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

Joachim Taelman, Bogdan Mijovic, Sabine Van Huffel
ESAT-SCD, Katholieke Universiteit Leuven, Kasteelpark Arenberg 10, 3001 Heverlee, Belgium

Stéphanie Devuyst, Thierry Dutoit
TCTS Lab, Université de Mons, Mons, Belgium

Keywords: Single channel-blind source separation, Ensemble empirical mode decomposition, ECG interference artifact, Data preprocessing.

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 (Zhou, 2006. 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).

A new trend in biomedical signal processing is employing blind source separation (BSS) to unmix a set of recorded signals into its original sources. Independent Component Analysis (ICA) is one of these BSS techniques assuming independency between the sources. 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 (EEMDICA) (Huang, 1998) and wavelets (wICA), and compared their performance

Taelman J., Mijovic B., Van Huffel S., Devuyst S. and Dutoit T. (2011).
ECG ARTIFACT REMOVAL FROM SURFACE EMG SIGNALS BY COMBINING EMPIRICAL MODE DECOMPOSITION AND INDEPENDENT COMPONENT ANALYSIS.
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, pages 421-424
DOI: 10.5220/0003136804210424

with the SCICA method. 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.

2 METHODS

2.1 Algorithms

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). In contrast with wavelets, EMD is a data driven algorithm that 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. 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). These parameters were set to 0.2 for the np and 100 for the number of trials. 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. We used 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. The number of independent components in FastICA to be extracted was set to 5 according to the study by Mijovic et al (Mijovic, 2010).

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.

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

The simulation signals are derived from real-life contamination-free recordings. The sEMG signals are 60 second excerpts from measurements of the right M. Biceps Brachii, selected from three different sEMG recordings at different contraction levels. The ECG artifact templates were extracted from representative real-life contaminated sEMG measurements of the left and right M. trapezius. Using these templates, seven artificially contaminated ECG signals are generated. All reference sEMG and artificial ECG signals are normalized. By mixing up the reference sEMG signals and the generated ECG signals for different SNR, the simulation data set is defined.

To validate the simulation data, the relative root mean square error (RRMSE) is calculated to compare the performance of the different algorithms.

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.

3 RESULTS

Figure 1 shows a fragment of the original contaminated sEMG data. After applying EEMDICA, 5 independent components are derived (Figure 2). 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.

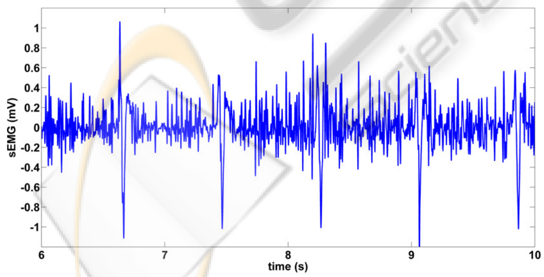

Figure 1: Typical sEMG with the ECG interference signal.

The performance of the three algorithms on the data set is presented in Figure 4. For a changing SNR the results are presented with their mean and standard error. 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.

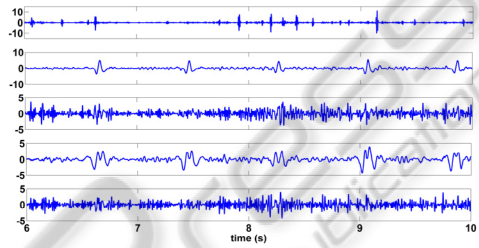

Figure 2: 5 Independent sources after performing ICA on the EEMD decomposition. Source 2 and 4 are related to the ECG interference signal.

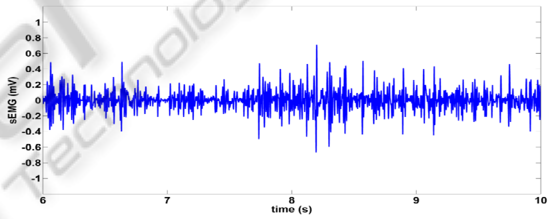

Figure 3: Cleaned sEMG after ECG interference removal.

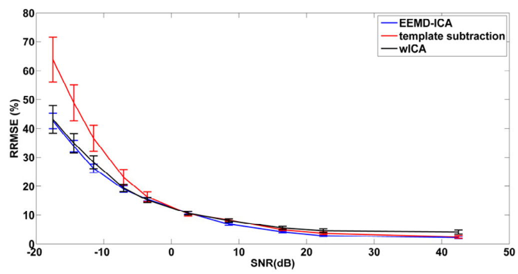

Figure 4: Comparison of algorithm performances in function of the RRMSE (in %) for the described simulation. The results are presented as mean and standard error for the different SNR.

4 DISCUSSION

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 difficult. 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.

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, 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.

ACKNOWLEDGEMENTS

Research supported by: Research Council KUL: GOA Ambiorics, GOA MaNet, CoE EF/05/006 Optimization in Engineering (OPTEC), IDO 05/010 EEG-fMRI, IDO 08/013 Autism; Belgian Federal Science Policy Office: IUAP P6/04 (DYSCO, `Dynamical systems, control and optimization', 2007-2011; EU: FAST (FP6-MC-RTN-035801), Neuromath (COST-BM0601)

REFERENCES

Azzerboni, B., Carpentieri, M., La Foresta, F., Morabito, F. C., 2004. Neural-ICA and Wavelet Transform for artifacts removal in EMG. In *Proc. Of the IEEE International Joint Conference on Neural Networks*,. 4, 3223–3228.

Bartolo, A., Roberts, C., Dzwonczyk, R., Goldman, E., 1996. Analysis of diaphragm EMG signals: comparison of gating vs. subtraction for removal of ECG contamination. In *J. Appl. Physiol*, 80, 1898–1902.

Davies, M. E., James, C. J., 2007. Source separation using single channel ICA. In *Signal Processing*, 87 (8), 1819 – 1832.

Huang, N. E., Wu, M. L., Long, S. R., Shen, S. S., Qu, W. D., Gloersen, P., Fan, K. L., 1998. The Empirical Mode Decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In *Proceedings of Royal Society Lond*, 454A, 1971, 903–993.

Hyvarinen, A., Oja, E., 2000. Independent Component Analysis: algorithms and applications. In *Neural Networks*, 13 (4-5), 411 – 430.

Mijovic, B., De Vos, M., Gligorijevic, I., Taelman J., Van Huffel, S., 2010. Source separation from single-channel recordings by combining empirical mode decomposition and independent component analysis. In *IEEE transactions on biomedical engineering*. Accepted.

Taelman, J., Spaepen, A., Van Huffel, S., 2007. Wavelet Independent Component Analysis to remove electrocardiography contamination in surface electromyography. In Proceedings of Engineering in Medicine and Biology Society, 2007, pp. 682–685.

Zhou, P., Kuiken, T. A., 2006 Eliminating cardiac contamination from myoelectric control signals developed by targeted muscle reinnervation. In *Physiol Meas*, 27, 1311–1327.