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Real Time Acquisition and Analysis of Neural Response for Rehabilitative Control

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Abstract**—**Non-invasive Brain Computer Interface like Electroencephalography (EEG) which directly taps neurological signals, is being widely explored these days to connect paralytic patients/elderly with the external environment. However, in India the research is confined to laboratory settings and is not reaching the mass for rehabilitation purposes. An attempt has been made in this paper to analyze real time acquired EEG signal using cost effective and portable headset unit EMOTIV. Signal processing of real time acquired EEG is done using EEGLAB in MATLAB and EDF Browser application software platforms. Independent Component Analysis algorithm of EEGLAB is explored to identify deliberate eye blink in the attained neural signal. Time Frequency transforms and Data statistics obtained using EEGLAB along with component activation results of EDF browser clearly indicate voluntary eye blink in AF3 channel. The spectral analysis indicates dominant frequency component at 1.536000Hz representing the delta wave component of EEG during voluntary eye blink action. An algorithm is further designed to generate an active high signal based on thoughtful eye blink that can be used for plethora of control applications for rehabilitation.

Keywords**—**Brain Computer Interface, EDF Browser, EEG, EEGLab, EMOTIV, Real time Acquisition

I. Introduction

CONVENTIONALLY, Brain Computer Interface (BCI) technology mainly focuses on invasive and non-invasive methodology where the latter is ahead due to simple design and ease to use. A brain computer interface needs some brain signal as an input for its functionality. So far, various EEG signals such as Virtual Evoked Potentials (VEPs), Slow Cortical Potentials (SCPs), P300, and sensorimotor rhythms, have been explored for controlling BCI functionality. Both transient VEPs (TVEPs) and steady-state VEPs (SSVEPs)) have been used immensely for BCI control [1]-[7]. Although efficiencies of these systems are acceptable but have failed to comply with problems like maintaining continuous permanent attention to external stimuli and regular control. Another feature of EEG i.e. slow cortical potentials can be used for BCI technology. Even with some considerable research involving SCPs in past [8]-[12], they are not so favorite among current BCI researchers. The reason behind this approach is low transmission rate and involvement of long tedious training and testing sessions. Other option for BCI control is P300. BCIs based on visual P300 evoked potentials comprising matrices of numbers, letters and other commands have also been broadly surveyed [13]-[15]. Sensorimotor rhythms have also been researched extensively for BCI control. Wadsworth [16], Berlin [17] and Graz [18] employ sensorimotor rhythms in their BCIs, as control signals. Disadvantages of these technologies are lower bit rate and requirement of multichannel EEG recording for good performance. Most of the methods involving BCI control using these brain signals involve certain significant drawbacks. Hence we use a simple and easy to implement method for generating brain signals for BCI control, i.e neural potentials generated from deliberate eye blink.

Only countable research work has been done on eye blink detection and its use as a trigger for control applications. Pander et al. uses EOG signals and detection function generator for eye blink detection with moderate results on various eye blink parameters [19]. Udayashankar et al. designed an eye blink based control unit using face tracking with the help of HAAR cascade classifier (trained) and template matching technique [20]. Sammaiah et al. provided a system using cornea-retinal potentials [21]. Panning et al. presented an algorithm for eye blink detection using color based approach in facial images [22]. Jiang-Wei et al. provided a multi-oriented Gabor response analysis of eye images [23]. These responses were analyzed to detect eye blink. Most of the work referred above involved modalities other than EEG for eye blink detection. However, Chambayal et al. developed an algorithm to detect eye blink from EEG signals using LABVIEW platform [24] and Rihana et al. used BioRadio portable device to acquire EEG signals and Probabilistic Neural Network for signal classification [25]. Both these techniques used conventional methods for detection of eye blink neural responses and efficiencies of their systems are quite moderate.

Lot of researchers explored controlling of various mechanical and electrical devices using BCI, but very few of them are non-invasive. The most suitable non-invasive option for interfacing a brain and computer is EEG. However, to acquire EEG signal in research institutes is quite a difficult process and require trained staff. For these reasons, our work involves the use of commercially manufactured EEG acquisition device, the Emotiv EPOC. There are several other headsets present commercially for EEG acquisition but because of higher bit rate and better resolution, Emotiv Epoch is best suitable for our studies. A comparative study of various

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models of EEG acquisition systems is given in Table I [26]. The motive of this research is to explore the methodology and control application of non-invasive and inexpensive eye blink based brain computer interface for rehabilitation.

II. Material & Method

TABLE I
COMPARISON OF HEADSETS

Headset	Sensors & Interpretation	Cost
Mindwave	1 Electrode Captures 2 Mental states	$ 99.95
Emotiv EPOC	14 Electrodes Captures 4 Mental states Cognitive analysis Bluetooth Interface	$ 299
Mindset	1 Electrode Captures 2 Mental states	$ 199
Xwave (with Neurosky)	1 Electrode 8 EEG Bands Bluetooth Interface	$ 90
Muse	4 Electrodes Can be worn whole day Bluetooth Interface	$ 269

In this work, an EEG-based BCI for the rehabilitative control is developed by analyzing neural responses of the human subject corresponding to distinct actions. The functional work flow of the developed BCI is shown in Fig. 1. It consists of signal acquisition, signal processing and algorithm development.

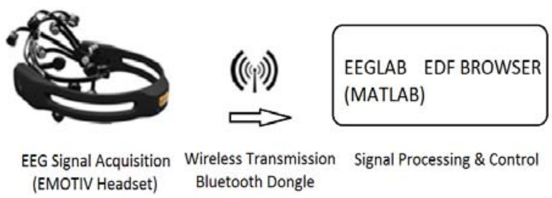

Fig. 1 Block Diagram for real time acquisition and processing of EEG signal

A. Signal Acquisition

Real time EEG dataset is acquired from subject's scalp using cost effective and portable EEG 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, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 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. EEG dataset is recorded for single subject's deliberate eye-blink action.

B. Signal Processing

Signal processing of real time acquired EEG is done using EEGLAB v 13.0.1 in MATLAB workspace and EDF Browser application software platforms. Independent Component Analysis (ICA) algorithm of EEGLAB is explored to identify deliberate eye blink in the attained neural signals through scalp channels. The ICA decomposition of signals leads to the extraction of maximally temporally independent EEG signals corresponding to any activity present in the channel data [27]. This provides a basis for locating voluntary eye blinks and other subject actions. Different ICA decomposition algorithms available in EEGLAB toolbox are runica.m (selects neural components having super-gaussian activity distribution) and jader.m (utilizes fourth order moment to identify the neural activity in response to certain deliberate action). In this work, runica.m is implemented for 10s length input EEG data in order to extract their time-frequency transforms and data statistics. Furthermore, spectral analysis is done to extract the frequency component of the EEG signal at voluntary eye blink.

C. Algorithm Development

An algorithm is further designed to decode an active high signal based on thoughtful eye blinking that can be used for EEG based BCI for controlling applications for rehabilitation. Fig. 2 illustrates the designed algorithm to use EEG as a trigger that can also be used to develop a prosthetic device controlled by human neural signals. The recorded EEG signal (.edf) is imported to MATLAB workspace in order to obtain its absolute/maximum value. Then the corresponding mean is calculated from the band pass filtered signal to extract its threshold value. Now, signal filtered at each point is compared with the threshold obtained via K-NN algorithm, and divide and conquer method. If it is found larger than the threshold value, the selected action's neural response can be used as a trigger for control applications.

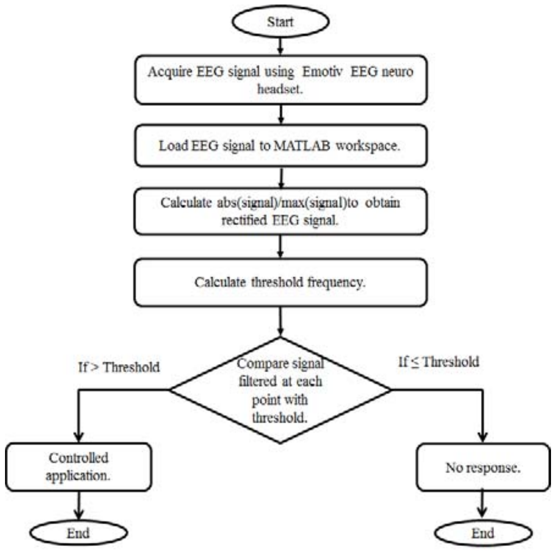

Fig. 2 Flow chart for algorithm to use EEG as a trigger

III. Result & Discussion

The various results obtained for EEG-based BCI for control applications is discussed in this section. The proposed approach is developed and implemented using MATLAB R2011a on Core i5(4th Gen) processor with speed 2.40 GHz. The real time EEG signal (.edf) acquired through EMOTIV EEG Neuro-headset corresponding to double and single eye-blink action is plotted in Fig. 3 using EDF Browser. The signal is filtered using butter-worth high pass filter and the corresponding power spectrum using Fast Fourier transform is plotted in Fig. 4. The spectral analysis indicates the dominant frequency component at 1.536000Hz representing the delta wave component during deliberate eye blink action. This also interprets that the intensity of action corresponds to standard frequency range of the EEG signal.

Thus, component activation results of EDF Browser clearly indicate forced eye blink in AF3 channel.

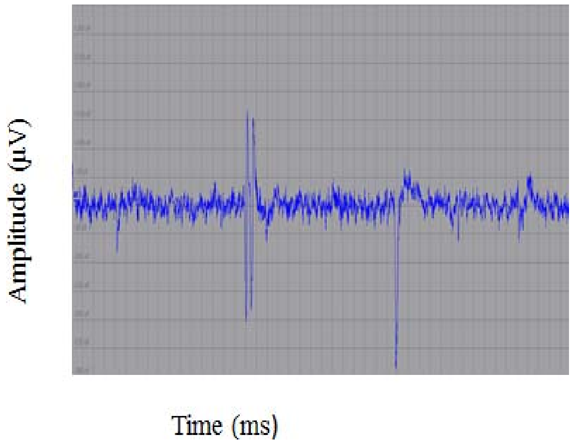

Fig. 3 EEG signal acquired at channel AF3 during eye blink

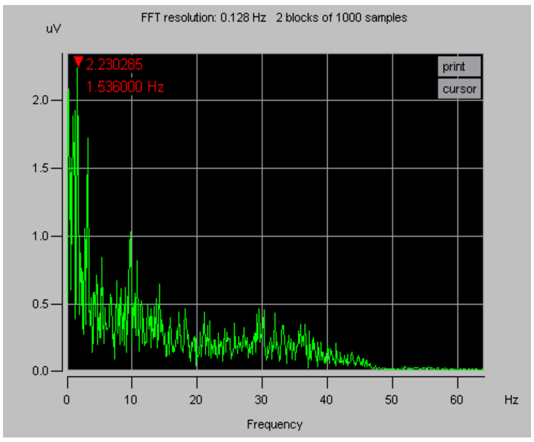

Fig. 4 Power spectrum during eye blink

Further, EEG signal is processed using EEGLAB v 13.0.1 in MATLAB workspace. Independent Component Analysis (ICA) decomposition is performed to identify deliberate eye blink in the attained neural signals through scalp channels. Fig. 5 shows signal statistics plot for ICA decomposition using ‘runica.m’ algorithm during voluntary eye blink. It represents the component activation using super Gaussian activity distribution. Component time-frequency plot during eye blink is depicted in Fig. 6. It represents the time-frequency decomposition of component activation and is an index of changes in the spectral content of the dataset in response to some voluntary action. The upper left part corresponds to the baseline mean power spectrum. As clear from component time-frequency plot, the power increases in the upper panel during the frequency range 0-4Hz thus, represents the delta wave component during eye blink action. The lower image represents the Inter-Trial coherence (ITC) at all frequencies and the lower most part corresponds to the ERP’s (event related potentials) that clearly indicates component activation prior to 4ms due to the appearance of oscillatory activity in the ERP. This is reflected in the spectrogram with brighter color bars.

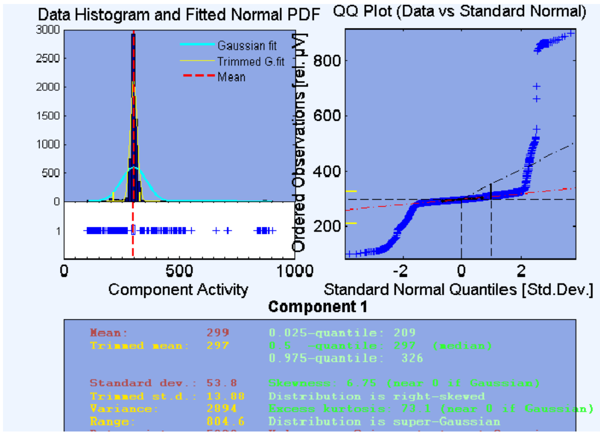

Fig. 5 Signal statistics plot for ICA decomposition during eye blink

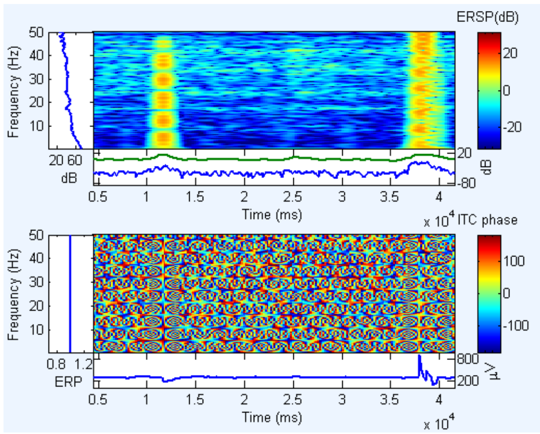

Fig. 6 Component time-frequency plot during eye blink

In order to determine the degree of synchronization between component activations, component phase coherence plot during eye blink is plotted in Fig. 7. Clusters (highlighted area with red circle) of high correlation are noted again around 4ms representing the component activation (eye blink) region. Component activation scroll plot during eye blink is shown in Fig. 8. It is important to scroll EEG activation data to completely interpret the neural responses for certain subject actions. While scrolling, component ‘1’ (red circle) appears to account primarily for eye blink action. The activity spectrum of different data channels is plotted in Fig. 9. Different colored traces in channel spectra correspond to the activity spectrum of individual data channels. The results verify component activation in different spectra plots during deliberate eye blink. This identified component activation is further utilized to design an algorithm (Fig. 2) to generate an active high during eye blinking. This reflects the use of EEG as a trigger that can also be used to develop EEG-based BCI for the rehabilitative control applications.

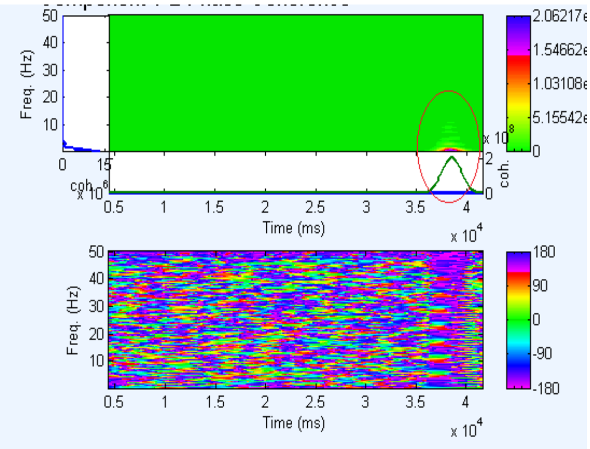

Fig. 7 Component phase coherence plot during eye blink

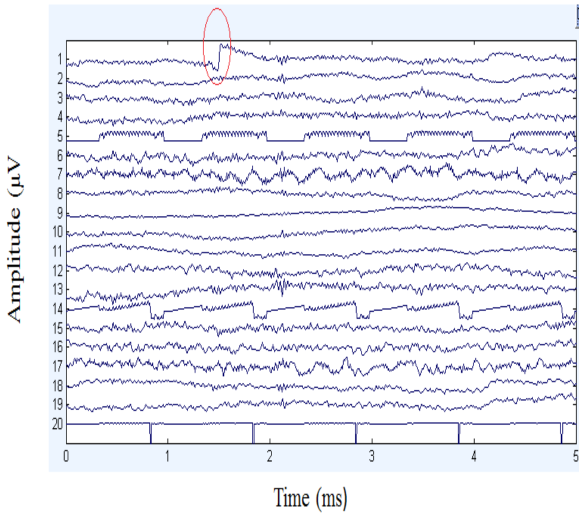

Fig. 8 Component activation scroll plot during eye blink

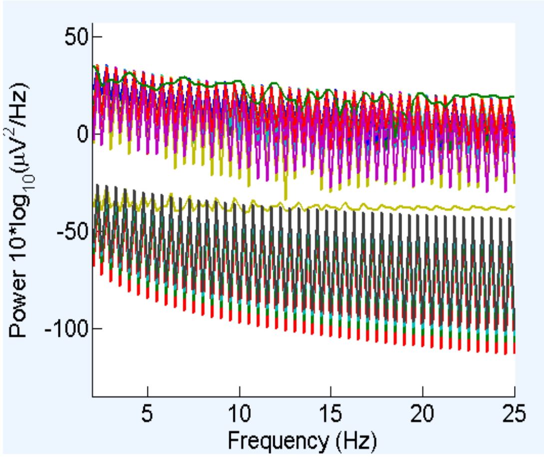

Fig. 9 Channel spectra and maps during eye blink

IV. Conclusion

An efficient, cost-effective and portable EEG based BCI using EMOTIV EEG neuro-headset is implemented in this research. An independent component decomposition using EEGLAB toolbox is employed to identify the component activation in the acquired neural signals during deliberate eye blink. Different spectral analysis techniques viz. power spectrum, time-frequency plot and phase coherence plot have been efficiently explored in order to accurately recognize the dominant frequency component corresponding to single and double eye blink action of human subject. This leads to the development of an algorithm to use EEG as a trigger for various control applications for rehabilitation. The future work may include development of a prosthetic device which can be externally used as a medical tool to assist complete or partial paralyzed patients and also patients suffering from voluntary motor disorder such as speech loss or amputation.

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