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Wiener Filtering of Surface EMG with *a priori* SNR Estimation Toward Myoelectric Control for Neurological Injury Patients

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Abstract

Voluntary surface electromyogram (EMG) signals from neurological injury patients are often corrupted by involuntary background interference or spikes, imposing difficulties for myoelectric control. We present a novel framework to suppress involuntary background spikes during voluntary surface EMG recordings. The framework applies a Wiener filter to restore voluntary surface EMG signals based on tracking *a priori* signal to noise ratio (SNR) by using the decision-directed method. Semi-synthetic surface EMG signals contaminated by different levels of involuntary background spikes were constructed from a database of surface EMG recordings in a group of spinal cord injury subjects. After the processing, the onset detection of voluntary muscle activity was significantly improved against involuntary background spikes. The magnitude of voluntary surface EMG signals can also be reliably estimated for myoelectric control purpose. Compared with the previous sample entropy analysis for suppressing involuntary background spikes, the proposed framework is characterized by quick and simple implementation, making it more suitable for application in a myoelectric control system toward neurological injury rehabilitation.

Keywords

Surface EMG; myoelectric control; neurologic injuries; involuntary muscle activity

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1. INTRODUCTION

Surface electromyogram (EMG) has been used as a control signal for myoelectric prostheses, rehabilitation robots or other assistive devices [1]. In studies involving neurological injuries, it happens often that voluntary surface EMG signals might be contaminated by spontaneous motor activity. For instance, when recording EMG signals from paretic muscles of stroke or spinal cord injury patients, abnormal hyper-excitability motor unit discharges may induce spontaneous tonic spikes, consequently compromising the voluntary EMG signals [2] [3]. From the point of view of implementing a myoelectric (proportional or pattern recognition) control system, such involuntary background spikes will impose two difficulties. First, the involuntary background spikes make automatic detection of muscle activity a challenging task with classical EMG amplitude thresholding based methods. Second, amplitude estimation of voluntary surface EMG can be severely affected by the presence of involuntary muscle activities.

It follows that, to develop a myoelectric control system for neurological injury rehabilitation, a surface EMG filtering algorithm is required to mitigate the effects of involuntary background spikes. Thus, the system can differentiate between user's voluntary intention and involuntary activity from the surface EMG signals. Unfortunately, involuntary background spikes and voluntary surface EMG signals usually have overlapping frequency components. Indeed, both voluntary and involuntary EMG signals have the same origins (i.e. muscle fibers), making it very difficult to apply conventional digital filters to remove involuntary spikes.

In this study, toward developing a myoelectric control system for patients with neurological injuries, we present a novel denoising framework for mitigating the effects of involuntary background spikes in voluntary surface EMG signals. The framework applies a Wiener filter [4] to restore voluntary surface EMG signals based on tracking *a priori* signal to noise ratio (SNR) by the decision-directed method [5] [6]. We demonstrated that after the processing, the onset detection of voluntary muscle activity can be significantly improved against involuntary background spikes. Furthermore, using the processed signals the magnitude of voluntary surface EMG can be reliably estimated for myoelectric control purpose.

2. METHODS

2.1 Background Theory

2.1.1 Intergration of Wiener filtering and a priori SNR—Wiener filtering is a linear technique consisting of a Fourier filter in the frequency domain, where the original Fourier coefficients are rescaled according to the ratio between the desired and actual signal spectrum [4]. A measured signal $y(t)$ in the time domain is considered as the linear summation of the true signal $x(t)$ and the noise $s(t)$, i.e.

$$y(t)=x(t)+s(t) \quad (1)$$

The estimate of expected signal can be obtained in the frequency domain by filtering the measured signal, assuming known stationary signal and noise spectra:

$$\hat{X} = G \cdot Y \quad (2)$$

where $\hat{X}$ is the estimate of X , which is the frequency domain representation of $x(t)$, Y is the frequency domain representation of $y(t)$, G is a gain or filtering function which minimizes the mean square error between the estimated and desired processes. According to [5], the concept of *a priori* SNR $\xi_k(n)$ can be integrated into the Wiener filtering (here n is the index of the processed frame for a specific k th frequency bandwidth), by assuming that $E\{\gamma_k(n)\} = \xi_k(n)+1$, where $E\{\gamma_k(n)\}$ denotes the estimator of the *a posteriori* SNR $\gamma_k(n)$. Thus, we have

$$G(\xi_k(n), \gamma_k(n)) = \frac{\xi_k(n)}{\xi_k(n)+1} \quad (3)$$

The Wiener amplitude estimator is given by

$$\hat{A}_k(n) = \frac{\hat{\xi}_k(n)}{1 + \hat{\xi}_k(n)} Y_k(n) \quad (4)$$

where $\hat{A}_k(n)$ denotes the corresponding k th spectral component of the true signal $x(t)$ in the n th frame. $\hat{\xi}_k(n)$ is the estimator of $\xi_k(n)$, $Y_k(n)$ is the k th spectral component of the noisy observations $y(t)$ in the n th frame. In order to proceed with a Wiener filter, it is critical to extract the noise spectrum to get $\hat{\xi}_k(n)$. In the current study, the noise spectrum for the Wiener filter is estimated from the noisy signal spectrum by tracking *a priori* SNR as described below.

2.1.2 A priori SNR estimation—We adopted the decision-directed approach to estimate *a priori* SNR for noise reduction in the frequency domain [5] [6]. After applying a short-time Fourier transform of the measured signal $y(t)$, it can be expressed in the frequency domain as:

$$Y_k(n) = X_k(n) + S_k(n) \quad (5)$$

where k denotes k th spectral component, n is the analysis frame index. Let $\xi_k(n)$, $A_k(n)$, $\lambda_s(k, n)$ and $\gamma_k(n)$ denote the *a priori* SNR, the amplitude, the noise variance, and the *a posteriori* SNR, respectively, of the corresponding k th spectral component in the n th analysis frame of the noisy input signal $y(t)$. According to [6], the *a priori* SNR estimator is based on the definition of $\xi_k(n)$, and its relation to the *a posteriori* SNR $\gamma_k(n)$, hence the *a priori* SNR can be estimated by

$$\xi_k(n) = \frac{E\{A_k^2(n)\}}{\lambda_s(k, n)} \quad (6)$$

$$\xi_k(n) = E\{\gamma_k(n) - 1\} \quad (7)$$

Where $E\{\cdot\}$ denotes the estimator.

The estimator $\hat{\xi}_k(n)$ of $\xi_k(n)$ is given by

$$\hat{\xi}_k(n) = \alpha G^2(\hat{\xi}_k(n-1), \gamma_k(n-1)) \gamma_k(n-1) + (1-\alpha) \max\{\gamma_k(n) - 1, 0\} \quad (8)$$

$$\hat{\xi}_k(0) = \alpha + (1-\alpha) \max\{\gamma_k(0) - 1, 0\} \quad (9)$$

where $0 < \alpha < 1$, the nonlinear gain of the signal $G(\cdot, \cdot)$ is the Wiener noise suppression function, as given below:

$$G(\xi_k(n), \gamma_k(n)) = \frac{\gamma_k(n) - 1}{\gamma_k(n)} \quad (10)$$

$$\gamma_k(n) = |Y_k(n)|^2 / \lambda_s(k, n) \quad (11)$$

$$\lambda_s(k, n) = (\lambda_s(k, n-1) \cdot L + |Y_k(n)|^2) / (1 + L) \quad (12)$$

where L is the smoothing factor used for the noise updating.

In summary, the gain of the signal $G(\cdot, \cdot)$ is updated using $\hat{\xi}_k(n)$, and $\hat{\xi}_k(n)$ is updated based on a previous estimate $\hat{\xi}_k(n-1)$ and $\gamma_k(n-1)$ according to (8) and (3), thus $\hat{A}_k(n)$ is calculated as (4). In brief, the gain of the signal $G(\cdot, \cdot)$ is updated using the SNRs.

2.2. Framework Implementation

Figure 1 summarizes the framework used in this study for suppressing the involuntary background spikes contaminating the voluntary surface EMG. The EMG signal was processed in 25 ms frames with a Hamming window and a 40% overlap between successive frames. The Fast Fourier Transform (FFT) of each frame was calculated, and then the phase component of the FFT was calculated. The decision-directed approach was used to estimate the *a priori* SNR using the noise power spectrum. Subsequently, the Wiener amplitude estimator was applied in the frequency domain to obtain an estimate of the voluntary EMG signal. Finally, to reconstruct the EMG signal in the time domain from its spectrogram after denoising, we applied an inverse FFT and synthesized the signal using the overlap-add (OLA) method [7].

2.3. Performance Evaluation

2.3.1 Testing dataset description—The testing data of this study were selected from the previous database recorded from the partially paralyzed muscles of 9 subjects with incomplete spinal cord injury (6 male, 3 female; age range 31–62 year; Neurological injury level C4–C8; ASIA class C or D), approved by the Institutional Review Board of

Northwestern University (Chicago, USA). As detailed in [8], over 50 channels of surface EMG signals were recorded from the forearm and hand muscles with a Refa EMG system (TMS International B.V., Netherlands) at a sampling rate of 2 kHz per channel, during the subject's actuating or trying to actuate a series of hand movements.

To perform quantitative evaluation, semi-synthetic signals were constructed by combining two types of signals selected from the database: "clean" voluntary surface EMG data free of spontaneous background interference and "pure" involuntary background interference recorded during the subject's rest period. Specifically, 10 segments (each 2 s in length) of typical involuntary background spikes and 10 segments (each 1 s in length) of surface EMG free of background spikes were selected. Each of the 10 "clean" voluntary surface EMG segments was scaled over a range of magnitudes, and summed with each of the 10 "pure" spontaneous interference segments (starting from 0.5 to 1.5 s in the 2 s period). To simulate semi-synthetic surface EMG signals with different involuntary spike levels, the signal segments were artificially scaled to generate semi-synthetic surface EMG signals in such a way that the background spike or noise level resulted in different SNRs (22, 20, 18, 15, 12, 10, 8, 5 and 2 dB, respectively).

2.3.2 Evaluation of onset detection—After denoising the EMG signal, the muscle activity onset detection was performed. Three approaches were used including:

1. Amplitude thresholding. Three times standard deviation (SD) of the baseline was utilized as the threshold for the conventional amplitude thresholding method for muscle onset detection.
2. Thresholding in the Teager Kaiser Energy (TKE) domain. The TKE operation is able to simultaneously highlight the instantaneous frequency and amplitude changes for muscle activity onset detection [9–11]. The TKE operator is defined as:

$$\psi[x(i)] = x^2(i) - x(i+1)x(i-1) \quad (13)$$

where ψ is the discrete TKE operation in the time domain and $x(i)$ represents the input signal. In this study, the TKE operation output was smoothed with a second order, 25 Hz Butterworth low pass filter to avoid errors induced by the rapid variations in the unsmoothed signal [11]. Threshold was set to 15 times SD of the baseline in the TKE domain for onset detection.

3. Double thresholding in the TKE domain. To reduce the dependence of onset detection on the baseline EMG signal, the double threshold method was used to create an alternative threshold by combining the amplitude and rate of change in the TKE domain [12]. The rate of change of the TKE output was measured by the slope of the line between the amplitudes of two successive data points. Muscle activation was determined when the TKE operation output exceeded 2.5% of its maximum amplitude and when the slope between two successive data points exceeded 10^{-3} , for at least 22 data points in a 25 point sliding window.

For performance comparison, the onset detection was also performed on signals before suppressing involuntary spikes. The semi-synthetic surface EMG signals with preset onset

time (i.e. at 500 ms for each testing signal) were used to evaluate the performance under different conditions. The onset performance was evaluated by the latency τ , defined as the absolute difference between the true onset time t_0 (i.e. 500 ms) and the detected onset time t_d :

$$\tau = |t_d - t_0| \quad (14)$$

The statistical difference in onset detection accuracy from various methods was evaluated by one-way repeated-measures ANOVA. Post hoc analysis, paired t-test, was conducted to compare the differences between conditions.

2.3.3 EMG amplitude estimation—To evaluate the application of the proposed method for myoelectric control, the intensity of muscle contraction was estimated by calculating the root mean square (RMS) amplitude of the surface EMG after suppression of the involuntary background spikes. Sliding analysis windows were used to segment the EMG data and compute RMS. The length of the sliding windows was 256 ms (increment step 64 ms). The correlations between RMS amplitudes of the EMG signal after involuntary spike suppression and the corresponding “clean” voluntary EMG signal were examined.

3. RESULTS

Figure 2 shows a comparison of two representative semi-synthetic surface EMG signals (with different SNRs) and the outputs after the proposed processing. It demonstrates that the Wiener filtering based on tracking *a priori* SNR via the decision-directed method can suppress the involuntary background spikes while the voluntary surface EMG signal can be remained. Figure 3 shows an example of one channel experimental (rather than semi-synthetic) surface EMG signal recorded from the forearm muscles of an SCI subject during his performing four repetitions of voluntary muscle contractions, and the restored voluntary surface EMG signal with the proposed framework. It was observed that the recorded surface EMG signal had significant involuntary background spikes, which were suppressed after the processing.

The muscle onset detection performance with different conditions or methods is summarized in Figure 4, using a series of semi-synthetic surface EMG signals. We observed that after the denoising, the onset detection of voluntary muscle activity was significantly improved against involuntary background spikes (paired samples t-test, $P < 0.001$ for each method before and after denoising, for all the tested SNRs). We also observed that as the SNR of the signal decreased from 20 to 2 dB, the latency of the onset detection for all the methods tended to increase. For each signal condition, significant differences were observed between different methods after the denoising (one-way repeated measures ANOVA, $F_{[2, 16]} = 4.78$, $P = 0.02$). Paired samples t-tests were used to make post hoc comparisons between conditions. Across all SNRs, there was a significant difference in the detection accuracy of the double threshold in the TKE domain versus any of the other two methods ($P < 0.03$). Among all the methods, the double threshold in the TKE domain after the denoising with the proposed framework exhibited the best performance at all the SNR levels.

The EMG amplitude estimation indicated that after processing using the proposed framework it was feasible to estimate RMS amplitudes of the EMG signals contaminated by background spikes. To evaluate the performance, the RMS values of each analysis window of the semi-synthetic signals during EMG bursts were calculated for both the signals after the processing and the corresponding “clean” voluntary surface EMG signals. Figure 5 shows the correlation between the RMS amplitude of the two signals (SNR = 5 in this example). Using linear regression analysis, the RMS of the processed EMG signals was highly positively correlated with the RMS of the “clean” voluntary EMG signals ($R = 0.92$, $P < 0.05$).

4. DISCUSSION

It is common to observe involuntary background activity from paretic muscles of neurological injury patients. Such involuntary activity might distort voluntary surface EMG processing, thus imposing challenges for implementing a myoelectric control system. This study presents a novel framework for suppressing the effects of the involuntary background spikes by combining a Wiener filter [4] and *a priori* SNR estimation via the decision-directed method (using the power spectrum of the noisy EMG signal) [5] [6].

The results indicate that the combination of a Wiener filter and tracking of *a priori* SNR can be used as an effective tool to suppress involuntary background spikes towards facilitating myoelectric control using surface EMG signals recorded from paretic muscles. After the processing, previously developed onset detection methods can be used to detect the onset of voluntary muscle activity [13–17]. The amplitude of voluntary muscle activity can also be reliably estimated, demonstrated as a strong positive linear correlation between RMS amplitudes of the EMG signals after involuntary spike suppression and the corresponding “clean” voluntary EMG signals.

The proposed framework has several advantages for myoelectric control compared with previous studies. For example, a Wiener filtering based approach was used to remove noise in surface EMG signal, composed by non-stationary sharp spectral line of variable intensity and frequency [18]. The approach required simultaneous acquisition of the environmental noise via a separate channel. In contrast, the current study combines the Wiener filter with a noise estimator. The noise spectrum for the Wiener filter is extracted by tracking *a priori* SNR of the processed signal via the decision-directed approach.

To suppress the effect of spontaneous background spikes on surface EMG processing, the sample entropy (SampEn) analysis has been used to perform muscle activity onset detection [19]. A primary limitation of the SampEn based method is the high computational cost imposed by the algorithms for computing the SampEn. The method also requires estimation of the global tolerance for SampEn calculation. The framework of the current study requires low computational load. For example, It took approximately 1.2 s to calculate the SampEn of a 2 s semi-synthetic surface EMG signals by a series of analysis windows (window length of 32 ms and a window increment of 4 ms [19]). In contrast, it took less than 0.05 s to denoise the same signal by using the proposed framework (performed on a 3.30-GHz Core i5 based PC using a Windows 7 operating system with 8-GB Memory). Such an advantage

makes it suitable for real time implementation toward overcoming involuntary background spikes for myoelectric control.

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Highlights

- Voluntary surface EMG from neurological injury patients are often corrupted by involuntary background interference or spikes.
- We develop a novel framework to suppress involuntary motor activity contaminating voluntary surface EMG.
- The framework applies a Wiener filter based on tracking *a priori* SNR.
- The framework is characterized by quick and simple implementation.

Fig. 1. The denoising framework, including signal conditioning, *a priori* SNR estimation, Wiener filtering and time domain signal reconstruction modules.

Fig.2. Semi-synthetic surface EMG signals (top panel) and the voluntary surface EMG signals obtained after the processing (bottom panel).

Fig. 3.
An example of experimental surface EMG signal corrupted by significant involuntary background spikes (top panel) and the voluntary surface EMG signal after the processing (bottom panel).

Fig. 4.

Comparison of onset detection performance under different conditions (mean $\pm$ standard error). AMP: the conventional amplitude thresholding method before the processing; Denoising+AMP: the conventional amplitude thresholding method after the processing; TKEO: the TKEO thresholding method before the processing; Denoising+TKEO: the TKEO thresholding method after the processing; TKEO Double: double threshold algorithm in the TKE domain before the processing; Denoising+TKEO Double: the double threshold algorithm in the TKE domain after the processing. For each SNR level, the mean latency was averaged over 100 trials of semi-synthetic surface EMG signals.

Fig. 5.

Correlation between the RMS amplitudes of the voluntary surface EMG signals after the processing and the corresponding “clean” EMG of the semi-synthetic signals. The RMS amplitude were obtained from analysis windows of the semi-synthetic signals (SNR=5). The linear function was tested for fitting the data.