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Analysis of Singular Value Decomposition as a Dimensionality Reduction Technique and Sparse Representation Classifier as a Post Classifier for the Classification of Epilepsy Risk Levels from EEG Signals

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ABSTRACT

The main aim of this paper is to perform the analysis of Singular Value Decomposition (SVD) as a Dimensionality Reduction technique and Sparse Representation Classifier (SRC) as a Post Classifier for the Classification of Epilepsy Risk levels from Electroencephalography signals. The data acquisition of the EEG signals is performed initially. Then SVD is applied here as a dimensionality reduction technique and then Sparse Representation Classifier is used for the Classification of Epilepsy Risk levels from EEG signals. The performance of the SVD with the SRC are compared based on the parameters such as Performance Index (PI) and Quality Value (QV).

Keywords - EEG Signals, SVD, Sparse, Performance Index, Quality Values

1. INTRODUCTION

Epilepsy is the second most common neurological disorder in humans after stroke and about twenty five percent of the world's people with the epilepsy cannot be controlled by the treatment (Gabor A.J (1998). Epileptic seizures result from abnormal, excessive or hyper synchronous neuronal activity in the brain (Joel J, 2004). "Epileptic seizure" is the term that is used to represent the epilepsy. During a seizure, neurons may fire as many as 500 times a second, much faster than normal. In some people, this happens only occasionally; for others, it may happen up to hundreds of times a day (Mark van Gils, 1997). About 25 to 30 percent of people with epilepsy still continue to experience seizures even with the best available treatment. The electroencephalogram is the method that records the cumulative firing of neurons in the various part of the brain (Naresh C, 2006). It contains information regarding changes in the electrical potential of the brain obtained from a given set of recording electrodes. The EEG signal analysis is the non-invasive, multi-channel recording of the brain's electrical activity. It is also essential to classify the risk levels of the epilepsy so that the diagnosis can be made easy (Srinivasan, 2005). The organization of the paper is as follows: Section 1 introduces the paper and materials and methods are discussed in the Section 2. Section 3 describes about the analysis of Singular Value Decomposition, Section 4 gives an insight to the Sparse Representation Classifier and the results are discussed and concluded in Section 5.

2. MATERIALS AND METHODS

2.1 Data Acquisition of EEG Signals: For the performance analysis of the epilepsy risk levels using singular value decomposition as a dimensionality reduction technique and sparse representation classifier 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 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 artefacts 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 artefacts present in the data is four. Chewing artefact, motion artefact, eye blink and electromyography (EMG) are the four number of artefacts present and approximately the percentage of data which are artefacts is 1%. No attempts were made to select certain number of artefacts which are of more specific nature. The main objective to include artefacts is to differentiate the spike categories of waveforms from non-spike categories.

3. SINGULAR VALUE DECOMPOSITION

The decomposition of a matrix into several individual component matrices can be done easily by the SVD. This technique always exposes many vital properties of the given original matrix. The matrix decomposition is termed here as factorization. Thus the SVD always serves the purpose of dimensionality reduction. Initially the decomposition of the matrix into several orthogonal and independent set of factors is done which is considered to very optimal based on some criterion. For instance, the criterion can be the reconstruction of the decomposition matrix or it can be the linear dependence property of the decomposition matrix. The principal components of a multi-dimensional signal can be determined easily by the SVD.

To determine the principal components of a multi-dimensional signal, we can use the method of Singular Value Decomposition can be used. Consider a real M x N matrix 'X' of observations which may be decomposed as follows;

$$X= USV^T$$

where S is an M non square matrix with zero entries anywhere, except on the leading diagonal with elements S_i arranged in descending order of magnitude. Each S_i is equal to $\sqrt{\lambda_i}$ the square root of the Eigen value of $C= X^TX$.

4. SPARSE REPRESENTATION CLASSIFIER

The main idea of Sparse Representation Classifier (SRC) is to take the test sample as a linear combination of the training samples (Bob Zhang, 2014). The requirement is that the representation of the coefficients must be as sparse as possible. The test sample's class label can be easily determined. Assume that the test sample is taken from a particular class 'i', then among the representation coefficients over all the training samples, only those from the particular samples in class 'i' will be significant while others will be insignificant. In general, the l_1 norm minimization is used to solve the sparsest linear samples of the i^{th} object class as follows

$$A_I = [S_{i.1,} S_{I.2,} ...., S_{i,n}] \in R^{m \times n_i}$$

where dimensionality of the object is denoted as m and the number of training samples of the i^{th} class is denoted as n_i If a test sample $y \in R^m$ is considered from the same class, then y could be easily approximated by a linear combination of the samples within A_i

$$\text{(i.e)}\ y = \sum_{j=1}^{n_i} \alpha_{i,j} S_{i,j} = A_i \alpha_i$$

where $\alpha_i = [\alpha_{i,1,} \alpha_{i,2,} .....\alpha_{i,n_i}]^T \in R^{n_i}$ are the representation coefficients.

If the total number of object classes are considered to be C and let $A_i = [A_{1,} A_{2,.....} A_c]$ be the concatenation of the n training samples from all the C classes, where $n = n_1 + n_2 + ... + n_c$.In the most general case, the linear representation is represented as a total number of vector coefficients whose entries are all zeros except those which are associated with the i^{th} class. In reality, l_0-norm minimization is used to solve such problems, however this type of non-convex optimization is difficult to perform. Therefore, l_1-norm minimization has to be performed

$$\hat{\alpha} = \arg \quad \min\{ \|y - A\alpha\|_2^2 + \lambda\|\alpha\|_1 \}$$

where λ is considered to be a positive scalar and thus we could get the real sparse coding vector $\hat{\alpha}$ of y over A.If the denotion of the characteristic function is done as $\delta_i(.) : R^n \to R_i^n$ then the sparse coding coefficients can be easily associated with the class i can be easily selected [6]. The reconstruction error can then be easily computed by using the reconstruction of the object as $\hat{A}\delta_i(\hat{a})$ and so we obtain

$$r_i(y) = \|y - A\delta_i(\hat{a})\|_2^2$$

If y belongs to the i^{th} class, then $r_i(y)$ should be expected to be very minimum among all $r_i(y)$, where i=1,2…..c. Therefore the classification can be easily achieved by letting the following equation

$$identify(y) = \arg \quad \min \quad r_i(y)$$

5. RESULTS AND DISCUSSION

For sparse representation classifier based on the Performance Index, Quality values, Sensitivity, Specificity, Time and Accuracy the results are computed and tabulated in Table 5.1. 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,

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The Sensitivity, Specificity and Accuracy measures are stated by the following

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

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

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

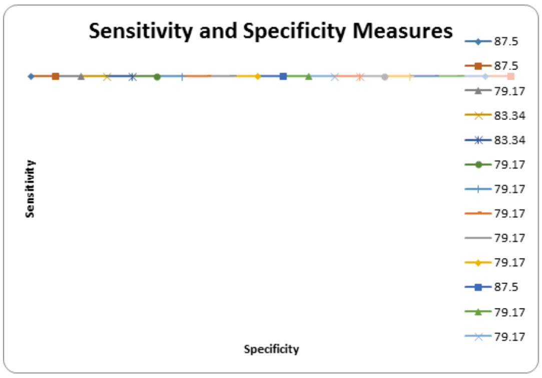

Figure.1.Sensitivity and Specificity Analysis when SVD acts as a dimensionality Reduction technique followed by the SRC as the Post Classifier

Figure.1.shows the sensitivity and specificity analysis using SVD as a dimensionality reduction technique and SRC as the post classifier for the perfect classification of epilepsy risk levels from EEG signals. It is inferred that the specificity remains constant throughout and there are no abrupt variations at all and the reason for this constant nature is due to the absence of the false alarm.

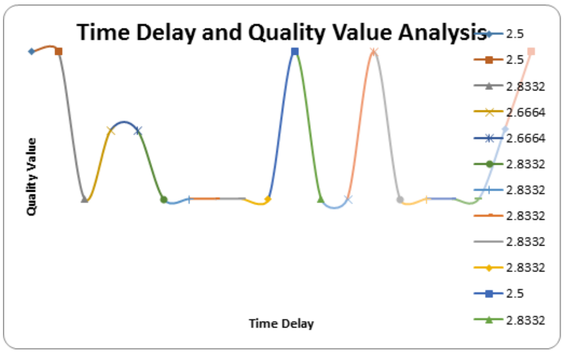

Figure.2.Time Delay and Quality Value Analysis when SVD acts as a dimensionality reduction technique followed by the SRC as the Post Classifier

Figure.2.shows the time delay and quality value analysis when SVD acts as a dimensionality reduction technique followed by the SRC as the post classifier. The time delay is somewhat constant at certain intervals of time whereas at other time instants there is a somewhat deflection in the quality values.

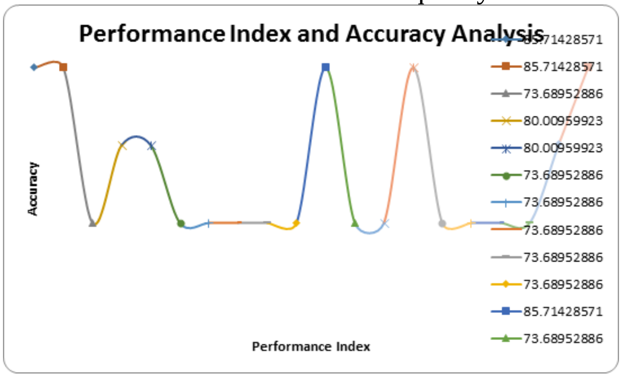

Figure.3.Performance Index and Accuracy Analysis using SVD as the dimensionality reduction technique and SRC as the Post Classifier

From figure.3.it is inferred that the accuracy also shows abrupt variations throughout the performance index series and it is does not remain constant throughout. The table 5.1 shows the average values for all the 20 patients when SVD is used as a dimensionality reduction technique and SRC is employed as a Post Classifier.

Table.5.Average Values for all the 20 patients when SVD is used as a dimensionality reduction technique and SRC is employed as a Post Classifier

Parameters	Average Values for all the 20 patients
Average Perfect Classification	81.88
Average Performance Index	77.64
Average Sensitivity	100
Average Specificity	81.88
Average Time Delay (sec)	2.72
Average Quality Value	18.40
Average Accuracy	90.94

Thus the paper gives a performance analysis by considering the Singular Value Decomposition (SVD) as a dimensionality reduction technique and Sparse Representation Classifier (SRC) as a post classifier for the perfect classification of the epilepsy risk levels obtained from Electroencephalography (EEG) signals. Performance Index (PI) and Quality Values (QV) were the two parameters that were used to assess the performance of sparse representation classifier. It is concluded that the average perfect classification is 81.88 % and the average performance index is 77.64%. The average sensitivity and specificity values are 100% and 81.88% respectively. The average time delay computed in seconds is obtained to be 2.72. The average Quality Value obtained in this case is 18.4 and the average accuracy obtained is 90.94 %. Future work may incorporate the usage of a variety of dimensionality reduction techniques followed by the classification of epilepsy risk levels using different types of classifiers.

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