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# Fast Extraction of Somatosensory Evoked Potential using RLS Adaptive Filter Algorithms

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**Abstract**—This paper evaluates the efficacy of the recursive least squares (RLS) in adaptive noise canceller (RLS-ANC) for fast extraction of somatosensory evoked potentials (SEPs). The RLS-ANC method was verified by simulation of electroencephalography (EEG) and Gaussian noise contaminated SEP signals at different signal-to-noise ratios (SNRs). RLS was found to converge faster than the least mean squares (LMS) algorithm in ANC, i.e. SEP extraction by RLS-ANC required fewer trials than LMS-ANC. Experimental results showed that RLS-ANC with less than 50 trials could provide similar performance in SEP extraction to those extracted by the conventional ensemble averaging with 500 trials even at SNR of -20dB.

**Keywords**—SEP; Adaptive Filter; RLS-ANC; LMS-ANC

## I. INTRODUCTION

Somatosensory Evoked Potentials (SEPs) are brain electrical physiological signals elicited by the direct electrical stimulation of peripheral nerves [1]. SEP has been widely used during the clinical testing and monitoring of the spinal cord and the central nervous system. However, a severe problem in practice is that the SEP signals recorded in operating theaters are always contaminated by both electrical and biological noises in nature. Hence the noninvasive measurement of the SEP suffers from very poor signal-to-noise ratio (SNR), which is typically less than 0 dB and less than -20 dB in the presence of larger noise interference [2].

Ensemble Averaging (EA) is the most commonly-used technique to extract the measurable and reliable SEP signals [3]. However, it needs a huge number of the SEP samples and a long period of time. Moreover, SEP is not a deterministic stationary signal, therefore, the response waveform of each stimulus may be different from each other. This variation property of the SEP cannot be reflected after averaging of thousands of trials [4]. Therefore, a more effective and reliable technique is expected to minimize the number of trials of EA and to extract SEP dynamically and rapidly.

Recently, adaptive filtering emerged as a reliable and efficient technique for the extraction of the evoked potential [5], and the least mean squares (LMS) based adaptive noise canceller (ANC) was found to be a fast, simple, and reliable SEP extraction method for intraoperative spinal cord monitoring [5]. The LMS algorithm is famous for its simplicity in concept and implementation, but it has a relatively slow convergence rate and is sensitive to the noise disturbance, which is remarkable in SEP monitoring. Therefore, we try to

employ other adaptive filtering algorithms in ANC for SEP extraction instead of the conventional LMS algorithm.

Recursive least squares (RLS) is a stable and accurate adaptive filtering algorithm because it updates the estimate using all the past available information, instead of the instantaneous measurement and error values in LMS. In principle, compared with LMS, RLS exhibits faster convergence rate and is less sensitive to noise disturbance, but at expense of a heavier computational load [6]. Although the RLS algorithm has been employed in a number of ANC applications, its application to the extraction of evoked potentials is very limited and the comparison between RLS-based and other adaptive filtering algorithms based ANC methods is never conducted.

In this paper, we propose the adoption of the RLS algorithm in the ANC method and applying the RLS-ANC method to extract simulated and recorded SEP signals. The performance of the RLS-ANC, LMS-ANC, and EA methods regarding to SEP extraction are evaluated and compared quantitatively.

## II. MATERIALS AND METHODS

### A. RLS-ANC

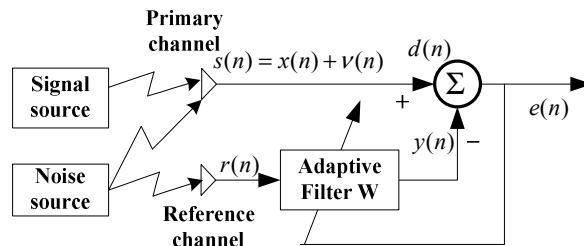


Figure 1. A block diagram of adaptive noise canceller (ANC) with one reference channel

RLS-ANC in this paper means the ANC filter using RLS algorithm. In Figure 1., a block diagram of ANC [7] is illustrated. The primary channel receives the signal  $x(n)$  plus an uncorrelated noise  $v(n)$ . The reference channel receives a noise  $r(n)$  which is uncorrelated with the signal  $x(n)$ , but correlated in some unknown way with the noise  $v(n)$ . In Fig 1,  $s(n)$  represents the raw SEP recordings, which is composed of the SEP signal  $x(n)$  and the noise  $v(n)$ . The reference channel  $r(n)$  represents a noise source correlated with the noise  $v(n)$ . The noise  $r(n)$  is filtered to produce an output which is a close

replica of  $v(n)$ . This output is subtracted from the primary channel to produce the system output. The basic objective of the adaptive filter is to set its weight vector in such a way that its output tries to minimize a meaningful objective function involving the reference channel signal.

The recursive formulas of RLS algorithm operate in seven major steps:

**Step1.** Initialization

$$W_M(-1) = 0, P_M(n-1) = \delta^{-1} I_M \quad (1)$$

where  $M$  is the filter order of the RLS-ANC,  $\delta$  can be the inverse of an estimation of the input signal power.

**Step2.** Calculation of the adaptive filter output

$$y(n) = r_M^T(n) W_M(n-1) \quad (2)$$

**Step3.** Estimation of the error

$$e_M(n) = d(n) - y(n) \quad (3)$$

**Step4.** Calculation of the Kalman gain vector

$$K_M(n) = \frac{P_M(n-1)r_M^*(n)}{\lambda + r_M^T(n)P_M(n-1)r_M^*(n)} \quad (4)$$

where  $\lambda$  is the forget factor.

**Step5.** Update of the inverse correlation matrix

$$P_M(n) = \frac{1}{\lambda} [P_M(n-1) - K_M(n)r_M^T(n)P_M(n-1)] \quad (5)$$

**Step6.** Calculation of the filter weights

$$W_M(n) = W_M(n-1) + K_M(n)e_M(n) \quad (6)$$

**Step7.** Go to the next instant,  $n=n+1$

Since  $K_M(n)$  is a square matrix changed with  $n$ , as a measure of the autocorrelation matrix, it indicates that, at different time, every element of  $W_M$  is adjusted with the new input data at a different weight, which explains why RLS has a fast convergence [8].

**B. Simulation Signals**

To compare the performances of ANC and EA, a simulation study was conducted. The SEP signals were collected over Cz' (2 cm posterior to Cz, 10-20 international system for EEG electrode placement) versus the Fz of the 10-20 system. The stimulation for SEP recording was applied on the posterior tibial nerve with the duration of 0.3 ms, the rate of 5.1 Hz and the constant current of 10 to 30 mA. The signals were amplified one hundred thousand times, band-pass filtered at 20-3000Hz. All the SEP signals were acquired and recorded to a computer with 12-bit resolution and the sampling rate of 5 kHz. We collected 500 trials for one subject and then the average of these trials is taken as a standard template for the simulation. Figure 2. shows the SEP template.

The reference noise was simulated by continuous EEG plus white Gaussian noise (WGN). Continuous EEG is the major

source of noise found in the SEP recordings. The simulated EEG was recorded from the awoken subjects at a sitting position in a quiet environment. White Gaussian noise is a kind of noise having a frequency spectrum continuous and uniform over a specified frequency band. EEG signals were collected over Cz and A1 (auricular) versus Fz, respectively. The Cz-Fz EEG plus WGN was superimposed onto the SEP to form the noise-contaminated SEP. A1-Fz EEG was used for the simulation of input to reference signals of the adaptive filter. Figure 3. shows the simulated SEP signal at -15dB with EEG and WGN.

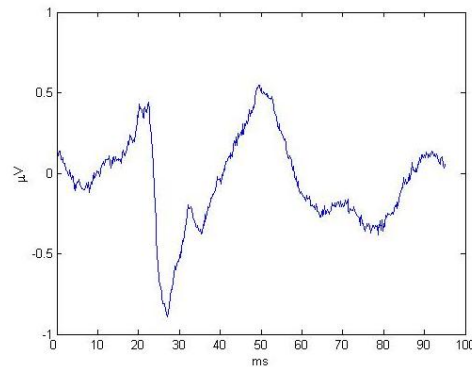


Figure 2. A SEP template obtained from ensemble averaging of 500 trials.

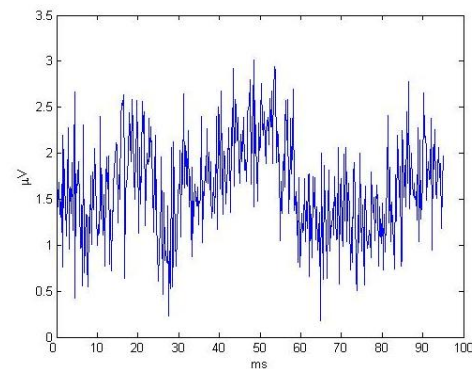


Figure 3. Simulated SEP signal at -15 dB with EEG and WGN

**C. Signal Processing and Data Analysis**

In this study, the step size  $\mu$  and the filter order  $N$  of the LMS were chosen as 0.000002 and 10, respectively, while the forgetting factor  $\lambda$  and the filter order of the RLS were chosen as 0.99 and 10, respectively. All the processing programs were implemented in MATLAB 7.0.

To quantitatively evaluate the performance of three different algorithms, three measures were employed: signal distortion index, waveform correlated coefficients, latency and peak-to-peak amplitude differences. Due to page limitation, the details of three measures can be found in [5].

**III. EXPERIMENTAL RESULTS**

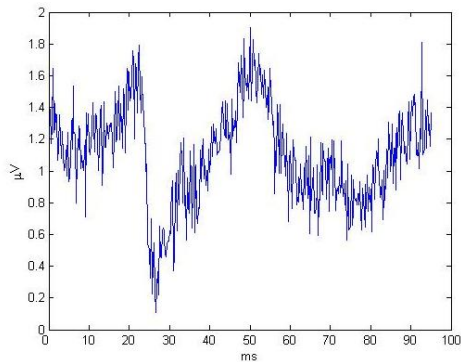
Figure 4. gives the SEP plots for EA, LMS-ANC, and RLS-ANC algorithms.

From Figure 4, it's apparent that the RLS-ANC algorithm could extract the most similar signal with the template. Experimental results also showed that the RLS-ANC needs about 50 trials for convergence at -10dB.

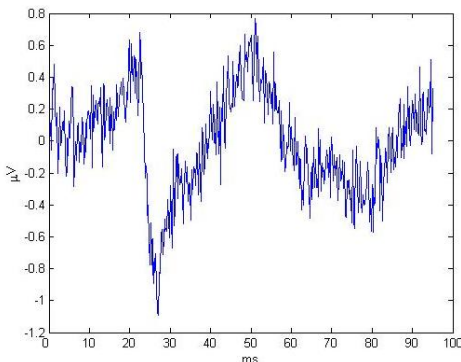
Using signal distortion index as a guideline, the RLS-SEP displayed the best results. By 10 trials at -10dB, the RLS-ANC gives a SDI below 0.1 (Figure 5. a). On the contrary, the EA-SEP didn't reach the 0.1 after 50 trials and the LMS-SEP just reached the 0.2 after 25 trials. When SNR was chosen as -20 dB, the difference was more obvious. After 50 trials, the SDI of the RLS-SEP was lower than 0.2 while the SDI of EA and the LMS-SEP reached almost the 0.6 and 0.4, respectively (see Figure 5. ).

Among 5 simulated cases, the mean correlated coefficients between the EA-SEP waveform, LMS-SEP waveform, RLS-SEP waveform and the template waveform are shown in Table 1. For all the SNR levels, the correlation coefficients between RLS-SEP and the template were always the highest among three SEP signals. The correlations between the SEPs and the template decreased while the input SNR decreased. At -10dB SNR, the correlation coefficients were almost at 0.9, which had small differences in the EA-SEP, LMS-SEP, and RLS-SEP waveforms than those in lower SNR levels.

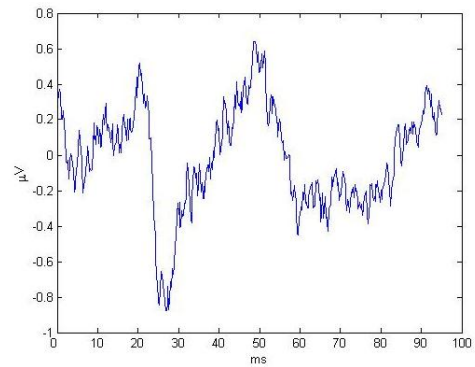
The latency and the amplitude are two important clinical parameters in the nervous system examination and the intraoperative spinal cord monitoring. Their percentage differences are presented in Table 2. According the data in the table, RLS-SEP didn't show a significant difference from the template.



(a) 50 trials EA-SEP waveform

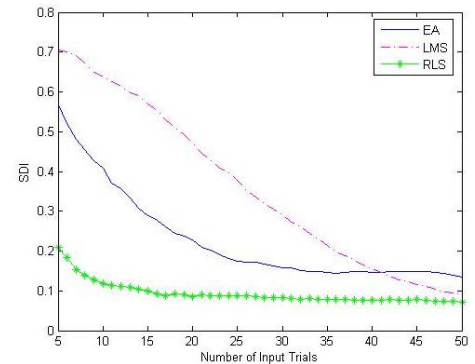


(b) 50 trials LMS-SEP waveform

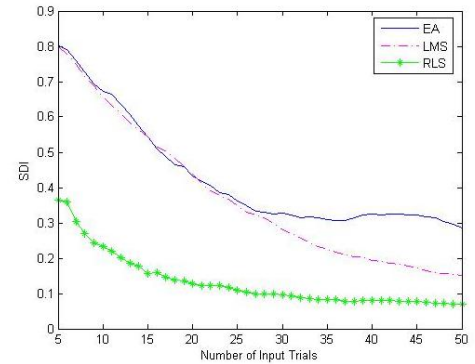


(c) 50 trials RLS-SEP waveform

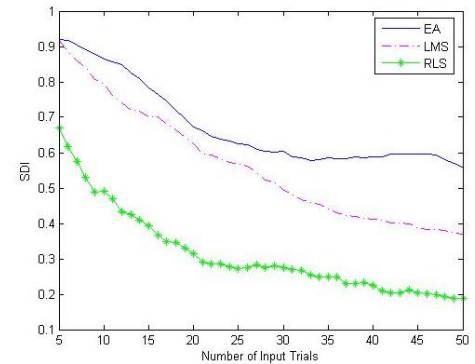
Figure 4. SEP waveforms by 50 trials at -15dB: (a) EA-SEP; (b) LMS-SEP; (c) RLS-SEP



(a) Comparison of EA-SEP, LMS-SEP and RLS-SEP with template distortion index against trial number (-10dB)



(b) -15dB



(c) -20dB

Figure 5. Comparison of EA-SEP, LMS-SEP and RLS-SEP with template distortion index against trial number at different SNR

TABLE 1. MEAN WAVEFORM CORRELATION COEFFICIENTS (MEAN  $\pm$  SD) FOR FIVE CASES BETWEEN (I) EA-SEP, (II) LMS-SEP, (III) RLS-SEP, AND THE TEMPLATE

SNR	EA-SEP	LMS-SEP	RLS-SEP
-10dB	0.90 $\pm$ 0.01	0.90 $\pm$ 0.01	0.93 $\pm$ 0.02
-15dB	0.76 $\pm$ 0.03	0.78 $\pm$ 0.03	0.89 $\pm$ 0.01
-20dB	0.53 $\pm$ 0.04	0.58 $\pm$ 0.05	0.74 $\pm$ 0.04

TABLE 2. MEAN PERCENTAGE DIFFERENCE (MEAN  $\pm$  S.D.) OF THE PEAK LATENCY AND THE AMPLITUDE (N1-P1) BETWEEN (I) EA-SEP, (II) LMS-SEP, (III) RLS-SEP, AND THE TEMPLATE AT DIFFERENT SNR

SNR	Latency N1	Latency P1	Amplitude
<b>EA-SEP</b>			
-10dB	5.2 $\pm$ 3.3	1.2 $\pm$ 1.5	3.5 $\pm$ 6.8
-15dB	3.6 $\pm$ 3.6	4.4 $\pm$ 6.0	2.2 $\pm$ 0.1
-20dB	5.6 $\pm$ 3.0	3.3 $\pm$ 2.1	3.0 $\pm$ 0.4
<b>LMS-SEP</b>			
-10dB	5.2 $\pm$ 3.3	1.2 $\pm$ 1.5	3.3 $\pm$ 5.6
-15dB	3.8 $\pm$ 3.4	1.8 $\pm$ 1.7	2.1 $\pm$ 0.1
-20dB	4.9 $\pm$ 3.1	2.9 $\pm$ 1.6	2.8 $\pm$ 0.4
<b>RLS-SEP</b>			
-10dB	2.9 $\pm$ 3.9	1.7 $\pm$ 1.2	6.5 $\pm$ 3.4
-15dB	6.5 $\pm$ 3.1	0.3 $\pm$ 0.4	1.5 $\pm$ 0.2
-20dB	9.0 $\pm$ 5.2	3.3 $\pm$ 3.0	1.9 $\pm$ 0.2

#### IV. DISCUSSION

The objective of this paper is to compare the performance of three algorithms used for SEP extraction. Except for the EA, the other two are all used in ANC. As an ANC filter, the key point of the effectiveness lies in how to choose the reference channel. This requires the knowledge of the categories of noise, which arises from the human scalp. Practically, noises could be classified as the bio-inspired and system-related [5]. From the clinical experience, EEG is the most influential bio-inspired noise to the surface SEP recorded from conscious subjects, because EEG signals are generated continuously by the subject as long as the acquisition process lasts [9]. Continuous EEG recorded from A1-Fz was noted to contain less SEP signal [10]. The A1-Fz and the Cz-Fz should be correlated with each other but not exactly the same since the waveform may change during the propagation [11]. Regarding those system related

noises, most of them are considered to be white Gaussian. Therefore, in this simulation study, the background noise of SEP is the sum of EEG and WGN.

#### V. CONCLUSION

This paper proposed the RLS-ANC for SEP extraction. The performance of RLS-ANC was compared with the LMS-ANC in simulation and experimental study. The experimental results showed that the RLS-ANC outperforms than the LMS-ANC and EA for SEP extraction. It is confident to conclude that the RLS-ANC is able to provide valuable medical information for practical spinal cord function detection and monitoring in operating theaters.

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