An Integral Atrial Wave Identification based on Spatiotemporal Source Separation: Clinical Validation

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Abstract

This contribution presents a new methodology for the estimation of the atrial activity (AA) in supraventricular arrhythmias. The method is an adaptation of source separation techniques to this specific problem, including spatial and temporal information. An extensive clinical study over 45 patients demonstrates the suitability of the method. A spectral analysis of the estimated AA shows that the spectral concentration around the main peak is 13% in average higher than in the AA obtained with other source separation methods. Spectral differences between atrial fibrillation (AF) and atrial flutter (AFL) were also found: AF and AFL have main frequencies over 5Hz and below 5Hz respectively. In addition, AFL spectrum is characterized by the presence of harmonics.

1. Introduction

The analysis and characterization of supraventricular arrhythmias from the surface electrocardiogram (ECG) requires the previous extraction of the atrial activity (AA). Several techniques have been proposed for this purpose, as the explicit QRST cancellation from a matching template [1], or other techniques based on source separation (BSS) like principal component analysis (PCA) [2] and independent component analysis (ICA) [3].

Regarding separation methods, they estimate the original sources from the spatial information contained in all leads. Depending on the statistical nature of sources, several BSS techniques have been developed. For non-Gaussian sources, ICA provides the optimal solution [4]. For Gaussian sources with different spectra, a second order blind identification (SOBI) approach gives a reliable solution [5]. For white Gaussian sources, the problem becomes more simple and can be solved by means of PCA techniques. PCA and ICA techniques only use spatial information, whereas SOBI also takes into account temporal source information. Therefore, in order to select or design a suitable separation algorithm, a previous statistical analysis of sources must be performed.

This paper describes first a new separation method adapted to the AA estimation problem, followed by a brief description of the database and the criterion employed for measuring performance. Finally, the results of the methodology over the signals in the database are expounded in detail, extracting interesting conclusions which are discussed immediately after.

2. Methods

2.1. 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. A statistical analysis of ventricular activity (VA) sources reveals that they possess supergaussian random distributions [6]. Regarding AA sources, they consist of small and continuous wavelets with a cycle length that is closely related to the refractory period [7]. A statistical analysis shows that AA sources have quasi-Gaussian distributions [6]. However, AA waves have a characteristic spectrum, with a main frequency peak. In atrial fibrillation (AF) episodes the main frequency is located around 6-8Hz approximately, depending on the patient and the treatment [8]. Finally, noise and other artefacts are at the amplitude order of the atrial sources, whose behaviour is well-modeled by additive white Gaussian noise (AWGN) [6].

2.2. Two step strategy

The fact that VA have supergaussian distributions allow us to remove ventricular components in a first stage by means of an ICA approach. Ventricular components are those with highest amplitude, and therefore, if this stage is successfully achieved, the most critical part of the job will be done. The non-ventricular components (AA, 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, by means of a SOBI algorithm.

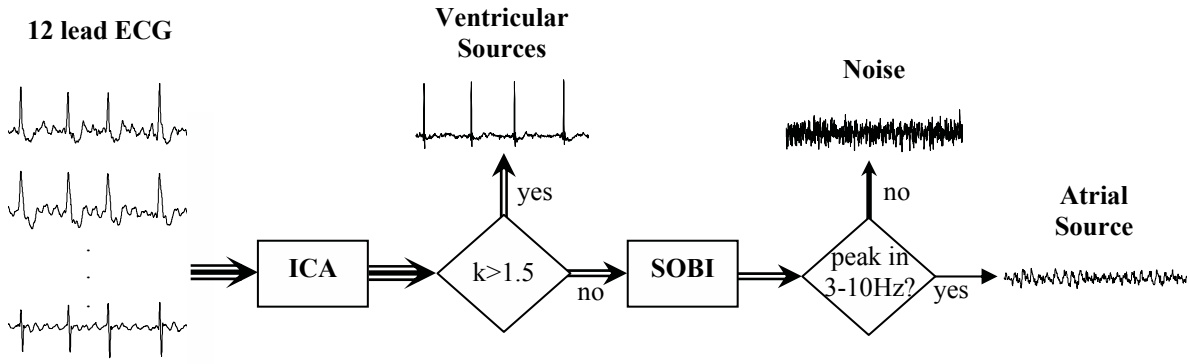

Figure 1.: Block diagram of the AA estimation methodology

2.2.1. First Stage: ICA

Following a BSS formulation,

$$\mathbf{x} = \mathbf{A} \cdot \mathbf{s}\,, \tag{1}$$

where **s** are the bioelectric sources (AA, VA, respiration, muscular movement, etc.), **A** is the channel-parameter matrix and **x** are the observations, i.e. the multilead ECG. 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. Most ICA methods are based on the optimization of a contrast function that maximizes non-Gaussianity [4]. Considering the model in (1), ICA methods estimate the separation matrix **B** that recovers the independent sources:

$$\hat{\mathbf{s}} = \mathbf{B} \cdot \mathbf{x}\,, \tag{2}$$

where $\hat{\mathbf{s}}$ are the estimated sources. Among all existing ICA algorithms, in this study we have chosen an algorithm that estimates non-Gaussianity as a function of an approximation of negentropy. Furthermore, the maximization of the contrast function will be carried out with a fixed point algorithm that provides robustness and very fast convergence [9].

ICA algorithms are able to separate all non-Gaussian sources, but can not separate more than one Gaussian sources. Consequently, all Gaussian sources will appear mixed. The real effect over AF recordings is that VA sources will be correctly separated, but the AA will be mixed with other Gaussian sources like noise and artefacts. 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 (see figure 1).

2.2.2. Second Stage: SOBI

SOBI techniques consist of separating a mixture of independent sources with different spectral content. The estimation of the independent sources is achieved through second order analysis considering also temporal source information. Let us consider at first a simple scenario of two sources and two observations. Assuming pre-whitening of the observations, the whitened signals **z** and the original sources are related through an unitary transformation:

$$\mathbf{z} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \cdot \mathbf{s}\,, \tag{3}$$

where θ is the rotation angle. After this transformation, the correlation matrix **C** of the sources at a lag τ_k is:

$$\mathbf{C}(\tau_k) = \begin{bmatrix} a_k & b_k \\ c_k & d_k \end{bmatrix}. \tag{4}$$

Independence of sources is equivalent to null cross-correlation values at all lags. Hence, the goal is to find a rotation angle that diagonalize **C** at several lags simultaneously. Since there may exist none solution that satisfies that condition, a joint diagonalization criterion must be defined. In [5] it is derived a function that measures joint diagonalization, which depends exclusively on the rotation angle. Hence, the independence criterion can be transformed into a maximization problem. The rotation angle that maximizes the joint diagonalization function allows us to recover the original sources. 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. The existence of QRS complex in the ventricular sources impose that the ventricular sources have very high kurtosis values (typically 30). As it has been aforementioned, AA is a quasi-Gaussian random variable, and hence its kurtosis values are very close to zero. 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.

Since the AA has a narrow-banded spectrum, a SOBI algorithm is appropriate for estimating the AA. The number of matrices for joint diagonalization and their time lags must be properly designed. In order to achieve high performance without increasing excessively computational load, a total of 17 correlation matrices at equispaced lags of 20ms will be employed for joint diagonalization.

3. Database

45 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 from persistent supra-ventricular arrhythmias. All patients were under treatment of amiodarone in order to maintain sinus rhythm after cardioversion [10].

4. Performance Measurements

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, which can be computed as:

$$SC = \frac{\int_{0.82 f_p}^{1.17 f_p} P_{AA}(f)df}{\int_{0}^{f_s/2} P_{AA}(f)df}, \quad (5)$$

where P_{AA} is the power spectral density function of the estimated AA source, f_p is its the main frequency and f_s is the sampling frequency.

The suitability of this parameter for measuring performance lays on the fact that the AA has a narrow-banded spectrum with a main frequency, whereas other components as VA or noise have spectral content in a wide frequency range. If the estimated AA signal is contaminated with other non-desired components, the spectral content out the main frequency of the AA 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.

5. Results

5.1. Performance Analysis

Since ICA techniques have been already proposed for the estimation of AA, i.e. the first stage of the proposed algorithm, the suitability of the second stage as a refinement of the AA estimated with ICA must be proven. The study over the 45 patients demonstrates that the spectral concentration obtained after SOBI processing is considerably higher (fig. 2). The third box corresponds to the difference of the spectral concentration obtained with both methods. The fact that this only has positives values indicates that the second stage always improves the AA estimation. In the worst case, the quality obtained in the first stage is just maintained, but in the best case the spectral concentration obtained with the full approach is 30% above. In average, the spectral concentration of the estimated AA after the second stage increases 13%. Figure 3 shows an example where the proposed algorithm overperforms ICA.

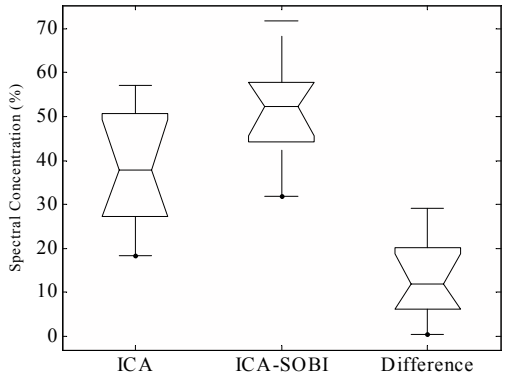

Figure 2: Box and whisker plot of spectral concentration

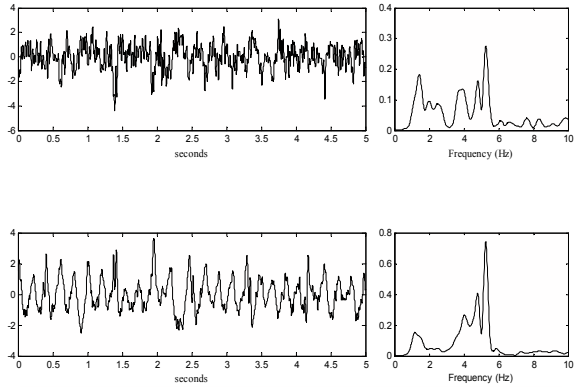

Figure 3: An example where ICA-SOBI (down) overperforms ICA (up)

5.2. AA Characterization

An in-depth analysis of the AA let us distinguish two different behaviours. The most frequent scenario (34 patients) was given by an irregular pattern with a main frequency within the range 5-7Hz approximately, and with the absence of harmonics. A second situation (11 patients) corresponds to a regular waveform with a main frequency within the range 3.5-5Hz approximately and with several harmonics, what provides a saw-tooth

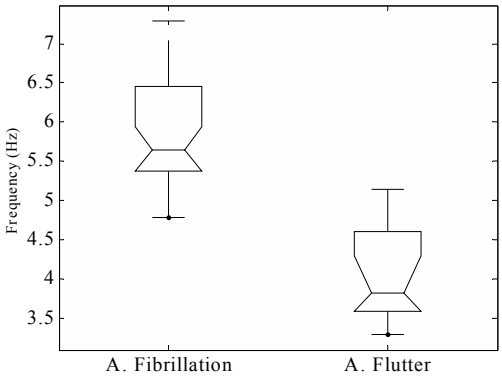

Figure 4: Box and whisker plot of main frequency

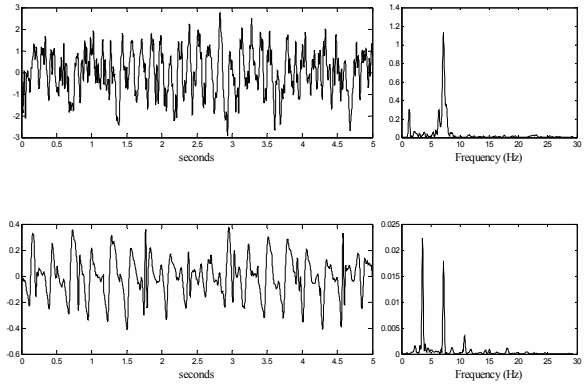

Figure 5: Spectral comparison of AF and AFL

waveform (figures 4 and 5). Clinicians identified the first pattern as atrial fibrillation arrhythmias and the second one as atrial flutter. In most cases the main frequency parameter allows the discrimination of both arrhythmias. However, special care must be taken if the main frequency is around 5Hz, and additional parameters must be considered. A boolean parameter as the presence or absence of harmonics may be useful.

It is important to consider that the patients were under treatment of amiodarone. Patients without treatment may present shorter refractory periods, and hence, higher main frequencies.

6. Conclusion

In this contribution it has been proven that the inclusion of temporal information in the separation model enhances AA estimation in comparison to other source separation methods. A spatio-temporal separation method based on the statistical properties of VA and AA optimises the estimation of the AA.

Furthermore, in order to measure the performance of a method for AA estimation, the spectral concentration of the AA around its main frequency is proposed. The technique that provides an AA signal with higher spectral concentration is the technique that provides the purest AA, with less noise and QRS residua.

The robustness of this AA estimation method and the spectral parameters that can be extracted will allow us to deal with clinical problems, some of them with an immediate solution as AF and AFL discrimination, but also with other more complex challenges as the prediction of AF recurrence after successful cardioversion, etc.

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