Automatic extracellular spike detection with piecewise optimal morphological filter

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A B S T R A C T

Neuronal spike detection is a technical challenge because of large amounts of background noise and contributions of many neurons to recorded signals. In this paper, we propose an automatic spike detection algorithm in which piecewise optimal morphological filters are designed to separate action potentials (spikes) from background noise. The structure elements of morphological filters are constructed with Gaussian function and a concise criterion is introduced to piecewise optimized structure elements. An adaptive amplitude threshold is utilized to detect spike events when the spikes are extracted by the morphological filter, which increases the detection accuracy. We evaluate our algorithm with both synthesized neural recordings and real neural data, and compare it with two established spike detection methods.

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1. Introduction

Nowadays extracellular neural recordings have become standard techniques for investigating individual or ensemble neuronal responses to physical stimulus or cognitive process in various research fields ranging from basic research in neuroscience to neural engineering. In view of the fact that the accuracy of detection and localizing the occurrence of individual spikes will critically impact the accuracy of all subsequent analysis, spike detection is a prerequisite for analysis of spike trains. Many factors, however, make it a challenging work. Firstly, extracellularly recorded spike trains are inevitably corrupted by the superimposed activity of multiple neurons and the noise from the recording hardware. Secondly, implanted microelectrodes generally pick up the simultaneous electrical activities with different size and shapes from an unknown number of neurons in a local region.

The amplitude threshold crossing is the most widely used for spike detection because of its simplicity and low computational complexity, which offer the feasibility of real-time implementation in hardware. 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. Moreover, the performance degrades rapidly with the presence of background noise and baseline shift of spike trains [1].

Several algorithms based on the instantaneous energy of signal are also widely used for spike detection, all of which exploit the fact that spikes have greater energy than the noise within the same time interval. The nonlinear energy operator (NEO) has been used to identify spike event by means of estimating the instantaneous frequency and amplitude of signal [2]. Its output is proportional to the product of instantaneous amplitude and frequency of signal. The slight computational burden enables NEO to be implemented in real time, but it is reported to be sensitive to any discontinuity and noise in the signal [3]. In a similar scheme, referred as normalized cumulative energy difference (NCED) [4], the instantaneous burst of energy over a specified threshold is identified as a spike event by calculating the slope of cumulative energy. This algorithm is also sensitive to the background noise, and furthermore, there is no criterion to adjust the threshold level.

Matched filters based on template matching are different techniques for spike detection, in which the spike event is identified when the similarity between signal amplitudes and standard template waveforms recognized as a typical spike shape is over a threshold level [1,4–6]. The matched filters require manual identification of the templates for each signal analyzed. Therefore, it is impractical to automatic operation for multi-electrode recordings

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and the accuracy of spike detection deteriorates with the changes in shapes and amplitudes of spikes [7,8].

Recently morphological filter, originating from image processing field, has been applied to one-dimensional signal such as ECG and EEG signals [1,9,10]. Nishida and colleagues present an approach to separate the epileptic spikes from the background EEG with morphological filter [10]. They utilize two polynomial functions of second order to design structuring elements and determine the parameters of structuring elements by minimizing a cost function. Nevertheless, their method is hard to be implemented automatically because of its high complexity of the cost function. In a recent study [9] addressing the signal separation of epileptic spikes and background EEG with morphological filters, two parabolas are used to construct the structure elements and an optimization criterion is established to guide how to appropriately adjust parameters of the structuring elements. In these studies [9,10] a hard threshold is used for spike detection after the epileptic spikes are separated from the background EEG. The approach based on hard threshold works poorly for multi-spike trains due to several factors. The electrode can pick up more than one spike from different neurons. The closer the neuron is to the tip of electrode the higher its spike is. In addition, the amplitude and shape of these spikes change with time.

Morphological filter can reinforce the action potential peak with respect to the geometrical shape of the structuring element and restrain effectively the background noise by selecting an appropriate structuring element and combining four basic operators of erosion, dilation, opening and closing. In this paper, we propose an automatic spike detection approach for extracellular neural recordings with piecewise optimal morphological filter and present a spike detector with adaptive amplitude threshold to detect the spike event. In our approach, Gaussian function is adopted to construct structuring element in view of that it is the optimal approximation to the typical action potential waveform in the sense of the minimum mean square error [11]. A new concise criterion is also proposed to piecewise optimized structuring elements, which should be constructed to approximate the geometrical feature of spikes presented in signals. When the range of amplitude and width of structuring elements and the analysis period are determined through observing a small slice of recorded signals, the spike extraction and detection can be performed automatically by means of our approach.

The reminder of the paper is organized as follows. In Section 2, we briefly review the concept of morphological filters in a self-contained way for readers’ convenience. In Section 3, for spike detection of extracellular neural recordings, we present an approach to design and optimize the structuring elements constructed by Gaussian function, and to construct the operators for spike extraction and the adaptive threshold for spike detection. In Section 4, the performance of the proposed approach is tested with both simulated signals of extracellular recordings and real neural data recorded from the hippocampus of rats. Some concluding remarks are given in Section 5.

2. Morphological filters

Morphological filter with functional structuring elements consists of four basic operations: erosion, dilation, opening and closing, which are defined as follows:

Erosion: 
\[ f \ominus g(n) = \min_{m=1,2,...,M} \left( f(n+m-1) - g(m) \right) \]
\[ n = 1,2,...,N-M+1; \]

Dilation: 
\[ f \oplus g(n) = \max_{m=1,2,...,M} \left( f(n+m-1) + g(m) \right) \]
\[ n = M, M+1,...,N; \]

Opening: 
\[ f \ast g(n) = (f \ominus g) \oplus g(n) \]

Closing: 
\[ f \ast g(n) = (f \oplus g) \ominus g(n) \]

where \( f(n) \) is a one dimensional input signal of length \( N \), and \( g(n) \) is a predefined structuring element of length \( M < N \).

The morphological filter is designed for a specific purpose by combining these four basic operations and by constructing appropriate structuring element.

3. Morphological filtering of neural spike trains

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. By moving the structuring element, opening operation can remove positive peaks of \( f(n) \) that match the shape of the structuring element and closing operation can fill the pits (negative peaks) of \( f(n) \) that the structuring element fit into. However, the extensiveness property of the opening and closing operators has a significant effect on the output of a 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

\[ \text{PNE}(f(n)) = f(n) - \frac{1}{2} (f \ast g_1) \ast g_2 + (f \ast g_2) \ast g_1(n), \quad \text{for } n = 1,2,...,N \]

where \( g_1(n) \) and \( g_2(n) \) are different structuring elements for opening operator and closing operator, respectively.

3.1. Constructing and optimizing structuring elements

In this paper, Gaussian function is chosen to construct structuring elements because it can fit typical neuronal spikes with the minimum mean square error [11]. Owing to the fact that the spike consist of positive peak and negative peak, two different structuring elements, \( g_1(n) \) for opening operator and \( g_2(n) \) for closing operator, are designed to approximate the positive peak and negative peak, respectively:

\[ g_j(t) = A_j \exp(-t^2/(2\sigma_j^2)), \quad j = 1,2 \]

where \( g(n) \) is a discrete form of \( g(t) \). The parameter \( A_j \) determines the center amplitude of structuring elements and the parameter \( \sigma_j \) reflects the width of structuring elements, both of which determine the shape of structuring elements, which has a decisive effect on the outputs of morphological filter. Since the extracellular recording contains spikes from more than one neuron, and these spikes are characterized by different amplitudes and shapes due to the property of the transfer path from neuron to electrode. The structuring elements should be constructed with appropriate size by adjusting the amplitude and width of structuring elements in order to extract all these spikes exactly. We propose a criterion to optimize the parameters of structuring elements, which is described as follows. Let \( X = \{x|i\} \), \( i = 0,...,N-1 \) be the output of morphological filter with the formula (5).

Define

\[ Q = \frac{\sum_{i=0}^{N-1} |x_{p,p} - P(n)|}{|P(n)|} \]

where

\[ x_{p,p} = |\sup(X) - \inf(X)| \]
The peak-to-peak value can be deemed as an estimation of the energy of extracted spikes. The constructed by these extreme points of \( x_{p} \) is sensitive to the pulsed components presented in signals. A between the negative peak value and the positive peak value and method. Generally the larger the \( Q \) represents a rough measure of the spike detection ability of the points \( f_{d} \) determined based on the statistical characteristics of extreme signals. Then, we roughly count the number of spikes in the slice. In order to estimate the average firing interval, we first arbitrarily extract a slice of data of several seconds (e.g. 2–3 s) from the signals. Then, we roughly count the number of spikes in the slice by visual screening. Finally, the average firing interval is obtained by dividing the slice length by the number of spikes in the slice.

\[
\hat{\lambda} \text{ is a gain factor, which is generally taken as } \hat{\lambda} = N; \{x(i)\} \text{ is series constructed by these extreme points of } X \text{ (Fig. 1).}
\]

The sum of absolute value of all extreme points in \( X \), can be deemed as an estimation of the energy of extracted spikes. The peak-to-peak value \( x_{p} \) reflects the magnitude of the change between the negative peak value and the positive peak value and is sensitive to the pulsed components presented in signals. A relatively larger \( x_{p} \) indicates that the spikes appear. In (7), \( Q \) represents a rough measure of the spike detection ability of the method. Generally the larger the \( Q \) is, the better the morphological filtering performs.

### 3.2. Adaptive amplitude threshold for spike detection

An amplitude threshold should be set to detect the occurrence of individual spikes. In our approach, the amplitude threshold is determined based on the statistical characteristics of extreme points \( \{x(i)\} \). The bidirectional amplitude threshold is set as follows:

\[
\text{threshold} = \mu \pm b\hat{\sigma}
\]

where

\[
\mu = \frac{1}{M} \sum_{i=1}^{M} x(i)/M,
\]

\[
\hat{\sigma} = \left( \frac{1}{N-M-1} \sum_{i=1}^{M} [x(i) - \mu]^{2} \right)^{1/2}
\]

\( b \) is a constant generally taken 3~5, \( M \) is the length of \( \{x(i)\} \).

### 3.3. Spike detection procedure with morphological filter

The structuring elements are piecewise optimized successively with a fixed-length window along the spike trains in order to improve the accuracy of spike detection due to the non-stationary nature of the neuronal spike trains. The length of window is generally taken as 10–15 multiples of the average firing interval. To estimate the average firing interval, we first arbitrarily extract a slice of data of several seconds (e.g. 2–3 s) from the signals. Then, we roughly count the number of spikes in the slice by visual screening. Finally, the average firing interval is obtained by dividing the slice length by the number of spikes in the slice.

We describe the procedures for automatic spike detection by the morphological filter with piecewise optimal structuring elements and with adaptive amplitude threshold as follows:

### I. Preparation

The search range of both amplitude and width of structuring elements can be set by visually inspecting morphological characteristics of spikes presented in the recorded signals. Let \( A, L \) and \( T \) denote amplitude of structuring element, width of structuring element and the length of window, respectively. These parameters of two structuring elements, \( A_{1}, A_{2}, L_{1} \) and \( L_{2} \), and the length of window \( T \) should be determined initially. Set \( j = 0, Q(0) = 0 \) and \( \varepsilon = 10^{-4} \).

### II. Load data

\( f(n) (n \in [(i-1)T iT]), i = 1,2, \ldots \) is a segment of the input neural signal \( s(n) \).

### III. Optimize structuring elements

**Step 1:** Given \( A_{1}(j) \) and \( A_{2}(j) \), construct a set of structuring elements with the obtained \( A_{1}(j) \) and \( A_{2}(j) \) and each element of sets \( L_{1}(j) \) and \( L_{2}(j) \). Given the signal \( f(n) \), we obtain a series of \( Q \) for each structuring element. Selecting the maximum of \( Q \), denoted as \( Q_{\text{max}}^{S} \), the corresponding \( L_{0}^{S}(i) \) and \( L_{1}^{S}(i) \) are denoted as the optimal width of structuring elements.

**Step 2:** Likewise, a new set of structuring elements are constructed with the selected \( L_{1}(j) \) and \( L_{2}(j) \) and each element of sets \( A_{1}(j) \) and \( A_{2}(j) \), and a new series of \( Q \) is obtained for each structuring element. Selecting the maximum of \( Q \), denoted as \( Q_{\text{max}}^{S} \), the corresponding \( A_{0}^{S}(i) \) and \( A_{1}^{S}(i) \) are denoted as the optimal amplitude of structuring elements.

**Step 3:** Taking \( Q(j) = \text{Max}(Q_{\text{max}}^{S}, Q_{\text{max}}^{S}) \). If \( |Q(j) - Q(j-1)| < \varepsilon \), the optimal parameters of structuring elements, \( A_{0}^{S}(i), A_{1}^{S}(i), L_{0}^{S}(i), L_{1}^{S}(i) \), are obtained. Else, let \( j = j + 1 \), go to step 1.

### IV. Process the input data \( f(n) \) by means of morphological filter with the optimal structuring elements.

### V. Calculate the adaptive amplitude threshold as described in Section 3.2. Once the amplitude of the output of morphological filter exceeds the threshold, a spike event is detected.

### VI. Move the window and repeat this process till the end of \( s(n) \).

A block diagram of this algorithm is also illustrated in Fig. 2.

### 4. Analysis from synthesized data

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, the noise level and so on, is unknown to us. 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 [12]. 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:

\[
\text{Hit rate} = \frac{N_{\text{correct}}} {N_{\text{true}}} \times 100\%,
\]

\[
\text{Precision} = \frac{N_{\text{correct}}} {N_{\text{detected}}} \times 100\%.
\]

where \( N_{\text{correct}} \) is the number of correctly detected spike events (true positive), \( N_{\text{true}} \) is the number of true spike events in the signal (true positive and false negative) and \( N_{\text{detected}} \) is the number of spike events detected by the method.

The simulated data is constructed according to the approach [12], which models extracellular recordings as a linear combination
of the background noise, multi-unit and single-unit activity and replicates the amplitude and spectral distributions of these three components. The data sets include three sets of simulated extra-cellular recording signals with a sampling rate of 24 kHz and they are available at http://www2.le.ac.uk/departments/engineering/research/bioengineering/neuroengineering-lab/spike-sorting. Each set of signals consists of 4 simulations with the noise level determined by background noise's standard deviation set to 0.05, 0.1, 0.15 and 0.2. Each simulation is 5 s long and contains three distinct dominant single-unit spikes with normalized amplitude. In all simulations, the three distinct spike trains have a Poisson distribution of inter-spike intervals with the mean firing rate of 20 Hz and the refractory period between spikes within the same category is set to 2 ms [13].

We firstly observe the performance of the new algorithm for a set of signals, which contains 3 spike trains and 23 spike events in total marked with the symbol ‘+’ and is presented in Fig. 3a. Following the procedure described in Section 3.3, these parameters are firstly initialized according to the properties of simulated data. Here the searching range of amplitude is set to [0.1, 1.0] and the searching range of width is set to [5, 36]. Accordingly, these parameters are set as follows: $A_1(0) = 0.1$, $A_2(0) = 1.0$, $L_1(0) = 5$, $L_2(0) = 36$, $T = 500$ ms, $Q(0) = 0$ and $\varepsilon = 10^{-4}$. The results are shown in Fig. 3b where the detected spikes are marked with the symbol ‘o’. The optimized parameters of structure elements are $A_{1o}^{op} = 1$, $L_{1o}^{op} = 7$, $A_{2o}^{op} = 1$, $L_{2o}^{op} = 9$. As shown in Fig. 3b, the piecewise optimal morphological filter has restrained all the background noise. The spikes are reinforced effectively and detected with adaptive amplitude threshold in terms of (6). Both the hit rate and precision are 100%.

We exploit the same data set to compare the new algorithm with the traditional morphological filters in which the structure elements are constructed by parabolas function. The parameters of structure elements are set as follows: $A_1 = 0.7$, $L_1 = 55$, $A_2 = 0.7$ and $L_2 = 55$. The result is presented in Fig. 3c. Although the hit rate is 100%, the precision is only 88.46%. We also compare the new algorithm with another established method, amplitude threshold crossing (ATC). The amplitude threshold is calculated by

$$\text{Threshold} = 4\sigma, \quad \sigma = \text{median}\{\frac{|y(n)|}{\text{median}}\}$$

(7)

As shown in Fig. 3d, the hit rate is 69.57% and the precision is only 94.12%.

For physiological time series [9,10], the structure element of morphological filter is always constructed to approximate all the spikes presented in signals, then it is used throughout the entire calculation invariably. This inevitably deteriorates the performance of morphological filter because of the non-stationary nature of physiological signals. In our method the neural time series are segmented into some slices and the structuring elements are optimized piecewise. Fig. 4 shows the results on the same data of the morphological filter with piecewise optimized structuring elements and those without piecewise optimized structuring elements. Although the structuring elements are optimized by maximizing the criterion $Q$ (optimal parameters of structuring elements $(A_1 = 1$, $L_1 = 5$, $A_2 = 1$, $L_2 = 5))$, some true spikes are attenuated greatly due to the mismatch of the shape with the structure elements. Consequently seven true spike events are missed as shown in Fig. 4b. For our method, the input signal slice is divided into two parts, and optimal parameters of structuring elements are $(A_1 = 1$, $L_1 = 9$, $A_2 = 1$, $L_2 = 11)$ and $(A_1 = 1$, $L_1 = 9$, $A_2 = 1$, $L_2 = 7)$ for each part. Each of them is processed separately. As shown in Fig. 4e and f, the background noise is restrained completely and all the spike events are detected correctly.

We further compare our method with the two established spike detection algorithms on simulated signals at different noise levels. The results are summarized in Table 1. As can be seen in Table 1, our method performs with higher hit rate and precision with respect to the same set of simulation compared with the other two methods. When the noise level increases, our method still performs better and it maintains over 95% hit rate and approximately 100% precision in contrast to the fact that the performance of the other two methods deteriorated gradually.

### 5. Application of our approach to real neural recordings

We also evaluate the performance of our approach on real signals since the real neural spike trains always differ from simulated signals. Public available data sets of neural recordings are used, which are recorded from the right dorsal hippocampus of a rat by the Buzsaki Lab with a sampling rate of 10 kHz, which can be downloaded from http://crcns.org/data-sets/hc [7]. Six 10-s long real neural signals are taken and then band-pass filtered with the frequency ranging from 300 Hz to 3000 Hz. Three signals, spike trains 1–3, are taken from data file d1492102 (channel 5) and the rest, spike trains 4–6, are taken from data file d533101 (channel 1). We apply the new approach to a slice of neural signal and show the outputs in Fig. 5. The original signal is shown in Fig. 5a and the spikes contained in it are labeled with sign ‘+’ through visual screening. As shown in Fig. 5d, the noise and other uncorrelated signals are obviously suppressed meanwhile the spike events are highlighted with our new approach. The outcomes of amplitude
Fig. 3. Results for simulated extracellular recording signals. (a) Original simulated extracellular recording signal with 23 spike events labeled out. (b) Results of our method. (c) Results of traditional morphological filter. (d) Results of amplitude threshold detection. The horizontal coordinate denotes sampling point.

Fig. 4. Effect of piecewise optimized structure elements on the performance of morphological filter. (a) Original simulated extracellular recording signal. (b) Results of morphological filter with the same structuring elements applied to the whole signal. In our method, the signal slice can be divided into two parts (c) and (d). The structuring elements are optimized and the relevant results are (e) and (f). The signal slice segmentation is not unique and it is determined by the parameter $T$. The horizontal coordinate denotes sampling point.
threshold crossing method and traditional morphological filter methods on the same signal are presented in Fig. 5a and c, respectively. In contrast, type I error occurs for both of them. We further compare the performance of our algorithm and other established ones on real extracellular recording signals, and the results are presented in Table 2. It can be observed that our algorithm outperforms the other two ones. The precision of our algorithm is over 96%. In contrast, the precision of the other two is lower than 85.94% and 94.02%. Moreover, the hit rate of our algorithm is comparable to the other two.

<table>
<thead>
<tr>
<th>Spike trains</th>
<th>Noise Level</th>
<th>Amplitude threshold detection</th>
<th>Traditional morphological filter</th>
<th>Piecewise optimal morphological filter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Noise standard variance (SNR)</td>
<td>Hit rate</td>
<td>Precision</td>
<td>Hit rate</td>
</tr>
<tr>
<td>Set 1</td>
<td>0.05 (10.6 dB)</td>
<td>95.12</td>
<td>85.19</td>
<td>94.97</td>
</tr>
<tr>
<td></td>
<td>0.10 (4.2 dB)</td>
<td>95.83</td>
<td>98.63</td>
<td>93.37</td>
</tr>
<tr>
<td></td>
<td>0.15 (1.9 dB)</td>
<td>91.55</td>
<td>99.64</td>
<td>91.69</td>
</tr>
<tr>
<td></td>
<td>0.20 (0.8 dB)</td>
<td>76.84</td>
<td>99.70</td>
<td>89.71</td>
</tr>
<tr>
<td>Set 2</td>
<td>0.05 (7.7 dB)</td>
<td>94.92</td>
<td>98.43</td>
<td>97.18</td>
</tr>
<tr>
<td></td>
<td>0.10 (2.2 dB)</td>
<td>95.51</td>
<td>99.75</td>
<td>98.26</td>
</tr>
<tr>
<td></td>
<td>0.15 (0.8 dB)</td>
<td>95.07</td>
<td>99.85</td>
<td>97.64</td>
</tr>
<tr>
<td></td>
<td>0.20 (2.8 dB)</td>
<td>90.41</td>
<td>99.93</td>
<td>96.30</td>
</tr>
<tr>
<td>Set 3</td>
<td>0.05 (7.3 dB)</td>
<td>95.66</td>
<td>99.97</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>0.10 (2.3 dB)</td>
<td>96.37</td>
<td>99.88</td>
<td>99.40</td>
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<tr>
<td></td>
<td>0.15 (0.7 dB)</td>
<td>95.55</td>
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<tr>
<td></td>
<td>0.20 (2.4 dB)</td>
<td>88.52</td>
<td>99.95</td>
<td>97.67</td>
</tr>
</tbody>
</table>

*SNR = 10 \log_{10}(P_s / P_n) (dB), the ratio of the power of useful signals to the power of background noise.

**Table 1**

Performance of algorithms applied to simulated data.

6. Discussion and conclusion

In this paper, an automatic spike detection algorithm based on piecewise optimal morphological filter is described. The piecewise optimal morphological filter can reinforce spikes categorized by structure elements and effectively restrain background noise. We adopt Gaussian function to construct structure elements and a new simple criterion is proposed to optimize structure elements within a sliding window along the input signal with a fixed length T. To avoid the statistical amplitude deflection, an average of the
weighted combination of opening–closing and closing–opening operation is used to carry out the computation. We also propose a method to calculate the adaptive amplitude threshold. Therefore, our algorithm can perform automatically once users set the parameter range of amplitude and width of structure elements and analysis period \( T \) previously. Three parameters determine the performance of our algorithm to some extent and they can be set simply by observing and preprocessing a slice of the input signal. A reasonable range of amplitude and width of structure elements can significantly improve the performance of piecewise optimal morphological filter. Therefore, the width range of structure elements should be relatively small but can cover the shape of most of the distinct spikes occurred in the input signal. For example, in Section 4 the range of width of structuring elements for simulated signals is set to \([5, 36]\) instead of \([1, 48]\). The analysis period \( T \) can be determined by the average firing rate of spikes in extracellular recording signal ensuring that not too many spikes are present in the data window. The average firing rate of spikes can be obtained roughly by observing a slice of signal. In previous methods \([9, 10]\), the structure element of morphological filter is constructed to approximate all the spikes presented in signals, and then it is used throughout the entire calculation invariably. This inevitably deteriorates the performance of morphological filter because of the non-stationary nature of physiological signals. In our algorithm the neural time series are segmented into some slices and the structuring elements are optimized piecewise. In this paper the structure elements can be optimized with the Q-criterion proposed to approximate most of the spike events within the analysis period \( T \), so our algorithm can minimize the potential of false detection of spike events (false positive). Unfortunately, it is impossible to avoid missing of spike events with different morphological characters from most of spike events presented in data window (negative positive), which greatly contributes to the false detection rate in our algorithm. This is partly due to the burst of one or two types of spikes making the rest type of spikes infrequent within the data window, which leads to the bias of optimal structuring elements to bursting spikes.

Our algorithm has been tested on simulated extracellular recording signals and real signals, and compared with traditional morphological filter and amplitude threshold detection. The results show that our algorithm achieves not only a higher hit rate but also higher precision for spike detection.

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Table 2

<table>
<thead>
<tr>
<th>Spike trains</th>
<th>Number of spikes</th>
<th>Amplitude threshold detection</th>
<th>Morphological filter</th>
<th>Piecewise optimal morphological filter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hit rate</td>
<td>Precision</td>
<td>Hit rate</td>
</tr>
<tr>
<td>1</td>
<td>103</td>
<td>99.03</td>
<td>79.07</td>
<td>100</td>
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<td>100</td>
</tr>
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<td>100</td>
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<td>100</td>
</tr>
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<td>5</td>
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<td>85.94</td>
<td>100</td>
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References


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