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EEG Spectral Feature Based Seizure Prediction using Sparse Feature Selection

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Abstract—This paper proposes an efficient method for feature selection for a seizure prediction algorithm which is capable of being implemented in a patient specific seizure prediction system. The algorithm uses spectral powers and their ratios from 8 different subbands of the EEG signal and uses these as the features. The most relevant features are selected using a sparse feature selection technique. The proposed algorithm achieves an accuracy of 87 % while being evaluated with the seizure records from the MIT Physionet database. The system has low complexity and good feature selection capability.

Index Terms— sparse feature selection, spectral power ratios, ictal, seizure

I.INTRODUCTION

Epilepsy is basically a neurological disorder which is becoming increasingly common these days. Epilepsy is also termed as 'seizure disorder' because it is mainly characterized by unpredictable, recurrent seizures. The main characteristic of epileptic seizures is that there is no immediate underlying cause. It is the result of abnormal neural activity in the cortex of the brain. Seizures can either be partial wherein it affects only a part of the brain or generalized wherein the entire brain region gets affected. Partial seizures might sometimes extend to generalized ones as well. During a seizure, people become confused and lose consciousness and it might even get fatal if not properly attended. Thus, being able to know the occurrence of a seizure in advance becomes a life-savior in many cases. Here comes the relevance of an efficient seizure prediction algorithm which is capable of predicting the occurrence of seizures before a considerable amount of time. If seizures can be predicted before a considerable amount of time, then appropriate precautions can be taken. These precautions include either giving appropriate medicines in advance or providing brain stimulation to prevent it or decrease its strength. Thus seizures can be made controllable to a great extent thereby enabling the victims to lead a normal life.

II. LITERATURE SURVEY

Seizure prediction is a hot topic of research these days. Certain algorithms use adaboost for feature selection as well as classification [1]. Certain researchers rely on Adaptive Neuro Fuzzy Inference Systems for seizure prediction [2]. There are also methods which uses the spike rate as the feature to predict the onset of an ictal event [3]. Some methods consider the spatial and temporal covariance matrix between different EEG channels and takes this as the feature set for prediction [4]. Another method uses an HPD (Henze Penrose Divergence) measurement as the factor to decide the reliability of a feature and thus make a feature selection [5]. There are methods which utilizes the cross correlation coefficients between different EEG electrodes as features for predicting seizure [6].

Feature selection techniques like Principal Component Analysis finds the "principal components" in the data which are uncorrelated eigen vectors each representing some proportion of variance in the data. When computing the principal components (PCs) of a dataset there is no guarantee that the PCs will be related to the class variable. Therefore, supervised principal component analysis (SPCA) came into existence, which selects the PCs based on the class variables. Even though the supervised version of PCA performs better than the unsupervised, PCA has an important limitation: it cannot capture nonlinear relationships that often exist in data. Adaboost feature selection becomes very complex when more number of features needs to be analyzed. Certain feature selection techniques like T-test involves computation of probability and associated metrics like cumulative distribution function etc. which makes it computationally more intensive. Independent component analysis has also been widely used for feature selection but it is often said that it works well only on data that has already been applied with PCA.

The major requirement of the time is a feature selection system with high accuracy and lesser processing time which eventually leads to lesser hardware complexity and power consumption making it appropriate for an implantable usage. The system must also be suitable for a patient specific application wherein the system might be demanded to perform well even in the absence of a large training data. The sparse feature selection technique is efficient in this manner. The features used to distinguish a

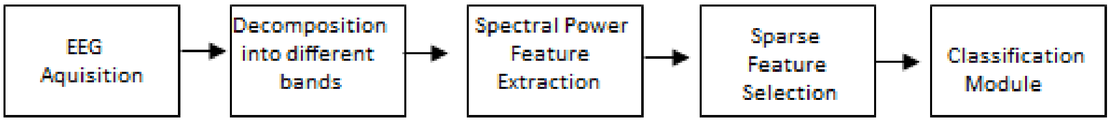

Fig 1. Basic Block Diagram

preictal record are also very robust compared with many other methods.

III. PROPOSED METHOD

A basic block diagram of the proposed algorithm is shown in Fig 1.

A .DATASET

The algorithm has been evaluated on MIT Physionet EEG database which contains 78 seizures from 17 children in 647 hours of recordings. Seizure and non-seizure EEG records from different patients were analyzed to find the characteristics of the preictal period. 45 seizure records were analyzed to train the samples. All signals in the database are sampled at 256 samples per second with 16 bit resolution. The EEG recordings of this dataset was measured using the 10-20 system of EEG measurement.

B .WINDOW BASED SIGNAL PROCESSING

In a typical signal processing system, we need to process each and every sample one by one. In the window based method used here, the signal is segmented into windows of length 4 seconds so that each and every sample need not be processed separately. This helps in reducing the processing time.

C .FEATURE EXTRACTION

Here, for feature extraction, the EEG signal is decomposed into different sub bands. Eight different sub bands are considered here namely (1)Theta (4–8 Hz), (2)Alpha (8–13 Hz), (3) Beta (13–30 Hz),(4) Gamma 1(30–50 Hz), (5) Gamma 2 (50–70 Hz), (6) Gamma 3 (70–90 Hz), (7) Gamma 4 (90–110 Hz), (8) Gamma 5 (110–128 Hz). The spectral power features that are evaluated here are:

Absolute Spectral Power: Absolute spectral power of a particular band is the power of the signal in that particular frequency band.

Relative Spectral Power: Relative spectral power of a particular band is the ratio of power of the signal in that frequency band to the total power of the signal considering all the frequency bands.

Spectral Power Ratio: Spectral Power ratio between two bands is the ratio of spectral powers in those frequency bands.

Spectral power alone is not a reliable feature as it is not consistent even in the interictal states. This problem is overcome here by considering spectral power ratios also which is more indicative of an upcoming ictal event.

D .FEATURE SELECTION

In the feature extraction stage, 8 absolute spectral powers, 8 relative spectral powers and 28 spectral power ratios are extracted every 4 seconds for each electrode. Considering all the windows, this feature set tends to be very large. We need to reduce the number of features to an optimum level so as to make the system computationally less intensive. For this, it is necessary that only those features that contribute the most to seizure prediction need to be taken. A method that has been considered here for feature selection is the sparse feature selection method. Considering the training data to be $X^k = [x_1^k, x_2^k, x_3^k, \ldots, x_n^k]^T$. Let $Y = [y_1, y_2, y_3 \ldots y_N]$ be the response vector and $W = [w^1, w^2, w^3 \ldots w^k]$ be the weight vector. Here k denotes the window segment which is taken for evaluation. This can be formulated as:

$$\min_{W} \sum_{k=1}^{K} \| Y - X^K w^K \|_2^2 + \lambda \| W \|_{2,1} \qquad (1)$$

The first term in Eq. (1) is the empirical loss on the training data. The second one is a group-sparsity regularizer to encourage the weight matrix $\boldsymbol{W}$ with many zero rows, $\| W \|_{2,1}$ term has the sum of the l_2-norm of the rows in matrix $\boldsymbol{W}$. For feature selection purpose, only features corresponding to those rows with non-zero coefficients in $\boldsymbol{W}$ are selected, after solving Eq. (1). That is, the $l_{2,1}$ – norm regularization term makes sure that the number of common features selected across different window segments are reduced. The parameter λ is a regularization parameter used to balance relative contributions of the two terms in Eq. (1). Particularly, a large λ leads to the selection of less number of features, while a small λ urges the algorithm to select more features. After the efficient sparse feature selection stage, the redundant features are removed and only those features that has a significant contribution towards seizure prediction are retained.

V.SIMULATION RESULTS

The algorithm has been evaluated on Matlab 2013 software. Figure 2 shows the signal after being split into 4 sec width windows and this is the input that is given to the feature extraction stage. The red portion in Fig 2 indicates the window that is currently being processed. Figures 3, 4 and 5 represents the different features that is being extracted from a particular window segment. Fig 6 shows the selected set of features from among the 44 features in a window.

The performance of the feature selection method used in the seizure prediction system has been mainly measured in terms accuracy which is basically indicative of the number of true positives out of the total number of predicted samples. Accuracy comes out to be around 87 % while evaluated with 45 seizure records.

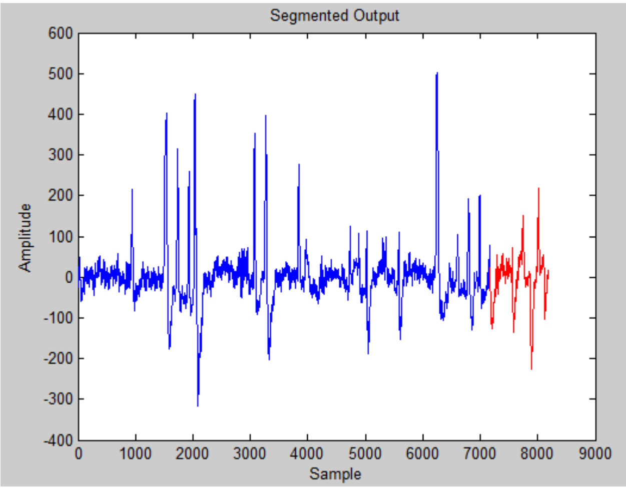

Fig 2. Windowed Signal

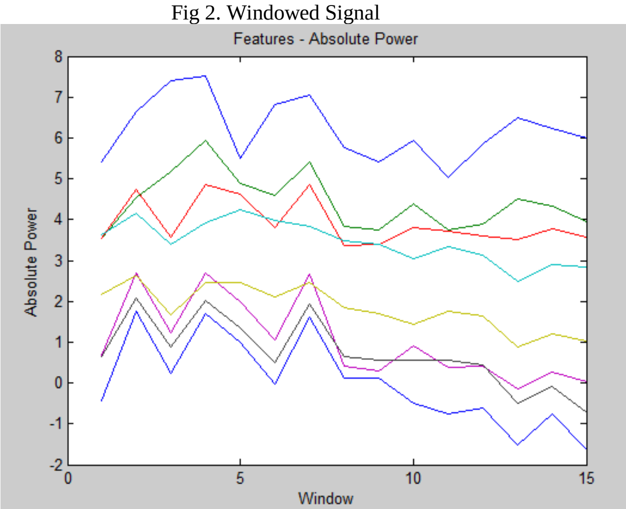

Fig 3. Feature – Absolute spectral power

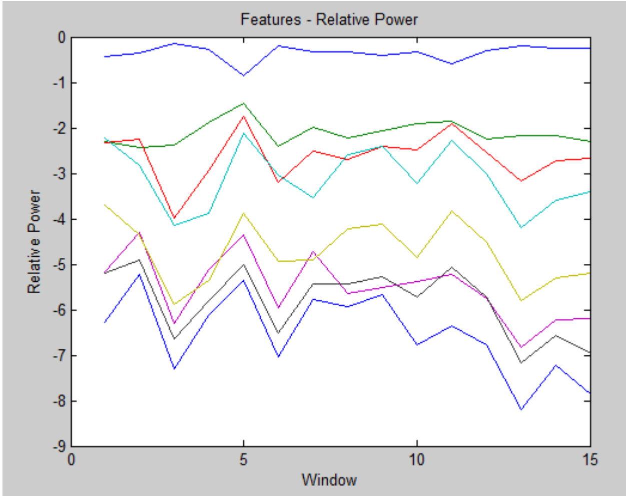

Fig 4. Feature – Relative spectral power

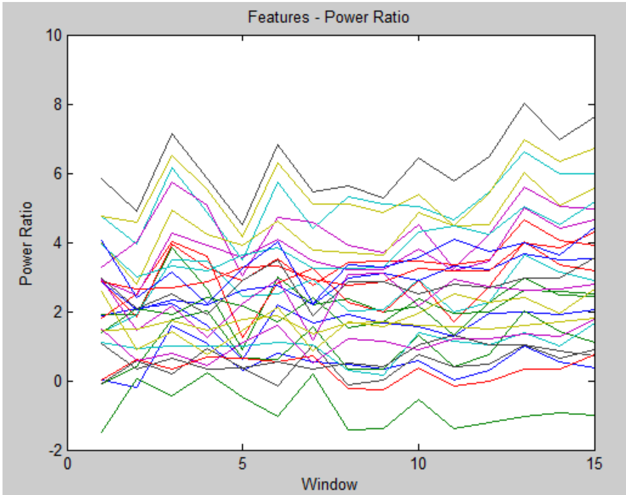

Fig 5. Feature – Spectral Power Ratio

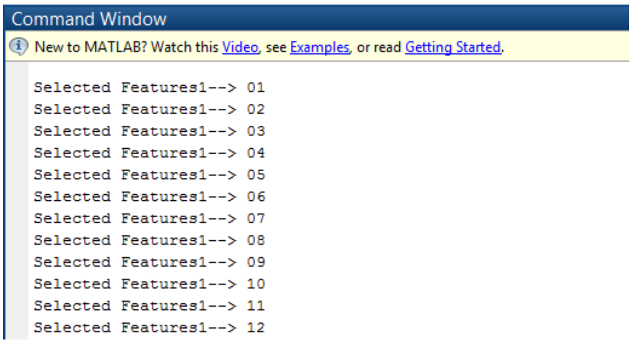

Fig 6. Selected Features

VI CONCLUSION

Seizure prediction has a major relevance today as far as the safety and health of an epileptic person is concerned. It gives an opportunity to take the required remedial action before a strong seizure strikes the patient. Accuracy and reliability of such systems are really important to extract the maximum benefit out these. The algorithm discussed above extracts the spectral power features from different EEG bands and then, a sparse feature selection technique is used to select the best out of these features. The algorithm is a good choice for being used in seizure prediction systems that can be implemented in a portable device that can be implanted within the epileptic person to give a timely support in case of strong ictal events.

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