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Challenges in Design and development of EEG based BCI: A Review

Vaishali Kadam[1] , Dr. R. R. Deshmukh[2]

[1]*Department of Computer Science and I.T.*
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad (M.S.), INDIA

[2]*Prof. and Head Department of Computer Science and I.T.*
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad (M.S.), INDIA

Abstract: This paper proposes and creates a new generalised view towards BCI with its related application and recent challenges that can notice through the field of application of BCI e.g. designing the new local neural classifier for the recognition of mental tasks from on-line spontaneous EEG signals. The classifier may be embedded in a portable brain-computer interface called ABI, which has been evaluated with young healthy normal persons. Subject's performance is analyzed off-line and also online with the presence of proper bio feedback. Correct recognition is the challenge; modest rate is largely compensated by few properties of BCI wrong responses, and its decisions making ability with time factor. In this the subject and his/her personal ability and mental strength learn simultaneously from each other. Sometimes subject grasps it rapidly and so one of the subjects achieved excellent control over the system but few facing problems. Training to each subject is having a complex and individual independent challenge every time. How much the system or machine is convenient to the subject and how much the subject adopts to machine in just little training, making it time frequent and subject convenient is the challenge.

Keywords: BCI, EEG, LTEEG, ALS

I. Introduction

A brain-computer interface (BCI) system can provide a communication method to convey brain messages independent from the brain's normal output pathway [1]. Brain activity can be monitored using different approaches such as standard scalp-recording electroencephalogram (EEG), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), electrocorticogram (ECoG), and near infrared spectroscopy (NIRS). However, EEG signals are considered as the input in most BCI systems. In this case, Electroencephalography (EEG) is a technique of recordings brain signals.

As we know today most people facing health related problems caused by over tension and mental stress it affects the whole body neurons activities. In biological approach possibility to recognize a few mental tasks from online EEG signal and have them associated to simple commands and to be interactive to both man and machine communication. This communication device and whole the computerised channel is called a brain-computer interface [2] e.g. during right and left hand motor imagery can be used to move a cursor to a target on a computer screen. Such an EEG-based brain-computer interface (BCI) can provide a new communication channel to replace an impaired motor function. It can be used by handicap users with amyotrophic lateral sclerosis (ALS) and other brain related disorders some groups demonstrated that some subjects can learn to control their brain activity through appropriate, lengthy training in order to generate fixed EEG signal patterns or its relative auditions. A BCI system transforms EEG signals into certain external actions. In this rather than putting all the training effort on the subject if both the user and the BCI system adapt to each other in a very easy way Anderson's approach (1997) lies at the other extreme in that only the BCI is trained but the results are not so good as with the other approaches. In this related design approaches a new local neural classifier for the recognition of mental tasks from on-line spontaneous EEG signals. Most research have applied standard neural networks based on multi-layer perceptions skills to build EEG-based classifiers (e.g., Anderson, 1997; Penny and Roberts, 1999). Many other indicate that local neural classifiers are to be preferred and explored satisfactorily e.g. local adaptive classifiers based on neural networks (Kalcher et al., 1996). They use LVQ networks (Kohonen, 1997), which have failed in this case. This paper describes the scope for new local classifiers that achieves the best performances for all the subjects we have worked with. In particular, obstacle to the deployment of BCI systems is the acquisition of high-quality EEG signals in unshielded environments [3]. Brain-computer interfaces (BCI) are systems which enable a user to control a device using only his or her neural activity [4]. An important part of a brain-computer interface is an algorithm for classifying different commands that the user may want to execute. There are several neurological phenomena that can be used in a BCI. One of them is event related de-synchronization (ERD), which is a temporary decrease in power of the mu and beta brain waves. This phenomenon can be registered using electroencephalography (EEG) and occurs when a subject performs or imagines a limb movement [5]. The different motor imagery tasks, in which a user imagines a movement of one of the following parts of the body: left hand, right hand, both feet and tongue. The data and the classification task formulation.

Following are the challenges and fields that need more concentration with advance development skills and technologies:

A. *Computational Intelligence:*

In Neurophysiologic analysis and related diagnosis brain activities are important to consider as it is one of the important tool enabling to investigate various aspects of cognitive brain activities and its functions [6]. The relevance of electroencephalogram (EEG) in particular, due to its inexpensive and most importantly, non-invasive BCI data acquisition procedure, it reflects the medical applications and the diversity of areas of research studies it has contributed to embracing and linking inter related fields of Neuro-imaging, cognitive psychological investigation and neurophysiology among others. EEG is used more pragmatically in medical application and also support advance technical development.

B. *Uncertainty effects in EEG-based BCI:*

There are a large number of neurophysiologic factors that are used to determine the characteristics of transitions between complex cognitive brain states but consequently, electrophysiological signals generates inconsistent patterns due to a varying level of subject's awareness, mental status , motivation and fatigue among others (Wolpaw et al., 2002)[7]. Uncertainty as an inseparable feature of BCI operation it needs to be properly handled to develop practical and robust systems (Wolpaw et al., 2002). Effective handling of uncertainty effects, strongly reflected in EEG signals, has been recognised as a key challenge in BCI (Vaughan et al., 2003)

C. *Advance BCI automated device operators:*

New type of BCI systems are need to develop that are rapidly perform fast transition of various types of parameter estimation as well as classification algorithms to real-time implementation and testing. System needs to automate real-time experiments and perform the action between on-line experiments and offline analysis. [8].The system is able to process Multiple EEG channels on-line .The BCI can be controlled over the Internet, LAN or modem

D. *Learning to control brain activity:*

The skill of controlling a cursor with EEG activity can or should become fully automated. One possible advantage of an automated skill is that once it becomes automatic, it requires little or no conscious effort and may therefore reduce mental fatigue. Many times we are unaware of how and when our brain sends messages to our muscles, how the muscles work, in what order and so on. Despite being unaware of exactly how movements take place, they are under our control. They are, in other words, voluntary, even though they sometimes require little or no conscious effort or 'attention,' for example when riding a bicycle. The acquired skill of riding a bicycle, therefore, can be voluntary but automatic.

E. *Real-time Recognition of Noisy Signals to Knowledge:*

Real time classifiers are needed for the real-time recognition of signals in the time domain - in contrast to the established frequency domain methods. System need to be more efficient and expert to remove noise occur during recording a highly time frequent classifier and noise detection techniques are needed to support accuracy and success rate of BCI system.

F. *Advance LTEEG monitors Designing*:

Long-term EEG (LTEEG) monitoring device is used to closely monitor patients over extended periods, which have relatively infrequent but recurring a typical "turns" or seizures patient. LTEEG monitoring comprises continuous multichannel EEG and video recording over several days. This allows the seizures to be "captured" for in-depth off-line analysis.

G. *Extended Multichannel communication BCI systems Designing:*

Whatever BCI currently used are just support few communication channels that make possible the interface between user and the machine but sometimes subject's low response rate of interface is not proper due to complex mental situation in such cases with EEG signal pattern recognition other channels are used to collect the data for further processing.

H. *Hybrid Brain-Computer Interface Systems*

Research activities and different types of studies related in brain-computer interface (BCI) systems that show potential in this research area. Research teams have studied features of different data acquisition techniques, brain activity patterns, feature extraction techniques, methods of classifications, and many other important componenets of a BCI system. it is observed that the conventional BCIs have not become totally applicable, due to the lack of high accuracy, reliability, low information transfer rate, and user acceptability. So a new approach suggested to create a more reliable BCI that takes advantage of each system is to combine two or more BCI systems together with different brain activity input signal. This hybrid BCI may reduce disadvantages of conventional BCI system. This hybrid BCIs may useful in various different areas of applications and automatically increase the accuracy and the information transfer rate.

II. CONCLUSION

Most of the previous attempts of recognition with the use of EEG signals are mainly focused on collecting data from the autonomic nervous system but they having low accuracy of classification using EEG signal only. This paper suggest the dual side approach towards the advance multi modal design and implementation of hardware BCI devices as well the software BCI tools to create a wonderful real time neurophysiology efficient response from both the user and machine to generate more accurate brain status so that it support the medical application which is time as well cost efficient and also having great challenges and scope for BCI system implementation.

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