Three Novel Spike Detection Approaches for Noisy Neuronal Data

Hamed Azami, *Student Member, IEEE*
Department of Electrical Engineering
Iran University of Science and Technology
Tehran, Iran
hamed_azami@ieee.org

Saeid Sanei, *Senior Member, IEEE*
Faculty of Engineering and Physical Sciences
University of Surrey
Guildford, United Kingdom
s.sanei@surrey.ac.uk

***Abstract*— In this paper three new methods based on smoothed nonlinear energy operator (SNEO), fractal dimension (FD) and standard deviation to detect the spikes for noisy neuronal data are proposed. In many cases, especially when there are several noise sources, these methods may not be acceptable as spike detectors. To overcome this problem, we use Savitzky-Golay filter and discrete wavelet transform (DWT) as pre-processing steps. Results show that when there is too much noise in the signal, the proposed method using the standard deviation and DWT can detect the spikes better than the other methods. The average detection rate and false detection of spikes for the proposed method based on standard deviation and DWT are respectively 100% and 43% for semi-real signals with SNR=-5 dB.**

Keywords- spike detection; fractal dimension; nonlinear energy operator; standard deviation; Savitzky-Golay filter; discrete wavelet transform

I. INTRODUCTION

Multiple electrode arrays (MEAs) or micro electrode arrays are standard tools for collection of neural signals. Simultaneous activity of several neurons in a piece of neural tissue can be studied by the MEAs. These studies can answer questions about how the brain works [1]. It should be mentioned that neuronal data is completely different with electroencephalography (EEG).

Neural action potentials (also known as nerve impulses or spikes) play an important role in understanding the central nervous system [2,3]. Extracting useful information from these measurements depends on the ability to correctly detect the recorded neural spikes [1]. The noises from brain tissues, muscle movement from behaving animals, and other biological and instrumental interferences, and contributions of many neurons to recorded signals are two main problems to detect spikes in neuronal data [3,4].

Nonlinear energy operator (NEO) is a powerful tool to segment and detect abnormalities in electroencephalogram EEG signals [5,6]. Also, this operator has been used in the spike detection in EEG signals [6], and automated detection and elimination of periodic electrocardiogram (ECG) artifacts in EEG signals [7,8]. In this paper we use the smoothed NEO (SNEO) to detect the spikes in neuronal data.

The changes in fractal dimension (FD) refer to the underlying statistical variations of the signals and time series including the transients and sharp changes in both amplitude and frequency. If the amplitude and frequency of a signal change, the dimension of FD will change

Since spike is a part of signal that its amplitude and frequency is considerably different with other parts of signal, FD can be used as a spike detector. There are several methods to compute FD of a signal such as Hiaguchi's and Katz's methods. Although the Hiaguchi's method computes the FD more precisely than Katz's method, due to high sensitivity of Hiaguchi's method to noises, the Katz's method is often used in signal processing applications [9].

We have used the standard deviation to detect segmentation boundaries of the signal and have shown that the standard deviation can be used as a detector for changes of the amplitude and/or frequency [10]. Since in spikes, amplitude and frequency significantly change, in this paper we propose the standard deviation for detecting of the spikes in neuronal signals. Like two other proposed methods, standard deviation is very sensitive to noises. Therefore, in this paper, discrete wavelet transform (DWT) and Savitzky-Golay filter as pre-processing steps are proposed for all of the mentioned methods.

Time series measured in real world is commonly nonlinear and to extract significant information from the measured time series, it is important to use pre-processing steps such as wavelet transform and filters to reduce noises [11]. Savitzky-Golay filter is an effective tool for de-noising and smoothing signals [12]. Compared with moving average (MA) filter, Savitzky-Golay tends to keep features of the distribution such as relative with maxima and minima [12].

In the next section DWT, Savitzky-Golay filter, and FD are briefly explained. Section 3 explains three proposed methods. Section 4 provides introduction on the dataset used in this paper and then, the comparison between the results of the proposed methods are presented. The last section concludes the paper.

II. BACKGROUND KNOWLEDGE FOR THE PROPOSED METHODS

A. Discrete Wavelet Transform

DWT is a powerful tool which is widely used to analyze a signal in the time series such as diagnosis of various central nervous system abnormalities like seizures, epilepsy, and brain damage [13-15]. DWT decomposes a signal into different scales with different level of resolutions. Majority of signal information is in low frequency which is the most important part of the signal. The information in high frequency indicates details of the signal. Therefore, DWT utilizes low-pass and high-pass filters like Fig. 1 [16].

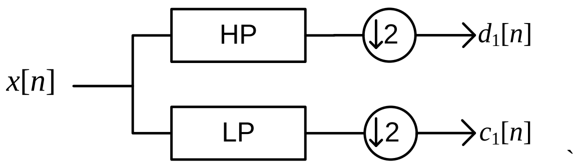

Figure 1. Decomposition of $x[n]$ into one-level.

where $x[n]$ is the input data and $d_1(n)$ and $c_1(n)$ describe the sub-bands signal components. After filtering, because each of the two outputs has the same length with the input signal, these outputs are downsampled by a factor of two. Thus, both $d_1(n)$ and $c_1(n)$ have half the length of the input signal [17].

B. *Savitzky-Golay filter*

The Savitzky-Golay filter is a powerful tool for smoothing a signal that was proposed by Savitzky and Golay in 1964. The filter is defined as a weighted moving average with weightening given as a polynomial of specific degree [18-20]. The coefficients of a Savitzky-Golay filter, when applied to a signal, perform a polynomial P of the degree k, is fitted to $N = N_r + N_l + 1$ points of the signal, where N describes window size. N_r and N_l are signal points in the right and signal points in the left of a current signal point, respectively. One of the best advantages of this filter is that it tends to keep features of the distribution such as relative with maxima and minima which are often flattened by other smoothing techniques such as the MA [18-20]. This property causes the Savitzky-Golay be a good filter to detect the spikes.

C. *Fractal Dimension*

In Euclidean space, line and page are known as one dimensional and two dimensional, respectively and non-integer dimension does not exist. However, FD represents a non-integer dimension regarding to the concepts of modern mathematics. It is commonly used in analysis of biomedical signals such as EEG and ECG, image processing and electrochemical processes [21-23]. There are some methods to calculate the FD of a signal such as Hiaguchi, Petrosian, and Katz's methods [9]. Because FD is directly estimated from the time-varying signal, it has low computational cost. Katz's algorithm has a lower sensitivity to noise and good speed in contrast to the two other algorithms [9]. Using Katz's algorithm:

$$FD = \frac{\log_{10}(n)}{\log_{10}(d/L) + \log_{10}(n)} \tag{1}$$

where L is sum of the distances between consecutive points and d is the maximum distance between the first data of time series and data that has maximum distance from it. Also, $n=L/a$ shows the step size in time series [9].

III. PROPOSED METHODS

A. *Spike Detection Using Improved Smoothed Nonlinear Energy Operator*

Kaiser has suggested an operator, NEO, to measure the instantaneous energy of the signal as follows [24]:

$$\psi[x(n)] = x^2(n) - x(n-1)\,x(n+1) \tag{2}$$

If the $x(n)$ is a sinusoidal wave, then, $\psi[x(n)]$ will be defined as:

$$Q(n) = \psi[ACos(\omega_0\, n + \theta)] = A^2\, Sin^2\, \omega_0 \tag{3}$$

when ω_0 is much smaller than the sampling frequency, then, $Q(n) = A^2\,\omega_0{}^2$. In other words, the operator can detect changes in the instantaneous amplitude (A) and/or instantaneous frequency (ω_0) of the signal [25]. Therefore, the NEO can be used for amplifying the spiky activities in a signal. However, the NEO is sensitive to noise and has the problem of cross terms operator [25]. To reduce these problems, Mukhopadhyay and Ray have suggested SNEO to detect spike events in EEG signals by convolving $\psi[x(n)]$ with a time domain window that is expressed as:

$$\psi_S[x(n)] = w(n) * \psi[x(n)] \tag{4}$$

where * denotes the convolution operator and $w(n)$ shows the window. The choice of window type and width of the window are very important to achieve sufficient reduction of interference without loosing much of its time resolution which it is very important for spike detection. For this aim, Barlett window function with an integer filter implementation is selected to hold on the complexity of the algorithm as low as possible [7].

The local optimum from the output of the SNEO that is higher than a predefined threshold, Tr, is selected as a spike at that location in the time series. A threshold as a scaled version of the mean of the output filter is defined as follows:

$$Tr = c\frac{1}{N}\sum_{n=1}^{N}\psi_S[x(n)] \tag{5}$$

where N is the number of samples and c is a scaling factor. First in a particular type of signal the scaling factor "c" is adjusted by trial and error, then, it is used as a constant. However, the SNEO method is still sensitive to noise [25]. It should be noted that this method has not been used for neuronal data spike detection at all.

B. *Spike Detection Using Fractal Dimension*

In this method, two sliding windows move along the signal like Fig. 2 and for each window the FD is calculated with the katz's algorithm to find the spikes of the signal. The FD variations are computed as below:

$$G_t = FD_{t+1} - FD_t \quad t=1, 2, \ldots, L\text{-}1 \tag{6}$$

where t is the number of analyzed window and L is the total number of analyzed windows. Then, the threshold is defined as the mean value in the distribution. When the local maxima of G are bigger than threshold, these times are chosen as spikes of the signal.

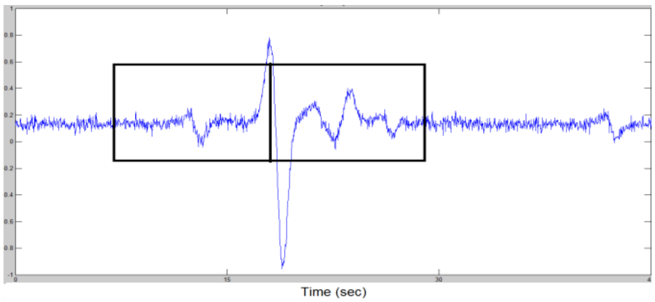

Figure 2. Illustration of joint sliding windows along the time

C. *Spike Detection Using Standard Deviation*

In this method like spike detection method with FD, two similar scrolling windows move along the signal. For each window, the standard deviation is computed. H function is used to detect spikes of the signal as follows:

$$H_a = \left| std_{a+1} - std_a \right|, \quad a=1, 2, \ldots, m\text{-}1 \tag{7}$$

where a and m are the number of analyzed window and the total number of analyzed windows, respectively. std_a denotes the standard deviation of a part of signal that located in a^{th} analyzed window. If the local maximum is bigger than the threshold, the mean value of the H_a, the current time is selected as a spike of the signal.

IV. SIMULATION RESULTS

As stated before, to enhance the performance of the presented methods, we propose to apply DWT and Savitzky-Golay filter as pre-processing steps. Because of the lack of ground truth data (i.e., spike timings for each neuron) spike detection methods are often difficult to evaluate. In [26] an analysis of the transmission of intracellular signals from neurons to an extracellular electrode, and a set of MATLAB functions based on this analysis were presented. This code due to having high performance was widely used to test proposed methods for spike detection in neuronal data. This produces realistic signals from neighboring neurons in addition to interference from more distant neurons, and Gaussian noise. Therefore, this code generates realistic but controllable synthetic signals (for which the ground truth is known) for evaluating spike detection methods. By following this paper, we randomly generated 20 semi-real neuronal data that each data included Gaussian noises with SNR=-5, 0, 5, 10, 20 and 50 dBs. One of 20 signals that contains five spikes with SNR=5 dB is accidentally selected as the test signal. This signal is shown in Fig. 3.a. The output of the SNEO method is shown in Fig. 3.b. The scaled factor and window length are selected 1 and 400 samples, respectively. These parameters are selected by many tries. As can be seen in Fig. 3 the SNEO cannot properly detect the spikes.

The test signal in Fig. 4.a is initially decomposed using four-level DWT. In this paper we used the DWT with Daubechies wavelet of order 8. This decomposed signal is shown in Fig. 4.b. As we can see, the decomposed signal is smoother than the original signal. Fig. 4.c shows the output of the SNEO method. Also, the Savitzky-Golay filter is applied for the test signal in Fig. 4. The result is shown in Fig. 5.c. In this paper, we used an order 3 polynomial Savitzky–Golay filter. A frame size of 101 samples was chosen for the filter. As can be seen in Fig. 4.c and 5.c, the spikes for all five spikes can be accurately detected. Comparing these figures with Fig. 3 demonstrates the effect of pre-processing steps in the SNEO method. Note all used parameters for the SNEO methods are the same.

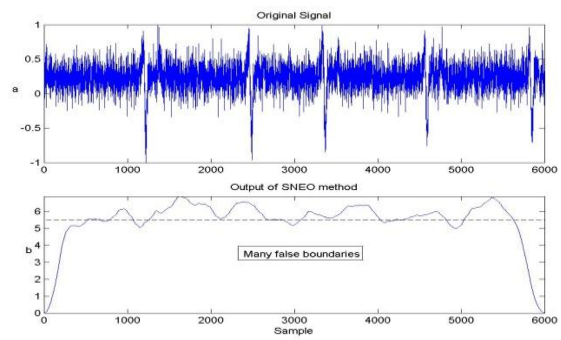

Figure 3. Spike detection in semi real EEG signal using SNEO; (a) original signal, (b) output of SNEO method

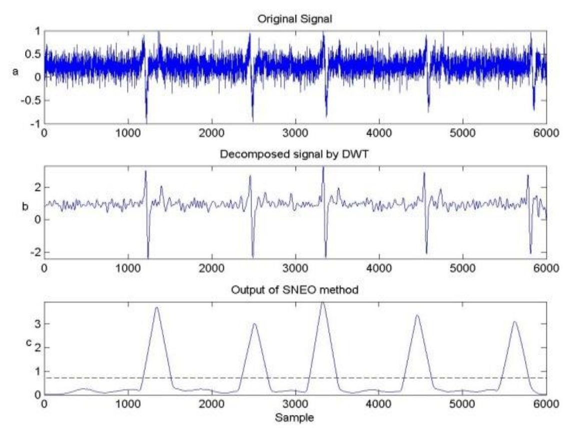

Figure 4. Spike detection in test signal using the SNEO and DWT; (a) original signal, (b) decomposed signal after applying four-level DWT, (c) output of SNEO method. It can be seen that all five spikes can be accurately detected.

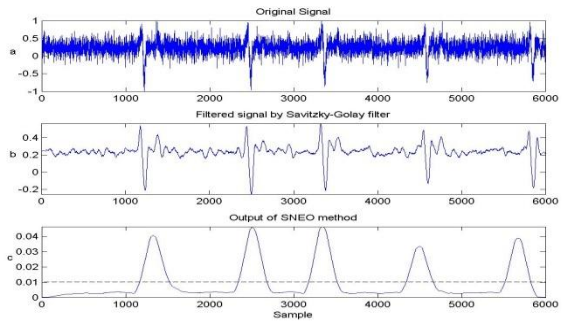

Figure 5. Spike detection in test signal using the SNEO and Savitzky-Golay filter; (a) original signal, (b) filtered signal by Savitzky-Golay, (c) output of SNEO method. It can be seen that all five spikes can be accurately detected.

First, the Savitzky-Golay filter is applied for the test signal in Fig. 6. Since DWT can be a powerful tool for de-noising in biomedical signals, the test signal in Fig. 7.a is decomposed using the four-level DWT with Daubechies wavelet of order 8. Fig 7.c and 7.d illustrate the FD of the decomposed signal and changes in *G* function, respectively. The parameters of the DWT and Savitzky-Golay filter are selected exactly the same as ones are selected for improved SNEO methods.

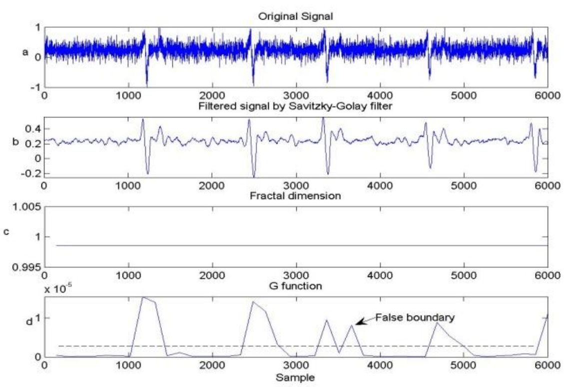

Figure 6. Spike detection in test signal using FD and Savitzky-Golay filter; (a) original signal, (b) filtered signal by Savitzky-Golay, (c) output of FD, (d) *G* function result.

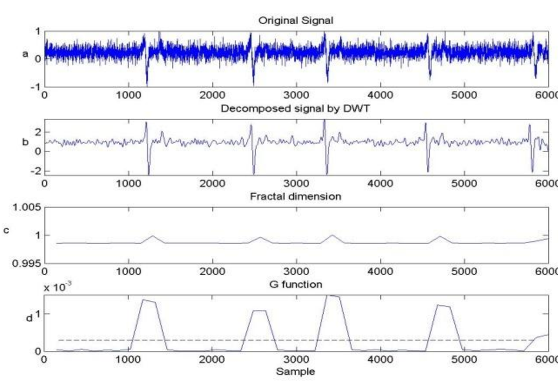

Figure 7. Spike detection in test signal using the FD and DWT; (a) original signal, (b) decomposed signal after applying four-level DWT, (c) output of FD, (d) *G* function result. It can be seen that all five spikes can be accurately detected.

Fig. 8.a, Fig. 8.b and Fig. 8.c show the test signal, the filtered signal by Savitzky-Golay, and the result of applying the standard deviation, respectively. As can be seen one spike is inaccurately detected. Fig. 9.c shows the obtained output of applying the standard deviation with DWT. As can be seen in this figure, all five spikes are accurately detected. Therefore, for standard deviation, the DWT has better performance than Savitzky-Golay filter. Also, the parameters of DWT and Savitzky-Golay filter are selected the same as ones are selected for improved SNEO methods. In this paper for all mentioned methods, the mean value of the output is selected as the threshold that it is selected by trial and error.

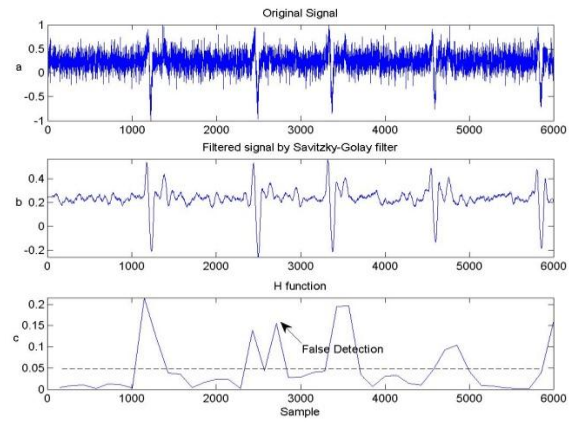

Figure 8. Spike detection in test signal using standard deviation and Savitzky-Golay filter; (a) original signal, (b) filtered signal, (c) *H* function result.

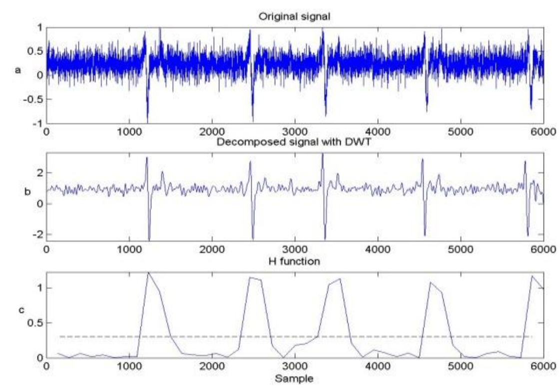

Figure 9. Spike detection in test signal using standard deviation and DWT; (a) original signal, (b) decomposed signal after applying four-level DWT, (c) *H* function result. It can be seen that all five spikes can be accurately detected.

Three different parameters, namely, the true positive (TP) miss or false negative (FN) and false positive (FP) ratios were used to evaluate the performance and effectiveness of the proposed methods. These parameters are defined as

$$TP = \left({N_t}/{N} \right), \quad FN = \left({N_m}/{N} \right), \text{ and } FP = \left({N_f}/{N} \right).$$

where N_t, N_m and N_f represent the number of true, missed and falsely detected spikes and N shows the actual number of spikes. In Table 1 the results of spike detection for 20 semi-real data using the proposed methods with DWT and Savitzky-Golay filter are shown next to the results of the SNEO method and improved SNEO with DWT and Savitzky-Golay filter and spike detection methods based on FD. For a high SNR, the SNEO is very good method to detect spikes, while the noises is increased, the performance of this method is reduced significantly. In order to overcome this problem, we use DWT and Savitzky-Golay filter as pre-processing steps. The results show that DWT has better performance than Savitzky-Golay filter and both of them can considerably improve basic spike detection methods. Although TPs and FNs of spike detection methods with the FD and DWT are the same as FD and Savitzky-Golay filter, obtained FPs of spike detection method using FD and DWT is better than FD and Savitzky-Golay filter. The standard deviation with DWT can detect spikes better than the standard deviation with Savitzky-Golay filter. Also, only standard deviation with DWT could detect all spikes for 20 signals with various SNRs. Therefore, the best method regarding to TPs and FNs is achieved using the standard deviation with DWT. Also, in generally, in this application the DWT can be affected more than the Savitzky-Golay filter for detecting of spikes. As can be seen in Table 1, although all of the methods have the acceptable consuming times, each method with DWT is slower than one with Savitzky-Golay filter. In this paper the simulations have been carried out using a DELL-PC with Intel (R) Core (TM) i3 CPU M350 2.27 GHz and 2-GB RAM by MATLAB R2010a. In Table 2 we assess the CPU times for mentioned methods. As can be seen in this table, the SNEO method is faster than spike detection using FD and the FD can detect spikes faster than spike detection using standard deviation. Also, the Savitzky-Golay can filter the signal quicker than the DWT.

V. CONCLUSIONS

In this paper three novel methods to detect the spikes in noisy neuronal data using SNEO, FD and standard deviation have been proposed. Noises and short-term variations mixed in pure signals have significantly reduced the performance of the spike detection methods. In order to overcome these problems, the DWT and Savitzky-Golay filter have been used as pre-processing steps. Savitzky-Golay filter could keep features of the distribution. These include those related to the minima and maxima which are often flattened by other smoothing techniques. This is a very important issue in spike detection methods. DWT could remove destructive noises often occurred in higher frequencies of the noisy neuronal data. The speed of the Savitzky-Golay approach is much higher than that of the DWT. Finally, the results of applying the methods to all the proposed methods have indicated the effectiveness and superiority of these methods.

Table 1. Results of these suggested methods on 20 semi-real neuronal signals

Proposed Methods	Parameters	-5 dB	0 dB	5 dB	10 dB	20 dB	50 dB
Spike detection using standard deviation and DWT	TP	100%	100%	100%	100%	100%	100%
	FN	0%	0%	0%	0%	0%	0%
	FP	43%	22%	10%	14%	17%	11%
Spike detection using standard deviation and Savitzky-Golay filter	TP	98%	96%	100%	100%	100%	100%
	FN	2%	4%	0%	0%	0%	0%
	FP	68%	24%	30%	14%	19%	18%
Improved SNEO by DWT	TP	96%	96%	100%	100%	100%	100%
	FN	4%	4%	0%	0%	0%	0%
	FP	48%	30%	0%	0%	0%	0%
Improved SNEO by Savitzky-Golay filter	TP	96%	96%	100%	100%	100%	100%
	FN	4%	4%	0%	0%	0%	0%
	FP	53%	24%	2%	0%	0%	0%
SNEO	TP	40%	48%	64%	84%	98%	100%
	FN	60%	52%	46%	16%	2%	0%
	FP	184%	147%	98%	54%	18%	0%
Spike detection using FD and DWT	TP	96%	98%	100%	100%	100%	100%
	FN	4%	2%	2%	0%	0%	0%
	FP	46%	18%	2%	0%	0%	0%
Spike detection using FD and Savitzky-Golay filter	TP	96%	98%	100%	100%	100%	100%
	FN	4%	2%	0%	0%	0%	0%
	FP	68%	44%	39%	25%	32%	25%

Table 2. Comparison of detection rate and CPU time for proposed methods

Proposed Methods	Spike detection using standard deviation and DWT	Spike detection using standard deviation and Savitzky-Golay filter	Improved SNEO by DWT	Improved SNEO by Savitzky-Golay filter	SNEO	Spike detection using FD and DWT	Spike detection using FD and Savitzky-Golay filter
CPU time	0.417 s	0.128 s	0.193 s	0.054 s	0.033 s	0.385 s	0.064 s

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