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CleanEMG - Power line interference estimation in sEMG using an adaptive least squares algorithm

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Abstract—**This paper presents an adaptive least squares algorithm for estimating the power line interference in surface electromyography (sEMG) signals. The algorithm estimates the power line interference, without the need for a reference input. Power line interference can be removed by subtracting the estimate from the original sEMG signal. The algorithm is evaluated with simulated sEMG based on its ability to accurately estimate power line interference at different frequencies and at various signal-to-noise ratios. Power line estimates produced by the algorithm are accurate for signal-to-noise ratios below 15 dB (SNR estimation error at 15 dB is 14.7995 dB ± 1.6547 dB).**

I. Introduction

Surface electromyography (sEMG) is the non-invasive measurement of the electrical activity associated with the contraction of skeletal muscles. SEMG applications include detection of muscle fatigue, determining muscle fibre-type composition, determining motor unit recruitment patterns, and clinical neuromuscular assessment. Confidence in sEMG results is confined by signal contamination with various types of noise and/or distortions.

CleanEMG is an ongoing project with researchers from Carleton University and the University of New Brunswick. The objective of *CleanEMG* is to develop an open source, user friendly software tool for automatic quantitative assessment of sEMG signal quality [1]. With such a tool, reliable sEMG could be acquired without requiring the presence of a trained EMG technician to ensure proper equipment setup for noise minimization. *CleanEMG* will be able to automatically make an assessment of signal quality and provide feedback in terms of the estimated levels of different types of noise.

A significant source of noise in EMG which will be addressed as part of *CleanEMG* is power line interference. It has been shown that power line interference can compromise the analysis of EMG signals [2]-[4]. Traditionally, power line interference is removed from sEMG signals using a notch filter centered on the contaminated frequency components (60 Hz in North America). A number of disadvantages exist with this approach. Firstly, the notch filter will remove all frequencies in the cutoff band and not just those due to power line interference. The removal of these frequencies can adversely affect measurements such as mean/median frequency in fatigue detection and spectral slope analysis [5]. Secondly, real notch filters are not ideal and will have finite roll-off on each side of the cutoff band which will cause distortion in those sEMG frequency components [6]. This is a serious problem for shorter signals due to their poor frequency resolution. Lastly, there exists variance in the power line interference frequency. A notch filter could miss the power line interference entirely [7].

Adaptive algorithms can be used to filter a reference input assumed to be correlated with the power line interference [8]. This reference input must either be a recorded signal, which is expensive in terms of memory, or a synthetic signal which presupposes a known power line frequency.

In this paper, an adaptive algorithm is presented which estimates the unknown amplitude, phase, and frequency of the power line interference, with no need for a reference input. The power line interference can subsequently be removed from the sEMG by subtracting this noise estimate. The algorithm is evaluated in terms of its ability to accurately estimate the power line interference at different frequencies in simulated sEMG of varying signal-to-noise ratio (SNR).

II. Methods

A. Least Squares Adaptive Algorithm

An iterative least squares steepest descent algorithm adapted from [9] is used to estimate the parameters of the power line interference, which is assumed to consist of a single frequency component; that is, the power line interference is a sinusoid with an unknown amplitude, frequency, and phase. Such a sinusoid can expressed as a linear combination of a cosine and sine function as:

$$\hat{m}[n] = \hat{a}\cos(\hat{\omega} \cdot n) + \hat{b}\sin(\hat{\omega} \cdot n) \tag{1}$$

where $\hat{a}$ and $\hat{b}$ are the amplitudes of the in-phase and

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quadrature components, and $\hat{\omega}$ is the frequency.

At iteration k of the least squares algorithm, the mean squared error function is defined as:

$$E_k = \frac{1}{N}\sum_{n=0}^{N-1}(s[n]-\hat{m}_k[n])^2 \qquad (2)$$

$$E_k = \frac{1}{N}\sum_{n=0}^{N-1}(x[n]+m[n]-\hat{m}_k[n])^2 \qquad (3)$$

In (2), s is the noisy sEMG signal. In (3), x is the clean sEMG signal, m is the power line noise, $\hat{m}_k$ is the power line noise estimate, and N is the signal length. It can be shown that minimizing the mean squared error (E_k) between s and $\hat{m}_k$ is equivalent to minimizing the mean squared error between m and $\hat{m}_k$ given that x and $\hat{m}_k$ are uncorrelated. If x and $\hat{m}_k$ are uncorrelated, the noise estimate can at best estimate the noise and $\hat{m}_k$ will converge to m.

The mean squared error function in (2) and (3) is minimized using an iterative steepest descent algorithm in the frequency parameter space. The frequency is updated as specified by (4).

$$\hat{\omega}_{k+1} = \hat{\omega}_k - 0.5\mu\frac{\partial E_k}{\partial \hat{\omega}_k}$$
$$\frac{\partial E_k}{\partial \hat{\omega}_k} = -2[x - Qh_{\text{opt}}]^T Qh_{\text{opt}} \qquad (4)$$
$$h_{\text{opt}} = \begin{bmatrix}\hat{a}_{\text{opt}} \\ \hat{b}_{\text{opt}}\end{bmatrix}$$

In (4), h_{opt} can be determined using the linear least squares estimator since $\hat{m}$ is linear in terms of $\hat{a}$ and $\hat{b}$ as given in (4). The parameter μ is the learning rate.

$$h_{\text{opt}} = (Q^T Q)^{-1} Q^T x$$
$$Q = \begin{bmatrix}\cos(\hat{\omega}_k \cdot n) \\ \sin(\hat{\omega}_k \cdot n)\end{bmatrix}^T \qquad (5)$$

A disadvantage of the iterative steepest descent approach is that it can converge on a nonoptimal local minimum if the search space is not properly confined. To mitigate this, we assume the frequency is in the range of 59.5 Hz to 60.5 Hz. The initial frequency for the search was determined by minimizing the mean squared error defined by (3) using the least squares estimator in terms of $\hat{a}$ and $\hat{b}$. For each frequency in the desired range at intervals of 0.001 Hz, (4) was used to calculated h_{opt}, $\hat{m}_k$ was then calculated from (1) and E_k from (3). Once the mean squared error, E_k, is calculated for each initial frequency, the minimum can be located and the corresponding frequency is chosen as the starting point for the steepest descent algorithm.

The algorithm terminates when the frequency step size is less than 10^{-7} Hz, or if this condition is not met after 10000 iterations. The learning rate μ was initialized to 10^{-8} and was reduced by 10% whenever the frequency step changed direction.

B. sEMG Simulation

For this study, sEMG data are simulated by passing white Gaussian noise through a shaping filter [10]. The shaping filter transfer function is given in (5).

$$H_{\text{EMG}}(\omega) = \frac{jK\omega_h^{\,2}\omega}{(\omega_l + j\omega)(\omega_h + j\omega)^2} \qquad (6)$$

In (6), ω_l and ω_h are parameters which adjust the shape of the EMG spectrum and K is the gain factor. Values of 30 Hz and 60 Hz were chosen for ω_l and ω_h, respectively (after multiplying by 2π rad/cycle) [11]. Typically, these shaping parameters are varied in time to support the nonstationarity of the EMG signal; however for simplicity we assume a short enough signal duration (less than 5 seconds) such that stationarity can be reasonably assumed. The gain factor K was adjusted to normalize the power of the sEMG signal to 1.

Power line interference is added to the sEMG signal by generating a sinusoid with a given amplitude and frequency; the phase is randomized using a uniform distribution in the range [-π,π]. The amplitude of the sinusoid is calculated based on the desired SNR. For the simulations, SNR is varied between -10 dB and +40 dB in 5 dB increments. The frequency of the synthetic power line interference is varied between 59.5 Hz and 60.5 Hz at 0.25 Hz increments.

The simulated sEMG with added power line interference is generated with a signal length of 4096 samples and a sampling rate of 1 kHz (i.e., just over 4 seconds). Each SNR (-10 dB to +40 dB) and power line frequency (59.5 Hz to 60.5 Hz) combination are simulated 1000 times.

III. Results

In Fig. 1, we see a sample sEMG signal with 60.25 Hz power line interference and SNR of 10 dB. In Fig. 2, we see the same frequency spectrum of the resultant signal with estimated power line interference subtracted, and the original synthetic sEMG before noise was introduced. We observe that the spectra in Fig. 2 around the 60.25 Hz region are nearly identical with the power line interference being removed.

Fig. 3 is a plot of the estimated SNR as a function of the actual SNR. Ideally, the plot should have a linear one-to-one relationship, however, we see the SNR estimate fall below the actual SNR for values above 15 dB; that is, the SNR is underestimated for high SNR values. The plots are almost identical for each power line frequency.

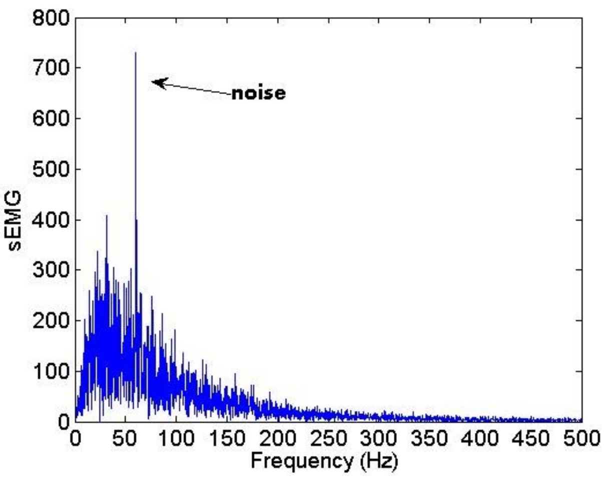

Fig. 1. Frequency spectrum of sEMG with power line interference at 60.25 Hz (SNR = 10 dB).

The error between the estimated power line frequency and the actual power line frequency was calculated for each of the 1000 iterations. This error was averaged over all iterations for each actual power line frequency. The frequency error is plotted as a function of the SNR in Fig. 4. We notice that for large noise power (SNR between -10 dB and 15 dB), the error in power line frequency estimate is small. For SNR above 15 dB, the power line frequency estimate is not as reliable, with the variance in the error noticeably larger. For high SNR sEMG signals (> 15 dB), the power line interference is small and there may exist larger sinusoidal components in the sEMG signal that the least squares adaptive algorithm can mistakenly identify as power line interference.

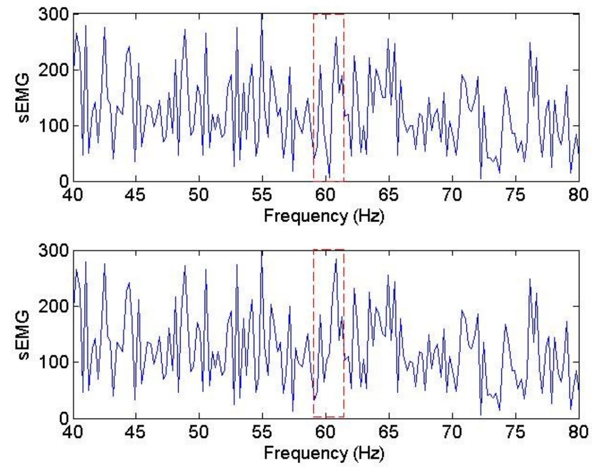

Fig. 2. Frequency spectra of sEMG with power line estimate subtracted (top) and the original noiseless sEMG (bottom). Estimate was at 60.265 Hz and 11.7 dB.

IV. Discussion

The least squares adaptive algorithm performed very well for an SNR of 15 dB and below. Once the SNR begins to increase beyond 15 dB, the frequency estimate of the algorithm becomes inaccurate. This is because the power line interference is small and the least squares adaptive algorithm may be falsely tracking sinusoidal components that are part of the sEMG signal. This hypothesis is supported by examining the error in the estimate of the power line interference frequency, which also becomes inaccurate for SNR values above 15 dB. The range of power line frequency (i.e., [59.5 Hz, 60.5 Hz]) is larger than what would be anticipated in reality. Narrowing this range may help mitigate the error in power line frequency estimate.

At an SNR as high as 10 dB, we see a significant spike at the power line frequency in the sEMG spectrum (Fig. 1). The subtraction of the noise estimate from the noisy signal is compared to the ideal clean signal in Fig. 2. Although the signals are not identical, they are quite close and the estimate is a very reasonable approximation of the original signal. We see that a frequency component between 60 Hz and the power line frequency (60.25 Hz) was erroneously removed from the original signal. It is tempting to fault the algorithm for this, however we must note that the frequency resolution of the Fast Fourier Transform (FFT) is F_s / N which in our case is 0.24 Hz and these discrete frequency intervals do not coincide with our chosen power line frequencies. Thus, the influence of the power line interference on the frequency spectrum will affect adjacent frequency components. The only way to avoid this is to increase the time duration of the signal and as the duration of an sEMG signal segment increases, the assumption of stationarity becomes less reasonable.

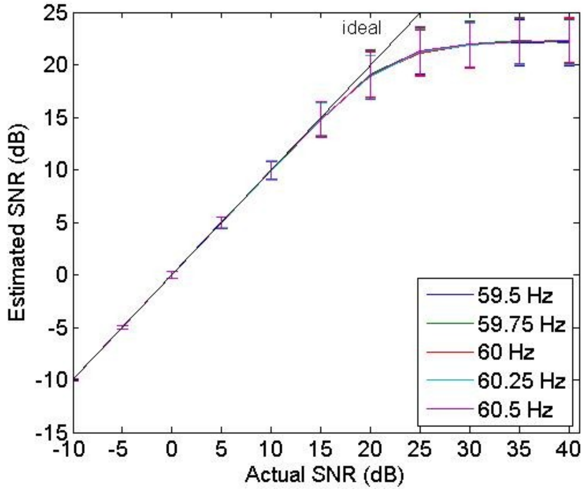

Fig. 3. Mean estimated SNR for each actual SNR for the noisy sEMG signal at various power line frequencies. Ideal case is shown for reference. Error bars are at plus or minus one standard deviation.

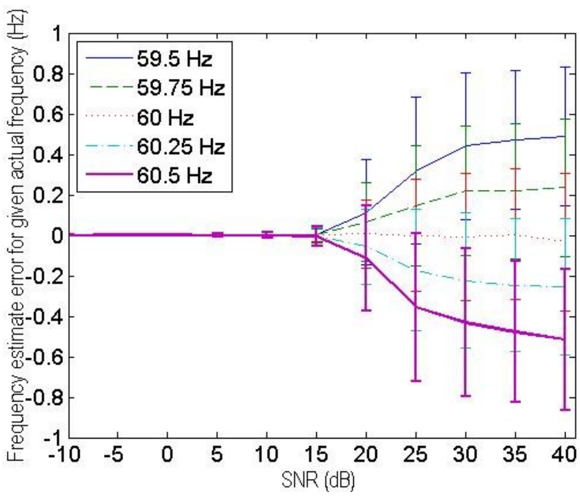

Fig. 4. Mean frequency error for 5 different power line frequencies at various SNRs. Error bars are at plus or minus one standard deviation.

It should also be mentioned that real power line interference includes the odd harmonics of the fundamental power line frequency. These harmonics are much lower in power and are typically inconsequential. This algorithm was designed to track a single frequency component, however it could easily be applied individually to the odd harmonics of the calculated power line frequency.

Whenever an attempt is made to remove the power line interference, there will likely be distortion of the sEMG signal. When the amount of interference is large (i.e., low SNR), the tradeoff between reducing the effect of the interference and distorting the sEMG is justified. The tradeoff may not be justified, or even required, for low levels of interference (i.e., high SNR). This algorithm provides an accurate estimate of the SNR up to 15 dB. This SNR estimate can be used to decide whether or not any power line interference removal should be attempted or not.

V. Conclusion

The application of the adaptive least squares algorithm to quantify power line interference in sEMG produced reliable results for SNR below 15 dB. For sufficiently short sEMG signals such that the signal can be assumed to be stationary, this method facilitates the removal of power line interference with minimal distortion to the original signal and can do so in a timely manner. The method is not appropriate for signals with too few samples or signals with minimal power line interference. If the SNR is high, it is unlikely that the power line interference will have much of an impact on the signal and filtering may not be necessary. Otherwise, an adaptive least squares method can significantly improve sEMG signal quality when contaminated with power line interference. While the power line interference estimation method was presented here in the context of sEMG, this method would be just as applicable to other data collection setups (e.g., electrocardiograms and electroencephalograms).

Acknowledgment

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