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## Filtering of surface EMG using ensemble empirical mode decomposition

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### Abstract

Surface electromyogram (EMG) is often corrupted by three types of noises, i.e. power line interference (PLI), white Gaussian noise (WGN), and baseline wandering (BW). A novel framework based primarily on empirical mode decomposition (EMD) was developed to reduce all the three noise contaminations from surface EMG. In addition to regular EMD, the ensemble EMD (EEMD) was also examined for surface EMG denoising. The advantages of the EMD based methods were demonstrated by comparing them with the traditional digital filters, using signals derived from our routine electrode array surface EMG recordings. The experimental results demonstrated that the EMD based methods achieved better performance than the conventional digital filters, especially when the signal to noise ratio of the processed signal was low. Among all the examined methods, the EEMD based approach achieved the best surface EMG denoising performance.

### Keywords

Surface electromyography (EMG); Denoising; Empirical mode decomposition (EMD); Ensemble empirical mode decomposition (EEMD)

## 1. Introduction

Electromyography (EMG) signal is electrical manifestation of a contracting muscle. The acquisition of a clean EMG is a prerequisite for an appropriate interpretation and application of the signal. Surface EMG signals, like most of the electrophysiological measurements, are frequently corrupted with three categories of noise [1], i.e. power line interference (PLI), white Gaussian noise (WGN), and motion artifact or baseline wandering (BW). In particular, efforts in multiple-channel surface EMG recording have been developed in recent years using high density electrode arrays. Due to the large number of the recording electrodes and their tiny electrode-skin contact area, noise contamination emerges as an even more challenging problem. Situations are sometimes encountered where the signal to noise ratio (SNR) is poor in a few channels.

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Noise contamination may compromise the efficacy of the EMG signal processing. Thus, several methods have been proposed to reduce the noise from surface EMG signals, among which the most simple and cost-efficient solution is to use conventional digital filters. Although such filters substantially reduce the noise, they also attenuate the EMG signal due to spectral overlap of the noise and the surface EMG. It, therefore, remains a challenging problem to reduce noise without distortion of the useful EMG signals, which might require more advanced methods than the conventional digital filters. For example, adaptive or nonlinear filtering has been proposed to reduce the noise contamination while minimally sacrificing sections of the surface EMG signal [2,3]. On the other hand, taking advantages of the time-frequency resolution of the wavelet transform, wavelet thresholding has been used for noise reduction in various electrophysiological signals, including surface EMG [4]. As an alternative tool for processing nonlinear and non-stationary signals, the empirical mode decomposition (EMD) can also be used for de noising and conditioning of the electrophysiological signals [6–11], primarily using a similar approach to the wavelet based method. In contrast to the wavelet transform, the EMD decomposes a signal into a series of intrinsic mode functions (IMFs), which are zero-mean, amplitude- and frequency-modulated (AM–FM) time series representing oscillations within the processed signal [12]. The EMD is implemented via a sifting process, which is a purely data-driven, signal-dependent iterative procedure and makes no assumption about the original signal.

In this study, a novel framework based on EMD was developed to eliminate noise contamination in surface EMG. In contrast to most of the previous de noising methods that solely target a specific category of noise, a major feature of the current study is the primary reliance on the EMD for dealing with three different types of noise often present in surface EMG, particularly in high density surface electrode array recordings. Moreover, the ensemble EMD (EEMD) was used to overcome the limitation of the mode mixing routinely induced by the regular EMD [13], thus further improving the surface EMG denoising performance. The advantages of the EMD or EEMD based methods were demonstrated by comparing them with the traditional digital filters, using signals derived from our routine electrode array EMG recordings.

## 2. Methods

### 2.1. Background

**2.1.1. Empirical mode decomposition (EMD)**—The EMD is designed to adaptively decompose a time-series signal  $s(t), 1 \leq t \leq L$ , into a sum of intrinsic mode functions (IMFs)  $c_i(t), 1 \leq i \leq N$ ,

$$s(t) = \sum_{i=1}^N c_i(t) + T_N(t) \quad (1)$$

where  $t$  is the time index,  $N$  denotes the number of IMFs, and  $T_N(t)$  is the residual signal [12]. An IMF is defined as a function satisfying two conditions, i.e. (1) the difference between the number of extrema (including both the local maxima and minima) and zero-crossings in the time-series must be no more than one; (2) the mean value of the upper envelop (defined by maxima) and lower envelop (defined by minima) is zero through the entire time-series. Thus, an IMF is a simple oscillatory mode being symmetric with respect to zero.

The decomposition technique that sequentially extracts each IMF from the original signal is known as the sifting processing. It was detailed elsewhere [12] and is described in brief here. The processing starts from identification of the local maxima and minima of  $x(t)$ , an

auxiliary variable of the original signal  $s(t)$ . Two cubic spline curves are fitted to the local maxima and minima to form the upper envelope  $E_u$  and lower envelope  $E_l$ , respectively. The mean of the  $E_u$  and  $E_l$ , designated as  $E_m$ , is calculated and used to update  $x(t)$  by subtracting it from the  $x(t)$ . The previous steps are iteratively executed until  $x(t)$  is updated into an IMF  $c_1(t)$ , which satisfies the two definition conditions. The residual  $r_1(t)$ , calculated by subtracting the first IMF  $c_1(t)$  from the initial  $x(t)$ , is then treated as a new signal and the previous sifting process is repeated to obtain all the possible IMFs until the residual  $r_N(t)$  is either a constant, a monotonic slope, or a function with only one extremum. If we refer the residual  $r_N(t)$  as the  $(N+1)$ th order IMF  $c_{N+1}(t)$ , the formula (1) can be reorganized as:

$$s(t) = \sum_{i=1}^{N+1} c_i(t) \quad (2)$$

With the above sifting process, the lower-order IMFs carry the fast oscillation modes whereas the higher-order IMFs carry slow oscillation modes.

**2.1.2. Ensemble empirical mode decomposition (EEMD)**—The EEMD is a noise-assisted approach developed to improve the standard EMD [13]. For EEMD, the sifting process is performed on an ensemble of noise-added signals  $u(t)$ , each derived from a summation of the original signal  $s(t)$  and a different white noise  $w(t)$  of finite amplitude, i.e.  $u(t) = s(t) + w(t)$ . Each  $u(t)$  can be decomposed by the EMD algorithm. The resultant IMFs, namely  $c_{ij}(t)$ , are averaged across trials to obtain the final IMFs:

$$c_i(t) = \frac{1}{N_T} \sum_{j=1}^{N_T} c_{ij}(t) \quad (3)$$

where  $i$  is the IMF order,  $j$  denotes the trial index, and  $N_T$  is the total number of trials.

By such an average, it is assumed that the added noise in each trial can be cancelled. The rationale for addition of the white noise is to facilitate the final IMFs in comparable scales that are relatively independent of the local time-domain characteristics of the signal, thus reducing the mode mixing induced by the regular EMD. In this study, the white noise was added to the original signal at a 5 dB SNR and  $N_T$  was set to be 100.

## 2.2. EMD/EEMD-based filtering method

The EMD/EEMD-based filtering methods can be summarized into two categories: (1) partial reconstruction, and (2) IMF filtering. In the first category, the noisy EMG could be filtered with partial reconstruction of IMFs:

$$\tilde{s}(t) = \sum_{i=p}^q c_i(t) \quad (4)$$

where  $1 < p < q < N+1$ . By choosing different  $p$  or  $q$  values, a low-pass, high-pass, or band-pass filter can be designed [9]. For the other category, each IMF  $c_i(t)$  can be filtered respectively, resulting in  $c_i(t)$ . The filtered signal can be reconstructed as:

$$\tilde{s}(t) = \sum_{i=1}^{N+1} \tilde{c}_i(t) \quad (5)$$

In this study, three IMF filtering schemes targeting PLI, WGN and BW were proposed within the EMD/EEMD-based filtering framework.

**2.2.1. PLI reduction**—After EMD or EEMD of a surface EMG signal contaminated by PLI, several IMFs may carry both PLI and useful signals. To assess the PLI components, a second order notch filter (cutoff frequencies 60 Hz and harmonics) was applied to each of the IMFs. Assuming  $a_i(t)$  is the notch filter output of the  $i$ th-order IMF  $c_i(t)$ ,  $1 \leq i \leq N+1$ , we define  $\varepsilon_i$  to quantify the PLI involvement in each IMF:

$$\varepsilon_i = \frac{\text{var}[c_i(t) - a_i(t)]}{\text{var}[c_i(t)]} \quad (6)$$

where  $\text{var}[\cdot]$  is an operator to calculate the variance of a time-series. Each of the filtered IMFs  $\tilde{c}_i(t)$  is defined as:

$$\tilde{c}_i(t) = \begin{cases} c_i(t), & \varepsilon_i < 0.1 \\ a_i(t), & \varepsilon_i \geq 0.1 \end{cases} \quad (7)$$

In other words, if there is a clear PLI component involved in the IMF (above 10% energy proportion), the notch filter will be applied. Otherwise, the IMF remains unchanged.

**2.2.2. WGN reduction**—To reduce WGN using EMD or EEMD, a similar approach to wavelet-based denoising methods can be used, described as

$$\tilde{c}_i(t) = \begin{cases} c_i(t), & |c_i(t)| > T_i \\ 0, & |c_i(t)| \leq T_i \end{cases} \quad (8)$$

for hard thresholding and as

$$\tilde{c}_i(t) = \begin{cases} \text{sgn}(c_i(t))( |c_i(t)| - T_i ), & |c_i(t)| > T_i \\ 0, & |c_i(t)| \leq T_i \end{cases} \quad (9)$$

for soft thresholding, where  $\tilde{c}_i(t)$  denotes the thresholded version of the  $i$ -th order IMF, and  $T_i$  denotes a threshold for the order  $i$ .

To overcome the discontinuity of the reconstructed signals induced from the above hard or soft thresholding, an alternative strategy, namely EMD interval thresholding (EMD-IT), was developed to adapt the EMD characteristics [5]. For EMD-IT, the entire time-series of the  $i$ th-order IMF  $c_i(t)$  can be divided by its zero-crossings  $z_{i,j}$  into several concatenated intervals  $z_{i,j} = [z_{i,j}, \dots, z_{i,j+1}]$ , where  $j$  is the index of the zero-crossings. Whether a specific interval  $z_{i,j}$  is noise-dominant or signal-dominant can be identified by the amplitude  $c_i(t_{i,j})$  of its extreme instant  $t_{i,j}$  located in the interval,  $z_{i,j} < t_{i,j} < z_{i,j+1}$ . As a result, the EMD-IT translates to

$$\tilde{c}_i(z_{i,j}) = \begin{cases} c_i(z_{i,j}), & |c_i(t_{i,j})| > T_i \\ 0, & |c_i(t_{i,j})| \leq T_i \end{cases} \quad (10)$$

for hard thresholding and to

$$\tilde{c}_i(z_{i,j}) = \begin{cases} c_i(z_{i,j}) \frac{|c_i(t_{i,j})| - T_i}{|c_i(t_{i,j})|}, & |c_i(t_{i,j})| > T_i \\ 0, & |c_i(t_{i,j})| \leq T_i \end{cases} \quad (11)$$

for soft thresholding, where the  $c_i(z_{i,j})$  indicates the samples in the interval  $z_{i,j}$  from instant  $z_{i,j}$  to  $z_{i,j+1}$  of the  $i$ th-order IMF. Similarly, the EMD-IT can also be applied to the EEMD algorithm.

In this study, the EMD-IT soft thresholding was used. The thresholds were adaptively set as [5,14]:

$$T_i = \sigma_i \sqrt{2 \ln L} \quad (12)$$

where  $L$  is signal length and  $\sigma_i$  is the noise level for  $i$ th-order IMF estimated as [14]:

$$\sigma_i = \frac{\text{median}(|c_i(t)| : t=1, \dots, L)}{0.6745} \quad (13)$$

**2.2.3. BW reduction**—The BW components mainly involve in the higher-order IMFs. A signal with BW can be decomposed into a sum of IMFs  $c_i(t), 1 \leq i \leq N+1$ . To assess the BW components, a bank of low pass filters  $h_i(t), 1 \leq i \leq N+1$ , were utilized to process each of the IMFs:

$$d_i(t) = h_i(t) * c_i(t) \quad (14)$$

where  $*$  denotes the convolution and  $d_i(t)$  is the filtered IMF. The cut-off frequencies  $\omega_i$  of the lowpass filters  $h_i(t)$  can be set as [7]

$$\omega_i = \frac{\omega_0}{M^{N+1-i}} \quad (15)$$

where  $\omega_0$  is the cut-off frequency of  $h_{N+1}(t)$  and  $M > 1$  is a frequency-folding coefficient. The selection of the cut-off frequencies in such a form is based on the fact that relatively large BW components are present in the higher-order IMFs [7]. In this study,  $\omega_0$  and  $M$  were set to be 30 and 1.02 respectively. Similarly,  $\varepsilon_i$  was defined to quantify the BW involvement in each IMF:

$$\varepsilon_i = \frac{\text{var}[d_i(t)]}{\text{var}[c_i(t)]} \quad (16)$$

Thereby, the BW component  $b_i(t)$  in each IMF was extracted according to  $\varepsilon_i$

$$b_i(t) = \begin{cases} 0, & \varepsilon_i < 0.05 \\ d_i(t), & \varepsilon_i \in [0.05, 0.5] \\ c_i(t), & \varepsilon_i > 0.5 \end{cases} \quad (17)$$

Consequently, the denoised signal can be reconstructed from the filtered IMFs defined as:

$$\tilde{c}_i(t) = c_i(t) - b_i(t) \quad (18)$$

and the BW can be estimated as:

$$\tilde{b}(t) = \sum_{i=1}^{N+1} b_i(t) \quad (19)$$

### 2.3. Performance evaluation

The performance of the proposed methods was examined using our routine surface electrode array EMG recordings with a Refa EMG system (TMS International BV, Enschede, Netherlands). Sample surface EMG recordings from the thenar group muscles of amyotrophic lateral sclerosis patients were used for this analysis [15]. Two relatively high clean surface EMG signals (denoted as EMG1 and EMG2) and each of the three typical noises were selected to simulate different testing signals. All the selected signals were recorded in a time period of 1 s and with a sampling rate of 2 kHz. A noisy surface EMG signal  $s(t)$  can be generated as:

$$s(t) = x(t) + \delta n(t) \quad (20)$$

where  $x(t)$  is the highly clean experimental surface EMG,  $n(t)$  is a noise segment, and  $\delta$  is the scale factor used to adjust the signal to noise ratio (SNR):

$$\text{SNR} = 10 \lg \left\{ \frac{\text{var}[x(t)]}{\text{var}[\delta n(t)]} \right\} \quad (21)$$

The performance of the proposed methods were compared with the conventional IIR filters, including second-order notch filters (cutoff frequencies: 60 Hz and harmonics) and a fourth-order Butter worth band-pass filter (cutoff frequencies: 30–450 Hz) [16]. Both causal and non causal filters were implemented [17]. To compare the different methods, the signal to error ratio (SER) was used as the performance index, which is defined as

$$\text{SER} = 10 \lg \left\{ \frac{\text{var}[x(t)]}{\text{var}[x(t) - \hat{x}(t)]} \right\} \quad (22)$$

where  $\hat{x}(t)$  is the signal after the denoising.

## 3. Results

The typical results from EMD and EEMD are presented in Fig. 1, where a relatively clean surface EMG signal contaminated primarily by PLI was decomposed into IMFs by EMD and EEMD, respectively. The IMF distribution indicates that the lower-order IMFs contain

relatively high-frequency components while the higher-order IMFs contain relatively low-frequency components. Such a distribution is similar to filter bank but not exactly band-restricted, due to the fact that IMF was adaptively extracted based on the inherent signal oscillation structure, not the predetermined frequency band.

It is noted that because of the reduced mode mixing effect, each IMF derived from EEMD contains more concentrated and band limited components, as compared to that from EMD. For example, the PLI oscillation mode is assigned in three different IMFs (IMF 2, 3 and 4) as a result of EMD (Fig. 1a); whereas it is primarily involved in only one IMF (IMF 5) of EEMD (Fig. 1b). In addition, IMF 1 resulted from EEMD usually contains high-frequency noise free of any useful EMG signal. Therefore, the first IMF of EEMD can be removed for the signal reconstruction, thus effectively reducing high frequency noise. These advantages of EEMD can improve the denoising performance, as demonstrated in the following examples.

A comparison of the different surface EMG denoising methods is demonstrated in Figs. 2–4, with each example targeting a different category of noise, respectively. From the outputs of each method, it can be observed that the EMD/EEMD-based methods achieved better performance than conventional filtering methods to remove different noise from surface EMG. To quantitatively compare the denoising performance, the SER values of different methods were compared when they were applied to simulated noisy surface EMG signals derived from highly clean experimental surface EMG and typical noise recordings. The performance for different SNR levels' surface EMG is presented in Table 1. We found that the SER values from the IIR causal filter were the lowest due to the imposed nonlinear phase response. In general, the EMD or EEMD-based methods achieved higher SER values than the conventional digital filtering methods. The EEMD-based method achieved the highest SER values among all the methods, particularly when the processed signal had low SNRs.

Fig. 5 shows a comparison of different denoising methods when they were applied to an experimental surface EMG signal contaminated by all of the three categories of noise. The processed surface EMG signal, the filtered outputs, and the residuals from the different methods are all demonstrated. Consistently, the EMD- or EEMD-based methods demonstrated better performance compared with traditional digital filters.

#### 4. Discussions and conclusion

An EMD/EEMD-based IMF filtering framework was presented in this study to remove all the three common categories of noise (i.e. PLI, WGN, and BW) from surface EMG recordings. EMD is a powerful tool for processing nonlinear and nonstationary physiological signals with complex temporal-spatial structure. It can adaptively separate an original complex signal into a set of IMFs with different oscillation levels, thus offering an interpretation of the dynamic processes underlying the system generating the signal. Since the origins of multiple noises can be viewed as having different dynamic properties from the origins of the useful signal, the noise components are prone to be separated in limited number of band-restricted IMFs. Taking advantage of the EMD, we demonstrated that different noise contaminations in surface EMG can be adaptively removed based on an IMF filtering framework, where different IMFs were appropriately filtered according to the characteristics of each specific noise.

The advantage of EMD method for noise removal from a variety of physiological signals has been recently demonstrated in different studies [5–11]. Most of them, however, only targeted one specific category of noise [5,6,8,10] or simply assumed that the noise can be ideally separated in a specific IMF to be deleted for the purpose of noise removal [8–10].

The EMD-based method for noise reduction from surface EMG in this study can be viewed as the combination and extension of the previous methods. By integrating and optimizing different noise reduction solutions within a uniform IMF filtering framework, we are able to remove different categories of noise from surface EMG at the same time. The effectiveness of the proposed EMD-based method was validated by our experiment results which showed better performance than the conventional digital filters.

Furthermore, an important feature of this study is the employment of the ensemble EMD (EEMD), which produces a set of more strictly band-restricted IMFs by eliminating the problem of mode mixing routinely induced from the standard EMD. Based on such a property, the EEMD method can separate each category of noise within fewer IMFs, thus facilitating the removal of such noises with different time-frequency distribution. For example, the narrowband noise (here PLI) in Fig. 1b is prone to be concentrated in one IMF (IMF 5), so the appropriate processing can be performed accordingly. From Table 1, it is observed that the EEMD-based methods achieved the best performance for PLI or WGN elimination at all the tested SNR levels. For BW reduction, the advantage of the EEMD over the EMD or conventional digital filtering based methods was also demonstrated when the SNR of the processed signal was relatively low. The customized filtering performed on a limited number of IMFs generated by the EEMD mostly contributed to such improved performance of the noise removal while reducing distortion of the signal of interest.

We acknowledge that compared with conventional digital filters, the proposed EMD/EEMD based methods are more computationally complex. Particularly, the EEMD algorithm includes repetitive implementation of regular EMD over a number of trails, thus dramatically increase the computational burden. In a general sense, methods that rely on complicated signal processing techniques (e.g., wavelet transform [14], adaptive filter [2,3], and EMD [6]) may improve denoising performance compared with conventional digital filters, as demonstrated in this study. Nonetheless, they also impose additional computational complexity. Thus, a tradeoff or balance between denoising performance and computational efficiency is to be determined, depending on specific applications.

In conclusion, we present a surface EMG filtering method based on EMD, targeting three common categories of noise that majorly contaminate surface EMG recordings under clinical and laboratory condition. The performance of the EMD based methods were compared with the traditional digital filters, using signals derived from our routine electrode array EMG recordings. The EMD based method achieved better performance than the conventional digital filters. Furthermore, the performance of the ensemble EMD (EEMD) was also examined for surface EMG denoising. We found that the noise components were prone to be separated in limited number of band-restricted IMFs, thus facilitating the removal of different noise. Among all the examined methods, the EEMD achieved the best surface EMG denoising performance when the SNR of the processed signal was relatively low.

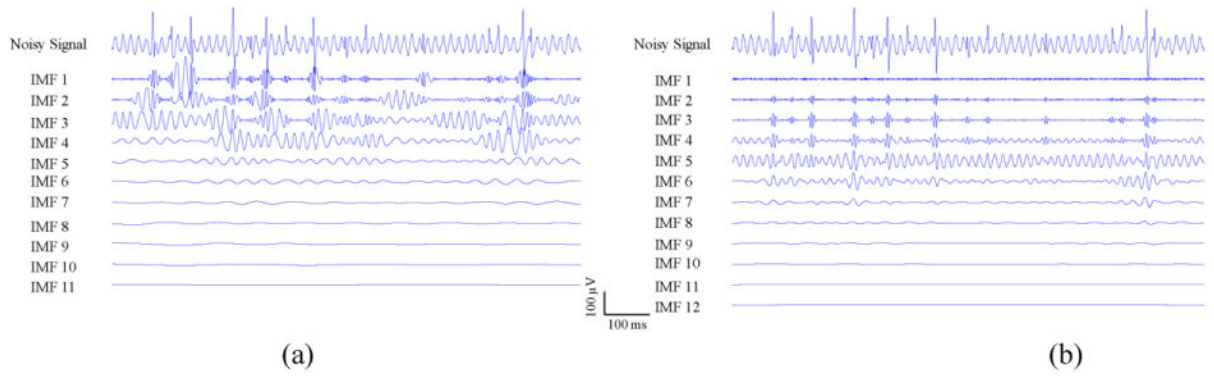
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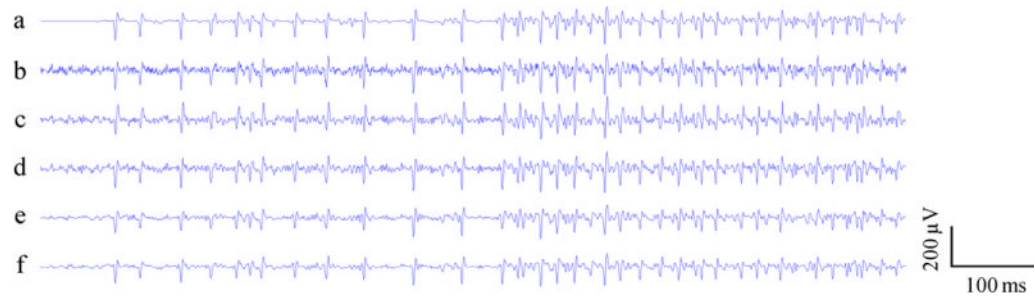


**Fig. 1.** An example of the EMD (a) and EEMD (b) decomposition of a surface EMG signal contaminated by PLI.



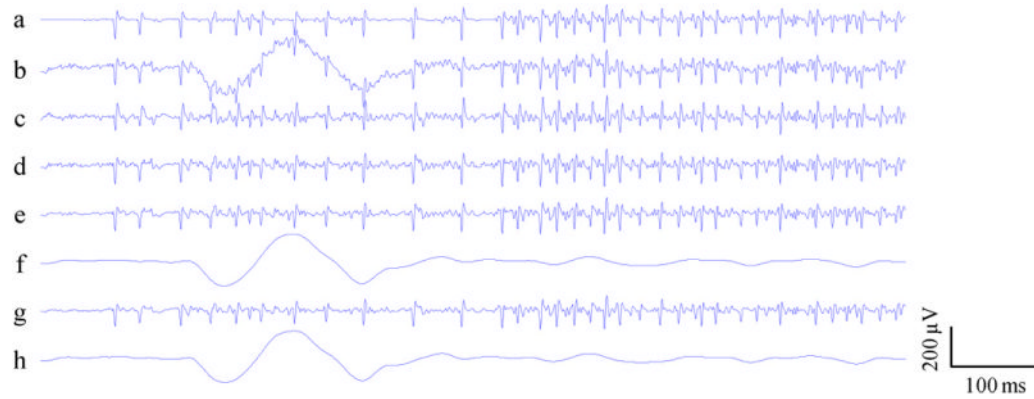
**Fig. 2.**

An example of reducing PLI from surface EMG using different methods. From top to bottom: (a) the original highly clean surface EMG signal (denoted as EMG1); (b) the surface EMG signal contaminated by PLI noise; (c) the output of the IIR causal filter; (d) the output of the IIR noncausal filter; (e) the output signal after EMD filtering; and (f) the output signal after EEMD filtering.



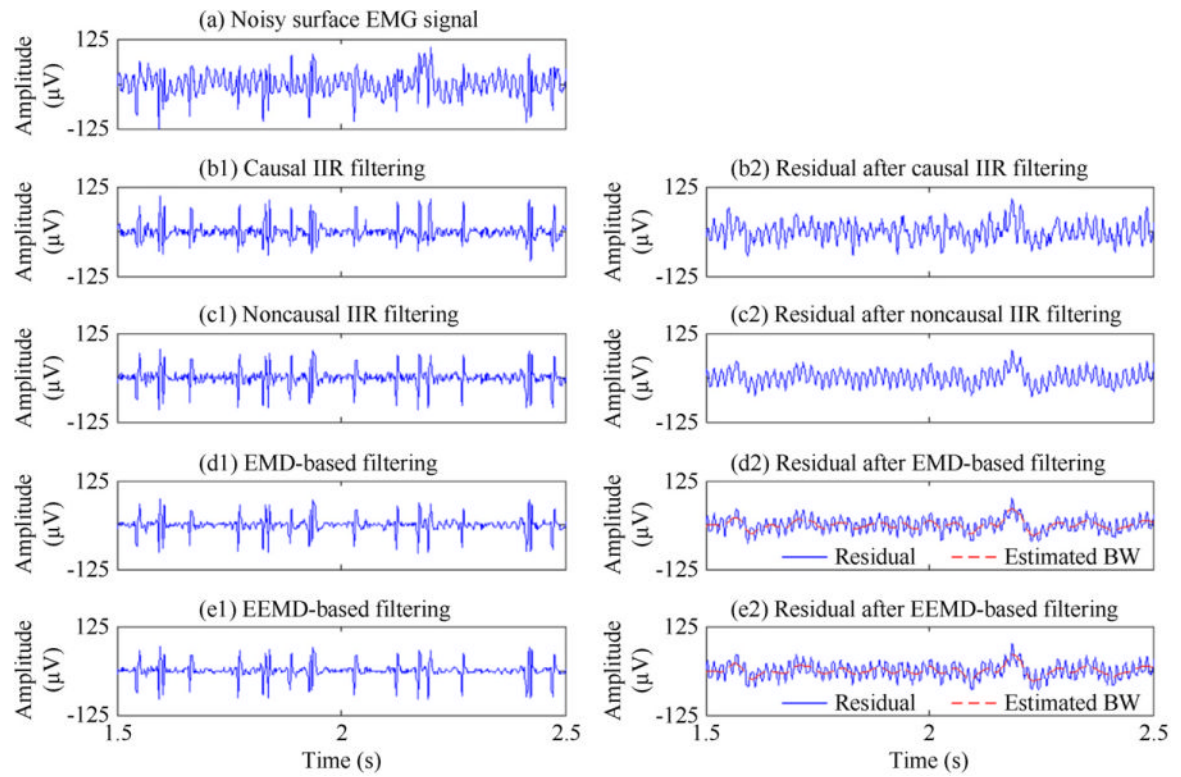
**Fig. 3.**

An example of reducing WGN from surface EMG using different methods. From top to bottom: (a) the original highly clean surface EMG signal (denoted as EMG2); (b) the surface EMG signal contaminated by WGN; (c) the output of the IIR causal filter; (d) the output of the IIR noncausal filter; (e) the output signal after EMD filtering; and (f) the output signal after EEMD filtering.



**Fig. 4.**

An example of reducing BW from surface EMG using different methods. From top to bottom: (a) the original highly clean surface EMG signal (denoted as EMG2); (b) the surface EMG signal contaminated by BW noise; (c) the output of the IIR causal filter; (d) the output of the IIR noncausal filter; (e) the output signal after EMD filtering; (f) the estimated BW noise after EMD filtering; (g) the output signal after EEMD filtering; and (h) the estimated BW noise after EEMD filtering.



**Fig. 5.** An example of reducing three different noise contaminations from surface EMG using different methods. The residual was calculated as the difference between the original signal and the filtered output. For EMD/EEMD-based methods, the estimated BWs are also demonstrated along with the residual signals.

Table 1

A comparison of the SER (dB) from four different filtering methods. Maximum SER values of the same noise category and level are marked in bold.

Noise type	Method	EMG 1						EMG 2					
		SNR = -6 dB	SNR = -2 dB	SNR = 2 dB	SNR = 6 dB	SNR = -6 dB	SNR = -2 dB	SNR = 2 dB	SNR = 6 dB	SNR = -6 dB	SNR = -2 dB	SNR = 2 dB	SNR = 6 dB
PLI	IIR Causal	3.138	4.025	4.390	4.515	2.198	3.257	3.828	4.110				
	IIR Noncausal	7.062	10.27	12.75	14.34	7.120	10.41	13.01	14.74				
	EMD	7.305	10.50	12.70	14.18	7.569	11.28	13.45	15.81				
WGN	EEMD	<b>9.150</b>	<b>11.22</b>	<b>13.56</b>	<b>15.10</b>	<b>8.699</b>	<b>11.59</b>	<b>14.16</b>	<b>16.03</b>				
	IIR Causal	-4.777	-1.881	1.203	2.996	-4.633	-1.272	1.400	3.154				
	IIR Noncausal	-4.036	-1.458	3.944	7.905	-4.037	-0.041	3.950	7.929				
BW	EMD	1.891	4.469	6.301	8.383	0.687	2.905	5.481	8.130				
	EEMD	<b>3.155</b>	<b>5.785</b>	<b>8.707</b>	<b>11.30</b>	<b>1.476</b>	<b>3.670</b>	<b>6.121</b>	<b>9.475</b>				
	IIR Causal	3.186	4.087	4.696	4.955	3.132	4.008	4.415	4.590				
EMD	IIR Noncausal	8.506	12.37	16.05	<b>19.38</b>	8.624	12.59	16.39	<b>20.19</b>				
	EMD	9.382	12.95	15.62	18.66	9.316	<b>12.75</b>	<b>16.40</b>	20.04				
	EEMD	<b>10.67</b>	<b>13.88</b>	<b>16.22</b>	18.36	<b>9.355</b>	12.43	15.34	17.75				