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EEG Signal Processing Based on Multiclass Brain-Computer Interface

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ABSTRACT: Over the past 20 years, the relatively new field of brain-computer interface (BCI) research has experienced an increase in attention and publications. Direct human-computer connection is made possible by brain-computer interfaces (BCIs), which eliminate the requirement for muscular involvement. Variabilities between subjects and sessions present a significant difficulty for brain computer interface (BCI) systems that rely on electroencephalograms (EEGs). Furthermore, because there are so many channels involved, high dimensional EEG montages add a significant computing overhead. Designing a BCI-based upper-limb rehabilitation program for stroke patients may benefit from the detection of numerous directional motions. Numerous characteristics gleaned from EEG recordings have shown themselves to be sufficiently distinct between people for use in biometric applications. Brain computer interfaces (BCIs) often use multichannel EEG, where EEG channel selection is performed which improves the following 1) enhances user convenience through the use of fewer channels, and 2) improves BCI performance by eliminating unnecessary or noisy channels. This project looks on two experimental variations of EEG dynamics during motor imagery (MI) tasks, namely inter-session and inter-subject. Specifically, the impact of daily fluctuations in EEG dynamics during cognitive stage changes on BCI performance is investigated. In the context of classifying single trial multiclass MI tasks, this project describes how offline BCI results differ as a result of inter-subject and inter-session variabilities. The viability of creating calibration-free BCIs within subjects with similar sensorimotor dynamics is demonstrated by the suggested inter-subject BCI.

KEYWORDS: EEG, ANN,BCI, SVM

I. INTRODUCTION

Without causing any muscle contraction, the Brain Computer Interface (BCI) can be thought of as a direct line of communication between the brain and the computer. It makes it possible for people with physical disabilities, such as tetraplegia, to operate an artificial limb or communicate with a computer. Among the other uses of BCI are mood evaluation, brain-to-brain interface (BBI), lie detection, and brain fingerprinting.

Electrocorticogram (ECoG), functional Near Infrared Spectroscopy (fNIRS), functional Magnetic Resonance Imaging (fMRI), Magnetoencephalogram (MEG), and Electroencephalogram (EEG) are among the invasive and non-invasive methods used for signal acquisition. The latter relies on noninvasive electrode montages to record brain electrical activity from the scalp. Although a multichannel EEG signal offers rather strong temporal resolution, inter-session and inter-subject variabilities have a significant impact [17].A Brain Computer Interface (BCI) provides a non-muscular method of operating a device by measuring, analyzing, and decoding brain signals. Therefore, brain-computer interfaces (BCIs) allow people with severe movement limitations to communicate and control themselves using their brain signals. Because EEG is less expensive and has a higher time resolution than other modalities like fMRI and fN, it is typically used in BCI applications to measure brain signals.

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First, a Butter worth filter of order 10 is used to filter the raw EEG data using a band pass filter (8Hz to 40Hz). Next, any one of the three spatial filtering methods—CSP, RCSP, and J JAD—is applied.

II. RELATED WORK

Brain Computer Interface (BCI) analyzes brain activity by measuring the chemical changes from human's brain. The measurement method of brain activity is used in Functional Near Infrared (FNIR), Functional Magnetic Resonance (FMIR), Electroencephalogram (EEG)[6].
Brain-Computer interfaces (BCIs) are systems that enable brain activity to manipulate external devices. One type of BCI is the non-invasive BCI, which acquires brain signals from scalp Electroencephalography (EEG), for example. EEG is a technique in which electrical potentials produced in the brain are recorded with high temporal resolution. The EEG is able to record rhythmic electrical activity from the human scalp.
Related literature reviews are presented in table 1.

Table 1: Related literature reviews

REF. NO.	PURPOSE	ALGORITHM	CONCLUSION	FUTURE WORK
01.	Emotion recognition.	Empirical mode decomposition (EMD)	To detect emotion form non stationary EEG signals.	Advanced properties of EMD.
02.	To locate the best time window in EEG signals.	Filter Bank Common Spatial Patterns (FBCSP)	Modification of the FBCSP algorithm.	Intend to combine FBSCP with other feature extraction techniques.
03.	To improve peoples quality of life in their daily activities.	Brain Computer Interface(BCI)	First bi bliometric study of the BCI literature.	To explore the growth of BCI literature,
04.	Upper-limb rehabilitation system for stroke patients.	Wavelet Common Spatial Pattern W-CSP)	Regularized wavelet-CSP method for classification of movement directions.	Extend the CSP feature extraction in sensor domain to source domain.
05.	Estimate grasping patterns from EEG data.	EEG data	Extract features from EEG data by CSP filter.	Required to investigate difference between features from EEG data.
06.	Designing on portable wireless EEG device.	Functional Near Infrared(FNIR)	Low power consumption is critical.	Reduce system power with the proper selection environment.
07.	Demonstrate to improve the system performance	EEG	Hand and foot iamgery movement etc can be extracted.	Focus on extracting maximum possible information from EEG signal.
08.	Recorded from left and right hand during MI.	Time Delay Fractal Dimension (TDFD)	Strong influence in the accuracy and speed of processing.	Apply in a BCI application to move two robotics hands.
09.	Skin temperature variation and	KNN	Real-time EEG-based BCI System for attention recognition.	To measure a human subjects attention level.

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	electrodermal activity.			
10.	Minimizes the number of channels.	Sparse Common Spatial Pattern (SCSP)	Solving an optimization problem. .	Improves BCI performance by removing noisy channels.
11.	Easy to find out performance of BCI.	Linear Discriminate Analysis (LDA)	Much higher and consistent MI task detection accuracy.	Exposes a propitious technique for detecting different brain states
12.	Simulation of realistic usage of BCI .	Common Spatial Patterns (CSP)	Performance is better compared to the primitive model.	Improving the sub window parameter tuning process.
13.	Identification and quantification of relevant frequency patterns in MI.	YuleWalker algorithm	Sets representing entire BCI trials has been evaluated offline.	The extensive complementary online analysis.
14.	To measure the depth of anaesthesia (DOA) during operation.	Multiscale entropy (MSE)	Artifact reduction.	Remove the artifacts from EEG signals for monitoring DOA accurately.
15.	It is used to evolve linear classifier.	Random Hill Climbing(RHC)	CMA-ES can be effective in the solution of BCI.	Required to investigate the potential implications.
16.	Processing and classification of brain signals with respect to motor action .	Constraint Induced Movement Therapy (CIMT)	Development of new cerebral cortex pathways.	Emotiv BCI can generate the PSD plot of any channel.

III. PROPOSED METHODOLOGY

The generic overview of the proposed algorithm is shownin Block Diagram. Firstly, the raw EEG data are filtered by Band pass filter(8Hzto40Hz) using a Butter worth filter of order10. The selection of this frequency range comprising two important MI-related EEG waves, i.e., alpha (8-13Hz) and beta (13-30Hz) , was based on a study carried out on the same dataset, that has implicated 8Hz40Hz as a suitable band for CSP-based feature extraction. Then, any one of the three different spatial filtering techniques, i.e., CSP, RCSP and JAD is applied to extract spatially discriminative features for four MI tasks, i.e., Left/Right-Hand, both Feet and Tongue movement. For each of the four classes, two optimal spatially filtered components are chosen correspondingly which result in eight optimal spatially filtered components altogether for four classes. From each of the eight optimal components, wavelet decomposition (using Daubechies db3 basis) based sub band energy and sub band entropy up to level 3 are extracted.

IV. RESULT AND ANALYSIS

Results and discussions are presented in this chapter. The acquired EEG signals for different motor activities are presented first. Next identification of artifacts in EEG signals and removal of artifacts are presented using the signal processing techniques of EMD and the extensions, EEMD and MEMD. Excessive EEG channels introduce high computational latencies and effect of outliers, which cause burden for on-line BCI implementation and degrade its performance, respectively. We have previously addressed the comparison of computational latencies in different cases while considering different number of channels. The following figures indicates different waveforms that are obtained during the process.

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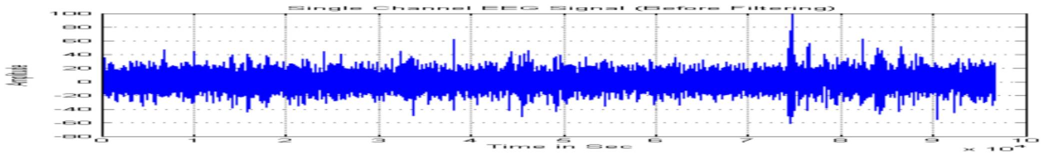

Figure 1: Single Channel EEG Signal

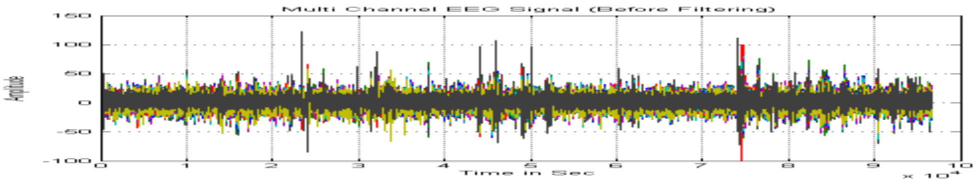

Figure 2 Multi Channel EEG Signal

The recorded EEG data is shown in figure 1 that is single channel EEG signal and figure 2 that is multi channel EEG signal both signals are consists of noise. That noise is noisy data, to eliminate noise use filter. That is band pass filter .

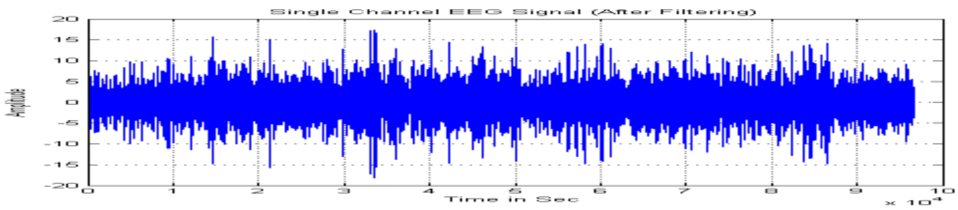

Figure 3 Single Channel EEG Signal (After Filtering)

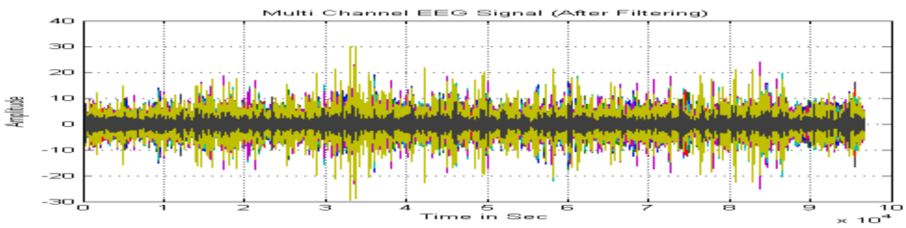

Figure 4: Multi Channel EEG Signal (After Filtering)

When filtering is done, the output of signals are shows in figure 3 and figure 4 that are single channel EEG signal and multichannel EEG signal respectively .The feature is extracting when the frequency range is 8 to 12 and 14 to 30. Next load the data, here we have to load the training (Tr) and test data (Ts), different class is labeled by different label sampling rate 250Hz.

Here A01T .mat is the training data and A01E. mat is testing data training data is lablled by class 1 and testing data is labeled by class 2, taking testing signal input to training signal and then calculate the accuracy. Here figure 7 and figure 8 are shown that class 1 EEG signal and class 2 EEG signal respectively. In the for loop when j=1 and i=1 for band pass filtering for training data is done.

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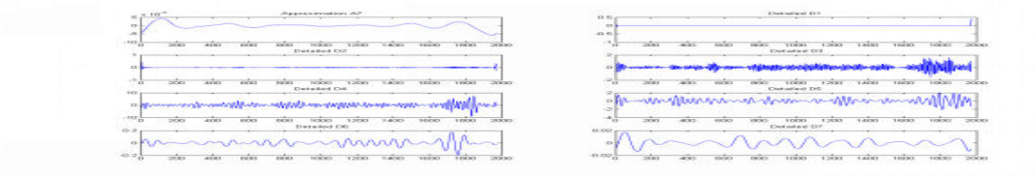

Figure 5 Class 1 decomposed EEG Signal using wavelet

DWT it means discrete wavelet transformer, from this EEG raw data is decomposed [different sub band feature extraction], dwt using because of in signal consist of α, β those are useful importance are there, these are helpful for analysis accuracy calculation. Figure 9 shows that class 1 decomposed EEG signal using wavelet. Next calculate the CSP projection matrix, next we have to train the classifiers on training data. Here mdl is the trained model it is used for classification. Input are train X is train religial value and train Y corresponding trained labeled values. Here we use "Naive-base classifier". Label (1)is algorithm result, when label and test data is same, then it gives 100% accuracy. Finally the result analysis of the project as shown in the table 2

V. CONCLUSION

In the context of classifying single trial multiclass MI tasks, this research describes how offline BCI results differ as a result of inter-subject and inter-session variabilities. The viability of creating calibration-free BCIs within subjects with similar sensorimotor dynamics is demonstrated by the suggested inter-subject BCI. This study is unable to determine the sources of the variabilities since the given dataset lacks prior secondary information. To fully comprehend the causes of these variations and the brain bases that correspond to them, a longitudinal research can be conducted. Comprehensive experimental facilities are necessary for real-time implementations of the suggested approaches, which we view as future work.

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