate subject’s SMR band power level during training.

Person A performed 20 sessions in total, 4 sessions a day, with 1 hour pauses in between. Person B performed 10 sessions in total, 2 a day, with 5 hours in between. One session without setup lasted about 4 minutes on average.

5.2 Analysis Methodology

This section will specify the methods used to analyze the data collected during the study, the goals of the analysis and the rationale behind the methods used.

Absolute or Relative Power Values

The application uses measure SMR band power for control purposes. Due to the inherent inconsistency of recorded voltage values of the dry electrode headset, the general magnitude of the absolute SMR band power differs wildly even in consecutive recordings taken during

the same day. An example of four recordings taken during a single day, spaced one hour apart can be seen in figure 5.1. The fourth recording has values that are consistently much higher than the other three. This discrepancy could provide problematic when it comes to analysis.

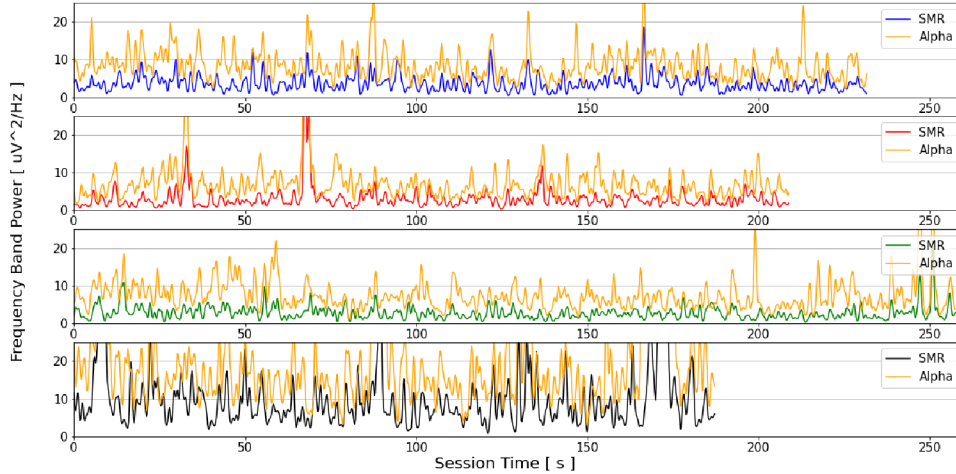


Figure 5.1: Absolute SMR power recorded across four sessions. Recordings are spaced one hour apart. The bottom graph illustrates the problem with analyzing absolute power values — both SMR and Alpha powers here seem scaled up when compared to the other three. This “scaling up” is present across all frequency bands.

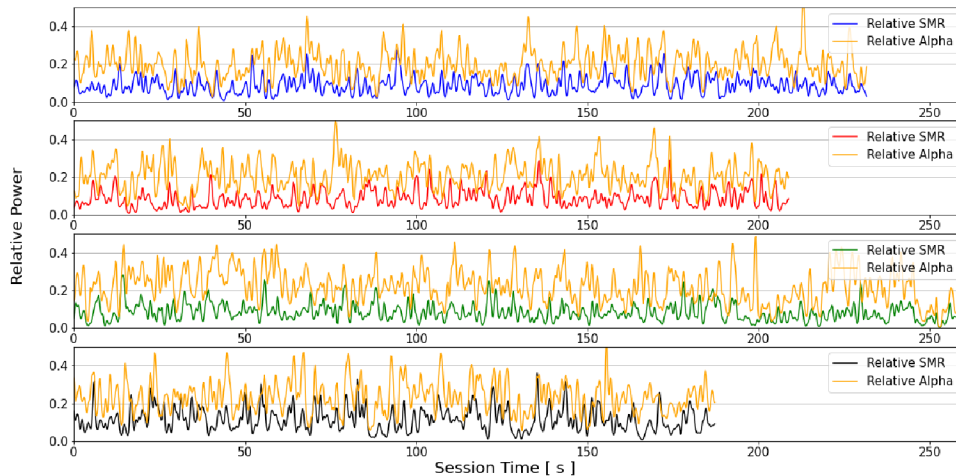


Figure 5.2: Relative SMR power recorded across the same sessions as 5.1. These graphs show that when relative power values are used, the scale of data is consistent across the recording, thus allowing for better comparison.

To address this, instead of using absolute power values, relative power¹ is used. Example of recording represented with relative band power can be seen on figure 5.2. Using relative band power provides the benefit of being able to compare recorded value from multiple sessions without the problem of varying scale. It also preserves the ratios between the different frequency bands, as can be seen when comparing the two example figures, which both show the SMR and Alpha powers of the same four recordings.

SMR Power and Classifier Threshold Accross Sessions

The goal of the studied application is SMR band power enhancement in users in order to train attention. The application itself is controlled by comparing current SMR band power against a dynamic threshold. Example of SMR and threshold during recording can be seen on figure 5.3. These two variables are a prime candidate for analysis, as their change in time could provide some information on whether the user is making progress or the app has no noticeable effects. The analysis will explore if there are any noticeable differences in the relative SMR power values or relative threshold values when compared in early and later sessions. Example of relative SMR power values accross sessions can be seen on figure 5.4.

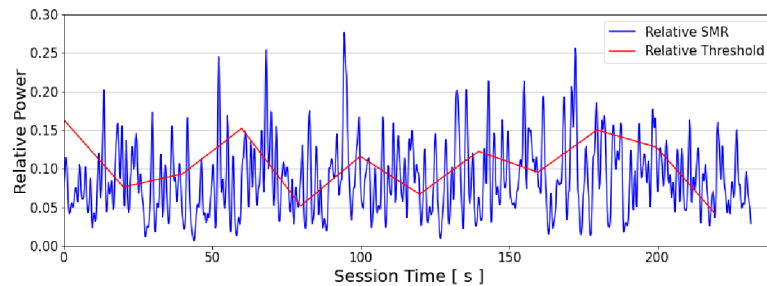


Figure 5.3: Example of relative SMR and relative threshold during a session.

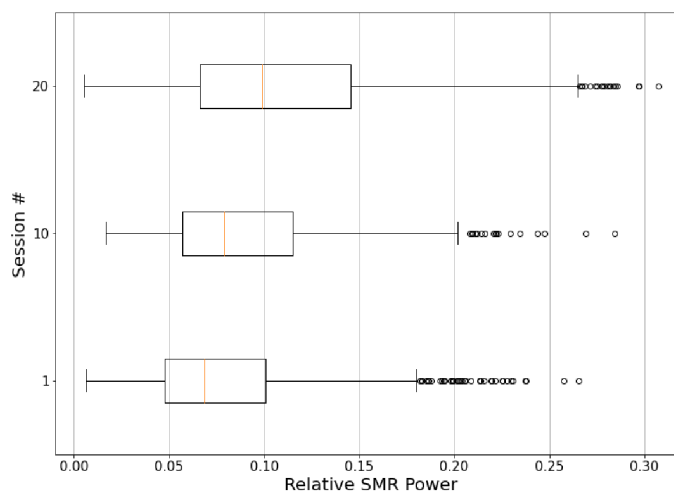


Figure 5.4: Example of relative SMR power values of a user accross 20 sessions.

¹Calculated as $BandPower/TotalPowerAccrossAllBands$

SMR/Theta and SMR/High Beta Ratios

While the SMR band can generally be taken as a measure of a person's calm attention, there are two more notable bands that are important for attention neurofeedback. The theta band represents deep calm, inattention and meditative state. During periods of attention, theta should be as suppressed as possible. Hence, ratio of SMR/Theta shows another valuable metric of attention besides just SMR power. High Beta, on the other hand, represents a state of strong focus and anxiety. While it is desirable to enhance this band to a certain point to enhance attention, it should not exceed high values, as that, instead of the desired attention and focus, indicates undesirable anxiety. The application should therefore ideally show increasing SMR/High Beta ratio at a similar rate as the SMR band power alone throughout the training. An example SMR/Theta ratio and power values are shown in figure 5.5

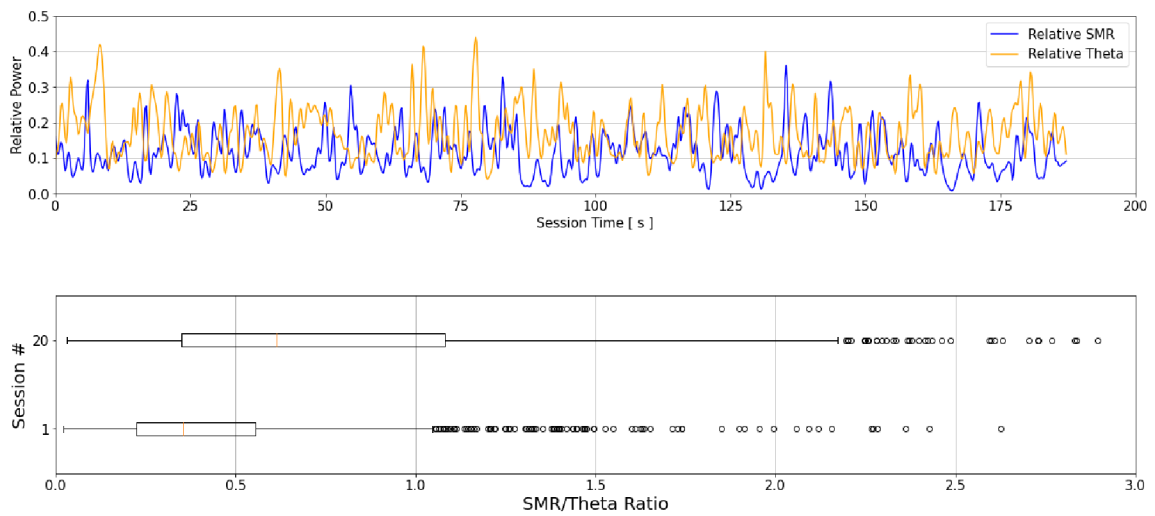


Figure 5.5: Example of SMR and Theta relative band power in the upper graph and changes in SMR/Theta ratio over 20 sessions on lower.

Correlation Analysis

The last part of analysis is searching for any interesting correlations in the recorded variables. The specific variables, that will be explored in this manner are:

- SMR, Alpha, Low Beta, High Beta, Theta, Delta band absolute and relative power values.
- The ratios of all couples of band powers.
- The total power value of all bands.
- The absolute and relative value of classifier threshold.

For mathematical evaluation of correlation, the Pearson correlation coefficient (PCC) was employed. This coefficient is used to measure linear correlation between two sets of data. The results are in the range of $< -1, 1 >$, where 0 denotes no correlation, 1 perfect linear correlation and -1 perfect linear inverse correlation. It is computed as:

$$r_{x,y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} - \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (5.1)$$

where n is sample size, x_i, y_i are individual sample points and $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ is sample mean (analogously \bar{y}).

The PCC results are represented by a 30x30 correlation matrix. Example of a slice of one such matrix can be seen on figure 5.6

	SMR	Alpha	Low Beta	High Beta	Delta	Theta	Threshold
SMR		0.684329	0.589694	0.393459	0.348130	0.431238	0.074756
Alpha	0.684329		0.465212	0.433494	0.486574	0.546152	0.051148
Low Beta	0.589694	0.465212		0.457974	0.356260	0.405256	0.053806
High Beta	0.393459	0.433494	0.457974		0.353343	0.348659	0.055495
Delta	0.348130	0.486574	0.356260	0.353343		0.589407	0.068967
Theta	0.431238	0.546152	0.405256	0.348659	0.589407		0.098349

Figure 5.6: Slice of a correlation matrix with correlation coefficient over 0.5 highlighted.

5.3 Person A Results

SMR Power and Classifier Threshold Accross Sessions

The figure 5.7 shows the relative SMR power values recorded during all 20 sessions. The data shows no noticeable trends in SMR power values, positive or otherwise, as is the case with relative threshold data, visible on figure 5.8. There are minor deviations across the sessions, but nothing that would point to any consistent change, be it in maximal values, minimal values or the median.

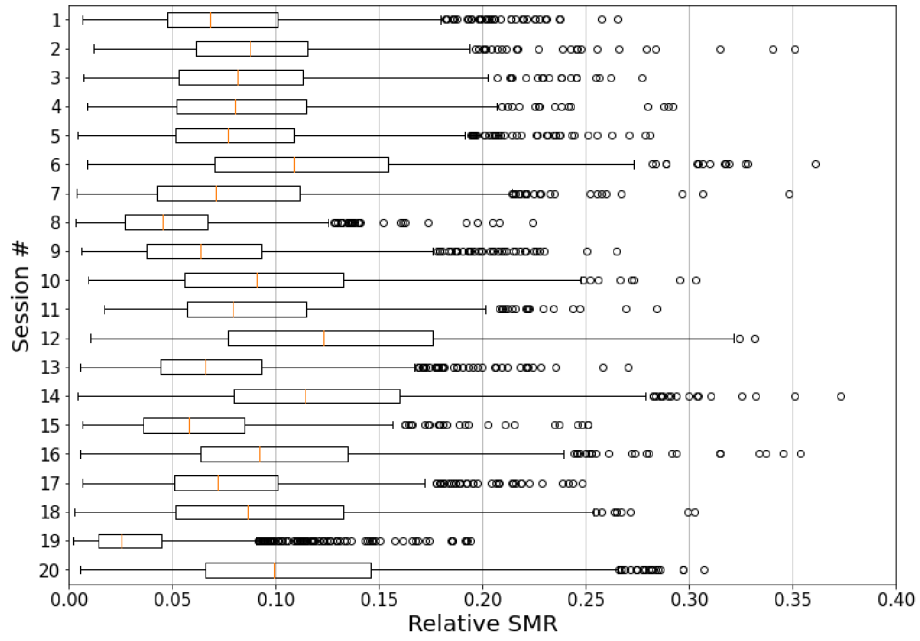


Figure 5.7: Person A's Relative SMR band power values over the course of all 20 sessions

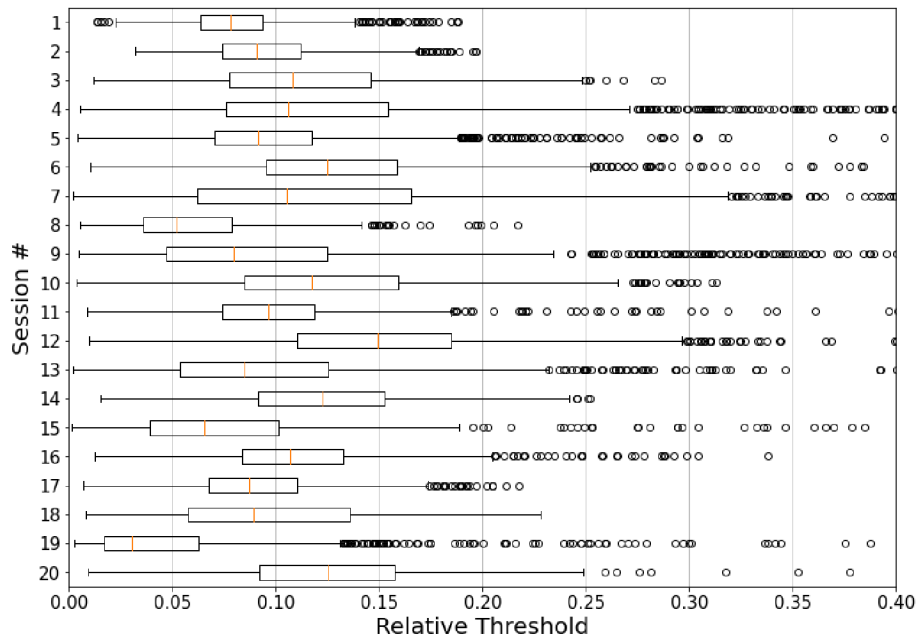


Figure 5.8: Person A's Relative threshold values over the course of all 20 sessions

SMR/Theta and SMR/High Beta Ratios

Both SMR/Theta and SMR/High Beta band power ratios are mostly consistent, which is expected, considering the minimal deviation of SMR band power over sessions.

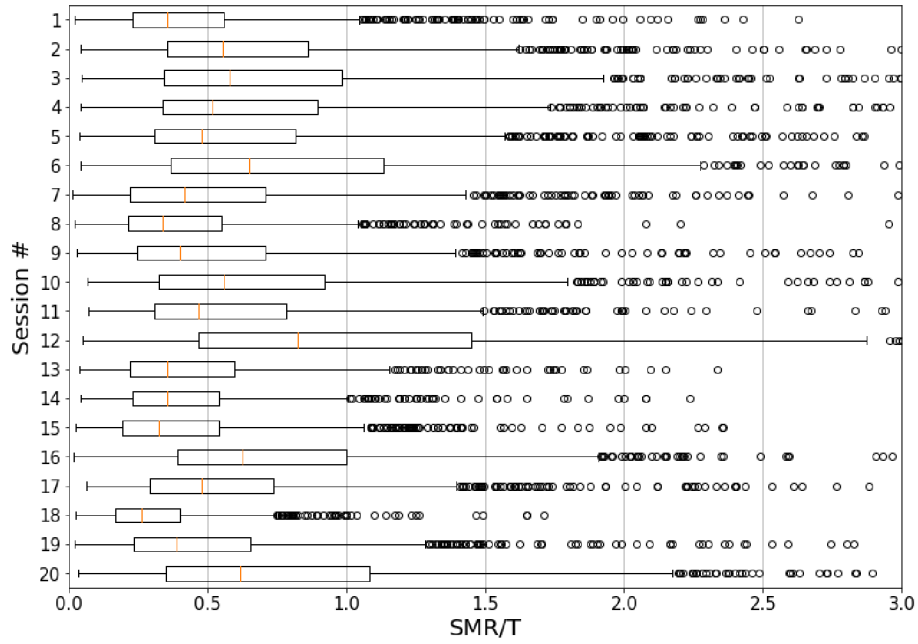


Figure 5.9: Person A's SMR/Theta ratio over the course of all 20 sessions

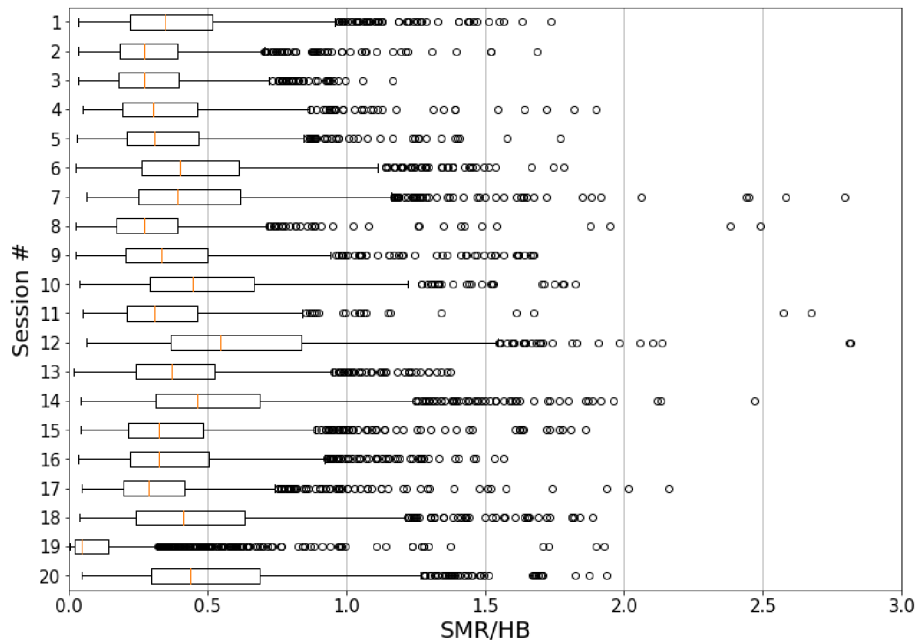


Figure 5.10: Person A's SMR/High Beta ratio over the course of all 20 sessions

Correlation Analysis

The correlation analysis has shown no unexpected correlations. Only expected ones (e.g. SMR correlating with SMR/Theta ratio) were found. For reference, the figure 5.11 shows correlations for relative band power values. The rest of the correlation matrix can be seen in appendix B.

	Relative SMR	Relative Alpha	Relative Low Beta	Relative High Beta	Relative Delta	Relative Theta	Relative Threshold
SMR/A	0.627360	-0.241379	0.370749	0.060953	-0.045668	-0.018964	0.048335
SMR/LB	0.504433	0.346605	-0.423053	-0.029233	-0.019133	-0.009362	0.012803
SMR/HB	0.734683	0.348205	0.189304	-0.430182	0.004080	0.023995	-0.016514
SMR/D	0.700946	0.448854	0.349640	0.273524	-0.586038	0.059657	0.173998
SMR/T	0.706325	0.388199	0.279349	0.170959	-0.133379	-0.532262	0.091201
A/LB	0.011335	0.478912	-0.587385	-0.085558	0.009476	-0.001264	-0.032798
A/HB	0.232326	0.601693	-0.083261	-0.574536	0.057830	0.036310	-0.097114
A/D	0.404301	0.668526	0.205173	0.284063	-0.661090	0.078287	0.174192
A/T	0.314378	0.628233	0.078233	0.154917	-0.129888	-0.616736	0.060633
LB/HB	0.221244	-0.005446	0.710185	-0.466104	0.047516	0.043529	-0.032591
LB/D	0.352929	0.221804	0.691499	0.299456	-0.600130	0.067103	0.171988
LB/T	0.268657	0.092844	0.675032	0.196639	-0.115752	-0.558673	0.067989
HB/D	0.214682	0.241116	0.221585	0.665445	-0.683565	0.059342	0.200123
HB/T	0.086093	0.105069	0.105878	0.618870	-0.142473	-0.655872	0.081045
D/T	-0.212870	-0.286514	-0.222868	-0.314919	0.742049	-0.561310	-0.222416
Power Total	-0.241190	-0.261364	-0.259781	-0.373955	0.467071	-0.033449	-0.407052
Relative SMR		0.503552	0.371852	0.095295	-0.388571	-0.067985	0.188471
Relative Alpha	0.503552		0.081698	0.068538	-0.503467	-0.097175	0.178171
Relative Low Beta	0.371852	0.081698		0.128061	-0.393949	-0.064690	0.178588
Relative High Beta	0.095295	0.068538	0.128061		-0.616494	-0.195408	0.243231
Relative Delta	-0.388571	-0.503467	-0.393949	-0.616494		-0.285236	-0.319896
Relative Theta	-0.067985	-0.097175	-0.064690	-0.195408	-0.285236		0.066921
Threshold	-0.014325	-0.044529	-0.044794	-0.067863	0.039859	0.050360	0.693036
Relative Threshold	0.188471	0.178171	0.178588	0.243231	-0.319896	0.066921	

Figure 5.11: Person A’s frequency band correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.

5.4 Person B Results

SMR Power and Classifier Threshold Across Sessions

The figure 5.12 shows the relative SMR power values recorded during all 10 sessions. As with person A, the results display no noticeable SMR enhancement. A slight SMR inhibition can be seen on the last few sessions. This may relate to wrong headset setup or person B’s wellbeing, as the sessions 7 to 10 were conducted when they were suffering from an illness. The threshold data 5.13 shows the same pattern of no significant change during most of the sessions and an inhibition during the last few.

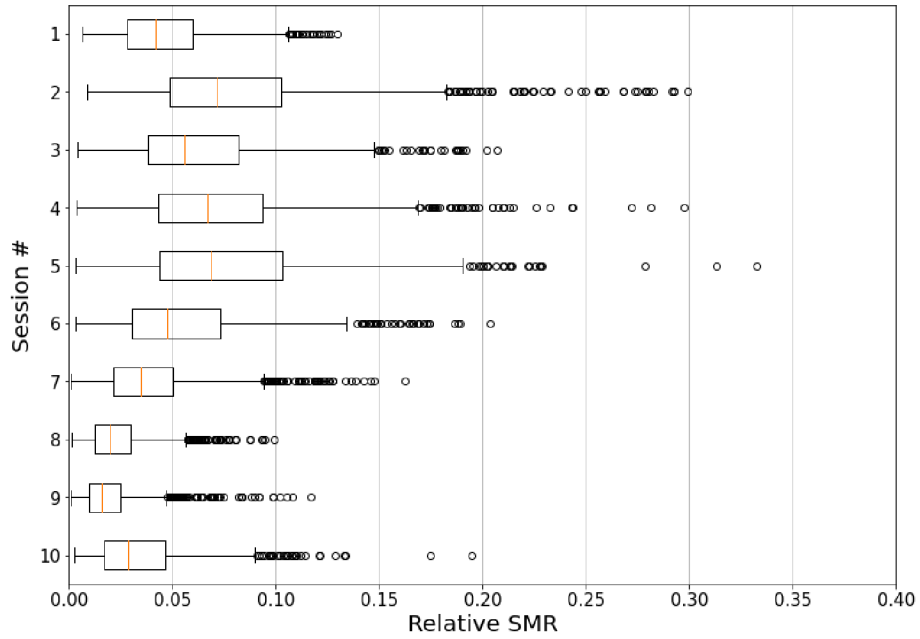


Figure 5.12: Person B's Relative SMR band power values over the course of all 20 sessions

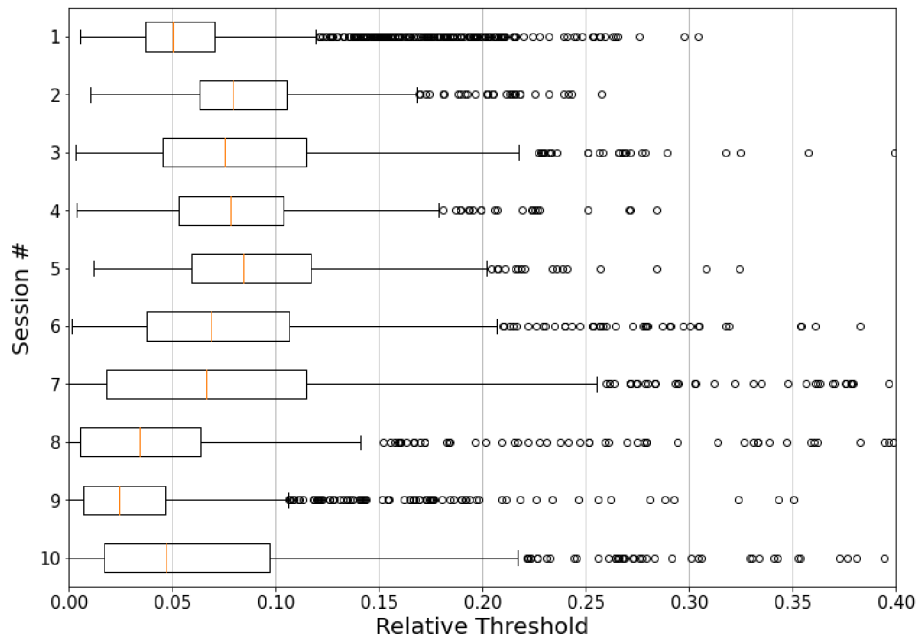


Figure 5.13: Person B's Relative threshold values over the course of all 20 sessions

SMR/Theta and SMR/High Beta Ratios

The SMR/Theta ratio, shown in figure 5.15, shows the same pattern as the SMR power, with the same inhibition during sessions 7 to 10, which is expected. In SMR/High Beta ratio, however, the expected decrease during later sessions is instead replaced by an increase, as can be seen in figure 5.15. The figure 5.14 shows that during these sessions, high beta

frequency was extremely low. Values so low probably indicate that there were recording problems during the sessions that were not identified prior to analysis.

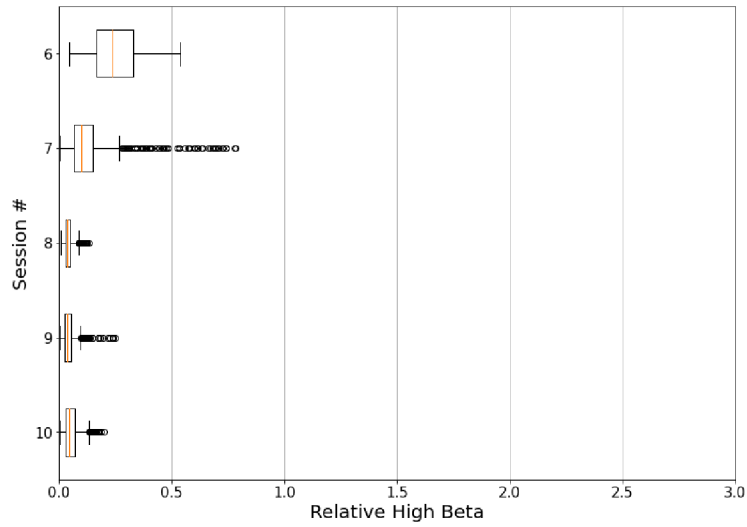


Figure 5.14: Person B's relative High Beta band values during sessions 6 to 10.

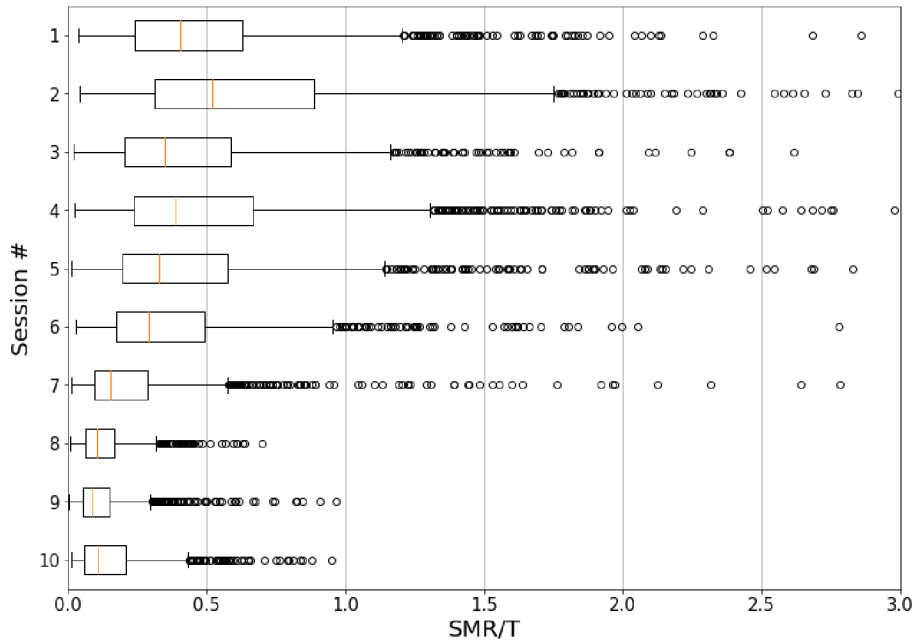


Figure 5.15: Person B's SMR/Theta ratio over the course of all 20 sessions

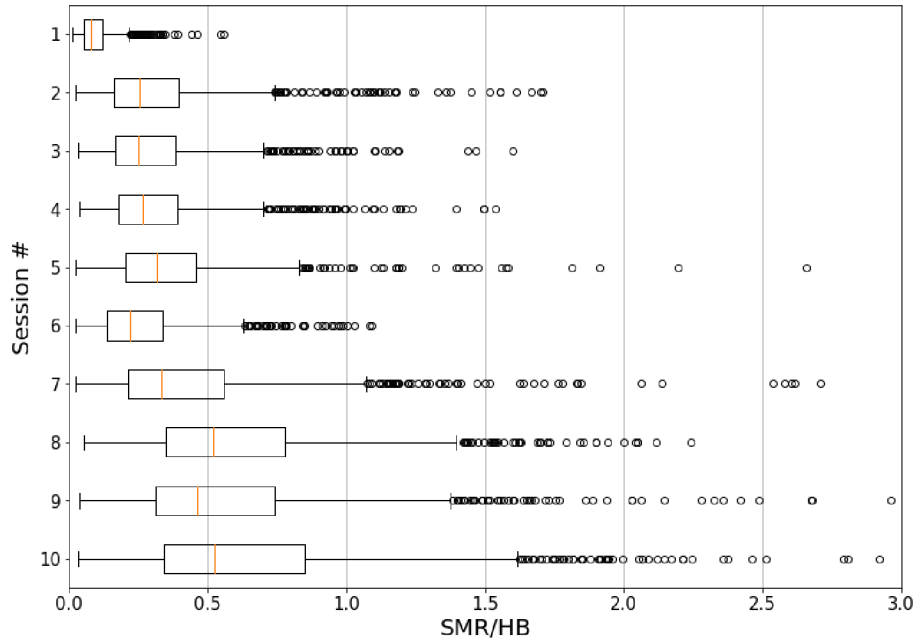


Figure 5.16: Person B's SMR/High Beta ratio over the course of all 20 sessions

Correlation Analysis

As with person A, the correlation analysis has again shown no unexpected correlations. For reference, the figure 5.17 shows correlations for relative band power values. The rest of the correlation matrix can be seen in appendix B.

	Relative SMR	Relative Alpha	Relative Low Beta	Relative High Beta	Relative Delta	Relative Theta	Relative Threshold
SMR/A	0.609933	-0.233342	0.346911	0.144207	-0.024553	-0.072518	0.044358
SMR/LB	0.463930	0.266357	-0.386116	-0.050481	0.010427	0.016954	0.004258
SMR/HB	0.620723	0.288033	0.130167	-0.385185	0.054359	0.044726	-0.023288
SMR/D	0.763913	0.496296	0.447857	0.428983	-0.618357	0.089156	0.184912
SMR/T	0.706040	0.330581	0.359567	0.283736	-0.085816	-0.497669	0.146746
A/LB	-0.065653	0.415829	-0.537577	-0.162533	0.010505	0.078612	-0.051329
A/HB	0.133434	0.525415	-0.125969	-0.527862	0.061055	0.115433	-0.069966
A/D	0.424748	0.738066	0.303129	0.386314	-0.702441	0.147052	0.188696
A/T	0.375453	0.606083	0.203905	0.243783	-0.109070	-0.563263	0.162127
LB/HB	0.198130	0.034143	0.577751	-0.394515	0.055900	0.024929	-0.017577
LB/D	0.417646	0.320360	0.770824	0.466269	-0.624650	0.070951	0.180233
LB/T	0.333422	0.125886	0.707867	0.330386	-0.102750	-0.515675	0.123215
HB/D	0.289353	0.292319	0.345926	0.784587	-0.677106	0.058882	0.194032
HB/T	0.197422	0.100141	0.250932	0.679989	-0.145198	-0.570636	0.142226
D/T	-0.193092	-0.294959	-0.207289	-0.278024	0.725782	-0.628622	-0.128986
Power Total	-0.161548	-0.222872	-0.188323	-0.300056	0.379974	-0.072710	-0.214728
Relative SMR		0.521016	0.461466	0.260135	-0.407921	-0.053741	0.203239
Relative Alpha	0.521016		0.215716	0.177723	-0.537653	0.017113	0.219961
Relative Low Beta	0.461466	0.215716		0.336264	-0.437902	-0.088127	0.194582
Relative High Beta	0.260135	0.177723	0.336264		-0.619127	-0.172325	0.235021
Relative Delta	-0.407921	-0.537653	-0.437902	-0.619127		-0.421844	-0.249280
Relative Theta	-0.053741	0.017113	-0.088127	-0.172325	-0.421844		-0.040771
Threshold	0.042654	0.010125	0.020215	-0.051286	0.076289	-0.075883	0.630172
Relative Threshold	0.203239	0.219961	0.194582	0.235021	-0.249280	-0.040771	

Figure 5.17: Person B's frequency band correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.

5.5 Study Conclusion

The study has shown no concrete evidence of any change in either user's EEG signal. All analyzed values stayed mostly the same during the sessions, with slight deviations. While both users reported, that the difficulty of controlling the neurofeedback app felt lower after a number of sessions, the data shows no evidence of actual changes in EEG activity or higher thresholds being set by the application.

More testing has to be done in order to sufficiently evaluate any potential effect of the application. Longer training regimens with more spaced out training sessions should be explored. Another proposition is the use of other measuring devices, such as wet electrode headsets or different types of dry electrodes.

Chapter 6

Conclusion

The main goal of this project was the design and development of a new neurofeedback application for attention training. For this purpose, the existing solutions regarding attention enhancement neurofeedback were explored, along with the underlying theory. Multiple varying approaches to neurofeedback training regimens, which targeted varying sets of EEG frequency bands were considered. In the end, it was decided to target SMR band enhancement in order to increase attention in the user. Multiple methods of processing and translating the EEG signal into application commands were researched.

The final application has been developed using the Unity3D game engine and the open source Brainflow library. The Brainflow library was used to capture and process EEG signal from a Cyton board with Daisy extension, which was used for EEG recording along with an Ultracortex Mark IV dry electrode headset. The application uses the same approaches seen in typical neurofeedback application — user focusing on controlling the application with their brain for a set period of time, while receiving positive or negative feedback. This process was enhanced by gamifying the process. This was done by creating a simple narrative of user learning spells and casting them. The goal was to break up the monotony of usual neurofeedback applications and try to set actual goals for the user with no set session time. The application also, unlike typical ones, does not require an operator that would modify the thresholds evaluating the user's input. Here, the thresholds are set automatically during session by evaluating the ratio of successful/unsuccessful inputs and increasing/lowering the threshold accordingly. This both ensures the user does not get frustrated when not able to produce the desired brain activity and that the user is sufficiently challenged when successful.

A case study has been designed and carried out to evaluate the effectiveness of this neurofeedback application with regards to two main user groups — adults with attention problems and neurotypical adults. Two university students, one from each group, were selected as testing subjects for the study. They both underwent a rigorous training regimen consisting of multiple daily training sessions. The recorded EEG data was analyzed to find out if any noticeable changes to SMR band power value or application threshold values across sessions were present. No significant changes in brain activity were discovered during the study. While the users both reported that they found the application much easier to control after few sessions, there was no evidence of change in the EEG signal. More evaluation could be done by employing different training regimens or different recording hardware.

The gamification of the application could be further expanded upon, in order to obfuscate the training process and increase immersion in the users. Different, more complex

control methods could be used, such as event-related potentials, or even EEG controls combined with traditional controllers, such as gamepads.

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Appendix A

Source Structure and Building

The application source files mainly follows the standart Unity project folder structure, as can be seen on figure [A.1](#). Additions are the *Recordings* and *Analysis* folders, which contain EEG logs and analysis tools respectively. Another added folder is *BrainflowToUnpack*, which contans brainflow C++ libraries. To build this project, the whole folder should be opened in Unity3D editor and built for the desired platform. It was only tested on windows, but Linux version should also be buildable out of the box. After building the project to the desired path, the contents of the *BrainflowToUnpack* folder should be copied to the same directory that contains the app executable file. The app is then launchable through the executable. The *Recordings* directory will be created when necessary in the app root folder. The Jupyter notebook used for analysis requires the pip packages specified in the file *Analysis/requirements.txt* to be installed.

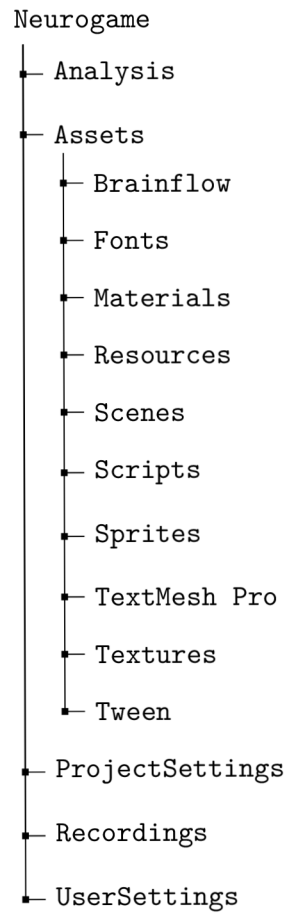


Figure A.1: Project Directory Tree

Appendix B

Ratio Correlation Matrices

Person A

	Relative SMR	Relative Alpha	Relative Low Beta	Relative High Beta	Relative Delta	Relative Theta	Relative Threshold
SMR/A	0.627360	-0.241379	0.370749	0.060953	-0.045668	-0.018964	0.048335
SMR/LB	0.504433	0.346605	-0.423053	-0.029233	-0.019133	-0.009362	0.012803
SMR/HB	0.734683	0.348205	0.189304	-0.430182	0.004080	0.023995	-0.016514
SMR/D	0.700946	0.448854	0.349640	0.273524	-0.586038	0.059657	0.173998
SMR/T	0.706325	0.388199	0.279349	0.170959	-0.133379	-0.532262	0.091201
A/LB	0.011335	0.478912	-0.587385	-0.085558	0.009476	-0.001264	-0.032798
A/HB	0.232326	0.601693	-0.083261	-0.574536	0.057830	0.036310	-0.097114
A/D	0.404301	0.668526	0.205173	0.284063	-0.661090	0.078287	0.174192
A/T	0.314378	0.628233	0.078233	0.154917	-0.129888	-0.616736	0.060633
LB/HB	0.221244	-0.005446	0.710185	-0.466104	0.047516	0.043529	-0.032591
LB/D	0.352929	0.221804	0.691499	0.299456	-0.600130	0.067103	0.171988
LB/T	0.268657	0.092844	0.675032	0.196639	-0.115752	-0.558673	0.067989
HB/D	0.214682	0.241116	0.221585	0.665445	-0.683565	0.059342	0.200123
HB/T	0.086093	0.105069	0.105878	0.618870	-0.142473	-0.655872	0.081045
D/T	-0.212870	-0.286514	-0.222868	-0.314919	0.742049	-0.561310	-0.222416
Power Total	-0.241190	-0.261364	-0.259781	-0.373955	0.467071	-0.033449	-0.407052
Relative SMR		0.503552	0.371852	0.095295	-0.388571	-0.067985	0.188471
Relative Alpha	0.503552		0.081698	0.068538	-0.503467	-0.097175	0.178171
Relative Low Beta	0.371852	0.081698		0.128061	-0.393949	-0.064690	0.178588
Relative High Beta	0.095295	0.068538	0.128061		-0.616494	-0.195408	0.243231
Relative Delta	-0.388571	-0.503467	-0.393949	-0.616494		-0.285236	-0.319896
Relative Theta	-0.067985	-0.097175	-0.064690	-0.195408	-0.285236		0.066921
Threshold	-0.014325	-0.044529	-0.044794	-0.067863	0.039859	0.050360	0.693036
Relative Threshold	0.188471	0.178171	0.178588	0.243231	-0.319896	0.066921	

Figure B.1: Person A's frequency band correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.

	SMR/A	SMR/LB	SMR/HB	SMR/D	SMR/T	A/LB	A/HB	A/D	A/T	LB/HB	LB/D	LB/T	HB/D	HB/T	D/T
SMR	0.387356	0.371216	0.627356	0.309002	0.389006	0.076420	0.341580	0.111600	0.146800	0.223591	0.085539	0.098992	-0.027121	-0.052658	0.039860
Alpha	-0.202986	0.217187	0.310065	0.047349	0.100220	0.380513	0.591893	0.156804	0.275058	0.072616	-0.070777	-0.049841	-0.093765	-0.076371	0.082962
Low Beta	0.207473	-0.285295	0.208265	0.078880	0.100357	-0.370009	0.084318	-0.026833	-0.016710	0.559254	0.289537	0.379749	-0.034503	-0.030578	0.060012
High Beta	-0.012893	-0.018853	-0.237519	-0.034252	-0.006456	-0.001302	-0.262788	-0.041472	0.008389	-0.259038	-0.022016	0.029582	0.170553	0.288734	0.077429
Delta	-0.065766	0.019445	0.076221	-0.294532	-0.126717	0.072307	0.175705	-0.327825	-0.106958	0.073221	-0.303907	-0.120827	-0.348938	-0.149161	0.534597
Theta	-0.058378	0.034874	0.123980	-0.120748	-0.322631	0.095948	0.234385	-0.126195	-0.350735	0.091804	-0.132587	-0.342661	-0.160050	-0.405286	-0.070228
SMR/A		0.236265	0.480064	0.356899	0.435691	-0.356487	-0.226244	-0.080723	-0.133134	0.266120	0.221995	0.253012	0.049455	0.026380	-0.010914
SMR/LB	0.236265		0.463164	0.272090	0.345445	0.665995	0.277717	0.167345	0.204556	-0.341476	-0.208055	-0.275491	0.008180	-0.016496	-0.003197
SMR/HB	0.480064	0.463164		0.391359	0.483477	0.075628	0.628853	0.163400	0.187631	0.490448	0.110282	0.107535	-0.152584	-0.229235	0.001258
SMR/D	0.356899	0.272090	0.391359		0.435543	0.002769	0.107757	0.812446	0.216159	0.112820	0.744748	0.195990	0.690957	-0.101854	-0.342152
SMR/T	0.435691	0.345445	0.483477	0.435543		0.013243	0.13243	0.148916	0.235903	0.730674	0.124394	0.208681	0.650282	0.132107	0.573368
A/LB	-0.356487	0.665995	0.075628	0.002769	0.013243		0.444243	0.212573	0.294254	-0.454106	-0.303285	-0.383098	-0.025892	-0.034016	0.000645
A/HB	-0.226244	0.277717	0.628853	0.107757	0.148916	0.444243		0.248498	0.345321	0.342664	-0.051586	-0.069101	-0.227416	-0.293739	0.022800
A/D	-0.080723	0.167345	0.163400	0.812446	0.235903	0.212573	0.248498		0.337915	-0.005392	0.675198	0.094933	0.754325	-0.104054	-0.391204
A/T	-0.133134	0.204556	0.187631	0.216159	0.730674	0.294254	0.345321	0.337915		-0.026151	0.093355	0.547623	0.117328	0.643597	0.263482
LB/HB	0.266120	-0.341476	0.490448	0.112820	0.124394	-0.454106	0.342664	-0.005392	-0.026151		0.356111	0.423790	-0.181643	-0.249817	0.015945
LB/D	0.221995	-0.208055	0.110282	0.744748	0.208681	-0.303285	-0.051586	0.675198	0.093355	0.356111		0.413745	0.706410	0.114655	-0.353264
LB/T	0.253012	-0.275491	0.107535	0.195990	0.650282	-0.383098	-0.069101	0.094933	0.547623	0.423790	0.413745		0.129567	0.623861	0.245848
HB/D	0.049455	0.008180	-0.152584	0.690957	0.132107	-0.025892	-0.227416	0.754325	0.117328	-0.181643	0.706410	0.129567		0.307753	-0.393810
HB/T	0.026380	-0.016496	-0.229235	0.101854	0.573368	-0.034016	-0.293739	0.104054	0.643597	-0.249817	0.114655	0.623861	0.307753		0.279293
D/T	-0.010914	-0.003197	0.001258	-0.342152	0.221634	0.000645	0.022800	-0.391204	0.263482	0.015945	-0.353264	0.245848	-0.393810	0.279293	
Power Total	-0.070531	0.022347	0.088709	-0.195533	-0.125536	0.090964	0.205694	-0.212277	-0.096122	0.069011	-0.200208	-0.115038	-0.224958	-0.132601	0.356810
Relative SMR	0.627360	0.504433	0.734683	0.700946	0.706325	0.011335	0.232326	0.404301	0.314378	0.221244	0.352929	0.268657	0.214682	0.086093	-0.212870
Relative Alpha	-0.241379	0.346605	0.348205	0.448854	0.388199	0.478912	0.601693	0.668526	0.628233	-0.005446	0.221804	0.092844	0.241116	0.105069	-0.286514
Relative Low Beta	0.370749	-0.423053	0.189304	0.349640	0.279349	-0.587385	-0.083261	0.205173	0.078233	0.710185	0.691499	0.675032	0.221585	0.105878	-0.222868
Relative High Beta	0.060953	-0.029233	-0.430182	0.273524	0.170959	-0.085558	-0.574536	0.284063	0.154917	-0.466104	0.299456	0.196639	0.665445	0.618870	-0.314919
Relative Delta	-0.045668	-0.019133	0.004080	-0.586028	-0.133379	0.009476	0.057830	-0.661090	-0.129888	0.047516	-0.600130	-0.115752	-0.683565	-0.142473	0.742049
Relative Theta	-0.018964	-0.009362	0.023995	0.059657	-0.532262	-0.001264	0.036310	0.078287	-0.616736	0.043529	0.067103	-0.558673	0.059342	-0.655872	-0.561310
Threshold	0.000808	0.024109	0.028578	-0.014362	-0.030730	0.015761	0.016286	-0.028757	-0.052417	0.005251	-0.027743	-0.053450	-0.030966	-0.063631	0.015669
Relative Threshold	0.048335	0.012803	-0.016514	0.173998	0.091201	-0.032798	-0.097114	0.174192	0.060633	-0.032591	0.171988	0.067989	0.200123	0.081045	-0.222416

Figure B.2: Person A's frequency ratios correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.

Person B

	Relative SMR	Relative Alpha	Relative Low Beta	Relative High Beta	Relative Delta	Relative Theta	Relative Threshold
SMR/A	0.609933	-0.233342	0.346911	0.144207	-0.024553	-0.072518	0.044358
SMR/LB	0.463930	0.266357	-0.386116	-0.050481	0.010427	0.016954	0.004258
SMR/HB	0.620723	0.288033	0.130167	-0.385185	0.054359	0.044726	-0.023288
SMR/D	0.763913	0.496296	0.447857	0.428983	-0.618357	0.089156	0.184912
SMR/T	0.706040	0.330581	0.359567	0.283736	-0.085816	-0.497669	0.146746
A/LB	-0.065653	0.415829	-0.537577	-0.162533	0.010505	0.078612	-0.051329
A/HB	0.133434	0.525415	-0.125969	-0.527862	0.061055	0.115433	-0.069966
A/D	0.424748	0.738066	0.303129	0.386314	-0.702441	0.147052	0.188696
A/T	0.375453	0.606083	0.203905	0.243783	-0.109070	-0.563263	0.162127
LB/HB	0.198130	0.034143	0.577751	-0.394515	0.055900	0.024929	-0.017577
LB/D	0.417646	0.320360	0.770824	0.466269	-0.624650	0.070951	0.180233
LB/T	0.333422	0.125886	0.707867	0.330386	-0.102750	-0.515675	0.123215
HB/D	0.289353	0.292319	0.345926	0.784587	-0.677106	0.058882	0.194032
HB/T	0.197422	0.100141	0.250932	0.679989	-0.145198	-0.570636	0.142226
D/T	-0.193092	-0.294959	-0.207289	-0.278024	0.725782	-0.628622	-0.128986
Power Total	-0.161548	-0.222872	-0.188323	-0.300056	0.379974	-0.072710	-0.214728
Relative SMR		0.521016	0.461466	0.260135	-0.407921	-0.053741	0.203239
Relative Alpha	0.521016		0.215716	0.177723	-0.537653	0.017113	0.219961
Relative Low Beta	0.461466	0.215716		0.336264	-0.437902	-0.088127	0.194582
Relative High Beta	0.260135	0.177723	0.336264		-0.619127	-0.172325	0.235021
Relative Delta	-0.407921	-0.537653	-0.437902	-0.619127		-0.421844	-0.249280
Relative Theta	-0.053741	0.017113	-0.088127	-0.172325	-0.421844		-0.040771
Threshold	0.042654	0.010125	0.020215	-0.051286	0.076289	-0.075883	0.630172
Relative Threshold	0.203239	0.219961	0.194582	0.235021	-0.249280	-0.040771	

Figure B.3: Person B's frequency band correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.

	SMR/A	SMR/LB	SMR/HB	SMR/D	SMR/T	A/LB	A/HB	A/D	A/T	LB/HB	LB/D	LB/T	HB/D	HB/T	D/T
SMR	0.365244	0.323769	0.542670	0.363892	0.470945	-0.002515	0.243954	0.145605	0.230795	0.239968	0.174130	0.221460	0.057578	0.081240	0.061406
Alpha	-0.128928	0.193163	0.317386	0.175913	0.189012	0.308046	0.496002	0.253818	0.295833	0.138594	0.064765	0.052388	0.009610	-0.017515	0.034589
Low Beta	0.235373	-0.224804	0.200890	0.196657	0.229761	-0.316938	0.049419	0.068656	0.093964	0.483037	0.382567	0.449230	0.082026	0.087026	0.036303
High Beta	0.096964	0.011803	-0.186554	0.177640	0.190333	-0.036265	-0.258864	0.100160	0.120657	-0.215626	0.179807	0.193993	0.355757	-0.393347	0.033181
Delta	-0.030917	0.057527	0.136671	-0.252871	-0.069328	0.073512	0.171901	-0.283540	-0.085236	0.101947	-0.265601	-0.094901	-0.294469	-0.138553	0.461899
Theta	-0.042184	0.047185	0.158231	-0.062048	-0.262403	0.107166	0.235562	-0.077501	-0.301076	0.122697	-0.091486	-0.273795	-0.130065	-0.339516	-0.111425
SMR/A		0.257524	0.418416	0.371847	0.467765	-0.405593	-0.283553	-0.107544	-0.083961	0.208550	0.198657	0.275313	0.080344	0.141393	0.025800
SMR/LB	0.257524		0.459179	0.277866	0.318092	0.580784	0.232913	0.125609	0.172865	-0.320600	-0.216134	-0.251299	-0.015736	-0.026210	0.026663
SMR/HB	0.418416	0.459179		0.328929	0.399093	0.047962	0.623345	0.099255	0.162506	0.547568	0.044870	0.058468	-0.205173	-0.227352	0.034646
SMR/D	0.371847	0.277866	0.328929		0.498226	-0.047521	0.042138	0.768942	0.295052	0.088152	0.722615	0.275496	0.687087	0.221843	-0.333357
SMR/T	0.467765	0.318092	0.399093	0.498226		-0.076471	0.038048	0.228984	0.742367	0.114696	0.263496	0.674343	0.198993	0.632974	0.286284
A/LB	-0.405593	0.580784	0.047962	-0.047521	-0.076471		0.463765	0.196552	0.204945	-0.404631	-0.304958	-0.375619	-0.083928	-0.129223	-0.020085
A/HB	-0.283553	0.232913	0.623345	0.042138	0.038048	0.463765		0.222328	0.248983	0.401665	-0.097669	-0.137702	-0.270422	-0.341512	-0.000327
A/D	-0.107544	0.125609	0.099255	0.768942	0.228984	0.196552	0.222328		0.391813	-0.012243	0.674160	0.143978	0.706290	-0.152115	-0.390573
A/T	-0.083961	0.172865	0.162506	0.295052	0.742367	0.204945	0.248983	0.391813		0.007601	0.182519	0.581401	0.182722	0.631168	0.317450
LB/HB	0.208550	-0.320600	0.547568	0.088152	0.114698	-0.404631	0.401665	-0.012243	0.007601		0.292101	0.349245	-0.214262	-0.234882	0.025574
LB/D	0.198657	-0.216134	0.044670	0.722615	0.263496	-0.304958	-0.097669	0.674160	0.182519	0.292101		0.483890	0.721075	0.234166	-0.336736
LB/T	0.275313	-0.251299	0.058468	0.275496	0.674343	-0.375619	-0.137702	0.143978	0.581401	0.349245	0.483890		0.224470	0.675715	0.279941
HB/D	0.080344	-0.015736	-0.205173	0.687087	0.198993	-0.083928	-0.270422	0.706290	0.182722	-0.214262	0.721075	0.224470		0.437647	-0.360626
HB/T	0.141393	-0.026210	-0.227352	0.221843	0.632974	-0.129223	-0.341512	0.152115	0.631168	-0.234882	0.234166	0.675715	0.437647		0.281174
D/T	0.025800	0.026663	0.034646	-0.333357	0.286284	-0.020085	-0.000327	-0.390573	0.317450	0.025574	-0.336736	0.279941	-0.360626	0.281174	
Power Total	-0.010749	0.063428	0.149759	-0.130653	-0.032113	0.080993	0.184370	-0.162410	-0.060247	0.109773	-0.149671	-0.057337	-0.174274	-0.101757	0.317436
Relative SMR	0.609933	0.463930	0.620723	0.763913	0.706040	-0.065653	0.133434	0.424748	0.375453	0.198130	0.417646	0.333422	0.289353	0.197422	-0.193092
Relative Alpha	-0.233342	0.266357	0.288033	0.496296	0.330581	-0.415829	0.525415	0.738066	0.606083	0.034143	0.320360	0.125886	0.292319	0.100141	-0.294959
Relative Low Beta	0.346911	-0.386116	0.130167	0.447857	0.359567	-0.537577	-0.125969	0.303129	0.203905	0.577751	0.770824	0.707867	0.345926	0.250932	-0.207269
Relative High Beta	0.144207	-0.050481	-0.385185	0.428983	0.283736	-0.162533	-0.527862	0.386314	0.243783	-0.394515	0.466269	0.330386	0.784587	0.679989	-0.278024
Relative Delta	-0.024553	0.010427	0.054359	-0.616357	-0.085816	0.010505	0.061055	-0.702441	-0.109070	0.055900	-0.624650	-0.102750	-0.677106	-0.145198	0.725762
Relative Theta	-0.072518	0.016954	0.044726	0.069156	-0.497669	0.078612	0.115433	0.147052	-0.563263	0.024929	0.070951	-0.515675	0.058882	-0.570636	-0.628622
Threshold	0.026184	0.036649	0.083947	0.027111	0.085146	0.010829	0.069024	-0.001480	0.070528	0.064575	0.017204	0.052369	-0.008158	0.017254	0.093458
Relative Threshold	0.044358	0.004258	-0.023288	0.184912	0.146746	-0.051329	-0.069966	0.188696	0.162127	-0.017577	0.180233	0.123215	0.194032	0.142226	-0.128986

Figure B.4: Person B's frequency ratios correlation matrix. Yellow fields indicate correlation coefficient over 0.5 and orange ones coefficient under -0.5.