COMBINATION OF CONVOLUTIVE BLIND SIGNAL SEPARATION AND WAVELET DECOMPOSITION TO EXTRACT THE ATRIAL ACTIVITY IN ATRIAL FIBRILLATION

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Abstract: In order to use the ECG as a tool for the characterization of atrial fibrillation (AF), we need to dissociate atrial activity (AA) from ventricular activity. On the other hand, the reduced number of leads recorded from a Holter system limits the necessary spatial diversity required by Blind Source Separation (BSS) techniques to accurately extract the AA. In this work, we propose a new method, the Convolutive Multiband Blind Separation (CMBS), to solve the problem of reduced number of leads by combining the Wavelet transform with the convolutive BSS algorithm Infomax. Our analysis shows up that CMBS improves the extraction performance of AA from Holter systems in comparison with previous extraction methods. This improvement is accomplished in two different scenarios, one for synthetic signals and another one for real signals. A high accuracy of the estimated AA for synthetic and real AF ECG episodes is reached in both scenarios. In addition, results prove that CMBS preserves the original AA spectral parameters.

1 INTRODUCTION

The analysis of the surface ECG is the most extended noninvasive technique in medical diagnosis and treatment of atrial fibrillation (AF). In order to use the ECG as a tool for the characterization and analysis of AF analysis, we need to separate the atrial activity (AA) from the ventricular activity (VA) and other bioelectric signals (Langley et al., 2006). Given that the spectra of AA and VA overlap, they cannot be separated by simple linear filtering, and nonlinear processing techniques must be used instead. In this sense, Blind Source Separation (BSS) techniques (Hyvärinen et al., 2001) are able to perform a multi-lead statistical analysis of the ECG with the aim to obtain a set of independent sources where the AA is included (Rieta et al., 2004). In a previous work, we made a performance comparison of AA extraction between convolutive BSS algorithms and Independent Component Analysis (ICA) algorithms (Vay et al., 2007). As a main conclusion of the aforementioned work, the Infomax algorithm was the convolutive BSS algorithm with the best extraction performance, but an adjustment to the specific problem of the AA extraction was still mandatory to improve results obtained by ICA algorithms. On the other hand, the limited numbers of leads recorded from a Holter system reduces excessively the necessary special diversity required by BSS techniques to accurately extract the AA. Consequently, other extraction techniques diferent from BSS, as Average Beat Substraction (ABS) (Slocum et al., 1992), are prefered when multi-lead ECG recordings are not available and individual leads are used instead (Bollmann et al., 2006). Sanchez et all partially solved this difficulty by including a wavelet decomposition of Holter leads prior to ICA analysis, what was called the Wavelet Blind Separation (WBS) method (Snchez et al., 2004). In this work, we present an improvement of WBS where the ICA stage has been replaced with the convolutive BSS algorithm Infomax (Amari et al., 1996). We will subsequently refer to this new method as Convolutive Multiband Blind Separation (CMBS).

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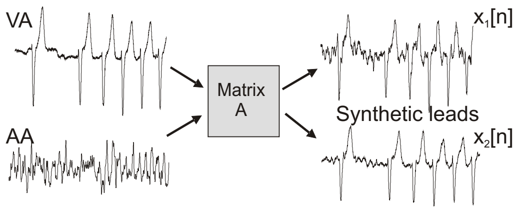

Figure 1: First scenario synthetic ECG generation. Separated AA and VA recordings of AF ECG episodes are convolutively mixed by the aleatory mixing matrix **A**.

2 DATABASE

Two different scenarios were proposed to test the AA extraction performance of CMBS. In the first scenario, 15 pairs of separated atrial and ventricular activities of AF episodes were mixed convolutively in order to obtain two leads of synthesized ECGs. This mixture was made by random mixing matrices. The mixing process in the first scenario can be expressed using matrix notation as:

$$\mathbf{x}[n] = \mathbf{A} \cdot \mathbf{s}[n] \tag{1}$$

where $\mathbf{s}[n]$ contains the mixed AA and VA, the $\mathbf{s}[n]$ contains two synthetic ECG leads, and $\mathbf{A}$ is a 22 random mixing matrix. This mixing process is schematized in Fig 1 .

In the second scenario, the AA extraction performance is analyzed on 18 real two-lead Holter recordings from leads V1 and V5 of AF episodes. Tree levels of white additive Gaussian noise were studied in both scenarios: no noise, a signal to noise ratio (SNR) of 5 dB, and a SNR of 15 dB.

3 METHODS

The main difficulty for applying BSS techniques to extract the AA from Holter recordings is the lack of ECG leads. The number of observation required to solve a BSS problem is, at least, the number of mixed sources (Hyvärinen et al., 2001). Given that AA, VA, noise and other bioelectric signals are always present in the ECG generation, two Holter leads are not enough to determine the AA. One way to increase the number of leads was first introduced in the WBS method in (Snchez et al., 2004) by the inclusion of a wavelet decomposition stage prior to the application of ICA. The Wavelet analysis transforms the signal under investigation into a set of signals. These signals are called detail and approximation coefficients, each of them carrying the ECG information in different frequency bands (Addison, 2001).

The function *symlet8* with eight levels of decomposition was used, because several wavelet families (Addison, 2001) were tested and the best outcomes were achieved with this configuration. A detailed description of this functions can be found in (Addison, 2001). Detail and approximation coefficients were considered, so that nine observation signals resulted from each Holter lead. Consequently, eighteen signals were used as inputs of the BSS stage. The FastICA algorithm (Hyvärinen et al., 2001), used in WBS, was replaced by an infomax algorithm. The infomax algorithms belong to an important family of algorithms based on the information theory. Mutual information is a natural measure of the dependence between random signals (Hyvärinen et al., 2001). Asano et al proposed a BSS algorithm for convolutive mixture that works in the time-frequency domain (Asano et al., 2001). We will subsequently refer to this algorithm as convolutive Infomax. The general process is illustrated in Fig 2 .

The selection of the AA from the sources estimated by convolutive Infomax is made regarding to the spectral morphology of the signals. The typical power spectrum of AA signals contains a sharp peak between 4 an 8 Hz and insignificant content in the rest of frequencies (Bollmann et al., 1999). This selection can be made either by visual observation of the extracted sources spectra, or by using the Spectral Concentration (*SC*) index, which automatizes the decision (Castells et al., 2005). The *SC* will be later defined as a index that is also used to measure the performance of the AA extraction.

4 PERFORMANCE INDEXES

In order to test CMBS, four performance indexes were computed from the extracted AA in the first scenario. These indexes are the temporal correlation (R_t) with the original mixed AA, the spectral correlation (R_s) with the Fourier transform of the original AA, the main peak frequency (f_p), and the *SC*. The *SC* is defined as (Castells et al., 2005):

$$SC = \frac{\sum_{f=0.82 f_{p1}}^{1.17 f_{p1}} P_{AA}(f)}{\sum_{f=0}^{0.5 f_s} P_{AA}(f)} \tag{2}$$

where P_{AA} is the power spectral density of the AA signal, f is the frequencies vector, f_s is the sampling rate (1024 Hz), and f_{p1} is the main peak frequency of the AA. In the second scenario, only the two last

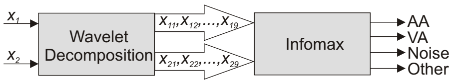

Figure 2: General CMBS process for AA extraction.

indexes were applicable since the original AA is unknown. Good performance of AA extraction is characterized by values of R_t and R_s near to one and high values of *SC* expressed in percentage.

5 RESULTS

The results for R_t in the first scenario are shown in Fig 3. The mean values of R_t obtained by CMBS (0.8526

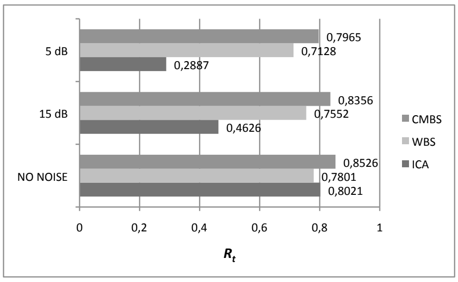

Figure 3: Mean R_t between the original AA and the one extracted by ICA, WBS and CMBS from synthesized ECG recordings at three levels of SNR.

for no noise, 0.8356 for 15 dB of SNR, 0.7965 for 5 dB of SNR) are higher than mean values obtained by WBS (0.7801 for no noise, 0.7572 for 15 dB of SNR, 0.7128 for 5 dB of SNR) and ICA (0.8021 for no noise, 0.4626 for 15 dB of SNR, 0.2887 for 5 dB of SNR).

The results for R_s in the first scenario are shown in Fig 4. The mean values of R_s obtained by CMBS

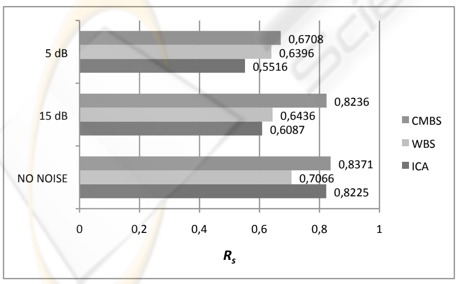

Figure 4: Mean R_s between the original AA and the one extracted by ICA, WBS and CMBS from synthesized ECG recordings at three levels of SNR.

(0.8371 for no noise, 0.8236 for 15 dB of SNR, 0.6708 for 15 dB of SNR) are higher than those obtained by WBS (0.7066 for no noise, 0.6436 for 15 dB of SNR, 0.6396 for 5 dB of SNR) or ICA (0.8225 for no noise, 0.6087 for 15 dB of SNR, 0.5516 for 5 dB of SNR).

The results for f_p in the first scenario are shown in Fig 5. The mean f_p estimated by CMBS (5.49 Hz

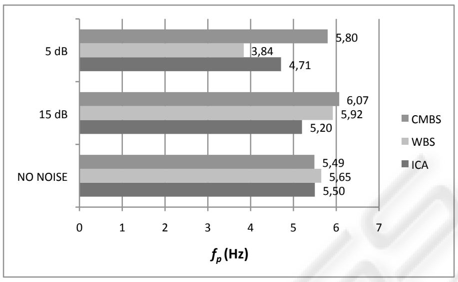

Figure 5: Mean f_p of the AA extracted by ICA, WBS and CMBS from synthesized ECG recordings at three levels of SNR.

for no noise, 6.07 Hz for 15 dB of SNR, 5.80 for 5 dB of SNR) is the best approach to the mean f_p of the original mixed AA sources (5.46 Hz). Also the *SC* obtained by CMBS (62.82% for no noise, 61.64% for 15 dB of SNR, 60.04% for 5 dB of SNR) improves the results of WBS (57.00% for no noise, 55.71% for 15 dB of SNR, 47.61% for 5 dB of SNR) and ICA (61.78% for no noise, 60.86% for 15 dB of SNR, 44.68% for 5 dB of SNR), and it is the best approach to the mean *SC* of the mixed AA sources (62.92%). The results for *SC* in the first scenario are shown in Fig 6.

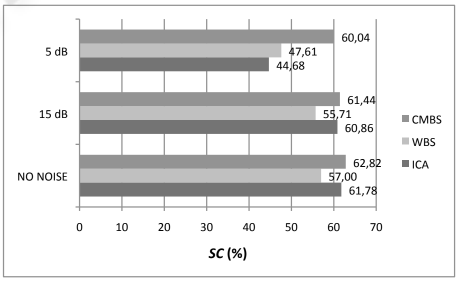

Figure 6: Mean *SC* of the AA extracted by ICA, WBS and CMBS from synthesized ECG recordings at three levels of SNR.

In the second scenario, the estimation of f_p by CMBS (5.46 Hz for no noise, 5.21 Hz for 15 dB of SNR, 5.35 Hz for 5 dB of SNR) is less affected by the level of noise than the estimation made by WBS (5.24 Hz for no noise, 4.52 Hz for 15 dB of SNR, 4.77 Hz for 5 dB of SNR), and the one estimated by ICA (5.40 Hz for no noise, 4.91 Hz for 15 dB of SNR, 4.19 Hz for 5 dB of SNR). The estimated *SC* values for real Holter ECG obtained by CMBS (71.83% for no noise, 71.53% for 15 dB of SNR, 64.70% for 5 dB of SNR) exceed the values obtained by WBS (67.13% for no noise, 65.18% for 15 dB of SNR, 64.32% for 5 dB of SNR) and ICA (43.23% for no noise, 40.77% for 15 dB of SNR, 38.94% for 5 dB of SNR). The results of f_p and SC in the second scenario are depicted in Fig 7 and Fig 8, respectively.

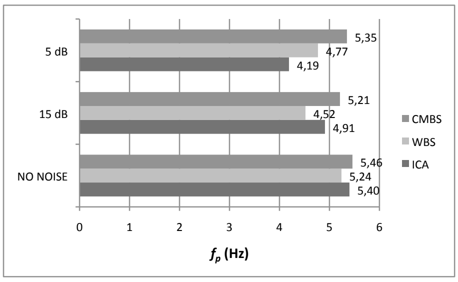

Figure 7: Mean f_p of the AA extracted by ICA, WBS and CMBS from real ECG recordings at three levels of SNR.

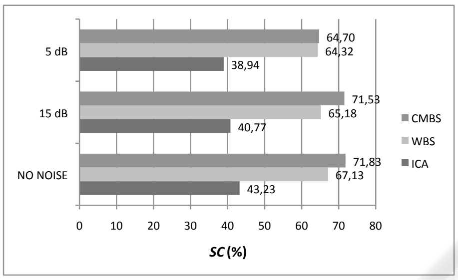

Figure 8: Mean SC of the AA extracted by ICA, WBS and CMBS from real ECG recordings at three levels of SNR.

6 CONCLUSIONS

Our analysis showed up that CMBS improves the extraction performance of WBS and ICA in both scenarios so that a high accuracy of the estimated AA for synthetic and real AF ECG episodes is accomplished, what is proved by the high values of R_t. In addition, the high values of R_s and SC and the low error of f_p estimation prove that the original spectral parameters of the AA are preserved in the AA estimated by CMBS from both synthetic and real signals. This fact enables CMBS as a suitable previous step to the analysis of AA signals in the spectral domain.

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