Design and Simulation of Simplified Epilepsy Risk Level Classification Technique from EEG Signals

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Abstract. EEG signals not only represent the brain function but also the status of the whole body, i.e. a simple action as blinking the eyes introduces oscillation in the EEG records. Then, the EEG is a direct way to measure neural activities and it is important in the area of biomedical research to understand and develop new processing techniques. EEG signal pre-processing and post-processing methods include EEG signal modeling, segmentation, filtering and de-noising, and EEG processing methods which consist of two tasks, namely, feature extraction/dimensionality reduction and classification. In this paper, the performance analysis of Independent Component Analysis (ICA) is considered as a dimensionality reduction technique followed by Singular Value Decomposition (SVD) as a Post Classifier for the Classification of Epilepsy Risk Levels from EEG Signals. The analysis is done in terms of benchmark parameters such as Performance Index (PI), Quality Values (QV), Sensitivity, Specificity and Time Delay.

1 Introduction
Dimensionality Reduction (DR) is a pre-processing step that reduces the dimension of the EEG data [1]. Conventional decomposition methods such as Principle Component Analysis (PCA) and Independent Component Analysis (ICA) reduce the dimensions of the data by isolating a set of features or electrodes that comply with some certain criteria regardless of their influence on classification [2]. In addition, these techniques require the entire trials of a recording session of subject for the dimensionality reduction process. Techniques that can introduce low-dimensional feature representation with enhanced discriminatory power are of paramount importance, because of the so called curse of dimensionality [3]. Feature extraction consists of finding a set of measurements or a block of information with the objective of describing it in a clear way the data or an event present in a signal [4]. These measurements or features are the fundamental basis for detection, classification or regression tasks in biomedical signal processing and is one of the vital steps in the data analysis procedure. Features constitute a new form of expressing the data, and can be binary, categorical or continuous in nature, they represent attributes or direct measurements of the bio signal [5]. For example, features may be the age, health status of the patient, family history, electrode position or EEG signal descriptors (amplitude, voltage, phase, frequency, etc.).

The aim of extracting features is to identify “patterns” of brain activity: features can be used as input to a classifier [6]. The performance of a pattern recognition system depends on both the features and the classification algorithm employed. More formally, feature extraction assumes there are Q samples and F features, for an $Q \times F$ data matrix. It is also possible to obtain a feature vector at the sample q from the feature matrix, that is, $z$ is a uni-dimensional vector $z=[z_1, z_2, ... z_F]$ called as “pattern vector”. In this paper, rather than the feature extraction procedure, utmost importance is given to the reduction of the dimensions of the EEG sampled data.

More specifically in EEG detection and classification scenario, there are several features proposed in the literature for EEG signals such as methods on power spectral density, report on wavelet transform, discussion on lyapunov exponent with wavelets, methods on sampling techniques and application of time frequency analysis [7]. The advantages of the regularization dimension are i) it is more precise than other approximation methods; ii) it is easy to derive an estimator in the presence of noise due to the fully analytical definition. One first computes smoother and finer versions of the original signal and are obtained simply through convolution with a kernel. This paper is organized as follows: In Section 2, the materials and methods are discussed, followed by the concepts of ICA as a dimensionality reduction technique and SVD as a Post Classifier for the Classification of epilepsy risk levels from EEG signals in Section 3. Section 4 gives the results and discussion followed by conclusion in Section 5.

2 Materials and Methods

For the performance analysis of the epilepsy risk levels using ICA as a dimensionality reduction technique followed by SVD as a Post Classifier, 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 about 30 minutes 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. In this paper the exhaustive analysis and results are shown only for a single epoch. 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 number 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 1 shows the block diagram of the procedure.

The block diagram of the procedure is given in the Figure 1. Initially the raw EEG Signals are taken and it is sampled. ICA is then applied as a dimensionality reduction technique followed by the SVD as a Post Classifier and then the benchmark parameters are analyzed.

3 Dimensionality Reduction and Post Classifier Concept

Similar to the Principal Component Analysis, the dimensionality reduction such as Independent Component Analysis is applied to the samples to reduce the dimensions of the data. Then Singular Value Decomposition is applied as a Post Classifier for the classification of epilepsy risk levels from EEG Signals.

A. Independent Component Analysis as a Dimensionality Reduction Technique

The random observed vector $X$ is denoted as $X = [X_1, X_2, ..., X_m]^T$, whose $q$ elements are mixtures of $q$ independent elements $[2]$ of a particular random vector $S = [S_1, S_2, ..., S_m]^T$ and is given by the equation

$$X = AS$$

where the $q \times q$ mixing matrix is denoted by $A$. The sample value of $X_j$, is denoted as $x_j$, where $j$ can take the values such as $1, 2, ..., m$.

The goal of ICA is to find the mixing matrix $W$, which is the actual inverse of $A$, which would yield $Y$ and it is considered as the best and versatile approximation of $S$ and is mathematically expressed as follows:

$$Y = WX \approx S$$

To use the ICA in practise, certain assumptions must be met always, firstly, it is important to assume the statistical independence between each source, and each source signals cannot have a Gaussian pdf except for one particular single source which can be Gaussian $[8]$. To work on ICA, it is also assumed that the data are centered which implies that it has a zero mean.

B. Singular Value Decomposition as a Post Classifier

The SVD is used as a Post Classifier for the Classification of epilepsy risk levels from EEG Signals. The matrix present here can be decomposed into individual several component matrices, so that the interesting properties of the original matrix are exposed. To determine the principal components of a multidimensional signal, we can use the method of Singular Value Decomposition easily. Consider a real $M \times N$ matrix $X$ of observations which may be decomposed as follows $[9]

$$X = USV^T$$

where $S$ is an $M \times N$ matrix with zero entries anywhere, except on the leading diagonal with elements $S_{ii}$ arranged in descending order of magnitude. Each $S_i$ is equal to $\sqrt{\lambda_i}$ the square root of the Eigen value of $C = X^TX$. A stem plot of these values against their index $i$ is known as the singular spectrum. The smaller the Eigen values are, the less energy along the corresponding eigenvector there is. So, the smallest eigen values are often considered to be due to noise. The columns of $V$ are an $N \times N$ matrix of column vectors which are the eigenvectors of $C$. Therefore the $M \times M$ matrix $U$ is the
matrix of projections of X onto the eigenvectors of C. If a truncated SVD of X is performed then the truncated SVD is given by $Y = US_P V^T$ and the columns of $M \times N$ matrix $Y$ are the noise reduced signal. SVD is advantageous since it combines two different uncertainty representations into a metric as total uncertainty and it also decomposes uncertainty measures (possibility, belief, probability etc.) as a collection of vectors of different units, into a particular principle space. SVD is also used in various other techniques to reduce coupled non linear behaviour to uncoupled collections of linear behavior.

4 Results and Discussion

For ICA as a dimensionality reduction technique and SVD as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Table 1. 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

$$Q_V = \frac{C}{(R_{fa} + 0.2) \times (T_{dl} \times P_{dc} + 6 \times P_{msd})}$$

where $C$ is the scaling constant,

$R_{fa}$ is the number of false alarm per set,

$T_{dl}$ is the average delay of the onset classification in seconds

$P_{dc}$ is the percentage of perfect classification and

$P_{msd}$ is the percentage of perfect risk level missed.

The time delay is given as follows

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

The Specificity and Sensitivity Analysis for the application of ICA as a dimensionality reduction technique followed by the SVD as a Post Classifier is shown in Figure 2. The Time Delay and Quality Value Analysis for the application of ICA as a dimensionality reduction technique followed by the SVD as a Post Classifier is shown in Figure 3. Similarly the Performance Index and Accuracy Analysis for the application of ICA as a dimensionality reduction technique followed by the SVD as a Post Classifier is shown in Figure 4.

Figure 2 Sensitivity and Specificity Analysis for ICA as Dimensionality Reduction Technique and SVD as Post Classifier.

On the careful analysis of the figure 2, it is inferred that the sensitivity and specificity analysis hold variations throughout the series and it is not constant throughout.

Figure 3 Time Delay and Quality Value Measures for ICA as Dimensionality Reduction Technique and SVD as Post Classifier.

The time delay is almost high and low at alternating intervals and it is not constant throughout the series. There are abrupt variations throughout the series.
Figure 4 Performance Index and Accuracy Measures for ICA as Dimensionality Reduction Technique and SVD as Post Classifier.

From the figure 4 it is inferred that the performance index varies throughout the series with respect to accuracy. A low performance index and high performance index is shown in the figure and there are random abrupt variations throughout the series.

Table I Average Values for 20 Patients for a Single Epoch

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Average Values for all the 20 patients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Perfect Classification</td>
<td>75%</td>
</tr>
<tr>
<td>Average Performance Index</td>
<td>61.75%</td>
</tr>
<tr>
<td>Average Sensitivity</td>
<td>84.16%</td>
</tr>
<tr>
<td>Average Specificity</td>
<td>90.83%</td>
</tr>
<tr>
<td>Average Time Delay (sec)</td>
<td>2.05</td>
</tr>
<tr>
<td>Average Quality Value</td>
<td>16.61</td>
</tr>
<tr>
<td>Average Accuracy</td>
<td>87.5%</td>
</tr>
</tbody>
</table>

The average values for 20 patients for a single epoch is shown in the Table I. It is observed that the average perfect classification rate is obtained to be around 75%. The average performance index is 61.75% and the average sensitivity and specificity values are found to be 84.16% and 90.83% respectively. The average time delay in seconds is found to be around 2.05 seconds. Quality Value for this case is around 16.61 and the average accuracy is around 87.5%.

5 Conclusion

This research utilizes the ICA as a dimensionality reduction technique followed by the utility of SVD as a Post Classifier for the perfect classification of epilepsy risk levels from EEG Signals. Future work may incorporate the analysis of various types of dimensionality reduction technique followed by various types of post classifiers for the classification of epilepsy risk levels from EEG signals.

References

[1] Prabhakar, SK, Rajaguru, H "Development of Patient Remote Monitoring System for Epilepsy Classification", 16th International Conference on Biomedical Engineering (ICBME), Singapore, December 7-10, 2016