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Fast Extraction of Somatosensory Evoked Potential Based on Robust Adaptive Filtering

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1. Introduction

Somatosensory Evoked Potentials (*SEP*s) 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 & Lovely 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 *SEP*s 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
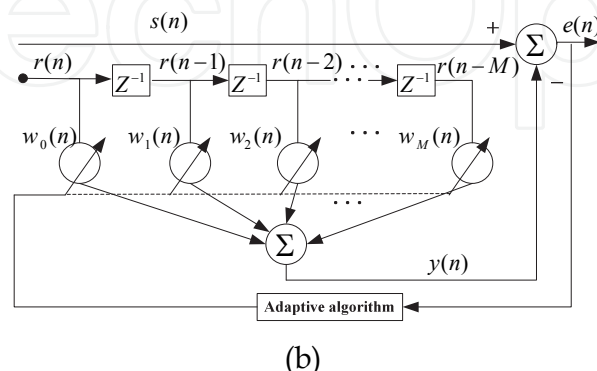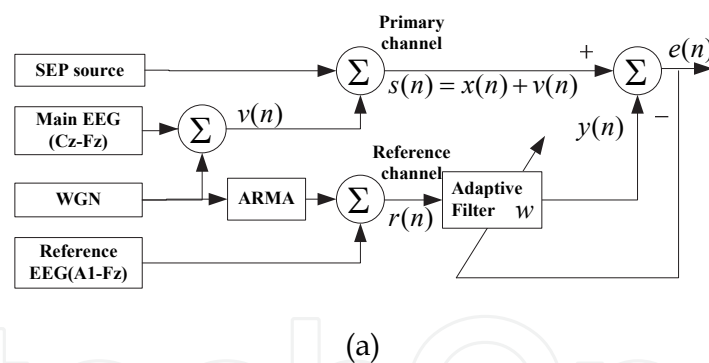

(a)

(b)

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

$$s(n) = x(n) + v(n) \tag{1}$$

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

$$e(n) = s(n) - y(n) = x(n) + v(n) - \mathbf{w}^T(n)\mathbf{r}(n) \approx \hat{x}(n) \tag{2}$$

where the output of the adaptive filter is denoted as $y(n) = w^T(n)r(n)$. $r(n) = [r(n),...,r(n\text{-}M)]^T$ 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
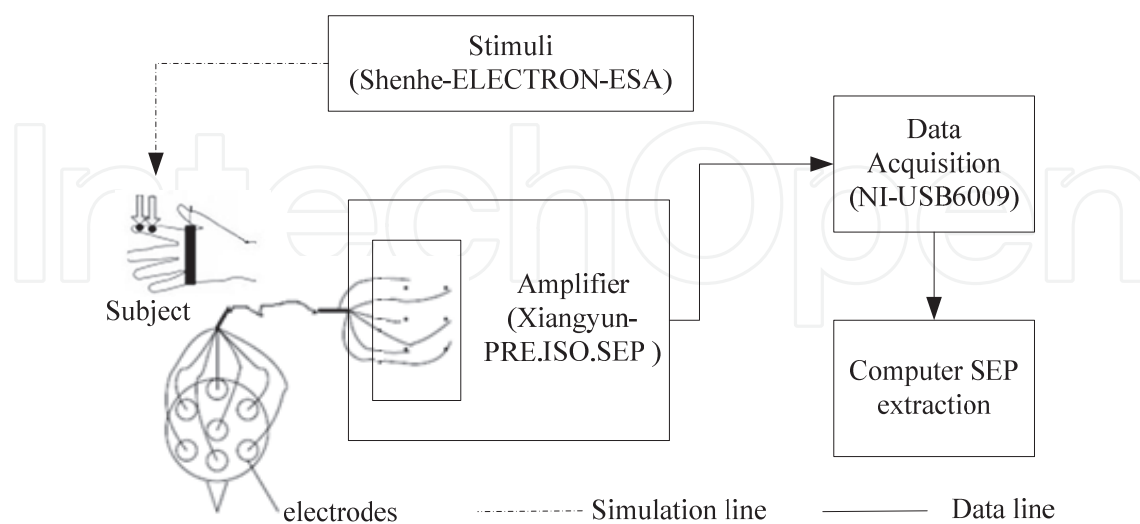## 2.2.1 SEP extraction system setup and signals

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 *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, 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 xn.
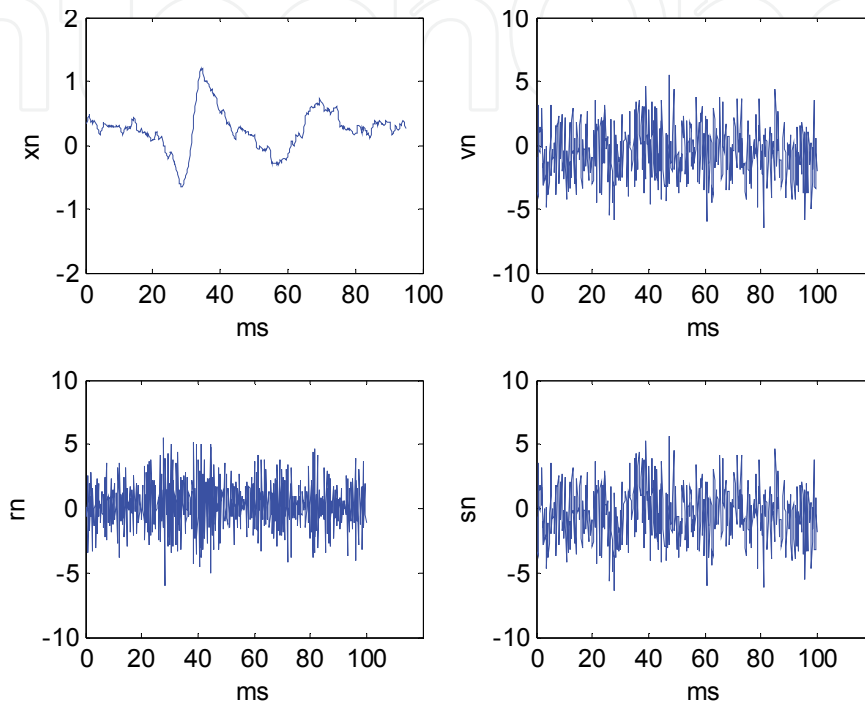

Fig. 3. *SEP* signals. (1) *xn*: An example of a *SEP* template obtained from ensemble averaging of 500 trials; (2) *vn*: one example of recorded *A1-Fz* used as *EEG* together with *WGN* for primary channel; (3) *rn*: one example of recorded *Cz-Fz* recording used as *EEG* together with correlated *WGN* as the reference channel signal; (4) *sn*: one example of the primary channel signal (*EEG* +*SEP*+*WGN*) at SNR=-15 dB.

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-Fz* recording signal has much less *SEP* component, and *A1-Fz* recording is suitable used for the generation of the reference channel signal *r(n)* (MacDonald et al., 2005). Meanwhile, the *Cz-Fz* 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-Fz EEG* signal and *Cz-Fz EEG* signal recorded from scalp is plotted in Figure 3 as *vn* and *rn*, respectively. The *SNR* of *EEG*-

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 -15dB with *EEG* and *WGN*.

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:

$$\mathbf{w}_{opt}(n) = \mathbf{R}_{mse}^{-1}(n)\mathbf{P}_{mse}(n) \tag{3}$$

where $\mathbf{P}_{mse}$ is the cross-correlation vector between $s(n)$ and $r(n)$, and $\mathbf{R}_{mse}$ is the autocorrelation matrix *of r(n)*, which can be written as

$$\mathbf{P}_{mse} = E[s(n)\mathbf{r}(n)]$$

$$\mathbf{R}_{mse} = E[\mathbf{r}(k)\mathbf{r}^T(k)] \tag{4}$$

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)

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

where μ_{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 μ_{lms} (details can be referred to (Haykin, 2001). Usually, the choice of μ_{lms} is suggested by the following condition in the *LMS* algorithm (Haykin, 2001)

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

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 $\mathbf{R}_{mse}$. 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 $r(n)$.

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)

$$J_{LS}(n) = \sum_{k=1}^{n} \lambda^{n-k} |e(k)|^2 \text{ , and } \mathbf{w}_{opt}(n) = \mathbf{R}_{Ls}^{-1}(n)\mathbf{P}_{LS}(n) \tag{6}$$

where, λ 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 λ goes to one, the lower will be the steady-state misadjustment error of the *RLS* algorithm. Its tracking ability, however, will also be slower. $\mathbf{R}_{LS}(n)$ is the autocorrelation matrix of the input vector at time index n and $\mathbf{P}_{LS}(n)$ is the cross-correlation vector between the input vector and the reference signal at time index n. Generally, they can be estimated as

$$\mathbf{R}_{LS}(n) = \sum_{i=1}^{n} \lambda^{n-i} \mathbf{r}(i)\mathbf{r}^T(i) = \lambda \mathbf{R}_{LS}(n-1) + \mathbf{r}(n)\mathbf{r}^T(n) \tag{7}$$

$$\mathbf{P}_{LS}(n) = \sum_{i=1}^{n} \lambda^{n-i} s(i)\mathbf{r}(i) = \lambda \mathbf{P}_{LS}(n-1) + s(n)\mathbf{r}(n) \tag{8}$$

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.

---

1) Initialization: $\mathbf{w}_{RLS}(-1) = 0$, $\mathbf{P}_{RLS}(n-1) = \delta^{-1}\mathbf{I}_M$, $n=0$, where M is the filter order of the adaptive filter using in *ANC*, δ can be the inverse of an estimation of the input signal power.

2) Calculation of the adaptive filter output: $y(n) = \mathbf{r}^T(n)\mathbf{w}_{RLS}(n-1)$

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

4) Calculation of the Kalman gain vector:

$$\mathbf{K}_{RLS}(n) = \frac{\mathbf{P}_{RLS}(n-1)\mathbf{r}^*(n)}{\lambda + \mathbf{r}^T(n)\mathbf{P}_{RLS}(n-1)\mathbf{r}^*(n)}$$

5) Update of the inverse correlation matrix:

$$\mathbf{P}_{RLS}(n) = \frac{1}{\lambda}\left[\mathbf{P}_{RLS}(n-1) - \mathbf{K}_{RLS}(n)\mathbf{r}^T(n)\mathbf{P}_{RLS}(n-1) \right]$$

6) Update of the filter weights: $\mathbf{w}_{RLS}(n) = \mathbf{w}_{RLS}(n-1) + \mathbf{K}_{RLS}(n)e(n)$

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

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

$$J_R(n) = \sum_{i=1}^{n} \lambda^{n-i} \rho(e(i)) = \sum_{i=1}^{n} \lambda^{n-i} \rho\left(s(i) - \mathbf{w}^T(n)\mathbf{r}(i)\right) \tag{10}$$

where λ is the positive forgetting factor and ρ 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

$$\rho(e) = \begin{cases} e^2/2, & 0 < |e| < \xi \\ \xi^2/2 & otherwise \end{cases} \tag{11}$$

where ξ 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

$$\mathbf{R}_R(n)\mathbf{w}(n) = \mathbf{P}_R(n) \tag{12}$$

where

$$\mathbf{R}_R(n) = \lambda\mathbf{R}_R(n-1) + q(e(n))\mathbf{r}(n)\mathbf{r}^T(n) \tag{13}$$

$$\mathbf{P}_R(n) = \lambda\mathbf{P}_R(n-1) + q(e(n))s(n)\mathbf{r}(n) \tag{14}$$

$$q(e) = \frac{d\rho(e)/de}{e} = \begin{cases} 1, & 0 < |e| < \xi \\ 0, & otherwise \end{cases} \tag{15}$$

where, $\mathbf{R}_R(n)$ and $\mathbf{P}_R(n)$ 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 ξ, 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 ξ has been determined (shown in Table 2) when there is 95% confidence to detect and reject the impulses (Chan & Zou, 2004).

1) Initialization: $\mathbf{w}_{RLM}(-1) = 0$, $\mathbf{P}_{RLM}(n-1) = \delta^{-1}\mathbf{I}_M$, *n*=0, where *M* is the filter order of the *ANC*, δ can be the inverse of an estimation of the input signal power.

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

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

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

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

where λ_σ is the forgetting factor, $A_e(n) = \{e^2(n), \cdots, e^2(n-N_w+1)\}$, 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: $\mathbf{K}_R(n) = \dfrac{q(e(n))\mathbf{P}_{RLM}(n-1)\mathbf{r}(n)}{\lambda + q(e(n))\mathbf{r}^T(n)\mathbf{P}_{RLM}(n-1)\mathbf{r}(n)}$

6) Update of the inverse correlation matrix:

$$\mathbf{P}_{RLM}(n) = \frac{1}{\lambda}\Big[\mathbf{P}_{RLM}(n-1) - \mathbf{K}_{RLM}(n)\mathbf{r}^T(n)\mathbf{P}_{RLM}(n-1)\Big]$$

7) Update of the filter weights: $\mathbf{w}_{RLM}(n) = \mathbf{w}_{RLM}(n-1) + \mathbf{K}_R(n)e(n)$

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 (*xn*), simulated primary signals (s*n, vn*) and reference signal (*rn*) are the same as those shown in Figure 3 at *SNR*=-15dB. The order of the adaptive filter *M* is set to be 10, the step size *μ* of the *LMS-ANC-SEP* is chosen as 2x10^{-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 λ_σ =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.
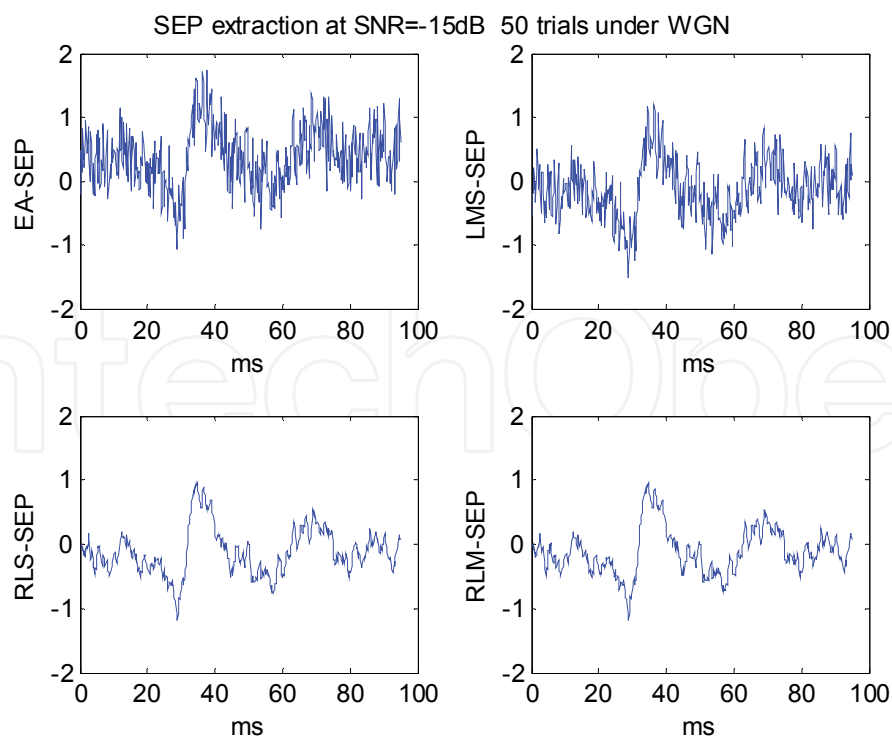

Fig. 4. 50-trial *SEP* extraction results obtained by *EA-SEP*, *LMS-ANC-SEP*, *RLS-ANC-SEP*, and *RLM-ANC-SEP* method, respectively (*SNR*=-15dB)

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 $P_{ar}=2\times10^{-3}$ 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.
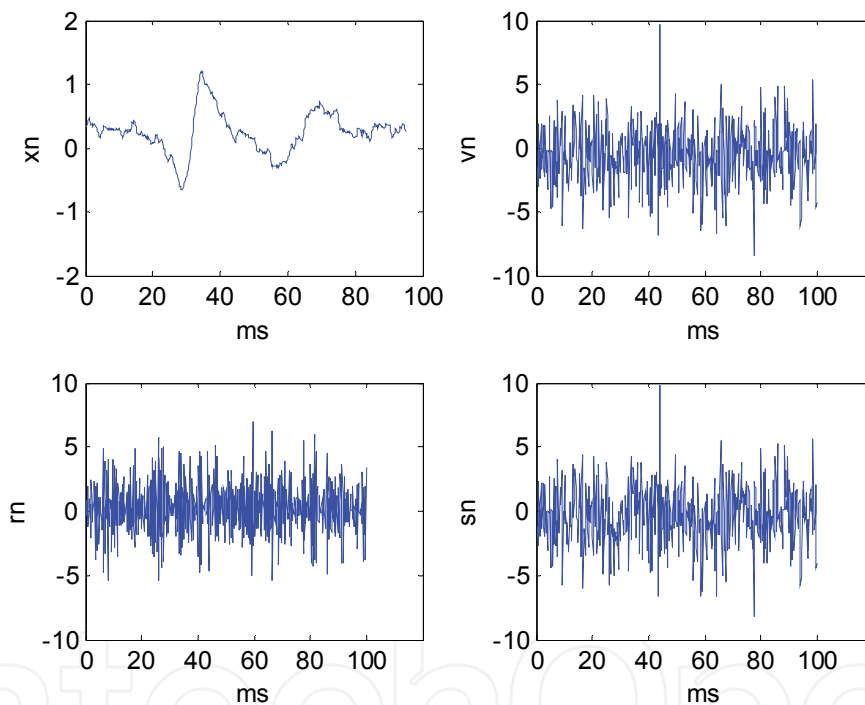

Fig. 5. *SEP* signals with impulsive noise, (1) *xn* and *rn* are the same as those in Figure 3. (2) *vn*: one example of recorded *A1-Fz* used as *EEG* together with *CG* noise for primary channel; (3) *sn*: One example of the primary channel signal (*EEG +SEP+CGN*) at -15 dB.

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*.
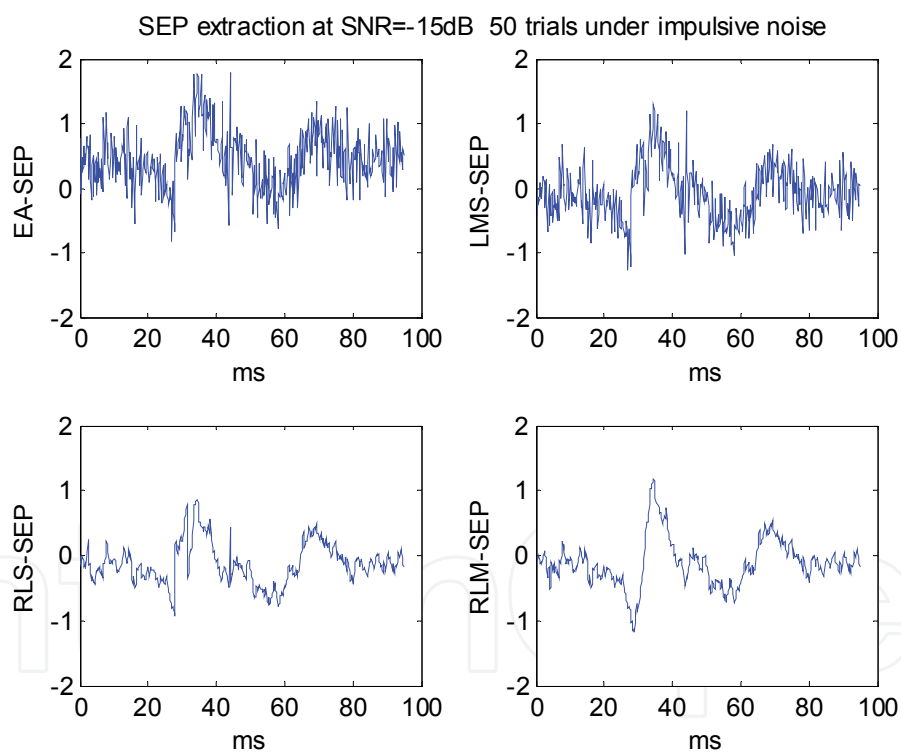

Fig. 6. 50-trial *SEP* extraction results obtained by *EA-SEP*, *LMS-ANC-SEP*, *RLS-ANC-SEP*, and *RLM-ANC-SEP* method, respectively (*SNR*=-15dB)

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.

5. Acknowledgment

6. References

Chan, S. C. & Y. X. Zou (2004). A Recursive Least M - Estimate Algorithm for Robust Adaptive Filtering in Impulse Noise: Fast Algorithm and Convergence Performance Analysis, *IEEE Transactions on Signal Processing*, Vol. 52, No.4, pp. 975-991.

Cui, H., C. Shen, et al. (2008). Study on Adaptive Noise Canceller Based on Fixed-Point Algorithm for Real-Time Somatosensory Evoked Potential Monitoring, *Bioinformatics and Biomedical Engineering*, Vol. 3, pp.2213 – 2216.

El-Hawary, R., S. Sparagana, et al. (2006). Spinal Cord Monitoring in Patients with Spinal Deformity and Neural Axis Abnormalities: A Comparison with Adolescent Idiopathic Scoliosis Patients, *SPINE*, Vol. 31, No. 19, pp.E698-E706.

Etter, D. M. & S. D. Stearn (1981). Adaptive Estimation of Time Delays in Sampled Data Systems, *IEEE Transactions on Acoustic, Speech, Signal Processing*, Vol. 29, pp. 582–587.

Haweel, T. I. & P. M. Clarkson (1992). A Class of Order Statistic LMS Algorithms, *IEEE Transactions on Signal Processing*, Vol. 40, No. 1, pp. 44-53.

Haykin, S. (2001). *Adpative Filter Theory* (4th Edition), Prentice Hall.

Hazarika, N., A. Tsoi, et al. (1997). Nonlinear Considerations in EEG Signal Classification, *IEEE Transactions on Signal Processing*, Vol. 45, pp. 829–836.

Hu, Y., B. Lam, et al. (2005). Adaptive Signal Enhancement of Somatosensory Evoked Potential for Spinal Cord Compression Detection: An Experimental Study, *Computers in Biology and Medicine*, Vol. 35, pp. 814-828.

Kong, X. & T. S. Qiu (1999). Adaptive Estimation of Latency Change in Evoked Potentials by Direct Least Mean p-Norm Time-Delay Estimation, *IEEE Transactions On Biomedical Engineering*, Vol. 46, No.8, pp. 994-1003.

Krieger, D. & R. Sclabassi (2001). Real-Time Intraoperative Neurophysiological Monitoring, *Methods*, Vol. 25, pp. 272-287.

Lam, B., Y. Hu, et al. (2005). Multi-adaptive Filtering Technique for Surface Somatosensory Evoked Potentials Processing, *Medical Engineering & Physics*, Vol. 27, pp. 257-266.

Lange, D. H. & G. F. Inbar (1996). A Robust Parametric Estimator for Single-Trial Movement Related Brain Potentials, *IEEE Transactions on Biomedical Engineering*, Vol. 43, pp. 341-347.

Lin, B. S., B.-S. Lin, et al. (2004). Adaptive Interference Cancel Filter for Evoked Potential Using High-Order Cumulants. *IEEE Engineering in Medicine and Biology Society*, Vol. 1, pp.396-398.

MacDonald, D. B. & A. Z. Zayed (2005). Tibial Somatosensory Evoked Potential Intraoperative Monitoring: Recommendations Based on Signal to Noise Ratio Analysis of Popliteal Fossa, *Optimized P37, Standard P37, and P31 Potentials, Journal of Clinical Neurophysiology*, Vol. 116, No.8, pp. 1858-1869.

MacLennan, A. R. & D. F. Lovely (1995). Reduction of Evoked Potential Measurement Time by a TMS320 Based Adaptive Matched Filter, *Medical Engineering & Physics,* Vol. 17, pp. 248-256.

McGillem, C. & J. Aunon (1981). Signal Processing in Evoked Potential Research: Applications of Filtering and Pattern Recognition, *Critical Reviews in Bioengineering, CRC*, Vol. 9, pp. 225-265.

Nash, C. L., R. A. Lorig, et al. (1977). Spinal Cord Monitoring During Operative Treatment of the Spine, *Clinical Orthopaedics and Related Research*, Vol. 126, pp. 100-105.

Nishida, S. & M. Nakamura (1993). Method for Single-Trial Recording of Somatosensory Evoked Potentials, *Journal of Biomedical Engineering*, Vol. 15, pp. 257-262.

Ren, Z. L., Y. X. Zou, et al. (2009). Fast Extraction of Somatosensory Evoked Potential using RLS Adaptive Filter Algorithms, *The 2nd International Congress on Image and Signal Processing (CISP'09)*, pp. 4444-4447.

Turner, S., P. Picton, et al. (2003). Extraction of Short-Latency Evoked Potentials Using a combination of Wavelets and Evolutionary Algorithms, Medical Engineering & Physics, Vol. 25, pp. 407-412.

Wei, Q. & K. Fung (2002). Adaptive Filtering of Evoked Potentials with Radial-Basis-Function Neural Network Prefilter, IEEE Transactions on Biomedical Engineering, Vol. 49, pp. 225-232.

Woody, C. D. (1967). Characterization of an Adaptive Filter for the Analysis of Variable Latency Neuroelectric Signals, Medical Biology Engineering, Vol. 5, pp. 539-553.

Adaptive Filtering Applications

Edited by Dr Lino Garcia

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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