ACCURATE IDENTIFICATION OF EVOKED POTENTIALS BY WAVEFORM DECOMPOSITION USING DISCRETE COSINE TRANSFORM MODELING

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Abstract— **This paper introduces a method for decomposing the component responses of the evoked potentials. The decomposition was realized by zero-pole modeling of the evoked potentials in the discrete cosine transform (DCT) domain. It was found that the DCT coefficients of a component response in the evoked potentials could be modeled sufficiently by a second order transfer function in the DCT domain. The decomposition of the component responses was approached by using partial expansion of the estimated model for the evoked potentials, and the effectiveness of the decomposition method was evaluated both qualitatively and quantitatively. Because of the overlap between the component responses, the proposed method enables an accurate identification of the component responses in the evoked potentials, which is useful for clinical and neurophysiological investigations.**

Keywords— **Evoked potentials, component response, discrete cosine transform, zero-pole modeling, decomposition**

I. Introduction

Evoked potentials (EPs) are generated by exogenous excitation of peripheral nerves with a precise stimulus, and are measured by placing electrodes on several well-defined positions on the scalp. Because of the superimposed background activity, the EPs are usually averaged to generate a suitable waveform for analysis. In clinical practice, the evoked responses in EPs are valuable for assessing various kinds of neuronal diseases. The averaged evoked potentials usually consist of several component responses, in which the peak latency and the peak amplitude of each response can be used to investigate the disease of a corresponding neuronal ensemble.

The general measurement of the peak latencies as well as the peak amplitudes encounters a problem that the precision is low because of the overlap between the component responses in the EPs. As the EPs recorded on the scalp of brain are a spatial compounded signal generated from various neuronal resources in the different regions of brain, the scalp signal of the EPs include many neuronal responses transmitted. The problem of the overlap is that the potential change generated by a latter response appears before the former component response ends. Then, the peak latency and peak amplitude of a component response are closely related to those of the former and latter component responses, so that the features of a neuronal response cannot be identified precisely from the direct measurement of the EPs.

In this paper, we introduce a method for decomposing the component responses in the EPs by appropriate modeling. The model was constructed based on the transformed signal of the EPs. By using discrete cosine transform (DCT) of the EPs, the DCT coefficients of each EP component response were sufficiently represented by a second order transfer function with a conjugate pole pair. The pain-evoked somatosensory evoked potentials (pain SEP) were adopted in the current analysis. The effectiveness of the proposed method was evaluated both qualitatively and quantitatively from the simulation and experimental study.

II. Methods

A. Subjects and data acquisition

Eight healthy subjects, aged from eighteen to thirty-eight, volunteered for the present study. The pain stimulus method can be found in [2]. For all subjects, EEGs were recorded with shallow cup electrodes (1 cm in diameter) placed at Cz site on the scalp and earlobes (A1 and A2) according to the International 10-20 System. The analog EEG signals referenced to the linked F3-F4 were amplified and filtered with the bandpass of 10-200 Hz, and then converted to digital data with the sampling rate of 500 Hz, and finally stored into the disk. For each subject, the pain SEP trials of 200 stimuli unassociated with any artifact within the period of 0.6 s after the stimulus were selected. The pain SEPs averaged from 200 trials were used for the current analysis.

B. Procedure of component decomposition

The whole procedure of the component decomposition for the EPs consists of four operations; DCT, estimation of model parameters, partial expansion and inverse DCT (IDCT).

1. Discrete cosine transform Instead of the direct modeling in the time domain, we adopted the methodology of modeling in the DCT domain. The EP signal is previously transformed into its DCT coefficients $y(k)$ by using discrete cosine transform [3]

$$y(k) = \begin{cases} \sqrt{2/N} \displaystyle\sum_{n=0}^{N-1} x(n) \cos \frac{(2n+1)k\pi}{2N} & k = 1, 2, \cdots, N-1 \\ \sqrt{1/N} \displaystyle\sum_{n=0}^{N-1} x(n) & k = 0 \end{cases} \tag{1}$$

where $x(n)$ denotes the averaged EPs in the time domain and $y(k)$ the DCT coefficients of $x(n)$ in the DCT domain, n and k series numbers for $x(n)$ and $y(k)$ respectively, N the data length (300 in the current study).

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2. Estimation of model parameters The DCT coefficients $y(k)$ of the EPs are modeled by a system transfer function. The model parameters are determined using the least square method based on the DCT coefficients $y(k)$ of the EPs. The detail explanation is presented in the section II-C.

3. Partial expansion The partial expansion [4] is to decompose the estimated system transfer function into several fractions with a conjugate pole pair. The impulse response of each fraction $\hat{y}_i(k)$ is used to represent a component response of the EPs. The explanation is given in section II-D

4. Inverse discrete cosine transform The component responses of the EPs in the time domain are obtained by taking the inverse discrete cosine transform of the model output $\hat{y}_i(k)$. The inverse discrete cosine transform is given by

$$\hat{x}_i(n) = \sqrt{1/N}\hat{y}_i(0) + \sqrt{2/N}\sum_{k=1}^{N-1}\hat{y}_i(k)\cos\frac{(2n+1)k\pi}{2N} \quad n = 0, \quad 1, \quad \cdots, \quad N-1 \tag{2}$$

where $\hat{y}_i(k)$ and $\hat{x}_i(n)$ represent the component responses in the DCT domain and the time domain, respectively.

C. DCT domain modeling

The system transfer function $H(z^{-1})$ for representing the DCT coefficients of the EPs is given by

$$H(z^{-1}) = \frac{\beta_0 + \beta_1 z^{-1} + \cdots + \beta_{2m} z^{-2m}}{1 + \alpha_1 z^{-1} + \cdots + \alpha_{2m} z^{-2m}} \tag{3}$$

where α_i and β_i are model parameters, and $2m$ the model order. z^{-1} is a complex value.

As the averaged EPs is still noise contaminated, the parameter set $[\alpha_1, \alpha_2, \cdots, \alpha_{2m}, \beta_0, \beta_1, \cdots, \beta_{2m}]^T$ in (3) was determined by the least square method in order to minimize the square sum of the difference between the impulse response of the system transfer function (3) and the DCT coefficients of the averaged EP signal $y(k)$. The minimization was realized using an iterative least square algorithm of the Steiglitz-McBridge method [5].

D. Component decomposition

The decomposition of component responses of the EPs was approached by decomposing the system transfer function (3) in the DCT domain. The waveform of the EPs in the time domain can be considered as the sum of several bell-shaped monophasic component waves, in which each component wave has a positive or negative peak.

A second order model with a conjugate pole pair was constructed as

$$\begin{aligned} H_i(z^{-1}) &= \frac{K_i(1-o_i^1 z^{-1})(1-o_i^2 z^{-1})}{(1-p_i^1 z^{-1})(1-p_i^2 z^{-1})} \\ &= c_i + \frac{a_i + b_i z^{-1}}{1 - 2r_i\cos\theta_i z^{-1} + (r_i)^2 z^{-2}} \\ & \quad r_i < 1, \quad 0^\circ \le \theta_i \le 180^\circ \end{aligned} \tag{4}$$

where $a_i = K_i - c_i$ and $b_i = 2c_i r_i \cos\theta_i - (o_i^1 + o_i^2)K_i$.

It was found that the IDCT of the impulse response of $H_i(z^{-1})$ generated a bell-shaped waveform similar to the component waves in the EPs. If the parameters in $H_i(z^{-1})$ is well adjusted, a sufficient fit between them can be obtained. Therefore, the second order model $H_i(z^{-1})$ was used to represent a component response of the EPs.

When the system transfer function (3) for representing the EPs is optimally determined, the EPs can be decomposed into several second order fractions with a conjugate pole pair by using z-transform partial expansion.

III. Results

A. Simulation study of component decomposition

A simulation study was implemented for examining the effectiveness of the proposed method of the component response decomposition. The signal simulating the EPs in the time domain was generated by the summation of two second order system transfer function in the DCT domain. The parameters of the two second order transfer functions was given in the format $[a_i, b_i, r_i, \theta_i]$ as [-208.9, 107.9, 0.458, 41.1°] and [185.8, 77.1, 0.447, 127.1°], and their time signals were illustrated in Fig. 1(a) and (b), respectively. As the averaged EPs were still noise contaminated, the model parameters were estimated under the signal-to-noise ratio of 40, in which the noise was simulated by using an AR model (order=10) estimated from the background activity of EEG [6].

A general method of modeling evaluation was adopted in the current study. The effectiveness of the proposed model was evaluated by the percent root mean square difference Prd, i.e., the residue between the model output and the signal for modeling.

The peak latencies [s] and the peak amplitudes [μV] of the original component 1 x_1 (Fig. 1(a)) and component 2 x_2(Fig. 1(a)) were (0.254, 8.34) and (0.356, 10.09), respectively. In order to explain the relationship between the component 1 and the component 2, the changes of the peak latencies and the peak amplitudes were investigated. First, the signal illustrated in Fig. 1(c) for simulating the EPs was obtained by the sum of x_1 and x_2. The peak latencies and the peak amplitudes of the component 1 and the component 2 in the signal $x_1 + x_2$ were (0.252, 6.70) and (0.368, 11.45), in which the baseline was referenced to the beginning of the signal. Second, the amplitude of the component 1 was enlarged three times of the original component 1, and the corresponding time signal $3x_1$ was shown in Fig. 1(f), in which the peak latency and peak amplitude were (0.254, 25.02). The compounded signal $3x_1+x_2$ shown in Fig. 1(h) was obtained by the sum of Fig. 1(f) and (g), in which the component 2 was kept the same. The peak latencies and the peak amplitudes of the component 1 and the component 2 in the signal $3x_1 + x_2$ were detected as (0.256, 23.13) and (0.380, 16.14).

By comparing Fig. 1(c) and (h), large changes of the component 2 were found, although the component 2 was the same in the two signals. For the component 2, the peak latency was changed from 0.368 s to 0.380 s, and the

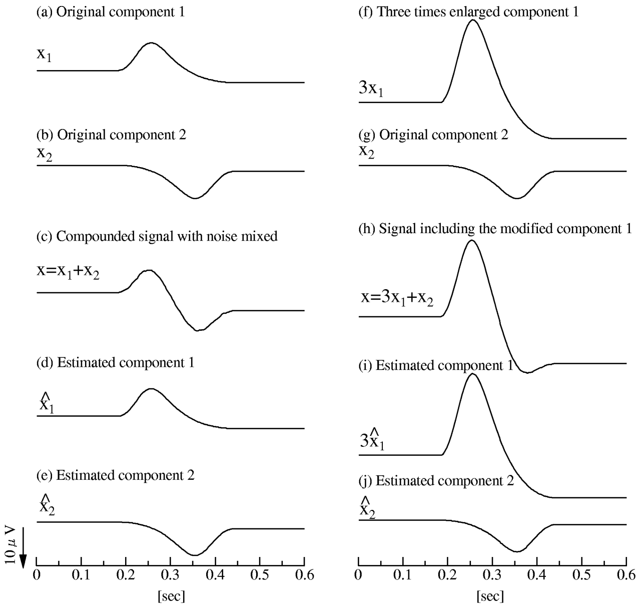

Fig. 1. Simulation study shows the peak latencies and the peak amplitudes as well as the waveforms of the same component 2 in the EPs are changeable with the different amplitude of the component 1 so that the direct measurement of them may be inaccurate because of the mutual overlap. Identical component 2 can be extracted by the decomposition of the EPs using the DCT domain modeling.

peak amplitude was changed from 11.45 μV to 16.14 μV. These results suggest that the peak latency and the peak amplitude of a component response in the EPs are closely related to those of the other responses so that the direct measurement of the peaks in the EPs cannot get accurate peak latency and peak amplitude of a component response. Further, because the error of the direct measurement of the component 2 (0.380, 16.14) detected from the signal $3x_1+x_2$ was larger than those from the signal x_1+x_2 (0.368, 11.45) by comparing with the original component 2 (0.356, 10.09), it indicated that if the difference of the potential changes between the two components in the compounded signal was larger, the direct measurement might be more questionable.

For the two compounded signals $x_1 + x_2$ and $3x_1 + x_2$, the component decomposition was approached. As each of the simulated signals was composed of two component waves, the model order of $H(z^{-1})$ in (3) was selected as four because each component wave could modeled sufficiently using a second order transfer function. The model parameters given in (3) were estimated using least square method, and the decomposition was realized by partial expansion of the estimated $H(z^{-1})$.

The component waves $\hat{x}_1$ and $\hat{x}_2$ decomposed from the signal $x_1 + x_2$ were illustrated in Fig. 1(d) and (e), respectively. From visual inspection, the estimated component waves were in a good agreement with the original component waves. The estimated parameter sets $[a_i, b_i, r_i, \theta_i]$ for the two component waves were [-217.6, 109.1, 0.452, 40.8°] and [173.1, 74.5, 0.460, 126.8°]. As the waveform of a system response was mainly determined by the distribution of the poles, the estimated parameters for the component waves also demonstrated a satisfactory component decomposition, where the quantitative differences of Prd were less than 5%. The peak latencies and the peak amplitudes of the decomposed component waves were (0.256, 8.35) and (0.354, 10.2). Comparing with those of the original component waves, the proposed decomposition method demonstrated such a good consistence.

The component waves $3\hat{x}_1$ and $\hat{x}_2$ decomposed from the signal $x_1 + x_2$ are illustrated in Fig. 1(i) and (j), respectively. The estimated parameter sets $[a_i, b_i, r_i, \theta_i]$ for the two component waves are [-649.4, 326.0, 0.452, 40.9°] and [174.3, 74.8, 0.460, 127.7°]. The quantitative differences of Prd were also less than 5%. The peak latencies and the peak amplitudes of the decomposed component waves were (0.256, 24.80) and (0.356, 9.56). Thus, from both of the signals $x_1 + x_2$ and $3x_1 + x_2$, an identical signal of the component 2 was extracted, which was in a good agreement with the original component 2. As the decomposition results were very close to those of the original component waves, the accuracy of the detection of the peak latencies and the peak amplitudes can be improved by using the proposed decomposition method.

B. Experimental study on the pain SEPs

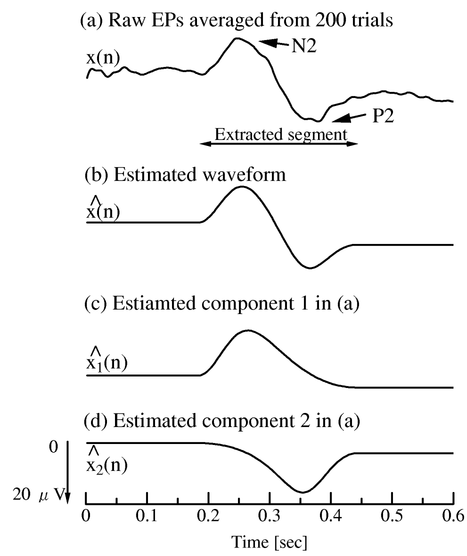

Fig. 2. Component response decomposition for the pain SEPs using DCT domain modeling.

The pain SEP signals recorded from eight subjects were processed by the proposed method of the component decomposition for the EPs. The estimation results were illustrated in Fig. 2. The pain SEP signal shown in Fig. 2(a) was obtained by averaging 200 pain SEP trials. The data length of the averaged signal was 0.6 s with the sampling interval of 2 ms, i.e., the total data number was 300. The electrical stimulus added on the hand was presented at the beginning of the signal. The pain SEP signal was composed of one large negative (N2) and one large positive

(P2) bell-shaped monophasic component waves during the time periods of 0.2 s to 0.3 s and 0.3 s to 0.4 s, respectively. For decomposing the component responses, pain SEP signal from 0.18 to 0.438 s was extracted, which were depicted by the arrows.

In the procedure of model parameter estimation, the model parameters $[\alpha_1, \alpha_2, \ldots, \alpha_{2m}, \beta_0, \beta_1, \ldots, \beta_{2m}]^T$ in (3) were optimally determined using the least square method, in which m was selected as two. Although the averaged pain SEP signal was noise contaminated, the model outputs for the pain SEP signal illustrated in Fig. 2(b) demonstrated a good agreement with the corresponding signals, where the quantitative difference was less than 10%. The decomposition of model transfer function was achieved by partial-fraction expansion, i.e., the model transfer function was decomposed into two fractions with a conjugate pole pair. The model output for the pain SEP signal was shown in Fig. 2(b). By using partial-fraction expansion of model transfer function, the model outputs for two component responses of the pain SEPs were illustrated in Fig. 2(c) and (d). The decomposed component responses were also in a good agreement with the pain SEPs.

IV. Discussion

A. Component decomposition using DCT domain modeling

The reason for the excellent decomposition is that the IDCT of the impulse response of a second order transfer function can generate a bell-shaped monophasic waveform, which is in a good accordance to the EP signal. Compared with other parametric modeling of the EPs [8], a monophasic wave is modeled sufficiently in the DCT domain, whereas the model order of the direct time domain modeling is much higher such that the error of decomposition may be large.

B. Neurophysiological consideration

A component response of the EPs was assumed of a bell-shaped monophasic waveform, which was modeled effectively in the DCT domain. This assumption is in accordance to the common acceptance that a neurophysiological response is in a bell-shaped waveform [7]. As the model output is in a good agreement with the EPs, the proposed method is appropriate for modeling the EPs as well as the component responses.

In this study, the pain SEPs were adopted for the analysis. The pain SEPs have two early components; a negative peak (N2) and a positive peak (P2), as marked in Fig. 2(a). From the neurophysiological understanding, N2 might, to some degree, be affected by exogenous factors, and an endogenous aspect of N2 was reported that it was modulated by arousal states or distraction [9]. In a recent investigation, it indicated that P2 was hardly affected under the different human status of task handling so that P2 was most likely a pain-related component that might serve as an anchor for the following processing of CO_2 laser induced pain sensation [2]. From the above literatures, the difference of the peak amplitudes of N2 in the recorded pain SEPs may be large because it is related to the exogenous factors. From the analysis in the simulation study, the waveform as well as the peak latency and the peak amplitude of P2 is greatly affected by the component of N2 because of the overlap between them. Therefore, the direct measurement of the peaks in the pain SEP trials may be inaccurate for the detection of P2 because of the difference in the amplitudes of the N2. From the results of the proposed method demonstrated both in the simulation and experimental study, an accurate investigation of the peak amplitudes and peak latencies can be approached by the appropriate decomposition of the component responses in pain SEP using the DCT domain modeling.

V. Conclusion

Component response decomposition for the EPs was approached by decomposing the EP model in the DCT domain. A good result of component decomposition was demonstrated both in the simulation and experimental study. The successful approach enables a reasonable decomposition for the EPs, which is useful for the accurate detection of the component responses in the physiological and clinical investigation.

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