A statistical framework for EEG channel selection and seizure prediction on mobile

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Abstract

This paper presents a patient-specific approach for electroencephalography (EEG) channel selection and seizure prediction based on statistical probability distributions of the EEG signals. This approach has two main phases; training and testing phases. In the training phase, few hours of multi-channel nature for each patient representing normal, pre-ictal, and ictal activities are selected. These hours are segmented into non-overlapping 10-s segments and probability density functions (PDFs) are estimated for the signals, their derivatives, local means, local variances, and medians. These PDFs have multiple bins, which are studied separately as random variables across different segments of the same nature. Depending on the PDFs of these random variables for different signal activities and on predefined prediction and false-alarm probability thresholds, bins are selected from certain channel distributions for seizure prediction. In the testing phase, the selected bins only are used for classification of each signal segment activity into pre-ictal or normal states in the prediction process. In the final prediction step, an equal gain decision fusion process is performed leading to a discrete decision sequence representing the activities of all segments. This sequence is filtered with a moving average filter and compared to a patient-specific prediction threshold. Moreover, we have studied the effect of a lossy compression technique on the accuracy of the proposed algorithm using discrete sine transform (DST) compression. This system can be implemented for communication between headset and mobile to give alerts for patients.

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1 Introduction

Since the first EEG signal acquisition by Berger (1929), researchers have directed so much effort to processing of these signals. EEG signal processing has a variety of application; medical applications such as seizure detection and prediction (Tzallas et al. 2012; Alickovic et al. 2018), and non-medical applications such as games and safety (Scherer et al. 2013; Makeig et al. 2012). Epilepsy-related studies are dominant in the field of EEG signal processing. Epilepsy is a brain disorder affecting 1% of world population, and it is characterized by EEG seizures (Thurman et al. 2011; Tzimourta et al. 2018). The research objective of seizure detection is to check the existence of the seizure in EEG signals. We would like to anticipate the seizure with as long prediction time as possible in the so-called seizure prediction process. The early anticipation of seizures helps to alert patients or caregivers to save patients from possible hazards by implementing the seizure prediction system through a communication process between headset and mobile. The efficiency of a seizure prediction algorithm is determined by the prediction rate, false-alarm rate, and prediction horizon.

Different trends have been investigated in the literature for EEG seizure prediction using time-domain techniques, signal transforms, and signal decompositions. Zandi et al. (2010, 2013) adopted a time-domain zero-crossing rate seizure perdition approach based on histograms of different window intervals. They achieved a sensitivity of 88.34%, a false-prediction rate of 0.155/h and an average prediction time of 22.5 min. Arabi and He (2012) adopted statistical features including correlation entropy, correlation dimension, Lempel–Ziv, noise level, largest Lyapunov

exponent, and nonlinear independence in their patient-specific approach. In the simulation experiments, their maximum sensitivity was 90.2% and the average false prediction rate was 0.11/h. Shelter et al. (2011) presented a seizure prediction algorithm depending on the interaction between pairs of EEG signals, and this algorithm achieved a sensitivity of 60%. Wang et al. (2010) presented a seizure prediction system depending on reinforcement learning with online monitoring. They achieved an accuracy of 70%. Li et al. (2013) investigated the use of morphological operations and averaging filters for EEG seizure prediction. They achieved a 75.8% sensitivity and a false-alarm rate of 0.09/h.

Wavelet transform and its versions have also been used for EEG seizure prediction. Hung et al. (2010) developed a wavelet-based seizure prediction algorithm using correlation dimension and its correlation coefficients. They achieved an average sensitivity of 87% with a false-alarm rate 0.24/h, and an average of 27 min warning time. Chiang et al. (2011) developed a wavelet-based seizure prediction algorithm adopting nonlinear independence, cross correlation, difference of Lyapunov exponents and phase locking. This algorithm achieved a sensitivity of 74.2% on MIT database. Gadhoumi et al. (2013) developed a wavelet-based seizure prediction method from iEEG signals depending on measuring the similarity with a reference signal. They achieved a sensitivity of 85% with a false-alarm rate of 0.35/h. Wang et al. (2013) exploited Lyapunov exponent, correlation dimension, Hurst exponent, and entropy features in the wavelet domain for seizure prediction. They achieved an average sensitivity of 73%, and a specificity of 76%. Costa et al. (2008) developed a seizure prediction method based on wavelet energy features. They achieved an average

Table 1 A comparison between some time and wavelet-based seizure prediction methods

Method	Domain	Features	Performance metrics
Zandi et al. (2010, 2013)	Time	Histograms of different window intervals	Sensitivity of 88.34%, a false prediction rate of 0.155/h, and an average prediction time of 22.5 min
Arabi and He (2012)		Correlation dimension, correlation entropy, noise level, Lempel–Ziv complexity, and largest Lyapunov exponent	Maximum sensitivity of 90.2% with an average false prediction rate of 0.11/h
Schelter et al. (2011)		Interaction between pairs of EEG signals	Sensitivity of 60%
Wang et al. (2010)		Distance values to measure similarity	Accuracy of 70%
Li et al. (2013)		Morphological features	Sensitivity of 75.8% and a false-alarm rate of 0.09/h
Hung et al. (2010)	Wavelet	Correlation dimension and its correlation coefficients	Average sensitivity of 87% with a false-alarm rate of 0.24/h and an average of 27 min warning time
Chiang et al. (2011)		Nonlinear independence, cross correlation, difference of Lyapunov exponents, and phase locking	Sensitivity of 74.2% on MIT database
Gadhoumi et al. (2013)		Similarity with a reference signal	Sensitivity of 85% with a false-alarm rate of 0.35/h
Wang et al. (2013)		Lyapunov exponent, correlation dimension, Hurst exponent, and entropy features	Average sensitivity of 73% and a specificity of 76%
Costa et al. (2008)		Wavelet energy features	Average sensitivity of 83% and an average accuracy of 96%

sensitivity of 83% and an average accuracy of 96%. Table 1 gives a comparison between some different seizure prediction methods in time and wavelet domains.

The compression of EEG signals is of great importance in the biomedical field. The reason for this is to overcome the limitations of channel capacity, achieve small memory usage, and avoid high bandwidth transmission. The effective compression of EEG signals is very difficult due to the random nature of these signals (Sriraam 2012). Compression techniques are basically classified to lossy and lossless compression techniques (Ruchi et al. 2016).

In the lossless compression process, no data is lost, and the original data can be exactly reconstructed from their compressed form. All information is saved with no distortion. In contrast, lossy compression is an irreversible process that provides only an approximate version of the original data with some losses. Lossy compression can provide high compression rates. Various algorithms have been adopted for EEG data compression based on lossy techniques.

This paper presents a proposed time-domain approach for EEG channel selection and hence seizure prediction based on simple statistics. Its main idea is how to discriminate between different signal activities based on their probability density functions (PDFs). Simulation experiments have shown that if the signals are segmented into non-overlapping segments, the PDFs of these segments differ even for segments of the same category. This means that we can treat the bins of each PDF as random variables across segments and select the most appropriate bins for discrimination through simple thresholding processes. Section 2 introduces a brief description of compression techniques. Section 3 gives a detailed explanation of the proposed seizure prediction approach. Section 4 gives the pre-processing steps implemented prior to PDF calculations. Section 5 gives the simulation results. Finally, sect. 6 gives the concluding remarks.

2 EEG signal compression

Compression of EEG signals is one of the most important solutions to speed up the signal transfer and save storage capacity. Compression techniques are basically partitioned into two different and important branches (Aiupkumar and Bej 2013): lossy and lossless compression techniques.

2.1 Lossless compression techniques

2.1.1 Huffman coding

Huffman coding is one of the lossless compression techniques. In Huffman coding, variable-length codes are generated for the input symbols based on their probability of occurrence. Huffman coding is a sort of entropy encoding.

It can be applied in the encoding process of EEG signals for the compression purpose.

2.1.2 Shannon Fano coding

It is another lossless compression technique, which also falls under the category of entropy encoding. The main concept of this technique the generation of variable-length codes for the symbols based on Shannon's theorem.

2.1.3 Lempel–Ziv–Welch (LZW) compression

This compression technique is named according to Abraham Lempel, Jacob Zev, and Terry Welch. It is based on creating a dynamic dictionary based on the choice of a sub-string from the original file, and then this string is matched with the dictionary. If the string is obtained, the reference is mentioned in the dictionary, and if the string is not obtained, a new dictionary is created with a new reference entry.

2.2 Lossy compression techniques

2.2.1 Discrete sine transform (DST) technique

DST is similar to discrete Fourier transform (DFT) but with a purely real matrix. The DST can be represented with Eq. 1. The basic idea of DST compression is the neglection of some coefficients in the DST domain based on their significance. Figure 1 illustrates an example of an EEG signal before and after compression.

$$y(k) = \sum_{n=0}^{N-1} x(n) \sin\left(\pi \frac{(k+1)(n+1)}{N+1}\right) \tag{1}$$

where $k = 0, 1, 2, \ldots N\text{-}1$, $n = 0, 1, 2, \ldots N\text{-}1$, and $y(k)$ is the DST of $x(n)$.

3 Proposed seizure prediction approach

The proposed channel selection and seizure prediction approach depends mainly on estimating the PDFs of signal amplitude, derivative, local mean, local variance, and median of the different signal channels as illustrated in Fig. 2. This approach comprises two phases: training and testing as shown in Fig. 3. In the training phase, few hours are selected randomly for normal activities and two or three intervals for ictal and pre-ictal activities. The selected periods with multi-channel nature are segmented into 10-second segments. For each channel in each segment, five PDFs are estimated for amplitude, derivative, local mean, local variance, and median of the signal.
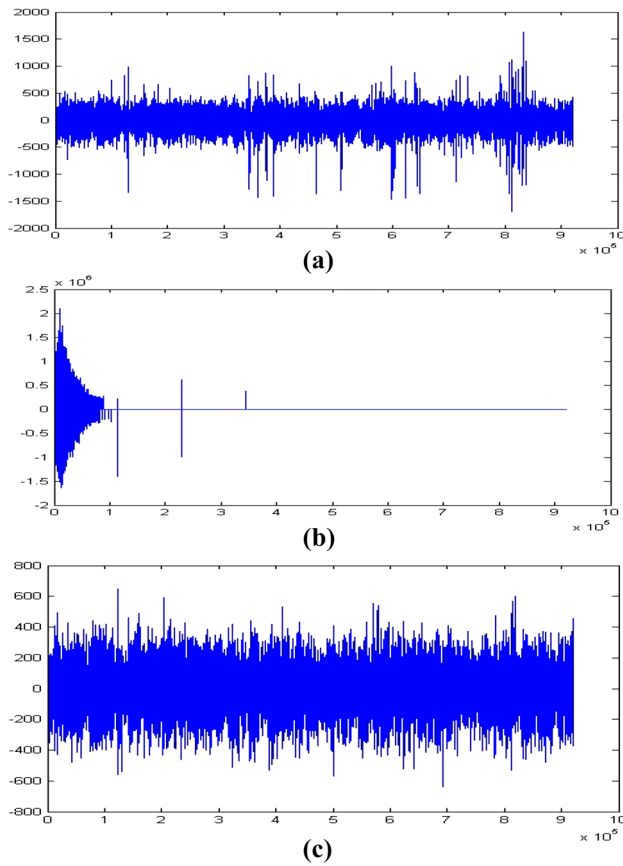
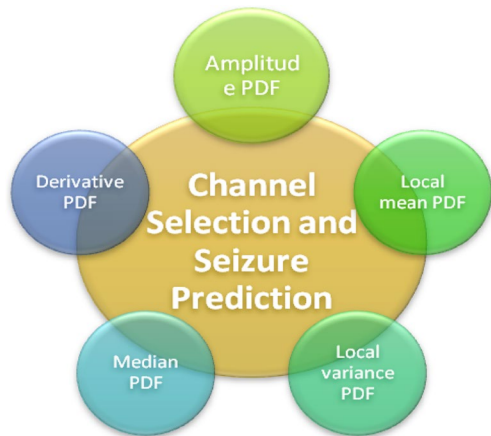**Fig. 1** EEG signal **a** before compression, **b** after compression in DST domain, **c** after IDST

Fig. 2 PDFs estimated from EEG signals for channel selection and seizure prediction

Fig. 3 Training and testing phases of the proposed channel selection and seizure prediction algorithm. **a** Training phase, **b** testing phase

classes are selected for discrimination in the testing phase. The effect of DST compression is also studied with the proposed approach to estimate its sensitivity to lossy EEG signal compression.

4 Pre-processing of EEG signals

The proposed approach depends on some pre-processing operations carried out on the signal channels including the derivative, local mean, local variance, and median as discussed below. The derivative of an EEG signal reinforces the rapid transitions in the signal and damps slow transitions,

We treat each PDF bin (9 bins) as a random variable across segments for each of the normal, ictal, and pre-ictal histogram classes. Based on predefined false-alarm and prediction probability thresholds, the bins and the channels that discriminate between normal and pre-ictal
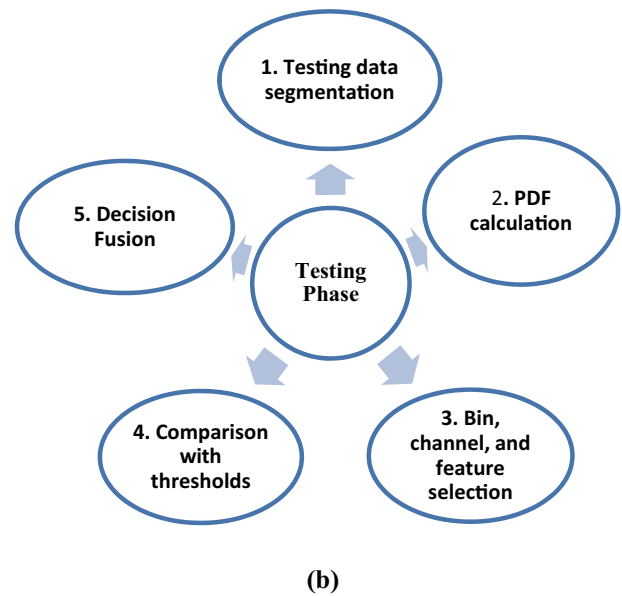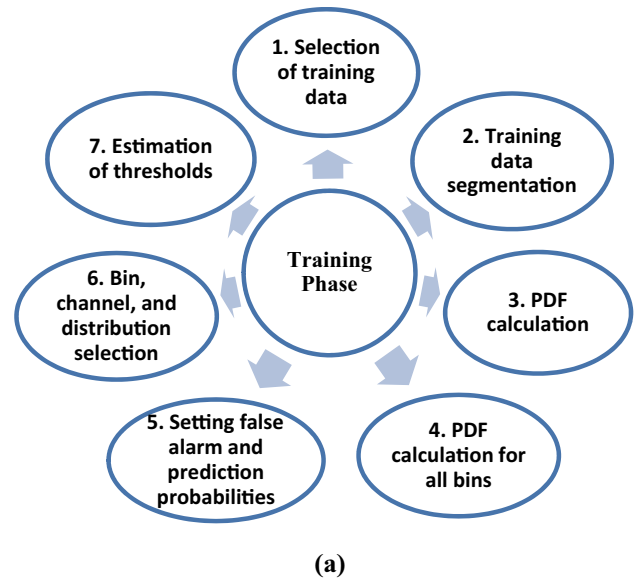
and hence the different activities of the signal will yield more distinguishable derivatives through their PDFs. The local mean is a good indication of the signal trend, and the local variance characterizes the signal power very well from sample to sample. The median filtering process removes spikes that may result from impulsive noise during the signal recording process. Based on the five estimated PDFs: signal amplitude, derivative, local mean, local variance, and median for any EEG segment, we can discriminate between normal, ictal, and pre-ictal signal segments.

4.1 Signal derivative

In EEG signals, abnormal activities are accompanied with abrupt changes in signal amplitude. To reinforce these abrupt changes, a signal differentiator can be utilized. We use a digital first-order differentiator filter for this purpose. This filter is given by (Kuo et al. 2006; Milić et al. 2013):

$$H(z) = 1 - z^{-1} \tag{2}$$

4.2 Local mean

We can estimate the local mean of a signal $X(n)$ as follows (Abd El-Samie 2011):

$$\widehat{X}(n) = \frac{1}{(2K+1)} \sum_{k=n-K}^{n+K} X(k) \tag{3}$$
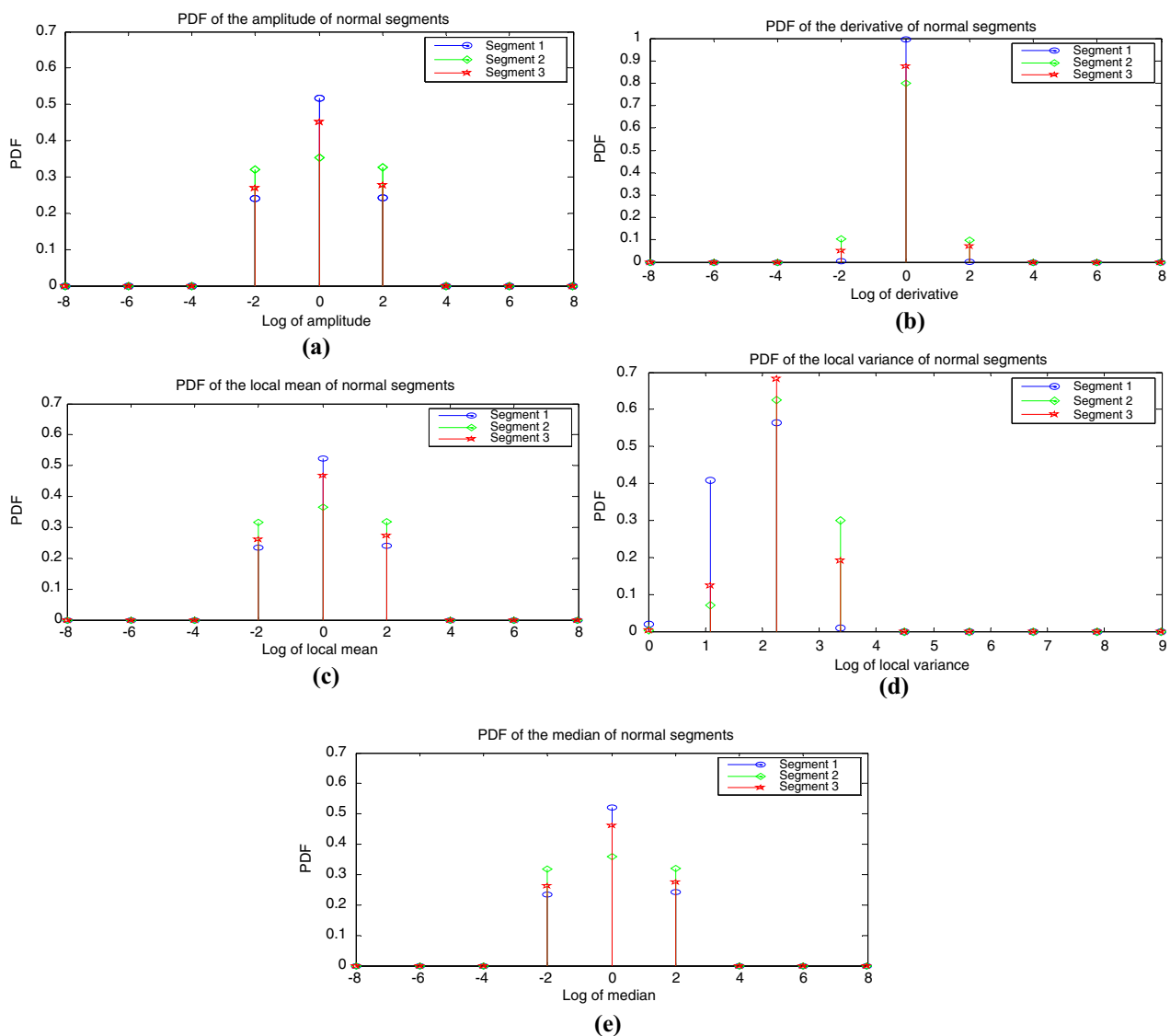

Fig. 4 PDFs of the amplitude, derivative, local mean, local variance, and median for three randomly selected normal segments. **a** Amplitude distribution, **b** derivative distribution, **c** local mean distribution, **d** local variance distribution, **e** median distribution

where $(2K + 1)$ is the number of samples in the short segment used in the estimation.

4.3 Local variance

We can estimate the local variance of a signal $X(n)$ as follows (Abd El-Samie 2011):

$$\hat{\sigma}_X^2(n) = \frac{1}{(2K + 1)} \sum_{k=n-K}^{n+K} \left(X(k) - \hat{X}(n) \right)^2 \tag{4}$$

4.4 Median filtering

Median filtering is a sort of nonlinear smoothing of signals. It aims at reducing some of the spikes in the signals that may occur due to impulsive noise. In the median filtering process, an odd number of signal samples is stored and sorted. The middle value after sorting is extracted. For a median filter of length $N = 2K + 1$, the filter output is given as (Yin et al. 1996):

$$Y(n) = MED[X(n - K), \dots, X(n), \dots, X(n + K)] \tag{5}$$

Fig. 5 PDFs of the amplitude, derivative, local mean, local variance, and median for three randomly selected ictal segments. **a** Amplitude distribution, **b** derivative distribution, **c** local mean distribution, **d** local variance distribution, **e** median distribution
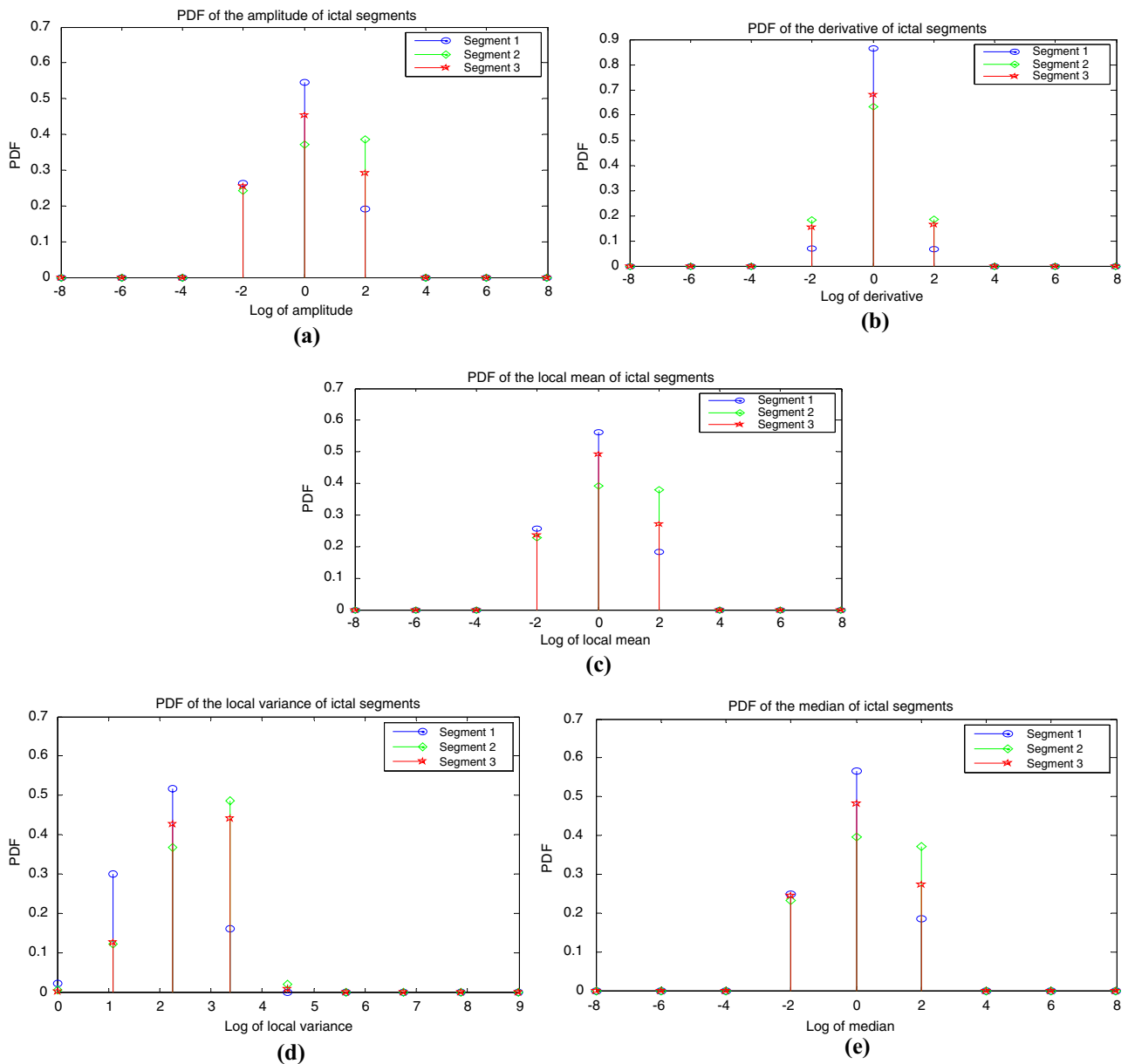
Fig. 6 PDFs of the amplitude, derivative, local mean, local variance, and median for three randomly selected pre-ictal segments. **a** Amplitude distribution, **b** derivative distribution, **c** local mean distribution, **d** local variance distribution, **e** median distribution
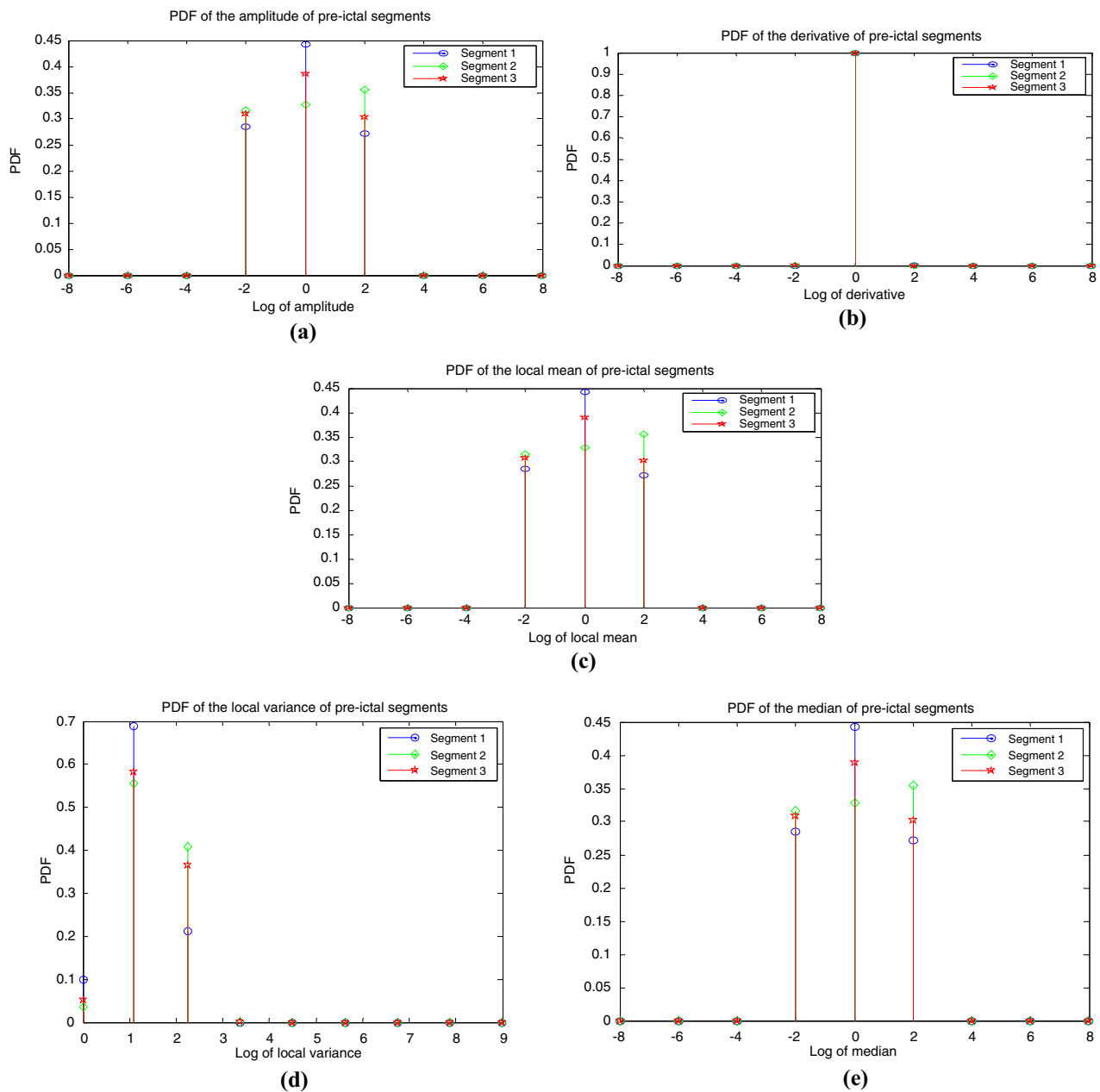
where $X(n)$ and $Y(n)$ refer to the nth sample of the input and output sequences, respectively.

This type of median filtering is non-recursive in the sense that an estimate of the median filter output at any sample time is independent of the median filter output history. There is another type of median filtering which is recursive. For a recursive median filter with window length $N = 2K + 1$, the output is defined as (Yin et al. 1996):

$$Y(n) = MED[Y(n - K), Y(n - K + 1) \dots ,$$
$$Y(n - 1), X(n), \dots , X(n + K)] \tag{6}$$

This recursion process is a type of feedback that reduces noise more efficiently.

Table 2 Six rows of the prediction matrix of patient 20

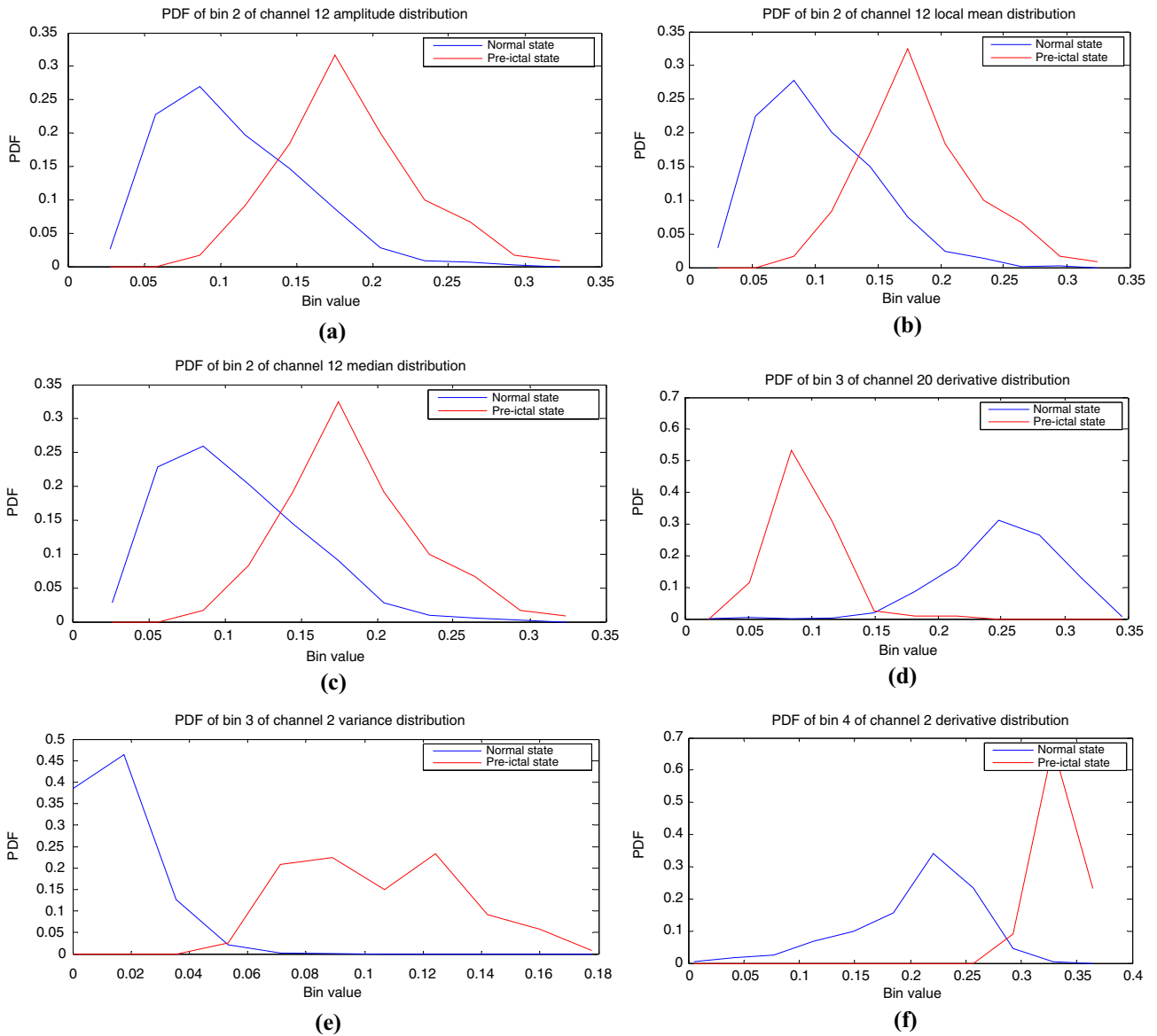|						
1.0000	12.0000	2.0000	0.7083	0.2792	0.1606	1.0000
3.0000	12.0000	2.0000	0.7000	0.2667	0.1587	1.0000
5.0000	12.0000	2.0000	0.7083	0.2806	0.1599	1.0000
2.0000	20.0000	3.0000	0.9917	0.2847	0.1986	0
4.0000	2.0000	3.0000	1.0000	0.1514	0.0444	1.0000
2.0000	2.0000	4.0000	1.0000	0.2847	0.2745	1.0000

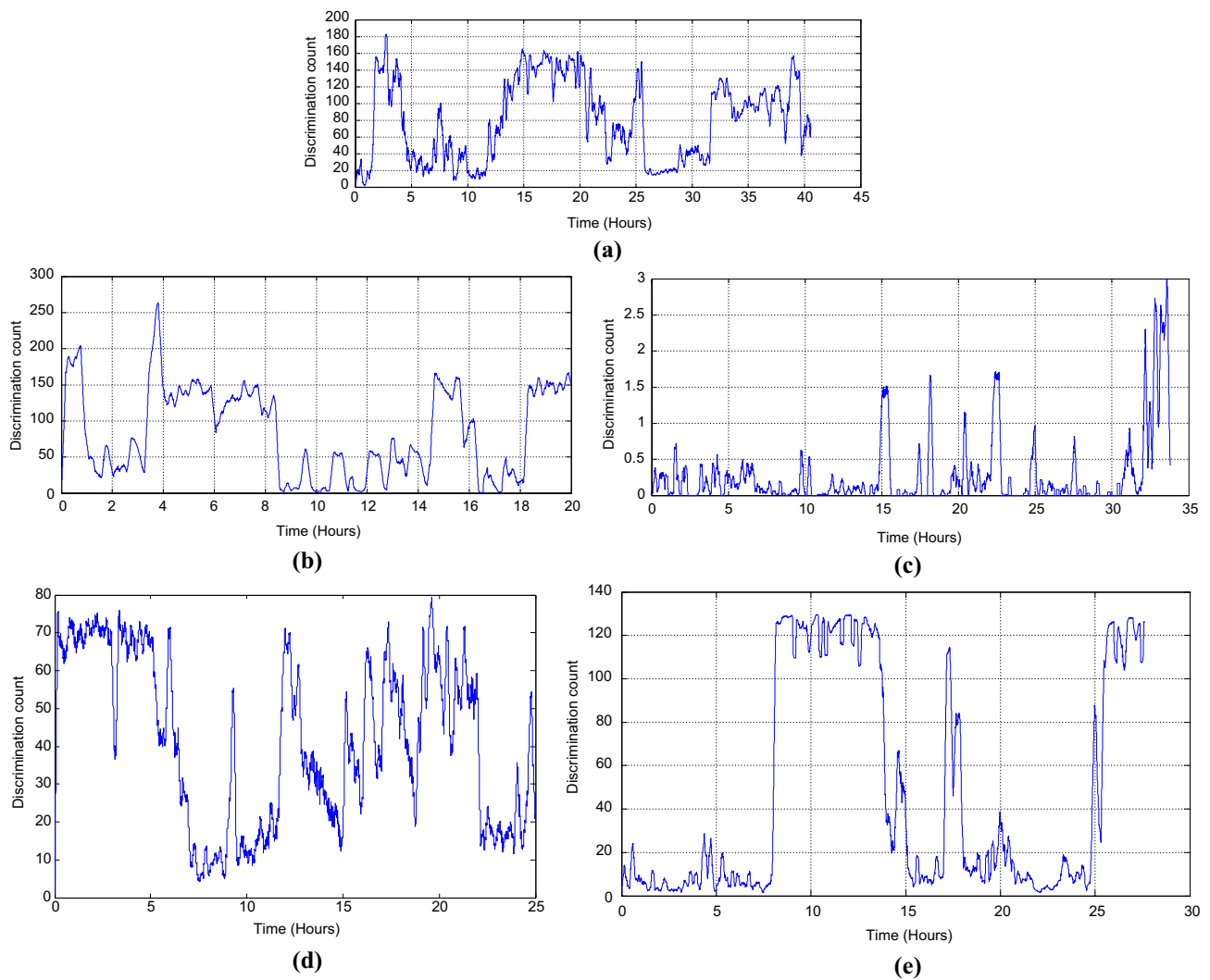**Fig. 7** PDFs of selected bins in Table 2

Fig. 8 Variation of the discrimination count with time for the selected five patients. **a** Patient 1, **b** patient 8, **c** patient 11, **d** patient 14, **e** patient 20

5 Simulation results and discussion

Simulation experiments have been carried on five patients from MIT database (patients 1, 8, 11, 14, 20) with 148.6133 hours containing 31 seizures (http://physionet.org/pn6/chbmit/). To better understand the steps of the proposed approach, we display some results for patient 20. Firstly, we begin by estimating the PDFs of the normal, ictal, and pre-ictal 10-s segments. Examples of these PDFs are shown in Figs. 4, 5, and 6 for normal, ictal and pre-ictal segments for patient 20. Three PDFs of three randomly-selected segments of each type are shown in the figures. The histograms are estimated for log values of the amplitudes to cover the large dynamic range of the signals. It is clear from these figures that each bin has different values from segment to segment, and hence it is

necessary to consider each bin value as a random variable across segments and determine its PDF.

Our main objective is to distinguish between normal and pre-ictal activities for early seizure prediction. Hence, we have estimated the PDF of each bin from the normal and pr-ictal PDFs among all segments. If we can distinguish between these PDFs with a certain threshold for some selected bins, we can carry out a prediction process with these bins and their corresponding channels. Towards this objective, we set predefined prediction and false-alarm probability thresholds as 70% and 30%, respectively, for patient 20 for instance. The histogram bins from the channels, which satisfy these two constraints, are selected to create a prediction matrix for each patient.

Table 2 illustrates five rows of the prediction matrix obtained for patient 20. The first column in this matrix represents the feature type: amplitude (1), derivative (2), local
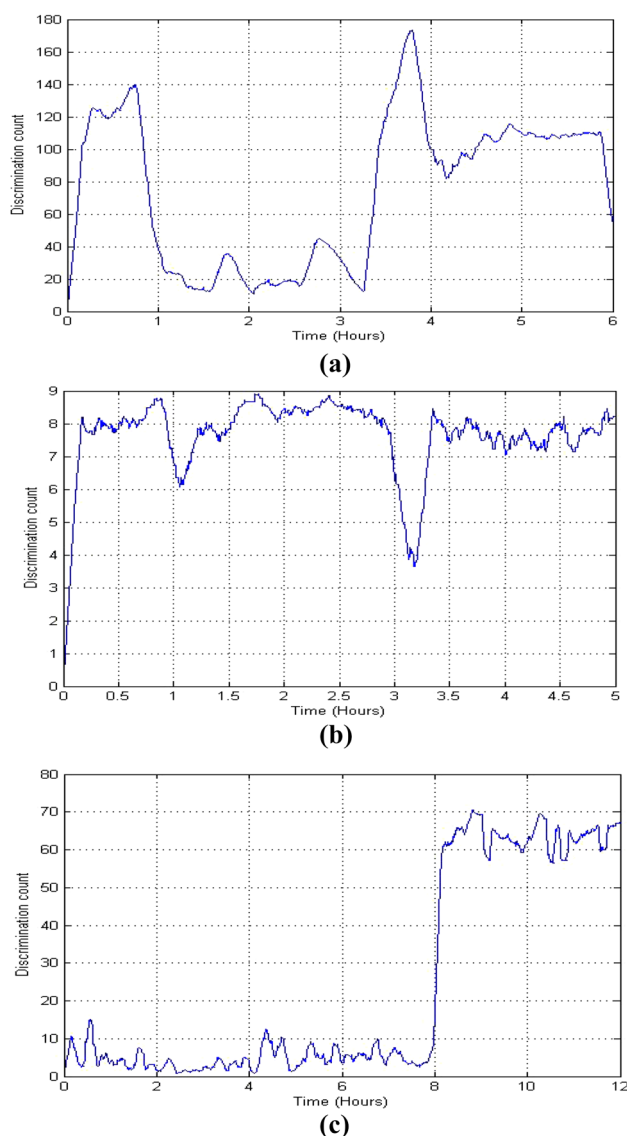
Fig. 9 Variation of the discrimination count with time for three patients (8, 14 and 20) with DST Compression technique. **a** Patient 8, **b** patient 14, **c** patient 20

mean (3), local variance (4), and median (5). The second column represents the index of the selected channel ranging from 1 to 23 for patient 20. The third column represents the index of the selected bin form the histogram of the feature of the first column ranging from 1 to 9. The sixth column represents the estimated threshold value to which we compare the corresponding bin value from each incoming segment of the same channel in the testing phase. The last column has a value of 1 for an incoming bin value that must be greater than or equal to the threshold and zero, otherwise. The fourth and fifth columns represent the prediction and false-alarm probabilities, respectively, achieved with the selected bin from the selected channel and selected feature.

The prediction probability must be $> 70\%$, while the false-alarm probability must be $< 30\%$.

Figure 7 illustrates the PDFs of the bins in Table 2. It is clear from the figures and the table that the selected threshold is not exactly the curve intersection point. It is selected as the value that maximizes the prediction probability, while maintaining the false-alarm probability below 30%. So, we accept more false alarms in order to maximize the prediction probabilities, depending on the fact that we will have multiple decisions that will be combined for each signal segment, which in turn reduces the false alarms. A binary decision is taken for each row of the prediction matrix and an accumulative sum is estimated for each 10-s incoming segment in the testing phase to be classified as a pre-ictal segment or not. A moving average filter is used to refine the results as shown in Fig. 8, because a decision of a certain activity is not taken with a single signal segment. Multiple segments are required in this decision, and hence the moving average process is appropriate for this action. The discrimination count on the vertical axis is compared with a selected threshold to determine the pre-ictal regions (Fig. 9).

In the simulation experiments, we have tested three different prediction horizons of 30, 60, and 90 min. In addition, a 15-min post seizure horizon has been adopted in the interpretation of the results. The obtained results for five MIT patients are given in Tables 3, 4, 5 and 6. From these results, it is clear that long prediction horizons are preferred to short prediction horizons from the prediction and false-alarm rates perspectives. In addition, the moving-average strategy contributes to the reduction of false alarms in the interpretation of seizure prediction results.

6 Conclusions

This paper presented a statistical time-domain approach for EEG channel selection and seizure prediction, which depends on estimating the PDFs of the signals and pre-processed versions of them. This approach is of multi-channel nature, and it depends on pre-defined constrains on the required prediction and false-alarm probabilities. Decision fusion and moving average post-processing steps are utilized to reduce the false-alarm effects and to make robust decisions regarding signal activities. The proposed approach has been tested for different prediction horizons. It achieved prediction rates of 90.32%, 93.55%, and 93.55% for prediction horizons of 30, 60, and 90 min, respectively with false-alarm rates of 0.148/h, 0.074/h, and 0.054/h, respectively. The average prediction times were 22.63 min, 34.25 min, and 40.96 min for the 30, 60, and 90 min horizons, respectively. These obtained results revealed that the proposed EEG seizure prediction

Table 3 Summary of the prediction results (without compression)

Patient no. and data	30 min horizon	60 min horizon	90 min horizon
Patient no. 1 Total no. of hours = 40.5522 h Total no. of seizures = 7 Pred. prob. constraint = 70% False-alarm prob. constraint = 30% Filter length = 60 Decision threshold = 140	No. of predicted seizures = 6 No. of false-alarms = 8 Average prediction time = (30 + 6.7 + 30 + 30 + 8.4)/6 = 22.52 min	No. of predicted seizures = 6 No. of false alarms = 4 Average prediction time = (60 + 6.7 + 32.4 + 60 + 0 + 8.4)/6 = 37.9 min	No. of predicted seizures = 6 No. of false alarms = 4 Average prediction time = (65.4 + 6.7 + 32.4 + 90 + 90 + 8.4)/6 = 48.82 min
Patient no. 8 Total no. of hours = 20 h Total no. of seizures = 5 Pred. prob. constraint = 70% False-alarm prob. constraint = 30% Filter length = 60 Decision threshold = 150	No. of predicted seizures = 5 No. of false alarms = 3 Average prediction time = (30 + 22.7 + 30 + 30 + 8.55)/5 = 24.25 min	No. of predicted seizures = 5 No. of false alarms = 2 Average prediction time = (35.3 + 22.7 + 44.97 + 3.3 + 57.38)/5 = 38.73 min	No. of predicted seizures = 5 No. of false alarms = 1 Average prediction time = (35.3 + 22.7 + 44.97 + 33.3 + 57.38)/5 = 38.73 min
Patient no. 11 Total no. of hours = 34.6151 h Total no. of seizures = 3 Pred. prob. constraint = 70% False-alarm prob. constraint = 30% Filter length = 20 Decision threshold = 2	No. of predicted seizures = 2 No. of false alarms = 3 Average prediction time = (2.1 + 30)/2 = 16.05 min	No. of predicted seizures = 3 No. of false alarms = 0 Average prediction time = (2.1 + 60 + 58.7)/3 = 40.2667 min	No. of predicted seizures = 3 No. of false alarms = 0 Average prediction time = (2.1 + 78.5 + 61.7)/3 = 47.4333 min
Patient no. 14 Total no. of hours = 25.851 h Total no. of seizures = 8 Pred. prob. constraint = 70% False-alarm prob. constraint = 30% Filter length = 60 Decision threshold = 70	No. of predicted seizures = 7 No. of false alarms = 6 Average prediction time = (30 + 27.4 + 8.75 + 29.6 + 30 + 19.3 + 30)/7 = 25 min	No. of predicted seizures = 7 No. of false alarms = 4 Average prediction time = (55.7 + 27.4 + 8.75 + 29.6 + 35.3 + 19.3 + 36.8)/7 = 30.4 min	No. of predicted seizures = 7 No. of false alarms = 3 Average prediction time = (81.6 + 27.4 + 8.75 + 29.6 + 35.3 + 19.3 + 36.8)/7 = 34.1 min
Patient no. 20 Total no. of hours = 27.595 h Total no. of seizures = 8 Pred. prob. constraint = 70% False-alarm prob. constraint = 30% Filter length = 60 Decision threshold = 120	No. of predicted seizures = 8 No. of false alarms = 2 Average prediction time = (30 + 24 + 2.1 + 30 + 18 + 6 + 30 + 30)/8 = 21.26 min	No. of predicted seizures = 8 No. of false alarms = 1 Average prediction time = (53 + 24 + 2.1 + 35.6 + 18 + 6 + 57.4 + 42.6)/8 = 29.84 min	No. of predicted seizures = 8 No. of false alarms = 0 Average prediction time = (53 + 24 + 2.1 + 35.6 + 18 + 6 + 57.4 + 90)/8 = 35.76 min
Total no. of seizures = 31 Total no. of hours = 148.6133	Total no. of predicted seizures = 28 Prediction rate = 90.32% Total no. of false alarms = 22 False-alarm rate = 0.148/h Average prediction time = 22.63 min	Total no. of predicted seizures = 29 Prediction rate = 93.55% Total no. of false alarms = 11 False-alarm rate = 0.074/h Average prediction time = 34.25 min	Total no. of predicted seizures = 29 Prediction rate = 93.55% Total no. of false alarms = 8 False-alarm rate = 0.054/h Average prediction time = 40.96 min

Table 4 Prediction results for patient 8 with DST compression

Patient 8	Horizon 30	Horizon 60	Horizon 90
Decision threshold	118	118	118
No. of predicted seizures	5	5	5
No. of false alarms	1	No	2
Average prediction time	29.53 min	31.3834 min	31.3834 min

Table 5 Prediction results for patient 14 with DST compression

Patient 14	Horizon 30	Horizon 60	Horizon 90
Decision threshold	8	8	8
No. of predicted seizures	7	7	7
No. of false alarms	2	1	1
Average prediction time	19.327 min	32.1714 min	42.947 min

Table 6 Prediction results for patient 20 with DST compression

Patient 20	Horizon 30	Horizon 60	Horizon 90
Decision threshold	62	62	62
No. of predicted seizures	7	7	7
No. of false alarms	2	2	2
Average prediction time	31.10677 min	42.556 min	46.889 min

approach can be appropriately used in a mobile application for epilepsy patients and caregivers.

References

Aarabi, A., & He, B. (2012). A rule-based seizure prediction method for focal neocortical epilepsy. *Clinical Neurophysiology, 123*, 1111–1122.

Abd El-Samie, F. E. (2011). *Information security for automatic speaker identification* (1st ed.). New York: Springer.

Aiupkumar, B., Bej, T., & Agarwal, S. (2013) Comparison study of lossless data compression algorithms for text data. *IOSR Journal of Computer Engineering, 11*, 15–19.

Alickovic, E., Kevric, J., & Subasi, A. (2018). Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. *Biomedical Signal Processing and Control, 39*, 94–102.

Berger, H. (1929). Über des Elekrenkephalogramm des Menschen. *ArchivfürPsychiatrie und Nervenkrankheiten, 87*(1), 527–570.

Chiang, C. Y., Chang, N. F., Chen, T. C., Chen, H. H., & Chen, L. G. (2011). Seizure prediction based on classification of EEG synchronization patterns with on-line retraining and post-processing scheme. *International Conference of the IEEE EMBS*. https://doi.org/10.1109/IEMBS.2011.6091865.

Costa, R. P., Oliveira, P., Rodrigues, G., Direito, B., & Dourado, A. (2008). Epileptic seizure classification using neural networks with

14 features. *Proceedings of KES*. https://doi.org/10.1007/978-3-540-85565-1_35

Gadhoumi, K., Lina, J. M., & Gotman, J. (2013). Seizure Prediction in patients with mesial temporal lobe epilepsy using EEG measures of state similarity. *Clinical Neurophysiology, 124*, 1745–1754.

Hung, S. H., Chao, C. F., Wang, S. K., Lin, B. S., & Lin, C. T. (2010). VLSI implementation for epileptic seizure prediction system based on wavelet and Chaos theory. In *Proceedings of the IEEE TENCON*.

Kannan, R. S., & Eswaran, C. (2007). Lossless compression schemes for EEG signals using neural network predictors. *EURASIP Journal on Advances in Signal Processing, 2007*, 102.

Kopsinis, Y., & McLaughlin, S. (2009). Development of EMD-based denoising methods inspired by wavelet thresholding. *IEEE Transactions on Signal Processing, 57*(4), 1351–1362.

Kuo, S. M., Lee, B. H., & Tian, W. (2006). *Real-time digital signal processing, implementations and applications*. New York: Wiley.

Li, S., Zhou, W., Yuan, Q., & Liu, Y. (2013). Seizure prediction using spike rate of intracranial EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21*(6), 880–886.

Liu, Y., Li, Y., Lin, H., & Ma, H. (2014). An amplitude-preserved time–frequency peak filtering based on empirical mode decomposition for seismic random noise reduction. *IEEE Geoscience and Remote Sensing Letters, 11*(5), 896–900.

Makeig, S., Kothe, C., Mullen, T., Bigdely-Shamlo, N., Zhang, Z., & Kreutz-Delgado, K. (2012) Evolving signal processing for brain–computer interfaces. *Proceedings of the IEEE, 100*, 1567–1584.

Milić, L. D., Lutovac, M. D., & Ćertić, J. D. (2013). Design of first–order differentiator utilising FIR and IIR sub–filters. *International Journal of Reasoning-based Intelligent, Systems, 5*(1), 3–11.

Miri, M. R., & Nasrabadi, A. M. (2011). A new seizure prediction method based on return map. In *Proceedings of the Iranian Conference on BioMedical Engineering*, Tehran.

Qi, Y., Wang, Y., Zheng, X., Zhang, J., Zhu, J., & Guo, J. (2012). Efficient epileptic seizure detection by a combined IMF-VoE feature. In *Proceedings of the International Conference of the IEEE EMBS*.

Rishita, S., & Shahare, P. (2017). Digital image compression using hybrid scheme using DWT and quantization with DCT for still digital image. *International Research Journal of Engineering and Technology*. e-ISSN: 2395-0056, p-ISSN: 2395–0072, .

Ruchi, G., Kumar, M., & Bathla, R. (2016). Data compression—Lossless and lossy techniques. *International Journal of Application or Innovation in Engineering & Management (IJAIEM), 5*(7), 120–125.

Schelter, B., Drentrup, H. F., Ihle, M., Bonhage, A. S., & Timmer, J. (2011). Seizure prediction in epilepsy: from circadian concepts via probabilistic forecasting to statistical evaluation. In *Proceedings of the IEEE International Conference of IEEE EMBS*.

Scherer, R., Moitzi, G., Daly, I., & Müller-Putz, G. R. (2013). On the use of games for noninvasive EEG-based functional brain mapping. *IEEE Transactions on Computational Intelligence and AI in Games, 5*(2), 155–163.

Sriraam, N. (2012). A high-performance lossless compression scheme for EEG signals using wavelet transform and neural network predictors. *International Journal of Telemedicine and Applications*. https://doi.org/10.1155/2012/302581.

Thurman, D. J., Beghi, E., Begley, C. E., Berg, A. T., Buchhalter, J. R., Ding, D., et al. (2011). Standards for epidemiologic studies and surveillance of epilepsy. *Epilepsia, 52*(Issue Supplement s7), 1–26.

Tzallas, A. T., Tsipouras, M. G., Tsalikakis, D. G., Karvounis, E. C., Astrakas, L., Konitsiotis, S., et al. (2012). Automated epileptic seizure detection methods: a review study. In D. Stevanovic (Ed.), *Epilepsy—Histological, electroencephalographic and psychological aspects*. Rijeka: InTech. ISBN: 978-953-51-0082-9.

Tzimourta, K. D., Tzallas, A. T., Giannakeas, N., Astrakas, L. G., Tsalikakis, D. G., & Tsipouras, M. G. (2018). Epileptic seizures classification based on long-term EEG signal wavelet analysis. In: N. Maglaveras, I. Chouvarda, P. de Carvalho (Eds.), *Precision medicine powered by pHealth and connected health* (pp. 165–169). Singapore: Springer.

Wang, S., Chaovalitwongse, W. A., & Wong, S. (2010). A novel reinforcement learning framework for online adaptive seizure prediction. In *Proceedings of the IEEE international conference on bioinformatics and biomedicine*, Hong Kong

Wang, S., Chaovalitwongse, W. A., & Wong, S. (2013). Online seizure prediction using an adaptive learning approach. *IEEE Transactions on Knowledge and Data Engineering, 25*(12), 2854–2866.

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

Xie, S., & Krishnan, S. (2011). Signal decomposition by multi-scale PCA and its applications to long-term EEG signal classification. In *Proceedings of the IEEE international conference on complex medical engineering*.

Yin, L., Yang, R., Gabbouj, M., & Neuvo, Y. (1996). Weighted median filters: a tutorial. *IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing, 43*(3), 157–192.

Zandi, A. S., Tafreshi, R., Javidan, M., Dumont, G. A. (2010). Predicting temporal lobe epileptic seizures based on zero-crossing interval analysis in scalp EEG. In *Proceedings of the 32nd annual international conference of the IEEE EMBS*.

Zandi, A. S., Tafreshi, R., Javidan, M., & Dumont, G. A. (2013). Predicting epileptic seizures in scalp EEG based on a variational bayesian gaussian mixture model of zero-crossing intervals. *IEEE Transactions on Biomedical Engineering, 60*(5), 1401–1413.