Linear Features, Principal Component Analysis, and Support Vector Machine for Epileptic Seizure Prediction Progress

Peyvand Ghaderyan[1], Ataollah Abbasi[2], and Mohammad Hossein Sedaaghi[3]

[1] M.Sc. Student, Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran. peyvand.ghaderyan@gmail.com

[2]Assistant professor, Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran, ata.abbasi@sut.ac.ir

[3] Associate professor, AIIA, Department of Electrical Engineering, Sahand university of Technology, Tabriz, Iran, sedaaghi@sut.ac.ir

Abstract: *One of the main issues in seizure prediction is to provide a workable approach to apply in implantable devices. For this purpose, power consumption and computational resources should be taken into account. Hence, our motivation for pursuing this work was to propose an algorithm in which not only implementation requirements could be adopted but also sufficient sensitivity and specificity could be obtained.*
Low computational burden of linear features make them as a proper choice for seizure prediction. With Selection of optimal features using Principal components analysis (PCA) technique, the speed of algorithm can be increased. Support Vector Machines (SVMs) have robust performance in high dimensional and imbalanced data. Therefore the proposed solutions are concentrated on power spectrum over different frequency bands and PCA for dimensionality reduction of features. Finally, SVM is applied for distinguishing brain states. In this study, seizure prediction method has been applied to EEG of 9 patients in the Freiburg database and has been achieving high sensitivity of 88.9 % and low false alarm rate of 0.21 per hour.

Keywords: Seizure Prediction, Principal Component Analysis (PCA), Support Vector Machine (SVM), Electroencephalogram.

1. Introduction

Unpredictable nature of epileptic seizures can cause many limitations in patients during daily lives. Therefore, the major current focus is to predict impeding seizure [1]. This can be advantageous to patients and may provide possibility of protection from hurts or seizure prevention. An algorithm which can be reliably capable of predicting seizure to use in implantable device is attracting widespread interest. This algorithm with some suppressing or abating seizure methods like stimulation in an effort to reset brain dynamics [2] or focal cooling of the cortex [3] can be suitable in closed-loop therapy systems for epileptic patients.

It has been observed that EEG signals, recorded from the brain can show changes prior to the onset of a seizure [4] and about 50% of 562 patients experienced "auras" before the seizures [5]. Notwithstanding limitation of recent findings about neuronal mechanisms of the preictal states, researchers guess that synchronization patterns might be effective in distinguishing preictal, interictal and ictal states [6]. There are many literatures on seizure prediction using EEG processing, but no algorithm has yet been presented that can be applied in an implantable device [2].

The majority of techniques employed to predict epileptic seizures in recent years have focused on pattern recognition methods. Depending on its configuration, a method can be included preprocessing, feature extraction, feature selection, classification and post processing. EEG feature selection plays an important role in seizure prediction. Although nonlinear features showed hopeful performance [7], many studies demonstrated that nonlinear features may not prefer to linear features [8, 9]. Moreover, a drawback of nonlinear features was their complexity in calculation by comparison with the linear features.

This study aims to consider computational and performance requirements in implantable devices. Hence, linear features have been employed due to its low computational burden and principal components analysis (PCA) has been used to reduce the dimension of data. Then, support vector machines SVMs and post processing have applied to the proposed algorithm in order to distinguish between preictal and interictal states.

The rest of the paper is organized as follows. Section 2 presents description of each component of the method used in this study. The performance of the proposed algorithm on the Freiburg dataset is evaluated in section 3. Remarks for future works are presented on conclusion.

2. Methods

Despite many researches have been done in seizure prediction field, there were some limitations in these algorithms. The focus of these studies was limited to achieving high sensitivity and specificity, time and computational complexity for real time application were not appropriately considered. Therefore this study attempts to tackle these issues.

Seizure prediction algorithms have been faced the dilemma between selecting linear and nonlinear features. The previous studies have not shown a preference for nonlinear features over linear features [9]. Furthermore main property of linear features was low computational burden; therefore linear features have been chosen in this paper.

However applying linear method for feature extraction may obtain high dimensional feature space. In some previous works all features have been participated in classification and as a result training time has been increased. On the other hand dimensionality reduction methods which can be used for minimizing within-class scatter and maximizing between-class scatter, can improve process time and classification quality [10]. Hence in previous study PCA has been used in seizure detection [10] not in seizure prediction with linear features. Applying PCA in seizure prediction can overcome to high dimensional feature space resulted from linear features.

SVM classification due to good performance in seizure prediction in previous works and its property in mapping data to new space with better distinguishing using kernel function has been used [11]. In proposed algorithm dimensionality reduction step optimize training time and parameter selection of radial basis function can overcome over fitting and under fitting problems.

Our seizure prediction algorithm contains 6 steps, as outlined in Fig.1. Main objective in proposed algorithm is to distinguish between preictal (30 min before seizure onset) and interictal states in a way that reliable seizure prediction can be done without time and computational complexity in order to use in implantable devices. Therefore in this work applies steps with simple and robust procedures for obtaining higher sensitivity and specificity.

Fig. 1: Schematic representation of the proposed seizure prediction algorithm

Each step will be described in following subsections in details.

2.1 EEG Database

In this study, EEG data for 9 patients have chosen from a database provided by epilepsy center of university hospital of Freiburg, Germany. The database contained the intracranial EEG (iEEG) recordings, which were collected using a Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16 bit analogue-to-digital converter. For each patient, there were the recordings of three focal and three extra-focal electrodes [12].

Also times of seizure onset and artifacts were determined by some epileptologists in the database. And for each patient, "ictal" and "interictal" datasets were available, which is containing at least 50 min preictal data and approximately 24 hours recording without seizure activity [12].

2.2 Preprocessing and Feature Extraction

EEG signals are typically disturbed by artifacts like movement artifacts and AC power supply disturbance which make their interpretation problematic. In order to eliminate the influences of these disturbance, the windows which marked by epileptologists as containing artifacts, have been omitted from feature extraction. Furthermore in feature extraction procedure, power line noise at 50 and 100 Hz has been removed from analysis.

After initial analysis, moving window technique with 20 second length [13] and half overlap have been used for extracting spectral power in different bands. These bands contain delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), gamma band (30-100 Hz) and the spectral power can be defined as [2]:

$$\delta_r = \frac{1}{P}\sum_{f=0.5}^{4} p_f \quad (1)$$

$$\vartheta_r = \frac{1}{P}\sum_{f=4}^{8} p_f \quad (2)$$

$$\alpha_r = \frac{1}{P}\sum_{f=8}^{13} p_f \quad (3)$$

$$\beta_r = \frac{1}{P}\sum_{f=13}^{30} p_f \quad (4)$$

$$\gamma_r = \frac{1}{P}\sum_{f=30}^{100} p_f \quad (5)$$

Where P is total power of the EEG signal. Hence, features from 6 electrodes and different frequency bands are extracted. Preictal features are assumed to be calculated in 30 min before seizure onsets.

2.3 Feature selection

Dimension of features that typically used for seizure prediction are high, and this is inappropriate in real time applications due to time and computation complexity. On the other hand, all dimensions of data may be comprised redundancy information, thus their elimination are required and don't arise any problems.

Recently, PCA has become a popular tool in dimensionality reduction and feature extraction. This technique has been applied to reduce dimensions of the features in seizure detection [10]. This study applies PCA in seizure prediction to reduce dimensionality of features.

PCA is a mathematical technique defined as an orthogonal linear transformation [14]. In PCA approach after mean centering, each feature eigenvalue decompositions are computed by covariance matrix of data [15] and the eigenvectors (PCs) are sorted according to the decreasing eigenvalues. Then largest L such as PCs are selected in a way that cumulative energy divided by total energy of eigenvalue should be above a certain threshold.

In proposed algorithm, L is specified according to the number of dimension that describes 90% of features' variance. Figure 2 shows both ratings 30 min preictal data projected on the first three principal components and principal component coefficients for each variable. Fig 3 depicts the reduced feature vectors based on the PCA method in 30 min preictal and interictal states.

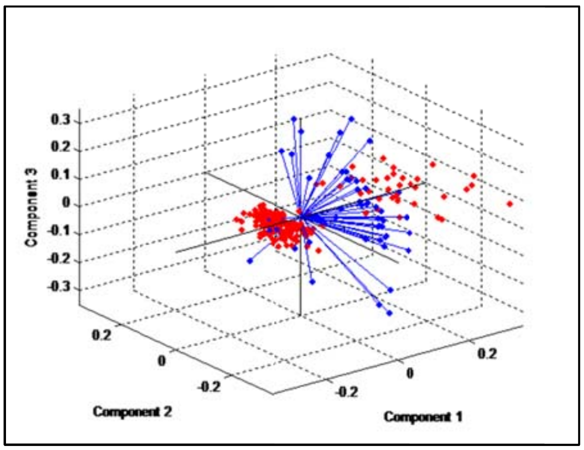

Fig. 2: Data projected on the first three principal components

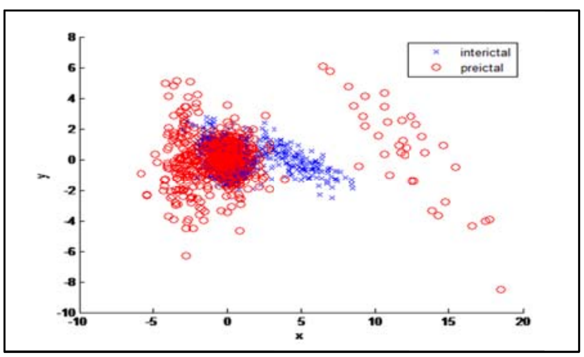

Fig. 3: Reduced feature vectors based on the PCA

2.4 Classification

SVM has been performed for classification. SVM is a pattern recognition technique which attracts remarkable attention in biomedical signal applications. It is a maximum margin statistical learning method [16] which in contrast to neural network always find a global solution and does not minimize training error alone [17]. From this point of view, SVM is a superior classifier by comparison with the neural network for seizure prediction.

Double cross validation function has been used in sample optimization and out of sample testing. Data has been segmented to train and test sets and the training set has been spilt into validation and learning sections [18, 19]. In order to prevent from over-fitting, fivefold cross validation has been employed and radial basis function has been selected as the kernel function. To optimize C and γ parameters of radial basis function, a grid search has been done on C$\in [2^0, 2^1, \dots, 2^{10}]$ $and\ \gamma \in [2^{-15}, 2^{-14}, \dots, 2^0]$ [20].

2.5 Post processing

In the last step, SVM classification outputs have been filtered by 20 tabs of moving average filter. It has been indicated that moving average filter is a good smoothing filter and this simple filter is a proper choice for random noise reduction [21]. Post processing step has been used for omitting sporadic false positives and false negatives.

3. Results and Discussion

In order to evaluate performance of proposed algorithm, sensitivity and false prediction rate per hours are measured by below equations.

$$sensitivity = \frac{TP}{TP+FN} \tag{6}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\text{all data in Hour}} \tag{7}$$

Experimental results on Freiburg dataset are summarized in table I and figure 4 depicts classification results for each patient. As shown in the table, high sensitivity of 88.9% and low false prediction rate of 0.21 leads to deduce that utility of this algorithm can improve performance gains. Also it is revealed that the algorithm can predict all seizures for 3 patients without any false prediction, and for the other patients, can attain high sensitivity and low false prediction rate. As depicted in the table I, the proposed system with low computational complexity steps can timely and reliably predict epileptic seizures.

Classification results by comparison with other studies [22-26] depict noteworthy improvement. Figure 5 compares the proposed algorithm with each other. In this figure sensitivity and false prediction rate per hour for different algorithms are shown.

The proposed algorithm has reached notable sensitivity and specificity with better time and energy consuming. Furthermore in order to obtain reliable results on untouched testing set double cross validation has been used to test the method. However some studies did not use this method for testing [2]. Results demonstrate SVM classification using PCA can achieve better performance than without dimensionality reduction. Proposed algorithm in addition to computational benefits can attain good performance in classification and seizure prediction. Also these results depict the ability of linear features and PCA method coupled with SVM for seizure prediction methods with low computational complexity. Therefore this system can be useful in practical application.

TABLE I: Result of Proposed Algorithm

Patient NO.	Number of seizure	interictal hours	sensitivity	Fpr/hour
Pat1	4	23.9	95	0.7
Pat3	5	23.9	85	0.65
Pat4	5	23.9	100	0
pat7	3	24.5	50	0.2
Pat12	3	24.7	90	0.1
Pat15	3	23.9	90	0.1
Pat16	3	23.9	100	0
Pat17	5	24	100	0
Pat18	5	24.8	90	0.1
Average	-	-	88.9	0.21

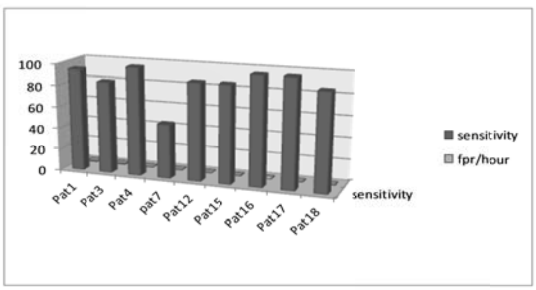

Fig. 4: SVM Results for each patients

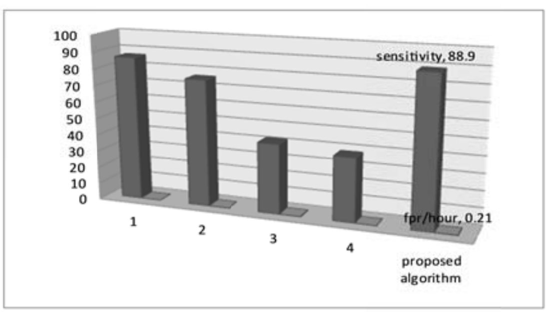

Fig. 5: Comparison of different methods together

4. Conclusion

As mentioned previously, main idea in this study was to provide suitable trade-off between computational burden and good predictive capability so this article proposed a method based on extraction linear features contains power spectral density over different frequency bands and optimal feature subset selection using PCA coupled with SVM classifier. This approach attained 88.9% sensitivity with 0.21 false prediction rates per hour. Results demonstrated that support vector machine trained with optimal features achieved improvement in predictive capability of seizure prediction system and speeded it up.

Adding other linear features containing univariate or bivariate features and applying other machine learning techniques can be further work in this field.

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