Boston University
Electrical & Computer Engineering
EC463 Capstone Senior Design Project

Problem Definition and Requirements Review

EEG-based Brain-Computer Interface

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EEG-based BCI

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Customer Sign-Off ____

EEG-Based Controller for Navigating a Virtual 3D Space

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Abstract—This project demonstrates the capabilities of non-invasive electroencephalograms (EEGs) in predicting an intended movement of a user. A wearable headset containing an array of sensors relays neural information to a signal processing unit, which transforms the raw input into data more suitable for further processing. From there, a trained machine learning algorithm determines a user's intended action in a virtual 3D space. This grants the user three degrees of freedom. The intended actions will be displayed on a screen depicted as an object moving through a videogame-like three-dimensional space. This will provide feedback to the user and allow them to make adjustments. The user will be given a task to complete within the virtual environment to demonstrate the effectiveness of the device.

Index Terms—algorithm design and analysis, machine learning, signal processing, virtual environment modeling

1. Need for this Project

Since the dawn of the 21st century, brain-computer interfaces have drastically grown in popularity. Publications surrounding the topic of brain-computer interfaces (BCIs) have nearly doubled in size since 2014 [1]. In many cases, invasive BCI technologies, which communicate with the brain without interference via medical implant, have been reported to improve the lives of people with neurological illnesses [2]. With this implication in mind, the technology behind reading neural activity has incredible potential.

However, invasive technologies may come with an onslaught of arguably disastrous consequences for the human brain. One particular result of an implanted neural electrode is an unanticipated microglia immune response. Microglial Cells release neurotoxins in response to pathological stimuli; neural implants may inadvertently amplify this response, causing major injury [3].

Invasive methodologies of reading brain activity are also becoming increasingly more expensive. It is predicted that invasive BCIs will experience the fastest compound annual growth rate compared to non-invasive and partially invasive techniques [4]. The invasive approach also includes hefty expenses for its physical implementation as well as periodic medical check-ups [5]. As a result, invasive BCIs used for curing neurological-related illnesses will only be more difficult for patients to obtain.

Our solution to avoid encountering the dangerous risks and burdens of electrode implants by implementing a safe and cost-effective method of non-invasive electroencephalogram (EEG) pattern reading. It is hoped that invasive methods of measuring brain activity may dwindle as more non-invasive EEG brain pattern recognition techniques become further improved.

2. Problem Statement and Deliverables

2.1 Problem Statement

The non-invasive approach of reading brain activity derives from a common methodology used among researchers studying brain-computer interfaces (see "Competing Technologies"). This method involves the user wearing a relatively compact and lightweight headset with electrodes attached to read signals from the user's brain activity.

An external signal processing unit will be connected to the headset using a wire. Within this unit, signals will be read consistently from the headset. Then, the data read from the brain will be automatically transferred to a computer also connected via wire.

The computer will serve a significant level of importance throughout the making of this project. While the computer is on, a machine learning model will be running in order to appropriately classify the user's choice of action. Once a choice of action is classified, a virtual simulation will account for the user's decision in real-time. This simulation will contain a 3D object controlled by the user via brain activity; the object will move in a specific direction depending on the user's course of action.

2.2 Deliverables

For this project, we will be dividing the work into three main priorities. Each respective component will serve an essential role in meeting our objectives. They are the following:

1. A cost-effective, non-invasive EEG headset capable of taking accurate measurements of electrical activity in the brain will be created. It should do so without an excess of diodes and glue placed on the head. The time to set up and use the product should be as quick and painless as possible.
2. A simple 3D virtual space comprised of 1) an open field with enough space to test out the full scope of user maneuverability, and 2) an obstacle course field for the user to maneuver the object through in a controlled environment.
3. A machine learning algorithm capable of processing the EEG signals with minimal delay. The algorithm should be capable of translating those signals into up, down, left, and right movements and counterclockwise and clockwise rotation commands that navigate the object through the virtual space.

3. Visualization

The system broadly follows the datapath shown in Figure 3.1. It begins with the user's thought of motion. An EEG machine then records the electrical signals emitted from the brain that results from their thoughts. The EEG recording is then sent into a signal-processing module that will preprocess the data. Following the signal processing module, the clean data goes into a machine learning algorithm to classify the user's different motion-related thoughts. The virtual space is then updated based on the predictions the machine learning algorithm made.

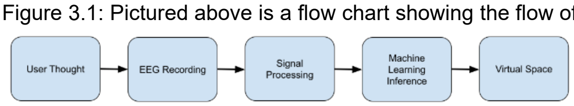

Figure 3.1: Pictured above is a flow chart showing the flow of data through the system, tracking the User's thought to the virtual space.

3.1 EEG Recording

In order to extract the EEG from the brain we will need an apparatus that rests on the user's head and records their brain's electrical activity. This apparatus would be optimally positioned to read the portions of the brain linked with pre-motion activity (electrical signals that precede actual bodily movements). A conceptual drawing of the apparatus can be found below in figure 3.2.

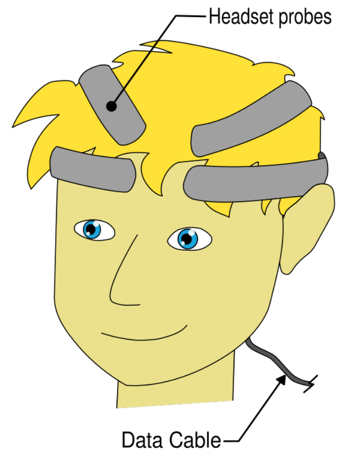

Figure 3.2: Pictured above is a mock drawing of the apparatus that would integrate the EEG reader into a wearable device.

3.2 Signal Processing

The raw EEG inherently has artifacts introduced from variations in the system and from the own user. For instance, EEGs vary in structure based on age and the presence of psychological conditions. They can also have artifacts from involuntary movements such as blinking. The literature points to advanced signal processing techniques as a viable and even suggested method of correcting the waveforms.

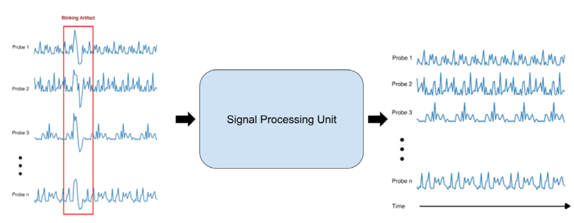

Figure 3.3: Shows an artifact from blinking corrected.

3.3 Machine Learning Inference

The processed EEG waveforms are dense in information, but there is no intuitive method of determining what in the waveform corresponds to the motions of interest. Therefore it makes sense to use a machine learning algorithm to find an optimal way of identifying the presence and type of motion in the EEG.

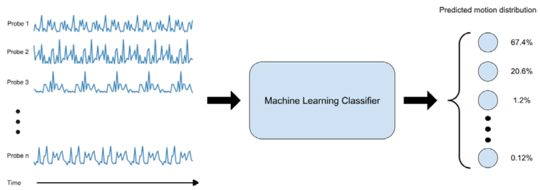

Figure 3.4: Shows how a machine learning algorithm maps time series information to a classification probability distribution.

4. Competing Technologies

The competing technologies in the brain-computer interface industry are described under three categories: EEG-based devices, invasive electrode technology, and alternative non-invasive approaches. Since brain-computer interfacing is a new industry, much of the work has been completed for research purposes, and there is only a small subset of companies with products on the market. There are a vast number of US patents pertaining to wearable technology; however, machine learning algorithms are lawfully considered abstract ideas and are therefore ineligible for receiving patents in the United States [6].

4.1 Emotiv

The first category of competing technologies, EEG based devices, applies closest to this project. Typically constructed as a wearable device, EEG devices offer a low- risk, low- reward solution. Since the electrodes are placed atop the scalp, the signal to noise ratio is much lower when compared to invasive techniques.

Emotiv is the most established brain computer interface company in the industry. Founded in 2011, Emotiv offers non-invasive neuroheadsets and an accompanying software suite. They have four headsets on the market containing a range of two to thirty-two sensors on a single headset [7]. The Emotiv software can be trained to recognize a new command within twenty seconds and is capable of detecting six different emotions as well as twelve facial expressions. Similar to this project, the headsets contain a control unit that samples up to thirty-two channels with an applied bandpass filter. The data is wirelessly transmitted to the user's computer containing an easy-to-use graphical interface for further processing. This project will incorporate only action commands, and will likely utilize fewer sensors. Though this project will contain only six designated actions, creating a flexible algorithm to account for new actions will be a stretch goal. Some of Emotiv's headsets have adjustable sensor locations. This allows the user to read from different locations on the scalp for their intended purpose. This project will likely have a static placement of sensors; However, it may be beneficial to create the headset in this manner for experimental purposes.

4.2 Neuralink

The next category pertains to technologies that take an invasive approach to designing a brain computer interface. An invasive approach comes with significant complications that non-invasive approaches do not. For example, the device must be made of materials that can withstand the brain environment within the brain, and surgical methods of placing electrodes must be done as safely as possible.

Neuralink is the most popularized company in the brain-computer interface industry. Though Neuralink does not have any products in the market, it has made substantial steps in developing their invasive device. Neuralink is developing a robotic device that can accurately and quickly place electrode wires through a single twenty-five millimeter opening in the skull. Neuralink will use a chip containing one thousand electrode wires capable of wireless charging and complex signal processing. Since there is a large amount of data passing through this chip, the chip simplifies the raw electrical input into neural spikes to reduce power consumption [8]. This project does not need to deal with these complications in the same manner. However, electrode placement and signal processing are significant challenges that must be addressed. A unique implementation only achieved via invasive approaches is neural stimulation. By sending an electrical signal through the electrodes, action potentials in surrounding neurons can be induced. Neuralink hopes to use this process to create patterns of activity within the brain to elicit a desired sensation.

4.3 Kernel

The last category contains non-invasive techniques that do not utilize EEGs. The fundamental science behind this upcoming device is described as time-domain functional near-infrared spectroscopy, or TD-fNIRS. This technique measures changes in hemoglobin levels within the brain, allowing accurate, high-resolution observations of neural activity [9]. This method is more complex and more expensive than EEGs. However, it is considered the gold standard of non-invasive optical imaging.

Kernel is the first company to create a wearable headset that utilizes TD-fNIRS for optical neural imaging. When designing their device, Kernel had to ensure full-head coverage, scalability, relatively-low cost, and freedom of user motion. Though the fundamental technology is different, these design constraints are universal. Similar to the Emotiv headset, this device has a signal-processing chip mounted to the headset. This allows for the user's greater flexibility, but it does require the wireless transmission of data. Our design has a standalone unit to reduce the headset weight and limit the potential issues surrounding wireless transmission. However, in future iterations of our design, it may be beneficial to mount the signal processing chip onto the headset itself.

5. Engineering Requirements

The requirements for this surround modern issues with developments in hardware and software. For ease of use, transmissibility, and overall speed, these requirements will be essential for a safe and accurate deployment.

5.1 Hardware

1. The headset and connected cables must not weigh more than 1 kg.
2. The headset must fit a human head with a maximum circumference of 62 cm.
3. The headset must resist water and dust at a minimum IP54 equivalent level.
4. The total cost of the hardware must not exceed 250 USD.

5.2 Virtual Environment

1. The screen refresh rate must be at least 60 Hz.
2. In response to a user's choice of action, the on-screen delay must be less than 500 ms.
3. Using a desktop computer with at least 8 GB ram and an NVIDIA 1000 Series GPU (or equivalent), the virtual environment should run at minimum 60 fps.
4. Should not use more than 25% of the CPU's memory.

5.3 Machine Learning Model

1. Be able to classify a user's choice of action within 100 ms.
2. Algorithm must have a best-case efficiency of at least O(nlogn).
3. Achieve 75% accuracy when classifying a user's input.

6. Appendix A References

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