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Construction of Morphological Filter for Single Trial Recording of Event-Related Potentials

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Abstract

We constructed a morphological filter for single sweep records of event-related potential (ERP), especially P300 waveform. By combining 4 basic operations; erosion, dilation, opening and closing, we can derive any desired filters whose property fits the current objectives. The morphological filter for single sweep records of ERP was constructed by taking account of the features of the signal and noise components. The morphological filter has superior properties of separating the signal and the noise even existing within a same frequency band. The constructed morphological filter was tested by using simulation data of ERP and then applied to actual ERP data of a normal subject. The results proved that the constructed morphological filter was an appropriate tool for single sweep records of ERP.

1. Introduction

Event-related potentials (ERPs) are responses related to recognition of certain stimulus. P300 waveform is one of the most important positive peak component in the ERP and appears around 300 msec after the stimulus[1]. In order to improve the signal-to-noise (S/N) ratio of the raw data of ERP, the averaging method has been widely used for data of repetitive stimuli. The averaging method is adopted based on an assumption that the P300 has the same waveform and latency to each stimulus. However, the waveform of ERP for each stimulus changes according to the recording conditions of the subject during the recording time. Therefore, the averaging method is not so appropriate tool for extracting the features of the ERP waveform. A method for extracting the P300 from the single sweeps of ERP data is required. We had proposed a method for the automatic detection of single sweep P300 waveform by taking into account of the features of the P300 waveform[2], and another method by using a neural network[3]. Those methods gave satisfactory results in the recognition of the P300 of healthy adults. In the methods, a band-pass filter was used to improve the S/N ratio of the sweep of ERP data. The band-pass filter was designed so that the frequency component of the signal(P300) was extracted by filtering out the noise component of background electroencephalogram(EEG). The frequency component of the P300 was concentrated within 8 Hz, and the major component in the background EEG (dominant rhythm) was around 10 Hz for healthy adults. Then, the band-pass filter of 1-8 Hz was used. This filter worked well for data of adult ERP because the frequency band of the signal component did not overlap with that of the noise component. However, in case of child ERP, the mean frequency of the dominant rhythm of children tends to be lower, therefore, the frequency band of the signal component overlaps with that of the noise component. If we adopt the band-pass filter to data of child ERP, the noise component will remain in the processed data because of the overlap of the signal and noise components.

The morphological filter[4] which is designed in the time domain, can extract the signal component by shaping the waveform. The morphological filter has been applied to image processing of two dimensional data[5], however, to the knowledge of authors, design method using the morphological filter for one dimensional time series data has not been established yet.

In this paper, we investigated the characteristics of the morphological filter for the analysis of time series, and clarified the characteristics of the 4 basic operations of the filter; erosion, dilation, opening and closing. We constructed the morphological filter for the single seep records of child ERP by combining the 4 basic operations appropriately. The constructed morphological filter was tested by using the simulation data of ERP. Furthermore, the morphological filter was applied to actual ERP data of a child and gave satisfactory results.

2. Construction of Morphological Filter for Single Trial Recording of ERP

2.1 Recording Condition of Single Trial ERP

ERP was recorded from the human scalp as follows. Two tone stimuli of different frequencies, 1000 Hz and 2000 Hz, were given to the subject in pseudorandom order. The 2000 Hz tone was given at a low rate (20 %) as the target stimulus, and the 1000 Hz tone given at a high rate (80 %) as the non-target stimulus. The subject was asked to push the button quickly as soon as he heard the target stimulus. In the record, the ERP was expected to appear after the target stimulus, because the subject recognized the 2000 Hz tone as the target stimulus. On the other hand, the ERP rarely appeared after the non-target stimulus according to the state of one's mind. The interstimulus interval was 2.5±0.28 sec. An exploring electrode was fixed at Pz following the guidelines of the International 10-20 System. The linked earlobes were used as the reference.

The positive peak P300, which appears 300 msec after the stimulus, is regarded to be the most important component of the ERP. The P300 waveform is not visible in the raw time series for each stimulus, because of contamination with the noise component of background EEG, especially dominant rhythm. The mean frequency of the dominant rhythm of adult cases is about 10 Hz, however, that of children tends to be lower, about 8Hz. Therefore, for child ERP cases, it is difficult to improve the S/N ratio of single sweep ERP by using the band-pass filter, since the frequency band of the ERP overlaps with that of the dominant rhythm. To circumvent this difficulty, we constructed a morphological filter. The subject for evaluation of the filter was a boy aged 9 years old.

2.2 Characteristics of Basic Operations of Morphological Filter and The Filter Construction

(a) Definitions and Characteristics of Basic Operations of Morphological Filter

Morphological filter consists of the basic operations: erosion, dilation, opening and closing as

$$\text{Erosion} \quad (f \ominus B^s)(t) = \inf_{x \in B_t} \{f(x)\} \quad (1)$$

$$\text{Dilation} \quad (f \oplus B^s)(t) = \sup_{x \in B_t} \{f(x)\} \quad (2)$$

$$\text{Opening} \quad (f_B)(t) = [(f \ominus B^s) \oplus B](t) \quad (3)$$

$$\text{Closing} \quad (f^B)(t) = [(f \oplus B^s) \ominus B](t) \quad (4)$$

where, $f(t)$ is raw time series, and B is a structuring element which regulates properties of the filter. The sets B^s and B_t are defined as $B^s = \{-b; b \in B\}$ and $B_t = \{b + t; b \in B\}$, respectively. Erosion (dilation) is an operation such that any value of function $f(t)$ during the analysis interval is substituted by its minimum (maximum) value within the interval B_t. Opening (closing) consists of the two operations of erosion and dilation. By combining the 4 basic operations, we can construct morphological filters with various characteristics.

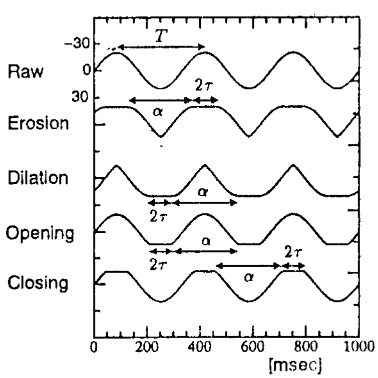

Figure 1 Characteristics of the basic operations (erosion, dilation, opening, closing) of the morphological filter for data $20\sin(6\pi t)$. T is the period, 2τ the width of cut off peak, $\alpha(=T-2\tau)$ the width of remained peak.

In order to clarify the characteristics of the basic operations, we analyzed the processed signal of the sinusoidal function $f(x)$ regulated by symmetric element $B = \{b; -\tau \le b \le \tau\}$. Figure 1 illustrates the raw data $f(t)$ $(= 20\sin(6\pi t))$ and processed time series operated by using each basic operation with τ=50 msec. A positive value of ERP is usually described downward and a negative value is described upwards. Therefore, we here describe the graph according to this rule.

Erosion is the operation which cuts off negative peaks and reduces widths of positive peaks. Dilation is the operation which cuts off positive peaks and reduces widths of negative peaks. The widths of the cut off peaks are 2τ, and the widths of the remained peaks are $\alpha(=T-2\tau)$, where T is the period of the sinusoidal function. Opening only cuts off positive peaks with the width of 2τ, and closing cuts off negative peaks with the width of 2τ. By combining the two operations of opening with 2τ and closing with $2\tau'$ $(2\tau+2\tau' \ge T)$, we can diminish the sinusoidal wave completely.

(b) Construction of Morphological Filter

We constructed a morphological filter for single sweep records of child ERP by taking account of the features of the signal and the noise components of the raw data. The P300 waveform of signal component has a positive peak whose peak latency exists within 200-500 msec after the stimulus with the width of 100-200 msec. The mean frequency of noise component of the dominant rhythm for healthy children (under 15 years-old) is about 8 Hz. By taking account of these characteristics of signal and noise components, we constructed the morphological filter as follows.

(i) Negative peak is required to be cut off, since the signal component P300 is a positive peak. Then, the operation of closing was used to cut off negative peaks without any distortion of the shape of the positive peak. The parameters of the structuring element 2τ were set at 50msec so that negative peaks above 10 Hz vanished completely.

(ii) In order to eliminate positive peaks of the noise component without distortion of the P300 waveform, we reduced the widths of positive peaks by using the erosion, and cut off the positive peaks by using the opening. Appropriate selection of the parameters of the erosion and the opening are essential so as to eliminate noise components and remain the original shape of the P300. We selected the widths for the erosion, and the opening as 2τ=20 msec (10-20 % of the width of the P300), respectively.

2.3 Simulation Data

In order to evaluate the constructed morphological filter, we used the simulation data whose characteristics were known. We made target data of 20 segments and non-target data of 20 segments. The target data

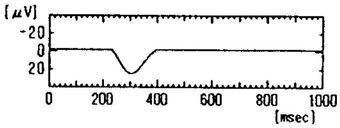

Figure 2 Artificial P300 waveform for simulation.

included the signal component of P300 with the peak latency being 300±30 msec, and the noise component of background EEG. The non-target data only included the background EEG. The P300 wave of the signal component was represented by the waveform shown in Figure 2.

The background EEG, which consisted of δ wave, dominant rhythm, and β wave, was simulated by using the model of sinusoidal waves with Markov process amplitude[6],

$$x(n\Delta t) = \sum_{k=1}^{3} a_k(n\Delta t)\sin(2\pi m_k n\Delta t - \theta_k) \qquad (5-1)$$

$$a_k((n+1)\Delta t) = \gamma_k a_k(n\Delta t) + \xi_k(n\Delta t) \qquad (5-2)$$

where $\xi_k(n\Delta t)$ was an independent white noise with zero mean and variance $(\sigma_k)^2$, Δt (=2 msec) denoted the sampling interval. The simulation data of child ERP whose frequency band overlapped with that of the dominant rhythm were generated by using the models with the following parameters: $m_1 = 1$, $\gamma_1 = 0.98$, $\sigma_1 = 1.5$, $m_2 = 8$, $\gamma_2 = 0.992$, $\sigma_2 = 1.0$, $m_3 = 25$, $\gamma_3 = 0.96$, $\sigma_3 = 0.7$.

The constructed morphological filter were evaluated by the error between the processed data $\hat{y}_r(n\Delta t)$ and the original P300 waveform $y_r(n\Delta t)$ as

$$e = \sqrt{\frac{1}{20N}\sum_{r=1}^{20}\sum_{n=0}^{N-1}\{(\hat{y}_r(n\Delta t) - \hat{y}_r^*) - (y_r(n\Delta t) - y_r^*)\}^2} \qquad (6)$$

where $\hat{y}_r^*$ and y_r^* were constant bias components of $\hat{y}_r(n\Delta t)$ and $y_r(n\Delta t)$ respectively, r denoted the segment number, and N denoted the number of data.

3. Results

3.1 Single Trial Record for Simulation Data

Figure 3 illustrates the results of the target data of the simulation, (a) the raw data, (b) the data processed by the constructed morphological filter, and (c) the data processed by the band-pass filter of 1-8 Hz as for comparison. The raw data involve 3 rhythms (δ wave, dominant rhythm and β wave) of the background EEG model and the artificial P300 waveform shown in Fig. 2. In Fig. 3 (b), the noise components were reduced and the P300 waveform was recognized evidently around 300 msec after the stimulus. By the operation of closing, erosion and opening in the morphological filter, the negative peaks were almost eliminated and the P300 waveform was extracted with a little distortion of the shape, although the shape of the waveform become slightly rectangular. In Fig. 3 (c), the P300 waveform was recognized also in the processed data by the band-pass filter, although oscillatory noise components remained. By comparing Fig. 3 (b) and (c), the P300 could be recognized more clearly in the processed data by the morphological filter as contrasted with that by the band-pass filter.

The errors defined by eq. (6) were calculated as fol-

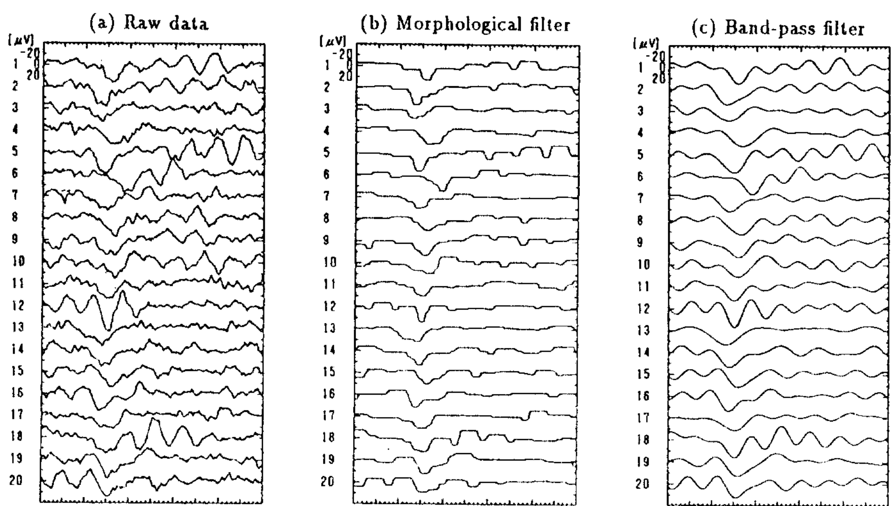

Figure 3 Single sweeps of target data of the simulation for child ERP: (a) raw data, (b) processed data by the constructed morphological filter, and (c) processed data by the band-pass filter of 1-8 Hz. The P300 waves were recognized clearly in the sweeps in (b).

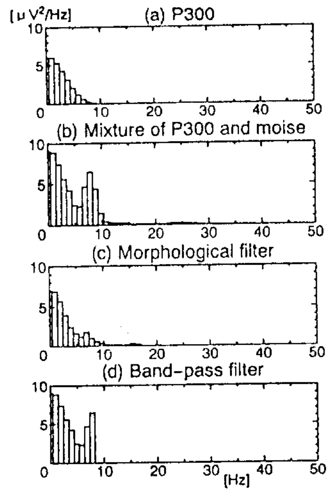

Figure 4 Power spectra of the target data of the simulation for child ERP. (a) P300 wave of the signal component, (b) raw ERP data of mixture of the P300 wave contaminated with background EEG, (c) processed data by the morphological filter, (d) processed data by the band-pass filter of 1-8 Hz. The spectrum (c) was almost similar to the spectrum of the original artificial P300 wave (a).

lows: $e = 4.76$ [μV] for the morphological filter and $e = 5.81$ [μV] for the band-pass filter. This result shows that the processed data by the morphological filter was closer to the original P300 waveform shown in Fig. 2 than that of the band-pass filter.

Figure 4 illustrates the power spectra for the original P300 waveform of the signal component (a), the raw data of mixture of the signal and the background EEG (b), the processed data by the morphological filter (c) and the processed data by the band-pass filter of 1-8 Hz (d), respectively. Fig. 4 (b) shows that the frequency band of the signal component overlapped with that of the noise component. Both Figs. 4 (c) and (d) show that the high frequency components over 8Hz were eliminated and the low frequency components were remained. However, the shapes of the power spectra (c) and (d) were quite different. In the power spectrum by the band-pass filter (d), we found noise component around 6-8 Hz in the processed data. The power spectrum by the morphological filter (Fig. 4 (c)) was almost similar to the spectrum of the original P300 waveform (Fig. 4 (a)).

3.2 Results for Actual Data

Figure 5 illustrates 20 single sweeps of raw ERP target data from the boy aged 9 years old (a), the corresponding processed data obtained by using the constructed morphological filter (b) and that by the band-pass filter of 1-8 Hz (c). In Fig. 5 (c) by the band-pass filter, P300 waveforms were hardly recognizable in any sweeps because of oscillatory noise. However, we could recognize the P300 more evidently in the 3, 6, 7, 8, 10, 19, 20th sweeps processed by the morphological filter in Fig. 5 (b).

4. Discussion

The P300 component was extracted from each single sweep of the child ERP appropriately by using the proposed morphological filter. Effectiveness of the morphological filter was evident for the data whose signal frequency band was overlapped with that of noise com-

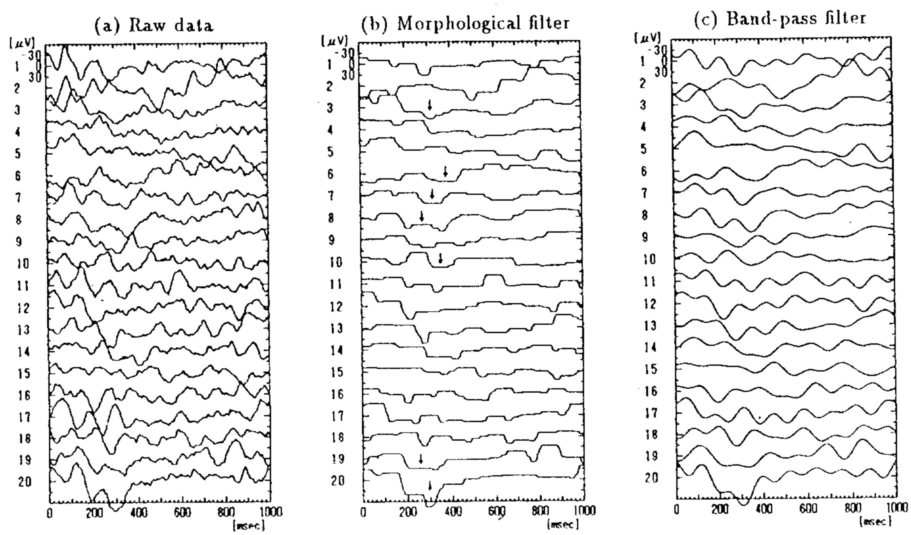

Figure 5 Single sweeps of target data of child ERP recorded from a boy aged 9 years old: (a) raw data, (b) processed data by the constructed morphological filter, and (c) processed data by the band-pass filter of 1-8 Hz. The P300 waves were recognized in the 3, 6, 7, 8, 10, 19, 20th sweeps in the processed data by the morphological filter (arrows).

ponent as the child ERP. In the case of adult ERP, extraction of the signal component is rather easy because that the frequency of dominant rhythm (10 Hz) of adult EEG is higher than that of the P300. The morphological filter was also applied to the simulation data of an adult ERP ($m_2 = 10$ Hz), and gave satisfactory results too.

The waveform of the data processed by the morphological filter shows rectangular rather than smooth one. However, if the objective of the signal processing is to detect whether P300 exists or not in the single sweep ERP records, the rectangular waveform do not cause any troubles. The processed data by the morphological filter was applied to the automatic P300 detection method (see appendix). The detection error of the automatic detection for the simulation data (20 target data and 20 non-target data) processed by the morphological filter was only 2 % whereas the error of the detection for the data by band-pass filter of 1-8 Hz was about 12 %. This reveals that the morphological filter is superior to the band-pass filter, especially for the child ERP data whose the frequency bands of the signal and noise components are overlapped.

We can furthermore obtain more smooth waveform processed by the morphological filter, if we just adopt the different parameters of the morphological filter depending upon subintervals of the single sweep duration: the parameters 2τ of the erosion and the opening were set at small value 16 msec each in the interval of 100-600msec in order not to distort the shape of the P300, and were set at 50 msec in the rest of the intervals (0-100 msec and 600-1000 msec) to eliminate the noise component as much as possible. The error e, defined by eq. (6), of the processed data by the morphological filter with variable parameters was improved to 4.58 [μV], whereas the error of the processed data by the proposed morphological filter (fixed parameters) was 4.76 [μV], then we could obtain a smooth waveform of the processed data closer to the original P300 waveform.

We conclude that we can construct the appropriate morphological filter by taking account of the characteristics of the signal and noise components of raw data. The morphological filter proved to be powerful to process the data whose frequency bands of the signal and noise components were overlapped, and would be applicable to wide range of biomedical data.

5. Conclusion

We constructed the morphological filter to extract the P300 from the raw ERP data contaminated with noise. We clarified the characteristics of the basic operations of the morphological filter, and constructed the filter by taking account of the features of the signal and noise components. In order to evaluate the proposed method, we analyzed the simulation data by extracting the P300 waveform from the raw ERP data which consisted of the background EEG model and an artificial P300 waveform. The P300 was recognized clearly in the data processed by the morphological filter as contrasted with that by the band-pass filter. Furthermore, we applied the morphological filter to the actual ERP data of a normal child, and obtained satisfactory results.

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Appendix

The automatic detection of P300 from single sweeps of ERP data was described[2]. The criterion of the automatic detection adopted in this study was slightly simplified as follows: (i) the latency of the positive peak exists within 200-500 msec after the stimulus, (ii) the time between the negative peak before and after the positive peak (duration) is above 100 msec, (iii) difference between the positive peak value and the prior negative peak value (amplitude) is above 12 μV, and (iv) all the following positive peaks which satisfy both (ii) and (iii) are smaller than 83 % of the amplitude of P300. If the positive peak satisfies all 4 criteria, it is regarded as P300 waveform.