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SPIKE DETECTION IN BIOMEDICAL SIGNAL LIKE EEG AND ECG USING TEO

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Abstract: We propose a novel approach aimed at adaptively setting the threshold of the smoothed Teagor energy operator (STEO) detector to be used in extracellular recording of neural signals. Many types of spike detectors have been proposed all with their advantages and drawbacks. Most of the times there is a trade off between simplicity and performance. The performance of such systems is generally gauged by correct detections and false alarms. The Teagor energy operator is a time frequency analyser that gives high output when both instantaneous amplitude and frequency are high (typical characteristics of the spikes), that is why it is very effective in detecting spikes. The basic TEO gives output after processing three consecutive samples of data, but for signals with high frequency noise it gives more false alarms than the correct detections. To overcome this problem the MTEO (multiresolution TEO) has been proposed. It is observed that for the best performance of any algorithm optimal decision threshold is required. In this we fixed the threshold of MTEO detector based on these parameters and a constant that depends on the tolerance for false alarms. Setting the decision threshold in this way increases the detection performance. If we have some prior knowledge about the spike shape, we can first apply wavelet transform on the signal using suitable mother wavelet and then apply TEO to get better results.

Keywords: Adaptive threshold, robust theory, spike detection, Teagor energy operator.

1. INTRODUCTION

In the analysis of biomedical signals, spikes are important for diagnosis [3]. Biomedical Signal is generally acquired by a sensor, a transducer, or an electrode, and is converted to a proportional voltage or current for processing or storage.

The study of electroencephalogram (EEG) signal include nervous system is both the controlling and communications system of the body. This system consists of a large number of excitable connected cells called neurons that communicate with different parts of the body by means of electrical signals, which are rapid and specific. Neurons are highly specialized cells that conduct messages in the form of nerve impulses from one part of the body to another [2].Electrocardiogram (ECG) is a standard tool to monitor heart function. Regular monitoring of ECG helps in early detection of irregularities in the heartbeats. Some heart- beat arrhythmias, although not immediately life threatening may need timely detection and attention to prevent future complications. In order to provide continuous health monitoring, devices must integrate seamlessly into the patient's life and not interfere with daily activities [1].

For biomedical signals, most of the statistical characteristics of these signals are nonstationary. In particular, the analysis of biological signals should exhibit good resolution in both time domain and frequency domain

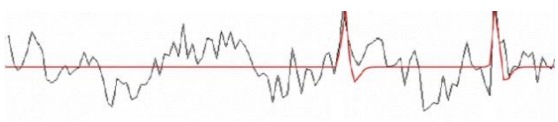

Figure 1: EEG spike signal

In fig.1 nonstationary signal is consist of detecting action potentials (spikes) immersed in background noise during extracellular recordings of neural signal. In the present case the power frequency interference is simulated by a 50 Hz sinusoid; all noises associated with EEG are also simulated by Gaussian white noise with zero mean and wide sense stationary [10].

Various spike detectors have been studied and developed [1]–[4], with each method having advantages and drawbacks. It is important to know that the need for adaptive and unsupervised spike detection algorithms has been growing over the past years. Such algorithms are useful in many research areas and applications

In a typical spike detector, the signal is pre-processed to accentuate spikes and attenuate noise, and then passed through a threshold detector to determine spike locations

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[6]. . Static detectors use either a single threshold to detect one edge [7] or a pair of thresholds to detect both rising and falling spike edges [8]. Adaptive thresholds contend with the changing background noise levels common to the nonstationary extracellular neural signal [9] interestingly, approaches based on energy detection [e.g., energy detector (ED) and Teagor energy operator (TEO)] have similar advantages.

After the pre-emphasis, peaks are identified by the output of the filter compared to a threshold. In any spike detection algorithm the threshold is optimized to minimize missing of true peaks, while keeping the number of false detection of peaks within a reasonable limit

In [13], 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 spikes 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].

We introduce in this paper a new method to set an adaptive spike detection threshold for the smoothed TEO (STEO). An overview and comparison of various existing detection methods are given in [1] - [4]. We selected these methods for their relatively good performances and simplicity, and because they require no prior knowledge about spike waveform shapes.

In the remaining parts of this paper, we expose the proposed detection approach in Section 2, and present the methodology in Section 3. We then report our results in Section 4, discussion in Section 5, and finally, we conclude in Section 6.

2. ADAPTIVE SPIKE DETECTION PROCESS:

There are several spike detection methods in the literature [1-4].Time domain spike detection characteristics are complicated process in nonstationary biomedical (EEG, ECG) signal and by using frequency domain for spike detection temporal characteristics of signal may be loss [11]. A time-frequency domain characteristics of the signal represents the both time domain and frequency domain characteristics simultaneously for a given signal f(x) [12].

The TEO detector and its variants are among the commonly used spike detectors [8]–[10]. The definition of the discrete-time TEO is given by

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

Where x(n) is the input neural signal that can be decomposed into a spike s(n) embedded in the background noise b(n). In this paper, the background noise b(n) is assumed to be a zero-mean colored Gaussian random and wide-sense stationary (WSS) process.

The TEO is a time–frequency analyzer that can simultaneously consider the instantaneous amplitude and frequency in- formation of the input signal. This property makes it to be sensitive to “spikes,” where a spike, in signal processing, means a signal that is concentrated in a short time interval and at a high frequency band.

Fig. 2 depicts the block diagram of the entire spike detection System adopted in this paper. In the next sections, each part composing this system will be explained in detail. In Fig. 2, the spike detector is implemented in two steps. The first one, which is based on the TEO here, emphasizes the spike portion of the signal, while the second one is the decision-making step. The detector aims at deciding whether there is a spike embedded into the noise or there is only noise. Values of *z(n)* at the output of the emphasizing block are continuously compared with a threshold *T* (see Fig. 2). At the decision making step, a spike is considered present if *z(n)>T*; otherwise, the signal is considered to contain only noise.

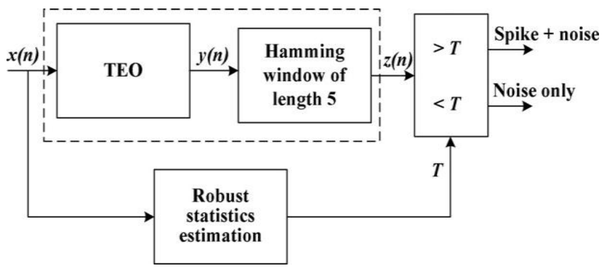

Figure 2: Block diagram of the spike STEO detection with adaptive threshold.

Where *T* is a threshold to be determined Since the goal of this paper is to set the threshold, only the probability density function (pdf) under the null hypothesis and a value of probability of false alarm *P*fa are required [7], [11]. However, as the TEO is a nonlinear operator, the pdf cannot be evaluated in a closed form.

In statistics, several approaches are proposed to circumvent this limitation. However, in line with the need for simplicity, a direct parametric approach was adopted in this paper. Where only noise is present at the input *x(n) = b(n)*

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Thus, as the noise is a random process, the output $E\{\psi[x(n)]\}$ is also a random process having a mean μ and a standard deviation σ. The boundary line (or threshold) can therefore be approximated as follows:

$$T = \mu + p\sigma \qquad (2)$$

Where T can then serve as an adaptive detection threshold to detect the presence of spikes, and the multiplier p depends on P_{fa} [11]; in practice, p and P_{fa} are defined by the user. In fact, in a typical spike detection algorithm, setting a small value for p increases both P_{fa} and probability of detection P_d , while choosing a large value decreases both P_{fa} and

Finally, since neural signal is a nonstationary process, the $E\{\psi[.]\}$ operator cannot be replaced by a simple time-domain averaging but by a frequency-domain windowing as suggested in [8]. Hence, to estimate $E\{\psi[.]\}$, the STEO $\Psi s[x(n)]$ is introduced and defined as

$$\Psi s\,[x(n)] = w(n) * \Psi[x(n)] \qquad (3)$$

Where ($*$) represents the convolution product and $w(n)$ the smoothing window of length L [8].From (6), we have

$$\psi s\,[x(n)]) = \sum_{k=0}^{l-1} w(k)\psi[x(n-k)]. \qquad (4)$$

A) Value of μ of Ψs[x(n)] in (2)

$$\mu_{\psi s} = 2.24(r_{xx}(0) - (r_{xx}(0)$$

B) Value of σ of Ψs[x(n)] in (2)

$$\sigma_{\psi_s} \approx 4.8r_{xx}^2 + 0.7\, r_{xx}^2\ (1) + 4.4\, r_{xx}^2\ (2) + 0.6\, r_{xx}^2\ (3) - 9.3r_{xx}\ (0)\, r_{xx}\ (2) - 1.2r_{xx}\ (1)\, r_{xx}\ (3)$$

3. MATERIALS AND METHODS

All the algorithms and data analysis procedures were implemented in MATLAB.

In order to evaluate the adaptive detection threshold of the STEO, simulations using synthetic neural signals constructed from real neural recordings were conducted. This approach is more appropriate for evaluating the performance of spike detection methods. Indeed, it provides known solutions under different conditions, e.g., FR (firing rate), SNRs, and spike times.

In an attempt to evaluate the proposed method, free noise segments were first extracted from the available data to construct background noise libraries. To build large datasets of the background noise, neural noise was modeled by an autoregressive model [3], [7], [8].

Finally, to construct the synthetic neural signals, the extracted spikes from each set of data were taken and pass to the TEO for taking detection values greater than threshold and few further use window having length 5. Here threshold is making adaptive so that value of threshold may change according to the spike pattern which include random noise.

4. SIMULATION RESULTS

The threshold T was automatically set to p and σ [2]. On the other hand, the ED method estimates instantaneously input signals energy, and this is accomplished in this paper by squaring the input signal. For both methods, the estimation of the standard deviation σ of the background noise was based on Finally, in the S_TEO method, the threshold T was estimated according to (2), where μ and σ were calculated using the MATLAB functions *std* and *mean* (i.e., classical estimation) of the STEO signal.

Comparison of Results:

It is observed by experimentation on various EEG data having high frequency spikes that the TEO detector gives very good detection performance and few false alarms. For high frequency spikes, some results are shown below-

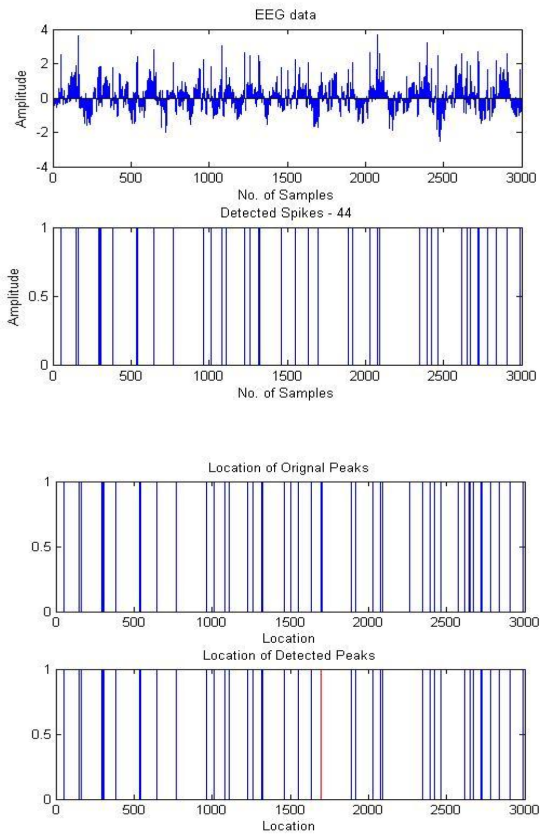

Figure 3: MATLAB output for EEG signal using TEO

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TEO based detectors perform very well for high frequency spikes but their performance is very poor when spike frequency is low compared to background noise. For such cases the proposed algorithm gives much better performance. Results obtained by both detectors at various spike frequencies are as below.

Case: 1
For TEO:
Spike frequency = 60 Hz
False alarms = 2
Detected spikes = 6

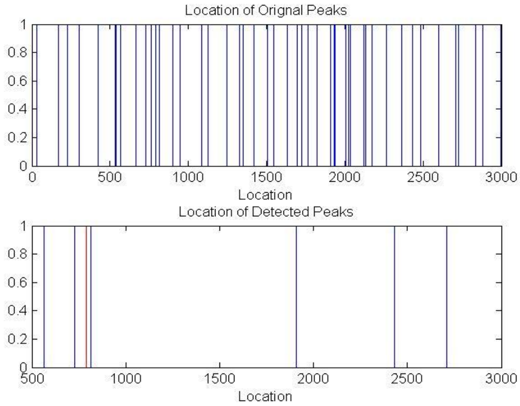

Figure 4(a): MATLAB output form TEO method

For proposed technique
Spike frequency = 60 Hz
False alarm = 12
Detected spikes = 38

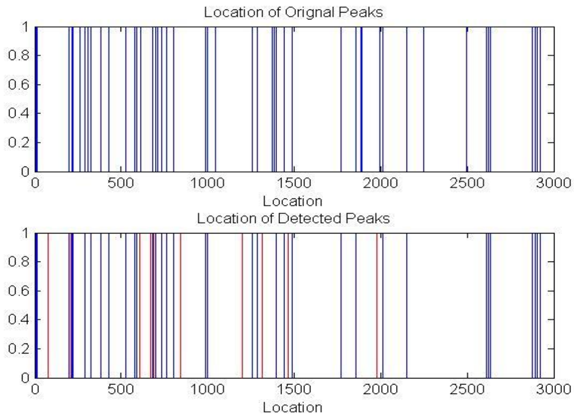

Figure 4(b): MATLAB output from proposed method

Case: 3
For TEO:
Spike frequency = 25 Hz
False alarms = 4
Detected spikes = 5

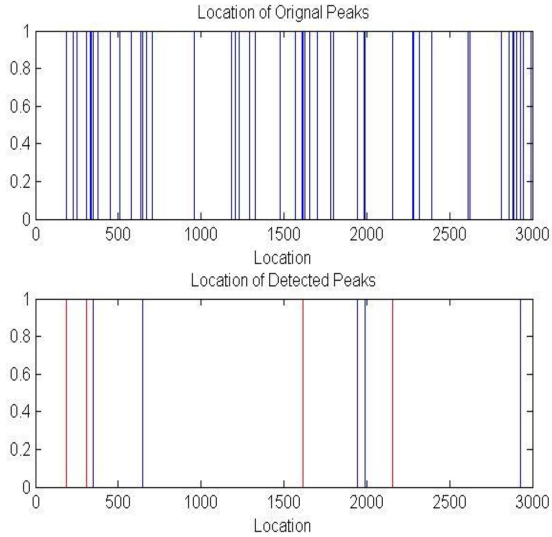

Figure 5(a): MATLAB output from TEO method

For proposed technique
Spike frequency = 25 Hz
False alarm = 5
Detected spikes = 45

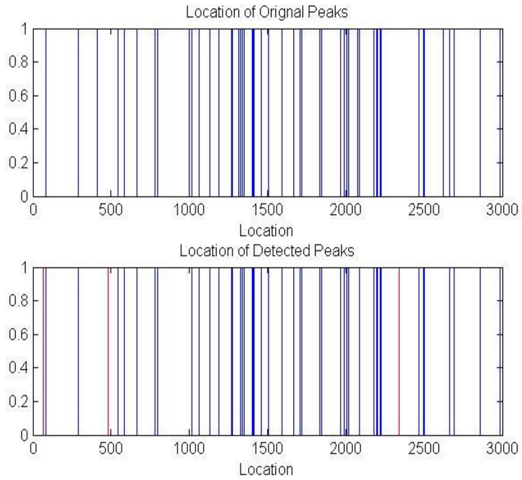

Figure 5(b): MATLAB output from proposed method

5. DISCUSSION OF RESULT

The efficacy of TEO as spike detector is observed to be good in case when spike frequency is higher than background noise frequency. It does not need any prior knowledge about waveform shape or amplitude. In this work the threshold of TEO detector was set adaptively using robust statistics. This ensures that the estimate of the mean and variance of the noise is not adversely influenced by the presence of spikes. Another mathematical tool that is used a lot for spike detection is Wavelet Transform. The shortcomings of TEO detector are overcome by using

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CWT based proposed algorithm. The only complexity is that we need prior knowledge about spike width.

Table.1 Result at different frequency value

Spike Frequency	TEO Detection		Proposed Method	
	False Alarms	Correct Detection	False Alarms	Correct Detection
5 Hz	9	10	9	41
10 Hz	7	7	5	45
25 Hz	4	5	5	45
30 Hz	7	7	8	42
40 Hz	5	6	9	41
50 Hz	3	4	4	46
60 Hz	2	6	12	38

6. CONCLUSION

A novel approach based on the STEO combined statistics theory has been described and applied to extracellular neural recordings to efficiently and adaptively detect spikes immersed in back ground noise. In this approach, to set the adaptive threshold, we derived the relationship between the unbiased estimation of background noise in low-order statistics at the STEO detector input and the mean and standard deviation of the output STEO detector. These low-order statistics are estimated directly from the input neural signal using robust statistics theory techniques. As shown in this study, this processing allowed to efficiently setting an adaptive detection threshold to the STEO detector to make it an adaptive process. To validate the efficacy of the proposed method, we have used synthetic neural signals constructed from real neural recordings signals. Four different sets of extracellular recordings from four distinct neural sources have been exploited to that purpose. Finally, as anticipated, the performance of the proposed approach varies with the multiplier p; a higher value for p induces a failure to detect lower magnitude spikes, while a lower value increases the false alarm ratio (FAR).

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