Denoising of surface EMG with a modified Wiener filtering approach

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**Abstract**

The correlation dimension \( D_2 \) yields good results in several biomedical fields. Nonetheless, no clinical application to electromyography has been developed yet. One reason is the high electromagnetic noise typical of clinical environments. This noise is characterized by sharp spectral lines of variable intensity and frequency. The filtering techniques commonly implemented in electromyographs can efficiently deal with this kind of noise. They allow a safe estimate of linear quantities like the root mean square (r.m.s.) or the median frequency (MF). Their performance is not as good for nonlinear purposes. The filters may modify the nonlinear properties of the signal, leading to unacceptable estimates of \( D_2 \). We consider a simple procedure based on a modified Wiener filter. Its performance is compared with that from a bandpass followed by multiple notch filters. Our procedure leads to a gain in precision and accuracy when estimating \( D_2 \). The two filtering approaches are also compared with respect to a biomedical application proposed by others. Using data from 12 healthy subjects, the modified Wiener procedure raises the percentage of successes in that application from 17% to 83%. New experimental data suggest \( D_2 \) carries information not carried by r.m.s. or MF.

**1. Introduction**

Surface electromyography (sEMG) is by now considered an acceptable aid for kinesiology and for disorders of motor control but not for the diagnosis of neuromuscular diseases (Pullman et al., 2000). For the latter application the American Academy of Neurology explicitly issues a negative recommendation, “based on evidence of ineffectiveness or lack of efficacy” (Pullman et al., 2000). This conclusion was based on a thorough screening of the existing literature, but no study involving chaos and nonlinear theories applied to sEMG was taken into consideration. It is a fact that only a few articles were published concerning chaos and nonlinearity in sEMG, and all of them were in a pre-clinical phase.

Such a situation is odd, because a nonlinear approach could provide a deep insight into the physiology of muscular systems. A nonlinear approach has already been proved to be useful for several physiological systems (Andrzejak et al., 2001; Guevara, 1997; Wang et al., 2004; Small et al., 2002). Although nonlinearity does not necessarily imply deterministic chaos, the mathematical tools developed for the theory of chaotic dynamical systems can be of help. In a field closely related to sEMG, i.e. electroencephalography, good results were obtained for epilepsy (Andrzejak et al., 2006; Elger et al., 2000; Mormann et al., 2003), while in electrocardiography the application of these techniques suggested ways to control arrhythmia (Garfinkel et al., 1992; Ditto et al., 2000).

Although the nonlinear tools are not of common use in the clinical practice yet, some scarce but meaningful results can already be found in the literature. Swie et al. (2005) prove that nonlinear analysis is useful to compare different muscle contraction conditions. A recent work (Meigal et al., 2009) deals with Parkinson’s disease from the point of view of deterministic chaos, and finds that some nonlinear quantities extracted from sEMG, “unlike traditional spectral or amplitude parameters” correlate with the Unified Parkinson’s Disease Rating Scale (UPDRS). These two papers study the same nonlinear quantity we are interested in, i.e. correlation dimension, but other works concern different nonlinear quantities. Good results for the Parkinson’s disease had already been obtained in 2004, showing that the physiological mechanisms are better understood when the usual linear analysis proceeds side by side with nonlinear analysis: "their joint use provides a more complete view of the muscle status than spectral analysis only” (Fattorini et al., 2005). Filligoi and Felici conclude that a nonlinear tool performs better than the power spectrum median frequency (MF) “in detecting sEMG changes determined by brisk transients of force output” (Filligoi and Felici, 1999). Felici also exploits nonlinear methods to study muscle activation and myoelectric fatigue (Felici, 2006). More recently other researchers, dealing with low back pain, find that “entropy reveals properties of the sEMG signal that are not captured by the power spectrum” (Sung et al., 2007); and Morana et al. adopt nonlinear tools “to detect potentiation and to determine the fatigue components” (Morana et al., 2009). Overall,
these successes encourage further research on nonlinear and chaotic behavior in sEMG signals.

At least three reasons can be identified for the scarcity of widespread clinical applications of these results obtained with nonlinear analysis.

First, chaos theory is not easy to apply to experimental data. Several numerical indicators can be calculated from biological signals, e.g. the correlation dimension \( D_2 \) (Grassberger and Procaccia, 1983a,b) or the Lyapunov exponents (Eckmann et al., 1986; Rosenstein et al., 1993; Kantz, 1994; Sbriccoli et al., 2001) or the approximate entropy (Pincus and Goldberger, 1994; Ting Chen et al., 2006), but the calculation is much more complex (Sauer et al., 1991; Abarbanel et al., 1993) than for the usual linear quantities like the root mean square (r.m.s.) or the MF.

Second, if the results have to be of any clinical interest, the sEMG data have obviously to be recorded inside a clinical environment. A clinic or a hospital is usually crowded with electrical supplies. The electromagnetic pollution is inevitably picked up by the sEMG electrodes and wires, and the signal to noise ratio (SNR) is therefore lowered. Situations where SNR = 0.3 or less are not uncommon in our hospital, and the SNR is nonstationary on a time scale of a few minutes. Under these constraints no useful calculation of nonlinear indicators can be performed, as their computation is severely dependent on the SNR and, which is worse, on the noise spectral shape (Theiler and Eubank, 1993; Grassberger et al., 1993; Kantz and Schreiber, 1995; Jaeger and Kantz, 1996; Kostelich and Bergethon, 1995b; Vorst et al., 1995; Theiler et al., 2006) than for the usual linear quantities.

Third, it is clear from the foregoing that the main issue here is proper filtering. The problem is that filters often incorporate some kind of feedback. The most common case is represented by the class of recursive filters. Filters of this kind are commonly implemented in biomedical hardware, including electromyographs. Their presence modifies the degrees of freedom of the whole system (Badii and Politi, 1986; Badii et al., 1988; Mitschke et al., 1988; Mitschke, 1990; Broomhead et al., 1992; Sauer and Yorke, 1993; Theiler and Eubank, 1993). As a result, \( D_2 \) can be significantly altered. The use of this kind of filters should be discouraged for nonlinear applications.

Our opinion is that the scarcity of results for nonlinearity (and possibly chaos) in the sEMG field is due to the combined action of the three above-mentioned reasons. In this paper we consider the sEMG signals from the point of view of nonlinearity and chaos. Our specific aim is to calculate the correlation dimension for a sEMG signal even in a highly noisy clinical environment. We focus on that component of the electromagnetic noise which is similar to the power line, with sharp spectral lines at single frequencies. We show that the signal obtained from an electromyograph, which is notoriously clean enough to provide good estimates of r.m.s. or MF, without post-processing is useless for the estimate of \( D_2 \). We also show that the common forms of filtering implemented in electromyographs, based on highpass, lowpass, and notch filters, are insufficient for at least one biomedical application proposed in the literature (Hu et al., 2005). We also describe a simple denoising procedure, based on windowed Wiener filtering and on the real-time acquisition of the environmental noise via a separate channel. We test this procedure, and we find that it provides more precise results, good enough for the cited biomedical application. As a final remark, we show original experimental data suggesting that \( D_2 \) carries information not carried by, or at least not easily deducible from, the r.m.s. and MF.

Our final aim, which extends beyond the scope of this article, is to smooth the way for more clinical applications of chaos theory to sEMG. We believe that, whenever nonlinear methods are of interest, the peculiar characteristics of the sEMG noise have received an insufficient attention.

2. Methodology

2.1. Basic theory of correlation dimension

As a nonlinear indicator for the sEMG we chose the correlation dimension. The concept was introduced by Grassberger and Procaccia (1983a,b). An exhaustive framework can be found in Abarbanel et al. (1993) or in the classic textbook by Kantz and Schreiber (2005).

In short, the time series \( s_n \), i.e. the electromyogram, is rearranged in a multidimensional phase space, a procedure called “time delay embedding” (Takens, 1981; Casdagli et al., 1991; Sauer et al., 1991). Points \( s_n \) in the phase space are given by:

\[
s_n = (s_{n-(m-1)\tau}, s_{n-(m-2)\tau}, \ldots, s_{n})
\]

where \( m \) is the embedding space dimension and \( \tau \) is the time delay. The subsequent points \( s_n \) in the phase space form a trajectory. The probability for two arbitrary points on the trajectory to be closer than \( \epsilon \) is called correlation sum \( C(\epsilon, N) \) (Grassberger and Procaccia, 1983b; Theiler, 1986), where \( N \) is the number of points \( s_n \) in Eq. (1). The correlation dimension \( D_2 \) is the logarithmic slope of the curve \( C(\epsilon) \) versus \( \epsilon \), according to the usual definition (Grassberger and Procaccia, 1983a,b):

\[
\tilde{D}_2 = \lim_{\epsilon \to 0} \lim_{N \to \infty} \frac{\ln C(\epsilon, N)}{\ln \epsilon}
\]

The actual numerical estimate of \( \tilde{D}_2 \) will be indicated as \( D_2 \) in the following. The choice of \( D_2 \) among other nonlinear quantities will be considered in Section 6.

The embedding procedure of Eq. (1) requires two parameters. The time delay was chosen according to the standard method proposed by Fraser and Swinney (1986). The embedding dimension was chosen according to the “False Nearest Neighbors” method (Kennel et al., 1992; Hegger and Kantz, 1999), anyway the alternative method proposed by Cao (1997) yielded consistent results.

2.2. Noise characterization in clinical environments

Surrounding electronic equipment, engines and lights may give rise to unexpected electromagnetic frequencies in the sEMG signal. Cables, wiring, electrodes and skin itself inevitably pick-up part of the electromagnetic noise. A typical spectrum for the sEMG signal in our hospital is shown in Fig. 1. The spectral lines at 50 Hz and

![Fig. 1. Typical power spectrum for an EMG recorded in a noisy clinical environment. The spectrum is normalized to unity at its maximum peak, therefore arbitrary units (a.u.) are shown for the ordinates. The original periodogram was smoothed with a 100-point Daniell window. The sharp lines occur at 50 Hz and subsequent harmonics, but other frequencies are also visible.](image-url)
subsequent harmonics are evident. Several sharp lines that are not multiple of the power line frequency are also observable. The behavior in Fig. 1 is not exceptional, but rather the norm in several hospitals.

During our recording sessions, the intensity and frequency of the single spectral lines was not stationary. The observed r.m.s. ascribable to the sharp spectral lines varied continuously during the working hours, in a range 0.1–4 times the overall r.m.s. Some spectral lines often vanished and reappeared later, obviously following the activity in the closest departments. The technical European Norms EN 50160 (European Norm EN 50160, 1999) state that the nominal power line frequency must be stable within 1% for at least 95% of the time; anyway the lower and upper limits for the remaining 5% of the time are –6% and 4% respectively. The noise picked up by the electromyograph is the concurrent result of several different electromagnetic sources. The EN 50160 must therefore be regarded as a “best case”, occurring when the noise is due to one electromagnetic source only (i.e. the power line), and no secondary sources are switched on. In our hospital the power line frequency varied within ±0.2%, i.e. 0.1 Hz, within the 24 h. On the time scale of 20 min, the frequency variations were usually one order of magnitude lower. Fluctuations of up to 0.4 Hz during a single measurement session (about 20 min) were not uncommon, including flickering but disregarding microinterruptions. The overall SNR ranged from 0.2 to 3 for sEMG recordings obtained in different days.

In brief we deal with a noise composed by sharp spectral lines, whose frequencies are not necessarily confined to the power line harmonics, and whose intensity is not stationary during time, even during a single sEMG measurement session. In this paper we disregard other sources of noise, which can anyway be treated with other techniques.

2.3. Choosing the filtering criteria

The sEMG signals are affected by several different kinds of noise, and extensive research on sEMG has by now provided efficient filtering techniques for the estimate of the r.m.s. or MF. However, great care should be applied when a nonlinear approach is taken. For example, methods referable to autocorrelation techniques may lead to spurious results, and an alteration of the spectral shape may overwhelm the chaotic properties of the signal (Theiler and Eubank, 1993). Any recursive approach should be thoroughly evaluated, because it could be a source of chaotic behavior itself. In fact, several time series commonly used as a workbench for chaos theory are defined as recursive maps, like the well known Hénon, logistic, Ikeda, or Baier and Klein maps. Generally speaking, filtering can mimic low-dimensional chaotic behavior (Rapp et al., 1993), thus spoiling the determination of the original D2.

Apart from the usual linear techniques, several methods have been developed to reduce noise in chaotic time series data (Kostelich and Schreiber, 1993; Schreiber and Grassberger, 1991; Sauer, 1992; Cawley and Hsu, 1992; Grassberger et al., 1993). An updated survey can be found in Kantz and Schreiber (2005). All of these methods take a generic approach, and although they have never been explicitly customized for the case of sEMG they can indeed be applied.

Our filtering procedure will be described in 2.4. It is not alternative, but rather complementary, to these linear and nonlinear techniques. Its aim is to reconstruct the original sEMG signal, trimming the electromagnetic environmental contributions, but in such a way to preserve the nonlinear properties. This environmental part of the noise is considered in details in the following paragraph. The reduction of the other contributions to noise is not considered in this paper, because the general techniques cited above are already well described in the literature.

2.4. Filtering techniques

With these considerations in mind, we decided to compare the performance of two different filters. The first, described in Section 2.4.1, is representative of the common approach to sEMG filtering. This filter works very well for the estimate of r.m.s. and MF, i.e. the conventional quantities estimated in clinical electromyography. Its performance has never been tested for nonlinear applications. The second, described in Section 2.4.3, is our modification of a Wiener filtering technique, customized for noisy sEMG in the case of nonlinear applications.

2.4.1. Bandpass and notch (BPN)

The lowpass filtering of sEMG signals has become common practice, as components over 400–500 Hz are considered irrelevant (van Boxtel, 2001; Merletti, 1997). In nonlinear applications it has been found that, if the high frequencies are not wiped off, the estimate of D2 is useless for distinguishing different muscular patterns (Hu et al., 2005). The low frequencies in the sEMG might carry useful information, but some highpass filtering is needed to cancel the artifacts due to the small movements, either of the patient or of the electrodes. What is usually intended by “sEMG signal” in clinical studies is therefore that portion of the sEMG ranging from about 10 Hz to 400–500 Hz. In addition, in order to eliminate the power line frequency, one or more notch filters are commonly used.

The filter implementation reported by Mello et al. (2007) was identified as a convenient standard implementation of this kind of filtering in sEMG. The filter is composed by a Butterworth second order highpass filter, a Butterworth eighth order lowpass filter, and six second order notch filters. The cutoff frequencies are 10 Hz for the highpass, 400 Hz for the lowpass. The six notch filters were customized for the European power line frequency, considering the first six harmonics from 50 Hz up to 300 Hz, width 2 Hz. The filter was applied forward and backward. Mello and colleagues report that “the filter effectively removed the mains noise components, with attenuations greater than 96.6%”.

This filter will be referred in the following as “BPN” (BandPass and Notch).

2.4.2. Wiener filtering for sEMG

Wiener filtering is a well known linear technique (Wiener, 1964). Basically it consists of a Fourier filter in the frequency domain, where the original Fourier coefficients are rescaled according to the ratio between the expected signal spectrum and the actual spectrum. A measured signal z in the time domain is considered as the linear superposition of one desired component x (true signal to be recovered) and one undesired component y (noise). The best estimate of the desired signal can then be obtained in the frequency domain by:

\[
\begin{align*}
\hat{x} &= W \cdot z \\
W &= S_x / S_z
\end{align*}
\]

where X and Z are the frequency domain representations of x and z, respectively, \(\hat{x}\) is the best estimate of \(X\), W is the Wiener filter, \(S_x\) and \(S_z\) are the power spectra of x and z. A convenient way to compute \(S_x\) and \(S_z\) is via the Fourier transform of the autocorrelation function. The explicit form for W given in Eq. (3) results from a least-squares minimization of the distance between \(X\) and \(\hat{X}\) and Eq. (3) holds if x and y are statistically independent.

A Wiener filter is typically applied when the noise spectrum is known, or it is easily identifiable. One remarkable case is when
the noise is due to the power line. Kantz and Schreiber (2005) report a successful application of this technique for the nonlinear analysis of the output of electrical amplifiers.

In its usual form the Wiener filter cannot be always profitably applied to the sEMG for nonlinear purposes for two reasons.

First, as described in Section 2.2, the noise we deal with is nonstationary. The frequency of some spectral lines is not known and varies even within a single recording session (except obviously for the constant presence of the 50 Hz frequency and its harmonics, which nonetheless may vary in intensity).

Second, when the noise spectrum for the Wiener filter is unknown, it is usually extracted from the noisy signal spectrum by a smoothing procedure. For example Kantz and Schreiber (2005), in presence of a 50 Hz contamination, suggest to “construct a filter by interpolating between the adjacent unaffected frequency bins”, in order to proceed with a Wiener filter. Such an interpolation, that is a smoothing procedure, is difficult when multiple lines are crowded as in Fig. 1. The problem is worsened by the fact that the main 50 Hz frequency and its first three harmonics fall inside a spectral zone where a high component of the sEMG signal is expected (van Bostel, 2001). An interpolation may also be misleading for the sEMG signals. The sEMG spectrum has not a smooth single peak behavior (Lindstrom et al., 1970; Hägg, 1992; Farina and Merletti, 2001). This is mainly a consequence of the motor unit firing statistics and of the shape and distance of the electrodes. It has not been studied yet how these characteristics of the spectrum affect the estimate of $D_2$, or of other nonlinear quantities. A blind smoothing or interpolation of the sEMG spectrum in order to identify the noise components is therefore hazardous.

2.4.3. Wiener noise reconstruction (WNR)

Altogether, the two previous considerations led us to adopt the following filtering procedure. While the SEMG signal $S$ is acquired, a second signal $N$ is also acquired from a second channel of the electromyograph, short-circuited on a small resistor (details in Section 3). The first signal $S$ is regarded as the superposition of a true sEMG signal $S_{\text{true}}$, a random noise component $S_{\text{rnd}}$, and a noise component $S_{\text{pow}}$ similar to the power line but composed by more spectral lines. The second signal $N$ is regarded as raw noise, composed by a random component $(N_{\text{rnd}})$ and a series of sharp spectral lines $N_{\text{pow}}$:

\[
\begin{align*}
S &= S_{\text{true}} + S_{\text{rnd}} + S_{\text{pow}} \\
N &= N_{\text{rnd}} + N_{\text{pow}}
\end{align*}
\]

The hypothesis that $S_{\text{pow}}$ is locally proportional to $N_{\text{pow}}$ is then made. The power spectrum of $N$ is computed, and the spectral components whose intensity is above a given cutoff are identified. The actual choice of the cutoff is easy, because the spectral lines emerge sharply from the power spectrum of $N$. A Wiener filter is then applied to $N$, with the aid of its trimmed power spectrum, so that an estimate $N'_{\text{pow}}$ of $N_{\text{pow}}$ is obtained. The linear regression of the original noisy signal $S$ versus $N_{\text{pow}}$ is computed, according to the model:

\[
S = \alpha + \beta N_{\text{pow}}
\]

The residuals, i.e.:

\[
S' = S - \alpha - \beta N_{\text{pow}}
\]

are retained as the best estimate of the original sEMG signal.

This entire procedure is applied by a moving window. With our sampling frequency of 5000 samples/s, the choice of windows 1024 samples wide, and with an overlapping of 50% between two subsequent windows, gives the best results. In the overlapping zones, the mean value from the two windows is assumed as best value. The windowing is necessary due to the nonstationarity of the noise, specifically of its $N_{\text{pow}}$ component.

This filter will be referred in the following as “WNR” (Wiener Noise Reconstruction).

3. Subjects and experimental setup

With the aim to compare the two procedures described in Sections 2.4.1 and 2.4.3, an electromyogram from 12 healthy subjects (6 males and 6 females), age 40–65, was recorded. The electromyograph was a BioEMGCSTM II (BioResearch Associates, Inc.) with BioFLEXSTM no-gel EMG electrodes by the same farm. A 16-bit USB A/D board (USB1608FS, Measurement Computing) acquiring at 5 kHz was used to digitize the signals. Acquisition was performed in differential mode. After cleaning the skin with water and pure alcohol, the two main electrodes were placed over the abductor digiti minimi manus, with an inter-electrode distance of 0.4 cm. The reference electrode was placed over the forearm, one palm proximal from the wrist. Each electromyogram corresponded to a single non-fatiguing abduction of the finger, lasting 12 s. The muscular contraction varied from 1% to 10% of the maximum voluntary contraction. Each sEMG was recorded in a clean room, several kilometers far away from any active power line source. The entire instrumentation was powered by an autonomous battery. The electromyograph, the acquisition board and the portable computer were connected to the same common ground in order to provide a stable reference path. The resulting sEMG signal was therefore very clean, with none of the spectral lines visible in Fig. 1. This clean signal will be referred to as $S_0$.

Separately, on the same day, an electromyogram was recorded from each of the 12 subjects in our hospital, during ante meridian working hours. The other experimental conditions were the same as before, but an additional signal was recorded from the electromyograph, short-circuiting the two electrodes through a 71 kΩ resistor. The reference electrode for this additional channel was directly connected to one of the main electrodes. Placing the electrodes of the additional channel over the contralateral muscle and keeping the contralateral muscle at rest during the recording did not lead to a significant improvement in the final results. The sEMG signal from the first channel was discarded. The signal from the additional channel was kept, and will be referred to as $N_0$ in the following.

The sum $(S_0 + N_0)$ for each subject was considered as a simulation of an actual sEMG signal recorded in a noisy environment, i.e. in reference to Eq. (4) it was assumed that:

\[
\begin{align*}
S &= S_0 + N_0 \\
N &= N_0
\end{align*}
\]

In this way the nonlinear properties of the clean signal $S_0$ can be estimated a priori. The $D_2$ calculated for $S_0$ can be used as a target value, with which the results of either BPN or WNR on $S$ can be compared. Over the pool of the 12 subjects, the $S_0/N_0$ ratio varied from 1 to 0.3.

4. Data analysis

Four $D_2$ were computed for each subject: one for the original clean signal $S_0$ ($D_2(S_0)$), one for the noisy signal $S$ of Eq. (7) ($D_2(S)$), one for $S$ after filtering with WNR ($D_2(WNR)$), and one for $S$ after filtering with BPN ($D_2(BPN)$). Prior to the computation of $D_2$, each signal was cut with a second order highpass Butterworth filter, cutoff 10 Hz, and an eight order lowpass Butterworth filter, cutoff 400 Hz.

The original $D_2(S_0)$ was kept as a reference. The statistical comparisons concerned the difference between the filtered signal and the reference:
\[
\begin{align*}
\Delta D_2(BPN) &= D_2(BPN) - D_2(S_0) \\
\Delta D_2(WNR) &= D_2(WNR) - D_2(S_0) \\
\Delta D_2(S) &= D_2(S) - D_2(S_0)
\end{align*}
\]

The time delay \( \tau \), the false nearest neighbors and the correlation dimension \( D_2 \) were computed with the Visual Recurrence Analysis (VRA) package by Belaire-Franch and Contreras (2002). The calculations for the method of Cao and for the filter described in Section 2.4.1 were performed using Matlab\textsuperscript{6} (version 5.3.1, The MathWorks Inc., Natick, MA, USA). The filter described in 2.4.3 and the statistical comparisons made use of the R package (R Development Core Team, 2006).

5. Results

Table 1 reports the \( D_2 \) computed for each subject. The first column \( D_2(S_0) \) works as an expected value. The second column reports the \( D_2 \) from the noisy signal, without filtering. All values are higher than in the first column, which is consistent with the presence of noise. The last two columns show the effect of filtering, respectively with WNR or BPN.

Fig. 2 graphically shows the relative gaps \( \Delta D_2(S) \), \( \Delta D_2(BPN) \) and \( \Delta D_2(WNR) \) for each of the 12 subjects. When only the bandpass is applied (\( \Delta D_2(S) \)), the gap is too high to be of any practical use \((\text{mean } \pm \text{sd} = 4.0 \pm 2.3)\). On the contrary, neither \( \Delta D_2(BPN) \) nor \( \Delta D_2(WNR) \) are statistically different from 0 (coupled t-Student test, \( p\)-level \( < 0.001 \)). Therefore the estimate of \( D_2 \) with WNR leads to a higher precision than with BNP.

In one biomedical application (Hu et al., 2005) considered in more details in the Section 6, an error \( |\Delta D_2| \approx 0.40 \) can be assumed as the limiting threshold, above which a limb prosthesis based on \( D_2 \) could not be reliably used. The actual situation is shown in Fig. 3, where \( |\Delta D_2(BPN)| \) and \( |\Delta D_2(WNR)| \) are compared. The two variances for \( |\Delta D_2(BPN)| \) and \( |\Delta D_2(WNR)| \) are statistically different \((F = 4.95, p\text{-level} < 0.01)\).

Assuming a binomial model, we can consider as a “success” for the cited biomedical application each case in Fig. 3 where \( |\Delta D_2| \leq 0.40 \). The percentage is 10 out of 12 (83%) for WNR, 2 out of 12 (17%) for BPN. The null hypothesis (percentage of success equal to 50%) is rejected in both cases \((\text{exact Fisher solution for the contingency tables, } p\text{-level} < 0.001)\). The performance is therefore remarkably better with WNR than with BPN. The percentage of successes for the simple bandpass, without BPN or WNR, is 0 out of 12. Clearly the usual choice of a simple bandpass is not an efficient choice. It should never be adopted for the computation of \( D_2 \).

Fig. 4 reports the average r.m.s., MF and \( D_2 \) during a progressive load of the biceps brachii. The average is computed over 10 trials.

![Fig. 2. Gaps \( \Delta D_2(S) \) (triangles), \( \Delta D_2(BPN) \) (empty squares) and \( \Delta D_2(WNR) \) (filled squares) between the computed and the expected \( D_2 \), for each of the 12 subjects. The connecting lines are only meant as a visual aid.](image1)

![Fig. 3. Absolute gaps \( |\Delta D_2(BPN)| \) and \( |\Delta D_2(WNR)| \). The threshold value for the prosthetic application hypothesized by Hu et al. (2005) is 0.40. Beyond this value the computed \( D_2(S) \) might be assigned to the wrong cluster (see text).](image2)

![Fig. 4. MF (descending line), r.m.s. (ascending line) and \( D_2 \) (filled squares) normalized to unity with reference to their maximum (w.r.t.m.). On the right side the absolute scale for \( D_2 \) is also shown. The normalization maxima are 204.3 µV, 98.3 Hz and 8.9 for the r.m.s., MF and \( D_2 \) respectively. A sudden jump in the \( D_2 \) values and in their first derivative is clearly identifiable, and time is shown relative to this jump.](image3)
from the same subject, with 10 min of rest between two successive trials. Throughout each trial the forearm is maintained at 90 deg with respect to the biceps, while the applied load varies linearly from 1 kg to 11 kg. All the other experimental conditions are as described above. Each experimental point is calculated over a time window of 4 s. We took care of the (slight) nonstationarity using the “over-embedding” technique (Hegger et al., 2000). In each single trial (not shown here) a discontinuity in the $D_2$ behavior can be easily detected; the discontinuity is taken as a reference point ($t = 0$ s) to build up the average shown in the graph. Accordingly, the abscessiae report time relative to the discontinuity point. In correspondence to $t = 0$ s neither the r.m.s. nor the MF exhibit an evident marker. Graphs similar to Fig. 4 were obtained both with very clean data and with the WNR denoising procedure. In several trials, when the sEMG was recorded in a normal clinical environment, the noise prevented from computing $D_2$. If a BPN filter was then adopted, the discontinuous behavior often blurred, so that the final average could not be computed.

6. Discussion

Several different nonlinear tools can be exploited to study sEMG clinical applications. Among these tools, we chose $D_2$. Four reasons led to identify $D_2$ as a good nonlinear descriptor for electromyography. First, it is a convenient single-number summary of the entire electromyogram, like the r.m.s. or the MF. Second, $D_2$ is a nonlinear quantity, and its information content is intrinsically different from the information carried by the r.m.s. and the MF. That is, $D_2$ deals with aspects of the muscular behavior which are not usually considered. Third, $D_2$ is a “correlation” dimension, in that it discloses some aspects of correlation among data beyond the simple measures of linear correlation. In some cases a small $D_2$ hints that deterministic low dimensional chaos is present. Anyway, this is not a sufficient condition (Provenzale and Osborne, 1990; Rapp et al., 1993), and great care should be exerted before claiming that data show a chaotic behavior. Fourth, some interest was shown in the past for the application of the correlation dimension (or its mathematical precursor, the correlation sum) to sEMG (Stylianou et al., 2005; Hu et al., 2005; Padmanabhan and Pattusserypady, 2004), but the high dispersion of the results seemed to hamper the development of clinical applications.

Having identified $D_2$ as the nonlinear quantity of interest, the main problem becomes the determination of the maximum acceptable error $\Delta D_2^{\text{mis}}$. Obviously, $\Delta D_2^{\text{mis}}$ depends on the muscular physiological behavior and on the specific clinical application. As the research on the nonlinear properties of sEMG is still at its beginning, a general term of comparison is still lacking. We have to point out that, after more than 20 years of research on the correlation dimension, no standard clinical application for electromyography has been developed yet. Either $D_2$ is of no use in this field or its usefulness has been masked by an insufficient attention to noise. We incline to the second hypothesis.

A term of comparison of biomedical interest can be obtained from the work of Hu et al. (2005). Hu and colleagues use the $D_2$ from sEMG signals to distinguish between forearm supination and pronation. They find that the $D_2$ values split up into two clusters, with a cluster-to-cluster distance of 0.87. In their case, the problem is to assign a new estimate of $D_2$ to its correct cluster. Assuming gaussian distribution, given the standard deviations for each cluster, the threshold where the probabilities of assignment to the respective cluster are equal is $\Delta D_2 = 0.36$ from the center of the nearest cluster. This value is not far from the half distance 0.43, and to analyze Table 1 we used $\Delta D_2^{\text{mis}} = 0.40$ as a convenient order of magnitude. When $\Delta D_2$ is higher than this value, it may happen that a new measurement of $D_2$ is assigned to the wrong cluster. Our results (Table 1, Fig. 3) show that, when WNR is used, $\Delta D_2$ is sufficient for this clinical application. On the contrary, the $D_2$ computed with BPN does not yield satisfactory results. When only a simple bandpass is used, the $D_2$ is affected by a high dispersion, and it is completely useless.

Apart from that, the spreading of $D_2$ is lower with WNR than with BPN. This is a more general result, not depending on the specific biomedical application. Therefore WNR should be preferred to BPN, although its implementation is slightly more difficult, whenever the $D_2$ is the quantity of interest and the noise content of the sEMG is high.

Fig. 4 is shown as a further indication that $D_2$, in presence of a proper filtering, can be exploited for sEMG physiological studies. The estimated correlation dimension abruptly changes its slope at $t = 0$ s, and a gap is also detectable. Nothing comparable happens for the r.m.s. and the MF. This behavior suggests that the $D_2$ carries some information that is not carried by the two linear quantities, or at least is not immediately deducible from them. Of course Fig. 4 is a preliminary result: more experimental data and more statistics are needed to confirm this behavior, and to find an explicit correlation with muscular physiology. Anyway, if we could prove that the $D_2$ computed for sEMG preserves the mathematical properties of $D_2$, an interpretation of Fig. 4 in terms of order and synchronism of motor units would be straightforward. We have already considered this problem, on an experimental basis, and the results will be described in a following paper. What we are interested in here is that either a proper filtering or very clean data are needed. Noisy data taken in clinical environments, as shown before, raise the variability of $D_2$. The result is that no discontinuity of behavior can be safely identified anymore. Together with the recent literature cited in Introduction, this new result hints that the correlation dimension is a promising tool for sEMG studies, but it is easy to forecast that no sound conclusion will be drawn in this field until a correct filtering is adopted.

Throughout this paper we focus on that specific part of the noise that is composed by sharp spectral lines and is nonstationary. This noise is highly correlated. A certain amount of random noise typically increases the estimate of $D_2$ (Schreiber, 1993), whereas correlated noise (like our $N_{\text{corr}}$) greatly affects any estimate of $D_2$ in complicated ways, difficult to foresee, especially if the noise is nonstationary (Kantz and Schreiber, 1995; Schreiber and Kantz, 1995).

Therefore the kind of noise we are considering is particularly dangerous for $D_2$. Several techniques have been developed to eliminate the power line frequency. All of them suffer from potential drawbacks when the $D_2$ must be estimated from the filtered signal. Adaptive filters are briefly considered by Levkov et al. (2005). We agree that “Adaptive filtering introduces unacceptable transient response time”, and this is particularly true for short time series like those of interest in sEMG. Such a response time is equivalent to a temporary parameter drift of the system, and the delay embedding of deterministic systems with a parameter drift poses additional problems (Kantz and Schreiber, 2005). Notch filters have the same disadvantage, and to be effective they require a bandwidth of at least 1 Hz, thus covering only 95% of the fluctuations (European Norm EN 50160, 1999). They therefore tend to unnecessarily cut too much of the signal. As noted by Clancy et al. (2002) for sEMG, “notch filtering... will remove signal as well as power line components, altering the spectral content and rotating the phase of the recorded EMG”. Kalman filters provide a good performance, and can be extended to the nonlinear case (Walker, 1998). Anyway Budhiraja et al. (2007) show that, in nonlinear settings or when the SNR is particularly low, “an extended Kalman filter... can perform quite poorly”. A spectrum interpolation can be used (Mewett et al., 2004), and it gives good results for the estimate of the r.m.s. or the MF. In 2.4.2 we have already explained why we consider
hazardous this technique, in the nonlinear case. The “subtraction method” described by Levkov et al. (2005) for electrocardiography can be very effective, but it relies on the identification of “segments with frequency bands near zero” in the signal. No such segments are available in the sEMG, and the additional acquisition channel described in 2.4.3 is an attempt to provide a surrogate. The “Baseline noise spectrum subtraction” reported by Baratta et al. (1998) is an approach similar to ours, but it assumes constant power line noise, which is not applicable in our case. It also requires “a rest or silent period of little or no muscle activity”, which is equivalent to the segments cited from Levkov et al. (2005).

More generally, some doubt can reasonably be raised for any conceivable filtering technique, ours included. The performance depends both on the kind of noise and on the quantity to be estimated. Different filters can be of use for different situations. Therefore, the good performance of even well-known filters should not be taken for granted when a nonlinear application is of interest. That is why we considered mandatory to explicitly test our procedure against the estimate of $D_2$.

7. Conclusions

In this paper we deal with the estimate of the correlation dimension $D_2$ for noisy sEMG signals. We compare two filtering procedures, BPN and WNR. WNR leads to a lower dispersion of $D_2$ with respect to the expected value. Therefore a gain in precision is achieved. Taking as a reference the requirements of one specific biomedical application, the accuracy obtained with WNR is sufficient for the application, whereas it is not with BPN. The higher dispersion of data and the lack of accuracy resulting from an insufficient or inappropriate filtering may have discouraged in the past further research on the nonlinear analysis of the sEMG signals. Although the WNR procedure is slightly more difficult to apply than other techniques, we suggest that it is used as a pre-filtering technique for sEMG, whenever $D_2$ is the quantity of interest and the electromyogram is recorded in clinical conditions, with high electromagnetic noise. Other nonlinear techniques can always be applied as a post-filtering, to improve the accuracy of $D_2$.

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References


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