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LDA, GA AND SVM'S FOR CLASSIFICATION OF EPILEPSY FROM EEG SIGNALS.

Harikumar Rajaguru[1], and Sunil Kumar Prabhakar[2].

[1]Department of ECE, Bannari Amman Institute of Technology, Sathyamangalam, India.
[2]Department of ECE, Bannari Amman Institute of Technology, Sathyamangalam, India.

ABSTRACT:

In this paper, a performance comparison is made between the post classifiers such as GA and SVM (polynomial kernel) for the classification of epilepsy from EEG signals. Initially the dimensions of the EEG data are reduced with the application of Linear Discriminant Analysis (LDA) as a dimensionality reduction technique. The dimensionally reduced values are then given to the post classifiers and the benchmark parameters such as specificity, sensitivity, time delay, accuracy, quality values and performance index are measured.
Keywords: EEG, GA, LDA, SVM

Corresponding author

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INTRODUCTION

The number of persons suffering from epilepsy in the whole world is increasing day by day. People affected by epilepsy often have a troubled life which leads to a lot of disturbances in their personal and professional lives. The people with epilepsy often have more symptoms like migraines and frequent falls. To diagnose epilepsy, Electroencephalograph is used. The EEG is quite a versatile tool for diagnosing neurological disorders like epilepsy and other disorders related to it. The presence of epileptic forms in the EEG assures the presence of epilepsy. EEG is just a measure of the assessment of cumulative firing of neurons in different parts of the brain. The vital information with respect to the electrical potential of the brain is obtained with the help of EEG. Because of metabolic, circulatory, biochemical and hormonal disturbances or factors, the EEG patterns vary easily. The paper is organized as follows: In section 2, the materials and methods are discussed followed by the usage of LDA as dimensionality reduction technique in section 3. In section 4, the post classifiers such as GA and SVM are utilized followed by the results and discussion in section 5.

MATERIALS AND METHODS

For the performance analysis of the epilepsy risk levels using LDA as Dimensionality Reduction technique followed by GA and SVM (Polynomial kernel) as Post Classifiers, the raw EEG data of 20 epileptic patients who were under treatment in the Neurology Department of Sri Ramakrishna Hospital, Coimbatore in European Data Format (EDF) are taken for study . The pre processing stage of the EEG signals is given more attention because it is vital to use the best available technique in literature to extract all the useful information embedded in the non-stationary biomedical signals. The EEG records which were obtained were continuous for 30 seconds and each of them was divided into epochs of two second duration. Generally a two second epoch is long enough to avoid unnecessary redundancy in the signal and it is long enough to detect any significant changes in activity and to detect the presence of artifacts in the signal. For each and every patient, the total number of channels is 16 and it is over three epochs. The frequency is considered to be 50 Hz and the sampling frequency is considered to be about 200 Hz. Each and every sample corresponds to the instantaneous amplitude values of the signal which totals to 400 values for an epoch. The total number of artifacts present in the data is four. Chewing artifact, motion artifact, eye blink and electromyography (EMG) are the four numbers of artifacts present and approximately the percentage of data which are artifacts is 1%. No attempts were made to select certain number of artifacts which are of more specific nature. The main objective to include artifacts is to differentiate the spike categories of waveforms from non spike categories. The figure 2.1 shows the block diagram of the procedure.

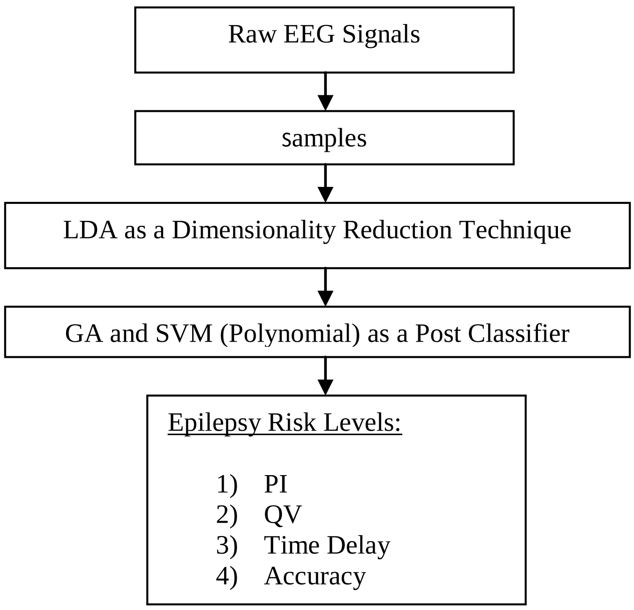

Figure 2.1 Block Diagram of the Procedure

DIMENSIONALITY REDUCTION TECHNIQUES:

The dimensionality reduction technique employed here is Linear Discriminant Analysis (LDA).

Linear Discriminant Analysis (LDA):

Linear Discriminant Analysis (LDA) is just a generalization of Fisher's linear discriminant. It is widely used in methods employed for statistics, pattern recognition, machine learning etc.. to find out the linear combination of feature dimensions that splits two or more classes of events. Such a resulting combination may be used for both classification purposes and dimensionality reduction processes. It is quite closely related to Regression Analysis and Analysis of Variance (ANOVA). All these techniques try to express a dependant variable as a linear combination of various other feature measurements. The main objective of LDA is to perform dimensionality reduction while it still preserves as much of the class discriminatory information. Assuming that there are a set of D dimensional samples $\{x_1, x_{2,....,} x_N\}$, in which N_1 belongs to class w_1 and N_2 belongs to class w_2. A scalar $'y'$ is obtained by projecting the samples x onto a particular value as

$$y = w^T x;$$

The one line which maximizes the scalars separability is selected out of all the possible lines. In order to find a good projection vector, a definite need for the measurement of separation in between the projection is required. For each class, the scatter is defined as follows which is an equivalent of the variance as follows

$$\hat{S}_i^2 = \sum_{y \in w_i} (y - \hat{\mu}_i)^2$$

Thus the solution proposed by Fischer is to always maximize a function that represents the difference between the means and normalized by a measure of the within class scatter.

POST CLASSIFIERS FOR THE CLASSIFICATION OF EPILEPSY FROM EEG SIGNALS

The most important classifiers used here are for the classification of epilepsy from EEG signals are the Genetic Algorithms and Support Vector Machine (with polynomial kernel alone).

Genetic Algorithm (GA) as a Post Classifier:

The Genetic Algorithms are actually optimization and machine learning algorithms based on the process of biological evolution. Interest in genetic algorithm has become more and in par with the most important algorithms like simulated annealing artificial neural networks. Genetic algorithms generally solve optimization problems by the manipulation of a set of chromosomes. A fitness is assigned to each and every chromosome and is generally related to its grand success in solving a particular problem.

The main advantages to employ Genetic Algorithms for classification and optimization processes over other methods in comparison are quite good and versatile in nature. A very simple GA can be written in seven steps as follows:

1) A population of $'n'$ chromosomes is generated randomly initially
2) The fitness of each and every chromosome is calculated.
3) A pair of parent chromosomes is selected from the initial population
4) The crossover is performed with a possibility $'P_{cross}'$ in order to produce two offsprings
5) The two offsprings are then mutated with a mutation probability (P_{mut})
6) The offspring is then replaced in the population.
7) The termination procedure is checked or else go to step 2.
8)

Each iteration involved in the above steps is called as a generation. The termination step consists of generally number of generations anywhere from 50 to 500 or in some cases it may extend that limit also. After each and every generation, a global minimum is checked and when this condition is reached, the algorithm is terminated. The binary genetic algorithm is one type of GA which works with a finite parameter space. This trait of GA makes it ideal to optimize a cost value because the parameters here represent only finite number of values. Quantization concept is applied where optimization parameters are continuous. The parameter is represented as a set of strings comprising of binary digits of either 0 or 1. Such a composition permits a simple crossover and mutation functions that operates on every chromosome.

Support Vector Machine (SVM) as a Post Classifier:

SVM is used widely for pattern classification. SVM represents an important example of kernel techniques. In SVM, a hyper plane is constructed as the decision surface in a manner that the margin of separation between the negative and positive examples is reduced. SVM is more or less similar to structural minimization procedure. The following points are taken into

a) The hyperplane is considered as a decision function and a simplest case is analyzed initially with the linear data.
b) For the dimensionally reduced values, a non linear classification is performed by means of implementing quadratic discrimination.
c) Then for large data, K-means Clustering is performed for large data with many sets of clusters provided each cluster has a centroid for each.
d) A proper shape is obtained by mapping the centroid to the Kernel functions.
e) SVM's with various kernels and other clustering algorithms are used to obtain a linear separation. The following solution constrains are implemented

Step 1: With the help of Quadratic optimization, the linearization and convergence is done. Transformation of the primal minimization problem into its corresponding dual optimization problem is performed by maximizing the dual Lagrangian L_D with respect to

$$Max \;\; L_D = \alpha_1$$

$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (X_i . X_j)$$

Subject to

$$\sum_{i=1}^{l} \alpha_i y_i = 0, \text{ where } \alpha_i \geq 0 \quad for \quad i = 1....n$$

Step 2: Quadratic programming is used to solve the construction of the optimal separating hyper plane condition. The non-zero Lagrangian multipliers are obtained as solutions and are hence termed as support vectors.

Step 3: To the decision boundaries, the support vectors always lie closely. So, the support vectors in the training data set is used to determine the optimal hyperplane.

Step 4: Any clustering algorithm can be performed after determining the optimal hyperplane and here we employ k-means clustering. A group of clusters is formed with the help of k-means functions in accordance to step 2 and step 3.

Step 5: So totally there are 6 centre points, three from each and every epoch and then the SVM training process is computed with the help of Kernel methods. In the training algorithm, only the kernel function is used and the explicit form of ϕ is not known. The Kernel function used here is Polynomial function:

$$K(X,Y) = (X^T Y + 1)^d$$

A set of the testing data is being provided which primarily acts as 'basis' for single and multiple input patterns when expanded into hidden space. The Mean Square Error (MSE) and Average MSE is performed from the set of kernel testing values and the error values are computed. Matlab V.7.10a is used as a tool for this study.

RESULTS AND DISCUSSIO:

For LDA as a dimensionality reduction technique and GA and SVM (Polynomial Kernel) as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Table I respectively. The formulae for the Performance Index (PI), Sensitivity, Specificity and Accuracy are given as follows

$$PI = \frac{PC - MC - FA}{PC} \times 100$$

where PC – Perfect Classification, MC – Missed Classification, FA – False Alarm,
The Sensitivity, Specificity and Accuracy measures are stated by the following

$$Sensitivity = \frac{PC}{PC + FA} \times 100$$

$$Specificity = \frac{PC}{PC + MC} \times 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2} \times 100$$

The Quality Value Q_V is defined as

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})}$$

where C is the scaling constant,
R_{fa} is the number of false alarm per set,
T_{dly} is the average delay of the onset classification in seconds
P_{dct} is the percentage of perfect classification and
P_{msd} is the percentage of perfect risk level missed
The time delay is given as follows

$$\text{Time Delay} = \left[2 \times \frac{PC}{100} + 6 \times \frac{MC}{100} \right]$$

Table I Performance Comparison Table

Parameters	LDA + Poly SVM	LDA + GA
PC	81.94	86.52
MC	17.08	0.763
FA	0.972	12.70
PI	76.78	83.56
Sensitivity	99.02	87.29
Specificity	82.91	99.23
Time Delay	2.66	1.77
Quality Values	18.38	18.03
Accuracy	90.97	93.26

CONCLUSION

It is thus concluded that when LDA is used as a dimensionality reduction technique followed by the usage of Genetic Algorithms, the accuracy obtained is 93.26% when compared to the classification done with the help of Polynomial Kernel SVM. Future work is planned to implement various other types of dimensionality reduction techniques and other post classifiers for the classification of epilepsy from EEG signals.

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