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Wavelet-based unsupervised learning method for electrocardiogram suppression in surface electromyograms

Maciej Niegowski, Miroslav Zivanovic*

Deptartment Ingeniería Eléctrica y Electrónica, Universidad Pública de Navarra Campus Arrosadía, 31006 Pamplona, Spain

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ABSTRACT

We present a novel approach aimed at removing electrocardiogram (ECG) perturbation from single-channel surface electromyogram (EMG) recordings by means of unsupervised learning of wavelet-based intensity images. The general idea is to combine the suitability of certain wavelet decomposition bases which provide sparse electrocardiogram time-frequency representations, with the capacity of non-negative matrix factorization (NMF) for extracting patterns from images. In order to overcome convergence problems which often arise in NMF-related applications, we design a novel robust initialization strategy which ensures proper signal decomposition in a wide range of ECG contamination levels. Moreover, the method can be readily used because no a priori knowledge or parameter adjustment is needed. The proposed method was evaluated on real surface EMG signals against two state-of-the-art unsupervised learning algorithms and a singular spectrum analysis based method. The results, expressed in terms of high-to-low energy ratio, normalized median frequency, spectral power difference and normalized average rectified value, suggest that the proposed method enables better ECG–EMG separation quality than the reference methods.

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1. Introduction

Analysis of surface electromyography signals (EMG) is a key issue in a number of biomedical signal processing applications e.g. muscle onset/offset detection, conduction velocity estimation, fatigue analysis, to name a few. Often, the presence of electrocardiogram (ECG) disturbances gives rise to distortions in EMG signals, jeopardizing the accuracy of the analysis and possibly leading to misjudgments. Removal of the heart muscle electrical activity from a single-channel surface electromyogram recording remains a challenging task, because the ECG and clean (undistorted) EMG simultaneously overlap in both the time and frequency domain.

Related work encompasses a number of approaches, where the problem of ECG suppression from surface EMG recordings is treated as a source separation from a linear signal mixture [1,2]. The most straightforward approaches include filtering [3–5], gating and subtraction [6,7]. These methods lack efficiency, due to a simplistic approach to the issue of time-frequency signal overlap. More sophisticated methods include singular spectrum analysis (SSA) [8] and various noise cancelling algorithms based on the theory of adaptive filtering [9–12]. They can achieve a good separation quality at the expense of making use of external reference signals and supplementary electrodes. Methods like in [13] exploit statistical properties of the signals in a mixture to perform independent component analysis (ICA) for multiple-recording EMG signal denoising. The use of wavelets in ECG signal processing applications e.g. QRS detection, compression, denoising [14–16] has inspired a number of wavelet-based EMG–ECG separation approaches, where the temporal features of an electrocardiogram are captured in the multiresolution time-scale domain. Such an analysis is typically carried out by performing the Discrete Wavelet Transform (DWT) of the input signal plus thresholding, followed by adaptive filtering [17,18], independent component analysis [19,20], matching pursuit [21], and pitch-synchronous extraction [22]. Let us also mention an approach [23] which makes use of explicit quasi-harmonic time-variant modeling of ECG signals in surface EMG recordings. Recently, an attempt was made towards applying non-negative matrix factorization for an ECG–EMG separation application, with promising preliminary results [24].

Non-negative Matrix Factorization (NMF), a popular unsupervised learning algorithm for dimensionality reduction, has attracted a lot of attention in the scientific community due to its straightforward interpretability for a number of applications e.g. image deblurring [25], audio source separation [26], electroencephalogram classification [27], and multichannel EMG recognition [28]. Starting from an initial guess, NMF decomposes iteratively

* Corresponding author. Tel.: +34 948169024; fax: +34 948169720.
E-mail addresses: maciej.niegowski@unavarra.es (M. Niegowski), miro@unavarra.es (M. Zivanovic).

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the intensity representation (e.g. spectrogram) of an input signal mixture into a sum of non-negative components with time-varying gain. Once a minimum of a cost function is reached, the separated components typically exhibit an additive low-rank approximation of the input data. Moreover, if the constituent signals in the input mixture are sparse in the time-frequency (TF) domain, the separated components may naturally correspond to organic properties of the data [26].

In spite of increasing popularity in the biomedical signal processing community, NMF enclose some serious drawbacks which often make impossible the straightforward use of available "off-shelf" algorithms. It turns out that the spectrogram is very sensitive to the choice of analysis parameters: the window size and overlap between contiguous analysis frames. This means that rather small value changes in those parameters can give rise to important variations in the TF decomposition of the input signal. Another problem that needs to be tackled when working with spectrograms is the back-conversion to the time domain. A vast majority of applications requires time-domain waveforms in order to properly characterize the corresponding signals. Since NMF operates on spectrograms, the phase information, which is crucial for recovering time-domain waveforms, is not available.

Another drawback is that sparseness can guarantee the convergence only to a local minimum of the cost function; accordingly, the outcome might not be an interpretable representation of the input data. In order to ensure convergence to a global minimum, a proper initialization of an NMF algorithm is crucial. Typically, initialization is performed through matrices containing random non-negative entries. Such an initialization is very general and easy to implement, because it does not assume any kind of a priori information about the input signal. However, it often leads to convergence to a local minimum and accordingly result in unsatisfactory source separation. In the literature there are only a few attempts at non-random initialization that aim at reaching smaller overall error at convergence e.g. the methods based on PCA, fuzzy clustering, wavelets [29,30].

In the current work we present two novelties which can successfully circumvent the aforementioned drawbacks: 1) we design a robust initialization algorithm to NMF in order to ensure convergence to the global minimum of the cost function, 2) we carry out low-rank matrix decomposition over wavelet-based intensity patterns, which ensures a correct reconstruction of the time-waveforms by means of the inverse transform. Wavelets are shown to be an adequate tool for generating local scale-dependent descriptions of individual features in the electrocardiogram [31]. Such descriptions are typically supported by a small number of relevant transform coefficients, which in turn provide sparse time-frequency (TF) intensity representations. In addition, we generate an intelligent initial guess for an NMF iterative algorithm by incorporating some a priori knowledge about the components present in the input electromyogram. By the combined action of low and high-pass filtering of the input surface electromyogram we obtain rough ECG–EMG estimates, which are then used to establish the starting point for the iterative procedure. Although very coarse, it can be shown that these estimates yield a significant reduction in the initial cost function values and lead to global minimum convergence most of the time. An additional benefit of such an approach to NMF initialization is that no explicit QRS complex time localization estimation is needed [20].

2. Method

We describe in the present section a novel strategy that couples the wavelet theory to NMF initialization and matrix decomposition. This particular approach to EMG denoising is designed in such a way to mitigate the drawback of the "off -shelf" NMF algorithms, as explained in the previous section. We will first briefly review the wavelet function basis we chose as the basis for non-negative signal representation. Then, we will describe the way to generate the initial NMF matrices which reflect the natural ECG–EMG signal structure. It will be shown in Section 3 that such an approach to NMF initialization ensures a very good ECG–EMG separation quality.

2.1. Non-dyadic wavelet analysis

In the context of the present application, the choice of wavelet basis was determined by the following constraints. On the one hand, we need non-dyadic wavelet analysis which would provide a non-uniform frequency resolution in the band up to 500 Hz approximately. This is connected to the fact that most of the ECG–EMG energy overlap is clustered at low frequencies (up to 50 Hz) where more resolution is needed to obtain a clear picture. Towards higher frequencies the spectrum of the input signal is dominated by the EMG, which means that low resolution would be sufficient. On the other hand, we need wavelets that are easy to implement and provide fast and efficient direct and inverse transform calculation, in order not to slow down the overall ECG–EMG separation process.

Among a plethora of available wavelet bases, probably the most adequate for the problem at hand are so called complex-valued wavelets [32]. Such wavelets, defined either in the time or frequency domain, are known to have good temporal localization properties and at the same time, they can provide a variable user-defined frequency resolution. Unlike the classical dyadic wavelet analysis where the frequency bands are progressively halved from high towards low frequencies, the complex-valued wavelets can be defined more flexibly through a set of frequency responses of a bank of band-pass filters. Examples of such wavelets are frequency B-spline wavelets [33] and Cauchy-type non-linearly scaled wavelets [20]. Both wavelet classes are characterized by a flexible design of the filter bank by means of orthogonal adjustment of the bandwidth and central frequency.

We had no preference when choosing a specific wavelet basis, given that both are well suited for the problem at hand. Our choice has fallen on the Cauchy-type non-linearly scaled wavelets, because they have recently been used in combination with the FastICA algorithm for ECG–EMG separation. Those wavelets are characterized by a set of $P = 18$ band-pass filters of the following frequency response $B_k(F)$:

$$B_k(F) = F_k^m e^{(-F_k+1)m}, \quad k = 1 \ldots P \tag{1}$$

$$F_k = \frac{f}{f_c^{(k)}}, \tag{2}$$

$$f_c^{(k)} = \frac{1}{m}(1.45 + k)^{1.959}, \tag{3}$$

where the parameter m represents a scaling factor typically equal to 0.7. The graphical representation of the filter bank is shown in Fig. 1. According to Von Tscharner et al. [20], the frequency responses (1) are inverse-transformed by the Inverse Fast Fourier Transform and the corresponding filter impulse responses are obtained. Next, these complex waveforms of length N samples are arranged in a $36 \times N$ matrix $\mathbf{B}$.

Let $\mathbf{s}$ be an N-point vector containing a single-channel recording of a surface electromyogram. Then, we will refer to $\mathbf{v}$ as the wavelet transform of $\mathbf{s}$ i.e. $\mathbf{v} = \mathbf{B} * \mathbf{s}$, where the symbol '$*$' stands for row-wise convolution. The corresponding intensity image is obtained by squaring all entries in $\mathbf{v}$ and adding the first 18 rows to the last 18 rows. We will call the resulting $18 \times N$ matrix $\mathbf{V}$, which is the basis for the proposed WNMF algorithm.

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