Evaluation of Blind Source Separation Methods for Noise Reduction in BSPM Recorded During Exercise

Heriberto Zavala-Fernandez, Michal Kania, Roman Maniewski, Dariusz Janusek

Nalecz Institute of Biocybernetics and Biomedical Engineering, PAS, Warsaw, Poland

Abstract

The application of Blind Source Separation (BSS) is now an accepted technique in the field of biosignal processing. The reduction of noise (biological and technical artifacts) in body surface potential mapping recorded during exercise is a frequent goal. Two BSS methods (FastICA and temporal decorrelation) for removing noise are compared with respect to the ability to isolate artifacts. Datasets from 13 subjects were studied. For quantification of the results the changes of the root-mean-square (RMS) before and after denoising were analyzed. The use of both BSS methods improved the signal-to-noise-ratios (SNR) in a range of -4 *to* -10 *dB.*

1. Introduction

Body surface potential mapping (BSPM) by increased number of sensors covering the whole surface of the thorax (e.g. 256 sensors) offers higher selective sensitivity to individual cardiac regions [1]. A limitation in applying BSPM in clinics is the time needed for electrode placement (around 10-20 min.). Particularly, when ECG recordings are acquired during stress test the power of the muscle activity increase considerably, as well as, the cable drifts in comparison to rest signals [2]. Two techniques used for denoising are independent component analysis (ICA) [3] and temporal decorrelation separation (TDSEP). Both techniques belong to the class of blind source separation (BSS) methods. ICA is a widely used method whose usefulness has been demonstrated in many publications for other kinds of biosignals as electroencephalogram, magnetoencephalogram, electrogastrogram [2–10]. In many studies ICA was carried out in conventional 12-Lead ECG systems [8,11,12]. The common goal by using ICA for the analysis of ECG data is the separation of components that are assumed to belong to electrocardiac activity and components related to noise (artifacts). After signal decomposition denoising can be applied by suppressing the components related to noise [2, 8]. ICA has only been applied to the ECG for very special purposes: separating atrial signal from ventricular signals [13–15], separating fetal and maternal heart beats [16, 17], or separating heart beats from noise[17, 18].

This study aimed on evaluation of BSS methods for noise reduction in BSPM recorded during exercise. Two BSS algorithms will tested: one based on higher order statistics (FastICA) and the other on second order statistics (TDSEP).

2. Materials and methods

The BSPMs were acquired during exercise on supine ergometer using a 64-lead high-resolution ECG system (Biosemi Active Two) with sampling frequency 4096 Hz and referenced to the Wilson's Central Terminal (see Fig. 1). Then, data were downsampled by a factor of 4 to 1024 samples/s and subsequently, a Butterworth passband filter was applied with cut frequencies from 0.05 to 250 Hz and zero phase delay. The study was carried out on 13 healthy volunteers. All subjects were asked to keep frequency of pedaling of around 60 cycles per minute during examination at fixed load of 25 watts. Each recording session lasted 5 minutes.

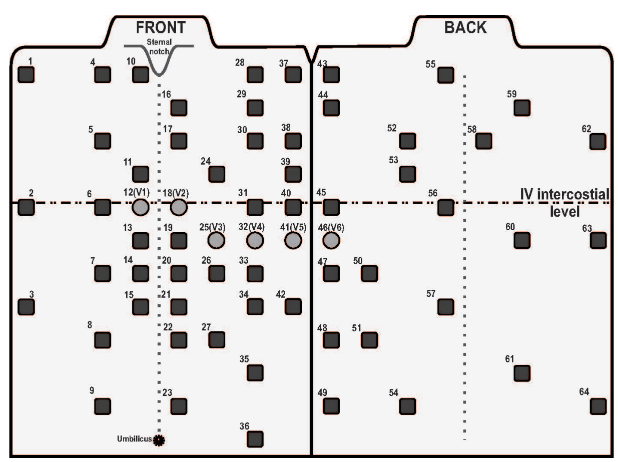

Figure 1. Channel layout for ECG electrodes of 64 channels. Standard leads V1-V6 are indicated.

The **FastICA**[19] algorithm estimates the non-gaussianity of the signal distributions using higher-order statistics and the negentropy, which is a non-negative function of the differential entropy. FastICA is based on an iteration scheme for finding a projection $\mathbf{y} = \mathbf{W^T x}$ maximizing non-Gaussianity. It can be summarized by the update rule $\mathbf{W} \propto \langle \mathbf{x}\, g(\mathbf{W^T x}) \rangle - \langle \mathbf{x}\, g'(\mathbf{W^T x}) \rangle\, \mathbf{W}$, and the subsequent normalization of the updated W until convergence is reached. The non-linear function $g(\mathbf{y}) = \mathbf{tanh}(\mathbf{y})$ was used in this study. The calculation was performed for each of the subjects separately.

The basis of the **TDSEP** (temporal-decorrelation source separation) algorithm is a set of time-lagged covariance matrices $R_x(\tau) = \langle x(t+\tau) \cdot x^T(t) \rangle$ with $\tau \neq 0$. For independent sources these matrices have to be diagonal. To estimate the sources a joint diagonalization of the time-lagged covariance matrices is performed. To use a set of τ values is an empirically established procedure to avoid an inferior source separation as there is no theoretically proven choice of τ values. As time delays τ the set of prime numbers lower than 200 was chosen in the calculations. In total, a set of 46 time-lagged covariance matrices had to be simultaneously diagonalized. The calculation was performed for each of the subjects separately.

After BSS decomposition, the selection of the components to be removed was performed by looking at the time-series, the power spectra and the field distribution. Then a back-projection was performed for every dataset with the suppressed components. From the FastICA and TDSEP algorithms, the estimated mixing matrix $\mathbf{W^{-1}}$ have been obtained. Let $\mathbf{W^{-1}}(:, \mathbf{i})$ denote the i-th column(s) of $\mathbf{W^{-1}}$, and $\mathbf{y}(\mathbf{i}, :)$ denotes the i-th row(s) of $\mathbf{y}$, then the back-projection of component(s) i is

$$\mathbf{bp_i} = \mathbf{W^{-1}}(:, \mathbf{i}) \cdot \mathbf{y}(\mathbf{i}, :). \qquad (1)$$

To assess quality of denoising, the root-mean-square (**rms**) in each channel was computed before and after noisy component suppression and then the signal-to-noise ratio (**SNR**) in the corresponding sensor was calculated by using the equation

$$\mathbf{SNR_{dB}} = \mathbf{20} * \mathbf{log_{10}}(\mathbf{rms}(\mathbf{bp})/\mathbf{rms}(\mathbf{x})). \qquad (2)$$

3. Results

The BSS methods (FastICA and TDSEP) were applied separately to 5 minutes recordings in each dataset. Individual recordings are separately arranged in data matrix $\mathbf{x}$ (array of $[channels \times samples]$). After the calculations with FastICA and TDSEP algorithms the components due to the heart activity were identified manually by comparison with the typical ECG morphology in the component time series. The power spectra show frequencies related to the heart beating. An spatial representation of the estimated independent component is generated by interpolation of a column of the estimated mixing matrix $\mathbf{A} = \mathbf{W^{-1}}$ computed by both algorithms.

This way of representation (time, spectrum and space) allowed us to recognize noisy sources more easily. As can be observed in Fig. 2(left), the body surface map related to heart activity present a well defined dipolar pattern arising from the heart location a little bit shifted to the left while noisy components did not show the regular dipolar pattern (see Fig. 2(right)).

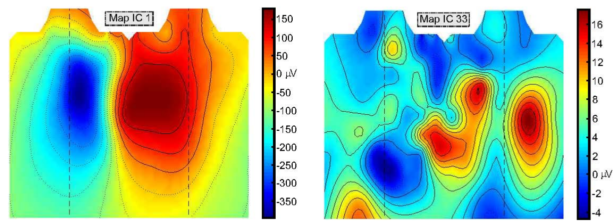

Figure 2. Example of body surface maps of two independent components (ICs) obtained after applying FastICA to the BSPM. Left: Component related to heart activity (IC 1); and right: related to noise (IC 33).

After the components to be removed are selected, a back projection is computed using Eq.1. This procedure is repeated individually for every dataset. Figure 3 presents the improvements after denoising with FastICA for a single channel. Clearly the signal spectrum shows that the slow signal drifts are rejected (frequencies bellow 1 Hz) and in time representation the heart beating appear more visible.

The SNR values were computed individually for every dataset and channel using the Eq. 2. The improvements of denoising by applying the BSS methods are presented as the SNR parameters in Fig.4 for the 64 channels. Both, FastICA and TDSEP methods presented similar performance with median, 25th and 75th percentiles values: -2.55 ± 3.03 dB, -5.15 ± 2.22 dB and -1.64 ± 4.64 dB respectively for FastICA and -2.49 ± 2.97 dB, -4.89 ± 2.12 dB and -1.56 ± 4.29 dB for TDSEP respectively.

4. Conclusions

Obtained results show that BSS methods could reject the noisy components without much loss of information related to the heart activity. The SNRs show an improvement of about -4 to -10 dB in leads located on the back and close to the extremities. The gain observed in channels close to heart was about -0.5 dB. BSS methods are easy to implement and suitable to remove the motion (pedaling) artifact since this signal presents a quasi-stationary behavior. Artifact suppression by removal of selected components might be a valuable pre-processing step to enhance the SNR of multi-channel ECG recordings.

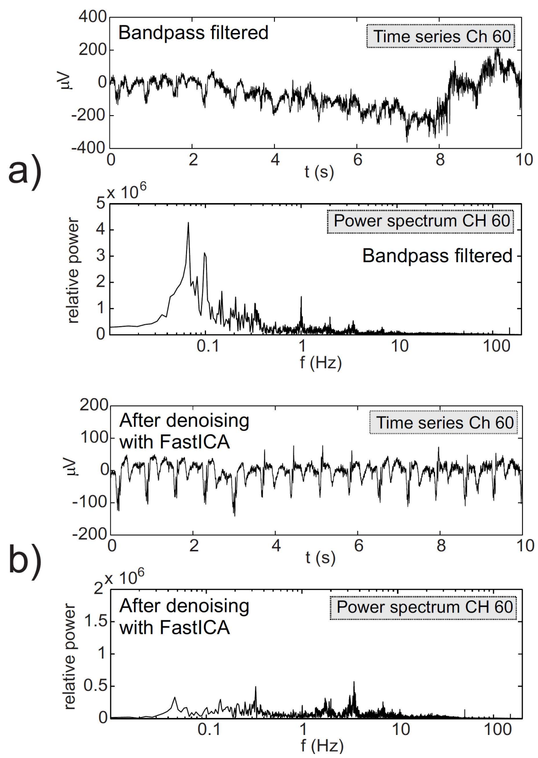

Figure 3. Channel comparison: a) after bandpass filtering and b) after denoising with FastICA. Both presents: time series (top) and power spectrum (bottom) of channel 60.

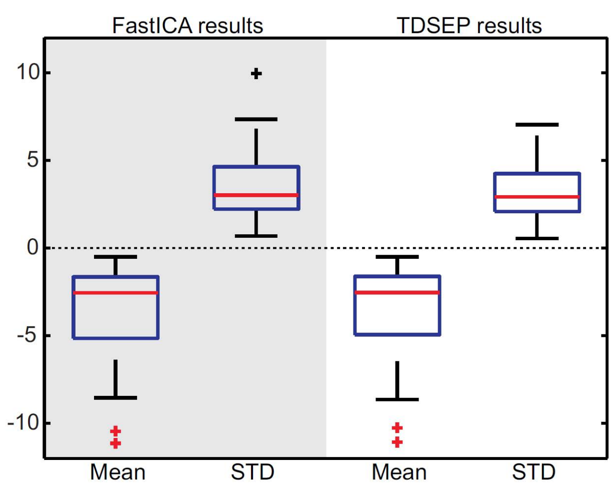

Figure 4. Summarized SNR values for all channels after denoising with FastICA and TDSEP. Mean and standard deviation (STD) values are presented. The red line corresponds to the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually (+).

Acknowledgments

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References

[1] Fereniec M, Stix G, Kania M, Mroczka T, Janusek D, Maniewski R. Risk assessment of ventricular arrhythmia using new parameters based on high resolution body surface potential mapping. Medical Science Monitor 2011; 17(3):MT26–33.

[2] Clifford G. Advanced Methods And Tools for ECG Data Analysis. Artech House, Inc., 2006.

[3] Hyvärinen A, Karhunen J, Oja E. Independent Component Analysis. Wiley Series on Adaptive and Learning Systems for Signal processing, Communications, and Control. Wiley-Interscience, 2001.

[4] Castells F, Cebrian A, Millet J. The role of independent component analysis in the signal processing of ecg recordings. Biomedizinische Technik 2007;52(1):18–24.

[5] James C, Hesse C. ICA for biomedical signals. Physiol Meas 2005;26:15–39.

[6] Phlypo R, DÁsseler Y, Lemahieu I, Zarzoso V. Extraction of the atrial activity from the ecg based on independent component analysis with prior knowledge of the source kurtosis signs. Conf Proc IEEE Eng Med Biol Soc 2007; 29:6499–6502.

[7] Stone J. Independent component analysis: a tutorial introduction. MIT Press, 2004.

[8] He T, Clifford G, Tarassenko L. Application of independent component analysis in removing artefacts from the electrocardiogram. Neural Computing and Applications 2006; 15(2):105–116.

[9] Zhu Y, Shayan A, Zhang W, Chen T, Jung TP, Duann J, Makeig S, Cheng C. Analyzing high-density ECG signals using ICA. IEEE Transactions on Biomedical Engineering 2008;55(11):2528–2537.

[10] Hubka P, Rosík V, Zdinák J, Tysler M, Hulín I. Independent component analysis of electrogastrographic signals. Measurement science review 2005;5, Section 2.

[11] Chawla M, Verma H, Kumar V. Artifacts and noise removal in electrocardiograms using independent component analysis. Int Journal of Cardiology 2008;129:278–281.

[12] Barros A, Mansour A, Ohnishi N. Removing artifacts from electrocardiographic signals using independent component analysis. Neurocomputing 1998;22:173–186.

[13] Castells F, Mora C, Millet J, Rieta J, Sanchez C, Sanchis J. Multidimensional ICA for the sepration of atrial and ventricular activities from single lead ECGs in paroxysmal atrial fibrilation episodes. Lecture Notes in Computer Science Independent Component Analysis and Blind Signal Separation ICA 2004 2004;3195:1229–1236.

[14] Haigh A, Murray A, Langley P. Separating the atrial and ventricular components in atrial fibrillation. are 64 leads better than 12? Computers in Cardiology 2007;34:281–284.

[15] Sörnmo L, Stridh M, Husser D, Bollmann A, Olsson S. Analysis of atrial fibrillation: from electrocardiogram sig-

nal processing to clinical management. Phil Trans R Soc A 2009;367(1887):235–253.
[16] Comani S, D. M, Alleva G, Di Luzio S, Romani G. Fetal magnetocardiographic mapping using independent component analysis. Physiol Meas 2004;25(6):1459–1472.
[17] Steinhoff U. Signal identification and noise suppression in multi-channel ECG and MCG by Iindependent Component Analysis ICA. Biocybernetics and biomedical engineering Polish Academy of Sciences 2005;25(4):59–68.
[18] Steinhoff U. Selected Methods for Signal Analysis in High-Resolution Electro- and Magnetocardiography. Warsaw: PhD thesis. Akademicka Oficyna Wydawnicza EXIT., 2005.
[19] Hyvärinen A, Oja E. A fast fixed-point algorithm for independent component analysis. Neural Computation 1997; 9:1483–1492.

Address for correspondence:

*Heriberto Zavala-Fernandez
Nalecz Institute of Biocybernetics and Biomedical Engineering,
Laboratory for Bioelectromagnetic Measurements and Imaging
ul. Trojdena 4, 02-109 Warsaw, Poland.
hzavala@ibib.waw.pl