EEG Alpha Wave Detection

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Abstract—The purpose of this project was to implement a system that could recognize and detect the presence of alpha waves via EEG. The product of our system was not expensive and the size of combined hardware was pretty small.Our design used an EEG to sense electronic signals from differential electrode pairs on the forehead. An electrical signal from the brain will be amplified and sent from the EEG channel to an H7.

I. INTRODUCTION

A. History

Electroencephalography (EEG) is a method to record electrical impulses generated by neurons in the brain.

The field of EEG began more than a century ago. In 1875, Richard Caton (1842-1926) discovered that the brains of rabbits and monkeys produced electrical phenomena, and started to study these electrical signals generated by the brain[1]. In 1812, another Russian scientist named Vladimir Pravdich-Neminsky was able to measure the electrical pulses of a dog's brain[1]. Then in 1890, Polish physiologist Adolf Beck published experiments showing that the electrical signals generated by the brains of dogs and rabbits oscillated when there was a change in light[1]. These experiments in the field of EEG led to Hans Berger, a German doctor (1873-1941) to conduct one of the first experiments to measure human "brain waves" with EEG, using electrodes mounted on the scalp, and measured alpha waves (also called Berger wave) at a frequency of about 8-12Hz[1].

B. Global Constraints

External constraints on your product over which you have no control.

- Logistics

  Due to the current pandemic, in-person collaboration was not possible. This made project logistics extremely difficult. Each team member had to implement their own hardware, instead of working together on one build. In addition, communication through online channels presented a challenge.

- Cost

Project materials were one of the main constraints in this project. As each team member had to implement their own hardware, a budget of around $100 was proposed. This meant the entire build was budget-constrained as to the particular components that could be selected.

- Time constraints

  As the project was limited to a ten week quarter, time was a major constraint. Coordinating the project to meet the week three and seven milestones presented challenges, and meeting these project deadlines meant sacrificing further development in certain areas.

II. MOTIVATION

The EEG method has many applications in medical treatment. It can be used to analyze abnormalities of the brain, and help diagnose various neurological disorders. Brainwave samples are examined and monitored for abnormal wave patterns that lead to seizures and other problems. From brain waves recorded during EEG, it is possible to diagnose headaches, epilepsy and other brain disorders. Commercial EEG devices can vary in cost and performance, with the higher end systems selling for over six figures. The purpose for this project was to create a low-cost EEG system while still achieving high performance. The final build would end up totaling to less than $100, but still achieved the desired performance and project goals.

III. Approach

Introductory sentence.

A. Team Organization

The team was organized in accordance with our project timeline plans, documented in the next section. The general allocation of tasks was as follows:

Noa would be responsible for data acquisition and preprocessing/filtering, as well as H7 implementation.

Hoang would be responsible for neural network training/implementation and observe the result.

Brandon would be responsible for data visualization, feature extraction, and neural network training/implementation.

B. Plan

The plan for the project was to divide the software and hardware implementation into two stages, and then further divide the tasks in those stages amongst the team. Initially, the goal was to have all three team members working together to implement the hardware in the first three weeks of the project timeline. This was due to a couple of reasons. As this project was done remotely it was mandatory that each team member build their own circuit, whereas in a traditional lab setting the team would work collectively on one build. Furthermore, the entire project relied on the proper acquisition of an EEG signal, which could not be accomplished without at least one member implementing the circuit. After the hardware stage was completed, the tasks in software would be divided according to the rough framework outlined in the previous section.

In reality however, issues were encountered in the hardware stage, and the final circuit was not completed until week five. This effectively delayed the week three milestone by two weeks. Comparing the original project goals to the finished design:

Original Plan	What Happened
Have the hardware implemented by week three	Hardware implemented by week five due to circuit issues
Implement a six channel EEG	Only a one channel EEG implemented due to time delays in hardware stage
Train a classifier using EEG datasets available online	Trained on our own data instead, as it provided better accuracy
Detect a subject's eye-state by week seven	Detected eye-state at week eight, also due to time delays encountered earlier

C. Standard

A few methodologies were followed in compliance with industry standards. In the field of EEG, the 10-20 system refers to the location of electrode placement on the head (see figure below)

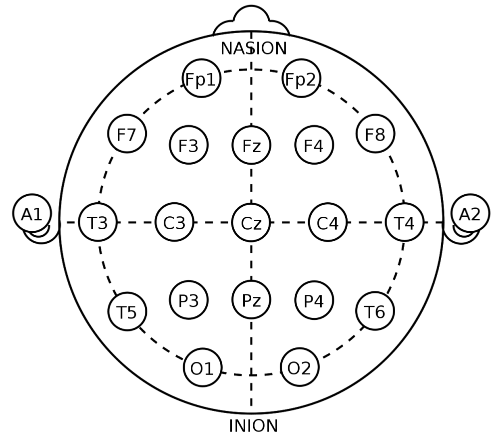

Figure 2: 10-20 EEG System
Source: Adapted from [2]

In the context of this project only electrodes Fp1, Fp2, and O2 were used to make up one channel. Another industry standard used was USB, which enabled the storage of EEG samples.

D. Theory

The human brain contains billions of neurons, which function by generating electrical potentials via ion-transport systems[3]. These electrical potentials can be detected by electrodes placed on the surface of the scalp, which forms the basis of EEG technology[4]. When monitoring the aggregate electrical activity of many neurons through an EEG, patterns of neural oscillations, or brainwaves, at specific frequencies can be observed. Brainwaves at different frequencies can correspond to different brain functions such as emotional states, sleep patterns, or sensory stimuli [5]. In this project, alpha waves were of particular interest. Alpha waves occur in the frequency range of 10-12 Hz, and they correspond to a relaxed state of mind and absence of visual stimulus [6].

In order to detect brain waves at specific frequencies, it makes sense to analyze the EEG signal in the frequency domain. Therefore, the Fourier Transform was used to transform the EEG signal from a sequence of voltages over time into a frequency domain signal. The presence of alpha waves would then become easier to recognize by looking at the magnitude of the Fourier Transform, which indicates how much energy is carried by different frequencies.

Another mathematical concept that was very useful in this project was digital filtering. Since our data consisted of a sequence of measurements at discrete time intervals, theory from discrete signal processing was necessary. In particular, digital filtering was used to remove noise and make the signal easier to interpret. A digital filter can be represented by its transfer function, $H(z)$, such that the input and output are related in the frequency domain by $Y(z) = X(z)H(z)$. A rational transfer function of the form $H(z) = B(z)/A(z)$ can then be written as a difference equation, which can be implemented in real time. If $B(z) = b_0 + b_1z^{-1} + b_2z^{-2} + \ldots$ and $A(z) = a_0 + a_1z^{-1} + a_2z^{-2} + \ldots$, then in the time domain we have

$$a_0y(n) + a_1y(n-1) + a_2y(n-2) + \ldots =$$

$$b_0x(n) + b_1x(n-1) + b_2x(n-2) + \ldots$$

In this way, each output $y(n)$ can be calculated from the previous inputs and outputs.

E. Software / Hardware

The electrical signals on the surface of the scalp from neuronal activity in the brain are very small in amplitude, so hardware tools are necessary to acquire these signals and amplify them to a point where they can be detected.

First, a differential amplifier was used to amplify the difference between two electrodes. For this project, an AD620 differential amplifier was used, which has a common-mode rejection ratio of 100 dB. This means that signals common to both electrodes, such as electrical noise, should be amplified 100,000 times less than the differential signal that we hope to measure. However, this differential amplifier alone did not boost the signal to a level that could be read on the H7, so its output was further amplified using a simple inverting amplifier built from an op-amp.

This project was implemented using the STM Nucleo-H7 board, which was used for both data acquisition and the final implementation. Amplified EEG signals were sampled at a rate of 2 kHz and digitized using one of the GPIO pins on the H7 board. In order to perform training and analysis, raw signals were saved to a USB and copied to a computer. Later, the final implementation was built using the same input pin, but instead of saving to USB processing was performed on the H7. In order to perform an FFT, the FFT function from the CMSIS-DSP library was used.

The initial data analysis and development of the neural network were done using MATLAB. The MATLAB fft() function was used to visualize the PSD of the signals and verify the presence of a spike near 10 Hz when the eyes were closed. MATLAB's filter design tool was used to design a 60 Hz notch filter to remove the 60 Hz noise in the signal. The filter coefficients were then used to implement the same filter on the H7 using a difference equation. After preprocessing and filtering the signal, MATLAB's Pattern Recognition Neural Network app was used to train a neural net to classify the labelled samples.

F. System Build / Operation

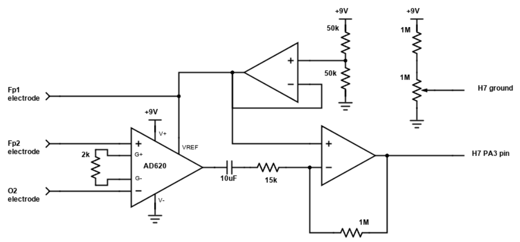

Figure 3: Diagram of the amplifier circuit. (Image was created using Digi-Key Scheme-it https://www.digikey.com/schemeit/home)

The first step in building the system was setting up the EEG probes and the amplifier circuit. Electrical signals were obtained using EEG electrodes attached to the head with conductive gel and an elastic strap. Next, the signals had to be amplified using the circuit shown in figure 3. The circuit first uses a differential amplifier, the AD620 in this case, which amplifies the difference between the two electrodes placed at Fp2 and O2. A third electrode is also connected to the reference voltage of the differential amplifier, which is set to half of the supply voltage by an op-amp buffer. This electrode serves as a ground for the scalp to ensure all the voltages are at the same level. In order to get the signal to a level readable by the H7, an additional op-amp is used, this time as a simple inverting amplifier. This increases the total gain to about 1600 times the original amplitude. In order to set the DC offset to the middle of the H7's range, the ground of the H7 is connected to a potentiometer between the supply and ground so that its DC level can be adjusted.

Next, the EEG signal was recorded on the H7. 40 trial of eyes open and eyes closed were gathered for two subjects. For each trial, 8192 samples were gathered at a sampling rate of 2 kHz. These were then saved onto a USB and copied onto the computer.

The samples were then processed using MATLAB. First, the 60 Hz noise was filtered out using a 2nd order IIR notch filter, and then the samples were normalized by subtracting out the mean and dividing by the RMS. Next, an FFT was performed using MATLAB's fft function, and the fft magnitude was calculated. The total power contained in each of 24 overlapping bins of width 3.9 Hz (8 samples each) was calculated in order to use for the neural net. These bins covered samples 1-8, 5-12, 9-16, etc. These were chosen to roughly correspond to the frequency ranges for different brain waves, such as delta, theta, alpha, and beta. The 24 features from each trial were then used to train a neural network to classify whether the eyes were open or closed.

Finally, the preprocessing and neural network were implemented on the H7 board, which can then be used to detect alpha waves in real time. In the final implementation, the electrodes are applied and a 2 second sample is recorded on the H7, then after this is done recording a prediction is printed to the data console.

IV. RESULTS

A. Description of Results

Figure 4: Confusion matrix for the final neural network.

The neural network was trained on 94 samples and the final network chosen had an accuracy of 98.9% overall, only misclassifying one of the test samples, as shown in Figure 4. On the final H7 implementation, the first sample recorded upon starting up the H7 was often misclassified, but after that this network had 100% accuracy on 20 samples for two test subjects.

B. Discussion of results

The final classifier was able to accurately classify samples of EEG signals based on whether the subject's eyes were open or closed, which suggests that it was able to detect the alpha waves that become prominent when the eyes are closed.

However, the assumption that detecting whether the eyes are open or closed is equivalent to detecting the presence of alpha waves is not completely accurate. For example, some of the earlier neural networks seemed to have a high accuracy when training, but when they were tested on the H7 they were actually detecting whether or not blinking occurred, since blinking can only occur when the eyes are open.

This was fixed by simply retraining the network and testing again, but this suggests some possible improvements to the setup. One idea would be to remove the signals that arise from muscle movements in order to only look at brain signals. One possible method would be to use independent component analysis to separate out signals from different sources [7].

Some additional improvements could be to increase the number of test subjects. Due to limitations on meeting in person and difficulties with setting up the physical implementation, only two test subjects were used. However, this system could be made more robust if more subjects from different demographics were used for training and testing.

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