Paper ID #39920

A Smart Warning System Design Based on Brainwaves to Maintain Attention

Haylee Haik, Eastern Michigan University, College of Engineering and Technology

I'm a senior at Eastern Michigan University studying Electrical Engineering. In addition to conducting research, I enjoy leading as president of the Society of Women Engineers organization on campus.

Jennifer Meng
Dr. Qin Hu, School of Engineering, Eastern Michigan University

Qin Hu received her B.S. and M.S. degrees in Electrical Engineering from the University of Electronic Science and Technology of China, Chengdu, China, and the Ph.D. degree in Electrical Engineering from Old Dominion University, Norfolk, VA. She is current

A Smart Warning System Design Based on Brainwaves to Maintain Attention

Haylee Haik, Qin Hu
School of Engineering,
Eastern Michigan University,
Ypsilanti, MI 48197
Email: hhaik@emich.edu, qhu1@emich.edu
Jennifer Meng
School of Neuroscience,
University of Michigan,
Ann Arbor, MI 48109
Email: jenmeng@umich.edu

Abstract

The rise of digital technology and increasingly busy lifestyles around the world has surrounded people with a growing number of distractions. These distractions may affect an individual's ability to retain focus in various areas of life that require concentration, especially learning or driving. Utilizing biotechnology can closely monitor an individual's brain state and provide valuable feedback about how and when to adjust their daily habits to maintain better concentration. This technology can help students regain attention during class periods, leading to better focus on class material, and can help drivers refocus during driving, which can prevent accidents and promote safer driving.

The purpose of this project is to develop a warning system that utilizes data collected from electroencephalography (EEG) technology to evaluate user focus. A 16-channel EEG cap with 19 Ag/AgCl coated electrodes will record brainwave data for a user performing a set of tasks requiring active or passive engagement. The EEG signals will be preprocessed using filters to remove artifacts and confounding events from the data. The data will then be analyzed using Fast Fourier Transform (FFT) to abstract features of the EEG signals associated with active and passive tasks. After these initial calibrations, an external device will be created to alert the user when they enter or exit a focused state. Lastly, a machine learning algorithm will be developed to continuously refine the accuracy of the focus monitoring system for individual users as more data is collected.

1. Introduction

Studies have shown that selective attention can be negatively affected by scrolling on social media (even after 12 minutes of use), making it more difficult for the brain to focus on a task for extended periods of time [1]. This distraction can interfere with many aspects of life, such as learning in a classroom setting or driving for long periods, which may put an individual at higher risk of making errors in these daily tasks. A smart warning system that alerts a user when they lose focus on a task may help the user regain concentration and prevent or reduce the occurrence of errors.

EEG is a technology that utilizes electrodes to detect small electrical charges emitted from the activity of brain cells. This electrical activity is then amplified and displayed as waveforms that can provide information about brain activity, including abnormalities [2]. The frequency ranges of these EEG signals are categorized as delta (1 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz) and beta (13 to 30 Hz), and gamma (30 to 40 Hz). Particular brain states are associated with one or more of these frequency ranges. For example, when a person is in deep sleep or under anesthesia, delta frequencies of 1 or 2 Hz are most dominant. Alternatively, when an individual is 1 in an awake and restful state, a mix of low amplitude delta, theta and beta frequencies may be present, but alpha activity will typically be the most dominant frequency bands [3]. Thus, various combinations of these frequency bands may be associated with cognitive states and brain locations. In general, alpha waves are associated with a restful or relaxed mental state, while beta waves are often associated with an active mental state and concentration. In order to alert a user of a loss of attention, a warning system may evaluate the user’s current level of focus by measuring the occurrence of beta waves in the EEG data being generated by the user’s brain activity.

2. Method

The system diagram for the smart warning system to maintain attention is shown in Fig. 1. This system contains four function blocks: brain signal collection and preprocessing, signal feature extraction, classification and warning device. The brain signals were collected by the OpenBCI EEG cap with a total of 19 Ag/AgCl coated electrodes, with one ground electrode, one reference electrode and 16 channels of signals. Fig. 2 shows the layout of the electrodes that was referred to when collecting the data for each test subject. The signal preprocessing was done by an OpenBCI CytonDaisy Board as shown in Fig. 3(a). This board contains PIC32MX250F128B Microcontroller, two low noise, 8 channel analog-to-digital converter (Texas Instruments), and RFduino for sending data from the board to computers. Signal feature extraction and classification are the main focus of our study. Features are extracted from time-domain and frequency-domain through deep learning since it makes feature extraction more efficient. Deep learning algorithms also provide more powerful classifiers such as Support Vector Machine (SVM) [5], Linear discriminant analysis (LDA) [6] and Convolutional Neural Networks (CNN) -based. The warning device could be customized as simple as lighting up a red LED or making a buzzing sound.

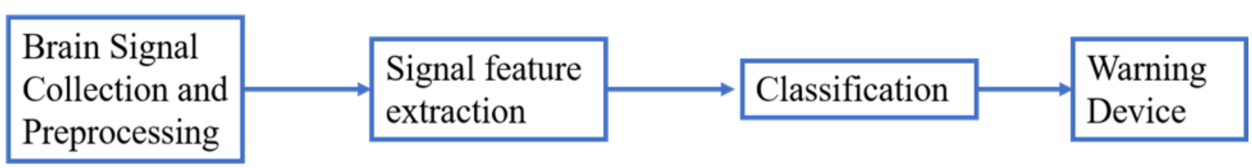


Fig. 1 Block diagram of the smart warning system for attention.

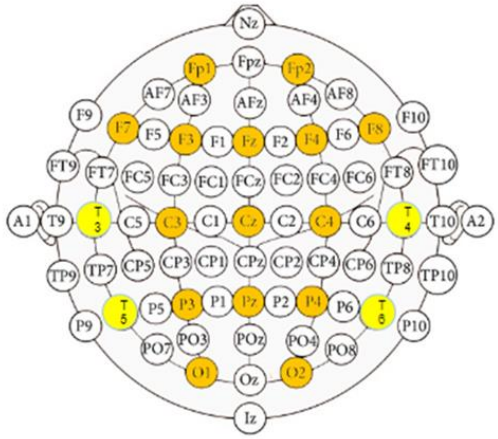
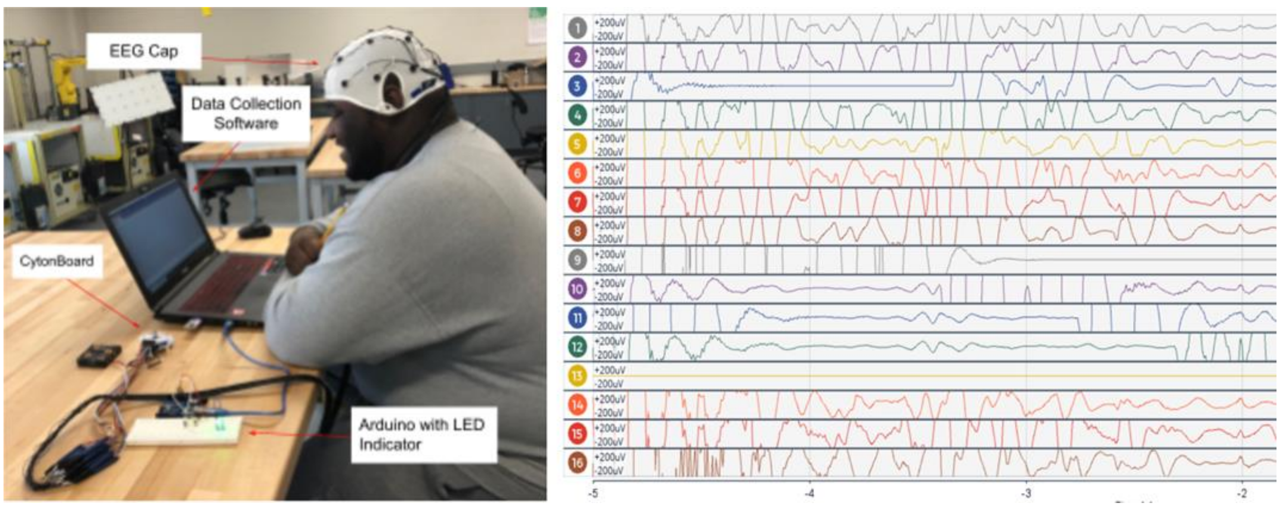


Fig. 2 Location of electrodes on the cap [5].



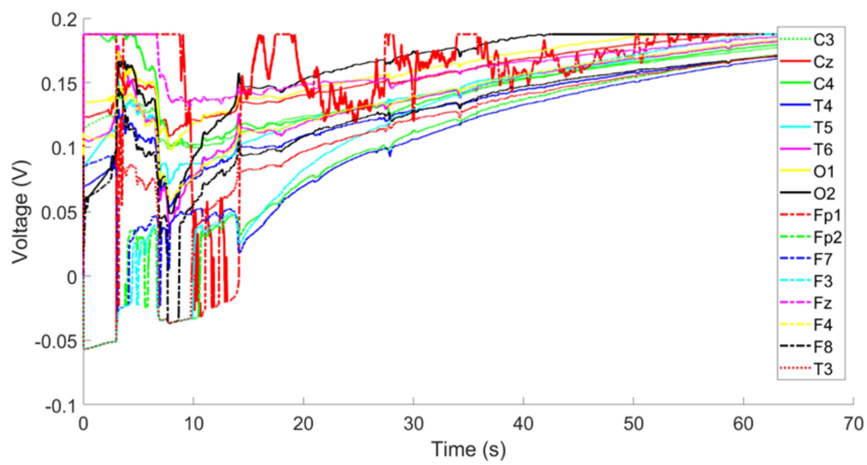
(a) (b)

Fig. 3 OpenBCI (a) EEG hardware setup and (b) Raw EEG signal data

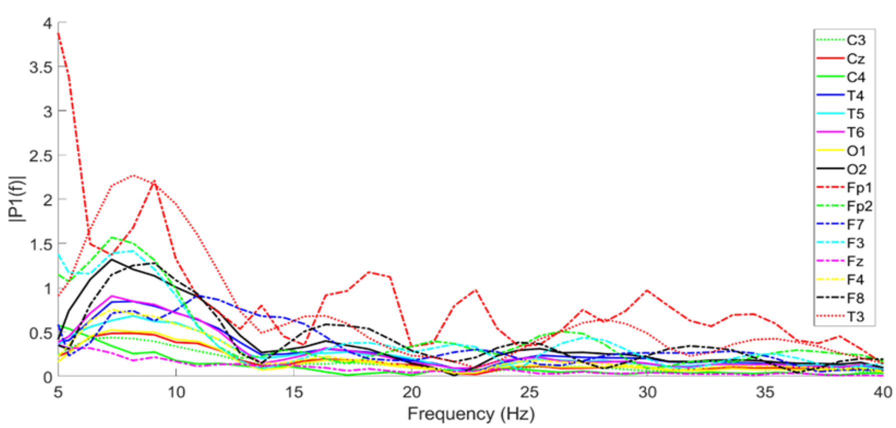
The Event-Related Potential (EPR) was collected from a total of 10 test subjects. Each subject was prompted to perform two passive tasks and three active tasks while wearing the EEG cap. The two passive tasks were relaxing in a chair with eyes closed and using a phone to look at social media. The three active tasks included performing multiplication tables, answering a series of questions, and watching a short informative video. Each task was performed for roughly two minutes. For every task, the potential (μV) and frequency (Hz) for each of the 16 electrodes as a 3 function of time was stored in a txt file and then uploaded to MATLAB. This data was plotted into two separate graphs, voltage with respect to time and frequency spectra. From these graphs, particular electrodes with the greatest frequency response could be identified and focused on for future data collection.

3. Results and Discussion

The EPR data were collected from multiple college students. The time and frequency response of a sample set of data from 16 channels can be found in Fig. 4. This experimentee was focusing on doing multiplication tables. From Fig. 4 (a), the signal from channel Fp1 varies the most compared to the signals from the other 15 channels. In the frequency domain as shown in Fig. 4 (b), Fp1 has the highest potential values within the Beta brainwave range (13 – 30 Hz). It turns out that the 7 channels on the frontal lobe output much higher voltage than the other 9 channels on the back.



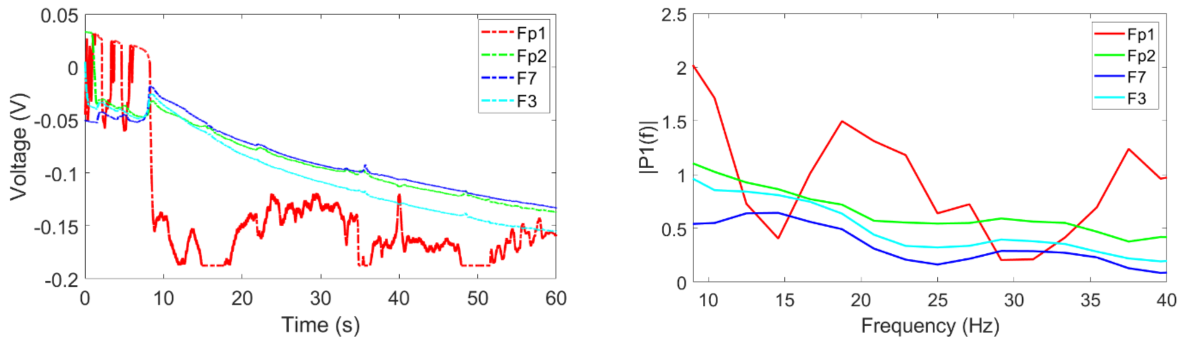
(a)



(b)

Fig. 4 (a) Time and (b) frequency response for the event that student was doing multiplication tables.

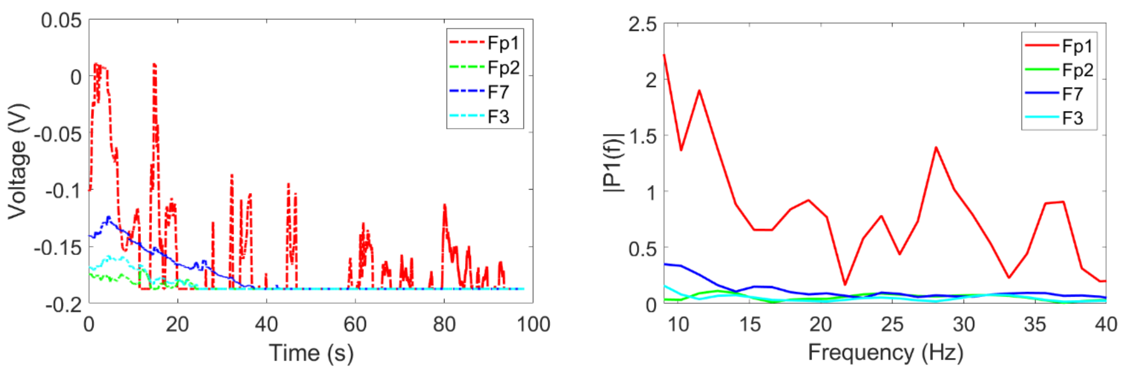
Among the 7 electrodes on the frontal lobe, the 4 with the strongest signals are Fp1, Fp2, F7, and F3. Fig. 5 shows the time and frequency responses for the event that the student was doing multiplication tables, for these four channels. The interested frequency range is from 9 Hz to 40 Hz in the frequency domain, and the EPR is the strongest from channel Fp1 as shown in Fig. 5 (b).



(a) (b)

Fig. 5 (a) Time and (b) frequency response for the event that student 1 was doing multiplication tables.

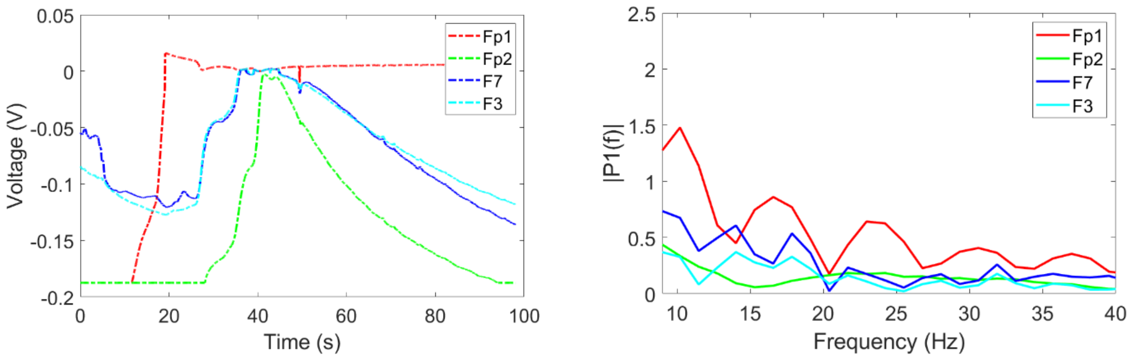
The ERP pulses can be seen in Fig. 6 (a) as the student was answering interview questions, showing a highly-focused brain status. In the frequency domain, the EPR from Fp1 is much higher than the rest channels, which makes identification of the focus state much easier.



(a) (b)

Fig. 6 (a) Time and (b) frequency response for the event the student was answering interview problems.

During the relaxing status, the ERP signal from Fp1 is close to zero after the first 20 seconds, indicating the brain is in a non-focus state as shown in Fig. 7 (a). The frequency response of the signal from Fp1 is very similar to the rest signals, with slightly higher values. However, the frequency response is much weaker than those for the two focus states in Fig.5 and Fig. 6.



(a) (b)

Fig. 7 (a) Time and (b) frequency response for the event that the student was relaxing.

Only the Fp1, Fp2, F7, F3 electrodes will be used as indicator electrodes to determine the user's brain state in future recordings, as they appear to be most reactive to active engagement activities. The EPR from EEG shows that alpha and beta brainwaves (~9 to 30 Hz) are much stronger when the students are focusing, such as doing multiplication tables and answering interview questions.

For the warning system, an Arduino communicates with the OpenBCI program to read the frequency range of each electrode. If all the indicator electrodes are within 9-40 Hz, the Arduino will deem the user in a focused state, and turn on a green LED as shown in Fig. 8. And if any of the indicator electrodes are below 9 Hz, the Arduino will turn on a red LED to inform the user they are no longer in a focused state.

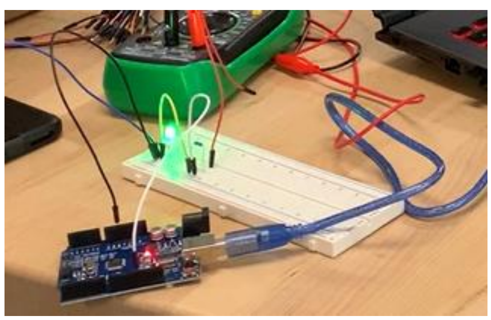


Fig. 8 An example of a simple warning system. A green light indicates a focused state.

4. Conclusion and Future Work

There are several changes that will be made to improve this research. The accuracy of the results will be improved by recruiting more test subjects to diversify the data and performing more test activities to increase the range of results. Ideally, all test subjects will be asked to repeat each task multiple times. For future data collection, test subjects will be placed in a more controlled environment to reduce the introduction of external noise and distractions, and they will be asked to avoid excessive movement to reduce unwanted artifacts in the data. The warning system will be improved by adding more features such as a buzzer or LCD display to alert the user when they lose focus. Additionally, a deep learning algorithm will be implemented to continuously add more user data to the database and decide which electrodes to prioritize for the smart warning system.

Acknowledgements

The authors would like to acknowledge EMU's Society of Women Engineers for their ongoing dedication and support by contributing data to this research. The authors would also like to acknowledge EMU's Women in Philanthropy and GameAbove College of Engineering and Technology for their financial support of this research project.

References

[1] R. M. Branch and T. A. Dousay, Survey of Instructional Design Models - Association for Educational Communications and Technology. Bloomington, Indiana.

[2] H. J. Choi and J.-H. Park, "Difficulties that a novice online instructor faced: A case study," Quarterly Review of Distance Education, vol. 7, no. 3, p. 317, 2006.

[3] Nunez, P., & Srinivasan, R. (2007). Electroencephalogram. Scholarpedia, 2(2), 1348. https://doi.org/10.4249/scholarpedia.1348

[4] R. M. Branch and T. A. Dousay, Survey of Instructional Design Models - Association for Educational Communications and Technology. Bloomington, Indiana.

[5] OpenBCI: Electrode Cap Getting Started Guide | OpenBCI Documentation

[6] A. Hag, D. Handayani, M. Altalhi, T. Pillai, T. Mantoro, MH. Kit, F. Al-Shargie. "Enhancing EEG-Based Mental Stress State Recognition Using an Improved Hybrid Feature Selection Algorithm". Sensors (Basel), Dec 15;21(24), p.8370, 2021.