Wavelet Blind Separation: A New Methodology for the Analysis of Atrial Fibrillation from Holter Recordings

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Abstract

This study shows the possibility of atrial activity (AA) extraction from atrial fibrillation (AF) episodes in Holter registers using only two leads (V1 and V5) with a new technique, the Wavelet Blind Separation (WBS). The WBS increases the observed mixtures of the original signal from the decomposition of each lead into six transformed signals using a wavelet transform. These mixtures provide enough useful information to a Blind Source Separation implemented system and the extraction can be achieved. To evaluate the suggested algorithm, artificial AF signals have been synthesized adding fibrillation activity to normal sinus rhythm. Results indicate that the WBS technique can be an important tool to perform the atrial extraction in short duration registers with a reduced number of leads like paroxysmal atrial fibrillation, which have to be usually detected from Holter systems.

1. Introduction

Atrial fibrillation (AF) is one of the most common arrhythmias, with a increase incidence in the elderly population [1]. This arrhythmia may impact the quality of life and increase the risk of stroke. AF can be classified in three types: recurrent, paroxysmal and permanent. The paroxysmal AF (PAF) appears in episodes with lengths below 48 hours and in most cases have to be detected in Holter registers where the number of leads is reduced. The prediction of PAF could make new cardiological therapies possible because the PAF becomes a permanent AF in a high percent of the cases [2, 3].

An initial processing stage for the extraction or cancellation of the ventricular activity (VA), QRS complex and T-wave, can help in the study of these sustained arrhythmias using the surface electrocardiogram (ECG), where the proper detection and characterization of AF needs the isolated study of the registered atrial activity. Nowadays, there are several techniques that can extract the AA with a good performance- Blind Source Separation [4], Spatio-Temporal Cancellation [5]- but poor results are obtained when the number of used reference signals (leads) is less than three, or when the duration of these signals is reduced. On the other hand, classic techniques- Average Beat Subtraction (AVBS) [6]- have developed AA extraction from only one lead, but these systems are very sensitive to the presence of ectopic complexes.

In previous works [7, 8], the Wavelet Transform (WT) has been presented as a possible cancellation technique of VA in short duration registers and reduced number of leads. Different methodologies have been analysed; Packet Wavelet Transform (PWT) and Adaptive Wavelet Analysis (AWA). The obtained results showed an AA with spectral and temporal behaviour very similar to the expected AA. However, the presence of residual QRS complexes (specially in PWT technique) or unexpected behaviours of the extracted signal in the zone of the canceled complexes (specially in AWA technique) and the low performance in the case of real AF episodes required further studies and complementary processing stages.

The WBS is presented as an improvement of the aforementioned methodologies based on the wavelet transform methods for the AA extraction. The WBS consists of an analysis of several decomposition levels obtained with the wavelet transform using Blind Source Separation (BSS) algorithms. The obtained correlation coefficients, the spectral concentration levels in the typical band of AF and the complete elimination of QRS complex justify the development of this new method.

2. Methods

2.1. Wavelet transform principles

Wavelet are used to transform the signal under investigation into another representation that presents the signal information in a more useful form, joining spectral and temporal analysis. The signal is decomposed in basic blocks corresponding to different frequency bands. Local and global parameters of the original signal can be identified using certain characteristics of these blocks.

Mathematically speaking, the WT is a convolution of the wavelet function with the signal $f(t)$ and can be expressed as follows, in its most general form:

$$C(a,b) = \int_R [f(t) \cdot \psi_{a,b}(t) \cdot dt] \quad (1)$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \cdot \psi(\frac{t-b}{a}) \quad (2)$$

The function $\psi_{a,b}$ is a dilated and displaced version of the "mother wavelet" ψ, where the parameters a and b indicate scale and translation, respectively. The discrete wavelet transform (DWT) results from discretizing scale and translation parameters. The definition of parameters as $a = 2^j$ and $b = n \cdot 2^j$ leads to the dyadic DWT (DyWT) which is usually implemented with dyadic filter banks. The Discrete Packet Wavelet Transform can be considered as a generalization of the DWT with more levels of decomposition which offer a more useful information about the original input signal. The possibility of reconstruction of the original signal from some of the obtained basic blocks has been used for noise and interferences elimination in ECG, abnormal pattern recognition, complex detection, etc [9].

2.2. BSS principles

BSS, as a processing tool, is able to recover signals from a linear combination of these same signals without any *a priori* knowledge about the signal or the mixtures. The simplest model of BSS takes on the presence of n statically independent signals and n observed linear and instantaneous mixtures. In this work, the independence and nongaussianity of the atria and ventricle as signal sources is taken on. Recent works have studied the propagation mechanisms and uncoordinated atrial activation of the AF to demonstrate this assumption [10].

The Independent Component Analysis (ICA) based on higher order statistics is the most extended support for the different methodologies that solve the problem of BSS. The BSS model in its more compact form is given by

$$x(t) = \sum_{j=1}^{n} [a_{i,j} \cdot s_j(t)] \quad (3)$$

$$x(t) = \mathbf{A} \cdot s(t) \quad (4)$$

where, $s(t)$ is a vector of $n \times 1$ columns which contains the estimated sources, $x(t)$ is the vector of the mixtures and $\mathbf{A}$ is the square mixing matrix. As BSS tries to recover $s(t)$ from the observations, $x(t)$ is necessary to estimate the matrix $\mathbf{A}$. If the ICA methods can estimate the separation matrix, the independent sources can be expressed as follows

$$\hat{s}(t) = \mathbf{B} \cdot x(t) \quad (5)$$

where $\hat{s}(t)$ is the estimated sources and $\mathbf{B}$ is the separation matrix that recovers the independent sources.

2.3. Database and WBS methodology

A database of artificial signals has been created, where the AA is known and simulated. A synthesized AF signal has been added to sinus rhythm recordings using linear combination, according to the studies and references of several authors [5], Figure 1. The shape and behaviour of the atrial signal is known and the WBS method can be evaluated fast and efficiently. The used signals are created from recordings obtained at the Universitary Clinical Hospital of Valencia. All the registers have been pre-processed and normalized to remove possible fluctuations of the base line, interferences, noises, etc. The final configuration of the database is shown in Table 1.

Table 1. Registers in database

Number of Patients	12 leads ECG	Holter System
19	14	7

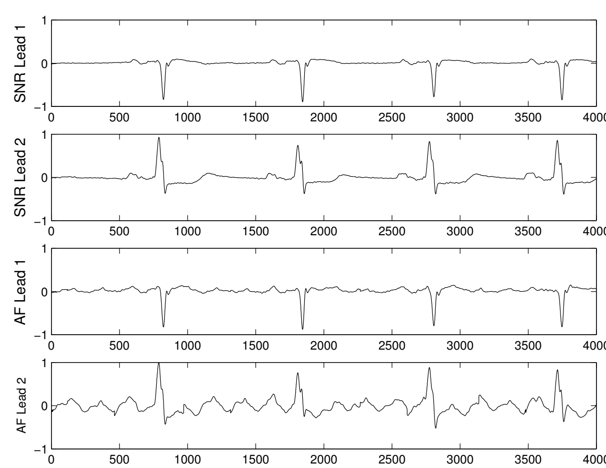

Figure 1. Simulated fibrillation signals. Original input leads and simulated fibrillation pattern superimposed on SNR episodes.

The principal aim of this study is to provide enough useful information to the BSS implemented system, only from the leads V1 and V5 to achieve efficiently the AA extraction, Figure 2. This rise of useful information is obtained by increasing the observed mixtures of the signal from the decomposition of each lead into six transformed signals using a DyWT with the corresponding levels.

This idea has been studied in several recent works that probe the increase of the blind source separation quality if the sparse representability of the sources is exploited [11].

This methodology can be expressed by

$$\begin{aligned} V1 &\Rightarrow [C_{V1_1}, C_{V1_2}, \cdots, C_{V1_6}] \\ V5 &\Rightarrow [C_{V5_1}, C_{V5_2}, \cdots, C_{V5_6}] \\ x(t) = [C_{V1_i}, C_{V5_i}] &= \mathbf{A} \cdot s_{V1,V5}(t) \end{aligned} \quad (6)$$

where the coefficients $C_{V_{ij}}$ represent the six obtained signals from the original leads V1 and V5 yielding several spectral and temporal representations for each lead, that can be considered as different mixtures. This wavelet stage uses denoising techniques that intensify the AA in the sources. The function *symlet7* and six levels of decomposition are the wavelet family and configuration that offer the best performance respectively. Several BSS algorithms have been tested, but the *FastIca* is the most efficient for the BSS stage and offers the lowest computational load. Spectral analysis has been used to identify the AA between the obtained signals, $s1$ and $s2$. The signal with a principal frequency peak in the band of 5-8 Hz and higher spectral concentration in this range -as it is usual in an AF episode- is identified as AA.

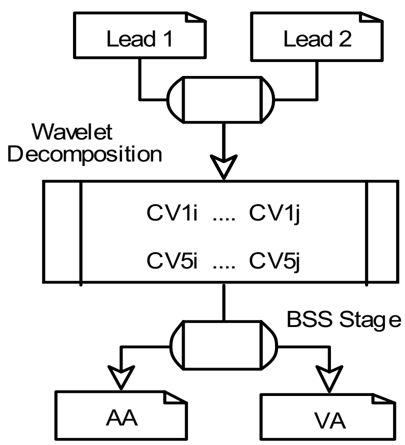

Figure 2. Wavelet Blind Separation Methodology.

3. Results

In Figure 3, the differences between the wave form of the original leads and the form of the main extracted sources (identified as possible AA) using the WT and WBS methods are shown. As it can be observed, the obtained wave forms are very similar in both methods with more presence of residual complexes in the case of the WT technique.

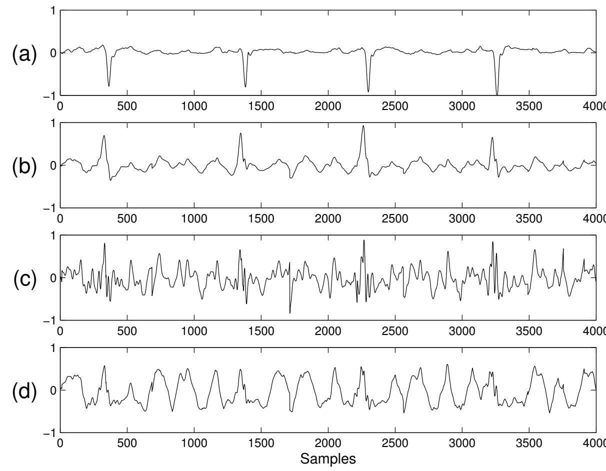

Figure 3. Results of WT and WBS methods. (a) Original First Input Lead. (b) Original Second Input Lead. (c) Estimated AA obtained with WT method. (d)Estimated AA obtained with WBS method.

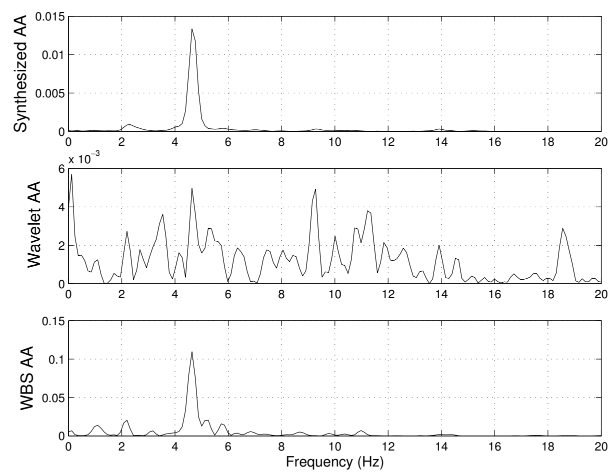

Figure 4. Power Spectral Densities from synthesized AA, estimated AA obtained with WT method and estimated AA obtained with WBS method for the same recording.

A BSS stage without the previous wavelet transform has been considered too, but in this case the useful references are not enough and the extraction can not be achieved properly. These results and the comparison of different BSS algorithms (Jade, FastIca, ..) are analyzed in [12].

More differences are observed in the obtained power spectral densities (PSD), specially the increase of spectral concentration which is more important in the WBS case, Figure 4. The Welch's averaged, modified periodogram method (50% overlap, Hamming window, NFFT=8192) has been used to estimate the PSD.

Cross correlation coefficients in the spectral and time domain have been used to compare the extracted

AA and the expected one. Also others important spectral parameters have been calculated as amplitude and frequency of main peak (fp) and spectral concentration in the AF frequency band (SCBP-AA). Both methods have been applied to the registers in Table 1 with their mean value and standard deviation ($p \leq 0.05$). All results have been presented in Table 2. As it can be observed, the adaptability of WBS makes spectral features more similar to an AF episode possible. The presence of residual complexes in the signal obtained with the WT reduces notably the spectral concentration and the cross correlation coefficients.

Table 2. Correlation coefficients and spectral parameters in wavelet method and proposed methodology.

Parameter	WT Method	WBS Method
Spectral correllation	0.66±0.24	0.94±0.09
Temporal correllation	0.45±0.12	0.61±0.12
Main Peak (Hz)	4.27±1.56	6.23±0.67
SCBP-AA	0.56±0.08	0.91±0.16

4. Discussion and conclusions

Throughout this paper, the possibilities, as an AA extraction technique, of the systems that implement the DyWT and BSS jointly have been shown. The initial hypothesis of statistical independence atria-ventricle and the increase of useful information obtaining from the wavelet decomposition have been demonstrated.

The presence of unexpected behaviors of the extracted signal in the zone of the canceled complexes is reduced, in contrast with the results obtained using the WT methods, even if the registers have short duration (5 seconds in all the presented cases) and the number of leads is reduced (two leads, usually V1 and V5).

The positive results reported in this paper show that the WBS process should be applicable in arrhythmia detection and analysis, like paroxysmal atrial fibrillation, which have to be usually detected from Holter systems where the number of reference signals is reduced.

Acknowledgements

This work was partly funded by several research grants from the University of Castilla-La Mancha (IEEA Department and Technical College of Cuenca) and the TIC2002-00957. The authors would like to thank cardiologists R. Ruiz, S. Morell, F.J. Chorro and R. Garcia, for their clinical advices and kind help in obtaining the signals.

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