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Technical note

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.

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-excitable 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

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voluntary surface EMG can be reliably estimated for myoelectric control purpose.

2. Methods

2.1. Background theory

2.1.1. Integration 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.*

$$y(t) = x(t) + s(t) \tag{1}$$

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

$$\hat{X} = G \cdot Y \tag{2}$$

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 Scalart and Vieira [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 kth 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

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

The Wiener amplitude estimator is given by

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

where $\hat{A}_k(n)$ denotes the corresponding kth spectral component of the true signal $x(t)$ in the nth frame. $\hat{\xi}_k(n)$ is the estimator of $\xi_k(n)$, $Y_k(n)$ is the kth spectral component of the noisy observations $y(t)$ in the nth 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:

$$Y_k(n) = X_k(n) + S_k(n) \tag{5}$$

where k denotes kth 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 kth spectral component in the nth analysis frame of the noisy input signal $y(t)$. According to Ephraim and Malah [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

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

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

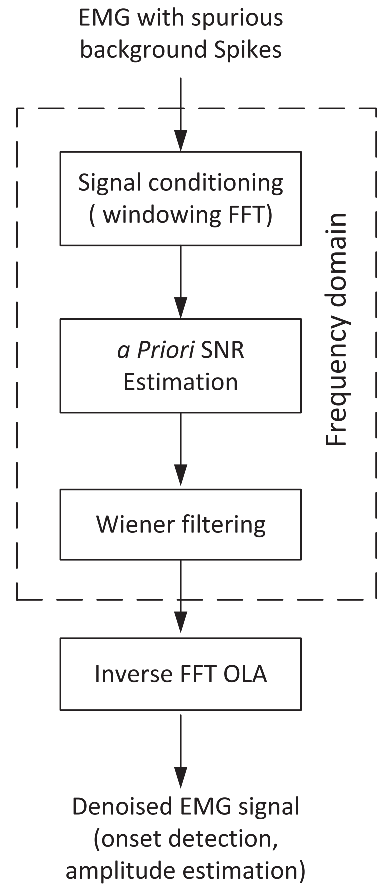

Fig. 1. The denoising framework, including signal conditioning, *a priori* SNR estimation, Wiener filtering and time domain signal reconstruction modules.

where E{·}denotes the estimator.

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

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

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

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

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

$$\gamma_k(n) = \frac{|Y_k(n)|^2}{\lambda_S(k, n)} \tag{11}$$

$$\lambda_S(k, n) = \frac{\lambda_S(k, n-1) \cdot L + |Y_k(n)|^2}{1 + L} \tag{12}$$

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

Fig. 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