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Comparison of Classifiers with Brain Computer Interface for Steady State Evoked Potentials

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ABSTRACT

Bio signals based control system has been employed into the biomedical devices and prosthetic limbs for improving the life of severely disabled and elderly people. In this paper, a Brain computer interface (BCI) is presented using steady state evoked potential (SSVEP) for comparison of accuracy of four movements i.e. forward, backward, right and left of brain signals. The performance of subjects is analyzed with four classifiers at different fatigue levels. The experiment when performed using various classifiers resulted in different accuracy.

Keywords: Brain computer interface (BCI), Steady state evoked potential (SSVEP)

I. INTRODUCTION

Brain computer interface (BCI) is an advanced technology for communication and is highly used to establish a direct link between computer and the human brain [1,2]. People who are severely disabled and lose their voluntary muscular movements are unable to participate in the mainstream of society and feel deprived and isolated. Brainstem stroke, amyotrophic lateral sclerosis (ALS), spinal cord injuries and other diseases impede the function and movement of the muscles [3]. Therefore, the BCI systems provide assistance and control of the muscular movements to all such people. The electrical brain signals play vital role and can be used for detecting and analysing the intentions of the people. In real time applications, a BCI system should work in asynchronous mode i.e. the system works only when user wishes to operate and is not bounded by any predefined protocol as in cue based synchronous BCI. SSVEP is utilized for the proposed BCI where electrical potential differences are extracted from the scalp after a visual stimulus. Depending upon application and requirement of the system, the number and structure of the stimulus can be varied. In SSVEP, multiple classes can be defined without using much training because the subject has to just shift his/her gaze to various stimuli. Hence, it can be used in multiple applications where more number of movements are required. Transient VEPs occur at frequency below 3.5 Hz and When Stimulation frequency is greater than 3.5 Hz then VEPs are called as steady state VEPs. At steady state condition the individual responses are overlapped and apparently equal frequency as stimulus [4][5]. The main goal is to detect this frequency accurately and reliably, and also detect the frequency which is not present i.e. when the person does not gaze at the stimulus.

II. METHODS AND MATERIAL

A. EEG Experiment

1. Subject

Four healthy male volunteers, aged between 18 and 29, and had normal vision participated in the experiment. Initially, subjects took full rest before the experimentation and were asked to quiet and relaxed during the experiment. Subjects were seated in a comfortable armchair in a slightly dimmed room in front of the stimulation unit (SU).

2. Stimulation unit (SU)

Stimulation unit, a 13x13 cm box (as shown in figure1) equipped with four LEDs, provides the visual stimulation for training. The frequency and the pattern of the LEDs are directly controlled through computer. Each stimulating LED has a diameter of 9 mm and a light intensity of 1550 mcd. Also, each stimulating LED is accompanied by a small LED indicating on which stimulating LED the user has to shift his sight next. Between the two trials there is sufficient time given to the user to switch his focus on next LED.

Figure1. Stimulation Unit

3. Data Acquisition

Eight electrodes are used to acquire the signals from the subjects and placed over visual cortex according to international 10-20 system. The positions of electrodes (as shown in figure 2) are PO4, PO3, P08, PO7, O1, O2, OZ, POZ whereas right ear lobe and F_{pz} are used as reference and ground respectively. Abrasive gel is used for proper connection between electrodes and scalp and also to maintain impedance of electrodes below 5Ω. The electrodes are connected to the EEG amplifier (g.USBamp, g.Tech medical engineering, Austria) which fed the signals over a USB connection into the computer directly.

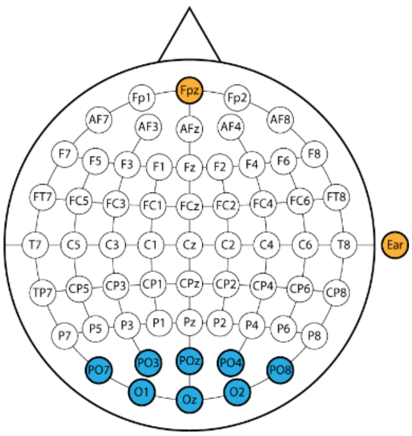

Figure 2. Placement of EEG Electrodes

B. Signal Processing

The signals are acquired through eight channel EEG system with 256 Hz sampling rate. The raw EEG data has many artefacts and they affect the accuracy and performance of the system. Hence, a band pass filter of frequency range 0.5 to 30 Hz is used to filter all the noises and artefacts from the signals.

In SSVEP, the voltage between a reference electrode and an electrode 'i' when subject is gazed at stimulus can be estimated as:

$$y_i(t) = \sum_{k=1}^{k=N_h} \left(a_{i,k} \sin\left(2\pi k f t + \varphi_{i,k}\right)\right) \quad + b(t)$$

where $0 \leq t < T$, b, T and N_h are the number of harmonics, noise and number of harmonics. ($a_{i,k}$) and ($\varphi_{i,k}$) are the amplitude and phase of each electrode. There are several sources of noise such as environmental effects, physical disturbances, improper connections of electrodes with scalp. Hence, main goal is to improve signal to noise ratio and detection of desired frequency. A channel c is used as a linear combination of the signals measured by the My electrodes. c is defined by:

$$c(t) = \sum_{i=1}^{M_y} U_{i,p}\, y_i\,(t)$$

Where, $0 \leq p < Ns$ and Ns is the number of channels. The first goal for EEG signal processing is to find an optimal set $U_{i,p}$, $1 \leq i < M_y$ where desired frequency is present.

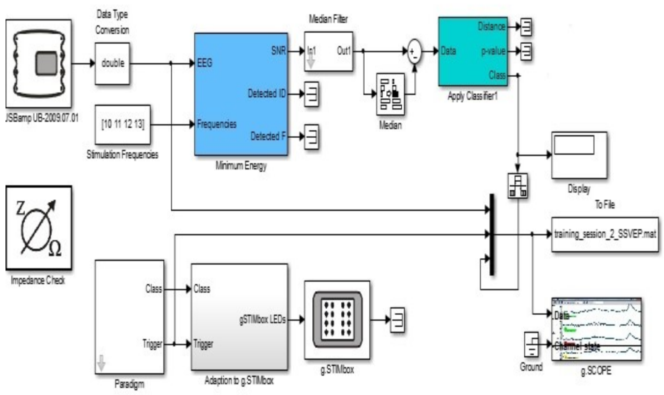

Figure 2. Simulink Model of SSVEP Paradigm

The minimum energy combination is used to cancel the noises as much as possible by combining not only pairs of electrodes but also arbitrary number of electrodes. The Simulink model for SSVEP is shown in Figure3 where various blocks are interconnected to make real time paradigm. Discrete Fourier transform(DFT) provides us the frequency analysis of the signals so that power can be calculated which helps in evaluation of features of the signals. these features are fed to the classifiers for better evaluation of the results.

III. RESULTS AND DISCUSSION

The experiment when performed using various classifiers and varied fatigue levels resulted in different accuracy means. At 10% fatigue level, the percentage of accuracy using linear discriminant analysis (LDA) with subjects 1,2,3 and 4 resulted in 92.20, 90.40, 88.25 and 87.64% respectively. However, the mean accuracy using Learning vector quantization (LVQ) was 82.96%. Similarly, using K-nearest neighbor (KNN) and Support vector machine (SVM), the percentage accuracy came out to be 81.87 and 88.96% respectively as shown in

Table 1. TABLE1. PERCENTAGE ACCURACY WITH 10% FATIGUE LEVEL

Classifier	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**	**Mean accuracy**
Linear discriminant analysis (LDA)	92.20 %	90.40 %	88.25 %	87.64 %	89.62%
Learning vector quantization (LVQ)	88.25 %	82.36 %	81.24 %	80.00 %	82.96%
Support vector machine (SVM)	81.12 %	84.85 %	82.25 %	79.26 %	81.87%
K-nearest neighbor (KNN)	91.21 %	88.40 %	87.34 %	88.90 %	88.96%

Also, after whole day experimentation when the subjects were tired and their fatigue level reached somewhat between 60-70%, the accuracy percentages were again measured. It came out to be 64.48, 58.12, 54.48 and 61.94% respectively as shown in Table 2 for the same order of classifiers as used above. So, it can be deduced that the percentage accuracy of the subjects reduces with the increasing fatigue level. Also, LDA comes out to be the classifier with best percentage accuracy followed by KNN.

TABLE 2. PERCENTAGE ACCURACY WITH 60-70% FATIGUE LEVEL

Classifier	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**	**Mean accuracy**
Linear discriminant analysis (LDA)	62.23%	64.34%	66.24%	65.12%	64.48%
Learning vector quantization (LVQ)	58.34%	56.78%	59.12%	58.22%	58.12%
Support vector machine (SVM)	52.23%	54.34%	56.24%	55.12%	54.48%
K-nearest neighbor (KNN)	60.34%	61.78%	64.30%	61.35%	61.94%

IV. CONCLUSION

The study was conducted to analyse the performance and accuracy of the designed BCI system using various classifiers. Accuracy always plays an important role in real time application systems. Each classifier has its own methodology and computational procedure for analysing the signals. In our study, Linear discriminant analysis (LDA) provided us highest accuracy among all other classifiers at various fatigue levels.

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