# A ROBUST ALGORITHM TO DETECT INTENDED MOVEMENT FROM NON-INVASIVE EEG

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**Abstract**
**A brain-computer interface (BCI) can be used as tool to provide support to persons with amputee of limbs. Idyllically, such a BCI detects imagined movements, like upper or lower limb movements, and converts them into a control signal for a robotic arm or a prosthesis reinstating movement. These imagined movement have features in lower frequency spectrum unlike actual movement. These frequencies can effectively provide features that not only detects intended movement but can also differentiate between different intended movements. We have used wavelet transform to detect event related and highly correlated features for imagined movement. These detected features than fed to different linear and nonlinear classifiers. Out of which support vector machine (SVM) has provided highest classification rate and lowest False Positive rate. We have presented robust algorithm that can detect intended movements from non-invasively measured Electroencephalography (EEG).**
**Index Terms: Brain Computer Interface, Imagined Movement, Support Vector Machine, Wavelet Decomposition**

## I. INTRODUCTION

Highlight a Brain-computer interface (BCI) renders movements from EEG recordings and predicts cognitive state of persons mind. Currently actual movement detection from EEG has gained much emphasis and researchers have improved tremendously. But imagined movement has attracted less focus due to fact that it requires rigorous training to detect imagined movement [1], [2], [3]. The reason behind such training is that imagined movement EEG are largely attributed by interference of EMG originating from surroundings and other cognitive activity of brain [4]. Most of the time this interference can be reduced by training subject well but that approach lead to more training time, which makes it difficult to achieve practically. So practically we can remove such interferences by using normalization of each channel by correlation, since each channel have same residue of this interference. Another factor affects accuracy of Motor Imaginary (MI) activity is its low power signals which changes signal to noise ratio drastically. A robust BCI system based on MI must decode actual movement to such a degree that it can control prosthesis device attached to amputee patient. So we have taken approach that decodes MI to such precision it can detect intended upper limb movement from EEG signals.

MI detection can be done with invasive as well as non-invasive approach. But invasive approach require to implant sensor or sensor array to part of patient's brain [5]. Thus surgery required to perform such tasks and since it causes opening of the skull which can cause serious infections, so it is preferable to use non-invasive method such EEG or MEG so it reduces risk of infection and cost of such method is negligible to surgery. Several researcher have utilize non-invasive method to detect MI listed here. Saugat Bhattacharyya et. al. have proposed MI detection approach which controls position of 2D robot based on ERD/ERS and ErrP [1]. ERD/ERS activates movement of robot and ErrP detection stops movement. They have recorded EEG signal around sensory motor cortex and filtered window around 8-24Hz. They found features from 4th and 5th order power coefficient of wavelet decomposition from daubechies mother wavelet. They have utilized Correlation based feature selection method which have maximum impact on classification. The classification is done by support vector machine (SVM).

Patrick Ofner et. al. have presented approach where they have determined trajectory of MI movement[2]. But unlike previous researcher they have utilize lower frequency band around 0.5Hz. They have used Partial Least Square (PLS) regression method which not only reduces size of large data but provides modelling and classification data. They have decoded vertical and horizontal movement and correlated those using previously modelled EEG data from different subjects. Marianne Severens et. al. have utilized actual and imagined walking EEG data of subject [3] [6]. They proposed an algorithm which takes ERD signals during walking and resting state and produced classification. They have used power spectrum density between 8-24Hz frequencies using Welch's method with a hanning window. Followed by feature selection and classification by L2 norm. They have utilized ANNOVA test for significance of power over different frequencies. Chuang Lin et. al. propose a discriminant manifold learning method the locality sensitive discriminant analysis (LSDA) [7]. This procedure is based on constructing training set from graphs within-class and between-class to find a linear transformation matrix that maps high-dimensional data to a low-feature space. This transformation matrix contains local neighbor information as well as global discriminant information. Nearest neighbor classifier will further classify trials. The data used here are filtered around 0.05 to 3 Hz to preserve information in low frequency domain.

Rafal Kus et. al. have also utilized same approach to detect ERD/ERS of alpha(8-12Hz) and beta(13-30 Hz) band to determine imagined movement [8]. Actual movement and imagination of movement (MI) of a limb are characterized by decrease of power in alpha band and beta bands relative to baseline level followed by a rebound of power in the beta band [9]. They have extracted both bands applied Autoregressive model on each channel and identified alpha and beta band spectral peaks. Than features are selected based on movement in each of different intentions and classified using mahalanobis distance. Bradley J. Edelman et. al. [10] have utilized fundamentals of EEG source imaging where data of EEG are back projected to determine activity of brain region. Identification of region interest is determined by source imagined and EEG data than processed by Independent Component Analysis (ICA). Features were selected from waveforms obtained using a Morlet wavelet which was centred on 1Hz. Classification was done using Mahalanobis distance.

In our work we have utilized lower frequency band around 0.05-7 Hz because during imagined movement on-set alpha band and beta band possess lesser power [7]. We can also verify this using spectrum of EEG channel in fig. 1. The signal captured for 3s has onset movement from 0.5s and extends until 2s. Throughout all channel we found that some channels near motor Sensory region. As we know that wavelet decomposition can precisely get us this components power coefficient. We have utilized daubechies4 mother wavelet family and decomposed up to 7$^{th}$ band where our lower frequency component lies. These will be treated as feature set for training of classifier. This feature passed to feature selection process to reduce this dimensions further. Finally selected feature were classified using various linear and nonlinear classifier.

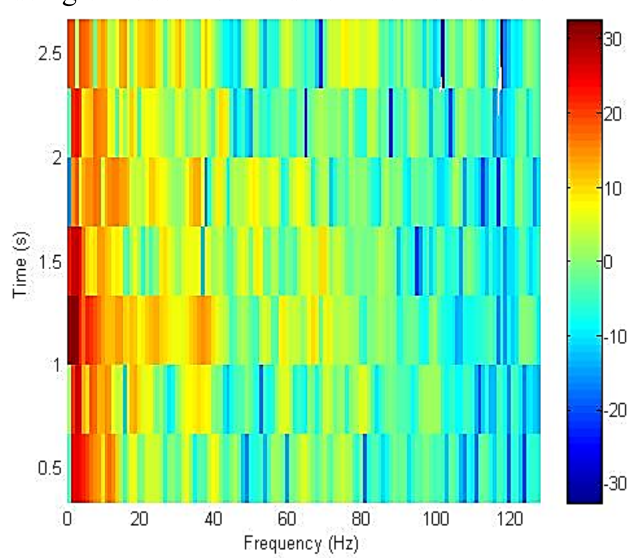



Fig 1. Spectrogram for EEG signal

## II. METHODOLOGY

### A. Database

For this paper we have used EEG recordings available from PHYSIONET website [11]. Subjects performed different motor/imagery tasks while 64-channel EEG were recorded using the BCI2000 system. They have performed different activity with total three trial runs. This trial were taken with 2second base line followed by closed eyes and open eyes trial. Subject have imagined movement of upper limb with right and left hand imagined in single trial several times. Data collected with BCI2000 for 64 channels and 160Hz of sampling rate. Channels used for analysis is around sensory motor region and supplementary motor area region for good accuracy [2], [7], [10]. Channels selected are FC1, FCz, FC2, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2 and CP4. To remove common interference all channels were normalized with common average referencing (CAR) [12]. CAR eradicates stray noise and optical artefacts picked up by the individual channels by simple means.

### *B. Feature extraction*

After basic Pre-Processing Steps we get channels with common feature removed. This signal are passed through a basic band pass filter with 0.05 to 10Hz using IIR (impulse invariant response) elliptical filter with 10th order [7]. Elliptical filter has good frequency domain characteristics and better attenuation for ripples in pass band and Stop band [1]. Normally Fourier transformation used to determine frequency component contribution from signal of interest but it does not provide any details regarding which frequency component appeared at a particular time. Since EEG signals imaginary component are arising at particular time and their frequency response is fixed at particular frequency band. So it is necessary to localize frequency components with respect to time as well. Wavelet transforms have an infinite set of possible basis functions. Thus wavelet analysis provides access to information that can be buried by other time-frequency methods such as Fourier analysis.

Wavelets are classified according to their number of vanishing moments. For EEG signal our analysis we should have more such vanishing moment as possible so we have chosen Daubechies' mother wavelet. We can construct a basis from the scaling function and wavelet function with two parameters: scaling and translating.

$$\phi_{j,k}(t) = 2^{\frac{j}{2}}\phi(2^j t - k) \tag{1}$$

$$\varphi_{j,k}(t) = 2^{\frac{j}{2}}\varphi(2^j t - k) \tag{2}$$

Where j is the parameter about dilation, or the visibility in frequency and k is the parameter about the position. By combing above equation we can form the basis for mother wavelet and both equations are orthogonal to each other. Since both equations are orthogonal so we can have dot product of them in order to get wavelet coefficient.

$$W_\phi[j_0,k] = \frac{1}{\sqrt{M}}\sum_n f[n]\,\phi_{j_0,k}[n] \tag{3}$$

$$W_\varphi[j_0,k] = \frac{1}{\sqrt{M}}\sum_n f[n]\,\varphi_{j,k}[n]\,/\, j \ge j_0 \tag{4}$$

These functions are called approximation coefficients and detailed coefficients respectively. In our paper we have considered detailed coefficient as feature for 6th and 7th level decomposition where our frequency of interest lies. The signal generated through Wavelet decomposition contains maximum power around D7 and D6 level. Fig. 2 shows the processed signal contains maximum information 21% and 20% in D7 and D6.

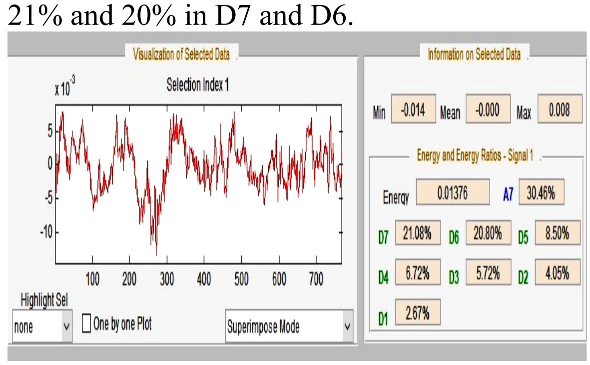



Fig. 2 Wavelet Decomposition of signal with power around different decomposition level

We have performed the same analysis shown in figure with all 13 channel across seven subjects. We have considered detail coefficient of all the channels for 6th and 7th band of decomposition. Total features generated were 13x13, where 13channels and 13 detailed coefficient were used.

### *C. Feature selection*

Considering the features generated in above steps yielded total of 169 for each trial. In order to make the detection algorithm robust we can have steps that can select most effective feature out total feature, which will reduce complexity on classifier side. Good feature subsets comprise features very much correlated with the class, but uncorrelated with each other. That means CFS selects only those features, which are highly correlated within the class but are uncorrelated with other classes [13]. These characteristics of the algorithm make CFS suitable for EEG data.

$$r_{xy} = \frac{\sum x_i y_i}{n\sigma_x\sigma_y} \quad (5)$$

Above equation calculates covariance matrix generated where it assigns 1 to correlated feature and assigns 0 to uncorrelated features. Deviation and mean is used from different feature set for continuous variable x and y is desired correlation.

*D. Classifier*

We have implemented SVM nonlinear classifier along with several other classifier like linear discriminant, Artificial Neural Network and PCA with LDA for comparison purpose [14][15][16]. Support vector machines (SVMs) are learning algorithms that have many applications in pattern classification and nonlinear estimations. SVMs attempt to find a Hyperplane surface.

$$\prod_{w,x} = w \cdot x + b = 0, x \in R^n \quad (6)$$

That separates the data points xi (meaning that all xi in a given class are on the same side of the surface), corresponding to a decision rule

$$\mathfrak{h}(\vec{x}) = sgn(b) + \vec{x} \cdot \vec{w} \quad (7)$$

Where w is frequently alluded to as the weight vector; b is known as the predisposition (a term received from neural systems). The innovation of SVMs lies in how this surface is resolved, SVMs pick the isolating hyperplane w.x+b = 0 that is uttermost far from the information focuses xi, that will be, that has most noteworthy edge. The basic thought is that a surface a long way from any watched information focuses ought to limit the threat of settling on incorrect choices while ordering new information. To be exact, in SVMs we amplify the separation to the nearest information focuses. We solve equation 8.

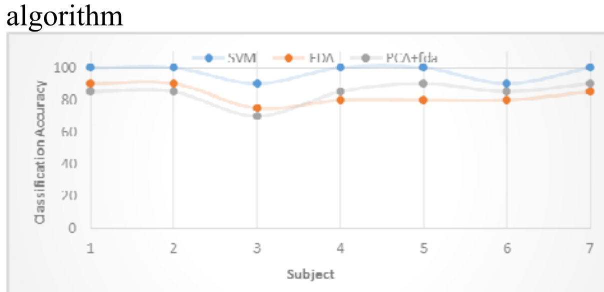
$$max_{w,b}\left(min_i\, d\left(\prod_{w,b}, x_i\right)\right) \quad (8)$$

is the distance between data point i and the plane Πw, having constraint that, this plane still separates the classes. The plane Πw that satisfies condition equation 8 and provides solution and it is called the ideal separating Hyperplane and it is unique. The separating plane is assumed to be linear often an issues serious limitation, as our pattern classification problem is characteristically nonlinear in the input data and require nonlinear separating planes. We have multiple numbers of feature vectors so we have to find out Hyperplane surface which maximizes the distance. Linear models can get more power if instead of working directly with the input features x, we first calculates new structures ϕ1(x), ϕ2 (x)… ϕq (x) from the input. Together, these structures form a vector, ϕ (x). One then uses linear methods on the derived feature-vector ϕ (x). Thus we get new features and our problem becomes linear classification. The conversion of input feature is known as kernelization. We have used RBF as a kernel function with sigma level of 0.8.

## III. RESULTS AND DISCUSSION

As we have implemented this algorithm on database with 7 subjects we get better result in SVM classifier as compared to others shown in Table 1. Here classification rate is determined as correct classification of left and right hand imagined movement. Total 169 features are available in form of coefficient coming from 6th and 7th detailed coefficient of total 13 channels. These number of features reduced to 50 using CFS and we have chosen these features according to their weightage determined by CFS. Here it is worth to note that subject 2and subject 6 have lesser accuracy as compared to others. Artificial Neural network (ANN) was tried here but could not get proper classification accuracy due to lesser number of subjects.

Table 1.Classification accuracy of different algorithm




## IV. CONCLUSION

From above results and discussion we can conclude that in order to classify imagined movement their activation frequency band is around 0.05 to 10 Hz. This holds true for almost all subjects and that's why we can use features from 6th and 7th decomposition band. Since they are having higher power as discussed in feature extraction section. Another conclusion we can draw out of this experimentation is that if we have limited data than nonlinear classifier like SVM have predominance in classification accuracy as compared to other methods. But this can be improved if we can take larger data base than methods like PCA can attain more meaningful feature vector. Same way ANN can also model nonlinear dynamics lies in the EEG data to identify intended movement. Several other researcher have concentrated on alpha and beta band for ERD and ERS respectively but we have used lower band but we get good accuracy in comparison.

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