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EMG signal filtering based on Empirical Mode Decomposition

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Abstract

This paper introduces a procedure for filtering electromyographic (EMG) signals. Its key element is the Empirical Mode Decomposition, a novel digital signal processing technique that can decompose any time-series into a set of functions designated as intrinsic mode functions. The procedure for EMG signal filtering is compared to a related approach based on the wavelet transform. Results obtained from the analysis of synthetic and experimental EMG signals show that our method can be successfully and easily applied in practice to attenuation of background activity in EMG signals.

Keywords: Electromyography; Empirical Mode Decomposition; Wavelets; Adaptive filters

1. Introduction

Electromyographic (EMG) signals are usually affected by noise, which may be generated by different sources, such as the hardware employed for signal amplification and digitization, the movement of cables during data collection and the activity of motor units distant from the detection point. Some useful procedures aimed at minimizing the influence of noise on the detected signal are highlighted by Cram et al. [1].

Such practical procedures may indeed contribute to the acquisition of EMG signals with good signal-to-noise ratio, but in practice, the collected signal may still be corrupted by noise. If the type of noise present in a signal is known a priori then optimal filters, e.g. the Wiener filter, may be applied to attenuate its presence [2]. The main disadvantage of this approach is that in many practical applications the noise is unknown.

A very common filter used in many studies concerning the analysis of electromyographic signals [3–6] is the low-pass differential (LPD) filter defined by Usui and Amidor [7]. This filter is implemented in the time-domain as:

$$y_k = \sum_{n=1}^{N} (x_{k+n} - x_{k-n}), \tag{1}$$

where x_k is the discrete input time-series and y_k is the filtered output. N is the window width to adjust the cut-off frequency. Increasing N will reduce the cut-off frequency of the filter. Its transfer function $H(z)$ is given in Eq. (2),

$$H(z) = \left(\sum_{n=1}^{N} (z^n - z^{-n}) \right) \Bigg|_{z=e^{j2\pi f/f_{sr}}} \tag{2}$$

where f is the frequency (Hz) and f_{sr} is the sampling frequency (Hz).

The main advantages of using the LPD filter are that it is easy to implement and fast in real-time applications. Some of its drawbacks, however, are discussed by Xu and Xiao [8]. First, under conditions of low signal-to-noise ratio the relatively strong high frequency noise (background activity) may be accentuated. Furthermore, since the LPD filter is not an ideal low-pass filter, there will exist severe Gibbs phenomenon, that is, the leakage of energy frequency out of the filter pass-band. As a result, many high frequency noise components will pass through the filter.

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An alternative to the LPD filter, known as the weighted low-pass differential filter (WLPD), was proposed by Xu and Xiao [8]. The main difference between these filters is that the latter includes an appropriately weighted window for reduction of the Gibbs effect. However, results presented in [9,8] show that phase distortion may be present in the filtered signal and depending on the level of noise false spikes may be introduced into the filtered signal.

Recently, wavelets have been successfully applied to noise removal from corrupted signals [10–13]. A general procedure for signal de-noising using wavelets involves the following three steps: signal decomposition, detail coefficients thresholding and signal reconstruction. The main advantages of this technique are that no artificial information is introduced into the filtered signal and that the signal components may be independently thresholded in order to generate the filtered signal. This allows for some flexibility that may be required in different applications. The main drawback of this method is that a mother wavelet has to be defined a priori and this choice may influence the final results.

In this paper we introduce a novel practical procedure for filtering EMG signals. This new technique is similar to and was motivated by the de-noising procedure based on wavelets. The main difference is in the way that the signal is decomposed. We employ the Empirical Mode Decomposition (EMD), a novel digital signal processing tool introduced by Huang et al. [14].

In contrast to the wavelet approach, the EMD does not decompose the signal in terms of basic atoms like the mother wavelets. Instead, a decomposition procedure, known as the sifting process, is employed. This procedure is data-driven, adaptive and makes no assumptions about the input time-series. As a result of the sifting process, intrinsic mode functions (IMFs) are yielded. These are signal components that highlight distinct time-scales (frequencies) of the input time-series. Thus, some IMFs may capture the presence of noise in signals. The procedure proposed for signal filtering in this work takes advantage of this feature of the EMD method for reduction of the level of noise in signals.

The next sections of this paper describe the EMD method and the strategy (algorithm) for filtering EMG signals. Furthermore, we compare the performance of the EMD and wavelet based filters. For this, synthetic and experimental signals are employed.

2. The Empirical Mode Decomposition

Huang et al. [14] described a new technique for analysing non-linear and non-stationary data. The key part of the method is the Empirical Mode Decomposition method, in which any complicated data set can be adaptively decomposed into a finite, and often small, number of intrinsic mode functions. The name intrinsic mode function is adopted because these components represent the oscillation modes embedded in the data. In the case of Fourier analysis, oscillation modes (i.e. components) in a signal are defined in terms of sine and cosine waves. The EMD defines oscillation modes in terms of IMFs, which are functions that satisfy two conditions [14]:

1. In the whole time-series, the number of extrema and the number of zero crossings must be either equal or differ at most by 1. Note that extrema are either local minima or local maxima. Furthermore, a sample g_i in a time-series is a local maximum if $g_i > g_{i-1}$ and $g_i > g_{i+1}$, and a sample q_i is a local minimum if $q_i < q_{i-1}$ and $q_i < q_{i+1}$, where i is a discrete time.
2. At any point in the time-series, the mean value of the envelopes, one defined by the local maxima (upper envelope) and the other by the local minima (lower envelope), is 0. This mean is computed for all available samples in the time-series.

The definition above is empirical and currently there is no explicit equation for estimating IMFs. Thus, any arbitrary time-series that satisfies conditions 1 and 2 is an IMF. From the analysis of the power spectrum of IMFs it is possible to verify that these functions represent the original signal decomposed into different time-scales (or frequency bandwidths). This is illustrated by Andrade et al. [15,16]. Thus, both wavelets and the Empirical Mode Decomposition provide the decomposition of a signal into different time-scales. The main difference is that the former performs the signal decomposition adaptively and based solely on the available data, whereas the latter normally uses a set of pre-fixed filters based on the choice of a mother wavelet.

The EMD method is a sifting process that estimates IMFs. This process is depicted in Fig. 1. It involves the following steps, leading to a decomposition of the signal $S(t)$ into its constituent IMFs:

(a) x (an auxiliary variable) is set to the signal $S(t)$ to be analysed, and a variable k, which is the number of estimated IMFs, is set to zero.
(b) Splines are fitted to the upper extrema and the lower extrema. This will define the lower (LE) and upper envelopes (UE).
(c) The average envelope, m, is calculated as the arithmetic mean between UE and LE.
(d) A candidate IMF, h, is estimated as the difference between x and m.
(e) If h does not fulfill the criteria defining an IMF, it is assigned to the variable x and the steps (b)–(d) are repeated. Otherwise, if h is an IMF then the procedure moves to step (f).
(f) If h is an IMF it is saved as c_k, where k is the kth component.
(g) The mean squared error, mse, between two consecutive IMFs C_{k-i} and c_k, is calculated, and this value is compared to a stopping condition (usually a very small value, i.e. 10^{-5}).
(h) If the stopping condition is not reached, the partial residue, r_k, is estimated as the difference between a previous partial residue r_{k-1} and c_k, and its content is assigned to the dummy variable x and the steps of (b)–(d) are repeated.
(i) If the stopping condition is reached then the sifting process is finalized and the final residue r_{final} can be estimated as the difference between $S(t)$ and the sum of all IMFs.

The criterion used to state whether h is an IMF or not is to verify whether h satisfies the two conditions that define an IMF.

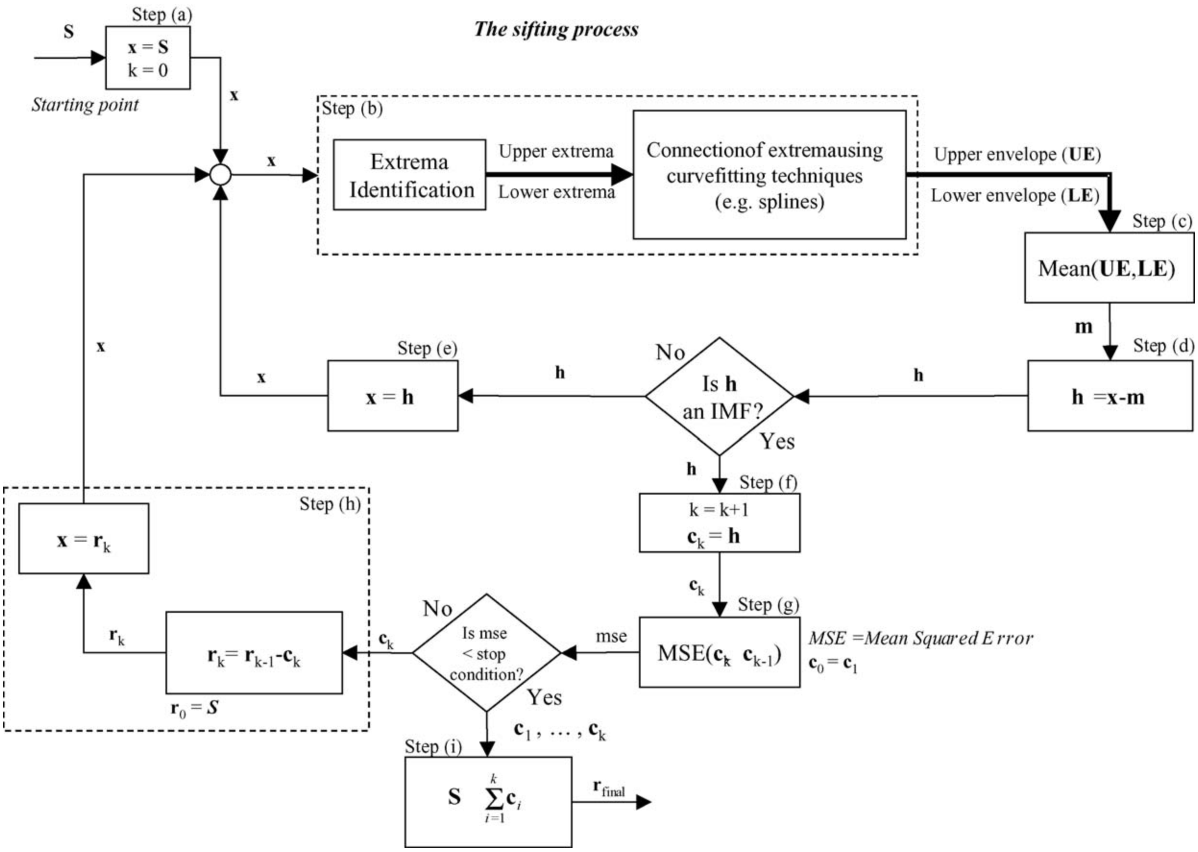

Fig. 1. Block diagram of Empirical Mode Decomposition showing the sequence of steps required for estimation of intrinsic mode functions.

Currently, there is no set of equations to estimate IMFs; therefore, the sifting procedure described above (proposed by Huang et al. [14]), which is an empirical technique, is employed for this purpose.

When the sifting process stops, the original signal $S(t)$, can be represented as,

$$S(t) = \sum_{k=1}^{n} c_k + r_{\text{final}} \tag{3}$$

where n is the number of IMFs, c_k the kth IMF and r_{final} is the final residue, which is estimated as described in the step (i).

Eq. (3) indicates that IMFs can be linearly combined in order to obtain the decomposed signal $S(t)$. The filtering procedure that is proposed in this work takes into account this property of the decomposition in order to filter signals. This process is detailed in the next sections.

Fig. 2 shows examples of upper, lower and mean (or average) envelopes for two arbitrary time-series, y_1 and y_2. y_1 is a random signal sampled from a normal probability distribution function, whereas y_2 is a single sinusoidal waveform oscillating at 10 Hz. As the mean envelope obtained from the upper and lower envelopes of y_1 is different from zero, y_1 does not satisfy the conditions imposed by the definition of IMFs so it is not an IMF. Therefore, the sifting process described above could be employed for estimation of IMFs in this signal. However, y_2 satisfies the definition of IMFs, and thus is an IMF already.

3. The algorithm for signal filtering based on the EMD

The success of the general procedure for noise removal using wavelets is based on the fact that it is possible to filter signal components individually instead of filtering the original signal. This is desirable because some components may highlight the noise and thus it may be easier to attenuate its presence.

Similarly, the Empirical Mode Decomposition also provides the decomposition of a signal into different time-scales or IMFs. This means that it is also possible to filter signal components individually instead of the original signal. This suggests that the strategy for signal de-noising based on wavelets may also be applied to intrinsic mode functions. Thus, we propose the following procedure for EMG signal filtering:

1. Decompose the signal into IMFs.
2. Threshold the estimated IMFs.
3. Reconstruct the signal.

This procedure is practical, mainly due to the empirical nature of the EMD method, and it may be applied to any signal as the EMD does not make any assumption about the input time-series. A block diagram describing the steps for its application is shown in Fig. 3. First, the EMD method is used for decomposing the input signal into intrinsic mode functions, $\text{IMF}_1, \ldots, \text{IMF}_N$, where N is the number of IMFs. These IMFs are then soft-thresholded, yielding $t\text{IMF}_1, \ldots, t\text{IMF}_N$, which are

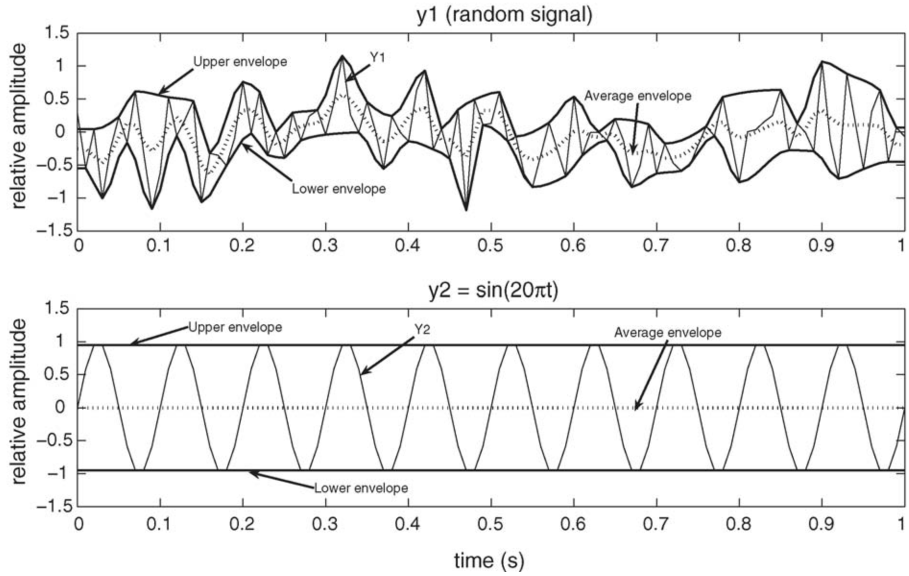

Fig. 2. Examples of upper, lower and mean envelope for two distinct time-series. y_1 is a random signal sampled from a normal probability distribution function, y_2 is a sine wave oscillating at 10 Hz and t is time in seconds. Note that y_1 is not an IMF as its mean envelope is not zero, and that y_2 is an IMF.

thresholded versions of the original components. The filtered signal is obtained as a linear summation of thresholded IMFs.

A very common strategy used in the filtering procedure based on wavelets is to use the soft-thresholding technique described by Donoho [10], i.e. first the signal is decomposed by means of wavelets and the detail coefficients resulting from this decomposition are thresholded through soft-thresholding, and then employed for reconstruction of the filtered signal.

Similar idea is used for thresholding IMFs. For each IMF from 1 to N a threshold, t_n, $n = 1, \ldots, N$, is selected and soft-thresholding (defined in Eq. (4)) is applied to individual IMFs as shown in Eq. (4),

$$t\mathrm{IMF}_n = \mathrm{sign}(\mathrm{IMF}_n)(|\mathrm{IMF}_n| - t_n)_+ \tag{4}$$

where $t\mathrm{IMF}_n$ is the de-noised (or thresholded) version of the nth IMF and the function $(x)_+$ is defined as

$$(x)_+ = \begin{cases} 0, & x < 0 \\ x, & x \geq 0. \end{cases} \tag{5}$$

The threshold t_n is estimated by using the following strategy: a window of noise is selected from the original signal and then the boundaries of this window are used to extract a region of noise from IMFs. The standard deviation of each region is then estimated and regarded as the required thresholds ($t_1, \ldots, t_N$). Fig. 4 illustrates the procedure for estimating t_n.

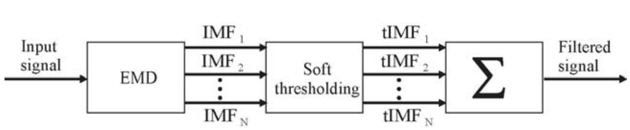

Fig. 3. The EMD method is employed for decomposing the input signal into IMFs ($\mathrm{IMF}_1, \ldots, \mathrm{IMF}_N$, where N is the number of IMFs). These IMFs are soft-thresholded, yielding $t\mathrm{IMF}_1, \ldots, t\mathrm{IMF}_N$, which are thresholded versions of the original components. The filtered signal is obtained as a linear summation of thresholded IMFs.

4. Acquisition of EMG signals

Ethical approval for this research was granted by the Ethical Committee of the National Health Service of the United Kingdom (Berkshire Local Research Ethics Committee—REC 33/04) and also by the Ethical Committee of the University of Reading (Project 03/44). Before data collection a consent form was signed by each subject. In total 10 healthy subjects were involved in this study.

Standard passive surface electrodes (MedTech Systems Ltd., type pellet, Ag/AgCl, diameter of 1 mm, inter-electrode distance of 1 cm) were used for signal detection from the First Dorsal Interosseous (FDI), which is a very superficial muscle of the hand located between the thumb and the index finger. A disposable reference electrode (TECA NCS2000, Oxford Instruments Medical, pre-gelled, Ag/AgCl, self-adhesive) located at the back of the hand was employed.

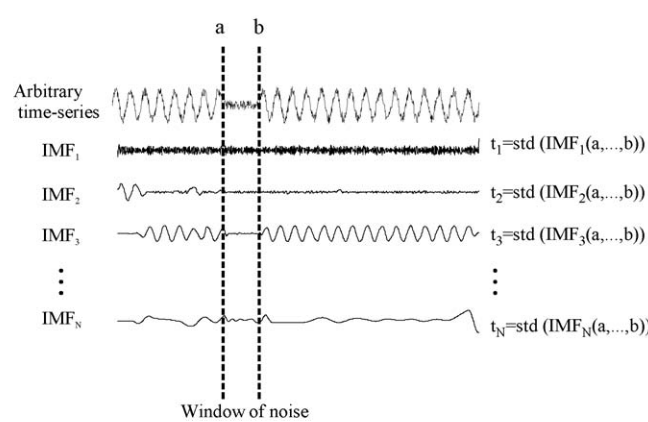

Fig. 4. Illustrative example showing the estimate of thresholds t_n. First, a window of noise (i.e. samples within the interval $[a, b]$) is selected from the arbitrary time-series. The interval $[a, b]$ is employed for selection of noise in the IMFs. From each IMF, thresholds $t_1, \ldots, t_N$ are then defined. Note that 'std' is the standard deviation.

The skin was abraded and cleaned with alcohol and then electrodes were positioned in the direction of muscle fibres.

The FDI muscle was activated by an isometric contraction during abduction of the index finger. Subjects executed six distinct trials of 30 s each. In the first trial, subjects performed weak muscle contraction without supporting any load (0 g). In subsequent trials they were asked to apply and maintain a force, which was measured by a force sensor, equivalent to loads of 100 g, 200 g, 300 g, 400 g and 500 g. Thus, in total, 60 different sets of signals were available for study. Tailor-made software provided visual feedback for subjects about the required level of force to be applied and maintained (see Fig. 5).

EMG signals were differentially amplified via a commercial amplifier (Delsys Inc., CMRR > 80 dB, input impedance $> 10^{15}\ \Omega$, noise level $< 1.2\ \mu$V) with gain set to 10,000, band-pass filtered (10 Hz–2 kHz) and digitized by a 16-bit A/D converter (PC-card DAS 16/16 Measurement Computing) at 10 kHz.

5. An example of application of the filter based on the EMD method

In this section we exemplify the application of the procedure for filtering EMG signals based on the EMD, which provides an overview of the application of the method before comparison is made with the wavelet approach. For this, the experimental surface electromyographic signal shown in Fig. 6(a) is used.

The first step of the algorithm is to use the EMD (or sifting process) to decompose the original EMG signal into intrinsic mode functions. Eight IMFs (IMF_1, …, IMF_8) are obtained, and they are presented in Fig. 7(a).

The next step is to threshold the components IMF_1, …, IMF_8. Eq. (4) was employed for de-noising individual IMFs. The results of this procedure are shown in Fig. 7(b). Note that in order to estimate thresholds for IMFs the boundaries of the window of noise indicated in Fig. 6(a) were selected.

In the last step, the resulting (de-noised) components were combined to generate a filtered version of the original signal as shown in Fig. 6(b). In Fig. 6(c), the residue, which is the difference between the original and filtered signals, is also presented. The random nature of this component and the attenuation of the noise in the EMG signal is apparent.

6. Analysis of synthetic signals

In this section the performance of the procedure based on the EMD is compared to that of the procedure based on wavelets. For this, synthetic signals are employed.

6.1. Protocol for generation of artificial signals

Artificial signals were generated from the experimental EMG signal (EMG_{exp}) shown in Fig. 8. This will be subsequently used as a reference signal as it has a very good signal-to-noise ratio. The following protocols were adopted for generation of synthetic signals corrupted by noise:

$$S_1 = EMG_{exp} + 0.2\mathcal{N} \tag{6}$$

$$S_2 = EMG_{exp} + 0.4\mathcal{N} \tag{7}$$

$$S_3 = EMG_{exp} + 0.6\mathcal{N} \tag{8}$$

$$S_4 = EMG_{exp} + 0.8\mathcal{N} \tag{9}$$

$$S_5 = EMG_{exp} + 1.0\mathcal{N} \tag{10}$$

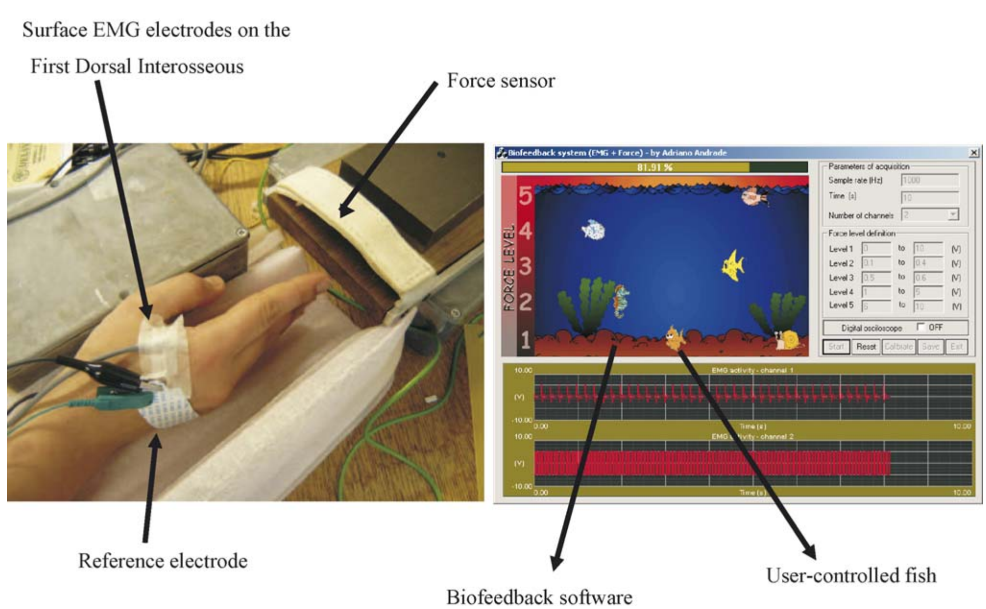

Fig. 5. (Left) Illustration of the positioning of surface EMG electrodes on the First Dorsal Interosseous, and the reference electrode on the back of the hand. During experiments subjects were asked to abduct the index finger against the force sensor. (Right) Tailor-made software that provided feedback for subjects about a pre-defined force level to be maintained. During experiments subjects were asked to keep a user-controlled fish at one of the five available force levels (represented by the other sea animals).

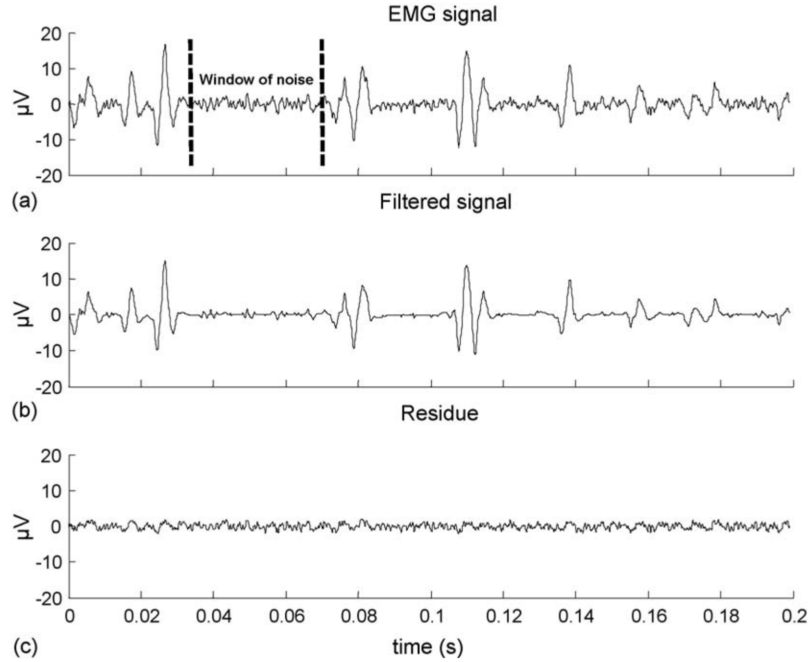

Fig. 6. (a–c) EMG signal and its filtered version. The residue, which is the difference between those signals, is also shown.

where $\mathcal{N}$ is a random variable sampled from a Gaussian distribution with mean 0 and standard deviation 1. In a further step, the amplitude of this variable was normalized between 0 and the maximum of EMG_{exp}. Fig. 8 shows examples of synthetic signals generated with distinct protocols.

6.2. Signal filtering and selection of parameters

Artificial EMG signals were filtered using both wavelet and EMD algorithms. Three different Daubechy (db) wavelet prototypes or mother wavelets were analysed (db2, db3 and

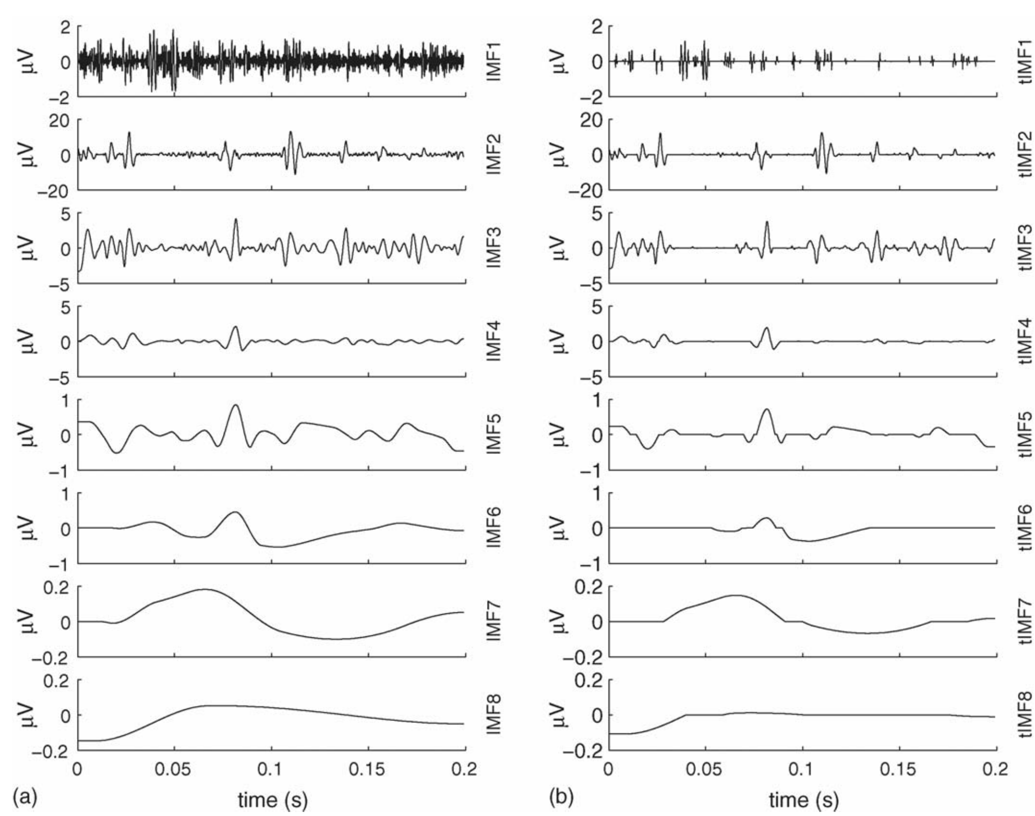

Fig. 7. (a) Intrinsic mode functions (IMF_1, . . ., IMF_8) obtained from the EMG signal presented in Fig. 6(a). (b) De-noised intrinsic mode functions.

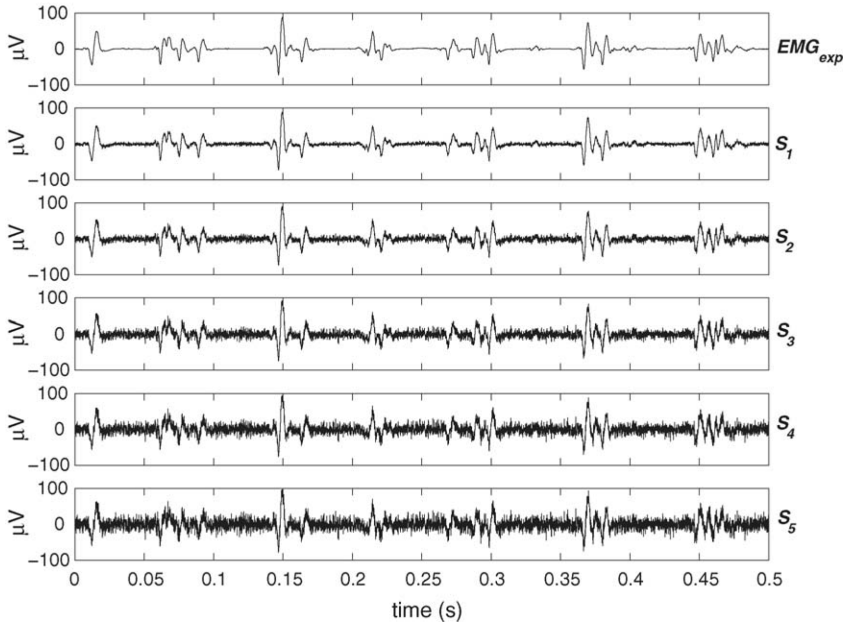

Fig. 8. Example of generation of synthetic EMG signals from the experimental EMG signal EMG_{exp} and by means of protocols $S_1, \ldots, S_5$ defined in Eqs. (6)–(10).

db4) and signals were decomposed into five levels when employing wavelets. These Daubechy wavelets were chosen because of their reported success in removing/attenuating noise from electromyographic signals, and in their use for feature extraction from motor unit action potentials (MUAPs) [12,17,18].

The thresholding procedure for de-noising IMFs (obtained from EMD) or detail coefficients (obtained from wavelets) is the one already discussed in Section 3; therefore, it was the same for both methods.

6.3. Strategy for data analysis

The following procedure was employed for data analysis:

For $i = 1$–N:

1. Generate artificial signals using one of the protocols defined in Eqs. (6)–(10).
2. Filter corrupted signals using wavelets and the EMD procedure.
3. Estimate the error signal e, which was defined as the difference between the original EMG_{exp} (shown in Fig. 8) and the filtered signal.
4. Estimate the mean μ_e of e.
5. Assign μ_e to an auxiliary vector, $v(i) = \mu_e$.
   end
6. Compute the mean and standard deviation of v. Note that the smaller the mean of v the closer the filtered signal is to the reference signal EMG_{exp}.

In the procedure above N is the number of times the sequence of steps from 1 to 5 are repeated. At each iteration the random variable $\mathcal{N}$ (defined in Section 6.1) is re-generated, which implies that a new set of artificial signals is employed.

Fig. 9 presents an example, resulting from a single iteration, of the procedure described above. The artificial signal at the top was generated with the protocol S_5 defined in Eq. (10). This signal was then filtered by using EMD and wavelets. The filtered signals are shown in the figure. The estimated mean μ_e for each of the those signals was: 0.7476 μV (EMD); 1.0582 μV (db2); 1.0595 μV (db3); 1.0322 μV (db4). These results indicate that the filtering procedure based on the EMD method yielded a filtered signal closer to EMG_{exp}.

6.4. Results and discussion

The procedure for data analysis described in Section 6.3 was executed 100 times (i.e. N was set to 100), and the mean and standard deviation of v were estimated as described in step 6. The results are presented in Table 1. They show that the mean of v is smaller for signals filtered with the EMD, which suggested that those signals were closer to EMG_{exp}.

Note that standard deviations obtained for the EMD technique were considerably larger than those obtained using the wavelet procedure. This may be explained by the fact that the EMD is a non-linear method, and therefore more sensitive to the presence of noise.

Furthermore, these results suggest that the performance of all investigated wavelets is very similar.

7. Analysis of experimental signals

In this section the filtering procedures based on the EMD and wavelets are compared by employing experimental surface EMG signals.

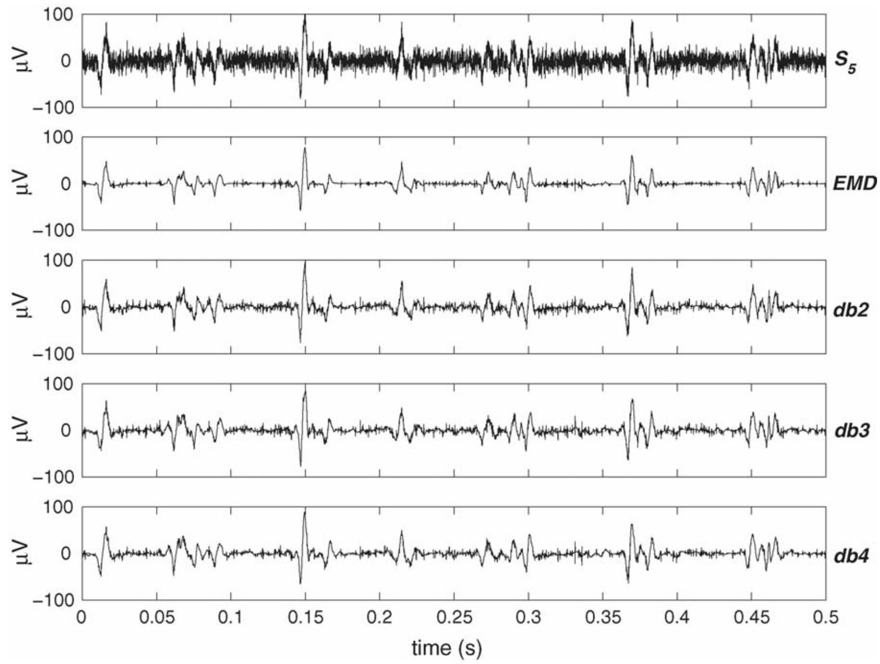

Fig. 9. The artificial signal (top) was generated with the protocol S_5 defined in Eq. (10). The filtered signals using the EMD procedure and the three distinct wavelets are presented.

7.1. Signal filtering and selection of parameters

Experimental EMG signals were filtered using both algorithms, EMD and wavelets. The selection of parameters is the same described in Section 6.2.

7.2. Strategy for feature selection

From each of the 60 collected EMG signals two regions of interest were manually/visually selected and classified either as noise or signal activity. The region of noise corresponded to background activity in the EMG signal, whereas signal activity represented electromyographic activity. An example of a typical window of noise is provided in Fig. 6. Any other section of the EMG signal in the figure which is not background noise could represent a typical window of signal activity.

7.3. Definition of hypothesis

In order to compare both filtering methods the following hypotheses were tested:

- If the filters can remove or attenuate the background activity of signals then the level of the total power of the window of noise should decrease after filtering.
- Ideally a filter is only expected to remove/attenuate noise from signals. In practice the total power of regions of useful information is also attenuated, which may be justified by the fact that even those regions are also corrupted by noise. Nevertheless, most of the total power of those regions is expected to be preserved.

7.4. Definition of the performance index

The total power of either a region of signal or of noise, which is used as the index of performance in this study, is defined in Eq. (11) [19],

$$P_o = \int \mathrm{PS}(f)\,\mathrm{d}f \qquad (11)$$

where P_o is the total power, PS the power spectrum and f is the frequency. PS was estimated by Welch's technique.

Table 1
Mean and standard deviation of v obtained for distinct simulation protocols and filtering techniques

Simulation protocol	EMD (μV)	db2 (μV)	db3 (μV)	db4 (μV)
S_1	0.3648 ± 0.3089	1.0072 ± 0.0088	1.0070 ± 0.0079	0.9961 ± 0.0064
S_2	0.5342 ± 0.4041	1.0226 ± 0.0172	1.0159 ± 0.0160	0.9922 ± 0.0122
S_3	0.6404 ± 0.3325	1.0390 ± 0.0254	1.0232 ± 0.0244	0.9927 ± 0.0175
S_4	0.6199 ± 0.4764	1.0529 ± 0.0325	1.0287 ± 0.0335	0.9963 ± 0.0230
S_5	0.7039 ± 0.4019	1.0644 ± 0.0394	1.0331 ± 0.0424	1.0000 ± 0.0286

The definition of v and the procedure for estimating these results are detailed in Section 6.3.

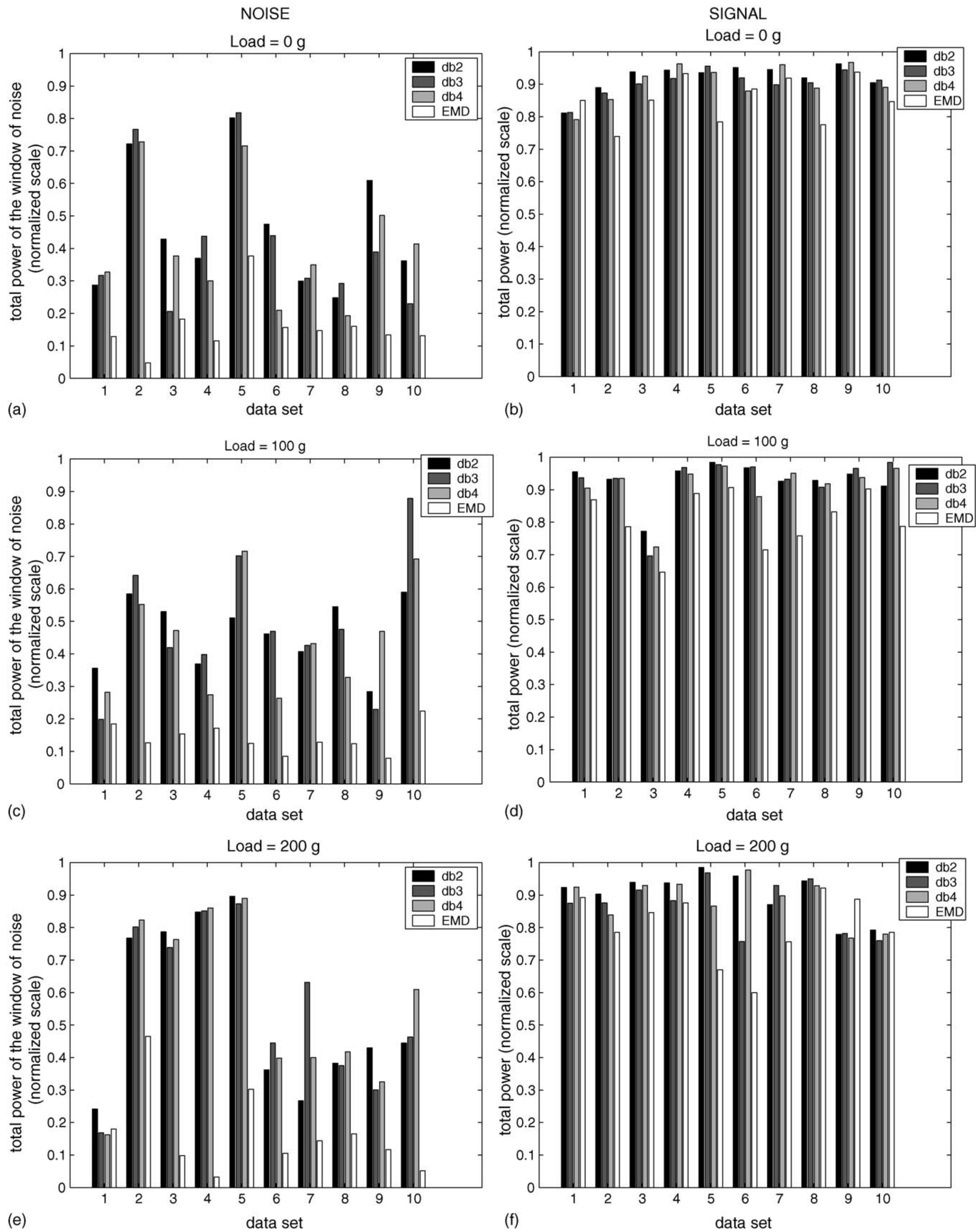

Fig. 10. Total power of windows of noise (a, c and e) and signal (b, d and f). Loads vary from 0 g to 200 g.

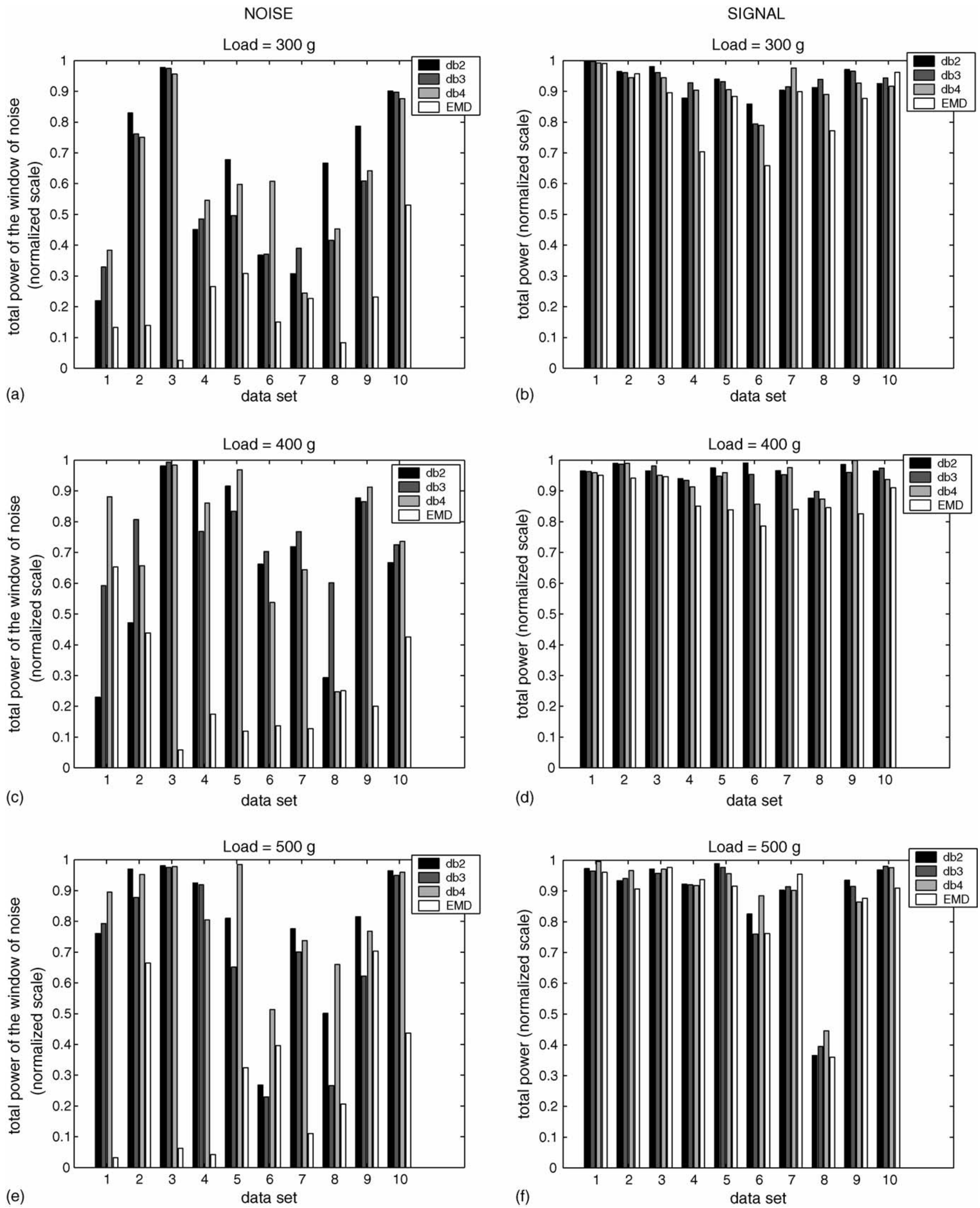

Fig. 11. Total power of windows of noise (a, c and e) and signal (b, d and f). Loads vary from 300 g to 500 g.

P_o was then normalized by the total power of the original signal before filtering. When studying a window of noise $P_o = 0$ means that the noise is completely attenuated and $P_o = 1$ indicates that there is no reduction in the level of noise. Conversely, for the window of signal $P_o = 1$ means that the total power of the original signal is completely preserved, whereas $P_o = 0$ implies that the total power of the window of signal is totally destroyed.

7.5. Results and discussion

The results are shown in Figs. 10 and 11. Distinct data sets are signals from different subjects, for instance, data set 1 is the EMG signal collected from subject 1. Observe also that results from signals of different levels of contraction, represented by different loads, e.g. 0 g, 100 g, 200 g, 300 g, 400 g and 500 g, are presented. This is important because it allows for the evaluation of the filtering procedure with signals that have different levels of complexity and signal-to-noise ratios.

The results presented here show that both the noise procedure based on wavelets and the one based on the EMD reduced the total power of the window of noise and at the same time preserved the majority of the energy of the window of signal. In order to better understand the implications of this a cumulative distribution function (CDF) may be employed. This function computes the proportion of data points less than value x, and plots the proportion as a function of x. The CDFs for the attenuation of the total power of the window of noise and for the total power of the window of signal are, respectively, shown in Fig. 12(a and b).

From careful study of the CDFs the following conclusions can be drawn:

- Only 22% (0.22) of the observations had an attenuation level of the total power of the window of noise less than 70% when using the filtering procedure based on EMD.
- More than 80% (0.80) of the observations had an attenuation level of the total power of the window of noise inferior to 70% when employing wavelets.
- For both methods, over 90% (0.90) of the observations had a total power of the window of signal greater than 70%.
- The investigated wavelets (db2, db3 and db4) had similar performance as they have similar cumulative distribution functions.

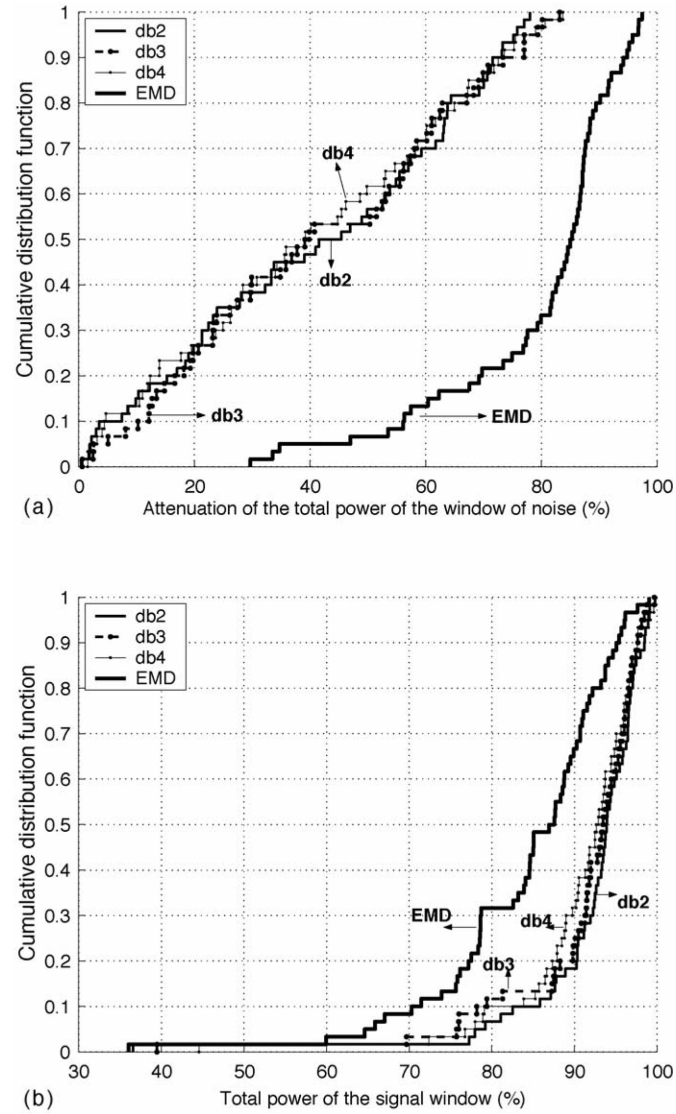

Fig. 12. Cumulative distribution functions for windows of: noise (a) and signal (b).

Our conclusions can be supported by a hypothesis test, that is, the results of this statistical test can confirm whether the cumulative distributions presented in Fig. 8 may be considered significantly different. A suitable test for comparing different distributions of two samples is the Kolmogorov–Smirnov [20]. An attractive feature of this test is that it is independent of the underlying distribution being tested. The null hypothesis for this test is that the two distributions are the same, whereas the alternative hypothesis is that they are different. The result of the test is 1 if the hypothesis that the distributions are the same may be rejected, or 0 if they may not be rejected. Normally, a null hypothesis may be rejected if the test is significant at the 5% level.

The application of the Kolmogorov–Smirnov test to the CDFs shown in Fig. 12(a and b) confirmed the hypothesis that the CDFs obtained from wavelet analysis may be considered the same. This test also showed that those distributions are different from the ones obtained via the EMD method with a significance less than the 5% level.

The results showed also that the reduction level of the total power of the window of noise was superior when employing the filtering procedure based on the EMD. This may be explained by the adaptive nature of the EMD algorithm in contrast to the linear wavelet filters employed in this study. Note that in some applications, for instance, feature extraction, this aspect of the EMD algorithm might be a drawback, as non-linearities are often introduced by noise and could be easily captured by the method.

8. Conclusion

This paper introduced a novel practical procedure for filtering EMG signals based on the Empirical Mode Decomposition. The main advantages of this procedure are that it does not make any prior assumption about the data being analysed, no artificial information is introduced into the filtered signal (e.g. spikes) and that the access to different time-scale components (IMFs) allows for a customized filtering required in different applications. Perhaps the main flaw of this procedure is its empirical nature that is a consequence of the EMD method.

A comparative study between our procedure and a similar algorithm based on wavelets was performed. The results of the analysis of synthetic and experimental signals showed that our method could be successfully applied for attenuation of EMG background activity (noise).

From the analysis of experimental signals we noted that the power of windows of noise could be greatly reduced, whereas the signal energy preserved. The effectiveness of the method for noise reduction was shown by the analysis of the attenuation of the energy of the noise. Furthermore, the distortion of filtered signals was analysed in the time and frequency domains. This analysis showed that the proposed filter is capable of reducing noise activity and preserving signal information.

It was also shown that the different wavelet prototypes investigated in this study (db2, db3 and db4) provide similar results.

The methodology proposed in this work was designed for offline analysis of signals. This is because the estimation of IMFs, as it was described here, requires that all data are available before signal decomposition. Therefore, some variables, such as computation time, were not taken into account in the comparative results. However, the computation of IMFs is a time-consuming process and this is a disadvantage of the proposed technique when compared to wavelets.

Finally, the results and ideas presented in this study are useful for any application that requires the filtering of EMG signals in the pre-processing stage. For instance, studies concerning the decomposition of EMG signals would benefit from a reduction in the background noise activity for a better selection of useful information (e.g. single motor unit action potentials).

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