# Optimizing the Design of a Wearable EEG System for Improved Data Quality

by

Megan Ngo

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**Abstract**

This thesis aims to evaluate the impact of various form factors and magnetic interference on the quality of EEG signals acquired by a wearable EEG device. In order to determine an optimal design that minimizes artifact contamination, various cognitive tasks were observed, and users provided feedback while data was collected. Signal quality was assessed based on the distribution of power across specific frequency bands. The EEG data collected from the glasses demonstrated high sensitivity in detecting brain activity while in the proximity to magnets. Limitations in distinguishing between different brain states were observed due to increased impedance and noise from the design changes. The results thereby call for further investigation and testing to isolate artifacts and improve the wearable EEG technology.

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# Contents

# List of Figures

# Chapter 1

# Introduction

In the last decade there has been an increasing demand for continuous, noninvasive monitoring of brain activities for remote wellness management. According to a report by Grand View Research, Inc. the market for health and wellness solutions such as wearable medical devices and remote patient monitoring systems is expected to increase to $187 billion by 2030 [1]. The general shift in public preference towards a healthier lifestyle, along with the increasing incidences of diseases that require the aid of medical devices has bolstered the development of connected health technology. Brain disorders, such as dementia, epilepsy, Parkinson's, autism, and seizures, have increased significantly over the years [2]. As many of these disorders are progressive and their risk increases over time, it is becoming increasingly important to develop technology that can monitor a person's brain and neurological functions as they age. The availability of products, such as remote sensors, adapters, and connected mobile communication devices, is further augmenting the growth of this market.

In the market of noninvasive brain monitoring technology, the most common and most frequently used measures are functional Magnetic Resonance Imaging (fMRI), functional near-infrared spectroscopy (fNIRS) and electroencephalography (EEG). fMRI has two major limitations: its requirement for patients to remain immobile during testing and its tremendous operational cost [3]. The former does not allow the patient to be studied during everyday activities such as walking, eating, etc. The latter hinders smaller scaled organizations from using the technology, limiting the availability of public literature on its findings. fNIRS offers favorable portability and could be integrated into a compatible experimental setup, though it is constrained by its poor temporal resolution. This makes it difficult to measure real-time brain reaction to stimuli. EEG amplifiers can be lightweight and portable while providing high temporal resolution of the recorded signal, rendering EEG the most suitable brain imaging device to measure human brain activity during common everyday tasks. EEG devices are commonly used in clinical settings to diagnose and monitor neurological disorders such as epilepsy, sleep disorders, and brain injuries. More recently, there has been a growing interest in consumer EEG devices that interface with mobile apps and other devices to provide immediate feedback to users for self-monitoring purposes [example in Figure 1].

**Figure 1.** Muse, a “smart” headband that comes built-in with EEG brain sensors. The company allows the user to be able to interact with the live data after being filtered with their classification algorithm through a friendly user interface [4].

EEG signals, however, can be highly susceptible to artifact contamination which can affect the algorithms that classify signals into behavior. Causes such as cable/electrode movement, the presence of other electromagnetic devices, or even physiological signals such as eye movements or muscle activity can cause artifacts in the signal [5]. Creating a device for EEG measurement requires a careful consideration of several factors to ensure the best possible data collection experience for patients. In this study, we focus on a wearable device in the form of glasses that incorporate both EEG sensors for analyzing the user's brain behavior. Our research aims to investigate the impact of various form factors on the quality of EEG signals and to examine the artifacts that can arise when the electrodes are in close proximity to magnets.

# Chapter 2

# Background

## 2.1 Introduction to EEG

A single action potential traveling into the central nervous system along a single nerve can carry enough information to notify the body of its presence and occurrence. More complex messages can be carried by variations in the frequency of these action potentials [7]. The discovery of electroencephalography in the early 1930's was a historical breakthrough, providing a new neurologic and psychiatric diagnostic tool at the time [8]. An electroencephalogram (EEG) records variable potential differences between two electrodes placed on the scalp. During data collection, the electrodes are positioned on the scalp and attached to electrically active tissue. Traditionally each pair of electrodes (usually termed active and reference) is connected to an amplifying system, and the potential difference is then displayed on an ink-writing oscillograph or on an electronic oscilloscope. The strength and distribution of such potentials reflects the average intensity and position of a group of underlying neurons [9]. These recorded oscillations over time in electrical potential differ in frequency and amplitude from place to place and in different states of awareness [visualized in Figure 2].

Hans Berger made the first EEG recording on the human scalp by using radio equipment to amplify the electrical activity of the brain. He claimed that the data he observed from EEG changed in a consistent, recognizable fashion when the state of the patient changed, such as relaxed to anxious or alert to lack of sleep [10]. This led researchers to believe that human behavior can be measured through these changes in the electrical activity of the brain and termed these changes ERPs, or event-related potentials.

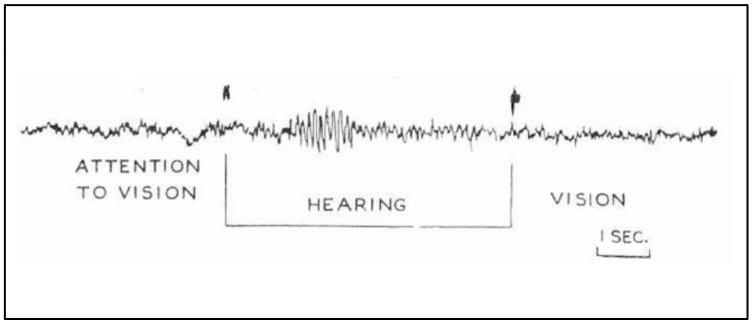



**Figure 2.** An EEG signal from a study where participants were instructed to shift their focus between visual and auditory stimuli. The alpha power increased with an increase in attention towards hearing. (Reproduced from Adrian 1944).

### 2.1.1 Classifying EEG Waveforms

Motor and sensory states such as eye movement, lip movement, remembrance, attention, hand clenching, etc. are related with specific signal frequency ranges which helps to understand functional behavior of the complex brain structure [11].

EEG waveforms are classified according to their frequency, amplitude, shape, as well as position of the electrodes on the scalp. Frequency is measured in Hertz, or oscillations per second. Most commonly, researchers in the field refer to these classifications as alpha, beta, theta, delta, and gamma based on the frequency of the recording. The alpha rhythm (the most dominant) varies from 8 to 13 Hz. In a typical human subject at rest with eyes closed in a quiet room, the alpha rhythm is seen at its greatest amplitude in the parietal and occipital regions [diagram presented in Figure 3] [12]. Several conditions may produce a blocking or suppression of the alpha rhythm, such as opening the eyes, intense sensory stimulation, alert attention, or mental activity, e.g., solving mental or arithmetical problems. The beta rhythm is of lower amplitude and higher frequency (14- 30 Hz). Theta (3-8 Hz) and delta (0.5-3.5 Hz) rhythms are slower than the alpha and rarely occur in normal individuals during the waking stage. When they do occur in waking subjects other than newborn infants, they usually indicate disease or injury of the brain.

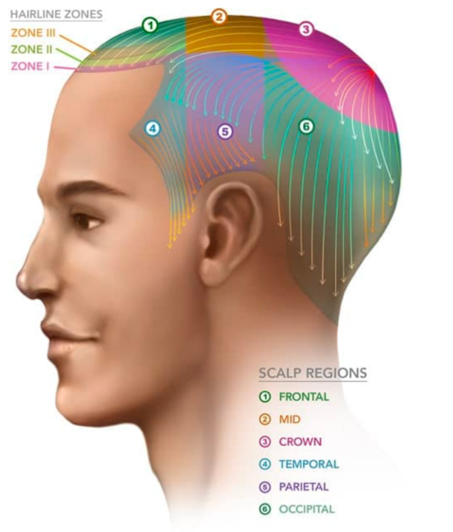



**Figure 3.** Diagram of the regions of the scalp. Majority of the frequency picked up by EEG recordings are the alpha waves which are associated with the parietal (5) and occipital (6) parts of the scalp.

### 2.1.2 Artifacts in the EEG Signal

Artifacts are unwanted signals that can contaminate EEG recordings and interfere with accurate interpretation of the data. Physiological artifacts can include muscle activity, eye movements, and heartbeat. Eye movements, for example, can generate electrical signals that can interfere with EEG recordings, especially if the electrodes are placed near the eyes [example in Figure 4]. Non-physiological artifacts can include electrical noise from nearby electronic devices, such as fluorescent lights, computers, or power lines. These sources of interference can be particularly problematic in clinical or research settings, where EEG recordings are often conducted in environments with multiple sources of electrical noise.

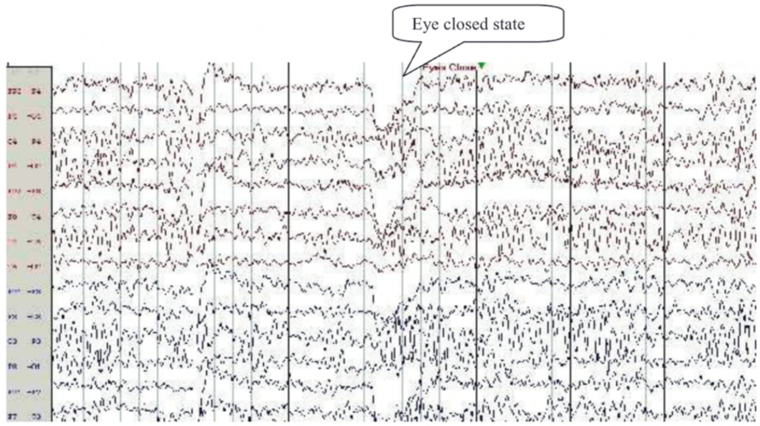



**Figure 4.** Example of an EEG recording in which the subject was asked to close their eyes. Displayed are the alpha activities responsible for eye-closing on the frontal, temporal, occipital, central, and parietal lobes of the brain [11].

## 2.2 EEG Limitations

Although many studies use fMRI to study task-related and resting state functional connectivity, EEG/magnetoencephalography(MEG) are preferable due to their high temporal resolution. Samples are taken within a few milliseconds of each other, typically under 5ms, and thus studied in real time. In other words, by the time it takes a subject to blink, an EEG recording could have taken over 4,000 samples to analyze. Both fMRI and MEG are highly sensitive to motion artifacts, making both techniques largely impractical for young children and/or children with repetitive, stereotyped behaviors [13].

The disadvantage of using EEG is the poor spatial resolution, making it difficult to pinpoint where activity occurs in the brain [14]. Moreover, conducting a sufficient number of trials necessitates longer experiments, which may result in participant fatigue. Noisy data, connectivity issues, and physical interference can also create artifacts that affect the results. Specific instructions may be given to participants to minimize artifacts, but this can also lead to attention loss and exhaustion [14]. It is important to keep these factors in mind when creating a device for EEG measurement.

## 2.3 Feature Extraction

In order to interact with EEG in a readable format, the raw signal is almost always processed in the following stages. The acquisition phase, where the raw data is collected directly from the scalp and logged in a time series. The second phase is a preprocessing stage in which artifacts are removed as well as data is filtered. Artifact removal can be done differently depending on the purpose of the study. The third phase is feature extraction where the feature of the signal can be derived using various signal processing techniques such as Fourier transform, Wavelet, Principal Component Analysis, etc.

The power spectral density (PSD) was used as the feature extraction method in this study for signal processing and spectral analysis. It is a common signal processing technique that distributes the signal power over frequency and shows the strength of the energy as function of frequency [visualized in Figure 5]. Welch's algorithm was used for estimating PSD by first dividing the signal into overlapping segments of equal length. The periodograms are then computed by taking the squared magnitude of the discrete Fourier transform (DFT) of each windowed segment. Finally, the periodograms are averaged to estimate the PSD. The signal to noise ratio for Welch's method is high, reducing the estimated power spectra in exchange for improving the frequency resolution.

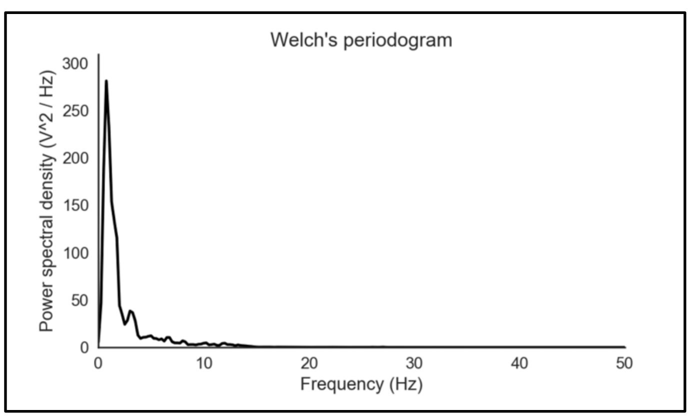



**Figure 5.** Example of a PSD plot over frequency using Welch's periodogram. Power is plotted in units of $\frac{V^2}{Hz}$ [15].

# Chapter 3

# Design and Development

This project aims to refine the prototype of a wearable device in the form of glasses that incorporate dry EEG sensors to analyze brain behaviors of the user. The glasses can wirelessly transmit voltage data from the electrodes located on the bridge of the nose as well as behind the ear [visualized in Figure 6] via Bluetooth. Data was received at a sampling rate of 250 Hz, about 0.004 seconds apart.

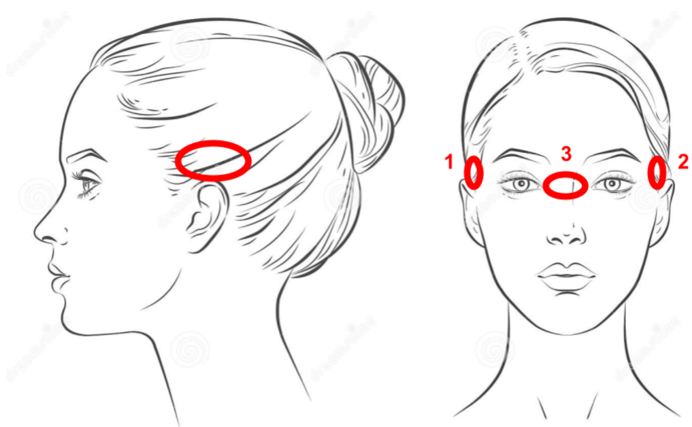



**Figure 6.** Diagram of physical locations of the electrodes placed on the bridge of the nose (Channel 3) as well as behind the ears (Channels 1 and 2).

Iterative versions of the prototype were designed on Fusion 360 and printed using a SLA 3D printer for quick proof of concept. Once an iteration of a full pair of glasses was finalized, the CAD was sent to a third-party manufacturer to be printed in a more durable material for the subsequent round of prototyping.

## 3.1 Design Requirements

The glasses were designed to mimic an accessory that seamlessly fits into daily routine. The aim was to collect user data during everyday activities to assess their regular brain activity patterns. Maintaining data quality in this preliminary prototyping stage proved challenging, as the design changes had to prioritize data integrity, durability, and reliability over several uses. Additionally, user experience was optimized for simplicity and comfort, as patients' constant readjustment could compromise clean data collection. Especially for patients that have a hard time sitting still, keeping the glasses firmly on the head posed a significant challenge. Users also preferred glasses that could fold for portability.

## 3.2. Iterations

### 3.2.1 Original Design (#020) and Areas of Improvement

The initial design of the glasses featured a hinge on the inside of the arms [pictured in Figure 7]. The hinge was situated at the juncture of the arms and lens frame. Wires running across the frames of the glasses connect the battery, microcontroller, and 3 electrodes. Although this configuration allowed for the wires to run across the glasses uninterrupted, the amount of slack in the wire required to fully close the arms risked getting caught when closed. Conversely, if the glasses were constructed with no slack in the wires, the arms would be unable to fold entirely.

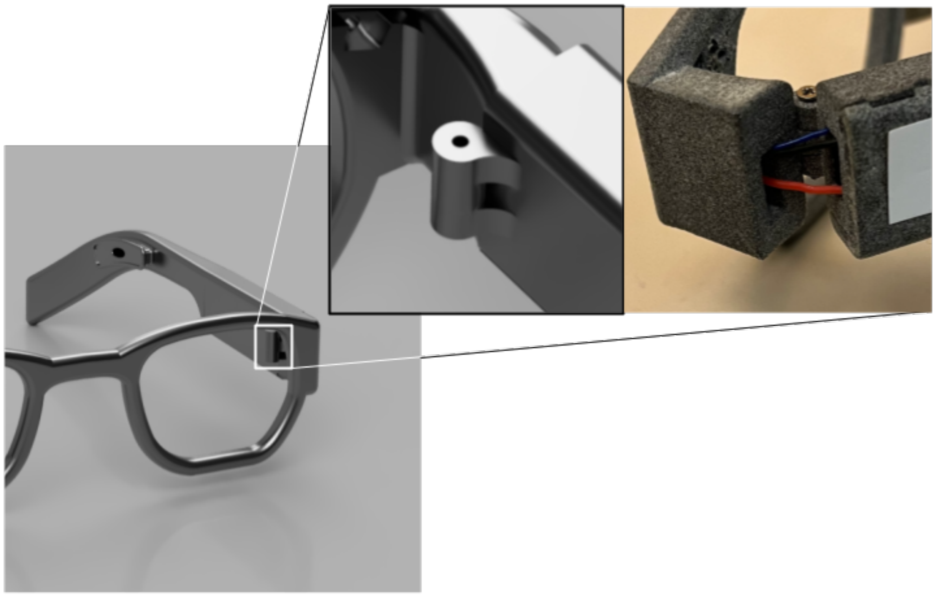


**Figure 7.** Blown-up rendering and photo of the hinge for glasses #020. Wires were attached to the microcontroller without any slack, the arms could only be closed at a maximum angle of 10° from the vertical position.

### 3.2.2 Magnetic-Close Prototype (#025)

The following prototype iteration aimed to achieve full circuitry connection exclusively in the "ON state" of the glasses. Instead of relying on direct wire connection from the electrodes to the microcontroller, the design incorporated spring-loaded pogo pins [Figure 8] into the circuitry. Each hinge was fitted with a pogo pin that was soldered to the wires which would have otherwise run through the open channel [as shown in Figure 9]. This design necessitated the addition of 24 new points of connection, comprising of 12 female and 12 male pins.

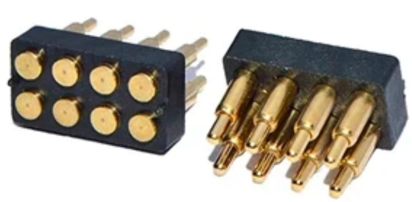


**Figure 8.** Spring-loaded pogo pins

To improve the user experience and ensure accurate data collection, magnets were added to the hinge of the glasses. These magnets, made of Neodymium Iron Boron (NdFeB) and with a Gauss strength of approximately 13000 G [16] helped keep the glasses in an "open and connected" state until the user consciously ended the experiment. By design, the two halves of the pogo pins lose contact if the arms close accidentally thus also causing the microcontroller to lose connection to the battery. To ensure that the pogo pins maintained contact while the glasses were open, the magnets needed to be strong enough to hold the arms in place, but weak enough to allow for easy closure. The strength of the magnets used in this prototype was found through trial and error, selecting the weakest magnet needed to hold the arms open. The effect of magnets on the resulting EEG signal integrity is further investigated in this thesis.

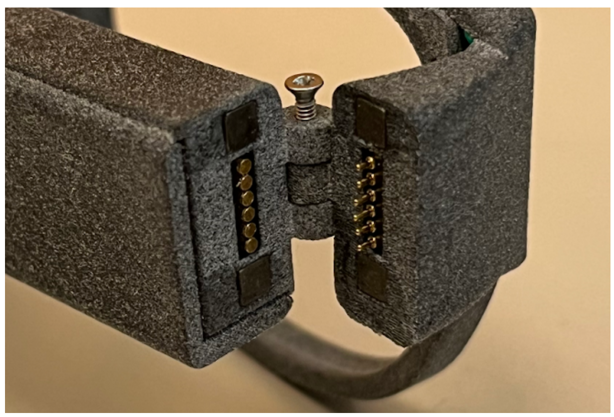


**Figure 9.** Zoomed in photo of the hinge for glasses #025. After full assembly, the arms could be closed at a maximum angle of 90° from the vertical position.

### 3.2.3 Manual Half-Close Prototype (#028)

Further investigation was required to assess the potential impact on signal quality due to the addition of magnets and new connections. Thus, more manual closing prototypes were developed and tested. The subsequent design iteration offered many advantages. The hinge placed on the arm just before the back electrodes allowed for only one wire (the one leading to each of the back electrodes) to be stretched while the glasses were folded. Additionally, the folding location enabled the user to still easily compact the glasses during transport [visualized in Figure 10].

**Figure 10.** Frame assembly of glasses #028 with arms folded. Wires were attached with slight slack. After fully assembled, the lower half of the arms can close past 90° from vertical.

The hinge geometry was altered to shift the pivot point closer to the center and thereby reduce the wire length required to stretch [as shown in Figure 11]. This design choice facilitated constant connection between the electrodes to the microcontroller and decreased the risk of wire exposure when the arms were folded. A challenge encountered during this process was building the hinge within the limited space between the lens frame and the microcontroller.

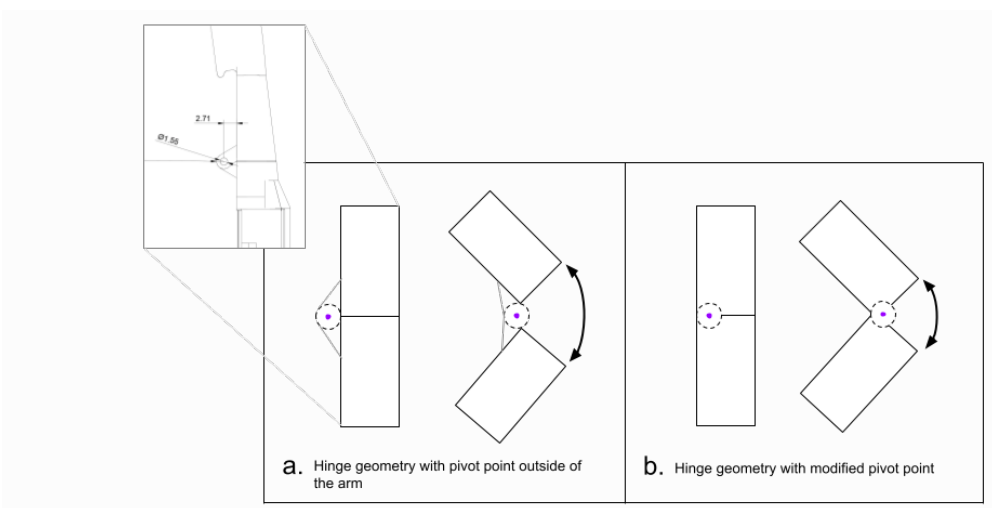



**Figure 11.** a) Original hinge geometry with pivot point placed on the side of the arm b) Modified hinge geometry with pivot point placed in line with the arm. Necessary exposed wire length is referred to by the arrows.

To ensure durability and prevent damage caused by excessive stress on the frame, the pivots' outer diameter needed to be sufficiently large. Furthermore, the distance between the electrodes had to be maintained to ensure data consistency with other models, resulting in design constraints that influenced the final prototype dimensions. Iterative experiments were conducted on the hinge alone to achieve the necessary tolerances and dimensions, as illustrated in Figure 12.

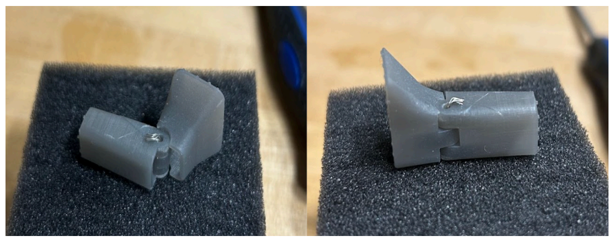


**Figure 12.** Photos of one iteration of the modified hinge, maximum bending angle of 75° from vertical. Prototype printed with SLA printer in Form labs Draft v2 resin.

The placement of the pivot point had to be optimized given the limited outer width of the glasses. Moving the pivot point closer to the centerline of the arm minimized the distance required for the wires to travel. However, this posed a challenge for the ease of assembly, as the manufacturer would encounter difficulties snaking the wires through a small channel [as seen in the bottom left of Figure 13].

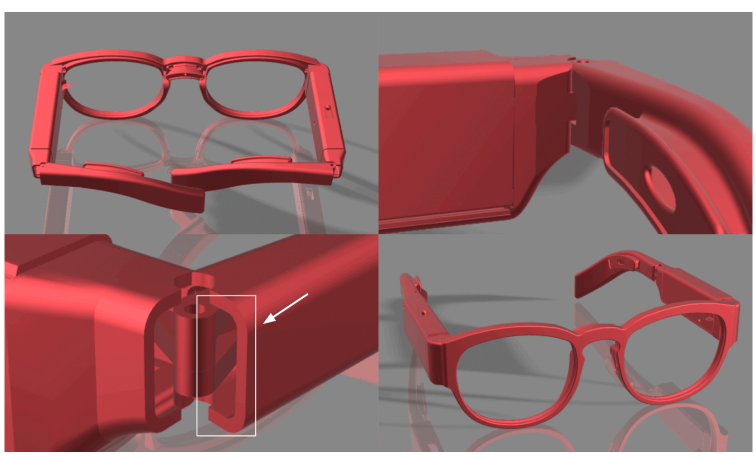


**Figure 13.** Multiple views of glasses prototype #028. Rendering done on Fusion 360. Opening channel for wires is highlighted in the bottom left image.

# Chapter 4

# Methodology

In order to assess the consistency of the signal, four tests were conducted with each pair of glasses for multiple trials and the averaged results were used to compare between prototypes. From these tests, conclusions can be drawn for which design offers the best user experience without compromising the integrity of the signal.

## 4.1 Testing Procedure

The four tests chosen are standard protocol procedures used by our lab group when conducting tests with patients. The first is a common diagnostic test for EEG sensors. The last three tests are common tasks to mimic one's daily routine: eating, reading, and "knowledge-based" such as writing emails, doing schoolwork, etc. Each test begins in an identical fashion. The glasses are powered up and connected via Bluetooth through an interface developed separately by the lab. Once connected, data can be streamed from the glasses for any duration so long as the battery is fully charged, and the circuitry remains connected.

Aside from the open/close eyes test, each test was conducted for a duration of 15 minutes on different days over the course of 2 weeks. Each test was done roughly at the same time each day. There was a minimum of 5 trials for each test, however some have 6 or more. Lastly, each test was run once more for a duration of 30 minutes. The minutes segments 5-10, 15-20, and 22-27 were selected in empirical manner and analyzed as well.

### 4.1.1 Open/Close Eyes Test

The open/close eyes test is a very common experiment to quickly determine the validity of the EEG signal. It is an initial diagnostic test for every new pair of glasses built to ensure data consistency. The state of one's eyes being closed is considered an "interoceptive" state and characterized by visual cortex activation. The state of eyes open is considered "exteroceptive" and characterized by ocular motor system activity. These states use two very distinct parts of the brain that allow clear distinction. The user was asked to place the glasses on their head in which they would wear any normal pair. They were told to close their eyes while data was being collected for 30 seconds. During this time the participant was asked to not make any sudden movements, swallow, or open their mouth. After 30 seconds the participant was instructed to open their eyes and visually fixate on a small cross presented on a computer screen in front of them. They are also requested to blink as few times as possible. The data continues to be collected for another 30 seconds. Afterwards the data stream was interrupted, and the glasses were powered off for the next test.

### 4.1.2 Knowledge-Based Test

The user was asked to wear the glasses in which they would wear any normal pair. They are told to perform a task that requires active recall and information retention for 15 minutes, such as writing emails or doing homework problems. During this time the participant was asked to not make any sudden movements, however swallowing and blinking are allowed when necessary. After a total of 15 minutes the data stream was interrupted, and the glasses were powered off for the next test.

### 4.1.3 Eating Test

The user was asked to pick a meal that they have at a consistent time every day for at least 15 minutes. During this time the participant has much more liberty in their facial movements. It was only requested that the participant does not stand mid test or do any other activity besides eating.

After a total of 15 minutes the data stream was interrupted, and the glasses were powered off for the next test.

#### 4.1.4 Reading Test

The user was asked to wear the glasses in which they would wear any normal pair. They are told to read for 15 minutes. They must read something of the same sort for each trial (i.e. research papers, the same book, etc.) During this time the participant was asked to not make any sudden movements, however swallowing, blinking, and adjusting the glasses are allowed when necessary. After a total of 15 minutes the data stream was interrupted, and the glasses were powered off for the next test.

## 4.2 Data Processing

#### 4.2.1 Data Extraction

The EEG data from each trial was extracted as a csv file under the patient's name and prototype number. In each file, the raw EEG data (in microvolts) for each channel was recorded as a time series. The data was then formatted into NumPy arrays for easy processing. Plots were produced on Jupyter Notebook using python data visualization libraries. The MNE python package was used to compute the power spectral density (PSD) using Welch's method. The main advantage of Welch's algorithm is that it reduces variance by averaging multiple estimates, which can improve the accuracy of the estimated PSD. The choice of window function and segment length can affect the trade-off between frequency resolution and variance reduction. Typically, longer segments and narrower windows provide better frequency resolution but may increase variance, while shorter segments and wider windows reduce variance but may sacrifice frequency resolution.

### 4.2.2 Data Preprocessing and Filtering

For each subject in each condition, PSD plots are generated [flowchart of the process can be seen in Figure 14]. The raw data from the channels was averaged and power spectra was calculated using Fast Fourier Transforms with 1 second overlap between each Welsh window.

For each trial, absolute power (measured in dB) in the frequency range 0-80 Hz was calculated. Two filters were applied to the data before the PSD plots were created: a high pass filter and a notch filter at 60Hz. Because the U.S. power grid transmits power at 60 Hz, this frequency was seen with the highest power in every PSD plot generated and thus must be filtered out. It was also decided to apply the high pass filter at 5Hz to filter out most of the delta and theta waves. These frequencies, although could be necessary for other EEG tests, are not looked at for this study while we only try to assess the consistency and integrity of the data signal.

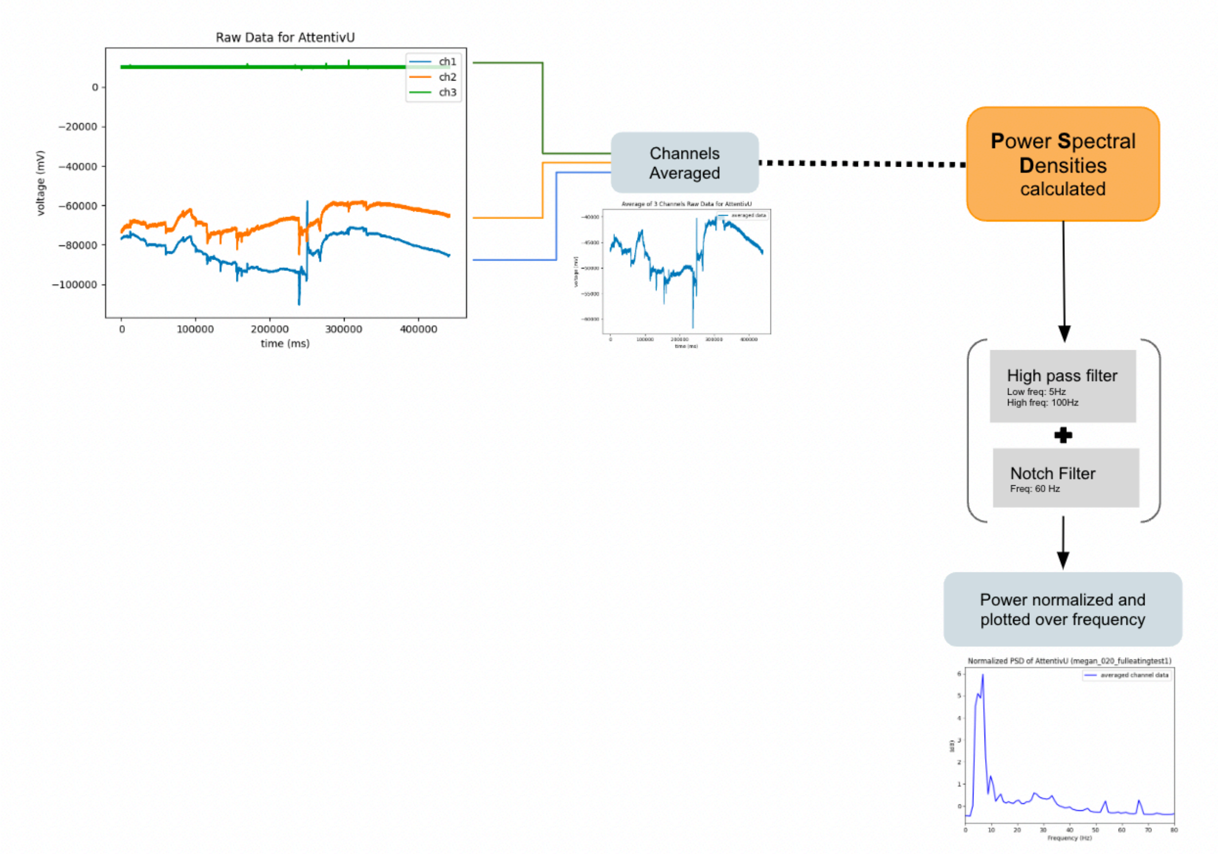



**Figure 14.** Data preprocessing pipeline to produce normalized PSD plot of the data signal

# Chapter 5

# Results/Findings

Using the normalized PSD plots for each pair of glasses we look at the frequency range of 0-50Hz even though the waveforms in the alpha and beta range (8-25Hz) are typically the most common activity window for patients in the waking stage. Examining the entire frequency band provides a more wholistic understanding of the data being received in order to inform the data-filtering process. To minimize result variability, each plot corresponds to the tests conducted on a single patient.

## 5.1 Assessing Data Quality

The PSD plot in Figure 15a shows the two newest prototypes picking up a lot of noise surrounding the 60 Hz frequency (approximately ±5 Hz). This electrical noise can interfere with the EEG signal and make it difficult to analyze. To mitigate this issue, a notch filter is often applied to remove the 60 Hz frequency component from the EEG signal. However, the notch filter may not remove all the noise around this frequency, which is why some noise may still be observed in the PSD plot at frequencies near 60 Hz.

After normalization of the data, glasses #028 (manual half-close) was revealed to pick up very little frequencies in the range 16-44 Hz, as well as less power at most other frequencies compared to the other two designs. This could be attributed to the tremendous peak near 60 Hz, which is too broad for the notch filter to effectively remove. The smaller frequencies having lower power compared to the 55-65 Hz range could result in the diminishing of their power values after normalization. Figure 15b shows the normalized PSD plot after applying a low-pass filter with a cutoff frequency to see the signal without the effects of the higher frequencies. The original and manual half-close pairs behaved similarly at lower frequencies (below 25 Hz). From this it can be extrapolated that glasses #028 does receive more noise around 60 Hz, but it does not affect the intensity of the other frequencies being observed. It is difficult to determine the exact reason for the noise without further analysis, but one possibility is that the design similarities between glasses #020 and #028 result in similar signal filtering and noise reduction capabilities at lower frequencies. Interestingly, the magnetic-close prototype (#025) appeared to pick up fewer lower frequencies than the two manual-close prototypes regardless of the low-pass filter. One possibility is that the electrodes in glasses #025 might not have as good contact with the skin as the manual-close prototypes, resulting in a weaker signal. Additionally, the magnetic-close design may have different material properties that affect signal transmission.

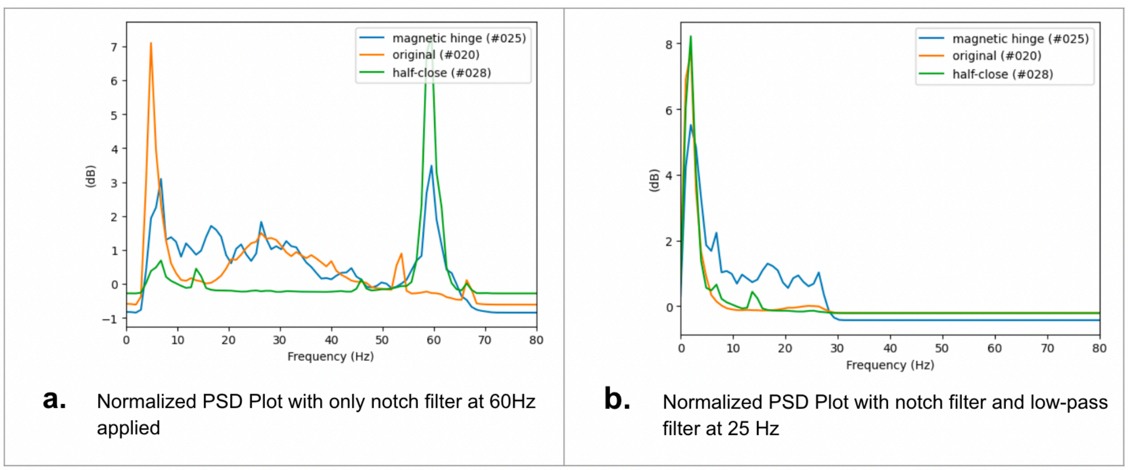
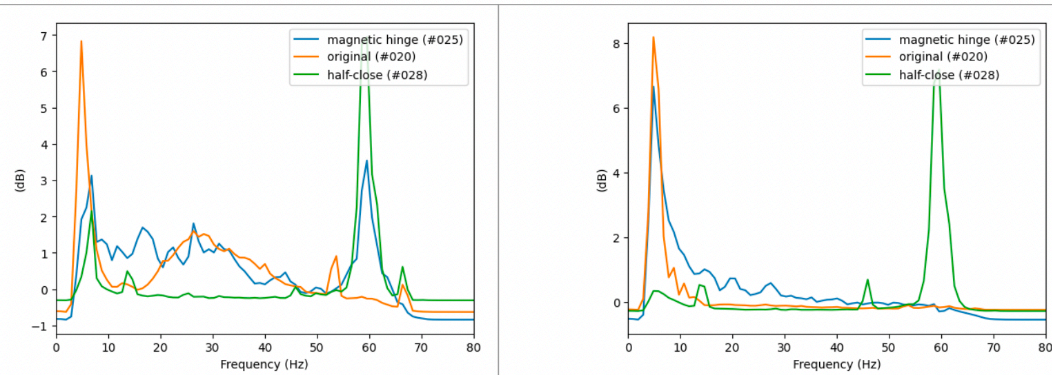



**Figure 15.** Knowledge test PSD plot of all three prototypes with a) only notch filter at 60 Hz or b) notch filter and low pass filter with a cutoff frequency of 25 Hz applied to the data.

Multiple trials for each test were conducted with the pairs #020 and #025 in order to determine the consistency and reliability of the magnetic-frame performance, as well as to assess any potential differences in signal quality between trials. Figure 16 displays the averaged data over 5 trials, revealing that the magnetic pair detected frequencies at relatively higher power, except for the spike at 5-8 Hz from the original frames. The eating test and knowledge-based test demand different cognitive processes, so if the PSD plots from both tests show similar patterns, it could suggest that the sensors are not accurately detecting the brain activity. The peak in power observed in the alpha range for the original frames is a typical finding, as this frequency is among the most prevalent frequencies in the brain during the waking state. The behavior of the magnetic frames is more interesting.




**a.** Normalized PSD Plot of 15 min knowledge-based tests over multiple trials

**b.** Normalized PSD Plot of 15 min eating tests over multiple trials

**Figure 16.** PSD plots of 15-minute a) Knowledge-Based Tests and b) Eating Tests averaged over 5 trials for all three prototypes.

PSD results from glasses (#025) exhibited a higher number of frequency spikes compared to the original pair. This suggests that the magnet pair may be more sensitive to picking up activity than the original pair. The consistent detection of high alpha waves in the longest test [as depicted in the Figure 17], regardless of the activity being performed, could indicate that the magnet pair is not as reliable in distinguishing between different brain states. The noise around 60 Hz may be due to external sources of interference. The lack of signal in the 20-50 Hz range in each test could suggest that the magnet pair is not picking up as much activity in this frequency range, which is necessary for measuring certain brain functions. Overall, these results suggest that the magnet pair may have some advantages in sensitivity but may also have limitations in reliability and specificity compared to the original pair.

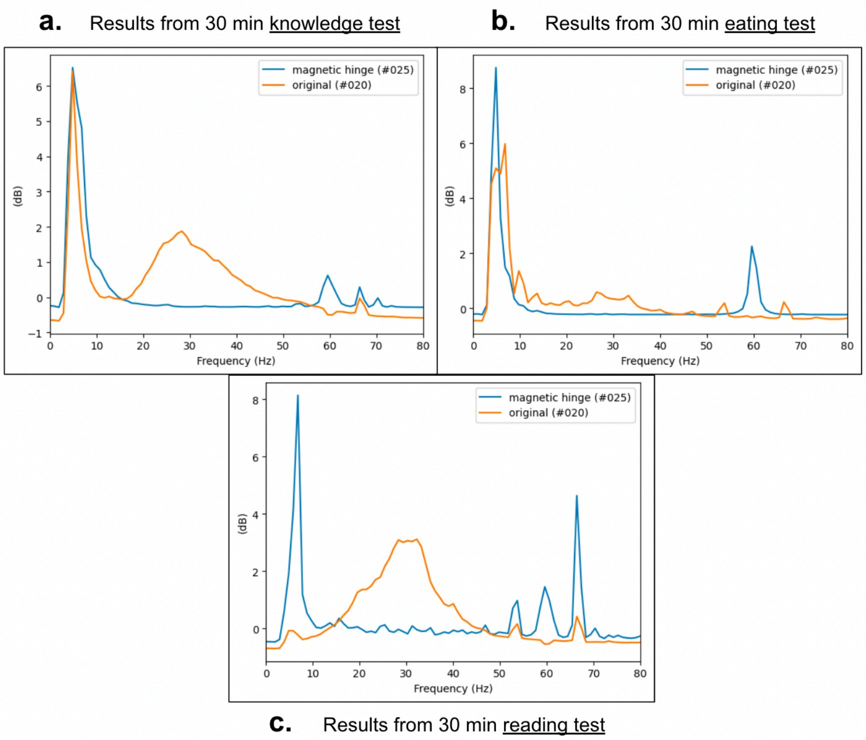



**Figure 17.** Plots of 30-minute a) Knowledge-Based Tests and b) Eating Tests and c) Reading Tests comparing the magnetic-close prototype (#025) and the original prototype (#020). Glasses #028 omitted from long tests.

## 5.2 Design Conclusions

The manual half-closed prototype (#028) was the worst performer during user testing. While the PSD plots did not reveal a significant difference in the frequencies detected by this design, users experienced issues with the glasses sliding down their nose more frequently compared to the other designs. This could be due to the hinge's position not allowing the arms to grip the user's head properly. Users also expressed confusion at the location of the hinge, trying to bend the arms at the wrong location initially. As a result, this design was halted from further investigation before the longer duration testing began.

The PSD results suggest that the magnetic pair may be more sensitive to picking up activity. However, it also exhibited consistent detection of high alpha waves regardless of activity, which could indicate a lack of reliability in distinguishing between different brain states. One explanation for this could be due to the number of extra soldering connections required to assemble the pogo pins. Wires running across the frames of the glasses connect the battery, microcontroller, and 3 electrodes. With each point of connection, impedance and noise increases. Another explanation to this sensitivity could be the proximity of magnets to the wires carrying the voltage signal. More experiments must be conducted to make further conclusions.

The tests themselves were chosen alongside the goal to be used during daily tasks in a convenient and unobtrusive manner. This does, however, introduce much more uncontrolled variables than if the experiments were to take place in controlled environments, such as a hospital room or noise-controlled isolated space. The ability for long-term recordings in real-life scenarios comes at the expense of reduced spatial resolution (i.e. fewer electrodes) and more noise. The result plots showed high variability amongst each trial for each pair. Only the original frames (#020) and magnetic prototype (#025) were tested in real-world hospital settings. Patient feedback showed that designs users enjoyed the feeling of the magnets holding the arms open. A “snap-in-place” opening mechanism should be explored in further iterations.

# Chapter 6

# Conclusion/Future Work

Wearable EEG technology offers the potential for long-term recordings of brain behavior in real-life scenarios, but with reduced spatial resolution and less control over interference and artifacts. The implications for further development and research are significant.

The magnetic pair exhibited higher sensitivity to picking up brain activity, but also had limitations in distinguishing between different brain states. This is most likely due to increased impedance and noise from the extra soldering connections required for the pogo pins. This highlights the importance of designing for minimal connection points to ensure reliable signal detection. Further tests will be done with the manual-closing hinge and attachable magnets given that the magnetic closure received positive user feedback. Investigating the effects of different types of magnets and exploring alternative recording methods such as ear-EEG [17] could offer valuable avenues for development.

The variability in the results among each trial and the uncontrolled variables of real-life scenarios suggest the need for further investigation and testing to isolate artifacts. Exploring different parameters of the Welsh algorithm could potentially improve the accuracy of the EEG readings. For instance, adjusting the length of each Welch segment or the amount of overlap between segments could lead to better identification of specific frequency spikes in the data. Isolating the waveforms depending on what literature predicts will be most prevalent for a given experiment could also be very beneficial to further investigating these artifacts. It would be advantageous to perform different tests in order to isolate artifacts related to physical surroundings, for example reading at different times in the day or in different buildings where the noise can be anticipated. Currently the channel data is averaged in order to account for this variance, but a more effective approach would be to isolate and remove the artifacts specific to these surroundings. Incorporating a larger sample size and controlling for variables such as age, gender, and cognitive ability can also help to reduce variability and increase the generalizability of the results.

Once the sample size expands, it would be interesting to investigate the physical tendencies of users. This can allow us to better understand the most common locations for stresses applied, and better inform our stress analysis. Once a final design is chosen, the stress mapping at those locations will influence the dimensions as well as distribution of material across the frames. Additionally, a new prototype with manual close and attachable magnets are being currently developed and tested to further investigate the effects on data quality.

These findings present notable implications for further development and research. More investigation is needed, as well as several prototypes for the final product. The improvement of wearable EEG technology also comes with the possibility of understanding the complexity of brain behavior.

# Chapter 7

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