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Multichannel Techniques for Motion Artifacts Removal from Electrocardiographic Signals

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Abstract— **Electrocardiographic (ECG) signals are affected by several kinds of artifacts, that may hide vital signs of interest. Motion artifacts, due to the motion of the electrodes in relation to patient skin, are particularly frequent in bioelectrical signals acquired by wearable systems. In this paper we propose different approaches in order to get rid of motion confounds. The first approach we follow starts from measuring electrode motion provided by an accelerometer placed on the electrode and use this measurement in an adaptive filtering system to remove the noise present in the ECG. The second approach is based on independent component analysis methods applied to multichannel ECG recordings; we propose to use both instantaneous model and a frequency domain implementation of the convolutive model that accounts for different paths of the source signals to the electrodes.**

I. INTRODUCTION

The electrocardiogram (ECG) is the recording on body surface of the electrical activity generated by heart. Many cardiac diseases, like arrhythmia, ischemia or atrial fibrillation, are related to the morphology of the ECG signal. Unfortunately the occurrence of noise from various sources can invalidate the extrapolation and the analysis of the main ECG cycles, i.e. QRS complexes, P and T waves.

The most common undesired signals, superimposed on the components of interest present in the ECG channels, are power line interference, muscle activity contamination in form of electromyographic (EMG) signals, and motion artifacts. As Webster [1] pointed out, motion artifacts are originated by patient moving which may cause both a skin potential change due to skin stretch and the electrode metal-to-solution interface movement. Both these conditions result in base line wanders in the biopotential collected at the ECG electrodes.

Bioelectrical signals recordings are particular noisy when acquired by wearable systems. These systems are based on knitted integrated sensors [2] and can be used by a subject during everyday activity. The presence of motion artifacts is due to the displacement of the electrodes. Even if the contact between skin and fabric can be improved by a double layer sticky hydrogel membrane, which acts as the gel in standard Ag-AgCl electrodes, the influence of artifacts increases with increasing movement activity.

In order to have an efficient removal of motion artifacts, many ECG filtering algorithms have been developed. But as motion artifacts bandwidth overlaps with the ECG's [3], linear filtering techniques showed to be inefficacious [1]. Some methods, like ensemble averaging [4], exploit the recurrence of ECG cycles but require a large number of records to obtain a good estimation of the signal and are not able to follow rapid change of the signal shape.

In this paper we follow two different approaches with the aim to get information about motion from a multichannel acquisition scheme.

The first one is based on adaptive filtering techniques [5]. In fact, in noise canceling application, the adaptive filter minimizes the mean-square error between a primary input, i.e. the noisy ECG, and a reference input that can be noise correlated in some way with the one superimposed on the ECG. Within this framework we investigate the use of a sensor for measuring the electrode movements under the hypothesis that the electrode motion contains information on motion artifact in ECG signal [6], [7]. Therefore an accelerometer is attached on the ECG electrode and the signal acquired by this motion sensor becomes the reference input for the adaptive filter.

The second kind of algorithms developed in this work, is based on independent component analysis (ICA) [8] that model the signals available at the ECG electrodes as a mixture of several components, belonging to different physiological phenomena. Neither the source signals nor the mixing processes are known in this model. ICA techniques try to decompose the acquired signals into components that can be classified either as 'signal of interest' or as 'signal of no interest' for each detected channel under the hypothesis of statistical independence among them. Applications of the ICA model in removing artifacts from biomedical signals have been presented in several publications [9], [10].

Both linear instantaneous model, where no time delay is involved in the mixing process, and new convolutive mixtures separation by frequency domain approaches [11], [12], [13] are tested on multichannel ECG acquisitions. In convolutive model weighted and delayed contributions of the sources are considered in generating the observations thanks to unknown finite impulse response (FIR) filter included in the mixing process. All ECG acquisitions are carried out with the wearable system developed by Smartex Srl partner in MyHeart IST-2002-507816 European project. The adaptive

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filtering and ICA algorithms performances are evaluated and compared on the same recordings thanks to a performance index.

II. METHODS

A. Adaptive filtering

The general structure of an adaptive filter for noise canceling utilized in this paper requires two inputs [5], called the primary and the reference signal. The former is the $d(t) = s(t) + n_1(t)$ where $s(t)$ is an ECG signal and $n_1(t)$ is an additive noise. The noise and the signal are assumed to be uncorrelated. The second input is a noise $u(t)$ correlated in some way with $n_1(t)$ but coming from another source. The adaptive filter coefficients w_k are updated as new samples of the input signals are acquired. The learning rule for coefficients modification is based on minimization, in the mean square sense, of the error signal $e(t) = d(t) - y(t)$ where $y(t)$ is the output of the adaptive filter. A block diagram of the general structure of noise cancelling adaptive filtering is shown in Fig. 1.

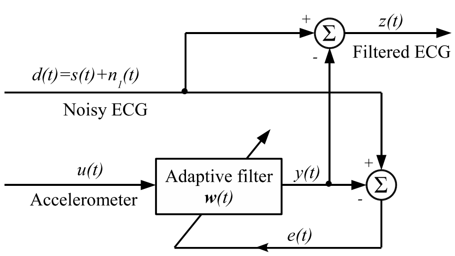

Fig. 1. Block diagram of adaptive filtering scheme.

The two most widely used adaptive filtering algorithms are the Least Mean Square (LMS) and the Recursive Least Square (RLS) [5].

B. Instantaneous ICA model

Another approach for artifacts removal is based on ICA: this multivariate statistical technique is used to estimate a set of signals (sources) of which only a mixture is available (observations). Both the source signals and the mixing process are unknown. The only hypothesis made to estimate the original signals is that they are statistically independent among each other. If no time delay is involved in the mixing process the ICA model is known as basic or instantaneous model and each of the $x_i(t)$ is a linear combination of the sources according to the following equation: $x_i(t) = a_{i1}s_1(t) + a_{i2}s_2(t) + \ + a_{iN}s_N(t)$, with $i = 1, \dots, M$. In matrix notation the basic model can be expressed by $\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t)$, where A is called the mixing matrix and an estimate of the latent sources is obtained by $\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t)$ through maximization of the statistical independence among the sources. In the following the number of the sources is assumed to be equal to the number of the observation, that is $N = M$. Higher order statistics can be used for extracting the most independent components from the observations. We used the FastICA [14] algorithm based on maximization of negentropy.

The estimated components can be returned to the space of the observations by:

$$x_{iy_j}(t) = \left(\mathbf{W}^{-1}\right)_{ij} \begin{pmatrix} 0 \\ \vdots \\ 0 \\ y_j(t) \\ 0 \end{pmatrix} \tag{1}$$

where x_{iy_j} represents the j-th estimated independent component contribute in the i-th channel and $(\mathbf{W}^{-1})_{ij}$ is the ij-th element of $\mathbf{W}^{-1}$. After performing all this linear transformations, we can group the $x_i y_j(t)$ in the following way:

$$x_i^{'}(t) = \sum_j x_{iy_j}(t) \tag{2}$$

Independent components, returned to the observation space, that are not significant for the information provided by the channel i, can be set to zero in (1). This procedure guarantees artifacts removal from a multichannel acquisition.

C. Convolutive ICA model

The basic ICA model assumes that the mixing process is instantaneous, meaning that every single component produced by original sources reaches each sensor at the same time. In some applications this assumption seems to be too strong: in fact it can be assumed that the source signals are filtered by unknown transfer functions before they reach the sensors. In this case the convolutive ICA model, expressed by the following equation, can be introduced:

$$x_i(t) = \sum_{j=1}^{M}\sum_{k=1}^{L} a_{ij}(k)\, s_j(t-k) \quad \text{for} \quad i = 1, 2, \dots, N \tag{3}$$

where $a_{ij}(t)$ are the coefficients of the FIR filters of length L that compose the mixing matrix.

A frequency domain approach to convolutive model has been proposed by authors [12], [13] for automatically removing artifacts from biomedical signals. This method allows to estimate the independent components by splitting the analysis in a number of frequency bins, by means of a short time Fourier transform (STFT), and exploits the property that convolution in time domain becomes product in frequency. Hence it is possible to solve an instantaneous model in each frequency bin after adapting the basic ICA algorithm to work on complex data [12]. Then the generative model, for each frequency bin, becomes:

$$X_i(f,t) = \sum_{j=1}^{n} A_{ij}(f)\, S_j(f,t) \tag{4}$$

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

In order to return to the observation space only the ECG component without the artifacts, the same procedure described for time domain ICA in (1) and (2) can be performed in each frequency bin. In complex ICA it is possible to analyze only the frequency band where the signals overlap and leave the acquired channel unchanged in the remaining bins.

III. EXPERIMENT PROTOCOL

Some experiments have been carried out to asses the capability of our methods in artifacts removal from ECG acquisitions. Three limb leads ECG were recorded: DI and DII with Smartex wearable systems and DIII with 3M^{TM} Red Dot standard Ag/AgCl electrodes. The latter was acquired as a reference, more stable, signal. A triaxial accelerometer (STMicroelectronics LIS3L02AQ) was sewed on right shoulder fabric electrode with axis x, z parallel to the body surface and y perpendicular. The ECG signals underwent an analog band-pass filter with cut-off frequencies 0.3-50 Hz and then were sampled at $f_s = 256$ Hz, while the three accelerometer outputs were amplified and band limited at 0.3-10 Hz before being sampled at 25.6 Hz.

The subject was asked to move in order to induce motion artifacts in the acquired signals. Thorax flexions and extensions, shoulders abduction and adduction were performed randomly together with walking in place. Both adaptive filtering technique, with LMS and RLS algorithm, and ICA, employing an instantaneous and a convolutive approach, were tested as artifacts removal processing methods.

As primary input for the adaptive filter ECG lead DII was chosen because it usually shows greater magnitude than DI. Accelerometer axis z, oriented vertically and parallel to body surface, was used as reference input and assumed to be correlated with the motion artifact in ECG channel. Only this channel was used because single axis noise reference was proved to give better results in this kind of applications [7]. The accelerometer signal was linearly interpolated to get the same sampling frequency of the ECG. Both RLS and LMS algorithms worked on a time windows of 3 seconds for a 48 seconds overall acquisition period. The adaptive filter order was fixed at 20.

The ICA and convolutive ICA methods were applied on ECG leads DII and DI. The analysis was carried out on time frames of 3 seconds, like in adaptive filtering application. A 120 milliseconds long Hamming window was used for the STFT in the convolutive ICA. To discriminate between the ECG and motion artifact components, an automatic method that exploits the periodicity of the ECG signal has been proposed by authors in previous publications [12], [13]. Once identified, the noisy component can be set to zero into the observation space. The FastICA was adapted for the Fourier domain implementation. As performance index between ECG lead DII, analyzed by the proposed methods, and the reference signal acquired with standard Ag-AgCl we defined:

$$Er = \frac{\sum_{t=t_i}^{t_i+3} (\mathit{after} - \mathit{ref})^2}{\sum_{t=t_i}^{t_i+3} (\mathit{before} - \mathit{ref})^2} \times 100 \qquad (5)$$

where *before* and *after* indicate respectively ECG lead DII before and after filtering , and *ref* is reference DIII Red Dot noise free signal. Note that Er indicates the percentage of the residual noise, after applying the proposed filtering techniques. Er was computed over each of the analyzed 3 seconds long segments. The mean value and standard deviation were evaluated as statistical indexes for the overall 48 seconds.

IV. EXPERIMENTAL RESULTS

Fig. 2 shows seconds from 5 to 25 of the 48 seconds raw ECG lead DII (a), DI (b), DIII (c), and the z axis accelerometer output (d), while in Fig. 3 we can observe the result of the adaptive filtering LMS (a) and RLS (b) on DII. The instantaneous and complex ICA results are shown respectively in Fig. 3(c) and 3(d). Only processed DII is visible because the performance is computed only on this lead for all the described methods.

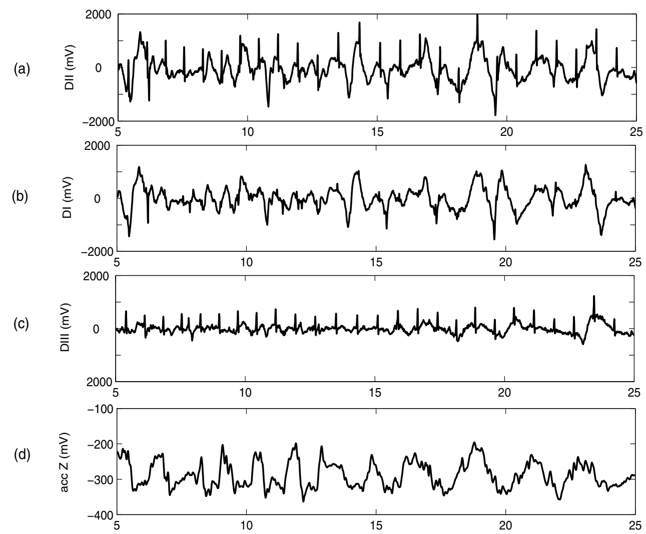

Fig. 2. ECG lead DII (a), DI (b), DIII (c), and z axis accelerometer (d).

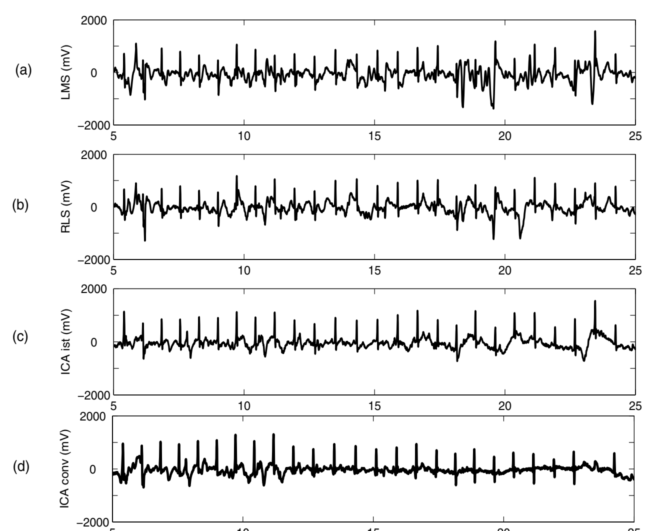

Fig. 3. Result of LMS (a) and RLS (b) filtering, on ECG lead DII and z axis accelerometer, instantaneous (c), and convolutive (d) ICA on ECG lead DII and DI.

In Table I the mean values in of Er expressed in dB are shown for all the processing methods.

TABLE I
MEAN VALUE (ER MEAN) AND STANDARD DEVIATION (ER STD) OF PERFORMANCE INDEX

	ECG + Accelerometer (adaptive filtering)		2 ECGs (ICA)	
	LMS	RLS	Instantaneous	Convolutive
Er mean	0.45	0.30	0.08	0.17
Er std	0.15	0.19	0.04	0.08

V. DISCUSSION AND CONCLUSIONS

In this paper two different approaches for artifacts removal from ECG signals acquired by wearable systems have been discussed and tested. The first one employs an adaptive filtering scheme with an accelerometer sewed on right shoulder fabric electrode as reference input. The axis z of the accelerometer, vertically parallel to body surface, was considered the most correlated with the motion artifact present in ECG recording. The RLS algorithm obtained better results, on ECG lead DII, than the LMS one as shown by Table I. It is worth noting that the rate of convergence of RLS algorithm is one order of magnitude greater than the LMS one. Although this means an improvement in performance for RLS approach, its computational complexity increases.

The multichannel nature of ECG acquisitions was exploited for the second approach based on independent component analysis. Two ECG leads DII and DI were processed by basic and convolutive ICA model. For the latter a frequency domain implementation was chosen. According to the percentage of the residual noise present in lead DII evaluated after the artefact removal stage, the basic ICA showed the better results.

On the whole, the ICA outperforms adaptive filtering techniques demonstrating to be a powerful tool for this kind of applications. Nevertheless the chosen performance index does not give information about the recovery of the ECG signal morphology obtained by the proposed methods. Moreover it must be noted that the adaptive filtering technique can be efficacious only if the reference input is strongly correlated with the motion artifact superimposed on the ECG. Further investigations are necessary to asses which is the best location for the accelerometer and whether to include more than one axis output.

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