Spatiotemporal Blind Source Separation Approach to Atrial Activity Estimation in Atrial Tachyarrhythmias

F. Castells*, J. J. Rieta, J. Millet, and V. Zarzoso, *Associate Member, IEEE*

***Abstract*—The analysis and characterization of atrial tachyarrhythmias requires, in a previous step, the extraction of the atrial activity (AA) free from ventricular activity and other artefacts. This contribution adopts the blind source separation (BSS) approach to AA estimation from multilead electrocardiograms (ECGs). Previously proposed BSS methods for AA extraction—e.g., independent component analysis (ICA)—exploit only the spatial diversity introduced by the multiple spatially-separated electrodes. However, AA typically shows certain degree of temporal correlation, with a narrowband spectrum featuring a main frequency peak around 3.5–9 Hz. Taking advantage of this observation, we put forward a novel two-step BSS-based technique which exploits both spatial and temporal information contained in the recorded ECG signals. The spatiotemporal BSS algorithm is validated on simulated and real ECGs from a significant number of atrial fibrillation (AF) and atrial flutter (AFL) episodes, and proves consistently superior to a spatial-only ICA method. In simulated ECGs, a new methodology for the synthetic generation of realistic AF episodes is proposed, which includes a judicious comparison between the known AA content and the estimated AA sources. Using this methodology, the ICA technique obtains correlation indexes of 0.751, whereas the proposed approach obtains a correlation of 0.830 and an error in the estimated signal reduced by a factor of 40%. In real ECG recordings, we propose to measure performance by the spectral concentration (SC) around the main frequency peak. The spatiotemporal algorithm outperforms the ICA method, obtaining a SC of 58.8% and 44.7%, respectively.**

***Index Terms*—Atrial fibrillation, biomedical signal processing, blind source separation, independent component analysis, QRST cancellation, spatiotemporal signal processing.**

Manuscript received October 6, 2003; revised July 18, 2004. This work was supported in part by the Spanish Ministry of Science and Technology under Grant TIC2002-00957 and in part by the Universidad Politécnica de Valencia through a research incentive program. *Asterisk indicates corresponding author.*

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Digital Object Identifier 10.1109/TBME.2004.840473

I. Introduction

ATRIAL FIBRILLATION (AF) is the most frequent cardiac arrhythmia, and has a prevalence of 10% in population over 70 years old [11]. The interest in the study and understanding of AF has considerably increased during the last years. Many studies have been carried out to analyze the underlying mechanism on isolated hearts of animals [28] but, unfortunately, these results are not directly applicable to humans. The analysis and characterization of AF and other atrial tachyarrhythmias such as atrial flutter (AFL) from noninvasive techniques requires the previous estimation of the actrial activity (AA) signal from the surface electrocardiogram (ECG). Several approaches have been proposed for this purpose. The explicit QRST cancellation from a matching template has demonstrated its effectiveness, as in Average Beat Subtraction [5], [14] or in the spatiotemporal QRST cancellation [32]. A model based on blind source separation (BSS) [37] introduces an interesting point of view, and two solutions based on principal component analysis (PCA) [21] and independent component analysis (ICA) [29] have been proposed. Recently, a study has been carried out to compare and validate all these techniques [22]. Finally, other approaches based on neural networks allow the introduction of nonlinearities in the estimation model [35]. BSS proves a powerful formulation which has also been successfully applied to other biomedical problems [38].

By exploiting the spatial diversity introduced by the multiple spatially-separated electrodes, previously proposed BSS solutions are able to estimate the independent bioelectric sources—comprising ventricular activity (VA), AA and other bioelectric artefacts—from a statistical analysis of the ECG. However, any temporal information which may be present in the sources is disregarded. Motivated by the observation that AA signal typically exhibits a narrowband spectrum with a main frequency of between 3.5–9 Hz [6], [14], [21], [26], [31], [33], the main goal of this contribution is the design of a new BSS-based algorithm which aims to utilize more fully the spatiotemporal information of the ECG recordings. Experimental results demonstrate that the proposed spatiotemporal algorithm enhances AA estimation relative to a BSS technique exploiting only spatial information (ICA).

Measuring performance is a difficult issue in inverse problems. Objective assessments can be accomplished by means of synthetic recordings in which AF contributions are artificially added to normal sinus rhythm (NSR) signals [30], [32]. Some authors have created simulated signals by adding known activity which is generated from an equivalent current dipole (ECD) with a moment of a determined frequency [18]. The forward problem of this ECD using a volume conductor model of the

torso/head provides the observations. However, in this model the observations of the ECD are mathematically a linear combination of each other. Hence, the generated observations perfectly match the BSS model of instantaneous linear mixtures and, as a result, the performance obtained by ICA would be too satisfactory so as to be considered realistic. Another contribution of the present paper is a novel methodology for the synthetic generation of ECGs with realistic AF episodes. This methodology includes a simple but judicious comparison between the added and the estimated AA.

The paper is structured as follows. Section II briefly reviews the state of the art on atrial tachyarrhythmias and BSS techniques. The methods are put forward in Section III, whereas Section IV describes the signal databases used for validation and comparison. To evaluate the performance of the proposed technique, synthesized ECGs with known AA have been created, but the algorithm has been validated on real signals as well. The results obtained with both databases are reported in Section VI, whose conclusions bring the paper to and end in Section VII.

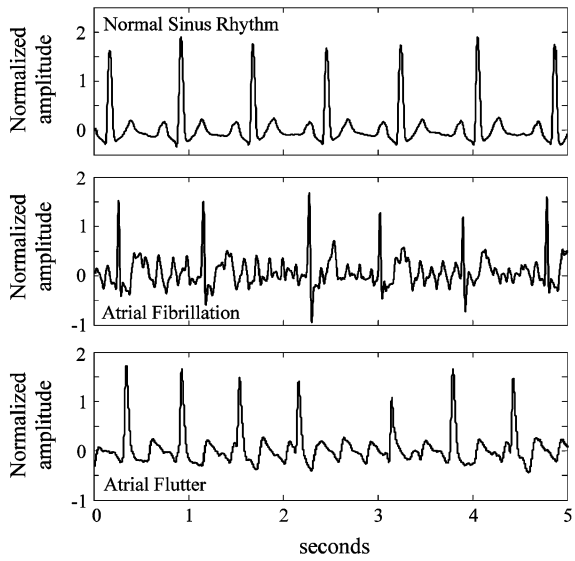

Fig. 1. Typical examples of NSR, AF, and AFL signals.

II. State of the Art

A. Atrial Tachyarrhythmias

Atrial tachyarrhithmias are cardiac arrhythmias in which normal atrial electrical activation is substituted by continuous activation, with multiple wavelets depolarising the atria simultaneously [1], [13]. On the ECG, normal atrial activity (P wave) is no longer visible, being substituted by rapid oscillations or fibrillatory waves that vary in size, shape and timing. The most frequent atrial tachyarrhythmias are AF and AFL, where AF is characterized by apparently chaotic atrial activation with a cycle length typically of around 160 ms, and an irregular and frequently rapid ventricular response (QRS complex) [1], [6], [14], [26], [34]. The ventricular response to AF depends on electrophysiological properties of the atrioventricular node, and the R-R interval becomes more irregular. On the other hand, AFL is characterized by a more regular atrial activation with a cycle length of around 250 ms [1], [25], [34], [36]. Fig. 1 shows an example of NSR, AF, and AFL ECGs.

B. Blind Source Separation

The body-surface potentials as a result of cardiac electrical activity can be modeled as a BSS problem [29]

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{1}$$

where $\mathbf{x}(t)$ is a length-m vector which represents the electrode outputs at time instant t, i.e., the standard multilead ECG, $\mathbf{s}(t)$ is a length-n $(\mathrm{n} \leq \mathrm{m})$ random vector that represents the bioelectric sources (AA, VA, respiration, muscular movement, etc.), and $\mathbf{A}$ is the mxn channel-parameter matrix. For the standard ECG, we have $\mathrm{m} = 12$. Neither the original sources nor the transfer coefficients from the epicardial surface toward the body surface are known.

The main advantage of the BSS model lies in its flexibility. Indeed, only two conditions must be fulfilled to recover the original sources from the exclusive knowledge of the observations [12], [37]. Firstly, the sources must be mutually statistically independent. Secondly, the transfer channel must be linear and instantaneous, and must generate linearly independent observations (in the sense that matrix $\mathbf{A}$ be full column rank). Since the AA, the VA, and other sources arise from physically independent bioelectric phenomena, it can also be assumed that they are statistically independent. Furthermore, for the frequency range of the ECG (below 100 Hz), bioelectric theory has modeled the torso as an inhomogeneous volume conductor [23], [27]. Consequently, any signal recorded at the body surface can be assumed to arise as a linear instantaneous transformation of the independent bioelectric sources and, therefore, BSS techniques are appropriate for the estimation of the AA [29].

Depending on the separation problem, several BSS techniques have been developed. For orthogonal mixtures (i.e., when the columns of $\mathbf{A}$ are orthogonal), PCA provides the optimal solution and it only requires the sources to be uncorrelated (second-order independence) [19]. However, the mixing matrix may well have an arbitrary structure, which discards PCA as an appropriate solution. For a more general situation of nonorthogonal mixtures, techniques based on ICA must be employed [17], [20], which typically resort to the higher order statistics (HOS) of the signals. Since the higher-order cumulants of Gaussian signals are zero, ICA is unable to separate Gaussian sources. For nonorthogonal mixtures of Gaussian sources, some additional structure must be exploited. If the sources have different spectra, temporal information may be useful, and an algorithm based on the joint diagonalization of several (second-order) autocorrelation matrices at different lags [4] offers a reliable solution.

III. Methods

A. Statistical Source Analysis

Depending on their nature, the sources contained in an ECG recording can be divided into three types. VA sources are the ECG components with the highest energy. These components have a high amplitude during ventricular depolarization and repolarization (QRS complex and T wave, respectively), but the rest of the time they present values close to zero due to the period

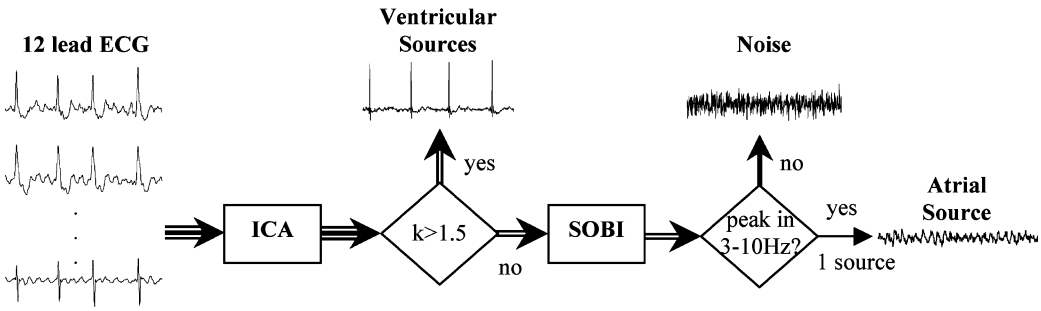

Fig. 2. Diagram block of the proposed spatiotemporal algorithm for AA estimation.

of inactivity of the myocardium cells. Therefore, VA sources possess supergaussian random distributions [8], even with kurtosis values above those of Laplacian distributions, which will be confirmed in Section VI by computing the kurtosis of the estimated VA sources. In AF and AFL episodes, AA consists of small and continuous wavelets with a cycle typically around 160 and 250 ms, respectively. A statistical analysis of the sources shows that AA has quasi-Gaussian distributions [8], with kurtosis values very close to zero (as will be discussed later on). However, AA waves have a characteristic spectrum, with a main peak due to the refractory period, which can be located between 3.5 and 9 Hz depending on the patient. Finally, noise and other artefacts are the contributions with the lowest energy, although in more than a few leads they could show an amplitude of the same order of magnitude as the atrial sources, or even higher. The statistical behavior of the noise may be different for each recording; even several noise sources with different statistical behavior may be found in a single ECG. Hence, no assumption about the noise pdf or correlation is made. The only noise assumption included in the separation model we propose is that the noise has a different spectrum from the AA source, which is verified in practically all cases.

B. Two-Step Strategy

The fact that VA presents supergaussian distributions can be exploited to remove ventricular components in the first stage, which is implemented with ICA. Since ventricular components appear at the ECG recording with higher energy than any other components, this stage eliminates the major source of interference. The nonventricular components (AA, artefacts and noise) are the inputs of the second stage. In this stage, the characteristic spectrum of the AA source is exploited in order to enhance AA estimation. Fig. 2 illustrates a block diagram of the proposed two-step methodology. Using this method, the AA can be estimated in both AF and AFL arrhythmias.

1) First Stage: ICA: As it has been stated above, ICA techniques are most suitable to separate independent non-Gaussian sources. They are able to estimate the independent sources from the analysis of the higher order statistics (HOS) of the multilead signal [17]. Most ICA methods are based on the optimization of a contrast function that maximizes non-Gaussianity. Indeed, from the Central Limit Theorem it follows that maximization of non-Gaussianity is equivalent to the maximization of independence. Several algorithms have been developed for this purpose: some of them are based on information-theoretic concepts, such as entropy and mutual information [3], [12]; a solution based on the joint diagonalization of fourth-order cumulant matrices has also been proposed [7]; etc. All these algorithms employ (explicitly or otherwise) HOS to maximize statistical independence, and provide equivalent solutions under mild assumptions. Considering the model in (1), ICA methods estimate the separation matrix $\mathbf{B}$ such that the estimated sources

$$\hat{\mathbf{s}}(t) = \mathbf{B}\mathbf{x}(t) \tag{2}$$

fulfil certain statistical independence criterion. Among all existing ICA algorithms, in this study we have chosen an algorithm that estimates non-Gaussianity as a function of the following approximation of negentropy $J(\cdot)$ [17]

$$J(y) \propto [\mathrm{E}[G(y)] - \mathrm{E}[G(v)]]$$
$$G(y) = \log\cosh y \tag{3}$$

where y is the output signal and v is a unit variance Gaussian variable. The approximation of the negentropy combines the simplicity of kurtosis with the robustness of negentropy, providing a solution which is both reliable and computationally efficient [17]. Furthermore, the maximization of the contrast function can be carried out by means of a fixed point algorithm that provides very fast convergence [16]. Nevertheless, the aim of this paper is not to emphasize the convenience of a determined ICA algorithm, but to demonstrate the suitability of ICA as a more general concept for this first processing stage.

ICA algorithms are especially equipped to extract all non-Gaussian sources, but are unable to separate Gaussian sources since their HOS are null. Hence, all Gaussian sources will appear mixed at the ICA output. The practical consequence over AF recordings is that VA sources will be correctly extracted, but the AA source can appear combined with other Gaussian-like sources such as thermal noise and other artefacts. Due to the very low energy of the AA signal, the separation of AA from all these additional sources of interference becomes an important necessary task. This task will be carried out in the second stage, which is described in the next section.

The inputs to the second processing stage are the nonventricular source components estimated by the first stage. The decision as to which components belong to the ventricular subspace and which components belong to the nonventricular subspace can be done automatically. Due to the existence of the QRS complex, the ventricular sources show high kurtosis values. On the other hand, AA is quasi-Gaussian and, thus, it usually displays kurtosis values marginally different from zero. Consequently, a kurtosis-based threshold can be employed to distinguish between ventricular and nonventricular sources. Preliminary experiments show that a conservative kurtosis threshold of around 1.5 allows

us to retain the AA information in the nonventricular subspace (the signal subspace which lies orthogonal to that spanned by the mixing-matrix columns associated to the ventricular sources) and reject all other sources that contain QRS complexes.

2) Second Stage: Second-Order Blind Identification (SOBI): The so-called SOBI technique aims at separating a mixture of uncorrelated sources with different spectral content through a second-order statistical analysis which also takes into consideration the source temporal information [4]. For this purpose, SOBI seeks a transformation that simultaneously diagonalizes several correlation matrices at different lags. Since, in general, no transformation may exist that accomplish such a stringent condition, a function that objectively measures the degree of joint (approximate) diagonalization (JD) at different lags is employed instead.

Let us assume that the observations have been previously whitened (which is the case in our problem, since the ICA step involves prewhitening), and let us focus on the elementary case of two sources and two observations. The correlation matrix $\mathbf{C}$ of the whitened observations at a lag τ_i is

$$\mathbf{C}(\tau_i) = \begin{bmatrix} a_i & b_i \\ c_i & d_i \end{bmatrix} \tag{4}$$

with

$$\mathbf{C}(\tau_i) = \mathrm{E}[\mathbf{z}(t)\mathbf{z}^{\mathrm{T}}(t-\tau_i)] \tag{5}$$

where $\mathrm{E}[\cdot]$ represents the expectation operator.

The real sources $\mathbf{s}$ and the whitened observations $\mathbf{z}$ are related through a Givens rotation

$$\mathbf{z} = \mathbf{Q}\mathbf{s}, \quad \mathbf{Q} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{6}$$

where θ is an unknown rotation angle. The correlation matrix of the sources, $\mathbf{C}'$, at a lag τ_i is

$$\mathbf{C}'(\tau_i) = \begin{bmatrix} a'_i & b'_i \\ c'_i & d'_i \end{bmatrix} \tag{7}$$

where

$$\mathbf{C}'(\tau_i) = \mathrm{E}[\mathbf{s}(t)\mathbf{s}^{\mathrm{T}}(t-\tau_i)]. \tag{8}$$

The goal of separating the AA from other sources of interference is equivalent to finding an orthogonal transformation $\mathbf{Q}$ from the whitened observations $\mathbf{z}$. The source signals being uncorrelated, their covariance matrix at any lag shows a diagonal structure. Hence, for sources with different spectra (i.e., with different autocorrelation function) the goal is shown to be equivalent to finding an orthogonal transformation that diagonalizes $\mathbf{C}'$ for each τ_i, i.e., at all lags simultaneously. Since no solution may exist that satisfies that strict condition, a JD criterion must be defined.

Assuming that N different lags will be employed for JD, N correlation matrices $\mathbf{C}'(\tau_i)$ are evaluated, $i = 1 \ldots N$ **.** The JD criterion proposed in [4] (which is also employed in the ICA method of [7]) is given by:

$$\hat{\mathbf{Q}} = \arg\max_{\mathbf{V}} J(\mathbf{V}), \quad J(\mathbf{V}) = \sum_{i=1}^{N} ||\mathrm{diag}[\mathbf{V}^{\mathrm{T}} C(\tau_i)\mathbf{V}]||^2 \tag{9}$$

and $\mathbf{V}$ is a unitary matrix. Let us define a $Nx2$ matrix $\mathbf{G}$ and a column vector of N elements $\mathbf{u}$

$$\begin{aligned} \mathbf{G} &= [\mathbf{a} - \mathbf{d} \quad \mathbf{b} + \mathbf{c}] \\ \mathbf{u} &= \mathbf{G}[\cos 2\theta \quad \sin 2\theta]^{\mathrm{T}} \end{aligned} \tag{10}$$

where $\mathbf{a}, \mathbf{b}, \mathbf{c}$ and $\mathbf{d}$ are column vectors containing the respectives matrix entries of the ith correlation matrix $\mathbf{C}(\tau_i)$. Then, JD can be measured through the following cost function [4]

$$F(\theta) = \mathbf{u}^{\mathrm{T}}\mathbf{u} \tag{11}$$

which is exclusively a function of the rotation angle θ. Hence, the independence criterion has been transformed into the maximization problem of (11). The rotation angle that maximizes the JD criterion allows the recovery of the original sources. Remark that the maximization of this quadratic form can be efficiently computed in closed-form as the eigenvector corresponding to the largest eigenvalue of the 2×2 matrix $\mathbf{G}^{\mathrm{T}}\mathbf{G}$; also, the calculation of θ does not even require trigonometric functions. For more than two sources and two observations, the problem can be solved by Jacobi-like pairwise iterations until convergence [4].

Since the AA has a narrowband spectrum, the SOBI algorithm is appropriate for estimating the AA. The number of matrices for joint diagonalization and their time lags must be properly selected. Since the autocorrelation of the AA source in AF episodes is quasiperiodic with a period around 160 ms—i.e., 160 samples at a sampling rate of 1 KHz —, correlation matrices with time lags involving two cycles (that is, 320 ms) are chosen. This choice guarantees that even for AF signals with larger AA cycle the lag range spans at least one complete cycle length. This condition is fulfilled even in the case of AFL arrhythmias, with a cycle length between 200 and 300 ms. Choosing correlation matrices at evenly spaced lags of 20 ms (i.e., a total of 17 correlation matrices) guarantees a high proportion of significant (nonzero) autocorrelation values among the selected lags with an affordable computational complexity. Indeed, this choice achieved a good AA extraction performance in preliminary experiments, as confirmed in the more thorough results reported in the following sections.

IV. Databases

The fact that the AA is unknown in real recordings hinders an in-depth experimental comparative study of AA extraction methods. Hence, suitable simulated AF ECGs must be designed in order to evaluate the performance of the proposed approach. With the formulation described in Section IV-B, pseudoreal ECGs are generated with known AA, which allows us to easily compare the estimated and the real AA. Ultimately the method is to be applied over actual AF episodes and, thus, a database of such recordings (Section IV-B) is also employed to demonstrate the suitability of the algorithm in real scenarios.

A. Pseudoreal AF Recordings

Several models for simulated AF signals have been already proposed in previous works [30], [32]. However, the simulated AF recordings created with those models differ considerably from real AF recordings, since the AA which is added to each

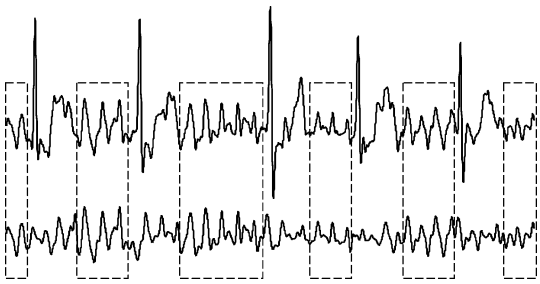

Fig. 3. Generation of synthesized AF ECG. The boxed areas are the regions where the AF contribution dominates. These regions are singled out and then extrapolated to generate the synthetized AA signal.

lead is generated from a single AA waveform. One of the objectives of this work is to develop a new model for synthesized AF recordings that simulate as realistically as possible genuine AF recordings. This new model is described as follows.

Since the AF signals are the superposition of VA and AA, both activities can be obtained separately from real recordings and then added together. VA can be obtained from NSR episodes, after correctly removing P-waves. The acquisition of AA signals is more involved. A first idea would be to record ECGs during ventricular asystole periods of AF patients, but this option is unfortunately nonviable in most practical situations. Another alternative might consist of estimating the AA from the ECG by employing a QRST cancellation technique, like template matching and subtraction [5], [14] or the spatiotemporal cancellation method [32]. However, this alternative has been discarded, since the estimated AA could contain some QRS residual, which could be particularly important in those leads where the AA is hardly appreciable. In addition, the resulting simulation model would not be applicable to evaluate such QRST cancellation techniques since the simulation model would match the AA estimation methodology. Taking into consideration those limitations, we aim to define a simulation model valid for different methodologies, which would allow their fair comparison in a further study. We propose to simulate the atrial wave by isolating the AA from T-Q intervals during AF episodes and carefully extrapolate it between those segments. An example of AA generation is shown in Fig. 3. The AA within T-Q intervals matches the ECG signal, and the AA within Q-T intervals is reconstructed from the extrapolation of two adjacents T-Q segments [8]. A simple extrapolation method is used, where the fibrillatory cycles prior to the QRST complex are replicated within the QRST interval, but linearly weighted such that the weights are one at the beginning of the interval and decrease down to zero at the end of the interval. Analogously, the fibrillatory cycles following the QRST complex are replicated within the QRST interval, and are weighted from zero at the beginning of the interval rising up to one at the end of the interval. The segments to be replicated are selected so as to preserve the phase of the fibrillatory wave observed within the T-Q intervals. Both contributions are combined to build up the extrapolated AA wave within the QRST interval [32]. This process is repeated for each lead, thus obtaining a 12-lead synthesized AA. Although the reconstructed AA samples do not exactly correspond to the true AA signal masked by the QRST complex, this model preserves the general features

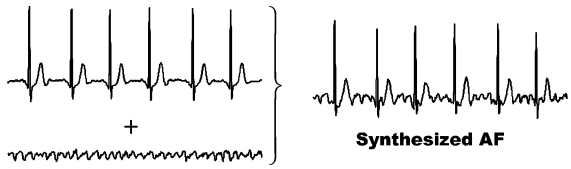

Fig. 4. Generation of AF-episode ECG lead from synthesized VA and AA signals.

of the AA signal observed in the different leads according to a real AF recording. The resulting composite AA signal is more realistic than that obtained by the ECD model [18], which follows ICA's generative pattern and, as a result, would produce too optimistic results.

Following the proposed simulation model, the statistical properties of both VA and AA on which is based the separation algorithm as well as the autocorrelation cycle of AA are preserved. In this sense, the kurtosis of VA and AA is 12.2 ± 5.8 and -0.17 ± 0.68, respectively, for our simulated database. As will be confirmed in Section VI-B, the kurtosis values of the real VA in AF episodes also follow a super-Gaussian distribution. On the other hand, it is known that the heart rate variability in AF episodes is higher than in NSR. However, this observation does not influence our approach, since the degree of Gaussianity is not affected by this temporal oscillation. Also, time information (correlation at different time lags) is only considered in a second processing step where VA is mostly cancelled.

Furthermore, a rigorous model for synthesized AF signals requires an additional constraint: the AF episode for the AA generation and the NSR episode must be acquired from the same patient. If both episodes came from different patients, the mixing matrix for the AA would generally be different from that of the NSR and, hence, the simulation model would not be realistic. However, if both episodes are obtained from the same patient, the synthesized AF signal approximates very accurately the conditions and characteristics of an ECG recording with genuine AF. In addition, it is desirable that both signals be acquired during the same session, in order for the electrode position to remain unaltered. This is only possible during a cardioversion process at an electrophysiology lab. The AF episode is taken at the beginning of the recording, before the cardioversion. The cardioversion restores and stabilizes the NSR, which can then be neatly recorded. The AA is synthetized from the AF episode as described in the previous paragraph, whereas the VA is obtained from the NSR episode after cardioversion. Finally, the synthesized signals are created through the superposition of VA and AA for each lead (Fig. 4). Following this simulation model, 10 pseudoreal ECGs were generated for our analysis, including 6 AF ECGs and 4 AFL ECGs.

B. Real AF Recordings

Twenty-five ECGs digitized during 30 s at 1-KHz sampling rate with 16-bit amplitude resolution were employed for our study. In order to demonstrate that the method is valid for AF as well as AFL arrhythmias, the database included 14 AF ECGs and 11 AFL ECGs. All recordings were obtained at an electrophysiological laboratory from patients suffering from persistent AF or AFL. All patients were under amiodarone treatment in order to increase the refractory period.

V. Performance Measurement

A. Simulated AF ECGs

As explained in the previous section, the fact that the AA is known in simulated AF ECGs enables a more accurate performance analysis. The observations $\mathbf{x}$ are the combination of VA $(\mathbf{x}_{\mathrm{VA}})$ and simulated AA waves $\mathbf{x}_{\mathrm{AA}}$: $\mathbf{x} = \mathbf{x}_{\mathrm{VA}} + \mathbf{x}_{\mathrm{AA}}$. Hence, the estimated sources can be decomposed as

$$\hat{\mathbf{s}}(t) = \mathbf{B}\mathbf{x}(t) = \mathbf{B}\mathbf{x}_{\mathrm{VA}}(t) + \mathbf{B}\mathbf{x}_{\mathrm{AA}}(t) \tag{12}$$

that is, the ith source is recovered from a linear combination of the leads given by the ith-row coefficients of the $\mathbf{B}$ matrix. Accordingly, the AA source is recovered from a row, say $\mathbf{b}_{\mathrm{AA}}$, defining a linear combination which aims to cancel the contribution of the QRS complexes while trying to maximize the contribution of the AA

$$\hat{s}_{\mathrm{AA}}(t) = \mathbf{b}_{\mathrm{AA}}\mathbf{x}(t) = \mathbf{b}_{\mathrm{AA}}\mathbf{x}_{\mathrm{VA}}(t) + \mathbf{b}_{\mathrm{AA}}\mathbf{x}_{\mathrm{AA}}(t). \tag{13}$$

As observed in (13), the estimated AA source $\hat{s}_{\mathrm{AA}}$ presents two components

$$\begin{aligned} e(t) &= \mathbf{b}_{\mathrm{AA}}\mathbf{x}_{\mathrm{VA}}(t) \\ s_{\mathrm{AA}}(t) &= \mathbf{b}_{\mathrm{AA}}\mathbf{x}_{\mathrm{AA}}(t). \end{aligned} \tag{14}$$

Since s_{AA} is reconstructed from the actual AA and is not contaminated by VA, it can be considered as the pure AA source. The term e mainly consists of residual VA, and hence can be considered as an error or nondesired component. Note that this error term is not only due to ventricular contributions, but also to the noise present in $\mathbf{x}_{\mathrm{VA}}$. The noise that may be present in $\mathbf{x}_{\mathrm{AA}}$ is inherent to this problem formulation of the problem and it can neither be measured nor cancelled. However, due to the higher amplitude of VA, the residual VA in the estimated AA will usually be more important than any residual noise or interference caused in the reference AA (s_{AA}) by an erroneous estimation of the separating matrix $\mathbf{B}$. Therefore, in general the noise present in $\mathbf{x}_{\mathrm{AA}}$ will have a negligible effect on the proposed performance measure.

In the light of this model, performance can be objectively measured using a number of indexes. In the first place, the normalized mean square error (NMSE) is defined as

$$\mathrm{NMSE} = \frac{\mathrm{E}[(\hat{s}_{\mathrm{AA}} - s_{\mathrm{AA}})^2]}{\mathrm{E}[s_{\mathrm{AA}}^2]}. \tag{15}$$

Since $\mathrm{E}[(\hat{s}_{\mathrm{AA}} - s_{\mathrm{AA}})^2] = \mathrm{E}[e^2]$, low values of NMSE indicate an effective rejection of VA and associated interference in x_{VA} and, thus, an improved AA estimation performance. Another objective performance parameter is the Pearson cross-correlation coefficient (CC) between s_{AA} and $\hat{s}_{\mathrm{AA}}$. In addition, we propose the spectral concentration (SC) around the main frequency peak f_p as another indicator. This indicator will later be shown to be useful in measuring performance in real AF recordings. The SC in the band of the peak is based on the parameters employed for measuring the SC in ventricular fibrillation arrhythmias [2], [24], and is computed as

$$\mathrm{SC} = \frac{\sum_{0.82f_p}^{1.17f_p} P_{\mathrm{AA}}(f_i)}{\sum_{0}^{f_s/2} P_{\mathrm{AA}}(f_i)} \tag{16}$$

where P_{AA} is the power spectrum of the AA signal, which is computed using the Welch's method, with a 8192 points FFT, 4096 sample size Hamming window and 50% overlapping; f is the frequencies vector, and f_s is the ECG sample frequency. The bandwidth considered for the SC computation is of 2 Hz for a typical f_{p} of 6 Hz, which is sufficient even for those AF episodes that show a wide-band spectrum with several peaks. In the cases where the bandwidth of the AF signal was wider, this parameter would be no longer valid and should be redefined. For the simulated signals under test, it was verified that the SC of the AA increased according to the error reduction (NMSE), which in turn is associated with an improved AA estimation performance. Hence, the correlation between SC and NMSE points to the validity of the former as performance index of AA estimation quality in real AF recordings, where the NMSE cannot be measured. This outcome was consistent with the results obtained on real signals, as confirmed in Section VI-B.

B. Real AF ECGs

AA extraction performance in real AF ECGs is very difficult to measure objectively, because the signal to be estimated is not known *a priori*. A sensible performance parameter is the degree of SC around the main frequency peak [9]. The rationale for this parameter lies in the fact that the AA spectrum is typically condensed around a single frequency, whereas the spectral content of other components such as VA or noise is more spread out over the frequency range. If the estimated AA signal is contaminated with other nondesired components, the spectral content outside the main frequency peak will become more significant and, thus, the estimated AA will suffer a decrease in the SC around the main peak. Hence, the method that provides an AA signal with higher SC can be considered as the technique with higher performance. The justification of SC as a valid performance index (at least for the proposed method) is further endorsed by the correlation between SC and NMSE found in simulated AF ECGs, as commented at the end of the preceding section.

VI. Results

A. Results With Simulated AF ECGs

The proposed two step approach was applied over a set of 10 simulated recordings with known AA content, and was compared to the results obtained by applying only the first step, i.e., an ICA algorithm. As explained above, the FastICA fixed-point algorithm was chosen as ICA method [16]. Several approaches included in the ICALAB toolbox [10] have also been tested (JADE, AMUSE, etc.), obtaining equivalent solutions. After applying ICA, at least one AA source was identified among the whole set of 12 independent sources. Performance evaluation was then measured in terms of NMSE and CCs. In addition, the spectral concentration (SC) around the main frequency peak was also computed. In those cases where more than one source contained AA, it was selected the source that better matched the known AA according to the performance parameters NMSE and CC. However, after applying SOBI, the AA was present in only one source for the signals under study.

Table I. shows the results obtained. After applying the second stage (i.e., SOBI), the NMSE is reduced up to 40% in average. Correlation indexes also indicate an improvement in the estima-

TABLE I
PERFORMANCE INDEXES OF THE ESTIMATED AA IN SIMULATED ECGS

	Type	Main Frequency	ICA			ICA - SOBI		
			NMSE (%)	CC	SC (%)	NMSE (%)	CC	SC (%)
Patient 1	AF	5.74	128.54	0.656	20.18	68.96	0.752	38.03
Patient 2	AF	4.78	114.02	0.687	32.76	74.04	0.759	42.32
Patient 3	AFL	3.59	42.61	0.825	31.74	31.13	0.861	38.15
Patient 4	AF	6.45	117.32	0.677	28.53	49.7	0.812	49.96
Patient 5	AF	5.38	45.60	0.830	50.70	21.54	0.906	65.55
Patient 6	AF	6.45	109.90	0.688	27.86	98.09	0.722	37.23
Patient 7	AFL	3.35	72.16	0.766	19.53	27.08	0.889	35.37
Patient 8	AF	7.29	148.14	0.640	13.14	59.39	0.787	62.43
Patient 9	AFL	4.42	43.03	0.831	20.76	20.08	0.906	60.88
Patient 10	AFL	3.60	19.55	0.908	55.18	19.77	0.907	60.39
Mean			**74.19**	**0.751**	**30.04**	**46.98**	**0.830**	**49.03**

TABLE II
SPECTRAL ANALYSIS OF ESTIMATED AA IN REAL ECGS

	Main Frequency (Hz)	Spectral concentration	
		ICA	ICA-SOBI
AF Patients	6.19 ± 0.73	37.1 ± 11.8 %	53.7 ± 11.7 %
AFL Patients	4.06 ± 0.65	54.5 ± 19.4 %	65.2 ± 13.9 %

tion of the AA. After applying ICA, there exists a 0.751 correlation between the estimated and the real AA. However, if SOBI is also applied, the correlation indexes arise up to 0.830. Concerning the spectral concentration around the main frequency peak, it can be observed that the AA estimated by using the complete spatiotemporal approach has higher spectral concentration than that estimated by ICA. The validity of this parameter for performance evaluation will be further discussed in the next section.

B. Results With Real AF ECGs

ICA and ICA-SOBI were applied to the database of 14 AF ECGs and 11 AFL ECGs. In all cases, it was possible to estimate the AA source. A spectral analysis was carried out in order to detect the main frequency. The AA source estimated with ICA provides the same frequency as the AA source estimated with ICA-SOBI, being of 6.19 ± 0.73 Hz for AF and 4.06 ± 0.65 Hz for AFL. However, the AA source obtained with ICA-SOBI has a higher spectral concentration around the main frequency peak. In average, ICA obtains a spectral concentration of 37.1% for AF and 54.5% for AFL. The spectral concentration is increased with ICA-SOBI up to 53.7% and 65.2% for AF and AFL, respectively. Table II and Fig. 5 summarize the spectral analysis of the AA. The higher spectral concentration of the AA signal obtained after SOBI processing indicates that part of the noise present in the AA signal after ICA has been removed. Fig. 6 shows the results from patient 3, where the estimated AA obtained by ICA (top) is free from QRS complexes but it still contains noise, giving rise to a smeared frequency distribution with spurious peaks. After the SOBI stage, the estimated AA (bottom) is successfully denoised, its frequency spectrum closely resembling that of a typical AF signal.

Regarding the kurtosis values of the VA and the AA, the results confirm the hypothesis employed in the separation model. Indeed, VA is supergaussian, with a kurtosis value of 16.5 ± 5.9 for the ECGs under test. By contrast, AA cannot be assumed not to be Gaussian, with a kurtosis value of -0.21 ± 0.45 for this database. Table III details the kurtosis values of VA and AA sources for AF and AFL patients. The significance level (p-value) of these results was obtained by means of a kurtosis statistical test about the gaussianity of VA and AA sources. A t-student test where the null hypothesis is that the sources are Gaussian (i.e., the kurtosis distribution have zero-mean value)

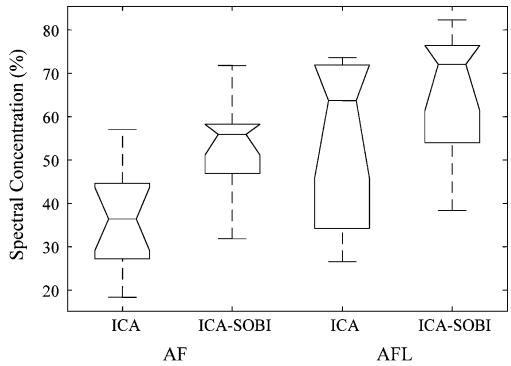

Fig. 5. Spectral concentration of the AA for AF and AFL ('box-and-whiskers' plot).

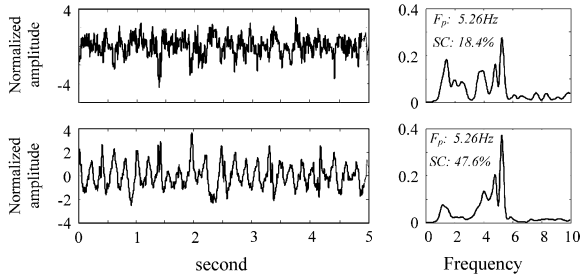

Fig. 6. An example where the proposed ICA-SOBI outperforms ICA.

TABLE III
KURTOSIS VALUES OF VENTRICULAR AND ATRIAL SOURCES

	k_{VA}	k_{AA}
Simulated ECGs	12.2 ± 5.8	-0.17 ± 0.68
AF Patients	14.9 ± 5.6	0.03 ± 0.34
AFL Patients	18.5 ± 5.9	-0.52 ± 0.38

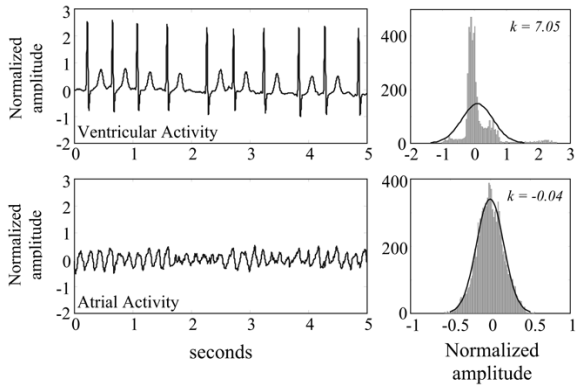

Fig. 7. Histogram and kurtosis values (k) of the estimated VA and AA sources. The continuous solid lines on the right-hand side plots represent the closest Gaussian approximations to the observed distributions.

was performed. For the kurtosis distribution of AA, we obtain $p = 0.236$ (the hypothesis null should not be discarded), and for the kurtosis distribution of VA we obtain $p = 1.22 \cdot 10^{-13}$ (the hypothesis null can be discarded). The histograms of VA and AA sources from patient 10 are shown in Fig. 7, where the normalized Gaussian distribution has been superimposed for comparison. As can be observed, the VA is supergaussian, clearly more 'peaky" and with heavier tails than the Gaussian pdf, whereas the AA exhibits a near-Gaussian distribution. The fact that the estimated ventricular and atrial sources fulfil the hypothesis assumed in the problem formulation regarding their statistical behavior and spectral characteristics validates the proposed approach for the enhanced estimation of AA in patients with AF.

VII. Study Limitations

The BSS-based AA-extraction approach presented in this paper has been validated using a self-constructed database of simulated AF recordings and an own database of real AF ECGs, as previously explained. Although the proposed validation methodology introduces some useful concepts and the results are consistent, this study presents some inherent limitations that are considered next.

Regarding the simulation model for generating AF recordings, the 12-lead synthesized AA contains reconstructed samples within the intervals corresponding to the QRST waves. Therefore, the number of reconstructed points is considerable with respect to the number of true AA samples. This fact could render the extrapolated AA information rather inaccurate, specially near the center of the extrapolation window. This limitation could be addressed, e.g., by employing ventricular asystole periods registered from AF patients. These recordings consist of several seconds length ECG segments without any VA, which can be triggered by blocking the atrioventricular conduction (His bundle) within the heart. This action is highly invasive and, therefore, is not applicable or convenient in most situations.

In addition, the SC parameter may not be sufficiently discriminating in real AF recordings. Indeed, the SOBI algorithm employed in the second separation stage tends to enhance narrow-band components (with high SC) in wide-band noise. Although the SC parameter has been contrasted and shows a high degree of correlation with other objective parameters in simulated recordings, this index could unfairly benefit the proposed approach against other methods. Alternative parameters should also be employed to assess the performance of the estimated AA. In this respect, further research is needed to search for new parameters to determine either numerically or qualitatively (e.g., more clinical indexes) the correct estimation of the desired source.

VIII. Discussion and Conclusions

A typical feature of ICA-based BSS techniques is that they are able to estimate independent sources by exploiting spatial information from multilead signals. Usually, temporal information is not taken into account. This paper has demonstrated that the source temporal information is indeed relevant in the estimation of AA from ECG recordings of AF episodes. A spatiotemporal BSS algorithm adapted to this specific problem has been designed and implemented. The algorithm consists of an initial spatial-HOS based separation stage (ICA) aiming to remove non-Gaussian interference (mainly VA), followed by a time-SOS based separation stage (SOBI) aiming to cancel Gaussian-like noise. Hence, the AA can be separated not only from VA, but also from other independent sources of noise and interference regardless of their distribution. As an important advantage, the BSS-based approach does not require a previous R-peak detection, thus avoiding any subsequent problems such as sensitivity to ectopic beats, false negatives/positives in automated processes, etc. With this new method, results on synthesized AF signals have experienced a significant improvement in AA estimation performance. A study with real AF signals has further validated the suitability of the proposed method.

This work has also tackled the problem of synthesizing pseudoreal signals for ICA. The proposed approach does not take into account the generative model of instantaneous linear mixtures of the bioelectric sources assumed by BSS techniques in this biomedical problem. This detachment from the assumed underlying signal model allows the definition of more significant indexes for objective performance evaluation and comparison.

In addition, the lack of objective parameters to measure performance in real AF recordings has led us to propose a new parameter based on the spectral concentration, which shows a correlation with the AA estimation quality. In the experimental results, AA estimation has always improved with the application of the second separation stage based on the exploitation of temporal information. Even in some ECGs where ICA had already estimated the AA accurately (e.g., because the existing AA was far from Gaussian), the second step has been able to maintain the separation quality. Since the statistical behavior of the AA source is not *a priori* known, it seems sensible to make use of the full two-step approach in all cases.

This contribution improves the existing solutions for AF analysis. Once the AA has been extracted, it can be further analyzed for spectral characterization, pattern recognition, time-

frequency parameter extraction, etc. Some clinical applications derived from the AA analysis could involve, e.g., the prediction of AF recurrence after successful cardioversion. A significant number of patients return to sustained AF in few days after electrical cardioversion. The analysis of the AA could contribute to the prediction of AF recurrence in order to prevent some patients from suffering ineffective electrical discharges. Other interesting application could be based on the analysis of paroxysmal AF (PAF), which appears and terminates spontaneously. It is commonly accepted that PAF is a precursor of persistent AF. Improved knowledge about the mechanisms that cause PAF and its spontaneous termination may introduce improvements in the treatment of AF. The proposed methodology, thus, emerges as a helpful tool in clinical diagnosis.

ACKNOWLEDGMENT

The authors would like to acknowledge the helpful support received from Servicio de Hemodinámica of the Hospital Clínico Universitario the Valencia, and specially from R. Ruiz, S. Morell, and R. García Civera, for providing signals and for the high quality of their clinical advice. V. Zarzoso has carried out part of this research work while on leave at Laboratoire I3S, Universite de Nice—Sophia Antipolis, France. He gratefully acknowledges Dr. P. Comon for his kind hospitality.

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