Adaptive filtering of evoked potentials using higher-order adaptive signal enhancer with genetic-type variable step-size prefilter

B.-S. Lin¹ B.-S. Lin¹ F.-C. Chong¹ F. Lai²

¹Institute of Electrical Engineering, National Taiwan University, Taipei, Taiwan

²Department of Computer Science & Information Engineering, National Taiwan University, Taipei, Taiwan

Abstract—An adaptive signal enhancer based on third-order statistics with a genetic-type, variable step-size prefilter is introduced to recover evoked potentials (EPs). EPs are usually embedded in the ongoing electroencephalogram with a very low signal-to-noise ratio (SNR). As a higher-order statistics technique has a natural tolerance to Gaussian noise, it is applicable for filtering EPs. An adaptive signal enhancer based on third-order statistics was used as the major filter in this study. However, the efficiency of the adaptive signal enhancer was reduced when the total power of uncorrelated noises was large. To improve the performance for EPs under poor SNR, a low-noise signal is required. Therefore a prefilter with a genetic-type, variable step-size algorithm was employed to enhance the SNR of the signal in this study. The fundamental idea of a genetic-type, variable step-size algorithm is that its step-sizes are regularly readjusted to optimum. Therefore this algorithm can be used as a prefilter with different noise levels. Experimental results showed that, for filtering EPs, the proposed scheme is superior to the adaptive signal enhancer with a normalised least mean square algorithm.

Keywords—Evoked potentials, Adaptive signal enhancer, Higher-order statistics, Genetic-type, variable step-size algorithm

Med. Biol. Eng. Comput., 2005, 43, 638–647

1 Introduction

EVOKED POTENTIALS (EPs) are the usual responses to external stimuli such as sounds and lights. They are small and hidden in the spontaneous brain activity. They have a very poor signal-to-noise ratio (SNR), even less than -20 dB. The traditional practice for obtaining EPs is the ensemble averaging (EA) method (MCGILLEM *et al.*, 1981). It needs many stimulus repetitions in the recording and is highly sensitive to minor changes in both the latencies and amplitudes of EPs.

Adaptive filtering techniques (HAYKIN, 1991) have been widely used in biological estimations. They were first applied for the estimation of evoked potentials by THAKOR (1987). If filter coefficients are adapted with a least mean square (LMS) algorithm, no *a priori* knowledge of the statistics characteristic of signals and noises are needed for evoked potentials to be estimated well. In general, noisy EPs are taken as the primary inputs, and noise references are not easily available. Thus various kinds of basis structure for obtaining EPs have

been constructed (MADHAVAN, 1992; PARSA and PARKER, 1994; YU *et al.*, 1994; FUNG *et al.*, 1996; GRIEVE *et al.*, 2000). VAZ and THAKOR (1989) used a finite number of sine and cosine waves as the reference in the time domain. LAGUNA *et al.* (1992) designed the reference input as a unit impulse sequence synchronised with the beginning of each recurrence.

All these methods basically involve an adaptive filtering technique with the LMS algorithm. However, it is well known that the LMS algorithm based on second statistics is sensitive to the eigenvalue spread of the autocorrelation matrix of the reference signals (HAYKIN, 1991). Moreover, it cannot suppress the effect of the uncorrelated noises well, in particular, the coloured noise. Thus adaptive filtering techniques using an LMS algorithm for evoked potentials are problem-dependent.

In recent years, higher order statistics (or cumulants) techniques (NIKIAS and PETROPULU, 1993; HADJILEONTIADIS and PANAS, 1997) have been widely developed and applied to bio-medicine processing. GHARIEB and CICHOCKI (2001) reduced noise in brain EPs using third-order statistics. The utilisation of higher-order statistics can efficiently suppress coloured and white Gaussian noise processes of unknown spectral characteristics in deterministic signals. Therefore this method is more insensitive to both the input signals and the step-size.

Correspondence should be addressed to Dr Bor-Shyh Lin;
email: d8921033@ee.ntu.edu.tw

Paper received 24 January 2005 and in final form 10 May 2005

MBEC online number: 20054047

© IFMBE: 2005

However, adaptive filtering techniques with higher-order statistics may not work better than those with second-order statistics when the total power of the uncorrelated noise is quite large (SHIN and NIKIAS, 1994). The reason is that the adaptive signal enhancer cannot effectively remove the power of uncorrelated noises. To improve this issue, a low-noise signal is required.

Given this consideration, we added a prefilter with a genetic-type, variable step-size (GTVS) algorithm to improve the adaptive signal enhancer based on third-order statistics (ASE-TOS) for evoked potentials. QIU *et al.* (2002) employed a radial-basis-function neural network (RBFNN) as a prefilter to enhance the SNR of measured signals. Although the performance is effectively improved, this performance is influenced by its learning rate parameter, and it is difficult to select optimum learning parameters in the unknown condition. The genetic-type, variable step-size algorithm can overcome this issue. Most other variable step-size algorithms only provide a moderately fast convergence rate and are unsuitable for local minimum cases (HARRIS *et al.*, 1986; KWONG and JOHNSTON, 1992; ANG and FARHANG-BOROUJENY, 2001). The GTVS algorithm provides a parallel search technique that uses the principles of genetics and evolution to perform a directed random search from a population of controllers to select the best to implement at a specific sampling time period (NG *et al.*, 1996, NG *et al.*, 1999). It is suitable to solve eigenvalue disparity and local minimum issues owing to its property of global optimisation. With the GTVS combined as the prefilter of the ASE-TOS, the new scheme is superior to the other methods in the unrestricted condition.

2 Method

2.1 Basic scheme of adaptive signal enhancer

The adaptive signal enhancer, illustrated in Fig. 1, is a device used to detect a period-like signal buried in a broadband noise background (HAYKIN, 1991). It contains two inputs: the primary input and reference input. The primary input contains a signal of interest and a noise signal. The reference input is closely related to the signal of interest but is not necessarily the same as it. In general, the reference input consists of a delayed version of the primary input. The delay, denoted by Δ in Fig. 1, is called the prediction depth of the adaptive signal enhancer. The prediction depth Δ must be large enough to remove the correlation between the noises in the primary input and those in the reference input.

Let $d(t)$ and $u(t)$ be the primary and reference input signals, and let $y(t)$ be the filtered output signal. They are given by

$$d(t) = s(t) + v(t) \quad (1)$$

$$u(t) = d(t - \Delta) \quad (2)$$

$$y(t) = \mathbf{u}(t)^T \mathbf{w}(t) = \hat{s}(t) \quad (3)$$

Fig. 1 Basic scheme of adaptive signal enhancer

$s(t)$ is the signal of interest and is non-Gaussian at iteration t ; $\hat{s}(t)$ is the estimation of the signal of interest; $v(t)$ is coloured or white, Gaussian, uncorrelated noise. $\mathbf{u}(t) = [u(t), u(t-1), \dots, u(t-M+1)]^T$ and $\mathbf{w}(t) = [w_0(t), w_1(t), \dots, w_{M-1}(t)]^T$ are, respectively, the reference vector and the tap-weight vector of ASE.

The tap-weights can be adapted using the normalised LMS algorithm (HAYKIN, 1991)

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \frac{\mu}{(a + P_u)} \mathbf{u}(t)(d(t) - y(t)) \quad (4)$$

where P_u is the sum of the power of the tap-reference signals, a is a small positive constant, and the step-size μ for the normalised LMS algorithm is constrained to $0 < \mu < 2$.

As $d(t)$ contains noise $v(t)$, the system output noise $e(t)$ is also correlated to noise $v(t)$.

$$e(t) = d(t) - y(t) = s(t) + v(t) - \hat{s}(t) \quad (5)$$

From (4), we can find that the adaptation formula of tap-weights is affected directly by these uncorrelated noises, because $\mathbf{u}(t)$ contains the uncorrelated noise $v(t)$, and the system output contains the system output noise $e(t)$. Thus the ASE-NLMS cannot estimate the signal of interest effectively.

2.2 Genetic-type, variable step-size algorithm

The genetic-type, variable step-size algorithm is a parallel search technique where the step-sizes are regularly evolved in a random and controlled manner. In each evolution, a few sets of step-sizes are generated and evaluated. The one that provides the optimum performance over an evolution period is retained and used for the next stage. The basic structure of the GTVS algorithm is illustrated in Fig. 2.

In this implementation, we set the evolution period to be identical to T . At the beginning of the k th interval of evolution, the offspring of step-sizes $\mu_i^k, 1 \leq i \leq R$ are generated from the optimum parent step-size $\mu_{optimum}^{k-1}$ at the $(k-1)$ th interval by a random perturbation function (NG *et al.*, 1999).

$$\begin{cases} \mu_1^k = \mu_{optimum}^{k-1} \\ \mu_{2j}^k = (1 - \rho)\alpha^{-j}\mu_{optimum}^{k-1} + \rho\mu_{optimum}^{k-1} \\ \mu_{2j+1}^k = \rho\alpha^j\mu_{optimum}^{k-1} + (1 - \rho)\mu_{optimum}^{k-1} \end{cases} \quad 1 \leq j \leq \frac{R-1}{2} \quad (6)$$

Here, α is a positive constant correlated to the perturbation of new offspring step-sizes, and ρ is a random number distributed over $(0, 1)$. All generated step-sizes must also follow the convergent and stable condition $0 < \mu_i^k < 2$.

Next, $y_i^k(t)$, $e_i^k(t)$, and $\eta_i^k(t)$ are calculated to evaluate fitness in evolution. Let $\mathbf{w}_i^k(t)$, $y_i^k(t)$, $e_i^k(t)$ and $\eta_i^k(t)$ denote the tap-weight vector, the filtered output, the *a priori* estimation error and the *a posteriori* estimation error respectively, corresponding to μ_i^k at time t .

$$y_i^k(t) = \mathbf{u}(t)^T \mathbf{w}_i^k(t) \quad (7)$$

$$e_i^k(t) = d(t) - \mathbf{u}(t)^T \mathbf{w}_i^k(t) \quad (8)$$

$$\begin{aligned} \eta_i^k(t) &= d(t) - \mathbf{u}(t)\mathbf{w}_i^k(t+1) = e_i^k(t) \\ &\times \left(1 - \frac{\mu_i^k}{a + \mathbf{u}^T(t)\mathbf{u}(t)} \mathbf{u}^T(t)\mathbf{u}(t) \right) = e_i^k(t)\vartheta(\mu_i^k) \end{aligned} \quad (9)$$

$$\mathbf{w}_i^k(t+1) = \mathbf{w}_i^k(t) + \frac{\mu_i^k}{a + P_u} \mathbf{u}(t)e_i^k(t) \quad 1 \leq i \leq R \quad (10)$$

Fig. 2 Structure of adaptive signal enhancer with genetic-type variable step-size algorithm

The criterion for fitness in the k th interval is then defined as follows:

$$J_i = \sum_{t=0}^{T-1} \frac{[(1-\beta)e_i^k(t)^2 + \beta\eta_i^k(t)^2]}{T} = (1-\beta)J_i^e + \beta J_i^\eta \quad (11)$$

Here, β is a parameter in $(0, 1)$, and J_i^e and J_i^η denote the estimations of the mean-squared *a priori* and *a posteriori* error, respectively.

When the number t approaches infinity, the estimation of the excess mean-squared *a priori* error of J_i^e (HAYKIN, 1991) will approximate to

$$J_i^{e,\min} \sum_{i=1}^M \frac{\mu\lambda_i}{2-\mu\lambda_i} = J_i^{e,\min} v(\mu) \quad (12)$$

where $J_i^{e,\min}$ is the minimum mean-squared *a priori* error, and λ_i , $1 \leq i \leq M$, are the eigenvalues of the correlation matrix of the tap-reference signal. J_i^e is a monotonic decreasing function of μ owing to the fact that $v(\mu)$ is a monotonic decreasing function of μ . As $\vartheta(\mu)$ is a monotonic decreasing function of μ , it is straightforward that J_i^η is smaller than J_i^e when μ is larger. Thus, when β is larger, the criterion with a larger μ will be smaller than that with a smaller μ . Therefore we can adjust parameter β to determine fitness using these above properties.

Let β depend on the estimate of mean-squared *a priori* error normalised by $J_i^{e,\max}(k)$ in this interval.

$$\beta = \frac{J_0^e}{J_i^{e,\max}(k)} \quad (13)$$

where J_0^e and $J_i^{e,\max}(k)$ are, respectively, the estimates of the mean-squared *a priori* error using μ_0^k and maximum μ in the

k th interval. $J_i^{e,\max}(k)$ is calculated by

$$J_i^{e,\max}(k) = \gamma J_i^{e,\max}(k-1) + (1-\gamma)J_0^e \frac{v(\max \mu)}{v(\mu_0^k)} \quad (14)$$

where γ is a forgetting factor in $(0, 1)$. With this principle, this algorithm will prefer a larger step-size to increase the convergence rate when a larger β is detected.

Then, the optimum step-size μ_{optimum}^k , which gives a minimum criterion during the k th interval, will be retained and selected as the optimum parent step-size for the next interval. The tap-weights vector and filtered output with this optimum step-size are kept.

As the genetic-type, variable step-size algorithm is the modification of the LMS algorithm, its adaptation of filter weights is also directly affected by uncorrelated noises. However, by randomly generating new offspring of step-sizes covering a large range, it is efficient enough to search the optimum step-size without expensive computation of the different noise levels of input signals. Its advantage is that it is insensitive to the selection of its initial step-size in the unrestricted condition.

2.3 Adaptive signal enhancer based on third-order statistics

In Fig. 3, the basic scheme of the adaptive signal enhancer based on third-order statistics is presented. To develop the ASE-TOS algorithm, we assume that there exists a third-order cumulant of the input signal and that it is not identical to zero. Under this assumption, let $C_{duu}(m_1, m_2)$ and $C_{uuu}(m_1, m_2)$, respectively, denote the third-order cross cumulant between the primary and reference inputs, and the third-order cumulant of the reference inputs.

$$C_{duu}(m_1, m_2) = \text{Cum}[d(t), u(t+m_1), u(t+m_2)] \quad (15)$$

$$C_{uuu}(m_1, m_2) = \text{Cum}[u(t), u(t+m_1), u(t+m_2)] \quad (16)$$

where $\text{Cum}[\bullet]$ is the cumulant operator. The definition and properties of cumulants are described well in NIKIAS and PETROPULU (1993).

Fig. 3 Scheme of adaptive signal enhancer based on third-order statistics

As the signal of interest and noise are independent and the third-order cumulants of Gaussian noises are identically zero, from (1) and (2), we have

$$C_{duu}(m_1, m_2) = \text{Cum}[s(t), s(t + m_1 - \Delta), s(t + m_2 - \Delta)] \\ = C_{sss}(m_1 - \Delta, m_2 - \Delta) \quad (17)$$

$$C_{uuu}(m_1, m_2) = C_{sss}(m_1, m_2) \quad (18)$$

Calculating the third-order cumulants of both sides of (3), we have

$$C_{yuu}(m_1, m_2) = C_{sss}(m_1 - \Delta, m_2 - \Delta) \\ = [C_{uuu}(m_1, m_2), C_{uuu}(m_1 + 1, m_2 + 1), \dots, \\ C_{uuu}(m_1 + M - 1, m_2 + M - 1)]\mathbf{w} \quad (19)$$

We define the criterion ξ as the sum of the squared errors between these two third-order cumulants.

$$\xi = \sum_{n=0}^{N_s-1} \sum_{p=-L+1}^{L-1} [C_{yuu}(n+p, p) - C_{duu}(n+p, p)]^2 \quad (20)$$

Equation (20) can be rewritten in a matrix form

$$\xi = [\mathbf{C}_{uuu}\mathbf{w} - \mathbf{C}_{duu}]^2 \quad (21)$$

where $\mathbf{C}_{uuu}$ is an $N_s(2L-1) \times M$ matrix, and $\mathbf{C}_{duu}$ is an $N_s(2L-1) \times 1$ column vector.

To minimise this criterion ξ , the gradient descent technique is employed to adapt the filter weights. The gradient of this criterion is given by

$$\nabla_w(t) \equiv \frac{\partial \xi}{\partial \mathbf{w}} = 2[\mathbf{C}_{uuu}^T \mathbf{C}_{uuu} \mathbf{w} - \mathbf{C}_{uuu}^T \mathbf{C}_{duu}] \quad (22)$$

Consequently, the weights adaptation of ASE-TOS becomes

$$\mathbf{w}(t+1) = \mathbf{w}(t) - \frac{\mu}{\text{tr}(\mathbf{C}_{uuu}^T \mathbf{C}_{uuu})} \nabla_w(t) \quad (23)$$

where the step-size μ must follow stable condition $0 < \mu < 2$.

From (17), (18) and (22), we notice that (23) for weights adaptation is not directly affected by the uncorrelated noise. Moreover, the sensitivity of ASE-TOS to its step-size variations has been reduced through the improvement of the eigenvalue spread of the autocorrelation matrix of the reference signals.

In practice, the theoretical third-order cumulants need to be substituted by their estimates. These estimates of third-order cumulants can be recursively computed by

$$\hat{C}_{duu}(t; m_1, m_2) = \gamma \hat{C}_{duu}(t-1; m_1, m_2) + (1-\gamma) \\ \times d(t)u(t+m_1)u(t+m_2) \quad (24)$$

$$\hat{C}_{uuu}(t; m_1, m_2) = \gamma \hat{C}_{uuu}(t-1; m_1, m_2) + (1-\gamma) \\ \times u(t)u(t+m_1)u(t+m_2) \quad (25)$$

where γ , ($0 < \gamma < 1$), is a forgetting factor. $\hat{C}_{duu}(t; m_1, m_2)$ and $\hat{C}_{uuu}(t; m_1, m_2)$, respectively, denote the estimates of $C_{duu}(m_1, m_2)$ and $C_{uuu}(m_1, m_2)$ in the iteration t .

2.4 Adaptive signal enhancer based on third-order statistics with a prefilter for evoked potentials

As described above, to establish good tracking ability for EPs, a prefilter can be used to enhance EPs. Fig. 4 illustrates the proposed scheme. In this scheme, an ASE-TOS is used as a major filter, and an ASE-GTVS filter is employed as a prefilter to enhance the primary signal.

Before explaining the effect of this scheme, first we analyse the transient behaviour of the MSE of ASE. From (5), the system error is rewritten by

$$e(t) = d(t) - \mathbf{u}^T(t)\mathbf{w}(t) = d(t) - \mathbf{u}^T(t)[\mathbf{w}_{\text{optimum}} + \boldsymbol{\varepsilon}(t)] \\ = d(t) - \hat{s}_{\text{optimum}}(t) - \mathbf{u}^T(t)\boldsymbol{\varepsilon}(t) \quad (26)$$

where $\mathbf{w}_{\text{optimum}}$ and $\boldsymbol{\varepsilon}(t)$ are, respectively, the optimum solution of the tap-weight vector and the tap-weight error vector. Here, $\hat{s}_{\text{optimum}}(t)$ denotes the optimum estimation of $s(t)$ corresponding to $\mathbf{w}_{\text{optimum}}$ (HAYKIN, 1991). Then we obtained the estimation of the MSE of the adaptive signal enhancer.

$$E[e(t)^2] = E[(s(t) - \hat{s}_{\text{optimum}}(t)) + v(n) - \mathbf{u}^T(t)\boldsymbol{\varepsilon}(t)]^2 \\ = E[(s(t) - \hat{s}_{\text{optimum}}(t))^2] + E[v(t)^2] \\ - 2E[(s(t) - \hat{s}_{\text{optimum}}(t) + v(n))\mathbf{u}^T(t)\boldsymbol{\varepsilon}(t)] \\ + E[\boldsymbol{\varepsilon}^T(t)\mathbf{u}(t)\mathbf{u}(t)^T\boldsymbol{\varepsilon}(t)] \quad (27)$$

As $s(t)$ approximates to $\hat{s}_{\text{optimum}}(t)$, it is straightforward that the MSE of ASE is also influenced by the uncorrelated noises in the primary input and the autocorrelation matrix of the reference signal.

QIU *et al.* (2002) employed an RBFNN as a prefilter to improve the eigenvalue spread of the autocorrelation matrix of the reference signal. However, in general, the SNR of the primary input obtained from measured EPs is poor in clinic.

Fig. 4 Block diagram of ASE-TOS with GTVS prefilter

Thus the effect of the uncorrelated noise in the primary will be more significant than that of the autocorrelation matrix of the reference signal.

Under the assumption that the SNR of EPs is poor, we enhance the SNR of the primary signal by using a prefilter to reduce the influence of these uncorrelated noises. Moreover, we select an ASE-GTVS filter as a prefilter, as the GTVS filter can rapidly adjust its step-size to approach the optimum through generation and evaluation for unknown signals. The default evolutionary period T of the GTVS prefilter was set as 100 points in this study.

In practice, we use an exponential averager simply to enhance the SNR of the measured EPs before processing (SVENSSON, 1993). Let d_i and EP_{trial_i} , respectively, denote the i th trials of the primary input and the measured EPs. Then, the averager is presented by

$$d_i = \gamma d_{i-1} + (1 - \gamma) EP_{trial_i} \quad (28)$$

where γ ($0 < \gamma < 1$) is a forgetting factor. In this study, we set γ to 0.8. Thus the variation of measured EPs can be presented in the primary signals with less than five trials of measured EPs. We use the stimulus cycle of EPs as the prediction depth Δ .

3 Results and discussion

The objective of the following simulations is to identify the performance of adaptive filtering of EPs by various methods. A realistic visual evoked potential (VEP), shown in Fig. 6b and obtained by averaging 1000 trials, was used as a desired pattern of EP for simulation. Several simulated EEG with different gains were added to this VEP pattern to generate simulated trial sets. In all cases, the simulated ongoing EEG is characterised by

$$EEG(t) = h^T Rdn(t) \quad (29)$$

where $Rdn(t) = [r(t), r(t-1), \dots, r(t-10)]^T$, and $r(t)$ is white, Gaussian noise process, and $h = [-36, 9, 44, 69, 84, 89, 84, 69, 44, 9, -36]$. The simulated ongoing EEG is a coloured Gaussian noise process whose spectrum is close to the spectrum of realistic EEG. Each set contains 1000 trials, and each trial has 200 data points.

Relative mean square error (MSE) is used to analyse the performance in this study.

$$\text{relative MSE} \equiv \frac{E[(s - y)^2]}{E[s^2]} \quad (30)$$

where s is the signal of interest, and y is the filtered output.

3.1 Comparison of performances of various methods

The first simulation was carried out to compare the performances between ASE-NLMS, ASE-GTVS, ASE-TOS, and ASE-TOS with a GTVS prefilter and an RBFNN prefilter for evoked potentials. The error curve of relative MSE against trials with the SNR of -20 dB is illustrated in Fig. 5. The parameters of various methods were set as follows:

ASE-NLMS: $M = 16$, $\mu = 0.1$

ASE-TOS: $M = 16$, $N_s = 3$, $L = 15$, $\mu = 0.1$

ASE-GTVS: $M = 16$, $\mu_1^0 = 2$, $R = 9$

Fig. 5 Error curves of various methods for SNR of -20 dB. (---) ASE-NLMS; (—) ASE-GTVS; (—○—) ASE-TOS; (—◇—) ASE-TOS with GTVS prefilter; (—*—) ASE-TOS with RBFNN prefilter

The parameters of the GTVS prefilter were set the same as the above ASE-GTVS. In this simulation, the numbers of processing units of the RBFNN prefilter in the input layer, hidden layer and output layer were set to 16, 24 and 1. All learning rates of the RBFNN prefilter were identically set to 0.1. The algorithm and properties of RBFNN are well described in HAYKIN (1991). The result shows that the performances of various methods are similar. However, ASE-TOS and ASE-TOS with a prefilter have a better convergence rate.

Fig. 6 shows the simulated results of several representative trials. These results show that the latency of evoked potentials can be estimated well by all the above methods, and the ASE-TOS and ASE-TOS with a prefilter significantly improve the SNR of the filtered output.

From Fig. 5, we found that the performances for all the above methods approach the steady state after about 150 trials. Therefore we use the mean relative MSE of the first 150 trials and the last 100 trials to evaluate the convergence rate and the steady-state performance, respectively.

Fig. 7 shows the comparison of the convergence rate in the SNR of -20 dB. It shows that the ASE-NLMS is very sensitive to the selection of its step-size. ASE-GTVS can effectively avoid the influence of the selection of initial step-sizes, but its convergence rate is no better than the optimum of ASE-NLMS. Overall, ASE-TOS and ASE-TOS with a prefilter have a better convergence rate and are more insensitive to their step-size. With a prefilter, the convergence rate of ASE-TOS is significantly improved. However, the convergence rate of ASE-TOS with a GTVS prefilter is stable compared with that with an RBFNN prefilter. The reason is that an RBFNN filter is more easily influenced by its step-size. Moreover, the RBFNN filter has a property of slow learning. Thus the effect of the step-size for an RBFNN filter becomes significant while its step-size is small. This indirectly affects the convergence rate of ASE-TOS with an RBFNN prefilter.

Fig. 8 shows the comparison of the performance of various methods for the SNR of -20 dB. Although ASE-TOS can suppress noise in input signals to reduce the influence of the selection of step-sizes, the performance of ASE-GTVS is generally better than that of ASE-TOS and ASE-TOS with an RBFNN prefilter. In particular, when the step-size is small, the performance of ASE-TOS with an RBFNN prefilter becomes significantly poor. ASE-TOS with a GTVS prefilter has a slight better performance than the others.

From Figs 7 and 8, we find that the optimum performances of various methods are similar in the range of step-sizes from

Fig. 6 Results of filtered evoked potentials at iteration $t = 10, 50, 100$, and 400 : (a) simulated noisy EP; (b) underlying EP signal; (c) filtered outputs of ASE-NLMS; (d) filtered outputs of ASE-GTVS; (e) filtered outputs of ASE-TOS; (f) filtered outputs of ASE-TOS with GTVS prefilter; (g) filtered outputs of ASE-TOS with RBFNN prefilter

Fig. 7 Comparison of convergence rate of various methods with SNR of -20 dB. (----) ASE-NLMS; (—) ASE-GTVS; (—○—) ASE-TOS; (—◇—) ASE-TOS with GTVS prefilter; (—*—) ASE-TOS with RBFNN prefilter

Fig. 8 Comparison of steady-state performance of various methods with SNR of -20 dB. (----) ASE-NLMS; (—) ASE-GTVS; (—○—) ASE-TOS; (—◇—) ASE-TOS with GTVS prefilter; (—*—) ASE-TOS with RBFNN prefilter

about 0.1 to 0.001. This is because the filtered outputs of EPs using all these methods are processed by similar finite impulse response filters with the same filter taps. All these algorithms just improve the influence on the performance for EPs of step-size selection and the eigenvalue spread of the autocorrelation matrix of input signals.

Figs 9a and b, respectively, show the comparison of the convergence rate and the performance against different noise levels. The parameters of all methods are the same as above. Here, the learning rates of the RBFNN-1 and RBFNN-2 prefilters are separately set to 0.1 and 0.5. From Fig. 9a, it is found that the convergence rates of ASE-TOS and ASE-TOS with a prefilter are generally better. However, the convergence rate of ASE-NLMS is heavily influenced by the noise level. Fig. 9b shows clearly that ASE-GTVS and ASE-TOS with a GTVS prefilter have better performance. Therefore the genetic type, variable step-size algorithm is really applicable to the unknown noise level. In this simulation, we find that ASE-TOS with an RBFNN prefilter does not always improve the performance of ASE-TOS.

From the above results, we find that both the improvement of the convergence rate and the performance of ASE-TOS with a GTVS prefilter are slightly superior to those with an RBFNN prefilter. This is because the RBFNN filter may have a better optimum performance but it is easily influenced by its learning rate. The genetic type, variable step-size algorithm can avoid this issue and provides a better reference of the primary inputs.

3.2 Comparison of varying evoked potentials

In this Section, the ability of various methods to estimate varying EPs is discussed. To generate trial sets with varying underlying EPs, simulated ongoing EEG generated by (29) are superimposed on two visual evoked potentials. Each set consists of 1000 trials. Here, the first 500 trials and the remaining 500 trials are, respectively, adopted in EP_1 and EP_2 in Fig. 10a.

Fig. 10b is the error curve of various methods for varying evoked potentials with an SNR of -20 dB. The parameters of the various methods are the same as in Section 3.1.

Fig. 9 Optimum (a) convergence rate and (b) performance of various methods at different noise levels. (----) ASE-NLMS; (—) ASE-GTVS; (—○—) ASE-TOS; (—◇—) ASE-TOS with GTVS prefilter; (—*—) ASE-TOS with RBFNN-2 prefilter

In the first 500 trials, the error curve of various methods is similar to that in Fig. 5. The ASE-TOS and ASE-TOS with a prefilter have a better convergence rate and performance. In the last 500 trials, we find that ASE-GTVS and ASE-TOS with a GTVS prefilter have a good ability to track the variation of EPs. Although the steady-state performance of ASE-TOS can be improved by its combining with an RBFNN prefilter, the improvement for tracking the variation of EPs is insignificant.

Comparing the results in Figs 7 and 8, we find that the ASE-TOS provides a good performance by suppressing Gaussian noise to reduce the effect of the selection of its step-size. Although the ASE-TOS has a better performance to some optimum step-size than ASE-GTVS, ASE-GTVS is more insensitive to its step-size. In Fig. 10b, ASE-GTVS shows a good ability to track the variation of EPs. Actually, ASE-GTVS is an effective technique for EPs. Therefore, by combining with a GTVS prefilter, the ASE-TOS can reduce its sensitivity to step-size and improve its performance by enhancing the SNR of the primary signals.

3.3 Effect of evolutionary period in genetic-type variable step-size algorithm

To investigate the effect of the evolutionary period in the GTVS algorithm, the efficiency of ASE-GTVS and ASE-TOS with a GTVS prefilter and with different evolutionary periods is discussed in this Section. The same trial set with an SNR of -20 dB as used in Section 3.1 is used in this simulation. The parameters of ASE-GTVS and ASE-TOS are listed as follows.

ASE-TOS: $M = 16, N_s = 3, L = 15, \mu = 0.1$

ASE-GTVS: $M = 16, \mu_1^0 = 2, R = 9$

Fig. 10 (a) Two simulated underlying evoked potentials. (b) Error curve of various methods for varying evoked potentials with SNR of -20 dB. (----) ASE-NLMS; (—) ASE-GTVS; (—○—) ASE-TOS; (—◇—) ASE-TOS with GTVS prefilter; (—*—) ASE-TOS with RBFNN prefilter

Fig. 11 (a) Convergence rate and (b) performance of (—) ASE-GTVS and (—◇—) ASE-TOS with GTVS prefilter, against different evolutionary periods

Here, the evolutionary period in the GTVS algorithm varies from 10 to 200 points. Figs 11a and b, respectively, show the convergence rate and performance of both these methods against different evolutionary periods. They clearly show that both the convergence rate and the performance of these methods are insensitive to the variation of evolutionary periods, except when it is less than 40 points. This outcome could be due to the lack of data points, which could cause biased evaluation of fitness. As the results show that the performances with sufficient length of evolutionary period are similar, we refer to one, or one half of a, stimulus cycle of EPs as the evolutionary period.

3.4 Experimental results for human data

In this experiment, the ASE-TOS with a GTVS prefilter is used to process real human visual evoked potentials. EEG was sampled from the Cz 10–20 electrode system site using a sampling interval of 500^{-1} s. The cycle of the visual stimulus of a black and white checkerboard used to evoke VEPs was set to 1 s. A total of 1000 trials of VEPs were recorded. Each trial of the measured data set contained 500 points. The parameters of ASE-TOS with GTVS prefilter were set as $N_s = 3$, $L = 15$ and $\mu = 0.1$. The number of generating offspring and initial

Fig. 12 Filtered evoked potentials from real human subject at (a) o1, (b) oz, (c) o2. (—) Filtered results of ASE-TOS with GTVS prefilter across 50 trials. (---) Results obtained by averaging 1000 trials

Fig. 13 Variation of (a) latency and (b) amplitude of filtered VEP from human subject

step-size of the GTVS prefilter were given by $R = 9$ and $\mu_1^0 = 2$.

Fig. 12 shows the results of filtered real human evoked potentials. These were drawn from a male subject, aged 23 years, in the Chang Gung University. The recorded raw EEG is about the SNR of -10 dB. Here, Figs 12a, b and c are, respectively, filtered EPs measured at o1, oz and o2. The solid lines represent the filtered EPs across 50 trials, and the dotted lines denote the EP obtained by averaging 1000 trials. It is clear that ASE-TOS with a GTVS prefilter needs just a few trials to estimate the exact latency and amplitude of EPs.

Fig. 13 shows some isometric views of these VEPs measured at oz across trials. We observed the variation of the latency and amplitude of N_1 , P_1 and N_2 peaks of the filtered EPs. It clearly shows the measured VEPs were efficiently estimated across trials. The variations of latencies N_1 and P_1 of the measured EP are relatively slow and small, whereas the latency of N_2 shows a larger variation. The variations of amplitude of filtered EPs become stable after about 50 trials. Figs 14a and b, respectively, show the traces of the original and filtered VEPs measured at oz.

4 Conclusions

An adaptive signal enhancer based on third-order statistics with genetic-type, variable step-size for evoked potentials has been proposed. An ASE-TOS is used as the major filter in this scheme. The higher-order statistics technique is capable of suppressing Gaussian distributed noise and is more insensitive to both the step-size parameter and the reference signal statistics than the second order statistics. Simulation results show that both the convergence rate and performance of the ASE-TOS are superior to those of the ASE-NLMS.

Actually, the ASE-GTVS is also a useful technique for EPs. Although the performance of ASE-GTVS is not better than ASE-TOS in general, it is more insensitive to the selection of the step-size than ASE-TOS at different noise levels. Furthermore, it has a good efficiency for tracking the variation of EPs. However, it needs a long enough evolutionary period to avoid biased evaluation of fitness. There is a trade-off between the evolutionary period and the learning rate of step-size. Simulation results show the performances with different evolutionary periods are similar when the evolutionary period is large enough. We prefer one, or one half of a, stimulus cycle of evoked potentials as the evolutionary period.

Fig. 14 Isometric view of VEP from human subject: (a) raw VEP; (b) filtered VEP

Although an RBFNN prefilter also can improve the performance of ASE-TOS, it is easily influenced by the selection of the learning rate in the RBFNN prefilter. Combined with the advantages of ASE-GTVS, which is more insensitive to its initial step-size and has a good efficiency for tracking the variation of EPs, ASE-TOS with a GTVS prefilter can effectively improve the performance of ASE-TOS.

The results achieved in clinically realistic situations using ASE-TOS with a GTVS prefilter, show that it is efficient in tracking visual evoked potentials of human subjects. With this proposed scheme, it just needs a few trials to extract EPs. Moreover, the variation of the latency and the amplitude of the filtered evoked potentials are stable from trial to trial. In conclusion, the adaptive signal enhancer based on third-order statistics with genetic-type, variable step-size can be useful in extracting evoked potentials in the clinic.

References

- ANG, W.-P., and FARHANG-BOROUJENY, B. (2001): 'New class of gradient adaptive step-size LMS algorithms', *IEEE Trans. Signal Process.*, **49**, pp. 805–810
- FUNG, K. S. M., CHAN, F. H. Y., LAM, F. K., and POON, P. W. F. (1996): 'Visual evoked potential enhancement by an artificial neural network filter', *Biomed. Mater. Eng.*, **6**, pp. 1–13
- GHARIEB, R. R., and CICHOCKI, A. (2001): 'Noise reduction in brain evoked potentials based on third-order correlations', *IEEE Trans. Biomed. Eng.*, **48**, pp. 501–512

- GRIEVE, R., PARKER, P. A., HUDGINS, B., and ENGLEHART, K. (2000): 'Nonlinear adaptive filtering of stimulus artifact', *IEEE Trans. Biomed. Eng.*, **47**, pp. 389–395
- HADJILEONTIADIS, L. J., and PANAS, S. M. (1997): 'Adaptive reduction of heart sounds from lung sounds using fourth-order statistics', *IEEE Trans. Biomed. Eng.*, **44**, pp. 642–648
- HARRIS, R. W., CHABRIES, D. M., and BISHOP, F. A. (1986): 'A variable step (VS) adaptive filter algorithm', *IEEE Trans. Acoust. Speech Signal Process.*, **ASSP-34**, pp. 309–316
- HAYKIN, S. (1991): 'Adaptive filter theory', 2nd edn (Prentice-Hall, Englewood Cliffs, NJ, 1991)
- KWONG, R. H., and JOHNSTON, E. W. (1992): 'A variable step size LMS algorithm', *IEEE Trans. Signal Process.*, **40**, pp. 1633–1642
- LAGUNA, P., RAIMON, J., MESTE, O., POON, P. W., CAMINAL, P., RIX, H., and THAKOR, N. V. (1992): 'Adaptive for event-related bioelectric signals using an impulse correlated reference input: Comparison with signal averaging techniques', *IEEE Trans. Biomed. Eng.*, **39**, pp. 1032–1044
- MADHAVAN, P. G. (1992): 'Minimal repetition evoked potentials by modified adaptive line enhancement', *IEEE Trans. Biomed. Eng.*, **39**, pp. 760–764
- MCGILLEM, C. D., AUNON, J. I., and CHILDERS, D. G. (1981): 'Signal processing in evoked potential research: Application of filtering and pattern recognition', *CRC Crit. Rev. Bioeng.*, **9**, pp. 225–265
- NIKIAS, C. L., and PETROPULU, A. P. (1993): 'Higher order spectral analysis: a nonlinear signal processing framework' (Prentice-Hall, Englewood Cliffs, NJ, 1993)
- NG, S. C., LEUNG, S. H., CHUNG, C. Y., LUK, A., and LAU, W. H. (1996): 'The genetic search approach: a new learning algorithm for adaptive IIR filtering', *IEEE Signal Process. Mag.*, **13**, pp. 38–46
- NG, S. C., CHUNG, C. Y., LEUNG, S. H., and LUK, A. (1999): 'A variable step size algorithm using evolution strategies for adaptive filtering'. Proc. 1999 Congress on Evolutionary Computation, CEC99, **1**, pp. 542–545
- PARSA, V., and PARKER, P. A. (1994): 'Multireference adaptive noise cancellation applied to somatosensory evoked potentials', *IEEE Trans. Biomed. Eng.*, **41**, pp. 792–800
- QIU, W., FUNG, K. S. M., CHAN, F. H. Y., LAM, F. K., POON, P. W. F., and HAMERNIK, R. P. (2002): 'Adaptive filtering of evoked potentials with radial-basis-function neural network prefilter', *IEEE Trans. Biomed. Eng.*, **49**, pp. 225–232
- SHIN, D. C., and NIKIAS, C. L. (1994): 'Adaptive interference canceler for narrowband and wideband interferences using higher order statistics', *IEEE Trans. Signal Process.*, **42**, pp. 2715–2728
- SVENSSON, O. (1993): 'Tracking of changes in latency and amplitude of the evoked potentials by using adaptive LMS filters and exponential averagers', *IEEE Trans. Biomed. Eng.*, **40**, pp. 1074–1079
- THAKOR, N. V. (1987): 'Adaptive filtering of evoked potentials', *IEEE Trans. Biomed. Eng.*, **34**, pp. 6–12
- VAZ, C. A., and THAKOR, N. V. (1989): 'Adaptive Fourier estimation of time-varying evoked potentials', *IEEE Trans. Biomed. Eng.*, **36**, pp. 448–455
- YU, X. H., HE, Z. Y., and ZHANG, Y. S. (1994): 'Time-varying adaptive filters for evoked potential estimation', *IEEE Trans. Biomed. Eng.*, **41**, pp. 1062–1071

Authors' biographies

BOR-SHYH LIN was born in Changhua, Taiwan, in 1975. He received the B.S. degree in Electrical and Control Engineering from National Chiao Tung University, Taiwan, in 1997 and the M.S. degree in Electrical Engineering from National Taiwan University, Taiwan, in 1999. He is currently working toward the Ph.D. degree in Electrical Engineering from National Taiwan University. His research interests are in digital signal processing, and biomedical signal processing.

BOR-SHING LIN was born in Changhua, Taiwan, in 1973. He received the B.S. degree in Electrical Engineering from National Cheng Kung University, Taiwan, in 1997 and the M.S. degree in Electrical Engineering from National Taiwan University, Taiwan, in 1999. He is currently working toward the Ph.D. degree in Electrical Engineering from National Taiwan University. His research interests are in areas of EEG system, medical informatics, wireless communication system, embedded system, and RF IC design.

FOK-CHING CHONG was graduated with a B.S. degree from the Electrical Engineering Department of National Taiwan University in 1971. He then joined the same department till now. He had been the head of the Operation Division of University Computer Center in 1976-1989. He had been the group leader for the Medical Engineering Division of the EE Dept. His research interests are in biomedical signal processing, medical information system and e-learning in medical and health education.

FEIPEI LAI received a B.S.E.E. degree from National Taiwan University in 1980, and M.S. and Ph.D. degrees in computer science from the University of Illinois at Urbana-Champaign in 1984 and 1987, respectively. He is a professor in the Department of Electrical Engineering and in the Department of Computer Science and Information Engineering at National Taiwan University. Now, he is also the director of Computer & Information Network Center at National Taiwan University, and the vice superintendent of National Taiwan University Hospital. He was a visiting professor in the Department of Computer Science and Engineering at the University of Minnesota, Minneapolis, U.S.A. He was also a guest Professor at University of Dortmund, Germany, and a visiting senior computer system engineer in the Center for Supercomputing Research and Development at the University of Illinois at Urbana-Champaign. His current research interests are low power circuit design, high performance microprocessor chip design, computer architecture, optimizing compiler, VLSI design, MPEG4 design, and cryptography.