Atrial Fibrillation, Atrial Flutter and Normal Sinus Rhythm Discrimination by Means of Blind Source Separation and Spectral Parameters Extraction

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Abstract

Discrimination between normal sinus rhythm (NSR), Atrial Fibrillation (AF) and Atrial Flutter (AFL) using the surface electrocardiogram (ECG) through direct Fourier analysis is not effective because ventricular activity (VA) overlaps in frequency with atrial activity (AA) and, moreover, AA frequency components present considerably lower amplitude than VA. This contribution exploits the assumption that AA and VA can be considered as generated by independent sources of cardioelectric activity. Hence, AA free from spurious VA and other disturbances can be extracted through the application of blind source separation (BSS) techniques. After the blind separation and AA identification process, it was applied a logistic regression over a group of spectral parameters extracted from the power spectral density of the AA signal that was able to discriminate between AF, AFL and NSR with a 100% accuracy considering only two spectral parameters.

1. Introduction

Atrial fibrillation (AF) and atrial flutter (AFL) are among the most frequent cardiac arrhythmias, with a considerable prevalence in population and a significant impact on mortality[1].

To obtain a valid frequency domain characterization of AF and AFL episodes taken from the surface electrocardiogram (ECG), it is needed 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, and consequently AA frequency components will have lower amplitude than VA. Also, both phenomena possess spectral distributions notably overlapped, rendering direct linear filtering solutions unsuccessful.

To overcome this deficiency traditional methods have been focused on explicit QRST-cancellation through a template matching and subtraction technique [2]. Moreover, the correct spatiotemporal alignment of every QRST complex with the cancellation template has proved to be very effective to obtain the AA [3] and makes possible to carry out spectral AA characterization [4].

However, the key assumption that AA and VA are decoupled introduces another point of view which does not rely on direct QRST elimination. In effect, we can assume that AA and VA are generated by physically (and hence statistically) independent bioelectric sources. Hence, AA free from spurious VA and other disturbances can be extracted using techniques that measure statistical independence, like principal component analysis [5], based on second order statistics, or blind source separation (BSS) techniques based on higher-order statistics [6].

After applying BSS process to the ECG, the correct identification in time domain of the AA source is not guaranteed. Hence, spectral techniques applied to the extracted AA become useful for the characterization and discrimination of AA between atrial arrhythmias (AF or AFL) and NSR.

2. Database

Recordings were chosen from 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]. All rhythms were diagnosed by a cardiologist following standard criteria based on surface ECGs. A total of 30 episodes from 8 patients were selected, with length around 6 s. To take advantage of the spatial diversity which BSS methods are based on, all the signals consisted of 12-lead recordings. Within each register usually there were several atrial

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arrhythmia segments at the beginning, and NSR segments at the end. The last ones obtained after clinical cardioversion of the arrhythmia. Table 1 summarizes the configuration of the signal database.

Table 1: Patients and episodes with NSR, AF and AFL in the database.

	NSR	AF	AFL
Patients	8	5	3
Episodes	8	13	9

All signals were sampled (or re-sampled, if required) at 1 kHz. Then 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].

3. Methods

3.1. Blind source separation

The Blind Source Separation (BSS) problem consists in recovering a set of source signals from the observation of linear mixtures of the sources [8]. The term "blind" emphasizes that nothing is known about the source signals or the mixing structure, the only hypothesis being the source mutual independence [9]. Mathematically , if vector $\mathbf{s} = [s_1, s_2, ..., s_N]^T \in \mathbb{R}^N$ (the symbol ^{T} stands for the transpose operator) represents the N source signals and vector $\mathbf{x} = [x_1, x_2, ..., x_M]^T \in \mathbb{R}^M$ denotes the M-sensor output vector, i.e. the observation vector, the BSS model for instantaneous linear mixtures reads:

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

where $\mathbf{A} \in \mathbb{R}^{M \times N}$ is the unknown mixing matrix. The objective is to estimate **s** and **A** from the exclusive knowledge of **x**. Usually, to solve the BSS problem for instantaneous linear mixtures, the objective is to find a linear transformation that holds:

$$\mathbf{s} = \mathbf{W}\mathbf{x} \tag{2}$$

where **W** is a matrix to be determined that performs the suitable transformation. To solve this problem several techniques have been proposed mainly based on Higher Order Statistics (HOS) and Information Theory due to their ability to measure statistical independence [10].

The relevance of BSS in the problem of AF and AFL waveform extraction lies in the basic assumption that AA and VA are physically decoupled, so that both can be considered as generated by statistically independent bioelectric sources. Hence, the skin-electrode signal vector **x** complies with model (1), where vector **s** is composed of the independent sources of atrial and ventricular cardiac activity, as well as of additional sources of interference and noise [6]. Consequently, the atrial contribution to the recordings can be recovered and identified by extracting, via BSS, the sources of AA and the corresponding columns of the mixing matrix.

3.2. Spectral parameters extraction

After applying the source separation technique using BSS, the clear identification of the AA signal through the only inspection of the time-domain waveforms it is not immediate because the existence of several possible candidates. Therefore, a method that allows the clear identification of AA signal has to be established. Our chosen solution consisted in applying spectral analysis to the AA candidate sources by computing its power spectral density (PSD). The procedure consisted of obtaining the modified periodogram from the separated sources using the Welch-WOSA method with a Hamming window of 4096 points length, a 50% overlapping between adjacent windowed sections and a 8192 points length FFT. Later, the spectral content above 30Hz has been discarded due its low contribution. By means of this spectral analysis, it has been possible to correctly identify the AA separated source through the verification of the predominant frequencies and PSD typical morphology [2, 4, 5].

In order to verify the results, we applied the same methodology to *f*-wave sections (T–Q segments) from leads III, aVF and V1 (where the greater presence of AA can be found) obtaining a resulting PSD that was able to confirm the correct identification of the AA source.

Relying on the spectral analysis of the AA source estimated via BSS, we put forward a method based in applying logistic regression over the following spectral parameters: Main peak frequency (F_p), spectral content below the main peak (A_1), spectral concentration in the band of the peak (*SCBP*), first order moment (M_1), second order moment (M_2) and main peak to first harmonic ratio (*MPFHR*). The detailed description of these parameters can be found in [11].

4. Results

For a comprehensive explanation of the whole process Figure 1 plots the (usually accepted) leads with largest atrial components of one 12-lead ECG episode in AF. After the BSS technique application, the estimated cardioelectric independent sources were obtained. Fig.2 displays the 3 estimated sources with largest AA obtained from Fig. 1 episode. As it can be seen in Fig.2, it is not crystal-clear how to choose between the three estimated sources to select only one with largest AA. At this point

we used spectral analysis to obtain the PSD of every AA candidate source. Figure 3 plots the resulting PSD for the sources of Fig.2, thus allowing to select the proper AA based on its PSD morphology and dominant frequencies. Now it can be said, according with accepted spectral characteristics of AF [2, 4, 5], that the estimated source with largest AA from Fig.3 is source #5.

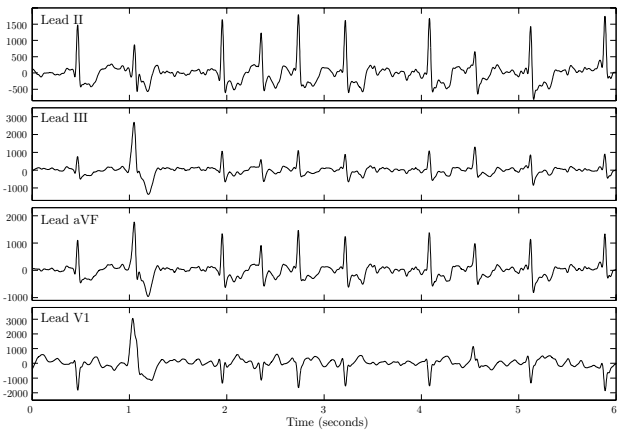

Figure 1. Leads II, III, aVF and V1 from a 12-lead ECG of an Atrial Fibrillation episode.

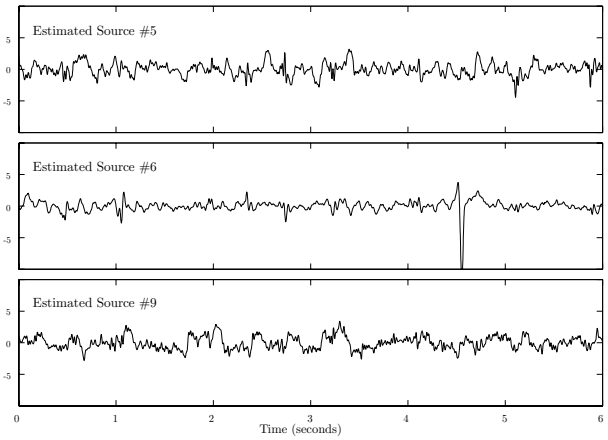

Figure 2. Estimated sources waveform with largest atrial activity content obtained from the application of BSS to the 12-lead ECG of Figure 1.

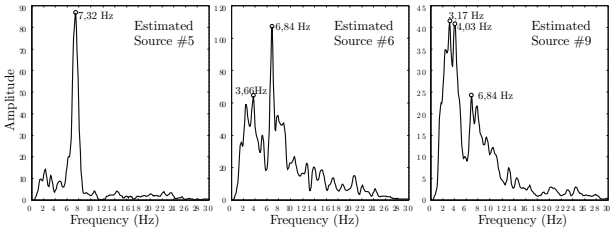

Figure 3. Power spectral density from the estimated sources with largest AA (Fig. 2).

To verify the latter selection of source #5, the PSD of a *f*-wave segment from the ECG was computed over the leads with largest atrial contribution (III, aVF, V1). Figure 4 shows the resulting PSD over a segment taken from the ECG or Fig 1. As it can be seen, the similarities between these PSDs and the PSD of source #5 (Fig.3) acts as an additional reinforcement to the previous spectral morphology based selection of source #5.

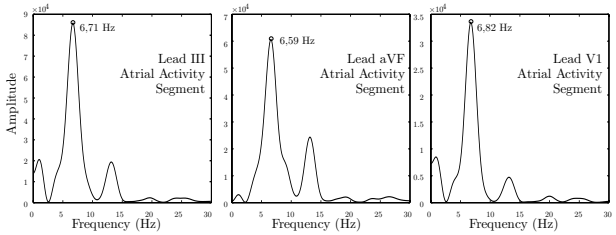

Figure 4. PSD computed over a *f*-wave [3400-4000ms] extracted from III, aVF and V1 leads of Figure 1.

The same described procedure has been applied to the AFL and NSR episodes in the analyzed database, computing the PSD of each AA extracted episode. Fig.5 shows the obtained PSD for three different patients in AFL and Fig.6 plots the similar scenario for NSR.

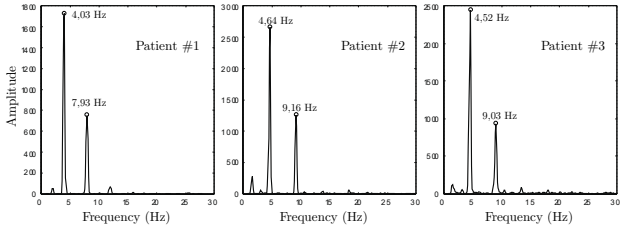

Figure 5. PSD from the BSS estimated source with largest AA from 3 different patients in AFL.

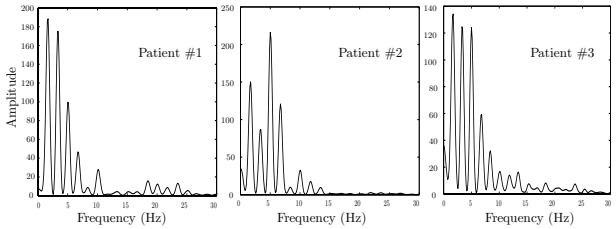

Figure 6. PSD from the BSS estimated source with largest AA from three different patients with NSR.

As it can be seen in Figs. 3, 5 and 6 each kind of atrial arrhythmia has its own spectral morphology. In the analyzed episodes AF always had its main peak frequency above 5Hz and AFL below this frequency, so F_p could be used for discrimination. Moreover, AFL had larger spectral concentration in the band of the main peak than AF, and AF larger than NSR, thus making *SCBP* a good starting point for classification between all the three sets of signals. In NSR, usually (but not always) the main peak frequency was below 5Hz and had the largest harmonic content, in comparison with AF and AFL. Table 2 summarizes the obtained results.

Table 2: Mean value and standard deviation of the PSD parameters extracted from each set of episodes.

Parameter		NSR	AF	AFL
F_p	Mean	4.50	6.32	4.27
	Std	2.25	0.90	0.29
A_1	Mean	0.182	0.21	0.056
	Std	0.099	0.093	0.031
SCBP	Mean	0.31	0.47	0.59
	Std	0.167	0.116	0.049
M_1	Mean	3.66	6.18	4.13
	Std	1.67	0.95	0.25
M_2	Mean	0.418	0.695	0.49
	Std	0.177	0.087	0.016
MPFHR	Mean	9.61	43.52	2.88
	Std	4.43	50.33	0.313

When all the parameters of each PSD were calculated it was carried out a multivariant study in order to select outstanding parameters. Discriminant functions were obtained via forward stepwise logistic regression to separate between NSR and arrhythmia (AF or AFL). The obtained accuracy was 100% with only two parameters: *SCBP* and M_2. After this previous stage, another discrimination was performed to separate between AF and AFL, obtaining 100% accuracy with only one parameter: it could be M_2 or F_p.

5. Conclusions

The present contribution has shown the utility of BSS based techniques to solve the problem of AA extraction from AF and AFL episodes in the surface ECG. Usually, direct QRST-complex cancellation techniques obtain as much AA signals as leads has been introduced to the algorithm. In contrast to this, BSS is able to obtain one signal that considers the contribution from all the leads to the cardioelectric AA.

With the use of spectral analysis is has been possible to identify correctly the separated source via BSS that contains the atrial activity. The importance of this step lives in the fact that not always it is possible to properly identify the separated AA by direct visual inspection of the time-domain waveform. Using the PSD of the extracted and identified AA source, we have been able to show the dissimilar spectral content and morphology of AF, AFL and NSR episodes. Using these differences, it has been possible to extract spectral parameters, allowing the discrimination between NSR and arrhythmia (AF or AFL) and also between atrial arrhythmias.

As a direct consequence of this positive results, BSS based techniques have proven their utility for AA extraction, analysis and characterization in time or frequency domains.

Acknowledgements

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References

[1] Kopecky S, Gersh B, McGoon M, et al. The natural history of lone atrial fibrillation: a population based study over three decades. N Engl J Med 1987;317:669-74.

[2] Bollman A, Kanuru NK, McTeage KK, et al. Frequency analysis of human atrial fibrillation using the surface electrocardiogram and its response to Ibutilide. Am. J Cardiol 1998;81:1439-45.

[3] Stridh M, Sörmo L. Spatiotemporal QRST cancellation techniques for analysis of atrial fibrillation. IEEE Trans. Biomed. Eng. 2001;48:105-11.

[4] Stridh M, Sörmo L, Meurling CJ, Olsson SB. Characterization of atrial fibrillation using the surface ECG: time-dependent spectral properties. IEEE Trans. Biomed. Eng. 2001;48:19-27.

[5] Langley P, Bourke JP, Murray A. Frequency analysis of atrial fibrillation. IEEE Computers in Cardiology 2000; 27:65-8.

[6] Rieta JJ, Zarzoso V, Millet J, García R, Ruiz R. Atrial activity extraction based on blind source separation as an alternative to QRST cancellation for atrial fibrillation analysis. IEEE Computers in Cardiology 2000;27:69-72.

[7] Millet J, Mocholí A, López JJ, García R, Ruiz R. A method capable of digitizing every type of biosignals paper recordings as a tool for database improving. Proc of 20th Ann Int Conference of the IEEE EMBS 1998:1238-41.

[8] Comon P. Independent component analysis, a new concept?. Signal Processing 1994;36:287-314.

[9] Cardoso J F. Blind signal separation: statistical principles. Proceedings of the IEEE 1998;86:2009-25.

[10] Hyvarinen A, Karhunen J, and Oja E. Independent Component Analysis. John Wiley & Sons, Inc. 2001, ISBN: 0-471-40540-X.

[11] Millet J, Rieta JJ, Zarzoso V, Cebrian A, Castells F, Sanchez C, Garcia-Civera R. Surface-ECG atrial activity extraction via blind source separation: spectral validation. Computers in Cardiology 2002;29 (in press).

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