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Research Article

A Versatile Approach to Epilepsy Classification Using Approximate Entropy as Post Classifier

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ABSTRACT

Abnormal transient behaviour of neurons in the cortical regions of the brain leads to a seizure which characterizes epilepsy. The physical and mental activity of the patient is totally dampened with this epileptic seizure. To detect such seizures, Electroencephalography (EEG) signals is used and it aids greatly to the clinical experts and it is used as an important tool for the analysis of brain disorders, especially epilepsy. This paper shows that Linear Graph Embedding (LGE) and Singular Value Decomposition (SVD) are as dimensionality reduction techniques followed by the usage of Approximate Entropy (ApEn) as Post Classifiers for the Classification of Epilepsy Risk Levels from EEG signals. The benchmark parameters assumed here are Performance Index (PI), Quality Values (QV), Specificity, Sensitivity, Time Delay and Accuracy.

Keywords: Epilepsy, SVD, LGE, EEG, ApEn

INTRODUCTION

The most used technique to capture the brain signals are the Electroencephalography (EEG) signals. EEG always provides an excellent temporal resolution[1]. Besides, it also provides non-invasiveness and it is quite easy to maintain. An EEG can easily show the various states of a human such as sleep state, awake state and so on. EEG is considered as a highly complex human brain signal which consists of valid information about the functions of the brain and the other neurological disorders[4]. EEG also plays a vital role for diagnosis of epilepsy, early detection of brain tumour, early detection of problems related to sleep etc. Epilepsy generally affects people from all ages but young infants and the elderly people are more prone to it. Epilepsy occurs due to abnormalities in the genetic mechanisms of humans or it may be due to developmental anomalies and infections in the central nervous system. It is quite difficult to extract the feature rhythms because the EEG signal is quite complex, stochastic and non-stationary in nature[5]. Due to the abrupt and unpredictable nature of the epileptic seizures, the everyday routine life of an epileptic patient is severely affected. Since epilepsy is witnessed by sudden disturbances of the mental functions which results due to the excessive discharging of groups of cells in the brain, the epileptic EEG obtained from the scalp is characterized by synchronized periodic waveforms which have very high amplitude. Spikes and sharp waves too are found in between the seizures and hence the detection of it by an encephalographer is quite difficult as it requires skilled technicians who are in great demand nowadays. This leads to a prolonged diagnosis time period and also the expenditures related to it is too much to bear. Surgery may not be suitable to all the patients because it demands the consideration of the other health risks also[2]. Therefore, the seizures have to be detected in an automatic manner and it forms an integral part of biomedical research. Research on epilepsy has therefore become an active interdisciplinary filed of biomedical research. The organization of the paper is as follows: In Section 2, the materials and methods are discussed followed by the dimensionality reduction techniques such as LGE and SVD in Section 3. Section 4 discusses the usage of Approximate Entropy (ApEn) as a Post Classifier followed by the results and discussion in Section 5.

MATERIALS AND METHODS

For the performance analysis of the epilepsy risk levels using SVD and LGE as Dimensionality Reduction Techniques and Approximate Entropy (ApEn) 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[2]. 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[2]. For

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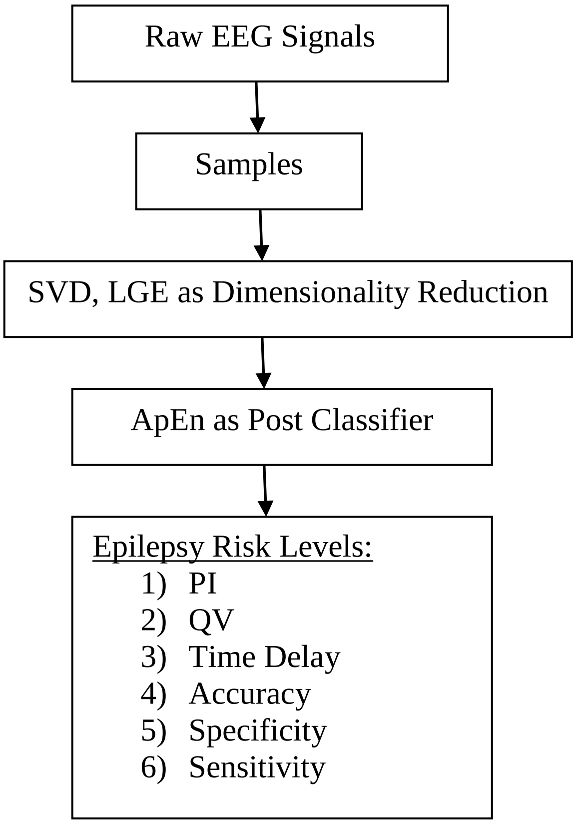

Figure 1: Block Diagram of the Procedure

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[2]. 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%[2]. Nil attempts were made to select certain number of artifacts which are of more specific in 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 raw EEG Signals are taken it is sampled initially. Since the dimensions of the EEG signal is too large, SVD and LGE are employed here as the dimensionality reduction techniques so that the dimensions of the EEG signal is reduced. Then the dimensionally reduced values is given as an input to the Approximate Entropy which acts as a post classifier for the perfect classification of epilepsy risk levels from EEG signals. The epilepsy risk levels are calculated in terms of PI, QV, Time Delay, Accuracy, Sensitivity and Specificity Measures.

Dimensionality Reduction Techniques

Dimensionality reduction is a basic pre-processing step which helps to reduce the dimensions of the EEG data. The data volume for a single patient alone in our case leads to around 25,600 samples. Therefore it is absolutely impossible to process such a huge data and so dimensionality reduction techniques are required for sure here. With such high-dimensional data sets, the basic underlying phenomena of interest cannot be understood easily and so, on employing the dimensionality reduction technique, it is easy to understand the procedure as it considers only the most important measured variables. With the advent of applications of several computationally novel, faster and expensive methods to process the high dimensional data are available, it is of paramount significance to reduce the dimension of any given original data prior to the modeling of it. The dimensionality reduction techniques employed here are the Singular Value Decomposition (SVD) and Linear Graph Embedding (LGE).

Singular Value Decomposition

Assume that $'A'$ be a $n \times d$ matrix, where $v_1, v_2 .....v_r$ are its respective singular vectors and $\sigma_1, \sigma_2, ...\sigma_r$ are its respective singular values. Then,

$$u_i = \frac{1}{\sigma_i} A v_i \text{ for } i = 1,2,.....r$$

are mainly the left singular vectors.

A can be generally be decomposed [2] into a sum of rank one matrices [] as follows

$$A = \sum_{i=1}^{r} \sigma_i u_i v_i^T$$

This decomposition is often called as SVD of A. In matrix notation, it is mathematically expressed as follows

$$A = UDV^T$$

Where U consists of left singular vectors, V consists of right singular vectors, D is the diagonal matrix where the diagonal entries are represented as singular values of A. The sequence of the singular values is always unique for any matrix A. The singular values must be always distinct so that only the sequence of the singular values in unique or else this condition would definitely fail [2]. If any singular values are equal in any particular set, then their respective singular vectors occupy some subspaces.

Linear Graph Embedding

This process generally involves Graph Embedding, Linearization and Kernelization procedures but for dimensionality reduction of EEG signals the following procedure is considered. A sample set for model training is represented as a matrix $X = [x_{1,} x_2, ..., x_N]$, where N represents the sample number. Consider $x_i \in R^m$, where m is the feature dimension [1]. In reality, the dimension of the feature $'m'$ is too high and so it is mandatory to transform the data from high-dimensional space (original data) to lower-dimensional space [1]. The main task of this Dimensionality Reduction is to just find a mapping function which is represented as follows

$$F : x \rightarrow \hat{y}$$

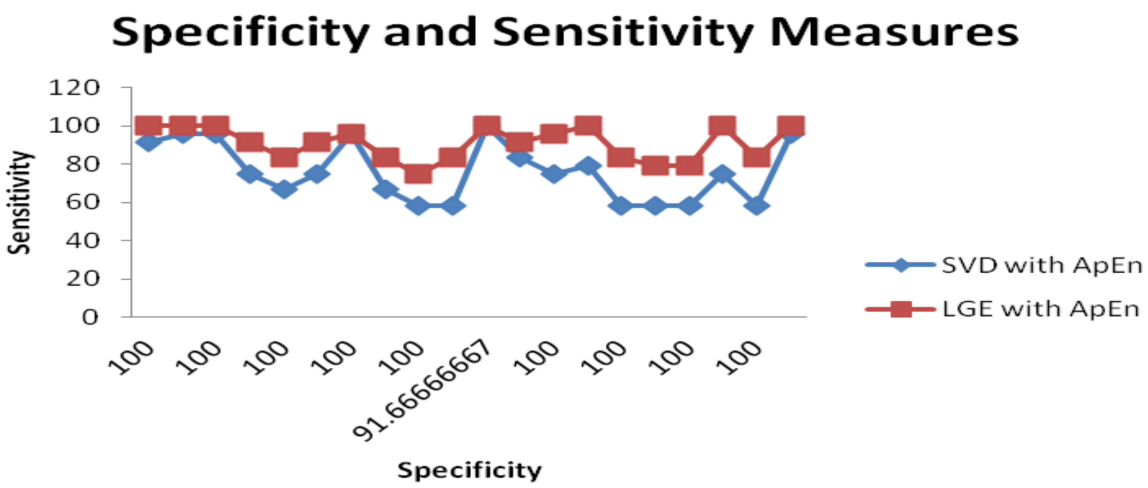

Figure 2: Specificity and Sensitivity Measures

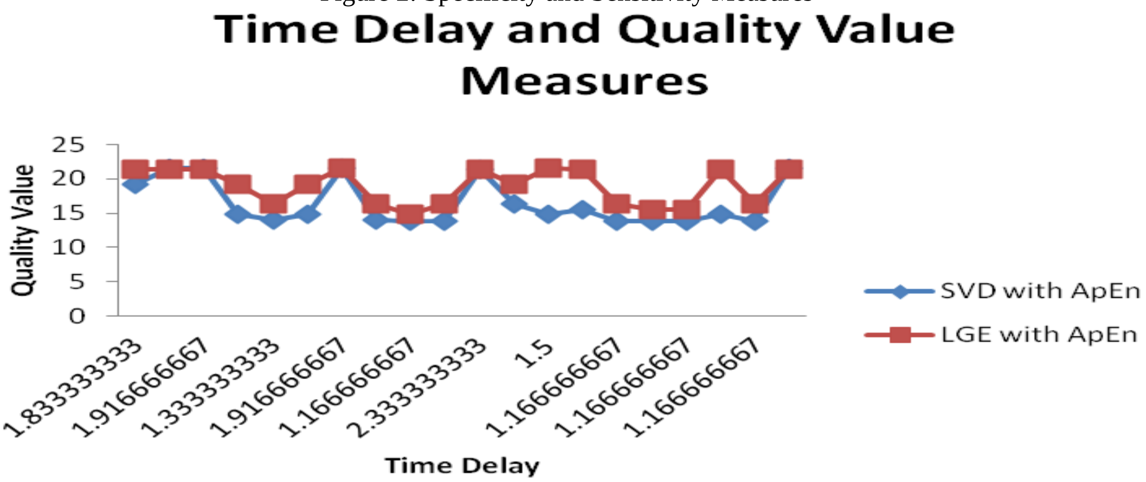

Figure 3: Time Delay and Quality Quality Measures

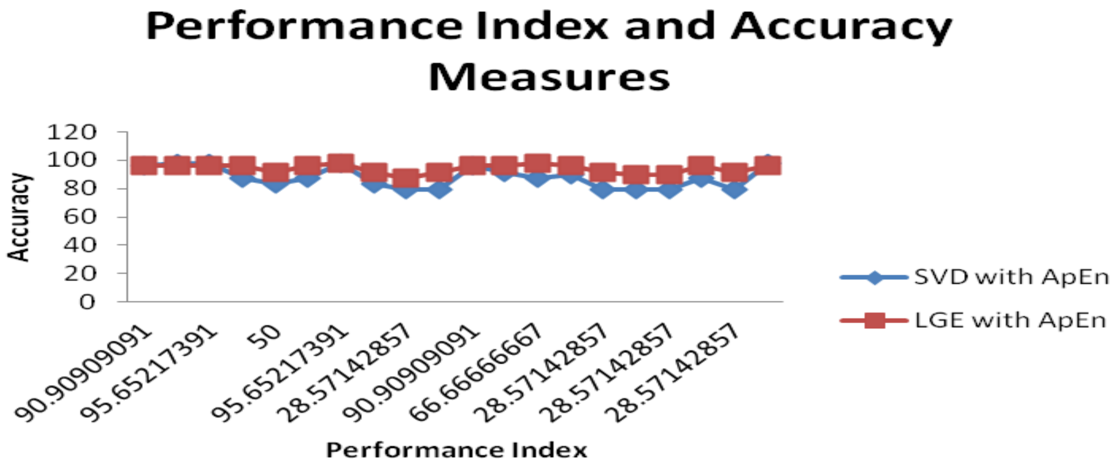

Figure 4: Performance Index and Accuracy Measures

This main function always transforms $x \in R^m$ into the desired low-dimensional representation $\hat{y} \in R^{m}$, where $m \succ\succ m'$.

Therefore it is mathematically represented as follows

$$\hat{y} = \frac{F}{x}$$

Approximate Entropy as Post Classifier

The dimensionally reduced EEG values are fed as inputs to the Approximate Entropy Post Classifier for the perfect classification of epilepsy risk levels from EEG signals. Initialize the sequence $Z = z(1), z(2), z(3).....z(N)$ with N data points. Initialize the subsequence of z also, such that $z(i)$ is a sub sequence of Z, so that $z(i) = [z(i), z(i+1),...., z(i+m-1)]$ is present,

Table 1: Performance of SVD with ApEn

Parameter	Epoch-1	Epoch-2	Epoch-3
PC (%)	75.62	74.37	75
MC (%)	0.41	3.12	2.08
FA (%)	25.21	22.5	22.91
PI (%)	62.81	61.72	62.00
Sensitivity (%)	76.04	77.5	77.08
Specificity (%)	99.58	96.87	97.91
Time Delay	1.53	1.67	1.625
Quality Value	16.48	16.27	16.53
Accuracy (%)	87.81	87.18	87.5

Table 2: Performance of LGE with ApEn

Parameter	Epoch-1	Epoch-2	Epoch-3
PC (%)	87.91	88.95	88.95
MC (%)	2.91	3.12	1.66
FA (%)	9.16	7.91	9.37
PI (%)	85.72	87.13	87.03
Sensitivity (%)	90.83	92.08	90.62
Specificity (%)	97.08	96.87	98.33
Time Delay	1.93	1.96	1.87
Quality Value	18.92	19.35	19.09
Accuracy (%)	93.95	94.47	94.47

where m represents the samples in between the sub sequences. The distances between the two vectors z_i and z_j are computed as follows

$$d(z_i, z_j) = \max_{k=1,2,..m}[Z(i+k-1) - Z(j+k-1)]$$

The count is initialized as $P^m(i)$ [3] and the ratio is computed as follows

$$C_r^m(i) = \frac{P^m(i)}{P-m+1},$$

where r denotes the pre-defined threshold level.

The natural logarithm of $C_r^m(i)$ [3] is found out and it is averaged for all the values of i, and it represented as follows

$$\phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\ln C_r^m(i)$$

Thus ApEn [3] is calculated as follows and is expressed as

$$ApEn = \phi^m(r) - \phi^{m+1}(r)$$

RESULTS AND CONCLUSION

For LGE and SVD as dimensionality reduction techniques and ApEn as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Tables 1 and 2 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 Specificity and Sensitivity Analysis for the application of SVD, LGE as dimensionality reduction techniques followed by the ApEn as a Post Classifier is shown in Figure 2. The Time Delay and Quality Value Analysis for the application of SVD, LGE as dimensionality reduction techniques followed by the ApEn as a Post Classifier is shown in Figure 3. Similarly the Performance Index and Accuracy Analysis for the application of SVD, LGE as dimensionality reduction techniques followed by the ApEn as a Post Classifier is shown in Figure 4. It is inferred from figure 2 that the specificity measures are not constant throughout and an average specificity of about 99.58% is obtained for epoch 1 for SVD with ApEn and an average specificity of about 97.08% is obtained for epoch 1 for LGE with ApEn. It is inferred from figure 3 that the time delay measures are abrupt throughout and it is not constant at all. An average time delay of about 1.53 seconds for epoch 1 is produced for SVD with ApEn while an average time delay of about 1.93 seconds is produced when LGE acts with ApEn. It is inferred from figure 4 that the performance index is not constant throughout and an average PI for epoch 1 is found as of 62.81% for SVD with ApEn while the average PI for epoch 1 is found as 85.72% for LGE with ApEn. On the careful analysis of the Table 1, it is inferred that for epoch 3 the quality values are higher as of 16.53 when compared to the other two epochs. On comparing the Table 1 with Table 2, it is inferred that the quality values are higher when LGE is performed with ApEn than performing with SVD-ApEn combination. Also the average perfect classification rates, accuracy rates and performance index of LGE-ApEn combination are higher when compared to that of the SVD-ApEn combination. Thus it is concluded that when LGE is used as dimensionality reduction technique followed by ApEn as post classifier the performance is much greater than the SVD-ApEn combination. Future works may incorporate the possible usage of different types of dimensionality reduction techniques and post classifiers for the classification of epilepsy risk levels from EEG signals.

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