



Epileptic seizure detection using cross-bispectrum of electroencephalogram signal

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ABSTRACT

Purpose: The automatic detection of epileptic seizures in EEG data from extended recordings can make an important contribution to the diagnosis of epilepsy as it can efficiently reduce the workload of medical staff.

Methods: This paper describes how features based on cross-bispectrum can help with the detection of epileptic seizure activity in EEG data. Features were extracted from multi-channel intracranial EEG (iEEG) data from the Freiburg iEEG recordings of 21 patients with focal epilepsy. These features were used as a support vector machine classifier input to discriminate ictal from inter-ictal states. A post-processing method was applied to the classifier output in order to improve classification accuracy.

Results: A sensitivity of 95.8%, specificity of 96.7%, and accuracy of 96.8% were achieved. The false detection rate (FDR) was zero for 10 patients and very low for the rest.

Conclusions: The results show that the proposed method distinguishes better between ictal and inter-ictal iEEG epochs than other seizure detection methods. The proposed method has a higher accuracy index than achievable with a number of previously described approaches. Also, the method is rapid and easy and may be helpful in online epileptic seizure detection and prediction systems.

1. Introduction

Epilepsy is a common neurological disorder associated with recurrent and sudden excessive electrical discharges in a group of brain neurons that can disrupt the patient's behavior and function temporarily [1]. Common treatments for epilepsy (medication and surgery), that often come with several side effects, are not able to control seizures in almost 25% of the patients. These patients must live with seizures that can happen anytime and anywhere [2]. Since epileptic seizures are related to the electrical activity of the brain, the electroencephalogram (EEG) signals are widely used in the epilepsy diagnosis and assessment. The most efficient method used to identify epileptic seizures is the visual analysis of the long-term EEG signals by the trained professionals [3]. This is a very tedious and time-consuming task, especially when the number of EEG electrodes increases. Automatic detection of epileptic seizures could assist epileptologists in assessing the long-term EEG recordings, and could also be used in closed-loop therapeutic systems such as implantable electrical stimulation devices [4].

Many methods have been proposed for the automatic seizure detection. Most of the current research in this field is based on extracting

features from the preprocessed window of an EEG signal [5]. This step is then followed by classification of the extracted features into inter-ictal and ictal groups. These features can be extracted from a channel, pair of channels or multiple channels of EEG signals simultaneously and are known as univariate, bivariate and multivariate measures respectively.

Recent studies have shown the benefits of using bivariate and multivariate over univariate measures [6–8], representing the interaction between different brain regions.

Numerous EEG analysis methods have been used for feature extraction that are derived from linear, nonlinear and chaos analysis in time domain, frequency domain, and time-frequency domain [9].

Automatic seizure detection has been proposed based on power spectral density features [10–12], wavelet features [13,14], different entropies [15–19], recurrence plot features [20,21], chaos based features [22], and visibility graph based features [23–25].

Several studies showed that the use of non-linear EEG analysis, particularly for improved characterization of epileptic brain states, provides promising results. The earliest attempts to use nonlinear time series analysis in the epileptic EEG analysis started in the 1990s using

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the Lyapunov exponent [26].

Higher order spectra (HOS) are known to be a good method for the analysis of non-linear complex systems like such as speech, EEG and ECG [27–30]. It can also be used as a powerful tool for non-linear dynamical analysis of biomedical signals and performs well for weak and noisy signals [31]. Detecting and predicting epileptic seizures from EEG signals [32,33], sleep stages classification using EEG signals [34], and cardiac abnormalities detection using heart rate signals [35] were done using HOS.

In this paper, a new feature set based on the cross–HOS method is proposed for the automatic detection of epileptic seizures from EEG signals. Multivariate analysis methods obtain promising results in EEG analysis especially in the seizure analysis field. Seizure can happen when normal interactions between different regions of brain are disrupted [35]. Cross–HOS method could therefore be a good base method for a multivariate and improved EEG signal analysis. The cross–HOS has already been employed for multivariate analysis of biological signals such as cardiorespiratory and EEG signals [36,37].

To evaluate the effectiveness of the feature set, a support vector machine (SVM) classifier was used on the Freiburg epileptic intracranial EEG (iEEG) data set, which is also the base for many other research papers [38–41]. A post-processing method was added to regularize the output of the classifier and to obtain more accurate results. Sensitivity, specificity, and false detection rate (FDR) were used as measures to evaluate the performance of the proposed method.

The experimental data and setup is explained in the Database section, followed by the Methods section that explains the algorithmic approach. In Section 4 the results are presented and discussed. The last section includes the conclusions derived from the interpretation of the results.

2. Database

The Freiburg iEEG database [42] is one of the most cited databases used in seizure prediction and detection methods. The database contains of iEEG signals of 21 patients suffering from epilepsy, in which several seizures occurred. These patients suffer from focal medically intractable epilepsy of different patient ages, seizure types and locality. The retrospective evaluation of the data received approval by the Ethics committee of the Medical Faculty, University of Freiburg [38].

The data was recorded using a 128-channel Neurofile NT digital EEG amplifier with a 256 Hz sampling rate. From these channels, six channels were selected by visual inspection of epilepsy experts. Three of them were in the epilepsy focal area of the brain, and three were far from the epilepsy focal area. The electrodes of focal recording and extra-focal recording were labelled from 1 to 3 and 4–6 respectively and the locations of these electrodes were different for each patient. There are 24–26 h of non-seizure data (inter-ictal files) and 2–5 h of seizure data (ictal files) for each patient. Seizure onset and offset times were detected by the epilepsy experts [39].

3. Method

3.1. Preprocessing

Due to the time-variant characteristics of the EEG signals, a time-varying bispectrum has to be computed through a sliding window. Therefore, window size and overlap are two important parameters. Choosing a large enough window size leads to good classification performance. In the preprocessing step, the EEG signals were windowed into non-overlapping four-second (1024 samples) windows, and were then filtered using an infinite impulse response (IIR) forward-backward 50 Hz notch filter to eliminate AC power supply noise without adding phase shift.

3.2. Cross-bispectrum analysis

Cross-bispectrum analysis [43] is a multivariate and non-linear method used for seizure detection. It is used to find the relation between different signal frequencies of different EEG channels from different regions of the brain rather than from an individual channel.

Higher order spectra are defined as the spectral representations of higher order cumulants of a random process. If $X(k)$ is a real, discrete time series from an n th-order stationary random process, then the n th-order moment of $X(k)$, m_n^x , can be calculated by taking an expectation over the process multiplied by $(n-1)$ lagged version of itself. The first, second, and third-order moments are defined as follows:

$$m_1^x = E[X(k)] \quad (1)$$

$$m_2^x(\tau) = E[X(k)X(k+\tau)] \quad (2)$$

$$m_3^x(\tau_1, \tau_2) = E[X(k)X(k+\tau_1)X(k+\tau_2)] \quad (3)$$

The n th-order cumulants of $X(k)$, c_n^x , can be easily calculated as certain nonlinear combinations of moments. The first, second, and third-order cumulants are defined as follows:

$$c_1^x = m_1^x \quad (4)$$

$$c_2^x(\tau) = m_2^x(\tau) - (m_1^x)^2 \quad (5)$$

$$c_3^x(\tau_1, \tau_2) = m_3^x(\tau_1, \tau_2) - m_1^x [m_2^x(\tau_1) + m_2^x(\tau_2) + m_2^x(\tau_2 - \tau_1)] + 2(m_1^x)^3 \quad (6)$$

Higher order spectral starts with bispectrum that is the 2D-Fourier transform of the third cumulant function:

$$B(f_1, f_2) = \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} c_3^x(\tau_1, \tau_2) e^{-j(\tau_1 f_1 + \tau_2 f_2)} \quad (7)$$

For a sampled signal, the Fourier spectrum repeats periodically out of Nyquist frequency interval and should be ignored. Thus, knowledge of the bispectrum region described as:

$f_2 \geq 0, f_2 \geq f_1, f_2 + f_2 \leq 1$ is enough to describe the rest (Fig. 1). This region is often designated as the non-redundant region of bispectrum

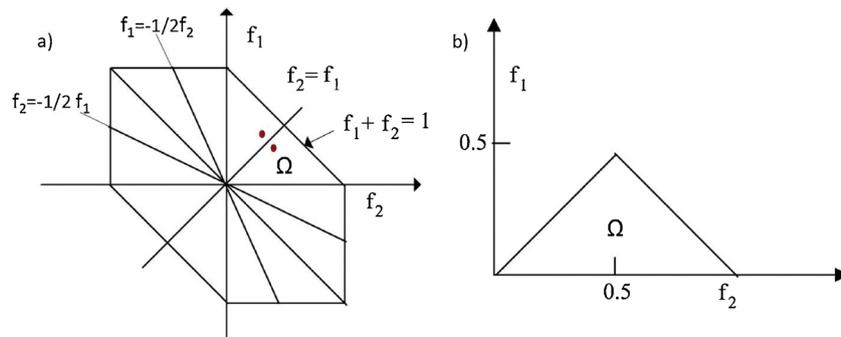


Fig. 1. a) bispectrum region b) Triangular region of bispectrum (non-redundant region of bispectrum computation) [44].

computation (region Ω).

In this work, the cross-bispectrum of a Fourier transform of the third order cross-cumulant of three signals was used. The cross-bispectrum of three signals x, y and z are defined as follows [36]:

$$S_{xyz}(f_1, f_2) = \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} c_3^{xyz}(\tau_1, \tau_2) e^{-j(\tau_1 f_1 + \tau_2 f_2)} \quad (8)$$

Where $c_3^{xyz}(\tau_1, \tau_2)$ is the third order cross-cumulant defined as follows:

$$c_3^{xyz}(\tau_1, \tau_2) = E[X^*(n)Y(n + \tau_1)Z(n + \tau_2)] \quad (9)$$

The cross-bispectrum values were calculated using Matlab (Version 2017) for both states: three signals near the focal and three signals away from the focal. After that selected features were extracted from these values for automatic seizure detection.

3.3. Feature extraction

In order to classify the EEG signals into two groups, ictal and inter-ictal, this paper proposes the use of the following linear and non-linear features of cross-bispectrum values in three EEG channels:

- **Linear features:** three energy-based features, to compute average, maximum, and minimum of the cross-bispectrum respectively (mean, max, min)
- Mean of cross-bispectrum magnitude:

$$M_{avg} = \frac{1}{L} \sum_{\Omega} |S_{xyz}(f_1, f_2)| \quad (10)$$

where L is the number of points within the region Ω .

2. Max of cross-bispectrum magnitude within the region Ω :

$$M_{max} = \text{Max} |S_{xyz}(f_1, f_2)| \quad (11)$$

- 3 Min of cross-bispectrum magnitude within the region Ω .

$$M_{min} = \text{Min} |S_{xyz}(f_1, f_2)| \quad (12)$$

- **Non-linear features:** six non-linear features, two are frequency-relation-based features, and two are entropy-based features for computing the degree of disorder in each cross-bispectrum computation.
- The sum of logarithmic amplitudes of diagonal elements in the cross-bispectrum matrix:

$$H = \sum_{\Omega} \text{Log}(|S_{xyz}(f_k, f_k)|) \quad (13)$$

- 5 The first-order spectral moment of amplitudes of diagonal elements in the cross-bispectrum matrix:

$$\sum_{k=1}^N k \text{Log}(|S_{xyz}(f_k, f_k)|) \quad (14)$$

- 6 Cross-bispectrum phase entropy (Ph):

$$P_h = \sum_n p(\psi_n) \log p(\psi_n) \quad (15)$$

Where:

$$p(\psi_n) = \frac{1}{L} \sum_{\Omega} l(\phi(S_{xyz}(f_1, f_2)) \varepsilon \psi_n) \quad (16)$$

$$\psi_n = \left\{ \phi, -\pi + \frac{2\pi n}{N} \leq \phi < -\pi + \frac{2\pi(n+1)}{N} \right\} \quad (17)$$

$n = 0, 1, \dots, N-1$

where ϕ is the phase angle of the cross-bispectrum, and $l(\cdot)$ is an indicator function which gives a value of 1 when the phase angle is within the range bin ψ_n depicted by in Eq. (17).

- 7 Cross-bispectrum amplitude entropies:

$$P_1 = -\sum_k p_k \log p_k \quad (18)$$

where:

$$p_k = \frac{|S_{xyz}(f_1, f_2)|}{\sum_{\Omega} |S_{xyz}(f_1, f_2)|} \quad (19)$$

$$P_2 = -\sum_i q_i \log q_i \quad (20)$$

where:

$$q_i = \frac{|S_{xyz}(f_1, f_2)|^2}{\sum_{\Omega} |S_{xyz}(f_1, f_2)|^2} \quad (21)$$

$$P_3 = -\sum_n r_n \log r_n \quad (22)$$

where:

$$r_n = \frac{|S_{xyz}(f_1, f_2)|^3}{\sum_{\Omega} |S_{xyz}(f_1, f_2)|^3} \quad (23)$$

All of the nine features above were calculated for two states: 1) three focal EEG channels, 2) three non-focal EEG channels. In total, 18 features were extracted at every sampling point by using a sliding window using Matlab.

3.4. Classification

Support vector machine (SVM) is commonly used as a supervised classifier. We used the SVM in this work because it has good generalization capabilities [45]. The simplest SVM classifier uses linear boundaries to classify two linear separable class data. In order to classify more complex and non-linear separable data, SVM uses a special transformation from features space into a higher order space where linear boundaries may eventually separate the data into two classes. In this work, the Gaussian Radial Basis Function (RBF) kernel was used as transformation. The RBF is defined by Eq. 24 and is one of the most used kernel function.

$$K(x, y) = \exp\left(\frac{-|x - y|^2}{2\sigma^2}\right) \quad (24)$$

Where σ is the scale parameter, also called the openness of the Gaussian kernel, and x and y are feature vectors from two classes [46]. The optimum value of σ was calculated using a grid search method, and the classification was carried out using LibSVM toolbox [47]. The patient-specific classifiers were trained for detection of seizures using ictal files in the Freiburg iEEG database. Only patients with at least 3 seizures were considered in this work. Two classifiers were trained for each patient. One classifier was trained with the features calculated from three focal channels and another one was trained with the features calculated from three non-focal channels. All epochs before each seizure interval in ictal files have been used as inter-ictal class and the data in seizure intervals has been used as ictal class. One seizure instance was used as a test set and the rest used for training. The results were averaged using cross validation method. Since the number of inter-ictal samples was higher than the ictal samples, and since the classifiers usually obtain higher accuracy for the class with more training samples, some samples of the inter-ictal training set were selected randomly to obtain an equal number of samples for the two classes. However, all of the test samples were used in the test stage and no resampling was carried out. Also, 24 h inter-ictal files data was used in test stage, for

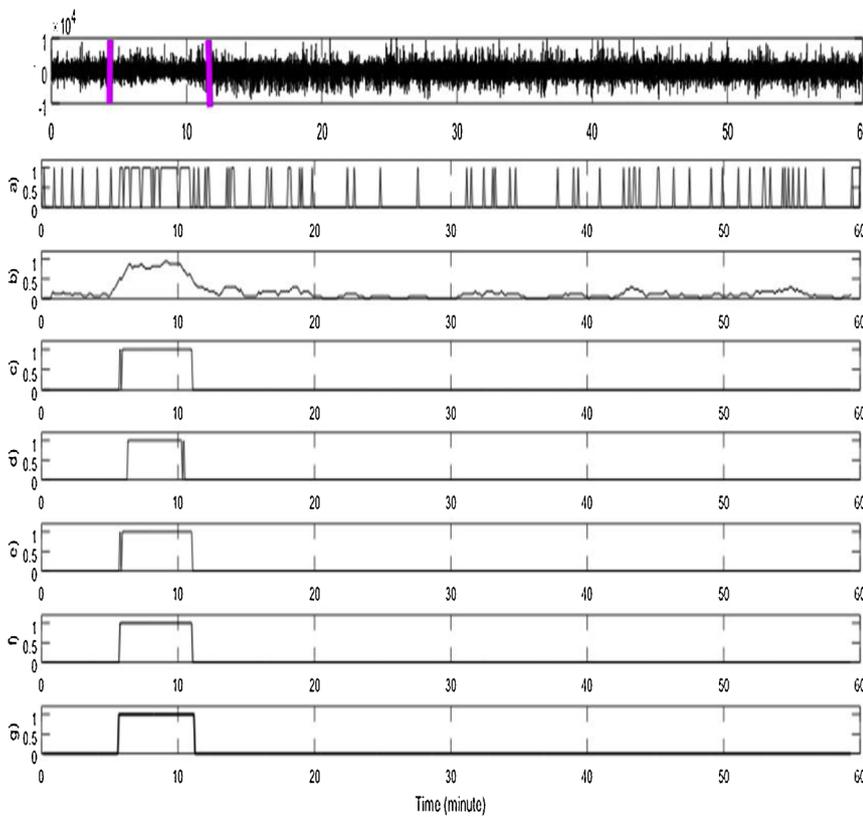


Fig. 2. The post processing method for patient 7 during the 3th seizure. From the top to the bottom: Main signal from the first channel (seizure interval was indicated with pink lines); a) Output of the first SVM for three focal channels; b) Smoothed output after the moving average filtering; c) Binary decisions with the smoothed output of the first SVM after thresholding; d) Binary decisions with the smoothed output of the second SVM for three far channels after thresholding; e) First stage fusion (OR) of two binary decisions; f) Second stage of fusion; g) Final decision after the collar operation, in which “1” indicates seizure (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

calculation of the FDR.

3.5. Post processing

The post processing step includes: two SVM output smoothing’s, decision making using the smoothed outputs for each patient and the collar technique.

During classification, labels ‘1’ and ‘.’ were assigned for ictal and inter-ictal classes respectively (Fig. 2a). Because of misclassification, smoothing methods were designed to reduce the noisy behavior of the SVM output through averaging of the output. A central linear moving average filter (MAF) [48] was applied to the output sequence of each SVM classifier (Fig. 2b). MAF is defined as follows:

$$Y[i] = \frac{1}{2N + 1} \sum_{j=-N}^N O[i + j] \tag{25}$$

where $O[i]$ is the SVM output, $Y[i]$ is the smoothed output, and $2N + 1$ is the number of points used in the moving average window (order of the MAF). The selection of N is very important, because small N causes large FDR and large N causes smaller sensitivity. The smoothed values were compared to a threshold from the interval $[0 \ 1]$. After experiments, we found that 0.5 is a good threshold for two SVMs and all patients. The comparison output is 1, for input more than 0.5, and 0 for input less than 0.5. Then binary decisions were taken per SVM for each patient (Fig. 2c). In order to reduce FDR, decision making was carried out using fusion of two binary outputs for each patient. The proposed fusion method in our approach has two steps: 1) a logical ‘OR’ operator applied to these binary outputs (Fig. 2f); 2) the ‘OR’ output is investigated and, if the windows before and after a non-seizure window are labeled as seizure, then this current window is labeled as seizure (Fig. 2g)

Finally, the collar technique [49] is applied to the fusion stage output in order to prevent cutting the ends of the window. Every seizure interval was extended from both sides (Fig. 3g) to compensate for

possible difficulties in detecting pre-seizure and post-seizure parts.

Figs. 3 and 4 also show a missing seizure and a falsely detected seizure after post processing respectively.

4. Results and discussion

Of the 21 iEEG patients provided in [42], patient 8 and patient 13 had 2 seizures and were therefore excluded from the analysis. The iEEG data from the other 19 patients with 78 seizures were subsequently analyzed using the proposed method.

Table 1 shows the mean of the bispectrum amplitude for all patients, all seizures, and for both states: 1) three focal EEG channels, 2) three non-focal EEG channels. In most cases and for two states, the mean of the bispectrum amplitude increased in the ictal period, with stronger frequency coupling between EEG signals from three channels during a seizure. This fact can easily be seen in Figs. 5 and 6, which are the summary of Table 1 for both states of 1 and 2.

The performance of the proposed method was evaluated in terms of sensitivity, specificity, accuracy and FDR [48] for each patient defined as:

- 1) Sensitivity: Number of true detected seizure windows divided by the total number of seizure windows labeled by the EEG experts.
- 2) Specificity: Number of true detected non-seizure windows divided by the total number of non-seizure windows labeled by the EEG experts.
- 3) Accuracy: Number of correctly identified windows divided by the total number of windows.
- 4) False detection rate: Number of false detections per hour.

The results for the 19 patients are shown in Table 2. The sensitivity of the proposed method varied from 61% to 100%; 17 patients had sensitivities above 90%. The FDRs for 10 patients were 0 and for the rest it was less than 0.98 per hour. Patient 1 had the lowest sensitivity

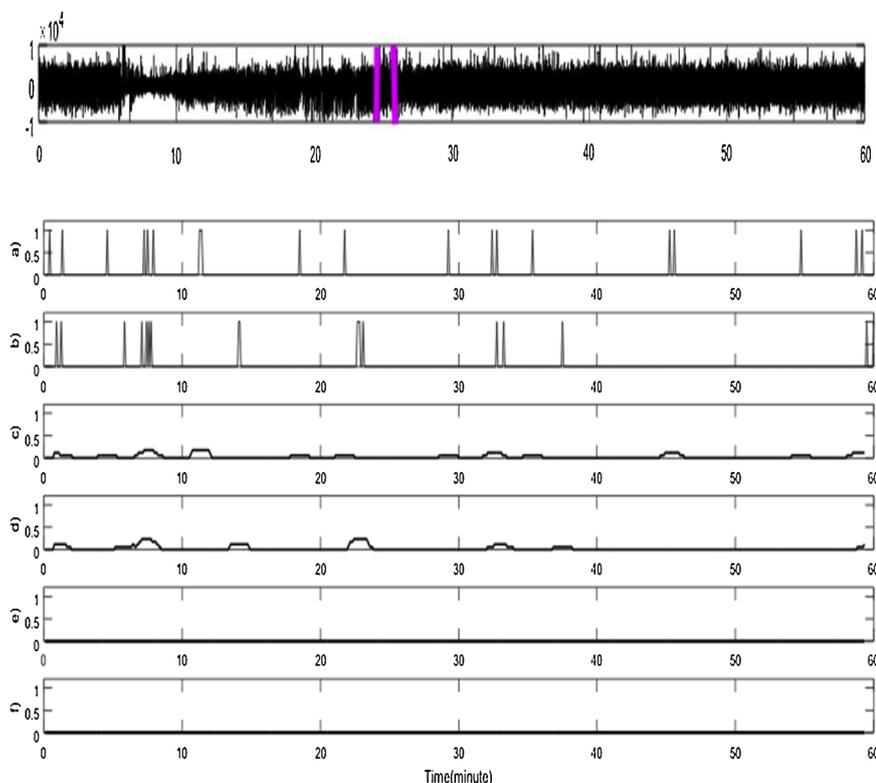


Fig. 3. Example of missing seizure for patient 1 and the 1th seizure. From the top to the bottom: Main signal from the first channel (seizure interval was indicated with pink lines); a) Output of the first SVM for three focal channels; b) Output of the first SVM for three non-focal channels; c) Smoothed output for three focal channels after the moving average filtering; d) Smoothed output for three non-focal channels after the moving average filtering; e) Binary decisions with the smoothed output of the first SVM after thresholding; f) Binary decisions with the smoothed output of the second SVM after thresholding (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

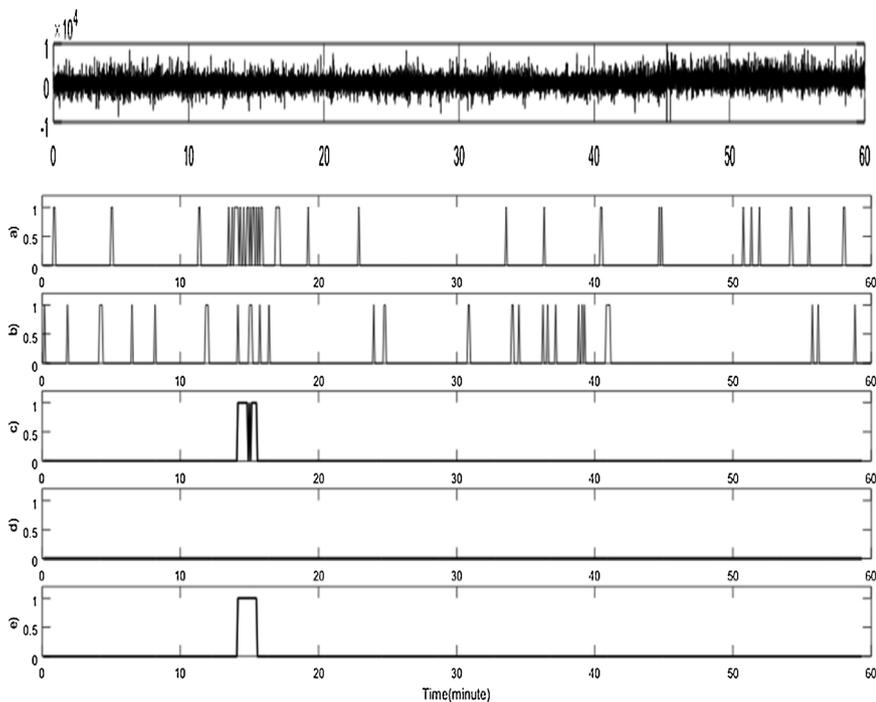


Fig. 4. Example of false detected seizure for patient 4 and inter-ictal file. From the top to the bottom: Main signal from the first channel; a) Output of the first SVM for three focal channels; b) Output of the first SVM for three non-focal channels; c) Output of the first SVM after smoothing and thresholding; d) Output of the second SVM after smoothing and thresholding; e) Final decision after fusion.

of 61%, because seizure durations were short for this patient. Patient 10 had the lowest specificity and the highest FDR, because the electrode disconnected and reconnected during the recording time and there were sharp jumps in signal, which were falsely detected as seizure by the proposed method.

On average a sensitivity of 95.8%, specificity of 96.7%, and accuracy of 96.8% with a FDR of 0.24/h were obtained. A total of 78 seizures were used in this study and 75 seizures were detected correctly

and only three short duration seizures from patient 1 and patient 11 were not detected. The average detection latency between the real seizure onsets and the proposed method was 9.42 s.

The Freiburg iEEG database has been used in several studies for automatic detection of epileptic seizures [50–53]. Majumdar et al. used the differential windowed variance method on 15 patients of this database and obtained the sensitivity of 91.5% [50]. Aarabi et al. proposed a method based on the fuzzy rules for all patients and obtained

Table 1

The mean of bispectrum amplitude for all patients and all seizures and for both states: 1) three focal EEG channels, 2) three non-focal EEG channels.

Seizure number	Seizure number 1		Seizure number 2		Seizure number 3		Seizure number 4		Seizure number 5	
	Before seizure	During seizure								
1 (state 1)	956	14896	263	14236	32	15981	214	14278	–	–
(state 2)	648	1895	875	1913	10.5	1087	74	1256	–	–
2 (state 1)	625	96857	7895	125698	98745	425639	–	–	–	–
(state 2)	214	42563	5642	4236	7841	96874	–	–	–	–
3 (state 1)	12356	569841	198756	123654	56841	321456	78956	698745	124785	987456
(state 2)	2874	98745	3598	5241	6984	68745	12654	45698	23541	89658
4 (state 1)	489874	32564	5698	745621	9547	874512	6547	89654	2658	136524
(state 2)	34589	87456	412	143652	1984	1874	254	1265	895	45621
5 (state 1)	87458	1236547	65478	1025647	62458	1564874	123564	1897456	98456	1256987
(state 2)	24514	654789	12415	785987	32145	756987	26512	548745	36521	798745
6 (state 1)	2136	654895	56987	5987456	49874	265897	–	–	–	–
(state 2)	5412	895641	48751	125469	25641	98745	–	–	–	–
7 (state 1)	123654	456987	654896	2365478	235478	1874562	–	–	–	–
(state 2)	5632	78954	9874	45698	12547	93254	–	–	–	–
9 (state 1)	5874	569874	4785	265489	87456	957841	789654	198745	4874	598745
(state 2)	5641	87456	6745	36547	5698	78456	2563	74569	1547	52365
10 (state 1)	7456	874569	58746	25641	5128	569874	12546	895745	5412	546987
(state 2)	541	7856	5478	27451	264	12546	1023	56412	314	54789
11 (state 1)	12452	256487	15423	129874	32145	1569874	23145	745689	–	–
(state 2)	208	312564	5984	895612	1048	321456	14562	61235	–	–
12 (state 1)	1235	458965	5412	1256987	2564	654789	10456	954123	–	–
(state 2)	4521	78541	9874	56984	1456	58945	1458	71256	–	–
14 (state 1)	6548	2365481	89651	2569874	56487	2198745	5098	1987456	–	–
(state 2)	7845	123564	2569	178985	8745	96512	10895	156849	–	–
15 (state 1)	15654	987456	78965	1987456	23569	3698745	69874	2987456	–	–
(state 2)	12654	256987	10236	789654	28564	498756	54874	–	–	–
16 (state 1)	6548	7896185	13951	65984	49875	23569	9651	87965	56321	50238
(state 2)	11256	89605	2658	78954	5698	63145	265	58741	1098	89745
17 (state 1)	1287450	6895741	2569874	8745109	1089654	9874562	5987451	3256412	2568741	8213065
(state 2)	698745	265417	214574	3621450	120654	906354	308721	256801	109854	508953
18 (state 1)	2154	856459	9654	2156489	6548	609165	326	205214	9603	1062154
(state 2)	5362	29874	3254	52698	12546	83405	2085	13650	2029	50816
19 (state 1)	156	608563	9860	1096541	7294	530984	41895	698541	–	–
(state 2)	2654	805314	508	53841	9436	125680	205	1268	–	–
20 (state 1)	987451	153298	5308	802485	80651	1569804	20852	348056	85040	1064890
(state 2)	9640	64208	1965	72096	27095	198345	15607	92036	25603	804609
21 (state 1)	56010	309874	608	98705	5060	406523	15905	726531	398	209875
(state 2)	2054	15608	2086	39045	2305	26089	1056	153026	1098	49050

sensitivity of 68.9% [51]. Tzimourta et al. proposed a method based on the Discrete Wavelet Transform (DWT) and the SVM classifier for all patients and could achieve sensitivity of 93% [52]. Zhou et al. used lacunarity with Bayesian linear discriminant analysis for detection of seizure in all patients and obtained sensitivity of 94.5% [53].

In comparison to some previous works, the sensitivity (95.8%) of the proposed method was better. Recently, many seizure detection and EEG classification tools based on bivariate and multivariate EEG analysis have been developed [54–57].

Measuring the determining relations between different channels to

characterize interaction between different brain regions, obtained a promising performance [58].

Altenburg et al. used Synchronization Likelihood (SL) for multivariate analysis of EEG signals in order to detect epileptic seizures. The SL was higher in all epochs with seizures compared to epochs without seizure (P -value < 0.01) [54].

Ravish et al. used coherence and phase synchronization for multivariate analysis of EEG signals and obtained a sensitivity of 95% [55].

Miaolin et al. investigated the temporal synchronization between the EEG signals from different channels using spectral graph theoretic

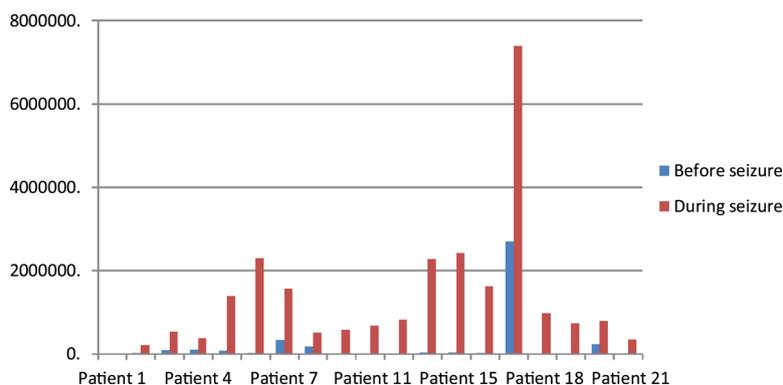


Fig. 5. The mean of bispectrum amplitude of state 1 for all patients.

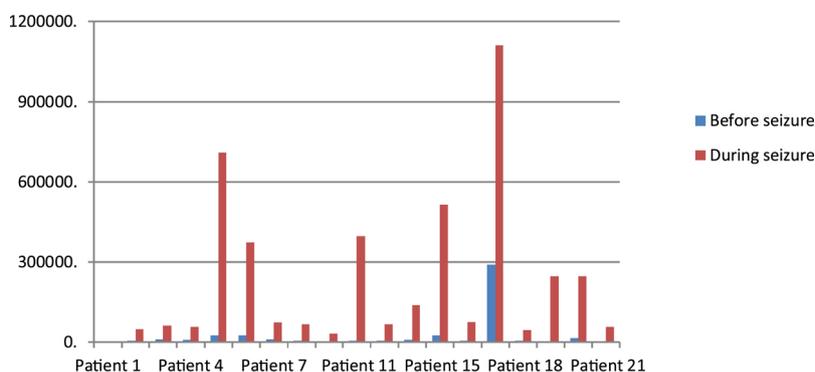


Fig. 6. The mean of bispectrum amplitude of state 2 for all patients.

Table 2
Performance evaluation of the proposed method.

Patient number	Accuracy (%)	Sensitivity(%)	Specificity(%)	FDR (/h)
1	99.5	62.9	99.5	0.7
2	99.7	99.9	99.7	0
3	93.5	98.7	93.2	0
4	99.5	100	99.5	0.8
5	99.7	100	99.6	0
6	97.6	100	97.5	0.4
7	92.5	98.7	92.3	0
9	83.4	95.4	81.2	0.5
10	94.8	97.2	94.7	1
11	96.9	75.6	97.3	0
12	100	100	100	0
14	96.5	100	96.4	0.3
15	99.3	100	99.3	.09
16	100	100	100	0
17	97.9	95.9	97.9	0
18	99.6	100	99.6	0.8
19	98.4	99.5	98.4	0
20	95	100	94.9	0
21	96.6	97.3	96.5	0.2

features. They tested this method on 23 patients from CHB-MIT Scalp EEG database and could obtain a high sensitivity of 95% [56].

Zhongjiang et al. used partial directed coherence (PDC) analysis of the EEG signals with a sensitivity of 91.4% [57].

To the best of our knowledge, this is the first experimental study in seizure detection field that estimates features from three channels. We have found that the proposed method can obtain high performance for automatic seizure detection in deep EEG signals. This method should also be applied to surface EEG database in order to investigate the ability of the method for seizure detection in different situations.

5. Conclusion

In this study, a new approach based on cross - bispectrum features was proposed to detect epileptic seizure in depth EEG database. A novel feature set with an SVM classifier and a post-processing method were proposed to detect the seizure interval in EEG signals. We obtained good performance for seizure detection with an average sensitivity of 95.83%, specificity of 96.7%, accuracy of 96.84%, and an FDR of 0.24/h.

Out of 78 seizures used in the study, 75 seizures were detected correctly and only three short length seizures from patient 1 and patient 11 were not detected. The average detection latency between the real seizure onsets and the proposed method was 9.42 s.

Compared with some other studies that also used the Freiburg iEEG database, our algorithm presented better results. The presented method also showed better performance than some other multivariate EEG analysis in seizure detection. Moreover, our method is fast, easy to implement, and effective as an automatic seizure detection technique.

The proposed cross-bispectrum features may also obtain good results in other biological signal processing field.

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