EMG Signal Smoothing Using Singular Spectrum Analysis

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Abstract

The application of Singular Spectrum Analysis (SSA) to the smoothing of electromyographic (EMG) signals represents an alternative to the use of traditional filtering and averaging methods. SSA is a non-parametric technique that decomposes original time series into set of additive time series each of which can be easily identified as being part of the noise present in the acquired signal. The procedure for EMG signal filtering is compared to a classical approach based on the Butterworth filter. The obtained results show that SSA can be successfully and easily applied in practice to EMG signal smoothing.

1. Introduction

Surface electromyographic (EMG) signal is one of the most important biological signals which directly reflect human muscle activities since it is generated when the muscle contract. Unfortunately, EMG signals are corrupted by noise, which may be generated by different sources, such as the hardware employed for signal amplification and digitization, the movement of electrodes, cables and connectors during data collection arising from the movement of the subject and the activity of motor units distant from the detection point [1-7].

In addition, cross-talk, which refers to a signal contribution originating from other muscles, can interfere with the EMG signal of the muscle under investigation [1-7]. Depending on the size and thickness of the muscle, crosstalk can be more or less problematic. Regarding on which muscles are investigated with surface EMG, also ECG contamination can be significant [1-2]. Moreover, external sources may cause deterministic contaminations of varying frequency content (best known is the 50 or 60 Hz interference from the electric mains). Specially at low contraction levels, the noise contribution in the signal can be relatively large and limit the precision of EMG amplitude estimates [1-3].

Contamination of the EMG signal can be reduced by filtering or smoothing. Namely, in most biomechanics studies the raw EMG signals are rectified and low pass filtered or averaged, in order to obtain the so called 'envelope EMG'. The choice of the smoothing filter parameters should take into account the frequency content of the desired information.

The filtering and smoothing of EMG signals has been extensively treated in the literature [1-8]. Traditional filtering techniques include Digital Butterworth filters, and filters based on spectral analysis [1-2]. Recently, advanced filtering techniques like the low-pass differential (LPD) filter [3], Discrete Wavelet Transforms [5-6], the Wiener Filter [7] and Empirical Mode Decomposition [8] have been used. Nonetheless, the drawback in these cases is the complexity of devising an automatic and systematic procedure. A mother wavelet function must be selected when using Discrete Wavelet Transforms and the filtering function parameters must be chosen when using the Wiener Filter.

The goal of this paper is to demonstrate the advantages of smoothing methods based on Singular Spectrum Analysis (SSA). SSA is a non-parametric technique that decomposes an original time series into a number of additive time series each of which can be easily identified as part of the noise present in the acquired signal. This work presents a heuristic smoothing procedure for processing EMG signals based on SSA. The SSA decomposition produces several independent components in the frequency domain. The proposed procedure eliminates the noise present in the signal in a simple and intuitive way.

2. Singular Spectrum Analysis

Singular spectrum analysis is a novel non-parametric technique of time series analysis based on principles of multivariate statistics. It decomposes a given time series into an additive set of independent time series. The set of series resulting from the decomposition can be interpreted as consisting of a trend representing the signal mean at each instant, a set of periodic series, and an aperiodic noise [9]. The original application of SSA was to extract trends from climatic and geophysical time series [10] and to identify periodic motion in complex dynamical systems [11-12]. SSA has also been applied to the diagnosis of machine failures using vibration signals [13] and to

EMG-onset detection using SSA-based change-point analysis [14].

The SSA method builds a Hankel matrix, called the trajectory matrix, from the original time series in a process called embedding. This matrix consists of vectors obtained by means of a sliding window that traverses the series. The trajectory matrix is then subjected to a singular value decomposition (SVD). The SVD decomposes the trajectory matrix into a sum of unit-rank matrices known as elementary matrices. Each of these matrices can be transformed into a reconstructed time series. Elementary matrices are no longer Hankel matrices, but an approximate time series may be recovered by taking the average of the diagonals (diagonal averaging).

The resulting time series are called principal components [9]. The sum of all the principal components is equal to the original time series. The objective is to obtain a frequency decomposition of the original signal in which the latent low-frequency signal (EMG amplitude) can be detected in a simple fashion. The SSA decomposition algorithm will be described in the following. A more detailed explanation may be found in Golyandina et al. [9].

The above description of SSA may be expressed in formal terms as follows:

Step 1. Embedding

Let $\mathbf{F} = (f_0, f_1, \ldots, f_{N-1})$ be the length N time series representing the original signal. Let L be the window length, with $1 < L < N$ and L an integer. Each column of the Hankel matrix corresponds to the "snapshot" taken by the sliding window:

$$\mathbf{X}_j = (f_{j-1}, f_j, \ldots, f_{j+L-2})^T,\ j = 1, 2, \ldots, K,$$

where $K = N - L + 1$ is the number of columns, i.e., the number of different possible positions of the said window. The matrix $\mathbf{X} = (\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_K)$ is a Hankel matrix since all elements on the diagonal $i+j$ = *constant* are equal. This matrix is sometimes referred to as the trajectory matrix. The form of this matrix is:

$$\mathbf{X} = \begin{pmatrix} f_0 & f_1 & \cdots & \cdots & f_{N-L} \\ f_1 & f_2 & \cdots & \cdots & f_{N-L+1} \\ \vdots & \vdots & \ddots & \cdot^{\cdot^{\cdot}} & \vdots \\ f_{L-2} & f_{L-3} & \cdot^{\cdot^{\cdot}} & \ddots & f_{N-1} \\ f_{L-1} & f_{L-2} & \cdots & \cdots & f_N \end{pmatrix} \quad (1)$$

Step 2. Singular value decomposition (SVD) of the trajectory matrix.

It can be proven that the trajectory matrix (or any matrix, for that matter) may be expressed as the summation of d rank-one elementary matrices $\mathbf{X} = \mathbf{E}_1 + \mathbf{E}_2 + \ldots + \mathbf{E}_d$, where d is the number of non-zero eigenvalues in decreasing order $\lambda_1, \lambda_2, \ldots, \lambda_d$ of the $L \times L$ matrix $\mathbf{S} = \mathbf{X} \cdot \mathbf{X}^{\mathbf{T}}$. The elementary matrices are given by $\mathbf{E}_i = \sqrt{\lambda_i}\mathbf{U}_i \cdot \mathbf{V}_i^{\mathbf{T}}$ $i = 1, 2, \ldots, d$, $\mathbf{U}_1, \mathbf{U}_2, \ldots, \mathbf{U}_d$ are the corresponding eigenvectors, and the vectors $\mathbf{V}_i$ are obtained from $\mathbf{V}_i = \mathbf{X}^{\mathbf{T}} \cdot \mathbf{U}_i / \sqrt{\lambda_i}$ for $i = 1, 2, \ldots, d$. The contribution of the first elementary matrices $\mathbf{E}_i$ to the norm of $\mathbf{X}$ is much higher than the contribution of the last matrices. Therefore, it is likely that these last matrices represent noise in the signal. The plot of the eigenvalues in decreasing order is called the singular spectrum, and gives the method its name.

Step 3. Reconstruction (diagonal averaging)

At this step, each elementary matrix $\mathbf{E}_i$ is transformed into a principal component of length N by applying a linear transformation known as diagonal averaging or Hankelization. The elementary matrices are not themselves Hankel matrices, so that to reconstruct each principal component the average along the diagonals $i + j$ = *constant* is calculated. The diagonal averaging algorithm [9] is as follows:

Let $\mathbf{Y}$ be any of the elementary matrices $\mathbf{E}_i$ of dimension $L \times K$, the elements of which are y_{ij}, $1 \le i \le L, 1 \le j \le K$. The time series $\mathbf{G}$ (principal component) corresponding to this elementary matrix is given by:

$$g_k = \begin{cases} \dfrac{1}{k+1} \sum_{m=1}^{k+1} y_{m,k-m+2} & \text{for } 0 \le k < L^* - 1 \\ \dfrac{1}{L^*} \sum_{m=1}^{L^*} y_{m,k-m+2} & \text{for } L^* - 1 \le k < K^* \\ \dfrac{1}{N-k} \sum_{m=k-K^*+2}^{N-K^*+1} y_{m,k-m+2} & \text{for } K^* \le k < N \end{cases} \quad (2)$$

Where $L^* = \min(L, K)$, $K^* = \max(L, K)$ and $N = L + K - 1$.

It can be shown that the squared norm of each elementary matrix equals the corresponding eigenvalue, and that the squared norm of the trajectory matrix is the sum of the squared norms of the elementary matrices [9]. The largest eigenvalues in the singular spectrum represent the large amplitude components in the decomposition. Contrariwise, the low–amplitude noise components of the signal are represented in the singular spectrum by the smallest eigenvalues.

3. Methods

To test the performance of the SSA smoothing method, a raw acquired EMG signal was smoothed using the SSA algorithm implemented in Matlab 6.1 (Mathworks, Inc.).

Standard passive surface electrodes (B&L Engineering) were used for signal detection from the Biceps Brachii, which is a very superficial muscle. The skin was abraded and cleaned with alcohol and then electrodes were positioned in the direction of muscle fibres, in the middle zone of the muscle, far from innervated and tendinous zones (see Figure 1). The Biceps Brachii muscle was activated by a contraction during weightlifting of a 2.5 kg weight in a movement confined into the sagittal plane. The captures were performed in a movement that comprises several weightliftings. EMG signals were differentially amplified via a commercial amplifier (B&L Engineering).

EMG signal was collected by means of Tektronix TDS1002B and its software Tektronix TDS1002B which permits the acquisition of the data and screen captures of the recorded signal. This software allows the exportation of the data to the PC to be treated. The SSA algorithm was implemented in MATLAB.

The acquisition process was completed using a motion capture system to compare and relate, in future works, the smoothed EMG signal and the muscle excitation-activation signal obtained by means of an inverse dynamic analysis. The movement acquisition was performed using 3 OptiTrack FLEX:V100R2 cameras and the data collected was processed with the ARENA Motion Capture software.

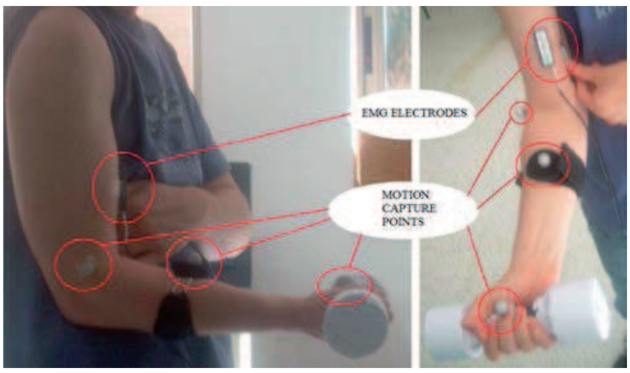

Figure 1. *EMG electrodes distribution.*

4. Results

The trajectory matrix of the EMG signal was generated by sliding a window of 10 elements in length. The plot of the eigenvalues of the matrix **S** (Singular Spectrum) is plotted in Figure 2. This figure shows that the contribution of the first eigenvalue to the norm of the trajectory matrix is much higher than the contribution of the rest. In fact, 61.09% of the norm of **X** is contributed by the first two eigenvalues, whereas the rest are much lower and vary slightly. This fact usually indicates that these last eigenvalues represent noise, or at least a non-periodic component without any latent structure as indicated by Golyandina et al. [9].

Figure 3 shows a graphical representation of the correlation matrix corresponding to the decomposition obtained. Cell *ij* represents the correlation between principal components *i* and *j*, gray-scale coded from black for *0* (no-correlation) to white for *1*.

It has been pointed out that the signals reconstructed using one elementary matrix at a time are called principal components. The first five principal components for the case under analysis are plotted in Figure 4. It is clear from the figure that the first leading component represent the main trend (note that the vertical axis is scaled differently for each component), whereas the next four components represent noise. The approximated reconstruction will then be carried out using the first principal component. The reconstructed signal is plotted in Figure 5(c) along with the original raw signal.

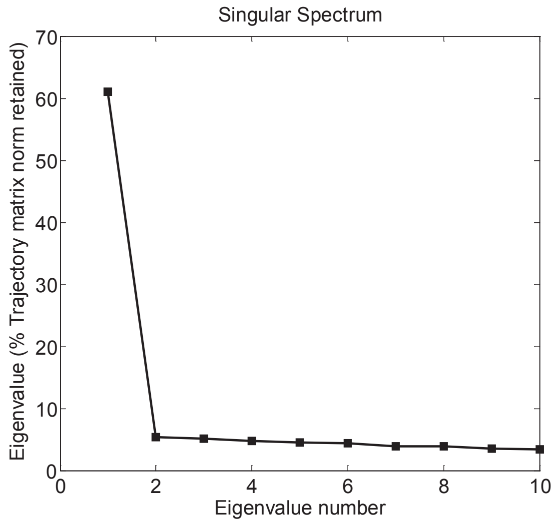

Figure 2. *Singular spectrum of EMG signal obtained using a window length L = 10.*

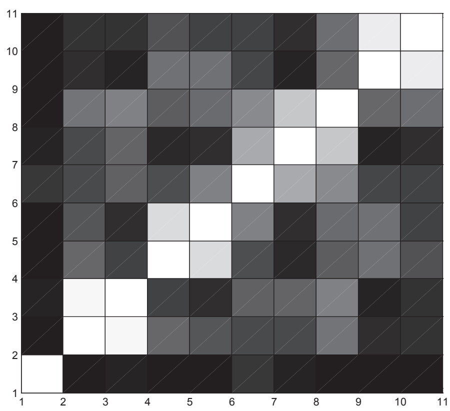

Figure 3. *Correlation matrix of the obtained decomposition.*

Finally, the original raw signal was passed through a second-order Butterworth filter with a 4 Hz cut frequency. The superiority of SSA is particularly relevant in the elimination of the so-called end-point errors, as seen in Figure 5. Methods based on signal extension have been proposed to reduce end-point error. No extension is necessary in the case of SSA smoothing. Errors due to this phenomenon are negligible.

5. Conclusions

This paper introduces a novel practical procedure for smoothing EMG signals based on the Singular Spectrum Analysis decomposition. The main advantages of this procedure are that it does not make any prior assumption about the data being analyzed, no artificial information is introduced into the filtered signal and that the access to different time-scale components (principal components) allows for a customized filtering required in different applications.

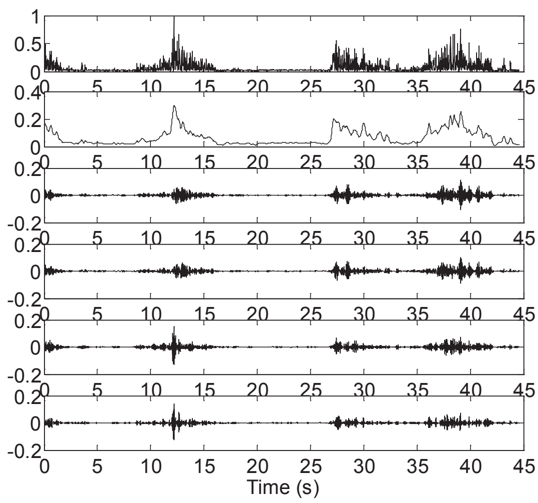

Figure 4. *Individual reconstruction of the five leading components (plotted in different scales) obtained from the SSA decomposition of raw EMG signal (window length L = 10).*

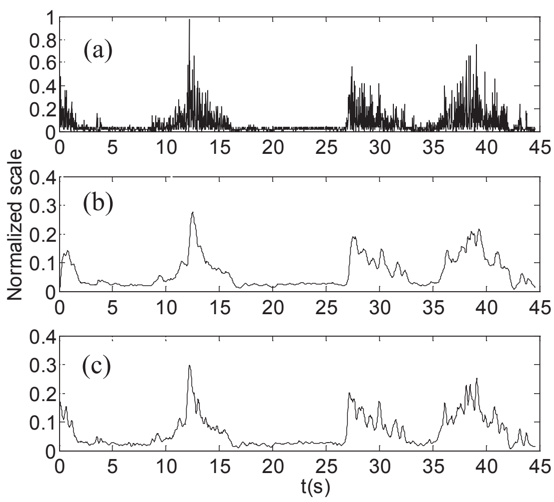

Figure 5. *(a) Original EMG signal. (b) Filtered signal using a 4 Hz cut frequency Butterworth filter. (c) SSA- smoothed signal.*

The main drawback is that there are no fixed, objective rules for selecting the window length. Nevertheless, the results are not very sensitive to window length. Moreover, the grouping strategy is usually clearly indicated by the singular spectrum.

Acknowledgments

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References

[1] C.J. De Luca, Physiology and mathematics of myoelectric signals, IEEE Trans Biomed. Eng. 26(6) (1979) 313–25.

[2] C.J. De Luca, The use of surface electromyography in biomechanics, J. Appl. Biomech. 13(2) (1997) 135–63.

[3] S. Usui, I. Amidor, Digital low-pass differentiation for biological signal processing, IEEE Transactions on Biomedical Engineering 29 (1982) 686–693.

[4] Z. Xu, S. Xiao, Digital filter design for peak detection of surface EMG, J. Electromyogr. Kinesiol. 10 (2000) 275–281.

[5] D. Zennaro, P. Wellig, V.M. Koch, G.S. Moschytz, T.Laubli, A software package for the decomposition of long-term multichannel EMG signals using wavelet coefficients, IEEE Trans. Biomed. Eng. 50 (1) (2003) 58–69.

[6] T. Grujic, A. Kuzmanic, Denoising of surface EMG signals: a comparison of wavelet and classical digital filtering procedures, Technol. Healthcare 12 (2) (2004) 130–135.

[7] G. Aschero, P. Gizdulich, Denoising of surface EMG with a modified Wiener filtering approach, Journal of Electromyography and Kinesiology 20 (2010) 366–373.

[8] A.O., Andrade, S.J. Nasuto, P. Kyberd, C.M. Sweeney-Reed, F. R. Van Kanijn, EMG signal filtering based on Empirical Mode Decomposition, Biomedical Signal Processing And Control 1 (2006) 44–55.

[9] N. Golyandina, V. Nekrutkin, A. Zhigljavsky, Analisys of time series structure - SSA and related techniques. Chapman & Hall/CRC, Boca Raton, Florida, 2001.

[10] R. Vautard, M. Ghil, Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series, Physica D, Nonlinear Phenomena 35 (1989) 395 – 424.

[11] R. Vautard, P. Yiou, M. Ghil, Singular spectrum analysis: a toolkit for short noisy chaotic signals, Physica D, Nonlinear Phenomena 58 (1992) 95–126.

[12] R.A. Pasmanter, Variational search of periodic motions in complex dynamical systems, Chaos, Solitons and Fractals 6 (1995) 447–454.

[13] W.J. Wang, J. Chen, X.K. Wu, The application of some non-linear methods in rotating machinery fault diagnosis, Mechanical Systems and Signal Processing 15 (2001) 697–705.

[14] L. Vaisman, J. Zariffa, M.R. Popovic, Application of singular spectrum-based change-point analysis to EMG-onset detection, J. Electromyogr. Kinesiol. 20(4) (2010) 750–60.