Removal of ocular artifacts from electro-encephalogram by adaptive filtering

P. He[1] G. Wilson[2] C. Russell[2]

[1]Department of Biomedical, Industrial & Human Factors Engineering, Wright State University, Dayton, Ohio, USA
[2]Air Force Research Laboratory, Wright-Patterson Air Force Base, Dayton, Ohio, USA

Abstract—*The electro-encephalogram (EEG) is useful for clinical diagnosis and in biomedical research. EEG signals, however, especially those recorded from frontal channels, often contain strong electro-oculogram (EOG) artifacts produced by eye movements. Existing regression–based methods for removing EOG artifacts require various procedures for preprocessing and calibration that are inconvenient and time-consuming. The paper describes a method for removing ocular artifacts based on adaptive filtering. The method uses separately recorded vertical EOG and horizontal EOG signals as two reference inputs. Each reference input is first processed by a finite impulse response filter of length M ($M = 3$ in this application) and then subtracted from the original EEG. The method is implemented by a recursive least-squares algorithm that includes a forgetting factor ($\lambda = 0.9999$ in this application) to track the non-stationary portion of the EOG signals. Results from experimental data demonstrate that the method is easy to implement and stable, converges fast and is suitable for on-line removal of EOG artifacts. The first three coefficients (up to $M = 3$) were significantly larger than any remaining coefficients.*

Keywords—*Adaptive filtering, EEG, EOG, Artifact removal*

Med. Biol. Eng. Comput., 2004, **42**, 407–412

1 Introduction

THE EYE forms an electric dipole, where the cornea is positive and the retina is negative. When the eye moves (saccade, blink or other movements), the electric field around the eye changes, producing an electrical signal known as the electro-oculogram (EOG). As this signal propagates over the scalp, it appears in the recorded electro-encephalogram (EEG) as noise or artifacts that present serious problems in EEG interpretation and analysis.

To correct or remove ocular artifacts from EEG, many regression-based techniques have been proposed, including simple time-domain regression (VERLEGER *et al.*, 1982; GRATTON *et al.*, 1983), multiple-leg time-domain regression (KENEMANS *et al.*, 1991) and regression in the frequency domain (WHITTON *et al.*, 1978; WOESTENBURG *et al.*, 1983). In all these regression-based approaches, calibration trials are first conducted to determine the transfer coefficients between the EOG channels and each of the EEG channels (CROFT and BARRY, 2000). These coefficients are then used later in the 'correction phase' to estimate the EOG component in the EEG recording for removal by subtraction. More recently, independent component analysis (ICA) has been proposed (JUNG *et al.*, 2000) to separate the EOG signals from the EEG signals. This method requires off-line analysis and processing of data collected from a sufficiently large number of channels, and its success largely depends on correct identification of the noise components.

When the applications require real-time removal of ocular artifacts, or when the calibration trials cannot be conducted owing to various constraints, the methods described above become unsuitable. For example, researchers in our laboratory are developing methods for accessing a pilot's functional state during flight, so that adaptive aid can be provided in the case of mental overload (WILSON, 2002; HANKINS and WILSON, 1998). In one of the approaches currently under investigation, spectral EEG information recorded at several sites over the scalp (e.g. F_z, F_7, P_z, etc.) is used by a neural network to perform real-time classification of the pilot's functional state (WILSON and RUSSELL, 1999; 2003). As the pilot's activity is accompanied by a significant amount of eye movement, either voluntarily or involuntarily, EOG contamination is a serious problem in EEG-based analysis.

In this paper, we describe a noise cancellation method based on adaptive filtering (WIDROW *et al.*, 1975; HAYKIN, 1996) to remove ocular artifacts from EEG. This method is particularly suitable to our applications because it does not require calibration trials, and the EOG artifacts can be removed on-line. Previous studies (CROFT and BARRY, 2000) have shown that there are at least two kinds of EOG artifact to be removed: those

Correspondence should be addressed to Dr Ping He; email: phe@cs.wright.edu

Paper received 17 November 2003 and in final form 15 March 2004

MBEC online number: 20043898

produced by the vertical eye movement (the corresponding EOG is called VEOG) and those produced by the horizontal eye movement (HEOG). Consequently, a noise canceller with two reference inputs is used in this application.

2 Principle of removing EOG artifacts by adaptive filtering

Fig. 1 shows the block diagram of the noise canceller used in this application. The primary input to the system is the EEG signal $s(n)$, picked up by a particular electrode (e.g. F_7). This signal is modelled as a mixture of a true EEG $x(n)$ and a noise component $z(n)$. $r_v(n)$ and $r_h(n)$ are the two reference inputs, VEOG and HEOG, respectively. $r_v(n)$ and $r_h(n)$ are correlated, in some unknown way, with the noise component $z(n)$ in the primary input. $h_v(m)$ and $h_h(m)$ represent two finite impulse response (FIR) filters of length M (the two filters can have different lengths). The desired output from the noise canceller $e(n)$ is the corrected, or clean, EEG

$$e(n) = s(n) - \hat{r}_v(n) - \hat{r}_h(n) = x(n) + [z(n) - \hat{r}_v(n) - \hat{r}_h(n)] \tag{1}$$

where

$$\hat{r}_v(n) = \sum_{m=1}^{M} h_v(m) r_v(n+1-m)$$

and

$$\hat{r}_h(n) = \sum_{m=1}^{M} h_h(m) r_h(n+1-m) \tag{2}$$

are the filtered reference signals. Under the assumption that x is a zero-mean stationary random signal that is uncorrelated with z, r_v and r_h, the expected value (denoted by [ ]) of e^2 can be calculated

$$\begin{aligned} E[e^2] &= E[(x + z - \hat{r}_v - \hat{r}_h)^2] \\ &= E[x^2] + E[(z - \hat{r}_v - \hat{r}_h)^2] \end{aligned} \tag{3}$$

The goal of the noise canceller is to produce an output signal $e(n)$ that is as close to $x(n)$ as possible, by adjusting the filter coefficients $h_v(m)$ and $h_h(m)$. Statistically, this requires a minimisation of $E[(z - \hat{r}_v - \hat{r}_h)^2]$. As $E[x^2]$ is not affected by the adjustment of the filter coefficients, minimising $E[(z - \hat{r}_v - \hat{r}_h)^2]$ is equivalent to minimising $E[e^2]$.

Among the various algorithms of adaptive filtering, we chose the recursive least-squares (RLS) algorithm for our application, because of its superior stability and fast convergence. Parallel to the derivation given by VASEGHI (1996) for the case of one reference input, we present here the algorithm development for the case of two reference inputs.

Assuming at time t_n we have obtained the following samples: $s(i)$, $r_v(i)$, $r_h(i)$ and $e(i)$, for $i = 1, 2, \ldots, n$, we form the following target function $\varepsilon(n)$ to minimise:

$$\begin{aligned} \varepsilon(n) &= \sum_{i=M}^{n} \lambda^{n-i} e^2(i) \\ &= e^2(n) + \lambda e^2(n-1) + \cdots + \lambda^{n-M} e^2(M) \end{aligned} \tag{4}$$

where $0 < \lambda \leq 1$ is called the forgetting factor, and

$$\begin{aligned} e(i) = s(i) &- \sum_{m=1}^{M} h_v(m) r_v(i+1-m) \\ &- \sum_{m=1}^{M} h_h(m) r_h(i+1-m) \end{aligned} \tag{5}$$

By minimising $\varepsilon(n)$ instead of $E[e^2]$, we simply use the sample mean to approximate the expected value. In addition, by introducing the forgetting factor λ, the algorithm can also be applied to a random process that is not strictly stationary.

The filter parameters $h_v(m)$, $h_h(m)$, $m = 1, 2, \ldots, M$, that minimise $\varepsilon(n)$ can be obtained by solving the following two sets of equations (a total of $2{*}M$ equations):

$$\begin{aligned} \frac{\partial \varepsilon(n)}{\partial h_v(m)} &= 2 \sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_v(m)} \\ &= -2 \sum_{i=M}^{n} \lambda^{n-i} e(i) r_v(i+1-m) = 0 \end{aligned} \tag{6}$$

$$\begin{aligned} \frac{\partial \varepsilon(n)}{\partial h_h(m)} &= 2 \sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_h(m)} \\ &= -2 \sum_{i=M}^{n} \lambda^{n-i} e(i) r_h(i+1-m) = 0 \end{aligned} \tag{7}$$

$$\text{for } m = 1, 2, \ldots, M$$

The above two sets of equations can be represented by the following matrix forms:

$$\boldsymbol{R}_{vv}(n) \cdot \underline{\boldsymbol{H}}_v + \boldsymbol{R}_{vh}(n) \cdot \underline{\boldsymbol{H}}_h = \underline{\boldsymbol{P}}_v(n) \tag{8}$$

$$\boldsymbol{R}_{hv}(n) \cdot \underline{\boldsymbol{H}}_v + \boldsymbol{R}_{hh}(n) \cdot \underline{\boldsymbol{H}}_h = \underline{\boldsymbol{P}}_h(n) \tag{9}$$

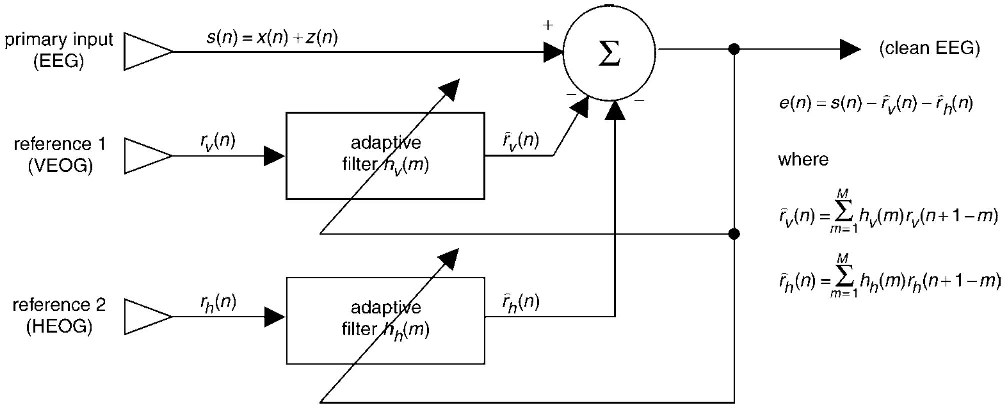

Fig. 1 *Block diagram of EOG noise canceller using adaptive filtering with two reference inputs*

where $\boldsymbol{R}_{vv}$, $\boldsymbol{R}_{vh}$, $\boldsymbol{R}_{hv}$ and $\boldsymbol{R}_{hh}$ are each an $(M \times M)$ square matrix, and $\underline{\boldsymbol{H}}_v$, $\underline{\boldsymbol{H}}_h$, $\underline{\boldsymbol{P}}_v$ and $\underline{\boldsymbol{P}}_h$ are each a column vector having a dimension of M

$$\boldsymbol{R}_{vv}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_v(i+1-j) r_v(i+1-k) \tag{10}$$

$$\boldsymbol{R}_{vh}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_v(i+1-j) r_h(i+1-k) \tag{11}$$

$$\boldsymbol{R}_{hv}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_h(i+1-j) r_v(i+1-k) \tag{12}$$

$$\boldsymbol{R}_{hh}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_h(i+1-j) r_h(i+1-k) \tag{13}$$

$$\text{for } j, k = 1, 2, \ldots, M$$

$$\underline{\boldsymbol{P}}_v(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_v(i+1-j) \tag{14}$$

$$\underline{\boldsymbol{P}}_h(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_h(i+1-j) \tag{15}$$

$$\text{for } j = 1, 2, \ldots, M$$

$$\underline{\boldsymbol{H}}_v = [h_v(1)\ h_v(2) \cdots h_v(M)]^T$$

$$(T \text{ stands for vector transposition}) \tag{16}$$

$$\underline{\boldsymbol{H}}_h = [h_h(1)\ h_h(2) \cdots h_h(M)]^T \tag{17}$$

Equations (8) and (9) can further be reduced to one matrix equation

$$\boldsymbol{R}(n) \cdot \underline{\boldsymbol{H}} = \underline{\boldsymbol{P}}(n) \tag{18}$$

where

$$\boldsymbol{R}(n) = \begin{bmatrix} \boldsymbol{R}_{vv} & \boldsymbol{R}_{vh} \\ \boldsymbol{R}_{hv} & \boldsymbol{R}_{hh} \end{bmatrix} \quad \underline{\boldsymbol{H}} = \begin{bmatrix} \underline{\boldsymbol{H}}_v \\ \underline{\boldsymbol{H}}_h \end{bmatrix} \quad \underline{\boldsymbol{P}} = \begin{bmatrix} \underline{\boldsymbol{P}}_v \\ \underline{\boldsymbol{P}}_h \end{bmatrix} \tag{19}$$

From (18), the filter coefficients that minimise $\varepsilon(n)$ can be solved

$$\underline{\boldsymbol{H}} = [\boldsymbol{R}(n)]^{-1} \cdot \underline{\boldsymbol{P}}(n) \tag{20}$$

3 Algorithm development

Calculating the filter coefficients by directly solving (20) involves matrix inversion, which is computationally expensive. The computation load can be greatly reduced by using a recursive least-squares (RLS) algorithm that calculates the filter coefficients by implementing (20) recursively in n. From (10)–(19), we can show that

$$\boldsymbol{R}(n) = \lambda \boldsymbol{R}(n-1) + \underline{\boldsymbol{r}}(n)\underline{\boldsymbol{r}}(n)^T \tag{21}$$

$$\underline{\boldsymbol{P}}(n) = \lambda \underline{\boldsymbol{P}}(n-1) + s(n)\underline{\boldsymbol{r}}(n) \tag{22}$$

where

$$\underline{\boldsymbol{r}}(n) = \begin{bmatrix} \underline{\boldsymbol{r}}_v(n) \\ \underline{\boldsymbol{r}}_h(n) \end{bmatrix}$$

$$\underline{\boldsymbol{r}}_v(n) = [r_v(n)\ r_v(n-1), \ldots, r_v(n+1-M)]^T$$

$$\underline{\boldsymbol{r}}_h(n) = [r_h(n)\ r_h(n-1) \cdots r_h(n+1-M)]^T \tag{23}$$

Now, using the matrix inversion lemma (VASEGHI, 1996), we can obtain the following recursive relationship:

$$[\boldsymbol{R}(n)]^{-1} = \lambda^{-1}[\boldsymbol{R}(n-1)]^{-1} - \lambda^{-1}\underline{\boldsymbol{K}}(n)\underline{\boldsymbol{r}}(n)^T[\boldsymbol{R}(n-1)]^{-1} \tag{24}$$

where

$$\underline{\boldsymbol{K}}(n) = \frac{[\boldsymbol{R}(n-1)]^{-1}\underline{\boldsymbol{r}}(n)}{\lambda + \underline{\boldsymbol{r}}(n)^T[\boldsymbol{R}(n-1)]^{-1}\underline{\boldsymbol{r}}(n)} \tag{25}$$

Finally, by substituting (24) and (22) into (20) and using (25), we can obtain the following formula for updating filter coefficients:

$$\underline{\boldsymbol{H}}(n) = \underline{\boldsymbol{H}}(n-1) + \underline{\boldsymbol{K}}(n) e\left(\frac{n}{n-1}\right) \tag{26}$$

where $\underline{\boldsymbol{H}}(n) = [\boldsymbol{R}(n)]^{-1} \cdot \underline{\boldsymbol{P}}(n)$ are the filter coefficients at sample n; $\underline{\boldsymbol{H}}(n-1) = [\boldsymbol{R}(n-1)]^{-1} \cdot \underline{\boldsymbol{P}}(n-1)$ are the filter coefficients at sample $(n-1)$; and

$$e\left(\frac{n}{n-1}\right) = s(n) - \underline{\boldsymbol{r}}(n)^T \underline{\boldsymbol{H}}(n-1) \tag{27}$$

The RLS algorithm is implemented in the following steps:

(*a*) Set initial values:

$$\underline{\boldsymbol{H}}(n-1) = 0 \quad (\text{i.e. } h_v(m) = h_h(m) = 0$$
$$\text{for } m = 1, 2, \ldots, M) \tag{28}$$
$$[\boldsymbol{R}(n-1)]^{-1} = \boldsymbol{I}/\sigma$$

where $\boldsymbol{I}$ is the $(2M \times 2M)$ identity matrix, and $\sigma = 0.01$. Starting from $n = M$, for every set of new samples $s(n)$, $r_v(n)$ and $r_h(n)$, perform the following steps:

(*b*) Form $\underline{\boldsymbol{r}}(n)$ based on (23);
calculate $\underline{\boldsymbol{K}}(n)$ using (25);
calculate $e(n/n-1)$ using (27);
calculate $\underline{\boldsymbol{H}}(n)$ using (26);
update $[\boldsymbol{R}(n)]^{-1}$ using (24);

$$\text{calculate } e(n) = s(n) - \underline{\boldsymbol{r}}(n)^T \underline{\boldsymbol{H}}(n);$$
$$n = n + 1, \text{ go back to } (b). \tag{29}$$

4 Experiments and results

EEG data were recorded from 12 sites positioned according to the International 10–20 Electrode System (JASPER, 1958). All EEG channels were referenced to the right mastoid. In addition, a pair of electrodes were placed above (negative terminal) and below (positive terminal) the right eye to record VEOG, and another pair of electrodes were placed at the left and right outer canthi of the eyes to record HEOG. All signals were bandpass filtered at 0.48–30 Hz and sampled at 256 Hz. The Multi-Attribute Task Battery (MATB) interactive software developed by NASA was used in this experiment. The MATB simulates tasks analogous to those a flight crew-member would encounter (COMSTOCK and ARNEGARD, 1992). Data were recorded while the operator was performing the tasks specified by the software. Although the algorithm for noise cancelling described above is suitable for real-time applications, in the present study, we first recorded all the data and then applied the algorithm off-line. Real-time filtering was simulated by sequential feeding of the sample data to the program.

The representative results of noise cancelling using the RLS algorithm are presented in Fig. 2. The particular parameters used by the algorithm are $M = 3$ and $\lambda = 0.9999$, and the procedure for selecting the values of these two parameters is discussed in the following Section. The Figure shows segments (each containing 2000 samples) of simultaneously recorded EEG at F_7 (Fig. 2*a*), HEOG (Fig. 2*c*) and VEOG (Fig. 2*d*), as well as the clean EEG after removal

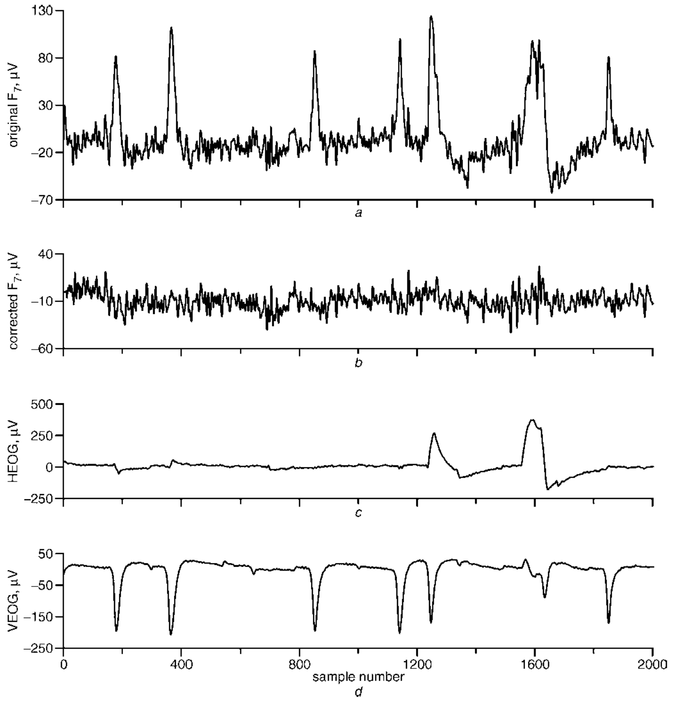

Fig. 2 *Demonstration of EOG artifact removal using adaptive filtering: (a) original F_7; (b) corrected F_7; (c) horizontal EOG; (d) vertical EOG. Total time duration of displayed signals is about 7.8 s, corresponding to sampling frequency of 256 Hz*

of the EOG artifacts using the RLS algorithm (Fig. 2*b*). The VEOG waveform shows several negative-going pulses corresponding to eye blinks, and the HEOG waveform shows two strong pulses around samples 1250 and 1600. The artifact corresponding to each VEOG or HEOG pulse can easily be identified in the original EEG waveform (Fig. 2*a*). By carefully comparing the waveforms of the corrected EEG at F_7 (Fig. 2*b*) and the original EEG, we can see that the algorithm effectively removes both kinds of artifact, while largely preserving the original waveform when there is almost no EOG interference (e.g. between 420 and 800, and between 900 and 1100).

In addition to the EEG recorded at F_7, we also applied adaptive filtering to EEGs recorded at each of 12 EEG channels, and the algorithm worked equally well in each case. We chose to present the results from F_7, because the signal recorded at this site shows strong EOG artifacts produced by either VEOG or HEOG, and consequently the effects of adaptive filtering can be demonstrated more dramatically. It should also be pointed out that, when the adaptive filtering algorithm is applied to an EEG recorded at a remote site, e.g. P_Z or O_2, that contains very few EOG artifacts, the filters are basically shut down automatically (the filter coefficients become very small), and the original EEG simply passes the system without visible changes.

5 Procedure for selecting the values of the two parameters: λ and *M*

There are two parameters that need to be determined: the forgetting factor λ and the filter length M. Mathematically, λ can be considered as being associated with a sample window that specifies how many (most recent) previous samples are used to calculate the current filter coefficients for producing the current output $e(n)$ according to (29). $\lambda = 1$ means that all the previous samples are weighted equally to update the filter coefficients, whereas $0 < \lambda < 1$ gives more weight to more recent samples, and the size of the window can be estimated by solving $\lambda^N = 0.5$.

The actual choice of λ depends on the stationarity of the process or, more specifically, the stability of the relationship between the reference inputs and the EOG components in the primary input in Fig. 1. Possible sources that could change such a relationship include variations in the characteristics of the skin–electrode interface or a drift of the electric property of the amplifier.

For our experiment, we assumed that the data recording process was relatively stable within a time window of 30 s. Based on the sampling rate of 256 Hz, this time window was translated to a sample window of $N = 7680$, and the corresponding value of λ was approximately 0.9999. The minimum value of λ can be determined by the average interval between two eye blinks. For example, if the average interval between blinks is 300 samples, using the relationship $\lambda^N = 0.5$, we obtain $\lambda_{min} = 0.9977$. It should be pointed out that the exact value of λ is not critical to the performance of the algorithm. Using our experimental data, we found that the results (corrected EEG) look almost identical for any value of λ between 0.995 and 1.

In theory, the choice of M should be determined by the characteristics of the EOG–EEG transfer function. When a simple time-domain regression was used for EOG correction (VERLEGER *et al.*, 1982; GRATTON *et al.*, 1983), it was implied, or assumed, that different frequency components of the EOG signal propagate in exactly the same way. This situation corresponds to $M = 1$. To remove such an assumption, KENEMANS *et al.* (1991) proposed a multiple-leg regression method that corresponds to the adaptive filtering method having one reference input and $M > 1$. As there is no available theory that describes the exact nature of the EOG–EEG transfer function, the suitable value of M can only be determined experimentally. Fortunately, the performance of the adaptive filter is not sensitive to M, as will be demonstrated below.

To determine a suitable M, we systematically increased the value of M from 1 to 12. For each value of M, the EEG at F_7 and VEOG and HEOG samples shown in Fig. 2 were used to produce a corrected EEG at F_7, and the mean square 'residual error' was calculated, which is defined as (see (4))

$$MSE = \frac{\sum_{i=M}^{2000} \lambda^{2000-i} e^2(i)}{2000 - M + 1} \tag{30}$$

The results show that, as M increases, MSE monotonously decreases. However, it was observed that the rate of decrease was noticeably reduced after $M = 3$. We then examined the actual filter coefficients at the last sample ($n = 2000$) for $M = 12$, which are listed in Table 1. For h_v, the (absolute) values of the

Table 1 Filter coefficients at last sample (n = 2000) for filter length M = 1, 3, 12

$M=1$		$M=3$		$M=12$	
h_v	h_h	h_v	h_h	h_v	h_h
−0.4973	0.2296	−0.5688	0.1365	−0.6055	0.1342
		0.0931	0.2627	0.3862	0.1415
		−0.0218	−0.1701	−0.3743	0.0568
				0.1408	0.0173
				−0.1249	−0.0452
				0.1108	−0.0481
				−0.0935	−0.0509
				−0.0928	−0.0263
				−0.1145	−0.0055
				0.1534	0.0094
				−0.2482	0.0504
				0.1956	−0.0036

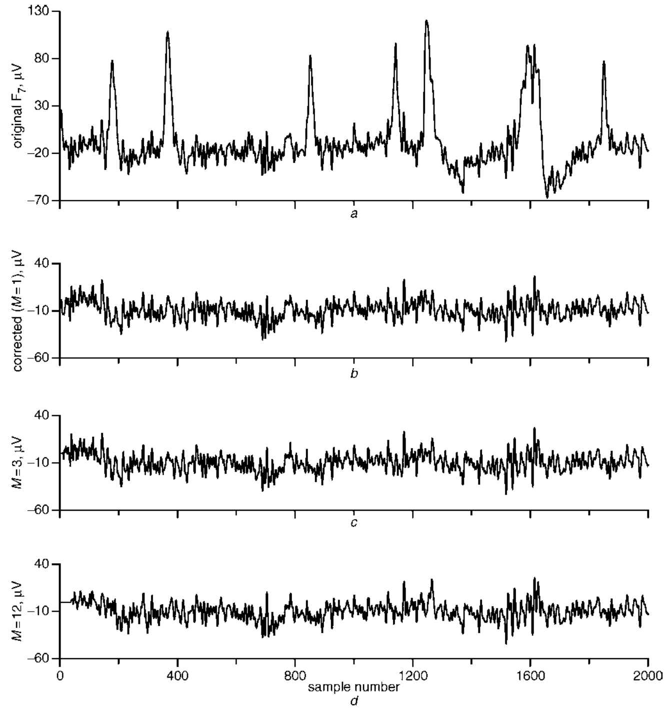

Fig. 3 *Comparison of results of adaptive filtering using three filter lengths: $M = 1$, 3 and 12*

first three coefficients (corresponding to $h_v(1)$, $h_v(2)$ and $h_v(3)$) were significantly larger than those of the remaining coefficients. For h_h, the first two coefficients were significantly larger. Based on both the behaviour of the MSE and the distribution of the filter coefficients, a choice of $M = 3$ seemed suitable.

The performance of the adaptive filter is actually not very sensitive to the choice of M. To demonstrate this fact, we compared the results of adaptive filtering using $M = 1$, 3 and 12. As shown in Fig. 3, the waveforms of the corrected EEG corresponding to the three values of M are almost identical after the first 200 samples. The actual filter coefficients used to generate these three waveforms are listed in Table 1. In general, our results are in agreement with the observation made by KENEMANS *et al.* (1991), who concluded that a filter length of 1 was sufficient to remove the noise produced by either eye blink or saccade.

6 Discussion and conclusions

A EOG noise canceller based on adaptive filtering has been described. The most appealing feature of this noise canceller is its ability to remove EOG artifacts without any preprocessing and calibration. The various procedures of calibration that are required by other regression–based methods (CROFT and BARRY, 2000) are often inconvenient and time-consuming. In addition, if, during a long period of recording, the measurement condition changes, the calibration data then become invalid. The method described in this paper, however, can automatically be adapted to a new condition without losing its effectiveness. By implementing a recursive algorithm, the method described in this paper is fast enough for real-time processing.

In our experiment, the program was written in MATLAB* and tested on a PC with a 1.8 GHz Pentium processor. The entire time to process the 2000 samples shown in Fig. 2 was 0.32 s, which was equivalent to a processing speed of 6250 samples s^{-1}. Compared with the sampling frequency of 256 Hz, real-time adaptive filtering is easily achievable.

Finally, the method is easy to implement, very stable and fast to converge. The only two parameters, λ and M, can be chosen within wide ranges without the performance of the method being compromised. The fast convergence of the method is actually demonstrated by Fig. 2. At the beginning of the process, the filter coefficients were initiated to zero, according to (28). The first two numbers of the 'corrected F_7' were also zero. 'Real-time' updating of the filter coefficients actually started from sample number 3, and the algorithm effectively removed even the first VEOG artifact at around sample number 190, without prior knowledge of the correlation between this VEOG pulse and the corresponding artifact in the original F_7.

For all the EEG data that we have collected, the algorithm effectively removes the EOG-related artifacts. It should be pointed out that this statement is based on a visual comparison between the original and corrected EEG signals, as depicted in Fig. 2. A truly rigorous evaluation requires an uncontaminated EEG waveform, which, unfortunately, is unavailable (CROFT and BARRY, 2000). An alternative approach may be to generate a simulated noisy EEG, by adding EOG artifacts to a clean EEG, and then to compare the corrected EEG with the clean EEG (KENEMANS *et al.*, 1991). The problem with such an approach, however, is that, by controlling the process of adding noise, the simulated data may favour one particular method for noise removal that matches the particular way in which the EOG is correlated with the noise in the EEG. We are currently devising other approaches for a more rigorous evaluation of the accuracy of the method.

Although the noise canceller developed in this paper contains two FIR filters having the same length, it can easily be shown that the algorithm development will be exactly the same when the two filters have different lengths. Finally, it is also straightforward to extend the method to cases having three or more reference inputs.

*MathWorks, Natick, MA, USA

References

COMSTOCK, J. R., and ARNEGARD, R. J. (1992): 'The multi-attribute task battery for human operator and strategic behavior research'. NASA Technical Memorandum 104174

CROFT, R. J., and BARRY, R. J. (2000): 'Removal of ocular artifact from the EEG: a review', *Neurophysiologie Clinique*, **30**, pp. 5–19

GRATTON, G., COLES, M. G. H., and DONCHIN, E. (1983): 'A new method for off-line removal of ocular artifacts', *Electroenceph. Clin. Neurophysiol.*, **55**, pp. 468–484.

HANKINS, T. C., and WILSON, G. F. (1998): 'A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight', *Aviat. Space Environ. Med.*, **69**, pp. 360–367

HAYKIN, S. (1996): 'Adaptive filter theory, 3rd edn' (Prentice-Hall, Englewood Cliffs, New Jersey, USA, 1996)

JASPER, H. H. (1958): 'The ten-twenty electrode system of the International Federation', *Electroenceph. Clin. Neurophysiol.*, **10**, pp. 371–375

JUNG, T. P., MAKEIG, S., WESTERFIELD, M., TOWNSEND, J., COURCHESNE, E., and SEJNOWSKI, T. J. (2000): 'Removal of eye activity artifacts from visual event-related potential in normal and clinical subjects', *Clin. Neurophysiol.*, **111**, pp. 1745–1758

KENEMANS, J. L., MOLENAAR, P. C. M., VERBATEN, M. N., and SLANGEN, J. L. (1991): 'Removal of the ocular artifact from the EEG: A comparison of time and frequency domain methods with simulated and real data', *Psychophysiology*, **28**, pp. 115–121

VASEGHI, S. V. (1996): 'Advanced signal processing and digital noise reduction' (John Wiley & Sons and B. G. Teubner, New York, USA, 1996), pp. 172–177

VERLEGER, R., GASSER, T., and MÖCKS, J. (1982): 'Correction of EOG artifacts in event-related potentials of the EEG: Aspects of reliability and validity', *Psychophysiology*, **19**, pp. 472–480

WHITTON, J. L., LUE, F., and MOLDOFSKY, H. (1978): 'A spectral method for removing eye movement artifacts from the EEG', *Electroenceph. Clin. Neurophysiol.*, **44**, pp. 735–741

WIDROW, B., GLOVER, J. R., MCCOOL, J. M., KAUNITZ, J., WILLIAMS, C. S., HEARN, R. H., ZEIDLER, J. R., DONG, E., and GOODLIN, R. C. (1975): 'Adaptive noise canceling: Principles and applications', *Proc. IEEE*, **63**, pp. 1692–1716

WILSON, G. F., and RUSSELL, C. (1999): 'Operator functional state classification using neural networks with combined physiological and performance features', *Proc. Human Factors and Ergonomics Society*, 43rd, Annual Meeting. pp. 1099–1101

WILSON, G. F. (2002): 'An analysis of mental workload in pilots during flight using multiple psychophysiological measures', *Int. J. Aviat. Psychol.*, **12**, pp. 3–18

WILSON, G. F., and RUSSELL, C. (2003): 'Real-time assessment of mental workload using psychophysiological measures', *Human Factors*, **45**, pp. 635–643

WOESTENBURG, J. C., VERBATEN, M. N., and SLANGER, J. L. (1983): 'The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain', *Biological Psychology*, **16**, pp. 127–147

Author's biography

PING HE received the BS degree in physics in 1968 from Fudan University, Shanghai, China, and the MS and PhD degrees in biomedical engineering in 1981 and 1984, respectively, from Drexel University, Philadelphia, USA. From 1984 to 1985, He was a Research Fellow in the Biodyname Research Unit, Mayo Clinic, where he worked on ultrasonic tissue characterization. He is currently a Professor in the Department of Biomedical, Industrial, and Human Factors Engineering, Wright State University, Dayton, Ohio, USA, where he has been a faculty member since 1985. Ping He is a senior member of IEEE. His research interests include medical ultrasonics, biomedical signal and image processing, and bioinstrumentation.