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Classification of EEG Signals during Meditation and Controlled State Using PCA, ICA, LDA and Support Vector Machines

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Abstract

In this work, the adaptable signal processing algorithm is proposed for Electroencephalogram (EEG) signals. In this algorithm, the Discrete Wavelet transform is applied to EEG signals for decomposing it into its frequency sub-bands. Statistical analysis is applied to these sub-bands to extract the statistical features which characterize the distribution of wavelet coefficient. Several classification algorithms such as Independent Component Analysis, Principal Component Analysis and Linear Discriminant Analysis which is popularly called as ICA, PCA, and LDA respectively is applied to these features to reduce its size. Then these reduced features applied to SVM classifier which categorizes the EEG signals into Meditation state and Controlled (Normal) state. Here Performance accuracy from different classifier is evaluated and then compare to know which classifier is best suited for EEG signal classification for meditation and controlled state. The meditation method used here was Vipassana Meditation which is a type of mindfulness meditation practice. The finding from above procedure gave the best classifier for classification of EEG signals during controlled and meditation state.

Keywords: Electroencephalogram (EEG); Meditation; Independent Component Analysis (ICA); Principal Component Analysis (PCA); Linear Discriminant Analysis (LDA); Support Vector Machines (SVM).

1. Introduction

Electroencephalograms (EEGs) are giving the electrical activity of the brain. EEG signals are a noninvasive method of detecting the brain status. These signals are nonstationary and nonlinear in nature. Hence, mathematical tools such as DFT, FFT are failed to give detail analysis of EEG signals. Hence wavelet Transform is used for analysis of EEG signals since it gives good time-frequency localization. Meditation technique which is used for this work is Vipassana meditation. This is mindfulness meditation technique frequently practices in Southwest part of the world. In this technique relaxing but the highly awake state of mind is achieved. The subject chosen for this research work consisted of 50 novice meditator (25 female and 25 male). These people were from educational and industry background with high-stress level. EEG signals were recorded during meditation practice of 50 novice meditators after 4-weeks of Meditation intervention training at Vipassana Research Institute (VRI), Mumbai.

Amongst the various available feature extraction techniques, Independent Component Analysis, Principal component analysis and Linear Discriminant Analysis (LDA) popularly known as ICA, PCA and LDA respectively are used for feature extraction. Feature extraction is nothing but converting the prevailing feature data into a lower size feature data. This was useful to avoid redundancy due to high dimensional data. Discrete Wavelet Transform (DWT) (dB4) has been applied to recorded EEG signals for time-frequency analysis. The wavelet coefficients extracted after application of wavelet transform to EEG signals is then used for classification of EEG signals into Meditation and normal state. EEG signals were decomposed into its corresponding frequency sub-band $\{\delta(0-4Hz), \theta(4-8Hz), \alpha(8-12Hz), \beta(13-40Hz)\}$ using wavelet transform (DWT). Statistical Analysis on these sub-bands is carried out to extract statistical features which represent the distribution of wavelet coefficient. The dimension of these features is reduced using several feature reduction techniques such as LDA, PCA, and ICA.

These reduced features are then applied as an input to Support Vector Machine with two discrete outputs: Meditation and Controlled state. The accuracy is then calculated using several classifiers. The results of these classifiers are then compared and limitations and advantages of these techniques are discussed. Feature Extraction techniques using LDA, PCA, and ICA along with SVM always perform better as compared to without using these techniques. Moreover, LDA with Support Vector Machine achieved the best performance as compared to PCA + SVM and ICA + SVM [2],[4],[9].

2. Materials and Methods

2.1 Subjects and Data Acquisition

The EEG data is acquired from the 50 healthy novice meditator from different age groups. The subjects recruited for this research lies in between 20 years to 60 years with an average age of 40 years. The data were acquired from these subjects using 8-channel NE's Enobio with a sampling frequency of 500 Hz and line filter to remove the AC frequency of 50 Hz. The Enobio was connected to different positions on the scalp with reference electrode connected to left earlobe as shown in Figure 1.

Figure 1. EEG data Acquisition using 8-channel NE's Enobio when Subject Practicing Vipassana Meditation.

The data is recorded for the duration of 2-mins during normal state and 2-mins during meditation state. During the entire duration of these experiments, volunteers were relaxed in an awake state with eyes closed and subjects were in the normal seating position. The data acquired from these methods were further pre-processed for removing noise. The Classification of recorded data is processed as shown in Figure 2.

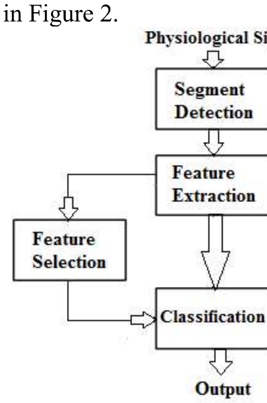

Figure 2. Block diagram of Classification of EEG signal during controlled and meditation state.

2.2 EEG signal Analysis using DWT

EEG signal is nonstationary in nature; discrete wavelet transform (dB4) is applied to EEG data for time-frequency analysis. It is essential to select the proper wavelet and its decomposition level. The proper decomposition level is chosen based on the dominant frequency of the EEG signal. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The criteria for selection of decomposition levels have been chosen such that the part of the signal correlates well with the frequencies necessary for signal classification and it has been preserved in the wavelet coefficients [2],[13],[15].

EEG signal frequency above 30 Hz is not useful, hence after several trails, the number of decomposition level was selected to be 5. The complete EEG signal is then decomposed into the detail coefficient D_1-D_5 and approximate coefficient A_5.

The extracted coefficient after wavelet transform applied to EEG signals gives a compact representation that shows the distribution of Energy in frequency and time domain. The representation of frequencies corresponding to different decomposition level for dB4 wavelet has been given in Table 1 with a sampling frequency of 500 Hz [12].

Table 1. Corresponding frequencies after each decomposition level using Daubechies-4 (dB4) filter wavelet with a sampling frequency of 500 Hz.

Decomposed Signal	Range of Frequencies
D_1	43–86 Hz
D_2	21–43 Hz
D_3	10 -21 Hz
D_4	5-10 Hz
D_5	2-5 Hz
A_5	0-2 Hz

The set of feature vectors and statistical features were further reduced with the help of the set of the wavelet coefficients.The following statistical features were used to represent the time-frequency distribution of the EEG signals:

(1) The Average of the absolute values of the coefficient in each frequency subband.
(2) The mean power of the coefficients of wavelet transforms in each frequency subband.
(3) The standard deviation of the wavelet coefficients in each frequency sub-band.
(4) The ratio of the absolute average values of nearby frequency sub-bands.

First and second features represent the distribution of the frequency components in the signal and the third and fourth represents the number of changes in a distribution of the frequency components. The features vectors These feature vectors derived from frequency bands D_3–D_5 and A_5, were utilized for EEG signal classification [12].

Figure 3 shows fifth level EEG signal decomposition using wavelet transform (dB4) with detail and approximation during the normal state. Figure 4 shows fifth level EEG signal decomposition using wavelet transform (dB4) with detail and approximation during meditation state. The reconstruction of these detail and approximation signals takes place using Daubechies 4 (dB4) wavelet filter.

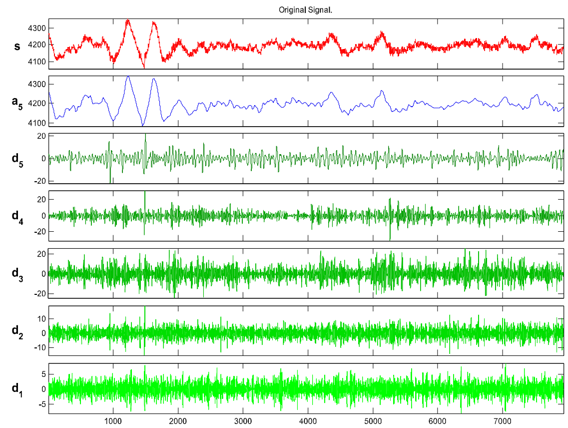

Figure 3. Approximate and detailed coefficients of EEG signal taken during normal State.

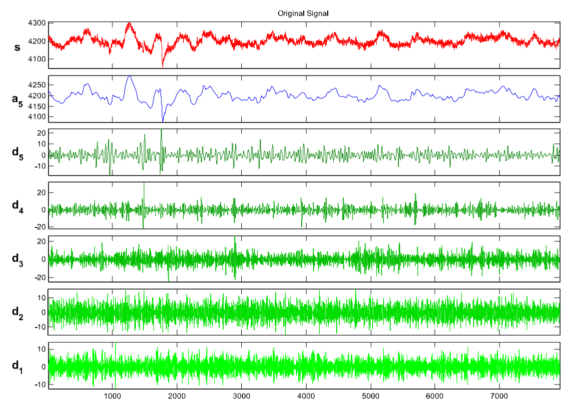

Figure 4. Approximate and detailed coefficients of EEG signal taken during Meditation State.

2.3 Methods of Feature extraction

2.3.1 Principal component analysis (PCA)

There are various methods for the features extractions and dimensional reduction of the EEG signal. Amongst all the available methods, Principal component analysis (PCA) is a well-known method. PCA is used to reduce the d-dimensional data into a lower dimensional space. It will help to decreased time complexities, the degrees of freedom and space. The main aim is to express the EEG data in a reduced space for the sense of a sum-squared error variation. This method is used to segment EEG signals into multiple sources. The basic concept in PCA is theoretically much simple than practically applying it [7],[19],[20].

Initially, the d-dimensional vector for mean values μ and $d \times d$ covariance matrix $\sum$ are calculated for the whole data set. Then the Eigen Values and Eigen Vectors are calculated and organized in decreasing Eigenvalues. These Eigenvectors is represented by e_1 for Eigenvalues by λ_1 and eigenvectors e_2 for Eigenvalues λ_2 and so on. Subsequently largest k such Eigenvectors are chosen. This is achieved by observing the spectrum of the eigenvector. It is often that dimension indirectly an inherent dimensionality of the subspace which regulates the ‘‘signal”. The remaining dimensions represent the “noise”. Then this will lead to the formation of matrix A of size $k \times k$. The matrix consists of a column of k eigenvectors that pre-process the data using:

$$x' = A^t (x - \mu)$$
(2)

This will represent the minimum square error criterion [7].

2.3.2 Independent Component Analysis (ICA)

Another popular features extraction technique is Independent Component Analysis (ICA) which transforms the multivariate random signal into mutually independent signal components. Independent components can be derived from the mixed signals by PCA method. In this way, independence indicates the particulars carried by one signal component cannot be deduced from the other signal components. It clearly indicates that the joint probability of independent quantities is acquired as the product of the probability of each of individual quantity as per the statistics.

Let $x_i(t)$ be the source signal which has *c* independent scalar for $i = 1,....,c$. Here *t* is time index which is $1 \le t \le T$. For writing the notation in a simplified way, *c* values are group into a vector $x(t)$ and assume that it has zero average. Since this is independent assumption where noise is zero, the multivariate density function can be written as,

$$p(x(t)) = \prod_{i=1}^{c} p(x_i(t))$$
(3)

If a d-dimensional data vector is noticed at each instant, then it is given by,

$$y(t) = Ax(t)$$
(4)

where *A* denotes the scalar matrix of size $c \times d$. The important point needs to note here is a condition $d \ge c$ .The main job of ICA is to retrieve the source signals from the sensed signals. Particularly, the real matrix *W* is written such that,

$$z(t) = Wy(t) = WAx(t)$$
(5)

Here *z* denotes an estimate of the sources $x(t)$ where $W = A^{-1}$. Here both *A* and its inverse A^{-1} are unknown. Maximum-likelihood techniques are used to determine the matrix A. Here, an estimate of density is used and it is parameterized by $\hat{p}(y;a)$. Here *a* represent parameter vector of Matrix *A*. It minimizes the difference between the source distribution and the estimate whereas $\hat{p}(y;a)$ is an estimate of the $p(y)$ [7],[10],[20].

2.3.3 Linear Discriminant Analysis (LDA)

The objective of linear discriminant Analysis (LDA) is to produce new variable which is a union of the real predictors. This is achieved by maximizing the distinction between the predefined groups and new variable. The main aim is to merge the predictor score such that single new compound variable, the discriminant score, is established. This is a dimension reduction technique where excessive data is reduced by compressing *p*-dimensional predictors into single dimensional line. In the last step of the process, each class has normal distribution scores of highest possible distinction in mean scores for the classes. In a real sense, the degree of overlap between the discriminant score distributions decides the success of this method. This score is calculated from the discriminant function as:

$$D = w_1 Z_1 + w_2 Z_2 + ... + w_p Z_p$$
(6)

The above equation shows that the discriminant score is a weighted sum of the linear combination of predictors. The weight is calculated to maximize the distinction between class mean discriminant scores. If it has larger differences then it has larger weights. And if weight is small then class means are homogeneous [11].

2.3.4 Support Vector Machines (SVMs)

Support vector machines (SVMs) are the supervised learning algorithm used for data classification. It has good accuracy as well as better ability to deal with a large number of predictors hence it is frequently used in Biomedical Signal Processing. SVMs can classify the data which cannot be separated linearly using hyperplane by mapping the optimize predictors onto a new, higher-dimensional space in which they can be separated linearly.

In this method, support vectors are the list of predictor values which lie nearest to decision boundaries that separate the classes. Practically it is assumed that these cases have the largest impact on the position of decision boundaries. In fact, if they have been removed then it has large effects on its position of Decision boundaries. Choosing the best position of decision hyperplane is actually a problem of optimization where different kernel functions are used to design the linear boundaries through mapping, the nonlinear transformation of the predictors. In this algorithm, the hyperplane is located in the predictor space as decided in terms of the input vectors and the dot product of features space. The distance between the vectors in high dimensional space can be found out using dot product. An SVM bifurcate the support vectors without representing the space explicitly and locates the hyperplane. The task of dot product played by the kernel function as an alternative in the feature space. The complex curve is used to separate the two classes absolutely in the real space of the predictor. Even the two classes cannot be separated by the best linear separator completely. On the other side, if real predictor values can be forecasted into more convenient feature space then classes can be separated completely with linear decision boundary. Hence, the critical problem is to obtain the appropriate transformation. Selection of kernel function and its parameter is crucial things in SVM. Proper selection of immensity of the penalty for breaching the soft margin between the classes is also one of the key factors in SVM. In short, SVM can be design successfully which depends on the types of data to be classified [1],[5],[6],[10],[11].

The perceptron is very much identical to basic support vector classifiers. Both of these classifiers are linear classifier and they considered data is separable. The SVM classifier separates the classes with maximal margin. The biggest 'tube' that doesn't contain the samples which can be drawn around the decision boundary is called a margin as shown in Figure 5. Hence, maximum generalization capacity can be achieved using this particular solution.

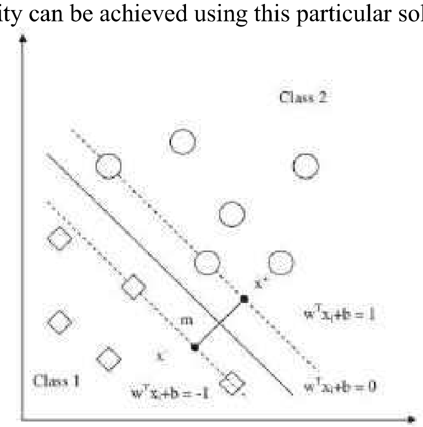

Figure 5. Linear SVM classifier.

The SVM classifier has a large number of advantages over other classifiers such as less computational efforts since it also uses nonlinear boundaries. It uses standard optimization software for finding a unique global optimum for its parameters. SVM's performance is also better as compared to another method. The main disadvantage of this method is that the problem complexity is similar to the order of the number of samples and not of the order of samples dimension. General Software often fails for large sample sizes $N_s > 1000$. Hence, to solve the problem of optimization special-purpose optimizers is used [1],[5],[6],[8],[10],[11],[17],[18].

3. Results and Discussion

In this research, EEG signal is acquired from the *50* subjects during normal and meditation state in order to do a comparison between the ICA, PCA, and LDA using SVM. EEG signal is divided into several frequency subbands such as $\delta(0-4Hz), \theta(4-7Hz), \alpha(8-12Hz), \beta(13-40Hz)$ and $\gamma(40Hz >)$ using Discrete Wavelet Transform. Then the EEG data is normalized and decomposed using wavelet transform. The Statistical features were extracted from these frequency sub-bands. These features were large in dimension and most of the data were redundant. Hence, these features were reduced using several feature reduction techniques such as ICA, PCA, and LDA. At the last, these data are classified using SVM.

The main aim of this paper was to design the classifier that is able to classify the input signal belongs to normal or meditation state. For designing the classifier based on neural network, 1500 samples were randomly chosen for training purpose and 500 samples were selected for the testing purpose from total 2000 samples. The distribution of sample's class training and testing data set is shown in Table 2.

Table 2. Distribution of the class samples in the testing and training data set.

Class	Training set	Test set	Total
Meditation	750	250	1000
Normal	750	250	1000
Total	**1500**	**500**	**2000**

In addition to this, Sensitivity and specificity were used as a performance measure for classification of data into two classes. Sensitivity (true positive ratio) and specificity (true negative ratio) are calculated from the data obtained from SVM classifier using confusion matrix. The formula for Sensitivity (True Positive Ratio) and specificity (True Negative Ratio) is as follows:

$$Sensitivity = TruePositiveRatio = \frac{TruePositive}{TruePositive + FalseNegative} \times 100 \tag{7}$$

$$Specificity = TrueNegativeRatio = \frac{TrueNegative}{TrueNegative + FalsePositive} \times 100 \tag{8}$$

3.1 Experiment Results

Meditation state from EEG can be a sort of Recognising pattern from the signal. The basic building blocks for classifying EEG signals into Meditation and normal state consists of EEG signal acquisition, Pre-processing, Extraction of Feature, Reducing features and finally classification. In this paper, a comparative classification of EEG using different methods is proposed, which is based on DWT. Redundancy in the data is reduced using various dimension reduction methods such as ICA, PCA, and LDA. SVM classifier is used for classification of data. The steps for classification of this data are as follows:

- Wavelet coefficient calculated from EEG signals using DWT and then statistical features estimated using wavelet coefficient.
- The extracted features have lots of redundant data. This redundant data has been reduced using PCA, ICA and LDA algorithm. This step is important as irrelevant features may even degrade the classifier performance.
- The classification process for meditation and the normal state is carried out using SVM-based classification.

These steps were repeated for all EEG signals recorded during normal and meditation state. Kernel function for SVM is chosen after several trails and Radial Basis Function (RBF) kernel is selected for SVMs. σ and γ are the two parameters related to RBF kernel. σ is the penalty term and γ is kernel parameter which is important in the performance of SVM. Improper value of σ and γ leads to several problems such as under-fitting and over-fitting. Hence the optimal value of σ and γ is necessary for accurately classifying the data. Here, 10-fold cross-validation is used for selecting proper values of σ and γ. Several combinations of σ and γ are tried for RBF kernel and finally the values of σ and γ are selected which has given better cross-validation accuracy. Finally, the classifier was designed with these values of RBF kernel function.

In this paper, training process has been started using several combinations such as ICA + SVM, PCA + SVM, and LDA +SVM. The result has been shown in Table 3. As per results in Table 3, the classification accuracy with LDA+ SVM is highest (95%) compared to other two combinations such as ICA +SVM (93.00 %) and PCA+SVM (93.00%). The simulation result reveals that SVM along with feature extraction using ICA, PCA or LDA can always give better results than without feature extraction (90%).

Table 3. Classification accuracy using PCA, ICA and LDA models for EEG signals

Feature extraction method	Accuracy	Specificity	Sensitivity
LDA (%)	95.00	100.00	90.00
ICA (%)	93.00	100.00	86.00
PCA (%)	93.00	100.00	86.00

Since the LDA has comparatively smaller support vectors than PCA and ICA. It has given better accuracy. Moreover, Training duration for Classification using LDA + SVM was longer than other two methods. Besides these, the problems of over-fitting and underfitting can be overcome by appropriate use of kernel function which can give best classification process.

3.2 Discussion

Many existing methods have shown better performance for classification of the EEG signal. But all the classification methods applied for seizure detection from EEG signal. This was the unique work for classifying the state of meditation from the EEG signal. Also in the previous work, all extracted features directly applied to classifiers that were affecting the classification accuracy. Here SVM is implemented along with Data reduction techniques such as PCA, LDA, and ICA. Depending upon the result following point can be discussed:

1. The large classification accuracy using SVM gives a better understanding for selecting the features for defining the EEG signal. The important conclusion which can be drawn here is DWT coefficient can be a good feature for representing EEG signals. This ultimately gives good distinction between the classes.
2. The results obtained here along with the selected statistical features reveals that SVM along with PCA, ICA, and LDA have a better success rate for EEG signal classification after comparing it with Artificial Neural Network (ANN). This proposed combination (SVM+LDA, SVM+ICA, SVM+PCA) can be a milestone in the classification of nonstationary Biomedical Signals.
3. The Performance of this proposed system is much more satisfactory and can be utilized in clinical studies also after it is developed.

4. Conclusion

Classifying EEG signal into normal and meditation state is actually a difficult task as it requires lots of observation and additional clinical information. Traditional methods for classification of EEG signal using either time domain representation of EEG signals or frequency domain representation of EEG signals. This conventional method fails to give efficient results. In this work, DWT was used to decompose EEG signals in time-frequency representation. Wavelet coefficient has been extracted using DWT is used to find the statistical feature. The statistical features are extracted using PCA, LDA and ICA were used with SVM for classification of EEG into two classes. This classification was based on two scalar performance measure which is derived from confusion matrices; namely specificity and sensitivity. The result shows that nonlinear feature extraction can improve the performance of classifier with respect to reduce the number of support vector for EEG Signal Classification. This concluded that the application of nonlinear feature extraction along with SVM will be a promising alternative for intelligent classification and diagnosis system in future. Also, it is clear that dimension reduction using PCA, LDA, and ICA can improve the performance of SVM.

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