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A Time-Frequency Approach For EEG Spike Detection

[1]*Hamid Hassanpour* and [2,3]*Boualem Boashash*

[1]School of Information Technology and Computer Engineering, Shahrood University of Technology, P.O. Box: 316, Shahrood, Iran
[2]University of Queensland, Centre for Clinical Research, Brisbane, Australia
[3]College of Engineering, Qatar University, Doha, Qatar

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Abstract: This paper presents a new method for detecting EEG spikes using the time-frequency distribution of the signal. As spikes are short-time broadband events, their energy patterns are represented as ridges in the time-frequency domain. In this domain, the high instantaneous energy of the spikes makes them more distinguishable from the background. To detect spikes, the time-frequency distribution of the signal of interest is first enhanced to attenuate the noise. Two frequency slices of the enhanced time-frequency distribution are then extracted and subjected to the smoothed nonlinear energy operator (SNEO). Finally, the output of the SNEO is thresholded to localise the position of the spikes in the signal. The SNEO is employed to accentuate the spike signature in the extracted frequency slices. A spike is considered to exist in the time domain signal if the spike signature is detected at the same position in both frequency slices. The performance of the proposed method is evaluated and compared with an existing spike detection method using both synthetic and newborn EEG signals.

Key words: EEG % Nonlinear energy operator % Spike detection % Time-frequency distribution % WVD % Seizure % Time-frequency analysis

INTRODUCTION

Studying the behaviour of spikes in the electroencephalogram (EEG) is important for detecting brain ab-normality [1]. Seizures, which are a result of synchronous discharge of a large number of neurons, can be detected using spikes and their firing pattern in EEG [1, 2]. In this application, performance of the EEG seizure detection technique can be improved by increasing the accuracy of the spike detection method. Traditionally, EEG signals are scanned for epileptic spikes by physicians. This process becomes very tedious and time-consuming in case of long EEG recordings. Therefore, it is increasingly necessary to present an efficient automatic method for spike detection.

Spikes can be defined as transient signals, clearly distinguishable from the background activity by a pointed peak [2]. From the signal processing point of view, spikes are nonstationary short-time broadband signals with high instantaneous energy [3]. Spike detection in such non-stationary environmentsas in the case of the EEG, is a challenging problem; in particular, it was shown that detection techniques based on the assumption that the background signal is stationary or quasi-stationary, such as the techniques in [3], are inefficient in this type of environment [17].

Time-frequency (TF) signal analysis is a technique that jointly represents both time and frequency domains of the signal [14]. It is the most suitable technique to overcome the problem raised by the non-stationary aspects of both spikes and EEG signals. In the TF domain, spikes are reflected as broadband localized energy patterns, whilst the background is spread over the TF plane depending on its characteristics in terms of their duration and frequency activities.

Fig. 1(a) shows a time series signal including one spike in background white Gaussian noise (signal to noise ratio, SNR=0 dB). The spike can be seen in Fig. 1(b). The TF representation (TFR) of the signal is shown in Fig. 1(c). In this figure the ridge-like localised patterns are the reflection of the spikes and the spike-like noise. However, the ridge related to the spike is more energetic and has a wider duration than the ridges resulting from the noise.

Corresponding Author: Hamid Hassanpour, School of Information Technology and Computer Engineering, Shahrood University of Technology, P.O. Box: 316, Shahrood, Iran. E-mail: h_hassanpour@yahoo.com

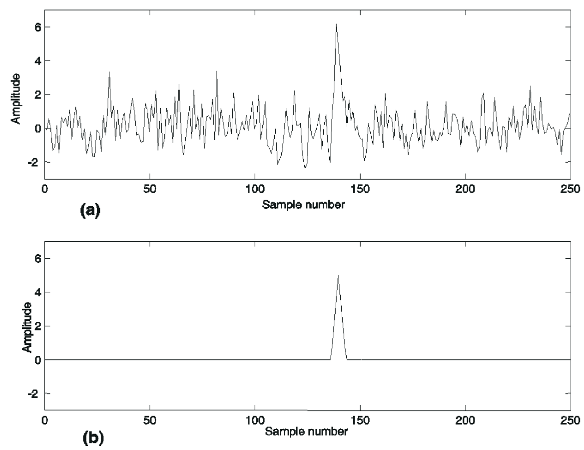

Fig. 1: (a) A time series signal including one spike in a 0 dB noise. (b) The time series spike

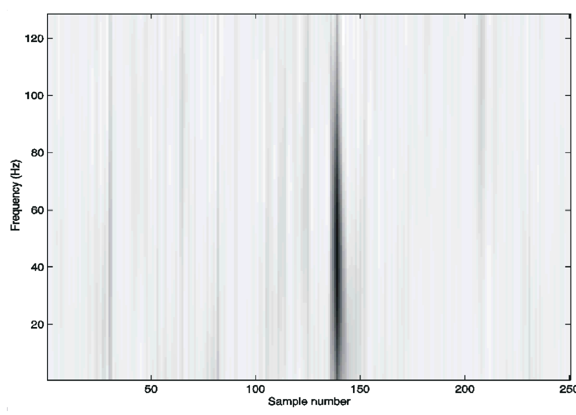

Fig. 2: TF representation of the signal shown in Fig. 1(a)

Depending on the signal to noise ratio, the presence of noise may prevent recognition and localisation of spikes. A two-stage spike detection technique is presented to deal with the problems of noise and nonstationarity. The first stage is a preprocessing stage whose goal is to reduce the effect of the noise in the TF plane by using a singular value decomposition (SVD)-based method [4]. The second stage is the detection stage. The detection process uses the above-mentioned characteristics of spikes in the TF domain along with the accentuating capacity of the nonlinear energy operator (NEO) [3], to detect spikes in the signal.

Spike Detection

Existing Methods: There are several spike detection methods in the literature such as [3, 5, 6]. In [5], segments of EEG are correlated with templates of EEG spikes. A high degree of correlation between the template and the EEG segment indicates the presence of spike. Since the frequency activity of the EEG signal varies widely, spikes can appear in many different formats. Hence, to detect spike events using the correlation based technique a large number of templates is needed to efficiently detect spike events. In another study, a rule-based method has been adopted for recognizing special features of spikes [6]. The method achieved a high positive detection rate at the expense of a high false alarm rate [7].

In [8], Kaiser has introduced an operator, named the nonlinear energy operator (NEO), to measure the instantaneous energy of the signal. The output of the operator is proportional to the instantaneous amplitude and instantaneous frequency of the signal. Hence, the NEO can be used for amplifying the spiky activities in a background signal. However, the NEO is sensitive to noise and has the problem of cross terms [3, 8]. To alleviate these problems, a smoothed nonlinear energy operator (SNEO) has been used in [3] for detecting spike events in EEG signals. In this technique the output of the NEO is convolved with a Barlett window in order to eliminate the spurious spikes due to the cross terms and background noise. This approach is, however, sensitive to noise as reported in [9].

All of the above techniques are based on the assumption that the background signal is stationary. In fact, these methods preprocess the signal for highlighting the nonstationary spike events in a stationary back- ground. These approaches have profound limitations for signals such as newborn EEG where the background is nonstationary [10]. Consequently, there is a need for a spike detection algorithm that takes this characteristic into account. We propose the TF-based detection approach which is the focus of this work.

TF-Based Detection: Time domain spike detection in newborn EEG signal is a complicated task due to the nonstationary nature of both spikes and EEG signals. By using the frequency domain for spike detection, the temporal information of the EEG is lost. Since spikes are broadband events and the background EEG has activity in wide frequency ranges, from almost DC to higher than 100 Hz [11], the signature of spikes in the frequency domain is not clear. For these reasons classical temporal and spectral analysis have limited success in EEG spike detection. We propose a TF-based method using both time and frequency domain information of the signal to detect spikes in a signal.

A time-frequency distribution (TFD) of a signal is a joint representation of both time and frequency domains of the signal. For a given signal, k(t), the TFD that belongs to the quadratic class can be expressed as [12]:

$$r_z(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} e^{j2pu(t-n)} g(u,t) z(n+\frac{t}{2}) \times z^*(n-\frac{t}{2}) e^{-j2p\,ft}\, du\, dn\, dt \quad (1)$$

Where $z(t)$ is the analytic signal associated with $x(t)$ and $g(\nu,\tau)$ is a two-dimensional kernel that determines the characteristics of the TFD. By setting $g(\nu,\tau)$ = 1, for example, $\rho_z(t,f)$ represents the Wigner-Ville distribution (WVD) [13].

Since spikes are broadband events with high instantaneous energy, they can be represented as ridges in the TF domain. The extension of spikes signature into the higher frequency area of the TF domain, as well as their high instantaneous energy allow them to be more distinguished from the background. Therefore, to detect spikes using a TF-based method there is no need to assume that the background has no high frequency activity as was assumed in [3].

To detect spike events, the signal is mapped into the TF domain. In this domain, the TFD tends to spread the noise throughout the TF plane, hence reducing its effects on the useful part of the signal. To further attenuate the effects of noise on the TFD of the signal, the SVD-based technique proposed in [4] is used. In this approach, the matrix-converted signal is divided into signal subspace and noise subspace using the SVD technique for reducing the noise. The author has shown that noise in the TFR of a signal is also reflected in the singular vectors (SVs) of the matrix. Hence, the SVs are filtered to further enhance the TFR. In [4], the author has shown that reconstructing the TFD of the signal using the filtered singular vectors significantly reduces the noise effect without altering the basic structure of the TF patterns of the signal.

Once the TFD of the signal has been enhanced, two relatively high frequency slices are extracted (in the TFD, the frequency slices are extracted from higher frequency area). If both frequency slices have any signature of a spike at the same position, the related time domain signal is judged to contain a spike at that position. The use of only two frequency slices instead of the whole TF domain allows a significant reduction in computation while not sacrificing detection performance. To further amplify these signatures, the NEO is applied to the frequency slices. Assuming that the NEO, ψ, is applied to the time-series $l(n)$ representing a given fre
output is given by:

$$\psi[l(n)] = l^2(n) - l(n+1)l(n-1) \quad (2)$$

The local peaks at the output of the SNEO that are higher than a predefined threshold are considered as an indication of the existence of a spike at that location in the time-series. In [3], the authors have shown that using Barlett window applied to the output of the NEO can help by better localising the local maxima. The process that combines the NEO and the windowing is called the smoothed nonlinear energy operator.

Applying the SNEO on the frequency slices can better highlight the signature of spikes than applying it on the related time domain signal. Because, the frequency slices have less noise and background activities compared to the related time domain signal as TFD spread the noise in the TF plane.

TF Distribution Selection: To detect spikes in a signal using the TF signal analysis techniques, a reduced interference distribution (RID) is needed in order to reduce the problem of cross-terms raised by the multicomponent nature of spikes. In [13], the author has shown the importance of RIDs in analysing nonstationary and multicomponent signals. There are a number of RIDs. Among those, the BD [14] and the CWD [15] have been largely used for EEG signal analysis [10, 15].

We independently compared four TFDs, namely MBD, CWD, WVD and Spectrogram, to find a suitable one for spike detection in EEG signals. Our investigations indicate that the CWD can display spike signature clearer than the other approaches. Indeed, the CWD has a better resolution for displaying spike signatures compared to the other distributions.

RESULTS AND DISCUSSION

The efficiency of the presented spike detection method has been evaluated using both a synthetic signal and real newborn EEG data. The results are compared with the results obtained when the SNEO is applied directly to the raw time-series as suggested by [3].

Synthetic Signal: For the purpose of evaluating the performance of the proposed method, we use the following synthetic signal [3]:

$$x(t) = s(t) + p(t) \quad (3)$$

Where s(t) and p(t) are the background signal and the spike train set, respectively. The background is chosen:

$$s(t) = \sin(\omega t) - \sin(2\omega t + \phi) + \sin(4\omega t) + \eta(t) \qquad (4)$$

Where $\omega = 2\pi / 75$, $\phi = \pi / 2$ and $\eta(t)$ is white Gaussian noise. The spikes are distributed randomly over the background signal. The spikes are taken as triangular symmetric pulses with random signs and amplitudes uniformly distributed between 2.5 and 7.5. The signal is sampled at a rate of 128 Hz (Fs= 128Hz).

To localise the spike events in x(t), the signal is firstly mapped into the TF domain. The TFD is preprocessed using the SVD-based approach to reduce the effect of noise [4]. Then, two frequency slices of the enhanced TFD are extracted. In this study, the frequency slices are extracted around 5 Fs /12 and Fs/2. Since high frequency background activities in EEG are less energetic, the spike signatures are more apperant in higher frequency slices. The SNEO is applied to the two frequency slices extracted from the enhanced TFD. The output of the SNEO is thresholded to isolate the most energetic areas. If the duration of a detected spike on the frequency slices does not meet the spike duration limits, it is not taken into account.

For the purpose of statistically evaluating the proposed technique and comparing its performance to the SNEO, 100 simulations of x(t) have been employed. In these simulations, the signals had 8 randomly distributed spikes. The false-negative (FN) and false-positive (FP) ratios are defined as

$$FN = \frac{N_m}{N} \quad FP = \frac{N_f}{N}$$

Where N_m, N_f and N represent the number of missed, falsely detected and actual number of spikes, respectively.

Table 1 represents the FN and FP of the two approaches. The table shows superiority of the TF-based technique.

EEG Signal: For evaluating the performance of the techniques on real signals, the EEG data of newborns have been used. Fig. 3 shows four seconds of the EEG signal. The position of spikes in the signal detected by

Table 1: Performance results of spike detection using the synthetic signal

Spike detector	SNR (db)	FN	FP
SNEO	20	11%	5%
	5	13%	35.7%
	0	19.5%	83.5%
TF	20	2.5%	4%
	5	9.3%	26%
	0	18.8%	55%

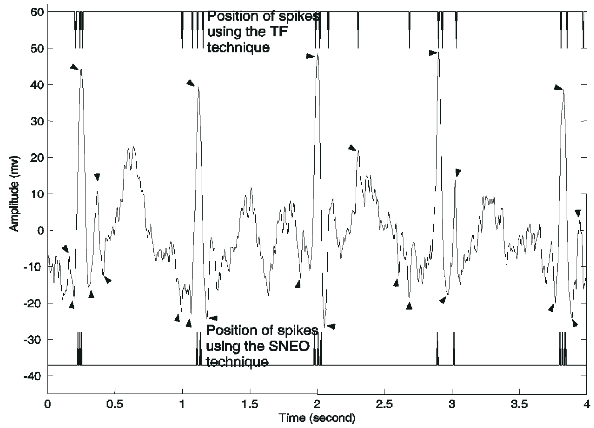

Fig. 3: Four seconds of a newborn EEG signal and the position of spikes using SNEO (bottom pointing pins) and TF (top pointing pins) techniques. Arrows show the positions of the thorough spikes

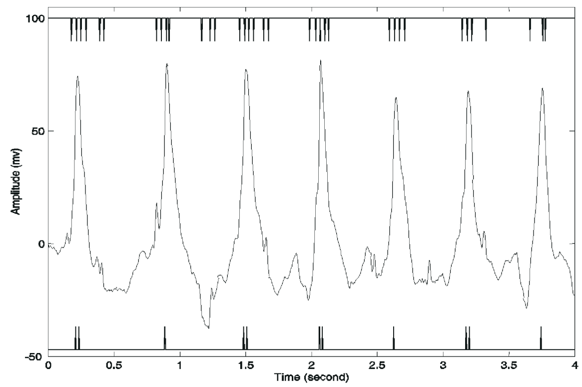

Fig. 4: Four seconds of a newborn EEG signal and the position of spikes using the SNEO (bottom pointing pins) and TF (top pointing pins) techniques

the SNEO and the TF-based techniques are shown by the pointing pins at the bottom and top of the signal. Comparison between positions of the spikes with those detected using the SNEO and TF-based techniques shows that the TF-based technique has better detection results.

For the second experiment, the EEG data of another newborn have been used. Fig. 4 shows four seconds of that EEG signal along with the results of the two spike detection techniques. This EEG signal contains seizure activity as diagnosed by the neurologist. The existence of the repetitive waves in the signal, as the low frequency signature of seizure [18], masked the lower amplitude high frequency activity in the signal. The signal was filtered using an IIR Butterworth filter to remove activities lower

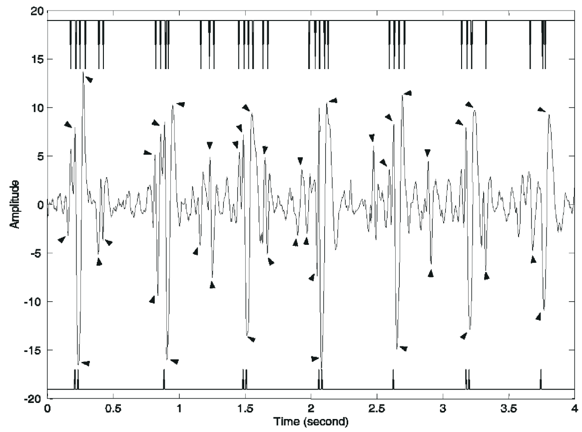

Fig. 5: Filtered signal represented in Fig. 4 and the position of spikes using the SNEO and TF techniques applied to the original signal

than 8Hz. The filtered signal and the results of the spike detection techniques on the original signal are shown in Fig. 5. This figure clearly shows the existence of spikes in the signal. Comparing the position of the spikes with those detected by the TF-based technique and the SNEO shows the better performance of the former spike detection technique.

CONCLUSION

This paper presents a new EEG spike detection technique. The technique is based on the analysis of the signal in the time-frequency domain. The time-frequency representation of the signal is enhanced to reduce the effect of noise. Two frequency slices of the enhanced time-frequency representation are used to detect spike events in the signal. The results of using this technique on both the synthetic and real signals have shown that the proposed technique outperforms the existing method based on time domain analysis.

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