**Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006**

SaEP13.4

Spike Separation from EEG/MEG Data Using Morphological Filter and Wavelet Transform

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Abstract—**In the analysis of epileptic electroencephalographic (EEG) and magnetoencephalography (MEG) data, spike separation is diagnostically important because localization of epileptic focus often depends on accurate extraction of spiky activity from the raw data. In this paper, we present a method to automatically extract spikes using the wavelet transform combined with morphological filtering based on a circular structuring element. Our experimental results have shown that this method is highly effective in spike separation. Comparisons with the wavelet, bandpass filter, empirical mode decomposition (EMD), and independent component analysis (ICA) methods show that the new method is more effective in estimating both spike amplitudes and locations.**

I. Introduction

SPIKES represent the most common form of epileptiform activity in clinically recorded epileptic EEG/MEG. According to Chatrian [1], a spike is described as "a transient, clearly distinguished from background activity, with pointed peak at conventional paper speeds and a duration from 20 to under 70 ms, approximately. Main component is generally negative relative to other areas. Amplitude is variable." In clinical studies, spikes in EEG/MEG provide evidence for epilepsy diagnosis and are often utilized to localize epileptogenic zones within the brain. Since visual inspection of large EEG/MEG datasets is time-consuming, automatic spike detection has been developed based on the Fourier transform, wavelet transform, template matching, inverse filtering, etc [2, 3, 4]. However, most spike detection methods can detect spikes but cannot extract spiky component from the EEG/MEG background. In practice, epileptologists are often interested in separating epileptic data (e.g. the EEG/MEG with spikes) into the background activity and epileptiform waves, which are interpreted independently. The presence of substantial irrelevant components may result in an erroneous interpretation of the recorded EEG/MEG [5]. Spikes may also provide important information for localizing epileptic foci and studying the propagation of epileptic activity within the brain. Unfortunately, the accuracy of localization may be distorted due to the superimposition of spikes on background EEG/MEG waveforms. Therefore, this procedure of spike separation must be taken into account before interpreting and localizing the original EEG/MEG data.

Algorithms using wavelet transforms, time-frequency analysis, and artificial neural networks have been utilized to extract the waveforms of early ictal events [6, 7, 8]. Morphological filters have been constructed to separate background EEG and spiky activity [5, 9, 10]. Because the criteria for identification of spikes in MEG are similar to that for EEG [11], the detection and separation algorithms utilized in EEG data are also applicable to MEG data. This paper studies an approach for spike separation from EEG/MEG signals by combining mathematical morphology and wavelet transforms. Because the multi-resolution property of the wavelet transform adapts well to the time-invariant nature of the EEG/MEG data, this method can separate the background spiky components more effectively.

This paper is organized as follows: Section II briefly describes the mathematical morphological filter and the wavelet transform. In section III, experimental results and comparisons with other signal separation algorithms are proposed. The final discussion and conclusion are presented in section IV.

II. Methods

Morphological filters use a simple structuring element (SE) to match a signal's geometrical shape. It is often utilized to detect the morphological characteristics in signals. If a signal contains features consistent with the geometrical feature of the structuring element, a morphological filter can recognize and extract these features. A morphological filter performs four basic operations: erosion, dilation, opening, and closing [12]. In our case, a circle is used as the structuring element. The morphological filter processes EEG signal by applying an opening operator followed by a closing operator, where morphological opening and closing smooth out the upward and downward peaks, respectively (Fig.1).

Although morphological filtering is able to extract spikes by computing the difference between the original and the filtered signals, the performance using a fixed SE is often unsatisfactorily since the duration and amplitude of spikes vary considerably even in the data recorded from the same patient. It is well known that the wavelet transform provides a powerful multi-resolution analysis to decompose a signal into multiple scale levels. Therefore, applying the SE at different

Manuscript received April 3rd, 2006. This research was supported in part by National Institutes of Health grants No. R01EB002309 and R01NS38494, and Computational Diagnostics, Inc.

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scale levels is equivalent to applying different SEs which is proportionally scaled.

The procedures of our method are summarized as follows:

1) Decompose an input signal into two coefficient sets by using the wavelet transform. After applying the morphological filter to both coefficients, the smooth component is extracted, as shown in Fig.2.

2) Decompose the filtered coefficients into two lower levels and filter them with the morphological filter.

3) Repeat step 2) until a pre-defined level of decomposition is reached. This level depends on the maximum duration of the spikes because the lower level coefficients are at a half scale of the higher level. A detailed description of this process can be found in [9, 10].

4) Reconstruct the subsets of filtered coefficients using the inverse wavelet transform to obtain the smooth component of the signal.

5) Subtract the smooth component from the original signal to obtain the separated spiky component.

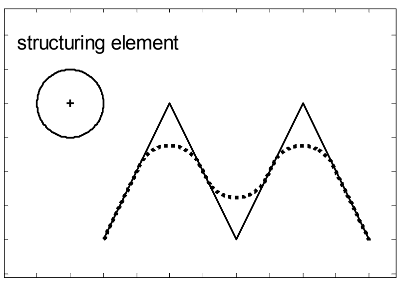

Fig.1 Conceptual illustrations of Morphological filtering. The solid line represents the signal, the dashed line is the filtered result combined with morphological opening followed by closing. The SE is a circle

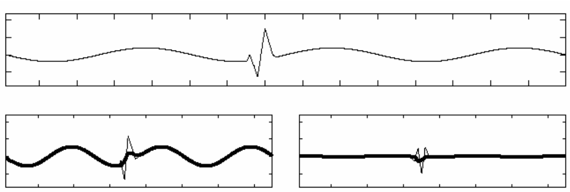

Fig.2 Top panel: Input signal; Bottom left panel: approximated coefficients (thin line) and filtered approximated coefficients (thick line); Bottom right panel: detail coefficients (thin line) and filtered detail coefficients (thick line).

III. EXPERIMENTAL RESULTS

A. Simulated spiky data

In order to evaluate both the amplitude and location of the extracted spikes, simulated spiky data were used in our initial experiments. First, typical spikes were identified by epileptologists from scalp EEG signals. Then, these patterns were isolated, scaled, and superimposed to a set of manually selected clinical EEG segments where epileptic spikes were absent. These EEG segments thus served as the background components. Two such segments with simulated spikes superimposed are shown in Fig. 3. Slow waves were dominant in the simulated signal 1 (top panel) while not in the signal 2 (bottom panel), representing two different types of spiky signals. It can be seen that each signal contains a number of spikes whose durations and amplitudes vary in a wide range. The sampling rate was 256 Hz and the data lengths were 6 and 8 seconds for signal 1 and signal 2 respectively.

We also utilized a dataset [13] which has been previously studied by other groups [14] to evaluate the performance of our method. EEG data in this dataset, sampled at 240 Hz, were acquired from juvenile epileptic patients according to the international 10-20 standard system. Seven segments of test signals with spikes or sharp waves followed by slow waves with comparable amplitudes were studied in our experiment.

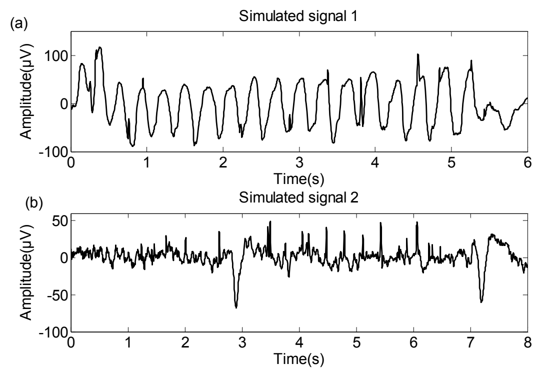

Fig.3 Simulated signals with (top) and without (bottom) dominating slow waves.

B. Results of simulation

Using our method, each EEG segment was separated into a background component and a spiky component. The morphological filter was applied to three levels of the wavelet transform. In this simulation, we used the biorthogonal wavelet transform. The reconstruction from the morphologically filtered coefficients produced the separation result. The original spikes and the separation result for simulated signal 1 are shown in the Fig. 4. It is clear that spiky patterns in the simulated signal have been extracted successfully. The position of each spike was then detected by setting a proper threshold. The maximum value

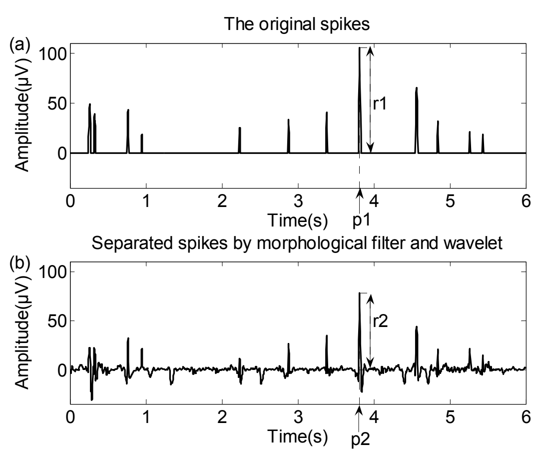

Fig.4 (a): Original spikes in Signal 1; (b): Result of spike separation by the wavelet transform and morphological filtering method.

and its position of the spike were recorded as the amplitude and the location, respectively, as shown in Fig. 4. For every spike, the localization error was defined as p1-p2 and relative amplitude error was (r1-r2)/r1×100%. The average localization and amplitude errors over the 12 spikes in simulated signal 1 were about 0.65ms and 26.9%.

C. The influence of noise

We simulated noisy signals by adding normally distributed white noise to the signals without noise. Then, our spike separation method was applied. Fig. 5 shows the results of two cases where the signal-to-noise ratio (SNR) equals to 20dB and 30dB, respectively.

Further statistical analysis was performed to reflect the relationship of the separation result with the changes of SNR in the simulated signals. We calculated the true positive (TP), false positive (FP), and false negative (FN) errors in the numbers of the detected spikes, as well as the localization and relative amplitude errors. The results are shown in Fig. 6. It can be observed that, for SNR > 25 dB, the separated result is similar to that of the original signal 1. Similar results were obtained for signal 2.

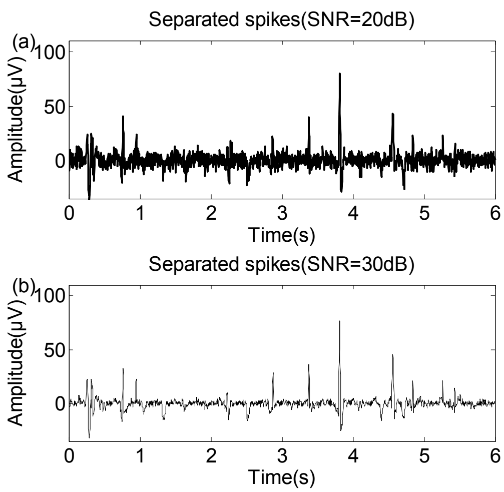

Fig.5 Separation results for noisy signals. (a) SNR=20dB; (b) SNR=30dB.

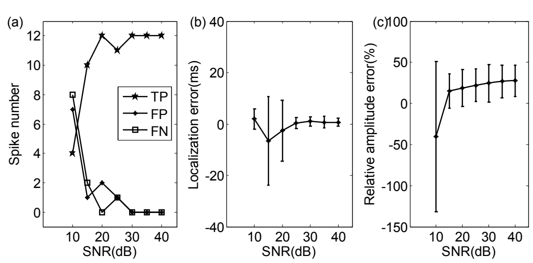

Fig.6 SNR vs. errors in spike separation: (a) numbers of TP, FP and FN; (b) location error; (c) amplitude error.

D. Comparison with the results using other methods

We compared our method with other signal processing algorithms, such as bandpass filter, empirical mode decomposition (EMD), and independent component analysis (ICA). In the EMD method, the signal was decomposed into Intrinsic Mode Function (IMF) components [15] based on signal extremes. In the ICA method, the signal in each channel was first reconstructed into multi-channel signals using an embedded method. Then, the signals were re-whitened and an orthogonal matrix was formed by the principle component analysis (PCA). ICA was applied to decompose this matrix into independent components. The decomposed spiky components were selected to reconstruct the spiky component. Detailed description has been provided in [16].

Figs.7 and 8 compare our method with the wavelet, bandpass filter, EMD, and ICA methods. The wavelet method used the same biorthogonal wavelet as that in our method. The spiky component was kept during the computation while the smoothed background was discarded. The frequency band for the bandpass filter was 14~50Hz. In the EMD and ICA methods, only the spiky components were selected to reconstruct the separated spiky signal. It can be observed from these two figures that our method provides better spike separation in both spike localization and amplitude.

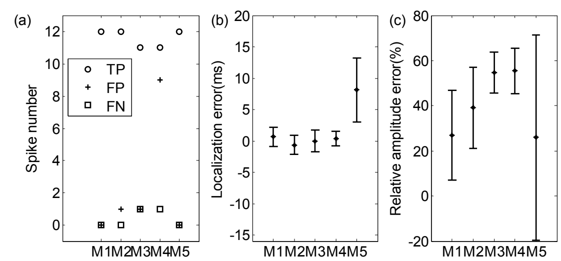

Fig.7 Statistical results of simulated signal 1. M1-M5 represent, respectively, wavelet and morphological filter; wavelet; bandpass filter, EMD, and ICA.

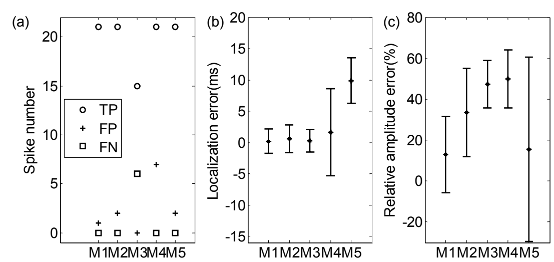

Fig.8 Statistical results of simulated signal 2. The definitions of M1-M5 are the same as those in Fig.7.

E. Results of real epileptic EEG signals

As previously described, we use Group 2 of epileptic EEG datasets in [14] as our inputs. This group contains spike-slow waves and sharp-slow waves. Seven segments of EEG signals containing 76 transient events (spike or sharp waves) were analyzed and the results were evaluated by neurologists specialized in EEG. A fixed threshold was used to detect spikes in all separated components. A total of 73 transient events were detected with 3 FNs and 9 FPs. A typical spike-slow wave EEG signal and separated result are shown in Fig. 9(a) and (b). From our separation results, we found that most FP errors came from one segment which contained a special form of spike-slow waves (see Fig. 9(c) and (d)). Nevertheless, our method (M1), in general, produced better performance.

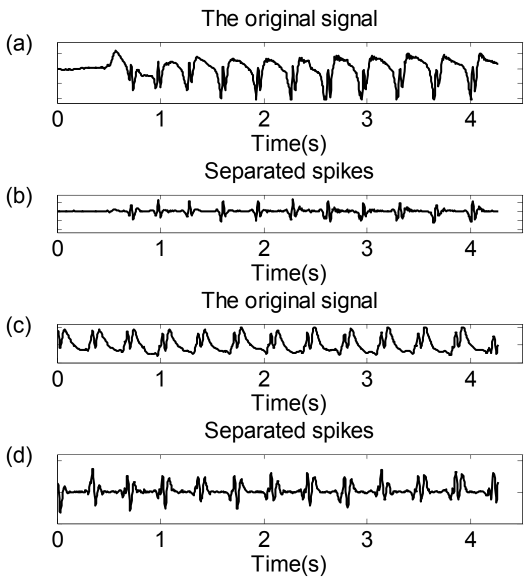

Fig.9 A typical spike-slow wave (a) and its separated result (b); a more difficult case (c) where the result is less satisfactory (d).

IV. Discussion and Conclusion

The multi-resolution property of the wavelet transform was utilized in our method to improve morphological filtering for detection and extraction of epileptic spikes with varying duration. When compared with other separation methods, encouraging results have been obtained for both simulated spikes and real epileptic data. However, our experimental results were limited to two types of spiky data. More EEG/MEG data containing other types of spikes will be further investigated. Due to the use of a simple structuring element, this method has limited ability to extract irregularly-shaped spiky waves. Other structures, such as parabola [5], may be also utilized in the design of morphological filter.

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