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Design of a Smart Alert System Based on Electroencephalography Signal Analysis

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Abstract

The rapid evolution of technology provides us with diverse opportunities to enhance our lives and well-being, addressing essential aspects such as socialization and health analysis. Expanding on this potential, utilizing brain-computer interface (BCI) would allow us to explore and improve aspects like attention deficits. Distractions present persistent challenges to sustained focus across various aspects of life, potentially resulting in compromised academic performance or risks to road safety. This shows how life-changing it would be to design an alert system that boosts efficiency and safety in these areas by targeting to minimize attention losses. By analyzing electroencephalography (EEG) signals associated with concentration levels, the proposed system aims to deliver timely alerts, prompting users to refocus when attention falls below a predefined level. Consequently, avoiding prolonged distractions and encouraging a greater self-awareness of the issue.

This research aims to create a comprehensive warning system by combining EEG technology with deep learning techniques. According to some research, it may be possible to determine a person's level of concentration by monitoring the frequency ranges of different areas of the brain. Therefore, the initial phase of this project involves non-invasive data collection using a 16-channel EEG cap, complemented by Fast Fourier Transform (FFT) analysis to extract features linked to active and passive tasks. During this phase, adhering to the guidelines of the Office for Human Research Protections (OHRP) and the relevant university department is essential to maintain ethical standards and safeguard participant confidentiality and privacy. The collected data will then be used to write a Python code that employs deep learning to identify parameters indicative of various attention levels. The software will utilize this data to set an attention range and send alerts to an external device, notifying when the user has lost focus. Additionally, the system will exhibit intelligent recognition of recurrent short concentration periods, suggesting breaks to prevent mental fatigue. As the project advances, there is potential to enhance the system's capabilities by exploring signal classifications, particularly emphasizing evoked signals associated with external stimuli.

1. Introduction

Distractions are undoubtedly a damper to the efficiency and safety of simple tasks such as driving, learning, or working. Driver distractions are considered one of the leading causes of vehicle crashes globally. It can be caused by cognitive distractions, where the driver's attention is not on driving; manual distractions, where the driver's hands are off the wheel for other activities; and visual distractions, where the driver is not watching the road [1]. According to studies, using a phone while driving can increase traffic violations, such as stop sign infractions, by up to three times [2]. Oftentimes, our intent to ignore distractions is the culprit for low efficiency, rather than the distraction itself. Both acting upon or ignoring diminish the individual's cognitive resources for completing the task at hand [3]. Therefore, negatively affecting the performance of the individual. The proposed alert system aims to reduce incidents where the user loses focus by notifying them of their level of concentration and reminding them to stay focused. This system can also help users recognize when their unconscious attitude towards distractions is hindering their abilities and encourage them to act before continuing with the task.

BCI is a technology that allows the translation of mental processes into data that can be used to communicate with external devices. In this project, non-invasive EEG is used to achieve this. To use this method, electrodes are placed on the scalp of the user, enabling immediate interfacing between the brain and external devices [4]. Although this method is not as precise as invasive procedures, since the signals must pass through the skull and scalp [4], it is still considered the most efficient option for this device due to its versatility and quick placement, compared to the surgery required for other methods. In addition to being easy to set up, EEG is beneficial for our research since most signals come from the cerebral cortex, responsible for thoughts, emotions, and behavior. These electrical signals produced by the human brain have specific frequency ranges that fall under different categories such as delta (1 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz), or gamma (30 to 40 Hz) [5]. These categories are then associated with different brain states and can help in classifying brain activities. The smart alert system will evaluate the user's concentration level by analyzing beta waves, which are associated with an active mental state and focus.

2. Method

This system is composed of four main sections: brain signal collection and preprocessing, signal feature extraction, classification, and warning device. The system architecture is shown below in Figure 1. The data was collected using an OpenBCI EEG cap with 19 Ag/AgCl coated electrodes positioned in the configuration shown in Figure 2. Sixteen of these electrodes are channels of signals. The OpenBCI CytonDaisy was used for signal preprocessing. It includes a PIC32MX250F128B Microcontroller, two low-noise, 8-channel analog-to-digital converters from Texas Instruments, and RFduino to transmit data to computers. Our primary research emphasis is on extracting and categorizing signal features. Employing deep learning techniques enhances the efficiency of feature extraction, encompassing both time-domain and frequency-domain aspects. Additionally, deep learning algorithms play a crucial role in strengthening classifiers like Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Convolutional Neural Networks (CNN). Lastly, the alert device will be constructed using a microcontroller board and coded to light up an LED light or make a buzzing sound.

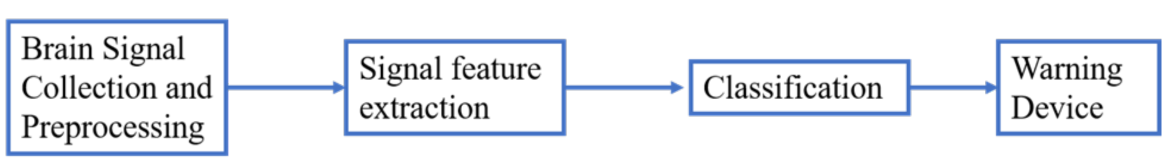

Figure 1. The system architecture of the smart warning system for attention.

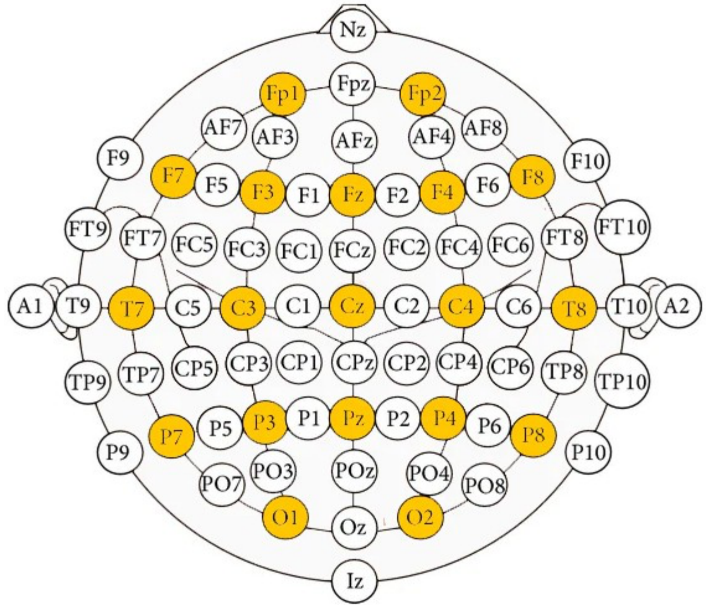

Figure 2. Location of EEG Electrodes [6].

To ensure ethical standards and protect participant confidentiality and privacy, all researchers underwent a mandatory course required by the University's representation of the OHRP before collecting data. Additionally, a consent form was redacted and provided to every participant before data collection. The Event-Related Potential (EPR) was collected in three groups. Group A was composed of 20 people, and groups B and C were formed of 10 and 5 people respectively. Each subject was prompted to perform two passive tasks and three active tasks while wearing the EEG cap. Organized so that they do one passive task at the start and the second at the end of the collection. The two passive tasks were relaxing in a chair with eyes closed and using a phone to scroll through social media. The three active tasks included performing multiplication tables, answering a series of questions, and watching an informative video. All groups performed the same activities in the same order, but the data was collected slightly differently to identify the most effective. Group A had activities lasting about 2 minutes each and the data was collected separately per activity. Group B also had 2 minutes per activity, but the data was collected without any breaks. Lastly, group C had 10 minutes per activity, and the data was also gathered without stopping the collection. During each session, the potential (in μV) and frequency (in Hz) for each of the 16 electrodes were recorded in a txt file and later uploaded to MATLAB. The recorded data was plotted into two separate graphs, one showing voltage with respect to time and the other showing the frequency spectra. By analyzing these graphs, we were able to identify specific electrodes that had the greatest frequency response, allowing us to focus on them for future data collection.

3. Results and Discussions

After the collection and comparison of the data of the three different groups, it was shown that the analysis was easier to perform with the data from group C. This was due to the time allocated for the electrodes to settle didn't affect the period of recording, therefore resulting in more accurate data. The first task was to relax, the frequency and time domain graphs are shown below in Figure 3. These graphs show little activity, which was expected as this is a passive task.

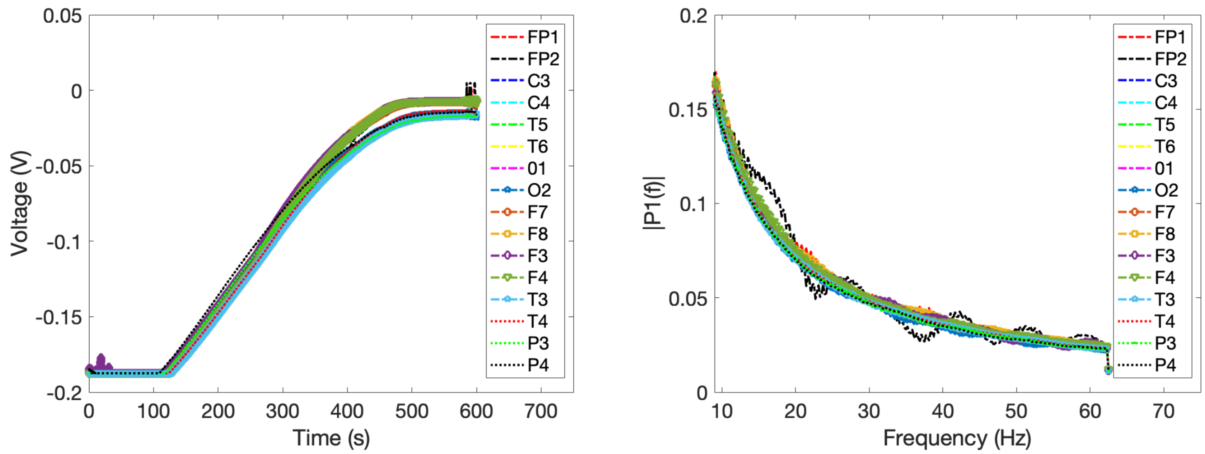

Figure 3. Time and Frequency Domain for Task 1.

The following activity was to watch an informational video, which is classified as an active task. The data collected is in Figure 4, and in contrast with the prior task, it is evident a lot more brain activity. In the time domain graph, it is noticeable the division between from frontal and occipital sections of the brain, with frontal sections such as F4, FP2, and F8 more active than occipital ones like O2, T3, and P3. Likewise, it is seen in the Frequency domain with FP2 being considerably more active than the rest of the channels.

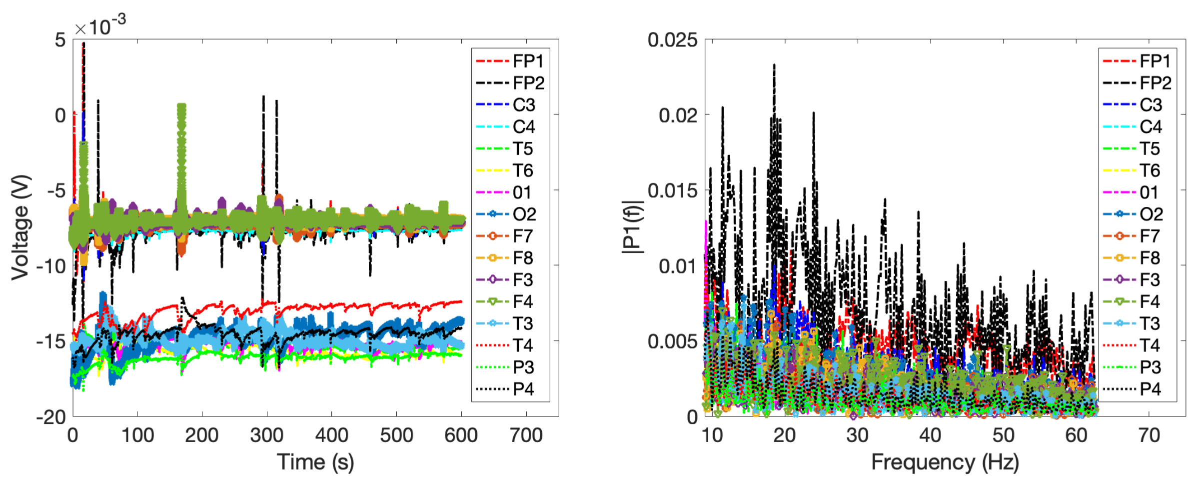

Figure 4. Time and Frequency Domain for Task 2.

Next was another active task, with solving multiplication tables. This showed a very similar behavior with the frontal lobe being more active than the occipital lobe. Additionally, this task showed an increase in concentration from the subject from the prior activity. The channels with higher activity were F3 and F4 as presented in Figure 5.

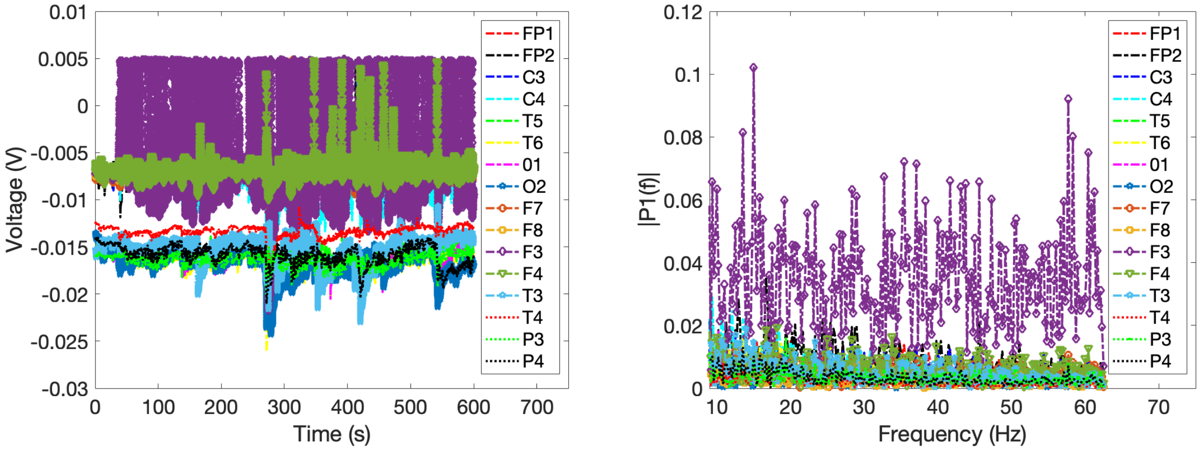

Figure 5. Time and Frequency Domain for Task 3.

The fourth activity was to answer some questions which is also considered an active task. By this data set, it is clear the relationship between the frontal lobe and the levels of concentration of the user. Once again, we can see a more predominant amount of brain activity on the channels in the frontal lobe, especially of F4, while the channels from the occipital lobe such as O2 are not as active. On the Frequency domain graph, it is also clear the high activity levels of other frontal channels like FP2 and F3. This is shown in Figure 6.

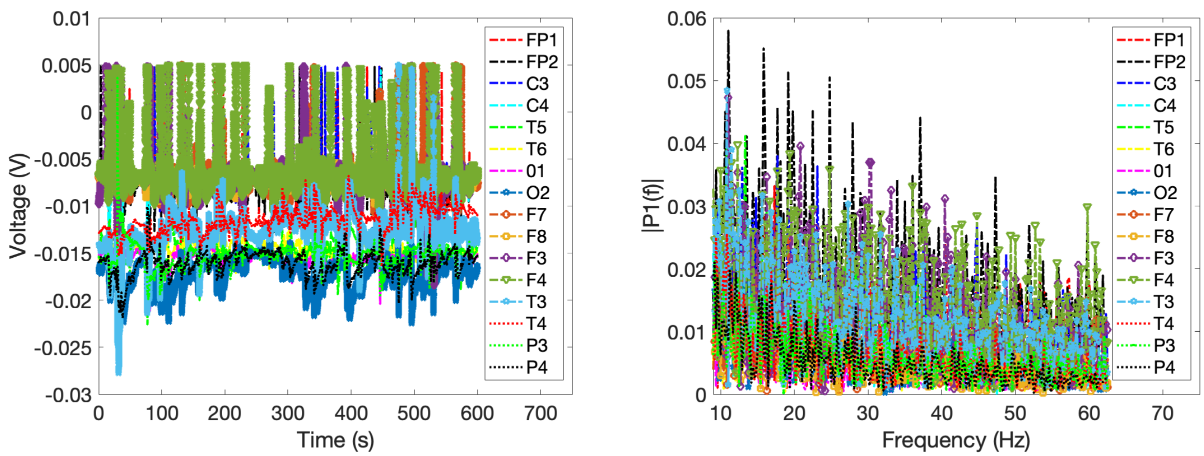

Figure 6. Time and Frequency Domain for Task 4.

The last task, to close the cycle was to scroll through social media on the phone. This is considered a passive task. The graphs for time and frequency domains are illustrated in Figure 7. For this task, there was a surprisingly high amount of activity from the frontal lobe in comparison with the other passive task of relaxing. However, it is more inconsistent than active tasks hinting at an unstable focus from the user. As the information in social media, it is varying, it is suspected that brain activity depends on how interesting the user finds the post that they are scrolling through.

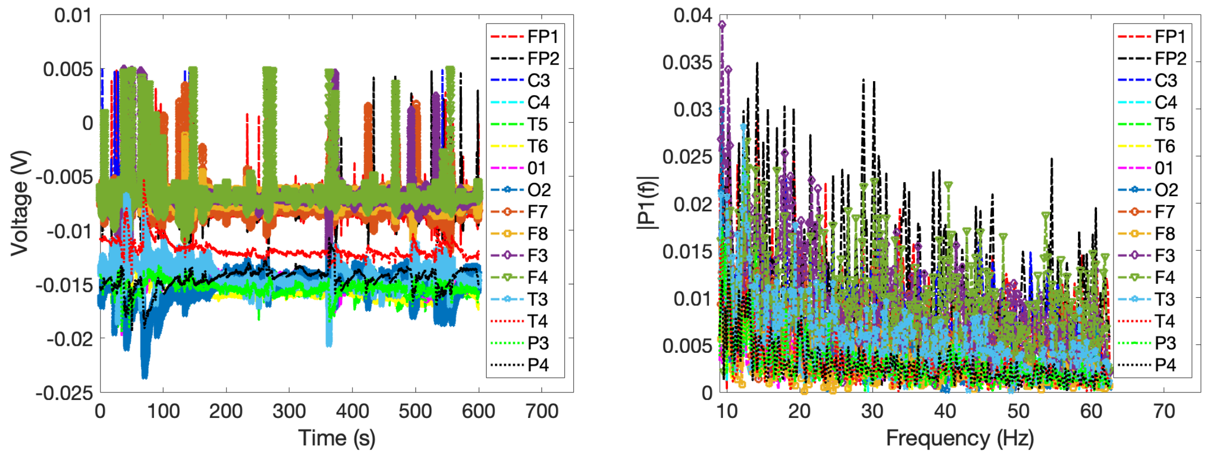

Figure 7. Time and Frequency Domain for Task 5.

The main component of the alert system is an Arduino microcontroller that communicates with the OpenBCI program. This microcontroller would read the frequency range of the channels in the frontal lobe and check if they are within 9-40Hz. If this is true then it would activate an external component to communicate to the user of their state of focus. This could be set up so that it buzzes if the user isn't concentrating (frontal lobe channels are not within 9-40Hz) or turns on an LED light if the user is focusing (frontal lobe channels are within 9-40Hz).

4. Conclusion and Future Work

To improve the quality of research, several key improvements can be implemented. Firstly, it is important to diversify the pool of test subjects by recruiting more participants. This will ensure a broader spectrum of data, leading to increased accuracy and generalizability of the results. Secondly, it is advisable to expand the range of test types conducted to provide a more comprehensive understanding of the subject matter. To enhance data precision, it is recommended to have test subjects repeat tasks multiple times. Additionally, for future data collection, creating a more controlled environment will help to mitigate external noise and distractions. Participants should also be instructed to minimize excessive movement during tasks to prevent unwanted artifacts in the collected data. To improve the warning system, incorporating additional features, such as an LCD display, can promptly alert users about shifts in focus. Finally, introducing a deep learning algorithm that continuously supplements the user data in the database will ensure an adaptive and evolving system. These enhancements will collectively contribute to a more robust and refined research framework.

5. Acknowledgments

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