Utilization of BCI for Eye-Controlled Smart-Home System

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***Abstract*— In this project, different approaches for constructing a smart-home system controlled by eyes using a brain-computer interface (BCI) are introduced. The current work aims to improve the quality of life for people who suffer from quadriplegia or other mobility disabilities. Different approaches for using the eye as a control are proposed and discussed. The first approach depends on peak detection of EEG blink signal, the second is based on the ratio between the power of the beta wave to that of the alpha wave to detect eye states, and the third and fourth approaches utilize neural networks for the detection of both eye blinks and eye movements. The performance of the different approaches along with the overall system is tested. Hence, the system is introduced to quadriplegic people for verification and further usability assessment. A desktop application has been developed, empowering users to control various devices within their homes. Moreover, the application enables communication through text input using sequences of eye blinks. A mobile application that can substitute the desktop application is also available.**

Keywords—Smart-home, BCI, IOT, Eye Blinks Detection, Neural Networks.

I. Introduction

Life becomes harder for many people who suffer from disabilities and aging. Aging and mobility disabilities like quadriplegia hinder people from practicing their daily life freely while being independent of others, thus reducing their quality of life. Smart homes controlled by Brain-Computer Interface (BCI) are great solutions to this problem. After the detection of user intention from EEG signals, any appliance in the smart home can be controlled and adjusted without any effort from the user.

A few previous works related to this application are discussed. References [1] and [2] proposed a method that utilizes the user's mental state (awareness or drowsiness) to interact with the smart home environment surrounding him. Besides that, references [3] and [4] utilized the visual brain wave P300 for a BCI system to control appliances in a smart home for users with disabilities. A GUI consisting of a 6x6 matrix of icons is created for users and each icon corresponds to a daily home-use appliance. Reference [5] proposed another non-invasive BCI for disabled people. It takes a smirk or an eyebrow raise as an input to stimulate a mouse click. A GUI is provided to the user to interact with a virtual home environment. The system uses a NeuroSky BCI headband to acquire EEG signals for an eye blink to control a desired device.

In this work, we introduce a prototype for a smart home system controlled through eye blinks, eye state, eye movement, head movement, or different combinations of all using the MUSE 2 headband. Since the majority of people, whether disabled or not can control their blinks and eye state, the eye is a reliable source of user intention detection.

The GUI of the system will be implemented in a desktop application as well as a mobile application that provides extra functionalities other than home control.

This paper is structured as follows. Section II gives a quick overview of commercial EEG devices. Section III analysis the whole IoT system architecture. In section IV, different eye blinks, eye states, and eye movement detection methodologies are discussed. Section V is about the implemented desktop and mobile applications. Finally, sections VI and VII are about overall system performance discussion and conclusionrespectively.

II. EEG Devices

The choice of friendly EEG devices with real-time operation and adaptation for people with motor functional diversity is required. Recently, different studies and companies have offered commercial products intending to open the EEG technology to applications not restricted to medical diagnoses, such as the NeuroSky, Mindwave, MUSE2 headbands, and the Emotiv Epoc11.

In this work, MUSE 2 headband is used because it has four electrodes, AF8 with TP10 on the right side of the head and AF7 with TP9 on the left side as shown in Fig. 1, while most commercial devices have one or two electrodes. MUSE 2 is equipped with gyroscopes and accelerometers, which we use in this work. It has a sampling frequency of 256 Hz which is more than enough for sampling EEG signals. It is wireless and uses a Bluetooth connection. It has a lot of open-source Python libraries and free GUIs that make it flexible and adaptable formany applications. The price of MUSE 2 is low relative to itsspecifications.

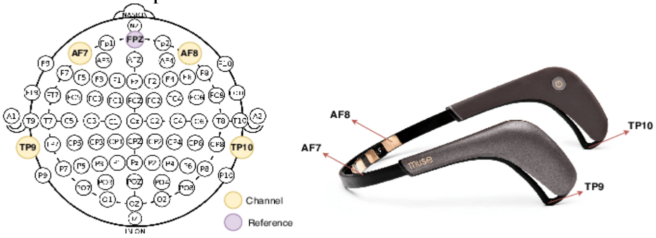

Fig. 1. The MUSE 2 headband and the placement of its electrodes [6]

III. System Design and Architecture

As shown in Fig. 2, the architecture of the whole IoT ecosystem is composed of the MUSE 2 headband, along with other home appliances. The system aims to detect eye blinks, eye movement, and the eye state and convert this acquired information to a control signal that controls different surrounding appliances.

The communication between the different IoT devices is based on the Message Queue Telemetry Transport (MQTT) protocol [7]. It is a publish/subscribe, lightweight extremely simple messaging protocol designed for low-bandwidth networks and constrained devices.

The publish/subscribe model is based on several clients connected to a central broker. Subscribers indicate to the broker their interest in one or more topics while publishers send messages to the broker on a specific one. The broker is an intermediary agent, responsible for matching the information that the publishers provide with the subscriber clients and dealing with controlling and authenticating who is permitted to subscribe or publish to certain topics. The topics can be created and combined easily, so the system can be simply expanded with the addition of new devices or topics.

The broker is utilized through a Raspberry Pi 3 Model B, except when the desktop application is used, the broker is integrated directly within the desktop. It is implemented using Eclipse Mosquitto [8], a lightweight open-source MQTT broker. The detection algorithm, which interprets eye blinks, eye state, or eye movement patterns into a binary signal (e.g., '1' for blink and '0' for no blink), is implemented within it.

Each topic relates to the system of one household device. Any household appliance (e.g. wheelchair, light bulbs, TV, kitchen burners) can be a part of the system by connecting it to the ESP 32. The ESP 32 is only subscribed to the topics related to the home devices it serves. It receives and processes the binary signal published by the broker to interpret it as a control signal that corresponds to a certain action. Finally, the ESP 32 drives the home device to perform this action.

For the architecture shown in Fig. 2, the MUSE 2 headband does not use MQTT protocol instead, it makes use of the built-in Bluetooth module to communicate with the broker. It detects, samples, and sends the EEG signal to the broker. The MQTT broker processes the received signal, then produces the corresponding binary signal, and finally forwards it to interested subscribers.

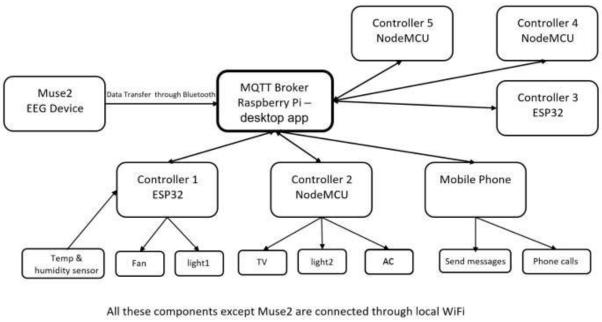

Fig. 2. IoT System Diagram

The mobile application is also a client in the IoT system. When the ESP 32 drives the device to perform a required action, it publishes feedback, a confirmation signal, to the mobile application on the topic it is related to. Since the mobile application is subscribed to all topics, it can receive and show feedback about the performance of all appliances to the user. More features are discussed further in section V.

IV. Eye Blinks, Eye State, and Eye Movements Detection Methods

Signals resulting from different eye movements in general are usually considered unwanted artifacts in the EEG. Thus, they are filtered out in most cases to enhance signal quality. However, this is not the case for applications that utilize eyes as the source of intention for controlling systems concerned.

Many methods for detecting eye blinks, eye state, and eye movements in real-time are emerging and they are based on different approaches. In this section, four different methods are proposed.

A. Peak Detection Method

This method detects eye blinks by using the readings from TP and AF electrodes for both eyes as an input EEG signal. The method relies on the characteristic waveform of an eye blink, which consists of a positive peak corresponding to eyelid closure followed by a negative peak corresponding to eyelid opening. This waveform is predominantly found in the low-frequency delta band. The two peaks of the waveform are easily detectable due to their relatively large magnitude compared to other brain waves.

To process the input signal in real-time it is divided into non-overlapping chunks called windows. Each window has a length of ten samples which means that nearly 25 windows are collected and processed each second.

Then the delta wave signal is extracted through a low pass filter to cancel out any brain waves except the one caused by eye blinks as shown in the lower curve of Fig. 3. To detect an eye blink, upper threshold (Tu) and lower threshold (Tl) values are needed. A positive peak is detected when its amplitude exceeds Tu while a negative peak is detected when its amplitude falls below Tl. A blink is only found when detecting a positive peak followed by a negative one. The time between the two peaks is called a blink length and is used to classify blinks into fast blinks or slow blinks. The period between two successive blinks is also calculated.

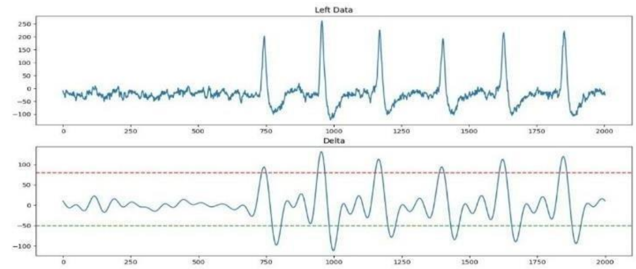

Fig. 3. The upper curve shows the unfiltered left eye blinks. The lower curve shows the left eye blinks filtered in the delta band.

To make this method suitable for any person, a calibration procedure is needed to find the values of Tu and Tl that are optimal for the user as they differ from one person to another. This is done by recording a window of five seconds in length in which the user is required to blink at least once. In this window, the amplitude of the greatest positive peak (Pmax) and that of the lowest negative peak (Pmin) are extracted. Then the optimum values of Tu and Tl are calculated.

B. Beta-Alpha Ratio Method

This method aims to determine the eye state so that the system can recognize if the user is in a closed eye (CE) state or an opened eye (OE) state. It uses the difference between readings of TP and AF electrodes for both eyes as an input EEG signal. For real-time processing, the input signal is divided into overlapping windows each has 256 samples. The actual period needed to wait for processing the next window is called the delay time.

The differentiation between the two eye states depends on a ratio called the beta-alpha ratio (R) which is the ratio between the power of the EEG signal of the window in the beta (β) and alpha (α) bands respectively as shown in (2). The alpha band ranges from 8 Hz to 13 Hz while the beta band ranges from 14 Hz to 25 Hz.

$$R = Pow(\beta) / Pow(\alpha) \tag{2}$$

It is a fact that R tends to be higher in value in the OE state compared to the CE state [7]. A threshold value (T) is used to classify the eye state of each window into CE and OE states as shown in (3).

A window is classified as CE if its value of Ris lower than T while it is classified as OE if R exceeds T.

$$\begin{cases} CE, & R \leq T \\ OE, & R > T \end{cases} \quad (3)$$

The execution of this method starts with a calibration procedure in which the optimal value of T is determined for a specific user as it varies from one person to another. This procedure ensures very accurate detection and makes the system more adaptable and flexible.

To determine T, the user is required to record two signals of twenty seconds period one with OE state and the other with CE state then, for each signal, the value of R of each window in the signal is calculated according to (2) so that a normalized distribution of the R values can be obtained for both signals.

In both distributions, any value of R outside ±3σ range is considered an outlier and discarded. After that, both the maximum R value in the distribution of the CE state (Rmax) and the minimum value of R in the distribution of the OE state (Rmin) are extracted. The average of Rmax and Rmin is the optimal value of T as shown in (4). Finally, the calculated T is used to predict the eye state of a specific window according to (3).

$$T = (Rmax + Rmin) / 2 \quad (4)$$

C. Convolutional Neural Networks Method (Blinking)

The goal of the convolutional neural networks (CNN) of one dimension layers (1D) method is to create a reliable and user-independent algorithm for detecting eye blinks in EEG signals without being affected by external factors like involuntary blinks or relying on filters and data processing [9].

Regarding network training, it has four features each one corresponding to a reading of the four electrodes in the MUSE 2. The proposed approach has been trained and tested using a dataset containing 40 records taken from 6 different subjects. Two sets of raw EEG data are collected. The first set is labeled as “1” and recorded during blinking (at least one blink per second). The other set is labeled as “0” and recorded in the normal (natural) state with involuntary eye blink artifacts.

Aiming to get the highest performance from the data, some data pre-processing techniques are applied for example,every data set is divided into windows with a size of two hundred samples (corresponds to four-fifths of a second). Then, the data windows of the two sets are mixed into one set of windows before feeding them to the CNN.

The architecture of the CNN model consists of five 1D CNN layers each one is followed by a pooling layer, a flattened layer, and finally four dense layers. The best hyperparameters were chosen based on experiments to get the best output. Finally, this model is converted to a “tflite” format so that it can be used by the system broker.

D. Convolutional Neural Networks Method (Directions)

Using the same algorithm for detecting eye blinks, the Convolutional Neural Networks Method was used to classify eye directions (left, right, and center).

The dataset was recorded from 6 subjects, three sets of EEG data from each one, two of them are for moving eyes in the left and right directions, while the last set is for eyes fixed on the forward position. Each recording includes 2 columns of data corresponding to the2 electrodes (AF7 and AF8) as it was noticed TP9 and TP10 effects can be neglected. Then, these signals were split into 2-second windows resulting in 512 samples per window [10].

The convolutional network used was simple. There were 9 layers, including the output softmax layer. Layer 1 was a Convolutional layer (with 32 filters), followed by a Maxpool layer (with (2, 2) pool size), followed by two successive convolutional layers (with 64 filters) and Maxpool layers (2, 2). Layer 7 was a Flatten layer, followed by two successive dense layers, the latter dense layer, was also the output layer using a softmax activation function with 3 nodes corresponding to our 3 actions (Left, Right, and Center). All other activation functions used were Relu activation functions [11].

Finally, the model was converted to the same format as in blinking detection with the Convolutional Neural Networks method.

V. Desktop and Mobile Application

A. Desktop application

The desktop application serves as the primary graphical user interface (GUI) for patients to control their homes. It is implemented using the PyQt5 library in Python and offers various functions, including:

1. Controlling function

The application includes a tap that contains icons of all rooms of the home. The user can select one of three control modes for controlling the system. The first mode is through using a sequence of blinks unique to a specific room or device. The second mode is through detecting eye movements in the left and right directions to navigate between the GUI icons. Eventually, the user can open the selected icon by blinking. The third control mode depends on utilizing gyroscopes embedded in the EEG device to detect the tilt position of the head to navigate between the icons similar to the previous mode. This mode is only useful if the user can move his head in a different position.

Once a specific room is selected, a menu with all the devices in that room appears. Users can choose the device they want to open by using a known blinking sequence.

The application also allows users to input and modify the sequence required to control each room and device whenever they need to.

2. Other feature

Sensors embedded in the Muse 2 like gyroscopes, accelerometers, and PPG are utilized to add other helpful functionalities to the desktop application. These sensors can monitor the user’s vital signs in addition to his safety by using a fall detection algorithm that sets an alarm if a fall is detected.

The application allows patients to calibrate and adjust the upper and lower thresholds of the blink signal to enhance the accuracy of blink detection.

To assess the patient in his communication disability, a message-typing functionality is added to the application. It adopts Morse’s code principle in which a sequence of only two special characters “-” and “.” are utilized to form alphabetic letters and hence words and sentences. The only difference in this application is instead of using special letters two types of blinks with different duration are used.

B. Mobile application

One component of the smart home system is the mobile application. It is implemented using Flutter, a cross-platform framework that utilizes the Dart programming language. The main purposes of the mobile application are discussed.

1. *Optional Control Source*

In addition to using the EEG device, the application offers two alternative control methods. The first method involves screen buttons integrated into the GUI, while the second method utilizes voice control.

2. *Provision of Additional Functionalities*

The user can use the mobile application for purposes other than home control. The application offers a reminder system that is fully customizable for the user so that he can use it to follow up on his daily schedule, drug intake, special events, and so on.

Emergency calls are a crucial feature of safety in smart homes thus the application enables the user to specify an eye blink pattern to call a chosen person from his contacts.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the performance of the four proposed detection methods is discussed. In addition, the results of the overall system performance tested by one quadriplegic person are shown.

A. *Peak Detection Method*

This is the simplest method in terms of coding and implementation compared to the other two methods. Thus, it can be improved and tested easily. The results show that it's a computationally fast method and can be calibrated on the user easily. Its main drawback is that it forces the user to use eye blinks only for control which can be quite bothersome and uncomfortable for the eyes.

B. *Beta-Alpha Ratio Method*

This method enables the user to use eye states for control which is more comfortable and precise than eye blinks. In addition, for fixed window size accuracy increases by reducing delay time. The main disadvantage is that it is quite low and complex, and its calibration process takes a long time.

C. *Convolutional Neural Networks Method (blink detection)*

After training the model, the evaluation process is completed with an accuracy of 94%. The main advantage of this method is that it can skip involuntary blinks accurately. Moreover, the network can be trained to detect the eye state. The main disadvantage is that the method requires a lot of data and time to be trained.

D. *Convolutional Neural Networks Method (directions)*

The model demonstrates remarkable accuracy of 90%, despite being trained on a limited number of subjects. However, this method has a notable drawback: it necessitates a substantial amount of data. Furthermore, any patient movement during eye movements can lead to misclassification.

E. *Overall System Performance*

The overall system was good in performance and usability according to the quadriplegic volunteer who tested it. Many other healthy volunteers agreed that the desktop and mobile application GUI is simple and user-friendly.

F. *Future Work*

Future work includes conducting more usability studies that consider the disabled to assess the overall system performance. In addition, all proposed detection methods need to be further tested and improved by adopting advanced signal processing and machine learning techniques.

Since MUSE 2 has fixed electrodes, it limits the capability of discovering and trying new ways of utilizing BCI for system control.

Thus, a simple EEG device is recommended to be designed and implemented to increase flexibility, reduce cost, and enable the addition of new control methods.

The control system also can address more devices to be controlled rather such as wheelchairs and robotic arms.

VII. CONCLUSION

Smart home systems controlled through BCI are an efficient solution for improving the quality of life for the disabled and senior citizens. To target great variations in disabilities, eyes are chosen for the control of the proposed smart home system. The system can utilize four proposed eye blinks and movement detection methods. The system was tested by a quadriplegic volunteer, results show that the peak detection method is fast and simple but not comfortable for the users' eyes. Regarding the beta-alpha ratio method, it is found that this method is more user-friendly and comfortable for the eyes but still slower. Finally, the CNN method provides more flexibility to the control system but requires a lot of time and data to get high accuracy.

Besides the eye blink detection, an approach that detects eye movement in the left and right directions using a machine learning model is developed.

Although the discussed results lack some confidence as more tests with more disabled volunteers are still to be conducted, it shows an initial sign of a great overall performance.

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