ECG ARTIFACT REMOVAL FROM SURFACE EMG SIGNALS BY COMBINING EMPIRICAL MODE DECOMPOSITION AND INDEPENDENT COMPONENT ANALYSIS

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Abstract: The electrocardiography (ECG) artifact in surface electromyography (sEMG) is a major source of noise influencing the analyses. Moreover, in many cases the sEMG signal is the only available signal, making this removal more complicated. We compare the performance of two recently described single channel blind source separation methods with the commonly used template subtraction method on both simulations and real-life data. These two methods decompose a single channel recording into a multichannel representation before applying independent component analysis to these multichannel data. The decomposition methods are the wavelet decomposition and ensemble empirical mode decomposition (EEMD). The EEMD based single channel technique shows better performance compared to template subtraction and the wavelet based alternative for both high and low signal-to-artifact ratio and for simulated and real-life data, but at the expense of a higher computational load. We conclude that the EEMD based method has its potential in eliminating spike-like artifacts in electrophysiological signals.

1 INTRODUCTION

The interference of the electrical activity of the heart on the surface electromyography (sEMG) in the shoulder girdle is a major source of noise influencing its analysis. Several applications require detection of small changes in sEMG signals: the control of prosthesis via myoelectric signals (Zhou, 2006), the estimation of muscle fatigue via the analysis the sEMG signals (Clancy, 2002), the effect of a mental load on the muscle activity of the trapezius (Lundberg, 1994). There is certainly a need to remove the electrocardiogram (ECG) artifact. In many cases however, the sEMG is the only available signal, making this task more complex.

The difficulty of ECG interference removal is mainly due to the large overlap between the ECG interference spectrum and that of the considered sEMG signal (0-75Hz for ECG, 5-500Hz for sEMG). High pass filtering is not applicable as it removes a substantial part of the sEMG information. Other methods, like adaptive filtering (Sahul, 1995) or convolutive ICA were also proposed (Devuyst, 2008), but they need an extra ECG reference signal that is not available in this study. The template subtraction algorithm (Bartolo, 1996) uses the quasi-periodic property, assuming a similar waveform of successive heartbeats in the sEMG signals. This data driven method estimates the template of the interference signal from the signal and subtracts this template on the occurrence of a heart beat to eliminate the interference signal. The template subtraction algorithm was applied successfully, but is sensitive to changes in the waveform of the ECG interference signal. Moreover, the occurrence of the heart beat needs to be estimated in the sEMG signal when the ECG is not available, which is more challenging.

A new trend in biomedical signal processing is employing blind source separation (BSS) to unmix a set of recorded signals (based on an extra constraint) into its original sources. Independent Component Analysis (ICA) is one of these BSS techniques assuming independency between the sources. Unfortunately, these techniques are only applicable to multichannel data. Recently, several approaches to extend this idea to single channel data are published in the literature. A first approach, single channel ICA (SCICA), was presented by Davies and James (Davies, 2007). The original data is chopped into several blocks of equal length and ordered in a matrix before applying the ICA algorithm. This algorithm separates successfully the sources of interest provided they have perfect disjoint spectra. The algorithm also requires stationary data. Both limitations are not fulfilled in this specific application. Another approach to enable the use of ICA in single channel analysis is to decompose the signal into a multichannel representation before applying ICA. Several decomposition methods exist. Mijovic et al (Mijovic, 2010) combined ICA with either of two decompositions, Ensemble Empirical Mode Decomposition (EEMD) (Huang, 1998) and wavelets, and compared their performance with the SCICA method. They referred to the EEMD and wavelet approach respectively as EEMD-ICA and wICA and this nomenclature will also be used in this paper. For electrophysiological signals, they showed that the latter two methods outperformed the SCICA algorithm. The wICA method has already been shown successful in removing the ECG artifact (Azzerboni, 2004).

The aim of this paper is to verify whether EEMD-ICA can be applied to single channel sEMG excerpts to remove the ECG interference signal on a bigger data set. Moreover, we compare its performance to wICA and template subtraction, which is to our opinion, still the golden standard in removing the ECG artifact. In a first simulation study, the effect of the parameter settings for EEMD on the removal of the artifact is investigated. Optimal parameters for EEMD-ICA are retrieved from this study and used further in the analysis. In a second part, the performance of EEMD-ICA is compared with wICA and template subtraction for both simulated and real data.

2 METHODS

2.1 Algorithms

In this study, the performance of three algorithms used for removing ECG contamination on a single channel sEMG measurement is investigated. These algorithms are template subtraction, wavelet decomposition in combination with Independent component analysis (wICA) and ensemble empirical mode decomposition in combination with Independent component analysis (EEMD-ICA).

2.1.1 Ensemble Empirical mode decomposition-Independent component analysis (EEMD-ICA)

The idea behind the algorithm is to decompose a single channel measurement into different components before applying a blind source separation technique. Here, the single channel is decomposed using Ensemble Empirical Mode Decomposition (EMD) before applying ICA (Mijovic, 2010).

EMD (Huang, 1998) is a novel signal analysis tool which is able to decompose any complicated time series into a set of spectrally independent oscillatory modes, called Intrinsic Mode Functions (IMFs). While wavelets and other signal decomposition techniques tend to map the signal space onto a space spanned by a predefined basis, EMD is a data driven algorithm which means that it decomposes the signal in a natural way where no a priori knowledge about the signal of interest embedded in the data series is needed. The advantage of EMD is that this technique is able to deal with nonstationary and nonlinear data. A major drawback of the EMD algorithm is its sensitivity to noise. Therefore, a more robust, noise-assisted version of the EMD algorithm, called Ensemble EMD (EEMD) (Huang, 1998) is used in this study. The algorithm defines the IMF set for an ensemble of trials, each one obtained by applying EMD to the signal of interest with added independent, identically distributed white noise of the same standard deviation (SD). The ratio of the noise SD to the SD of the signal will be further referred to as a noise parameter (np). Taking into account properties of the white noise, we expect noisy components to be cancelled out. The selection of np and number of trials is discussed in section 3.2.

After EEMD is performed and a set of averaged IMFs is derived, independent component analysis (ICA) is applied. The goal of ICA is to separate instantaneously mixed signals from the channel matrix X into their independent sources S, such that X = MS, where M is called the mixing matrix, without prior knowledge. It is possible to estimate the contributing sources from the mixtures provided they are statistically independent of each other. There are several ways to solve this problem. Here, the popular FastICA algorithm, based on a fixed-point iteration scheme for finding a maximum of the non-Gaussianity of the sources is used (Hyvarinen, 2000). ICA is applied to the whole set of IMFs. It is worth noting that no IMF subset has been preselected as input of the ICA algorithm in order to keep this part of the algorithm as automatic as possible.

Afterwards, the independent sources that represent the ECG artifact signal are set to zero before reconstruction of the cleaned sEMG signal without the ECG contamination.

2.1.2 Wavelet-Independent component analysis (wICA)

This algorithm is similar to the EEMD-ICA algorithm, but the single channel signal is decomposed into components of disjoint spectra using the discrete wavelet decomposition instead of EEMD. For this study we chose the Daubechies 6 wavelet, but similar conclusion holds for other mother wavelets. The order of decompositions was set to 8 according to a previous study (Taelman, 2007).

The algorithm was originally proposed by Azzerboni et al (Azzerboni, 2004), who decomposed different, simultaneously recorded sEMG channels via the discrete wavelet transform before performing independent component analysis (ICA) to select independent components of interest. Hence, the algorithm was not conceived for a single channel approach, but the extension to a single channel technique is straight forward.

2.1.3 Template subtraction

Template subtraction is a method that subtracts a data driven template of the artifact from its occurrence (Bartolo, 1996) in the signal. This method has proven its ability to remove the ECG contamination artifact in previous studies. The algorithm involves three steps: localization of the artifact, construction of the template and subtraction of the template from the occurrence of the artifact. This method is, to our opinion, still the golden standard in removing the ECG artifact.

2.2 Data

In this section the simulated and real-life signals, used in the study, are described.

2.2.1 Simulated data

The simulation signals are derived from real-life contamination-free recordings. The sEMG signals are 60 second excerpts, selected from three different sEMG recordings (in the text referred as ref(t)) at different contraction levels. The signals are extracted from measurements of the right M. Biceps brachii and are not influenced by an ECG interference signal. This is confirmed by visual inspection in time and frequency domain of the sEMG signal. The ECG artifact templates were extracted from representative real-life contaminated sEMG measurements of the left and right M. trapezius pars ascendens, transversus and descendens. Using these templates, seven artificially contaminated ECG signals (referred to as ecg(t)) are generated. All reference sEMG and artificial ECG signals are normalized. By mixing up the reference sEMG signals and the generated ECG signals, the simulation data set is defined.

$$\mathrm{sig}_i(t) = \mathrm{ref}_e(t) + \lambda\, \mathrm{ecg}_c(t) \qquad (1)$$

with *e* the selected sEMG reference signal, *c* the simulated ECG contaminated signal and λ the proportion factor. For this study, λ was selected as one of the values (0.01, 0.1, 0.2, 0.5, 1, 2, 3, 5, 7, 10), resulting in 21 simulations per value of λ.

2.2.2 Real-life data

The real-life signals were collected during a stress assessment task where the influence of stress on muscle activity in the shoulder girdle was studied. In a laboratory setting, the test subjects have to perform a mental task to induce a mental stressor. The muscles of interest were the three parts of the Trapezius muscle (pars ascendens, transversus and descendens) on both sides of the body. The sEMG data were recorded via EMG preamplifiers from Mega Electronics Ltd (Finland). These analog signals were preamplified (x360) and low pass filtered afterwards (450Hz) to avoid aliasing during digitization. The Daqbook 2005 (IoTech, Ohio, USA) was used to digitize the signals at a sampling rate of 1000Hz. The results of the stress assessment task are beyond the scope of this text.

During visual inspection of the sEMG-signals, specific types of sEMG signals could be identified: muscle in rest, firing of a single motor unit, low force contractions, high force contraction, non-stationarity. 7 different sEMG segments are selected from the various recordings, each lasting for 30s.

The selection was made to have a representative set of sEMG epochs compared to the complete data recordings of all the test subjects.

2.3 Validation

For the simulation data, the outcome of the ECG removal algorithms can be compared with the original reference signals for validation. Therefore, the relative root mean square error (RRMSE) is calculated to compare the performance of the different algorithms.

$$RRMSE(\%) = \left(\frac{\sqrt{\frac{1}{N} \cdot \sum_{t=1}^{N} \left(ref(t) - \hat{a}(t) \right)^2}}{\sqrt{\frac{1}{N} \cdot \sum_{t=1}^{N} \hat{a}^2(t)}} \right) \times 100 \qquad (2)$$

where â(t) is the estimate of the signal of interest and ref(t) the reference sEMG signal.

In all the simulations, the number of independent components in FastICA to be extracted was set to 5 according to the study by Mijovic et al (Mijovic, 2010).

We were able to fully automate the EEMD-ICA and wICA algorithms. After performing the ICA on the signal decompositions by both algorithms, the selection of the ECG sources needs to be done. Since we have the artificial ECG signal available during the analysis, the independent ECG sources can be estimated by calculating the correlation between the independent sources and the artificial ECG signal. This correlation is high compared to that between the non-ECG sources and the artificial ECG signal. Simple thresholding on the correlation index was sufficient to distinguish between the relevant and nonrelevant sources.

For the real-life data, the reference signal is not available, implying that the RRMSE cannot be calculated. Therefore, the outcome of the three different algorithms is scored visually by an expert regarding their performance in removing the ECG artifact. A good performance means a good removal of the ECG artifact while preserving the sEMG signal without distortion. Therefore, the outcome of the three algorithms applied to the seven signals is scored regarding their removal of the ECG artifact (1 to 5; no removal to perfect removal) and their distortion of the sEMG signal (1 to 5; sEMG signal is completely removed to no distortion of the sEMG signal).

3 RESULTS

We present the results of the algorithm for the different simulations. In the first part, the performance of the EEMD-ICA algorithm is presented. Afterwards, the results for the simulation study to find the appropriate parameter settings are presented and in the last part, the results for comparison of the three algorithms for both the simulation and the real-life data.

3.1 EEMD-ICA algorithm

Figure 1 shows a fragment of the original contaminated sEMG data. It clearly shows 5 heart beat interference peaks in the data with a larger magnitude of the sEMG signal. To this signal, the EEMD-ICA algorithm is applied, resulting in 5 independent components derived from the ICA step. Figure 2 shows clearly that the ECG and the sEMG signals are split up in separate independent sources. At the occurrences of the heart beats visible in figure 1, it is obvious that the ECG sources correspond to sources number 2 and 4. These two sources are set to zero and the cleaned sEMG signal is reconstructed with sources 1, 3 and 5. Figure 3 shows the sEMG signal after reconstruction with removed ECG interference sources. The ECG interference signal is visibly removed completely and the sEMG signal shows almost no distortion. These figures show that the EEMD-ICA algorithm is able to remove the ECG artifact.

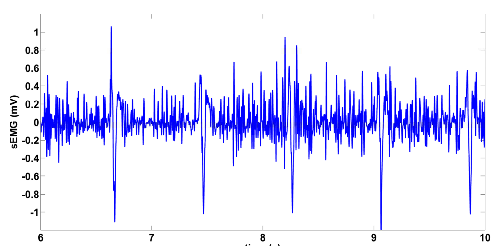

Figure 1: typical sEMG with the ECG interference signal

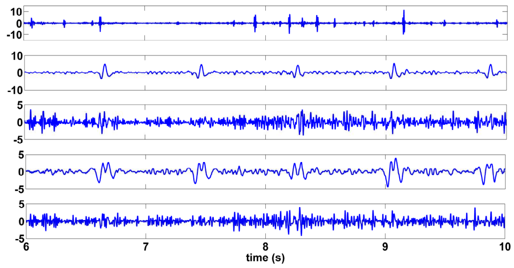

Figure 2: 5 independent sources after performing ICA on the EEMD decomposition. Source 2 and 4 are related to the ECG interference signal.

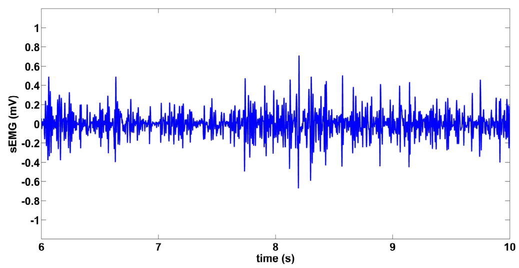

Figure 3: Cleaned sEMG after ECG interference removal

3.2 EEMD-ICA parameters

The noise parameter and the number of iterations play an important role while performing the ensemble empirical mode decomposition. The noise parameter (np) is defined as the ratio of the noise standard deviation to the standard deviation of the signal power. The np is varied between 0.2, 0.5 and 1. The second parameter is the number of trials used for ensembling, varying between 100 and 200. Figure 4 shows the RRMSE for 6 different settings. Each point is the mean of 21 simulations. To maintain the visibility of the figure, the standard error is not shown.

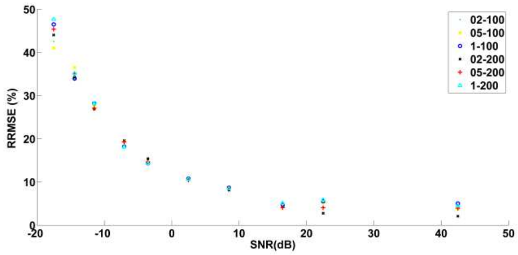

Figure 4: RRMSE after removing the ECG contamination for various settings of the EEMD-ICA-parameters.

The simulations reveal that the selection of parameter settings has limited effect on the RRMSE in the range of -10 to 10dB. Only for higher and lower SNR, differences in parameter settings can be seen. For higher SNR, a lower np results in a lower RRMSE (green and black dot on the plot), while for lower SNR, a lower number of trials offers a better RRMSE (yellow and green dot on the plot). Therefore, the decision is made to use a noise parameter np of 0.2 and an ensemble of 100 trials.

3.3 Removal performance

3.3.1 Simulated data

Figure 5 shows the performance of template subtraction, the wICA and the EEMD-ICA method on the simulation data set, described in section 2.2. For a changing SNR the results are presented with their mean and standard error. The parameters used for the EEMD-ICA were selected in section 3.2 and set to 0.2 for the np and 100 for the number of trials.

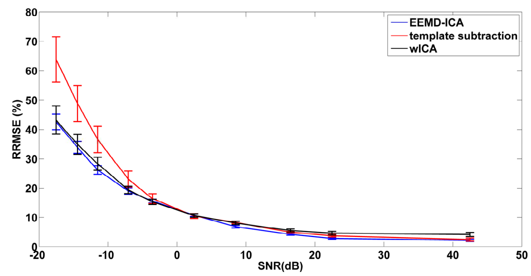

Figure 5: Comparison of algorithm performances in function of the RRMSE (in %) for the described simulation. The results are presented as mean and standard error for the different SNR.

The results of the simulations can be split up in two parts. Around the SNR of 2dB, the simulations reveal no difference between the three algorithms with a relative RMS error close to 10%. For SNR higher or lower, specific trends can be seen. When looking at higher SNR, meaning that the power in the sEMG signal is higher than the power in the ECG interference signal, the RRMSE is lower than 10% for all three algorithms. The error made by the template subtraction and EEMD-ICA is similar to each other and is lower compared to that of wICA. For the lower SNR, both ICA based algorithms perform much better compared to the template subtraction resulting in a clearly lower RRMSE from -5dB on.

3.3.2 Real-life data

Figure 6 shows a 5 second fragment of the removal of the ECG artifact in a representative real-life sEMG signal (signal 1). Both ICA based algorithms remove the ECG artifact completely, while template subtraction (D) fails to remove 1 peaks due to bad localization of the artifact. The wICA (B) algorithm left very small residues of the artifact. Only EEMD-ICA (C) is for this specific example able to remove the artifact perfectly. Both wICA and EEMD-ICA remove the baseline drift, and no distortion of the sEMG signal has been noticed.

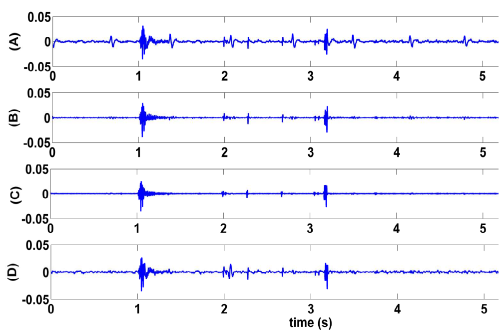

Figure 6: ECG removal of a 5 second fragment of signal 1. (A) shows the original signal; (B) shows the result after wICA; (C) shows the result after EEMD-ICA; (D) shows the result after template subtraction.

Table 1: Scores on the performance of the three algorithms when applied to 7 real-life signals (numbered in the 1st column from 1 to 7). The scores range from 1 (very bad) to 5 (perfect).

	ECG removal			EMG distortion		
	Templ. Subt	wICA	EEMD-ICA	Templ. Subt	wICA	EEMD-ICA
1	4	4	5	5	5	5
2	5	5	5	5	4	4
3	3	5	5	5	5	5
4	4	5	5	5	3	5
5	4	5	5	5	4	4
6	4	5	5	3	5	5
7	5	5	5	5	5	5

Table 1 gives the scores for the performance of the three algorithms on the real-life data set. A general trend can be noticed. Both ICA algorithms perform better compared to the template subtraction in terms of removing the ECG artefact. On the other hand, template subtraction does not distort the sEMG signal, while wICA and EEMD-ICA did. This problem is more present for wICA compared to EEMD-ICA. Signal 6 shows a distortion of the sEMG signal after applying template subtraction, in contrast to wICA and EEMD-ICA. This reduced performance for template subtraction is caused by the presence of the 50Hz component in this signal. Both ICA based algorithms extracted this component as a separate independent source, which was then removed in the ICA step. That's why their performance was not affected.

4 DISCUSSION

The use of independent component analysis for removal of ECG artifacts has been described before (Azzerboni, 2004; Devuyst, 2008). However, all these algorithms are using a simultaneously acquired ECG channel as input. These algorithms show good performance in removing the ECG. In real-life measurements, a simultaneous ECG channel is not always available, making the removal of the ECG artifact more complicated. In this study, we used recently developed single channel ICA techniques, described in the literature, to remove the interference signal and compared it with a widely used technique. The single channel is first decomposed into a multichannel signal using wavelets or ensemble empirical mode decomposition. The multichannel decomposition is then used as input to a subsequent independent component analysis in order to remove the ECG interference.

Both ICA based methods are able to remove the ECG artifact from the sEMG channel and perform better compared to template subtraction as soon as the ECG artifacts become more dominant (lower SNR). This can be explained by the limitations of the template subtraction technique. The algorithm uses the quasi-periodic property of the ECG artifact but assumes a constant waveform of successive heart beats. Furthermore, perfect localization of the occurrence of the heart beat is needed. If one of these assumptions is not fulfilled, the algorithm will introduce subtraction artifacts. In reality, the successive waveforms are slightly varying and perfect localization in the sEMG signal itself is more difficult, which is revealed in figure 6 for the real-life data. Thus, the larger the ECG interference signal is compared to the background sEMG signal, the larger these subtraction artifacts are. This explains the higher RRMSE for lower SNR. These limitations do not hold for both ICA based algorithms as these algorithms exploit statistical properties of both underlying signals to separate them.

The difference in performance between the results of wICA and EEMD-ICA can be explained via differences in decomposing the original signal.. The EEMD is a data-driven method and has a more natural decomposition that is able to cope with nonstationarities in the signal. Contrary to the wavelet decomposition, the extracted intrinsic mode functions can be spectrally overlapping. This leads to a more natural selection of the independent sources of the ICA afterwards, explaining the small differences in favor for the EEMD-ICA.

A major drawback of the EEMD-ICA algorithm is its computational cost. The empirical mode decomposition is a data driven, iterative process of selecting local maxima and minima for each empirical mode. This is a computationally intensive decomposition. The noise robust extension of EMD, called ensemble EMD (EEMD), needs more time as the algorithm ensembles the outcome of at least 100 trials of a single EMD. In contrary, the wavelet decomposition is a straight-forward method based on a predefined wavelet waveform. The computational load of wICA is similar to that of template subtraction, while EEMD-ICA is in the order of 100 times slower. This high computational load makes a real-time implementation impossible.

In general, EEMD-ICA is better compared to wICA and yields similar performance as the template subtraction for higher SNR, while for lower SNR, EEMD-ICA is significantly better than template subtraction and slightly better than wICA. We can conclude that for offline use, EEMD-ICA has the best performance.

5 CONCLUSIONS

In this paper, we reported on applying EEMD-ICA to remove the ECG interference signal from single channel sEMG recordings. The algorithm shows better performance compared to template subtraction and wavelet based ICA for both high and low signal-to-artifact ratio for both simulated and real-life data, but at the expense of a high computational load. We can conclude that this method has great potential in eliminating spike-like artifacts in electro-physiological signals.

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The scientific responsibility is assumed by its authors.

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