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Epileptic Seizure Prediction by Exploiting Signal Transitions Phenomena

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***Abstract*—**A seizure prediction method is proposed by extracting global features using phase correlation between adjacent epochs for detecting relative changes and local features using fluctuation/ deviation within an epoch for determining fine changes of different EEG signals. A classifier and a regularization technique are applied for the reduction of false alarms and improvement of the overall prediction accuracy. The experiments show that the proposed method outperforms the state-of-the-art methods and provides high prediction accuracy (i.e., 97.70%) with low false alarm using EEG signals in different brain locations from a benchmark data set.

***Keywords*—**Epilepsy, Seizure, Phase Correlation, Fluctuation, Deviation.

I. Introduction

A seizure is a brief episode of symptoms due to abnormal excessive or synchronous neuronal activity in the brain caused by structural abnormalities, encephalitis, lack of oxygen, injury, tumor, and some dysfunctions of the brain. Epilepsy is a brain disorder composed of spontaneously and recurrently occurring seizures. A world population greater than 65 million suffers from epilepsy (i.e., 1% individuals of the world) [1] and nearly 325 million people worldwide experience a seizure in their life time [2]. Epilepsy also major causes of many injuries [3] such as accidents, submersion, fractures, burns, and even death. This unwanted occasion can be avoided by correctly and timely predict epileptic seizures before clinical onset. Distress from epilepsy can be minimize through medication in 70% of cases [4]. *Electroencephalogram* (EEG) is a widely used device for epileptic seizure prediction that can measure the voltage fluctuations of the brain [5]-[7]. A segment of an EEG signal can be classified into different types such as ictal, preictal, interictal, and non-seizure signals based on the medical stages of seizure. Ictal represents the period of seizure, preictal represents the period prior to seizure onset, interictal represents the intermediate time period between two seizures; while non-seizure represents the period without seizure symptoms.

Seizure prediction methods are developed by extracting features from preictal/ictal and interictal EEG signals in real time with better accuracy using the Freiburg data set. Much research over the years has been devoted to the prediction of epileptic seizure. The techniques used usually involved the extraction of various features by analysing preictal/ictal and interictal EEG signals and predicted epileptic seizure in advanced using the features. Existing research involved the extraction of various features using techniques such as eigenspectra of space delay correlation and covariance matrices [8], autoregressive modelling and least-squares parameter estimator [9], bivariate features [10], spectral power from raw and bipolar time-differential signals [11], spike rate [12], and univariate features [13].

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Existing seizure prediction methods did not provide high accuracy and low false alarm for all patients from the Epilepsy Centre of the University Hospital of Freiburg data set [15]. It is a challenging task to develop a seizure prediction technique which is accurate and consistence with low false alarm for all patients due to the non-abruptness phenomena and inconsistency of the EEG signals in different brain locations for different patients. Parvez et al. [16] proposed a seizure prediction technique by using phase correlation extracted features between two adjacent epochs to capture relative changes in a signal. This provides high prediction accuracy and low false alarm compared to the state-of-the-art methods as the phase correlation feature is a good estimation on the transition between different types of EEG signals (e.g., interictal and preictal/ictal). However, sometimes it might fail to identify the transition if the transition is not aligned with the epoch. Our hypothesis is that if we consider local features extracted from the signal fluctuation/deviation from the frequent oscillation within an epoch and combine them with the global feature, we will get better accuracy and reduce false alarm significantly. Thus, we extract global and local features for correctly and timely predict seizures.

The order of the paper description is as follows: the data set, the detailed proposed technique for feature extraction, classification, and post-processing are described in Section II; the detailed experimental results and discussions is explained in Section III while Section IV concludes the paper.

II. Proposed Method

The goal of the paper is to exploit an automated way to predict epileptic seizure with high accuracy. Pre-processing, features extraction, classification, and regularization of EEG signals are general procedures for predicting seizure from EEG signals. Artifacts are removed from original EEG signals by filtering technique normally require pre-processing step. However, a curtain range of artifacts is tolerated in the proposed method avoiding filtering techniques. At first, various approaches are made to extract various features. Then different sorts of periods of EEG signals are classified using these features and regularization is applied on these classified signals to make final decision. Phase correlation and fluctuation/deviation are applied as a feature extraction procedure, *least square support vector machine* (LS-SVM) as a classifier, and windowing regularization as a post-processing step in the proposed method. This method contributes to the customization of existing cost function of fluctuation and deviation techniques applicable in the EEG signal analysis for the feature extraction of EEG signals. The final decision making on the type of interictal and preictal/ictal periods is considered by innovative regularization technique.

A. Data Set

The data set recorded from the Epilepsy Centre of the University Hospital of Freiburg, Germany [14], [15], which is publicly available and most cited resources in modern seizure detection and prediction approaches containing intracranial EEG (iEEG) recordings of 21 patients suffering from medically intractable focal epilepsy, is employed in this paper. Acquiring the data used Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and 16 bit analogue-to-digital converter. Ictal, preictal, postictal, and interictal are four periods of epileptic EEG signals described in this data set. Persistence of ictal period may be from a few seconds to 5 minutes. At least 50 minutes of preictal signals contains preceding each seizure is included in the ictal-records (which is tagged as ictal file). 87 seizures from 21 patients are recorded in the data set which is altogether 24-25 hours of interictal signals and 2-5 hours of ictal signals with preictal and postictal signals. So the data set is around 509 hours. Each seizure is considered to have 30 minutes preictal with ictal signals and 60 minutes interictal signals in the experiments. The point to be mentioned here is that six channels in each patient are used to capture EEG signals. The experiments exploited EEG signals recorded from different brain locations and different patients using focal electrodes that are three channels and another three extra-focal channels are considered.

B. Features Extraction Procedure

Information provided by phase correlation [16], [17] are relatively shifting in nature between current signals and reference signals of two correlated signals via Fourier Transformation. Thus, phase correlation can determine *global feature* (GF). Paul et al. [17] demonstrated that detection of reliable motion between two images or blocks is possible to phase correlation. The relative changes between two epochs of an EEG signal can similarly be captured by the phase correlation. Estimation of the transition between interictal and preictal/ictal periods can be done by this way. However, if the transition is not aligned with the epochs, identification of the transition may not be adequate. A local feature is also to be extracted from the signal fluctuation and deviation from the frequent oscillation within an epoch to avoid this situation. As illustrated by [18], fluctuation and deviation are able to identify defects of an image which inspired us to apply customized fluctuation and deviation [18] that can measure the fine changes of a specific epoch. Extracting *local feature* (LF) require calculation of a cost function comprises with weighted fluctuation and deviation in temporal direction. The *cost function of fluctuation and deviation* (CFD) cannot fully identify the phase lagging between two epochs alone because of non-stationary EEG signals. For this reason, this paper uses both features (i.e., GF and LF) for prediction of seizure onset with greater prediction accuracy and low false alarms.

In this study, we consider patient-specific approach where we rearrange an EEG signal of a patient from the data set so that a signal comprises ictal period, preictal period, and interictal period. To identify a particular signal type we divide a signal into 10 seconds epoch. We estimate global relative change using phase correlation and calculate *average energy concentration ratio* (AECR) using neighboring channels for first feature (detail procedure in [16]). We also use fluctuation and deviation to extract another feature by measuring the local fine change of EEG signal from an epoch. A classifier (i.e., LS-SVM) and regularization (see the procedure in Section II. *D*) are applied to the features to predict the seizure. The deviation is determined based on the difference between the signals and the most frequent signal within the sliding epoch (sliding by half second or 128 samples). The fluctuation is calculated based on the standard deviation of the shifted epoch. A cost function is determined based on the weighted summation of the fluctuation and deviation. At the t-th sliding epoch the cost function is defined as

$$C(t) = D^2(t)/16 + F^2(t) \tag{1}$$

where deviation is defined as

$$D(t) = X(t) - H_t \tag{2}$$

and fluctuation is defined as

$$F(t) = \sigma(X(t)) - 4. \tag{3}$$

where $X(t)$, Ht, and σ are the signals, the most dominant signal, and standard deviation of the sliding epoch respectively. The local feature is determined as the sum of energy of the $C(t)$ for 20 sliding epochs within an epoch.

Cost function is calculated by shifting 128 samples and the cost function is quantified 20 values of a 10 seconds epoch. From the current epoch, the *energy of cost functions of the fluctuation and deviation* (ECFD) is calculated as the second feature.

C. Classification

Classification of the preictal/ictal and interictal signals uses two features, AECR and ECFD. Being one of the best classifies, SVM [19] is used for classifying non-stationary signals like EEG signals. The extended version of SVM, LS-SVM [20] can minimize higher computational burden of the constrained optimization programming of SVM and LS-SVM is used in the experiments. The equation of LS-SVM is defined in as:

$$\Gamma(x) = sign\left[\sum_{m-1}^{N} \alpha_m y_m \Delta(x, x_m) + b\right] \quad (4)$$

where $\Delta(x, x_m)$ is a kernel function, α_m are the Lagrange multipliers, b is the bias term, x_m is the training input, and y_m is the training output pairs.

RBF kernel is used in our experiments as this is one of the most effective kernels for non-stationary EEG signals classification and this function can be defined as:

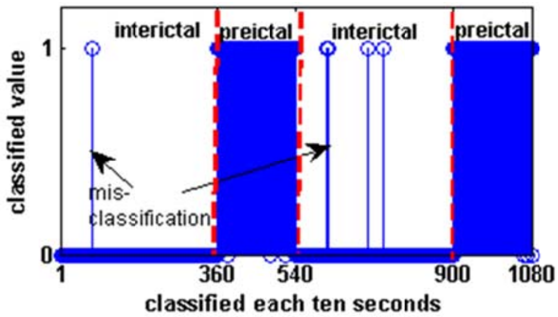
$$\Delta(x, x_m) = \exp(-\|x - x_m\|^2 / 2\Theta^2) \quad (5)$$

where λ controls the width of RBF kernel function.

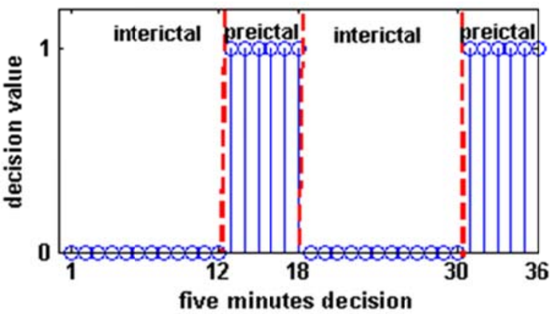
The aim of the classifier is to consider machine-learning approach to classify preictal/ictal and interictal EEG signals. The automated selection of the parameters is achieved through optimizing a cross-validation based model selection. Therefore, tuning the parameters is done by cross-validation and then they are tested. Finding mapping between training set and unseen test set is challenging issue. For leaning nonlinear mapping from the training set features {x}m=1… n_T, where n_T is the number of training features into the patient's state, preictal/ictal (1) and interictal (0), LS-SVM classifier is used. The whole trials are divided into M subsets to get unbiased results where M-1 is used for training and remaining is used for testing subset. Each seizure of each patient is passed through this process. The test output mapping of the LS-SVM validation is designated into two classes.

D. Regularization

Unwanted signals (i.e. artifacts) like artifacts with eye blinking, and muscle movement are inherently attenuated into local and global feature extraction technique. So misclassification of preictal/ictal and interictal EEG signals (Fig. 1 (a)) can occur and post-processing is required to get accurate prediction of epileptic seizure on LS-SVM classified signals. Two-phase u-of-v analysis is performed in the post-processing to predict an impending seizure by analyzing preictal/ictal and interictal EEG signals where preictal/ictal represents '1' and interictal represents '0'. The prediction horizon is labeled as preictal/ictal if there are equal or more than u number of '1' out of v number of consecutive windows (note that a five minutes window is used in the experiments), otherwise it is labeled as interictal. Identification of the prediction horizon of five minutes window in total prior to a seizure, in two-phase post-processing, 3-of-5 (i.e., u = 3 and v = 5) and 2-of-6 analysis are performed to. The five minutes decision is divided into two steps: the first step consists of 50 seconds i.e., five 10 seconds epochs; the second steps consist of six 50 seconds window. In the first step, if at least three epochs have classified value as '1' then all five epochs are considered '1'. In the second step, six 50 seconds window to be considered for the final decision. If at least two 50 seconds window have '1' results then the entire five minutes window is regulated as '1' otherwise '0'. It is to be noted that to prevent the impending seizure for administrating drug, the five minutes window is sufficient. Fig. 1 (b) shows the seizure prediction result as decision is taken in each five minutes based on the two-step decision. In each step, different size windows were investigated; however, the proposed two-step method is the best regarding the prediction accuracy and false alarms rate. Fig. 1 demonstrates the classified results from the LS-SVM and the final decision after regularization. The figure confirms that regularization is able to wipe out a number of misclassification.



(a)



(b)

Fig. 1 Seizure prediction using LS-SVM and regularization where (a) represents the classification output and the (b) represents the final output after regularization using all channels of Patient 17. Note that interictal represents as interictal stage and preictal represents as preictal/ictal stage of EEG signals

III. Results and Discussions

Prediction accuracy (PA) and false alarms per patient are the popular criteria used to evaluate performance of the techniques for prediction of epileptic seizure. Thus in the experiments, these are also used. The PA is defined in as:

$$\Omega = (\Pi_s / \Pi_a) * 100 \quad (6)$$

where Ω is the prediction accuracy, Π_s is the number of correctly predicted seizures and Π_a is the total number of seizures.

TABLE I
PATIENTS DETAILS AND PREDICTED SEIZURE USING THE PHASE CORRELATION AND PROPOSED METHOD

Patient No.	S/A	Seizure Type	Electrodes	Brain Location	Total Seizures	[9]		[10]		Only using GF, [16]		Proposed Method i.e., GF+LF	
						PA (%)	FA	PA (%)	FA	PA (%)	FA	PA (%)	FA
1	F/15	SP,CP	g, s	Frontal	4	100	0	100	1	75.0	6	100	5
2	M/38	SP,CP,GTC	d	Temporal	3	-	-	-	-	67.0	12	100	17
3	M/14	SP,CP	g, s	Frontal	5	100	3	100	1	80.0	4	100	5
4	F/26	SP,CP, GTC	d, g, s	Temporal	5	-	-	100	1	100	0	100	0
5	F/16	SP,CP, GTC	g, s	Frontal	5	100	23	100	21	100	3	100	3
6	F/31	CP, GTC	d, g, s	Temporal/Occipital	3	-	-	100	1	100	1	100	1
7	F/42	SP,CP, GTC	d	Temporal	3	-	-	100	1	100	0	100	0
8	F/32	SP,CP	g, s	Frontal	2	-	-	-	-	0.00	0	50.0	0
9	M/44	CP, GTC	g, s	Temporal /Occipital	5	100	3	100	4	100	3	100	3
10	M/47	SP,CP, GTC	d	Temporal	5	-	-	100	3	100	10	100	12
11	F/10	SP,CP, GTC	g, s	Parietal	4	100	9	75	2	75.0	5	100	4
12	F/42	SP,CP, GTC	d, g, s	Temporal	4	-	-	100	1	100	1	100	1
13	F/22	SP,CP, GTC	d, s	Temporal/Occipital	2	-	-	-	-	50.0	3	50.0	3
14	F/41	CP, GTC	d, s	Frontal/ Temporal	4	-	-	75	12	100	4	100	3
15	M/31	SP,CP, GTC	d, s	Temporal	4	-	-	100	4	50.0	11	100	5
16	F/50	SP,CP, GTC	d, s	Temporal	5	-	-	90	11	100	17	100	9
17	M/28	SP,CP, GTC	s	Temporal	5	100	10	100	1	100	5	100	0
18	F/25	SP,CP	s	Frontal	5	100	17	100	1	40.0	7	100	7
19	F/28	SP,CP, GTC	s	Frontal	4	100	25	75	24	75.0	20	100	5
20	M/33	SP,CP, GTC	d, g, s	Temporal /Parietal	5	100	0	80	16	100	11	100	13
21	M/13	SP,CP	g, s	Temporal	5	-	-	100	4	80.0	10	100	10

S/A=sex/age, SP=simple partial, CP=complex partial, GTC=generalized tonic-conic, d=depth electrode, g=grid electrode, s=strip electrode, PA= prediction accuracy, FA= false alarm, - indicated that experiment is not available for this patient.

We calculate PA and false alarms (FA) per patients to justify the performance of the proposed method against the existing state-of-the-art methods where PA is determined as the ratio in percentage between the numbers of correctly predicted seizures among total seizure. Comparisons of the performance of the proposed method with a number of relevant and recent methods [8]-[12], [16] are made. Patients' detailed information from the benchmark data set [14] and the comparison of prediction results of the proposed method with two state-of-the-art methods [9], [10] are given in Table I. Some entries in the table for the state-of-the-art methods are not available as the method in [9] used only 9 patients and the method in [10] used only 18 patients whereas the proposed method uses all available patients of the data set. Moreover, it is also tested using phase correlation [16] feature only and obtained 83.9% prediction accuracy with 6.33 false alarms per patients (Table I). The proposed method successfully provides 100% accuracy for 19 patients and the methods in [9], [10] provide 100% accuracy for 9 and 13 patients respectively. Moreover, the proposed method provides less false alarms per patient than the state-of-the-art methods. As Table I shows that the proposed method can predict 85 out of 87 seizures correctly with 106 false alarms. Thus, 97.7% average PA with 5.04 false alarms per patient is obtained by the proposed method.

Table II shows that the performance of the proposed method in terms of PA and false alarms per patient is comparatively better regarding the six existing relevant methods, by combining PA (i.e., 97.7%) and false alarms per patient (i.e., 5.04). A proper functioning (high sensitivity and low false alarms) of seizure prediction procedure is important to clinically prevent the seizure. Experiments prove the fact that the proposed method achieves low false alarms with high sensitivity.

TABLE II
COMPARISON RESULTS WITH PROPOSED METHOD AND EXISTING METHODS

Methods	Prediction Accuracy (%)	False Alarm	Total Patients
[8]	85.0	0.80	19
[9]	100	10.00	9
[10]	71.0	0.00	15
[11]	94.4	6.44	18
[12]	75.8	2.20	21
[16]	83.9	6.33	21
Proposed Method	97.7	5.09	21

IV. CONCLUSION

This paper proposes an effective prediction method based on signal transitions phenomena for epileptic seizure prediction that exploits global and local features along with a regularization technique. The global feature between two consecutive epochs of an EEG signal is extracted by the phase correlation and local feature within an epoch is extracted by a weighted cost function comprising fluctuation and deviation. Interictal, preictal, and ictal EEG signals are classified using the popular classifier, LS-SVM. A two-step post-processing regularization technique is then applied to purify the classified output to get ultimate output. The high prediction accuracy (97.7%) and low false alarms per patient (i.e., 5.04) considering all patients from a challenging benchmark data set without any explicit artifacts removal technique provided by the experimental results make it obvious that the proposed prediction method outperforms six existing relevant state-of-the-art methods.

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