JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A SVM Machine Learning Method for Drowsiness Detection Using EEG Signal

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Abstract : Electroencephalogram (EEG) signal-based emotion recognition has attracted wide interests in recent years and has been broadly adopted in medical, affective computing, and other relevant fields. Drowsiness has become a leading sleeping disorder worldwide. Evidence has shown that subjects with depression exhibit different spatial responses in neurophysiologic signals from the healthy controls when they are exposed to positive and negative. Drowsiness is a common reason for an increase in accident cases worldwide. This paper proposed a SVM machine learning method for drowsiness detection using EEG signal. The algorithm first extracts features from EEG signals and classifies drowsiness using machine learning techniques.

***IndexTerms* - EEG, Drowsiness, Machine Learning, E-healthcare, SVM.**

I. INTRODUCTION

Electroencephalography (EEG) recordings for further classification and analysis can be time consuming for a physician (expert), especially for long term monitoring (e.g. sleep stages). Active learning approach using machine learning classifiers seems to be a promising method for semi-automated label acquisition with expert in the loop as it can radically decrease the necessary training set needed for neural network to learn [3]. Driver drowsiness is receiving a lot of deliberation as it is a major cause of traffic accidents. This work proposes a method which utilizes the fuzzy common spatial pattern optimized differential phase synchrony representations to inspect electroencephalogram (EEG) synchronization changes from the alert state to the drowsy state. EEG-based reaction time prediction and drowsiness detection are formulated as primary and ancillary problems in the context of multi-task learning. Statistical analysis results suggest that our method can be used to distinguish between alert and drowsy state of mind [4].

Drowsiness is a cause of accidents in industrial and mining activities. A considerable amount of effort has been put into the detection of drowsiness, and since then it has been integrated into a large variety of wearable systems. Nevertheless, the technology still suffers from high intrusiveness, short battery life and lack of generality. An opportunity to address these shortcomings arises from the use of physiological and behavioral features for bio-signals like EEG and IMU sensors [5]. Early detection of driver drowsiness and the development of a functioning driver alertness system may support the prevention of numerous vehicular accidents worldwide. Wearable sensors and camera-based systems are generally employed in the driver drowsiness detection. Electroencephalogram (or EEG) is considered another effective option for the driver drowsiness detection. Various EEG-based drowsiness detection systems have been proposed to date [6].

Automatic drowsiness detection system plays a vital role to prevent the road accidents caused by drowsiness. In this regard, the electroencephalogram (EEG) signal provides valuable information of brain physiology for detection of drowsiness. EEG signals exhibit non-stationary nature which is tough to explore by prior defined and fixed number of basic functions [7]. Drowsy driving is one of the major causes that lead to fatal accidents worldwide. For the past two decades, many studies have explored the feasibility and practicality of drowsiness detection using electroencephalogram (EEG) based brain-computer interface (BCI) systems. However, on the pathway of transitioning laboratory-oriented BCI into real-world environments, one chief challenge is to obtain high-quality EEG with convenience and long-term wearing comfort. Recently, acquiring EEG from non-hair-bearing (NHB) scalp areas has been proposed as an alternative solution to avoid many of the technical limitations resulted from the interference of hair between electrodes and the skin [8].

Drowsiness driving is one major factor of traffic accident. Monitoring the changes of brain signals provides an effective and direct way for drowsiness detection. One 3D convolution neural network (3D CNN)-based forecasting system has been proposed to monitor electroencephalography (EEG) signals and predict fatigue level during driving. The limited weight sharing and channel-wise convolution were both applied to extract the significant phenomenon in various frequency bands of brain signals and the spatial information of EEG channel location, respectively [9]. Daytime short nap involves physiological processes,such as alertness, drowsiness and sleep. The study of the relationship between drowsiness and nap based on physiological signals is a great way to have a better understanding of the periodical rhymes of physiological states [10]. Drowsy states from one-second long sequences of full spectrum EEG recordings. This method uses time series of inter-hemispheric and intra-hemispheric cross spectral densities of full spectrum EEG as input to an artificial neural network (ANN) with two discrete outputs: drowsy and alert [11].

II. METHODOLOGY

Electroencephalograms (EEGs) are recordings of the electrical potentials produced by the brain. Analysis of EEG activity has been achieved principally in clinical settings to identify pathologies and epilepsies since Hans Berger's recording of rhythmic electrical activity from the human scalp. In this work, we proposed a versatile signal processing and analysis framework for Electroencephalogram (EEG). Drowsiness detection in EEG can be thought as a sort of pattern recognition concept. It consists of data acquisition, signal processing, feature extraction, feature reduction and drowsiness detection. A novel EEG signal classification method is proposed, which is based on DWT, the dimension reduction and SVM classification. Within this framework the signals were decomposed into the frequency sub-bands using DWT and a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. Discrete Wavelet Transform (DWT) is used to decomposition of the EEG signal data. Then these features were used as an input to a support vector machine (SVM) with two discrete outputs: present or not.

The proposed work methodology and flow of work is as followings-

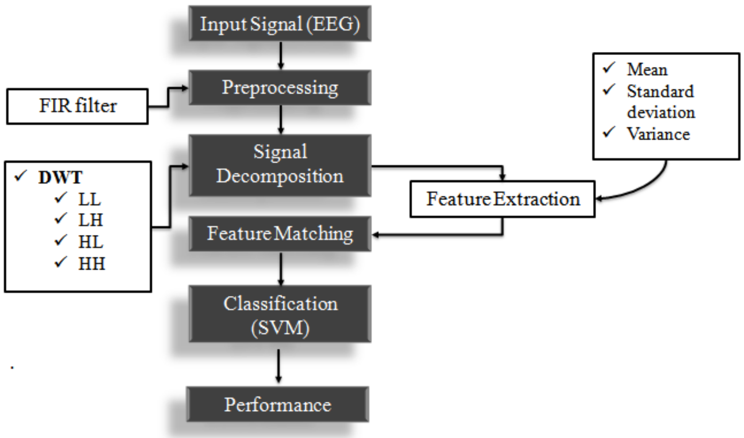

Figure 1: Flow Chart

Steps-

- Firstly, download the EEG dataset [12] from machine learning repository.
- Now apply the preprocessing of the data, here using FIR filter for pre-processing the EEG signal.
- Filters are networks that process signals in a frequency-dependent manner.
- Discrete wavelet transform (DWT) is used to extract characteristics from a signal on various scales proceeding by successive high pass and low pass filtering.
- The features extracted from the previous step were used as an input to a support vector machine (SVM) with two discrete outputs: present or not.
- Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative.
- Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F_measure, accuracy and error rate.

- Precision is a measure of the accuracy, provided that a class label has been predicted. It is defined by:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

- Recall is the true positive rate:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

- F1 Score is needed to a balance between Precision and Recall

$$\text{F1\_Score} = \frac{2\text{x (Precision x Recall)}}{\text{Precision} + \text{Recall}}$$

- Accuracy is the measurement of model, which is identifying relationships and patterns between variables in a dataset based on the input or training data.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

- Classification Error = 100- Accuracy

III. SIMULATION RESULTS

The simulation is performed using MATLAB software. MATLAB provides various library and function for perform the various operations.

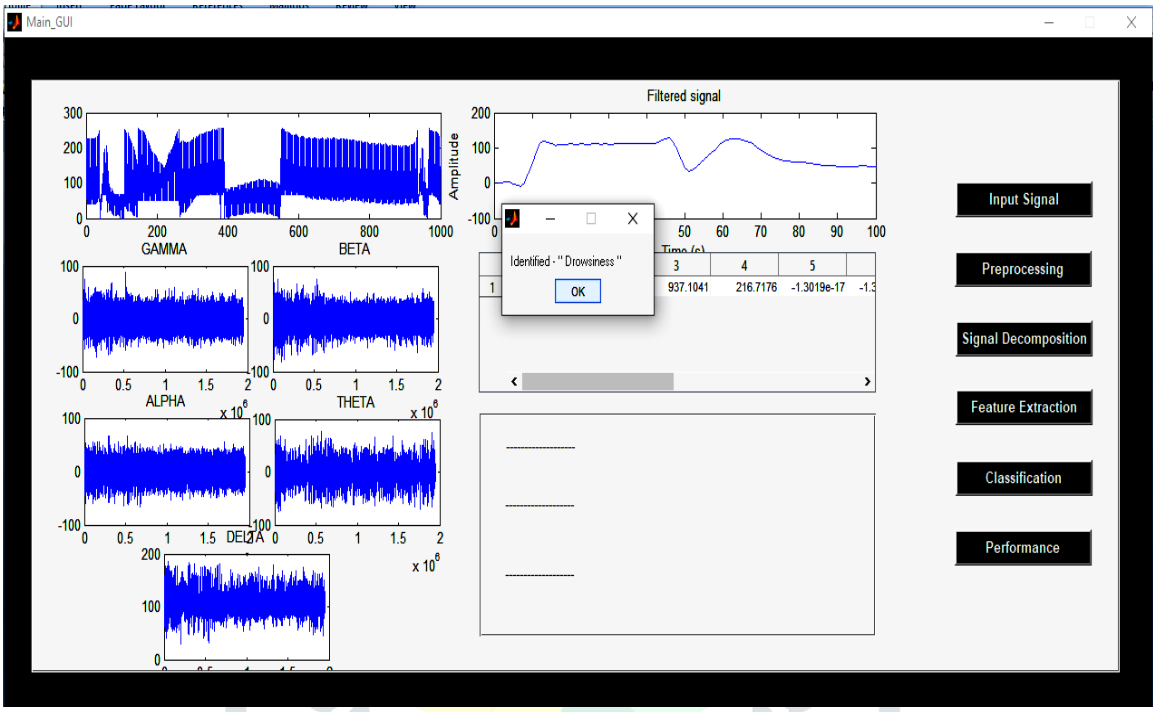

Figure 2: Classification (Drowsiness identified)

Figure 2 is presenting the classification technique that is support vector machine, after applied the classification it predict the EEG signal; signal number 5 is taken from dataset [12] and inform with pop-up window. The drowsiness is identified in this signal.

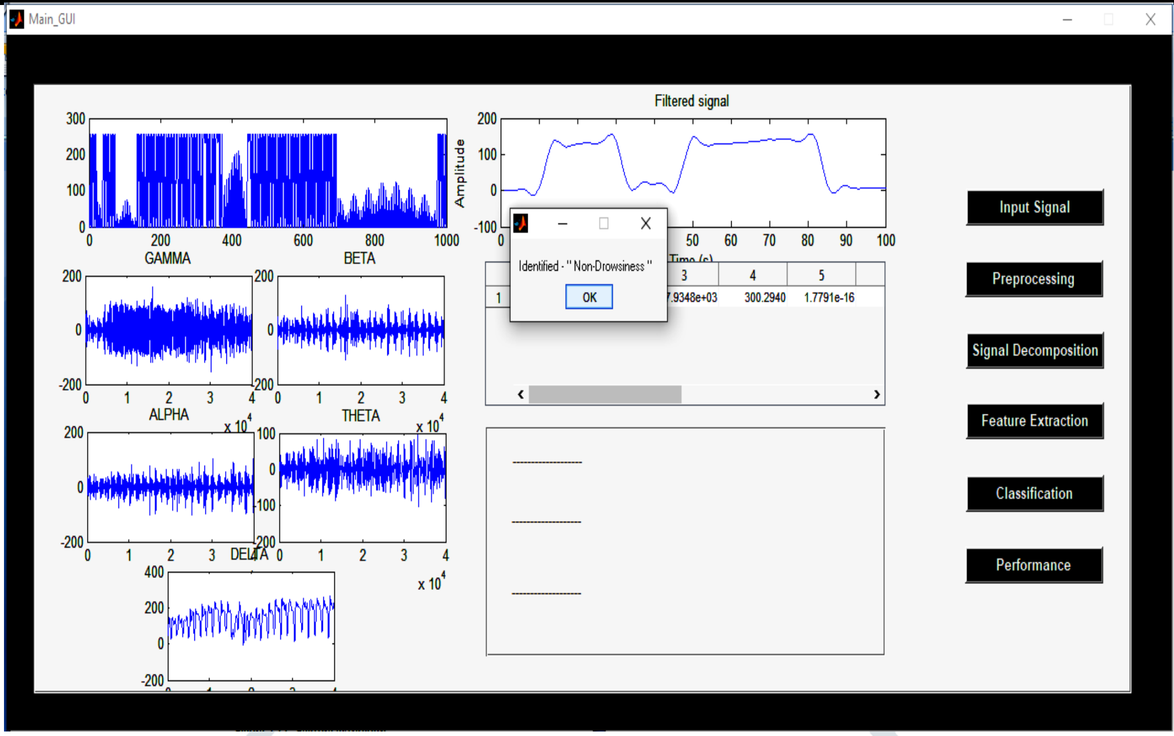

Figure 3: Classification (Non-Drowsiness identified)

Figure 3 is presenting identification of the EEG signal. The signal number 41 is taken from dataset [12]. The non-drowsiness is identified in this signal.

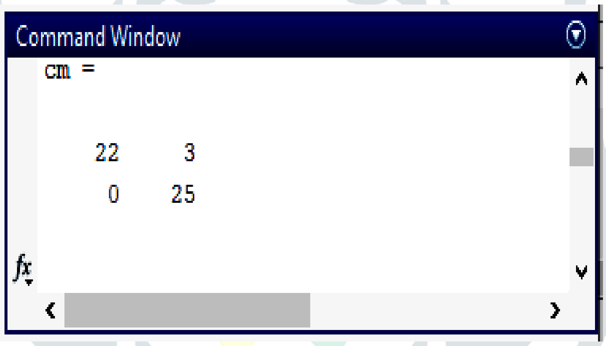

Figure 4: Confusion matrix

Figure 4 is showing the confusion matrix of the proposed SVM classifier. The confusion matrix provides the prediction classes that is followings-

Table 1: Result Comparison

Sr No.	Parameters	Previous work [1]	Proposed Work
1	Method	CNN	SVM
2	Precision	85.40 %	88%
3	Recall	89.36%	100%
4	Accuracy	75.87%	94 %
5	Classification error	24.13%	6 %

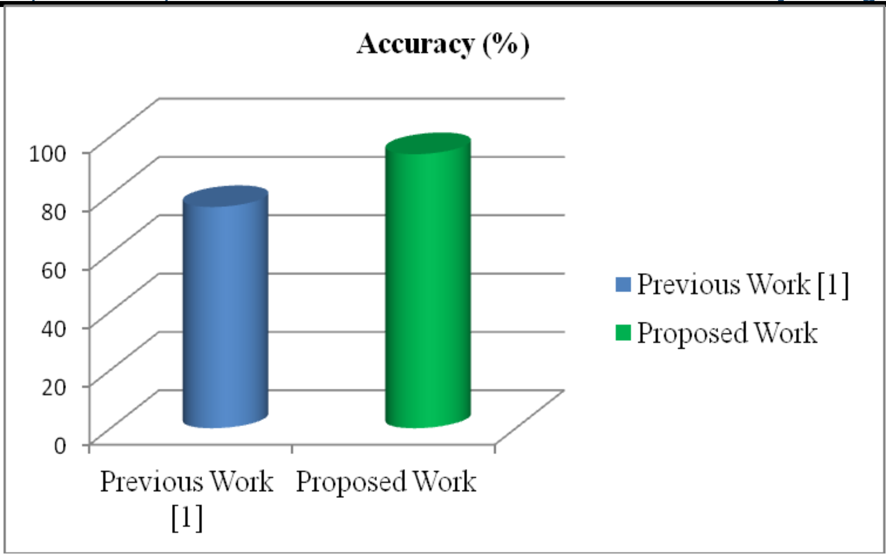

Figure 5: Comparison accuracy

Figure 5 is showing the graphical representation of the comparison of the accuracy parameter.

IV. CONCLUSION

This research proposed the machine learning technique to identify the prediction from given dataset. The MATLAB software is used to simulate the work. Machine learning SVM classifier approach is achieved 94% accuracy while previous classifier approach is achieved approx 76% accuracy. Therefore the simulation results shows that the proposed approach gives significant better results than existing work. In future the other set can be taken and apply more classification and the regression methods and predict various other parameters.

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