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Real Time EEG Based Cognitive Brain Computer Interface for Control Applications via Arduino Interfacing

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Abstract

Cognitive neuroscience is being widely explored to develop more interactive brain computer interfaces for control applications. An attempt has been made to translate a cognitive activity (deliberate eye blink) of human subjects captured via electroencephalography (EEG) into action. Channel power spectral and the highest peak related features have been extracted to identify eye blink related instances. A significant rise in event related potential is observed across frontal lobes of cerebral cortex. The developed model has been deployed in arduino using simulink to control output devices independently. The results demonstrate the feasibility of cognitive control network to translate deliberate intentions into commands via EEG based BCI for rehabilitation of physically challenged patients.

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Keywords: Cognitive; brain computer interface; electroenceplalogram (EEG); eye blink; emotiv unit; event related potential; neural; control, arduino.

1. Introduction

Recent research in the field of cognitive neuroscience provides a new direction to construct more interactive brain computer interfaces (BCI) which can translate human neural responses into control signals for computer-application

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devices through system's hardware and software[1]. It allows users to communicate via brain initiated control signals without any physical movement in the external world. A number of BCI approaches such as deliberate motor actions, imaginary motor tasks, audio/ video stimulations etc [1]. Cognitive analysis of human neural activity via electroencephalography (EEG) is an effective way of implementing various cognitive brain computer interface (BCI) applications. Neural driven BCIs involve the use of electroencephalograph (EEG), electrocorticography (ECoG), magnetic resonance imaging (MRI) or functional magnetic resonance imaging (fMRI) to capture brain signals from central nervous system. However, the EEG is a preferred clinical research as well as functional tool to monitor cognitive brain functionality because of its high temporal resolution, lesser expenditure cost and significant suitability to human subjects without any exposure to high intensity magnetic fields/radiations [2-5].

EEG is a non-invasive technique to analyze human brainwave responses. It can also be used to determine the strength of brain activity resulted from various types of cognitive functions of brain or its response to external interventions. The four sub-bands of the brainwave signals are beta, alpha, theta and delta. Delta has the lowest frequency range (0-3Hz) with highest amplitude followed by theta (4-7Hz), alpha (8-12Hz) and Beta with a range between 13-31 Hz but with lowest amplitude [6, 7]. The EEG sub band activity is associated with neural activity and hence, variations in cerebral blood flow (CBF). Thus, by identifying these temporal and spectral variations and analyzing them, it is possible to characterize the correlated cognitive state [8-10].

An extensive literature regarding emerging research in the field of cognitive computing using human neural responses has been explored. Focus has been paid to explore the ability of EEG signals to portray cognitive activity of human subjects to develop control applications. The importance of cognitive neuroscience and methods of detection of correlated activities is well discussed in the literature [11-13]. The progressive advancements in cognitive analysis techniques provide a strong scientific foundation to revolutionize neuro-rehabilitation and the field of biomedical informatics [14-15]. A diverse set of BCIs has been developed to implement external prosthetic devices such as robotic arm, wheel chair movement *etc* by translating neural signals into control signals [16-19]. Another research explored the variations in neural responses via EEG corresponding to upward and downward eye movement's captured from occipital region of cerebral cortex that can be utilized in the development of prosthetic devices [20]. BCI systems have been evolved tremendously even to provide hands-free applications through interpretation of silent thoughts captured via human neural responses. It resulted in mind controlling of machines/ robots without any muscle intervention [21].

The development and usefulness of these prosthetic devices is not only meant for physically challenged people but also for assisting healthy users in their normal routine and occupational work. Above findings reveal the discrimination ability of EEG, which can be explored further to map and capture specific events of neurocognitive processes. For relatively long cognitive events, the general practice is to divide the whole task into multiple trials [22]. Correlated EEG parameters can be extracted by calculating average across trials. By capturing and analysing cognitive activity related significant variations in acquired EEG, it is possible to develop a required control application. However, these subtle variations in EEG are difficult to monitor and analyse visually by naked human eye. Thus, computer assisted algorithms are gaining popularity to develop automated control applications via identifying variations in EEG. Most of the researches involve analysis of ERPs of the brain electrical activity. However, ERP events are very brief (500ms), thus a relatively large number of trials are required, that are averaged together to obtain resultant ERP [23]. To overcome this limitation, power spectral analysis can be utilized as an efficient tool to find the neural correlates during cognitive tasks [24]. However, power spectral analysis is not able to preserve Fourier phase of input signal which provides information related to morphological variations in the captured signal [25]. This may provide misguided results if variations in peak amplitude are not so prominent. This drawback of linear techniques has been addressed well in literature to further develop higher order spectra based non-linear feature extraction techniques [26]. The motive of this research is to explore the methodology for examining human neural responses via EEG during cognition and provide a substantial conclusion to generate commands for automated neural driven control applications.

The availability and features of commercially available EEG acquisition devices required to acquire neuro cognitive responses were explored. A vast set of acquisition devices *viz.,* NeuroSky brainwave (single channel), Emotive neuroheadset (14-channel), BioSemi Active-2 (280 channels), Muse (4-6 channels) are available [27]. Most of the reported work involve the use of more complex headset units like Biosemi Active-2 with 280 scalp channels involving tedious instrumentation or only a single channel device like NeuroSky covering only left frontal region of cerebral cortex to capture human neural responses. Due to a real user-friendly interface,a robust emotive EEG neuroheadset has been selected for this research to capture live EEG from human subjects to develop more interactive BCIs for control applications. Further, it is designed to capture EEG signals from 14 different electrode positions around the scalp at comparatively higher bit rate and resolution [27].

It can be observed from literature that very few works have been reported to develop control applications using volunteer eye blink via EEG as a modality and arduino as an interfacing device. An attempt has been made in this research, to develop an intentional eye blink based BCI via capturing corresponding EEGs. The performed single eye blink based instances have been identified at frontal channel AF3. An algorithm has been developed to translate the captured variations in EEG into commands to generate active high at interfaced arduino output. This high output at arduino port has been utilized to control the on-off instances of interfaced LED circuit. The developed model has further been deployed in arduino using simulink to be used independently while controlling output devices. The proposed model has the ability to be developed as a tool for neuro-rehabilitation by translating distinct cognitive brain states into operative control signals.

The following sections of the paper will include material and methodology used to acquire EEG signals, their analysis and algorithm for control application. Furthermore, results and analytical discussion will be done and finally concluded with future scope.

2. Materials and Methods

In this work, an EEG-based BCI is developed to capture and characterize variations in human neural responses via EEG while performing an intentional eye blink based cognitive activity. The functional work flow of the developed BCI is sketched in Fig. 1. It consists of signal acquisition unit to acquire human neural activity via EEG during the instance of deliberate eye blink, signal processing and algorithm development to characterize variations in EEG captured for performed cognitive activity. The output of signal processing module is interfaced with arduino uno board to control the output device.

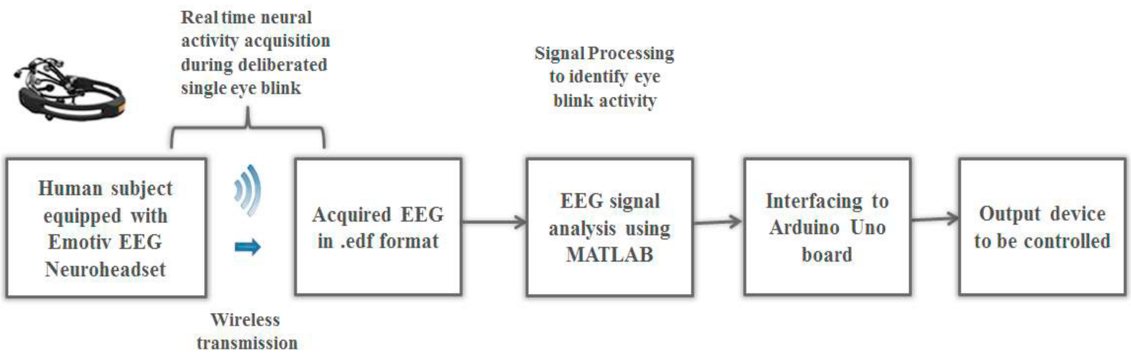


Fig. 1 Block Diagram for real time acquisition and cognitive analysis of EEG signal during intentional eye blink

2.1. Subjects

Ten subjects (7 females, 3 males), aged 14 to 18, all of whom were considered to be in good health with no consumption of any medicine or drug prior to the test, participated in the experiment to construct the required EEG signal dataset. Each participant equipped with EEG acquisition unit while performing designed cognitive activity *i.e.,* single intentional eye blink was made to sit in a quiet room and asked to be relaxed. All subjects volunteered with informed written consent before the experiment. Each subject is asked to perform a deliberate single eye blink action during a 20s record of each EEG. A total of 50 EEG trials have been obtained by capturing five trials from each subject. Human neural responses of participating subjects have also been acquired during relaxed state.

2.2. EEG data recording

The EEG signals for each subject were recorded while performing a designed cognitive task of single deliberate eye blink. The electrical activity of brain via EEG is attained using neuro headset unit EMOTIV. It is capable of acquiring neural signals generated in response to distinct actions of subject using its 14-assembly electrode sensors (AF3, AF4, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 with 2 reference electrodes P3 and P4). The acquired EEG signal is transmitted to laptop through the wireless Bluetooth dongle. The EEG dataset is recorded at a sampling frequency of 128Hz and is saved as .edf (European data format) file. The live EEG feed from Emotiv headset can be obtained directly in MATLAB workspace in .mat format. Emotiv headset is equipped with an internal high pass filter with cut-off frequency of 0.2Hz to remove low frequency noise components such as that of breathing. Further, notch filters have been incorporated to reject power supply based interference and thus helps in pre-processing of acquired EEG signals [28].

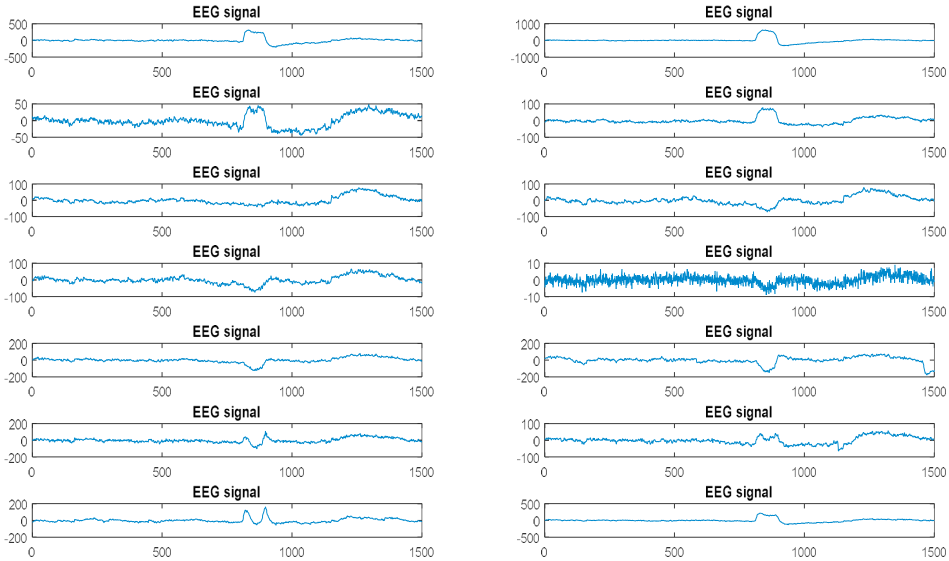


Fig. 2: Multichannel EEG acquired using 14-channel electrode sensors of Emotiv EEG Neuroheadset

2.3. EEG Signal Processing

The processing and analysis of real time acquired EEG signals is performed in MATLAB (2016b) workspace. The proposed approach is developed and implemented using Core i3 processor with speed 2.40 GHz. At first acquired EEG responses are imported to MATLAB workspace. Distinct epochs of the acquired dataset locked to actions of interest are extracted to study the corresponding EEG-dynamics. The volunteer eye blink related signals attained by each of the 14-electrodes of emotive headset are extracted and plotted as shown in Fig 2 for one subject. It can be observed that eye blink related variations in EEG are maximum captured by first four frontal channels *viz.,* AF3, AF4, F7 and F8 as shown in Fig 2. The similar instances have been observed in eye blink signals attained from other subjects. Thus, EEG captured at frontal channel AF3 has been utilized for further analysis and development of arduino interfaced on-off control of LED. The extracted signals at frontal channels are scaled by subtracting the mean value of signal from original signal. Once scaled EEG is obtained, threshold and maximum peak amplitude value from event related potential (ERP) obtained during intentional eye blink is calculated. The two values are compared and a decision is made to generate a control signal for neuro-rehabilitation if maximum peak amplitude is greater than calculated threshold as depicted in workflow shown in Fig. 3.

If this decision holds true, a 'high' output is generated at pin D11of arduino board to glow LED. Furthermore, channel power spectral analysis using fast Fourier transform (FFT) has been performed to extract the dominant frequency band *viz.,* delta, theta, alpha and beta of EEG signals during voluntary eye blink and relaxed state. Power spectra provides correlation of signal with itself and is calculated as:

$$P(f) = R_e^2[X(f)] + I_m^2[X(f)] \tag{1}$$

where *X(f)* is the Fourier transform of the input EEG signal.

Power spectral analysis facilitates detailed statistical analysis eye blink related subtle variations in acquired EEG that may get missed during visual inspection of records.

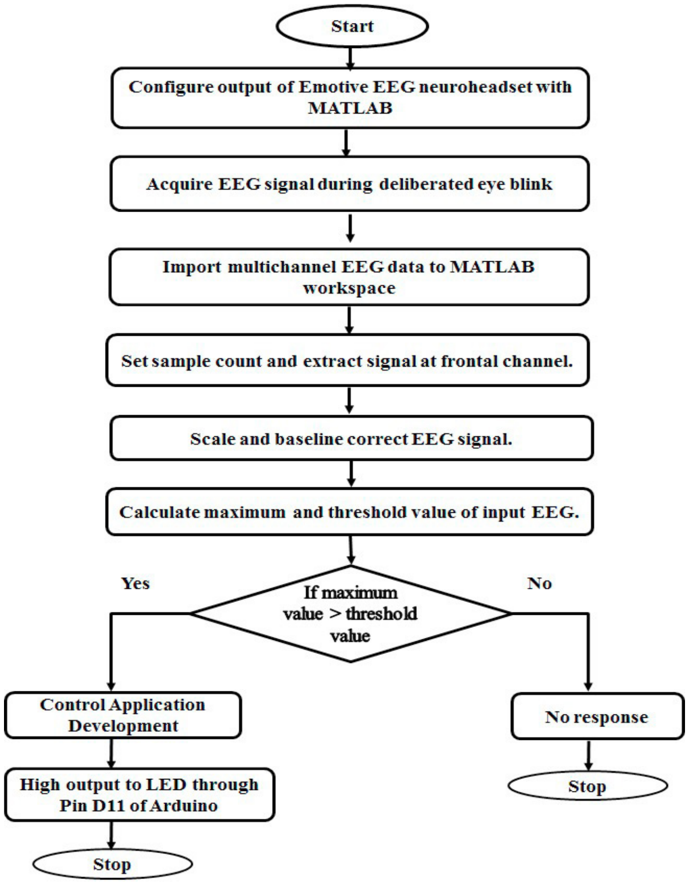


Fig. 3: Algorithm to use eye-blink EEG to control on-off instances of LED

*2.4. **Arduino interfacing with MATLAB/Simulink and controlling action***

An arduino uno board has been interfaced with MATLAB and Simulink both. At first the support packages of arduino for both MATLAB and Simulink has been installed for release 2016a. A 'com port' is identified through device manager to create a communication channel between MATLAB workspace and arduino board. An object is created to configure 'arduino' with MATLAB through port '5' using following command in MATLAB:

```
a = arduino('com5', 'uno');
     writeDigitalPin(a, 'D11', 1);
```

Once a communication channel is established, a 'high' output is obtained at pin D11 of arduino board if maximum amplitude value is greater than threshold. This will switch on the connected LED. The anode of LED is connected to pin D11 of arduino and cathode is grounded.

Similarly, arduino has been interfaced to Simulink so that designed model can be deployed in arduino to be used independently to control output devices. A new blank model was created in Simulink. A 'Simin' block was added from source library to import deliberate eye blink related EEG data through MATLAB workspace. The output has been interfaced with arduino by adding 'arduino digital block' from simulink library and write output at pin D11 of arduino. The anode of LED is connected to pin D11 of arduino and cathode is grounded. Once all the inputs and outputs are connected, the constructed simulink model as shown in Fig. 4 is deployed in arduino and can be used independently by applying supply from external source. The detailed step by step methodology is depicted in Fig 5.

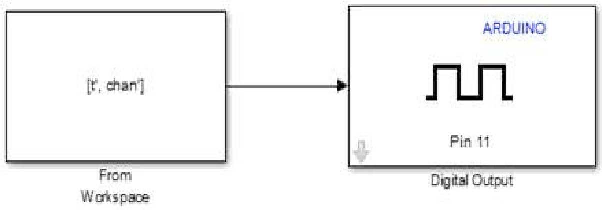


Fig. 4: Simulink model to use single eye blink EEG as a trigger to control ON/OFF instances of LED through arduino interfacing

3. Results and Discussion

The various results recorded from an experiment EEG-based cognitive BCI designed to map an intentional single eye blink of human subjects with respective neural activation via electroencephalography are presented and described in this section. The results shown here are for one subject but there has been a high incidence of similar results from other subjects as well. In this experiment the EEG signals for each subject were recorded in relaxed state and while performing a deliberate eye blink, respectively. The primary signal processing is provided by emotive headset itself. It provides clean EEG by filtering out noise components due to breathing process and rejecting power supply based interference.

At first the real time EEG signals at frontal channel AF3 during relaxed state through Emotiv headset is captured. The acquired neuro cognitive EEG signal is scaled around zero. The power spectrum is plotted as in Fig. 6a to analyze the subtle variations not visible with naked eye and to identify the dominant EEG sub band (delta δ, theta θ, alpha α, beta β). This was followed by acquisition of EEG signals at frontal channel AF3 while performing deliberate eye blink. The acquired signals are scaled and power spectrum is plotted as in Fig. 6b by calculating correlation of signal with itself.

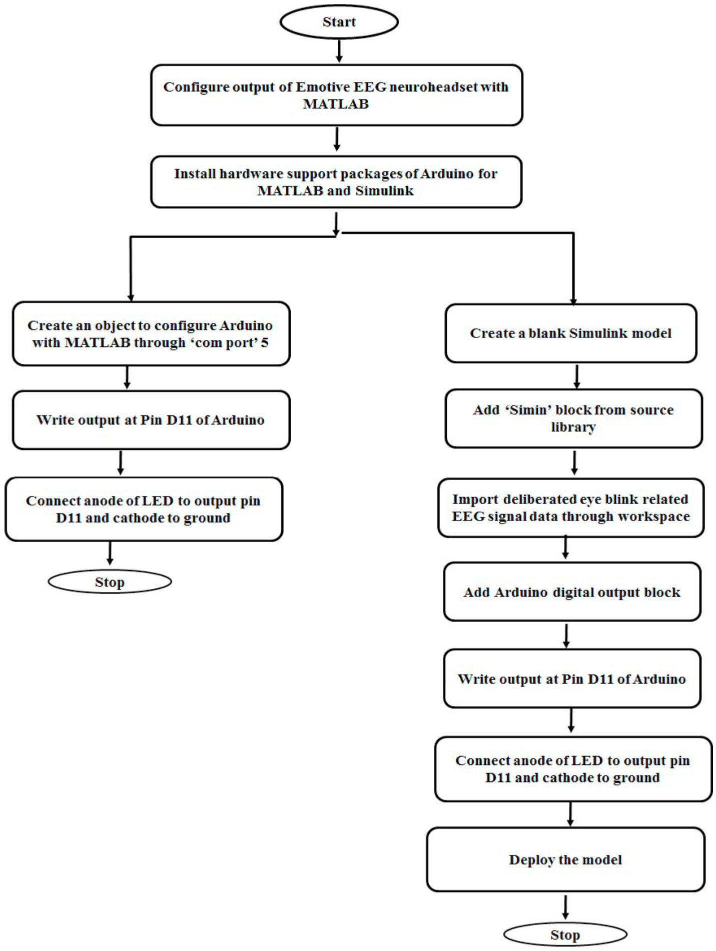
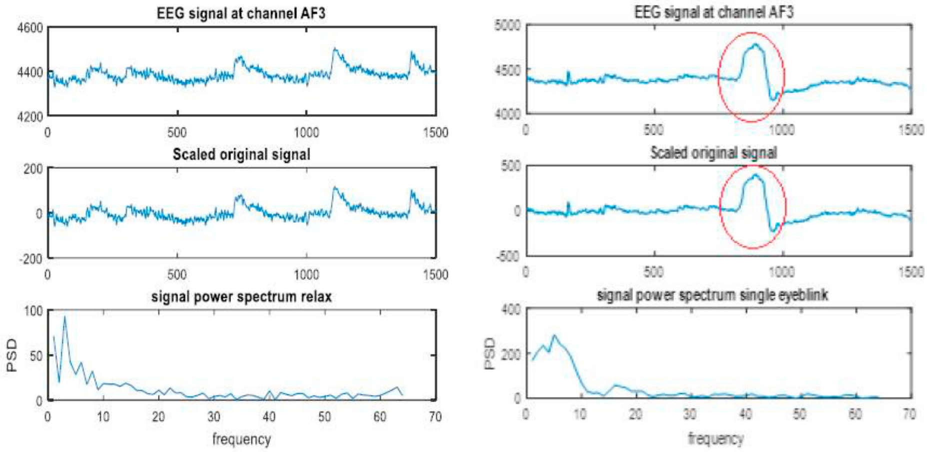


Fig. 5: Arduino interfacing with MATLAB/Simulink

The ERP (event related potential) variations are found to be very high in single eye blink EEG responses as highlighted in Fig. 6b with red circles. These captured ERP variations have been programmed in MATLAB to be utilized as trigger to develop a control application via arduino interfacing. The maximum and threshold values of captured EEG has been calculated for a window of 800 to 1000 samples where ERP is very high. The two values are compared and a decision is made to generate a control signal for neuro-rehabilitation if maximum peak amplitude is greater than threshold. This comparison is found to hold true in case of eye blink ERP response and thus a control signal is generated. A 'high' output is received by pin 11 of interfaced arduino board through port 'com 5'. The transmit /receive LED on arduino board will glow as soon as it will receive a 'high' output through MATLAB program as shown in Fig. 7. It indicated the process of transmission and reception. Once this 'high' output is received



a. b.

Fig. 6: EEG signal and Power spectrum a. Relaxed state b. Cognitive activity: single eye blink

at LED circuit on bread board, it will start glow as shown in Fig. 8a. Once the MATLAB program is verified, the Simulink model of the same has been created by importing the values through 'simin' source block. The output of this is interfaced to pin 11 of arduino output block. The model is build and is deployed in the interfaced arduino board. This deployment process will provide flexibility to the interfaced circuit. It will now provide output all the time even without getting input from MATLAB platform as shown in Fig. 8b.

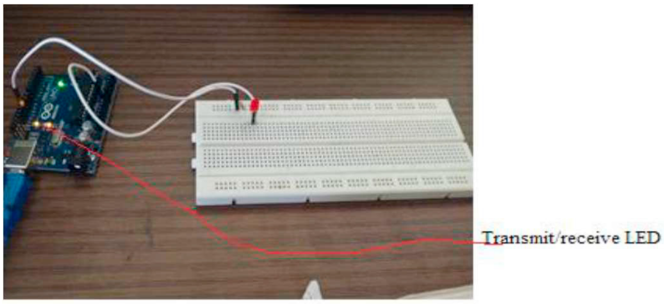
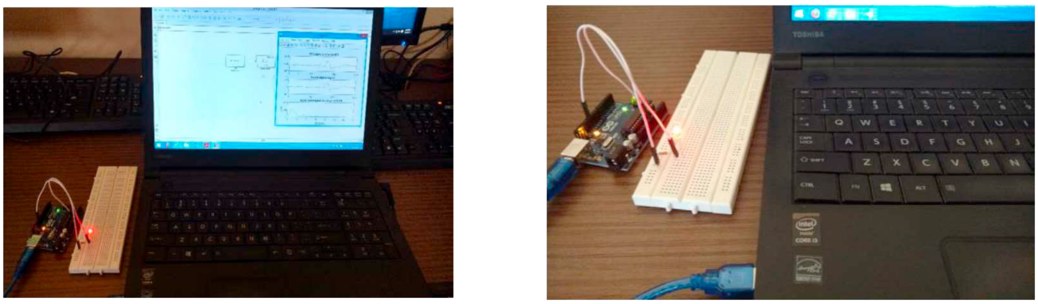


Fig. 7: Transmission/reception of 'high' output by arduino



a. b.

Fig. 8: a. On/Off instance control of external LED via single eye blink EEG, **b**. On/Off instance control of external LED after deployment of model in arduino (MATLAB is exited)

The results demonstrate the potential of deliberate eye blink based EEG to be used as a trigger to generate control signals for various applications such as home automation and development of prosthetics for paralyzed patients.

The spectral variations were captured in acquired multichannel EEG and plotted in Fig. 6. The spectral plot shows EEG sub band power distribution in four frequency bands *viz.,* δ (0.5-4Hz), θ (4-8Hz), α (8-13Hz) and β (13-30Hz), respectively. It is observed from power spectra plot that the human relaxed state is associated with maximum delta power (0-4Hz) wheras a cognitive activity of single deliberate eye blink is found to be associated with maximum delta (0-4Hz), theta (4-8Hz) and initial of alpha power band envelope (8-10 Hz) as depicted in Fig. 6a and 6b, respectively. This analysis of corresponding band power activation shall be carried out as our future work to develop a tool to investigate the intensity of cognition based on efficient machine learning techniques as an outcome.

4. Conclusion

Neural driven BCIs are gaining importance while providing assistance especially to paralytic/ physically locked-in patients in order to restore a useful life. An attempt has been made to map a cognitive activity of human subjects that involves deliberate single eye blink with respective neural activation via electroencephalography (EEG). The variations have been captured at frontal channels of cerebral cortex. The obtained high event related potentials have been programmed to translate an eye blink action into commands to generate active high at arduino output during deliberate eye blink. It is utilized to control the on-off instances of interfaced LED through low-cost arduino board. The developed model has been deployed in arduino using simulink to provide flexibility while controlling output devices. These findings demonstrate the feasibility of proposed algorithm in developing more interactive Brain Computer Interfaces in real time scenario to assist medically challenged people with severe motor disorders. The methodology adopted possess the ability to offer patients with severe motor neuron disorders an alternative means of communication and control over their environment via applications for neurorehabilitation of motor and cognitive functions.

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