Removal of Power Line Interference in EEG Signals with Spike Noise Based on Robust Adaptive Filter

Jianqiang Lin*, Xu Sun*,†, Jiafei Wu*, Shing-Chow Chan*, and Weichao Xu†
*Department of Electrical and Electronic Engineering,
The University of Hong Kong, Pokfulam Road, Hong Kong
†Department of Automatic Control, School of Automation,
Guangdong University of Technology, Guangzhou, P. R. China
Email: jqlin@eee.hku.hk; xusun@eee.hku.hk; jfwu@eee.hku.hk; scchan@eee.hku.hk and wcxu@gdut.edu.cn

***Abstract*—This paper proposes a robust adaptive noise canceller (RANC) for removing power line interference (PLI) from the Electroencephalogram (EEG) when both the input and desired signals of the ANC are contaminated by spike or impulsive noise. It is based on the least mean M-estimate (LMM) and normalized least mean M-estimate (NLMM) algorithms, which offer improved robustness to impulsive noises over conventional least mean squares methods. Methods for inpainting the corrupted EEG signals are also developed. Simulation results using the MIT-BIH Polysomnographic Database show that the proposed methods is effective in combating impulsive or spike noise in adaptive cancelling of PLI in EEG signals and similar applications.**

***Index Terms*—Power Line Interference; Electroencephalogram; Impulsive Noise; Adaptive Filters, Robust Adaptive noise canceller, LMM and NLMM algorithms**

I. Introduction

An Electroencephalogram (EEG) is the electrical recording of brain activity, which has been widely used for clinical diagnosis, brain-computer interaction, and event-related potentials (ERP) analysis [1], etc. An important issue in processing EEG is its low signal level and the presence of undesirable artifacts. In particular, EEG signals may be contaminated by a variety of artifacts such as Electrooculography (EOG), Electromyography (EMG), and power line interference (PLI) [2]. In particular, PLI is one of the most common types of artifacts in EEG signal, which is caused by the electromagnetic coupling from power lines. These undesirable artifacts should be suppressed to allow proper analysis and diagnosis to be performed. A number of techniques have been developed to suppress these artifacts from EEG simultaneously. Generally, they can be divided into two main approaches: 1) wavelet method, and 2) blind-source separation (BSS) method. The wavelet-based artifacts elimination algorithms [3] [4] assume that the statistical characteristics between the artifacts and EEG signals are very different in frequency domain so that the undesirable frequency components can be thresholded. On the other hand, BSS-based approaches [5]–[7] usually require off-line processing. In the context of PLI, notch filters (NF) [8] have been proposed to suppress its adverse effect. However it usually causes distortion of the frequency spectrum. Adaptive filtering, which automatically adjust its parameters, offers a good alternative for EEG artifacts suppression [9] [10], especially for PLI cancellation (PLIC). In [11], the authors proposed a least mean squares (LMS) algorithm-based adaptive filter to suppress PLI. However, in many circumstances, the observation of the EEG signal may also be corrupted with spike or impulsive noise. This may cause adverse effect on conventional least square-based adaptive filters leading to performance degradation.

To mitigate this problem, we propose a robust statistical approach to the adaptive noise canceller (ANC) problem for eliminating PLI in EEG signals with both its reference and input signals contaminated by spike or impulsive noise. A copy of the power line interference is assumed to be available and is used as the input to an adaptive filter to suppress the interference in the desired signal (i.e. the signal where the interference is to be suppressed). The conventional LMM or NLMM adaptive filter is used to safeguard the estimated system parameters from the adverse influence of the impulsive components. In particular, the input impulses are detected and suppressed by modelling the input as a low order autoregressive (AR) model, which is estimated again by the LMM or NLMM algorithms [12]–[14]. The difference between the desired signal and the output of the adaptive filter, i.e. the estimation error, of the ANC thus yields the signal to be estimated. Since the estimation error may be corrupted by impulsive noise, the corrupted error signal needs to be inpainted, which can be performed with the help of an AR model or simpler procedure such as a recursive median filter.

The proposed methods were evaluated by computer simulation using the MIT-BIH Polysomnographic Database. Experimental results show that the proposed method offers improved robustness over conventional ANCs using the least mean square criterion under impulsive noise environment. The rest of the paper is organized as follows. The proposed method is introduced in Section II. Computer simulation and performance comparison of the proposed method and other conventional algorithms are evaluated in Section III. Finally, conclusion is drawn in Section IV.

II. Model and Method

A. System Model

Fig. 1 shows the structure of the proposed robust adaptive noise canceller (ANC). A corrupted copy of the PLI

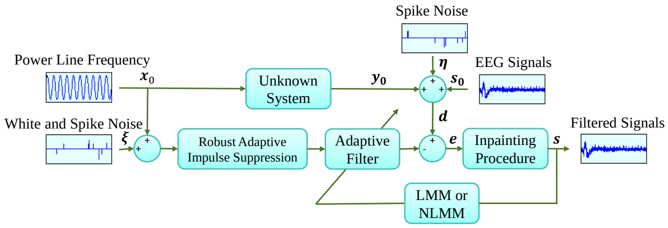

Fig. 1. Structure of Robust Adaptive Noise Canceller (ANC)

$x_0(n)$ is assumed to be available and it is used as the input $x(n)$ to an adaptive filter. The corruption is assumed to be an additive noise ξ with impulsive characteristics, which is modeled as a contaminated Gaussian noise. The EEG signal $s_0(n)$ is assumed to be corrupted by an additive contaminated Gaussian noise $\eta(n)$ and a PLI $y_0(n)$, which is obtained by passing $x_0(n)$ through an unknown finite duration impulse response (FIR) system with impulse response coefficients $\boldsymbol{W_0} = [w_1^*, w_2^*, \ldots, w_{L_0}^*]^\mathsf{T}$. The measured signal $d(n)$ is fed to the desired input of the adaptive filter. The adaptive filter is assumed to be a FIR filter $\boldsymbol{W}(n) = [w_1(n), w_2(n), \ldots, w_L(n)]^\mathsf{T}$ with length L and it aims to minimize the error between its output $y(n)$ and $d(n)$ according to certain criterion. Since the EEG signal is uncorrelated with the input $x(n)$, the minimization will force the adaptive filter to approximate $\boldsymbol{W_0}$ so as to cancel out the interference at $d(n)$.

Mathematically, the input signal $x(n)$ to the adaptive filter and the desired signal $d(n)$ are given by

$$x(n) = x_0(n) + \xi(n), \tag{1}$$

$$d(n) = \boldsymbol{W_0}^\mathsf{T}\boldsymbol{X_0}(n) + s_0(n) + \eta(n), \tag{2}$$

where $\boldsymbol{X_0}(n) = [x_0(n), x_0(n-1), \ldots, x_0(n-L_0+1)]^\mathsf{T}$. On the other hand, the output of the adaptive filter is given by

$$y(n) = \boldsymbol{W}^\mathsf{T}(n)\boldsymbol{X}(n), \tag{3}$$

where $\boldsymbol{W}(n)$ and $\boldsymbol{X}(n) = [x(n), x(n-1), \ldots, x(n-L+1)]^\mathsf{T}$ are respectively the weight vector of the adaptive filter and the input signal vector at time instant n. The PLI is assumed to be a sinusoidal signal with frequency of f, which is usually 50 or 60 Hz depending on geographic location:

$$x_0(n) = A\cos(2\pi f n/f_s + \varphi), \tag{4}$$

where A, f and φ are respectively the amplitude, frequency and phase of the sinusoidal PLI and f_s is the sampling frequency.

B. Robust Adaptive Noise Canceller (RANC)

The optimal weight vector of conventional adaptive filters is obtained by minimizing the mean squares error (MSE) criterion

$$\mathbb{E}[e^2(n)] \tag{5}$$

where $e(n) = d(n) - y(n) = d(n) - \boldsymbol{W}^\mathsf{T}(n)\boldsymbol{X}(n)$. In the LMS algorithm, the weight vector is recursively updated in the negative direction of the instantaneous gradient of the MSE with respect to the weight vector $-2e(n)\boldsymbol{X}(n)$, which yields

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + \mu e(n)\boldsymbol{X}(n), \tag{6}$$

where the constant μ is the step size which controls the convergence rate and steady state error. In the NLMS algorithm, the step size is normalized by the energy of the input vector so that the step size will not be too sensitive to the input signal power

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + \frac{\mu e(n)\boldsymbol{X}(n)}{\varepsilon + \boldsymbol{X}^\mathsf{T}(n)\boldsymbol{X}(n)}, \tag{7}$$

where ε is a small positive parameter to avoid division by zero. In order to ensure convergence, the step size μ should be chosen in the range $0 < \mu < 2$. It has been shown that the least squares criterion is very sensitive to impulsive noise [12]–[14] and the performance will deteriorate significantly. A more robust approach is to employ the LMM and NLMM algorithms which minimize the robust M-estimation function such as the modified Huber (MH) function

$$\rho_{MH}(e(n)) = \begin{cases} e^2(n)/2, & 0 \le e(n) \le \zeta \\ \zeta^2/2, & \text{otherwise} \end{cases}, \tag{8}$$

where ζ is the threshold parameter used to suppress the effect of impulsive noise, which can be adaptive updated. More sophisticated M-estimate function such as the Hampel's three parts redescending functions can also be used. Consequently, the weight update of the NLMM algorithm is given by

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + \frac{\mu\psi_{MH}(e(n))\boldsymbol{X}(n)}{\varepsilon + \boldsymbol{X}^T(n)\boldsymbol{X}(n)}, \tag{9}$$

where $\psi_{MH}(e(n))$ is the score function and for the MH function, it reads

$$\psi_{MH}(e(n)) = \begin{cases} e(n), & 0 \le e(n) \le \zeta \\ 0, & \text{otherwise} \end{cases}. \tag{10}$$

In the Adaptive Threshold Selection (ATS) method, the threshold ζ is updated as

$$\zeta = k_\zeta \tilde{\sigma}_e(n), \tag{11}$$

where k_ζ is a constant used to control the degree of suppression of impulsive noise and

$$\tilde{\sigma}_e^2(n) = \lambda_e\tilde{\sigma}_e^2(n-1) + c_1(1-\lambda_e)\mathrm{med}(\boldsymbol{A_{e^2}}(n)), \tag{12}$$

is a robust estimate of impulse-free variance. Here, $0 < \lambda_e < 1$ is a forgetting factor, c_1 is the correction factor for median estimation, $\boldsymbol{A_{e^2}}(n) = [e^2(n), \ldots, e^2(n-N_e+1)]$ and N_e is the window length. The median filter helps to suppress outliers in the error signals and its length N_e controls the consecutive impulses that can be suppressed. Usually N_e is chosen in the range 5 to 15, which can suppress 2 to 7 consecutive impulses respectively.

While the LMM and NLMM are effective in suppressing impulses in the desired signal, special care has to be taken to suppress the adverse effect due to input impulses. A usual approach is to construct a low order AR model for the input using say another LMM, NLMM or RLM algorithms [12]–[14]. The desired signal $\tilde{d}(n)$ can be chosen as $x(n)$ with input $\widetilde{\boldsymbol{X}}(n) = [x(n-1), \ldots, x(n-L'+1)]^{\mathsf{T}}$ and output $\tilde{y}(n) = \widetilde{\boldsymbol{W}}^{\mathsf{T}}(n)\widetilde{\boldsymbol{X}}(n)$. The prediction error

$$\tilde{e}(n) = \tilde{d}(n) - \tilde{y}(n), \tag{13}$$

can be used to detect the presence of impulses in $x(n)$ by checking its score function as in (9) and (10). Once an impulse is detected, the corrupted samples are replaced by the linear predicted value $\tilde{y}(n)$. This helps to suppress the adverse effect of input impulses to the ANC.

Different from robust channel estimation, the robust ANC aims to suppress the interference and extract the signal of interest, the EEG signal in our case, from the error signal $e(n)$. When the score function is equal to zero, it is very likely that the corresponding error signal is corrupted by an impulse occurring at the desired signal. Therefore, one needs to inpaint the corresponding values of $e(n)$, instead of using this corrupted value. This can be done by constructing a low order AR model from the estimated signal of interest and use the linear predicted value instead of the corrupted value. This can be viewed as a cleaning operation which shares much similarity in suppressing the input impulses to the robust ANC. Alternatively, one can use a recursive median filter to inpaint the corrupted samples as follows

$$\hat{e}(n) = \lambda_e' \hat{e}(n-1) + (1-\lambda_e')\mathrm{med}(\boldsymbol{A_e}(n)), \tag{14}$$

where λ_e' is a positive smoothing factor less than one, med$(\cdot)$ is the median filter operator $\boldsymbol{A_e}(n) = [e(n), \ldots, e(n-N_e'+1)]$, and N_e' is the length of the median filter. In our simulation experiments, the performance of the simple recursive median filter in (14) is found to be satisfactory.

III. Experimental Results

To illustrate the effectiveness of the proposed robust ANC, computer simulations are performed using real EEG signals in the MIT-BIH Polysomnographic Database as the ground truth. Due to page limitation, we only show the results from patient 41 since other records give similar results.

A. Experimental Setting

The power line frequency was chosen as 50 Hz and its amplitude was selected as $0.5R$ where R is the root mean square of the EEG signals. For illustrative purpose, the parameters of the unknown system $\boldsymbol{W_0}$ was set to be $[1, 0.5, 0.25]$. For simplification, we assumed the order of the FIR model is known as a priori, that is, $L = 3$. The additive noise ξ and η were both modeled as zero mean contaminated Gaussian (CG) processes

$$\xi \sim (1-\tau)\mathbb{N}(0, \sigma_{\xi_1}^2) + \tau\mathbb{N}(0, \sigma_{\xi_2}^2), \tag{15}$$

$$\eta \sim (1-\tau)\mathbb{N}(0, \sigma_{\eta_1}^2) + \tau\mathbb{N}(0, \sigma_{\eta_2}^2), \tag{16}$$

with the impulse occurrence probability chosen as $\tau = 0.005$. $\mathbb{N}(\mu_0, \sigma_0^2)$ denotes a univariate Gaussian process with mean μ_0 and variance σ_0^2, and the variance of the various components are chosen as $\sigma_{\xi_1}^2 = 0.1R$, $\sigma_{\xi_2}^2 = 15R$, $\sigma_{\eta_1}^2 = 0$, $\sigma_{\eta_2}^2 = 15R$. Fig. 2 shows the original EEG signal and the noise-free power line signals in comparison with their noisy counterparts.

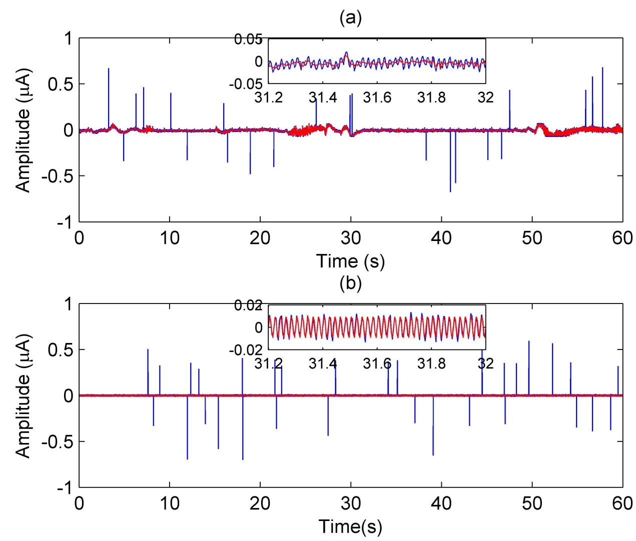

Fig. 2. (a) Real EEG signals and its noisy observations; (b) Noise-free power line signals and its noisy observations. In red: Noise-free signals. In blue: Noisy observations.

The step size for the LMS and LMM was chosen as $1/(0.05L)$, while the step size for the NLMS and NLMM was selected as $1/(50L)$. The rest of the parameters were set as follows: $f_s = 250$, $\varphi = 0$, $\lambda_e = \lambda_e' = 0.99$, $N_e = N_e' = 7$, $\varepsilon = 10^{-16}$, $c_1 = 2.13$ and $k_\xi = 3.576$. It should be noted that a relative large k_ξ is selected to avoid falsely detecting impulsive noise due to EEG fluctuations.

B. Effects of Impulsive Noise

To illustrate the adverse effect of impulsive noise to conventional least squares-based ANC, the differences between the real- and the estimated EEG signals for various methods in a single trial are presented in Fig. 3. We can observe that: 1) the NLMM and LMM have comparable performance except that the NLMM converges much faster than the LMM algorithm, 2) LMM and NLMM produce significantly lower error than the LMS and NLMS during the occurrence of the impulsive noise, and 3) NLMS recovers faster than the LMS after corruption by the impulses. To illustrate the effectiveness of the LMM and NLMM algorithms in detecting the impulses, we plot in Fig. 4 the noisy input and desired signals for the above trial. Whenever an impulsive noise is detected, a red line is drawn at the corresponding time location.

It can be seen that both LMM and NLMM can effectively detect the impulsive noise, either in the input signals or in the desired signals.

C. SNR Comparison

To further evaluate the performance of our proposed LMM and NLMM-based ANC for PLIC, they are further compared

TABLE I
COMPARISON RESULTS UNDER DIFFERENT NOISE LEVEL

Noise Level(dB)		SNR (dB) using different methods				
Reference Signal	EEG Observation	NF [8]	LMS	NLMS	LMM	NLMM
-23.68	-0.01	0.05	-0.56	-4.77	21.47	14.02
-9.70	-0.61	0.05	-0.87	-2.95	16.62	15.81
-3.68	-2.12	0.04	-2.75	-3.02	16.15	16.95

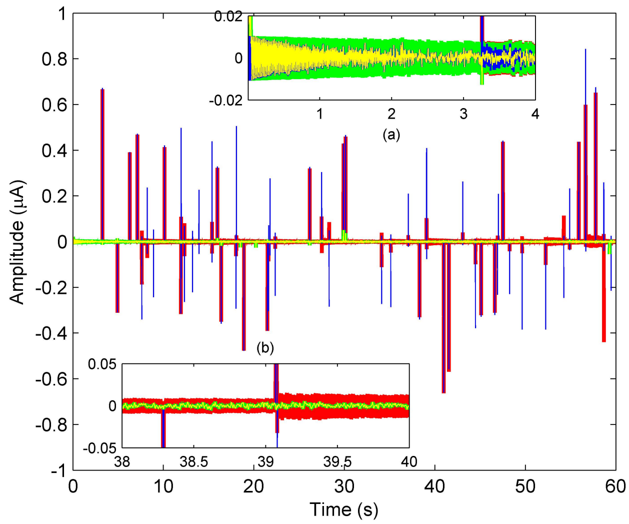

Fig. 3. Errors between the real EEG signals and the filtered outputs given by different methods: (red): LMS, (blue): NLMS, (green): LMM, (yellow): NLMM. (a) Enlarged result from 0-4s; (b) Enlarged result from 38s-40s.

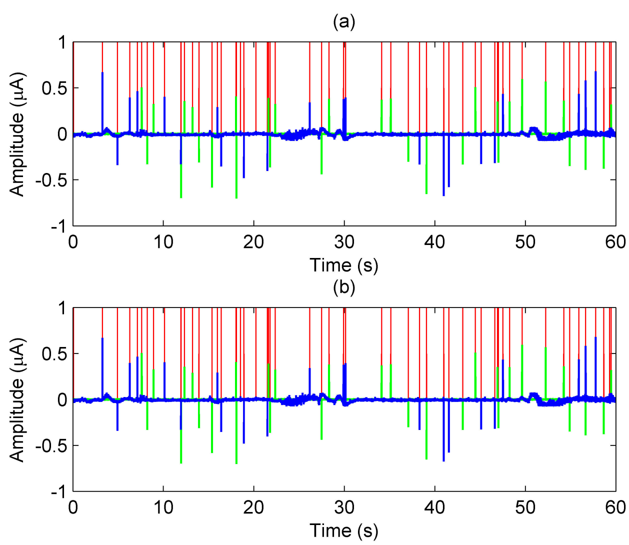

Fig. 4. Detection of the additive spike noise. (a) LMM; (b) NLMM. In red: Spike noise detected. In green: Noisy observations of the power line signal. In blue: Noisy observations of the EEG signal.

with other conventional algorithms such as NF [8], LMS, and NLMS. The experimental results were averaged over 100 Monte Carlo runs, and signal-to-noise ratio (SNR) was used as the quality measure metric. The notch of the NF was located at 50 Hz with the Q-factor being set to 60. The noise levels at the input signal (PLI with white and spike noise) and EEG observation (EEG with PLI and spike noise) were shown in Table I with different amplitude levels of PLI, namely $0.1R$, $0.5R$ and R. It can be seen from Table I that the proposed LMM and NLMM-based ANCs perform better than other compared algorithms due to their improved robustness against impulsive noise.

IV. Conclusion

A novel robust adaptive noise canceller for suppressing PLI corrupted by impulsive outliers has been proposed. It is based on the LMM and NLMM and a novel method for inpainting the corrupted EEG samples. Computer simulation results show that the proposed method offers improved robustness over conventional methods. The proposed method is also applicable to other ANC applications.

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