Atrial Activity Extraction Based on Blind Source Separation as an Alternative to QRST Cancellation for Atrial Fibrillation Analysis

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Abstract

Atrial fibrillation (AF) characterization from electrocardiogram (ECG) recordings requires the elimination of ventricular activity (VA). The present contribution demonstrates the potential of blind source separation (BSS) in atrial activity (AA) extraction from AF episodes. The applicability of BSS techniques relies on the assumption that AA and VA are decoupled, and hence can be regarded as generated by independent bioelectric sources. In the comparative experiments, a multi-lead AF signal model is synthesized by adding real AA from AF episodes to ECGs recorded from healthy patients. Two direct QRST-cancellation methods are also considered: template matching and subtraction, and adaptive noise cancellation. Further experiments are performed on real multi-lead recordings from 20 patients with AF episodes. The BSS approach shows a superior performance, thus manifesting the suitability of BSS techniques for AA extraction. As a favourable by-product, BSS arises as a novel technique for QRST-complex cancellation.

1. Introduction

Atrial fibrillation (AF) is one of the most frequent cardiac arrhythmia, with a considerable prevalence in population and a significant impact on mortality. Its proper characterization from electrocardiogram (ECG) recordings –regardless of the leads considered– requires the extraction or cancellation of the signal components associated to ventricular activity (VA), that is, the QRS complex and the T wave (QRST) Unfortunately, a number of facts hinder this operation. Firstly, atrial activity (AA) presents in the ECG much lower amplitude –in some cases well under the noise level– than VA. Also, both phenomena possess spectral distributions notably overlapped, rendering linear filtering solutions unsuccessful.

Traditional methods focus on explicit QRST-cancellation [1][2][3]. However, the key observation that AA and VA are decoupled [4] introduces an interesting new perspective which does not rely on direct QRST elimination. In effect, we can reasonably assume that AA and VA are generated by physically (and hence statistically) independent sources of bioelectric current. The situation then becomes a so-called *Blind Source Separation* (BSS) problem. Atrial and ventricular source contributions appear mixed at the electrode outputs. The extraction of the atrial sources from the electrode outputs via a suitable BSS method makes it possible to reconstruct the atrial contribution to each electrode free from VA and other interference. Note that, in addition, this procedure spares the need for explicit QRST-cancellation as carried out by traditional techniques.

The fact that BSS has already proven useful in other biomedical applications –such as the extraction of the fetal ECG from maternal cutaneous recordings [5][6]– made the authors anticipate promising prospects for its application to AA extraction and QRST elimination. The results reported in the present contribution corroborate this prediction.

2. Database

Since BSS relies on spatial diversity (as explained later in Section 4.1.), multi-lead recordings were preferred in this study. Recordings were chosen from both a commercial (MIT-BIH, AF directory and sinus-rhythm series 100 and 200) and the author's own database (real signals obtained at the Electrophysiology Lab of the Hospital Clínico de Valencia with Prucka Engineering's Cardiolab system) [7][8]. All rhythms were diagnosed by a cardiologist following standard criteria based on surface ECGs and intracardiac electrograms simultaneously recorded. A total of 74 multi-lead records were selected, with episodes of around 8 s. Table 1 summarizes the configuration of the signal database.

Table 1: Patients and episodes with normal sinus rhythm (NSR) and atrial fibrillation (AF) in the database.

	NSR	AF
Num. of Patients	20	20
Num. of Episodes	36	38

3. Preprocessing and AF-episode synthesis

All signals were sampled (or re-sampled, if required) at 1 kHz. After amplitude normalization, the signals were preprocessed using a notch adaptive filter to cancel out mains interference, followed by a band-pass filter with cut-off frequencies of 0,5 and 60 Hz to remove baseline wandering and thermal noise [2].

An AF source was synthesized from real recordings by means of visual detection and repetition of segments between two sufficiently separated, consecutive Q waves (Fig. 1.a–1.b). To avoid distortion, special care was taken in the interpolation and filtering of samples near the boundaries of adjacent segments. Next, a normal sinus rhythm (NSR) was selected from the same patient. This NSR signal was considered as a ventricular source (Fig. 1.c), which, after linear combination with the simulated AF wave, yielded a synthetic AF episode (Fig. 1.d).

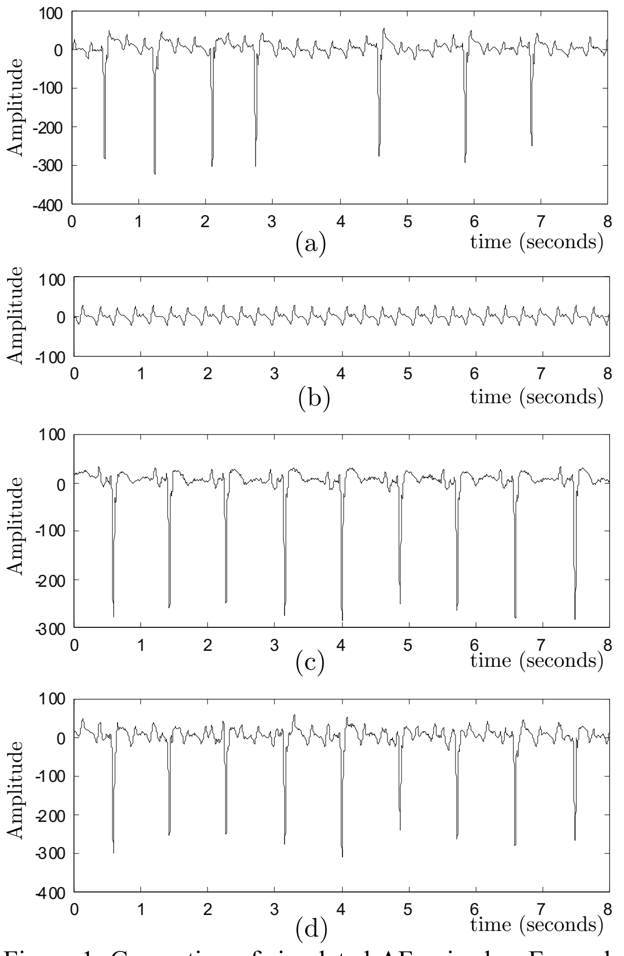

Figure 1: Generation of simulated AF episodes. Example over lead V1: (a) real AF episode, (b) AA segment extracted and concatenated, (c) NSR from same patient, and (d) linear combination of synthesized AF signal and NSR of (c).

The correlation between the AF wave estimated by the methods and the simulated AF source was able to provide an objective performance measure, from which the different methods could be assessed and compared.

4. Methods

4.1. Blind source separation

BSS consists of recovering a set of source signals from the observation of linear mixtures of the sources [5]. The term "blind" emphasizes that nothing is known about the source signals or the mixing structure, the only hypothesis being the source mutual independence. Mathematically , if vector $\mathbf{x} = [x_1, x_2, \dots, x_q]^{\mathrm{T}} \in \mathbb{R}^q$ (the symbol $^{\mathrm{T}}$ stands for the transpose operator) represents the q source signals and vector $\mathbf{y} = [y_1, y_2, \dots, y_p]^{\mathrm{T}} \in \mathbb{R}^p$ denotes the p-sensor output vector, the BSS model for instantaneous linear mixtures reads:

$$\mathbf{y} = M \cdot \mathbf{x} \qquad (1)$$

where $M \in \mathbb{R}^{p \times q}$ is the unknown mixing matrix. The objective is to estimate $\mathbf{x}$ and M from the exclusive knowledge of $\mathbf{y}$.

The relevance of BSS in the problem of AF extraction lies in the basic assumption that AA and VA are physically decoupled [4], so that both can be considered as generated by statistically independent bioelectric sources. Hence, the skin-electrode signal vector $\mathbf{y}$ complies with model (1), where vector $\mathbf{x}$ is composed of the independent sources of atrial and ventricular cardiac activity, as well as of (possibly) additional sources of interference and noise. The mixing coefficients contained in M depend on the body geometry, tissue conductivity, electrode position, etc., similarly as occurs in the BSS formulation of the fetal ECG extraction problem [5][6]. Consequently, the atrial contribution to the recordings can be recovered by extracting, via BSS, the sources of AA and the corresponding columns of the mixing matrix.

Several approaches to performing BSS exist [5], but most rely on higher-order statistics (HOS) due to their ability to measure statistical independence. Also, the exploitation of the fact that different linear combinations of the source signals appear at each sensor –a phenomenon known as spatial diversity– is crucial for the separation. This implies that, in general, a BSS method can only recover as many sources as sensors.

For this reason, two synthetic leads were produced from the same simulated AF signal and VA simply by altering the linear combination coefficients. The mixing matrix was chosen so that both waveforms resembled an AF episode; otherwise, its elements could be regarded as arbitrary. Source separation was performed on these simulated electrode signals through the HOS-based BSS method whose mathematical details are summarized in [9]. As well as to each synthesized 2-lead group, BSS was applied to real 12-lead ECGs.

4.2. Template matching and subtraction

The TMS method is based on the cancellation of each QRST complex through the subtraction of an average QRST complex computed over the recording under analysis[1][2].

In our case, for each simulated AF signal, R waves were detected over the 8-second segments by using a peak detection algorithm [10] and marking the maxima as fiducial points. A median complex was then obtained by aligning all the QRST waves at their fiducial points and performing a median operation. The window length for this operation was set as the minimum R–R distance found in the 8-second segment. In order to allow the window to include each QRST complex, the alignment was such that the first 30% of the window length preceded the fiducial point whereas the other 70% followed it [1]. Next, the median template was aligned with each QRST interval at their fiducial point and subtracted, aiming to leave AA only.

4.3. Adaptive noise cancellation

The adaptive noise cancellation (ACA) method –developed by Widrow [11]– tries to eliminate the interference present in a primary input by filtering and subtracting a reference input correlated with the undesired interference.

The implementation employed in our experiments was based on a power-normalized least mean square algorithm with same filter length as the optimal Wiener-Hopf solution [11]. The simulated AF episodes were introduced as primary inputs to the canceller. As reference inputs, two cases were considered. The first case consisted of the average QRST-complex repetition, where each repeat was aligned with the R waves (at the fiducial points). The second type of reference signal considered was the same signal of VA. Hence this latter case, which we refer to as ACA with prior knowledge (ACAk), implements a best-case scenario for adaptive cancellation.

5. Results

Since the relevant information is contained in the signal waveforms, rather than in their amplitudes, and in order to allow a more significant comparison, the atrial signals estimated by the methods were normalized.

Fig. 2 plots the original and the estimated atrial signals for the episode of Fig. 1. A straightforward visual examination reveals that the atrial source is perfectly separated by BSS (Fig. 2.b), whereas the estimation quality worsens for TMS (Fig. 2.c) and ACA (Fig. 2.d)

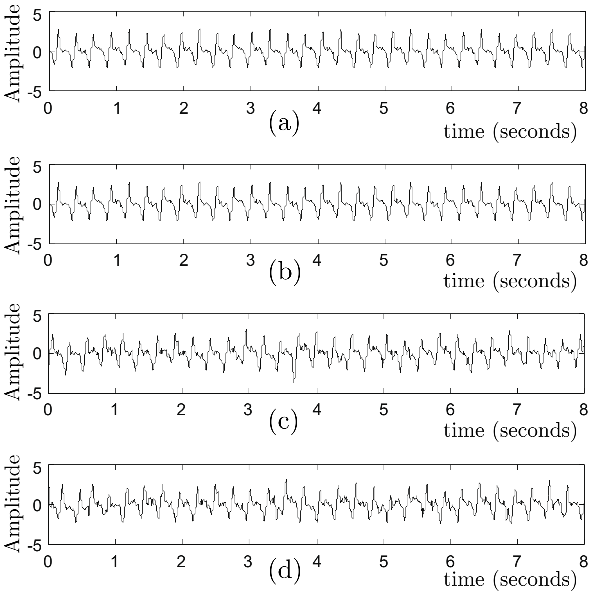

Figure 2: Comparison between (a) normalized simulated AF signal and normalized estimates via (b) BSS, (c) TMS and (d) ACA.

The correlation coefficient between the original and the estimated AF waveforms can be used as an objective performance measure, as suggested at the end of Section 3. As shown in Table 2, BSS clearly surpasses the two other methods, including ACAk.

Table 2: Normalized correlation coefficient between original and estimated AF signals.

	BSS	TMS	ACA	ACAk
Correlation	99,99%	93,35%	92,52%	97,60%

Fig. 3 displays the error signal obtained as the direct subtraction of the normalized estimated AF signal from the normalized original AF signal. Again, the BSS-based technique produces the best results (Fig. 3.a), even improving ACAk (Fig. 3.d).

Regarding the application of BSS to real 12-lead ECG recordings with AF episodes, results are also very satisfactory. The AA estimates obtained are considered by cardiologists as very approximate to real atrial waveforms typically observed in ECGs. This outcome is illustrated in Fig. 4, which shows lead V1 of a real AF episode (top) and the atrial source estimated via BSS from a 12-lead recording of such episode (bottom).

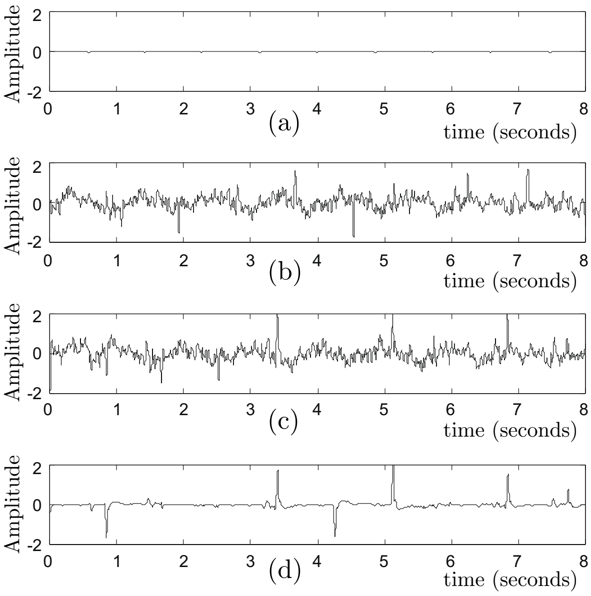

Figure 3: Error signal obtained through the direct subtraction of the normalized AF estimate from the normalized original AF source: (a) BSS, (b) TMS, (c) ACA, and (d) ACAk.

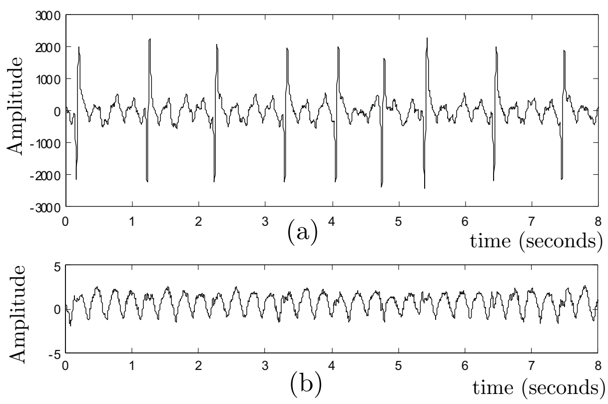

Figure 4: (a) Lead V1 of a real AF episode. (b) Normalized atrial source estimated by BSS from a 12-lead recording of the same episode.

6. Conclusions

The present contribution has evidenced the appropriateness of BSS techniques in the problem of AA extraction from AF episodes. With the aid of a simulated AF signal model, BSS has been compared with other methods for QRST cancellation, showing in all cases a superior performance, even before adaptive cancellation enjoying prior information about VA.

As a direct consequence of these positive results, BSS arises as a novel technique for QRST-complex cancellation, which is implicitly carried out through the exclusion of the estimated VA sources.

Note that the internal bioelectric sources that externally generate the ECG are not available, and hence the estimated AF sources cannot be contrasted with the real AF sources. Despite this difficulty –typical of inverse problems– BSS results on real AF episodes are very promising, and indeed the authors envisage that this preliminary study will open new paths of research on this exciting topic.

Acknowledgements

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