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A Comparative Study of the EEG Characteristics for Motor Execution and Motor Imagery

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Abstract

Brain Computer Interface (BCI) has been improving the lifestyle of differently abled people by boosting up their performance levels. In this paper, Welch and Yule Walker- Power spectral density (PSD) have been used as a measure to differentiate various characteristics of EEG signal based on limb movements and their imagery. Characterization of partial limb movement has been performed in order to increase the flexibility of the BCI. The higher estimate for C3 for right hand movement shows contra-lateral activation of the Brain. Both Yule walker and Welch based methods were able to distinguish partial limb movements effectively in both C3 and C4 electrode data. Our approach presented in paper has shown good supporting results for execution and computation of robust features which can be utilized for signal classification.

1. Introduction

Motor cognition is the mental process in which the motor system draws on stored information to plan and produce our own actions, as well as to anticipate, predict, and interpret the actions of others. Motor imagery involves the kinesthetic representation of the action where the subject feels himself to be executing a given action. Although, numerous inputs converge on each spinal motor neuron from the spinal segments, the brain stem, medullary mid brain and the cerebral cortex regulates posture of the body and coordinates voluntary movements as shown in Figure 1. Regarding, non invasive technique for movement control and EEG recording it is established that invasive technique had much better signal resolution but surgery and issues of long term stability of implants and protection from infections is the main cause of its drawback [1, 2, 3, 4.]. Also, the availability of expertise to incorporate such implants in the brain prompts many researchers to go for noninvasive techniques of acquisition.

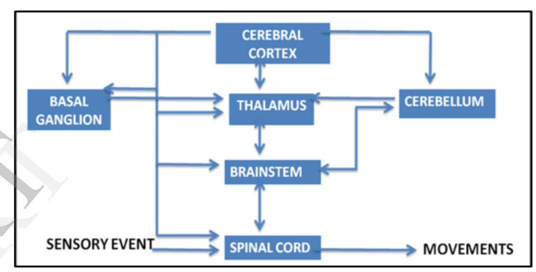

Fig. 1 Mechanism of movement control

The most common noninvasive recording of electrical activity of the brain is by using electroencephalography (EEG). Other recording techniques involves (Magnetoencephalography, MEG), (functional Magnetic Resonance Imaging, fMRI), Near Infrared Spectroscopy (NIRS). The advantages of MEG or fMRI over EEG are that they have better spatial resolution leading to the precise localization of cortical activation related to a specific task at hand and higher signal to noise ratio [15 - 20]. However, even considering their many advantages, MEG or fMRI are expensive and not portable. Also they have a lower temporal resolution as compared to EEG.

1.1. EEG and Waveforms

Electroencephalography is an electro-biological measurement technique that reads scalp to determine the electrical activity generated by brain structures with the help of millions of neurons. It is a non-invasive procedure that can be applied repeatedly to patients, normal adults and children with virtually no risk or limitation [5]. Figure 2 shows the characteristics of the some common EEG waveforms with their respective frequencies.

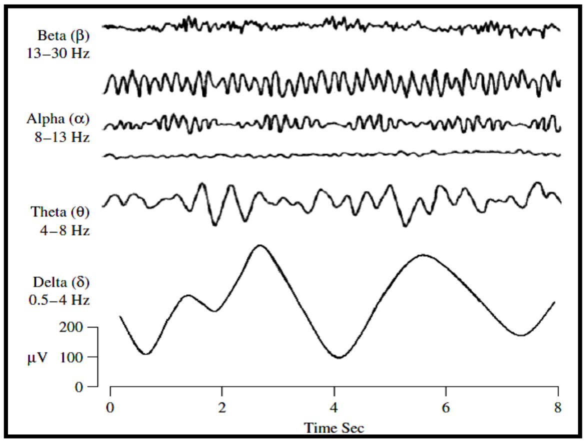

Fig. 2: Graphical representation of different frequency bands of EEG signal.
(ref. Reconstructed from Saeid S., Chambers J.A., "EEG signal processing", John Wiley & Sons Ltd., 2007)

The two types of oscillations that have importance for movement related BCI are the rolandic mu rhythm (8-12 Hz) and the central beta rhythm (above 13 Hz), both originating from the sensorimotor cortex. Sensory stimulation, motor behavior and mental imagery can change the functional connectivity within the cortex and results in the amplitude suppression (event related Desynchronization; ERD) or enhancement (event related synchronization; ERS) (Figure. 3) of mu and beta rhythms [23 - 25].

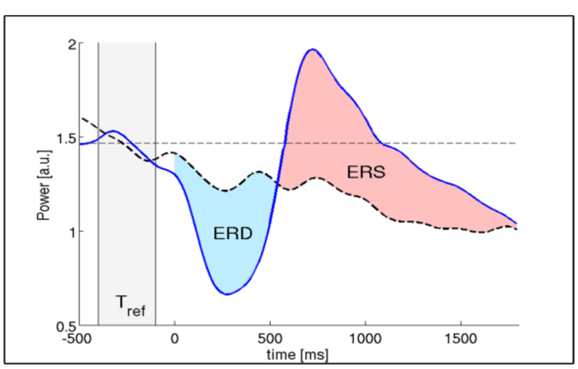

Fig. 3 Event Related Desynchronization / Synchronization

In this paper, to extract the relevant information from the EEG and to analyze, certain signal processing techniques are employed as features that have high discriminability among themselves like parametric and non-parametric technique of power spectral density.

2. EEG Signal Acquisition and Processing

2.1. Subject Description

For the motor execution task, five females and three males (right handed) in the age group of 23±2 years were employed as subjects in our experiment. None of the subjects suffered from any movement related disorders. For the motor imagery task, three females and three males were repeated from the above group

2.2. EEG Recording

EEG is a combination of the electrical activities in brain. Thus, to obtain relevant information from the EEG for any specific set of activities, it is of critical relevance that the information be easily available from the signal. For the purpose of EEG recording we have employed 10-20 International electrode System. For our study, recording has been taken from C3-Cz-C4 (Figure 4) as the three most relevant electrodes required for the recording of EEG signals for motor cognition as they are nearest to the various motor areas from the scalp [16, 19, 20].

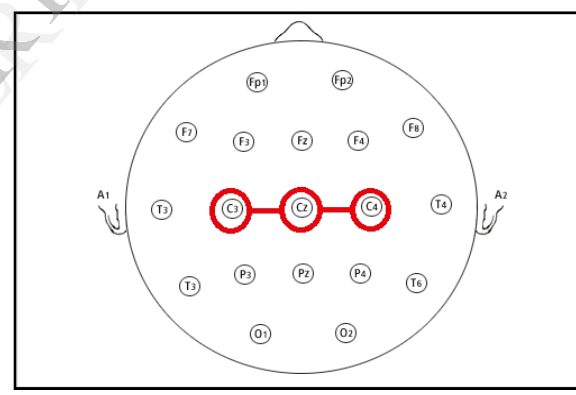

Fig 4 10-20 International Electrode recording

In this work, the recording of the EEG signal has been done through (NeuroWin, NASAN India) with 19 channel Ag/AgCl electrodes at a sampling frequency of 250 Hz and band-pass filtered between 0.01 Hz and 35 Hz. Especially, 3 channel electrodes: C3, Cz and C4 were selected and they are placed according to the International standard 10-20 system, the left ear (A1) was selected to be the point for the reference electrode and FPz as the ground electrode. The sensitivity of the amplifier is set to 100 uV and an additional 50 Hz notch filter had been utilized to suppress the line noise. The sampling frequency of the amplifier was set to 250, i.e., 250 bits of data were saved for each second. The data was also saved in ASCII format and for further processing of the data in MATLAB processing.

2.3. Pre-Processing of data

To obtain an artifact free EEG to extract the control signal, the EEGs have to be separated from the artifacts, such as eye blinking, movement related and any other internal or external noise. To minimize any external noise, the experiment was conducted in an isolated environment. Also a 50 Hz notch filter was incorporated in the amplifier to get rid of any line noise [23 - 25]. The participants were also asked to reduce their movement or blinking (other than the movement asked to perform). Rest of the noise was filtered out using some filter techniques (Digital IIR and FIR filters: Butterworth, Elliptical, Chebyshev, etc) in MATLAB.

2.4. Architecture of the Experiment

Each participant in our experiment was asked to perform two sets of tasks. The instructions of the task were given to the participant through a visual stimulus. In the first set, the participants were asked to perform the motor execution of left-right hand movement in a self paced manner. The participant performed this task in three sessions, in which the participant had to move their finger, elbow or shoulder for each session, according to the instructions given. After each session, few minutes break was given to the participant to obtain their normal state. In the second set, the participant was asked to perform motor imagination of left-right hand movement. The participant performed this task for one session.

Visual Stimulus was presented to each individual for performance in each task synchronously. The subjects were asked to move/imagine the right and left hand, according to the visual cue displayed on the screen. In each session, the subjects were also asked to either move/imagine their finger, elbow or shoulder. In each trial, a blank screen was displayed in the first second. After that a fixation cross '+' was displayed on the screen which indicates the beginning of the trial till the 2nd second. From the 2nd second, the visual cue (left-right arrow) is displayed followed by the fixation cross, and from this moment the subject is asked to move the limb according to the direction of the arrow, till the 6th second, i.e., till the fixation cross disappear from the screen. At the same time, the subject was asked to move their respective limb according to the visual cue, until the display is blank again. The timing scheme of the visual cue is given below in Fig 5. The visual stimulus was prepared in FLASH 8 which could run in any flash player.

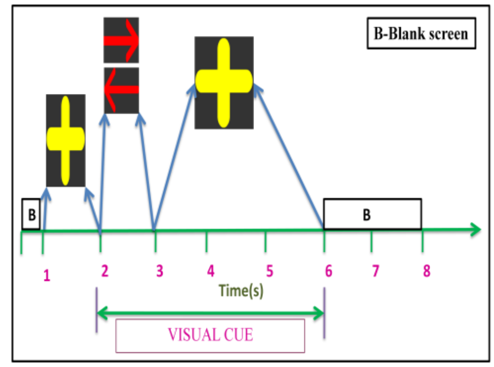

Fig. 5 Timing scheme of the experiment

3. The Power Spectral Density (PSD)

In this paper, Power Spectral Density (PSD) has been used for feature extraction. It is defined as the Fourier transform (FT) of the auto-correlation function of signal during stationary condition. The measure for power spectral estimates is commonly divided into two methods; non-parametric method and parametric method. Welch's Periodogram are the commonly used non-parametric methods, while the Yule Walker PSD is a commonly used parametric method.

In the discrete time signal $\{y(t);\ t=0,\pm1,\pm2,\ldots\}$ is assumed to be a sequence of random variables with zero mean, i.e., $E\{y(t)\}=0$ *for all* t, where, $E\{.\}$ denotes the expectation operator. Thus the power spectral density can be defined as

$$\Phi(w) = \lim_{N\to\infty} E\{\frac{1}{N} | \sum_{t=1}^{N} y(t)e^{-iwt} |^2\} \qquad (1)$$

$\Phi\ (w)$ is a periodic function, with the period equal to 2Π. Hence, $\Phi\ (w)$ is described by its variation in interval $w\ \varepsilon\ [-\Pi,\ +\Pi]$. PSD can also be viewed as a function of the frequency $f=w/2\ \Pi$, in the interval $f\ \varepsilon\ [-1/2,\ 1/2]$.

Conventionally, two methods are available for spectrum estimation: parametric method (Welch's method) and non-parametric method (Yule walker method). Parametric methods of spectral estimation assume that the signal satisfies a generating model with known functional form, and then proceed by estimating the parameters in the assumed model.

Non-parametric method is estimated directly from the signal itself.

3.1. Welch Method

In this method, the data segments overlap and windowed prior to computing the periodogram. To describe it mathematically, let $y_j\ (t)=y((j-1)K+t)$, $t=1,\ldots,M;\ j=1,\ldots,S$ denote the *jth* segment. In $(j-1)K$ is the starting point for the *jth* sequence of observations. If $K=M$, where M is total size of the sample points, then the sequence do not overlap. However, the value recommended for K in the Welch method is $K=M/2$, ie, 50% overlap between successive segments are obtained. [8,10]

The windowed periodogram corresponding to $y_j\ (t)$ is computed as:

$$\varphi_j\,(w) = \frac{1}{MP}\left|\sum_{t-1}^{M} v(t)\ y_j\,(t)e^{-iwt}\right|^2$$

where P denotes the power of the temporal window $\{v(t)\}$, given by $P=\frac{1}{M}\sum_{t=1}^{M}\left|v(t)\right|^2$

The Welch estimate of PSD is determined by averaging the windowed periodograms in:

$$\Phi_W\,(w) = \frac{1}{S}\sum_{j=1}^{S}\Phi_j\,(w)$$

By overlapping the data segments and hence by getting more periodograms to be averaged, the variance of the estimated PSD is decreased. Also by windowing the periodogram computation more control over the bias/resolution is obtained.

3.2. Yule Walker Method

This method determines the auto-regressive (AR) estimates of a rational signal. The Yule-Walker method of spectral estimation computes the AR parameters by forming a biased estimate of the signal's autocorrelation function, and solving the least squares minimization of the forward prediction error [12, 13, 15]. This results in the Yule-Walker equations

$$\begin{bmatrix} r(1) & r(2) & \cdots & r(p) \\ r(2) & r(1) & \cdots & r(p-1) \\ \vdots & \ddots & \ddots & \vdots \\ r(n) & \cdots & r(2) & r(1) \end{bmatrix}\begin{bmatrix} a(2) \\ a(3) \\ \vdots \\ a(p+1) \end{bmatrix} = \begin{bmatrix} -r(2) \\ -r(3) \\ \vdots \\ -r(p+1) \end{bmatrix}$$

The above equation is called the Yule walker equation.

4. Results

DFT based estimation by Welch's method and AR based PSD estimation by Yule Walker's method has been applied to the filtered EEG signal. For this purpose, the signal processing toolbox in MATLAB has been employed.

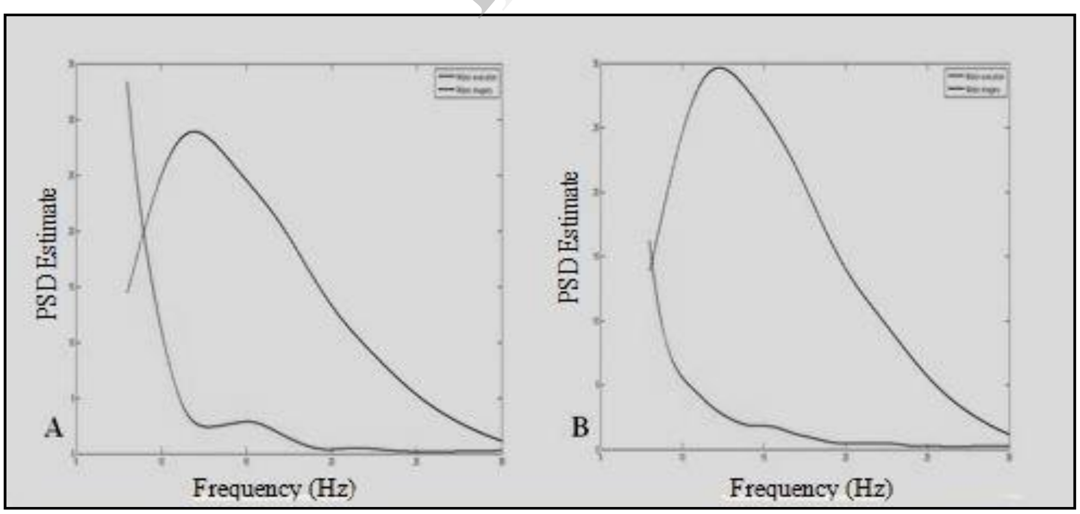

Fig.6 Welch's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for comparison of motor execution (in blue)/ motor imagery (in black).

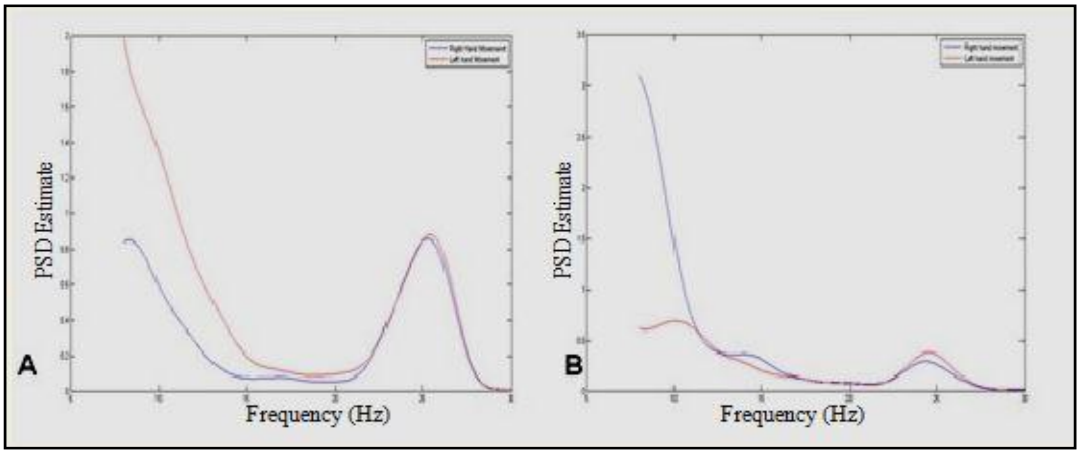

Fig. 7 Welch's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for left (in red)/ right (in blue) movement

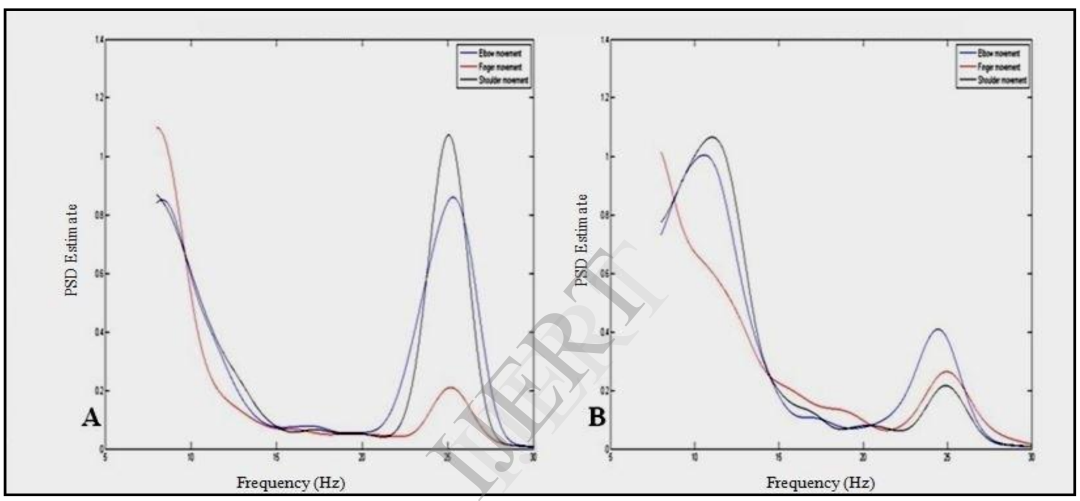

Fig. 8 Welch's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for elbow (in blue)/ finger (in red)/ shoulder (in black) movement

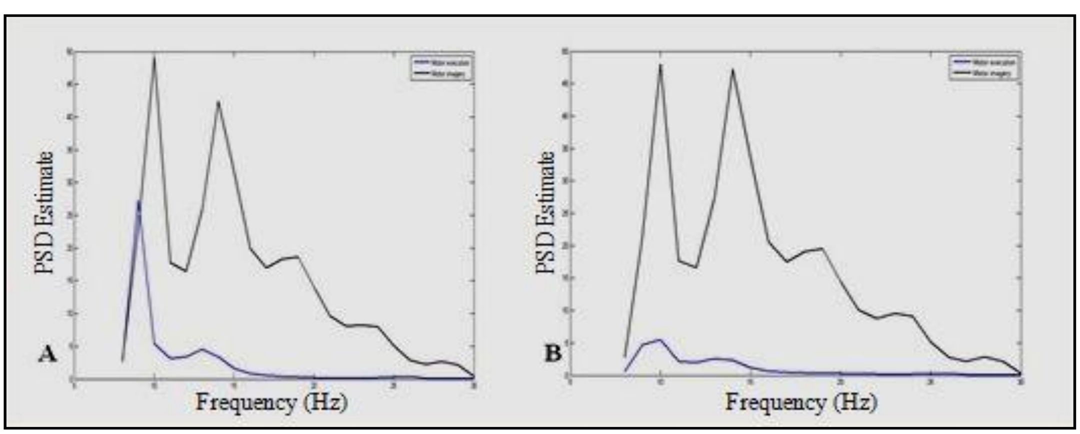

Fig. 9 Yule Walker's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for comparison of motor execution (in blue)/ motor imagery (in black).

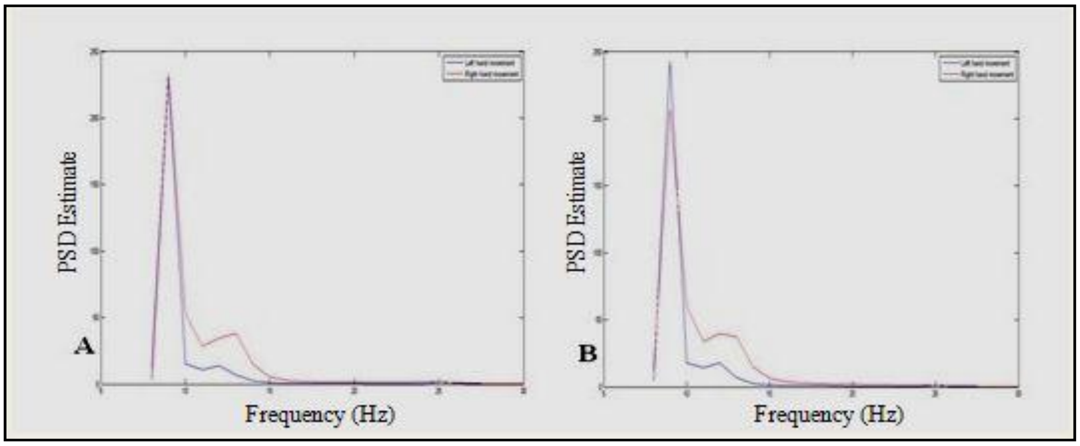

Fig. 10 Yule Walker's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for left (in blue)/ right (in red) movement.

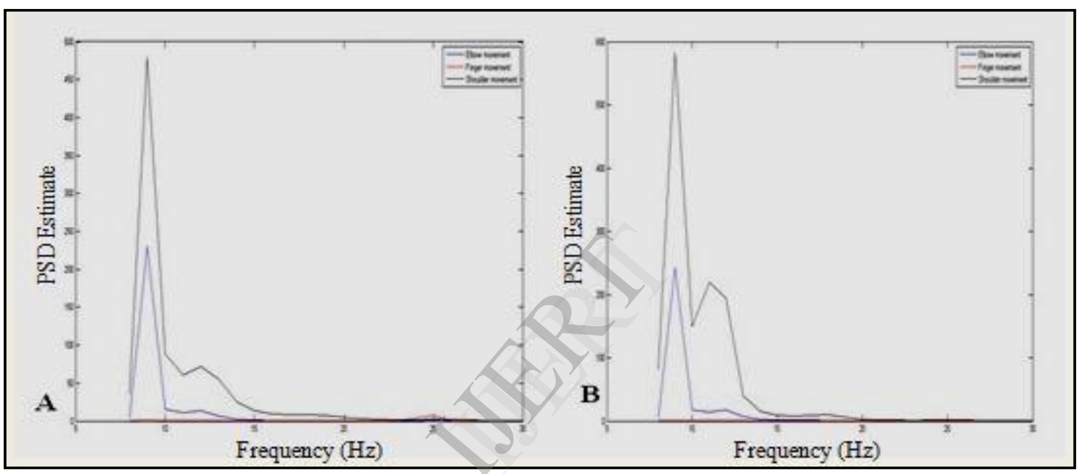

Fig. 11 Yule Walker's PSD estimates of the range 8-30 Hz of (A) C3 and (B) C4 electrode for elbow (in blue)/ finger (in red)/ shoulder (in black) movement.

4.1. Results using Welch Method

Figure 6 compares the motor execution and motor imagery in the frequency spectrum through their Welch's PSD for both the electrodes (C3 and C4). It is noticed that for motor imagery (in black), the curve increases till approximately 15 Hz and then it gradually decreases. While for motor execution (in blue), the curve is exponentially decreasing with small peaks on 15 Hz. In the imagery curve, it is shown that the there is an increase of PSD in alpha band, but a gradual decrease in the beta band.

Figure 7 compares the PSD estimates for left-right hand movement. It is seen in both the Figures that the estimate gradually decreases from 10 Hz with a small peak on 25 Hz. Left movement has a higher estimate in C3 than in C4, and vice-versa for right hand movement. Gradually left hand movement becomes predominat in both the electrodes in 25 Hz.

Figure 8 compares the PSD estimates for the elbow-finger-shoulder movement. It is observed that the three movements can be easily discriminated in 25 Hz. While for C3 electrode, there is a gradual decrease from 8 Hz with peaks on 25 Hz, but in C4 electrodes, a peak is obtained at 10 Hz too. The shoulder movement in both (in black) cases have got a slightly higher estimate than elbow (in blue), with the least being that for finger movement (in red) up to 20 Hz. But in 25 Hz a different trend is observed in C4 where, elbow has a higher estimate, followed by finger and then shoulder.

4.2. Results using Yule-Walker's Method

The comparison between the motor execution and motor imagery is shown in Figure 9. As observed, motor imagery has higher estimate than motor execution. Also, motor imagery has a dual peak in the alpha band, while motor execution curve has got a single peak in the alpha band.

Figure 10 compares the left and right hand movement. The left hand movement (in blue) has higher peak in C4 as compared to C3, and the vice versa for right hand movement. Again at near about 12 Hz, the right hand movement becomes dominant in both cases.

Figure 11 compares the elbow, finger, shoulder movement. It is observed in both the cases two peaks exist for shoulder (in black) and elbow (in blue) in the alpha band. The first peak near 8 Hz is sharper to that of the one in 12 Hz. Also, the shoulder movement has higher estimate, followed by elbow and then finger.

5. Discussion and Conclusion

The work presented in this paper gives an overview regarding the spectral characteristics of EEG signal based on motor movement and motor imagery. Welch's method and AR based PSD estimation by Yule Walker's method has been applied to the filtered EEG signal for three conditions namely motor execution and motor imagery, for left and right movement and movement of finger, elbow and shoulder from C3 and C4 channel recording respectively.

We can see from all the graphs that for every movement related to imagery tasks have shown change in EEG variation. In one case using Welch method, it increases PSD in alpha band, but a gradual decrease in the beta band. Similarly, at a frequency range of 25 Hz, it is concluded that left hand movement becomes predominat in both the electrodes i.e. C3 and C4. Whereas, method employing Yule Walker AR method, shows significant change where motor imagery has dominant change over motor execution.

Though this work gives a basic outline of the EEG characteristics for movement based activities, still there are scopes of improvement in this work. In the case implementation of obtained results on controlled mechanism for robotic arm movement could be studied for future scope along with new features that could be used for fusion with current work.

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