Epileptic Seizure Prediction in Scalp EEG using One Dimensional Local Binary Pattern based Features

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Abstract: Seizure prediction will deeply improve the quality of life of epileptic patients. In this paper, a new method of automatic seizure prediction is presented using one dimensional local binary pattern (1D-LBP) based features in scalp electroencephalogram (EEG). In the feature extraction stage, the preictal and interictal EEG signals were transformed to the 1D-LBP domain and histogram features were extracted. These features were submitted to two different types of classifiers: linear discriminant analysis (LDA) and support vector machine (SVM). In order to reduce the false prediction rate (FPR), a simple post processing stage was also incorporated. The classification using SVM showed improvement over LDA in terms of sensitivity, prediction time and FPR. The proposed method was evaluated using the scalp EEG recording from 13 patients with a total number of 47 seizures. It could achieve a sensitivity of 96.15%, an average prediction time of 51.25 minutes with an FPR of 0.463.

1 INTRODUCTION

Epilepsy is a common neurological ailment that is characterized by a sudden and recurrent brain discharges termed "seizure." These seizures reflect the clinical signs of an excessive and hyper synchronous activity of neurons in the brain (Fisher et al., 2005). The disturbance of consciousness and sudden loss of motor control often occur without any warning. Experiences of staring, walking aimlessly or loss of awareness may be harmless if they occur at home. However, it can be life threatening if they occur while the patient is driving, crossing a busy street or swimming. Epileptic patients may have some physiological changes prior to seizure onset. These changes include changes in heart rate, increase in cerebral oxygenation and blood oxygen levels (Kerem and Gena 2005; Adelson et al., 1999; Federico et al. 2005).

Recent studies show some changes in Electroencephalogram (EEG) indicative of an upcoming seizure and thereby give credence to the idea of predicting seizures. The ability to herald epileptic seizures far enough in advance would reduce patients anxiety, alleviate the constraints in everyday life and will improve the quality of life and safety of epileptic patients (Winterhalder et al., 2003). Knowing in advance that a seizure will occur will be helpful in developing new treatment strategies. It may lead to the design of more effective drugs for the disruption of the brain's preparedness for an oncoming seizure. The prediction will help many individuals whose epilepsy cannot be controlled by medications, or who are not in a position to undergo epilepsy surgery. Also, long-term treatment with antiepileptic drugs, which may cause cognitive or other neurological side effects, could be reduced to a targeted and short-acting intervention. The medications could be replaced by electrical stimulation or drug infusion activated only during the pre-seizure period. The state just before the occurrence of the seizure is termed as the 'preictal state' and the normal state of a patient as the 'interictal state'. Identifying the preictal states based on EEG has been the goal of many research studies on epileptic seizure prediction.

Based on the placement of electrodes the EEG can be classified into two: scalp and intracranial. In the scalp EEG, the electrodes are placed over the scalp whereas in intracranial EEG, the electrodes are placed inside the scalp. In this case, neurosurgeons typically implant strip, grid or penetrating depth electrodes under the dura mater. The signals

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recorded from intracranial EEG are on a different scale of activity than the brain activity recorded from scalp EEG. Scalp electrodes provide the global information, whereas the intracranial one provides the local information from the brain structure (Cosandier-Rimélé et al., 2007). Low voltage or high frequency components that cannot be seen easily in scalp EEG can be seen clearly in intracranial EEG. Also the scalp EEG is susceptible to different types of artifacts and noise compared to intracranial.

Several linear and nonlinear measures have been reported in the literature to predict seizures from intracranial EEG time series. Wavelet-based nonlinear similarity index (Ouyang et al., 2007), cross correlation and lyapunov exponents (Mirowski et al., 2009), autoregressive coefficients (Chisci et al., 2010), time, frequency and wavelet domain features (Soleimani-B et al., 2012), mean absolute deviation and wavelet entropy (Bedeeuzzaman et al., 2012), spike rate (Li et al. 2013), statistical dispersion measures (Bedeeuzzaman et al., 2014), dominant amplitude and frequency components (Wang and Lyu, 2014) are among the features implemented in intracranial EEG. To make the prediction techniques more clinically applicable, methods based on scalp EEG have also been a subject of research. Different features used for the seizure prediction using scalp EEG include non linear similarity (Quen et al., 2001), phase space similarity measures (Hively and Protopopescu, 2003), average spiking rate (Schad et al., 2008), phase synchrony measures (James and Gupta, 2009), wavelet coherence values (Chiang et al., 2011), variational Gaussian mixture model (Zandi et al., 2011; Zandi et al., 2013), statistical moments and spectral information (Direito et al., 2011) and spectral power (Bandarabadi et al., 2012).

Local binary pattern (LBP) has been extensively used for texture analysis of 2D images because of its discriminative power. One dimensional local binary pattern (1D-LBP), which is derived from LBP, has been successfully applied to voice activity in speech signals that are non-stationary in nature (Chatlani & Soraghan 2010). So, it can be considered as an effective approach of feature extraction of EEG signals, which are inherently non-stationary (Kaya et al. 2014).

The aim of this study is to develop a new algorithm for prediction of epileptic seizures with maximum possible sensitivity and prediction time. In this paper, an algorithm based on 1D-LBP is proposed to extract features from interictal and preictal scalp EEG signals. These features are used for the prediction of epileptic seizures. The proposed scheme consists of two stages: extraction of features from EEG signals and classification using the extracted features. In the first stage, features are extracted from interictal and preictal EEG signals. In the classification stage, these features are applied to two different classifiers: linear discriminant analysis (LDA) and support vector machine (SVM). The proposed method is tested on the scalp EEG dataset, which is obtained from Massachusetts Institute of Technology. Data from 13 epileptic patients with a total number of 47 seizures are used in the present study. The seizure prediction performance is assessed in terms of sensitivity, prediction time and false prediction rate (FPR).

Section 2 provides the details of the dataset used and the proposed feature extraction method using 1D-LBP. In section 3, the performance of the proposed system is evaluated by means of the results obtained with the scalp EEG dataset. This section includes the performance comparison with the reported works using the same database. The paper ends in Section 4 with some concluding remarks.

2 MATERIALS AND METHODS

2.1 Data used

The scalp EEG database used to evaluate the prediction algorithm was recorded from patients undergoing medication withdrawal for epilepsy surgery evaluation in Children's Hospital Boston (Shoeb, 2009; Goldberger et al., 2000; CHB-MIT Scalp EEG Database, 2015). Signals were recorded with a sampling frequency of 256 Hz and 16-bit resolution using the international 10-20 system of electrode placement scheme. The seizures experienced by the patients were judged by experts and indicated the start and end of each seizure in the EEG. The EEG data of each patient were segmented into records of typically one hour duration. The records containing one or more seizures are called seizure records and those without seizures are labeled as non-seizure records. Most of the EEG files contain 23 channels whereas a few contain 24 or 26 channels.

2.2 Local Binary Pattern

The local binary pattern(LBP) was introduced by Ojala et al., (1996) for the texture analysis, defined as gray scale invariant texture measure, derived from comparison with the local neighborhood. LBP has also been used for face recognition, dynamic texture recognition and shape localization (Guo et al., 2010).

An LBP code for each pixel in a two dimensional image is produced by thresholding the neighboring values with the value of the center pixel. The definition of LBP is extended to include all circular neighborhoods with any number of pixels. In general, LBP is denoted as $LBP_{P,R}$ where P is the number of neighbors involved and R is the radius of the model (Fig. 1).

The basic version of LBP considers only eight neighbors. As shown in Fig. 1, the LBP operator labels each pixel, using the value of the center pixel as a threshold value. Each pixel is assigned a value 1 if it is greater than or equal to the threshold value, otherwise it takes 0. Thus the binary code is produced using these values that gives the local structural information around the given pixel. Each pixel value is replaced with the decimal value corresponding to this binary code (Chatlani and Soraghan, 2010).

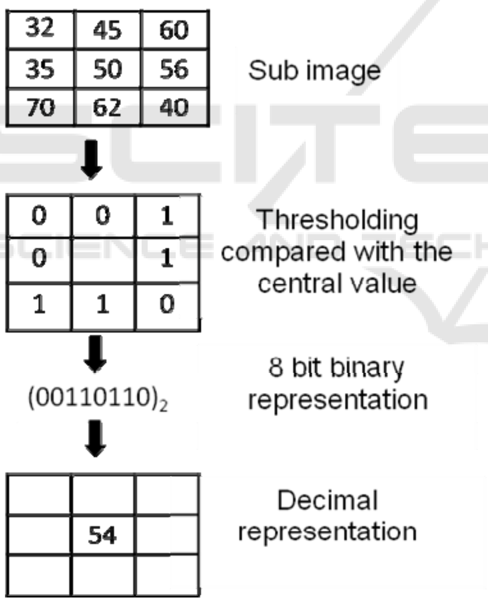

Figure 1: Calculation of LBP codes for a 3x3 sample block. P=8, R=1.

Given a pixel in the image, an LBP is computed comparing it with the local neighborhood.

$$z = G(v_i) - G(v) \tag{1}$$

$$LBP(v) = \sum_{i=0}^{P} S(z)2^i \tag{2}$$

where the sign function S(.) is given by,

$$S(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

v is the location of the center pixel, v_i is the location of the i^{th} neighboring pixel, $G(.)$ is the pixel intensity value.

2.3 One Dimensional Local Binary Pattern (1D-LBP)

1D-LBP was first introduced in (Chatlani and Soraghan, 2010) for applying in speech signals which are non stationary in nature. It is adapted from the implementation steps in 2D LBP. The LBP code for a neighborhood of sampled data is produced by thresholding the neighboring samples against the centre sample of a processing window. This procedure is iteratively done across the entire signal and a segment of the 1-D signal is alternatively described by a sparser occurrence histogram of LBP codes.

The 1-D LBP operating on a sample value *y[i]* is defined as

$$LBP_P(y[i]) = \sum_{r=0}^{P/2-1} \left\{ \begin{array}{l} S\left[y\left[i+r-P/2\right]-y[i]\right]2^r \\ +S\left[y[i+r+1]-y[i]\right]2^{r+P/2} \end{array} \right\} \tag{3}$$

Where $S[y] = \begin{cases} 1, & for\ y \geq 0 \\ 0, & for\ y < 0 \end{cases}$

Where P is the number of neighboring samples thresholded around the centre sample from the signal $y[i]$ of length N for $i = [P/2 : N - P/2]$. The sign function $S[.]$ makes a P- bit binary code from these differences. The decimal value of this binary code gives a unique LBP code. The 1D- LBP operator is described step by step in Fig. 2 using a sample segment of an EEG signal where P is set to 8. The four neighboring samples taken before (N0, N1, N2, N3) and after (N4, N5, N6, N7) are threshold against the centre sample (NC). If the neighboring value is greater than or equal to the center value, the assigned value is 1, otherwise 0. Thus a binary code of 11110000 is produced and the corresponding decimal gives the LBP code 240. The LBP codes represent the local structure information around the given sample using the difference between the sample and its neighbors. These differences cluster near zero for constant or slowly varying signals whereas at peaks and troughs the differences will be relatively large. At edges, the differences in some directions will be larger than those from other directions.

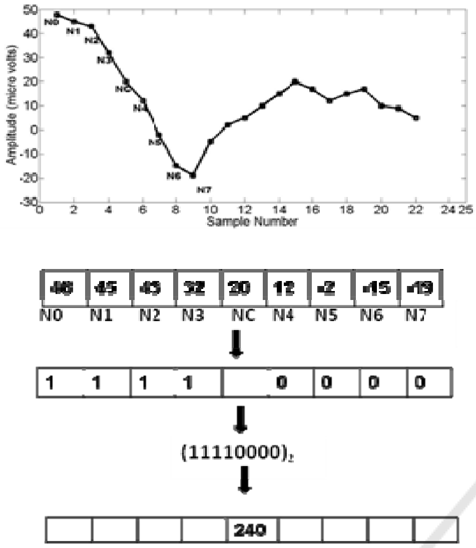

Figure 2: Computation of 1D local binary pattern.

LBP signal is formed by applying the above procedure to all samples, which has values ranging from 0 to 255. A segment of the interictal EEG signal of 1 second duration of patient 1 is depicted in Fig. 3 (a) and the corresponding LBP applied signal is given in Fig. 3(b). Fig. 3(c) and Fig. 3 (d) shows the values corresponding to one second of the preictal EEG of first seizure of patient1.

The distribution of LBP can describe the local patterns formed from $y[i]$.

$$H_l = \sum_{\frac{P}{2} \le i \le N - \frac{P}{2}} \delta\left(LBP_P\left(y[i]\right), l\right) \tag{4}$$

Where $l = 1,2 \ldots n$ and n is the number of histogram bins and $\delta(i, j)$ is the Kronecker delta function. The occurrences of each LBP code are plotted as a histogram. The numbers of occurrences corresponding to 8 histogram bins are selected as the features for classification between interictal and preictal signals.

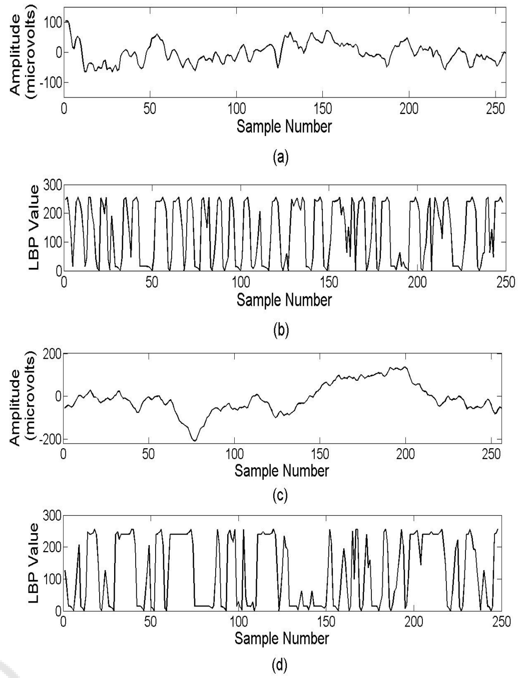

Figure 3: (a) A 1-second segment of interictal EEG signals of patient 1. (b) Interictal signal transformed to LBP domain, which has values ranging from 0 to 255. (c) A 1-second segment of preictal EEG signal from the first seizure of patient 1. (d) Preictal signal transformed to LBP domain.

3 RESULTS

The purpose of this study is to extract the representative features from EEG by utilizing the potential of 1D-LBP for the prediction of epileptic seizures. The EEG classification system using the proposed 1D-LBP based feature extraction is depicted in Fig. 4. The raw EEG signals were given as the input to the classification system and the output was the classified EEG pattern. The features were extracted over the non overlapping frames of 1 minute length. Firstly the EEG signal in the time domain is transformed into the LBP domain through the process described in section 2.3.

The histogram of LBP codes is produced as an alternative representation of the signal. The numbers of occurrences of the LBP values in 8 histogram bins are selected as the discriminating features. For 23 channels, this feature vector is of dimension 23x8 for each frame. In order to reduce the feature dimension, averaging is done across the channels, reducing the dimension to 1x8 for one frame. Sample histogram features, averaged across 23 channels for patient1 for 1 minute data is given in

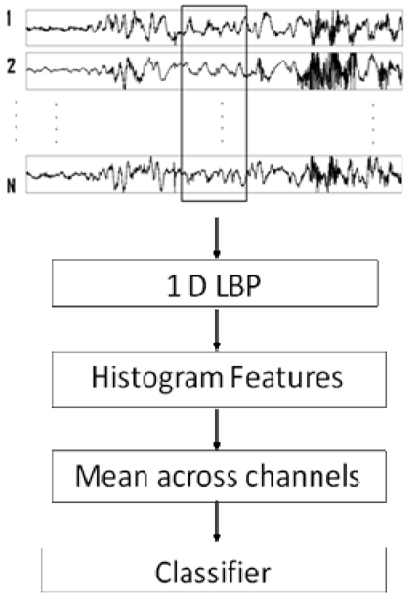

Figure 4: Schematic of the EEG classification system.

Table1. These values show a significant difference in magnitude and were given as input to the classifier.

In the classification stage, the 1D-LBP based features are applied to a classifier, for the classification between interictal and preictal EEG signals. Here the performances of the proposed method are evaluated using two different classifiers: Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM).

Only those seizures with at least one hour preictal data are considered for the study. In the case of seizures occurring without much time gap, only the first seizure is considered for the prediction.

Hence, the evaluation of the algorithm is done on 13 patients and 47 seizures that satisfy this condition. The number of seizures used for training and testing is given in Table 2. For example in the case of patient number 5 (P5), 2 seizures are used for training and 2 for testing. The one hour interval preceding each seizure onset has been used to produce training and test samples.

During classification, the labels ‘0’ and ‘1’ are assigned for interictal and preictal data respectively. Whenever a change from ‘0’ to ‘1’ occurs, the prediction system will raise an alarm. If the alarm is in the preictal period, it is considered as prediction and if it is in the interictal period, taken as false prediction. The one hour preictal period prior to each seizure under test is considered to evaluate the prediction. Prediction time is taken as the time gap between the first alarm and the seizure onset. The interictal data is tested to check whether it gives any misclassification. A simple post processing stage has also been incorporated to reduce the FPR. In the post processing phase, consecutive ‘1’ labels are searched for giving a ‘1’ in the output (Fig. 5).

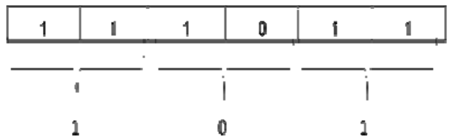

Figure 5: Post processing scheme for 2- minute window: Two consecutive ‘1’ labels give a ‘1’ in the output.

The performance of the prediction system is analyzed in terms of sensitivity, prediction time and FPR. Sensitivity and prediction time for each patient using LDA classifier is given in Table 2. For patient 5, 2 seizures were used for testing and 2 for training. The algorithm with a 1-minute window correctly predicted the two tested seizures, thus exhibited 100% sensitivity. The average prediction time (APT) of the 2 tested seizures for patient 5 is found to be 59 minutes. As the algorithm using 1-minute window predicted all the tested seizures of all the patients, an average sensitivity of 100% achieved.

Also, the average APT with a 1-minute window width was 57.08 minutes. FPRs of each patient for 1, 2, 3, 4 and 5 minute window widths are shown in Fig. 6(a). Although the results are good in terms of sensitivity and prediction time, the average FPR for 1 minute window width was 3.69, which is a bit high

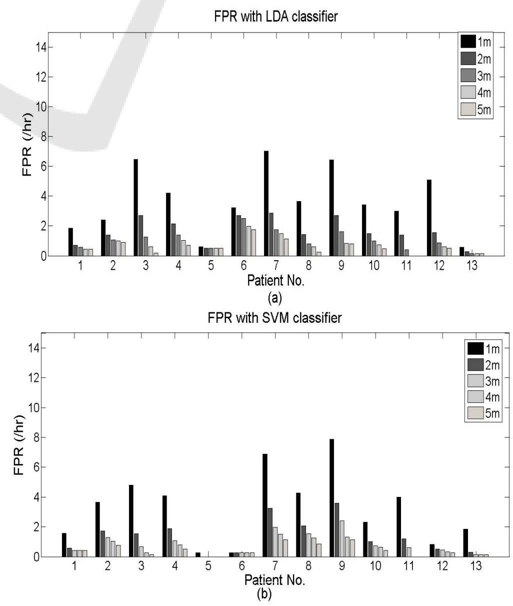

Figure 6: (a) FPR for each patient for different window widths using LDA classifier (b) FPR for each patient for different window widths using SVM classifier.

Table 1: Sample features extracted for one minute EEG of patient 1.

Class	Bin1	Bin2	Bin3	Bin4	Bin5	Bin6	Bin7	Bin8
Preictal	5027	851	228	752	545	350	855	23
Interictal	4126	1038	259	961	759	392	1016	25

Table 2: Sensitivity and prediction time using 1D-LBP based features and LDA classifier for different window widths. SE-Sensitivity, APT- Average prediction time, NS-Number of seizures.

Patient No.	NS for training	NS for testing	Window width in minutes									
			1		2		3		4		5	
			SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)
P1	2	2	100	59	100	58	100	57	100	56	100	55
P2	1	1	100	58	100	56	100	54	100	52	100	50
P3	3	1	100	59	100	58	100	57	100	56	100	55
P4	1	1	100	59	100	58	100	57	100	56	100	55
P5	2	2	100	59	100	58	100	57	100	56	100	55
P6	5	4	100	59	100	46.5	100	42	100	41	50	53.3
P7	2	1	100	38	0	-	0	-	0	-	0	-
P8	2	2	100	59	100	58	100	57	100	56	100	37.5
P9	2	2	100	59	50	58	50	57	50	56	50	30
P10	2	1	100	58	100	56	100	54	100	48	100	45
P11	2	1	100	59	100	58	100	57	100	56	100	50
P12	2	1	100	59	100	58	100	57	100	56	100	55
P13	1	1	100	57	100	56	100	45	100	44	100	45
Average			100	57.08	88.46	56.41	88.46	54.00	88.46	52.45	84.61	50.25

Table 3: Sensitivity and average prediction time using 1D-LBP based features and SVM classifier for different window widths. NS- Number of seizures, SE- Sensitivity, APT- Average prediction time.

Patient No.	Window width in minutes									
	1		2		3		4		5	
	SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)	SE (%)	APT (min)
P1	100	59	100	58	100	52.5	100	52	100	50
P2	100	58	100	56	100	54	100	48	100	45
P3	100	59	100	58	100	57	100	56	100	55
P4	100	59	100	58	100	57	100	56	100	55
P5	100	59	100	58	100	57	100	56	100	55
P6	100	56.25	100	46.5	100	44.5	100	43.25	100	40
P7	100	59	100	58	100	57	100	56	100	55
P8	100	59	100	58	100	57	100	56	100	55
P9	100	46	50	58	50	57	50	44	50	20
P10	100	59	100	58	100	57	100	56	100	55
P11	100	59	100	58	100	57	100	56	100	50
P12	100	59	100	58	100	57	100	56	100	55
P13	100	57	100	56	100	45	100	44	100	45
Average	100	57.55	96.15	56.70	96.15	54.33	96.15	52.94	96.15	51.25

for seizure prediction. The FPR for each patient, given in Fig. 6 (a), shows a decrease in FPR with respect to the increase in window width. Sensitivity and APT using the SVM classifier, given in Table 3, show a slight increase compared to the method using LDA classifier. The FPR using the SVM classifier for each patient is given in Fig. 6(b) and shows a small decrease compared to the other one. Comparison of average sensitivity, average APT and average FPR using LDA and SVM classifier is depicted in Fig. 7. The SVM classifier shows improvement in all the three parameters of evaluation, compared to the LDA classifier.

4 DISCUSSION

A seizure prediction method based on 1D-LBP in scalp EEG has been presented in this paper. The comparison of prediction time and sensitivity obtained using 5 minute window width and SVM classifier with other methods using the same dataset is given in Table 4. Wavelet coherence values were used as features and tested on 7 patients from the same dataset in (Chiang et al., 2011). They could predict seizures of 4 patients out of 7, giving a sensitivity of 57.14%, but it didn't report the prediction time and FPR. Another algorithm using the variational Bayesian Gaussuan mixture model for prediction was tested on 3 patients of the dataset in (Zandi et al., 2011). Compared to this, the proposed work which is experimented with 13 patients shows an improvement in sensitivity from 83.8% to 96.15%. Also, APT is increased from 19.8 to 51.25 minutes. But the FPR reported in (Zandi et al., 2011) is 0.165 whereas in this work it is 0.463. An increased window width may help to decrease the FPR. But it will affect the sensitivity and prediction time. Though the increased FPR obtained in the proposed work can be ascribed to the increased number of patients in contrast to the 3 patients used in (Zandi et al., 2013), this has to be reduced to make the method useful for real life situations.

Table 4: Comparison of results with other methods using same dataset.

Method	Feature	No. of patients analysed	APT (minutes)	Sensitivity (%)
(Chiang et al. 2011)	Wavelet coherence values	7	-	57.14
(Zandi et al. 2013)	Gaussian Mixture Model	3	19.8	83.8
Proposed method	**1D-LBP Based**	**13**	**51.25**	**96.15**

To the best of authors' knowledge, the only work reported in EEG signal analysis that used 1D-LBP is (Kaya et al., 2014). This work was for the epileptic seizure detection, a retrospective analysis of EEG signals to find out the seizure that has already happened. Whereas, in the proposed work 1D-LBP is used for epileptic seizure prediction which involves the analysis of EEG signals for an oncoming seizure well before its occurrence.

Even though the proposed method is developed for noninvasive scalp EEG, it may also be used for the intracranial EEG recordings. As the artifacts and noise will be less in the intracranial EEG, a better performance can be anticipated when applied to depth recording.

As the method presented in this paper used the data for training and testing for the same patient, the algorithm can predict only the seizures of a patient whose prior database is already available. Therefore, more studies should be performed by incorporating new features to make a patient independent method. Also the data used for this study was acquired from patients under medical care in hospitals. So to broaden the utility of the proposed method, it has to be applied to the continuous data recorded during routine daily activities.

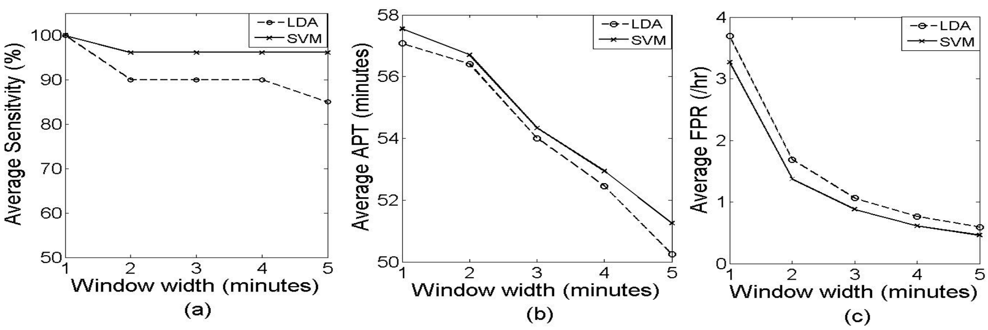

Figure 7: Performance comparison of classifiers: LDA and SVM. (a) Average Sensitivity (b) Average APT (c) Average FPR.

5 CONCLUSIONS

A new patient specific seizure prediction algorithm based on 1D-LBP in scalp EEG has been proposed in this study. The idea is to classify between preictal and interictal EEG using appropriate features. For this purpose, histogram features are extracted from the 1D-LBP applied signal. These features are submitted to two different classifiers: LDA and SVM. In order to reduce the false alarms, a simple post processing is also incorporated. The classification using SVM shows improvement over LDA in terms of sensitivity, prediction time and FPR. When this algorithm is applied to scalp EEG recordings from 13 patients with a total number of 47 seizures, it could achieve a sensitivity of 96.15%, an APT of 51.25 minutes with an FPR of 0.463. Comparison with the previous works using the same database shows improvement in terms of APT and sensitivity.

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