LIFTING WAVELET TRANSFORM BASED MENTAL ALERTNESS DETECTION FOR BRAIN COMPUTER INTERFACE

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Abstract: The human's brain electrical activity changes with the human reactions to the situations, thoughts, sleep stages and different alertness levels. Brain Computer Interface uses different features of brain electrical activity to create a communication pathway. Brain Computer Interface replaces traditional pathway of nervous system and helps in controlling applicationsby patients suffering from severe motor disorders. Efficiency of Brain Computer Interface largely depends on the human alertness level. Large variation in Electroencephalogramsignals due to change in alertness level may cause false interpretation of Electroencephalogram signals. In present work, a methodology is proposed for automatic alertness level detection of human brain using Electroencephalogram signals. In present methodology, the raw data is processed by Multi Scale Principle Component Analysis technique and further Lifting Wavelet Transform based features are extracted from processed signals. For classification or recognition of mental alertness level Support Vector Machine and Radom Forest Tree classifiers are used. The results of the classification illustrate the efficiency of the proposed methodology in automatic detection of alertness level of human brain.

Index Terms-- Brain Computer Interface (BCI), Electroencephalogram (EEG), Lifting Wavelet Transform, Support Vector Machine (SVM), Random Forest

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I. INTRODUCTION

Human brain consist millions of neurons. These neurons produce electric voltage field for each cerebral activity. The Electroencephalogram (EEG) is the 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 signal analysis is done for identification of various neurological disorders, diagnosis of neurological diseases, and also implementation of Brain Computer Interface (BCI). Brain Computer Interface (BCI) has wide spread applicability in the field of neuroprosthetics and rehabilitation for the patients of severe motor activity or diseases like Amyotrophic Lateral sclerosis (ALS) and Spinal cord injuries. Artificial communication channel established between human brain and external world by BCI is used to control a range of application or assistive devices by patients like controlling the motion of computer cursor, a mechanical artificial hand and others [2].

EEG signal contains lots of information in the terms of features. This makes recognition of EEG signals very crucial by visual inspection [3].For development of a BCI system, different EEG patterns can be used, like Farwell and Donchin [4] examined event related potential, left and right hand movement signalshave been discriminated by analyzing motor Imagery signals byPfutscheller and Neuper [5]. In order to implement a BCI system,the essential steps required are known as feature extraction and classification. Signal processing i.e. feature extraction and classification is performed on recorded EEG activity to translate brain activity to the meaningful external command [6].

Translation of human brain activity to meaningful command is a complex signal processing problem which is largely affected by various undesirable parameters viz. external noise, non-cerebral sources and user's mental vigilance or alertness levels. All these parameters are mainly responsible for change in the real EEG activity. If EEG activity or EEG signals change largely with different vigilance states of mind, it becomes difficult to recognize user intention by a BCI system. In addition, if user's mental alertness level is not appropriate to drive a BCI system, the generation of wrong command by BCI system could cause an accident. Hence, it is necessary to analyze patient's vigilance state before implementing BCI in order to avoid false interpretation and wrong command generation.Many researches have been carried out on EEG signals measured under different mental conditions such asalcoholic and/or 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].

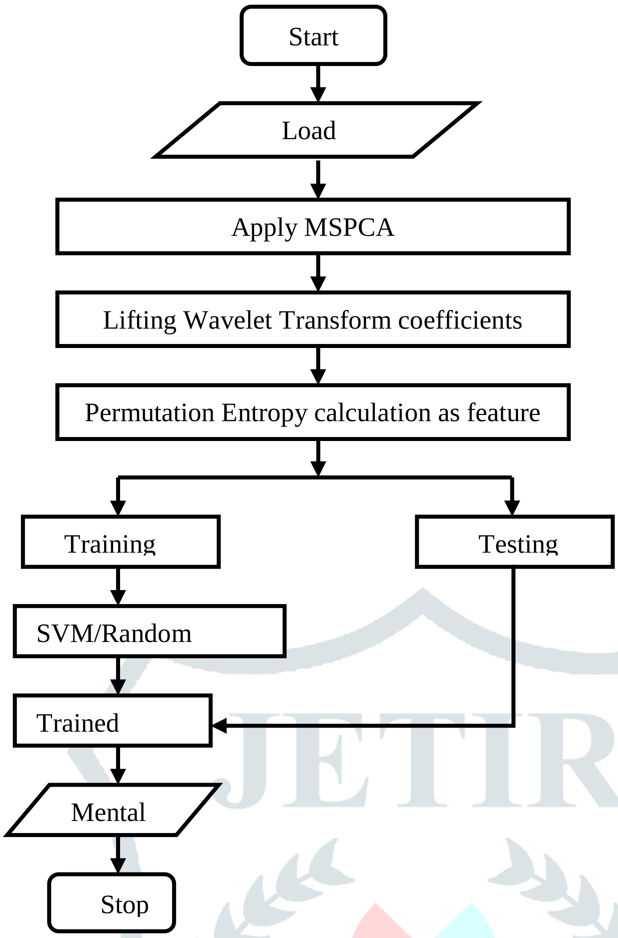


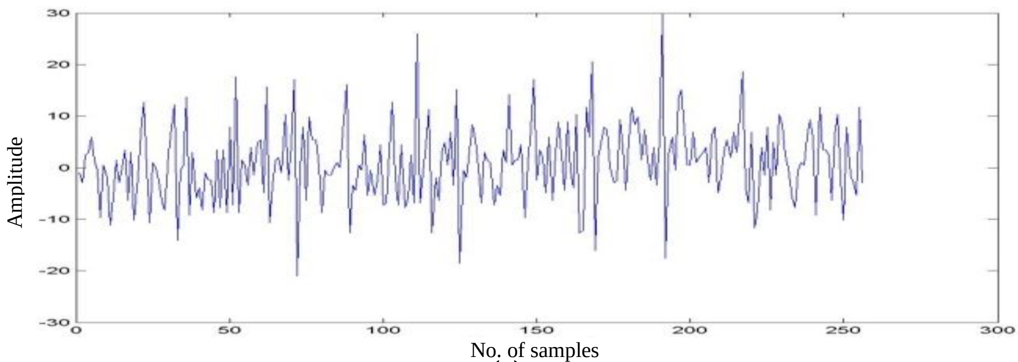
Fig.1 Flow chart of themethodology of automated vigilance/alertness level detection

Wavelet Transform (WT) is an efficient methodology for analyzing non-stationarysignals such as EEGs. It can extract the features of the signals in time and frequency domain effectively. However, a drawback of WT is that the frequency resolution is poor for high frequencies. Sweldens [10, 11] proposed to construct bi-orthogonal wavelets in the spatial domain by lifting technique, which is also known as second generation WT. The weak features, which are submerged with external or internal noise, can be extracted effectively using Lifting WT.

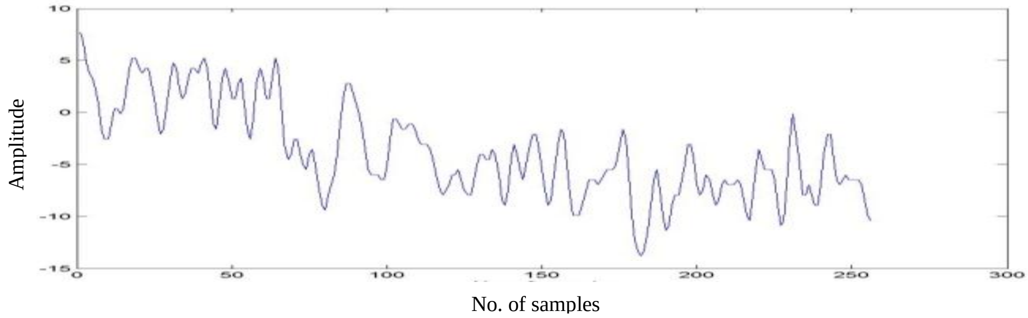
In present work, Lifting WT based methodology of Time-Frequency representation is employed for feature extraction of EEG signals. In proposed methodology initially, the signals are passed through Multi Scale Principle Component Analysis (MSPCA) model for reconstructing simplified and filtered EEG signals. Further, Lifting WT method is applied for decomposition of EEG signals into time-frequency domain. Further, Entropy based features are calculated from the Lifting WT coefficients as features of the EEG signals. Extracted feature are given to the machine learning technique for training of the classifier. Once the classifier is trained, features are input to the classifier algorithm for the validation of the methodology. In present work, Support Vector Machine (SVM) and Random Forest (RF) classifiers have been employed for training and validation of the methodology. Fig.1 shows overall methodology presented in this work for automated vigilance/alertness level detection.

II. EEG DATABASE

This data is recorded from a study to observe EEG correlates of genetic predisposition to alcoholism or drowsiness by Henri BegleiterNeurodynamics Laboratory, State University of New York Health Center Brooklyn. It includes measurements from 64 EEG electrodes placed on subject's scalps. The data is sampled at *256 Hz*where one epoch is *3.9-msec* long for 1 second. In the study, there were two groups of subjects present: alcoholic i.e. drowsy, and control i.e. alert. Each subject was exposed to either a single stimulus (S1) or to two stimuli (S1 and S2). The stimuli were pictures of objects chosen from the 1980 Snodgrass and Vanderwart picture set. When two stimuli were shown, they were presented in either a matched condition where S1 was identical to S2 or in a non-matched condition where S1 differed from S2. Fig. 2 shows the example plots of alert and drowsy subject. There were 122subjects and each subject completed 120 trials where different stimuli were shown. The electrode positions were located at standard sites recognized by IEEE as (Standard Electrode Position Nomenclature, American Electroencephalographic Association 1990) presented in Fig 3.



(a)



(b)

Fig.2 Sample EEG signal (a)under controlled condition from C3 channel (b) EEG signal under drowsy condition from C4 channel.

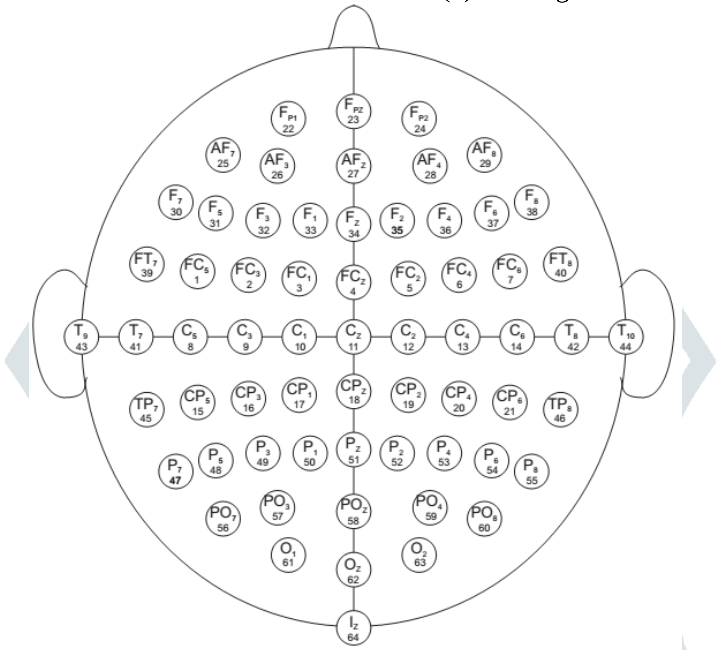


Fig.3 IEEE standard for EEG electrodes placement

III. OVERVIEW OF TECHNIQUES

3.1 MULTISCALE PCA

When the behavior of the events associated with various phenomenon changes rapidly with time and frequency, MSPCA is found to be suitable modeling technique. The modeling of single scale data can be efficiently performed by PCA alone, as algorithm considers relationship of data for same time-frequency localization. However, all practical data sources generate data which is multiscale in nature. Hence, it is viable to use PCA with multiscaleabilities. MSPCA performs computation of PCA on wavelet coefficients at each scale and combines results at significant scales [12]. In MSPCA algorithm, first the data is decomposed in time-frequency using certain wavelets. Then the PCA is applied for the coefficients of each scale irrelevant to one another. Combination of the models corresponding to important scales takes place to obtain a unified model [12].

In present work, we have applied MSPCA to simplify the EEG data matrix. For decomposition of EEG data, Symlets wavelet is selected and decomposition level was set to 4. However, Kaiser's rule is followed for retaining Principle Components (PCs). According to Kaiser's rule, only those components are retained which are having Eigen values (Variance) greater than the mean of all Eigen values.

3.2 LIFTING WAVELET TRANSFORM

The implementation of the lifting wavelet transform can be understood by the following methodological steps [13]:

1) ***Split:***The original signal Z =[z(k), k ∈ Z] is subdivided in to two parts: odd sample $A_0(k)$ and even sample A_e (k):

$$A_0(k) = \{z(2k+),k\in Z\},\ A_e(k) = \{Z(2k),\ k \in Z\}$$

2) ***Prediction*:** Since adjacent signal samples are highly correlated, the odd sampleis predicted based on the even sample through a predicting operator P, and the prediction error is defined as the detail signal d(k):

$$d(k) = A_0(k) - P[A_e(k)]$$

3) ***Updating*:** In order to reduce the frequency alias induced by the down-samplingin the splitting process and correct the difference between A_e (k)and Z, it is necessary to update the detail signal d(k) through an updating operator U and replace A_e (k) so as to acquire a smoother approximation signal

$$y(k) = A_e(k) + U[d(k)]$$

Since the lifting wavelet transform is performed completely in the time domain, the reconstruction course is very simple, including updating recovery, prediction recovery and merging [14].

3.3 SUPPORT VECTOR MACHINE CLASSIFIER

SVM is the statistical learning classification algorithm, which can be applied for classification of two or multi classes of data. SVM model was developed by Vapnik in 1995 [15]. SVM is being used by many researchers because of its attractive features such as Empirical Risk Minimisation (ERM) principle and Structural Risk Minimisation (SRM) principle. This makes SVM a strong classification tool [15]. In SVM a hyperplane is created which maintainsa large gap between the two classes of data. Support Vectors are closest point to this hyperplane and SVM model ensures maximum gap for closest support vectors of both the classes from hyperplane [16].

Let data set be (x_i, y_i),with L training points, where each input x_i has D attributes, and belongs only one of two classes $y_i = -1$ or $+1$.If w is normal to the hyperplane and b/w is perpendicular distance from the hyperplane tothe origin, expression for hyperplane can be written as:

$$w * x + b = 0$$

Fig.4 represents hyperplane, separating two linearly separable classes. $L1$ and $L2$ is the maximum distance of support vectors from hyperplane.

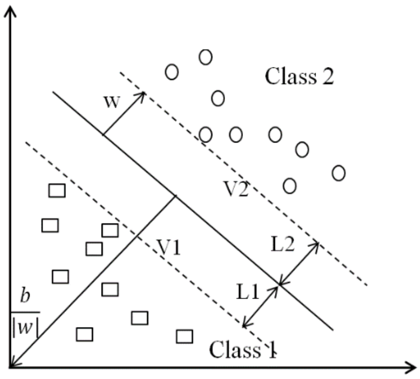


Fig.4 Hyperplane separating two classes of data.

3.4 RANDOM FOREST CLASSIFIER

Random Forest is a type of Artificial intelligence technique to identify the state of human brain i.e. alert or drowsy. The Random Forest algorithm was developed by Breiman [17] and is based on building a decision tree. In the initial stage, the training set consisting of features is divided into the in-bag and out-bags set. The method of bootstrapping is repeated several times on feature set to produce several in-bag sets and out-bag set subsets. A decision tree is modeled for each in-bag data set, and the out-of-bag set is used for evaluating the classification accuracy of each decision tree. The final outcomes based on algorithm are obtained from out-bag sets from the entire training dataset. Every decision tree casts a vote for one class, and this vote can be used to estimate the generalization capability of the classifier. The class from the feature set is recognized by gaining maximum vote [18]. The Random Forest error rate depends on the correlation between any two trees in forest and strength of each tree in the forest. Increasing the corelation increases the forest error rate. On the other hand, a tree with a low error rate is a strong classifier.

IV. FEATURE EXTRACTION AND CLASSIFICATION

Lifting WT based features are extracted from preprocessed EEG signals and feature vector is prepared to train classifier. The feature extraction is carried out in twomethodological steps. In the first step, Lifting WT is performed. This is followed by the calculation of Permutation Entropy, in the second step.The details of the Permutation Entropy can be found here.

In this process of calculation of Permutation Entropy, the continuous data series is mapped onto a symbolic series. The mapping is obtained by first embedding a scalar data series $\{f(n); n = 1, 2, ...\}$ to an e-dimensional space:

$$F_n = \begin{bmatrix} f(n), f(n+L), \dots . \\ , f(n+(e-1)L) \end{bmatrix}$$

where$e$ is the embedding dimension and L is the time delay. Each point in the e-dimensional embedding space can be mapped onto one of $e!$permutations. When each such permutation is considered as symbol, the reconstructed trajectory in e-dimensional space is represented by a symbol sequence *'i'*, and each having probability distribution of P_i. If the probability distribution of distinct symbols is given by $P_1, P_2, \dots, P_i$; $i \leq e!$, the PE, H_P of a given time series $\{f(n); n = 1, 2, ...\}$ based on Shannon entropy definition can be obtained by Eq. (23).

$$H_p(n) = -\sum_{i}^{I} p_i \, ln(p_i)$$

H_p gives a measure of the departure of the data series under study from complete random one. In present work, SVM and Random Forest classifiers are employed for classification or identification of the class of EEG signals. Once the classifiers are trained, it can be used for recognition of EEG signals and consecutively generate identify for the mental alertness level of the subject.

V. RESULTS

Lifting WT based Permutation Entropy features are obtained from brain signals recorded from alert and drowsy subject and are used to prepare input feature vector for training and validation of classification algorithm SVM and Random Forest. The EEG data from single subject under two different mental states drowsy and alert are employed for the feature extraction and classification purpose. In total, 250 instances have been employed corresponding to alert state of mind and similarly 250 instances are employed for drowsy state of mind. For classification of two mental states by SVM and Random Forest, 10-fold cross validation method is carried out in this work. The method of 10-fold cross validation ensures that there is no statistical biasing is present in the data. Hence, the results of the classification are valid results. Table 1 represents the confusion matrix for classification of two classes of EEG data by SVM classifier. In addition, Table 2 represents the confusion matrix for classification of two classes of EEG data by Random Forest classifier. It is observed from Table 1 that the SVM classifier classified 250out of 255 instances correctly corresponding to drowsy state and misclassified 5. Also, SVM classifier classified 252 out of 255 instances correctly corresponding to alert condition. The overall classification efficiency of the classifier is 98.4%. However, it is observed from Table 2 that the Random Forest classifier classified 245 out of 255 instances correctly corresponding to drowsy state and misclassified 10. Also, Random Forest classifier classified 247 out of 255 instances correctly corresponding to alert condition. The overall classification efficiency of the classifier is 96.4%.

TABLE 1 CONFUSION MATRIX SVM CLASSIFIACTION

S.NO.	Test set		Output
	Drowsy	***Controlled***	***Classification***
1.	250	5	Drowsy
2.	3	252	Controlled

TABLE II CONFUSION MATRIX RANDOM FOREST CLASSIFIACTION

S.NO.	Test set		Output
	Drowsy	***Controlled***	***Classification***
1.	245	10	Drowsy
2.	8	247	Controlled

VI. CONCLUSION

In this work a feature extraction and classification methodology is proposed for the processing of EEG signals for obtaining mental alertness level of human subject. The proposed methodology is established as an effective watchdog of the mental health of the subject, on whom Brain Computer Communication system is to be implemented. The methodology is based on the Lifting WT and the estimation of Permutation Entropy from the WT coefficients as feature. The efficacy of the present methodology of automatic alertness level detection can be confirmed by the high classification accuracy obtained using SVM and Random Forestclassifiers. The classification accuracies obtained by SVM and Random Forest classifiers is 98.4% and 96.4% correspondingly. In this study, it is observed that the SVM classifier is more suitable for mental alertness level detection from EEG signals as compared to Random Forest classifier. So, this work is established as a successful methodology for mental alertness detection from EEG signals. The present methodology can be employed in combination with Brain Computer Interface to improve its efficacy.

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