EEG-BASED BRAIN-COMPUTER INTERFACE FOR DIGITAL ACCESSIBILITY

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Introduction:

Human civilization is based on social interaction. It is this quality that enables people to express their emotions, aspirations and original thoughts to others. Human communication becomes more direct and less limited when it is done through speech, gesture or writing. However, not everyone has this ability. There are various limitations that different people have such as impairment, paralysis, locked-in syndromes, limited motor movements among others. Brain Computer Interface (BCI) offers a ray of hope for them in overcoming these limitations and getting closer to normal life. In recent years, the field of brain-computer interfaces (BCIs) has witnessed significant advancements, offering novel avenues for interaction between humans and machines. Among the various methods employed in Brain Computer Interface systems, Electroencephalography (EEG) stands out for its non-invasiveness and relatively low-cost setup.

We present a BCI project in which we use BioAmp EXG Pill, an Arduino UNO, and gel electrodes to capture EEG signals. Existing BCI systems often rely on complex mental tasks or external devices. This reduces the overall experience of using such a system. Due to the simplistic nature of signal processing that we use, we achieve real-time processing which is not a common feature in current systems due to complex algorithms and communication protocols. Cost was an important factor that we considered while developing the project and hence utilized low-cost hardware in contrast with the traditional BCIs which involve expensive proprietary hardware.

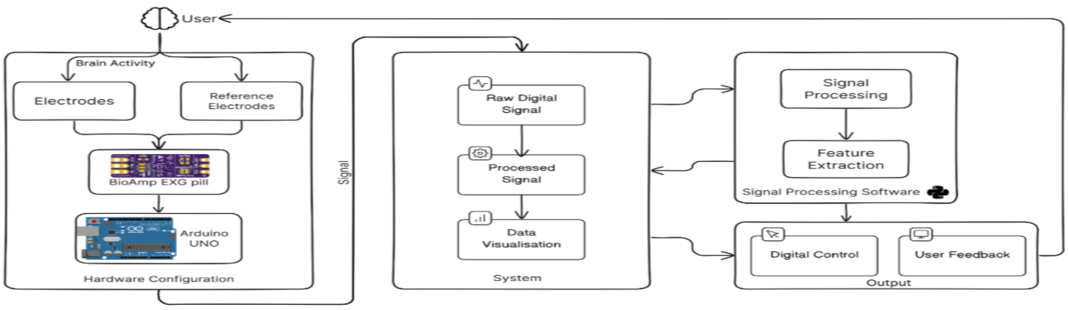
Objectives:

The primary objective is to develop a user-friendly system capable of recording EEG data, convert to digital signals in real-time using the Arduino UNO, and map eye blinks to a keyboard event. Visualization of the EEG signal is also done which aims to display EEG waveforms and discernible patterns, facilitating the awareness of cognitive states, particularly the levels of concentration on the basis of the eye blinking activity of the user.

The project's focus is placed on keyboard interactions, where the system simulates keyboard inputs corresponding to the user's eye blinks. Fields like cognitive training, neurofeedback therapy, and human-computer interaction can benefit from such feedback mechanisms. By combining accessible hardware components with real-time signal processing and visualization techniques, this project aims to improve EEG-based BCI technology, offering accessibility to individuals with disabilities. Through the seamless integration of hardware and software, our system empowers users to control digital actions using their brain signals, thereby overcoming physical limitations and enhancing their quality of life, therefore not be left behind in this digital world.

Methodology:

We plan to structure our EEG-based BCI system in the following way. The BioAmp EXG pill will acquire EEG signals using gel electrodes which will be processed through an Arduino UNO. The digitised signals are then analysed and visualised using Python. The system detects user-initiated eye blinks, inferred from EEG concentration levels, and translates them into keyboard keystrokes in real-time. The architecture diagram is shown below.



A. Data Acquisition:

EEG signals are acquired from the user using the BioAmp EXG Pill, a specialized biosensing device capable of capturing electroencephalogram (EEG) signals non-invasively. The BioAmp EXG Pill is equipped with three gel electrodes that are placed on the user's scalp to capture EEG signals associated with cognitive activities. Two of the electrodes are placed on Fp1 and Fp2 positions as stated in the 10-20 system which takes in the input EEG signal. The third electrode acts as the reference electrode whose primary purpose is to provide a stable electrical reference point against which the potential differences at the other two electrode sites can be measured.

B. Signal Processing and Threshold Calculation:

The extracted signals are sent to Arduino UNO for analog-to-digital conversion of EEG signals. These signals are then processed to extract relevant features indicative of user actions, particularly eye blinks.

The digitized signals are then processed using Python, where a dynamic threshold is calculated for event detection. Instead of using an average value which leads to lower accuracy of detection of event, the threshold calculation involves accumulating EEG signal values over a predefined window size and computing the average. A final threshold is derived by applying a predetermined factor to the average, enabling real-time event detection without the need for machine learning algorithms. The factor is applied to consider certain stray values which shouldn’t be picked up by the system.

C. Event Detection and User Interaction

Real time event detection is performed by comparing incoming EEG signal values to the dynamically calculated threshold. Upon detecting user-initiated event (eye blinks) corresponding actions are triggered, such as simulating keyboard key presses.

We used 3 different techniques to determine the suitable threshold for blinking action. The 3 techniques are:

Static thresholding: In this, we determined the average frequency from the previously collected data, and then increased it by a factor of 21.85% (also called threshold factor) and used this as the threshold limit for the next set of measurements.

Averaging thresholding: In this, instead of relying on the old datasets, we determine the threshold limit on run time. We divide the signals into groups called windows. The usual window size being 400 means, there are 400 signals in one group/window. Then the average of all signals in a group is calculated and set as the threshold value for next window. When the next window ends, the avg if this window and the previous window is clumped together for a new average for the next window.

Dynamic thresholding: It employs a mixture of both, static and averaging method. It calculates the average in the same way as averaging method but also increases its value by the threshold factor, therefore the at any given point of time the threshold for a window in this method is determined by the following equation:

Threshold = avg + avg * threshold_factor

And the average as: -

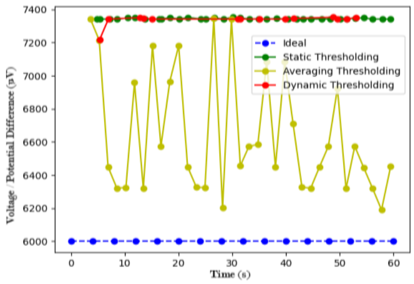
Avg = (old_avg + sum_of_Signals / window_size) / 2

<u>Results and Conclusion</u>:

We tested the three techniques introduced above. The setup we had is as mentioned next. The EEG headset was strapped to the user such that, the positive electrode was connected to the position FP1 and the negative electrode was connected to FP2, switching the position of the electrodes should have little to no impact on the results. The reference electrode was placed on A1 position, it can be placed on either A1 or A2. All these positions are with respect to the 10 - 20 International standards.

Then the programme started. At Every 4 seconds the user was prompted to blink and the programme would attempt to capture the same. At the end the programme would display the number of blinks it registered along with the timestamp of when it occurred. The user would be given a 10 seconds break and asked to repeat it again for the other method, so a total of 3 times in one set, one for every method. Between each set the user would be given a 30 second break before moving onto the next set.

Method	Accuracy (in %)			Min Value	Avg Value	Max Value
	60 sec	100 sec	150 sec			
Average Thresholding	89.47	85.71	80	1325	6040.715	10740
Static Thresholding	< 57	< 59	< 63	1325	6049.609	10740
Dynamic Thresholding	< 60	< 59	< 61	1325	6034.985	10740



The dots in the Fig.4 represent the times at which the blinks. From first glance we see a lot of green and yellow dots showcasing the inefficiency of those algorithms. We can see a comparable amount of red and blue dots and that too at similar timestamps, further supporting our theory of better accuracy for dynamic thresholding.
A point to note is that the voltage value for ideal is set to 6000, because this was the average voltage value for every trial and is of little to know significance, because our focus is on the timestamps and number of blinks occurred.

In conclusion we present a brain-computer interface (BCI) system designed to interpret eye blinks as input commands through the use of the BioAmp EXG Pill and an Arduino-based ADC, aimed at enhancing human-computer interactions. The system has been developed to enable users, particularly those with disabilities, to control computing devices via blink-induced keyboard strokes, thus offering a robust alternative to traditional input.

Our comparative analysis of three different thresholding techniques—static, averaging, and dynamic—has played a crucial role in refining the system's ability to detect blinks accurately. The results clearly demonstrate that the dynamic thresholding method has superior accuracy in detecting blink actions confirming its effectiveness and reliability over the methods.

Description of the Innovation in Project:

The innovation in this EEG-based Brain-Computer Interface (BCI) project lies in its unique combination of accessibility, cost-effectiveness, and real-time processing, which significantly enhances digital accessibility for individuals with disabilities. The project introduces several novel aspects that distinguish it from existing BCI systems:

- The project employs the BioAmp EXG Pill, a highly accessible and cost-effective biosensing device, to capture EEG signals. This device, coupled with gel electrodes, provides a reliable method for acquiring brain signals non-invasively. Its simplicity and affordability make it an excellent choice for developing user-friendly BCI systems, particularly for users who might not have access to more expensive, proprietary hardware.
- The project introduces a dynamic threshold calculation method for event

detection, which enhances the accuracy of detecting eye blinks. Unlike static thresholds that can lead to lower detection accuracy, the dynamic method adjusts in real-time based on the accumulated signal values over predefined windows. This ensures more precise and reliable detection of user-initiated events, which is critical for effective BCI operation.

- The system's ability to map eye blinks to keyboard keystrokes opens up a range of applications, particularly for individuals with severe motor impairments. This innovation not only facilitates basic computer interactions but also holds potential for more complex applications in cognitive training, neurofeedback therapy, and other fields that benefit from real-time brain signal interpretation.

Future Work Scope:

Future work on this EEG-based Brain-Computer Interface (BCI) can encompass several innovative directions. Enhanced signal processing techniques, particularly those involving machine learning algorithms, could significantly improve the accuracy and responsiveness of the system. Developing more sophisticated adaptive thresholding algorithms that learn and adjust to individual user patterns over time will further enhance reliability and usability. Transitioning to wireless and wearable EEG acquisition devices can increase user comfort and mobility, making the system more practical for everyday use. Integration with other assistive technologies, such as speech recognition and eye-tracking systems, could provide a more comprehensive solution for individuals with severe motor impairments. Expanding the application scope beyond keyboard inputs to include control of smart home devices, wheelchairs, and robotic arms can offer greater autonomy to users. Collaboration with neuroscientists and clinicians can ensure that the system addresses real-world needs and adheres to medical standards. Enhancing the user interface to be more intuitive and customizable will improve user experience and adoption. Research into minimizing signal interference and noise can lead to more robust performance in diverse environments. Long-term user studies will be essential to assess the system's effectiveness, durability, and impact on quality of life. Exploring the potential of hybrid BCIs that combine EEG with other bio-signals, such as EOG (electrooculography) and EMG (electromyography), could provide more versatile and reliable control mechanisms. Finally, ensuring data security and user privacy will be crucial as BCIs become more integrated into daily life. These advancements collectively promise to expand the capabilities and applications of BCI technology, making it a vital tool for digital accessibility and beyond.