Feasibility and Performance of Methods Based on Statistical Signal Processing to Study Atrial Fibrillation

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Abstract

In order to use the ECG as a tool for atrial fibrillation (AF) analysis, we need to separate the atrial activity (AA) from other cardioelectric signals. In this matter, some statistical signal processing techniques, such as Blind Source Separation (BSS), 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. BSS techniques can be divided in two groups depending on the mixing model. Firstly, in algorithms based on Independent Component Analysis (ICA) instantaneous mixture of the sources is assumed. Secondly, in convolutive BSS (CBBS) algorithms the more realistic case of weighted and delayed contributions in the generation of the observed signals is considered. In this paper, a comparison between the performance of ICA algorithms and CBSS algortihms in the extraction of the AA in AF episodes is developed.

1. Introduction

Atrial fibrillation (AF) is one of the most commonly encountered atrial arrhythmias in routine clinical practice [1]. The analysis of the ECG is the most extended noninvasive technique in medical treatment of AF. The exhaustive analysis of the AF requires previously to separate the atrial activity (AA) component from other bioelectric signals. To this extent, several techniques have been extensively used in order to extract the AA from ECGs of AF episodes. The early extraction techniques worked in time domain and obtained the atrial activity by the substraction of the average QRST complex. This family of techniques has been well accepted and widely used in medical applications. However, these techniques are only applied to the ECG lead where atrial fibrillation is more easily distinguishable, e.g. V1, and they do not make use of the information included in every lead. On the contrary, Blind Source Separation (BSS) techniques make a multi-lead statistical analysis with the aim to obtain a set of independent sources that include the AA [2].

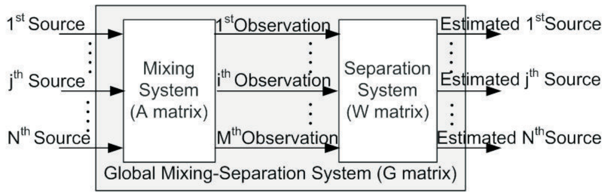

Figure 1. The Blind Source Separation (BSS) problem

The main objective of this essay is to test the performance of several BSS techniques in the extraction of atrial activity. In order to do this, we have proposed the testing environment and we have defined the parameters to measure the performance of the extraction.

2. BSS concepts

Blind Source Separation (BSS) consists of retrieving a set of N signals that cannot be directly observed from other set of M signals that can be observed. The signals to be retrieved are called 'sources', and those that can be observed are called 'observations'. The observations are formed by the contribution of all the original sources. The main condition of the source signals to correctly apply BSS to its extraction is their mutual independence [3]. Figure 1 shows an scheme of the BSS problem. The inputs of the mixing system, which is also unknown, are the sources and the outputs are the observations. The BSS algorithms try to find one separation system that inverts the previous mixture process, so that an estimation of the original sources is obtained.

The solution of the BSS problem, previously expressed in general terms, needs the assumption of a mathematical mixing model. The most frequent assumption is the linearity of the transformation [3]. Within the assumption of linearity, the simplest mixing model is the instantaneous linear model. In this case, we can express the observations $x_i[n]$ as [2]:

$$x_i[n] = \sum_{j=1}^{N} a_{ij}[n] \cdot s_j[n], \quad i = 1, 2, \ldots, M \qquad (1)$$

where $\{s_1[n], \ldots, s_N[n]\}$ is a set of original sources that includes the AA, the ventricular activity (VA), additive noise and other bioelectric phenomena of the human body. $\{x_1[n], \ldots, x_M[n]\}$ is the set of related observations, that is, the ECG registrations in our particular case. By using matrix notation, we can write:

$$\mathbf{x}[\mathbf{n}] = \mathbf{A} \cdot \mathbf{s}[\mathbf{n}] \tag{2}$$

The instantaneous linear mixing model is used by the Independent Component Analysis (ICA) algorithms. An extension of the linear model is the convolutive linear mixing model, where weighted and delayed contributions of the sources are considered in the generation of the observations [2]. This model is used by the convolutive BSS (CBSS) algorithms and can be expressed as [2]:

$$x_i[n] = \sum_{j=1}^{N} h_{ij}[n] * s_j[n], \quad i = 1, 2, \ldots, M \tag{3}$$

where $*$ is the convolution operator and h_{ij} factors represent Finite Impulse Response (FIR) filters.

In both linear mixing models, the solution of the BSS problem implies to approximate a $\mathbf{W}$ matrix as the inverse of $\mathbf{A}$, so that an estimation of the original sources ($\hat{s_i}$) can be obtained.

3. Tested algorithms

ICA algorithms, e.g. FastICA, have successfully been applied to extract the AA from ECG of AF episodes [4]. This successful application is obtained by considering that the error introduced as a consequence of assuming instantaneous mixtures is negligible. On the contrary, CBSS algorithms have not been applied yet to the extraction of the AA. In this work, we test the performances of four CBSS algorithms in the extraction of the AA from FA ECG registrations. All of them were originally developed to optimize the separation of audio sources in reverberant spaces (i.e. convolutive mixtures) [5]. Theses algorithms are the Multi-channel Blind Least Mean Square (MBLMS) algorithm [6], the Time-Delayed Decorrelation (TDD) algorithm for convolutive mixtures [7], the Infomax algorithm [8] based on the information theory, and the Convolutive Blind Signal Separation (CoBliSS) algorithm [9].

4. Notation

The performance of the algorithms is measured by using two parameters. On the one hand, SIR_{AA} measures the performance as an improvement of a signal to interference ratio. Considering x_i as the observation with the highest contribution of AA, the signal to interference of x_i is defined as [5]:

$$SIR^o_{AA} = 10 \log \frac{\mathbf{E}\{(\mathbf{h_{ij}} * \mathbf{s_j})^2\}}{\mathbf{E}\{(\sum_{\substack{k=1 \\ k \neq j}}^{\mathbf{N}} \mathbf{h_{ik}} * \mathbf{s_k})^2\}} \tag{4}$$

In the same way, considering that $\hat{s_p}$ is the estimated source with the highest contribution of AA, the signal to interference of $\hat{s_p}$ is [5]:

$$SIR^e_{AA} = 10 \log \frac{\mathbf{E}\{(\mathbf{g_{pj}} * \mathbf{s_j})^2\}}{\mathbf{E}\{(\sum_{\substack{k=1 \\ k \neq p}}^{\mathbf{N}} \mathbf{g_{pk}} * \mathbf{s_k})^2\}} \tag{5}$$

where g_{pk} are the FIR filters of the $\mathbf{G}$ global system matrix so that $\mathbf{G} = \mathbf{W} * \mathbf{A}$. Finally, by using logarithmic units the SIR_{AA} is defined as:

$$SIR_{AA} = SIR^e_{AA} - SIR^o_{AA} \tag{6}$$

On the other hand, we also measure the performance of the extraction as a cross-correlation between the original AA and the estimated AA [3]:

$$R_{AA} = \frac{\mathbf{E}\{\mathbf{s_{AA}} \cdot \hat{\mathbf{s}}_{\mathbf{AA}}\}}{\sqrt{\mathbf{E}\{\mathbf{s^2_{AA}}\}\mathbf{E}\{\hat{\mathbf{s}}^2_{\mathbf{AA}}\}}} \tag{7}$$

where s_{AA} and $\hat{s}_{AA}$ are the original and the estimated AA respectively.

5. ECG database

The calculation of the parameters defined in the previous section needs the original sources and the mixing matrix to be known. Given that all of them are unknown in the case of real ECGs, we have established two environments of synthesized AF ECGs, so that the measure parameters can be calculated.

In the first environment, 15 pairs of separated AA and VA recordings of FA ECG episodes are mixed by aleatory $\mathbf{A}$ mixing matrices which FIR filters length changes from 1 to 8. All recordings are 12 seconds long and were obtained at a sampling rate of 1 kHz. The length of the $\mathbf{W}$ matrix is an adjustable parameter in the CBSS algorithms that have been changed in the tests from the lowest allowed value (one or two depending on the algorithm) to 32. The value of 32 has been chosen by considering 32ms as a reasonable maximum propagation delay for all the bioelectric signals in the human body [10].

In the second environment, synthesized FA 12-leads ECG are obtained by adding separated AA and VA of every lead:

$$\mathbf{x} = \mathbf{x_{AA}} + \mathbf{x_{AV}} \tag{8}$$

where $\mathbf{x_{AA}}$ is a matrix that contains the 12 auricular signals, $\mathbf{x_{AV}}$ is a matrix that contains the 12 corresponding ventricular signals and $\mathbf{x}$ is the 12 leads synthesized ECG. All resulting ECG recordings last for 8 seconds and are sampled at 1 KHz. This second environment comprises 20 synthesized ECGs.

6. Results

Tables 1 to 8 show the first environment testing results for every tested CBSS algorithm. Mean and standard deviation (STD) values of SIR_{AA} and $R_{A\hat{A}}$ are calculated for different filters lengths of the mixing matrix (N_m) and different filters lengths of the separation matrix (N). Every table includes the FastICA algorithm results obtained in the same testing conditions as the corresponding CBSS algorithm. This was made to compare ICA and CBSS methods.

In table 1 we can appreciate that FastICA SIR_{AA} mean values are higher than MBLMS SIR_{AA} mean values for any value of N_m and N. More specifically, FastICA SIR_{AA} mean values are around 40 dB whereas MBLMS SIR_{AA} mean values are lower than 5 dB. In other words, the application of MBLMS to mixtures of AA an VA does not yield any source signal separation. We obtain the same conclusions by looking at table 2 where we can see that FastICA $R_{A\hat{A}}$ values are always near to one (i.e. the original and estimated AA are very similar) whereas MBLMS $R_{A\hat{A}}$ values are near to zero (i.e. the quality of the separation is very poor).

An equivalent analysis can be made on the rest of the CBSS algorithms results. Tables 3 and 4 show that values obtained by the TDD algorithm are much better than values obtained by MBLMS. The order of TDD SIR_{AA} mean values and FastICA SIR_{AA} mean values is the same. Nevertheless, FastICA SIR_{AA} mean values are in all cases around 4 dB higher than TDD SIR_{AA} mean values. Tables 3 and 4 also show that TDD behavior worsens when mixing matrix FIR filters length increases, since both SIRAA and $R_{A\hat{A}}$ decrease proportionally. Tables 5 and 6 show that Infomax algorithm presents a similar behavior to TDD, that is, both SIR_{AA} and $R_{A\hat{A}}$ are slightly lower than the respective FastICA values. Moreover, the higher N_m is the lower SIR_{AA} and $R_{A\hat{A}}$ are. Finally, tables 7 and 8 show the CoBliSS testing results. In this case, SIR_{AA} mean values are around two decades lower than FastICA SIR_{AA} mean values, that is, the performance in the extraction of the AA is much better than the performance obtained by MBLMS. However, it does not reach the performance obtained by TDD and Infomax.

Second environment performance was only tested for the Infomax algorithm, given that this is the only analyzed CBSS algorithm that simultaneously offers good AA extraction quality in the first environment and the possibility of being successfully adapted to the 12 leads ECG case. We summarize the results of the second environment in table 9, where the values of SIRAA and $R_{A\hat{A}}$ are presented together. We consider seven different unmixing FIR Filters length, i.e. N = 2, 4, 8, 16, 32, 64 and 32. It can be seen that FastICA SIRAA mean value is several decibels above Infomax SIRAA mean values. Furthermore, FastICA correlation is nearer to one than Infomax correlation.In other words, the AA estimated by FastICA is more similar to the original AA than the AA estimated by Infomax.

Table 1. MBLMS algorithm SIR_{AA}

N_m	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	0.987	2.321	0.320	0.266	0.274	0.280	0.192	0.202
4	0.999	2.216	0.964	0.948	0.846	0.999	0.590	0.720
8	1.669	4.533	2.137	2.609	1.896	2.547	1.469	2.099
16	1.701	5.849	2.747	3.160	2.354	2.704	2.127	2.964
32	1.417	6.585	2.514	2.886	2.275	2.616	2.265	3.069
ICA	37.643	17.031	28.316	10.391	28.370	7.458	23.995	8.692

Table 2. MBLMS algorithm $R_{A\hat{A}}$

N_m	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	0.232	0.194	0.220	0.143	0.172	0.118	0.152	0.103
4	0.082	0.076	0.074	0.048	0.058	0.032	0.049	0.019
8	0.143	0.126	0.136	0.096	0.103	0.088	0.085	0.075
16	0.129	0.109	0.131	0.081	0.091	0.068	0.074	0.046
32	0.116	0.080	0.116	0.077	0.089	0.070	0.081	0.063
ICA	0.997	0.002	0.923	0.183	0.943	0.115	0.847	0.182

Table 3. TDD algorithm SIR_{AA}

N_m	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	31.597	12.556	26.951	9.929	24.763	8.967	23.121	8.091
4	30.535	10.424	27.399	7.983	24.878	7.711	23.434	8.189
8	33.561	19.427	27.003	10.869	23.805	9.261	24.122	8.864
16	32.831	15.917	27.329	10.723	23.718	9.623	23.190	9.093
32	31.657	13.954	24.561	10.409	22.770	9.393	22.664	9.114
ICA	36.692	8.335	30.597	7.190	27.414	7.542	25.543	6.688

Table 4. TDD algorithm $R_{A\hat{A}}$

N_m	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	0.960	0.091	0.915	0.176	0.900	0.144	0.809	0.194
4	0.958	0.122	0.915	0.195	0.893	0.178	0.813	0.233
8	0.922	0.200	0.897	0.217	0.864	0.215	0.789	0.273
16	0.902	0.212	0.839	0.255	0.821	0.245	0.742	0.291
32	0.827	0.264	0.784	0.292	0.737	0.300	0.705	0.294
ICA	0.997	0.002	0.950	0.147	0.929	0.134	0.857	0.204

Table 5. Infomax algorithm SIR_{AA}

N_m	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	28.543	14.225	24.039	9.593	26.122	6.720	17.891	8.612
4	28.350	13.924	24.720	10.019	25.973	6.792	17.683	8.684
8	30.146	15.489	24.588	10.195	26.248	6.906	18.013	8.654
16	30.278	16.214	24.437	10.445	26.543	7.378	18.250	8.723
32	29.863	15.051	25.183	10.855	26.459	8.009	19.039	9.466
ICA	34.981	9.944	28.416	8.158	28.017	7.298	19.069	8.952

Table 6. Infomax algorithm $R_{A\hat{A}}$

N$_m$	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	0.949	0.127	0.924	0.141	0.924	0.119	0.763	0.247
4	0.955	0.091	0.926	0.111	0.910	0.119	0.741	0.245
8	0.938	0.079	0.900	0.115	0.876	0.120	0.713	0.238
16	0.835	0.134	0.804	0.141	0.779	0.150	0.647	0.222
32	0.627	0.162	0.584	0.193	0.567	0.180	0.479	0.203
ICA	0.997	0.003	0.930	0.113	0.937	0.125	0.783	0.247

Table 7. CoBliss algorithm SIR_{AA}

N$_m$	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
2	21.258	10.643	18.529	8.176	18.175	5.898	13.603	5.600
4	21.244	9.549	18.020	9.183	17.647	5.853	12.429	6.401
8	20.110	7.898	17.657	7.427	17.547	5.522	12.323	6.702
16	17.416	8.377	17.741	6.431	17.974	5.153	12.754	7.052
32	13.176	7.322	14.138	6.758	15.854	5.916	12.246	6.399
ICA	36.420	13.915	28.805	10.686	28.420	7.633	20.303	10.058

Table 8. CoBliSS algorithm $R_{A\hat{A}}$

N$_m$	1		2		4		8	
N	Mean	STD	Mean	STD	Mean	STD	Mean	STD
1	0.893	0.133	0.844	0.197	0.828	0.149	0.169	0.097
2	0.762	0.104	0.683	0.188	0.590	0.266	0.673	0.224
4	0.360	0.152	0.318	0.160	0.761	0.234	0.482	0.194
8	0.308	0.160	0.320	0.162	0.714	0.144	0.218	0.139
16	0.307	0.179	0.326	0.175	0.544	0.144	0.258	0.147
32	0.154	0.130	0.160	0.121	0.301	0.149	0.273	0.143
ICA	0.996	0.020	0.919	0.190	0.938	0.126	0.751	0.261

Table 9. Second environment Infomax SIR_{AA} and $R_{A\hat{A}}$

	SIR_{AA}		$R_{A\hat{A}}$	
N	Mean	STD	Mean	STD
2	18.6805	5.5026	0.7369	0.1625
4	18.4218	5.5948	0.7223	0.1698
8	19.7927	5.9762	0.7645	0.1549
16	18.9585	5.3326	0.7504	0.1525
32	18.7659	5.1429	0.7428	0.1625
64	17.2471	4.8498	0.7090	0.1314
128	16.7937	5.7177	0.6875	0.1759
ICA	22.8142	4.8623	0.8385	0.1635

7. Conclusions

The analysis of results leads us to conclude that not all CBSS algorithms are useful to extract AA from ECGs of FA episodes, given that the performances of these algorithms are very different. Another important conclusion is that CBSS algorithms performance is optimal when both N and N_m tend to one, that is, when both mixing and separation processes comply with the instantaneous model. Hence the instantaneous linear mixing model is a good model for the bioelectric mixtures in the human body.

TDD and Infomax are the CBSS algorithms with the best performance in the AA extraction. In addition, Infomax is the CBSS algorithm that best matches the 12-leads ECG case. Finally, even when when we assume controlled convolutive mixtures ($N_m > 1$ in the first environment), the FastICA algorithm, which uses the instantaneous linear mixing model, presents best performance than CBSS algorithms. Consequently, CBSS algorithms need an improvement to reach at least the performance of ICA algorithms. In fact, the instantaneous linear mixing model is a particular case of the convolutive mixing model where FIR filters length of the mixing and separation matrices are equal to one ($N_m = N = 1$).

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