An Adaptive Approach for Processing Evoked Potentials from the Auditory Cortex of Man

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Abstract We present an adaptive approach for the processing of evoked potentials from the an auditory association cortex in humans. The approach can be conceptualized as a bank of least mean square adaptive signal enhancers. The recording data of each trial is then divided into several segments and each segment of data is input to corresponding adaptive signal enhancers. This approach allows the temporal variations of the evoked potential signal to be estimated across individual trials. This is a powerful tool for both clincial and research neurosciences. Two illustrative cases are shown.

Keywords: Adaptive signal enhancement, Auditory evoked potential, Signal to noise ratio

I. INTRODUCTION

The cortical mechanisms mediating human ability to process information from complex sounds have been the focus of intense research. Powerful functional brain imaging methods such as positron emission tomography (PET), magnetoencephalography (MEG) and more recently functional magnetic resonance imaging (fMRI) have played important roles in advancing this field [3,4]. We currently examined the functional organization of human auditory cortex using a different experimental approach: direct intracranial recording and electrical stimulation. The most interesting quantities of the evoked potential (EP) from auditory association cortex are the latencies and amplitudes of the various components. These can be used to quantify neurological system properties.

From the signal processing point of view, EPs can be nonstationary signals, but the conventional ensemble average (EA) will not reveal the variation in amplitude and latency. These important components are buried in the much larger amplitude of the background EEG signal. Many techniques have been developed for extracting information from EPs [6,7]. The adaptive filtering technique is a powerful method to design time-varying filter for estimation of EP signals [1,2,5,7]. In early investigation we used EA method to estimate the EP from auditory cortex [3]. However, we could only obtain a brief EP estimation by EA. It will be more helpful to get the details of EP across individual trials. In this paper we present an adaptive approach to track the EP signal from the posterior superior temporal (PST) gyrus of humans.

II. METHODS

A bank of least mean square (LMS) adaptive signal enhancers (ASE) is used to estimate EP signals (Fig. 1). In the proposed adaptive filter bank every trial is divided into multiple time-sequenced segments. At each time segment, only one ASE is selected. Each ASE computes the data points of the corresponding segment in order to adapt towards its optimal point in terms of minimum mean square error (MMSE) using the LMS algorithm. Since EPs can be nonstationary, this approach will be more effective than a single ASE because it can divide the nonstationary signal into several stationary ones, each then processed by a corresponding ASE. To eliminate the discontinuities introduced by time switch β_k, some points between neighboring filters were overlapped. The estimated results at these overlap points are obtained by an average of both corresponding outputs of the contiguous ASEs.

Fig 2. represents a version of ASE. There are two inputs in the ASE: the primary input contains a signal s_0 plus noise n_0, while the reference input contains a signal s_1, related to but not necessarily having the same waveform as s_0, and an additive noise n_1. The noise n_0 and n_1 are assumed to be unrelated to each other and to both signals. The adaptive filter shown in Fig. 2 iteratively adjusts its impulse response via an adaptive algorithm so that, after convergence, the difference between the filter output y and the desired response d is minimized. It has been shown [1] that the filter output is an optimal estimate of s_0 alone in terms of MMSE.

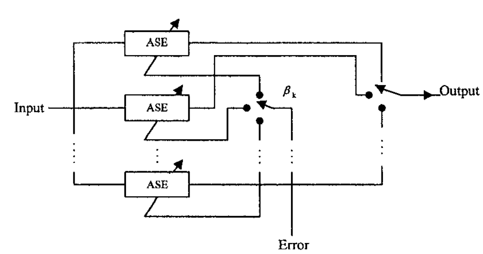


Fig.1 Input and output signals and a bank of LMS adaptive signal enhancers (ASE).

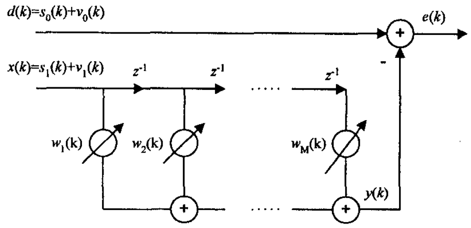


Fig. 2 The principle of LMS adaptive signal enhancer

It has been shown [5] that the improvement in SNR at the output of ASE is proportional to the SNR at the reference input. In order to obtain good results with less distortion and fast adaptation, it is desirable to reduce the noise components in the reference input. In other words, the reference input should be highly correlated with the signal. Ensemble averaging provides a good reference input since the variability of EP latency is relatively small over a short observation period. We used two methods to form the reference input to process EP from auditory cortex: the ensemble average (EA), and the moving window average (MWA).

Since EP signals can be time-varying across trials, MWA will form a reference input with a signal correlating highly with the primary input. However, the length of window must be selected properly to meet the condition of SNR in the reference input being higher than unity [5]. In our data, the SNR of the original data is relatively high because direct intracranial recording. MWA is then used to form the reference input of adaptive filter under this condition to improve the tracking ability. However, EA is also a useful method to form a reference input of the adaptive filter in the case of investigating whether the EP signal exists after some recording condition changed, e.g., before and after anesthesia.

Assuming that the weight vectors of ASEs are $\mathbf{W}_1, \mathbf{W}_2, \cdots, \mathbf{W}_M$, and M is the number of the ASE, then the LMS algorithm of each ASE will be modified as

$$y(k) = \mathbf{X}^{\mathrm{T}}(k)\mathbf{W}_{\beta_k}(k) \tag{1}$$

and

$$\mathbf{W}_j(k+1) = \begin{cases} \mathbf{W}_j(k) + 2\mu_j e(k)\mathbf{X}(k), & \beta_k = j \\ \mathbf{W}_j(k), & \text{other} \end{cases} \tag{2}$$

while

$$e(k) = d(k) - y(k) \tag{3}$$

and

$$\mathbf{X}(k) = \left[x(k) \quad x(k-1) \quad \cdots \quad x(k-N+1)\right]^{\mathrm{T}} \tag{4}$$

$$\mathbf{W}(k) = \left[w_0(k) \quad w_1(k) \quad \cdots \quad w_{(N-1)}(k)\right]^{\mathrm{T}} \tag{5}$$

where $\mathbf{W}_j(k)$ is the weight vector of jth ASE at k instant. And μ_j is the feedback factor of jth ASE, which is adjusted by its own input data points according to following equation

$$\mu_j = \frac{\alpha}{N(P_{\mathrm{in}})_j}, \quad \alpha << 1 \tag{6}$$

where $(P_{\mathrm{in}})_j$ is the mean power of the reference input at jth ASE, and N is the number of weight in j-th ASE. In the case of PST EP, we set α=0.05.

III. Results

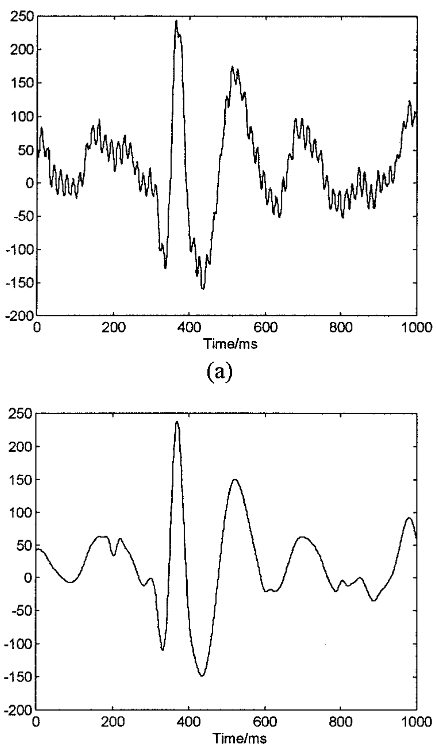
We have analyzed EP signals from the human auditory cortex by using above mentioned adaptive approach in two different conditions.

Case 1: PST evoked potential adaptive analysis

Study subjects were adult epilepsy surgery patients with normal hearing who were scheduled to have temporal lobe surface EEG recording arrays and/or depth electrodes placed as part of their standard surgical treatment plan [3]. Awake patients were studied acutely in the operation room or chronically on the epilepsy ward. Multi-contact surface recording arrays were positioned over the lateral surface of the exposed temporal lobe, including the posterior superior temporal gyrus. Modified depth electrodes were implanted into Heschl's gyrus of the non-speech dominant temporal lobe in selected patients. A train of five clicks at 100 Hz delivered to both ears at a moderate level was the acoustic stimulus. The recording time for each stimuli as 1000 ms; the acoustic stimulus was given at 200 ms. Evoked potentials recorded from PST were to be adaptively analyzed. We focus on the data sequence from one of the electrodes. Fig. 3 shows two average results before and after adaptive filtering. From Fig.3(a) it is clear that some power interference had been left in the original recordings during measurement. A notch filter was used to eliminate the power interference before the data processed by adaptive filter. The number of the filter bank was set to 5, i.e. the length of segment is 200ms. To determine the number of trials needed to form the proper reference input to adaptive filter, it is necessary to estimate the SNR of the original response first. A method called (+/-) averaging [1] is used to accomplish this. The estimated SNR of the original response is about -2dB. Therefore, MWA with window length of 9 trials was used to form the reference input of adaptive filter. Fig.3(b) is the result of averaging output of the adaptive system. It can be seen that PST EP signal components in (b) are much clearer than those in (a) while they keep high correlation relationship. It means that signal distortion is very small after adaptive filter processing. The most important respect of using adaptive analysis is that we can track EP signal trial by trial to demonstrate the possible variations in both amplitude and latency which cannot be obtained by EA. Fig.4 is the isometric views of PST EP signal trace across trials. Both amplitude and latency variations are shown in Fig.4.

Case 2: Monitoring EP before and after anesthesia

To study the anesthetic effect on the auditory EP, recordings were carried out before and after anesthesia. Fig.5(a) and (b) are the EA results before and after anesthesia, respectively. It can be seen from Fig.5(b) that after anesthesia EPs were suppressed. Since the duration of the recording was about 2 minutes, it is difficult to say when the EP was suppressed using conventional EA method. The adaptive system is used to track the EP signal. In this case we averaged recordings before anesthesia to form the reference input while the recordings after anesthesia are taken as the primary input of adaptive filter. Fig. 6 shows the output of the adaptive system, (a) before anesthesia and (b) during anesthesia induction. From Fig. 6 (b) it is clear that the EP disappered after the third trial.



(b)

Fig.3 Two average results of PST evoked potentials. (a) average result of original recordings, (b) average result of adaptive system output.

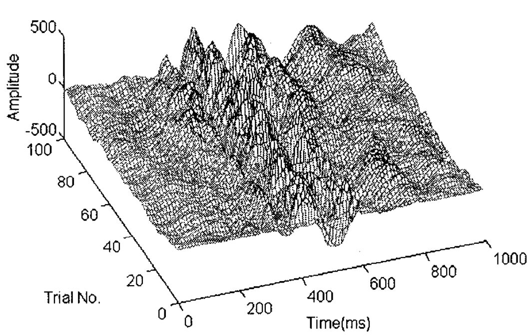


Fig.4 Isometric view of PST EP signal trace across trials.

IV. CONCLUSION

We presented an adaptive approach for tracking auditory EP signals. By using this method, it is possible to investigate the details of the EP with an adaptive filter. This method will be useful in further studies directed at determining the functional role of PST and other cortical fields.

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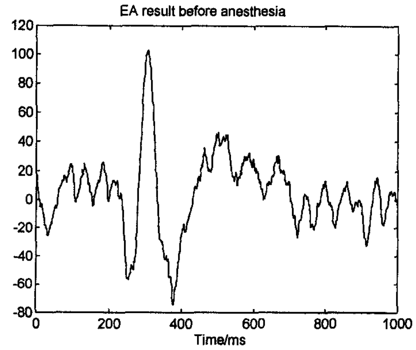
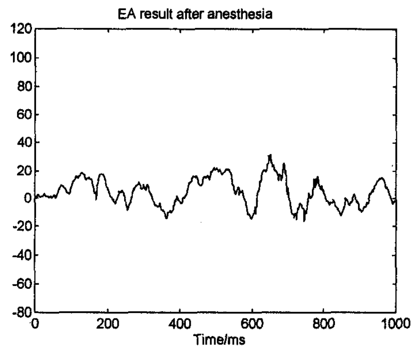
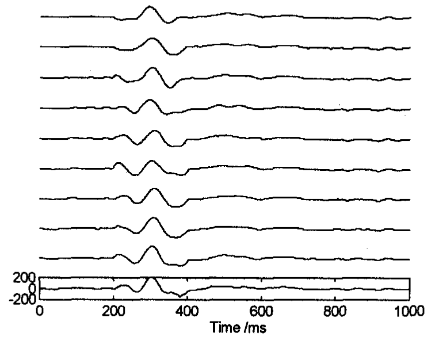


(a)

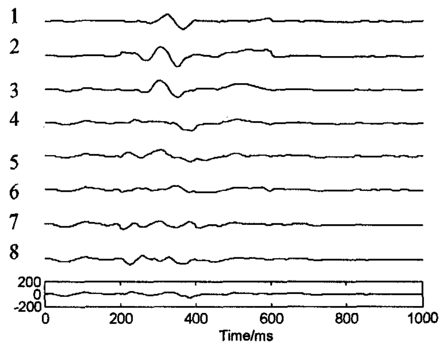


(b)

Fig.5 EA results of (a) before and (b) after anesthesia



(a)



(b)

Fig.6 Some outputs of adaptive filter (a) before and (b) after anesthesia.