New feature extraction approach for epileptic EEG signal detection using time-frequency distributions

Carlos Guerrero-Mosquera · Armando Malanda Trigueros · Jorge Iriarte Franco · Ángel Navia-Vázquez

Abstract This paper describes a new method to identify seizures in electroencephalogram (EEG) signals using feature extraction in time frequency distributions (TFDs). Particularly, the method extracts features from the Smoothed Pseudo Wigner-Ville distribution using tracks estimated from the McAulay-Quatieri sinusoidal model. The proposed features are the length, frequency, and energy of the principal track. We evaluate the proposed scheme using several datasets and we compute sensitivity, specificity, F-score, receiver operating characteristics (ROC) curve, and percentile bootstrap confidence to conclude that the proposed scheme generalizes well and is a suitable approach for automatic seizure detection at a moderate cost, also opening the possibility of formulating new criteria to detect, classify or analyze abnormal EEGs.

Keywords Time frequency distributions · Epilepsy · Detection · Sinwave analysis · McAulay-Quatieri sinusoidal analysis · Feature extraction

1 Introduction

The electroencephalogram (EEG) is the record of the electrical activity of the neurons in the brain, and can be a good indicator of abnormality in the central nervous system. An abnormal EEG is a dynamic signal which exhibits non-stationary behavior with focal or multifocal activity, spikes, sharp waves, and focal mono-rhythmic discharges. The particular abnormal EEG behavior we will deal with in this paper is associated to epilepsy, which is a neurological disorder in which patients suffer recurrent seizures with sudden incidence causing life-threatening situations and considerably perturbing their quality of life. This disease affects approximately 0.5% of the world population, 25% of which have incontrollable or medically intractable seizures.

In the 80s, EEG analysis was mainly based on two significant characteristics extracted from EEG: frequency and amplitude [33]. These approaches, which include EEG epoch analysis, spike detection, parametric models, methods of clustering, quantitative analysis, and spectral EEG signal analysis, assume quasi-stationarity, require long recordings and present relatively high false detection rates due to the presence of typical EEG artifacts [6, 41, 48, 47]. These methods give frequency and energy information but they do not provide temporal information about when seizure discharges begin. Another way of dealing with non-stationarity is to assume an underlying non-stationary stochastic EEG model, and describe the EEG record as a piecewise stationary signal. This strategy has been used in studies of seizure propagation, automatic recognition of epileptic seizures, and neuronal burst discharges [20, 21, 16]. The inability to accurately detect and quantify these changes and to automatically and efficiently analyze such long-time series has limited the understanding of epilepsy as well as the application of automatic detection systems in the clinical practice [42].

The typical procedure for epilepsy seizure detection is based on brain activity monitoring through EEG data. This usually involves identifying sharp repetitive waveforms or rhythmic patterns in the EEG data that indicate seizure onset. This processing consumes a lot of time, especially in the case of long recordings, but the major problem is the

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subjective nature of the analysis, due to the lack of agreement among specialists when analyzing the same record [2]. From this perspective, it could be necessary to try to identify hidden dynamical patterns which could yield important insight into the underlying physiological mechanisms. From such analysis we could characterize the non-stationary behavior of the abnormal EEG signals and isolate seizure activity in the EEG with the final objective of developing automatic seizure detection systems.

Automatic detection of EEG seizures has been investigated for years. However, so far, no detector has demonstrated to have competitive sensitivity and specificity values due to the presence of artifacts such as line noise, eye movements, muscle artifacts and so on, that makes the detection more difficult being sometimes necessary a visual inspection. The availability of a good algorithm for seizure detection would simplify the review of hours and hours of EEG recordings. It would also be of great value if the detector could help to distinguish between real epileptic seizures and artifacts during non-epileptic events (high specificity).

In the last few years, EEG epileptic detectors have evolved including new techniques such as neural networks [2], non-linear models [34], independent component analysis (ICA) [30], Bayesian methods [22], support vector machines [19], and variance-based methods [40]. Other group of methods potentially useful for detecting and analyzing non-stationary signals are time frequency distributions (TFDs) [11, 23, 44]. These methods allow us to visualize the evolution of the frequency behavior during some non-stationary event by mapping a one dimensional (1-D) time signal into a two-dimensional (2-D) function of time and frequency. Therefore, from the time frequency (TF) plane it is possible to extract relevant information using methods such as peak matching, filter banks, energy estimation, etc. [9, 10, 43].

In this paper, we propose a peak-matching approach based on the McAulay-Quatieri (MQ) sinusoidal model [39] in order to detect tracks in the TF plane, follow their frequency value and measure their energy and length. Our goal is to obtain a new feature vector able to considerably improve the accuracy with low computational cost. We tailor this technique to our detection task and evaluate the proposed method in real EEG databases.

This paper is organized as follows. Section 2 introduces the preprocessing method that provides an EEG without electrooculogram (EOG) artifacts and line noise. It also explains the different techniques that comprise the detection method: the segmentation algorithm, the SPWV distribution (Smooth Pseudo Wigner-Ville) as a suitable TFD chosen for epileptic EEG signals, the MQ peak estimation model applied to SPWV, and the feature extraction method. Section 3 shows the results of the seizure detection method applied to real EEG data from epileptic patients. In Section 4 the main results are discussed and the principal conclusions with further work are presented.

2 Methods

The design of our EEG detection system comprises several stages: acquisition of raw EEG, low-pass filtering and ICA processing, windowing, SPWV analysis, MQ sinusoidal analysis, extraction of features and decision. The EEG is represented as a graph of voltage versus time measured in a number of sensors or electrodes. After acquisition and preprocessing steps, the analysis of the EEG usually relies on windowing the signal using an sliding window. Each resulting segment is processed using time frequency analysis and then we apply peak energy matching on the TF plane based on the MQ sinusoidal analysis, with the objective of extracting features and using them for the task of detection. We assume the existence of some wave in epileptic seizures from results obtained by others authors [11, 23, 50] that have observed tracks along the time frequency plane during a seizure. Our approach is detailed in what follows.

2.1 Raw EEG

Some results show the existence of dominant low frequencies suggesting that a low pass filter with cut-off frequencies of 20 Hz is a reasonable preprocessing [26] before characterizing the EEG by its power spectral density (PSD). Furthermore, EEG activity can be severely contaminated by eye movements, blinking, muscle and heart artifacts, line noise, etc. The elimination of these artifacts demands a preprocessing stage. After sampling, the EEG signal can be modeled as a process $X(n)$ that relates the relevant activities as elementary waves, background activity, noise and artifacts [45]:

$$X(n) = F(n) + \sum_{i=1}^{n_p} P_i(n - t_{pi}) + \sum_{j=1}^{n_a} R_j(n - t_{aj}) + B(n) \tag{1}$$

where $F(n)$ is the background activity; the P_i terms represent brief duration potentials corresponding to abnormal neural discharges; the R_j terms are related to artifacts; and $B(n)$ is the measurement noise which is modeled as a stationary process. Our goal is to obtain neural discharge information (i.e., P_i and t_{pi}) corresponding to epileptic seizures from the signal $X(n)$.

If noise and artifacts are successfully eliminated, we can approximate Eq. 1 as:

$$X(n) \approx F(n) + S(n) \tag{2}$$

where

$$S(n) = \sum_{i=1}^{n_p} P_i(n - t_{pi}) \tag{3}$$

We could apply to Eq. 3 a stationary model for finding amplitude and frequency values that permit to describe the signal EEG characteristics by means of some features. Section 2.5 introduces this model, but we will firstly review in Sects. 2.2 2.4 the preprocessing tasks.

2.2 Artifact removal using independent component analysis (ICA)

After low pass filtering the EEG, it is necessary to separate artifacts such as muscle movements, eye blinks, and other interfering activities without altering important information related to seizure activity. Taking these requirements into account, it has been shown that ICA [31, 35, 32] allows to separate components in EEG signals with the possibility of discriminating between artifacts and brain waves. The ICA technique appears ideally suited for performing source separation in domains where, (i) the sources are independent, (ii) the propagation delays of the 'mixing medium' are negligible, (iii) the sources have probability densities not too different from the gradient of the logistic sigmoid, and (iv) the number of independent signal sources is the same as the number of sensors, meaning that if we employ M sensors, using the ICA algorithm we can separate up to M sources.

In EEG analysis, just the assumption (iv) is questionable [38], since we do not know the effective number of statistically independent brain signals contributing to the EEG recorded from the scalp, and this is the foremost problem in interpreting the output of ICA. However ICA still proves to be useful in this domain [31, 35].

We assume that at time "n" we build a vector of measurements from M sensors $\mathbf{x}(n) = [x_1(n), x_2(n), ..., x_M(n)]^T$ and that we store N such vectors as columns in matrix $\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), ..., \mathbf{x}(N)]$. In ICA, the observed signal $\mathbf{X}$ is assumed to be a linear combination of M unknown and statistically independent sources (assuming that the number of unknown sources is equal to the number of observations). The objective of the ICA algorithm is to find a separating or demixing matrix $\mathbf{W}$ such that we estimate the sources as $\mathbf{S}' = \mathbf{WX}$.

For EEG, the value of M depends on the montage used by the electrodes. It is possible then to estimate a signal $\mathbf{S}' = \mathbf{WX}$; where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_M]^T$ is the mixing matrix obtained by ICA and $\mathbf{S}'$ is the linear combination of the used channels. The columns of the inverse matrix $\mathbf{W}^{-1}$ give the projection strengths of the respective components onto the scalp sensors. These weights give the scalp topography of each component, and provide evidence about the physiological origin of the components [32].

"Filtered" EEG can be derived as $\mathbf{X}' = \mathbf{W}^{-1}\mathbf{S}''$, where $\mathbf{S}''$ is the matrix of activation waveforms, where those rows in $\mathbf{S}'$ that represent artifact sources are set to 0. The rank of "filtered" EEG data is less than that of the original data.

It is important to know that the spatial order in $\mathbf{S}'$ does not correspond to the spatial order in $\mathbf{X}$, nevertheless, we can use the scalp topographies of the components as an indicator of the biologic origin of the sources.

There are many well known procedures for solving the ICA problem, for instance those based on Fast-ICA or kernel-ICA [36] and in principle any ICA algorithm could be employed during the preprocessing. Without loss of generality we will use here the Joint Approximate Diagonalization of Eigen-matrices (JADE) that is based on the diagonalization of cumulant matrices [31, 12]. EOG artifacts were identified and visually eliminated on JADE components similarly as in a previous work [31], however we are also exploring automatic mechanisms for such elimination [24]. In the present paper, the detailed process followed to remove EOG artifacts and the problems presented for eliminating other artifacts have not been included, but the interested reader may refer to [24, 27] for more details.

2.3 Windowing

Since it is necessary to detect spikes or brief potentials, the window length should be taken as short as possible. Although the time frequency methods are oriented to deal with the concept of stationarity, increasing the data length implies to reduce the degree of stationarity of EEG because in longer windows more dynamics events come into play. We will work with quasi-stationary windows, defined as a period of time in which the EEG signal can be considered to be stationary. Taking all this into consideration, the preprocessed EEG signal was segmented using 5-s non-overlapping rectangular windows to obtain good resolution and low computational cost [23].

2.4 Time frequency analysis using the Smooth Pseudo Wigner-Ville distribution (SPWV)

In a series of papers, Cohen generalized the definition of time frequency distributions (TFDs) in such a way that a wide variety of distributions could be included in the same framework [14, 4]. Specifically the TFD of a real signal $x(n)$ is computed as:

$$P(t,\omega) = \frac{1}{2\pi}\int_{\infty}^{\infty}\int_{\infty}^{\infty} \mathrm{A}(\theta,\tau)\Phi(\theta,\tau)\mathrm{e}^{\ j\theta t\ \ j\omega\tau}\,\mathrm{d}\theta\mathrm{d}\tau \tag{4}$$

where,

$$A(\theta,\tau) = \frac{1}{2\pi}\int_{\infty}^{\infty} x\left(u+\frac{\tau}{2}\right)x^*\left(u-\frac{\tau}{2}\right)e^{j\theta u}\mathrm{d}u \tag{5}$$

is the so-called ambiguity function and the weighting function Φ (θ, τ) is a function called the kernel of the distribution that, in general, may depend on time and frequency.

When $\Phi(\theta, \tau) = 1$, we have the Wigner-Ville distribution $WV(t, \omega)$. The Smooth Pseudo Wigner-Ville (SPWV) distribution is obtained by convolving the $WV(t, \omega)$ with a two-dimensional filter in t and ω. This transform incorporates smoothing by independent windows in time and frequency, namely $W_w(\tau)$ and $W_t(t)$:

$$SPWV(t,\omega) = \int_{\infty}^{\infty} W_w(\tau)\left[\int_{\infty}^{\infty} W_t(u-t)x\left(u+\frac{\tau}{2}\right) x^*\left(u-\frac{\tau}{2}\right)\mathrm{d}u\right]\mathrm{e}^{\ j\omega\tau}\mathrm{d}\tau \tag{6}$$

Eq. 6 provides great flexibility in the choice of time and frequency smoothing, but the length of the windows should be determined empirically according to the type of signal analyzed and the required cross term suppression [3]. The SPWV in Eq. 6 does not satisfy the marginal properties, that is, the frequency and time integrals of the distribution do not correspond to the instantaneous signal power and the spectral energy density, respectively [29]. However it is still possible for a distribution to give the correct value for the total energy without satisfying the marginals [14, 15]. Therefore the total energy can be a good feature to detect signal events in the SPWV representation because the energy in EEG seizure is usually larger than the one during normal activity.

The TFDs offer the possibility of analyzing relatively long continuous segments of EEG data even when the dynamics of the signal are rapidly changing. Taking the most of these, we could extract features from the time frequency plane such as ridges energy, frequency band values, and so on. However, three considerations have to be taken. Firstly, a TFD will need signals as clean as possible for good results. Secondly, a good resolution both in time and frequency is necessary and as the "uncertainty principle" states, it is not possible to have a good resolution in both variables simultaneously. Thirdly, it is also required to eliminate the spurious information (i.e., cross-term artifacts) inherent in the TFDs [14, 15, 17].

The first consideration implies a good pre-processing stage to eliminate artifacts and noise. Second and third considerations have motivated the TFD selection or design, then it is important and necessary to choose a suitable TFD for seizure detection in EEG signals as well as for a correct estimation of the MQ sinusoidal model (next section). Indeed, it is desirable that the TFD has both low cross-terms and high resolution. Choosing a distribution depends on the information to be extracted and demands a good balance between good performance, low execution time, good resolution, and few cross terms. The SPWV satisfies these requirements and this distribution seems to provide the necessary information to efficiently analyze EEG data.

There are several other methods that improve the SPWV and provide a good concentration of the signal components and fewer cross-terms such as the reassignment method, the optimal kernel design, the ridge and skeleton method, wavelets, etc. They all provide similar results but exhibit much higher computational cost compared with the SPWV distribution [23].

One consideration before using the TFD is to convert each EEG segment into its analytic signal for a better time-frequency analysis. The analytic signal is defined to give an identical spectrum to positive frequencies and zero for the negative frequencies, which better reflects the physical situation and shows an improved resolution in the time frequency plane [15]. It associates a given signal $x(n)$ to a complex valued signal $y(n)$ defined as: $y(n) = x(n) + jHT\{x(n)\}$, where $y(n)$ is the analytic signal and $HT\{.\}$ is the Hilbert transform.

Once the preprocessed EEG signal is segmented and converted to its analytic signal we calculate the TFD of each segment, before proceeding with the MQ analysis described in the next section.

2.5 Tracks extraction using the McAulay-Quatieri (MQ) sinusoidal analysis

In 1986, Robert McAulay and Thomas Quatieri proposed a new method for analysis/synthesis of continuous time speech signals which turned out to be a reconstruction process that provided a close approximation of the original signal [39].

EEG waves represent the combined activity of many neuronal cells which can manifest as oscillatory waves. In this sense the EEG signal may be modeled as a collection of sinusoidal components of arbitrary amplitude, frequency and phase [7, 18], such that the elementary wave part in Eq. 3 can then be written as:

$$S(n) = \sum_{\ell=1}^{L} A_\ell \exp[jn\Psi_\ell] \tag{7}$$

where A_ℓ and Ψ_ℓ represent, respectively, the amplitude and frequency of the ℓ -th component (out of L components (waves) conforming the EEG signal). Here amplitudes and frequencies are implicitly related to the P_i terms of Eq. 3. The problem now is to estimate the terms A_ℓ and Ψ_ℓ in relation with epileptic seizures. The original MQ algorithm works with both the discrete Fourier transform (DFT) to estimate the frequency and the short time Fourier transform (STFT) to estimate the complex envelope (amplitude and phase). Our method performs this estimation by peak-matching based on the localization of peaks in energy on the time frequency plane. By linking peaks which occur at similar frequencies, we can define tracks along the time frequency plane.

The concept of sinusoidal birth and death is used to account for the appearance or disappearance of spectral peaks between frames, such that tracks are formed by connecting peaks between contiguous frames (see Fig. 1, upper). A new track is born if the frequency of a peak in the current frame does not appear in the $\pm\Delta$ interval of the frequency of that peak in the previous frame. Similarly, a track dies when a peak in the current frame is not followed by another peak in the $\pm\Delta$ interval in frequency in the next frame. A magnitude condition is also imposed so that contiguous peaks at the same frequency which have large magnitude differences are proposed to belong to different tracks (the partials). Using this magnitude condition, we follow a process of matching each frequency in frame t to some frequency in frame $t+1$ by quadratic interpolation [39]. The $\pm\Delta$ value was obtained empirically. Figure 1 illustrates the birth and death of frequency tracks formed by connecting peaks of similar frequencies between frames (upper) and the result of applying this method to an EEG seizure segment using the SPWV (bottom). In what follows, this procedure will be used and denoted as tracks extraction.

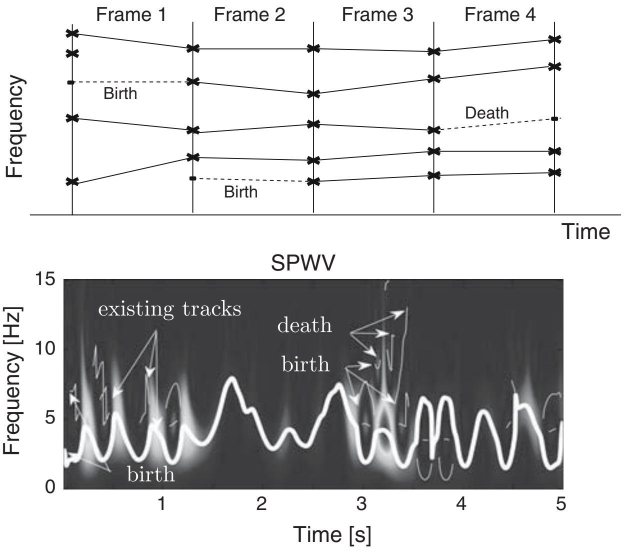

Fig. 1 *Upper* Frequency matching process for determining frequency tracking in a TFD window. Each path in the graph is called a track. The birth of a track occurs when there is no partial in the previous frame to connect a peak in the current frame. Conversely, death occurs when a partial does not exist in the next frame to connect a peak in the current frame. *Bottom* Peak matching on the SPWV from a real EEG segment in a seizure. There is a principal track (largest length), marked with a thick line, and other minor tracks, marked with a thinner line. These tracks serve to summarize the spectral content on the time frequency plane calculated by SPWV

2.6 Feature extraction from tracks

We will further process the obtained tracks after the MQ sinusoidal analysis to obtain relevant information to be used for detection of abnormal activity. We propose to use three features based on length, frequency, and energy of the principal track. Figure 1 (bottom) shows the existence of a principal track in the seizure corresponding to non-normal activity. Similarly in another EEG record with a duration of 75 s (see Fig. 2), we can observe a longer track $\hat{F}$ clearly visible during the seizure. These appreciations make it possible to introduce a new feature based on the duration of the principal track and use it in the detection task.

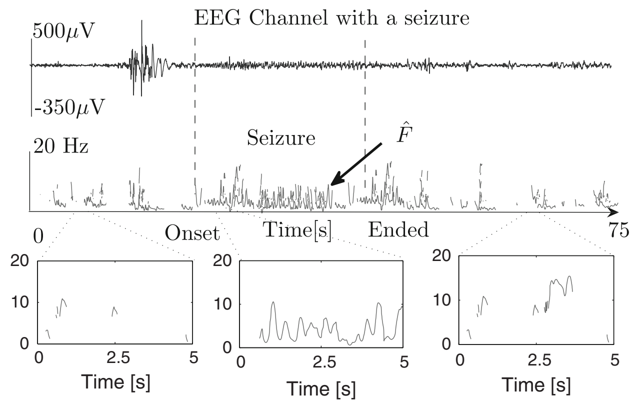

Fig. 2 Track extraction using a record with a seizure. The figure shows the EEG in time domain (*upper*) and time frequency domain using track extraction (*middle*). The length of the register is 75 s. Taking zoom in a window (5 s) on three different EEG parts, we can observe how a dominant and sustained frequency F appears when there is a seizure, while tracks appear discontinued in the non seizure periods

Apart from having the duration of the principal track, it also becomes necessary to measure other characteristics such as energy and frequency to bring better information about this principal track. We have an EEG segmented into K segments, each EEG segment gives us the values L_k, F_k, and E_k and we subsequently construct a three dimensional feature vector for each segment. The procedure to be applied to each segment is explained below.

We work with a discretized version of the k-th segment in the time frequency plane, $\vartheta_k(n, m)$, such that the track extraction procedure identifies the coordinates of every track with a dummy variable that is equal to 1 in those points:

$$T_{k,\ell}(n,m) = \begin{cases} 1, & \textit{if } \vartheta_k(n,m) \text{ belongs to the } \ell-\text{th track} \\ 0, & \text{otherwise} \end{cases}$$

The lenght of every track is computed as:

$$L_{k,\ell} = \sum_n \sum_m T_{k,\ell}(n,m) \tag{8}$$

the average frequency is

$$F_{k,\ell} = \left(\sum_n \sum_m T_{k,\ell}(n,m)m \right) / L_{k,\ell} \quad (9)$$

and the energy is

$$E_{k,\ell} = \left(\sum_n \sum_m T_{k,\ell}(n,m)\vartheta_k(n,m) \right) / L_{k,\ell} \quad (10)$$

We identify the principal track in segment k as the largest track:

$$\ell' = \arg\max_\ell \{L_{k,\ell}\} \quad (11)$$

such that the final features for segment k are:

$$L_k = L_{k,\ell'} \quad (12)$$

$$F_k = F_{k,\ell'} \quad (13)$$

$$E_k = E_{k,\ell'} \quad (14)$$

Remark If there is more than one track with the same length, the principal track is chosen by the largest energy.

2.7 Materials and settings

This paper uses two EEGs databases: one of them consisting in seven adult epileptic patients obtained in a restful wakefulness stage and recorded at the Clinica Universitaria de Navarra, Department of Neurophysiology (Pamplona, Spain). All of them contained focal epileptiform activity, according to experienced neurologists. We used 11 EEG records of 24-min length taken from 23-rd and 25-th channels using the 10 20 International System of Electrode Placement with additional anterotemporal electrodes T1/T2. The seizure duration is around few minutes. In practice, raw EEG data were digitized at a sample rate of 200 Hz using a "DAD-32" equipment (La Mont Medical) and were filtered by a digital low-pass filter with cut-off frequency of 20 Hz. The other database described in [49] was used to get more generalization. We created a detection task called N1, comprising both normal and seizure EEG segments. We have also used an EEG signal of 32.5-min length to evaluate the effect of the number of samples in the performance of our detector. This problem is called N2.

All computation has been carried out off-line in a Pentium III computer, using the Matlab (V.6) programming environment. The empirically obtained Δ value was 0.5 Hz and the magnitude condition for peak-matching was 4% of maximum energy per TFD segment.

3 Results

The elimination of undesirable information of the EEG improves our task detection or EEG feature extraction. For example, Fig. 3 shows the results of three time frequency representations of an epileptic EEG segment. We have the SPWV of the raw EEG (upper), the SPWV of the preprocessed EEG (middle), and track extraction using preprocessed EEG (bottom). Note how the ICA preprocessed EEG produces a SPWV transform that highlights the non-stationary signal in an epileptic episode permitting to better identify the tracks. We think that this improvement is due to the elimination of considerable contribution of noise, background, and artifacts that hide important information from seizure activity. This benefits the task of extracting features and detection of seizure activity, as will be shown in what follows.

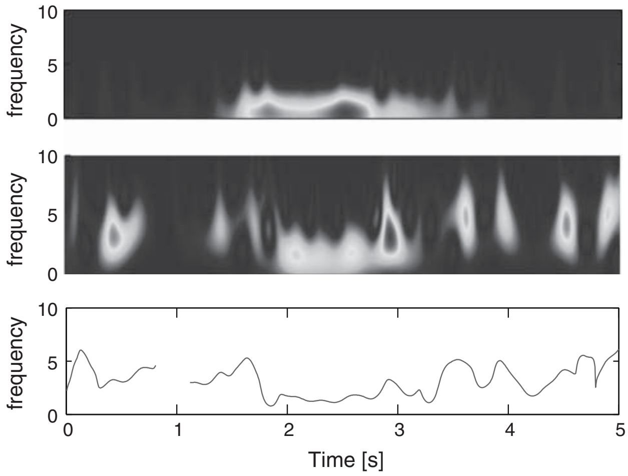

Fig. 3 EEG segment in a seizure. N=1000, and Kaiser 2 D filter (15,54) was used in SPWV. *Upper* SPWV of the raw EEG. *Middle* SPWV of preprocessed EEG. *Bottom* Track extraction from SPWV using preprocessed EEG. Note how it is easier to obtain a principal track (*bottom*) using a preprocessed EEG (*middle*) than a raw EEG (*upper*). We can also see the improvement in resolution obtained by this method highlighting the non stationary behavior of the seizure

Figure 4 shows the results of tracks extraction on three EEG segments. Note the correspondence between a larger track and its oscillatory frequency, demonstrating the typical non-stationary behavior during epileptic episodes. Figure 5 shows the feature vector in an epileptic EEG register for $k = 58$ segments, consisting in L , F, and E (upper, middle, and bottom pannels, respectively) and illustrates how these features grow during the seizure (segment between the arrows).

In every EEG register we identify L^* as the largest track, and F^*, and E^* the corresponding frequency and energy values, at the same position as L^* in the register. The threshold values are selected as the median values of all L^*, F^*, and E^* measures on the training set. The thresholds obtained by median values that we have used in what follows are $L = 2.7$ s, $F = 4.13$, and $E = 24\%$

To evaluate the performance of the proposed decision scheme, we use six random EEG records from patient 1 as training data, their L^*, F^*, and E^* values are depicted in

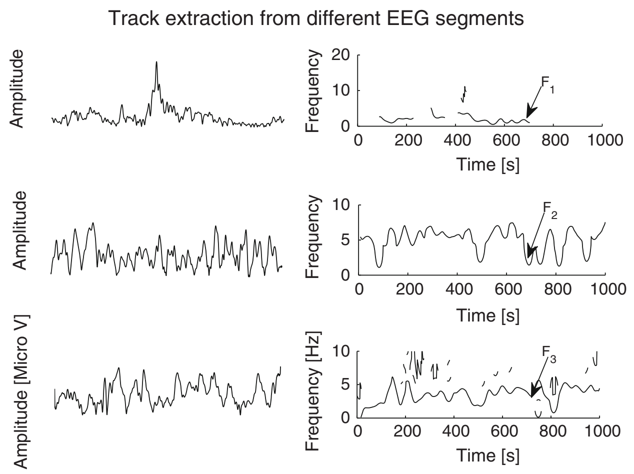

Fig. 4 Different EEG segments (5 s length) and track extraction. The frequencies F_1, F_2, and F_3 correspond to the higher track $F_k \quad F_{k,\ell'}$ applying Eq. 12. For this case, using three segments, $F \quad \{F_1, F_2, F_3\}$

Table 1. The rest of the EEG recordings from that patient, plus data from patients 2 7, plus the N1 data collection are used as test data. Table 2 presents the results of sensitivity and specificity, which are defined as follows:

Sensitivity: Percentage of EEG segments containing seizure activity correctly classified.
Specificity: Percentage of EEG segments not containing seizure activity correctly classified.

We also use another measure of performance of our detector as a function of dataset size called "F score" and defined as:

$$F_{\text{score}} = 2 * \text{sensitivity} * \text{specificity}/(\text{sensitivity} + \text{specificity}) \tag{15}$$

Note the good performance of our method when we test with different EEG data (patients number 2 7 and N1 problem in Table 2) and how this performance is also good when we try to detect epileptic activity from the same patient (patient number 1 in Table 2).

Since dataset used in the Table 2 is quite small (the larger EEG is 15.01 min that corresponds to 901 samples), we use a new larger EEG database (N2) to evaluate the effect of the dataset size in our detector. To evaluate this effect we compute the receiver operating characteristics (ROC) and area under a ROC curve (AUC) for a varying data size. A value of AUC of 0.5 indicates random detections, and a value of 1 indicates perfect detection. Note how the AUC increases when more data are used, up to a maximum value of 0.925 (see Fig. 6, upper).

A 95% confidence interval for the F_{score} is estimated using N bootstrap datasets [25]. Each bootstrap dataset is a simple random sample from 50 to n values selected with

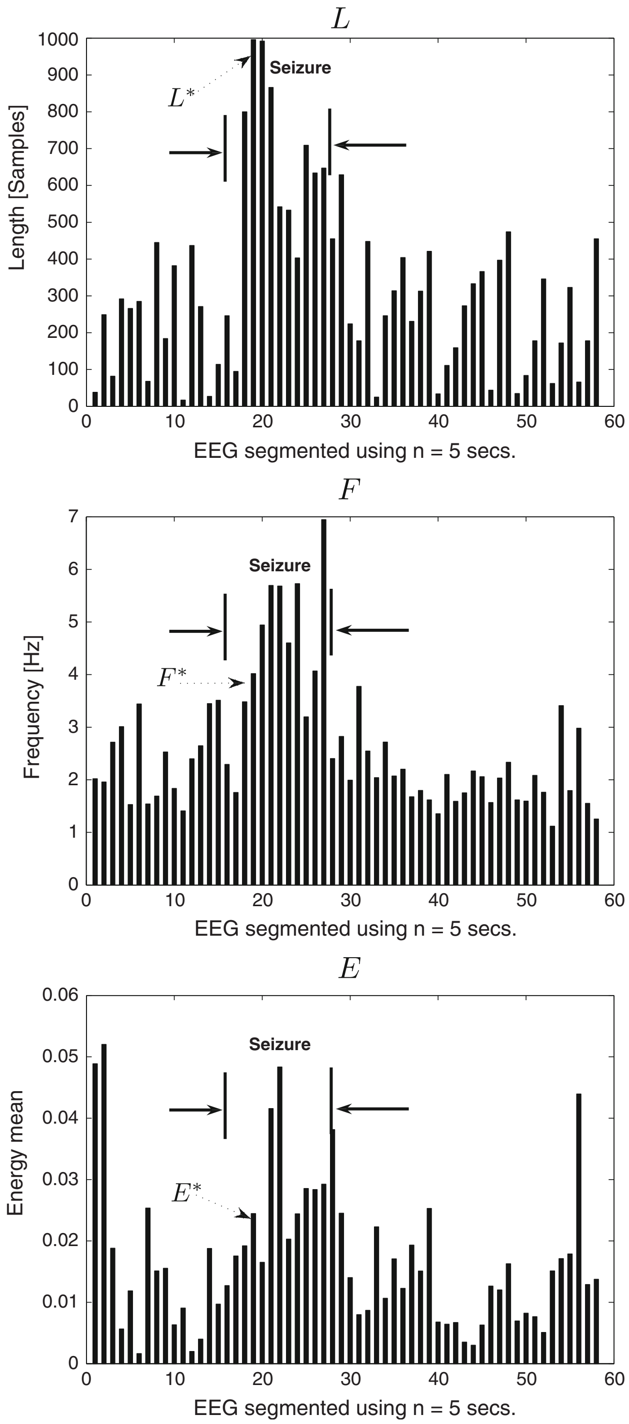

Fig. 5 Features extraction for an epileptic EEG register ($k \quad 58$ segments). The seizure is localized between the *arrows* and the EEG was segmented using $n \quad 5$ s. *Upper* Vector L. *Middle* Vector F. *Bottom* Vector E. The feature vector F gives us information about frequencies in seizure. We can visually choose the larger L^* value (*dotted arrow*) with its corresponding values in frequency F^* and energy E^* to test the classification algorithm in new EEG datasets

replacement from the original EEG data (the increment step is 50). Because a bootstrap dataset is drawn with replacement, some of the original observations are repeated more

Table 1 Analysis of different EEG's from patient 1 in seizure (training data)

EEG	L^* [s]	F^* [Hz]	E^* [%]
1	2	1.7	26
2	3	5.9	37
3	2.5	4.4	28
4	3.2	2.5	32
5	2.6	6.5	1
6	3	3.8	27

Table 2 Sensitivities and specificities of EEG's in different patients (test data)

Patient	EEG	Seizure	Sensitivity [%]	Specificity [%]	F score
1	03:02	00:31	89	97	92.8
	00:40	00:11	90	99	94.2
	15:01	00:22	80	89	84.2
	00:58	00:29	30	100	46.1
	01:34	00:13	77	94	84.6
2	04:54	00:42	72	99	83.3
3	05:24	01:15	88	93	90.4
4	06:45	01:46	56	97	71
5	05:36	00:44	90	99	94.2
6	10:52	01:43	66	100	79.5
7	04:53	01:31	30	100	46.1
N1	00:46	00:23	97	85	90.6
Average			72.1	96	82.3

The duration of EEG records and epilepsy episode are given in minutes

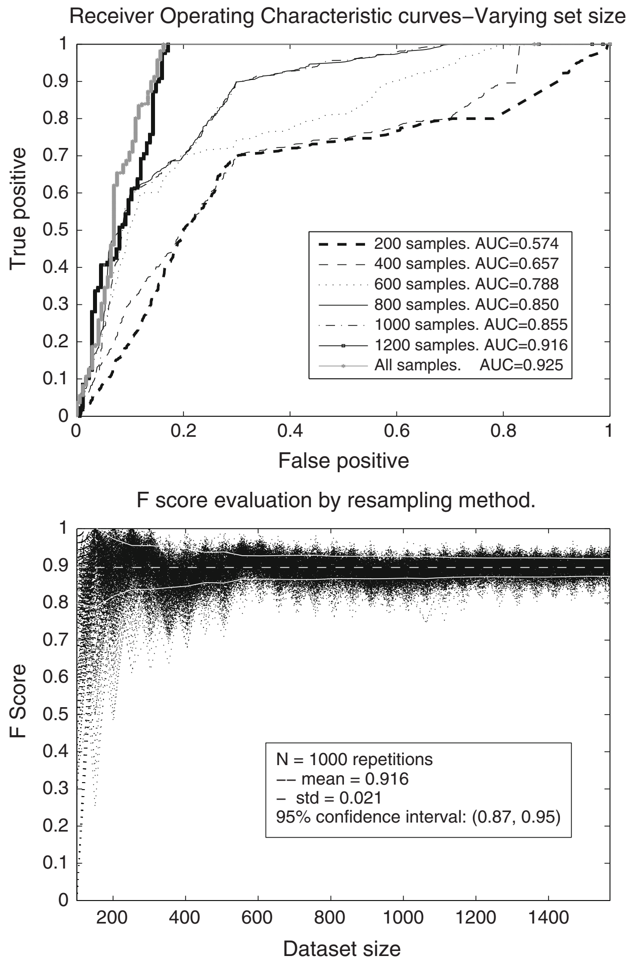

Fig. 6 Evaluation of the dataset size effect in the N2 detection problem. *Upper* Receiver operating characteristics (ROC) curves and area under a ROC curves (AUC) values. Observe the AUC values and note the normal behavior of the detector with the increasing data size. *Bottom* Confidence interval estimation for the F_{score} using N 1000 bootstrap samples. Note how the value of F_{score} is more stable when we increase the dataset size and present a good percentile bootstrap confidence (0.87, 0.954)

than once. The statistics are estimated for each bootstrap dataset and bootstrap confidence interval was computed as the percentile confidence, where the endpoints of the 95% confidence interval are given by the 25th and 975th sorted bootstrap values. For N2 problem, using $N = 1000$ and $n = 1569$ samples, the interval is (0.87, 0.95). Figure 6 (bottom) shows the evolution of F_{score} for $N = 1000$, the median $m = 0.91$ (dashed line), and standard deviation $\sigma = 0.0217$ (solid line curves represent $m \pm \sigma$). Note how the value of F_{score} is more stable when we increase the size of the data and it presents a good percentile bootstrap confidence. Although the percentile bootstrap illustrated here is one of the simplest bootstrap confidence interval methods, this experiment in large EEG data discards the hypothesis that our results are overfitted to the data.

4 Discussion and conclusions

A new feature extraction method in epileptic EEG signals relying on track extraction and analysis in a time frequency plane is presented. Our results suggest that the proposed method is a powerful tool for extracting features in EEG signals. The feature vector based on track measurements such as length, frequency, and energy (L, F, E) in every segment is simple and useful for the detection task. It gives us ℓ tracks on the time frequency plane $\vartheta(n, m)$ representing the true nature of the spectral components and really concentrates and localizes EEG frequencies with low computational cost. This opens up the possibility of classifying epileptic EEG channels in a new and promising way.

In order to account for noise, background, artifacts, and seizure activity, the EEG has been preprocessed using a low-pass filter and ICA. ICA has been reported to isolate multiple ictal components in EEG analysis [35] although there is a noticeable difference between ICA and low-pass filter when a visual inspection of the time frequencies plane is done. Automatic EOG removal has proved to be useful except when EEG is very contaminated with muscle artifacts because ICA is not able to eliminate them totally. Muscle artifacts are more difficult to suppress since its morphology and topography causes a confusion with the abnormal spikes. We think that this problem does not considerably affect the performance of the detection task because the seizure information is not affected if we do not eliminate the muscle artifacts. Additionally, a low-pass filter was chosen because it is possible to detect epileptic activity on low frequencies and the EEG typically has a frequency content from 1 to 40 Hz [37].

We have seen the presence of tracks on the time frequency plane during seizure events as also observed by other authors [11, 50]. In [11, 9, 10] the authors found a time frequency seizure criteria based on two calibrations in time and time frequency domain. In our case, we have proposed a new form of extracting features based on principal track by following the ridges (tracks) on the time frequency plane and obtaining measures such as duration, frequency, and energy. The length of the ridge of the main time frequency EEG component has been previously proposed in a number of applications including EEG [9, 10, 43]. Features such as energy and other frequency-based features have been widely used in the literature dealing with EEG. The extraction method proposed here is much simpler than others previously proposed in the literature, since they need many calibrations to properly work.

Another important issue is the applicability of the method to any distribution due to its non-dependency to a particular TFD. For example, the Ridges Extraction method [5], which is a good approach for the reassignment method [23], is able to extract relevant information from the time frequency plane, but it depends on the values obtained by reassignment method affecting the time computation [23]. This problem is presented in [13] when the frequency update is not easy because it is necessary to modify the ridge detection algorithm.

The proposed technique could also be used in any scenario where different types of EEG activity have to be detected and associated to particular events. In brain computer interface (BCI) applications, the model could be adopted to detect “brain actions”, e.g., moving up, left, right or down a cursor on a screen using EEG readings. The detection of other brain disorders could also be tackled [28, 46, 1]. However, further research is needed to validate the discriminative capability of the track extraction features in these new scenarios. Since the algorithm takes information from a TFD, it is necessary a suitable distribution for EEG signals, subject to the following compromise: high-quality resolution, good detection, and low computation time [8]. With a good TFD choice, the localizations of both amplitude and frequency peaks are less problematic. We have chosen the smooth pseudo Wigner-Ville (SPWV) as the TFD suitable for EEG signal detection as it provides good resolution, low cross-terms, and is computationally efficient [23].

Although the detector presented a good performance by the evaluation of receiver operating (ROC) curves, “F score” measure and confidence intervals, another important issue is how to select the threshold to yield high sensitivity. The particular value of magnitude threshold and Δ used during track extraction algorithm do not appreciably affect the results, but a good choice in these values is required. Likewise, it is necessary a long-term analysis to understand the epilepsy behavior and to account for all possible L values (maximum and minimum) in seizure, because our EEG data records were not very large. Further research into this matter including how to incorporate a threshold selection into an automatic seizure algorithm is worthwhile. Future works implies the study of a wide range of machine learning methods to better exploit the features proposed here to finally obtain improved seizure detections.

In conclusion, this paper presents a new EEG feature vector based on track measurements such as length, frequency, and energy (L, F, E) using the time frequency distributions (TFD) and MQ sinusoidal analysis. The performance during detection shows that our feature vector is a suitable approach for epileptic seizure detection, it generalizes well, and opens the possibility of using this method in other scenarios such as brain computer interface (BCI) and detection of other brain disorders.

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