PAPER

Feature Extraction and Identification of Transfer Function for Auditory Brainstem Response

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Abstract In this paper, we present an estimation algorithm for applying a Kalman filter to waveform data of the auditory brainstem response (ABR). The model parameters for extracting the features of the ABR waveform are obtained effectively by the proposed method. Usually, the ABR is analyzed by batch processing through signal averaging over a few minutes because the response has a slight potential. By using the Kalman filter, we expand the possibility of measuring it in real-time and minimizing the model error. First, we discuss, in particular, the type and the degree of the estimated transfer function. For this, we use the ABR waves obtained by adding less than 2000 click signals and estimate the transfer function in order to extract the features of the ABR waveform using the Kalman filter. Furthermore we analyze the characteristics of the coefficients of the transfer function in more detail to extract the ABR frequency characteristics. If we apply this method to clinical cases, we can expect that a significant reduction in the requirement for the addition of signals will contribute to reducing the burden for ABR monitoring in emergency medical care and surgical operations.

Keywords: auditory brainstem response, modeling, estimation, transfer function, Kalman filter, frequency characteristics

1. ABR with Clinical Application

The auditory brainstem response (ABR) is a brain wave that is released within ten seconds in response to sound stimulus of the ear. In the fields of physiology and anatomy[1], it is well known that the ABR has seven peaks which are denoted as waves I to VII (Fig. 1). The formation of each wave originates in a specific part of the auditory neural system in the brainstem. Therefore, the ABR is widely used as an inspection assistance index in hearing and brain function diagnoses. The ABR has multiple applications in audiology, otolaryngology and neurology, and is the test of choice for difficult-to-test patients, screening the hearing of newborn, retrocochlear pathology, and intraoperative monitoring.

On the other hand, it is well known that signal estimation techniques yield the shape of a signal through the estimation of its latency and amplitude characteristics, and that signal averaging (sweeps) is commonly used to obtain the evoked potential waveforms. The pattern of amplitude change with latency change defines the shape of the waveform, within the limits of the error of

estimation. The number of sweeps is increased until the residual noise or estimation error is only a fraction of the response amplitude. The smaller the ABR amplitude (e.g., a low potential of 1 μ V or less) or the greater the amplitude of the background EEG, the greater the number of averaging (sweeps) that is needed to define the ABR signal. In general, we need approximately 2000 averaging procedures to obtain the ABR signal [2] (Fig. 2).

This is one of the problems associated with ABR testing. For example, in the case of the Universal Newborn Hearing Screening Program (UNHSP) [3], about 35% of the 4,200 birthing hospitals in the USA adopt the UNHSP. Only 65% of infants born in the USA are screened for hearing problems (Reports of Deafness Research Foundation in Washington, DC). Early screening, detection, and intervention result in improved outcome of infants' hearing and language skills. Therefore it is important to conduct nationwide hearing screening for newborns (Marion Downs National Center for Infant Hearing, 1997). In Japan, the UNHSP has just started, and about 3,000 birthing hospitals have adopted

Fig.1 Brainstem structures and ABR wave components [1] (This comparison is based on the results of anatomy and CT scans; however, for waves VI and VII the origins are not verified. As an example of such work refer to Möller and Janneta [4].)

Fig.2 Method of averaging to obtain the signal [2]

the UNHSP.

In the automated testing devices, the Automated Auditory Brainstem Response (AABR) is mainly used. Only wave V of ABR is used for testing with the AABR. The outcome is reported as PASS or REFER. If REFER

is recorded, the newborn requires retesting using the ABR. However the current ABR test is not convenient for the UNHSP, because it takes about 20 minutes for a test and the method of testing is difficult. Therefore, ABR testing must be made fast, easy and accurate so as to cause minimal stress to patients.

In previous papers [5], [6], to improve signal averaging, we introduced a model for the ABR signal parameter using a minimum variance estimation algorithm in which a Kalman filter is applied. By using the Kalman filter, we can estimate a fairly accurate ABR signal using the observation value with a few averaging procedures. In this paper, we analyze the characteristics of the model in greater detail. That is, from a physiological viewpoint and on the basis of the experimental application of ABR analysis, waves IV and V are considered to be the main focus of the analysis. Taking this into consideration, we also conduct a more precise analysis of the coefficients a_i and b_i of the ABR transfer function. As a result, we obtain the optimum procedure for obtaining the ABR transfer function, and using it, we can extract the ABR frequency characteristics. If these characteristics can be used as the parameters of ABR analysis, it may be possible to achieve rapid and automated on-line measurement of the ABR signal.

2. Method and Results

2.1 ABR measurement and example pattern of normal waveform

The system for the measurement of the ABR signal consist of a stimulus generator, electrodes, an amplifier, a filter, a computer with signal averaging, a monitor, and a printer. In the measurement, a transducer presents a series of stimuli to the ear at a constant rate. The electrodes pick up the neural response, which is amplified, filtered and then averaged by a computer. As is shown in Fig.2, due to the computer's summing procedure, the magnitude of the response is increased, and the signal-to-noise ratio is improved.

In ABR analysis, to obtain an ABR signal in which the peak waves are apparent and which is suitable for clinical applications, we require about 2000 signal averaging procedures. However, the results of ABR waveform analysis do not necessarily indicate similarities in the peak shape of the waveforms, even in

normal adults. For instance, it is well known that the normal ABR waveform types are classified according to the separation or unification of waves IV and V. Waves IV and V are the most conspicuous and important among the seven waves [6]. The ABR waveform in which waves IV and V separate and that in which the amplitude of wave V is larger than that of wave IV, are classified as type 1. The ABR waveform in which waves IV and V separate, and that in which the amplitude of wave V is smaller than that of wave IV, are classified as type 2. Type 3 is the ABR waveform in which waves IV and V unite. Type 3 is further categorized into two more subtypes: for waves IV and V united completely, when wave IV appears on the shoulder of wave V, the classification is type 3-1, and when wave V appears on the shoulder of wave IV, it is type 3-2.

Fig.3 Normal ABR waveform types classified with respect to waves IV and V, obtained with 2000 averaging procedures

The four types of observed ABR values obtained by our experiment will be used as signals to calculate the ABR transfer function, as shown in Figs. 3(a) - (d). To obtain these data, we use clicks with the intensity of 80 dBnHL, duration of 0.1 milliseconds, and frequency of 20Hz as the stimulus. We use the electrode and system, "Neuropack Mini", made by Nihon Kohden Corporation.

2.2 Estimation algorithm of ABR transfer function [5], [6]

In our previous papers [5], [6], we presented the ABR transfer function using the Kalman filter, and simultaneously determined the optimum degree of the ABR transfer function using Akaike's Information Criteria (AIC). Here, the ABR transfer function is considered again. We provide the following difference equation that shows the input-output relationship of the system:

$$y(t) = -\sum_{i=1}^{n_a} a_i y(t-i) + \sum_{i=1}^{n_b} b_i u(t-i) + v(t) \quad t = 0, 1, \dots \quad (1)$$

$y(t)$, $u(t)$ and $v(t)$ are, respectively, the output, the input and the noise which is reproduced from the observed noise using a whitening filter (for time t).

In general, under the condition that the system is dynamical, we can set the degree $n_a = n_b = n$ in Eq. (1) [7].

When the degree of the model is assumed to be n , we can obtain the maximum information about the model in the case of $n_a = n_b = n$. Therefore, by assuming $n_a = n_b = n$, we can obtain the best coefficients of the model derived from the experiment data. If n_a or n_b is inevitably small as a result of a physical situation, it is possible to set it to be small. In the case of ABR analysis, because n_a or n_b to be small is not known, we consider it appropriate to assume $n_a = n_b = n$.

In fact, we verify the case of $n_a > n_b$ and $n_a < n_b$. Figure 4 shows the results of using Akaike's AIC for each combination of n_a and n_b . It shows an example of the AIC value in the case of type 1 (in Fig.3), for the combination of $1 \leq n_a \leq 20$ and $1 \leq n_b \leq 20$. The top figure shows the 3D graph and the bottom one is the 2D graph. We obtain the minimum n_a value of 11 or 12 for each case of n_b . On the other hand, the minimum value of n_b becomes small (close to 1) for each case of n_a .

For each case of n_a , the minimum AIC value is obtained with $n_b = 1$, which indicates $n_b = 1$ to be the best value. Then, we estimate the coefficients of the transfer

Fig.4 Example of AIC values in the case of type 1 (in Fig.3), for the combination of $1 \leq n_a \leq 20$, and $1 \leq n_b \leq 20$. Top: 3D graph, Bottom: 2D graph

function based on this hypothesis. However, we find that the coefficients in the original case of $n_a=n_b=n$ show better convergence than the coefficients of the transfer function based on the hypothetical case of $n_b=1$. Then the optimum combination of coefficient values and the optimum degree of the transfer function are calculated according to the algorithm described in our previous paper [6]. We set $n_a = n_b = 8$ in Eq. (1) [5], using the optimal value of AIC. The optimal value is determined by the proposed evaluation inequality [6] from each minimum value of AIC calculated for all types of ABRs. Figure 5 shows the AIC values and degrees for all ABR waveform types.

We also verify the convergency of the ABR transfer function coefficients using a Kalman filter. The results of the estimation are shown in Fig. 6 and Fig. 7. Figure 6 shows the case of $n=8$, which is calculated as the

Fig. 5 Relationship between AIC value and degree when the experimental model is applied to the four types of ABR waveforms and the number of averaging procedures is 2000. The relationship between AIC and the degree is shown for the case of $n_a = n_b$ for all types of normal ABR waveforms. The small arrows show each minimum degree, and vertical bold line shows the optimum degree.

optimum degree for all waveform types (shown in Fig.5). We obtained the convergence value for both transfer function coefficients a_i ($i=1, \dots, 8$) and b_i ($i=1, \dots, 8$). The coefficients a_i ($i=1, \dots, 8$) are similar for all four waveform types. On the other hand, the coefficients b_i ($i=1, \dots, 8$) appear to be different. The case of the minimum value [6] of $n=18$, as an example of type 3-1, is shown in Fig. 7. Here, $n=18$ is the minimum value only for type 3-1; for other waveform types, it is not the minimum value (see [6] for details). Also in this case, the coefficients a_i ($i=1, \dots, 18$) show similar tendencies.

However, the coefficients b_i ($i=1, \dots, 18$) of the ABR transfer function exhibit different tendencies.

On the basis of the above results, we adopt the following modeling procedure. First, when we estimate the coefficients of the transfer function, for modeling all waveforms of the ABR, we use the case of $n_a = n_b = n$. Then we obtain the estimated ABR value after a few averaging procedures (the results shown in Section 2.3) using a Kalman filter. The second step is as follows. The coefficient $\hat{b}$ is strongly affected immediately after the stimulation. On the other hand the coefficient $\hat{a}$ is affected some time after the response in the ABR signal. When waves IV and V are a part of the main focus of the ABR analysis, we utilize only the transfer function coefficient $\hat{a}$ (we explain the reason in Section 2.4). Then we analyze the feature extraction of the frequency

characteristics. We present the results of the frequency characteristics in Section 2.4.

Fig. 6 Convergence results for the coefficients of all types of ABR transfer functions, when number of averaging procedures is 2000 and models with $n=8$ are used. The vertical axis shows the value of the coefficient.

Fig. 7 Convergence results for the coefficients of all types of ABR transfer functions, when number of averaging procedures is 2000 and models with $n=18$ are used. The vertical axis shows the value of the coefficient.

2.3 Results of the ABR signal estimation

In a previous section, we evaluated the parameters, that is, the waveform type and the degree of the coefficients of the ABR transfer function by using the ABR observation signal obtained with 2000 averaging procedures. Here again, we propose to determine the coefficients of the ABR transfer function by using the ABR observation signal obtained with less than 2000 averaging procedures, and which contains noise. We also compare the correlation coefficients of conventional averaging and the correlation coefficients of the ABR estimated using the Kalman filter, both correlation coefficients compare each other for the ABR signal obtained with 2000 averaging procedures.

In this work, we attempt the modeling again for the four types of normal ABR waveforms denoted in Fig. 3. We present the following examples, selected from among the results. Figure 8-1 (example of type 3-2) and Fig. 8-2 (example of type 2) show the results of the comparison between the waveform modeled by our method and the observed waveform. From (a) to (j), the initial averaging is performed 10 times, with an increment of 10 times up to 100 times, and an increment of 100 times up to 600 times from (j) to (o). In each figure, the target signal obtained with 2000 averaging procedures, results estimated using the Kalman filter, and the signal obtained with conventional averaging, are shown.

To compare the correlation coefficients of the modeling and the observed results, we present Fig. 9 and Table 1. Figure 9 shows an example of type 3-2 waveform. There are two kinds of correlation coefficients. One is obtained by compared between each observed ABR with less than 2000 conventional averaging procedure, and the ABR signal with 2000 times averaging. The another one is obtained by compared between each ABR estimated with the Kalman filter and the ABR signal with 2000 averaging procedure. Figure 9 and Table 1 show the two correlation coefficients for several numbers of averaging procedures.

For each ABR obtained with averaging, the correlation coefficients of the ABR waveforms estimated using the Kalman filter are larger than those of observed ABR waveforms obtained with conventional averaging.

These results indicate the merits of the Kalman filter. At the same time, the results of using this model suggest that it will be possible to estimate the ABR signal from the observed ABR with fewer averaging procedure.

Fig.8-1 Waveforms of conventionally averaged ABR and waveforms by ABR transfer function estimated using Kalman filter when number of sweeps for averaging is 10–100 ((a)-(j): increment 10 sweeps), and when it is 100-600 ((j)-(o): increment 100 sweeps), for the example of type 3-2 waveform

Fig.8-2 Waveforms of conventionally averaged ABR and waveforms by ABR transfer function estimated using Kalman filter when number of sweeps for averaging is 10 – 100 ((a)-(j): increment 10 sweeps), and when it is 100-600 ((j)-(o): increment 100 sweeps), for the type 2 waveform

On the other hand, we understand that no further improvement in accuracy can be gained by this estimation, though the observed ABR data has good correlations itself, by increasing of averaging procedures. Therefore, we must also consider methods of improving the SNR (signal-to-noise ratio) itself.

Fig.9 Correlation coefficients of ABR estimated using the Kalman filter and the conventional averaging ABR. These results are for the type 3-2 waveform

Table 1 Correlation coefficients of the ABR estimated using the Kalman filter and the conventional averaging ABR, for type 2 and type 3-1 waveforms

Type & no. of sweeps	Correlation coefficient of model ABR	Correlation coefficient of observed ABR
Type 2		
90	0.69	0.68
300	0.78	0.75
600	0.8	0.78
Type 3-1		
100	0.3	0.04
200	0.65	0.61
300	0.8	0.75
1000	0.95	0.9

2.4 Frequency characteristics of ABR transfer function

The transfer function of Eq. (1) is given by

$$H(z) = \frac{b_1 z^{-1} + \dots + b_{n_b} z^{-n_b}}{1 + a_1 z^{-1} + \dots + a_{n_a} z^{-n_a}} \quad (2)$$

Here, we again consider the detailed behavior of these coefficients in Eq. (2). That is, in the following consideration, we categorize the coefficients of the transfer function [7]. We approximate the transfer function $H(z)$ of Eq. (2) by

$$H(z) = \sum_{i=0}^l h_i z^{-i} \quad (3)$$

where l is sufficiently large. From Eqs. (2) and (3), we obtain

$$H\theta = \underline{h} \quad (4)$$

where

$$\underline{H} = \begin{bmatrix} \underline{1} & -\underline{H}_1 \\ 0 & -\underline{H}_2 \end{bmatrix}, \underline{h} = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}, \theta = \begin{bmatrix} b \\ a \end{bmatrix},$$

$$\underline{H}_1 = \begin{bmatrix} h_0 & 0 & \dots & 0 \\ h_1 & h_0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ h_{l-1} & h_{l-2} & \dots & h_0 \end{bmatrix}, \underline{H}_2 = \begin{bmatrix} h_n & h_{n-1} & \dots & h_1 \\ h_{n+1} & h_n & \dots & h_2 \\ \vdots & \vdots & \ddots & \vdots \\ h_{l-1} & h_{l-2} & \dots & h_{l-n} \end{bmatrix},$$

$$\underline{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}, \underline{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}, \underline{h}_1 = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}, \underline{h}_2 = \begin{bmatrix} h_{n+1} \\ h_{n+2} \\ \vdots \\ h_l \end{bmatrix}$$

When l is finite, $H(z)$ of Eq. (3) is an approximation of Eq. (2). Therefore, we define

$$e = H\theta - \underline{h} \quad (5)$$

The least-squares solution $\hat{\theta}$ which minimizes $e^T \Omega e$ is given by

$$\hat{\theta} = (H^T \Omega H)^{-1} H^T \Omega \underline{h} \quad (6)$$

where Ω is a positive-definite matrix. If Ω is a block diagonal matrix given by

$$\Omega = \begin{bmatrix} \Omega_1 & 0 \\ 0 & \Omega_2 \end{bmatrix}$$

then Eq. (6) is decomposed to

$$\hat{\underline{a}} = -(H_2^T \Omega_2 H_2)^{-1} H_2^T \Omega_2 \underline{h}_2 \quad (7a)$$

$$\hat{\underline{b}} = H_1 \hat{\underline{a}} + \underline{h}_1 \quad (7b)$$

where Ω_1 is an $n \times n$ positive-definite symmetric matrix, and Ω_2 is an $(l-n) \times (l-n)$ positive-definite symmetric matrix such that $\hat{\theta} = [\hat{\underline{b}}^T, \hat{\underline{a}}^T]^T$ [7].

When we use Eqs. (7a) and (7b), it is evident that we

can consider $\hat{a}$ and $\hat{b}$ separately, that is, according to the previous result, we analyze only the coefficients $\hat{a}$ in which a useful and noteworthy tendency is shown (as in Fig.6 and Fig.7). Regarding the time domain t , on the basis of Eq. (1), it appears that the coefficients $\hat{b}$ is strongly affected immediately after the stimulation. On the other hand, coefficient $\hat{a}$ is affected some time after the response in the ABR signal. Nearly the same time lag arises for both the time when coefficient $\hat{a}$ is affected, and the time when the peaks of waves IV and V are detected. By the way, the peak latencies of waves IV and V are the indicated by the detection of the peaks. That is, the peak latencies are the length of time between the introduction of a stimulus and the elicitation of a response, and are detected during the latter half in the response time of the ABR signal (Fig.1). Because waves IV and V are part of the main focus of the current ABR analysis, this equivalence between the time when coefficient $\hat{a}$ is affected, and the time when the peaks of waves IV and V are detected is a very important result. Therefore, we consider that coefficient $\hat{a}$ is the most important parameter of the ABR transfer function. On the other hand, it is difficult to identify the similarities among the various waveform types using coefficient $\hat{b}$.

In this paper, we review those characteristics of the coefficients again from the viewpoint of clinical applications and the frequency characteristics of the transfer function. To examine the ABR frequency characteristics, we set $z = e^{j\omega}$ ($0 \leq \omega \leq \pi$). When we estimate the coefficients of the transfer function for modeling all waveforms of the ABR, we use the case of $n_a = n_b = n$. Then, from Eq.(2), we obtain the frequency characteristics of the ABR transfer function as.

$$H(e^{j\omega}) = \frac{C(\omega) - jD(\omega)}{A(\omega) - jB(\omega)} = |H(e^{j\omega})| e^{j\Phi(\omega)} \quad (8)$$

where

$$\begin{aligned} A(\omega) &= 1 + a_1 \cos \omega + a_2 \cos 2\omega + \dots + a_n \cos n\omega \\ B(\omega) &= a_1 \sin \omega + a_2 \sin 2\omega + \dots + a_n \sin n\omega \\ C(\omega) &= b_1 \cos \omega + b_2 \cos 2\omega + \dots + b_n \cos n\omega \\ D(\omega) &= b_1 \sin \omega + b_2 \sin 2\omega + \dots + b_n \sin n\omega \end{aligned}$$

Equation (9) shows the magnitude characteristics and Eq. (10) shows the phase characteristics.

$$|H(e^{j\omega})| = \sqrt{\frac{C^2(\omega) + D^2(\omega)}{A^2(\omega) + B^2(\omega)}} \quad (9)$$

$$\Phi(\omega) = \tan^{-1} \left(\frac{B(\omega)C(\omega) - A(\omega)D(\omega)}{A(\omega)C(\omega) + B(\omega)D(\omega)} \right) \quad (10)$$

Here, as we explained in the previous section, we can consider coefficients a_i and b_i independently [7], and further more, we utilize only the transfer function coefficient a_i for waves IV and V which is part of the main focus of the current ABR analysis. We obtain the frequency characteristics from the ABR transfer function.

$$H_1(z) = \frac{z^{-d}}{1 + a_1 z^{-1} + \dots + a_n z^{-n}}, \quad (d > n) \quad (11)$$

The magnitude characteristic of $H_1(z)$, $z = e^{-j\omega}$ is

$$|H_1(e^{j\omega})| = \frac{1}{|1 + a_1 e^{-j\omega} + a_2 e^{-2j\omega} + \dots + a_n e^{-nj\omega}|} \quad (12)$$

The phase characteristics of $H_1(z)$ contain the linear phase delay $-\omega d$, but the essential property depends on coefficient a_i ($i = 1, 2, \dots, n$). Therefore, we analyze only the denominator by setting $d=0$. This leads to $C(\omega) = 1$ and $D(\omega) = 0$ in Eq. (11),

We obtained almost the same results for the frequency characteristics of all normal ABR patterns, as shown in Fig. 10. Figure 10-1 shows the magnitude, and Fig. 10-2 shows the phase characteristics.

Figure 11 shows the case of fewer averaging procedures (number of averaging is 100). From these data, we also observed almost the same frequency characteristics as those for 2000 averaging procedures of the normal ABR.

Using our model, it is clear that even if the observed ABR waveform has a low correlation coefficient, we can obtain the frequency characteristics of the ABR.

3. Conclusions

The sequential estimation algorithm of the ABR parameter is obtained using a Kalman filter. We can set a model parameter for all patterns of a normal ABR waveform, and its frequency characteristics. Our method is appropriate for application to a small number of averaging procedures of the ABR. It is more effective (with a high correlation to the true ABR signal) than the conventional method. In particular, by using our method of modeling the ABR transfer function, we can obtain the frequency characteristics using a smaller number of averaging procedures of the ABR, and the results are

Fig.10-1 Magnitude characteristics of the ABR transfer function, shown sequentially for examples of type 1, 2, 3-1 and 3-2 waveforms

Fig.10-2 Phase characteristics of the ABR transfer function, shown sequentially for examples of type 1, 2, 3-1 and 3-2 waveforms

Fig.11 Magnitude and phase characteristics of the ABR transfer function, for the example of type 2 waveform, obtained with 100 averaging procedures.

almost the same as the frequency characteristics for 2000 averaging procedures of the ABR. It will be possible to test for the ABR in a short time. Therefore in terms of the improvement of the ABR measurement system, this is considered to be a significant advancement.

At the same time, for the frequency characteristics of the ABR transfer function, we are also very interested in the role of the brainstem. However, we must continue to analyze the noise frequency characteristics in more detail. That is, by using the frequency characteristics of the ABR, we will develop an estimation method of reproducing the ABR signal, from the observed values obtained with a smaller number of averaging procedures, that have a low SNR. We hope to explain this method in a following paper.

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