Epileptic Seizure Prediction by Exploiting Spatiotemporal Relationship of EEG Signals using Phase Correlation

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***Abstract*— Automated seizure prediction has a potential in epilepsy monitoring, diagnosis, and rehabilitation. Electroencephalogram (EEG) is widely used for seizure detection and prediction. This paper proposes a new seizure prediction approach based on spatiotemporal relationship of EEG signals using phase correlation. This measures the relative change between current and reference vectors of EEG signals which can be used to identify preictal/ictal (before the actual seizure onset/ actual seizure period) and interictal (period between adjacent seizures) EEG signals to predict the seizure. The experiments show that the proposed method is less sensitive to artifacts and provides higher prediction accuracy (i.e., 91.95%) and lower number of false alarms compared to the state-of-the-art methods using intracranial EEG signals in different brain locations of 21 patients from a benchmark data set.**

***Index Terms*— EEG, Epilepsy, Interictal, Preictal, Phase correlation, Seizure**

I. Introduction

Though discussing the whole mechanisms of seizure generation is beyond the limit of this paper, it can be simply stated as a neurological disorder arising from sudden surges of electrical activity in the brain caused by structural abnormalities, encephalitis, lack of oxygen supply, brain injury, tumor, and some other dysfunctionalities of the brain [1]. Epilepsy is characterized by spontaneously recurrent seizures [2]. More than 50 million (i.e., 1% of the world population) individuals are diagnosed with this illness [3]. Approximately 5% of whole populations have experienced a seizure in their life time [4]. Epileptic patients may suffer from intractable seizures which are likely to cause increased damage to the neural tissues [5]. Epilepsy also results many injuries [6] such as fractures, submersion, burns, accidents and even death. It is possible to prevent these unwanted events if seizure can be predicted correctly and timely before the actual onset. This disease can be controlled by medication in 70% of cases [7]. Epilepsy can be monitored by *Electroencephalogram* (EEG) [8]-[13], by following brain activities and discovering electrochemical disturbances in the neurons through the output of the electrodes [14].

First we review the prior research. Much work has been devoted to the prediction of epileptic seizure over the years. These works usually extract various features by analyzing preictal/ictal (before the actual seizure onset/ actual seizure period) and interictal (period between seizures) EEG signals and predict epileptic seizure using those features. There are many existing research works employed to extract various features such as eigenspectra of space delay correlation and covariance matrices [15], autoregressive modeling and least-squares parameter estimator [16], bivariate features [17], spectral power from raw and bipolar time-differential signals [18], spike rate [19], and univariate features [20].

Williamson *et al*. [15] used spatiotemporal features and the experimental results show that the method provides 85% prediction accuracy (i.e., 71 out of 83 seizures) with 0.8 false alarm per patient, where they used 19 patients out of 21 patients from the benchmark data set [21]. Chisci *et al*.'s [16] used autoregressive model and *support vector machine* (SVM) to predict seizure. They used 9 patients out of 21 patients from the benchmark data set [21]. The seizure prediction accuracy of the method is 100% with 10 false alarms per patient. They used a large number of channels for seizure prediction. Therefore, the process needed more computational time and sophisticated filtering techniques to remove artifacts from all channels. Mirowski *et al*. [17] proposed a seizure prediction

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technique based on bivariate features of EEG synchronization such as cross-correlation, nonlinear interdependence, dynamic entrainment, etc. They conducted experiments using 15 patients out of 21 patients [21] and the method provided prediction accuracy 71% with no false alarm. Park *et al*. [18] proposed a seizure prediction technique using linear features of spectral-power and non-linear classifier. They used 18 patients out of 21 patients [21]. The method provided prediction accuracy 94.4% with 6.44 false alarms per patient on average. Li *et al*. [19] applied spike rate using morphological filter to predict seizure. They obtained 75.8% prediction accuracy with 2.2 false alarms per patient using 21 patients [21]. A seizure prediction technique based on linear univariate features proposed by Rasekhi *et al*. [20] provided 73.9% prediction accuracy with 11.1 false alarms per patient. In the experiments Rasekhi *et al.* used different data set.

The prediction accuracies of the above mentioned seizure prediction techniques [15][17][19][20] are relatively low. On the other hand, the prediction accuracies of the seizure prediction techniques [16][18] are very good; however, the false alarm per patient is very high. Moreover, the above mentioned techniques [15]-[18] did not consider all patients of the data set [21] and they also used large number of channels for their approaches. Obviously using more channels requires more computational time and sometimes makes the systems more sensitive to the artifacts which requires sophisticated filtering. Prediction of epileptic seizure by analyzing EEG signals is a challenging task due to non-abruptness phenomena and inconsistency of the signals considering different brain locations, patient-age, patient-sex, seizure-type, etc. Therefore, there is scope for further research to improve in seizure prediction with better accuracy and lower false alarm using fewer numbers of channels without sophisticated filtering technique to remove artifacts.

Sharma *et al*. [22] prove that the nonlinear dynamics of a signal can be exploited through phase space to classify epileptic seizure in EEG signals [22]. Phase correlation [23] provides relative changes between the current signals and the reference signals i.e., shifting information between two correlated signals via Fourier Transformation. Paul *et al.* [23] show that the phase correlation has the capacity to indicate reliable motion between two images. Normally a seizure has interictal and preictal/ictal signals occurring one-after-another and different signals can be identified by analyzing phase correlation between two consecutive time-window in temporal direction to find the changes from one state (among interictal, preictal, and ictal) to another state. When a brain location (e.g., frontal lobe) of a patient is in one state, the different channels of that moment in the same location should provide almost the same state. Thus, it is always a good strategy to analyze more than one channel from the same location to predict the signal type. However, considering very large number of channels can negate the prediction results as some channels (normally away from the epicenter of the seizure onset) might not provide the same type of signal. Thus, a good seizure prediction strategy should exploit spatiotemporal relationship using an appropriate number of channels.

In this paper, a novel approach for seizure prediction based on phase correlation is proposed and evaluated with intracranial EEG signals of a benchmark data set [21] with all patients (i.e., 21 patients). In the proposed method, firstly, a differential window is applied to make the EEG signals smooth, and then phase correlation is applied to estimate relative change between two vectors of the EEG signals. By considering the relative change, the *phase-matched error* (PME) is calculated between the current vector and the matched-vector. Then the *energy concentration ratio* (ECR) is determined between the low-frequency coefficients against all coefficients after applying *discrete cosine transformation* (DCT). The ECR provides different characteristics in different states of the signals. These features (i.e., ECR) are then used to classify EEG signals through *least square-support vector machine* (LS-SVM) and finally post-processing is applied for epileptic seizure prediction. The experimental results expose that the proposed method provides better accuracy with low false alarm rate compared to the state-of-the-art methods using only a few numbers of channels without using any sophisticated filtering technique.

The paper is organized as follows: the data formation, the detailed proposed technique with preprocessing, feature extraction, classification, and post-processing are described in section 2; the detailed experimental results and discussions are explained in section 3, the results are analyzed in section 4 while section 5 concludes the paper.

II. PROPOSED METHOD

The paper mainly aims to predict the occurrence of epileptic seizure correctly and timely through an automated way. A diagram of the proposed process for seizure prediction is schematized in Fig. 1 and the detailed description of the process diagram is presented below. In the prediction process, normally a preprocessing step is applied to remove artifacts of the raw EEG signals using filtering technique. Then different features are extracted using different mechanisms and the extracted features are used to classify them into different states (i.e., preictal/ictal and interictal). The decision made by the classifier might not be accurate enough for the prediction purpose, thus a post-processing step is conducted to fine tune the prediction decision. The proposed method uses all the above mentioned steps without using any explicit filtering mechanism. In the proposed method differential window is used as a preprocessing step, phase correlation as a feature extraction step, LS-SVM as a classifier, and windowing regularization as a post-processing step. This paper contributes to the customization of existing phase correlation technique for the feature extraction of EEG signals and two-phase window regularization for predicting the seizure.

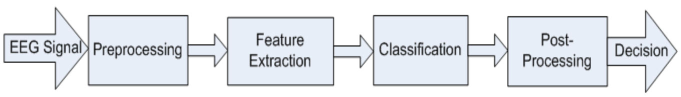


Fig. 1. Schematic representation of overall processing diagram for epileptic seizure prediction.

A. Data set

The data set used in the paper was recorded at the Epilepsy Centre of the University Hospital of Freiburg, Germany [21]. The data set contains *intracranial EEG* (iEEG) recordings of 21 patients suffering from medically intractable focal epilepsy [5]. It was obtained by the Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and 16 bit analogue-to-digital converter. This data set is the mostly cited and relevant data set used in the modern seizure detection and prediction approaches such as [2], [15]-[19], [24]-[27]. According to the data set, the epileptic EEG signals can be classified into ictal, preictal, postictal, and interictal periods. Duration of ictal period varies from a few seconds to 5 minutes. The ictal signals contain epileptic seizures with at least 50 minutes of preictal signal preceding each seizure. The data set contains 21 patients having a total 87 seizures. There are 24-25 hours of interictal signal and 2-5 hours of ictal with preictal and postictal signal [27]. Therefore, the data set is about approximately 509 hours from 21 epileptic patients. For the analysis and clear visualization purpose, preictal signal is consider as the 5-minutes prior to each seizure onset and interictal signal is also taken as 10-minute of interictal signal labeled by the Epilepsy Centre of the University Hospital of Freiburg, Germany [21]. Note that there are six channels used to capture EEG signals in each patient. In the experiments, focal electrodes (i.e., three channels) of EEG signals from different brain locations and different patients are considered only.

B. Preprocessing

Differential window (DW) [28] is applied on the raw EEG signals to get more distinguishable signals. Applying DW on EEG signals produces more differentiating values to recognize seizure (i.e., preictal/ictal) from interictal signals easily compared to the original signals. To justify the argument, DW is applied on raw EEG signal and then more distinguishing preictal/ictal EEG signals (see Fig. 2) are obtained where the top sub-figure represents the raw EEG signals of patient one from channel two and the bottom sub-figure represents the EEG signals after applying DW. It is easily observed that after applying DW, the signals are visually more distinctive.

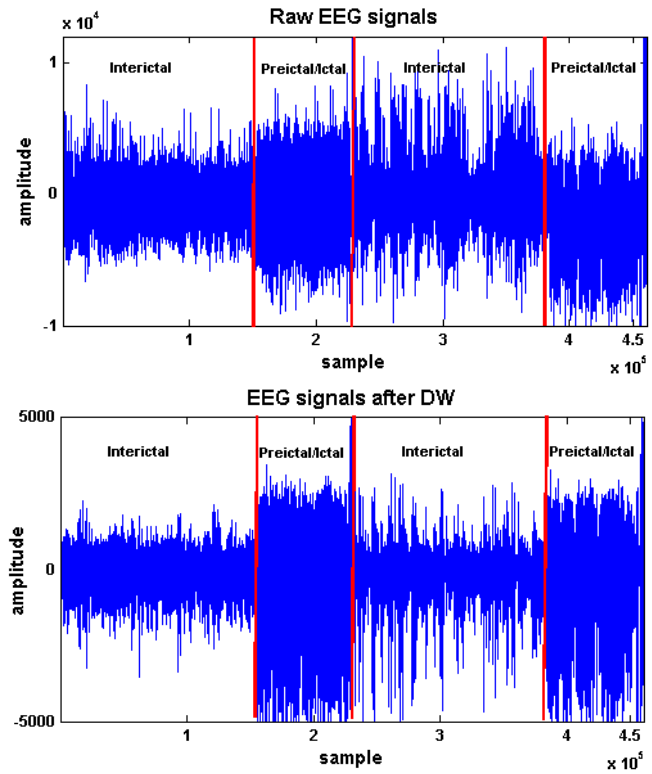


Fig. 2. Preictal/ictal and interictal EEG signal from patient one, channel two; the top sub-figure represents the raw EEG signal and the bottom sub-figure represents the EEG signals after applying differential windowed (DW).

C. Feature Extraction using Phase Correlation

In this paper, real time analysis of EEG signals is used employing phase correlation. Paul *et al*. [23] used phase correlation on 2D-blocks to predict translational displacement between two blocks from the current and reference images. However, in the proposed method phase correlation is applied on 1-D vectors to predict relative displacement between the vectors of adjacent time-windows of an EEG signal. A vector of fixed time window is taken as the current vector and is considered as immediate previous vector with the same time-window as the reference vector. The magnitude of the Fourier Transformed vector indicates to the presence of the frequency component and the phase indicates to the location of the frequency component of the vector. In the proposed method, the phase information has been used to estimate *prediction of relative change* (PRC) and *phase-matched error* (PME) between the current vector and the best-matched-reference vector (see the details process diagram in Fig. 3). Then the *energy concentration ratio* (ECR) is determined between the energy of low-frequency coefficients against the energy of all-frequency coefficients after applying DCT on PME vector. In this way, temporal correlation [26] is exploited to determine the relative change of the signal in time domain. The main reason of using DCT is that it is an effective transformation to convert signal from the time domain to the frequency domain and to arrange them from low to high frequency coefficients [29]. One notable property of the DCT is that if the original signal has less variations, then all energy of the transformed signals is concentrated in the first few coefficients; otherwise, the energy is distributed into all coefficients. This property is exploited in the proposed method to find the energy concentration ratio between low and all frequency coefficients. Normally preictal/ictal signal has more variation compared to the interictal signal (see Fig. 2), thus, it is expected that energy concentration ratio is relatively higher for interictal signals compared to the preictal/ictal signals (the results in Fig. 6 also supports the theory). Thus, DCT is used in the concentration ratio calculation. The average ECR of other neighboring channels are determined to exploit spatial correlation. The classifier uses the *average ECR* (AECR) as a feature. The classifier also uses *moving average* (MV) of the AECR (MVAECR) as another feature. The detail procedure of the feature extraction is described below.

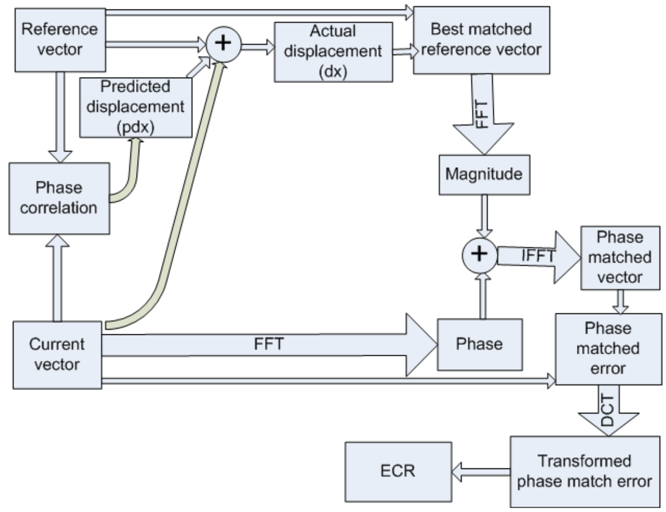


Fig. 3. Block diagram of energy concentration ratio generation.

Let r and c be the reference and current vector of the EEG signals, respectively. In the experiments 10 second window is used i.e., the size of both r and c is 2,560 (256×10) samples. The phase correlation is calculated by applying *Fast Fourier Transformation* (FFT) on the reference and current vectors, inverse FFT and FFT Shift operation on the phase difference as follows:

$$R = \varphi(r) \tag{1}$$

$$C = \varphi(c) \tag{2}$$

$$D = \Psi\left|\varphi^{-1}(e^{j(\angle R - \angle C)})\right| \tag{3}$$

where $\angle$ indicates the angle or phase, φ is the FFT function and φ^{-1} is the inverse FFT, Ψ is the FFT Shift function, R and C are the transformed vector of r and c respectively, and D is the phase correlation between r and c vectors. Then the predicted displacement (i.e., Φ) between r and c vectors is determined,

$$\Phi = \max_{\arg}(D(x)) - x_{middle} \tag{4}$$

where the middle position of D vector is considered as x_{middle}.

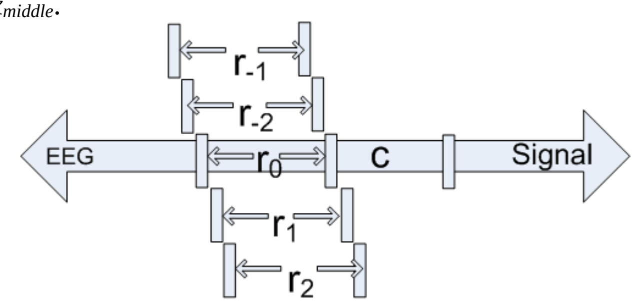


Fig. 4. The replacement vector (i.e., ε) is calculated from 0 to Φ positions based on the *mean square errors* (MSEs) between the current vector and the reference vectors of a signal.

To find the actual displacement ε between two vectors, the minimum *mean square error* (MSE) between a number of reference vectors and the current vector is examined by shifting the reference vector from the predicted displacement Φ to 0 locations (i.e., $0 \le \varepsilon \le \Phi$ if Φ is positive, otherwise $\Phi \le \varepsilon \le 0$). To demonstrate locations of the current and reference vectors of a signal, we assume that if the current vector starts at position 30th second, then the original reference vector starts from 20th second. If a given current vector provides Φ = 2, all reference vectors from the original reference vector shift (denoted as r_0) to other vectors such as r_1, and r_2 which are formed by shifting 1 and 2 sample(s) respectively (see in Fig. 4). In this case some portion of the reference vector (except the original reference vector) overlaps with the current vector. If Φ = -2, all reference vectors such as the original reference vector r_0 shift to other vectors r_{-1} and r_{-2} which are formed by shifting 1 and 2 sample(s) respectively in the opposite direction (see in Fig. 4). The best-matched reference vector is calculated as follows:

$$\Re = r(x+\varepsilon). \tag{5}$$

Then *phase-matched reference vector* (PMV) can be determined as follows:

$$\Theta = \left|\varphi^{-1}\left(\left|\varphi(\Re)\right| e^{j\angle C}\right)\right|. \tag{6}$$

The PME is calculated from the current and PMV vector

$$\Gamma = c - \Theta. \tag{7}$$

Then DCT is applied on the PME (i.e., Γ) in order to calculate the transformed residual

$$\Omega = dct(\Gamma). \tag{8}$$

Thus ECR is calculated by the ratio of low frequency coefficients against all coefficients of the DCT transformed vector as follows:

$$ECR = \frac{\sum_{v=1}^{\lfloor 3\mu/4 \rfloor} \Omega^2(v)}{\sum_{u=1}^{\mu} \Omega^2(u)} \tag{9}$$

where μ=10×256 as 10 second window with 256 as the sample rate is taken. The AECR is calculated using neighboring channels as follows:

$$\delta = \frac{1}{N}\sum_{i=1}^{N} ECR_i \tag{10}$$

where $0 < \delta < 1$ and N is the number of spatial channels. The AECR is used as one feature for the classifier. Another feature MVAECR is extracted from the moving average of AECR.

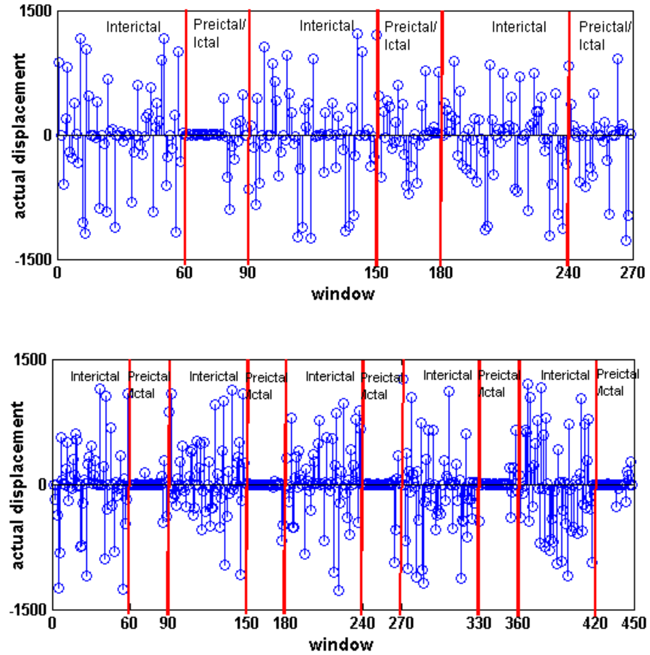
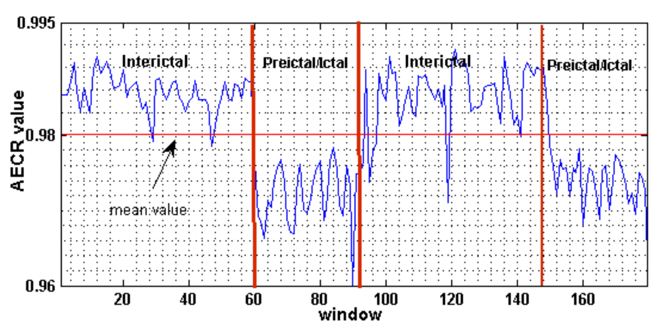


Fig. 5. The actual displacement values (i.e., ε) in different windows from patient 2 (top) and patient 4 (bottom).

The distributions of ε are shown in Fig. 5 for the patient 2 and patient 4. The distributions show interesting phenomenon. The ε values are relatively low for preictal/ictal compared to interictal i.e., more matching signals are found within preictal/ictal signals compared to interictal signals with short distance. According to the phenomenon, intra-signal phase similarity among preictal/ictal signals is larger compared to intra-signal phase similarity among interictal signals. This also indicates that if any feature is extracted by using the displacement, it is possible to distinguish different types of signals. Later it is shown that two features namely AECR and MVAECR extracted using the displacement for prediction of different types of EEG signals provide better results.



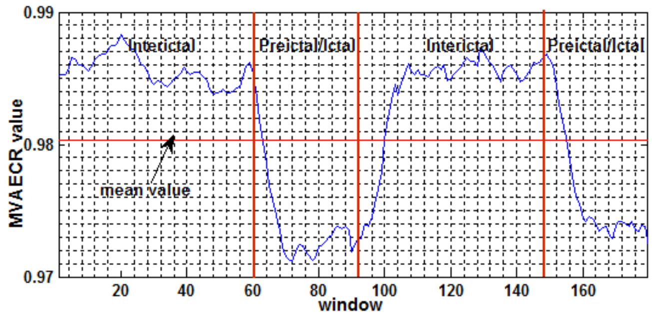


Fig. 6. The extracted features AECR using phase correlation where the first row represents AECR values and the second row represents moving average values of AECR.

Fig. 6 shows AECR (top row) and MVAECR (bottom row) of patient 1 using three focal channels. The figure demonstrates that the extracted features contain distinguishable characteristics for preictal/ictal and interictal EEG signals. For better visualization a red horizontal line is drawn as a mean of the AECR and MVAECR and a number of vertical lines are drawn to distinguish preictal/ictal and interictal periods. From the figure one can easily distinguish the different signal types from the mean values of AECR and MVAECR. However, the mean values varied not only from patient to patient but also from segment to segment of the signals. Thus, a sophisticated classifier is needed to make a prediction model.

D. *Classifier*

To classify the preictal/ictal and interictal signals, two features, AECR and MVAECR, are considered. For classification, SVM-based classifier is used as the SVM [30] is one of the best classifiers for the non-stationary EEG signals [25][31][32]. It is to be noted that SVM has shown a great promise for disease diagnosis in computational biology [33]. The LS-SVM [34][35] is the extended version of SVM and it is closely related to regularization networks and Gaussian process, and it also has primal-dual interpretations [34]. The major drawback of SVM is in its higher computational burden of the constrained optimization programming. However, LS-SVM can solve this problem [36] and for this reason in the experiments, LS-SVM is used. The equation of LS-SVM can be defined in [37] as:

$$f(x) = sign\left[\sum_{i-1}^{N} \alpha_i y_i K(x, x_i) + b\right] \qquad (11)$$

where $K(x, x_i)$ is a kernel function, α_i are the Lagrange multipliers [38], b is the bias term, x_i is the training input, and y_i is the training output pairs.

RBF kernel is used in the experiments and this function can be defined as:

$$k(x, x_i) = \exp(-\|x - x_i\|^2 / 2\sigma^2) \qquad (12)$$

where σ controls the width of RBF kernel function.

The goal of the classifier is to classify preictal/ictal and interictal EEG signals using machine learning approach with 10-fold cross-validation. The challenge is to find mapping between training set and unseen test set. The classifier is a LS-SVM, which learns nonlinear mapping from the training set features $\{x\}_i{=}1\ldots n_T$, where n_T is the number of training features into the patient's state, preictal/ictal (+1) and interictal (0). For unbiased classification results [39], the whole trial is divided into M subsets; where M-1 is used for training and the remaining is used for testing [40]. Let's $\{y_i\}_{i=C_{1,2}}$ designate the LS-SVM validation test outputs mapping to class 1 or class 2.

E. *Post-processing*

Although DW and phase correlation inherently attenuate unwanted signals (i.e. artifacts), still there is a probability of having some artifacts with eye blinking, muscle movement, etc. These artifacts may contribute to the misclassification of preictal/ictal and interictal EEG signals (see the first row of Fig. 7). Therefore, post-processing is applied to accurately predict epileptic seizure on LS-SVM classified signals. For post-processing, two-phase *k*-of-*n* analysis is performed to predict an impending seizure by analyzing preictal/ictal and interictal EEG signals whereas preictal/ictal represents positive 1 and interictal represents zero. If there are equal or more than *k* positives out of *n* consecutive windows, then the prediction horizon is labeled as preictal/ictal, otherwise, it is labeled as interictal. During post-processing using two-phase, 3-of-5 and 2-of-6 analysis are performed to identify the prediction horizon for five minutes in total prior to a seizure. In the first phase 10 seconds window is used, thus, if three windows are found as positive, it is considered that all five windows are positive. In the second phase, 6 windows with 50 seconds window are taken based on the first phase results. If the result is positive in any two 50 seconds windows, the 5 minutes (i.e., 6×50 seconds) window will be considered as positive (i.e. one). It is to be noted that five minutes window is enough to prevent the impending seizure by drug administration [4]. The seizure prediction result is shown in the second row of Fig. 7 where decision in each five minutes is taken based on the two-phase decision. Different sizes of windows are also tried in one phase and two-phase decision (see results in Table 3), however, the proposed two-phase is the best in terms of prediction accuracy and false alarm rate.

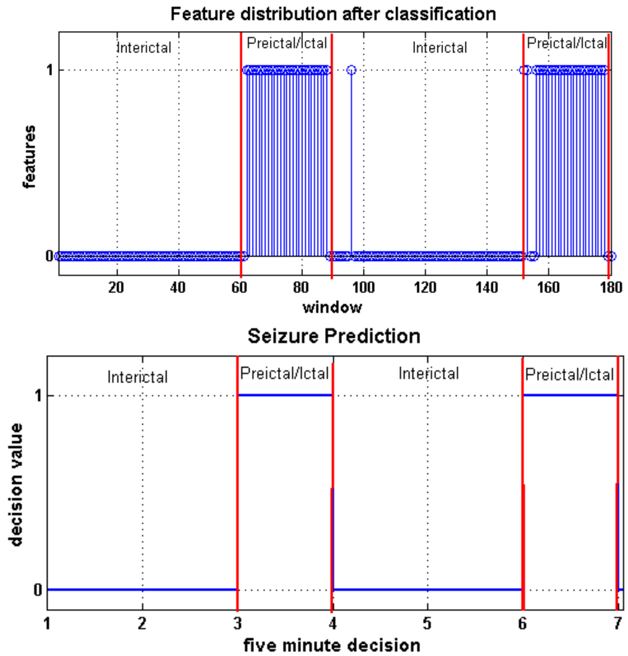


Fig. 7. Seizure prediction using LS-SVM and windowing where the first row represents the classification output using LS-SVM and the second row represents the decision of seizure prediction after windowing.

III. RESULTS AND DISCUSSIONS

In this paper a seizure prediction method is proposed based on the phase correlation using EEG signals from different patients with different brain locations, sex, age, and seizure types. The EEG signals from different brain locations are firstly smothered by DW technique. Then the two features are extracted using the customized phase correlation technique between the reference vector and the current vector of an EEG signal. A classifier is employed to classify interictal and preictal/ictal signals based on the extracted features. To get better accuracy, a regularization-based decision making strategy is applied.

Prediction accuracy (PA) and false alarms per patient are the good indicators to evaluate the experimental results of epileptic seizure prediction. The PA is defined in [41] as:

$$PA = (Ns / Na) * 100 \tag{13}$$

where Ns is the number of correctly predicted seizures and Na is the total number of seizures.

TABLE 1
PATIENTS DETAILS AND PREDICTED SEIZURE USING THE PHASE CORRELATION METHOD.

Patient	Sex	Age	Seizure Type	H/NC	Electrodes	Brain Location (Lobe)	Total Seizures	[16]		[18]		Proposed Method	
								PA (%)	FA	PA (%)	FA	PA (%)	FA
1	F	15	SP,CP	NC	g, s	Frontal	4	100	0	100	1	100	1
2	M	38	SP,CP,GTC	H	d	Temporal	3	-	-	-	-	100	2
3	M	14	SP,CP	NC	g, s	Frontal	5	100	3	100	1	80	4
4	F	26	SP,CP, GTC	H	d, g, s	Temporal	5	-	-	100	1	100	0
5	F	16	SP,CP, GTC	NC	g, s	Frontal	5	100	23	100	21	100	1
6	F	31	CP, GTC	H	d, g, s	Temporal/Occipital	3	-	-	100	1	67	4
7	F	42	SP,CP, GTC	H	d	Temporal	3	-	-	100	1	100	5
8	F	32	SP,CP	NC	g, s	Frontal	2	-	-	-	-	100	0
9	M	44	CP, GTC	NC	g, s	Temporal /Occipital	5	100	3	100	4	100	0
10	M	47	SP,CP, GTC	H	d	Temporal	5	-	-	100	3	100	4
11	F	10	SP,CP, GTC	NC	g, s	Parietal	4	100	9	75	2	75	3
12	F	42	SP,CP, GTC	H	d, g, s	Temporal	4	-	-	100	1	100	2
13	F	22	SP,CP, GTC	H	d, s	Temporal/Occipital	2	-	-	-	-	100	1
14	F	41	CP, GTC	H, NC	d, s	Frontal/Temporal	4	-	-	75	12	100	0
15	M	31	SP,CP, GTC	H, NC	d, s	Temporal	4	-	-	100	4	100	4
16	F	50	SP,CP, GTC	H	d, s	Temporal	5	-	-	90	11	100	3
17	M	28	SP,CP, GTC	NC	s	Temporal	5	100	10	100	1	100	3
18	F	25	SP,CP	NC	s	Frontal	5	100	17	100	1	80	0
19	F	28	SP,CP, GTC	NC	s	Frontal	4	100	25	75	24	75	5
20	M	33	SP,CP, GTC	NC	d, g, s	Temporal/Parietal	5	100	0	80	16	80	2
21	M	13	SP,CP	NC	g, s	Temporal	5	-	-	100	4	80	1

SP=simple partial, CP=complex partial, GTC=generalized tonic-conic, H=hippocampal origin, NC=neocortical origin, d=depth electrode, g=grid electrode, s=strip electrode, FA= False alarm, - indicated that results are not available for this patient

The performance of the proposed method is compared with a number of relevant and recent methods [15]-[20]. The detailed information of patients from the benchmark data set [21] and the comparison of the prediction results of the proposed method against two state-of-the-art methods [16] and [18] with patient-specific results are given in Table 1. A number of entries against some patients in the table for the state-of-the-art methods are not available as the method in [16] used only 9 patients and the method in [18] used only 18 patients whereas the proposed method uses all available patients of the data set. According to the results the proposed method successfully provides 100% accuracy for 14 patients whereas the methods in [16] and [18] provide 100% accuracy for 9 and 13 patients respectively. Moreover, the proposed method provides reduced number of false alarms per patient compared to the state-of-the-art methods. As it can be shown from Table 1, 80 seizures out of 87 seizures are predicted correctly by making 48 false alarms. Hence the proposed method obtains 91.95% average PA with 2.14 false alarms per patient.

Table 2 shows the performance in terms of PA and false alarm per patient against six existing relevant methods. According to the table the proposed method provides the best prediction results by combining PA (i.e., 91.95%) and false alarm per patient (i.e., 2.14) compared to all other methods. A proper performance (high sensitivity and low false alarm) of the seizure prediction method is important to clinically prevent the seizure. Experiments show that the proposed method achieves low false alarm with high sensitivity.

TABLE 2
COMPARISON RESULTS WITH PROPOSED METHOD AND EXITING METHODS.

Methods	PA	FA	Patients
[15]	85.0	0.80	19
[16]	100	10.00	9
[17]	71.0	0.00	15
[18]	94.4	6.44	18
[19]	75.8	2.20	21
[20]	73.9	11.10	10
Proposed Method	91.95	2.14	21
Prediction accuracy=PA, False alarm= FA			

IV. ANALYSIS

A. Selection of Different Time Widows

In the proposed method a fixed window size is used to exploit temporal relationship of an EEG signal. To verify the window size, the experiments are performed using different window sizes such as 5 seconds, 10 seconds and 15 seconds windows. Fig. 8 indicates that 10 second window is more consistent in term of AECR values of preictal/ictal and interictal signals i.e., the number of crossing of the AECR values against the mean value during preictal/ictal and interictal is minimum for 10 second-window compared to 5 or 15 second-window. Therefore, 10 second window is considered in the experiments.

B. Justification of Different Phases

In the proposed method, two-phase decision is considered to take the final decision for prediction. The performance of the proposed method is also investigated with one-phase decision and two-phase decision with two variations in each phase. In the one-phase decision, five minutes classification output is integrated and positive decision is taken if the number of positive outputs is more than 40% (or 50%) of total outputs, otherwise the decision is zero. The performance of the proposed method is also investigated with two-phase (see Section II.E for detail) with different combinations (such as 3-5/3-6 and 3-5/2-6). One and two-phase analysis are tested on 21 patients. However, Table 3 shows the results where zero false positive results are obtained for the proposed method. In most cases, it is observed that two-phase combination carries good results in terms of false alarm and false positive rate compared to the one phase analysis (see in Table 3). Moreover, 3-of-5 along with 2-of-6 combination of two-phase provides better prediction rate compared to 3-of-5 and 3-of-6 combinations. Therefore, 3-of-5 and 2-of-6 combinations are considered in two phases respectively in the experiments for the prediction of seizure.

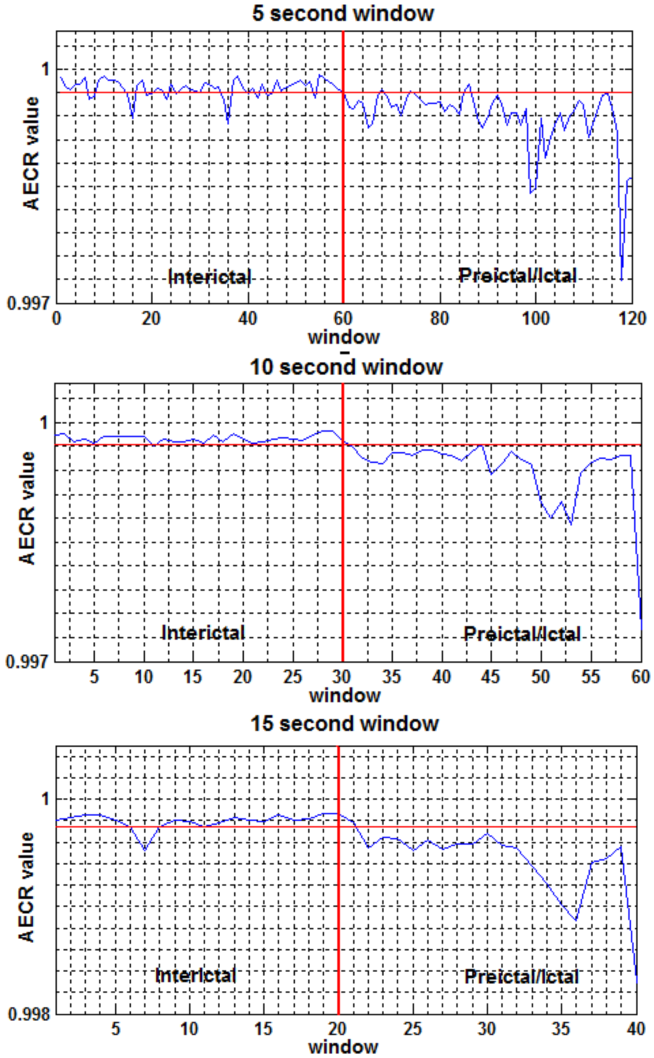


Fig. 8. The AECR values of preictal/ictal and interictal EEG signals using different window sizes; the first, second, and third row represent the 5 second, 10 second, and 15 second window, respectively.

TABLE 3

COMPARISON RESULTS BETWEEN ONE PHASE AND TWO PHASE ANALYSIS FOR DIFFERENT PATIENTS.

Patient	One- Phase				Two-Phase			
	40%		*50%*		*Analysis 3-3-5/3-6*		*Analysis 3-5/2-6*	
	FA	FP	FA	FP	FA	FP	FA	FP
1	0	0	0	0	0	0	1	0
2	2	1	2	1	2	1	2	0
5	1	0	1	1	1	0	1	0
7	3	1	2	1	1	1	5	0
12	2	1	1	1	2	1	2	0
13	0	2	0	2	0	0	1	0

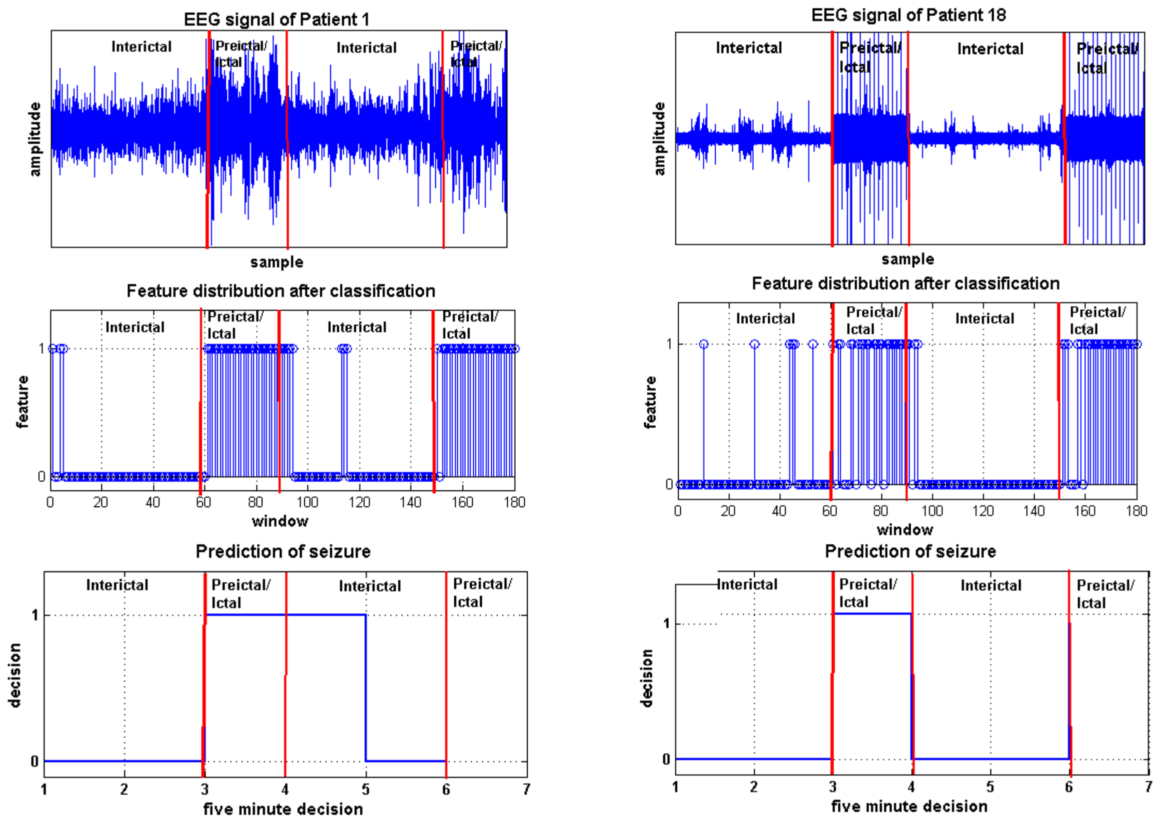


Fig. 9. False alarm generation by the proposed method for Patient 1 and Patient 18.

14	0	0	0	1	0	1	0	0
15	4	4	3	4	4	4	4	0
16	2	0	1	1	1	1	3	0
False alarm=FA, False positive= FP								

C. *Generation of False Alarms*

Similar to all other existing methods, the proposed method generates a number of false alarms. Differences in patients (in terms of age, sex, types of seizure, location of seizures), makes it a challenging task to design a unified method which can predict all seizure without any false alarm. It is obvious that a method that can predicts all seizures with relatively large numbers of false alarms is better than the method which cannot predict all seizures with a few false alarms. The strength of the proposed method is investigated by analyzing the failure and success cases in terms of false alarm and prediction rate. To do this, Patient 1 and Patient 18 are taken where the proposed method generates one false alarm from patient 1 with 100% prediction accuracy whereas it does not generate any false alarm from patient 18.

Fig. 9 demonstrates a false alarm generation by the proposed method using two distinguishing patients. Note that only a portion of the EEG signals for both patients are shown here to demonstrate the generation of false alarm. The figure shows that preictal/ictal and interictal signals are visually distinguishable in case of patient 18; however, it is quite hard to distinguish between preictal/ictal and interictal EEG signals from patient 1. Therefore, one false alarm is generated when signal is considered from the patient 1.

D. *Selection of Kernel*

The performance of the proposed method is verified using three popular kernels such as Linear, Morlet [36] and RBF in the LS-SVM classifier. The experimental results disclose that the prediction accuracies of the proposed method are 47.13%, 89.66%, and 91.95% using Linear, Morlet, and RBF kernels respectively (see Table 4). According to the prediction accuracy, RBF kernel is proved to be the best among three, thus, RBF kernel is used in the experimental results.

In order to make LS-SVM model, two tuning parameters (i.e., kernel and regularization) of RBF kernel are needed to determine the trade-off between the training error minimization and smoothness [34]. The selection of the kernel and regularization parameters can be automated by optimizing a cross-validation based model selection. In the experiments, cross-validation is conducted for tuning the parameters and then they are used for testing. Note that the patient specific training and testing approach is used in the experiments. For the experiments, if a patient has *M* number of seizures, (*M*-

1) number of seizures and their associated non-seizure signals are used for training and the remaining seizure and its associated non-seizure signals are used for testing. In this way, the training and testing sets are changed in a fashion so that all individual seizure and its associated non-seizure signals are tested and classified.

TABLE 4
TOTAL PREDICTED SEIZURES AND ITS PREDICTION ACCURACY USING DIFFERENT KERNELS OF LS-SVM.

Patient Number	Total Seizures	Predicted Seizures		
		Linear Kernel	Morlet Kernel	RBF Kernel
1	4	4	4	4
2	3	1	3	3
3	5	0	4	4
4	5	5	5	5
5	5	1	5	5
6	3	1	2	2
7	3	3	3	3
8	2	1	2	2
9	5	5	5	5
10	5	0	5	5
11	4	0	3	3
12	4	0	4	4
13	2	2	2	2
14	4	4	4	4
15	4	3	3	4
16	5	5	5	5
17	5	2	4	4
18	5	4	4	5
19	4	0	3	3
20	5	0	4	4
21	5	0	4	4
Total Predicted Seizures		41	78	80
Prediction Accuracy (%)		**47.13%**	**89.66%**	**91.95%**

For better understanding about the impact of parameters selection, further experiments are conducted by fixing the values of the tuning parameters. The parameters might be fixed in three possible ways: (i) obtaining the values of the tuning parameters from the training sets of all seizures and their associated non-seizure signals from all patients and using the average values for all patients in testing, (ii) obtaining the values of the tuning parameters from the first training set of seizures and their associated non-seizure signals of a patient and using the values for the patient in testing, and (iii) obtaining the values of tuning parameters from all training sets of a patient and using the average value for the patient in testing. The above mentioned three options provide 73.56%, 80.46%, and 90.80% prediction accuracy respectively. It is expected that the first option performs worst as it does not exploit individual optimized parameter values and the third option improves the prediction accuracy as it can exploit the patient-specific average values. However, the proposed method provides 91.95% prediction accuracy. Moreover, the parameter setting of the proposed method represents the real scenario as in practice unlike the third option where unseen data is needed to be used for testing.

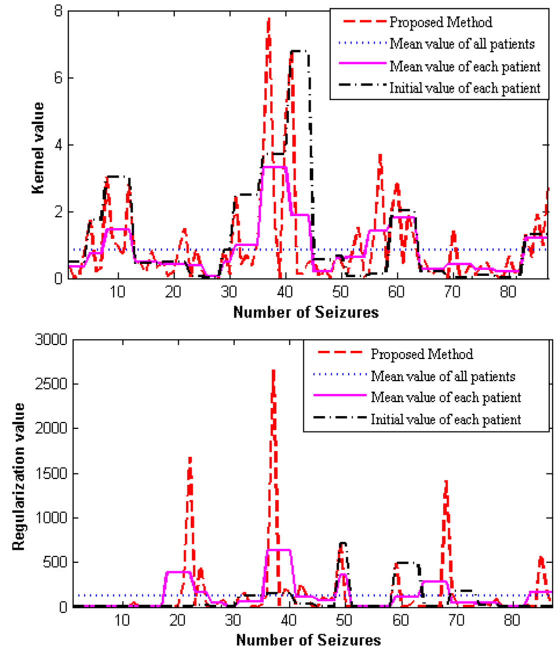


Fig. 10. Different values of kernel and regularization parameters in RBF kernel.

The values of kernel and regularization parameters for the above mentioned three options of fixed values and the proposed variable values in the proposed prediction technique are investigated to see the effect of different values of the parameters in the prediction accuracy. Fig.10 shows the different values of the parameters against individual seizure and its associated non-seizure signals of all patients using RBF kernel. Note that in Fig.10 the seizures of the individual patients are arranged in order. The figure demonstrates that the proposed technique using variable parameter values for different seizures and their associated non-seizure signals provides the best prediction accuracy compared to the fixed values (see Table 4).

V. CONCLUSION

In the image processing and video compression/coding areas, phase correlation is used to predict relative displacement between two blocks or images. In the paper, a seizure prediction method is proposed based on a customized phase correlation technique by exploiting spatiotemporal correlation among EEG signals. The experimental results show that the proposed method can extract important features which can be employed for classification of preictal/ictal and interictal signals. For better accuracy of prediction results a two-phase post-processing is performed. The experimental results reveal that the proposed prediction method provides not only higher prediction accuracy (91.95%) but also lower number of false alarms per patient (i.e., 2.14) with using a small number of channels without using any explicit artifact removal technique. The proposed method outperforms six existing relevant state-of-the-art methods in terms of prediction accuracy and false alarms using all patients from a benchmark data set.

REFERENCES

[1] S. Sanei and J.A. Chambers, EEG Signal Processing. NewYork: Wiley, 2007.

[2] M.Z. Parvez, and M. Paul. (2014, Dec). Epileptic seizure detection by analyzing EEG signals using different transformation techniques. *Neurocomputing*, 145, pp. 190-200.

[3] S. Santaniello, S. P. Burns, A. J. Golby, J. M. Singer, W. S. Anderson, and S. V. Sarma. (2011, Dec). Quickest detection of drug-resistant seizures: An optimal control approach. *Epilepsy & Behavior*, 22(2011), pp. S49-S60.

[4] T. Netoff, Y. Park, and K. Parhi, "Seizure prediction using cost-sensitive support vector machine," *IEEE Annual International Conference in Engineering in Medicine and Biology Society*, 2009, pp. 3322-3325.

[5] W. Zhou, Y. Liu, Q. Yuan, and X. Li. (2013, Apr). Epileptic Seizure Detection Using Lacunarity and Bayesian Linear Discriminant Analysis in Intracranial EEG. *IEEE Transactions on Biomedical Engineering*, 60(12), pp. 3375-3381.

[6] F. Mormann, R. G. Andrzejak, C. E. Elger, and K. Lehnertz. (2007). Seizure prediction: the long and winding road. *Brain*, 130 (2), pp. 314–333.

[7] Epilepsy Australia: Epilepsy Information. (2014, July). Available:http://www.epilepsyaustralia.net/Epilepsy_Information/Epilepsy_explained/Epilepsy_explained.aspx.

[8] Y. Tang and D.M. Durand. (2012, Mar). A tunable support vector machine assembly classifier for epileptic seizure detection. *Expert Systems with Applications*, 39 (4), pp. 3925–3938.

[9] M. Guttinger, V. Padrun, W. F. Pralong, and D. Boison. (2005, May). Seizure suppression and lack of adenosine A1 receptor desensitization after focal long-term delivery of adenosine by encapsulated myoblasts. *Experimental Neurology*, 193(1), pp. 53–64.

[10] R. Esteller, J. Echauz, and T. Tcheng, "Comparison of line length feature before and after brain electrical stimulation in epileptic patients," *IEEE Annual International Conference in Engineering in Medicine and Biology Society*, 2004, 2, pp. 4710–4713.

[11] O. A. Rosso, S. Blanco, and A. Rabinowicz. (2003, June). Wavelet analysis of generalized tonic-clonic epileptic seizures. *Signal Processing*, 83 (6), pp. 1275–1289.

[12] V. L. Dorr, M. Caparos, F. Wendling, J. P. Vignal, and D. Wolf. (2007, July). Extraction of reproducible seizure patterns based on EEG scalp correlations. *Biomedical Signal Processing and Control*, 2(3), pp. 154–162.

[13] F. H. Lopes da Silva. (2008). The impact of EEG/MEG signal processing and modeling in the diagnostic and management of epilepsy. *IEEE Reviews in Biomedical Engineering*, 1, pp. 143–156.

[14] M. Z. Parvez, and M. Paul, "Features extraction and classification for Ictal and Interictal EEG signals using EMD and DCT," *15th IEEE International Conference on Computer and Information Technology*, pp. 132 – 137, 2012.

[15] J.R. Williamson, D.W. Bliss, D.W. Browne, and J.T. Narayanan. (2012, Oct). Seizure prediction using EEG spatiotemporal correlation structure. *Epilepsy & Behavior*, 25 (2), pp. 230–238.

[16] L. Chisci, A. Mavino, G. Perferi, M. Sciandrone, C. Anile, G. Colicchio, and F. Fuggetta. (2010, May). Real-Time Epileptic Seizure Prediction Using AR Models and Support Vector Machines. *IEEE Transactions on Biomedical Engineering*, 57(5), pp. 1124-1132.

[17] P. Mirowski, D. Madhavan, Y. LeCun, and R. Kuzniecky. (2009, Nov). Classification of patterns of EEG synchronization for seizure prediction. *Clinical Neurophysiology*, 120(11), pp. 1927-1940.

[18] Y. Park, L. Luo, K. K. Parhi, and T. Netoff. (2011, Oct). Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. *Epilepsia*, 52(10), pp. 1761-1770.

[19] S. Li, W. Zhou, Q. Yuan, and Y. Liu. (2013, Oct). Seizure Prediction Using Spike Rate of Intracranial EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 21(6), pp. 880-886.

[20] J. Rasekhi, M.R.K. Mollaei, M. Bandarabadi, C.A. Teixeira, and A. Dourado. (2013). Preprocessing effects of 22 linear univariate features on the performance of seizure prediction methods. *Journal of Neuroscience Methods*, 217, pp. 9–16.

[21] EEG Data Set: Epilepsy Center of the University Hospital of Freiburg. (2012, June 10). Available: http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database.

[22] R. Sharma and R. B. Pachori. (2015, Feb). Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions. *Expert Systems with Applications*, 42(3), pp. 1106-1117.

[23] M. Paul, W. Lin, C. T. Lau, and B. Lee. (2011). Direct Intermode Selection for H.264 Video Coding Using Phase Correlation. *IEEE Transactions on Image Processing*, 20(2), pp. 461-473.

[24] N. Moghim and D. W. Corne. (2014, Jun). Predicting Epileptic Seizures in Advance. *PLoS ONE*, 9(6), e99334.

[25] V. Bajaj and R.B. Pachori. (2013, Mar). Epileptic seizure detection based on the instantaneous area of analytic intrinsic mode functions of EEG signals. *Biomedical Engineering Letters*, 3(1), pp. 17-21.

[26] M. Z. Parvez and M. Paul. (2015, Jun). Epileptic seizure detection by exploiting temporal correlation of electroencephalogram signals. *IET Signal Processing*. Available:http://digital-library.theiet.org/content/journals/10.1049/iet-spr.2013.0288.

[27] Y. Liu, W. Zhou, Q. Yuan, and S. Chen. (2012). Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 20(6), pp. 749-755.

[28] K.K. Majumdar, and P. Vardhan. (2011). Automatic Seizure Detection in ECoG by Differential Operator and Windowed Variance. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(4), pp. 356-365.

[29] M. Paul, W. Lin, C. T. Lau, and B. –S. Lee. (2014, Oct). A Long Term Reference Frame for Hierarchical B-Picture based Video Coding. *IEEE Transactions on Circuits and Systems for Video Technology*, 24 (10), pp. 1729-1742.

[30] S. Abe, Support vector machine for pattern classification, Springer, 2010.

[31] S. Mihandoost, M. Amirani, M. Mazlaghani, and A. Mihandoost. (2012). Automatic feature extraction using generalised autoregressive conditional heteroscedasticity model: an application to electroencephalogram classification. *IET Signal Processing*, 6(9), pp. 829-838.

[32] R. B. Pachori and V. Bajaj. (2011, Dec). Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition. *Computer Methods and Programs in Biomedicine*, 104(3), pp. 373-381.

[33] P. Sajda. (2006, Apr). Machine Learning for Detection and Diagnosis of Disease. *Annual Review of Biomedical Engineering*, 8, pp. 537-565.

[34] K. D. Brabanter, P. Karsmakers, F. Ojeda, C. Alzate, J. D. Brabanter, K. Pelckmans, B. D. Moor, J. Vandewalle, J. A. K. Suykens, LS-SVMlab Toolbox User's Guide, Katholieke Universiteit Leuven, 2011.

[35] J. A. K.Suykens and J. Vandewalle. (1999). Least Squares Support Vector Machine Classifiers. *Neural Processing Letters*, 9(3), pp. 293–300.

[36] H. Wang and D. Hu," Comparison of SVM and LS-SVM for Regression," *International Conference on Neural Networks and Brain*, 2005, 1, pp. 279 – 283.

[37] V. Bajaj and R. B. Pachori. (2012).Classification of Seizure and Non-seizure EEG Signals using Empirical Mode Decomposition. *IEEE Transactions on Information Technology in Biomedicine*, 16(6), pp. 1135-1142.

[38] M. Paul, M. Frater, and J. Arnold. (2009). An Efficient Mode Selection Prior to the Actual Encoding for H.264/AVC Encoder. *IEEE Transactions on Multimedia*, 11(4), pp.581-588.

[39] H. Xing, M. Ha, B. Hu, and D. Tian, "Linear feature- weighted support vector machine," *Fuzzy Information and Engineering*, Springer, vol. 1(3), pp. 289-305, 2009.

[40] J.D. Wichard and M. Ogorzalek, "Time series prediction with ensemble models," *IEEE International Joint Conference in Neural Networks*, 2004, 2, pp. 1625 - 1630.

[41] Z. Zhang, Z. Chen, Y. Zhou, S. Du, Y. Zhang, T. Mei, and X. Tian. (2014, Oct). Construction of rules for seizure prediction based on approximate entropy. *Clinical Neurophysiology*, 125(10), pp. 1959–1966.