QRS COMPLEX SEPARATION FROM CONVOLUTIVE MIXTURES OF BIOELECTRICAL SIGNALS ACQUIRED BY WEARABLE SYSTEMS

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Abstract: Independent component analysis (ICA) has been widely used to remove artefacts from multichannel biomedical signal acquisitions under the hypothesis that there is statistical independence among the original sources. However, the basic ICA model does not take into account the influence on the mixing process of the different paths from the signal sources to the sensors In this study we propose a convolutive mixtures model in order to overcome the limitations of the basic ICA approach. The independent components are estimated in the frequency domain, where the convolutive model can be solved through an instantaneous mixing model. The signals are reconstructed back to the observation space resolving the ICA model ambiguities. Simulations are carried out to optimize of the proposed method for convolutive mixtures of electrocardiographic (ECG) and motion artefacts signals. The algorithm is tested on real ECG signals acquired by wearable systems in order to preserve the QRS complex when the signals are degraded by real life conditions of acquisition.

Introduction

Wearable textile systems are designed to monitor, in real life environments, vital signals like electrocardiogram (ECG), electromyogram (EMG), breath patterns**.** In these systems conductive and piezoresistive materials, in form of fiber and yarn, are used to realize clothes where knitted fabric sensors and electrodes are distributed and connected to an electronic portable unit.

The acquired signals can be corrupted by several kinds of artefacts, like contaminations in the ECG caused by myoelectric or respiratory activity. Other artefacts can be caused by a displacement of the electrodes integrated in the textile garment during subject movements. These motion artefacts produce base line drifts which may cause the loss of the main features, like QRS complex or S and T waves.

Several methods can be applied to remove artefacts in biopotential recordings from wearable systems: the most known are linear and nonlinear filtering techniques [1,2] adaptive signal processing [3], and wavelets based methods [4].

Other techniques take advantage of multichannel data acquisitions, since both artefacts and signals of interest show common features in different channels. Thus we can suppose that signals available at the sensors are a mixture of several components belonging to different physiological phenomena and try to decompose these observations into components that can be classified either as 'signal of interest' or as 'signal of no interest' for each detected channel. This is what blind source separation methods carry out, assuming that neither the source signals nor the mixing processes are known. In order to estimate the source signals, several hypothesis can be made. Principal Component Analysis (PCA) for example looks at linearly independent components, while Independent Component Analysis (ICA) [5, 6] hypothesize the statistical independence among the original sources. This statement implies that components belonging to different physiological phenomena can be extracted from the signals detected by the sensors, even though they overlap in time and frequency.

The standard ICA model assumes an instantaneous mixing process, but this approach seems to be inadequate to account for the different paths from the signal sources to the sensors. Moreover, an instantaneous mixing process may fail to model the effects at the sensors of the spatio-temporal dynamics of some signals, as Anemuller [7] hypothesized for EEG data. For this reason we propose a method to remove artefacts using blind separation of convolutive mixtures by means of ICA and we choose to solve this problem in the frequency domain [8, 9].

In this work we hypothesize that the signals generated by the electrical activity of the myocardial muscle, measured by the ECG signal, are filtered by a transfer function that depends on the distance and on the tissues interposed between the sources and the electrodes.

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The effect of this model may cause a delay between common features in the signals measured at different locations. To support this hypothesis we estimate the time delay between three different ECG leads recordings using a method based on the Hilbert transform and discrete Fourier transform: this method was employed by Saad et al. [10] in order to highlight time shift between fMRI time series.

Then convolutive mixtures of an ECG signal and a manually generated motion artefact is simulated. The relevant decomposition process is performed and the parameters of the algorithm studied by a performance index is calculated.

The proposed algorithm for convolutive mixtures separation is tested also on real ECG acquired by the wearable system developed by Smartex S.r.l [11, 12], partner in MyHeart IST-2002-507816 project and Wealthy IST-2001-37778 project. During the acquisition, the subject is asked to cause intentionally displacements of the electrodes in order to produce ECG signals affected by motion artefacts on which apply our method. The aim is to separate the ECG complex component and reconstruct it in the observe channels in order to produce recordings in which at least the QRS complex is well detectable for further processing, like heart rate variability estimation.

Material and Methods

The basic or instantaneous ICA model assumes that a set of n measurements $\boldsymbol{x}(t)=(x_1(t),x_2(t),\ldots,x_n(t))^T$ is originated by a linear mixing process of some latent sources $\boldsymbol{s}(t)=(s_1(t),s_2(t),\ldots,s_m(t))^T$. Only the observed data $\boldsymbol{x}(t)$ are available while neither the sources nor the mixing process are known. The problem consists in finding an unmixing matrix $\boldsymbol{W}$, so that $\boldsymbol{y}(t)=\boldsymbol{W}\boldsymbol{x}(t)$ is an estimate of the original sources that are supposed to be statistically independent. In the following we will assume the number of sources equals the number of acquired signals, thus $n=m$.

If we assume that no time delay is involved in the mixing process, we can drop the time index and rewrite the instantaneous model in matrix notation as

$$x = As \tag{1}$$

In some applications this assumption may be too strong since the paths of the signals to each sensor may be different and the finite propagation speed in the medium may generate different time delays.

In order to highlight this time delay for bioelectrical signals, we made use of an efficient Hilbert Transform algorithm, employed by Saad to estimate the fMRI response delays [9]. This technique evaluates the delay between two time series by computing their cross correlation function and the relevant Hilbert transform, whose zero crossing gives an estimation of the delay.

In fact, for a time series, $x_1(t)$, and its time shifted version, $x_2(t)=(t-\Delta t)$, the time delay Δt can be evaluated by determining the maximum of their cross-correlation function $R_{x_1x_2}(\tau)=E[x_1(t)x_2(t+\tau)]$, which is presumably located at $\tau=\Delta t$. However, as we are dealing with discrete time signals, the time series are discrete series defined only at integers multiples of the sampling period. Thus the real maximum of the function $R_{x_1x_2}(\tau)$ may be located between two samples.

For this reason we prefer to use the analytic function $Z_{x_1x_2}(\tau)=R_{x_1x_2}(\tau)+jH[R_{x_1x_2}(\tau)]$, where $H[R_{x_1x_2}(\tau)]$ is the Hilbert transform of the cross-correlation function exploiting the property that when τ equals Δt, the envelope of $Z_{x_1x_2}$ is equal to $R_{x_1x_2}$ and $H[R_{x_1x_2}]$ is null. Looking for the maximum of the cross-correlation function means looking for its Hilbert Transform zero crossing, that can be estimated more precisely by higher order interpolation.

These concepts can be applied to the ECG signals in order to compare different leads registrations acquired simultaneously and verify the presence of a time delay between them. All the procedure is based on the hypothesis that the time structure of the signal (especially the QRS complex) remains approximately the same in different leads.

To take into account the underlying time delays, our ICA generative model of observed signals, seen in equation (1), can be modified by introducing a convolution operator in the mixing process

$$x_i(t)=\sum_{j=1}^{n}\sum_{k=1}^{L}a_{ij}(k)s_j(t-k) \quad \textit{for } i=1,\ldots,n \tag{2}$$

The element of the mixing matrix A become finite impulse response (FIR) filters.

The problem can be solved in the time domain by using natural gradient methods or as ordinary ICA, but these techniques take many iterations and much time to converge. Hence we decided to follow another approach which is called frequency-domain blind source separation [8, 9] exploiting the property that, since a convolution in the time domain can be expressed as a product in the frequency domain, the convolutive mixtures model can be transformed into an instantaneous linear mixing ICA model within each distinct frequency bin in which the spectral band is split. A Short Time Fourier Transform (STFT) is applied in order to obtain a time-varying spectral description of the signals. Consequently the whole separation problem is divided into a number of linear complex source separation problem, one for every frequency bin:

$$X_i(f,t)=\sum_{j=1}^{n}A_{ij}(f)S_j(f,t) \tag{3}$$

where $A_{ij}(f)$ are the discrete time Fourier transforms coefficients (DFT) of the FIR filters $a_{ij}(k)$ present in the mixing matrix **A.**

Hence it is possible to use the algorithms developed for the instantaneous ICA model like the ones based on nonlinear decorrelation, the maximum likelihood

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estimation methods, the infomax principle, and the minimization of mutual information (see [6] for a review). In this work we make use of the fast-fixed point algorithm developed by Hyvarinen [13] based on maximization of the nongaussianity of extracted components, whose one unit learning rule is:

$$\mathbf{w}_i \leftarrow E\left\{zf\left(\mathbf{w}_i^T x\right)\right\} - E\left\{f'\left(\mathbf{w}_i^T x\right)\right\}\mathbf{w} \qquad (4)$$

where *f(·)* is a nonlinear function used in order to take into account higher order cumulants that approximate the Neg-entropy of the data and can be chosen among $f(\mathbf{y})=\tanh(\mathbf{y})$, $f(\mathbf{y})=\mathbf{y}\exp(-\mathbf{y}^2/2)$ or $f(\mathbf{y})=\mathbf{y}^3$.

Note that as we are operating with complex valued data we need to reformulate these algorithms and perform two important modifications. First we must convert matrix transpositions to Hermetian transpositions (conjugate transpose). Then the nonlinear functions *f(·)* must be defined again in the complex domain. For example $f(\mathbf{y})=\tanh(\mathrm{Re}\{\mathbf{y}\})+\tanh(\mathrm{Im}\{\mathbf{y}\})i$ can be employed instead of $f(\mathbf{y})=\tanh(\mathbf{y})$ [8].

As pre-processing step, before performing ICA both a removal of the mean value and a whitening operation using PCA is performed. This operation simplifies the estimation of the unmixing matrix $\boldsymbol{W}$ that becomes orthogonal with only *n(n-1)/2* degrees of freedom instead of n^2.

In instantaneous ICA it is well known that it is impossible to determine the order in which the independent components are extracted. This permutation ambiguity becomes a serious problem in complex domain ICA. We need to align the estimated independent components along the frequency bins so that separated components, in the time domain, contain frequency components from the same source signal

To solve this permutation problem, inter-frequency correlations of signals can be used [14], since we suppose that two spectral envelopes belonging to the same source should have a higher correlation coefficient than the one they would have if they belonged to different sources.

$$corr\ (v_i^f, v_j^{f-1}) = \frac{\left[E\left\{v_i^f \cdot v_j^{f-1}\right\} - E\left\{v_i^f\right\}E\left\{v_j^{f-1}\right\}\right]}{\sigma_{v_i^f}\sigma_{v_j^{f-1}}} \qquad (5)$$

where $v_i^f(t) = |Y_i(f,t)|$ and $\sigma_{v_i^f}$ is the standard deviation of $v_i^f(t)$.

Hence, we compute the correlation coefficients between each $v_i^f(t)$ extracted in one bin and the others $v_j^{f-1}(t)$, with *j=1,...,n*, belonging to the preceding bin. The alignment is based on the correlation coefficient, through an iterative process. At the first step, the algorithm aligns $v_i^f(t)$ with the $v_j^{f-1}(t)$ component that shows the highest correlation coefficient. These two components are then eliminated from successive steps and the same practice is reiterated for the remaining *n-1* components. This procedure is repeated until the last frequency bin is aligned.

Another ICA drawback is that the components are always estimated up to a scale and a phase factor. This ambiguity is overcome by returning them to the space of the detected signals, the observation space.

$$X_iY_j(f,t) = \left(W_f^{-1}\right)_{ij}\begin{pmatrix} 0 \\ \vdots \\ Y_j(f,t) \\ 0 \end{pmatrix} \qquad (6)$$

where $X_iY_j(f,t)$ represents the *j-th* estimated independent component contribute in the *i-th* channel for the frequency bin *f*, and $(\boldsymbol{W}_f^{-1})_{ij}$ is the *ij-th* element of $\boldsymbol{W}_f^{-1}$

After performing all this linear transformations, we can group the $X_iY_j(f,t)$ in the following way*:*

$$X'_i(f,t) = \sum_j X_iY_j(f,t) \qquad (7)$$

If we move *j* go from *1* to *n*, extending the sum in each channel to the contribute given by all the estimated independent components, we obtain exactly the observed signals. But in the case some independent components returned to the observation space are not significant for the information provided by the channel *i* they can be set to zero in (7).

In order to identify which component could be related to the ECG signal and which one could be considered artefacts we made use of a method for automatically identifying components, extracted from convolutive mixtures, that can be associated to periodic signals [15]. This approach takes origin from the observation that the periodicity observed in a time domain source signal, is still present in the magnitude spectrogram. The autocorrelation function of the magnitude spectrogram, preserve a periodicity too, in each frequency bin. This property of the autocorrelation function can be used to discriminate the ECG (or at least the QRS) component from other non periodic components: in fact, in the magnitude spectrogram of a signal that has not important periodic components, the time over which a certain pattern is correlated is very short and settles rapidly to zero. Fixing a proper threshold, the area of the autocorrelation function of an ECG component, exceeding a prefixed threshold, will be larger than the other component areas, and this source can be identified. After the selected independent components have been returned to the observation space in the frequency domain, an inverse short time Fourier transform (ISTFT) can be used to obtain the reconstructed signals in the temporal domain.

Results

Time delays between different ECG recordings, were evaluated employing the Hilbert transform method outlined in the previous section.

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To validate the proposed approach when dealing with these kind of signals, we considered an ECG recording $e_1(t)$ sampled at 1KHz and its time shifted version $e_2(t) = (t - \Delta t)$ imposing a $\Delta t = 6ms$. We concentrated the analysis on 0.5 second long observation window centered around one QRS complex. We computed the cross-correlation function between two observation window of $e_1(t)$ and $e_2(t)$ and its Hilbert transform. The Hilbert transform was interpolated by increasing the sampling rate by a factor of 3 around its zero crossing were evaluated. Ten different observation windows of the QRS complex were considered and the zero crossings values of the cross-correlation Hilbert transforms were averaged, obtaining an estimated time delay equal to 5,996 ms.

Hence we extended this method also on real basal acquisitions of different leads, like limb leads DI and DII and precordial lead V5, acquired by Smartex wearable system. The sampling rate was 1 KHz and the observation window was 0.5 second long, centered around one QRS complex of the limb lead DI and placed in the same point for every leads. From these three time series we obtained three cross-correlation functions and the relevant Hilbert Transform. The time delay was evaluated by interpolating the Hilbert transform zero crossing by a factor of 3, like in the previous experiment. The values of ten different observation windows, of the same acquired signals, were averaged. The results are shown in table 1.

Table 1: Estimation of time delay between different ECG leads acquisition

$\Delta t_{V5,DI}$	$\Delta t_{V5,DII}$	$\Delta t_{DI,DII}$
1.822 ms	3.868 ms	4.766 ms

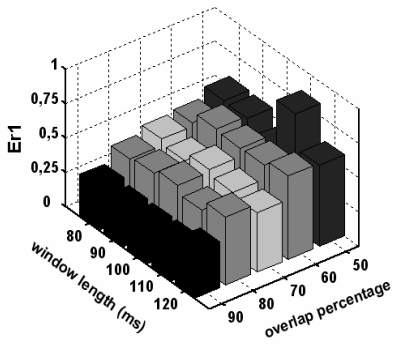
Starting from these observations, some simulations experiments were carried out to asses how our frequency domain independent component analysis algorithm works on convolutive mixtures of motion artefact and ECG signals. One noise-free ECG bipolar limb lead DI was acquired in basal condition by the Smartex System and a motion artefact was manually generated by pushing on the center of a standard red dot electrode. These two signals underwent an analog band-pass filter with cut-off frequencies *0.3-100Hz* and another filter with stop band at *50Hz*, and then sampled at f_s*=1KHz*. The ECG and the motion artefact were organized to form respectively the first and second row of the source signals matrix $\mathbf{s}(t)$. The windows method, based on the Hamming function, was used to design the FIR filters $a_{ij}(k)$ of the mixing matrix $\mathbf{A}(t)$, which simulates the effect of each source $s_j(t)$ in the detected signal $x_i(t)$. We assume that the artefact interests the whole frequency content of the ECG, which goes approximately from 0 to 50 Hz. Thus $a_{11}(t)$ was a 70 coefficient low pass filter with cut off frequency f_1*=50Hz* followed by ten zeros, while the other ones were shifted version of $a_{11}(t)$, with lower or higher gain, realized to introduce a time delay between the sources detected at the electrodes.

When estimating the independent components from the convolutive mixtures in the frequency domain, the first step is to choose the length of the window used in the STFT procedure and the shifting time between adjacent window. A four seconds observation of the data sets, $x_1(t)$ and $x_2(t)$, were initially analyzed with a Hamming window of the same length as the FIR filters, 80 ms, and 90% overlap. Thanks to a frequency domain approach it was possible to select the spectral bands in which carry out the source separation procedure. In this case we applied our analysis only in the frequency bins included between *0* and f_1, that delimitate the band where the ECG signal and the motion artefact overlapped after the mixing process.

After performing ICA in each bin and solving the permutation problem by (5) we returned the estimated independent components in the observation space by (6). In the frequency bins, where we didn't carry out ICA, no reconstruction is required and the observations were left unchanged. The ECG related component are identified by the procedure based on the magnitude spectrogram autocorrelation function described in the previous paragraph. After only this component had reconstructed in the two channels in each frequency bin, an inverse time Fourier transform was applied to obtain $x'_1(t)$ and $x'_2(t)$.

To get a performance index of this model, we compare $x'_1(t)$ and $x'_2(t)$ respectively with the signals obtained from the convolution of $a_{11}(t)$ and $s_1(t)$, and the one given by the convolution of $a_{12}(t)$ with $s_2(t)$. These latter signals represent what we would have actually observed at the electrodes if no artefacts were involved in the mixing process.

Thus our error index is defined as $Er_i = \sum_t |x'_t(t) - a_{1i}(t) * s_i(t)|^2 \Big/ \sum_t |a_{1t}(t) * s_i(t)|^2$, where $*$ indicates the convolution operator, and represents the energy of the error normalized by the energy of the noise free signals. Er_i were measured by changing the window length from 80ms, the minimum value allowed by the model (2), to 120 ms, while the overlap degree was decreased from 90% to 50%. As the unmixing matrix always started from random points in each bin, we carried out five different trials and took the mean values of the indexes to obtain statistical reliability. In figure 1 we can observe how the error index changes in both channels.



(a)

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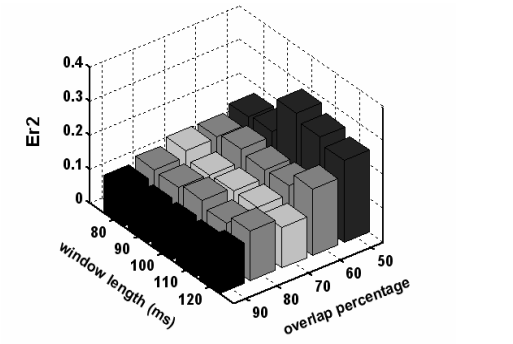
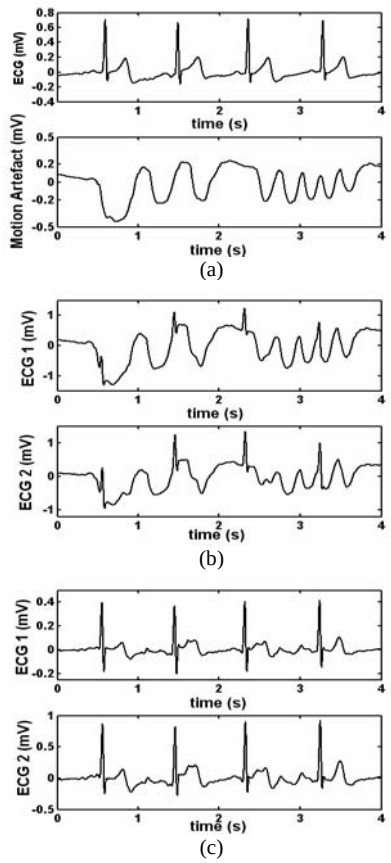


(b)

Figure 1: Error indexes for the two simulated acquired ECG channels: (a) Er_1 and (b) Er_2

Figure 2 shows the time domain evolution of the two original source signals $s_1(t)$ and $s_2(t)$, the simulated convolutive mixtures $x_1(t)$ and $x_2(t)$, and the signals $x'_1(t)$ and $x'_2(t)$ processed with a 80ms Hamming window with 90% overlap.



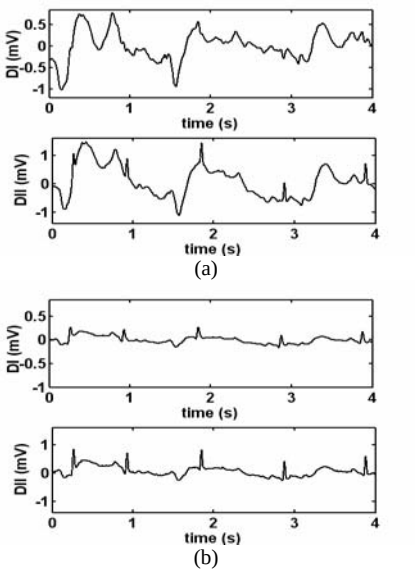
(a)

(b)

(c)

Figure 2: (a) original source signals $s_1(t)$ and $s_2(t)$, (b) simulated convolutive mixtures $x_1(t)$ and $x_2(t)$, (c) the processed signals $x'_1(t)$ and $x'_2(t)$.

Then the same algorithm was applied to two bipolar limb ECG signals, lead DI and lead DII, acquired by the Smartex wearable system. In order to cause motion artefacts in the observed signals, the subject was asked to move his arms back and forward during the acquisition. The analog filters were a band-pass filter with cut-off frequencies equal to 0.3 Hz and 100 Hz and stop band filter at 50 Hz. We carried out our analysis in the frequency interval included between 0 and 50 Hz, which approximately represents the whole ECG frequency content, and left the signals unchanged over 50 Hz. The window parameters were chosen as consequence of the simulation results. In figure 4 real data are depicted as they were acquired and after frequency domain ICA separation.



(a)

(b)

Figure 3: Real data (a) before and (b) after frequency domain ICA application.

Discussion

The method based on the Hilbert transform cross-correlation highlighted the presence of a time delay between different ECG recordings. Under the hypothesis that the Q, R and S waves are always present in every acquisitions with the same polarity, it was possible to estimate a time shift of some milliseconds between the observations of these waves in different ECG leads.

This allowed us to model our multichannel acquisition as a convolutive mixtures problem in order to take into account different paths of the source signals to the electrodes.

The frequency domain approach proposed in this paper was tested by some simulation experiments where the source signals were a noise free ECG recording and a manually generated motion artefacts.

The performance index in figure 1 indicated that the best result are achieved when the overlap percentage between two adjacent window, employed in the STFT of the observation signals, is higher. The best result is obtained, for both channels, with a 90% overlap.

The window length did not seem to influence the algorithm performance, once the overlap degree had been fixed. However it worth noting that larger windows increased the frequency resolution of the algorithm but decreased the ability to resolve changes with time. Consequently, the choice of the window

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length became a trade-off between frequency resolution and time resolution. This compromise affected the shape of the time series for which the algorithm estimated the independent components in each frequency bin.

A higher frequency resolution leads to a higher number of frequency bins and thus the computational load of the entire algorithm increases. The minimum number of bins is recommended when the target of the analysis is a real time implementation.

Our algorithm was successful in motion artefacts removal from ECG signals acquired by wearable systems in real life condition. The QRS complex was extracted and well reconstructed in the acquired channels by the proposed method. Displacements of the electrodes or degradation of the acquisition conditions, that are likely to happen in wearable systems, may compromise the detection of the QRS complex. However, our algorithm guarantees to use our ECG recordings for further processing, like heart rate variability.

As our method is completely blind (we know nothing about the sources and the mixing process) it may be extended to a wide collection of artefacts that can contaminate biomedical signals. Moreover, the algorithm in the frequency domain has another advantage since it can characterize the components and discriminate between signals of interest and of no-interest in each frequency bin. Sources associated with artefacts may only be present, for example, in a particular set of frequency bins, in which they should not be utilized during the reconstruction process.

Conclusions

We have proposed an algorithm based on blind separation of convolutive mixtures in order to remove artefacts from biomedical signals acquired by wearable systems. In this model the sensors are hypothesized as measuring a mixing of independent components after they have undergone a convolutive process to account for the different paths of the signals to the electrodes and complex spatio-temporal dynamics. The proposed algorithm follows a frequency domain approach, allowing the use of ICA algorithms developed to solve the instantaneous mixing problem. A procedure based on the correlation function calculated between adjacent frequency bins has been employed in order to overcome the indeterminacy of the order of the independent components.

Some experiments on simulated convolutive mixtures of an ECG and a manually generated motion artefact indicated the best parameters to be used in this application.

Real data analysis highlighted that the convolutive model can remove motion artefacts from ECG signals acquired by wearable systems preserving the QRS complex.

Acknowledgments

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