CLASSIFICATION OF MOTOR IMAGERY SINGALS BASED BRAIN COMPUTER INTERFACE

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ABSTRACT:

Brain computer Interfacing (BCI) is an emerging topic used in a wide range of fields from gaming machines to health aids. BCI technology aims to establish a direct communication path between the user's brain and any electronic device. A major challenge in building the MI-BCI system is to produce robust, informative and discriminatory features that can be converted into device commands. Automotive imaging is a BCI method in which the user's imagination of a leg movement is acquired without actual physical movement. Among the various BCI strategies, automotive images are the most popular BCI operating system due to its functionality and being an independent BCI system. Typically, the electroencephalogram (EEG) is used to detect motor image signals as it is an effective, cheap, fast and non-invasive method of analyzing brain signals. The objective of the project is to develop a method for classification of movement / imagery of a motor imagery signals and to build the classifier model to get better performance. For this purpose, existing methods and proposed methods is going to be introduced and their phased performance will be analyzed. The CSP will be embedded in class distortion which may be a hindrance to the EEG signal coordinating.

***Keywords**:* Motor Imagery-Brain Computer Interface, EEG Signals, Machine Learning (ML), Classify motor imagery signals, Build classifier model, Common Spatial Pattern (CSP)

INTRODUCTION:

Brain of the humans is the central control center for regulating and body functions in the humans. Our brain produces each idea, emotions, storage, training or activity and its weight is about 1.4 kgs, a tissue mass holds almost billions of nerve cells called neurons. Every nerve cell will connect with huge number by means of small constructions called neurotransmitters. Likewise, the example and power of the associations is continually swapping and make difficult by tracking down 2 minds the same. Brain can be thought as a CPU (central processing unit) of an electronic gadget wherein central processing unit sees that external society contains different detectors like conditions detector, optical lens or amplifier data where accomplishing actual activities contains servo engines, speechmakers or

LEDs. The wave is sent in the middle of the central processing unit and fringe through conductivity that follows, like fringe axon. Be that as it may, sometimes, for example ALS (amyotrophic lateral sclerosis) disorder, that way in the middle of the cerebrum and fringe appendage might be smashed and mind no longer have the capacity to govern the appendages. Subsequently, an elective way in the middle of the external society and the mind looks good on fundamental (Brain Computer Interface) is a control and communication component in the middle of the client and the framework. As indicated by its unique clarity, Brain Computer Interface is a control and communication framework that doesn't pivot on any capacity on the mind's ordinary neuro-muscular yield channel [1]. Clearly, CI framework provides the client capacity to transfer oppressive orders to a computerized gadget and for an impaired individual to utilize computerized gadgets. To maintain a BCI framework appropriately, the client ought to create distinctive mind actuation wave for various orders. While breaking down the cerebrum signs of the client and changing it over to a yield gadget called neuro-prosthesis, a BCI framework makes an immediate connection in the middle of the contemplations of the client and external society. In 1999, the primary worldwide BCI innovation meeting coordinated, a BCI framework is. characterized as a "control channel and communication in the middle of the mind and the PC that doesn't rely upon the cerebrum's ordinary yield networks of fringe muscles and nerves". Electrodes acquire the brain signals and prepared to separate explicit wave elements that mirror the client's aim. Those provisions were converted to orders which work as gadget

3.METHODOLOGY:

3.1. DATASET

The BCI competition IV dataset I, which includes hypothetical left and right-hand movements, was employed in our experiment. The people in these datasets were in good health. Motor imagery was used throughout the entire session without any kind of feedback. Two motor imagery courses—one for each subject's left hand, right hand, and foot movement—were chosen from the three classes. There were five hundred and nine EEG channels collected. During the first two runs of the calibration data session, arrows pointing down and left were displayed on a computer screen as visual signals. The cued motor imagery exercise had to be completed by the individual during a 4-second cue display time. Four runs of evaluation data were conducted, and the results were used to assess the competition submission.

Hemispheres left and right make up the skull. On the left are all the electrodes with odd numbers

Even numbers belong in the right hemisphere. Left motor movement imagery is represented by signals gathered from odd electrodes, and right motor imagery is represented by signals gathered from even electrodes.

motion. For instance, the left-hand movement signal from the C3 electrode is used, while the right-hand movement signal from the C4 electrode is used. Reference electrodes are those with a "Z" subscript. Here, the reference electrode is Cz. the recorded EEG signal with a 100 Hz sampling rate. Next, the signals are filtered in the 0.5–30 Hz frequency range using a band-pass filter. Before using the feature extraction approach, the signals are first preprocessed to eliminate artefacts and additional procedures.

3.2. METHOD

Brain activity is detected and translated into a command for the controlled device in a brain computer interface. There are numerous methods for determining the brain's activity, including electroencephalography (EEG), positron emission tomography (PET), magnetoencephalography (MEG), and functional magnetic resonance imaging (FMRI). Our method of choice for obtaining brain signals is through EEG signals since they require relatively simple and affordable equipment and have a shorter reaction time. The EEG signals utilized in our experiment were taken from the BCI competition dataset.

3.2.1. PRE-PROCESSING

Acquired EEG signals are chosen among channels, frequencies, and times in the preprocessing approach based on motor imagery information. EEG signals require amplification in order to be compatible with the device because of their low voltage variation. Get rid of the noises from the beginning. According to their respective frequency bands, EEG signals are classified into several rhythms, such as delta (up to 4 Hz), theta (4 to 8 Hz), mu/alpha (8 to 12 Hz), beta (13 to 30 Hz), and gamma (above 30 Hz). Both the mu and beta rhythms are used in motor imagining activities. Brain rhythms known as mu and beta are the subject of event-related desynchronization (ERD) and event-related synchronization (ERS). The dataset contains mu and beta rhythms, which is why a band-pass filter is used to filter the data.

3.2.2. FEATURE EXTRACTION

In order to meet the Fisher's requirements, this method is utilized to transform the time domain signal from the EEG into a feature set vector, which is the defined space with high inter and low intra class dispersion. Many features are used in the context of BCI, including time-frequency features, log-variation algorithm, band power, PSD (power spectral density), and CSP (common spatial filter).
PSD is an excellent tool for narrow band and stationary signal processing. This is a widely used technique in signal processing that shows the strength of energy as a function of frequency and attributes signal power over frequency. It's critical to place the response at frequency steps close to the neutral structure for accuracy.

The spatial filter is designed so that the filter data variance is maximized in one class step and then minimized in other class step. The result features by maximizing the inter variance and minimize the intra variance. The attribute of CSP makes it an effective spatial filter which is used to classify the MI tasks using multichannel selection. The first CSP-based spatial filter was implemented in to

effectively classify movement-related EEG for BCI implementation.

3.2.3. CLASSIFICATION

In order to raise the Fisher's criteria, this method is utilized to transform the time domain signal from the EEG into a feature set vector, which is the defined space having strong inter and low intra class dispersion. Many features are used in the context of BCI, including time-frequency features, log-variation algorithm, band power, PSD (power spectral density), and CSP (common spatial filter).
PSD is an excellent tool for narrow band and stationary signal processing. This is a widely used technique in signal processing that shows the strength of energy as a function of frequency and attributes signal power over frequency. It's critical to place the response at frequency steps close to the neutral structure for accuracy.

4. DIAGRAMATIC REEPRESENTATION:

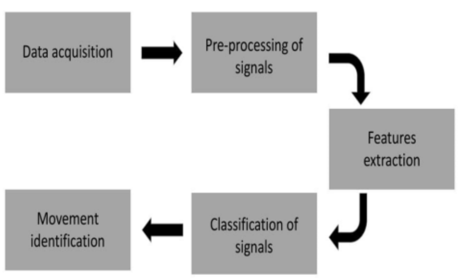

FIGURE 1. Block diagram for singal identification.

RESULT AND DISCUSSION:

TABLE 1. Classification accuracy by k-fold cross-validation method for the proposed method.

Subjects	k-fold cross validation accuracy (%) (mean)	
	118 channels	30 channels
aa	92.42	94.23
al	90.60	92.36
av	90.58	93.75
aw	91.79	93.56
ay	94.45	96.98
Average	91.96	94.17

TABLE 2. Values of TP, FP, TN, FN of confusion matrix, accuracy (%) and κ score of the proposed method of various folds

k-folds	Confusion Matrix				Accuracy (%)	κ score
	TP	FN	FP	TN		
k=1	800	43	39	798	95.11	0.90
k=5	807	39	32	802	95.77	0.92
k=10	805	40	34	801	95.59	0.91
Average	**804**	**41**	**35**	**800**	**95.47**	**0.91**

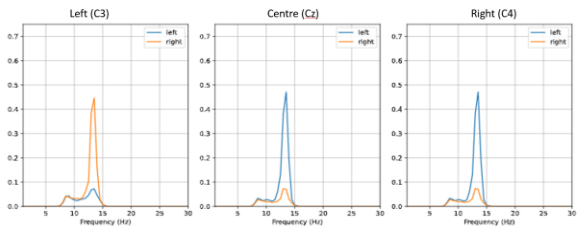

FIGURE 2. PSD plot of the Common Spatial Pattern (using Spatial Filters)

CONCLUSION:

BCI is an emerging technology used in a wide range of applications from gaming machines to health care equipment. Among the various types of BCI methods, MI is a popular theory that analyzes the user's motor movement without physical activity. The main reasons for its popularity are non-invasive and are classified as BCI independent of conventional brain ducts such as peripheral nerves in any way. These factors have led the literature to focus on researching BCI-based BCI systems and developing MI signal separation methods. Separating the MI signal is not an easy task. Frequency bands with MI signals, strong alpha waves from the occipital region are seen in the motor cortex. Less subject variability of local features of MI signals makes automated classification algorithms important. Location filtering is simply a combination of line EEG signals obtained from different EEG electrodes over the head. The CSP algorithm is the most popular way to filter area that calculates location filters by analyzing EEG input data. The CSP becomes embedded in class distortion which may be a hindrance to the EEG signal. The separation of a motor imagery in real time using advanced algorithms can be considered as a target alternative. However, real-time separation of a motor imagery is not an easy task. The advanced real-time algorithm should detect motor imagery on the plane without important information such as test-based image classification

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