Application of Independent Component Analysis for Rejection of Motion Artefact in BSPM Recorded During Exercise

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Abstract. *Acquisitions of body surface potentials require in some studies that, patients perform exercise on cycle ergometer to increase their heart rate. Under this condition recordings are highly affected by the muscular activity derived from the pedalling (motion artefact). To reject this interference we propose the use of independent component analysis (ICA) by applying two different algorithms (FastICA and temporal decorrelation). Datasets from 13 subjects were used. For quantification of the results, the signal-to-noise ratios were compared after suppressing the motion artefact. ECG signals showed an average improvement of about 4 to10 dB.*

Keywords: ECG Denoising, Exercise Recording, Motion Artefact, ICA.

1. Introduction

Body surface potential mapping (BSPM) is a technique for recording of electrical activity of the heart by measuring the ECG signal from large number of unipolar electrodes covering the whole surface of the thorax. Thus, the BSPM offers spatial resolution and higher selective sensitivity to individual cardiac regions than standard ECG [1-2]. This advantage is of great importance in interpretation and assessment of electrocardiographic exercise tests, however, the clinical application of BSPM is in this case limited not only by the time consumed electrode placement but also by increased level of noise caused by patients motion. The increase of physical load and heart rate is usually obtained by exercise on ergometers or treadmill where the power of muscular activity increases mainly by the movement of the legs. It causes the artefacts and noise in measured signals related to movement of whole body. An increase of noise related to cable movement is also observed at stress in comparison to ECG signals measured at rest [3-4]. Independent component analysis (ICA) [4] is a method used already in other applications for improvement of the quality of signals, e.g., in conventional 12-lead ECG [4-7]. The common goal by using ICA for the analysis of ECG data is the separation of components that are assumed to belong to heart activity and those related to disturbances (artefacts and noise). In spite of that there are a few papers addressing the application of ICA to body surface ECG recordings. Zhu et al. showed the potential of ICA to decompose BSPM in independent components related to P-, QRS-, and T-waves suggesting that ICA might be an useful tool for the analysis of high-density ECG recording [5]. In this paper, ICA is tested to its ability to decompose the motion artefact resulting from pedalling and its subsequent suppression from BSPM recordings acquired during exercise. Motion artefact is termed as the component originated by the movement of the legs.

2. Methods

The ICA belongs to the class of blind source separation (BSS) methods [3]. It is considered as blind because it tries to recover the sources **s** by looking only at the statistical information contained in the observations **x** assuming that the mixed sources are mutually statistically independent. ICA is based on the superposition model which states that signals **x** are the product of an unknown mixing matrix **A** and an unknown source vector **s**, given by

$$\mathbf{x} = \mathbf{As}. \quad (1)$$

In ICA signals are supposed to be stationary, which implies that the mixing matrix $\mathbf{A}$ does not change over time and there are as many independent components as provided signals $\mathbf{x}$. This supposition clearly holds for the motion artefact. Then sources can be separated theoretically by estimating a demixing matrix $\mathbf{W} = \mathbf{A}^{-1}$. Estimates $\mathbf{y}$ of the original sources $\mathbf{s}$ are found by applying the demixing matrix to the measured variables: $\mathbf{s} = \mathbf{Wx}$. The linear relationship in Eq. 1 corresponds to the forward formulation of the measured potentials at the electrodes as, $\mathbf{v} = \mathbf{Eu}$, where $\mathbf{v}$ is the electric potential recorded at the electrodes on the skin, $\mathbf{u}$ represents the dipole sources and rows of $\mathbf{E}$ specify the lead fields at the electrodes, i.e., how the potential varies with the strength of each dipole source [8].

Two ICA algorithms were tested: the fast independent component analysis (FastICA) based on higher order statistics [9] and the temporal decorrelation source separation (TDSEP) based on second order statistics [10]. The FastICA [9] algorithm is based on an iteration scheme for finding a projection that maximize the non-Gaussianity. The basis of the TDSEP algorithm is a set of time-lagged covariance $R_x(\tau) = \langle x(t+\tau) \cdot x^T(t) \rangle$ with $\tau \neq 0$. Independent components are carried out by simultaneous diagonalization of R_x. In this study, the $\tanh(\mathrm{y})$ was used as the non-linear function for FastICA and 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.

Thirteen healthy volunteers were recorded during exercise on supine ergometer using a high resolution BSPM system (Biosemi Active Two) with 64 leads covering the whole thorax, as shown in Fig. 1 [11]. The sampling frequency of 4096 Hz was applied. All subjects were asked to keep pedalling frequency of around 60 cycles per minute (shown in a display) during examination at fixed load of 25 watts. Each recording session lasted 5 minutes. These data were used as input for the ICA algorithms.

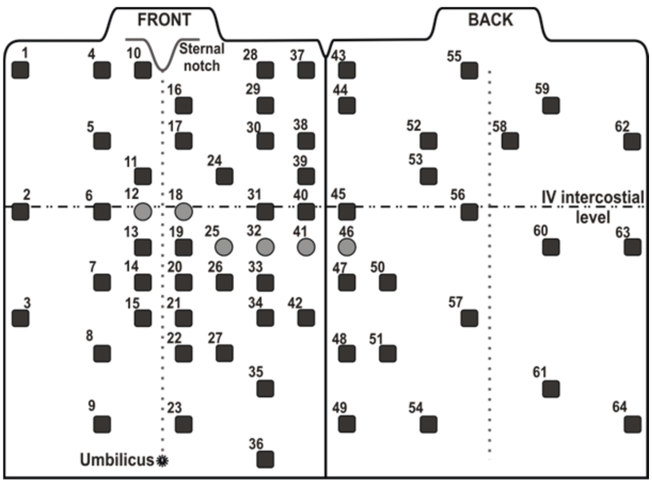

Fig. 1. ECG electrode layout on the thorax of 64 measurement channels. Standard leads V1-V6 are indicated by gray circles.

Independent components to be removed were performed manually by looking at the time-series, the power spectra and the field distribution of the components. Then a back-projection was performed for every dataset with the suppressed component(s).

To assess quality of denoising, the root-mean-square (rms) at every channel was computed before and after suppression of component related to motion and then the signal-to-noise ratio (SNR) in the corresponding sensor was calculated.

3. Results

The ICA methods (FastICA and TDSEP) were applied to 5 min recordings in each dataset. Individual data are separately arranged in data matrix $\mathbf{x}$ ([channels $\times$ samples]). After the calculations 64 independent components were obtained. Components due to the heart activity presented the typical ECG morphology visible in the time series, as well as, frequencies related to the heart beating (Fig. 2a). An spatial representation of the estimated component is generated by interpolation of a column of the estimated mixing matrix $\mathbf{A} = \mathbf{W}^{-1}$.

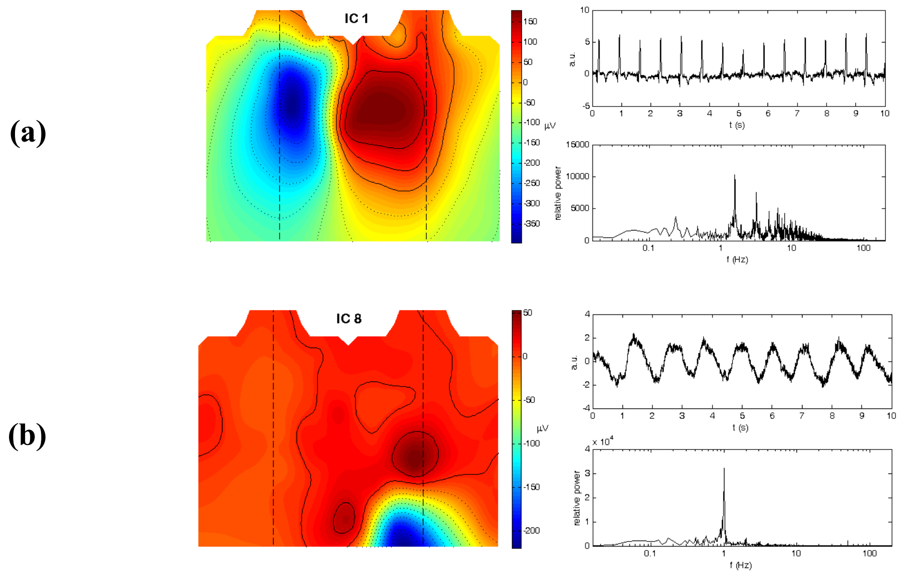

Fig. 2. Example of 2 of 64 computed independent components for one studied subject. (a) Related to heart activity. (b) Related to pedalling. It can be observed that the field distribution is concentrated in the lower part of the map which is the position of the left leg.

The motion artifact shows a dominant peak in the spectrum at 1 Hz, which is clearly related to pedaling (60 cycles/min) (see Fig. 2b). Moreover, it reflects a clear sinus wave as result of moving the leg synchronous. From the map, it can be observed that the field power is concentrated in the lower part of the map in the position of the left leg. The mean values of SNR calculated in the study group for each measured ECG channel showed a considerable benefit of using ICA based ECG denoising methods specially for channels placed close to the extremities (Fig. 3).

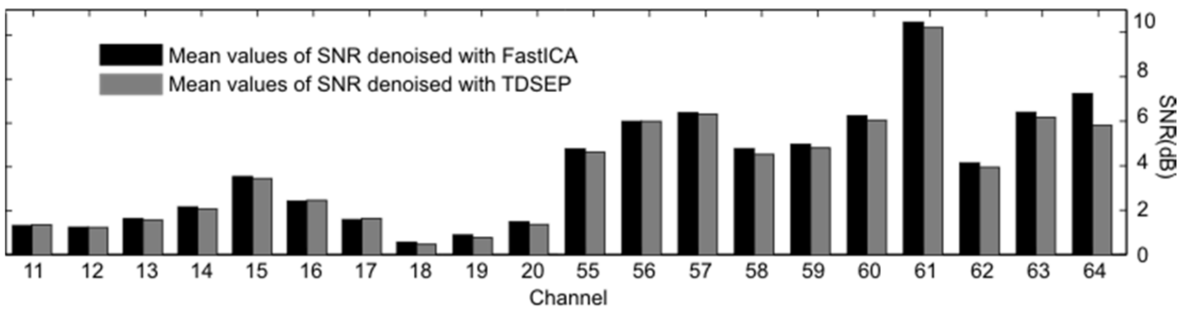

Fig. 3. Improvement of the group average SNR of selected channels after removing the motion artefact separated by ICA algorithms.

4. Discussion

During exercise test an increase of muscular activity is observed in BSPM recordings. This is reflected in considerable disturbances of the signals which most of the case make impossible the subsequent analysis. We have shown that the ICA method with proposed algorithms could be a powerful tool for removing of at least the motion artefact without much loss of information related to the heart activity. Since the motion artefact is considered stationary generated, it fulfil the restrictions for applying ICA to the data under analysis. After rejection of the motion artefacts, the SNRs show an average improvement of about 4 to 10 dB in leads located on the back and close to the extremities. ECG signals measured in electrode locations close to position of a heart were not as substantially affected (about 0.5 dB). Both ICA algorithms presented comparable results. Artefact suppression by removal of selected components might be a valuable pre-processing step to enhance the SNR in multi-channel ECG recordings, e.g. BSPM. Since, stationary of BSPM signals do not always hold [4], it is still under discussion whether the independent components appeared to be related to heart activity and can be treated as independently generated.

Acknowledgements

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