

Spike Detection from EEG signals with aid of Morphological Filters and Genetic Algorithm

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Abstract

In order to detect the abnormality in brain signals, it is essential to study the behavior of spikes in Electroencephalogram (EEG). Normally, recorded EEG signals contain large amount of artifacts like spikes whose detection is a technically challenged one. Morphological filters are generally used to separate these spikes from the recorded EEG signal. In existing techniques, the Gaussian function is used in morphological filter to find out the optimal structuring element. Using this function, the accurate optimal structuring element cannot be found. Here, it is proposed an optimization technique along with a spike detection method using morphological filter. In this method, initially the noise within EEG signals is removed by the wavelet technique and the resultant preprocessed EEG signals are given to the spike detection process. In the proposed method, Genetic Algorithm is used for the computation of optimal structuring elements in the Morphological filter used for the spike detection. After the computation, an amplitude threshold should be set to detect the occurrence of individual spikes. Hence, the spikes can be detected more effectively by achieving more number of correctly detected spikes rather than the conventional spike detection methods.

Keywords:

Spike Detection, Morphological Filter, Wavelet, Genetic Algorithm (GA).

1. INTRODUCTION

Decades ago, the primary focus of biomedical signal processing was on the removal noise from bio signals. Sources of noise arise from the inexactitude of instruments to interfering of power lines [1]. Biomedical signals are clarifications of the physiological activities of organisms, ranging from gene and protein sequences, to neural and cardiac rhythms, to tissue and organ images. Biomedical signal processing aims at extracting significant information from biomedical signals. With the aid of biomedical signal processing, biologists can able to discover new biology and physicians can able to monitor distinct illnesses [2] [3]. It is a rapidly mounting field with a wide range of applications. These range from the edifice of artificial limbs and aids for the disabled to the development of sophisticated medical monitoring systems that can operate in a non invasive manner to give real time views for the human body. There are a number of medical systems in common uses. These include ultrasound, electrocardiography and plythesmography, which are widely used for many resolutions [4] [5].

There are several types of biomedical signals that can be encountered. Accurate and efficient study and analysis of these signals can be facilitated by their proper identification as deterministic, random or chaotic, given that specific analysis techniques exist for each type of signals [6] [7]. Types of biological signals classified into two main groups: the deterministic and

the stochastic (or statistical) signals. The deterministic group is subdivided into periodic, quasi periodic and transient signals [8]. The stochastic signals are subdivided into stationary and non-stationary signals. The processing of biomedical signals usually consists of at least four stages [9]: i) Measurement or observation, i.e., signal acquisition. ii) Transformation and reduction of the signals. iii) Computation of signal parameters those are diagnostically significant. iv) Interpretation or classification of the signals [10].

The EEG signal is broadly used clinically to examine brain disorders. The language of communication with the nervous system is electric [11]. The study of the brain electrical movement, through the EEG records, is one of the most important tools for the diagnosis of neurological diseases. EEG is a tool for measuring electrical activity generated in the brain, which opens a window for exploring neural activity and brain functioning [12]. The EEG signal is acquired using electrodes placed on the scalp, which record the electrical field generated by the nerve cells [13]. The millisecond time-based resolution of EEG allows scientists to inspect not only vacillations of EEG activity as a function of task demand or subject samples but also to differentiate between functional inhibitory and excitatory actions [14] [15].

Traditionally, EEG is characterized as a linear stochastic process, which has been used as a golden standard in numerous clinical applications over the decades [16]. It is also an important method for studying the transient dynamics of the human brain's

large-scale neuronal circuits [17]. EEG shows a good correlation with the mental stress in terms of suppression of alpha waves and improvement of theta waves. Alpha waves are more active in occipital and frontal regions of the brain [18]. These waves are associated with idleness of the brain. So, in no stress condition, when the brain is doing no activity, alpha waves are dominant whereas in stressful situations, the power of alpha waves falls down showing the change in response under stress [19]. Beta waves show varying behavior in different frequencies in different parts of the brain and power in theta waves increases under stress or mental tasks. The accurate classification of electrical activity in a particular state of human brain helps in neurological diagnosis and also for establishing standards for instrumentation development. This classification also helps in the brain computer interfacing which has been gaining wide attraction in the research industry [20].

2. Problem Statement

During the literature survey, different wavelet, thresholding and filter based methods applied for performing spike detection and denoising process were studied. The thresholding and wavelet methods are widely used for spike detection. In thresholding based methods, the threshold can be set manually or automatically according to the statistical characteristics of spike trains. However, it fails to discriminate spikes with different morphologies but with similar amplitude. In the wavelet-based spike detection techniques, initially the coefficients are determined and then a threshold-based operation is performed to obtain the spikes from the signals. In such works, there is a lack of analysis in selecting the appropriate threshold value. In filter based methods, morphological filters are most widely used technique in the spike detection process. The morphological filters accomplish the spike detection process by using the optimal structuring elements and adaptive amplitude thresholding process. This morphological based method attains the high precision rate when the noise level of signal is high. But in this method, the performance is inadequate due to the selection of optimal structuring elements. Because, there is no standard optimization techniques exists in selecting the optimal structuring elements. So, these methods degrade the spike detection performance. To overcome the drawbacks in these existing methods, the wavelet technique is used to reduce the background noise from EEG recordings and the Particle Swarm Optimization is proposed for the computation of optimal structuring elements in the Morphological filter used for the spike detection

3. Spike Detection Method

Nowadays EEG recordings have become standard techniques for investigating individual or ensemble neuronal responses to physical stimulus or cognitive process in various research fields. The background noise in the EEG signal which gives the poor quality of

the EEG recording result. Spikes may form groups in EEG signal or appear as a single sharpness with some period on the same electrode. 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. The EEG consists of an underlying background process with superimposed transient non stationarities such as spikes. The detection of spikes in the EEG is of particular importance in the diagnosis of epilepsy. Spike detection can further reduce the data rate if spike counts are transmitted instead of spike waveforms.

In the proposed work, the effective spike detection mainly comprised of four stages namely,

- ❖ Preprocessing
- ❖ Morphological filter for spike detection
- ❖ Constructing an optimal structuring elements by GA
- ❖ Adaptive amplitude Thresholding

The proposed spike detection method using GA method is shown in Figure 1.

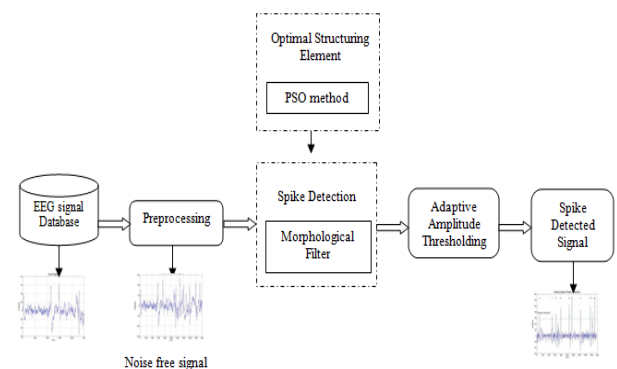


Figure 1: Proposed Spike detection using GA method

Consider S_n is the signal from the database, $D_s = \{S_1, S_2, \dots, S_n\}$, where $i = 1, 2, \dots, n$ and the signal S_n contains large amount of background noise and spikes. In the proposed work, the Preprocessing is applied to detect the spike signal. Using this preprocessed technique the noise present in the signal S_n can be removed and the output received from the preprocessing technique is now a noise free signal, called $N(S_n)$. The noise free signal $N(S_n)$ is then passed through a morphological filter for spike detection and the optimal structuring elements in morphological filter can be evaluated by using GA technique. Finally an adaptive amplitude threshold should be set to detect the occurrence of individual spikes.

3.1 Preprocessing

There are several methods that have been developed for EEG signal conditioning. Wavelet technique has been

widely used in signal processing for its ability to separate the signal and noise. Recently, wavelet theory has been applied in feature extraction and signal denoising. Haar wavelet, the first and simplest it is discontinuous, and resembles a step function. The output from the pre processing signal as a noise free signal, called $N(S_n)$.

3.2 Spike Detection by Morphological Filter

Morphological filter is an efficient tool in signal processing. It can decompose raw EEG signal into several physical parts. Background activity and spike component are separated and the main morphological characteristic of spikes is then retained. Morphological filter with functional structuring elements consists of four basic operations: addition, subtraction, opening and closing. Different operators smooth or extract different parts of the signal depending on the shape of the structuring element. Thus one of the tasks is the selection of the structuring element which separates the spiky areas of the signal. Combination of the morphological operators can produce a filter which separates an original signal into two signals and among them one signal is defined by the structuring element and the other is the rest of the signal.

$$\text{Addition: } (s \oplus h)(n) = \max_{m=1,2,\dots,M} \{s(n-m+1) + h(m)\} \quad (1)$$

$$\text{Subtraction: } (s \ominus h)(n) = \min_{m=1,2,\dots,M} \{s(n+m-1) - h(m)\} \quad (2)$$

$$\text{Opening: } (s \circ h)(n) = ((s \ominus h) \oplus h)(n) \quad (3)$$

$$\text{Closing: } (s \bullet h)(n) = ((s \oplus h) \ominus h)(n) \quad (4)$$

Where $s(n)$ is a one dimensional input signal of length N and time n , and $h(n)$ is a predefined structuring element of length $M < N$.

3.3 Combination of Morphological Operators

Spikes exist with positive and negative phase in an epileptic EEG. In order to detect bi-directional spikes, the morphological filters can be first applied with the opening operator followed by the closing operator or vice versa.

Open-Closing operation:

$$OC(s(n)) = s(n) \circ h_1(n) \bullet h_2(n) \quad (5)$$

Closing-Opening operation:

$$CO(s(n)) = s(n) \bullet h_1(n) \circ h_2(n) \quad (6)$$

Where $h_1(n)$ and $h_2(n)$ are different structuring elements. A morphological filter is designed to separate the input signal into two parts: one is categorized by the structuring element and the other is the rest of the signal. For spike detection, two structuring elements should be constructed to approximate the positive and negative peaks of spikes in signals. However, the extensiveness property of the opening and closing operators has a significant effect on the output of the morphological filter. To reduce this bias effect, an average of the combination of opening-closing and

closing-opening is introduced to replace simple opening-closing operation or closing-opening operation. So the peak-valley-extractor is defined as.

$$\phi(s(n)) = s(n) - \frac{1}{2} [(s \circ h_1) \bullet h_2 + (s \bullet h_2) \circ h_1](n), \text{ for } n=1,2,\dots,N \quad (7)$$

where with ϕ is the peak-valley extractor.

Step 1: Both amplitude and width of structuring elements can be set by visually inspecting morphological characteristics of spikes presented in the recorded signals. Let 'a', 'w' and 'l' denote amplitude of structuring element, width of structuring element and the length of window, respectively. The parameters of two structuring elements, and the length of the window should be determined initially. Set $j=0$, $M(0)=0$ and $\epsilon=10^{-4}$

Step 2: Load the data:

$N(S_n)$ ($S_n \in D_s$), $i=1,2,\dots,n$, is a segment of the input after preprocessing.

Step 3: Optimize the structuring elements.

Optimal structuring elements in morphological filter can be found out by using PSO technique.

Step 4: Process the input data $N(S_n)$ by means of morphological filter with the optimal structuring element.

Step 5: Calculate the adaptive amplitude threshold. Once the amplitude of the output of morphological filter exceeds the threshold, a spike event is detected.

Step 6: Move the window and repeat the process till the end of $N(S_n)$.

3.4 Genetic Algorithm

Genetic algorithm has been applied, such as, (a) elite, (b) crossover, (c) mutation. From that new updated particle the fitness value is calculated and the best one is selected.

Stopping Criteria: Check the termination condition. If the maximum generation number is reached or when the global best is not improving for a specific number of times, i.e. Count gbest variable is maximum than generation number, then stop the algorithm.

The best fitness valued signal is chosen and the corresponding width and amplitude of the signal is updated. The best fitness valued signal is called as $N_b(S_n)$. We can say that $F = N_b(S_n)$. In here the width and amplitude of the $N_b(S_n)$ has been updated and which is applied to equation (8) to getting optimal structuring element.

$$h_j(t) = a \exp\left[t\mu - |ct|^\alpha (1 - \beta w)\right]$$

(8)

Where $h(n)$ is discrete form of $g(t)$. Where c, α, β are the constants. In here a, w, μ are the amplitude, width and mean of the $N_b(S_n)$ respectively. Owing to the fact that the spike consist of positive peak and negative peak, two different structuring element, $h_1(n)$ for opening operator and $h_2(n)$ for closing operator, are designed to approximate the positive peak and negative peak, respectively. This two structuring element $h_1(n)$ and $h_2(n)$ are obtained from the noise free signal, $N(S_n)$. For defining the peak valley extractor the structuring element $h_1(n)$ and $h_2(n)$ are applied inequation. (7).

3.5 Adaptive Amplitude Threshold

In EEG signals, amplitude threshold is used for spike detection. The amplitude threshold that which detects the individual spike and is set as follows:

$$T = q\sigma \tag{9}$$

Where

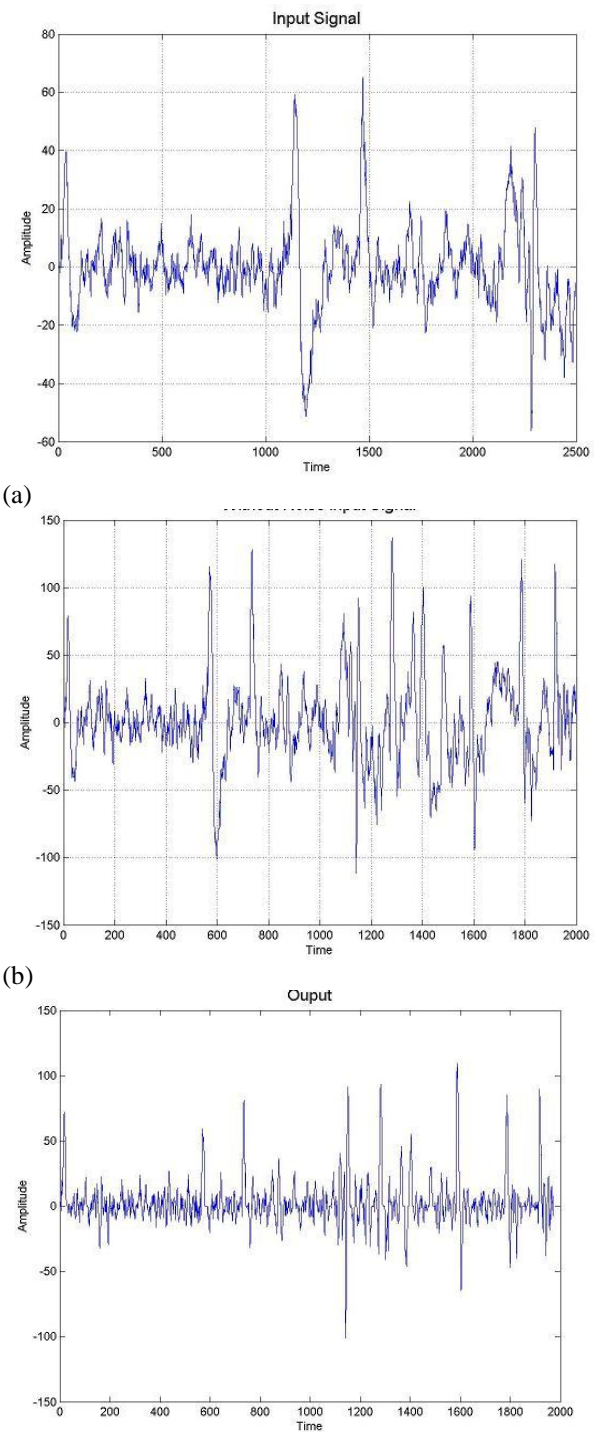
$$\sigma = \left(\frac{1}{M-1} \sum_{i=1}^M [b(i) - \mu]^2 \right)^{\frac{1}{2}} \tag{10}$$

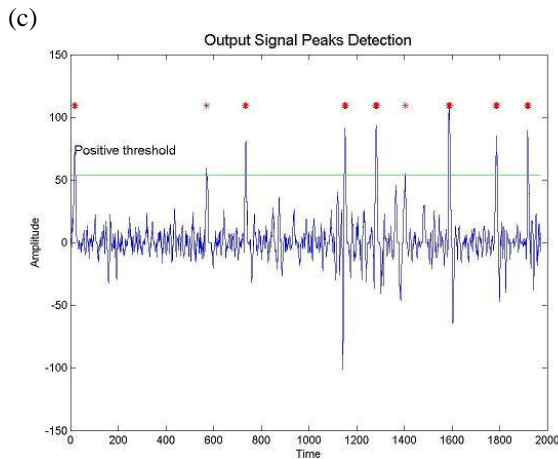
'q' is a constant generally taken 3~5 and 'M' is the length of $b(i)$.

4. Results and Discussion

The data set used to evaluate the spike detection is taken from the CHB-MIT Scalp EEG database and they were judged to be clinical seizures by experts.

Figure 2(a to d) shows the signals from the database and its corresponding spike detection. Here Figure 2(a) is the signal from the database which contains spikes. Figure 2(b) shows the preprocessed signal. Figure 2(c) shows the result of output signal. Finally Figure 2(d) shows the spike detected signal.





(d)

Figure 2: Spike detection

- (a) Original signal from the database,
 (b) Result of preprocessed signal,
 (c) Result of output signal,
 (d) Result of detected spikes from the signal

4.1 Performance Evaluation

In practice, it is hard to evaluate the performance of a new algorithm with real recorded neural data because the information, such as the number of spikes, the spike timings, the spike shape, and the noise level and so on, is unknown. A widely used framework to evaluate the performance of an algorithm is to compare the algorithm outcome of synthetic data with the original spike labels. Since the objective for spike detection is to minimize the number of falsely detected spike events (false positive) and maximize the number of correctly detected spike events (true positive), both hit rate and precision are used to evaluate the performance of the algorithm.

$$\text{Hitrate} = \frac{E_{cds}}{E_{trs}} \times 100\% \quad (11)$$

$$\text{Precision} = \frac{E_{cds}}{E_{ds}} \times 100\% \quad (12)$$

Where E_{cds} the number of is correctly detected spike events (true positive), E_{trs} is the number of true spike event in the signal (true positive and false negative) and E_{ds} is the number of spike event detected by the method.

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Here the performance of the proposed approach is evaluated with the above measures. If the hit rate and the precision rate are higher the better the performance and it is shown in Table-1.

Table 1: Performance Evaluation using Hit rate and Precision rate

Spike Train	Spike detection Using GA	
	Hit Rate	Precision Rate
1	76.92	83.33
2	59.61	65.95
3	11.11	11.11
4	46.66	46.66
5	46.29	50
6	85.71	87.09
7	77.77	80
8	70.58	72.72
9	87.17	89.47
10	68	68

5. CONCLUSION

The main aim of this research is to provide a better spike detection technique for EEG signals by solving the drawbacks that currently exist in the literary works. Hence, a spike detection method using morphological filter with an optimization technique is proposed. Using the proposed technique, the acquired EEG signals are to be preprocessed by using the wavelet technique and the noise was removed. GA procedural steps are to be carried out to determine the optimal structuring elements. The optimal value of the structuring elements from optimization technique will improve the performance of the proposed method. In spike detection process, the morphological filters closing and opening are utilized to detect both positive and negative peaks of spikes in EEG signals. Hence, the spikes were detected more effectively by achieving more number of correctly detected spikes rather than the conventional spike detection algorithms. The performance of the spike detection method was verified by using standard measures like hit rate and precision rate.

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