ANALYSIS OF EEG FOR MOTOR IMAGERY BASED CLASSIFICATION OF HAND ACTIVITIES

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ABSTRACT

EEG based Brain Computer Interface (BCI) establishes a new channel between human brain and the surrounding environment in order to disseminate instructions to the outside world. It is based on the recording of temporary EEG changes during different types of motor imagery such as imagination of different hand movements. The spatial pattern of activated cortical areas during motor imagery is similar to that of real time executed movement. Time domain features and frequency domain features are extracted with emphasis on recognizing discriminative features representing EEG trials recorded during imagination of different hand movements. Then, classification into different hand movements is carried out.

KEYWORDS

EEG motor imagery, Brain Computer Interface, event-related desynchronization (ERD), wavelet transform

1. INTRODUCTION

Patients in a late stage of amyotrophic lateral sclerosis (ALS), severe neuromuscular disorders and those paralyzed from higher level spinal cord injury are not able to produce any voluntary muscle movements. Sensory and cognitive functions are only minimally affected by such diseases. Communication based on EEG signals does not require neuromuscular control and the individuals who have no more control over any of their conventional communication abilities may still be able to communicate through a direct Brain Computer Interface (BCI). EEG recordings during hand motor imagery can be used as control signals for BCI applications like cursor control, selection of letters or words, control of prosthesis, navigation of wheelchair, etc.

Such systems will increase the disables' independence, leading to an improvement in quality of life and reduced social costs. A lot of other techniques can monitor brain activity like functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG), Positron Emission Tomography (PET) and Single Photon Emission Computer Tomography (SPECT). Although fMRI, PET and SPECT are more accurate and have better spatial resolution than EEG, they are not candidates for BCI applications because, due to their large size, heavy weight, they cannot act as portable devices. EEG, on the other hand has better temporal resolution, is portable and cost effective

Motor imagery is defined as imagining a motor action without any efferent information to neuromuscular system. Thoughts and actions are intimately linked. A confirmation of this prediction is found in the spatial patterning of activated cortical areas seen with functional brain imaging techniques such as PET and fMRI.

Studies have shown that when the subject performs or even imagines limb movement, specific frequency components of EEG such as mu and central beta rhythms are (de)synchronized over contralateral (ipsilateral) sensorimotor area.EEG recordings during left and right motor imagery can be used as control signals for a BCI.

Athena Akrami et al (2005) extracted quantitative changes in EEG due to movement imagination. The features extracted are logarithmic power of different frequency bands of EEG which are extracted from various combinations of channels [1].

Xiu Zhang and Xingyu Wang (2008) used Canonical Variate Analysis (CVA) for classification of mental imagery. Temporal features are extracted as squared band pass filtered EEG and frequency features are extracted as energy in specific rhythms. Features in time and frequency domains are projected into canonical discriminant spatial feature space and classification was done with Support Vector Machine [2].

Pawel Herman et al (2008) conducted a comparative study of spectral approaches and quantified relevant spectral content. Features were extracted from a variety of techniques like atomic decomposition, quadratic energy distribution, wavelet packets, Discrete Wavelet Transform and AR model. They concluded that the effective spectral method is subject specific. Few cases of techniques achieve good performance in one subject and poor performance in another one [3].
Kavitha P.Thomas et al (2009) proposed a new discriminative filter bank common spatial algorithm to extract subject specific frequency bands using Fisher ratio of filtered EEG signal from channels C3 or C4. Classification was done using Support Vector Machine [4].

In our work, multi-dimension feature extraction is done. Features are extracted using Discrete Wavelet Transform, FFT Power Spectrum, Event Related Desynchronization (ERD) and classification is done using Back Propagation Neural Network.

2. METHODOLOGY

Forty healthy volunteers mostly aged between 20 and 25, participated in the study. The subjects are seated in a relaxing chair with armrests, approximately 100 cm from a computer screen. Prior to the experiment, each subject is given the opportunity to practice and perform actual movements of the hand. Electrodes are positioned according to the international 10-20 system. The motor imagery EEG signal is predominant in sensorimotor cortex, corresponding to electrode positions C3 and C4. The block diagram is shown in Figure 1.

The recordings are made with 32 channel RMS EEG machine. The EEG signal is sampled at 256 Hz. Higher frequency can be seen as noise caused by muscle activity, blink of eyes and other noises. It is filtered between 1 and 35Hz with Notch filter ON. It is possible to set the sensitivity, filter cut-off frequencies for each channel individually.

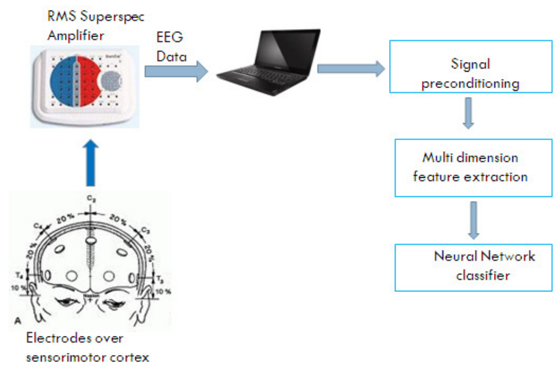


Figure 1. Block Diagram

2.1. Experimental paradigm

The experimental paradigm decides the environmental conditions in order to prompt the user to generate the controlling EEG activity.

Two different experimental paradigms are followed. One is using auditory cue and the other is using visual cue. The task is to perform left hand or right hand imagery according to the cue. Subjects are explicitly instructed to imagine the kinesthetic sensation of movement and not to imagine mere visualization of movement. The order of cues is random. The experiment consists of several runs with 12 trials each after each. Each trial lasts 20 seconds.

In the case of auditory cue, the subject is instructed to keep eyes closed. In this type of cue, there is no problem of EOG artifact. The EEG signal is elicited by having the subject executing different mental tasks such as imagination of left hand or right hand movement in response to the pre-recorded instructions, while remaining in a totally passive state. During execution, subjects are asked to perform only mild movement and not overt movement. The timeline of the trials is illustrated in Figure 2. The EEG activity of the rest period from 1-4 seconds is used as a baseline for subsequent analysis of the mental tasks.

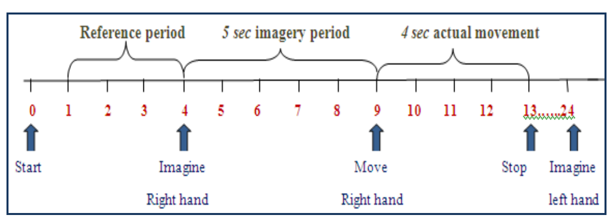


Figure 2. Auditory Cue

In the case of visual cue, arrows are used to indicate the imagination tasks to be performed (left vs. right arm movement imaginations). The timeline of the trials is illustrated in Figure 3. After trial begins, the first 3s are quiet, at t=3s an acoustic stimulus indicated the beginning of the trial, and a fixation cross "+" is displayed, which remained on screen for the rest of the trial period. The subjects are instructed to focus their gaze and attention at the centre of fixation cross. An arrow indicating the direction of the imagination task appears 3 seconds after the cross is made visible. The arrow remains on screen for 4 seconds, i.e. for the duration of the imagination period which starts at the appearance of the arrow. When, the arrow disappears, the subject instructed to perform actual movement. Blinking and swallowing are permitted only during rest time.

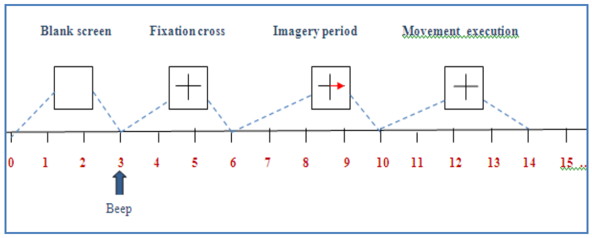


Figure 3. Visual Cue

2.2. EEG Referencing and Preprocessing

Three types of EEG referencing methods are adopted in this study, namely unipolar signals (signals with respect to ear reference), bipolar signals and Surface Laplacian (SL) filtered signals. The advantage of using unipolar is that, it localizes event of interest and that of using bipolar is that, it reduces shared artifact like ECG.

All the trials are visually checked for EEG artifacts during the movement imagery period. Hand movements during imagination period or EOG activity are omitted from further analysis. Eye blink is said to have occurred if change in magnitude of greater than 100 µV occurred within 10 ms period. EMG artifact may occur as a result of muscles that lift eyebrows, close the jaw. All the signals are filtered using a digital butterworth FIR band pass filter in the range 8-30 Hz because the mu band and central beta band fall within this range.

2.3. SL Estimation

Raw EEG scalp signals are known to have poor spatial resolution due to volume conduction effect. Only half the contribution to each scalp electrode comes from sources within 3 cm radius. This is in particular a problem if the signal of interest is weak like the sensorimotor rhythms. Surface laplacian (SL) method is superior to the ear reference method, because it is a high pass spatial filter, which uses linear combination of simultaneous input samples. It favours signals originating from hand areas over signals that originate from other areas. It takes the difference between target electrode and several electrodes that surround it i.e. between C3 electrode and its neighbouring electrodes and between C4 and its neighbouring electrodes. A low resolution SL computation needs a total of 9 electrodes whereas a high resolution SL computation needs 26 electrodes. In this work, data is collected from F3, F4, T3, T4, C3, C4, CZ, P3, and P4 of the international 10-20 system for SL computation. However there is an acceptable correlation between the two and hence a low resolution SL transform is applied to the acquired signal [5].

3. Feature Extraction

The signals are processed to extract distinct features. For this purpose, Multidimensional feature extraction is carried out. i.e. Features are extracted from both time domain and frequency domain for all three types of recorded signals namely raw, bipolar, SL filtered signals. The techniques used are ERD quantification, FFT Power Spectrum and Discrete Wavelet Transform.

3.1. ERD Quantification

Pfurtscheller and Aranibar first quantified event-related desynchronization (ERD) in 1977. Event Related Desynchronization (ERD) is a reduction of a specific frequency component and is related to an increase in neural activity. Event Related Synchronization (ERS) is an increase in a specific frequency component and is related to neural suppression. This technique is based on the assumption that if an assembly of neurons engaged in the same process works synchronously in frequency, the power at this frequency increases [6]. When EEG signal is recorded from sensorimotor area, alpha rhythm is called as Mu rhythm.

Movement or preparation for movement is typically accompanied by a decrease in mu activity over, specifically contralateral to the movement causing ERD. It's opposite, rhythm increase or "event-related synchronization" (ERS) occurs in the post-movement period and with relaxation. Thus, ERD and ERS can occur independent of activity in the brain's normal output channels of peripheral nerves and muscles, and can thus, be used as the basis for a BCI.

Steps to compute the time course of ERD are as follows:

1.Bandpass filtering of all event-related trials.
2.Squaring of the amplitude samples to obtain power samples.
3.Averaging of power samples across all trials
4.Averaging over time samples to smooth the data and reduce variability

ERD is quantified as percentage EEG power decrease or increase within specific frequency bands.

$$ERD\% = \frac{A-R}{R} *$$

where A is the power within the frequency band of interest i.e. mu band and R is the power of reference interval before the warning beep.

Figure 4. shows ERD% wherein during right hand imagery, at the contra-lateral (left) sensorimotor cortex there is a reduction in power when compared with baseline period. During right hand movement imagery, in the imagery period from 5-9s there is an attenuation in the C3 component when compared to C4.Features are obtained from this 5 to 9 second imagery period. A feature vector is constructed by taking the average ERD% for every second. For each channel, there are 4 ERD features. Thus, a total of 8 ERD features are obtained.

Figure 4. ERD%

3.2. Power Spectrum

The time domain signals obtained from EEG amplifier reflects only one side of EEG. For precise analysis, we need to look at the signal in the frequency domain. In the frequency domain, ERD is characterised by a reduction in the power spectrum corresponding to mu band in the contra-lateral cortex.Different segments of EEG like baseline, imagery and actual movement are analysed.

It is observed that the pattern of mu band spectrum of movement imagery is similar to that of actual movement. There is a difference only in terms of magnitude i.e. peaks of mu rhythm are higher in imagery than movement. This is illustrated in Figure 5. The actual movement spectrum depicted in green colour has reduced amplitude than the imagery spectrum.

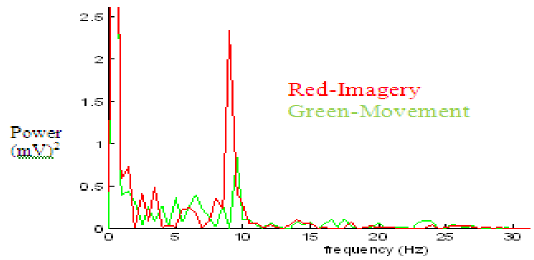


Figure 5. Power spectrum of movement vs imagery

Planning for movement leads to a short-lasting circumscribed attenuation in the mu rhythm. Hence, during right hand imagery, in the channel C3 imagery power spectrum, the 8-12 Hz component is attenuated when compared to the baseline. This is evident in Figure 6.

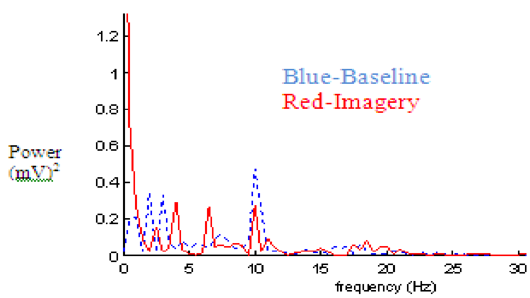


Figure 6. Power spectrum of baseline vs imagery

In right hand motor imagery, peak value of PSD is lesser in C3 than C4. This is depicted in Figure 7.In the case of left hand imagery, peak value of PSD is more in C3 when compared to C4.
The figures plotted are for the same subject. The location of the mu peak tends to vary from person to person. Generally it varies between 8 and 12 Hz. For the subject shown here it is observed that the characteristic peak is around 9 Hz.

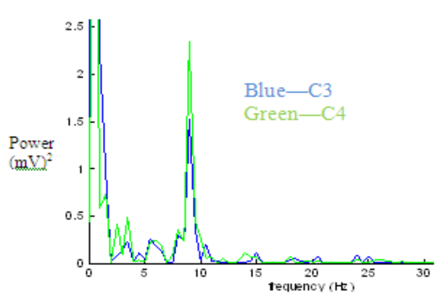


Figure 7. Power spectrum for right hand imagery

Motor imagery period of 4 sec length i.e. from 5th second to 9th second of the trial is considered for processing. The power values in the spectrum are averaged together in groups defined by frequency ranges to yield power in the mu and central beta bands since motor imagery information is available only in these bands. The features extracted are alpha and central beta mean values of C3 and C4 signals and also the relative alpha power percentage and beta power percentage are considered.

For each type of signal i.e. unipolar, bipolar and SL signal, the above mentioned features are considered. While recording EEG itself, the subjects are asked to perform actual movements. From the classification point of view, only imagery and baseline data are needed.

3.3. Discrete Wavelet Transform

Wavelet, which is called a mathematical microscope for analyzing signals, has the ability to analyze signal which is localized in time domain or frequency domain. EEG signal's non-stationary and transient characteristics make it difficult to extract the exact characteristics of EEG through the ordinary spectrum analysis methods. The wavelet transform decomposes a signal into a set of functions obtained by shifting and dilating one single function called mother wavelet.

$$|W_f(a,\tau) = \frac{1}{\sqrt{a}} \int_R f(t)\Psi^*\left(\frac{t-\tau}{a}\right)dt$$

In wavelet analysis there are the low frequencies, high scale component of the signal-approximation coefficient A and the high frequency, low frequency component - detail coefficient D. The hierarchically organized wavelet decomposition scheme is illustrated in Figure 8.

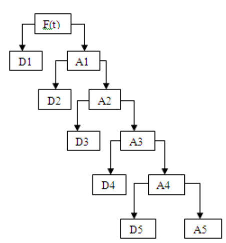


Figure 8. Wavelet decomposition

3.4. DWT of EEG

Daubechies6 wavelet is chosen as the wavelet base. Db6 is a 6 band orthogonal wavelet. The sampling frequency of the EEG data acquisition unit is 256 Hz. The number of levels of decomposition is chosen based on the dominant frequency components of the signal. We chose the level as 5. As a result, the EEG signal is decomposed into detail coefficients D1-D5 and approximation coefficient A5. D5 coefficients correspond to alpha band and D4 coefficients correspond to central beta band. The 1280 points of raw EEG data are considered in wavelet transform.

3.5. EEG Feature Selection

The wavelet decomposed sub-bands are illustrated in Figure 9.It shows the decomposition of both C3and C4 signal for right hand motor imagery. The above analysis shows that there is an obvious difference between the two signals at the level of D4 and D5.The C3 component has reduced magnitude when compared to the C4 component.

The Statistical features are extracted from the sub bands corresponding to alpha and central beta waves. The features considered are the mean of the absolute value of wavelet coefficients and standard deviation of the relevant sub band coefficients– D4 and D5. These features represent the frequency distribution and the amount of changes in the frequency distribution. Thus, for each channel, 4 features namely mean and standard deviations corresponding to alpha and beta sub-bands are extracted as features.

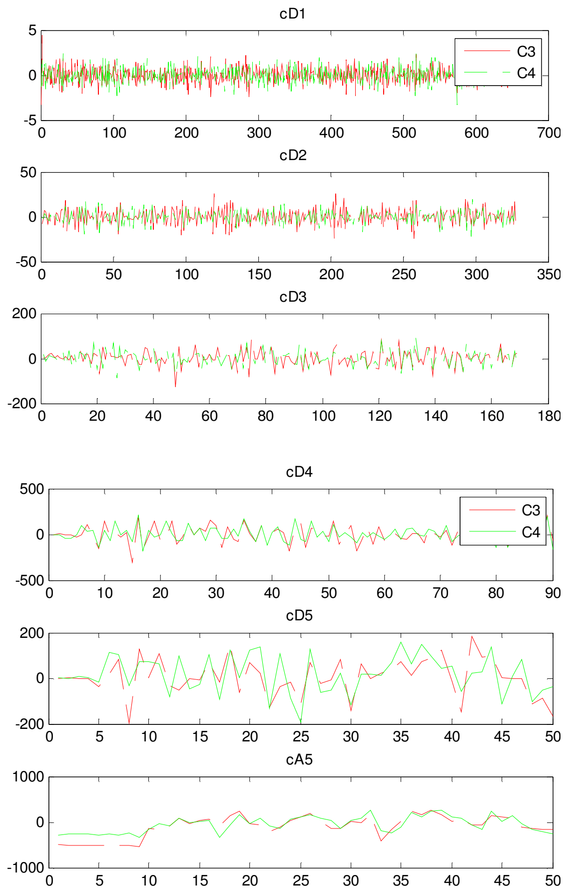


Figure 9. Wavelet decomposition of C3 and C4 for right hand imagery

The feature values computed for one subject during right hand imagery is shown in Table 1.

Table 1. Feature values during right hand imagery

SUBBAND	FEATURES	CHANNEL C3	CHANNEL C4
D4	Mean	5.3422	6.9454
	Standard Deviation	9.0729	8.6693
D5	Mean	7.7696	9.7530
	Standard Deviation	9.2774	13.418

4. CLASSIFICATION

The very aim of BCI is to translate brain activity into a command for a computer. The classification stage involves the identification of the feature patterns to facilitate the categorization of the user's intents. The output of the classification stage is the controlling input of the device.

The various classification algorithms used to design BCI systems are: linear classifiers (Linear Discriminant Analysis- LDA, Support Vector Machine- SVM), neural networks and non-linear Bayesian classifiers. Out of these, the Linear Discriminant Analysis and Neural Networks are widely used in BCI systems. The main drawback of LDA is its linearity that can provide poor results on complex non-linear EEG data.

Neural network is an assembly of several artificial neurons which enables to produce non-linear decision boundaries. A back propagation network with 3 layers as shown in Figure 10 is used for classification.

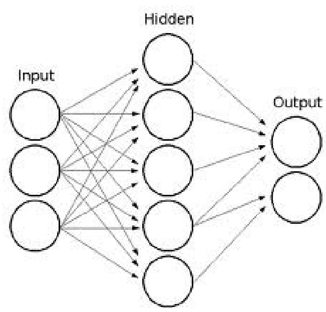


Figure 10. 3 layer Back Propagation Network

Traingdx learning algorithm is used to train the network. Traingdx uses gradient descend with momentum factor set as 0.86 to avoid a shallow local minimum and a variable learning rate to make the learning as fast as possible while maintaining stability. The initial learning rate is set as 0.05.Batch learning is used to update the network weights after all training data is presented. Maximum number of epochs for training is given as 1000. Two-thirds of the data is utilized for training and the remaining one-third is kept for testing. i.e. 23 samples are used for training and 12 samples are used for testing.

In this work, different combinations of signal (i.e. unipolar, bipolar, SL signals) and feature extraction methods are tried. This is shown in Table 2. Out of the 3 types of signals considered, it is found that bipolar and SL signals possess more discriminatory properties for right vs. left classification. 6 BPN's with different types of input features are tried in order to identify the processing method which yields best results. After many trials it is found that a BPN with 12 features namely ERD 1st second, ERD 2nd second, ERD 3rd second, ERD 4th second values in channel C3 and C4, Bipolar channel alpha mean and central beta mean in channels C3 and C4 provided the best results. This can be seen in row no. 1 in Table 2. The 4 seconds of ERD correspond to the period of motor imagery.

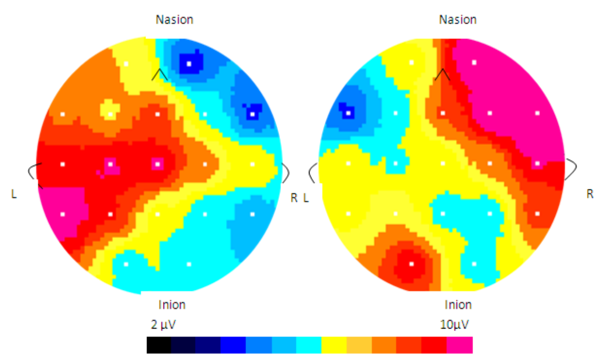
Table 2. BPN Classification Accuracies

S.No	Type of EEG Signal	Features	Accuracy	
			Right	Left
1.	Bipolar	C3 alpha mean,C4 alpha mean, C3 beta mean,C4 beta mean	70	87
2.	Surface Laplacian	C3 alpha mean,C4 alpha mean, C3 beta mean,C4 beta mean	60	72
3.	Bipolar	C3 alpha %,C4 alpha %, C3 beta %,C4 beta %	62	77
4.	Bipolar	DWT coefficients- alpha mean, standard deviation ,beta mean, standard deviation(8)	64	80
5.	Unipolar	ERD features- 4 per channel	77	64
6.	Bipolar	Mean features(4)+ ERD features(8)	73	70

5. RESULTS AND CONCLUSION

The EEG motor imagery data has been collected from 45 healthy volunteers in the age group of 20-25. Out of the forty five subjects, for 5 subjects, the imagery trials lacked notable variations. So, they are not considered for classification. Features associated with topographical variations of EEG activity offer significant information regarding the origins of the dominant neural community that contributes most to the recording.

First the EEG signal is filtered in the alpha range and the power spectrum is obtained for the 4 second imagery period. The mean alpha band power values are calculated for all the 19 electrode positions. The values at other locations are interpolated by 4 nearest neighbour interpolation method. Figure 11(a), shows the EEG map for left motor imagery and Figure 11(b), shows the EEG map for right motor imagery. The colour scale range is depicted below it**.**



(a) EEG map for left hand imagery (b) EEG map for right hand imagery

Figure 11. EEG mean alpha power spatial distribution

From the colour map, it is evident that during left motor imagery, there is a significant decrease in the mean alpha power seen in the right hemisphere (visible as blue shade). Also, during right motor imagery, there is a reduction in mean alpha power seen in the left hemisphere (visible as yellow shade).

A cluster plot is obtained for the features C3 and C4 alpha mean values vs. beta mean values are plotted for right hand imagery. It is shown in Figure 12(a). As seen in the scatter plot, there is variation between C3 and C4 values during right hand imagery. Figure 12(b) shows C3 and C4 alpha mean values vs. beta mean values for left hand imagery.

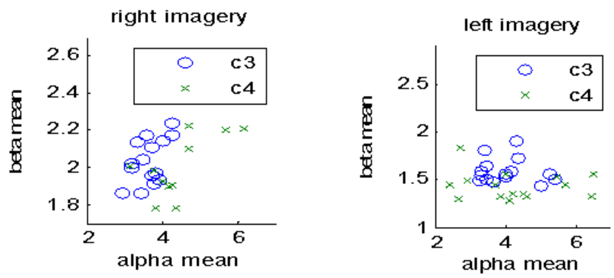


Figure 12. C3 vs. C4 features for motor imagery

The plot shown in Figure 13 depicts the C3 channel alpha and beta mean values during right hand and left hand imagery. Since the two classes are not linearly separable, we go for neural network classifier.

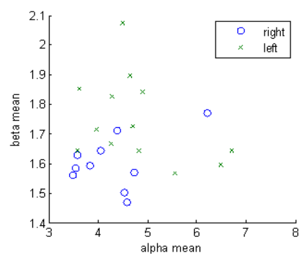


Figure 13. Right vs. Left imagery features from channel C

A BPN classifier with all 24 features taken at the same time (ERD features (8), Wavelet features (8), Bipolar mean values (4), Bipolar Percentage values (4)) yielded a classification accuracy of 69% for right hand imagery and 73% for left hand imagery, which is almost the same for classification of both the hands. The individual accuracies of the BPN taking few features at a time are discussed earlier in Table 2.It is identified that a bipolar EEG signal with alpha and beta mean as features yielded a better accuracy of 70% for right hand imagery and 87% for left hand imagery.

In future, this work can be expanded by using more electrode locations and feature sets to improve the classification accuracy.

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