30th Annual International IEEE EMBS Conference
Vancouver, British Columbia, Canada, August 20-24, 2008

The Exploitation of Spatial Topographies for Atrial Signal Extraction in Atrial Fibrillation ECGs

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Abstract— **The accuracy in the extraction of the atrial activity (AA) from electrocardiogram (ECG) signals recorded during atrial fibrillation (AF) episodes plays an important role in the analysis and characterization of atrial arrhythmias. The present contribution puts forward a method for AA signal extraction based on a blind source separation (BSS) formulation. The latter exploits spatial information on the different components in the ECG related or not to AF. The source directions or spatial topographies of the components not related to AF are used to determine the nullspace of the AA, so that the topographies related to AA become more suitable to describe AF sources. The comparative performance of the method is evaluated on real data recorded from patients with noticeable AF. The AA extraction quality of the proposed technique is comparable to that of previous algorithms.**

I. INTRODUCTION

Atrial Fibrillation (AF) represents the most common sustained cardiac arrhythmia in adults. It consists of a misfunction of the atria characterized by a modification of the normal atrial activity (AA) pattern on the electrocardiogram (ECG) signal. Its prevalence and incidence doubles with each advancing decade beyond 50 years and has direct impact on mortality and morbidity [1], [2]. There is an increased risk of stroke and thromboembolism compared to people not affected by it, associated physical impairments and increasing age of the population highlight a problem with steadily increasing social impact in the next decades. A deeper understanding of AF requires advanced evaluation tools for AA signal analysis and its relation to cardiac electrophysiology before and after specific interventions. The analysis and characterization of AF from the ECG recordings requires the cancellation of the signal components associated with ventricular activity (VA), that is, the QRS-T complex. However, this is not a simple task, since many difficulties hinder this operation. Among them, the much lower amplitude of the AA signal compared to the ventricular one and the spectral overlapping of the two phenomena, so that linear filters in the frequency domain are unsuccessful [3].

There exist in the literature two different families of methods to cancel out VA in the ECG. The first involves methods that aim for a direct suppression of the QRS-T complex, e.g., using an adaptive template in conjunction with the correct spatio-temporal alignment of every QRS-T complex [4], [5]. The second involves all the methods based on the direct estimation of the AA, e.g., by use of blind source separation (BSS). All the methods belonging to the first class share similar limitations such as high sensitivity to QRS morphological changes over time and inability to eliminate artifacts other than VA. Moreover, they do not exploit the global spatial diversity of an ECG recording. BSS techniques overcome these limitations, but they share other drawbacks, such as possible decrease in perfomance of the AA estimation due to the stationarity assumption made on the process, even if some studies reveal that it can be considered as pseudo-stationary in most patients (e.g., [6]). Another limitation is that the desired components must be detected among the estimated sources after the separation. However, the automatic detection of the AA signal is facilitated by measurable features such as its narrowband spectral character (spectral concentration). Under the assumption that AA and VA are decoupled [3], the AA extraction problem accepts a formulation based on instantaneous linear BSS, in which atrial and ventricular source contributions appear mixed at the electrode outputs in the ECG. The method proposed by Castells *et al.* in [7] used one complete independent component analysis (ICA, a technique for signal decomposition into independent components) of the observed signals, followed by a second-order blind identification (SOBI). SOBI exploits the time coherence of the source signals and relies on the decorrelation measured by stationary second-order statistics. The method proposed in this contribution divides the observed data into different signal sets associated with the most significant segments of the cardiac period. In each of these segments, the most important signal components interfering the AA (i.e., the QRS complex, the T wave, or both) are missing, thus allowing a more accurate description of the overall VA and AA present in the ECG recording and, in particular, an enhanced estimation of the latter.

II. METHODS

A. Data and Preprocessing

A dataset composed of 22 recordings (all presenting AF) was employed to analyze the proposed idea. All signals were recorded and digitized at a sampling rate of 1KHz. Among the segments employed in this analysis 20 were recorded using a standard 12-lead system while 2 were recorded using a 9-lead system. Pre-processing was done by applying a zero-phase high pass filter with a -3dB cut off frequency at 0.5Hz to remove physiologically irrelevant low frequency signal variations ($<$1Hz) [8]. A zero-phase notch filter at 50Hz was implemented to suppress power line noise [9].

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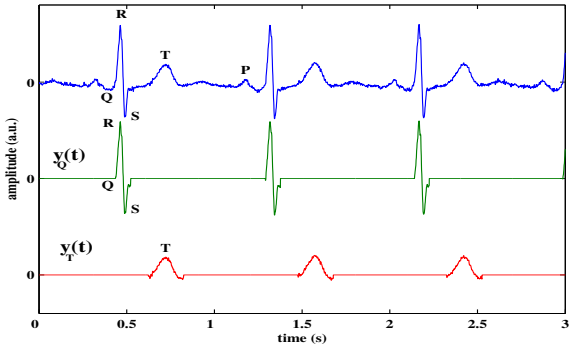

Fig. 1. Example of a Normal Sinus Rhythm ECG recording and of the different sets used to define the observation model in (4); a.u., arbitrary units.

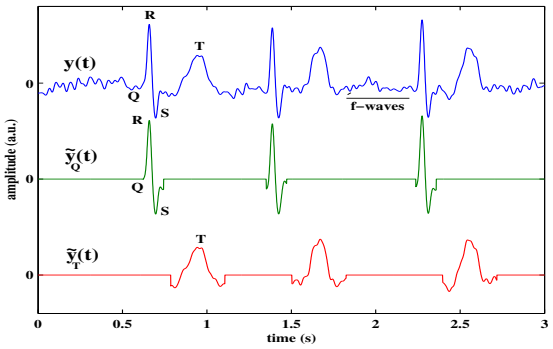

Fig. 2. Example of an AF ECG recording and the different sets used to define the observation model in (9); a.u., arbitrary units.

B. Blind Source Separation

BSS consists of recovering a set of source signals from the observation of linear mixtures of the sources. The term blind underlines that little is known about the source signals or the mixing structure, the only hypothesis being the sources' mutual independence [10], [11]. The model used in this paper is the linear instantaneous mixing model, wherein N observations of n time series $\mathbf{y}(t) \in \mathbb{R}^n$, the observed signals, can be written as a linear combination $\mathbf{M} \in \mathbb{R}^{n \times m}$ of the original sources $\mathbf{s}(t) \in \mathbb{R}^m$ $(m \leq n)$. In matrix form:

$$\mathbf{y}(t) = \mathbf{M}\mathbf{s}(t) \tag{1}$$

where the ith column of M represents the source directions or spatial topography that links the ith source $s_i(t)$ with the observed signals $\mathbf{y}(t)$. The spatial topography describes the relative contribution of the source amplitude on the different spatially separated electrodes, whatever the lead system employed. Starting from the hypothesis of sources' mutual independence, BSS can be carried out by ICA, a technique used to transform multisensor signals into statistically maximally independent components [10]. ICA aims to estimate the sources $\hat{\mathbf{s}}(t)$ and the separating matrix $\hat{\mathbf{W}}$ such that:

$$\hat{\mathbf{s}}(t) = \hat{\mathbf{W}}\mathbf{y}(t) = \hat{\mathbf{W}}\mathbf{M}\mathbf{s}(t) \tag{2}$$

with $\hat{\mathbf{W}} \approx \mathbf{M}^{\sharp}$, and where symbol $\sharp$ stands for the pseudo-inverse operator. Compared to ICA, principal component analysis (PCA) transforms multisensor signals into statistically uncorrelated components. Each component contains new information about the observation set, and is ordered so that the components are in decreasing order of variance accounted for in the observations. Spatial decorrelation (or whitening) involves a linear transformation of the mean corrected observed signals $\mathbf{y}(t)$, which produces a set of uncorrelated waveforms with unit variance $\mathbf{z}(t)$:

$$\mathbf{z}(t) = \mathbf{B}^{-1}\mathbf{y}(t) = \mathbf{B}^{-1}\mathbf{M}\mathbf{s}(t) \tag{3}$$

The whitening matrix $\mathbf{B}^{-1}$ can be obtained, e.g., from the singular value decomposition (SVD) of the observation matrix $\mathbf{Y} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathbf{T}}$, where $\mathbf{B}^{-1} = \sqrt{N-1}\mathbf{\Sigma}^{-1}\mathbf{U}^{\mathbf{T}}$.

C. Observation Model

The ECG is a useful inexpensive non-invasive tool to visualize the temporal evolution of the cardiac electrical activity as measured by electrodes located on the thorax and the limbs, wherein different waves or complexes related to different cardiac events are recognizable. Among these, the P-wave indicates the contraction of the atria, the QRS complex the ventricular contraction and the T-wave the ventricular relaxation (Fig. 1). During AF, the P-wave and the equipotential line between two consecutive heart beats (T-Q segment), are replaced by rapid oscillations or fibrillatory waves (Fig. 2). Starting from the above observations, the observed multichannel signal $\mathbf{y}(t)$ can be subdivided as follows:

$$\mathbf{y}(t) = \mathbf{y}_Q(t) + \mathbf{y}_T(t) + \mathbf{y}_A(t) + \eta(t) \tag{4}$$

where $\mathbf{y}_Q(t)$, $\mathbf{y}_T(t)$, $\mathbf{y}_A(t)$ and $\eta(t)$ represent the QRS, T, AA and noise components, respectively, in the observed data. The three sets $\mathbf{y}_Q(t)$, $\mathbf{y}_T(t)$ and $\eta(t)$ do not contain AA at all (Fig. 1), that is localized in $\mathbf{y}_A(t)$. Therefore, the linear mixture model (1) can be divided into three sub-problems. Hence, the linear instantaneous mixing model now becomes:

$$\mathbf{y}(t) = \mathbf{M}_Q\mathbf{s}_Q(t) + \mathbf{M}_T\mathbf{s}_T(t) + \mathbf{M}_A\mathbf{s}_A(t) + \eta(t) \tag{5}$$

in which mixing matrices for each problem are respectively sought such that:

$$\forall t \notin QRS \quad : \quad E\{(\hat{\mathbf{M}}_Q^{\sharp}\mathbf{y}(t))^2\} \text{ is minimal} \tag{6}$$

$$\forall t \notin T \quad : \quad E\{(\hat{\mathbf{M}}_T^{\sharp}\mathbf{y}(t))^2\} \text{ is minimal} \tag{7}$$

$$\forall t \quad : \quad \hat{\mathbf{M}}_A^{\sharp}\mathbf{y}(t) \approx \hat{\mathbf{s}}_A(t) \tag{8}$$

However, coping with the inability to get the two sets $\mathbf{y}_Q(t)$ and $\mathbf{y}_T(t)$ completely free from AA, model (5) is rethought to be:

$$\mathbf{y}(t) = \tilde{\mathbf{y}}_Q(t) + \tilde{\mathbf{y}}_T(t) + \tilde{\mathbf{y}}_{TQ}(t) + \eta(t) \tag{9}$$

where $\tilde{\mathbf{y}}_Q(t)$ contains both QRS and AA components, $\tilde{\mathbf{y}}_T(t)$ contains both T and AA components and $\tilde{\mathbf{y}}_{TQ}(t)$ contains

only AA component accounting for the AA present in the T-Q segments on the ECG (Fig. 2).

D. Spatial Topographies and Atrial Fibrillation Estimation

The two subsets $\tilde{\mathbf{y}}_Q(t)$ and $\tilde{\mathbf{y}}_T(t)$ are exploited to get more precise estimates of the QRS and T components in (5).

Thereto, first of all the whitening of the total observation set is derived:

$$\hat{\mathbf{z}}(t) \;=\; \hat{\mathbf{B}}^{-1}\mathbf{y}(t) \tag{10}$$

After that, the detection of R-wave fiducial points, Q-wave onsets and T-wave offsets from the ECG, allows us to define the two subsets $\hat{\mathbf{z}}_Q(t) = \hat{\mathbf{B}}^{-1}\tilde{\mathbf{y}}_Q(t)$ and $\hat{\mathbf{z}}_T(t) = \hat{\mathbf{B}}^{-1}\tilde{\mathbf{y}}_T(t)$. Secondly, the ICA model is derived for the uncorrelated set $\hat{\mathbf{z}}(t)$:

$$\hat{\mathbf{s}}(t) \;=\; \hat{\mathbf{M}}^{\sharp}\mathbf{y}(t) \;=\; \hat{\mathbf{M}}^{\sharp}\hat{\mathbf{B}}\,\hat{\mathbf{z}}(t) \tag{11}$$

while the PCA models are derived for subsets $\hat{\mathbf{z}}_Q(t)$ and $\hat{\mathbf{z}}_T(t)$:

$$\hat{\mathbf{s}}_Q(t) \;=\; \hat{\mathbf{H}}_Q^{-1}\hat{\mathbf{z}}_Q(t) \tag{12}$$

$$\hat{\mathbf{s}}_T(t) \;=\; \hat{\mathbf{H}}_T^{-1}\hat{\mathbf{z}}_T(t) \tag{13}$$

Then, a specific set of spatial topographies describing each one of the three subsets in (5) is extracted from each corresponding model (11)-(13). The sets are obtained as follows.

• In (11) AA is compressed on a low-dimensional subspace (associated to the highest singular values of the set $\hat{\mathbf{z}}(t)$), and the estimated source which best describes the AF, $\hat{s}_A(t)$, is searched inside the set $\hat{\mathbf{s}}(t)$. The criterion adopted is the spectral concentration (SC) of the AA around its main peak, computed according to the following expression [7]:

$$SC \;=\; \frac{\int_{0.82f_c}^{1.17f_c} P_{AA}(f)\,df}{\int_0^{f_s/2} P_{AA}(f)\,df} \tag{14}$$

That is, a measure for the compactness of the spectrum around the central frequency f_c (modal frequency in the 3-12Hz interval). The column $\hat{\mathbf{m}}'_A$ of the estimated mixing matrix $\hat{\mathbf{M}}$ associated to the selected source is chosen as the only topography describing the AA component.

• The QRS and T spatial topography sets are obtained from models (12) and (13), respectively. Only the topographies in $\hat{\mathbf{H}}_Q$ associated to the *i* highest eigenvalues and those in $\hat{\mathbf{H}}_T$ associated to the *j* highest eigenvalues are chosen to describe the QRS, respectively T, component, so that:

$$\hat{\mathbf{z}}_Q(t) \;=\; \sum_{k=1}^{i} \hat{\mathbf{h}}_Q^k \hat{\mathbf{s}}_Q(t) \tag{15}$$

$$\hat{\mathbf{z}}_T(t) \;=\; \sum_{k=1}^{j} \hat{\mathbf{h}}_T^k \hat{\mathbf{s}}_T(t) \tag{16}$$

and they are collected as follows:

$$\hat{\mathbf{M}}'_Q \;=\; \hat{\mathbf{B}}\left[\hat{\mathbf{h}}_Q^1 \cdots \hat{\mathbf{h}}_Q^i\right] \tag{17}$$

$$\hat{\mathbf{M}}'_T \;=\; \hat{\mathbf{B}}\left[\hat{\mathbf{h}}_T^1 \cdots \hat{\mathbf{h}}_T^j\right] \tag{18}$$

The transformation for $\hat{\mathbf{B}}$ allows to work directly with matrices $\hat{\mathbf{M}}_g$ (where g stands for "general model") on the full recording space $\mathbf{y}(t)$.

The number of principal components representing the QRS and T waveforms varies from subject to subject, due to their elevated patient-to-patient and beat-to-beat variability. Hence, it is not possible to define a general and suitable number of principal components. For that reason, the number of *i* and *j* topographies to store inside matrices $\hat{\mathbf{M}}'_Q$ and $\hat{\mathbf{M}}'_T$, respectively, are estimated for each subject in an exhaustive way, selecting the pair (i, j) that produces the AF source estimate with the highest SC.

Once all the topographies are estimated, define $\mathbf{G}$ as follows:

$$\mathbf{G} \;=\; \left[\hat{\mathbf{M}}'_Q,\;\; \hat{\mathbf{M}}'_T,\;\; \hat{\mathbf{m}}'_A\right] \tag{19}$$

and orthonormalize it, obtaining:

$$\mathbf{G}^{\perp} \;=\; \left[\mathbf{G}_Q^{\perp},\;\; \mathbf{G}_T^{\perp},\;\; \mathbf{g}_A^{\perp}\right] \tag{20}$$

Orthonormalization can be achieved using different methods, and we chose QR factorization. Bearing in mind that VA and AA can be properly supposed uncorrelated activities, the purpose in orthonormalizing matrix $\mathbf{G}$ is to make the QRS and T topographies linearly independent from the AA ones, i.e. $\left[\mathbf{G}_Q^{\perp},\;\; \mathbf{G}_T^{\perp}\right]$ forms a nullspace for $\mathbf{g}_A^{\perp}$.

Retaining the last column vector in matrix $\mathbf{G}^{\perp}$, that is $\mathbf{g}_A^{\perp}$, it can be used to define the weight vector of a spatial filter applied to the set $\mathbf{y}(t)$ of observed signals (original waveforms) for VA and noise removal, as in the following model:

$$\hat{s}_A(t) \;=\; \mathbf{g}_A^{\perp T}\mathbf{y}(t) \tag{21}$$

where $\hat{s}_A(t)$ is the output of the filter, that is, the estimated AF signal.

III. RESULTS

The proposed method is named Orthogonal Topographies ICA (OTICA) and was applied to a dataset of 22 recordings. Its performance is compared to those of a conventional ICA (COM2) [10], a spatio-temporal cancellation approach (ST-Canc) [5] and a spatio-temporal BSS approach (ST-BSS) [7]. SC of the estimated AA source around its main peak, excess kurtosis (k) of the estimated source and characteristic AF modal frequency ($\mathbf{f}_c$) are chosen as performance indices. Indices' values are presented in terms of mean value μ and standard deviation σ (Table I).

Fig. 3 shows the box-and-whisker plot of the SC parameter. Finally, a zoom on an example of final OTICA estimation of the AF source $\hat{s}_A(t)$ (projected back on lead V1) is shown in Fig. 4.

IV. DISCUSSION

This work points out the possibility of using well defined spatial topographies related to the components describing VA and AA when the extraction of the AF signal is addressed. The proper AA topography estimate can be obtained by projecting the AA topography estimated by ICA into the

TABLE I

MEAN PERFORMANCE INDICES FOR THE DIFFERENT METHODS UNDER ANALYSIS ($\mu \pm \sigma$).

	SC $(\%)$	**k** $(n.u.)$	$\mathbf{f_c}$ (Hz)
COM2	52.00 ± 14.69	-0.0951 ± 0.5587	5.5154 ± 1.29
OTICA	58.28 ± 10.89	0.0172 ± 0.7359	5.5098 ± 1.2547
ST − BSS	60.82 ± 9.21	-0.1391 ± 0.4967	5.3711 ± 1.3255
ST − Canc	57.01 ± 11.98	0.5511 ± 2.8898	5.4321 ± 1.2159

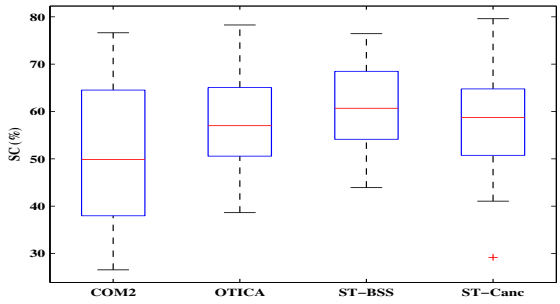

Fig. 3. Box-and-whisker plot of the Spectral Concentration (SC) values for different methods.

nullspace of the VA. This can be done through an orthonormalization of these topographies, to make them linearly independent. The suitability of the final AA topography estimate can be noticed from Table I and Fig. 3 and 4, where the ability of OTICA to get almost the same performance as other methods suitable for the extraction of the AF is shown. This is an important result. Indeed, OTICA offers a simple alternative to classical methods in solving the hard task to get rid of the ventricular components from ECG recordings for the AA signal estimate, simply exploiting the statistical decoupling between AA and VA. Due to the quasi-Gaussianity of the component of interest, the AA estimate by ICA is sometimes suboptimal. In such cases, its topography is not suitable to describe AF and may yield poor results if

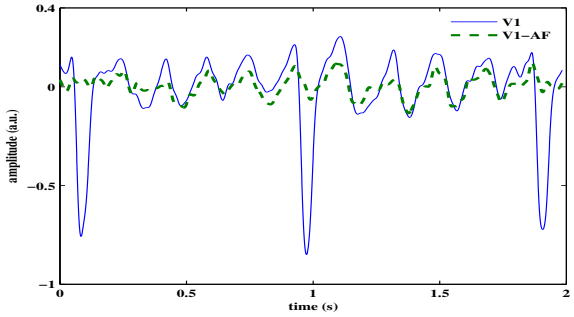

Fig. 4. Segment from V1 lead for one patient: original recording (thin solid line) and estimated Atrial Fibrillation signal (dashed line); a.u., arbitrary units.

applied directly as a spatial filter. This calls for a correction of the initial estimate with a method such as OTICA. All these facts underline the need to define proper subsets from the original recording, thus enabling the application of the proposed method.

V. CONCLUSIONS AND FUTURE WORKS

A new method for the extraction of AA signals in ECG recordings of AF has been presented. The method is based on an estimation of the AA, QRS and T source directions or spatial topographies from the whole original set, a QRS-wave specific set and a T-wave specific set, respectively. The hypothesis that VA and AA are decoupled is exploited to make the AA uncorrelated from the VA, under the constraint of linearly independent topographies. Results obtained on real data show the comparative performance of the proposed technique relative to classical methods.

Future work aims to define a criterion for the automated selection of the proper VA topography number for each specific subject under analysis.

VI. ACKNOWLEDGMENTS

The authors would like to express their gratitude to Leif Sörnmo and Francisco Castells for providing the real data. The work of Pietro Bonizzi is supported by the EU by a Marie-Curie Fellowship (EST-SIGNAL program: http://est-signal.i3s.unice.fr) under contract No MEST-CT-2005-021175.

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