A spike detection method in EEG based on improved morphological filter

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Received 20 March 2006; received in revised form 14 March 2007; accepted 20 March 2007

Abstract

In this paper, a spike detection method is introduced. Traditional morphological filter is improved for extracting spikes from epileptic EEG signals and two key problems are addressed: morphological operation design and structure elements optimization. An average weighted combination of open–closing and clos–opening operation, which can eliminate statistical deflection of amplitude, is utilized to separate background EEG and spikes. Then, according to the characteristic of spike component, the structure elements are constructed with two parabolas and a new criterion is put forward to optimize the structure elements. The proposed method is evaluated using normal and epileptic EEG data recorded from 12 test subjects. A comparison between the improved morphological filter, traditional morphological filter and wavelet analysis with Mexican hat function is presented, which indicates that the improved morphological filter is superior in restraining background activities. We demonstrate that the average detection rate of the improved morphological filter is much higher than that of the other two methods, and there is no false detection for normal EEG signals with the proposed method.

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Keywords: Epilepsy; Morphological filter; EEG; Optimal structure elements; Spike detection; Morphological operation design

1. Introduction

Electroencephalogram (EEG) is a summation of electrical activities generated by cortical neurons and widely used in diagnosis of disorders related to epilepsy. Epilepsy is the most common neurological disease and it may be caused by many pathological processes of genetic or acquired origin. Epileptic seizures may lead to transient disturbances of mental function and/or movements of different body parts. Spikes are typical epileptic activity and usually recorded in epileptic EEG signals. Generally, an EEG spike, which is different from the background activity, has a pointed peak and duration of 20–70 ms [1].

Therefore, spike detection is significant for clinical diagnosis of epileptic disorders. Traditionally EEGs are scanned for epileptic spikes by experienced physicians. This process becomes very time-consuming in case of long EEG recordings. At the same time, more and more EEG data are recorded with an ambulatory monitoring, which produces 24 h or longer continuous EEG data. Thus, it is increasingly necessary to find an efficient automatic method for spike detection. Many attempts have been made to detect spikes automatically by computer-based methods. Smith [2] used a mimetic method to detect the sharp changes of EEG. With the non-stationary characteristic of EEG data being approved, non-linear methods such as wavelet, ANN and mathematic morphology are utilized to spike detection [3–12]. Miroslaw [3] selected Mexican hat as mother wavelet to detect spikes. As a result, the algorithm marked 356 events out which 239 turned to be the epileptic events. With wavelet analysis, it is difficult to eliminate background activities completely because it spreads in the entire frequency domain. On the other hand, there is no mother wavelet that perfectly matches the spike component. Therefore, the result of spike detection based on wavelet analysis needs improvement.

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 retained. Lon
[6] selected a circle structure element and utilized mathematical morphology and wavelet transform to detect bi-directional spikes in epileptic EEG. Nishida [7] presented a detection method based on morphological filter, in which open–closing operation was selected as the basic algorithm and the general structure elements are designed by second-order polynomial functions. Using a morphological filter with proper morphological operation and structure elements, it is possible to restrain the background activity completely. Specially, the lack of analytic criteria to choose structuring elements is the primary difficulty [13].

In this article, we provide an efficient method based on morphological filter, which can be used in automatic spike detection. The traditional morphological filter is improved from two aspects: (a) morphological operation. Due to the defect of amplitude deflection with single open–closing and close–opening operation, an average weighted combination of open–closing and close–opening operation is used to detect transient component in EEG data; (b) design and optimization of structuring elements. Structure elements constructed by two parabolas are designed against characteristic of spike waves. Then, a new criterion (K-criterion) is proposed to obtain optimal center amplitude and width of the structure elements. Background activity is fully restrained and spike component is well extracted with the proposed morphological filter, using the optimized structure elements. Whereafter, 12 clinical EEG segments are utilized to evaluate the validity of the mentioned method. A comparison between the traditional morphological filter, Mexican hat wavelet analysis and the improved morphological filter is drawn. As a result, the improved morphological filter is superior in eliminating the background activities and it has higher spike detection rate than that of the other two techniques.

2. Methods

2.1. Data acquisition

EEG data used in this paper were collected from the patients of Zhejiang Provincial People’s Hospital, China. The test subjects include two normal adults (test subject 1 and 2, 32 year-old male and 28 year-old female) and 10 patients with epilepsy (test subject 3–12, 12–45 year-old males and females). Data acquisition system is Phoenix Unique Ambulatory EEG of EMS Handelsges.mbH company, Austria. The EEG data are amplified with bandpass filter of 0.15–60 Hz and the sampling rate is set to 256 Hz. Exploring cup electrodes were fixed to the scalp at Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5 and T6 according to the International 10–20 System, and the reference electrodes are located on the ipsilateral ear electrode.

2.2. Fundamental theory of mathematical morphology

The morphological filter with functional structure element for one-dimensional time series data, which is presented by Magaros [13,14] in 1987, consists of four basic operations:

- **Erosion:**
  \[
  (f \ominus g^s)(t) = \min_{\tau \in D} \{ f(\tau) - g(-(t - \tau)) \}.
  \]

- **Dilation:**
  \[
  (f \oplus g^s)(t) = \max_{\tau \in D} \{ f(\tau) + g(-(t - \tau)) \}.
  \]

- **Opening:**
  \[
  (f \circ g)(t) = [(f \ominus g^s) \oplus g](t).
  \]

- **Closing:**
  \[
  (f \bullet g)(t) = [(f \oplus g^s) \ominus g](t),
  \]

where \( f(t) \) is the original time series of time \( t \), and \( g(t) \) is a structure element function. \( g^s(t) \) points to the reflection of \( g(t) \), which is defined as \( g^s(t) = g(-t) \). \( D \) means the set of real number. The notation \( \ominus, \oplus, \circ \) and \( \bullet \) indicate Minkowski addition, Minkowski subtraction, opening and closing operation, respectively, as shown in Eqs. (1)–(4). As a result, erosion of \( f(t) \) by structure element \( g(t) \) reduces the peaks and enlarges the minima of \( f(t) \), while dilation of \( f(t) \) by \( g(t) \) increases the valleys and enlarges the maxima of \( f(t) \). By combining erosion and dilation operation, opening and closing are set up. Opening of \( f(t) \) by structure element \( g(t) \) smooths the signal \( f(t) \) from below by cutting down its peaks, and closing smooths the signal from above by filling up its valleys. Thus, opening and closing can be applied to detect peaks and valleys in signals.

2.3. Improved morphological filter for extracting spikes in epileptic EEG

The basic idea of the proposed method is to separate transient components (spikes) and background activity by the differences of their morphological characteristics. In the improved morphological filter, a complex morphological operation is utilized, which differs from the traditional one. More importantly, the structure elements are constructed with two parabolas and a new optimization criterion is put forward to select proper parameters of the structure elements. The detection procedure is briefly explained as follows: firstly, the morphological filters are constructed to extract background activity from the original EEG. Secondly, the transient signals including spikes are obtained by subtracting the background activity from the EEG with spikes. Finally, spikes are detected from the transient signals by the predetermined threshold criterion. Details of the filter for the detection of spike waves are described in the following sections.

2.3.1. Average weighted combination of open–closing and close–opening operation

In epileptic EEG, spikes exist with positive and negative phase. In order to detect bi-directional spikes, the morphological algorithm can be first applied with opening (or closing) operator followed by closing (or opening) operator, which are
defined as follows:

Open–closing operation:

\[ \text{OC}(f(t)) = f(t) \circ g_1(t) \bullet g_2(t). \] (5)

Clos–opening operation:

\[ \text{CO}(f(t)) = f(t) \bullet g_1(t) \circ g_2(t), \] (6)

where \( g_1(t) \) and \( g_2(t) \) are different structure elements. However, both open–closing and clos–opening operation can lead to a statistical deflection of amplitude, i.e., the result of open–closing operation has lower amplitude than original signal and the result of clos–opening operation has larger amplitude than original signal. At a given threshold, the distortion of amplitude may cause pseudo-positive or missing detection in spike detection. Here, an average weighted combination of open–closing and clos–opening is utilized to avoid the amplitude deflection, which is shown as follows:

\[ M_{\text{aw}}(f(t)) = \frac{1}{2} \left[ \text{OC}(f(t)) + \text{CO}(f(t)) \right]. \] (7)

With Eq. (7), not only the bi-directional spikes can be extracted but also false detection caused by individual open–closing or clos–opening operation is avoided.

2.3.2. Design and optimization of structuring elements

In order to separate the spike component and background activity, structure elements, which can insert into shape of background EEG but not into spike waves, are constructed by \( g_1(t) \) and \( g_2(t) \). The structure element pair is determined in Eq. (8) and shown in Fig. 1:

\[ g_i(t) = a_i t^2 + b_i, \quad i = 1, 2, \] (8)

where \( a_i \) accounts for the width of the structure elements and \( b_i \) stands for the center amplitude of the structure elements.

The amplitude and width of structure elements have a decisive effect on the processed result for original EEG. Since different spike waves may have various amplitude and frequency, the structure elements should be adjusted to proper size where the spike component can be best extracted.

Suppose that \( s(t) \) is the original EEG data and \( x(t) \) is calculated with \( x(t) = s(t) - M_{\text{aw}}(s(t)) \), the structure elements are optimized as follows:

\[ K = I_f / R_{pz} \] (9)

for which

\[ I_f = \hat{x} / \bar{x} \] (10)

and

\[ R_{pz} = N_{pz} / N \] (11)

where \( I_f \) is the pulse index for the input signal \( x \) and \( R_{pz} \) points to the zero-pass rate of signal \( x \). Thereinto \( \hat{x} \) is the peak value of \( x \) obtained by \( \hat{x} = \max \{|x(t)| \} \), \( \bar{x} \) is the average amplitude of \( x \) calculated with \( \bar{x} = \int_{-\infty}^{+\infty} |x| p(x) dx \). \( N \) is the total data length of \( x \) and \( N_{pz} \) is the number of zero-pass points in signal \( x \) determined by

\[ N_{pz} = \sum_{n=1}^{N-1} \mu[x(n) * x(n+1)] \] (12)

assuming

\[ \mu(x) = \begin{cases} 1, & x \leq 0, \\ 0, & x > 0. \end{cases} \] (13)

\( I_f \) is sensitive to the transient component which points to spike waves in the epileptic EEG and \( R_{pz} \) reflects the degree of restraining the background activity. So, \( K \) evaluates the degree of pulsive characteristic on the precondition of less low-frequency component in the signal \( x \). A larger \( K \) shows that spike waves in epileptic EEG are better extracted and background activity are better restrained. In the present paper, the amplitude and width of the structure elements are optimized, respectively, with the mentioned \( K \)-criterion. The process of calculating \( K \) is shown in Fig. 2.
2.4. Spike detection with improved morphological filter

Given an epileptic signal \( s(t) \), the process of spike detection with improved morphological filter can be described in Fig. 3.

(I) First, the search area on amplitude and width of structure elements is decided. The center amplitude of structure elements ranges from 10 to 200 \( \mu \text{V} \), which includes the probable amplitude of spike waves. Since the sample rate of EEG signal is 256 Hz, the width of spike waves is no more than 23 points. So, the width of structure elements is set from 1 to 23, which covers the frequency range of spike waves.

(II) Then, the structure elements are optimized with the following steps, which are shown in Fig. 4.

1. At the beginning of the optimization process, several parameters are initialized as follows: \( K(0) = 0 \), \( a_1(0) = -6.25 \times 10^3 \), \( a_2(0) = -9.88 \times 10^4 \), \( b_1(0) = 10 \mu \text{V} \), \( b_2(0) = 200 \mu \text{V} \), \( E_r = 1 \times 10^{-4} \). Where \( a_1(0) \) is calculated when the initial width of structure element \( g_1(t) \) is 1 and \( a_2(0) \) is calculated when the initial width of structure element \( g_2(t) \) is 23.

2. A structure elements set are decided by \( a_1, a_2 \) in the search area and the current \( b_1(n), b_2(n) \).

3. For all the structure elements, \( K \) is calculated. Maximum of \( K \) is marked as \( K_{\text{max}}(a(n)) \). The corresponding \( a_1(n), a_2(n) \) are obtained.

4. A new structure elements set are decided by \( b_1, b_2 \) in the search area and the obtained \( a_1(n), a_2(n) \).

5. For all the structure elements in the new set, \( K \) is calculated. Maximum of \( K \) is \( K_{\text{max}}(b(n)) \). The corresponding \( b_1(n), b_2(n) \) are obtained.

6. Let \( K(n) = \max[K_{\text{max}}(a(n)), K_{\text{max}}(b(n))] \), return to step (2) if \( |K(n) - K(n-1)| > E_r \).

7. If \( |K(n) - K(n-1)| < E_r \), \( a_1(n), a_2(n), b_1(n) \) and \( b_2(n) \) are the optimization result.

(III) After that, the optimized structure elements are used to perform \( M_{\text{aw}} \) operation on the original signal \( s(t) \). The processed data \( x(t) \) is obtained by subtracting the result of \( M_{\text{aw}} \) operation from \( s(t) \).

With the optimized structure elements, spike component in \( s(t) \) is extracted and background activity is fully restrained, which represents processed data \( x(t) \). Since the background activity is fully removed from \( x(t) \), spike waves are detected by using the predefined threshold.

3. Results

Fig. 5 shows the results obtained from an epileptic EEG at T3 (test subject 6); (a) clinical EEG with spikes, (b) processed data of improved morphological filter, (c) processed data of traditional morphological filter with circle structure element, (d) processed data of Mexican hat wavelet. The epileptic EEG is 10 s long with sampling rate of 256 Hz shown in Fig. 5(a). A bi-directional spike and two spikes with positive phase exist in the epileptic EEG.

Fig. 5(b) shows the result of spike detection with improved morphological filter. The width and center amplitude of structure elements are optimized with proposed \( K \)-criterion:

\[
\begin{align*}
    a_1 &= -5.91 \times 10^5, \quad b_1 = 28 \mu \text{V}, \\
    a_2 &= -6.67 \times 10^4, \quad b_2 = 36 \mu \text{V}.
\end{align*}
\]
With the optimized morphological filter, the background activity is completely restrained and spikes are detected with predefined threshold $T_h = 5 \mu V$.

Fig. 5(c) refers to the processed data by traditional morphological filter. We employ $M_{aw}$ operation and the structure element is defined as a circle with radius of 11. However, the background EEG is partially retained due to lack of optimization on the structure element.

Fig. 5(d) is the processed data of the epileptic EEG signal using wavelet analysis. The wavelet transform of a signal $f(x)$ is defined as

$$WT_a f(x) = f(x) \ast \psi(x) = \frac{1}{a} \int_{-\infty}^{+\infty} f(t) \psi \left( \frac{x-t}{a} \right) \, dt,$$

(16)

where $a$ is scale factor, $\psi(x) = (1/a)\psi(x/a)$ is the flex of the mother wavelet at scale $a$. Here we employ Mexican hat function

$$\psi(x) = \frac{2}{\sqrt{3}} \pi^{-1/4} (1 - x^2)e^{-x^2/2}$$

(17)
as the mother wavelet because it is suitable for detecting spikes in EEG at small scales $a$ [3,15,16]. Firstly, the original signal is first decomposed at a discrete scale set $\{a = 1, 2, \ldots, 20\}$ using (16). Since the shape of Mexican hat is very similar to spikes at scale $a = 6$ [3], we reconstruct the signal by setting the wavelet coefficients to zero at all scales except scale 6.

Compared with wavelet analysis and traditional morphological filter, the improved morphological filter is superior in characteristic extraction of spike waves, which can be demonstrated by signal noise ratio (SNR). Supposed that background activity is the noise and spike component is the target signal, then

the SNR of original EEG data, processed data calculated by Mexican hat wavelet analysis, traditional morphological filter and improved morphological filter are listed in Table 1, which is determined by

$$SNR = 10 \log (P_s/P_n)(dB).$$

(18)

Fig. 6 illustrates the results of a normal EEG at O1 (test subject 1); (a) normal EEG, (b) processed data of improved morphological filter. In the processed data for normal EEG, no spike waves are extracted and background activity is restrained near to zero.

<table>
<thead>
<tr>
<th>Number</th>
<th>Number of spikes</th>
<th>False detection rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Improved morphological filter</td>
<td>Traditional morphological filter</td>
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<tr>
<td>1</td>
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<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
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<tr>
<td>3</td>
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<td>4</td>
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<td>6.35</td>
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<tr>
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<td>8.73</td>
</tr>
<tr>
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</tr>
</tbody>
</table>

Fig. 6. Results for actual normal EEG data: (a) actual normal EEG, (b) processed data of improved morphological filter.
We choose 12 EEG segments from the selected test subjects for spike detection using the abovementioned three methods, respectively, with the predefined threshold 5 μV. Results are shown in Table 2.

Spike waves with both positive and negative phase exist in the epileptic EEG. From the results we can see that the improved morphological filter is more efficient in spike detection.

4. Conclusion and discussion

In this paper, a method for automatic spike detection by using improved morphological filter is proposed. An average weighted combination of general open–closing and close–opening morphological operation is employed in separating background activities and epileptic spikes. Structure elements are designed with two parabolas and especially, a new criterion on optimization of structure elements is also put forward. The proposed method, together with traditional morphological filter and wavelet analysis, are applied to 12 clinical EEG segments including epileptic and normal EEG. Results show that the improved morphological filter performs better in terms of background EEG activity elimination. When using thresholding-based detection strategy, we achieve a higher detection rate of the improved morphological filter than that of the other two methods.

The basic idea of the improved morphological filter is to separate spikes and background activity by the differences of their geometric characteristics. Once there exist artifacts with similar morphological features to spikes in EEG signal, false detection rate increases. For example, the artifact of electromyography caused by tic has nearly the same morphological features as spikes. Similar to the improved morphological filter, traditional morphological filter and wavelet analysis extract features from the original EEG signals according to the morphological characteristics of the predefined structure element and mother wavelet. So the performance of traditional morphological filter and wavelet analysis also reduces when artifacts exist. A preprocessing system which can remove artifacts in EEG signals and wavelet analysis also reduces when artifacts exist. A preprocessing system which can remove artifacts in EEG signals and wavelet analysis also reduces when artifacts exist.

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Acknowledgments

The support of Zhejiang Provincial People’s Hospital is greatly appreciated.

References


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