Classification of Drowsy and Controlled EEG signals

R. Upadhyay, P. K. Kankar, P. K. Padhy and V. K. Gupta

***Abstract*-- Electroencephalogram (EEG) signal analysis provides ground for evaluation of various neurological disorders and implementation of Brain Computer Interface (BCI) for such neurological disabilities. These capabilities of BCI system enable patients suffering from severe motor disability to control variety of applications by simply generating commands using BCI channel like, brain controlled arm or wheel chair. Successful realization of an efficient Brain Computer Interface depends upon accuracy maintained during EEG signals recording, processing, feature extraction and classification. The patients with more alcoholic medicines are seems to be drowsy. In that case, it is very difficult to extract and classify the brain signals accurately. In this work, a comparative study of EEG signals, recorded during drowsiness condition and controlled condition for same mental task, is performed for successful implementation of a BCI system. For classifying between recorded EEG signals for both situations, Fast Fourier Transform (FFT) and Power Spectral Density (PSD) are calculated. Comparison between FFTs and PSDs of EEG signals for both mental conditions shows clear difference between two mental conditions.**

***Index Terms*-- Brain Computer Interface (BCI), Electroencephalogram (EEG), Fast Fourier Transform (FFT), Power Spectral Density (PSD).**

I. INTRODUCTION

Human brain consist millions of neurons. These neurons produce electric voltages field for each cerebral activity. EEG is record of brain electrical signals. In a normal adult EEG signal ranges from 1 to 100 microvolts, when measured and recorded from electrodes placed on scalp [1]. EEG signals analysis is done for identification of various neurological disorders, diagnosis of neurological diseases, and also implementation of BCI. A BCI system uses computer ability to convey human intentions to the external world. EEG signal contains lots of information in the form of features. This makes identification of EEG signals very difficult simply by visual inspection [2].For implementation of a BCI system, different EEG patterns can be used [3], like Farwell and Donchin [4] worked on event related potential, Pfutscheller and Neuper [5] have discriminated left and right hand movement by analyzing motor Imagery signals. A typical BCI system is implemented in two steps. EEG signals acquisition from human brain and signal processing of recorded raw EEG signal. Signal processing on recorded EEG signals is performed to translate brain activity to the meaningful external command. Under signal processing of EEG signals feature extraction and classification of recorded EEG signals is performed [6].

Many researches have been carried out on EEG signals measured under different mental conditions, like epileptic, alcoholic and drowsy states. Z. Mardi and S. N. M. Ashtiani [7] worked on EEG based drowsiness detection methodology for safe driving, using chaotic features of EEG data. O. Faust and R.U. Acharya [8] analyzed and classified among EEG signals recorded during controlled, epileptic and alcoholic states using AR modeling techniques. Beta power estimation in the EEG of alcoholics was carried out by M. Rangaswamy, B. Porjesz [9]. EEG signals are very sensitive to thedifferent mental conditions, and for same task at different mental condition the recorded EEG signals can be different enough to be classified [10-11]. This can cause a false interpretation of the EEG signals, and therefore a false command is generated by BCI system. In this work, classification of EEG signals, recorded for controlled and drowsy state of mind, is carried out, for avoiding false interpretation of EEG signals and efficient implementation of BCI system when subject is in drowsy condition. In present work, signals recovered from C3 and C4 channels under drowsy and controlled condition are studied. FFT and PSD are calculated for both the cases, which produces clear difference between EEG signals recorded during two mental conditions.

II. EEG DATABASE

The EEG data used for this study includes EEG signals recorded from 244 subjects, from 122 subjects under controlled condition and from rest 122 subjects after consuming alcohol. Each subject has been examined for 120 times for same mental task. EEG database contains measurements from 64 electrode placed on the scalp. Data is sampled at the rate of 256 Hz.

In this work our primarily focus is on the EEG signals recovered from C3 and C4 channels, and data only for 5 trials is studied. The data recorded under alcoholic conditions are assumed to be taken under drowsy condition. This may occur for patient with highly alcoholic medicines. As patients suffering from different mental diseases, usually take high power medicines. The EEG data used for this study is taken from an open EEG database of State University of New York Health Centre.

Fig.1 (a) to 1(d) show an example of the EEG signals coming over C3 and C4 channels recorded under drowsy and controlled condition, used for this analysis.

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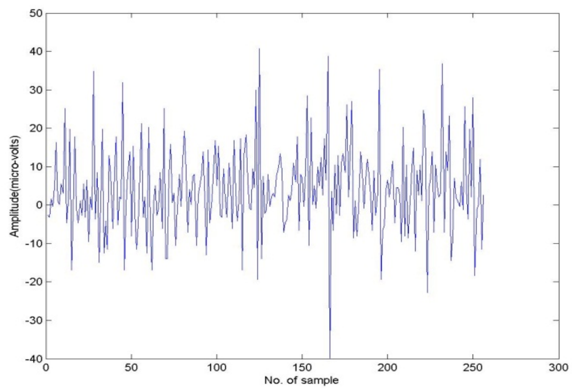


Fig.1 (a) EEG signal under drowsy condition from C3 channel.

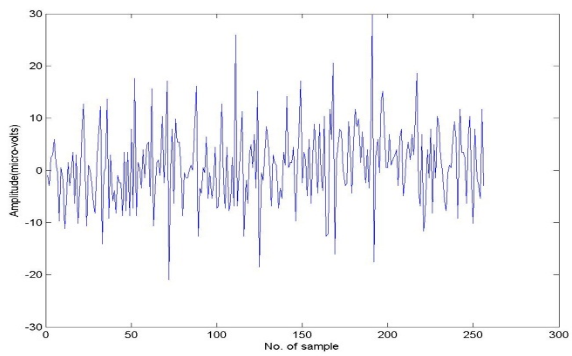


Fig.1 (b) EEG signal under drowsy condition from C4 channel.

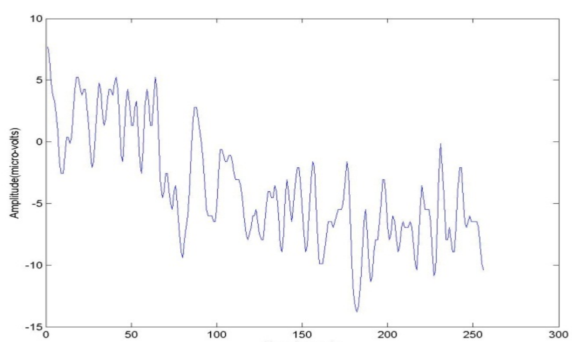


Fig.1 (c) EEG signal under controlled condition from C3 channel.

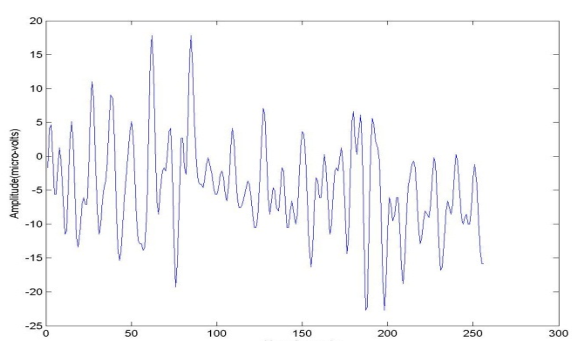
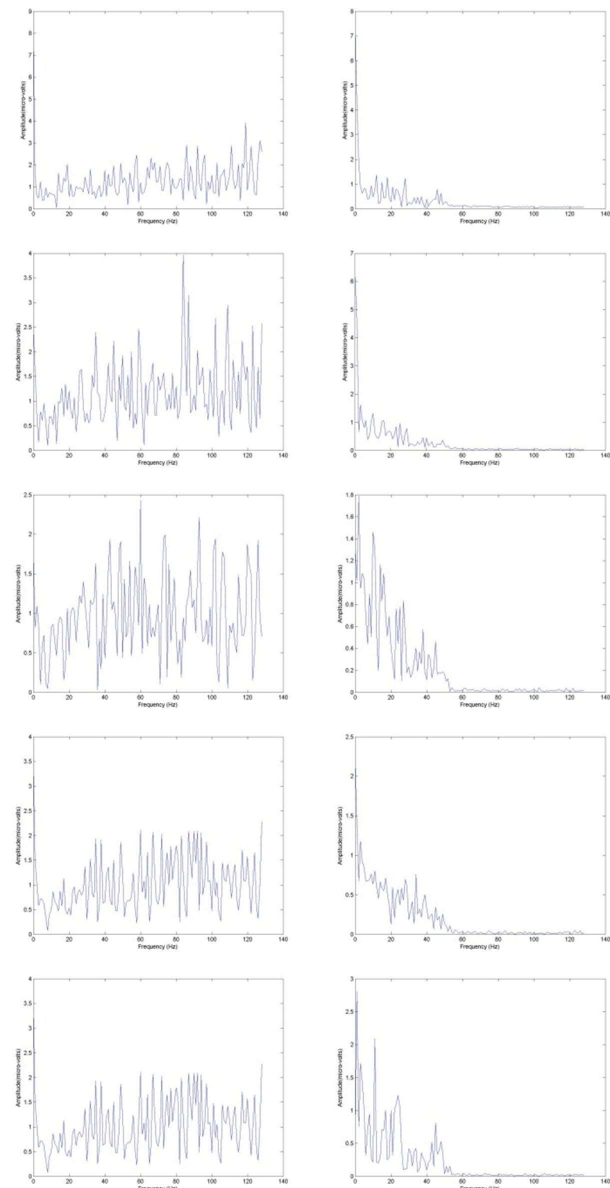


Fig. 1(d) EEG signal under controlled condition from C4 channel.

III. Classification using Fast Fourier Transform

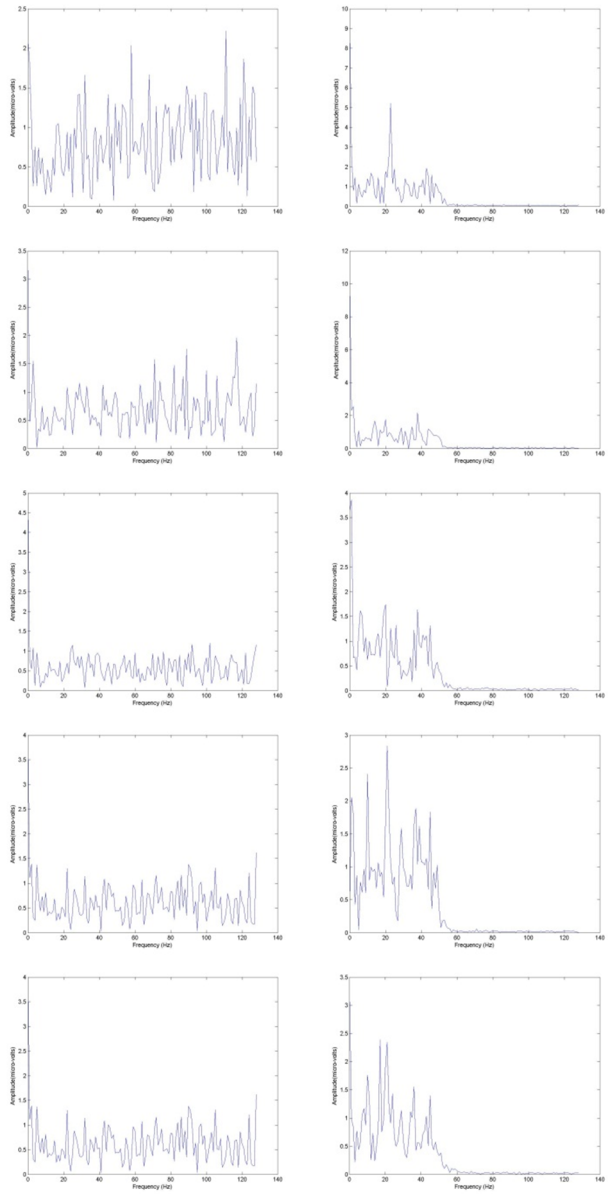
Fast Fourier Transform (FFT) is a fast algorithm to calculate Discrete Time Fourier Transform (DFT) of a time domain signal. When 2^n- point DFT is calculated with 2-point and 4-point DFT generalization, it becomes algorithm for FFT estimation [12].

EEG signals are very complex signals which carry lots of information in the form features. Some of these features are hidden and can only be remarked in frequency domain. It becomes necessary to analyze these signals in frequency domain as well. In present work we have calculated FFT of EEG signals recorded for two states of brain, and classified them on the basis of calculated FFT. Fig.2 and Fig.3 show FFT estimation for 5 trials in drowsy and controlled condition when signals are considered from C3 and C4 channels, respectively.



Drowsy sample Controlled sample

Fig.2 FFT of drowsy and controlled EEG data for C3 channel



Drowsy sample Controlled sample

Fig.3 FFT of drowsy and controlled EEG data for C4 channel

It is observed from Fig.2 and Fig 3 that the FFT of controlled condition shows almost similar and stable response. For all trials, the magnitude of frequency approaches to zero after 60 Hz of frequency. However, the FFT of EEG signals recorded for drowsy condition is much different from controlled one. The magnitude of signals is changes with very high randomness and does not settle down at any point of frequency for all 5 trials.

IV. Classification Using Welch's PSD Method

Welch's method, also known as periodogram method is used for power spectral density estimation of a time domain signal. In Welch's PSD estimation method, the time signal is divided into the successive blocks. The PSD of signals are estimated by averaging the squared-magnitude of DFTs of each blocks.

The u[th] block of the signal $f_u(n)$ can be expressed as

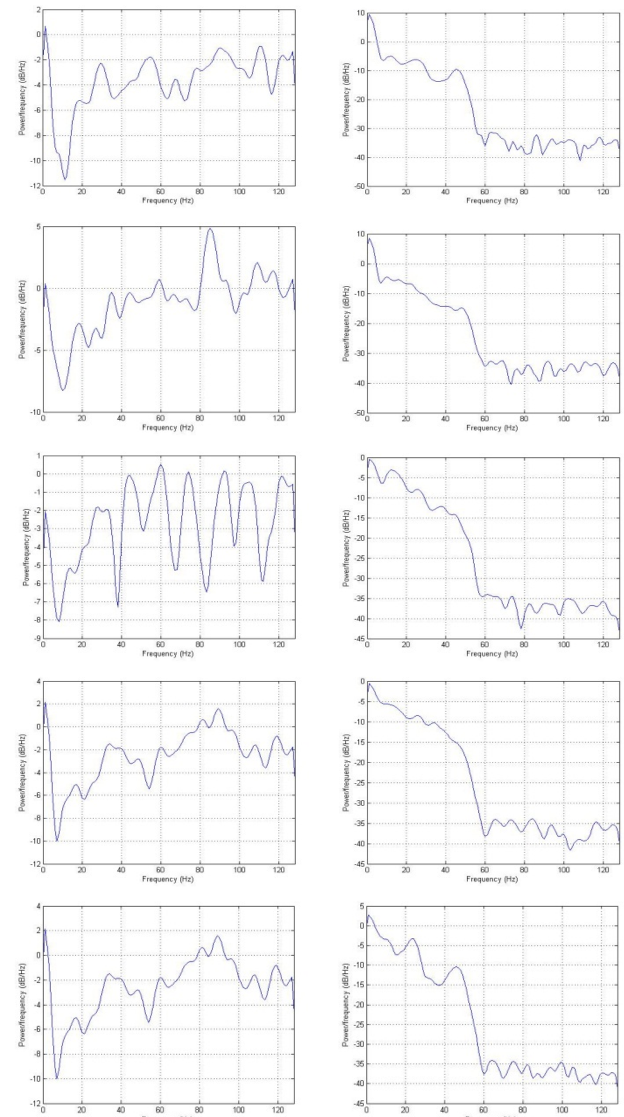
$$f_u(n) = f(n + uN) \quad (1)$$

Where *n=0, 1, 2,….N-1*

If U is total number of block, then Welch's PSD formula can be given as

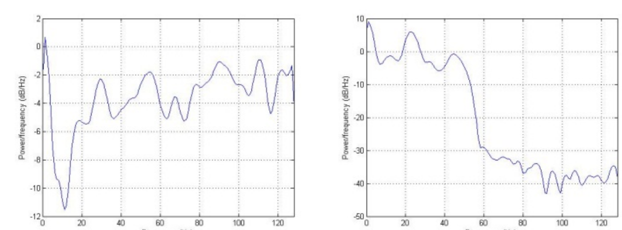
$$P_f(w_k) = \frac{1}{U}\sum_{u=0}^{U-1}|DFT_k(f_u)|^2 \quad (2)$$

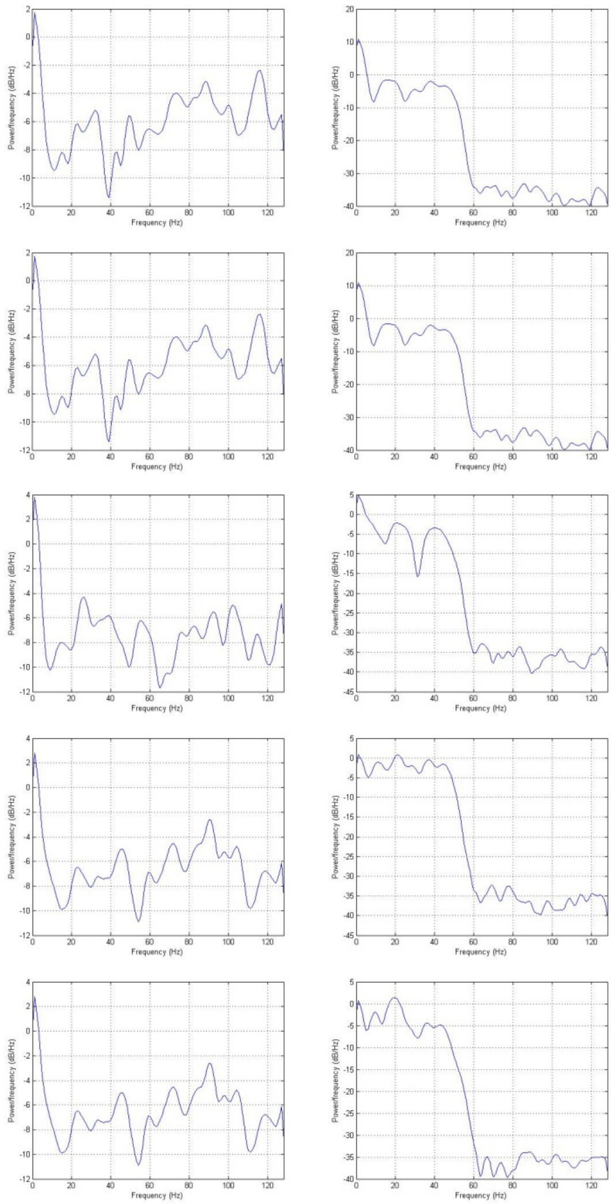
Fig.4 and Fig. 5 show the PSD for 5 trials in drowsy and controlled condition when signals are taken from C3 and C4 channels, respectively.



Drowsy sample Controlled sample

Fig4 PSD of Drowsy and controlled EEG data for C3 channel





Drowsy sample Controlled sample

Fig.5 PSD of drowsy and controlled EEG data for C4 channel

It is observed from Fig.4 and Fig.5 that the PSD of EEG signals recorded in controlled condition shows almost similar and stable response. The PSD has higher magnitude for lower frequencies and successively reduces with higher frequencies. PSD of EEG signals settle down between -40 to -30 db/Hz after 60 Hz of frequency. However PSD of EEG signals recorded in drowsy condition is much different from controlled one. The signals from C3 and C4 show that the PSD is very high initially and reduces drastically with random variation when the frequency increases.

V. Conclusion

It is observed from Fig.2 and Fig.3 that the FFT of EEG signals recorded under controlled condition reduces with increase in the frequency and becomes negligible after 60 Hz. However FFT of EEG signals recorded in drowsy condition are completely different from controlled one and very random in nature. Fig. 4 and Fig. 5, reveals that PSD of EEG signals recorded under controlled condition shows similar and stable response for all five trials. Power of EEG signals reduces after 60 Hz for each trial, however EEG signals recorded under drowsy condition do not represent such behavior. On analyzing all figures it can be concluded that for same mental task recorded EEG signals, from two persons, in two different mental conditions are completely different. EEG signals under controlled condition are similar and stable for all trials however under drowsy condition these signals are neither similar nor stable. That may lead a false interpretation of EEG signals during classification

VI. Acknowledgement

This project is financially supported by D.S.T., India.

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