Biomedical Signal Processing and Control 30 (2016) 117–126

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A simple SSA-based de-noising technique to remove ECG interference in EMG signals

Jorge Barrios-Muriel [a,*], Francisco Romero [a], Francisco Javier Alonso [a], Kostas Gianikellis [b]

[a] Dept. of Mechanical, Energy and Materials Engineering, School of Industrial Engineering, University of Extremadura, Spain
[b] Dept. of Didactics of the Musical, Plastic and Corporal Expression, Faculty of Sport Sciences, University of Extremadura, Spain

ARTICLE INFO

Article history:
Received 7 August 2015
Received in revised form 31 May 2016
Accepted 3 June 2016

Keywords:
Electromyography
Biomedical signal processing
Singular Spectrum Analysis
ECG cancellation

ABSTRACT

Electromyography (EMG) signals provide significant information of muscle activity that may be used, among others, to estimate the activation stages during a certain activity or to predict fatigue. Heart activity or electrocardiogram (ECG) is one of the main contamination sources, especially in trunk muscles. This paper proposes a novel method based on Singular Spectrum Analysis (SSA) and frequency analysis to separate both signals present in the raw data. The performance of the method has been compared in time and frequency domains with traditional high-pass filtering or novel techniques such as Complete Ensemble Empirical Mode Decomposition or Wavelets analysis. The results show that for both time and frequency domains the proposed approach outperforms the other methods. Thus, the proposed SSA approach is a valid method to remove the ECG artifact from the contaminated EMG signals without using an ECG reference signal.

1. Introduction

Surface electromyography (EMG) is a technique concerned with the development, acquisition and analysis of myoelectric signals. The main problems in EMG recordings arise from the environmental noise, as well as from other electrical signals within the body, such as the electrocardiogram (ECG) contamination, frequent in EMG recordings from trunk muscles [1,2]. The ECG signal influences both the amplitude and frequency content of the EMG signal [3,4]. These effects are reflected in the frequency domain by altering the lower frequencies of the power spectrum, and also by the distortion of the EMG signal amplitude in the time domain. Thus, the removal of ECG from EMG presents a major challenge in the subsequent extraction of accurate and useful information [5]. The ECG interference is characterized by a large amplitude and the overlapping of the EMG frequency causing a distortion of its frequency content. Conventional ECG removal procedures include high-pass filtering (HPF), usually employing finite impulse response, or Butterworth filters with a cut-off frequency of 30 Hz [6,7]. Nevertheless, these HPF techniques can fail since the ECG has a frequency spectrum that overlaps markedly with the EMG recording.

Hof [8] suggested a simple method that consists in the simultaneously acquisition of EMG and ECG signals. By combining a reference ECG measurement with a transfer function, the artifact signal can be removed from EMG. Alternatively, subtraction methods [9–12] and adaptive filters [4,5,13,14] have been proposed on the assumption that the ECG is independent of the EMG signal. Unfortunately, the interference between ECG and EMG signals depends on the location of the muscles and its position with respect to the heart [15]. Moreover, ECG removal methods based on the subtraction of a template signal require the identification of the time intervals corresponding to the ECG artifact in the EMG recordings. Thus, an automatic procedure based on this principle is not feasible, and semi-automatic ECG detection algorithms are required.

Recently, new approaches based on advanced statistical vectorial decomposition have been presented to remove the ECG from the electromyogram, namely independent component analysis (ICA) [16–18], wavelet transform [19,20] and combination of ICA with the previous one [21]. However, the major drawback of these methods are the selection of the appropriate wavelet mother and the corresponding decision thresholding. At the same time, ICA-based methods require significant time processing, as well as an adequate number of input signals from multiple muscles to successfully isolate the ECG component [22].

A relatively new decomposition technique, the empirical mode decomposition (EMD) has been found to be very advantageous to

* Corresponding author at: Dept. of Mechanical, Energy and Materials Engineering, School of Industrial Engineering, University of Extremadura, Avda de Elvas S/N, 06006 Badajoz, Spain.
E-mail address: jorgebarrios@unex.es (J. Barrios-Muriel).

http://dx.doi.org/10.1016/j.bspc.2016.06.001
1746-8094/

decompose non-stationary signals [26]. Its application to remove artifacts has been applied to de-noise ECG signals [23] and also combined with ICA [24]. The quality of the separation in noisy signals has even been improved with latest versions, first, the ensemble EMD (EEMD) [25] and then, the complete EEMD with adaptive noise (CEEMDAN) [26].

On the other hand, the use of non-parametric techniques such as Singular Spectrum Analysis (SSA) can be an effective and powerful tool to decompose the signal into a set of additive time series from which identify the interest signal from noise [27]. This methodology has been applied successfully to muscle activity onset detection and filtering of EMG signals in the time domain [28,29]. Nevertheless, this technique has not been applied to the frequency domain in ECG artifact removal, and may provide a powerful tool to automatically identify the frequency content of the ECG present in a contaminated EMG recording (EMG_c). In this paper we first describe the different advanced methods available in the literature. Afterwards, we present a novel method for ECG removal based on SSA in the frequency domain. The results, are then compared with the methodologies described.

2. Methods

There are different methods in the literature to separate the ECG artifact from the EMG signal. Here, the current methodologies are presented and discussed. These are compared and contrasted against the SSA-based method proposed in this work that allows us to identify and separate the interest signal, i.e., EMG, from noise (ECG).

2.1. High pass filtering

Traditional ECG removal procedures are based on high-pass filtering (HPF), as most of the ECG's spectral power is located below 30 Hz. Thus, the recommendation to remove ECG artifact is to use HPF with a cut-off frequency of 30 Hz. In fact, it is the most common used method compared to all other methods [5]. In this study, we use a 4th order bi-directional high-pass Butterworth filter (HPF) to obtain a de-noised EMG signal (EMG_u).

2.2. Complete ensemble empirical model decomposition

The EMD is a new signal analysis tool which is able to decompose any complex time series into a set of spectrally independent oscillatory modes [25]. These intrinsic mode functions (IMFs) are a finite and often a small number of amplitude and frequency modulated (AM/FM) zero-mean signals [30]. The advantage of EMD is the decomposition of the signal in a natural way where a priori knowledge of the signal of interest embedded in the data series is not needed. Despite its proven usefulness, one of the major drawbacks of the original EMD algorithm is its high sensitivity to noise and, in some cases, a mode-mixing problem due to the presence of very similar oscillations in different modes. To overcome these problems, a new method has been proposed: the Ensemble Empirical Mode Decomposition (EEMD) [31]. It performs the EMD over an ensemble of the signal plus Gaussian white noise. The EEMD algorithm defines the IMF set for an ensemble of trials (EMG_r), where each one was obtained by applying EMD to the interest signal (EMG_c) with independent, identically distributed and zero-mean, added white noise to the signal:

$$\mathrm{EMG_r}(n) = \mathrm{EMG_c}(n) + w_r(n), r = 1, \ldots, R \quad (1)$$

where $w_r(n)$ are different realizations of white noise with variance ε, producing $\mathrm{IMF}_k^r(n)$, R is the number of signals in the ensemble and $n = 1,\ldots,N$ where N is the number of samples. Then, the final oscillatory modes are obtained by averaging:

$$\mathrm{IMF}_k(n) = \frac{1}{R}\sum_{r=1}^{R}\mathrm{IMF}_k^r(n) \quad (2)$$

This procedure improves the quality of the separation, and the mode mixing alleviation, but EEMD created some new problems, e.g., the decomposition is not complete and different realizations of signal plus noise may produce different number of modes.

A variation of the EEMD algorithm has been proposed to correct these problems [32]. This method, namely "Complete Ensemble Empirical Mode Decomposition with Adaptive Noise" (CEEMDAN) adds a particular noise at each stage, and achieves a complete decomposition with no reconstruction error. The CEEMDAN procedure ensures the completeness property of the proposed decomposition and thus, provides an exact reconstruction of the original data, as well as a better spectral separation of the modes with a lower computational cost [32]. The CEEMDAN computes the first decomposition by averaging the R IMFs and a unique residue (res) is retained:

$$\mathrm{res}_1(n) = \mathrm{EMG}_c(n) - \overline{\mathrm{IMF}'_1}(n) \quad (3)$$

where $\mathrm{IMF_1}'$ is the same as the first IMF obtained by EMMD. Then EMD is performed over a set of signals obtained by adding different noise realization to $\mathrm{res}_1(n)$, so the next IMF (labeled $\mathrm{IMF_2}'(n)$) can be found by averaging the corresponding set of IMFs. The corresponding residue is, then, $\mathrm{res}_2(n) = \mathrm{res}_1(n) - \mathrm{IMF_2}'$, and so on, until the stop criterion is achieved. Once the $\mathrm{IMF}_k(n)$ are obtained, $x(n)$ can be expressed as:

$$x(n) = \sum_{k=1}^{K}\overline{\mathrm{IMF}_k} + R(n) \quad (4)$$

where the final residue $R(n)$ satisfies:

$$R(n) = x(n) - \sum_{k=1}^{K}\overline{\mathrm{IMF}_k} \quad (5)$$

with K total number of modes.

The CEEMDAN version of the EEMD algorithm is used in this study. In order to select the ε value several simulations have been carried out with different values of ε (2, 0.2, 0.02 and 0.002), the best results were obtained for $\varepsilon = 0.02$, which was used in all simulations. To reconstruct EMG_u, we used a number of IMFs between 6 and 8, which only depends on the noise of the signal. The number of simulation for CEEMDAN is executed 20 times per each value of Signal to Noise Ratio (SNR) and per each test, in order to obtain statistically meaningful results.

2.3. Wavelets analysis

Wavelet analysis (WA) is a sophisticated technique for signal compression and noise reduction, which is very useful in different fields of biomedical signal processing. WA is based on similar ideas as the EMD algorithm. Both methods decompose the signal into components of disjointed spectra. Discrete wavelet transform (DWT) uses filter banks for construction of the multi-resolution analysis with relatively low computation time [33]. With this approach, the EMG_c is passed through a low-pass filter and a high-