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Fast Extraction of Somatosensory Evoked Potential Based on Robust Adaptive Filtering

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1. Introduction

Somatosensory Evoked Potentials (SEPs) are brain electrical physiological signals elicited by the direct electrical stimulation of peripheral nerves. In other words, SEP is viewed as the nerve electric response produced by spinal cord sending or receiving sensory information in response to a stimulus (Turner et al., 2003). SEP has been widely used during the clinical testing and monitoring of the spinal cord and the central nervous system with the surface electrical stimulation. It can be said that the SEP is the most popular technique for intraoperative spinal cord monitoring in the operating room over 30 years (Nash et al., 1977; El-Hawary et al., 2006). However, in practice, the SEP signals recorded in the operating theaters are always contaminated by severe background noises (Krieger & Sclabassi 2001). The factors which cause noises may be electrical, physiological, anesthetic, surgical or abrupt event such as cough, body movement or adverse response to the stimulus of the patients. Generally, the recorded SEP signal is of a very poor signal-to-noise ratio (SNR) nature of the typical values between -20 dB to 0 dB (McGillem et al., 1981).

Literature review of SEP extraction techniques showed that the Ensemble Averaging (EA) is the most commonly used practical technique for SEP extraction (MacLennan & Lovel 1995). Research studies reveal that the EA-SEP approach is a kind of stimulus-locked signal averaging method, which is able to enhance the SNR in evoked potential recordings when a huge number of independent stimulus trails are used (such as hundreds or more than one thousands stimuli). This means that the EA-SEP extraction may lengthen the surgical time and hinder the surgical procedures (El-Hawary et al., 2006). Furthermore, EA-SEP approach is lack of ability to provide the timely warning of the eminent danger of cord injury in spine surgeon monitoring. In conclusion, the major drawbacks of EA-SEP approach are: First, the assumption that the captured SEP signals are truly deterministic and invariant between ensembles is dubious. Actually, a number of studies showed that SEPs are nonstationary and time-varying across stimulus trails (Nishida et al., 1993; Woody, 1967). Second, the procedure is very time-consuming, requiring up to 2000 ensembles to identify the SEP signal, which causes the discomfort to the subjects, and brings larger opportunity for the interference to degrade the SEP extraction. Moreover, careful evaluation of the working principle of the EA-SEP method reveals that the averaging process may merge the details carrying the information of certain neurological function in SEP. With the analysis above, we can conclude that EA-SEP method may fail to track trial-to-trial variations both in
latency and amplitude. A more effective and reliable technique is expected to minimize the number of trials for SEP extraction, and the single trail SEP extraction is desired. A lot of researches have been carried out for SEP extraction and various signal processing techniques have been investigated, including parametric modelling, nonlinear filtering, wavelet transform, adaptive filtering and independent component analysis (ICA) (Lange & Inbar 1996; Wei et al., 2002). It can be seen that a large number of records are still required to obtain a qualitative estimation in parametric model, and the study by Lange and Inbar suggested that it may not be able to provide adequate estimation of SEP (Lange & Inbar 1996).

In recent years, the present authors and some other researchers intensively investigated on the SEP extraction using adaptive filtering technique (AF-SEP) (Lin et al., 2004) (Lin et al., 2004; Hu et al., 2005; Lam et al., 2005). Research results showed that AF-SEP performs better compared with the EA-SEP or other parameter estimation approaches in either stationary or non-stationary situation, and AF-SEP was recommended as the most appropriate method to improve SNR of SEP (Lam et al., 2005). Specifically, AF-SEP under investigation usually employed the conventional linear transversal adaptive filter. There are two different structures have been proposed: one is the adaptive noise canceller (ANC) SEP extraction method (ANC-SEP) (Hu et al., 2005; Ren et al., 2009), another is the multi-filter SEP extraction method (MAF-SEP) for low SNR SEP estimation, where the ANC is used to remove the correlated noise in a primary signal and the uncorrelated noise, while the SEP components enhancement is carried out by the adaptive signal enhancer (ASE). Experimental results have shown that MAF-SEP method can greatly reduce the number of input trials for SEP extraction (Lam et al., 2005).

Adaptive filter theory tells that the different adaptive algorithms provide different filtering performances (Haykin, 2001). The least mean squares (LMS) based adaptive noise canceller SEP method (LMS-ANC-SEP) was found to be a fast, simple, and reliable SEP extraction method for intraoperative spinal cord monitoring (Lam et al., 2005). The LMS algorithm is famous for its simplicity at the price of having a relatively slow convergence rate and sensitive to the noise disturbance. To speed up the convergence, a Recursive Least Squares (RLS) based ANC-SEP (RLS-ANC-SEP) extraction algorithm was developed and studied in (Ren et al., 2009), where the Least Square cost function has been employed. RLS is a stable and accurate adaptive filtering algorithm (Haykin, 2001) since it updates the estimate using all the past available information, instead of the instantaneous measurement and error values in LMS.

Intensive experimental results demonstrate that the RLS-ANC-SEP extraction outperforms the EA-SEP and the LMS-ANC-SEP. It also showed that the RLS-ANC-SEP is much less sensitive to noise disturbance over its counterpart algorithms, but at the expense of a heavier computational load. Some research has shown than the conventional adaptive filters minimizing least squares (LS) or mean square error (MSE) are very sensitive to non-Gaussian or impulsive noise (Chan & Zou, 2004; Hazarika et al., 1997; Kong & Qiu, 1999). This is of increasing importance in biomedical signal processing field. Kong and Qiu (Kong & Qiu 1999) have done some preliminary research on a latency change detection and estimation algorithm under α-stable noise condition. They showed that the adaptive time delay estimation (TDE) algorithms based on the least mean square criterion failed to give an accurate estimation of the latency changes in the EP signal, and they employed the direct least mean square (DLMS) adaptive TDE algorithm derived based on the direct least mean p-norm criterion proposed by Etter and Stearn (Etter & Stearn, 1981). Theoretical analysis and simulation studies concluded that the DLMS algorithm is robust to the noises in EP signals with both Gaussian and non-Gaussian distributions.

SEP signals recorded in the operating room have illustrated the impulsive characteristics under certain circumstance, such as some orthopedic manipulations using saw, drill, bone
taps or bone bits. Based on our knowledge, there is no research carried out for the SEP extraction under the impulsive noise environment.

In this research, we will investigate the incorporation of robust M-estimator in the adaptive noise canceller structure for the SEP extraction. A recursive least M-estimate SEP extraction algorithm named as RLM-ANC-SEP has been developed by minimizing a robust M-estimator cost function. The performance of the RLM-ANC-SEP, RLS-ANC-SEP, LMS-ANC-SEP, and EA methods regarding to SEP extraction will be evaluated and compared quantitatively.

2. Materials and methods

In this section, the framework and the working principle of the adaptive noise canceller (ANC) using the finite impulse response (FIR) filter for SEP extraction is introduced. The SEP extraction system setup and data generation is presented accordingly. The SEP extraction methods using least mean square algorithm (LMS-ANC-SEP) and recursive least square algorithm (RLS-ANC-SEP) are provided for completeness and comparison purpose. The SEP extraction using the recursive least M-estimate (RLM) algorithm is derived and discussed at last.

2.1 Adaptive noise canceller (ANC) for SEP extraction

In Figure 1 (a), a block diagram of ANC for SEP extraction is illustrated, which mainly consists of a primary channel and a reference channel. The primary channel receives the source signal which refers to the raw SEP recording and can be modelled as

\[ s(n) = x(n) + v(n) \]

The adaptive filter in ANC

\[ y(n) = w^T(n) r(n) \]

Fig. 1. (a) A block diagram of adaptive noise canceller for SEP extraction, (b) Diagram of the M order FIR adaptive filter in ANC

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where $x(n)$ is the true SEP signal and $v(n)$ represents the background noise and interferences. In Figure 1, the reference channel represents a noise source denoted as $r(n)$, and $e(n)$ is the output of the ANC system, which is considered as the estimated version of the true SEP signal which can be formulated as

$$e(n) = s(n) - y(n) = x(n) + v(n) - w^T(n)r(n) \approx \hat{x}(n)$$

where the output of the adaptive filter is denoted as $y(n)=w^T(n)r(n)$. $r(n)=[r(n),...,r(n-M)]^T$ and $w(n)=[w_0(n),w_1(n),...,w_M(n)]^T$ are the output, input data vector and weight vector of the adaptive FIR filter (AF), respectively. The derivation of the adaptive filtering algorithm is governed by a meaningful cost function. As the result, after the convergence of the AF, the difference between the filter output and the desired response will be minimized.

It is worthy to note that for the ANC approach for SEP extraction, there are some important assumptions for achieving global convergence of the adaptive filter and the unbiased estimation of the desired signal. Firstly, the desired signal ($x(n)$) is corrupted by an additive interference (or noise) ($v(n)$) to form the primary signal $s(n)$; Secondly, if the reference signal ($r(n)$) is a correlated version of the interference signal ($v(n)$), then a FIR filter can be applied to transform $r(n)$ to approximate $v(n)$ and then suppress $v(n)$ from $s(n)$, which is illustrated in Figure 1(b); Thirdly, the reference signal ($r(n)$) must not contain a correlated component of $x(n)$, otherwise, the SEP signal component may also be cancelled at the output of the ANC. Therefore, it can be concluded that in the study of SEP extraction under ANC framework, the SEP recording and the reference signal generation must be designed carefully to satisfy the above requirements. Some discussion of the SEP extraction system setup will be presented in the next section.

### 2.2 SEP Extraction system setup and data generation

#### 2.2.1 SEP extraction system setup and signals

Fig. 2. A typical setup of the SEP extraction system

In our SEP extraction study, the SEP extraction system setup is illustrated in Figure 2. The SEP signals were collected over Cz' (2 cm posterior to Cz, 10-20 international system for EEG.
electrode placement) versus the $F_z$ 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, bandpass filtered at 20-3000Hz. 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 $SEP$ template in our study, which is shown in the first row of Figure 3 as $x_n$.

![Fig. 3. SEP signals. (1) $x_n$: An example of a $SEP$ template obtained from ensemble averaging of 500 trials; (2) $v_n$: one example of recorded $A1-F_z$ used as $EEG$ together with $WGN$ for primary channel; (3) $r_n$: one example of recorded $Cz-F_z$ recording used as $EEG$ together with correlated $WGN$ as the reference channel signal; (4) $s_n$: one example of the primary channel signal ($EEG + SEP + WGN$) at SNR=-15 dB.](image)

2.2.2 The primary channel signal and reference channel signal generation

It is observed that continuous $EEG$ is the major source of noise found in the primary $SEP$ recording channel and its variation version in the reference channel (Lam et al., 2005). In our study, $EEG$ is recorded over $Cz$ and $A1$ (auricular) versus $Fz$, respectively from the awaken subjects at a sitting position in a quiet environment. This is because the $A1-F_z$ recording signal has much less $SEP$ component, and $A1-F_z$ recording is suitable used for the generation of the reference channel signal $r(n)$ (MacDonald et al., 2005). Meanwhile, the $Cz-F_z$ recording was used to superimpose onto the $SEP$ template to generate the $EEG$-contaminated $SEP$ signal, that is, continuous $EEG$ signals of different SNR levels were added to each $SEP$ template to generate the $EEG$-contaminated $SEP$ trials (the primary channel signal $s(n)$ at different SNR level) for algorithm performance evaluation purpose. An autoregressive moving average (ARMA) filter was employed to simulate the correlated $WGN$ noise for the reference channel. One example of the $A1-F_z$ $EEG$ signal and $Cz-F_z$ $EEG$ signal recorded from scalp is plotted in Figure 3 as $v_n$ and $r_n$, respectively. The SNR of $EEG$-
2.3 Adaptive noise canceller for SEP extraction using mean square estimation

The SEP extraction method under the adaptive noise canceller (ANC) framework derived from the Mean-Square-Error was firstly introduced and evaluated by some of the present authors in (Lam et al., 2005). From the adaptive filter theory (Haykin, 2001) and the configuration of the ANC shown in Figure 1, the SEP extraction problem can be solved as a linear ANC problem since the FIR adaptive filter is used (named as ANC-SEP approach in this study). The commonly used error measure is the Mean-Square-Error (MSE defined as $J_{MSE} = E[e^2(n)]$, where $E[.]$ represents the ensemble operator). The minimisation of the MSE results in the Wiener normal equation under some statistically independent and signal wide-sense stationary (WSS) assumptions. The optimal solution of Wiener normal equation can be denoted as:

$$w_{opt}(n) = R_{mse}(n)P_{mse}(n)$$  \hspace{1cm} (3)

where $P_{mse}$ is the cross-correlation vector between $s(n)$ and $r(n)$, and $R_{mse}$ is the autocorrelation matrix of $r(n)$, which can be written as

$$P_{mse} = E[s(n)r(n)]$$

$$R_{mse} = E[r(k)r^T(k)]$$ \hspace{1cm} (4)

As discussed in many literatures, the well-known least mean squares (LMS) algorithm is a stochastic gradient based adaptive algorithm to obtain the optimal solution of $J_{MSE}$. The updating of the adaptive filter coefficient vector can be denoted as (Haykin, 2001)

$$w(n) = w(n-1) + 2\mu_{lms}e(n)r(n)$$ \hspace{1cm} (4)

where $\mu_{lms}$ is the stepsize which is one of the most important factors that controls the initial convergence rate and steady state error of the LMS-ANC for SEP extraction. Generally, a big stepsize yields rapid convergence but larger steady-state misadjustment error. A small stepsize yields slow convergence but a corresponding smaller steady-state misadjustment error. There exists a theoretical lower and upper bound of the choice of $\mu_{lms}$ (details can be referred to (Haykin, 2001). Usually, the choice of $\mu_{lms}$ is suggested by the following condition in the LMS algorithm (Haykin, 2001)

$$0 < \mu < 1 / (MP_{in})$$ \hspace{1cm} (5)

where $P_{in}$ and $M$ is the input power and the order of the adaptive FIR filter, respectively. In principle, the selection of the stepsize not only depends on the desired steady-state error level but also the statistical properties of the input signal of the adaptive filter. In other words, the convergence rate of the LMS algorithm is greatly affected by the dynamic range of the eigenvalues of the autocorrelation matrix $R_{mse}$. Considering this essential limitation, it is not difficult to understand that the performance of the ANC-SEP approach using LMS algorithm may suffer from the conflict to the WSS assumption for $s(n)$ and $r(n)$ and the nonstationary property of the $r(n)$. 

contaminated $SEP$ was set to $-10$, $-15$ and $-20$ dB. The last row of Figure 3 ($sn$) shows the simulated primary channel $SEP$ signal at $-15$dB with EEG and WGN.
2.4 Adaptive noise canceller for SEP extraction using least square estimation

Motivated by the performance enhancement of the ANC-SEP method using LMS algorithm compared with EA-SEP (Hu et al., 2005; Lam et al., 2005; Cui et al., 2008), some investigations of the ANC-SEP using RLS algorithm have been carried out and presented in (Ren et al., 2009). Instead of using MSE cost function, a conventional least square (LS) cost function is employed and the optimal solution of $J_{LS}$ is described as follows (Haykin 2001)

$$J_{LS}(n) = \sum_{k=1}^{n} \lambda^{n-k} |e(k)|^2,$$

and $w_{op}(n) = R_{LS}^{-1}(n)P_{LS}(n)$

where, $\lambda$ is the forgetting factor with the value between 0 and 1, which controls the effective amount of data used in the averaging and hence the degree to which the RLS algorithm can track the signal variation. The closer the value of $\lambda$ goes to one, the lower will be the steady-state misadjustment error of the RLS algorithm. Its tracking ability, however, will also be slower. $R_{LS}(n)$ is the autocorrelation matrix of the input vector at time index $n$ and $P_{LS}(n)$ is the cross-correlation vector between the input vector and the reference signal at time index $n$. Generally, they can be estimated as

$$R_{LS}(n) = \sum_{i=1}^{n} \lambda^{n-i} r(i)r^T(i) = \lambda R_{LS}(n-1) + r(n)r^T(n)$$

$$P_{LS}(n) = \sum_{i=1}^{n} \lambda^{n-i} s(i)r(i) = \lambda P_{LS}(n-1) + s(n)r(n)$$

By applying the matrix inversion lemma to the optimal solution in (6), the famous recursive least square (RLS) algorithm can be derived, and it is summarized in Table 1 for the completeness (Interested readers can refer to (Haykin, 2001)). From Table 1, it is noted that the computational complexity of the RLS algorithm is of order $M^2$.

| Step | Description |
|------|-------------|
| 1 | Initialization: $w_{RLS}(-1) = 0$, $P_{RLS}(n-1) = \delta^{-1}I_M$, $n=0$, where $M$ is the filter order of the adaptive filter using in ANC, $\delta$ can be the inverse of an estimation of the input signal power. |
| 2 | Calculation of the adaptive filter output: $y(n) = r^T(n)w_{RLS}(n-1)$ |
| 3 | Estimation error: $e(n) = s(n) - y(n)$ |
| 4 | Calculation of the Kalman gain vector: $K_{RLS}(n) = \frac{P_{RLS}(n-1)r^T(n)}{\lambda + r^T(n)P_{RLS}(n-1)r(n)}$ |
| 5 | Update of the inverse correlation matrix: $P_{RLS}(n) = \frac{1}{\lambda}[P_{RLS}(n-1) - K_{RLS}(n)r^T(n)P_{RLS}(n-1)]$ |
| 6 | Update of the filter weights: $w_{RLS}(n) = w_{RLS}(n-1) + K_{RLS}(n)e(n)$ |

Table 1. RLS-ANC-SEP algorithm
2.5 Adaptive noise canceller for SEP extraction using robust estimation

Carefully evaluating the properties of the recording SEP signals in the operating room, it noted that these SEP signals may have some nonstationary and impulsive like properties when the trial patients happen to the eye movement, cough and stimulus etc, which commonly exist. Under these kind of circumstances, the performance of the ANC-SEP methods using LMS or RLS will degrade or fail to extract SEP signal due to the adverse effect of the noise. The new method is desired. Motivated by the research work done by Chan and Zou (Chan & Zou, 2004), a new error measure method based on the $M$-estimate has been introduced and the corresponding cost function instead of $J_{MSE}$ or $J_{LS}$ is used for providing the robustness in the algorithm, which is given as

$$J_R(n) = \sum_{i=1}^{n} \lambda^{n-i} \rho(e(i)) = \sum_{i=1}^{n} \lambda^{n-i} \rho(s(i) - w^T(n)r(i))$$

(10)

where $\lambda$ is the positive forgetting factor and $\rho$ is an $M$-estimate function, which provides certain ability to suppress the adverse effect of impulsive noise on the cost function when the error signal becomes very large. In our study, the Huber $M$-estimate function and the related weighting function are used, which can be denoted as

$$\rho(e) = \begin{cases} 
\frac{e^2}{2}, & 0 < |e| < \xi \\
\xi^2 / 2, & \text{otherwise} 
\end{cases}$$

(11)

where $\xi$ is the threshold parameter. The optimal solution $w(n)$ for minimizing $J_R(n)$ can be obtained by differentiating (10) with respect to $w(n)$ and setting the derivatives to zero. This yields the following $M$-estimate normal equation

$$R_R(n)w(n) = P_R(n)$$

(12)

where

$$R_R(n) = \lambda R_R(n-1) + q(e(n))r(n)r^T(n)$$

(13)

$$P_R(n) = \lambda P_R(n-1) + q(e(n))s(n)r(n)$$

(14)

$$q(e) = \frac{d\rho(e)}{de} \begin{cases} 
1, & 0 < |e| < \xi \\
0, & \text{otherwise} 
\end{cases}$$

(15)

where, $R_R(n)$ and $P_R(n)$ are called the $M$-estimate correlation matrix of $r(n)$ and the $M$-estimate cross-correlation vector of $r(n)$ and $s(n)$, respectively. The adaptive algorithm for solving the normal equation (12) can be obtained in the same way as developing RLS algorithm, and the resulting algorithm is called recursive least $M$-estimate algorithm (RLM) and it is summarized in Table 2. From Table 1 and Table 2, it can be seen that the computational complexity of RLM and RLS is similar except the cost to determine the weighting function $q(e)$ in (15). It is also noted that when the signal is Gaussian distributed, RLS and RLM are identical. The contribution of the weight function $q(e(n))$ lies at the suppression of the adverse effects of the large estimation error due to the undesired impulsive interference on the adaptive filter weight vector $w(n)$. The degree of this suppression is controlled by the parameter $\xi$, in our study, a recursive estimation approach...
is adopted which directly connects to the variance of the estimation error under the assumption of the interference is with contaminated Gaussian (CG) or alpha-stable distributions. The parameter $\xi$ has been determined (shown in Table 2) when there is 95% confidence to detect and reject the impulses (Chan & Zou, 2004).

1) Initialization: $w_{RLM}(-1)=0$, $P_{RLM}(n-1)=\delta^{-1}I_M$, $n=0$, where $M$ is the filter order of the ANC, $\delta$ can be the inverse of an estimation of the input signal power.

2) Calculation of the adaptive filter output: $y(n)=r^T(n)w_{RLM}(n-1)$

3) Estimation error calculation: $e(n)=s(n)-y(n)$

4) Estimate the variance of the estimation error, determine the parameter $\xi$ and determine the weighting function (Chan & Zou, 2004):

$$\sigma^2(n) = \lambda_\omega \sigma^2(n-1) + (1 - \lambda_\omega) c_1 \text{med}(A_e(n)), \xi = 2.24\sigma(n), q(e) = \begin{cases} 1, & 0 < |e| < \xi, \\ 0, & \text{otherwise} \end{cases}$$

where $\lambda_\omega$ is the forgetting factor, $A_e(n) = \{e^2(n), \ldots, e^2(n-N_w+1)\}$, $N_w$ is the length of the estimation window, and $c_1 = 1.483(1+5/(N_w-1))$ is the finite sample correction factor.

5) Calculation of the Kalman gain vector: $K_R(n) = \frac{q(e(n))P_{RLM}(n-1)r(n)}{\lambda + q(e(n))r^T(n)P_{RLM}(n-1)r(n)}$

6) Update of the inverse correlation matrix:

$$P_{RLM}(n) = \frac{1}{\lambda} \left[ P_{RLM}(n-1) - K_{RLM}(n)r^T(n)P_{RLM}(n-1) \right]$$

7) Update of the filter weights: $w_{RLM}(n) = w_{RLM}(n-1) + K_R(n)e(n)$

8) Calculate the estimation error: $e(n) = \begin{cases} e(n), & q(e) = 1, \\ e(n-1), & q(e) = 0 \end{cases}$

$n=n+1$, back to step 2)

Table 2. RLM algorithm

3. Simulation study and discussion

As discussed above, we have introduced the SEP extraction approaches under the ANC framework by using different adaptive filtering algorithms. Specifically, employing LMS, RLS and RLM algorithms to update the weighting vector of the adaptive FIR filter in ANC results in the LMS-ANC-SEP method, RLS-ANC-SEP method and RLM-ANC-SEP method, respectively. In this section, the performance of these adaptive filtering methods for SEP extraction under Gaussian and impulsive noise environment has been evaluated and compared by intensive simulation experiments.

3.1 Experiment 1: SEP extraction under Gaussian noise

In this section, we aim to visually illustrate the SEP extraction performance of the algorithms discussed above under Gaussian noise condition. The detailed performance
comparison between EA-SEP, LMS-ANC-SEP, RLS-ANC-SEP and RLM-ANC-SEP methods under EEG and WGN contamination can be referred to the work presented in papers (Lam et al., 2005) and (Ren et al., 2009). Here, we only illustrate one set of the SEP extraction results for reader’s favorite review. Figure 4 shows the SEP extraction results from 50 SEP trails by different algorithms. In this experiment, the SEP template \( x_n \), simulated primary signals \( s_n, v_n \) and reference signal \( r_n \) are the same as those shown in Figure 3 at \( \text{SNR} = -15 \text{dB} \). The order of the adaptive filter \( M \) is set to be 10, the step size \( \mu \) of the LMS-ANC-SEP is chosen as \( 2 \times 10^{-4} \), the forgetting factor of the RLS-ANC-SEP and RLM-ANC-SEP algorithms is set to be 0.99. The parameters for RLM-ANC-SEP in Table 2 are set as \( \lambda_\sigma = 0.9 \) and \( N_w = 7 \).

From Figure 4, it is clear to see that the signals extracted from 50 trials by EA-SEP and LMS-ANC-SEP are difficult to detect the positive and negative peaks required for quantitative analysis and diagnosis of the SEP signal. More precisely, the positive peak around 35ms and the negative peak around 40ms, which are two most commonly-used criteria for the online monitoring during the spinal surgery, are still buried in the heavy background noise, so that their latencies and amplitudes cannot be measured accurately. On the other hand, we can see that the performance of RLM-ANC-SEP is almost the same as that of RLS-ANC-SEP, which outperforms than other two algorithms. It is apparent that two peaks around 35ms and 40 ms can be easily observed and their latencies and amplitudes can be precisely measured in the results using RLS-ANC-SEP and RLM-ANC-SEP methods. All these findings in practice can be well explained in theory. That is, the RLS/RLM-based algorithms have a fast convergence rate than LMS-based algorithm. Furthermore, the RLM-ANC-SEP algorithm is comparable to RLS-ANC-SEP algorithm under EEG and WGN environment. We next test and compare their performances when few SEP trials are contaminated with impulsive noises.

Fig. 4. 50-trial SEP extraction results obtained by EA-SEP, LMS-ANC-SEP, RLS-ANC-SEP, and RLM-ANC-SEP method, respectively (SNR=-15dB)
3.2 Experiment 2: SEP extraction under impulsive noise

This simulation is set up to compare the SEP extraction performance of the EA-SEP, LMS-ANC-SEP, RLS-ANC-SEP and RLM-ANC-SEP under EEG and individual impulse contaminated noise environment. Generally, the impulsive noise can be generated by a contaminated Gaussian (CG) model proposed in (Haweel & Clarkson, 1992). The impulses are generated individually with arrival probability \( P_{ar} = 2 \times 10^{-3} \) and the variance is chosen as 200. In our study, only for performance illustration purpose, the positions of the impulses are assumed to occur at 19ms, 28ms, 35ms, 44ms, and 78ms, respectively (which is not necessary to fix the position of the impulses, but here it is for us to gain the better performance visualization for different algorithms). The SEP template \( (xn) \), one sample primary interference \( (vn) \) with impulses, one sample of the reference signal \( (rn) \) and the resultant primary signal \( (sn) \) at -15dB are shown in Figure 5. The difference between Figure 3 and Figure 5 only lies at several impulses added in the primary interference signal \( (vn) \). In this case, the primary signal is composed of a SEP template, an A1-Fz EEG component, and a contaminated Gaussian noise.

![Figure 5](image)

Fig. 5. SEP signals with impulsive noise, (1) \( xn \) and \( rn \) are the same as those in Figure 3. (2) \( vn \): one example of recorded A1-Fz used as EEG together with CG noise for primary channel; (3) \( sn \): One example of the primary channel signal (EEG +SEP+CGN) at -15 dB.

For this simulation, all parameter settings are the same as those used in Experiment 1. The SEP extraction results from 50 SEP trails under impulsive noise by different algorithms are shown in Figure 6. If no impulsive noise occurs, the extraction results of four different methods should be approximately identical to their counterparts in Figure 4. As a result, Figure 5 can be regarded as a standard to evaluate the robustness of these methods when impulsive noises are added. From Figure 6, it is clear to see that the adverse impact of the impulses on the SEP extraction for EA-SEP, LMS-ANC-SEP and RLS-ANC-SEP algorithms compared with their counterpart algorithms under WGN shown in Figure 4. More specifically, for the EA-SEP
method, since the amplitudes of the impulsive noise are rather large compared to that of WGN, they cannot be averaged out completely using finite number of trials. As for the LMS-ANC-SEP and RLS-ANC-SEP methods, which employ an LS criterion for the updating of the filter coefficients in ANC, their performances are degraded severely because the coefficient estimates in ANC are unstable and may be greatly deviated from the reasonable values when impulsive noise occurs. The performance degradation can be more easily observed in the result of RLS-ANC-SEP in Figure 6, where the adverse impacts of impulsive noises around 35ms and 44ms are distinct and its difference with RLS-ANC-SEP of Figure 4 is obvious. Unlike those methods based on averaging or LS criterion, RLM-ANC-SEP employs an M-estimation function in ANC so that the impulsive noise can be detected and suppressed effectively. As the result, its harmful impact on SEP extraction is reduced considerably. The simulation results illustrate the advantage of RLM-ANC-SEP, and we can see that RLM-ANC-SEP shows its robustness to the impulsive interferences and its performance is close to that under WGN condition. In Figure 6, we can hardly find the traces of impulsive noise in the RLM-ANC-SEP result and peaks were clearly seen and measurable. In a simple word, impulsive noise which degrades the outputs of EA-SEP, LMS-ANC-SEP and other LS-based SEP extraction methods will do little harm to RLM-ANC-SEP.

As mentioned before, impulsive noise often occurs during spinal surgery in operating theatres and it will greatly decrease the quality of SEP recording. Current SEP recording technique works in this way when some SEP trials are contaminated with impulsive noise, they will be discarded. However, these trials with impulsive noise also contain useful SEP information, and the rejection of these trials will increase the time to record a useful SEP.
signal, and make the recording and monitoring discontinuous, which is undesirable. Therefore, making use of SEP trials contaminated with impulsive noise is necessary and robust SEP extraction method, such as the proposed RLM-ANC-SEP method, is advantageous. Our preliminary study and experimental results show that the RLM-ANC-SEP method has an excellent performance in impulsive noise environment, it may be taken as a good solution to achieve reliable and continuous SEP recording for monitoring under Gaussian and impulsive noise environment.

4. Conclusion

Aiming at developing the efficient SEP recording system, we have introduced the SEP extraction methods under the ANC framework using adaptive FIR filter. A new SEP extraction method called RLM-ANC-SEP was developed to obtain the the fast and robust performance under Gaussian and Contaminated Gaussian noise environment. RLM-ANC-SEP minimizes the modified Huber M-estimator based cost function instead of the conventional mean square error and least squares error based cost functions, which provides the robust ability when impulses occurring in the primary channel, and maintains the fast convergence as the RLS-ANC-SEP algorithm. Simulation study proved that either RLM-ANC-SEP or RLS-ANC-SEP has better and more robust convergence performance than LMS-ANC-SEP. The performances of RLM-ANC-SEP and RLS-ANC-SEP showed equivalent under WGN condition, but RLM-ANC-SEP presented its robustness to the impulsive interferences. Clinical application and validation study could be our future work on this proposed SEP signal extraction approach.

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Adaptive filtering is useful in any application where the signals or the modeled system vary over time. The configuration of the system and, in particular, the position where the adaptive processor is placed generate different areas or application fields such as: prediction, system identification and modeling, equalization, cancellation of interference, etc., which are very important in many disciplines such as control systems, communications, signal processing, acoustics, voice, sound and image, etc. The book consists of noise and echo cancellation, medical applications, communications systems and others hardly joined by their heterogeneity. Each application is a case study with rigor that shows weakness/strength of the method used, assesses its suitability and suggests new forms and areas of use. The problems are becoming increasingly complex and applications must be adapted to solve them. The adaptive filters have proven to be useful in these environments of multiple input/output, variant-time behaviors, and long and complex transfer functions effectively, but fundamentally they still have to evolve. This book is a demonstration of this and a small illustration of everything that is to come.

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