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Pázmány Péter Catholic University

Faculty of Information Technology and Bionics

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Development of an EEG-GNSS Integrated Headset for Mental State Monitoring and Prediction

Eszter Anna HUDRA

Molecular Bionics Engineering BSc

Supervisor: Dr. Gergely MÁRTON

Faculty Mentor: Dr. István ULBERT

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Chapter 1

Introduction

1.1. Background and Motivation

Understanding how the brain works has long captured the mind of researchers. The brain's network-level adaptive behaviour makes it especially unique, meaning it can adapt well to environmental influences. Several neurological and cognitive disorders may cause the degradation of brain functions, even leading to a complete loss of voluntary muscle control. This scenario led to the birth of Brain-Computer Interfaces (BCIs) originally developed as a potential solution for restoring functions to patients with neurological disorders. In recent years, BCIs have evolved, enabling not only control of external devices but also real-time monitoring and observation of human mental states and cognitive processes. This connection of biology and technology has brought us closer than ever before to understanding the brain.

The study of Electroencephalography (EEG), as a core technology in BCI development, represents an essential area of research at the intersection of neuroscience, psychology, and technology. EEG provides a unique insight into the human brain, allowing researchers to monitor and analyze neural activity with high temporal resolution non-invasively. On the other hand, BCIs promise to revolutionize human-computer interactions by enabling direct communication between the brain and external devices, offering new ways of monitoring and personalized treatment for individuals with neurological conditions. However, EEG-based BCIs are typically constrained to controlled environments, offering little context about how real-world circumstances, like urban or high-stress environments, might impact individuals' mental states or cognitive performance and influence those suffering from

mental disorders.

The idea of integrating a Global Navigation Satellite System (GNSS) receiver into an EEG headset emerged from the growing need to understand how environmental contexts influence mental states, like attention, mental fatigue or stress, emotions, and cognitive functions. The connection of location and EEG data opens new possibilities by adding a spatial dimension to mental state data. With the use of such a device, correlating brainwave activity with specific locations can reveal how environments affect the mental health and cognitive performance of users.

This project's motivation lies in the potential to bridge the gap between laboratory-based EEG analysis and real-world applications. Ultimately, while developing an EEG-GNSS integrated headset, we aim to provide an adaptable tool useful for a wide range of fields, enabling real-world applications such as urban planning, neuromarketing, mental health monitoring and personalized therapy.

1.2. Overview of the Project

At the beginning of the project, we developed a detailed plan for the development steps that led to the successful implementation of the device.

A brief overview outlining the steps:

- Gaining insight into the signal processing of electroencephalography, detection of mental states, brain-computer interfaces and their applications.
- Select a commercially available GNSS module for integration into the MindRove bright headband.
- Connect bright and GNSS module by a chosen communication protocol and update the hardware design of the headset.
- Update the MindRove firmware with the implementation of the location data transmission.
- Develop an Android application for real-time storing of the recorded data stream.
- Test the headset through processing and visualisation of both location and EEG data with a Python code. Ideally, detect and predict mental states.

1.3. Outline

Chapter 2 This chapter comprehensively reviews the literature and theoretical background of electroencephalography (EEG) and brain-computer interfaces (BCIs).

The focus is on the fundamental principles underlying EEG theory and signal processing techniques. In addition, the increasingly widespread topics of mental state detection and neurofeedback are reviewed. These are followed by a discussion of the categorisation aspects and the diverse applications of BCIs, addressing limitations and challenges too. Finally, a review of the related works and previous implementations of the titular EEG-GNSS integrated headsets is presented.

Chapter 3 Introduction of the applied components, that were used and improved to develop our EEG-GNSS Integrated Headset. After providing a review of the commercially available GNSS modules, the justification of the components chosen for the project is presented. The GNSS 10 click module, available from MIKROE, and the EEG headset named bright, developed by Mindrove Kft., are briefly described, with a strong emphasis on the features and benefits of both devices.

Chapter 4 This chapter provides an overview of the completed tasks, with a description of the methodologies used to provide the background of the decisions made during the project.

The chapter starts with an introduction to communication protocols while justifying the decision to implement I2C communication between the GNSS module and the bright headband.

This is followed by a detailed overview of the key tasks of the project. Firstly, we can get familiar with the concept of the NMEA protocol, and then the implementation steps and challenges present during the MindRove firmware update and development are reviewed. The topics covered include the choice of data structures and the idea behind the implementation of a unified data format for both EEG and location data transmission. In addition, the Android application developed as an add-on to the firmware is introduced. It is designed to allow users to easily perform measurements while saving all recorded data with a button push.

The data processing steps are presented along with the concept of UDP, providing

a background on why reordering of the stored data was needed. I will present the key functionalities of the implemented Python code that can decode, read and display the captured data location data. In the end, I give a detailed overview of the available EEG denoising techniques for signal processing, that need to be implemented for proper EEG signal processing and are applicable for frequency band identification and mental state detection for neurofeedback.

Chapter 5 The visualised results from the recorded data are assessed in this chapter. After presenting the plots and figures produced, I intend to critically analyze the success of the project and each step of the process, comparing them to future development opportunities.

The most relevant aspects of the development discussed are the evaluation of the firmware update, the Android application and the hardware implementation. Alongside this, the success and difficulties of EEG signal processing are tangentially discussed.

Chapter 6 A summary of the tasks accomplished and problems solved compared to the objectives presented in the introduction and the Thesis Proposal Form. Discussing the opportunities to move forward, with perspectives motivating future work, and an outlook on further development and plans.

Chapter 2

Literature Review

2.1. Methods to Record Brain Activity

2.1.1 Positioning in the Scientific Environment

Psychophysiology [1] is a field of science that examines physiological signals as they relate to psychological processes and disorders, essentially exploring the connections between body and mind [2].

Neuropsychology [3] mainly focuses on relations between a person's cognition, behaviour, brain functions or even their whole nervous system. The main motivations behind these research fields are not only to explore cognitive processes but also to identify various mental and neurological disorders. Both cases include experimental and clinical fields of patient-focused psychology, concentrating equally on diagnosing and treating behavioural and cognitive effects of neurological disorders.

Cognitive psychophysiology and neuropsychology [4] also share a wide palette of research tools, as they use methods as combinations of electrophysiological methods (such as EEG), neuroimaging (MRI, PET), and neurochemistry [5][6]. While the latter research field also aims to record single-cell electrical activity (or groups of cells).

2.1.2 Related Methods

Neuroimaging [7] studies the structure and function of the brain. It is a non-invasive way for quantitative research studies of brain diseases and psychiatric illnesses. Used either as a way to record high-resolution pictures of the central nervous system or

to examine the activations of different brain areas.

Mostly those neuroimaging technologies, which record data related to brain functioning are typically used in medical and physiological diagnostics. The methods worth mentioning in this context are functional magnetic resonance imaging (fMRI) [8], positron emission tomography (PET) [9], magneto-encephalography (MEG) [10], and near-infrared spectroscopy (NIRs) [11]

Unfortunately, they are quite difficult to access as they require very expensive [12] and cumbersome equipment and facilities [13].

Electrophysiology [14] studies the electrical properties of biological cells and tissues. It is concerned with electrical stimulation and its effects on the functions of living tissues. In recording and interpreting the electrical potential changes that accompany the function of certain types of tissues.

Several electrophysiological methods, noteworthy in this context, are used to process bioelectric signals while recording brain activity by measuring the electrical or magnetic fields generated by the nervous system. The two most well-known techniques (as MEG has already been mentioned between the neuroimaging techniques) are electroencephalography (EEG) [15] and electrocorticography (ECoG) [16].

ECoG may be the most popular and accurate method, however, it is a (partially) invasive technique. This means that a certain level of surgery is always needed to fit the electrodes onto the surface of the cortex of the patient, which is very circumstantial and leads to further difficulties.

This leaves us with EEG [17], which is non-invasive and most suitable for low-cost, easy-to-reproduce projects. This makes it the most compatible with my aims within the boundaries of feasibility, so I intend to give a more detailed discussion of the method of EEG.

2.2. Electroencephalography

Electroencephalography (EEG) [18] is primarily used to study the potential oscillations that result from the spatial and temporal summation of detected bioelectrical changes in cortical neuronal activity. EEG is also a clinical diagnostic technique.

There are several advantages of EEG, starting with its so-called non-invasive nature, which involves the placement of electrodes on the scalp. This technique guarantees that EEG is safe to use (in contrast with ECoG) [19]. EEG signals also have the potential to be integrated with other imaging modalities [20], to achieve a better understanding of brain functions and structure, therefore it gained worldwide popularity and is the most frequently used technique.

However, as all measurements are performed on the scalp, the recorded signals will be weak because of the presence of the skull in between the source of the signal and the electrodes. These signals may have a fine temporal resolution but a poor spatial signal resolution [21]. When working with EEG signals one must also consider their special characteristics, which leads to significant challenges in signal processing. Signals are nonlinear, non-stationary [22], meaning they are time-varying in nature, and susceptible to interference, resulting in a low signal-to-noise ratio (SNR) [23]. Noise in this context is a result of the presence of artefacts, derived mostly from ocular and muscular activities, such as blinks, eye movements, or even electrocardiogram signals [24].

2.2.1 Signal Processing

The pipeline of EEG signal processing [20] stands of four stages, represented in Fig. 2.1. The first step is the acquisition, which as described is a non-invasive EEG method. It can be performed with the use of portable, cost-effective, and easy-to-wear devices. [25]

The significance of the second denoising step is that it addresses the issue of SNR. The problem arises as multiple electrodes are placed on the scalp, where diverse artefacts

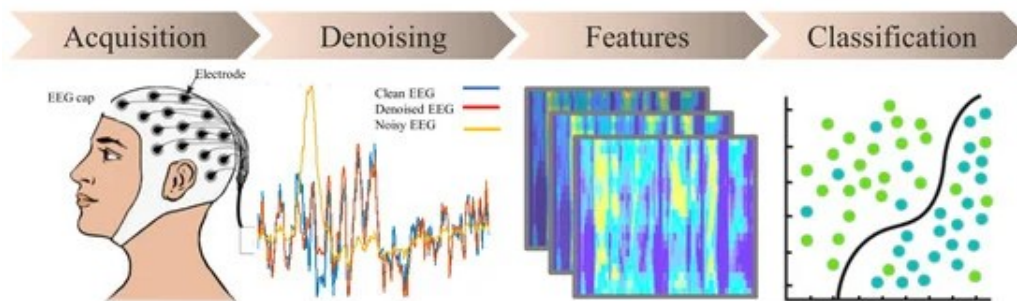


Figure 2.1: "The four-step process for EEG signal analysis. The EEG signal analysis involves four stages: acquisition, denoising, feature engineering, and classification." [20]

can appear in the recorded signal caused by external interference. A properly adapted denoising technique is capable of eliminating irrelevant and extracting relevant information from the recorded signals, simply put, it improves the quality of the signals.

While analyzing EEG data the aim is to make predictions based on the features extracted from the transformed signals. When the third step, feature engineering [26] is applied it can improve the accuracy of the predictions with the use of more expressive features. This step is a rather complex task that typically requires multiple human experts with specialised knowledge, according to Chaddad et al. [20]. To avoid this nowadays the use of machine learning techniques is getting increasingly common.

Classification is a fundamental task in the analysis of brain function. Various processing methods can be used to classify EEG signals, including classic statistics, deep learning, and other techniques. The choice of classification methods depends on the EEG application in question.

In summary, there are several stages of EEG preprocessing and feature extraction, where the right choice of the applied methods is essential according to the context of the desired application. Machine learning algorithms [27] are increasingly commonly used in feature extraction and classification. To date, AI-based algorithms have the potential to improve EEG analysis and diagnosis, even leading to better patient outcomes.

2.2.2 Mental State Detection

EEG measurements can be divided into two primary categories depending on the circumstances of the data retrieval: analysis of spontaneous EEG activity or event-related potentials [28]; the difference is whether an external stimulus or tasks affect the subject during the measurement. As this component is missing during the recording of spontaneous EEG, its results may be considered the brain's natural electrical activity.

When processing EEG data, the recorded signal forms continuous, ongoing brain waves, that can be segmented into five components according to their frequency range [20]. As the frequency of EEG signals is measured in Hz, the ranges are determined as shown in Table 2.1.

The post-signal processing and evaluation of these channels together can lead to further understanding of cognitive processes such as attention, memory, and emotions, and the diagnosis and treatment of mental health disorders [31].

Band name	Frequency range [Hz]	Occurance and state of subject
Delta	1-4	Deep, dreamless, non-REM sleep
Theta	4-7	Imagination, light sleep, relaxation, meditation
Alpha	8-13	Relaxed, awake, eyes closed
Beta	14-30	Focus, thinking, alert, open eyes
Gamma	>30	Motor functions, higher mental activity, excitement

Table 2.1: The frequency bands of EEG signals [29] [30]

While there are no absolute rules, some correlations have been commonly observed between EEG frequency bands and the detection of different mental states:

1. Mental fatigue [32] [33]: Increased alpha and theta activity, especially in the frontal region, may indicate fatigue and reduced cognitive alertness.
2. Attention and focus [34]: Increased beta activity in the frontal region during concentration and decreased alpha activity in the parietal and occipital lobes.
3. Stress [35]: High beta activity is not just a sign of stress but of anxiety and tension, especially in the prefrontal cortex. In addition with decreased alpha and theta activity.
4. Depression: Its most remarkable indicator is frontal alpha asymmetry, an increased activation on the left side, reflecting reduced engagement and motivation.

Although these general observations are becoming more widely known, in the case of successful applications, combining information across multiple bands and using advanced signal processing techniques or machine learning models is expected to be a more practical approach.

These may in the future be helpful to enhance the reliability and accuracy of analyses related to cognitive workload, sleep studies, neurological disorders and brain-computer interfaces.

2.2.3 Neurofeedback

Among the diverse applications of EEG neurofeedback has gained increasing public and research interest recently. It is a type of biofeedback based on the measurement of real-time brain activity, usually using EEG.

The basic concept is to teach individuals self-control over their brain activity and certain mental and emotional states, such as attention, relaxation, or stress [36]. The process itself consists of measuring brain waves and then providing a feedback signal in the form of visual, auditory, or tactile cues based on which the task of the users is to modify specific brainwave patterns. Positive or negative feedback can also be distinguished from desirable or undesirable brain activities.

Neurofeedback refers to a wide category of therapies, most of them designed for the treatment of different mental disorders. Although in many cases the relevance and effectiveness of these techniques still divide researchers and literature [37], the most frequently used is frequency/power neurofeedback which has been repeatedly confirmed to be effective in treating ADHD [38].

Since there are many unanswered questions around neurofeedback, the list of possible applications goes beyond the scope of successfully implemented BCIs. In the case of mental state management neurofeedback has shown greater success so far, for instance in the detection and managing of mental fatigue and cognition [39], stress [40] or even peak performance training for enhancing focus or athletic performance [41]. However clinical applications such as the treatment of anxiety, depression [42], epilepsy, insomnia and so on [43] [44] are showing more mixed results and waiting to be proven effective.

Even some of the most popular EEG headset manufacturers provide devices which are useful for neurofeedback, like Muse [45] and EMOTIV [46]. Although some of the findings from neurofeedback literature are promising, it remains a question for the future to answer precisely what exact effects neurofeedback training has on users and what its limitations are.

2.3. Brain–Computer Interfaces

"Brain-computer interfaces (BCIs) acquire brain signals, analyse them, and translate them into commands that are relayed to output devices that carry out desired actions."

says the definition proposed by Shih et al. [47].

Several neurological and cognitive disorders could lead to damage or even loss of voluntary muscle control. BCIs provide a potential solution for those patients who suffer from neuromuscular disorders by restoring functions to them. The key to overcoming motor impairments is to provide the brain with a new, non-muscular communication and control channel [48]. Therefore BCIs provide continuous interaction and a direct communication pathway between the brain and controlled devices. General BCI systems read neuronal oscillations from an array of neurons using different brain signals, recording methods, and signal-processing algorithms. They translate the signals into actions and can operate many different devices, from cursors on computer screens to wheelchairs or robotic arms [49].

The future progress of BCIs depends on three crucial areas [47], first their interfaces require convenient, portable, and safe signal-acquisition hardware, then validation through long-term real-world studies with people with severe disabilities is essential, and lastly, improved reliability to match natural muscle-based functions is needed. The everyday, long-term, and real-world application of BCIs is still not solved in cases of independent home usage, although several attempts have been made to demonstrate its feasibility [50] [51], there is still a long way to go in developing and testing future BCI equipment.

2.3.1 Categories

BCIs can be generally categorised along different aspects. Aggarwal et al. [27] distinguished three classification systems of BCIs (Fig. 2.2): dependability, imaging technique, and mode of operation.

Imaging technique [52] may be a wide term that can be referred to as the degree of invasiveness too. It also defines the type of acquisition used. The difference between invasive and partially invasive BCIs is that the former requires surgical insertion into the cerebral cortex while the latter takes place inside the skull, but outside of the brain. Electrocardiograms (ECoG) and single-neuron recordings are invasive techniques. However, EEG, which we work with, (as MEG, PET, fMRI, and NIRs too) is completely noninvasive, meaning it performs all measurements on the scalp's surface and no surgical intervention is needed.

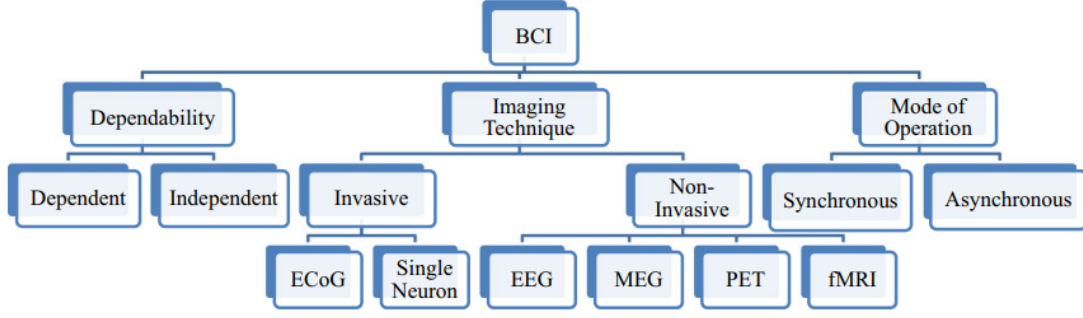


Figure 2.2: "Classification of types of BCI" [27]

Dependability divides BCIs into two groups, namely dependent and independent. The former allows individuals to use some forms of motor control, such as eye movements. Motor-imagery-based BCI is a good example of commonly used dependent BCIs. The latter do not require motor control and are ideal for people who have had a stroke or suffer from locked-in syndrome.

Mode of operation means that BCIs operate in either a synchronous or an asynchronous mode. In synchronous BCIs, the user communicates with the system for a fixed time in response to a signal from the system. In contrast, asynchronous BCIs allow the user to communicate with the application at any time.

Another informative categorisation, that is introduced by Bonci et al. [23], describes the connection between the user's mind and the device. The names of the four main features are active, reactive, passive, and hybrid [53]. Active means that the user voluntarily "drives" the BCI with predefined cognitive tasks while generating a command. In the case of the reactive type the user reacts to stimuli (often visual or tactile), while in passive, users are engaged in cognitively demanding tasks as the aim is to restore a lost function. Hybrid is a combination of active, reactive, and passive BCIs.

2.3.2 Applications

When discussing the wide range of possible applications of BCIs, I follow the system set up by Bonci et al. [23], but numerous other sources have also addressed the issue [54] using different systems themselves. One straightforward approach is to classify the fields

of applications into four usage scenarios:

1. Neuro medical applications
2. User authentication
3. Gaming and entertainment
4. Smartphone-based applications

In the following paragraphs, I would like to highlight a few of these examples, which I think are the most relevant or most related to the topic of my project.

In health care, BCIs can provide basic communication systems for disabled individuals (in case of locked-in syndrome [55]). They are commonly used in the prediction, identification, and rehabilitation of brain dysfunction-associated diseases, which may involve dystonia, essential tremor, cerebral palsy, cognitive impairment, etc. Some examples are Alzheimer’s disease [56], epilepsy, Parkinson’s disease, and Creutzfeldt–Jakob disease [57].

In the context of mental health BCIs can be an effective tool for emotion classification or recognition, identifying sleep disturbances or mental fatigue. These fields are significant because these problems affect the lives of the vast majority of the global population. More specific applications are the detection and treatment of mental diseases such as depression [58] or Schizophrenia [59].

Another growing and popular branch of applications is automation and robotics. This includes some hot topics related to unmanned vehicles [60], smart home systems [61], or virtual reality [62] even used for entertainment and video games [63]. But also the development of electrical prostheses and wheelchair control.

We may also allocate some more applications, which do not fit the previously defined categories. Wider popular areas of applications may be neuromarketing [64] and educational purposes.

2.3.3 Limitations and Challenges

In conclusion, we cannot fail to mention the major limitations of EEG-based BCIs, which mostly arise from the very nature of EEG signals. These signals are sensitive to interference and noise [21], which appear as artefacts, furthermore, they are non-stationary and vary across different users and sessions.

Machine learning plays [65] a significant role in addressing these challenges by allowing BCIs to adapt to each user's brain signals during new sessions, thereby improving its ability to identify thoughts and reducing the time required for basic calibration [27]. At the same time, the use of deep learning models may be challenging because of their interpretability [66]. If the deep learning model can be accurately interpreted, patients may have more trust in machine learning diagnosis.

Hardware design is also emphasised because the location of the reference electrode [20] and the structure of the electrodes have a great impact on the results.

Collecting data is often tedious and inconvenient for users. Therefore, reducing the need for subject-specific calibration is crucial for the market success of EEG-based BCIs as Aggarwal et al. [27] discussed, not to mention the ethical issues that arise around the topic and the security questions of personal data.

Despite all this, the future is still very bright for BCIs with countless possibilities for further development and refinement, all the more so Nature Electronics has named Brain-Computer Interface technology the Technology of the Year in 2023.

2.4. EEG-GNSS Integration

Once we understand the previously described theoretical background of the project, the question may arise of how all this can be connected in practice. If we overview the related literature, there are numerous examples of the implementation of EEG-based headsets and BCIs and their critical analysis of opportunities for improvement.

These opportunities often mention that a step of advancement could be to add new measurement disciplines. The most frequent additions next to accelerometers and gyroscopes, which can be found in almost all devices, are electrooculography (EOG), photoplethysmography (PPG) [67] and electrocardiogram (ECG) [68] [69].

What we specifically aim to achieve with this project Bisla et al. [70] have accurately covered. They suggest that a "lifestyle wearable EEG technology of the future has to be compatible for integration with sensors that can capture other physiological signals (e.g., ECG, GSR) or contextual information (cameras, GPS locators). Formats used for storing EEG recordings also have to be extended somehow or have the capability to be linked to the data coming from these secondary sensors." Accordingly, in addition to the

integration of the GNSS module in our device development project, we have sought to apply a standard format for recording and storing data.

Integrating geographical locators into EEG headsets is not an entirely new idea. Several researchers working with different applications of BCIs from EEG-based brain-controlled wheelchairs [71], where this could be a relevant step of improvement, to urban planning and computing [72], where it is essential for the success of the implementation, have proposed this integration. Salvaro et al. [73] even realised a highly comparable device, whose proposed development steps are also in parallel with our project outline. Nevertheless, the related literature is still rather undocumented on the idea of developing such a headset for mental state detection and prediction.

Chapter 3

Overview of Components

An EEG-GNSS integrated headset is, as the name suggests, a device that allows the recording of EEG measurements synchronised with location data. In our case, such a device was developed by the combination of a MindRove bright EEG headband and a MIKROE GNSS 10 click module.

3.1. GNSS Module Selection

Satellite navigation systems provide geopositioning, such a system with global coverage is called a global navigation satellite system (GNSS), formally defined as the "worldwide position and time determination system that includes one or more satellite constellations" [74].

There are four operational GNSS in service at present:

- U. S. Global Positioning System (GPS)
- Russian Global Navigation Satellite System (GLONASS)
- Chinese BeiDou Navigation Satellite System (BDS)
- European Union's Galileo

3.1.1 MIKROE GNSS 10 click

The key objective of the project was to develop an EEG headset equipped with a Global Navigation Satellite System (GNSS) module, which would allow us to monitor the mental states synchronised with the location data of the users. Moreover, the data of

multiple users could be accurately synchronised. To achieve this, it was first necessary to choose the right components.

My task was to improve a pre-engineered headset, which is operated by an ESP32-WROOM-32 module. Therefore during my review of commercially available GNSS modules, I was looking for add-on board GNSS development tools.

The research led to MIKROE, a company of the embedded electronics industry specializing in development tools, microcontroller boards, and software for embedded systems. Among their countless products, the GNSS click series seemed the most promising. After considering multiple factors we decided on the GNSS 10 Click [75], because of its low power consumption, concurrent reception of up to three GNSS and industry-leading -167 dBm navigation sensitivity. This latter characteristic means the module is capable of detecting extremely weak GNSS signals even in challenging circumstances with poor satellite visibility. This feature makes our device ideal for real-world applications that require reliable positioning in variable outdoor and semi-indoor environments.

3.2. EEG Headset

The theoretical background of why EEG technology is important and why EEG-based BCIs hold the potential to improve the quality of life at several levels and in multiple cases has been previously presented, however, for successful accomplishment, we also need a special, suitable tool.

3.2.1 Bright EEG Band by MindRove Kft.

During my project, I had the opportunity to work with a product of MindRove Kft. The company offer a handful of biometric wearable sensors. Such devices allow the users as they say to "extend human mental and physical capabilities through human-computer interfaces", as their products help innovators explore muscle and brain functions, create exoskeletons and prosthetic arms, and decode sign language, among other applications.

The tool I had the chance to work with is named bright [76], a wireless, wearable, and easy-to-use EEG band. They designed this device specifically for BCIs, the measurement of steady-state visually evoked potentials (SSVEP) and neurofeedback. The 'the brain of the mechanism' is an ESP32-WROOM-32 module [77].

The features of bright:

- EEG measurement on 4+2 channels, located on the frontal and occipital region (Fp1-2, O1-2)
- head movement detection for 6-axis motions
- wireless WiFi communication

Chapter 4

Development and Methodology

After having both components, the GNSS 10 click and the MindRove bright EEG headband, this chapter describes how we can connect them at both hardware and software levels. For both, we first need to choose a communication protocol that describes the rules of the relationship between them.

Software-level implementation required coding in three different languages, including firmware upgrade in C++, development of an add-on Android application and data processing in Python.

The chapter concludes with a discussion of denoising techniques for EEG signal processing, regarding amplitude-based artefact rejection, frequency-based filtering and epoching. Their implementation was needed to process EEG signals and extract bands and would be useful in predicting mental states.

4.1. Communication Protocols

A communication protocol in embedded systems is a scheme of rules enabling information and data transition between devices, like sensors and controllers. The most common protocols are UART, SPI and I2C, all having specific characteristics [78]. The devices that need to be connected are the GNSS 10 click and the ESP32-WROOM-32 modules. Their datasheets reveal that both are equipped with all three interfaces, so the choice is ours.

4.1.1 Evaluation of Decision Options

Universal Asynchronous Receiver-Transmitter (UART) [79] protocol is considered the most simple. It uses two wires point-to-point, enabling direct communication between devices. Operating asynchronously, it does not require a shared clock between the transmitter and receiver. UART operates in full-duplex mode and is suitable for long-distance transfers.

Inter-Integrated Circuit (I2C) [80] is a synchronous, two-wire protocol. Some additional communication steps are needed compared to UART, as I2C supports multi-master-multi-slave structures, so the address of the chosen slave should always be sent before transferring data. While it supports bidirectional communication, only one direction is active at a time, referred to as half-duplex mode. I2C generally perform poorly over long distances as a result of its sensitivity to interference.

The operation of the **Serial Peripheral Interface (SPI)** [81] protocol is the fastest of all, having almost twice the speed of I2C's ultra-fast mode. It is a synchronous full duplex serial data protocol, but differs from the previous two, considering it is four-wired. SPI supports a single master device with the ability to communicate with multiple slave devices.

The introduced serial communication protocols all have their strengths and weaknesses. The best way to make the right decision is to consider what the expectations of our device are. As a headband should remain an easy-to-wear head-fitting device, there is no need for long-distance compatibility, all the more important it is to keep the circuit design as simple and space-saving as possible.

Based on the criteria outlined it is clear that despite its many benefits and effectiveness, SPI would be unnecessarily complex in our implementation. Not to mention that the other sensors, EEG, accelerometers and gyroscopes, on the bright use SPI communication, and we do not want to risk any interference between the two streams of data.

The selection between UART and I2C is a more difficult question, likely both solutions could be implemented with similar effectiveness. After extensive consideration, we decided that I2C may be more suitable. It is not significantly more complicated to apply and lets us keep the possibility of further expansion for future development.

4.1.2 I2C Parameters

I2C communication protocol uses two wires to share information, one for the clock signal (SCL) and the other to send and receive data (SDA). The SDA and SCL lines are active low, so they should be pulled up with resistors, typically 2.4k Ohm for 3.3V devices.

There are 5-speed categories of I2C [82] mentioned briefly earlier:

- Low-speed mode 10KHz
- Standard mode 100KHz
- Fast mode 400KHz
- Fast mode plus 1MHz
- High-speed mode 3.4MHz
- Ultra-fast mode is 5MHz

The GNSS 10 click module [83] supports only operation in slave mode, with the address 0x42 and has internal pull-up resistors. It is fully compatible with fast mode, therefore the maximum SCL clock frequency is 400 kHz, and the maximum transfer rate is 400 kbit/s. State-of-the-art interfaces rarely support high-speed and ultra-fast modes. Moreover, the latter is uni-directional enabling only writing from master to slave.

4.2. Firmware Update

MindRove devices establish WiFi Direct connection made possible by the ESP32-WROOM-32, allowing direct communication and data transfer without using an existing network. A framework has been developed for properly transmitting the corresponding sensory and operational data and implemented in the MindRove Firmware.

After realizing the physical I2C connection by wiring between the GNSS 10 click and the ESP32-WROOM-32 modules, the protocol also needs to be implemented on the software level. Furthermore, during my work updating the firmware in C++, I had to make modifications to embed the location data into the existing data-storing format.

	checksum range			
\$	<Address>	<, value>		*<checksum> <CR><FL>
Start char	Data fields, all delimited by ','		Checksum field	End sequence Always <CR><FL>
Always \$				
	<XX>	<XXX>		
	Talker ID	Sentence formatter, determines the content		
Example:				
\$	GNGGA	,103609.00,A,4728.47138,N,01903.57858,E,6.294,69.68,230824,,,A		*46 <CR><FL>

Figure 4.1: NMEA Protocol Frame

4.2.1 NMEA Protocol

NMEA is an acronym for the National Marine Electronics Association [84]. Their protocol existed well before GPS was invented and since then it has become a standard data format supported by all GNSS manufacturers. What makes it a bit confusing to understand NMEA-coded messages is that they are composed of more than a dozen sentences in different encodings. Even the different satellite systems use their unique sentences for encoding the same data.

In the beginning, to understand the GNSS module and test its functionality I chose to work in Arduino IDE. The environment has integrated the Serial Monitor tool, which has proven very useful for familiarizing myself with the NMEA protocol format of the location data and for monitoring it.

Our GNSS receiver allows only NMEA as output messages, based on NMEA 0183 Version 4.10 [85]. The protocol frame is shown in Figure 4.1. One of the ways the standard

Configured GNSS	Talker ID
GPS (SBAS, QZSS)	GP
GLONASS	GL
Galileo	GA
BeiDou	GB
Any combination of GNSS	GN

Table 4.1: NMEA Talker IDs used by u-blox M8 Receivers [83]

differentiates between GNSS is by using a two-letter message identifier, the Talker ID. Table 4.1 shows the Talker IDs used for various GNSS configurations by the GNSS 10 click module. One additional information to note before manipulating and transmitting NMEA-coded data is that these sentences are received and stored in standard ASCII.

4.2.2 Location Data Integration

As I quoted earlier from Bisla et al. [70], finding a suitable form of format for our application is a key step towards the successful deployment of EEG technologies. Therefore we came up with an idea to embed the location data alongside EEG data without altering the existing data structure, thus maintaining compatibility while expanding functionality.

MindRove has a unified firmware for all devices, so depending on the particular number of electrodes, only one variable needs to be adapted. As bright has four active electrodes, and with other devices, it is well-tested in practice to transmit data from up to 6-8 channels within runtime without problems, the initial idea was to increase the size of the array initialised to store and forward the EEG channel data and fill the empty channels with location data.

First, the question of data type has to be addressed. EEG data is recorded and stored as type *int32_t*, meaning that each measured value is converted to a 32-bit representation. Location data in raw form is received in NMEA sentences coded in ASCII. Standard ASCII uses 7 bits to represent each character, though, in practice, it is often stored in 8 bits for compatibility with modern systems. All things taken into account, one EEG value can be replaced by four characters in ASCII.

A similarly important issue is reconciling the volume of incoming data. The measurement frequency of EEG is 500 Hz, so in one second, 500 measurements are made on each channel. If we initialise 2 additional channels for location data storage, there is place for transferring exactly

$$2 \text{ channel} \cdot 500 \text{ Hz} \cdot 4 \text{ bytes} = 4000 \text{ characters/sec.}$$

The recommended standard navigation solution update rate is 1 Hz. Other typically chosen values for wearable applications according to the datasheet are 2 or 4 Hz. Our module is compatible with a maximum update rate of 10 Hz for high-speed tracking, but navigation rates higher than 1 Hz may result in lower position accuracies, and our case,

it enables only a single GNSS constellation configuration. A further complication is that the length of NMEA messages varies with each measurement, depending on the number of satellites and GNSS available in the area. The average NMEA message size is in the range of 300-600 bytes per update with approximately 60-80 bytes per line.

For the proof-of-concept implementation, we decided to work with a 1 Hz update rate, but leaving room for future upgrades assigned the 4000 bytes space for location data.

4.2.3 Data Structure

Choosing the most appropriate data structure for correctly handling and storing data is a key decision. An important aspect was ensuring efficient data access and memory management to handle incoming data streams without significant delays or memory overflow.

C++ [86] offers several alternatives and initially, I considered using *std::vector*, which offers dynamic resizing and efficient access to elements by index. However, vectors are optimised for situations where data is frequently accessed in arbitrary order or modified mid-sequence, which is needless for our goals. Similarly, a doubly-linked *std::list* provides flexibility with insertions and deletions but at the cost of less space efficiency due to the need for additional pointers. It is most suitable when there is no need for random access, however, its capability for bidirectional access is unnecessary for us, as the data we will read requires continuous processing. In this regard, using a *std::forward_list* would be a more suitable solution considering it is a singly-linked list. However, it still allows accessing elements in the middle of the container, which leaves more room for potential data access errors.

If we are looking for a solution, a less general-purpose container for sequential data with minimal memory usage, an ultimate choice is a First-In, First-Out (FIFO) *std::queue* structure. It can be implemented using a circular buffer that does not require reallocating memory. It is specifically optimised for handling sequential, ordered data efficiently and does not allow accessing elements in the middle of the container, which can be useful for avoiding accidental misindexing. FIFO is ideal for real-time systems, especially when managing fixed-size windows or continuous input of data such as sensor readings seamlessly.

4.2.4 Runtime Optimisation

The greatest challenge in developing the firmware was to fit into the runtime. The processing of NMEA had to be adapted to match the EEG, which on 500 Hz leaves 2 milliseconds of runtime in each period.

An inevitable step, sooner or later, is to extract accurate information from the NMEA messages in a meaningful form. Therefore, an idea was that before the return of location data in the type *int32_t* variable, we could parse the sentences. This would require us, however, to request as much of bytes in one chunk as possible, because we cannot process information cut in half in sentences, and then locate the relevant details.

2 milliseconds might seem like enough time to run the code once, even if we need to retrieve data from the I2C slave, but as it turned out during the development it is not sufficient to interpret location data and I2C requests may not have enough processing time to handle larger chunks without impacting stability. When the code tries to perform an oversized request and/or the parse and return steps altogether we get an invisible timeout error. This does not prevent the measurement from running, as there is no apparent error in the code, no syntax issue or build-stopping error, but generates a buffer overload which can corrupt the entire data transmitted.

There are two effective ways of solving this problem: We can attempt to parallelise the tasks, leaving enough time for the I2C request and the parsing too or leaving the parsing for later data processing. While multi-threaded programming could be very practical, in our case it is unnecessarily complex to implement since it is essential to perform data processing after acquisition, due to the need to apply filtering and denoising on the raw EEG signals.

Overall, I chose the second alternative, which allowed me to significantly reduce the size of the I2C request, even for the number of bytes to be passed in one period. This ultimately led to a considerably more computationally efficient and time-saving implementation.

4.2.5 Implementation

The MindRove firmware is designed according to a well-structured hierarchy, so I added my modifications as new building blocks in a separate compilation unit. Only a few minor adjustments and the appropriate includes needed to be taken care of additionally.

The functions included in the new codes are designed to perform three tasks: implementation and management of I2C communication protocol, location data processing and conversion for storage and additional helper functions for testing. The most significant code parts concern the enqueue and dequeue operations, the bitwise encoding and transmission of the location data to integrate within the EEG data stream. Essentially, what is worth noting is that it is important to remember in which direction the 32 bits are filled with characters because the same sequence must be followed when reading out to recover the original message.

Additionally, I also explored the company’s Python SDK and developed a proof-of-concept code to ensure that the new firmware version works as expected. This proved to be very useful during debugging, so I was able to detect the overload buffer error and monitor the outputs in real time.

4.3. Application Development

Our goal is that the headset we develop is not only easy to wear but also easy to use. However, to perform the measurements, users currently need an additional device. In this section, I describe the development of an Android application designed to enable real-time data acquisition and storage of EEG and location data captured by the EEG headband. The application’s development focused on creating an intuitive user interface, handling data synchronisation, and ensuring minimal latency in data recording to support accurate, high-quality data logging.

The application connects to the EEG headband via WiFi Direct, as bright creates its WiFi network, establishing a peer-to-peer (P2P) [87] connection with a single device. In this setup, only the first device to connect can receive the acquired data. This method is effective for secure, seamless and stable data transfer directly to a single device. In order to receive and properly store these, a receiver-side application is needed.

The back-end functionality starts with a few key steps to establish the connection. First the application checks for permissions to write to external storage and access network state. If no network is available or the device is not connected to a MindRove network, it opens the WiFi settings of the device. Once connected to the appropriate network, data export can be started.

In the long term, we plan to exclude the use of the phone from the process, so there is no reason to develop a complex and robust application. Accordingly, using MindRove’s Android SDK, I created an intuitive, function-driven user interface. Using the application, data recording starts or stops with a button press, meanwhile, the data is exported into a CSV file. MindRove also has a visualiser app on desktop, which besides displaying data can save the raw EEG or EMG stream. For uniformity and consistency throughout all software of the company, I designed the Android app to use the same structure of CSV for the export.

4.4. Structural Preparation

Data processing is an essential step to make the recorded data interpretable, readable and visualizable. To accomplish data processing I created a Python code, which can be used on the relocated CSV files.

4.4.1 Data Reordering

Looking at the raw data, it can be noticed that the received data packets, meaning one line of the CSV, may not always follow each other in the order they were sent. This can be verified by checking the packets’ DRDY number. DRDY stands for Data Ready and is a commonly used term in electronics and embedded systems, especially in sensors and data acquisition devices. In the case of MindRove firmware, it is used not only for signalling the availability of new data ready for access but also as a unique ID, specific for each packet of data.

The observed phenomenon is completely common as UDP (User Datagram Protocol) [88] has been used since the original firmware for data transmission. Unlike TCP (Transmission Control Protocol), which guarantees in-order delivery by reordering packets at the receiver’s end, UDP does not provide any such guarantee but it is worth using in our case since it is faster than TCP. As a result, packets may arrive in a different sequence depending on network conditions or processing delays. Luckily, no packet loss occurred, which indicates that while the packets arrived out of order, they were still successfully delivered to the receiver without any being dropped. The lack of packet loss confirms that the hosted WiFi network through which UDP communication happens is reliable

and stable.

To prepare the data for further processing, additional mechanisms were implemented to reorder the packets correctly using the DRDY as packet ID.

4.4.2 NMEA Parsing

Messages coded following the NMEA protocol contain a combination of essential information, such as latitude, longitude, altitude, speed, timestamp, and sometimes additional data like the number of available satellites and signal quality. The encoding of a sentence indicates the type of parameters contained. Without the parsing of NMEA messages, in raw form, they are difficult to interpret and utilise, as they are designed for compactness and efficiency rather than readability. Therefore, parsing is crucial because it allows the extraction of relevant data fields after conversion into usable variables for precise location tracking or synchronisation.

After reordering the data packets, location data is readable from the appropriate columns in the CSV. Each recorded data value contains four characters of the original NMEA message, so the next stage of data processing involves decoding data in preparation for parsing. The implemented algorithm starts with converting the data values stored in decimal form to a 32-bit binary representation. This sequence is then split into four segments, each 8 bits long. Each 8-bit segment is then converted back to decimal, yielding an integer that corresponds to an ASCII code, which from the original characters can be retrieved and merged into the original message.

One specific type of information follows the same notation system whichever sentence it appears in. This is advantageous because even if a packet loss occurs, there is redundancy within the message and there is a high likelihood that we can find a full appearance of the needed parameters. In each full message, one location with latitude and longitude is present in two sentences, \$GNRMC and \$GNGGA. To locate and extract these positional parameters accurately, I applied regular expressions (regex). Regexes are patterns used to match sequences of characters within text. They are a powerful tool for searching, extracting, and manipulating text, widely used in programming languages, search engines, text editors, and data processing tools. Therefore, regexes are suitable for identifying and isolating specific parameters within NMEA sentences based on consistent patterns. The general rules of regexes are illustrated in Figure 4.2 with the help of the regex I used.

```
$ GNGGA ,103609.00,A,4728.47138,N,01903.57858,E,6.294,69.68,230824,,,A *46 <CR><FL>
```

Expression: **4728.47138,N,01903.57858,E**
Regex: **"\b \d{4} \. \d{5} ,N, \d{5} \. \d{5} ,E \b"**

Figure 4.2: Regex for matching the pattern of latitude and longitude parameters in NMEA sentences

To visualise the parsed locations, the *folium* library, a Python tool for creating interactive maps is used. It allows us to easily plot geographic coordinates on a map using OpenStreetMap (OSM). As OSM provides a variety of built-in map styles and functionalities, it makes this library ideal for monitoring real-world data and displaying the parsed data as markers on a map. One of the primary advantages of *folium* is its interactivity. Users can click on markers to see additional information and, thanks to OSM, zoom and pan while the map is constantly updated.

4.5. EEG Signal Processing

Signal processing, especially for EEG is essential, as it was introduced in Section 2.2.1. Raw EEG signals contain significant noise, artefacts, and irrelevant information that can obscure meaningful brain activity patterns. Denoising techniques [89], such as filtering, artefact removal, and epoching (splitting data into intervals) help separate relevant frequencies and remove unwanted interferences originating from muscle movements, eye blinks, and external electrical sources. Proper data processing allows the separation of brain frequency bands (delta, theta, alpha, beta, gamma). Which are associated with different cognitive and behavioural states and may be predicted and detected after further processing.

Frequency-based filtering includes a traditional set of denoising techniques, while artefact rejection methods are based on analysing signal amplitude. Each technique of EEG analysis is tailored to address specific types of noise, either based on frequency characteristics or amplitude variations, as no single filter or rejection method can comprehensively address all forms of EEG noise. In this section, I provide an overview of commonly ap-

plied denoising techniques, filters and artefact rejection methods, categorised by noise type, and discuss their importance, limitations, and key parameters.

4.5.1 Artefact Rejection Methods

Amplitude-based techniques are common in artefact rejection [90]. They do not rely on specific frequency bands but instead address non-physiological artefacts (e.g. muscle movement, blinks) resulting in amplitude irregularities like high-amplitude spikes in EEG data. The two primary techniques are simple thresholding and standard deviation-based Rejection. They differ in sensitivity to amplitude changes and adaptability across variable EEG recordings, so the choice of method should depend on the specific noise characteristics and analysis requirements.

Simple thresholding eliminates extreme amplitude outliers by setting specific amplitude limits, namely thresholds. Values outside the defined range are considered artefacts. It is straightforward and effective for removing crude artefacts that typically result from sudden movements or sensor malfunctions. However, this technique lacks specificity and can mistakenly eliminate genuine EEG signals depending on the limits set, leading to potential data loss.

In contrast, standard deviation-based rejection (STD) identifies artefacts based on deviations from the average amplitude range of the signal, allowing for context-sensitive data removal. Typically it is done by a multiplier of the STD relative to the mean amplitude. This approach is more beneficial in many environments, as it is sensitive to baseline fluctuation. However, it may miss artefacts in cases of high signal variability or baseline drift.

The limitation of both methods is that they cannot differentiate between physiological EEG events and artefacts solely on amplitude, requiring further signal enhancement with frequency-based filters. Combining these methods may lead to maximal noise reduction without compromising signal integrity.

Additionally, more advanced methods like Independent Component Analysis (ICA) [91] can be performed to complement artefact rejection. Since artefacts are often independent of brain activity, ICA can help isolate and separate these components based on their unique statistical properties. It decomposes the EEG signal into statistically independent components, hence the name, leaving room for further analysis and noise

classification. However, this method is not easy to perform, as the accurate identification of artefact-related components often requires expertise and experience, as misclassification can lead to the removal of genuine brain signals.

4.5.2 Low-Frequency Noise

Low-frequency drift, arising from changes in skin-electrode impedance or slow head movements, and baseline noise can obscure meaningful low-frequency EEG components. High-pass filters and detrend filters [92] are capable of removing the problem causing slow fluctuations from the signal.

While a high-pass filter removes frequencies below a defined threshold (often 0.1–1 Hz), a detrend filter subtracts linear or constant trends from the data, both reducing low-frequency drifts and baseline shifts. These techniques are ideal when the baseline changes gradually, for example during long-term monitoring and recording.

A high-pass filter, while effective against drift, may require careful tuning as it risks removing legitimate low-frequency components. An excessively high threshold may even distort delta and theta waves, valuable for sleep and attention studies. While detrending is effective only for linear baseline drifts and may not remove complex, non-linear trends. For the best results in highly variable environments, these methods should be used in combination or alongside each other or other filters too.

4.5.3 Powerline Interference

Powerline interference [93] results from nearby electrical devices or infrastructure, and is therefore nowadays present in almost all environments. It typically occurs in EEG signals at 50 or 60 Hz depending on local power systems. Notch filters and band-stop filters are commonly used against this type of interference.

A notch filter precisely targets a narrow frequency range, removing powerline noise effectively without significantly impacting neighbouring frequencies. This filter is preferred for precise noise removal and is ideal for controlled laboratory environments, which ensures minimal signal distortion.

In comparison, band-stop filters are more effective in noisy environments, where noise fluctuates over a wider range even with overlapping frequencies, like hospitals or industrial environments when high electromagnetic interference is present. This filter can be set

to attenuate a range surrounding the primary noise frequency. However, it must be handled wisely, because it may distort EEG data [94] if configured too broadly, while unintentionally removing relevant EEG frequencies. The most exposed are gamma bands, which are close to typical powerline noise.

4.5.4 High-Frequency Noise

Muscle activity and external electronic devices generate high-frequency noise, often overlapping with EEG gamma frequencies, impacting the accuracy of studies focused on rapid cognitive processing or BCI applications. Low-pass filters and band-pass filters [95] are useful to minimise interference and isolate desired frequencies while suppressing high-frequency noise. Both filters focus on the analysis of specific frequency bands but must be applied carefully so as not to cause data loss.

Low-pass filters are effectively the inverse of the high-pass filters, as they remove frequencies above a specified threshold, typically around 45–50 Hz. Preserving only lower frequencies, they are often used in routine EEG analysis, where higher frequencies are unnecessary. However, it is limitedly suitable for high- or multi-frequency studies, as an inappropriate cutoff can lead to the loss of data, especially in the gamma band.

The band-pass filter [96] is one of the most important in neurofeedback, as it is typically set to isolate frequency bands and is ideal for removing unwanted high and low frequencies in specific EEG bands. This filter is the key for applications requiring frequency-specific EEG data. It confines data to a desired range, usually 1–45 Hz, targeting only the most relevant brainwave bands. They are most effective when the desired EEG range is well-defined, but may introduce distortions near the band edges. If improperly configured, it may lead to information loss or aliasing, the overlapping of frequency components that cause high-frequency noise to appear as lower frequencies if improperly filtered, and misleading interpretations of EEG signals.

4.5.5 Broadband Noise

Broadband noise occurs across a wide range of frequencies due to sensor interference or environmental factors, potentially making it harder to isolate or interpret specific brain-wave activities. Moving average filters and median filters [97] are suitable for smoothing

and reducing this type of noise without distorting the core signal. The key idea is to calculate the average of the neighbouring points or take the median over a defined window.

The moving average filter is commonly applied for smoothing before frequency-specific filters, they can unintentionally smooth away important components of fast-changing signals. Conversely, a median filter replaces each point with the median of its surrounding values. It is particularly useful for maintaining sharp transitions and handling spikes by eliminating extreme outliers rather than smoothing across them. Both filters have limitations when used over incorrectly set, usually larger windows, leading to a potential loss of details or excessive smoothing.

4.5.6 EEG Band Identification

To separate and analyse specific EEG bands, already introduced in Section 2.2.2, spectral analysis techniques are often used to reveal power distribution across frequencies.

Power Spectral Density (PSD) [98] represents how the power (or variance) of a signal is distributed across different frequency components, typically measured in terms of power per unit frequency [$\mu\text{V}^2/\text{Hz}$]. Calculating the PSD of an EEG signal enables not just visualisation but quantification of power, allowing us to observe which frequencies dominate and evaluate the relative power in each frequency band. This is the key step for understanding neural activity patterns and the relationship between different brainwave bands with specific mental states.

PSD is typically estimated using the Fourier Transform or Welch’s method. Welch’s method [99] is unique for improving standard PSD estimation by dividing the EEG signal into overlapping segments, computing the Fast Fourier Transform of each segment, and then averaging these periodograms to reduce variance. The method can be sensitive to parameters, such as segment length, overlap in Welch’s method, or window type in the Fourier Transform, and be computationally demanding to calculate the FFT on multiple segments, especially for high-resolution EEG data. When applied correctly, it reduces the variance of PSD estimates and provides a smoother power spectrum that is less sensitive to random fluctuations.

4.5.7 Overview

Overall, each of the presented techniques has advantages and disadvantages, but no single technique is fully sufficient on its own. Experimenting with the right combination of methods and filtering techniques can lead to finding the best possible signal-processing recipe for any application.

In neurofeedback [100], permanent signal processing techniques such as band-pass filtering, to isolate relevant EEG bands, and power spectral density analysis, for identifying brainwave power, are essential. These techniques are crucial for extracting meaningful brain activity and ensuring interpretable signals for feedback. However, as noted, they are not sufficient by themselves for comprehensive signal denoising.

PSD and Welch’s method are fundamental tools for band identification providing insight into power distributions across frequencies. However, they are computationally demanding and their effectiveness depends on signal quality and the trade-off between frequency and temporal resolution. These limitations emphasise the importance of additional preprocessing steps, like filtering, to optimise signal quality before analysis.

Chapter 5

Results

This chapter presents the results obtained from measurements conducted with the developed EEG-GNSS integrated headset. The primary goal was to validate the device’s capability to simultaneously record EEG and GNSS location data and to assess the success of the firmware update. Visualisation of the signals makes them suitable for further critical analysis of the device and the applied signal processing approaches.

The recorded data have been processed using the Python code, previously described in Section 4.4, allowing for comprehensive analysis of the key variables. The results are presented in sections aligned by data type, beginning with location data processing and visualisation, followed by EEG signal analysis.

5.1. Results

5.1.1 Location Data Mapping

As previously mentioned, the *folium* Python library was utilised for displaying location data. Latitude and longitude coordinates were parsed from NMEA messages, which also contain supplementary parameters such as precise timestamps and velocity.

To enhance the clarity and interpretability of the mapping display, I also extracted velocity data using another regex. I later used these values to create the colour-coded markers on the map. For intuitive visualisation of velocity changes across the mapped path, I applied simple linear spacing ranging from the minimum to maximum value to implement the speed-color assignments. I also experimented with creating transitions

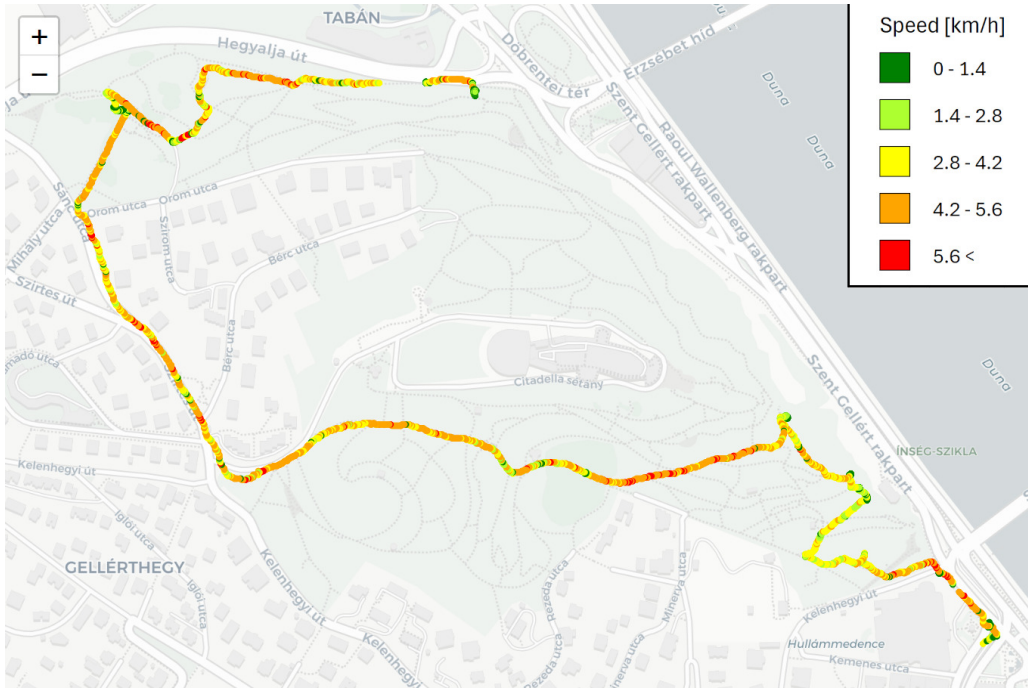


Figure 5.1: Measurements to test the resilience of the device over a 1-hour recording period, with markers coloured on a 5-step scale corresponding to the changes in velocity.

between colour levels for a more continuous visualisation. Of the figures included, one uses the 5-level colouring system (Fig. 5.1), while the other is plotted with transitions implemented (Fig. 5.2).

The first measurement aimed to test the system's resilience over an extended recording period, providing insights into data stability and integrity under continuous operation. A successful measurement was recorded over 1 hour while the subject was walking. The resulting map, along with a legend, is shown in Figure 5.1.

The next set of measurements aimed to test the sensitivity and accuracy of the GNSS module. I measured in more complex environments, for example, between tall buildings and while using public transport. In these cases, some weaknesses of the GNSS system could be identified.

The phenomenon of GNSS accuracy being compromised in areas with tall buildings is also called the "urban canyon" effect. It occurs when signals are obstructed or reflected by nearby buildings, leading to multipath errors where the signal bounces off surfaces before reaching the receiver. As a result, the GNSS receiver module may interpret incorrect

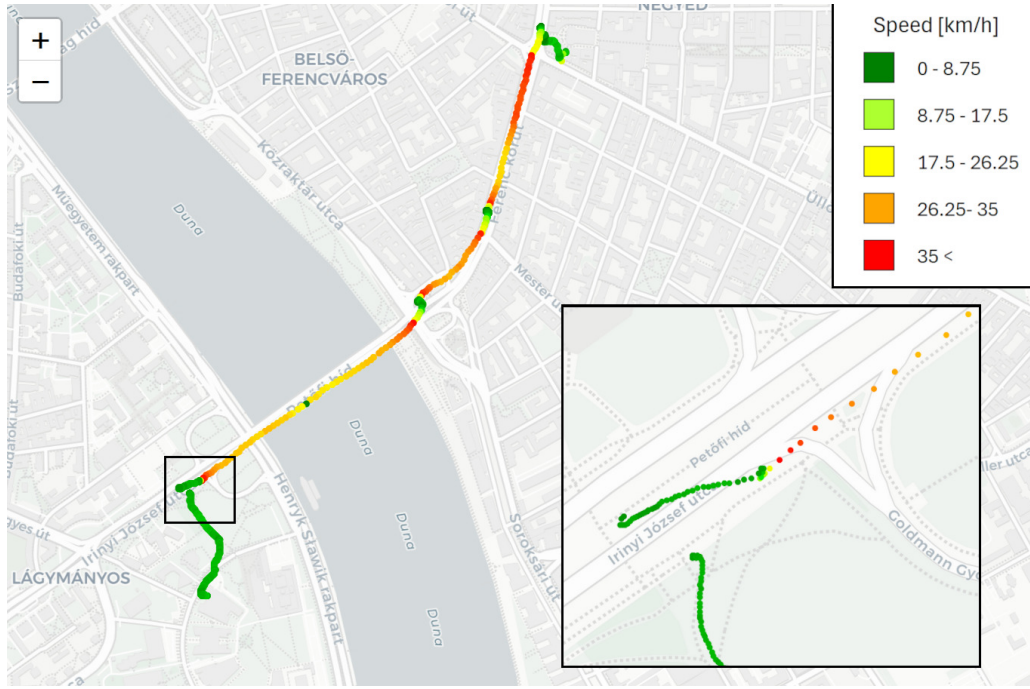


Figure 5.2: Measurements to test sensitivity and accuracy of the GNSS module

Measurements to test the sensitivity and accuracy of the GNSS module, in particular, to test the limits of semi-indoor measurements while using public transport, with colour-transition markers corresponding to the changes in velocity.

position information, showing deviations from the actual location. These interferences some cases created noticeable inaccuracies. In most cases, multiple navigation systems instantaneously handle these issues, but urban environments will generally produce less precise locational information compared to open areas.

Another observed signal disruption led to signal dropout, shown in the bottom right corner of Figure 5.2. During this part of the measurement, I crossed through an underpass. The explanation for the lack of data is due to the characteristics of the GNSS 10 click module, which is not suitable for indoor signal acquisition. However, the datasheet states that in semi-indoor conditions the module is capable of receiving high-accuracy signals. This I attempted to test when travelling on surface public transport, almost during the entire measurement.

5.1.2 EEG Analysis

EEG signal processing aims to separate meaningful neural signals from noise and artefacts, enhancing the accuracy of analysis and interpretation. Each filtering and artefact rejection method addresses specific types of noise, either based on frequency characteristics or amplitude variations. A wide range of these techniques have been introduced in Section 4.5. I also familiarised myself with them in practice by implementing many of them, of which STD-based artefacts rejection, high-pass, low-pass, and band-stop filters were used for processing the EEG signals. An example of the results obtained after noise reduction shows the signals over 1 minute, equivalent to 30000 measurements displayed in Figure 5.3. For better transparency, Figure 5.4 shows a closer view of the signal over 3 seconds.

Using the filtered signals, I was able to isolate the frequency bands and then estimate their power by calculating the PSD with Welch's method. First, I split the data into 5-second epochs to allow for a more manageable analysis of temporal variations in power. For each epoch, the band power was calculated across all channels, enabling a comparison of the power distribution across different frequency bands over time. Figure 5.5 presents the results of the averaged band powers for each waveband over all channels.

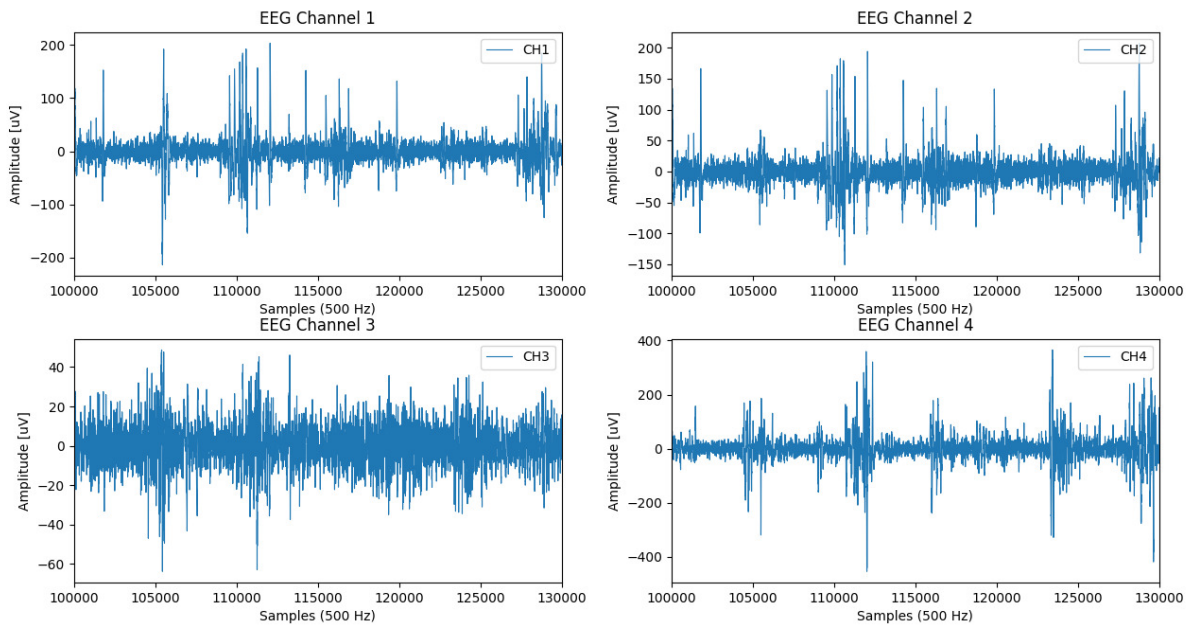


Figure 5.3: EEG signals after noise reduction over 1 minute

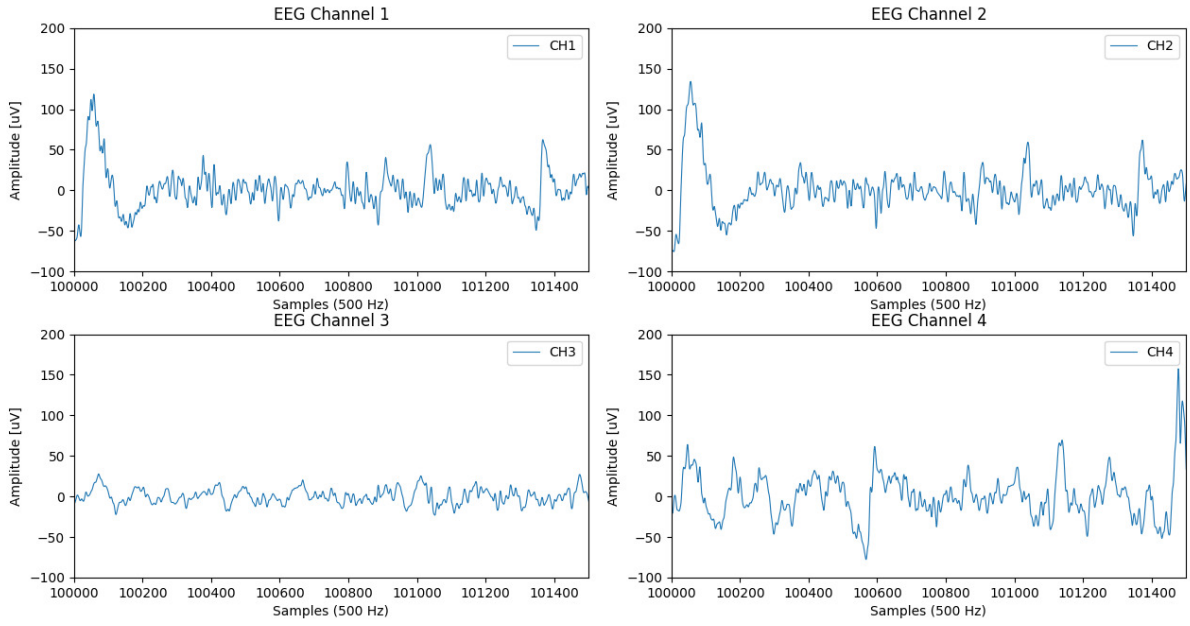


Figure 5.4: EEG signals after noise reduction over 3 seconds

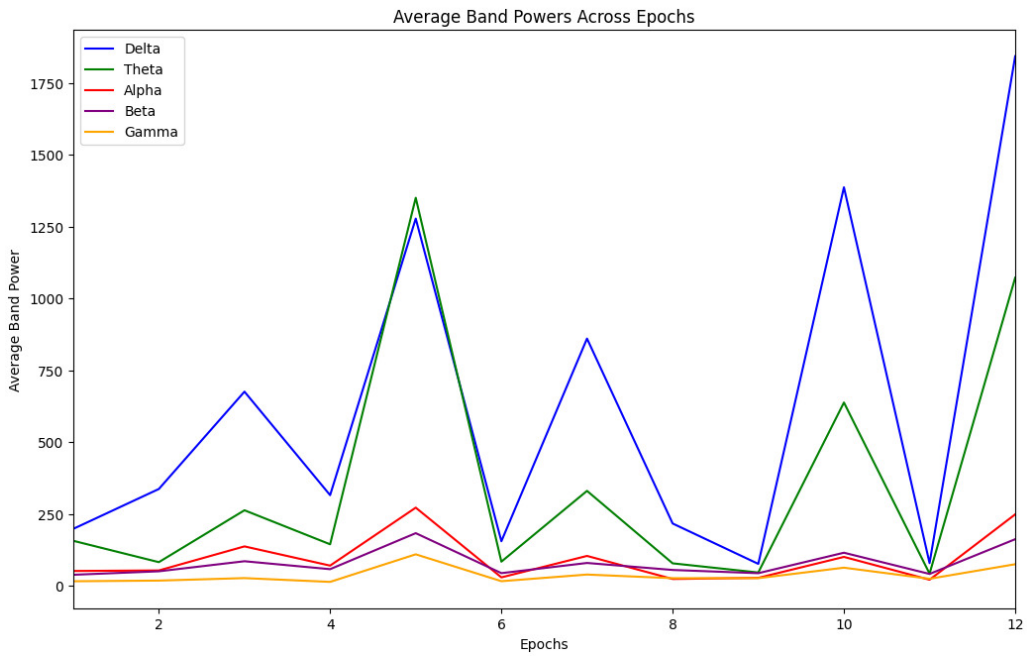


Figure 5.5: Average frequency band powers across 5-second epochs through 1 minute

5.2. Discussion

The main goal of this project was to develop an EEG-GNSS integrated headset, useful for synchronised recording of both EEG and location data of the user. The results of the measurements performed and presented demonstrate the success of the GNSS module

integration and the capability of the upgraded firmware. While there are many opportunities for future development and improvement of the device. In the following, I will provide an evaluation and critical analysis of the resulting product and the development steps, regarding the success and challenges of EEG signal processing too.

5.2.1 Firmware

I found the programming tasks challenging at first, but the firmware update is considered a complete success. The main objectives were to implement the I2C communication protocol and the transmission of location data. In the latter, with the key idea of transferring the data in an encoded form on unused EEG channels, we managed to provide a unified data format and a computationally efficient and time-saving solution for signal transmission. This approach not only ensured seamless integration of the new features but also minimized the intervention into the existing system and the current setup.

Testing and debugging were done with the additional use of MindRove’s Python SDK, which allows for real-time variable monitoring. I managed to overcome several initial challenges, such as ensure fitting into the allocated runtime, by adapting I2C communication processes. Finally, by leaving the parsing of the NMEA-encoded location data to the posterior data processing algorithms, we were able to transfer the requested data in a time-efficient manner. The solution ultimately allowed for synchronised data transmission, enhancing the system’s overall functionality and performance without compromising data accuracy or processing speed.

5.2.2 Android Application

The development of the application introduced me to the Kotlin language. The aim was to provide a simple and practical way to save the data stream of the headset measurement using an easy-to-use user interface. Although the app was successful enough to be able to store the recorded signals, there is still room for improvement, both in functionality and UI.

Mindrove already has a smartphone application for real-time data monitoring and visualisation. A possible improvement could be to link the two applications so that users do not have to use the two separately. Another important aspect may be integrity across different operating systems, as it is an important aspect of application development. As

both of the current apps are Android-based, it may be worth developing a cross-platform application in the future to reach a wider range of potential users, for example, first extending the app to iOS.

However, in terms of the current envisioned future of the project, it may not be worth going through these steps, as the long-term goal is to create a stand-alone device, where the use of any additional device becomes unnecessary.

5.2.3 EEG Noise Reduction

EEG signals are highly susceptible to noise and artefacts, particularly in real-time environments where external factors like movements, muscle activity and electrical interference can introduce substantial distortions. As most measurements were made while the subjects were walking, a significant level of artefacts was present in the results, from the sources of head movements, muscle contractions, and electrode displacement. The monotonous rhythm of movements generated low-frequency signals, which often meant a significant challenge as they overlapped with the frequency bands delta and theta. Unfortunately, the results show that this interference could not be completely removed from the signal.

Various filtering techniques were implemented during the data processing. Among the most effective filters, including a high-pass filter to remove low-frequency drifts caused by slow movements or baseline shifts, and a low-pass filter to eliminate high-frequency noise, particularly from muscle activity and electrical interference, were used during the final data processing. Additionally, a band-stop filter was applied to target and suppress power-line interference around 50 Hz.

Although, both standard deviation-based rejection and the high-pass filter aimed, they could not fully eliminate the transient spikes and sudden shifts in the signal caused by rapid movements. On the other hand, the low-pass filter was effective in reducing muscle artefacts, but we cannot yet say for sure whether it occasionally led to a slight attenuation of higher frequency brain waves such as beta and gamma, which could affect the accuracy of band power analysis. The implementation of adaptive filtering techniques, such as Independent Component Analysis (ICA) for artefact removal, would allow more precise and robust noise reduction.

Overall, although the implemented filters and methods significantly reduced the noise

from walking-related motion, achieving a pure EEG signal in real-time environments remains a challenge. The applied techniques were successful in reducing most of the unwanted noise, but careful post-processing and additional artefact rejection methods would be required to ensure the accuracy and reliability of the EEG data in motion-rich scenarios.

5.2.4 Frequency Band Determination

The observable differences in the order of the frequency band powers and maximum values are quite common in EEG analysis. Each frequency band often has its characteristic power range due to various factors related to both biological processes and the nature of EEG signals.

The high power in the delta and theta bands suggests a combination of physiological and motion-related influences on the signal. High delta and theta power are not typical in active states, as they are generally associated with sleep or deep relaxation. However, they can also increase with certain movement-related artefacts while walking that can introduce low-frequency artefacts, due to head movements, muscle contractions, or electrode shifting. The decrease in alpha power is also expected due to alertness and active engagement.

Even though the results obtained correlate with the expected behaviour, the previously described noise types and filter uses may have affected the already extreme behavioural values. Further advanced techniques could be explored to address these issues in more depth, though this is beyond the scope of the current study.

5.2.5 Mapping with *folium*

The use of *folium* Python library proved to be a particularly suitable way of data visualisation to create clear and interpretable figures. As the library is based on OSM, it inherits its interactivity and all its features, like the ability to zoom in and pan while the map is updated.

Experimenting with the colouring options was an interesting side track, even beneficial for future applications. In cases, like neurofeedback, it is essential to provide feedback in an easy-to-understand and straightforward way, while also appealing to users. Additional functionality can be built to allow users to choose which parameter changes or

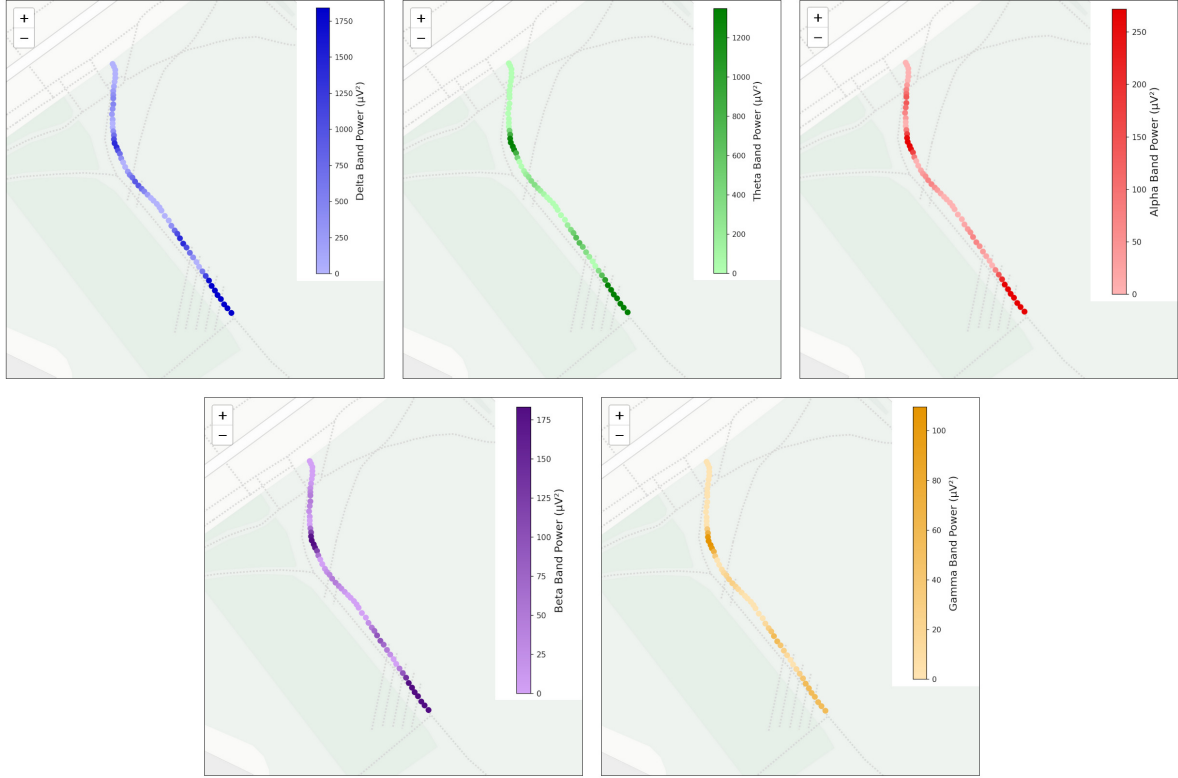


Figure 5.6: Representation of average frequency band powers over location data

mental states they want to monitor through colouring. Figure 5.6 shows such an approach, providing a transparent and intuitive representation to monitor temporal changes of frequency bands.

5.2.6 Appearance of the Headset

For the development of the headset, I enhanced the functionalities of the bright headband from MindRove Kft. This device has already been designed keeping the user experience in mind and is therefore promoted as an "easy-to-use and convenient EEG band". During both the selection and integration of the GNSS module, it was crucial to ensure that bright did not lose any of these strengths. The developed headset is shown in Figure 5.7.

In the interest of saving space and time, there is no need to redesign the entire structure when upgrading the hardware. The only modification needed is to increase the width of the control side box, to fit in the GNSS module. This component of the headband is made



Figure 5.7: MindRove bright

by 3D printing, as the adjustments increase the size of the box along only one dimension, hopefully, there will not be any difficulties or significant changes in printing time. Thus, although one side of the headband protrudes more to the side, it does not cause any difficulty or significant difference in user experience while wearing, neither in weight nor in size.

Chapter 6

Summary

6.1. Conclusion

In this paper, I demonstrate the development of an integrated EEG-GNSS headset for mental state monitoring and prediction. This work covers the essential background on electroencephalography (EEG) and brain-computer interfaces (BCIs), along with the detailed steps of both hardware and software development. These include the update of MindRove’s firmware, the creation of an Android application and the implementation of data preparation and processing algorithms for synchronizing EEG and location data. Following this outline I completed the headset, then tested it and evaluated the findings and its performance, concluding with suggestions for future development.

As the focus was on the successful integration of the GNSS module, the emphasis in the evaluation of the data was also more on confirming its success. Consequently, data processing allowed the denoising of the signal and frequency band detection for confirmation. While the noise reduction achieved has some issues and potential flaws, it was nevertheless fit for purpose. Overall, implementing the right combination of denoising techniques and analysis methods and adding more advanced techniques presented in this thesis, could allow more precise EEG signal processing, that may eventually lead to the detection of mental states.

The resulting device is suitable for monitoring the user’s mental states synchronised with their location data. The evaluation of such data provides a new and unique tool that opens up an extensive range of potential applications in areas like urban planning, where insights into mental states can guide the design of more cognitively engaging spaces or

smart cities; neuromarketing, where real-time brain activity could be linked to consumer behaviour in different locations; and mental health care, where patients can be monitored in everyday environments for personalised therapy or self-improvement training, or even for the treatment of disorders like PTSD, ADHD, autism, or even epilepsy. Specific use-case scenarios could be for example tracking stress levels in patients with anxiety disorders as they navigate different environments or enhancement of Cognitive Behavioral Therapy (CBT). The device is also applicable to synchronise the activity of user groups for mood monitoring, general reactions or to observe interactions.

While the project successfully meets its primary objectives, there remain substantial opportunities for future improvements to increase the robustness and uniformity of the system, along with building it more user-friendly. This work represents a step towards a new approach in neuro-monitoring, that may provide a suitable tool for future research and development in the field of neurofeedback and other areas of mental state prediction.

6.2. Future Plans

The long-term plan is to create a stand-alone, independent device. As long as we are reliant on using a phone to complement the headband's functionality, it may seem relatively unnecessary to integrate a GNSS module into the headset, as almost all devices are now equipped with GPS. Nevertheless, this development is already useful, as it allows EEG and location data to be synchronised instantaneously, free of any possible delay.

The main future plan is to equip the headset with a 4G or 5G chip, cutting out the need to use any other device in the process. Making our device a compact system that can be used to immediately upload data to the cloud, easily accessible from anywhere, without the need to store it temporarily. Further potential enhancements may include the incorporation of internal memory for backup purposes when no network coverage is available, or the augmentation of the device's functionalities through the integration of additional biometric sensors, such as those for blood oxygen saturation (SpO₂), electrooculography (EOG), or photoplethysmography (PPG). The overall objective is to make our system more user-friendly, flexible and applicable in a wide variety of environments. Hopefully the implementation of these improvements will result in the device becoming an even more valuable tool for future research and an exemplary product within the BCI market.

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Appendix A

Appendix

The thesis was spell-checked using Grammarly (<https://app.grammarly.com/>) and DeepL Write services (<https://www.deepl.com/en/write>).