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Performance Analysis of Different Techniques for Brain Computer Interfacing

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***Abstract*—Recent works on different types of Brain Computer Interface (BCI) and their performance analysis have provided some remarkable features for applications. The aim of this work is to compare the accuracies of different types of BCI to find out the suitable techniques. The study shows that each technique performance depends on the type of BCI. A batter performance of the BCI systems is supported by the artificial neural network.**

***Index Terms*—Brain computer interface, motor imagery, electroencephalogram, event-related de-synchronization, event-related synchronization.**

I. INTRODUCTION

A BCI system establishes a direct communication channel between a human brain and an external communication device without involving neuromuscular pathways. Such interfaces can be extraordinarily useful to the people with partial and total dysfunction of the neuromuscular system. Without using brain's normal output pathways (peripheral nerves) this system allows a person to commune or control the external world. It will enable a dysfunction of the neuromuscular patient to carry out the basic daily tasks more easily. It emerged as viable communication channels between a man suffered by a severe dysfunction and the whole world around him. Such systems use the bio-medical signals voluntarily generated by the individual, can be derived either from a muscle of the human body or the brain activity and acquisition done through the surface electrodes. Brain signals are used only when it is not possible to use muscular signals.

Several techniques have been used for BCI operations. Techniques depend on acquisition of electroencephalogram (EEG) signal, neuro-mechanisms, signal classification etc. It becomes the preliminary challenge to define specific technique for targeted system.

II. TYPES OF BCI

Based on the neuro-mechanisms and recording technology current BCIs fall into seven main categories. Fig. 1 shows few types of human BCI systems. Fig. 1(a), 1(b) and 1(c) are non-invasive, where Fig. 1(d) is invasive signals.

1. Sensorimotor activity

Motor cortex is the region of the cerebral cortex involved in the planning, controlling and execution of voluntary movements. The Sensory Motor Rhythm (SMR) is brain wave rhythm. It is an oscillatory idle rhythm of synchronized electromagnetic brain activity. It appears in spindles in recordings of EEG, MEG and ECoG over the sensorimotor cortex. Sensorimotor activity for BCI can be classified into three types.

i. Changes in brain rhythms (mu, Beta and gamma): For the awake people primary sensory or motor cortical areas often display EEG activity ranges from 8 to 12 Hz. It happens when they are not engaged in processing sensory input or are not in producing motor output [1]. If this activity is focused over somatosensory or motor cortex then this called as mu rhythm. When this focused over visual cortex then it called as visual alpha rhythm [2].
ii. Movement-related potentials (MRPs): MRPs are low-frequency potentials, which start about 1–1.5 s before a movement. They have bilateral distribution and they present maximum amplitude at the vertex. Close to the movement they become contra-laterally preponderant [3].
iii. Other sensorimotor activities: The sensorimotor activities that do not belong to any of the preceding types are categorized as other sensorimotor activities. These activities are usually not restricted to a particular frequency band or scalp location and usually cover different frequency ranges. An example would be features extracted from an EEG signal filtered to frequencies below 30 Hz. Such a range covers different event-related potentials (ERPs) but no specific neuromechanism is used [4].

From the several factors it is found that for EEG-based communication mu and beta rhythms could be good signal features. By the decrease in mu and beta rhythms movement or preparation for movement is typically accompanied by contra-lateral to the movement and this decreasing is known as event-related de-synchronization (ERD) [5].

2. Slow Cortical Potentials

Among the lowest frequency features of the scalp-recorded EEG are slow voltage changes generated in cortex. These potential shifts occur over 0.5–10.0s and are called slow cortical potentials (SCPs). While positive SCPs are associated with reduced cortical activation then the other functions become involved in cortical activation of negative CPSs. From the study of previous decades it is clear that user easily can learn the controlling of SCPs, also the control movement of an object in the computer screen [10]. BCI is referred as the

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thought translation device (TTD) and its main concern on developing clinical the application. At the vertex referred to linked mastoids, EEG is recorded from electrodes is shown in Figure 1(a). At first SCPs are extracted by proper filtering then corrected for EOG signals and finally it return to the user via visual feedback from the computer screen. In visual feedback it shows shows two choices, one at the top and another at the bottom. For selection it takes 4s. The system measures the user's initial voltage level in first 2s baseline period. By a criterion amount voltage level is been decreased or increased voltage level in next 2s. It happens by the user selecting top or bottom and the displayed as vertical movement of a cursor where in a varities ways the final selection is indicated[5].

3. P300

P300 can be detected while a subject is shown in two types of events, where one is occurring much less frequently than the other. The less frequently event elicits an ERP, which consist of an enhanced positive-going signal component with a latency of about 300ms after the stimulus onset. Typically a positive peak at about 300ms evoke in the EEG over parietal cortex.

4. Visual Evoked Potentials (VEPs)

To describe any computer-based system, produced detailed information on brain function in almost 4 decades before J. Vidal used term 'brain computer interface'. In his course of his work, Vidal developed a system that satisfied the current definition of dependent BCI. By the recording from the scalp over visual cortex that system used the VEP for determining the direction of the visual fixation point(as eye gaze). That is also used to move the cursor as the wishing of user. In 1990s Sutter described the similar BCI system that is used the VEPs produced by brief visual stimuli, which is recorded from the scalp(over the visual cortex).

5. Activity of neural cell (ANC)

It has been shown that the firing rates of neurons in the motor cortex are increased when movements are executed in the preferred direction of neurons. Once the movements are away from the preferred direction of neurons, the firing rate is decreased [10].

6. Response to mental tasks

BCI systems based on non-movement mental tasks assume that different mental tasks (e.g., solving a multiplication problem, imagining a 3D object, and mental counting) lead to distinct, task-specific distributions of EEG frequency patterns over the scalp [7].

7. Multiple neuro-mechanisms

BCI systems based on multiple neuromechanisms use a combination of two or more of the abovementioned neuromechanisms [4].

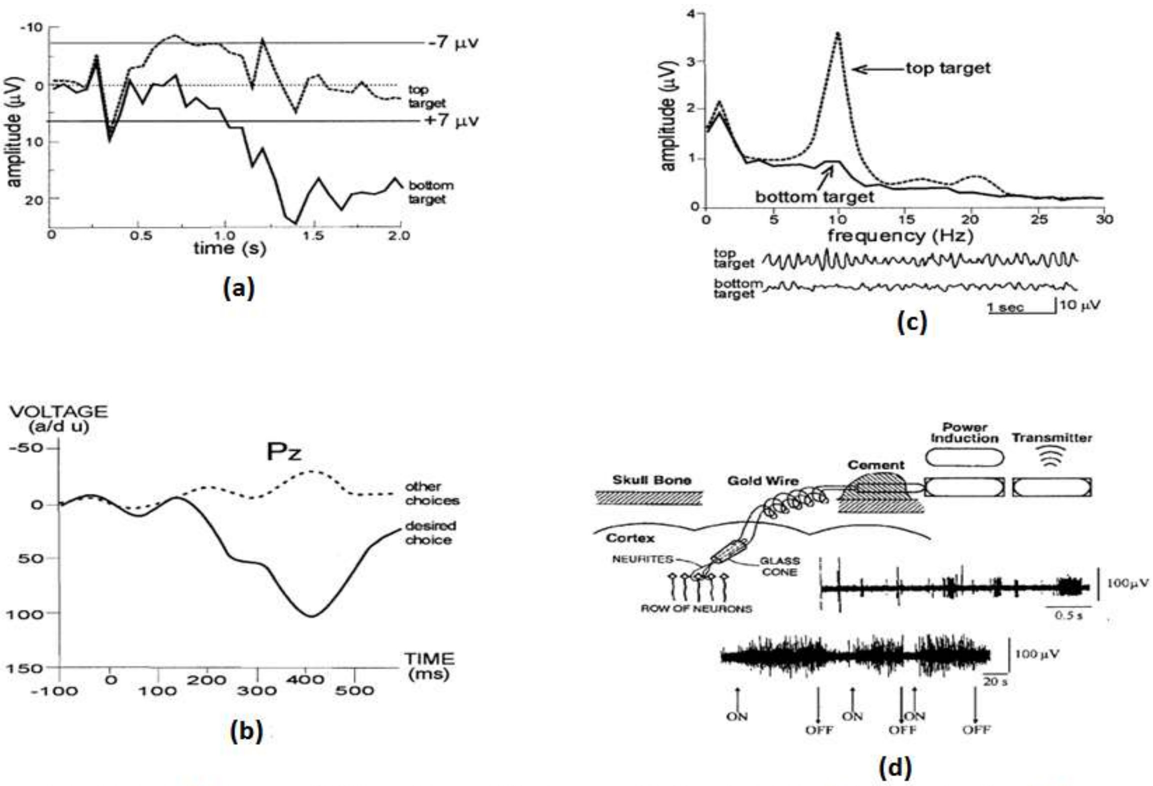

Fig.1.Typical human BCI systems: (a) slow cortical potentials, (b) sensorimotor rhythms, (c) P300 evoked potentials and (d) cortical neural activity

III. BCI APPROACHES

For EEG driven artificial limb control using state feedback PI controller, simulated result had found for some patients those who are injured by spinal cord or their sensory, motor and autonomous function for the limb movement is completely destructed. In this situation Brain computer Interface (BCI) provides a new communication pathway for those patients. In Fig. 2, they classified the movement of hindarm and forearm by QDA classifier and results they obtained with 5 able-bodied participants.

The classification result showed about the part of the limb subject wants to move. The classified direction fed into the controller as a binary input signal. However, they could use AR (Auto Regressive) parameter, PSD (Power spectral Density), amplitude value of the signal. By LDA (Linear Discriminant Analysis), SVM (Support Vector Machine), KNN (K nearest Neighbour), they only have used wavelet coefficients as feature. They have used only QDA (Quardratic discriminant Analysis) classifier because its classification accuracy higher than other classifiers [11].

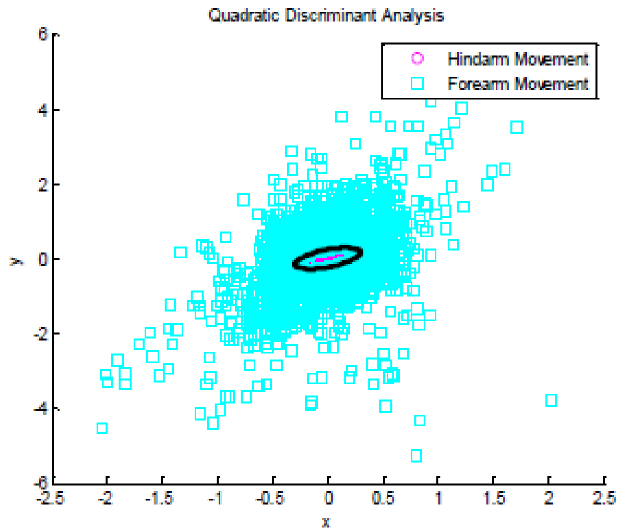

Fig. 2: Output from QDA classifier [16].

A multi-signature BCI had developed recently. There event-related potentials (ERPs) and the steady-state somatosensory evoked potential (SSSEP) have been used. Comparing the performance based on ERP and SSSEP features, no difference is found here in simulation conditions. However, they tried to get better performance, but the combination of ERP and SSSEP did not give the better result than the single ERP feature [12].

A very low-cost EEG-based BCI had designed to help handicapped persons, who are not able to talk and move to communicate with others by means of text and SMS. There, the signal is acquired through homemade silver electrodes and fed to the computer through the soundcard for further processing and features extractions. Its average accuracy they found 87% and it can be used for clinical and nonclinical purposes. They proposed 11 mm pure silver disk as electrode which is much cheaper than 10 mm pure silver or Ag/ AgCI disks [13]. To make a Human Machine Interface (HMI) a robotic wheelchair by eye blinks or brain activity had made that can be operated by command. The command presented to the user in the screen of a PDA (Personal Digital Assistant) [14].

The P300-based browser provides unrestricted access and enables free web surfing for paralyzed individuals. They added some criteria that the user is able to navigate to any page on the internet standard browser, user can achieve 70% navigational accuracy and time to execute a navigation decision for any link on a page is satisfactory by the user for true web access for evaluation of the presented and future internet browsers [15]. A self-paced and phantom finger movement's approach had developed for non-invasive BCI system with high-dimensional features from 128-channel EEG and advanced machine learning techniques. The developers also manifest that a very high information transfer rates can be achieved using the readiness potential (RP). It was a real movement made by a healthy subject is the more like the motor-command in disabled persons than an imagined movement [16].

A recent remarkable achievement in 2013 a hospital bed nursing system without training from the users based on asynchronous steady-state visual evoked potential (SSVEP). They presented a light-emitting-diode stimulation panel to induce the user's SSVEP signal used as the input signal of the system. Then, an SSVEP-amplifier circuit and a field programmable gate array-based SSVEP signal processor are respectively designed to acquire and process the subject's SSVEP. H-bridge dc motor drive circuit was implemented to adjust the attitude of the hospital bed and 15 subjects were invited to demonstrate the effectiveness of the proposed BCI based hospital bed control nursing system. Finally, they found average accuracy of 92.5% and an average command transfer interval of 5.22s per command [17]. Recently, also implemented a mental spelling system based on steady-state visual evoked potential (SSVEP), adopting a QWERTY style layout keyboard with 30 LEDs flickering with different frequencies. Previously, most of the mental spelling system had been implemented based on P300. Some recent approaches are on SSVEP [18].

In 2007 for Entropy-Based Epileptic EEG detection V. Srinivasan and his team had used Artificial Neural Network as the signal classifier [23].

IV. Performance of BCI techniques

QDA (Quadratic discriminant Analysis) classifier provides higher classification accuracy than AR, PSD, LDA, SVM, and KNN [11]. Multi-signature BCI did not increase performance and also there is not any negative impact of it [12]. To check the performance and accuracy of whole system they performed an experiment among 5 participants.

The participants were untrained but familiar with method of operating the system. Each of them was given three different tasks of typing a ten character phrase. All the participants performed the assigned tasks one by one and each one's accuracy rate was calculated. The accuracy rate was calculated by taking the percentage of correct characters in all three tasks. The average success rate was found 87% [13]. The highest information transfer rate (ITR) was obtained in the "rate controlled cursor" scenario which has an asynchronous protocol. In practical BCI could be operated at a high decision speed. In P300-based browser the fastest subject performed at an average speed of one decision every 1.7s. The most reliable performance achieved at the rate of only 2% of the total 200 trials in the rate controlled cursor were misclassified at an average speed of one decision per 2.1s [16]. The average accuracy was 87.58%, information transfer rate (ITR) 40.72 bits/min and letters per minute (LPM) found 9.39 letters/min, respectively.

The LPM of 9.39 letters/min obtained in this study was comparable with the best results previously reported in BCI literatures. From the online experimental results of the hybrid mental spelling system, it was confirmed that the hybrid mental spelling system could significantly reduce the total number of tapings, by preventing typing errors in advance. The 16.6 typing errors were prevented on average, demonstrating the practical feasibility of the hybrid mental typewriter. Sensorimotor activity is independent of any stimulation and can be operated at free will. The ITR is between 20 – 30 bits/minute. For a good performance multichannel EEG recordings are necessary. The average accuracy of target hits out of all the trials from the four subjects is 90.89 ± 3.39 and the average hitting time is at 2.57 ± 0.30 s [19].

From the training of the healthy subjects the average SCPs are found as the differentiation between negativity and positivity at the vertex was about 7μV and between horizontal lower panel SCPs the left and right motor cortex was about 5 μV. The normalized mean amplitude of ball movements for upward and downward conditions, respectively, which indicates the consistency of ball-movements in the particular direction. Out of 13 subjects participating in the single-session positivity-versus-negativity training attained significant SCP control. Most of them were able to produce significant positivity responses. Other generated significant negative and both kinds of responses in same percentages.

From the five subjects three participated in prolonged brain-asymmetry training demonstrated highly significant self-control over the asymmetry of SCP amplitudes between the right and the left motor cortex after 10–13 sessions. The point bi-serial correlations between SCP amplitude and direction of ball movement for one subject in the last three sessions were 0.65, 0.56, 0.48, respectively (all $P<0.01$). These correlations were 0.43, 0.60, and 0.47, respectively (all $P<0.01$) for another subject. Third subject showed 0.31, 0.37 and 0.40 correlation respectively (all $P<0.05$). The fourth subject who only took part in training sessions of six asymmetry also achieved a large asymmetry in the last two sessions (rpbis =0.19 and 0.17, respectively); But, this tendency did not reach the 5% significance level [20].

100 subjects were tested a P300- based BCI system to spell a 5-character word with only 5 min of training, there it was found that P300-based BCI systems were optimal for spelling characters with high speed and accuracy. 100 % accuracy showed 72.8 % of subjects for row/column speller (RC), while only 55.3% subjects showed 100% accuracy using single character speller (SC). Below the 3% of subjects did not spell any character correctly. Hence, RC paradigm showed superiority than SC paradigm [21]. From 10 subjects were used for multi-channel detection by using 1-s signal segments. The six different visual stimulation frequencies discriminated with an average 84 percentage of accuracy. It was fully online BCI [22].

Using Artificial Neural network for Entropy-Based Epileptic EEG detection the comparative better accuracy is achieved. A high overall accuracy values in the range 99.35% to almost 100% were achieved by using Elman networks (EN) for some combinations. The overall accuracy values obtained by EN for other combinations of the values at the range of 95.45% to 100%, which be also in the acceptable range of the clinical tests. It is calculated that for all the combinations EN performs better than Probabilistic neural network (PNN). May be as possible reasons for its superior performance were the feedback configuration and the incremental training process associated with the EN. For other input features the overall detection accuracy values obtained by the proposed method are also better than the value of 99.6% obtained with EN [23].

V. Conclusion

This paper shows some performance of BCI systems for different aspects by applying different techniques. Different techniques have given better performance for different types of BCI. Performance is measured by percentage of accuracy. The results show that a better performance can be achieved by using artificial neural network.

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