Spatiotemporal Separation Algorithm for Atrial Fibrillation Signal Estimation

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Abstract A new algorithm for the estimation of the atrial activity (AA) signal from the surface electrocardiogram during atrial fibrillation (AF) episodes is proposed. This algorithm has been based on blind source separation methods, and has been designed including statistical and temporal source information. With this new methodology, the estimation of the AA source is enhanced, comparing to the estimation obtained with other independent component analysis (ICA) algorithms. The validity of the proposed method is demonstrated with the analysis of 10 AF recordings. A performance parameter based on the spectral concentration of the AA around its main frequency was employed. The spatiotemporal analysis provided AA signals with an spectral concentration that was in average 13% above those obtained with ICA methods.

Keywords: atrial fibrillation, independent component analysis, QRST cancellation, blind source separation, second order blind identification

1 Introduction

Atrial fibrillation (AF) is the most frequent cardiac arrhythmia, and has a prevalence of 10% in population over 70 years old. The interest of scientic community in the study and comprehension of AF has been increased considerably during the last years [1]. The analysis and characterization of AF from non-invasive techniques requires the previous estimation of the actrial activity (AA) signal from the surface electrocardiogram (ECG). Several approaches have been proposed for this purpose, as QRST cancellation techniques [2], Blind Source Separation (BSS) [3], neural networks [4], etc.

Regarding BSS, the proposed solutions exploit the spatial diversity of the ECG to recover the independent bioelectric sources (ventricular activity (VA), AA and other bioelectric artifacts). However, temporal information of sources is not used. In this contribution we demonstrate that the temporal information of sources is also relevant, allowing us to develop a new algorithm based on source separation which is adapted to the problem of the AA estimation.

This paper is structured as it follows: next section reviews briefly the state of the art about AF and BSS techniques. Subsequently, the methods are described in detail, including a statistical analysis of the bioelectric sources as well as the proposed algorithm. The forth section describe the AF databases. The results obtained with both databases are shown in the fifth section, whose conclusions are discussed immediately after.

2 State of the Art

2.1 Atrial Fibrillation

Atrial fibrillation is an arrhythmia in which normal atrial electrical activation is substituted by aparently chaotic and continuous activation, with multiple wavelets depolarizing simultaneously the atria [5]. 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. AF is also characterized by an irregular and frequently rapid ventricular rate (QRS complex). The ventricular response to

DRAFT VERSION OF THE PAPER
Castells, F., Rieta, J. J., Millet, J., and Moratal, D., "Spatiotemporal Separation Algorithm for Atrial Fibrillation Signal Estimation," 5th International Conference on Neural Networks and Expert Systems in Medicine and Healthcare (NNESMED 2003), vol. 5 pp. 151-156, Sheffield (UK), July.2003.

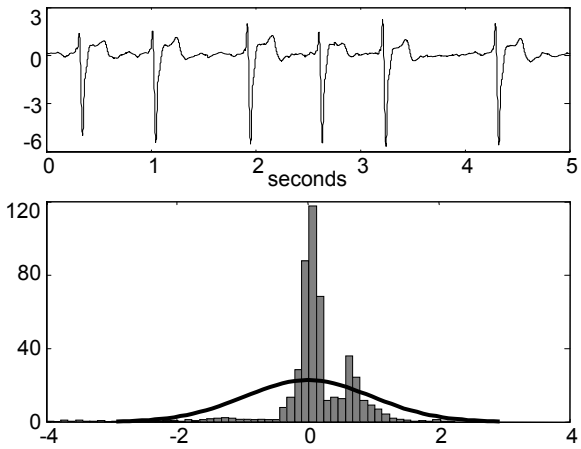

Fig. 1a.: Example of VA and its histogram.

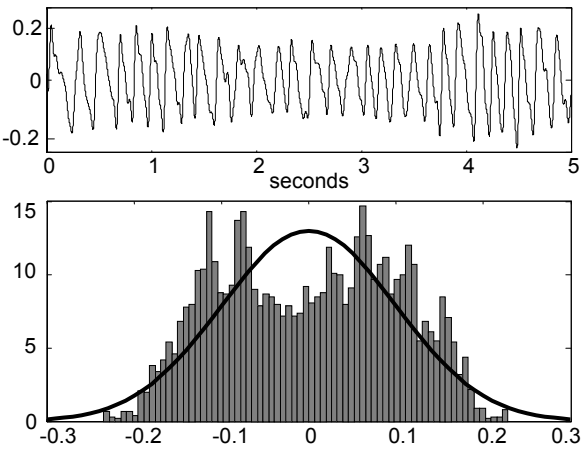

Fig.1b.: Example of AA and its histogram.

AF depends on electrophysio-logical properties of the atrioventricular node, and the R-R interval becomes more irregular.

2.2 Blind Source Separation

The fact that the AA and the VA appear mixed at the ECG, allow us to model the extraction of the AA as a blind source separation (BSS) problem. Following a BSS formulation [6],

$$\mathbf{x} = \mathbf{A} \cdot \mathbf{s}, \qquad (1)$$

where **s** are the bioelectric sources (AA, VA, respiration, muscular movement, etc.), **A** is the mixing matrix and **x** are the observations, i.e. the multilead ECG. The main advantage of a BSS model is the so few restrictions that must be fulfilled in order to be able to recover the original sources from the exclusive knowledge of the observations. Indeed, only two conditions must be accomplished: statistical independence of sources and linear mixing matrix. VA and AA are independent, since they arise from independent bioelectric phenomena. Furthermore, from the torso model as a resistor network, the mixing matrix can be assumed to be linear and instantaneus, and therefore, BSS techniques are appropriate for the estimation of the AA.

Several BSS techniques have been developed: principal component analysis (PCA) for Gaussian sources, independent component analysis for non-Gaussian sources and second order blind identification (SOBI) for sources with different spectra. Notice that PCA and ICA techniques only use spatial information, whereas SOBI also takes into account temporal source information.

In order to select or design a suitable separation algorithm, a previous statistical analysis of sources must be performed.

3 Methods

3.1 Statistical Source Analysis

The sources contained in an ECG recording can be divided in three classes with different nature. VA sources are the ECG components with highest energy, with high amplitudes during ventricular activity periods (QRST interval), and with values close to zero the rest of the time. A statistical analysis of VA sources reveals a supergaussian behaviour, with typical kurtosis values of 30. In AF episodes, AA consists of small and continuous wavelets with a cycle around 160ms. A statistical analysis of sources shows that AA have sub-Gaussian distributions, but with kurtosis values very close to zero (typically around –0.5). Figures 1a and 1b show examples of VA and AA sources and their histograms respectively. Supergaussianity of VA sources is always accomplished, but in occasions the AA is closer to a Gaussian model. However, AA waves have a characteristic spectrum, with a main peak due to the refractory period, which can be located between 5 and 8 Hz depending on the patient.

3.2 Two Step Strategy

The fact that VA present supergaussian distributions can be profitable to remove ventricular components in a first stage. The non-ventricular components (AA mixed with artifacts and noise) will be the inputs of a second stage. In this stage, the characteristic spectrum of the AA source will be exploited in order to enhance AA estimation.

3.3 First Stage: ICA

As it has been stated above, ICA techniques are the 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 [7]. 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 maximization of independence. Considering the model in (1), ICA methods estimate the separation matrix **B** that recovers the independent sources:

$$\hat{\mathbf{s}} = \mathbf{B} \cdot \mathbf{x}, \qquad (2)$$

where $\hat{\mathbf{s}}$ are the estimated sources. Among all existing ICA algorithms, in this study we have chosen a fixed-point algorithm that estimates non-Gaussianity from an approximation of negentropy which combines the calculus simplicity of kurtosis with the robustness of negentropy, and provides very fast convergence [8].

ICA algorithms are able to separate all non-Gaussian sources, but can not estimate Gaussian sources. Consequently, all Gaussian sources will appear mixed. The real effect over AF recordings is that VA sources will be correctly separated. Regarding AA source, in AF episodes where AA behaves statistically as a subgaussian random variable, its estimation is also achievable. In this cases, AA estimation is optimal by means of ICA methods, and little more can be done. However, in AF episodes where the statistical behaviour of the AA is Gaussian, ICA methods are not able to separate AA from other Gaussian sources like noise and other artifacts. Separation of AA not only from VA but also from other bioelectric sources is also desired. This task will be carried out in the second stage.

3.3 Second Stage: SOBI

SOBI techniques consist of separating a mixture of independent sources with different spectral content through second order analysis considering also temporal information of sources. For this purpose, SOBI methods aim to find a transformation that diagonalizes several correlation matrices at different lags simultaneously. Since there may exist none transformation which accomplish that condition, a function that measures the joint diagonalization at different lags must be defined in order to maximize independence of sources.

Considering a simple case of two sources and two observations, the correlation matrix **C** of the observations at a lag τ_i is:

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

The real sources **s** and the whitened observations are related through a Givens rotation:

$$\mathbf{z} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \cdot \mathbf{s}, \qquad (5)$$

where θ is the rotation angle. The correlation matrix of the sources at a lag τ_i is:

$$\mathbf{C}'(\tau_i) = \begin{bmatrix} a_i' & b_i' \\ c_i' & d_i' \end{bmatrix} \qquad (6)$$

The goal is to find independent sources, which is equivalent to find an orthogonal transformation that diagonalizes $\mathbf{C}'$ simultaneously at different lags. Since there may exist none solution that satisfies that condition, a joint diagonalization criterion must be defined. Assuming that N different lags will be employed, in [9] is derived the following contrast function for measuring joint diagonalization:

$$F(\theta) = \mathbf{u}' \cdot \mathbf{u} \qquad (7)$$

$$\mathbf{u} = \begin{bmatrix} \mathbf{a} - \mathbf{d} & -\dfrac{\mathbf{b} + \mathbf{c}}{2} \end{bmatrix} \cdot \begin{bmatrix} \cos 2\theta & \sin 2\theta \end{bmatrix}, \qquad (8)$$

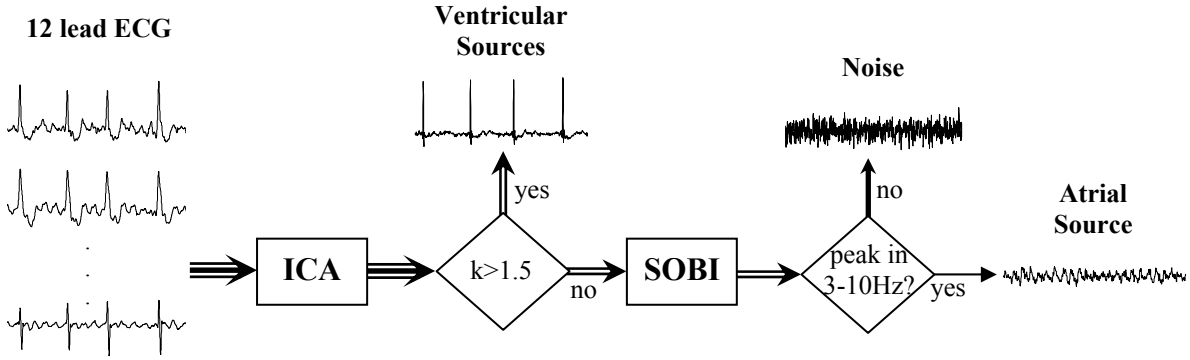

Figure 2.: Block diagram of the AA estimation methodology

where **a**, **b**, **c**, **d** and **u** are column vectors with *N* elements. The contrast function *F* depends only on the rotation angle. Hence, the independence criterion has been transformed into a maximization problem of (7). For more than two sources and two observations, the problem can be solved by iterations of each pairwise until convergence.

Concerning our specific problem of AA estimation, the inputs of this second stage are the non ventricular components that were obtained in the first stage. The decision of which components belong to the ventricular subspace and which components belong to the non-ventricular subspace can be done automatically by means of a kurtosis-based threshold. Empirical experiments show that a conservative kurtosis threshold around 1.5 let us include the AA in the non-ventricular subspace and reject all sources that contain QRS complexes. Figure 2 shows a block diagram of the two-step methodology.

Since the AA has a narrow-banded spectrum, a SOBI algorithm is appropriate for estimating the AA. In this study we consider 17 correlation matrices at equispaced lags of 20ms.

4 Databases

10 AF 12-lead ECGs digitised at a sampling rate of 1Khz and 14 bits, and with a duration of 30 seconds were employed for our study. The recordings were obtained at a electrophysiological laboratory from patients that suffer persistent AF. All patients were under treatment of amiodarona in order to increase the refractory period.

5 Results

When several AA estimation techniques are applied to real AF ECGs, performance is very difficult to be measured from an objective point of view, because it is not known a priori which is the signal to be estimated. One possible parameter that could be used to evaluate the results would be spectral concentration around the main peak. The reason lays on the fact that the AA spectrum has a main frequency, whereas other components as VA or noise have spectral content in all the range. If the estimated AA signal is contaminated with other non-desired components, the spectral content out of the main frequency peak will be higher, and thus, the estimated AA will suffer a decrease of the spectral concentration around the main peak. Hence, the method that provides an AA signal with higher spectral concentration will be selected as the technique with higher performance.

ICA and ICA-SOBI have been applied to the database of real AF ECGs. In all cases it was possible to estimate the AA source. Spectral analysis was done in order to detect the main frequency. The AA source estimated with ICA provided the same frequency as the AA source estimated with ICA-SOBI. However, the AA source obtained with ICA-SOBI had higher spectral concentration around the main frequency. Table 1 sumarizes the spectral analysis of the AA.

	Frequency (Hz)	Spectral concentration	
		ICA	ICA-SOBI
Patient 1	7.17	21.4%	37,0%
Patient 2	5.68	51.6%	57.6%
Patient 3	5.26	18.4%	47.6%
Patient 4	6.09	57.1%	71.8%
Patient 5	7.29	50.6%	58.3%
Patient 6	6.45	43.9%	44.3%
Patient 7	6.45	34.9%	55.1%
Patient 8	7.12	27.2%	31.8%
Patient 9	7.05	40.7%	49.6%
Patient 10	5.62	34.5%	56.7%

Table 1. Spectral analysis of estimated AA

The higher spectral concentration of the AA signal obtained after SOBI processing indicates that partly of the noise present in the AA signal after ICA has been removed. Figure 3 shows an example were ICA-SOBI overperforms ICA. The signal at the top is the AA estimated with ICA and its spectrum. The signal at the bottom is the estimated AA after the second stage.

6 Conclusions

A special feature of ICA techniques is that are able to estimate independent sources by exploiting only spatial information from multilead signals. Temporal information is not considered, and this may be a virtue or a limitation depending on each application. In this paper it has been proven that the temporal information of sources is also relevant in the estimation of the AA, and a separation algorithm adapted to this specific problem has been designed and implemented. Results with synthesized AF signals show the improvement of the performance in the estimation of the AA, and a study with real AF signals confirms and validates the suitability of the proposed method.

As it can be observed in the results, the AA estimation was always improved with the second stage. Even in some ECGs where ICA estimates the AA accurately, the second step maintain the quality already achieved.

This contribution gives solution to an important step in the AF analysis. Once the AA has been extracted, the AA can be further analyzed for spectral characterization, pattern recognition, etc., as a helpful tool in clinical diagnosis.

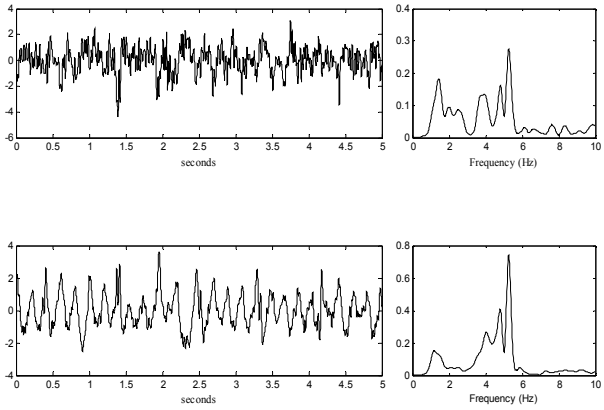

Figure 3.: An example where ICA-SOBI overperforms ICA

Acknowledgement

The authors would like to recognize the helpful support received from 'Servicio de Hemodinámica – Hospital Clínico Universitario the Valencia', and specially from Ricardo Ruiz, Salvador Morell and Roberto García Civera, for providing signals and for the high quality of their clinical advices. This project has been financed by TIC2002-00957 and 'Programa Incentivo a la Investigación UPV'.

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