EEG SPIKE DETECTION USING TIME–FREQUENCY SIGNAL ANALYSIS

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ABSTRACT

This paper presents a new method for detecting EEG spikes. The method is based on the time–frequency distribution of the signal. As spikes are short time broadband events, they are represented as ridges in the time–frequency domain. In this domain, the high instantaneous energy of spikes allows them to be 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 a signature of the spike is detected at the same position in both frequency slices.

1. INTRODUCTION

Studying the behaviour of spikes in the electroencephalogram (EEG) is important for detecting brain abnormality [1]. Despite the multitude of published papers on the analysis of EEG, very few considered the spike events.

Spikes can be defined as transient signals, clearly distinguishable from the background activity with a pointed peak. In EEG the duration of the spikes varies between 20 to 70 msec [1]. From signal processing point of view, spikes are nonstationary short–time broadband signals with high instantaneous energy [2]. Spike detection in nonstationary environments, such as in the case of EEG, is a challenging problem. Detection methods based on the assumption that the background signal is stationary or quasi-stationary are not useful in this type of environment [2, 3].

The nonstationarity of EEG makes time–frequency distributions (TFDs) a suitable tool for spike detection. As spikes are short time broadband events, they are represented in the TF plane as highly localised energy pattern especially in the high frequency area as shown in Figure 1. Depending on the signal to noise ratio (SNR), the presence of noise may prevent recognition and localisation of spikes.

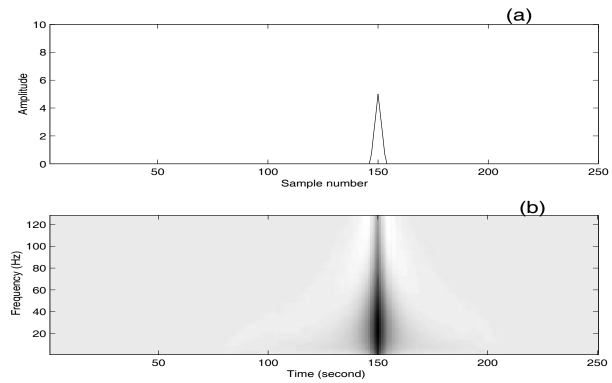

Fig. 1. A spike: (a) Time domain, (b) TF domain.

To deal with the noise and nonstationary problems, a new two-stage spike detection technique is presented in this paper. The first stage is a preprocessing stage whose goal is to reduce the effect of the noise in the TF domain 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) [2].

2. SPIKE DETECTION

2.1. Existing methods

There are several spike detection methods in the literature [2, 3, 5]. In [5], a rule–based method has been adopted for recognizing special features of spikes. The method is based on the time domain information of the signal and has a high good detection rate at the expense of high false alarm rate [6]. In another study, the NEO has been employed for spike detection in the EEG signal [3]. The output of the NEO is proportional to the product of the instantaneous amplitude and frequency of the input signal, and hence highlights the spike events in the signal. A smoothed nonlinear energy operator has been employed in [2] to detect spike events in EEG signals. This technique applies Barlett window to the output of the NEO for magnifying the local pointed peaks. Consequently, the output of the SNEO can be considered as the instantaneous energy of the highpass filtered version of a signal. However, the results show that this approach is sensitive to noise.

The NEO and SNEO 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 background. These methods have limited success for detecting spikes in signals such as EEG where the background is nonstationary [7]. This shows the need for a spike detection method that takes this characteristic into account.

Wavelet transforms (WTs) have been widely used for analysing nonstationary signals [8, 9]. However, the WT does not perform well in detecting spikes that are close in time [8]. The problem is that for large scale, the time resolution of the wavelets are wider than the width of the spikes.

2.2. TF-based spike detection method

Time–frequency distributions are suitable for analysing nonstationary patterns in a nonstationary environment such as in the case of EEG spikes. The extension of spikes signatures into the high frequency area of the TF domain, as well as the high instantaneous energy of spikes allow them to be distinguished from the background. In addition, at higher frequencies in the TF domain, spikes are more localised than at lower frequencies. Consequently, using high frequencies of the TFD is more suitable for spike detection. Therefore, before the actual spike detection process, the signal is first filtered using a high-pass filter.

In order to reduce the cross-terms, introduced by the quadratic nature of TFD, a reduced interference time-frequency distribution (RID) is used. A number of RIDs exists in the literature. In this study, the Choi-Williams distribution (CWD) has been adopted [10]. This distribution has been shown to outperform other distributions in representing spiky signals [11].

To attenuate the effects of noise on the TFD of the signal, the SVD-based technique proposed in [4] is used. This technique is based on low pass filtering the singular vectors associated with the matrix representing the TFD of the signal under analysis. It has been shown that reconstructing the TFD of the signal using filtered singular vectors significantly reduces the noise effect without altering the basic structure of the TF patterns of the signal [4].

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

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

The local peaks at the output of the NEO 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 [2] the authors have shown that using Barlett window applied to the output of the NEO can help in better localising the local maxima. The process that combines the NEO and the windowing is called 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. This is due to the fact that frequency slices have less noise and background activities comparing to the related time domain signal.

3. EXPERIMENTAL RESULTS

The efficiency of the presented spike detection method has been evaluated using both 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 [2].

3.1. Synthetic Signal

For the purpose of evaluating the performance of the proposed method we use the following synthetic signal [2]:

$$x(t) = s(t) + h(t)$$

where $s(t)$ and $h(t)$ are the background signal and the spike train set, respectively. The background is chosen:

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

where $\omega = 2\pi/75$, $\phi = \pi/2$ and $n(t)$ 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 5. The signal is sampled at a rate of 128 Hz ($F_s = 128Hz$). Figure 2(b) shows 250 samples of $x(t)$ with SNR=5 db. This signal includes 8 spikes represented in Figure 2(a) with a randomly varying duration of 3 to 9 samples. The duration of each spike meets the EEG spike duration limits (20 to 70 msec).

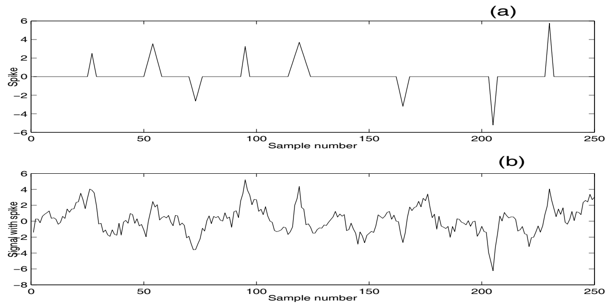

Fig. 2. (a) Spike train, (b) Signal with spikes.

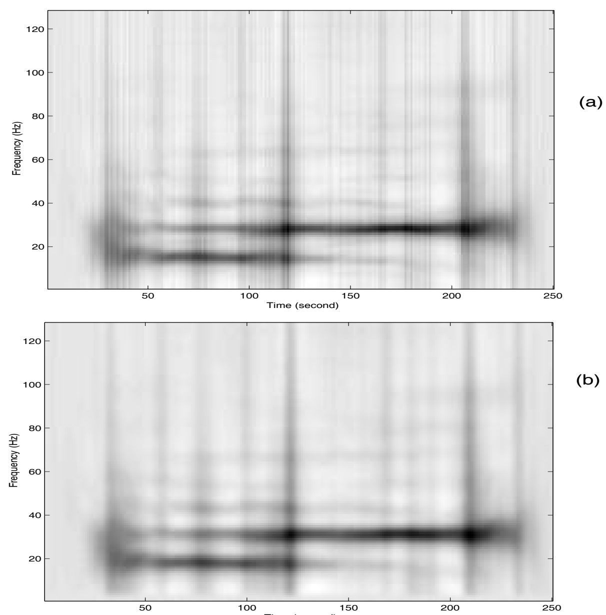

Fig. 3. TFD of signal represented in Fig. 2(b): (a) original TFD, (b) Enhanced TFD.

To localise the spike events in $x(t)$, the signal is firstly mapped into the TF domain. To reduce the effect of noise the TFD is preprocessed (see Fig. 3). Then, two frequency slices of the enhanced TFD are extracted. In this study, the frequency slices are extracted close to $5F_s/12$ and $F_s/2$. The SNEO is applied to the two frequency slices (see Figure 4(a) and 4(b)). The output of the SNEO is thresholded to isolate the most energetic areas. The threshold value, τ, is chosen as $\tau = \mu(l_F)$ where l_F is a vector representing the frequency slice and μ is the median function. If the duration of a detected spike on the frequency slices does not meet the spike duration limits, the detected spike is rejected.

The result of applying the TF–based technique to $x(t)$ for spike detection is shown in Figure 4(c). As it can be seen, all of the eight spikes have been successfully detected. The result of applying the SNEO technique on the same signal in time domain is shown in Figure 5. The figure shows that the technique has one false and one missed detections.

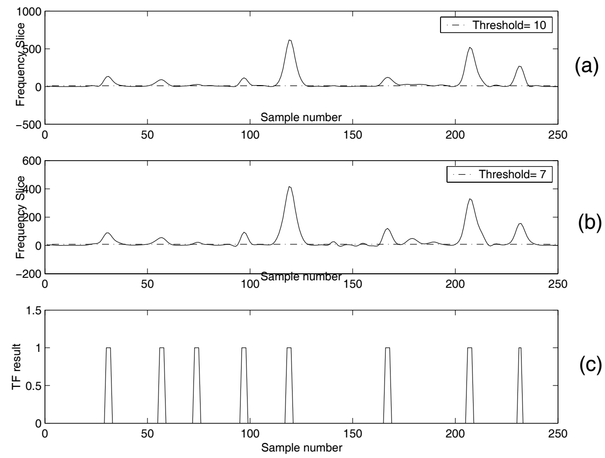

Fig. 4. TF spike detection on signal represented in Fig. 2b: (a) Frequency slice at $l_F = \frac{5F_s}{12}$, (b) Frequency slice at $l_F = \frac{F_s}{2}$, (c) Detection results.

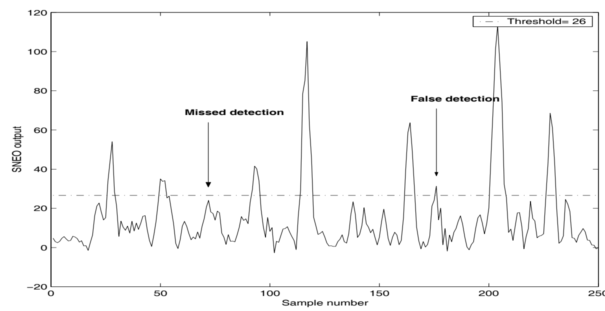

Fig. 5. The SNEO output to signal represented in Fig. 2(b)

3.2. EEG Signal

For evaluating the performance of the TF–based spike detection on real signals, the EEG of newborn baby has been used. The data have been sampled using $F_s = 256Hz$. Four seconds of the data are shown in Figure 6. In this figure the position of the spikes has been depicted by the arrows.

The TF-based and the SNEO techniques have been separately applied to the EEG signal and the results are shown in Figures 7 and 8, respectively. All of the spikes have been successfully detected using both the SNEO and TF-based techniques. However, Figure 6 shows that the SNEO has four false detections.

4. 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 results of using this technique on both the synthetic and real signals have shown that the

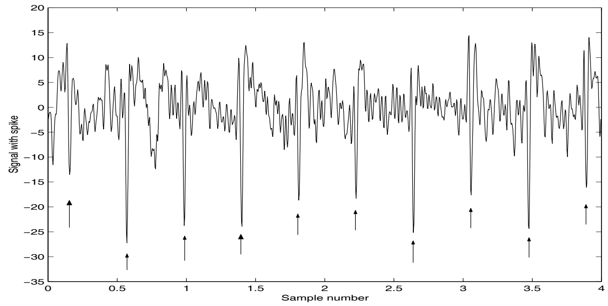

Fig. 6. Four seconds of newborn EEG signal. The spike locations are pointed by arrows.

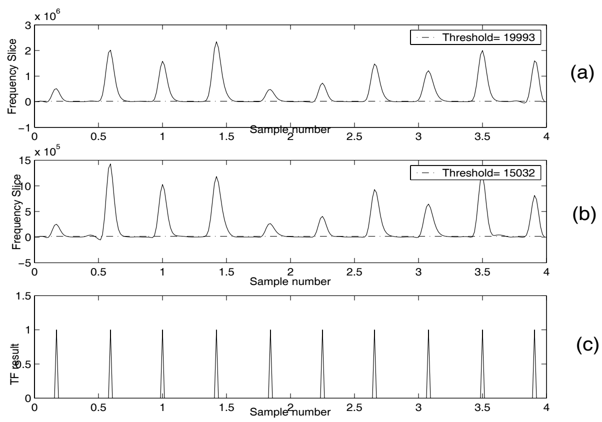

Fig. 7. Spike detection results using the TF-based technique applied on signal in Figure 6: (a) The first extracted frequency slice, (b) The Second extracted frequency slice, (c) The TF detector's output.

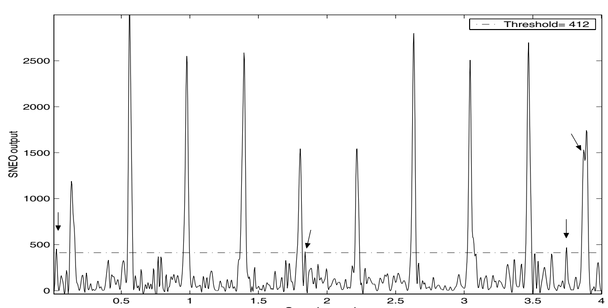

Fig. 8. The SNEO detector's output for signal represented in Fig. 6. False detected spikes are depicted by arrows.

proposed technique outperforms the original method based on time domain analysis.

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