Analysis of EEG Features to Control Multiple Devices

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***Abstract*—Brain-Computer Interface (BCI) or Human-Machine Interface (HMI) now becoming vital engineering and technology field which applying EEG technologies to provide Assistive Technology (AT) to humans. This paper presents the analysis of EEG signals from various human cognitive or mental states to determine the suitable EEG features that can be employed to control multiple devices. Here, EEG features in term of average of power spectrum, standard deviation of power spectrum and spectral centroid of power spectrum are selected to recognize human mental or cognitive state from 3 difference exercises; i) solving math problem, ii) Playing game and iii) do nothing (relax). We have calculated average power spectrum, average standard deviation of power spectrum and average spectral centroid of power spectrum of alpha and beta band for three mental exercises.**

Keywords—BCI, HMI, EEG features, Power spectrum, Standard veviation, Spectral centroid, Cognitive state

I. INTRODUCTION

Brain Computer Interface (BCI) can be familiarized as a direct communication pathway that makes an interaction between human brain and digital computer to control the external devices. The whole process is done without having any touch of muscular body part. Easiness in operations for disabled people can be ensured by this system, especially for those who have no control of their normal muscular body to operate the peripheral devices. Besides medical applications, currently, BCI field have been extended to playing games [1-2], BCI speller [3-4], cursor control [5-6], social interactions by detecting emotions [7-8], robotic arm control [9-10], wheelchair control [11-12], home appliances control [13] or Smart phone operation using Electroencephalogram (EEG) [14] to help disabled persons. Nowadays, BCI is an interesting, vibrant and highly interdisciplinary research topic which involves psychology, neurology, signal processing and machine learning.

Generally, BCI can be segmented into five different phases or segments. The first phase involved the acquisition of EEG signals from human's head, second phase is pre-processing of EEG signals to remove artifacts, third phase is to extract the most effective features, fourth phase is to classify the EEG signals according to the selected EEG features and the final phase is to control devices by translating the classified features into machine code [15-17]. Among all these phases, feature extraction acts as the most vital role in any BCI system based on EEG because of any incorrect selection of the EEG features will cause misclassification that may create wrong commands given to the devices. As a result, the BCI system might malfunction that may cause harm to the disabled people.

Subject Dependent Multivariate Empirical Mode Decomposition (SD-MEMD) is a technique for feature extraction used in MI based BCI that is proposed in [18]. With the help of MEMD algorithm, this feature decomposes the multi-channel EEG into a set of Intrinsic Mode Functions (IMFs). After a careful selection of the task related IMF subset an enhanced EEG is re-constructed. Classification accuracy can be improved by 5.76% by this feature. The amplitude frequency analysis (AFA), the density matrix (DM) and the recurrence quantification analysis have been merged to generate the phase space feature (PSF) vector [19]. This feature is efficient to classify the left hand and right hand movement. Here, the combination of EMD and BP from the EEG signals for feature extraction has been proposed in [20]. Here, EMD is applied to select only the IMFs corresponding to sensor motor rhythms (mu and beta) using Welch-based Power Spectral Density (PSD) to extract the reliable information of EEG signals. Analytic intrinsic mode functions (AIMFs) have been proposed in [21] as features for automatic classification of EEG signals based on MI tasks. Empirical mode decomposition and Hilbert transform are applied on raw data to form AIMFs. Spectral moment of power spectral density, raw moment of the first derivative of instantaneous frequency, peak value of PSD and area are the features obtained from AIMFs. During wavelet packet analysis (WPA), a slow cortical potential (SCP) has been studied instead of using traditional time or frequency domain methods. Applying WPA with the combination of log energy entropy enables to find cortical negativity as well as cortical positivity in self-regulation of SCPs, as discussed in article [22]. In article [23], the features have been computed from beta and gamma bands and the features were the combinations of Wavelet decomposition, standard deviation, mean and PSD. In this article, average spectral density, standard deviation and spectral centroid of EEG alpha and beta frequency band have been analyzed to find the best possible feature that may increase the classifier accuracy and can be employed by microcontroller to control device. This article has been organized in the following sections i.e. section II, III & IV discusses issues related to EEG Measurements and Protocols, methodology, results and discussion respectively; finally, section V deals with the conclusion.

II. EEG MEASUREMENT AND PROTOCOL

There are a lot of EEG headsets in the market to capture EEG raw data. In this research, Neurosky Mindwave mobile EEG headset was used for collecting EEG raw data. This EEG headset contains one electrode and this electrode is placed on the FP1 area of the human brain. There is a reference electrode which is connected with the ear lobe. This EEG amplifier captures the raw EEG data at 512 Hz sampling rate. During EEG data acquisition, a EEG mobile app called eegID in the mobile phone and the Neurosky Mindwave are paired through the Bluetooth shown in Figure 1.

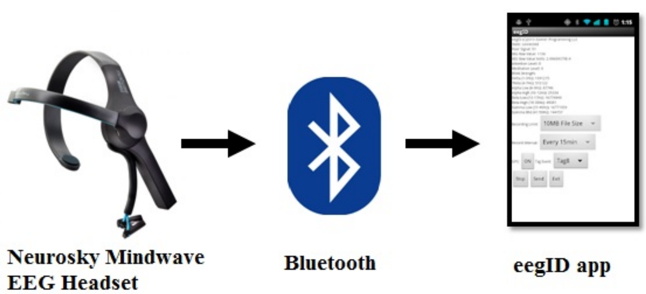

Fig. 1. Raw EEG data acquisition procedure.

For this research, two male and one female subject were selected and their age range is from 20 to 27 years old. There are three exercise modes are set-up for experimental procedure which are do nothing (relax), solving math quickly and playing game shown in table 1. The duration of every data was one minute.

TABLE I. RAW EEG WITH DIFFERENT MENTAL EXERCISE

Subject Number	**Mode of Exercise**		
	Solving Math Quickly-A	***Do Nothing (Relax)-B***	***Playing game-C***
Subject-1 Age-23 Male	1A	1B	1C
Subject-2 Age-25 Female	2A	2B	2C
Subject-3 Age-25 Male	3A	3B	3C

III. METHODOLOGY

There are some fundamental steps that must be done in to make a BCI system which are data acquisition, preprocessing, feature extraction, classification and translational algorithm. From these steps, feature extraction plays a vital role to form a BCI application because proper feature selection increases the classification accuracy as well as the performance of BCI devices. Various EEG features and feature extraction techniques have been come out by the BCI researchers that to be used in the BCI applications. The most usable EEG features by the BCI researcher are band power spectrum, energy spectral density, spectral centroid, common spatial pattern, wavelet transformations, wavelet packet decomposition, independent component analysis, autoregressive model, principal component analysis, cross-correlation, variant, co-variant, short-time Fourier Transform, Shannon’s entropy and z-score [24-27]. In this research, average power spectral density, standard deviation and spectral centroid of EEG alpha and beta band have been analyzed as EEG features.

A. Experiment Flow Chart

The experiment flow chart of this research is shown in figure-2.

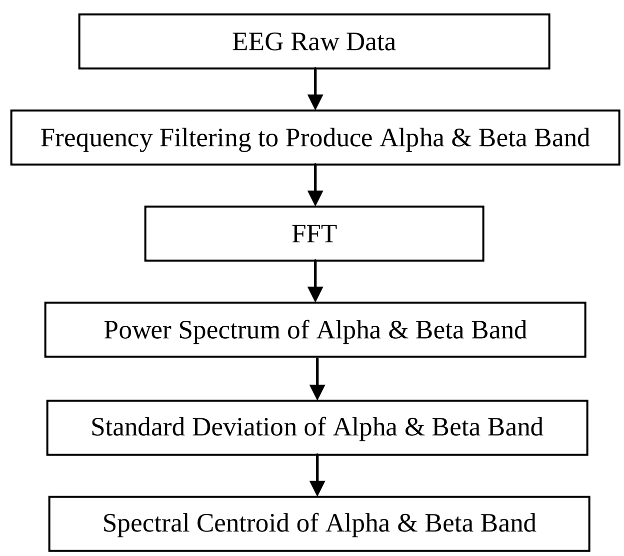

Fig. 2. Experimental flow chart.

Generally, artifact due to eye blinks and muscle movement generate EEG above 100 μV [28]. After collecting the EEG data according to measurement protocol, a threshold value of 100 μV was set and the EEG data above the threshold values were rejected to remove the eye movements and blinks artifacts. For each EEG channel, there are five frequency bands which are delta (0.5-4Hz), theta (4–8Hz), alpha(8–13Hz), beta(13–30Hz) and gamma(30–45Hz) [29]. In this research, the EEG data was filtered into alpha and beta band only. Then Fast Fourier Transform is applied on alpha and beta frequency band to calculate average power spectrum, average standard deviation and average spectral centroid.

B. Power Spectrum and Spectral Centroid

With the help of Fast Fourier Transformation (FFT), the power spectrum of the EEG data has been calculated. The equation (1) for FFT is given as: [30]

$$X(k) = \sum_{k=1}^{N-1} X(n)\, W_N^{kn} : k = 0, \dots\dots, N-1 \qquad (1)$$

$$W_N = e^{-j\frac{2\pi}{N}}$$

Where one value of ‘k’ has N complex multiplications, since ‘k’ = 0, 1… N-1. The multiplication of x (n) and w^{kn} was done for N times, since n = 0 to N-1. The Spectral Centroids are calculated using formula in equation (2).

$$C = \frac{\int x g(x)\, dx}{\int g(x) dx} \qquad (2)$$

Equation (2) shows the equation of Spectral Centroids which is used to find the centre value of the each EEG frequency bands [31].

IV. RESULTS AND DISCUSSION

A. EEG Raw Data

In Figure 3, the raw EEG data of subject-1 for three modes of exercise have been plotted in first row and in second row the FFT have been plotted. In the figure A, B and C denote the mental states of solving math quickly, do nothing (relax) and playing game respectively. Similar figure can be plotted for subject-2 and for subject-3.

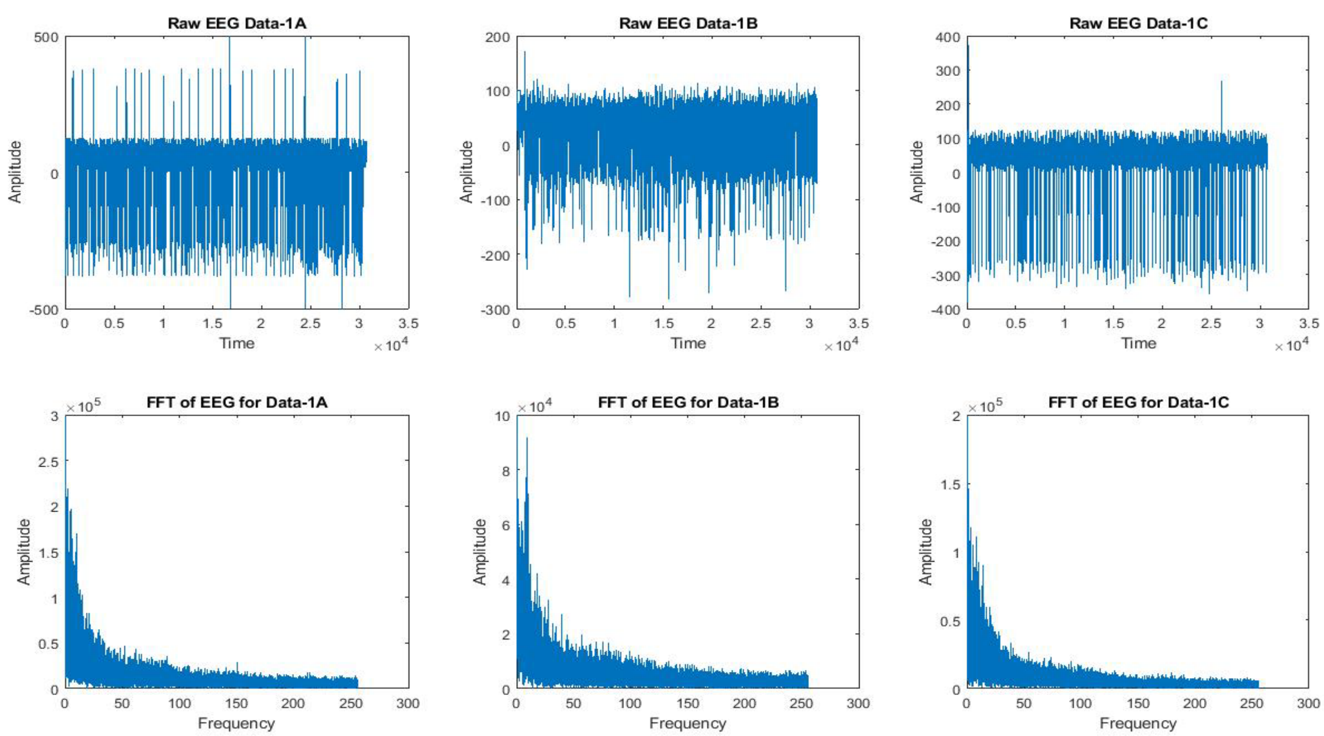

Fig. 3. Ploting raw and FFT of EEG data.

B. Filtered EEG Data

After preprocessing, the EEG data have been filtered into two frequency band known as alpha and beta frequency band. The frequency range of alpha and beta band are (8-13 Hz) and (13-30 Hz) respectively. Figure 4 shows the plotting of alpha and beta band in time domain for subject-1 with three mental exercises. Similarly, Figure5 shows the plotting of alpha and beta band in frequency domain for subject-1 with three mental exercises.

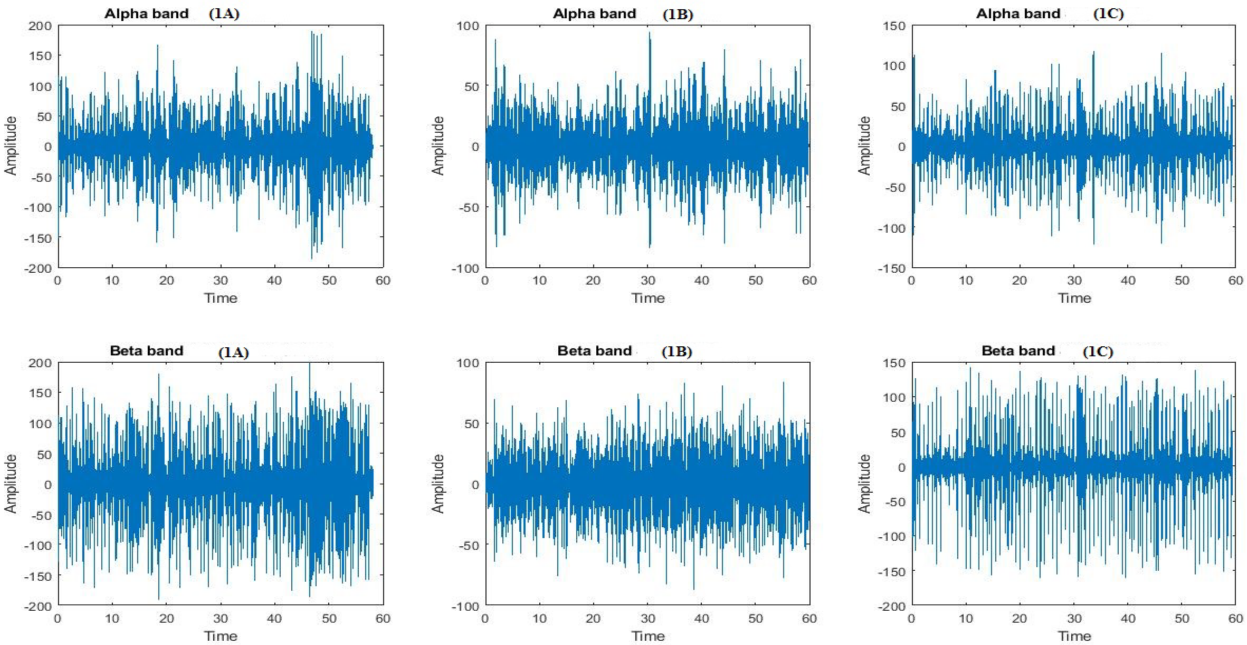

Fig. 4. Ploting raw EEG data of alpha and beta band for subject-1.

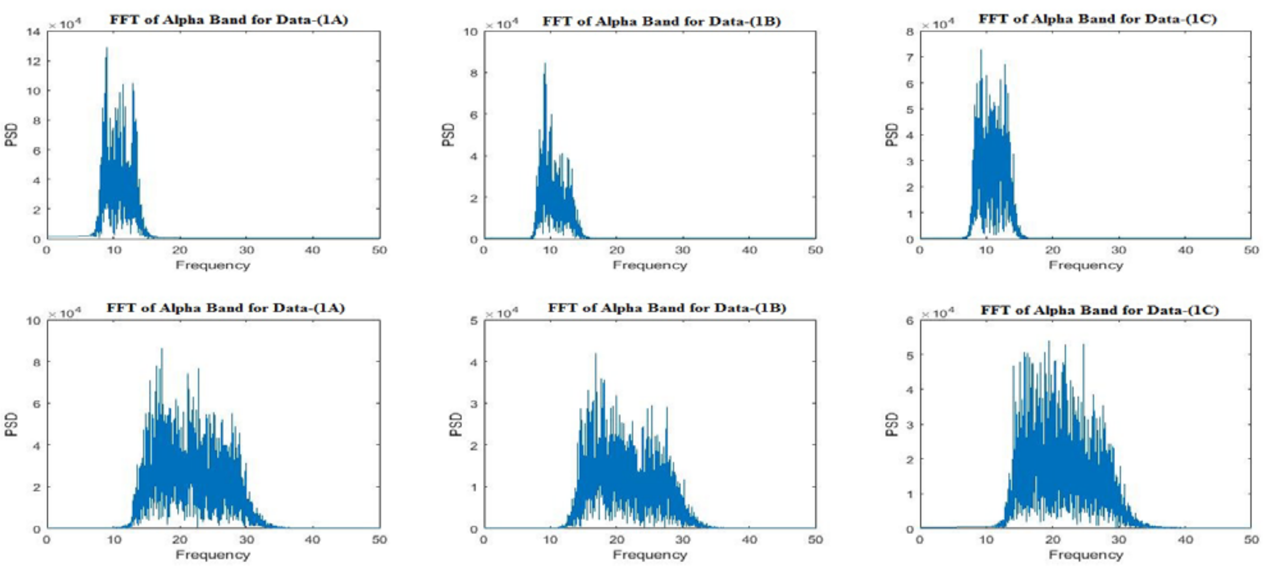

Fig. 5. Ploting FFT EEG data of alpha and beta band for subject-1.

C. Average Power Spectrum

Average power spectrum of EEG alpha and beta band for all subjects with three modes of mental exercise have been calculated and listed in Table II. These values have also been plotted in figure-6. From Figure 6, it is clear that the average power spectrum of beta band is higher than the alpha band for all subjects in three modes of mental exercise.

TABLE II. AVERAGE POWER SPECTRAL VALUES

Subjects	Frequency Band	EEG data for 3 mode of exercise		
		A	***B***	***C***
Subject-1	Alpha	1048.9	497.4	659.7
	Beta	1719.2	753.5	1211.3
Subject-2	Alpha	873.2	465.8	671.5
	Beta	1528.6	640.8	1213.9
Subject-3	Alpha	829.6	293.3	721.7
	Beta	1521	403.7	1326.4

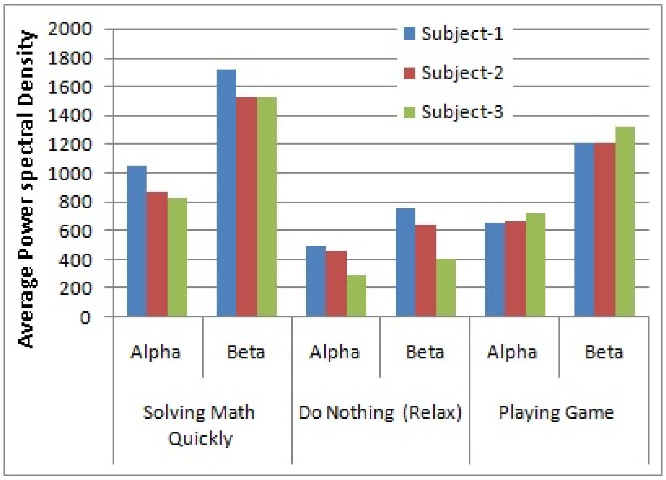

Fig. 6. Ploting average power spectral of alpha and beta band.

D. *Spectral Centroid*

Spectral centroid is another effective feature for BCI classification. Like average power, spectral centroids of EEG alpha and beta band for three subjects were computed in table-III and also plotted in figure-7. Here, the average spectral centroid of beta band is also higher than the alpha band.

TABLE III. AVERAGE SPECTRAL CENTROID VALUES

Subjects	Frequency Band	EEG data for 3 mode of exercise		
		A	***B***	***C***
Subject-1	Alpha	37.57	38.7	44.72
	Beta	135.7	113.4	82.5
Subject-2	Alpha	38.2	41.6	38.8
	Beta	148.7	135.2	145.9
Subject-3	Alpha	47.9	40.4	37.5
	Beta	159.2	103.8	93.1

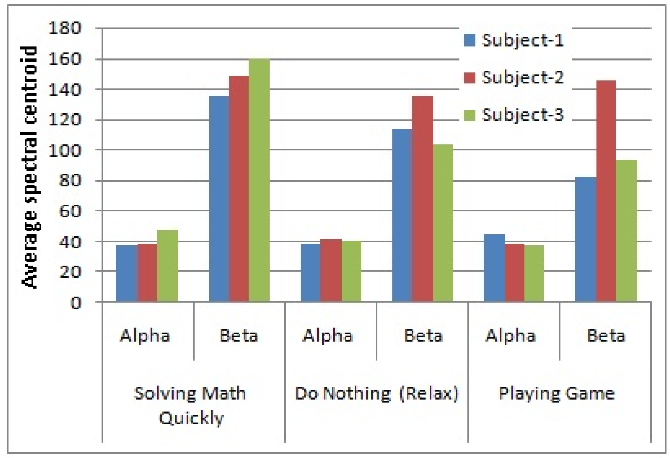

Fig. 7. Ploting average spectral centroid of alpha and beta band.

E. *Standard Daviation*

Average standard deviations of alpha and beta band for all data have been listed in table-IV and also plotted these values in figure-8. In case of standard deviation, the average standard deviation of alpha band is higher than beta band for all subjects when they were in relax (B) condition. When the subjects were doing math quickly (A) and playing game (C) then the average standard deviation of beta band is higher than alpha band.

TABLE IV. AVERAGE STANDARD DEVIATION VALUES

Subjects	Frequency Band	EEG data for 3 mode of exercise		
		A	***B***	***C***
Subject-1	Alpha	6694.2	3576	4429.4
	Beta	7075.5	3181	4886.1
Subject-2	Alpha	5900.2	3365.7	4689.2
	Beta	6305.3	2647.6	5044.2
Subject-3	Alpha	5763.1	2097.6	4760.1
	Beta	6324.8	1682.7	5437.9

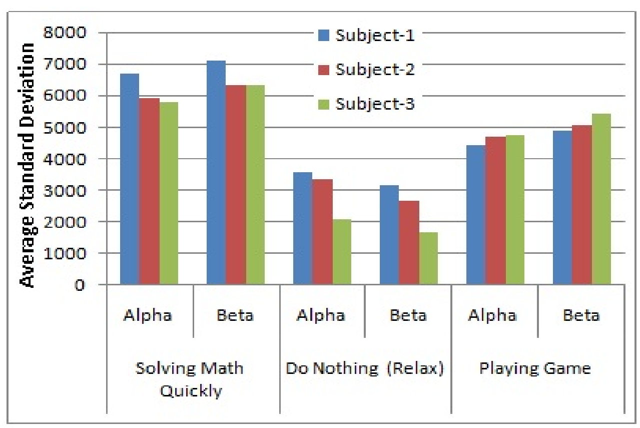

Fig. 8. Ploting average standard deviation of alpha and beta band.

V. CONCLUSION

This research is conducted to determine the suitable EEG features that can be used to control multiple devices. From the results of the research, it shows that the spectral centroid and standard deviation of power spectrum of EEG Alpha and Beta band can be used to indicate the change in human cognitive state apparently. Thus, those EEG features can be used in different classification algorithms to get the best result. Then the classifier result will be applied to the translation algorithm to control the device. To achieve the best classifier accuracy, number of subject should be increased.

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