ECG and power line noise removal from respiratory EMG signal using adaptive filters

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ABSTRACT:
Surface electromyography (SEMG) from respiratory muscles is a non-invasive and effective method of studying neuromuscular diseases, muscle fatigue, enhancement of muscular function and also human-computer interface. This signal is contaminated by different noises. These include environmental noises like power line noise and also internal noises such as electrocardiographic noise. The clean EMG signal can be extremely useful for pathological purposes. In this study, diaphragmatic EMG signals were recorded with Power Lab system from seven subjects. The signals showed contamination due to power line interference (PLI) and also cardiac activity. Adaptive filters were used to reduce cardiac noise as well as 50 Hz (the fundamental) power line noise and its harmonics. Recursive least squares algorithm was used for the structure of the adaptive filter. Different values of the filter parameters; filter order and forgetting factor were examined for the noise removal purpose. Performance of the adaptive filter was quantified by signal-to-noise ratio and coherence measures for simulated data. The results show that we can successfully eliminate PLI and ECG noise from SEMG signals with adaptive filters. The figures and tables obtained help to decide which parameters of the filter are the best for our study.

KEYWORDS: Surface electromyography, Adaptive noise cancellation, ECG noise, Power line interference, Recursive least squares algorithm.

1. INTRODUCTION

Surface electromyography signal of respiratory muscles is contaminated by different noises, such as electrocardiogram (ECG), motion artifact, random amplifier noise, and power line interference (PLI) [1, 2, 3, 4, 5, 6, 7]. Electrocardiography is the most common and subtle source of interference and often known as ECG artifact [6].

Various methods have been studied for ECG artifact removal from SEMG signal. One of the simplest ways is high-pass filtering using Butterworth filter. Nonlinear filtering has been used for removing ECG noise from diaphragmatic EMG [8]. Adaptive filter is another method that have been used for ECG artifact removal [1, 2, 4, 5, 7, 9].

For eliminating PLI, digital notch filter, spectrum interpolation [10] and adaptive filtering [3, 4] have been used widely. Adaptive filtering can be used for removing both power lines and ECG artifact interference [4].

Furthermore, there is work on using neural network for EMG noise removal purposes [11, 12]. Independent component analysis (ICA) has been used to separate the EMG and ECG signals recently [13, 14].

In the present work, we employ recursive least squares (RLS) adaptive filters to filter PLI and ECG noise from diaphragmatic SEMG. Although diaphragmatic SEMG and ECG present overlapping spectra, this method is able to remove ECG noise without alternating SEMG.

2. METHOD

2.1. Data

Data were recorded from seven healthy subjects, three men and four women, 25.14$\pm$11.8 years old. SEMGs were recorded from left diaphragm muscles below the chest bones with interelectrode spacing of 4 cm. The reference electrode was placed on the sternum. ECGs were recorded with Lead I configuration at the same time. Power Lab system at the Applied Physiology Research Center (APRC) of Isfahan University of Medical Sciences was used for recording data. Subjects were asked to breathe normally for at least 10 seconds. Signals were then sampled at 1KHz.

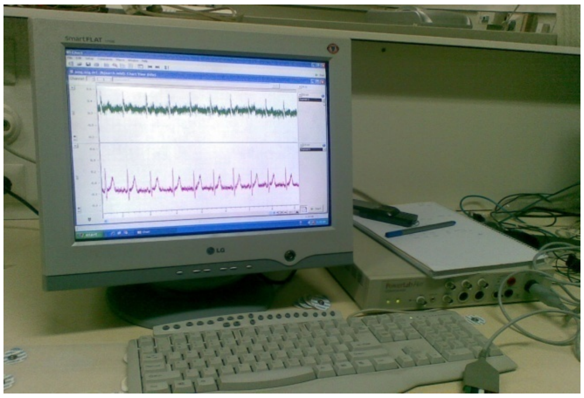

Fig. 1. Powe Lab System

If the recorded ECG signal was noisy, the high-frequency noise was extracted by wavelet denoising analysis using MATLAB toolbox [17]. Daubechies 6 mother wavelet was used because it is very similar to the ECG signal.

To test the proposed method a simulation was also performed. Pure EMG data were simulated with an impulse train of changing random amplitude (Fig 2). ECG noise (Fig 3) was separately built and added to EMG after filtering. This filtering was a representation of body impedance, which is very hard to estimate. FIR filter of length 40 in this simulation was employed. Fig 4 shows the simulated noisy signal. To consider PLI, a 50 Hz sinusoidal signal and its harmonics were added to EMG signal as well.

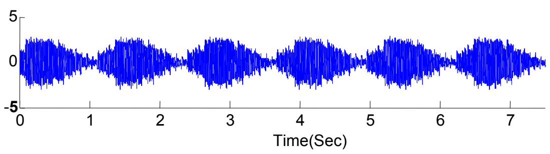

Fig. 2. Simulated Pure EMG

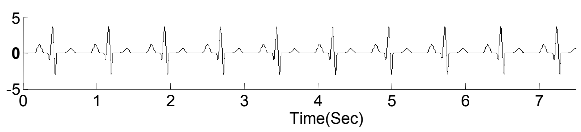

Fig. 3. Simulated ECG

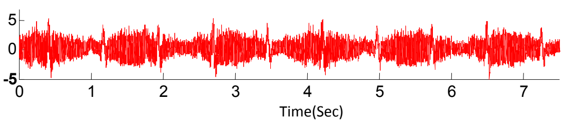

Fig. 4. Simulated contaminated EMG

2.2. The Algorithm

The block diagram of the adaptive noise canceller is shown in Fig. 4. The primary input to the noise canceller is the corrupted signal $x+d$ where x is the original signal and d is the noise. The reference input r, is the separately recorded noise. The noise is filtered through an adaptive filter to produce the output $\hat{d}$ which is subtracted from the primary input $x+d$ to produce the output that is the best fit in least squares sense to the signal x. This objective is accomplished by feeding the output of the filter back to adaptive filter and adjusting the coefficients (or weights) of the filter through an adaptive algorithm that minimizes the total output power.

$$e(n) = \hat{x}(n) = x(n) + d(n) - \hat{d}(n) \tag{1}$$

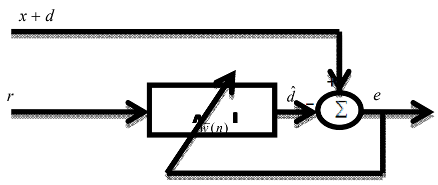

Fig. 5. Block diagram of the noise canceller

The estimation of the filter parameters and their adaptation was done by the minimization, for each time value, of a performance criterion.

TABLE 1. Summary of RLS Algorithm

- Calculates the output signal $\hat{d}(n)$ of the adaptive filter.
- Calculates the error signal $e(n)$ by using the following equation:

$$e(n) = x_1(n) - \hat{d}(n) \tag{2}$$

where, $x_1(n) = x(n) + d(n)$ (3)

- Updates the filter coefficients by using the following equation:

$$\bar{w}(n+1) = \bar{w}(n) + e(n).\bar{k}(n) \tag{4}$$

where $\bar{w}(n)$ is the filter coefficients vector and $\bar{k}(n)$ is the gain vector. $\bar{k}(n)$ is defined by the following equation:

$$\bar{k}(n) = \frac{P(n).\bar{U}(n)}{\lambda + \bar{U}^T(n).P(n).\bar{U}(n)} \tag{5}$$

$$\bar{U}(n) = [r(n) r(n-1) ... r(n-N+1)] \tag{6}$$

where λ is the forgetting factor, N is the filter order, and $P(n)$ is the inverse correlation matrix of the input signal.

P(n) has the following initial value $P(0)$:

$$P(0) = \delta^{-1}.I_N \quad 0 < \delta << 1 \tag{7}$$

where I_N returns the N-by-N identity matrix and δ is the regularization factor. The standard RLS algorithm uses the following equation to update this inverse correlation matrix.

$$P(n+1) = \lambda^{-1}P(n) - \lambda^{-1}\overline{K}(n).\overline{U}^{T}(n).P(n) \qquad (8)$$

With the noise cancelling system built, first PLI is eliminated from contaminated EMG and then ECG artifact is removed consequently (Fig.6). Noise canceller box shown in Fig 6 is the same adaptive noise canceller explained in Fig 5. To cancel PLI with this algorithm, we need to have a reference signal. The estimated PLI (reference) was considered as the summation of sinusoidal signals of frequencies from 50 to 450 Hz in 50 Hz steps. However, for the second reference, the simultaneously recorded ECG signals are used.

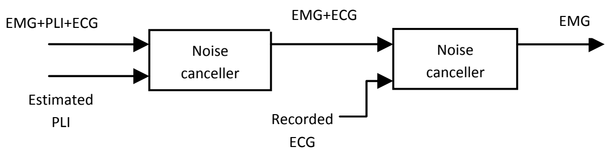

Fig. 6. Block diagram of noise cancelling system

Power spectra (P) of the clean EMGs and EMGs denoised through adaptive filtering are obtained by Welch's method, with 10-s EMG signals segmented into 50% overlapping sections.

$$SNR = 10\log_{10}\frac{\mathrm{var}(EMG)}{\mathrm{var}(EMG - EMG')} \qquad (9)$$

where EMG is the clean signal and EMG' is the denoised signal. Coherence factor computed between clean and denoised EMGs provides a quantitative measure of denoising performance in the frequency domain. Greater denoising performance results in higher coherence values [1].

$$Coh = \frac{\left|P_{EMGEMG'}(f)\right|^{2}}{P_{EMG}(f)P_{EMG'}(f)} \qquad (10)$$

where $P_{EMGEMG'}(f)$ is the cross-spectral density. $P_{EMG}(f)$ and $P_{EMG'}(f)$ are respective auto-spectra.

3. RESULTS

Results show that we can successfully eliminate power line noise by using RLS algorithm for different subjects. Power spectrum density of the contaminated EMG signal, and the cleaned EMG shows that the 50 Hz and its harmonics are extracted from the signal. Fig 7. displays the effect of RLS filter to cancel ECG noise from our simulated data. Please note that the contaminated red signal has consequent peaks, which are seen as vertical abruptions; however, the denoised green signal does not include this effect. Fig.8 shows the power spectrum of simulated noisy EMG and denoised signal in the frequency domain. Power spectrum of noisy signal is higher due to cardiac noise as well as PLI. It has sharp maximums at frequencies of 50 Hz and its harmonics due to PLI, which are removed after filtering.

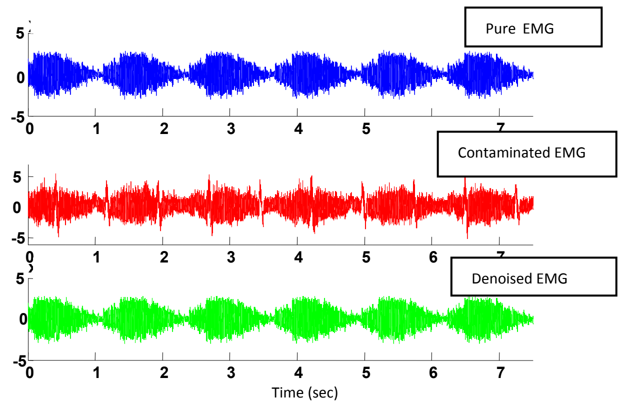

Fig. 7. Simulated data

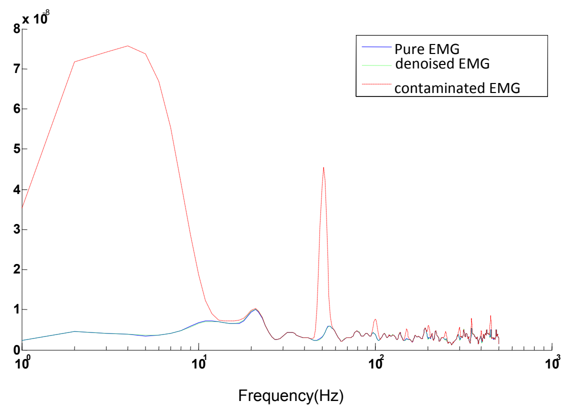

Fig 8. Power spectrum density of simulated data

Figures 9 to 11 are obtained with simulated data.

Fig 9. is the representation of SNR versus forgetting factor of RLS algorithm. It shows that SNR increases when forgetting factor is higher, and the best result is when the forgetting factor equals 0.999. However, if there is no forgetting factor (when forgetting factor is 1) the resulted SNR will diminish. These values are also declared in Table1.

Fig 10. is the representation of SNR versus filter order. As the figure shows the best results are obtained with filter order N = 40. Note that we could have SNR as high as 20 with this method. The values are also declared in Table 2.

Fig 11. is the representation of Coherence factor versus forgetting factor of RLS algorithm. This shows that if forgetting factor is equal to 0.999 we can have the best results. This is in agreement with Fig 9.

Simulated signals were used to evaluate the efficiency and effectiveness of the method through SNR measures and coherence analysis. Considering the figures represented we chose the values of forgetting factor equal to 0.999 and filter order equal to 40, and then we use these values to build the adaptive filter for real data. After this filter is applied to real data, which was recorded with the Power lab system, although the values of SNR and Coherence factor could not be calculated, however, figures represent a big difference between the contaminated signal and the denoised signal. Figures 12, and 13 show results of the real signals of one of the subjects. We have very similar plots for other subjects.

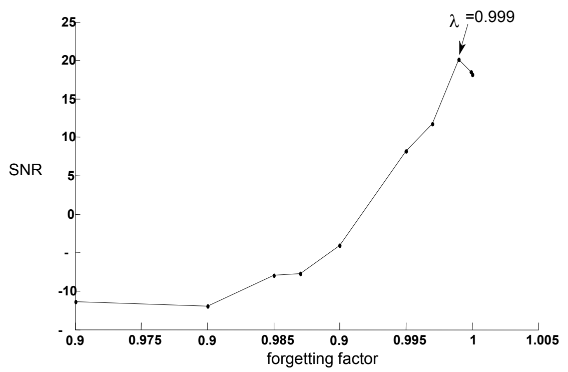

Fig 9. Signal to Noise ratio versus forgetting factor for simulated data

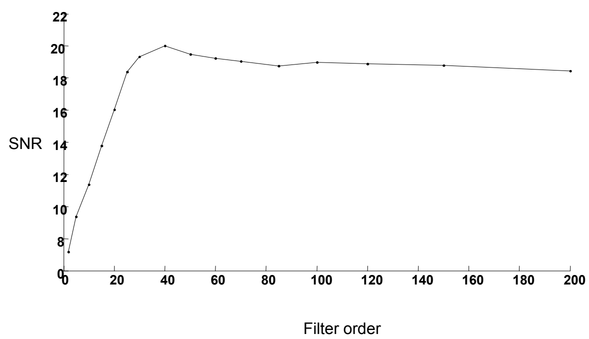

Fig. 10. Signal to Noise ratio versus filter order for simulated data

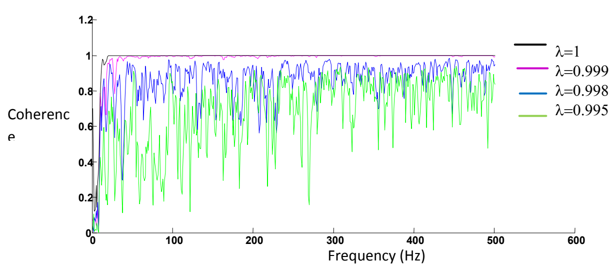

Fig. 11. Coherence versus forgetting factor

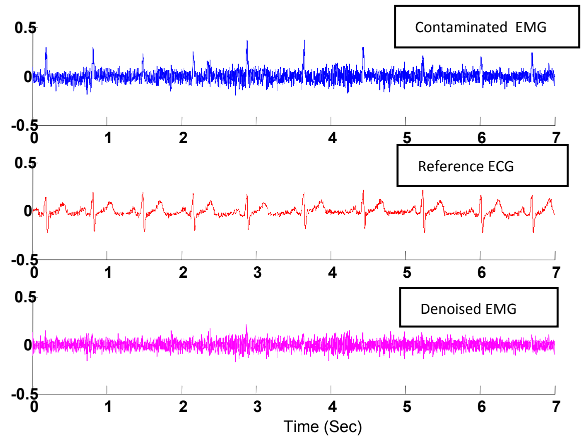

Fig. 12. Real data

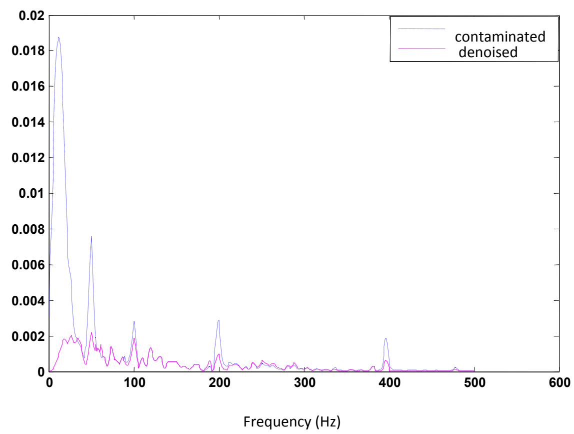

Fig. 13. Power spectrum of real data

Table 1. SNR versus λ for simulated data (filter order=20)

λ = Forgetting Factor	SNR
0.97	-11.5
0.98	-12
0.985	-7.5
0.99	-4
0.995	9.5
0.999	20
1	18

Table 2. SNR versus filter order($\lambda = 0.999$)

Filter order	SNR
3	5
7	8
10	11
20	16
30	18
40	20
60	19.5

4. DISCUSSION

Our results show that we can successfully eliminate PLI and ECG noise from SEMG signals with RLS adaptive filters, which are in agreement with the previous works [1, 2, 3, 7]. The high SNR and Coherent values show that the RLS algorithm works efficiently. The best SNR is 20 with the filter order of 40 and forgetting factor of 0.999 as they are shown in Fig. 9 and Fig. 10.

Notch filters, and high-pass filters have been used to cancel artifacts from EMG signals. These methods do suffer from losing frequency portions of the EMGs. In addition, recent methods including the application of nonlinear state-space projections [8], neural networks [11,12], independent component analysis (ICA) [13,14], empirical mode decomposition [17] and combinations of Neural-ICA and wavelet transforms [17] are very sophisticated and time consuming. The proposed algorithm overcomes formentioned drawbacks. The adaptive filters do not eliminate any frequency content of EMG signals as well as it is easy and time saving. As ECG and diaphragmatic EMG overlap in frequency domain, it is very important that we could extract EMG without losing any information of the signal due to noise. The clean EMG signal can be extremely useful for pathological purposes.

Traditionally, adaptive filters have been applied to remove PLI and ECG noise from SEMGs. In some studies, the least-mean-square (LMS) filters are used [5]. Due to a relatively slow convergence rate, the LMS algorithm is less capable of improving signal-to-noise ratio in rapidly varying environments. However, the RLS algorithm used in this study is typically ten times faster than that of the LMS algorithm due to whitening of the input data [1].

In some studies, ECG reference is derived directly from the contaminated EMGs by principle component analysis and independent component analysis [5,8], therefore, significant residual ECG artifacts are apparent in the derived ECG signal. However, in the proposed method, ECG is recorded separately but simultaneously with EMG signal giving higher accuracy.

For future work, we can employ our method for denoising electromyography signals from other parts of the human body close to the heart such as back muscles. This could improve the study of respiratory diseases.

In many of the biomedical devices for recording biosignals, notch filter is used to eliminate PLI. The technique proposed in this paper can be implemented in these devices. In addition, Adaptive Neuro Fuzzy Inference System (ANFIS) could be used to improve our method in future work.

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