Automated Extraction of Atrial Fibrillation Activity from the Surface ECG Using Independent Component Analysis in the Frequency Domain

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Abstract— **Background: Atrial fibrillation (AF) is the most common cardiac arrhythmia encountered by physicians. The analysis of AF from the surface electrocardiogram (ECG) requires the suppression of artifacts such as ventricular activity (VA) and noise corrupting the recordings. Independent component analysis (ICA) has recently been shown to tackle successfully the extraction of atrial activity (AA) in AF recordings. Methods: The present contribution puts forward a novel technique simultaneously exploiting the narrowband spectral character of AA and the statistical independence between AA and VA. The technique performs the iterative optimization of a sparsity and non-Gaussianity measure, the kurtosis, in the frequency domain. Results: On 35 ECG segments from 34 AF patients, the proposed one-stage technique obtains practically identical dominant frequency estimates than an existing technique based on two processing stages (Pearson's correlation equal to 0.9998). The proposed method extracts the AA with an average spectral concentration of $56 \pm 17\%$, against $49 \pm 17\%$ for the existing method, requiring also fewer computations. Conclusions: The proposed ICA-based technique achieves a more accurate AA waveform estimation and appears more suitable for real-time DSP implementations in clinical environments.**

Keywords— **Atrial fibrillation, electrocardiogram, independent component analysis, kurtosis, optimal step-size iterative algorithm.**

I. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia encountered in clinical practice, affecting up to 10% of the population over 70 years of age [1]. The trouble is characterized by an abnormal atrial electrical activation, whereby the organized wavefront propagation in normal sinus rhythm is replaced by wavelets wandering around the atria in a disorganized manner. This disorderly electrical activation leads to an inefficient atrial mechanical function and a subsequent increased risk of blood-clot formation and stroke. Despite its incidence, prevalence and risks of serious complications, the understanding of the generation and self-perpetuation mechanisms of this disease is still unsatisfactory.

Over recent years, signal processing has helped cardiologists in shedding some light over AF, as certain features of the atrial activity (AA) signal, or f-waves, recorded in the surface ECG provide information about the arrhythmia. The dominant frequency of the AA signal is shown to be related to the refractory period of atrial myocardium cells, and thus to the degree of evolution of the disease and the probability of spontaneous cardioversion [2], [3]. The analysis and characterization of AA from the ECG requires the suppression of interference such as the QRS-T complex of ventricular electrical activation (or ventricular activity, VA), artifacts and noise. Artifact suppression becomes indispensable when the actual AA waveform may play an important role in subsequent processing, as in the analysis of the ectopic activation of the atrio-ventricular node during AF [4].

The average beat subtraction (ABS) technique, the traditional approach to AA extraction from the surface ECG, assumes the AA and VA to be uncoupled and the QRS-T complex to have a regular morphology. Averaging consecutive QRS-T complexes results in a ventricular template that, after suitable time alignment and amplitude scaling, is subtracted from each lead in the recording [5], [6]. The main drawbacks of the ABS approach are its sensitivity to beat morphology variations and its inability to suppress other artifacts uncorrelated with VA. The fact that multiple electrodes record simultaneously the bioelectrical activity under examination (spatial diversity) is not exploited by this kind of techniques.

A more recent approach to AA extraction exploits naturally the spatial diversity available in the multi-lead surface ECG. This approach relies on the observation that AA and VA can be considered to be generated by statistically independent, but otherwise unknown, sources of bioelectrical activity [7]. Due to the propagation of bioelectrical signals across the body tissues, each lead outputs a linear combination of the source signals associated with AA, VA and other artifacts. Techniques for the separation of independent signals in linear mixtures, such as independent component analysis (ICA), can then be applied on the ECG to search for the AA source, thus allowing the reconstruction of AA in all leads free from VA and other interference. General-purpose ICA techniques such as those of [8], [9] usually fail to perform the AA extraction. This occurs because most ICA techniques are based on the maximization of non-Gaussianity measures such as kurtosis (fourth-order marginal cumulant) whereas the AA signal is often near-Gaussian. Additional prior information on the atrial source, in particular its narrowband character, can be exploited to improve AA extraction performance. A successful two-stage processing approach is adopted in [10]. The first stage suppresses impulsive interference, specially VA, through the maximization of non-Gaussianity. The remaining outputs are then fed into a second stage where AA is separated from near-Gaussian noise by exploiting, in the time domain, the narrowband character of AA.

The present contribution puts forward an ICA-based extraction technique exploiting concurrently the independence and narrowband character of AA in a single processing stage. This is achieved through the maximization of kurtosis in the frequency domain by an efficient iterative numerical algorithm. The proposed technique offers a superior AA extraction performance compared to the two-stage ICA-based method of [10].

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II. Materials and methods

A. AF ECG database and preprocessing

A database of 51 standard 12-lead ECG segments recorded from 48 AF sufferers is considered in the present study.[1] Each segment spans an observation window of around 12 seconds sampled at 1 kHz. Before further processing, baseline wander and high-frequency interference are suppressed by zero-phase Chebyshev type-II highpass and lowpass filters with cut-off frequencies of 0.5 and 30 Hz, respectively.

B. ICA-based approach to AA extraction

The ICA approach to AA extraction assumes that each ECG lead records an unknown linear mixture of different unknown sources of bioelectrical activity, including AA and VA, as well as other artifacts [7]. Mathematically, this is expressed as:

$$\mathbf{x}(t) = \mathbf{H}\mathbf{s}(t). \tag{1}$$

Vector $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_L(t)]^{\mathrm{T}}$ contains the L leads amplitudes at time instant t, vector $\mathbf{s} = [s_1(t), s_2(t), \ldots, s_K(t)]^{\mathrm{T}}$ represents the K source amplitudes at the same instant, and matrix $\mathbf{H} \in \mathbb{R}^{L\times K}$ stores the linear mixture coefficients linking the sources to the observations; symbol $^{\mathrm{T}}$ is the vector transpose operator. In the standard ECG, $L = 12$. Source independence is a plausible assumption in the problem of AA extraction in AF episodes [7], so that the separation can be achieved by the statistical tool of ICA [8]. A set of extracting spatial filters $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_K]$ is sought so that the entries of output vector $\mathbf{y}(t) = \mathbf{W}^{\mathrm{T}}\mathbf{x}(t)$ maximize a contrast function quantifying statistically independence; these entries are the independent components underlying the observation $\mathbf{x}(t)$. The search for the extracting vectors can be done jointly (all at the same time) or sequentially (one after another). Once the source of AA, say $s_{\mathrm{AA}}(t)$, is estimated from the above model, its contribution to the recording can be reconstructed as $\mathbf{x}_{\mathrm{AA}}(t) = \mathbf{h}_{\mathrm{AA}}s_{\mathrm{AA}}(t)$, where $\mathbf{h}_{\mathrm{AA}}$ denotes the corresponding column of the mixing matrix. Conventionally, the filtered ECG data are first spatially prewhitened via, e.g., the singular value decomposition of the data matrix (principal component analysis). The remaining mixing matrix relating the whitened observations to the source signals can be proven to be unitary. Its estimation requires the use of source properties such as non-Gaussianity or time coherence through suitable contrasts.

In [10], the impulsive nature of VA and the narrowband character of AA are exploited in a two-stage procedure. The first stage looks for extracting filters maximizing a suitable approximation of negentropy; the FastICA method, an iterative algorithm for ICA [9], is used for this task. Since negentropy can be considered as a distance to Gaussianity, this method is specifically adapted to the extraction of non-Gaussian sources, and in particular impulsive signals such as VA in the ECG. The remaining sources are typically mixtures of near-Gaussian AA and noise. Such sources are selected by a kurtosis-based threshold and passed on as inputs to the second-order blind identification (SOBI) method [11]. Through the joint approximate diagonalization of the input correlation matrices at several time lags, SOBI is particularly suited to the separation of narrowband sources (signals with long correlation functions). The correlation lags are chosen in accordance with typical AF cycle length values [10].

[1]Database kindly made available by the Hemodynamics Department of the Clinical University Hospital and the Bioengineering, Electronics and Telemedicine Research Group of the Polytechnic University, Valencia, Spain.

C. Kurtosis maximization in the frequency domain

The method proposed herein is also based on the observation that AA is a narrowband signal. Accordingly, its frequency-domain representation is sparse and can thus be considered to stem from an impulsive distribution with high kurtosis value. Relying on this simple observation, ICA can be applied on the ECG recording after transformation into the frequency domain. If a sequential extraction algorithm is used, the f-domain AA source is expected to be found among the first extracted components, typically those with higher kurtosis values; its time course can then be recovered by transforming back into the time domain.

When transformed into the frequency domain, signals become complex valued with possibly non-circular distributions (i.e., probability density functions without rotational invariance). Hence, an ICA algorithm valid for non-circular complex-valued sources is required. We resort to the RobustICA algorithm of [12], [13], whose MATLAB© implementation is freely available in [14]. This method for sequential source extraction aims at maximizing the normalized kurtosis contrast, defined as:

$$\mathcal{K}(\mathbf{w}) = \frac{\mathrm{E}\{|y|^4\} - 2\mathrm{E}^2\{|y|^2\} - \left|\mathrm{E}\{y^2\}\right|}{\mathrm{E}^2\{|y|^2\}} \tag{2}$$

where $y = \mathbf{w}^{\mathrm{H}}\mathbf{x}$ is the extractor output. The above expression of kurtosis is valid for real- and complex-valued, even non-circular, sources. The contrast for source extraction can be optimized through a gradient-based update of the form

$$\mathbf{w}^{+} = \mathbf{w} + \mu\mathbf{g}, \qquad \mathbf{g} = \nabla\mathcal{K}(\mathbf{w}). \tag{3}$$

In conventional iterative algorithms, the step size or learning rate μ must typically balance a difficult compromise between convergence speed and misadjustment after convergence. However, the step size leading to the global optimum of the contrast (2) along the search direction can be determined algebraically (without any iterations) by finding the roots of a 4th-degree polynomial [12], [13]. This confers the algorithm a very fast convergence and the ability of avoiding saddle points associated with spurious extraction solutions. To prevent extracting the same source twice, after each update the extracting vector can be made orthogonal to the vectors found for the previously extracted sources (deflationary orthogonalization), as in the FastICA algorithm [9]. RobustICA can spare prewhitening, in which case a different deflation procedure (e.g., linear regression) must be employed.

In the present AA extraction setting, the prewhitened filtered recordings are first transformed into the frequency domain by the zero-padded 16384-point fast Fourier transform (FFT). The sources extracted in the f-domain are then transformed back to the time domain via the inverse FFT and truncated to their original length for further analysis. We refer to this method

as *RobustICA-f*. The percentage of signal power around the dominant peak, or spectral concentration (SC), has been shown to correlate with AA extraction quality [10], and can hence be used as a measure of performance. Specifically, if f_p denotes the dominant peak position, SC is determined as the relative signal power between $0.82f_p$ and $1.17f_p$. As in [10], power spectra are estimated by Welch's method using averaged 8192-point FFT of 4096-point Hamming-windowed segments with 50% overlap. For the sake of a meaningful comparison, RobustICA-f employs the same initialization, maximum number of iterations per source and termination criterion as FastICA. The automated detection of the AA source $s_{\mathrm{AA}}(t)$ is performed be selecting the extracted component with highest SC and dominant peak in the 3 to 9 Hz interval, the typical AF frequency band. Computational complexity is measured in terms of floating point operations (flops); a flop is defined as a real-valued product followed by an addition and, in practical implementations, would naturally correspond to a multiply-and-accumulate cycle in a digital signal processor (DSP).

III. Results

Out of the 51 AF ECG segments available in the dataset, FastICA-SOBI and RobustICA-f failed to estimate a distinct AA source in 11 and 9 cases, respectively. The automated AA detection procedure acting on FastICA-SOBI and RobustICA sources was unsuccessful in 3 and 4 recordings, respectively, although it would have succeeded by extending the AF band upper bound over 9 Hz in one of such cases; in 2 of the 4 cases, the source retained by RobustICA-f seemed to represent T-wave activity rather than AA. Strong artifacts in 11 recordings were not sufficiently cancelled by the preprocessing frequency filters described in Sec. II-A, yet this did not prevent a good AA extraction in one case. Overall, the two ICA-based methods compared in this study yielded satisfactory fully automated AA extraction results in 35 out of the 51 recordings. Two of these 35 recordings were obtained within a seven-week interval from the same patient. The AA estimated in 12 such segments showed a significant harmonic structure, pointing out the presence of atrial flutter (AFL), a more organized form of AF. In 2 and 3 AFL segments processed by FastICA-SOBI and RobustICA-f, respectively, atrial harmonics seemed to spread over several sources and, consequently, a single source could not fully capture the whole AA present in the recording.

Figure 1(top) shows a 5-second segment of precordial lead V1 from the first AF patient's ECG in our database; its power spectral density is shown in Fig. 2(top). Figure 1(middle)–(bottom) shows a 5-second segment of the AA reconstructed, as explained in Sec. II-B, by the two methods in lead V1 from this patient's recording. The corresponding frequency spectra, together with the estimated dominant peak position and the associated SC values, are shown in Fig. 2(middle)–(bottom). As can be seen in the intervals between successive heartbeats, RobustICA-f obtained a more accurate estimate of the AA taking place in lead V1, as quantified by a higher SC value. The method required a total of 698 iterations or around 2725.3×10^6 flops to separate the whole mixture. This cost reduced to 53 iterations or 210.2×10^6 flops if stopped at the AA source, found in the 3rd extracted component. FastICA required 1178 iterations or 381.5×10^6 flops; its AA source was found in the 9th component.

Performance parameters averaged over the 35 selected segments are summarized in Table I. Pearson's correlation coefficient between the dominant frequencies estimated by the two methods was 0.9998. In terms of SC, FastICA outperformed RobustICA-f in 5 cases, with a average relative increase of 10.38%. In the other 30 cases, RobustICA-f yielded better SC figures, with a 25.40% average relative improvement compared to FastICA. If stopped at the AA source, RobustICA required an average of 62 ± 41 iterations or $244.9 \pm 159.9 \times 10^6$ flops.

IV. Discussion

This work compares two ICA-based techniques for AA extraction in ECG recordings of AF, namely, FastICA-SOBI [10] and the RobustICA-f method proposed herein. Both techniques exploit the narrowband spectrum of AA as well as its independence from VA and other artifacts. As opposed to FastICA-SOBI, which requires two consecutive processing stages, RobustICA-f is able to capitalize on both properties simultaneously by maximizing the extractor-output kurtosis in the frequency domain.

Over the 35 recordings successfully processed by the fully automated ICA-based procedures compared in this study, both methods provide virtually identical dominant atrial frequency estimates. Hence, either method could be used if the main frequency location and evolution is the only parameter required by further AF analysis, as in the prediction of spontaneous cardioversion [2]. RobustICA-f achieves an improved AA signal extraction quality in terms of SC. Higher values of this index are typically associated with more accurate AA waveform estimates [10]. Consequently, RobustICA-f should be preferred when subsequent AF analysis may involve a finer processing of the extracted AA; an example may be the study of the ectopic activation of the atrio-ventricular node [4]. RobustICA-f converges in fewer iterations than FastICA-SOBI but, if separating the whole mixture, becomes more complex due to its higher cost per iteration, which is about an order of magnitude greater than FastICA's in this particular setting. However, if stopped as soon as the AA source is found, RobustICA-f presents only half the computational burden of the alternative ICA-based method, and thus arises as a better alternative to real-time DSP implementations suitable for clinical environments.

Sixteen out of the 51 ECG segments available in the database could not be used in the experimental comparison because either method failed to perform good AA extraction in such cases. In 10 of these, bad performance could be attributed to strong artifacts giving rise to spurious sources among the estimated independent components. More elaborate preprocessing methods could alleviate this shortcoming and improve the applicability of the ICA-based techniques compared in this study. Similarly, the automated AA detection procedure should be rendered more robust to T-wave activity present in the typical AF band as well as AA spreading outside such an interval. Atrial source detection also needs to be extended to situations where the AA may not be concentrated in a single source, as may occur in AFL recordings. Likewise,

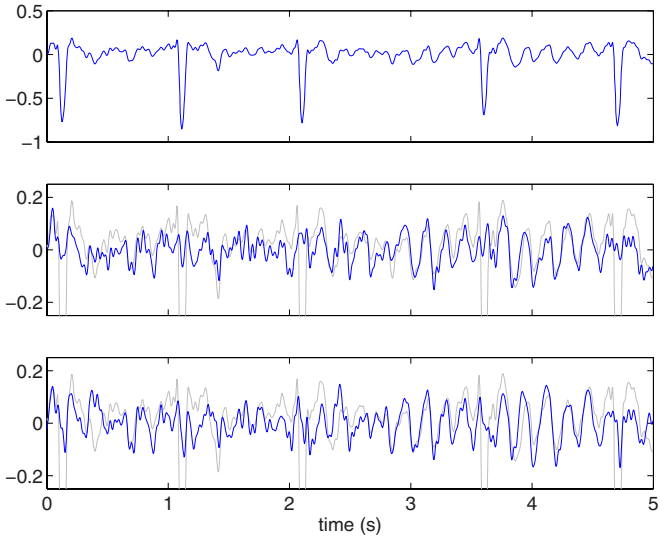

Fig. 1. Top: a 5-s segment of lead V1 from the first AF patient. Middle: AA contribution estimated by FastICA-SOBI from the 12-lead ECG. Bottom: AA contribution estimated by RobustICA-f from the 12-lead ECG.

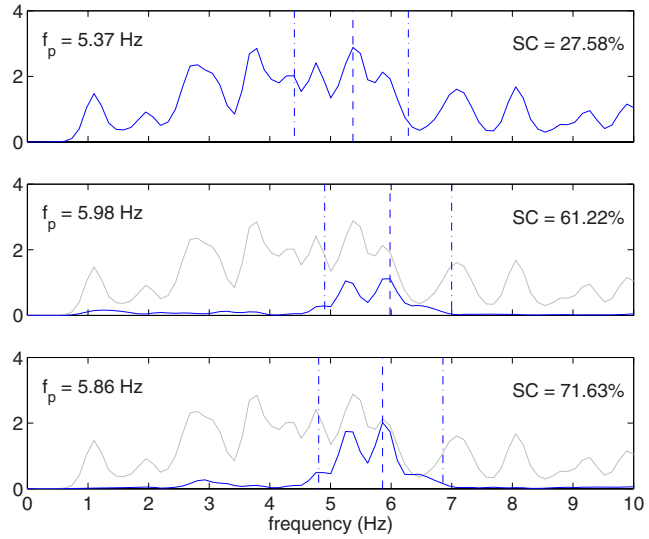

Fig. 2. Power spectral densities of the signals shown in Fig. 1. Dashed lines: dominant frequency locations. Dash-dotted lines: frequency bounds used in the computation of spectral concentration.

larger SC values would have been obtained if the harmonic structure of AFL had explicitly been taken into account. This limitation calls for the redefinition of SC along the lines of the compressed spectrum [15].

V. Conclusions

The proposed one-stage ICA-based AA extraction technique achieves a more accurate AA waveform estimate, as measured by the SC index, than the existing two-stage technique considered in this study. This feature may prove beneficial in subsequent AF analysis involving finer detail of the estimated AA signal. The reduced computational burden of the proposed technique makes it more suitable for real-time DSP implementations applicable in clinical environments. Further research should aim at more effective artifact-removal preprocessing methods, automated AA detection procedures more robust to T-wave activity leakage into the AF band and the presence of more than one atrial source, and alternative SC index definitions accounting for the AA harmonic structure in AFL.

TABLE I

Performance parameters averaged over the thirty-five ECG recordings where both methods yielded satisfactory automated AA extraction results. Symbol $[\cdot]$ represents the closest integer; 'std' denotes the standard deviation.

	FastICA-SOBI	RobustICA-f
f_p (Hz) (mean $\pm$ std)	5.40 ± 1.18	5.41 ± 1.18
SC (%) (mean $\pm$ std)	48.55 ± 17.06	55.67 ± 16.78
iterations ([mean] $\pm$ [std])	1245 ± 934	202 ± 99
flops $\times 10^6$ (mean $\pm$ std)	409.8 ± 302.8	790.5 ± 387.4
AA source position (median $\pm$ [std])	9 ± 2	3 ± 2

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