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# Mental State Prediction by Deployment of Trained SVM Model on EEG Brain Signal

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***Abstract*—Mental States are a function of brain activity; with advancements in Brain Computer Interface (BCI) tools, they can be effectively predicted. Generally, BCI researches are sophisticated requiring multi-channel electrodes, and often carried out in controlled lab environment. This paper illustrates that a simple BCI research, targeting specific region of brain, can be conducted with an elementary setup. A method is demonstrated to predict the level of attentiveness using Electroencephalography (EEG) signal obtained from single-channel, non-invasive, dry-electrode placed on prefrontal cortex region. The acquired raw signal was processed to obtain features which were used to classify the attention state into three classes. As Support Vector Machine (SVM) is more effective in training and classification of high dimensional data, it was implemented and its results were studied.**

***Keywords—Attention Prediction, Brain Computer Interface (BCI), Brain Signal, Electroencephalography (EEG), Fast Fourier Transform (FFT), Mental States Prediction, Power Spectral Density (PSD), Support Vector Machine (SVM)***

## I. Introduction

Every function carried out by the human body is, in some way, enabled by electrical signal from the brain [1]. The electrical signal produced by the brain is the result of large number of neurons that are fired in rapid pulses. The energy of these pulses emitted in synchronized frequency could be measured in the form of brain waves with the use of an electrode that measures a minute voltage.

Electroencephalograph (EEG) is the electrophysiological record of voltage fluctuations obtained using electrodes. EEG signal is non-stationary, noisy, difficult to detect and complex to classify [12]. Also, the amplitude of these signals is very low, in the range of µ volt. But in general, these signals can be classified into five major category based on the frequency: Delta (<4 Hz), Theta (4 - 8 Hz), Alpha (8 - 14 Hz), Beta (14 - 30 Hz) and Gamma (30 -50 Hz) [1]. Mental states classification from EEG signal requires specific signal processing and machine learning tools [2].

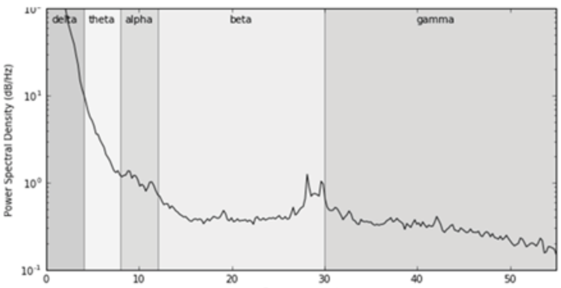


Fig. 1. Power Spectral Density Vs. Frequency Plot, Delta - Theta - Alpha - Beta - Gamma [13]

Most researches in Brain Computer Interface (BCI) are sophisticated. They employ large number of EEG electrodes requiring huge computational power to process the data. This has been serious limitation in the BCI research. This type of research is only possible in controlled lab environment and far from being applicable in real-life. But, small-scale researches focusing on specific brain activity can be dealt with reduced number of electrodes [3]. Also, their simplicity delivers a good promise to assistive technology for physically challenged people and also more applicable for real-life use.

Mainly, this research concentrates on the use of a single electrode to study the mental states in regard to the attention level. Prefrontal cortex is closely related with attention involving visual processing and alertness [8]. For this particular research, a single EEG channel system reliably predicts the attention states using signal obtained from the prefrontal cortex region.

For this research, Neurosky manufactured headset, a mobile headset equipped with single dry-electrode is used to collect EEG brain signal data from prefrontal-cortex region of the brain. This battery powered compact device is equipped with various Digital Signal Processing (DSP) chips to perform actions like analog to digital conversions, calculate Power Spectral Density (PSD) of various EEG bands and so on. It even has its own android and desktop application for visualizing raw and band separated EEG signal. In this research, we extracted digital representation of raw EEG data at 512 Hz with 16-bit resolution utilizing the Software Development Kit (sdk) provided by manufacturer.

For filtering noise, Butterworth filter is used, as it has monotonic and relatively large flat frequency response in the pass band. In addition, transition bandwidth of the Butterworth filter reduces with the increase in filter-order [4]. After denoising the signal, Fast Fourier Transform (FFT) is used to decompose the raw signal into frequency components. Then, band pass filter was used to separate the waves into five EEG bands.

The power level of the five EEG bands are used as key features/attributes for classification. Linear classifiers cannot separate these high dimensional features. For this reason, SVM classifier is used in this research. Support Vector Machine (SVM) classifiers are superior to other classifying algorithms for several reasons. Mainly, due to its ability to suppress the effects of noise, and produce results with higher accuracy and stability, even with sparse training data-set [2, 10]. Though, it is considered slower classifier, its speed is sufficient enough to classify BCI features in real-time [2].

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Moreover, SVM classifier provides different kernel functions and tuning parameters, which on proper tuning, help to make the classifier more robust.

## II. Methodology

### A. Experiment and Data Acquisition

To record the EEG data, an experiment was setup. Five volunteers, above 20 years of age, without any previous significant medical conditions, were recruited. Each experiment consisted of three sections and was conducted in a quiet room. Each of three sections was five minutes long where the data were fetched from each participant at 512 per second.

First, the participating individual was asked to wear the Neurosky Single Channel Headset. The individual's brain signal was recorded at normal state (without assigning any task). Then, the participating individual was asked to solve some mathematical problem mentally. Problems that demand visual interpretation for solving, requires a level of mental attentiveness which activates prefrontal cortex of the brain, where EEG electrode was placed [7,8]. Individual's brain signal was recorded while he/she was attempting to decode the problem. Finally, the individual was allowed to relax with a soothing sleep-inducing music from speaker [5,6]; the brain signal was recorded concurrently. In general, the brain signal was retrieved in 3 mental states.

### B. Data Processing

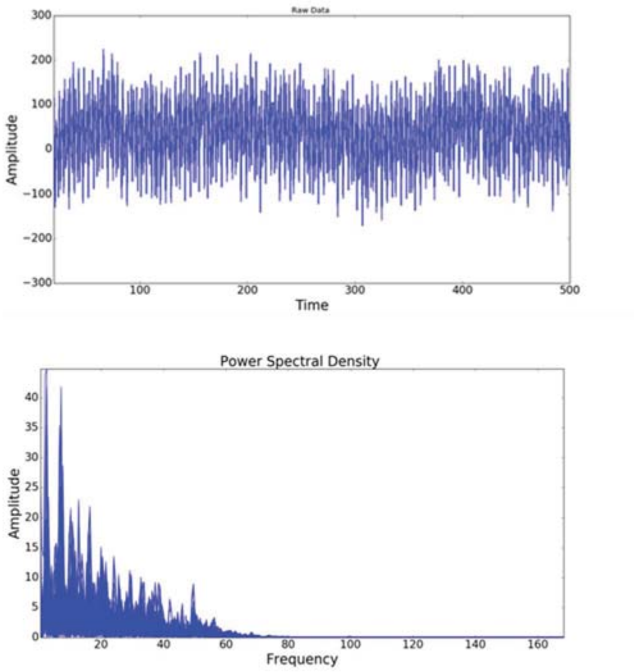


Fig. 2. Raw Data (Top) and Power Spectral Density (Bottom)

The signal obtained from the single channel headset has a large frequency spectrum with high frequency noise. It is important to pass the signal through a filter for noise removal. 6th order Butterworth low pass filter (cutoff at 60Hz) was used to filter the noise. The filtered signal has no distinguishable feature in the time domain. So, the signal was transformed to frequency domain using Fast Fourier Transform. Prior to that, a hamming window of 25 percent step size was implemented to maintain the continuity and to obtain clean frequency spectrum. Using FFT, a PSD was devised that gives the amplitude level for five brain waves (Delta, Theta, Alpha, Beta and Gamma) [9]. The signal with frequency higher than 60 Hz was rejected as noise, as it does not contain significant information.

### C. Training and Classification

Primary purpose of mental state classification is to classify 3 attention states - Attentive, Drowsy and Normal. The data were collected separately for these states and compiled into a single data set (about 10,000 rows of data) . We applied supervised learning using SVM to generate a computational model from the dataset.

The average power value of each 5 frequency dependent brain waves obtained from PSD was used as the key feature to train the model. The training set consisted of the average power value of five waves and three classes they refer to. These features may deviate from individual to individual, so the study has to be independent. So, separate models were created for each participant.

Fig. 3, Fig. 4 and Fig. 5 shows the power level at each frequency band for all three states respectively, which is the basis for classification.

Python Scikit-learn SVM module, was used for training the model. The classifier model was constructed using nonlinear Radial Basis Function as kernel function and the prediction accuracy was studied with different penalty parameter (c) and gamma ($\gamma$).

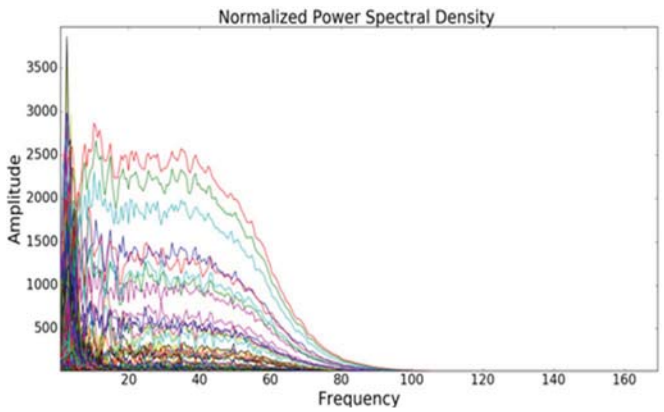


Fig. 3. PSD vs. Frequency of during Attentive State

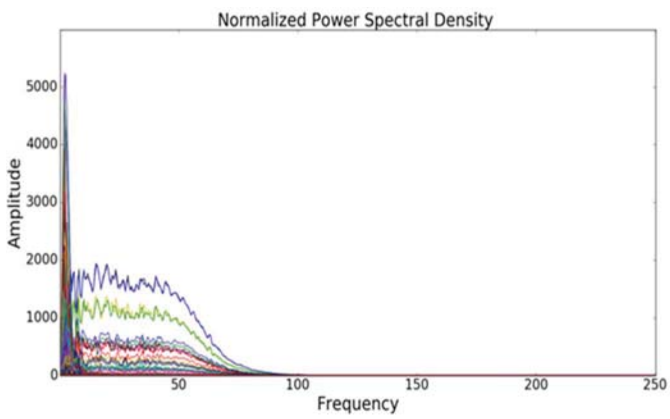


Fig. 4. PSD vs. Frequency during Normal State

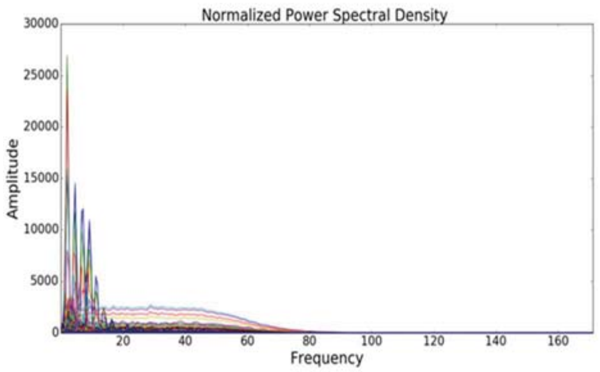


Fig. 5. PSD vs. Frequency during Drowsy State

## III. Results & Discussion

Fig. 3, Fig. 4 and Fig. 5 shows the power amplitude variation in relation to frequency, for 3 mental states. Relatively, attentive state has more power concentrated at higher frequency (20-40 Hz) components than that in normal state and drowsy state. Fig. 3 shows that the difference between the average power amplitude at lower frequency (0-5) and higher frequency (20-40) is less than that in the normal state (Fig. 4) and drowsy state (Fig. 5). On the other side, the power is concentrated more towards the lower frequency in drowsy state (Fig. 5) than that in other two states. This points out that, comparatively, higher frequencies are emitted when the individual is in an attentive state. Specifically, J.C. Geske mentioned in his research that beta waves are emitted more when an individual is fully alert and concentrated [11]. As the concentration dips down, the power shifts towards the lower frequency.

But, there is not much clear distinction between normal state (Fig. 4) and drowsy state (Fig. 5) when inspecting visually. It can be difficult to accurately predict normal and drowsy state by visual inspection or by a simple linear classifier. A powerful classifier like SVM can differentiate the states by mapping the data to higher dimension and separating them [10].

The feature sets are highly affected by sudden jerk or motion of head during data collection. This is because some electric pulse is induced in the sensor, appending noise to the signal. Such motions have to be avoided. The Butterworth filter helped in minimizing high frequency noise due to such physical activities.

TABLE I. PERCENTAGE ACCURACY OF SVM RADIAL BASIS FUNCTION (RBF) IN CLASSIFICATION OF THREE MENTAL STATES FOR DIFERENT PENALTY PARAMETER (C) AND GAMMA ($\gamma$)

| | **Penalty Parameter (c) = 1** | **Penalty Parameter (c) = 5** | **Penalty Parameter (c) = 10** |
|---|---|---|---|
| **Gamma** ($\gamma$) = 0.1 | 55.02 | 44.49 | 41.62 |
| **Gamma** ($\gamma$) = 1 | 50.71 | 25.59 | 23.92 |
| **Gamma** ($\gamma$) = 10 | 87.55 | 83.49 | 83.73 |

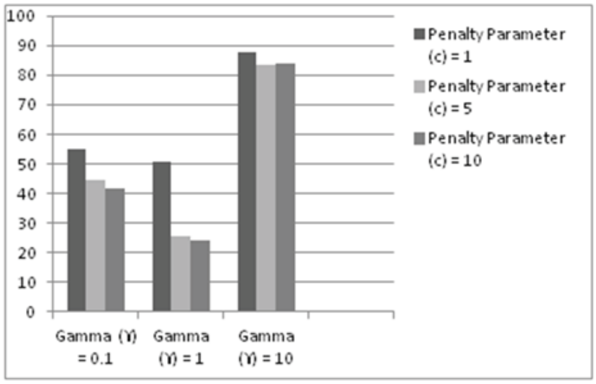


Fig. 6. Comparison of accuracy of SVM classifier for different penalty parameter (c) and gamma ($\gamma$)

As shown in Table 1 and Fig. 6, the tuning parameters: c and $\gamma$, highly influence the accuracy of the SVM classifier. The prediction accuracy is high when gamma ($\gamma$) is 10 ( accuracy is above 80 % in all case). Relatively, gamma ($\gamma$) plays a key role in tuning the model compared to penalty parameter (c) when RBF kernel function is used. The model performed the worst when gamma ($\gamma$) is 1 and penalty parameter (c) is 5, yielding prediction accuracy of 25.59 % only. The model performed the best when gamma ($\gamma$) is 10 and penalty parameter (c) is 1, yielding the prediction accuracy of 87.55 %. Higher value of gamma ($\gamma$) is able to capture the complexity of data whereas the c parameter trades off between simplicity of decision surface and misclassification.

## IV. Conclusion

Thus, it was studied that single electrode EEG system could effectively predict mental states like Attention, with the application of proper machine learning tools. A powerful classifier–SVM can differentiate Attention States by mapping the data to higher dimension. The accuracy of SVM model in predicting the 3 mental states: Attentive, Normal and Drowsy, on adjusting tuning parameters was also studied in the process. This experimentation can aid BCI researches focusing on specific mental activity utilizing reduced number of electrodes.

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