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Extraction of the Atrial Activity from the ECG based on Independent Component Analysis with Prior Knowledge of the Source Kurtosis Signs

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***Abstract*— In this work it will be shown that a contrast for independent component analysis based on prior knowledge of the source kurtosis signs (ica-sks) is able to extract atrial activity from the electrocardiogram when a constrained updating is introduced. A spectral concentration measure is used, only allowing signal pair updates when spectral concentration augments. This strategy proves to be valid for independent source extraction with priors on the spectral concentration. Moreover, the method is computationally attractive with a very low complexity compared to the recently proposed methods based on spatiotemporal extraction of the atrial fibrillation signal.**

I. INTRODUCTION

With a prevalence as high as 10% for people over the age of 70, atrial fibrillation (AF) and atrial flutter (AFL) are the most commonly encountered forms of cardiac arrhythmia. Since the origin and model of AF and AFL are barely understood until now [14], extraction of the electrical activity from the electrocardiogram (ECG) attributed to the AF/AFL is of great value for further understanding its underlying mechanisms. Therefore we propose a fully automated low complexity AF extraction technique. Contrary to the majority of the algorithms which try to unveil the atrial activity (AA) during AF periods by suppression of the QRS(-T) complex, the proposed method envisages the isolation of the AA as has been proposed in [5, and references therein].

However, most signal extraction techniques, whether in a single stage or in multiple stages are computationally expensive and are seldom fully automated, leaving the final component selection to the user. Moreover, there are only few methods that combine successfully both the spatial and temporal information without turning to an excessive computational cost.

The last point to tackle is surely the validation of the algorithms. The extraction of AF from the ECG is essentially an inverse problem where the unknown source is to be estimated from the total measurement. Hence, there is no objective performance index (i.e. based on the original sources or any a priori information about them) to compare against.

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In this contribution we will compare a spatio-temporal two stage method for extraction of AA during AF/AFL episodes [5] against a novel single stage AA extraction technique based on limited *a priori* knowledge about its spectrum and source kurtosis signs (sks). The method is based on the contrast function in [11] and the adapted version in [10] to extract AF signals. It uses the prior information that in the 3-12Hz band the AF is characterised by a single frequency waveform and its harmonics with slow frequency and amplitude modulation [13]. Since the AA exhibits quasi-sinusoidal behaviour, we may thus use the contrast proposed in [11] with a negative sign for the AA kurtosis and a positive sign for the other sources.

II. DATA & METHODS

A. Data

For a validation of the results we turned to both simulations (of which the results are published in [11]) and real data. The dataset consisted of 51 patients, all being diagnosed with AF. The recordings were registered with a standard 12-lead ECG, including the bipolar limb leads I-III, the augmented unipolar limb leads aVR, aVF and aVL and the six unipolar chest leads V1-V6. Since there is abundance in the information in the leads, a second set was constructed with 8 leads including all six chest leads and recalculations from the limb leads to the electrode potentials between LL and LA, respectively RA. The latter set of potentials will be called the 8-lead system from hereon.

B. Independent Component Analysis

Solving the biomedical inverse problems often relies on the statistical properties of the underlying sources [9], [1]. Independent Component Analysis (ICA) has already proven to be an appropriate measure for decomposition of an ECG dataset into its source contributions according to a linear model [12]

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \eta \quad , \tag{1}$$

where the projection of the source activities $\mathbf{x} \in \mathbb{R}^n$ onto the measurements $\mathbf{y} \in \mathbb{R}^m$ is determined by a linear mixing

matrix $\mathbf{H} \in \mathbb{R}^{m \times n}$ up to some noise $\eta \in \mathbb{R}^m$. To solve Eq. 1, we need some *a priori* assumptions on the sources, e.g. statistical independence. In this paper, the noise η will be neglected or be taken as a source signal, reducing Eq. 1 to $\mathbf{y} = \mathbf{H}\mathbf{x}$. The system of equations is then solved by searching for $\mathbf{W}$ in $\hat{x} = \mathbf{W}^{-1}\mathbf{y}$ [1] which yields estimates $\hat{\mathbf{x}} = \mathbf{W}^{-1}\mathbf{H}\mathbf{x} = \mathbf{Q}\mathbf{x}$ that are as independent as possible. From hereon, $\hat{\mathbf{x}}$ is considered a decorrelated version of $\mathbf{y}$. Left to estimate is the rotation matrix $\mathbf{Q}$, since they are the only group of matrices that preserve orthogonality in $\hat{\mathbf{x}}$. This paper presents the application of ICA based on sks (ica-sks) constrained in its updating by spectral concentration.

Any function $\Psi(\mathbf{Q})$ that can be optimised such that (1) Ψ is invariant under permutation and scaling and (2) it reaches its maximum if and only if $\mathbf{Q}$ yields maximally independent components $\hat{\mathbf{x}}$ is a contrast for independent component analysis (ICA) [6].

C. 2×2 Source Separation

For the case of 2 sources and 2 observations, an ICA contrast can be defined as a single planar rotation of the prewhitened data $\hat{\mathbf{x}}$. Since any rotation in a two dimensional plane can be expressed in matrix format as a Givens rotation

$$\mathbf{x} = \mathbf{Q}^T\hat{\mathbf{x}} \ \text{, where } \mathbf{Q}(\theta) = \begin{pmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{pmatrix} \ , \quad (2)$$

the estimation is reduced to a single parameter and can be expressed in analytical form. The contrast that will be used here is based on independence and prior knowledge of source kurtosis signs and reads $\Psi(\mathbf{Q}) = \varepsilon_1\kappa_{1111} + \varepsilon_2\kappa_{2222}$, where $\kappa_{iiii} = \left\langle \hat{\mathbf{x}}_i^4 \right\rangle / \left\langle \hat{\mathbf{x}}_i^2 \right\rangle^2 - 3$ is the standardised kurtosis of $\hat{\mathbf{x}}_i$. ε_1 is chosen negative and ε_2 is chosen positive. This yields as the solution for θ [11], [16]:

$$\theta_{opt} = 0.5 \arctan 2 \left(\kappa_{1112} + \kappa_{2221}\right)\left(\kappa_{2222} - \kappa_{1111}\right)^{-1} \ , \quad (3)$$

where κ_{ijjj} is the bivariate moment defined as $\left\langle \hat{\mathbf{x}}_i \hat{\mathbf{x}}_j^3 \right\rangle$.

D. Higher Dimensional Data

For higher dimensional data ($n > 2$), it is possible to express the orthogonal mixing matrix $\mathbf{Q}$ as subsequent Givens rotations, updating the current source estimate $\hat{\mathbf{x}}$. Since for plane rotations in higher dimensional data it suffices to fix all axes but two, we can express the rotation of the subspace spanned by two components in $\hat{\mathbf{x}}$ by Eq. 2 while the other components undergo a identity transformation. Based on the fact that maximal mutual independence of each pair guarantees maximal independence of the set, pairwise rotations with a fixed updating order will yield a solution to ICA [7]. Being interested in a single component only - the one that contains the atrial fibrillation - we define one sweep as such that it will compare our best current estimate $\hat{\mathbf{x}}_i^{(k)}$ to every other $\hat{\mathbf{x}}_{j\neq i}^{(k)}$ and process these pairs according to

$$\begin{bmatrix} \hat{\mathbf{x}}_i^{(k+1)} \\ \hat{\mathbf{x}}_j^{(k+1)} \end{bmatrix} = \mathbf{Q}^T \begin{bmatrix} \hat{\mathbf{x}}_i^{(k)} \\ \hat{\mathbf{x}}_j^{(k)} \end{bmatrix} \ . \quad (4)$$

[1]Since $\mathbf{W}^{-1}$ is defined as the inverse of $\mathbf{H}$, m is limited to be equal to n, and $\mathbf{H}$ and $\mathbf{W}$ must be full column rank.

However, there is no guarantee that the source of interest is the only source with negative kurtosis, nor is it guaranteed that the algorithm will return the source with a basic frequency in the 3-12Hz band, the band of interest for AF signals. Hence the need to use a constrained optimisation criterion as given in the next paragraph.

E. Constrained Optimisation

To further optimise the algorithm for the extraction of AA we include a constraint in the update rule in the form of a decision rule. This decision rule will allow for rotation at step $k+1$ if and only if the rotation augments the spectral concentration of the best estimate found in iteration k. After calculating our potential candidates for $\hat{\mathbf{x}}_i^{(k+1)}$ and $\hat{\mathbf{x}}_j^{(k+1)}$ we apply a decision rule characterised by the detection of augmentation in spectral concentration:

$$\max\left(\mathrm{SC}\left(\hat{\mathbf{x}}_i^{\star(k)}\right), \mathrm{SC}\left(\hat{\mathbf{x}}_j^{\star(k)}\right)\right) > \mathrm{SC}\left(\hat{\mathbf{x}}_i^{(k)}\right) \ , \quad (5)$$

where the function SC calculates the ratio of the power spectral density (PSD) in the 90-110% range of the frequency with maximal power in the 3-12Hz band to the PSD of half the spectrum (i.e. from 0Hz to half the sampling frequency Fs) given by:

$$\mathrm{SC}(a) = \frac{\int_{0.9f_c}^{1.1f_c} P_a(\tau)\, e^{-2\pi\tau f} df}{\int_{0}^{0.5\mathrm{Fs}} P_a(\tau)\, e^{-2\pi\tau f} df} \ . \quad (6)$$

If the decision rule of Eq. (5) is fulfilled, the new estimate $[\hat{\mathbf{x}}_i^{(k+1)}\hat{\mathbf{x}}_j^{(k+1)}]^T$ is replaced by the candidates $[\hat{\mathbf{x}}_i^{\star}\hat{\mathbf{x}}_j^{\star}]^T$ the component with the highest SC as the new reference. If not fulfilled the estimates do not get updated and the pair $\left(\hat{\mathbf{x}}_i, \hat{\mathbf{x}}_{j+1}\right)$ is processed. The updating process is finished when a full sweep has passed without finding candidates augmenting the spectral concentration, which is generally of the order of 3 sweeps.

F. Spatio-temporal Source Separation

As a reference technique we will use the technique proposed by Castells *et al.* [5] based on spatio-temporal source decomposition. The algorithm consists essentially out of an ICA step (FastICA [8]) with elimination of the components with a kurtosis higher than the threshold of 1.5 followed by a temporal decorrelation step, namely Second Order Blind Identification (SOBI) [3]. The iterative algorithm RobustICA [15] was used here as an implementation of FastICA. SOBI is known to be quite robust to estimation errors in the used time lags, but there is no rule on how to choose the optimal set. Therefore we also include a temporal decorrelation algorithm known as Canonical Correlation Analysis (CCA) [2] based solely on a single sample shift, to compare with.

TABLE I

THE DIFFERENCES IN ESTIMATION OF THE CENTRAL FREQUENCIES FOR 12-LEADS[1], 8-LEADS[2] AND 12-LEADS VERSUS 8-LEADS[3].

	rICA+SOBI	rICA+CCA	ica-sks	combEML
rICA+SOBI	0.85^3	1.38^1	1.09^1	1.05^1
rICA+CCA	0.69^2	0.16^3	-0.29^1	-0.32^1
ica-sks	-0.26^2	-0.95^2	-0.50^3	-0.03^1
combEML	-0.32^2	-1.02^2	-0.06^2	-0.53^3

TABLE II

SPECTRAL CONCENTRATION FOR THE SET OF 51 PATIENTS. 12-LEADS (UPPER ROW) AND 8-LEADS (LOWER ROW)

rICA+SOBI	rICA+CCA	ica-sks	combEML
29.80 ± 12.44	43.16 ± 14.99	57.89 ± 11.33	56.12 ± 10.47
40.36 ± 15.66	39.87 ± 14.21	53.72 ± 14.52	51.17 ± 10.29

TABLE III

COMPUTATIONAL COMPLEXITY PER ITERATION AND SOME AVERAGE NUMBERS OF ITERATIONS NEEDED FOR CONVERGENCE.

method	computational complexity	iterations until convergence
rICA	$\mathcal{O}\left((5n+12)nT\right)$	10
SOBI	$\mathcal{O}\left(17n^2T+2(n-1)(n-2)\right)$	$1+\lfloor\sqrt{n}\rfloor$
CCA	$\mathcal{O}\left(4nT^2+4n^2T+\frac{62}{3}n^3\right)$	1
ica-sks	$\mathcal{O}\left(7(n-1)T\right)$	5
combEML	$\mathcal{O}\left(8(n-1)T\right)$	10

G. Preprocessing

Having no significant information for AF in the frequency bands below 0.5Hz and above 30Hz, we apply a 12^{th} order Butterworth bandpass filter with the specified frequencies as -3dB points. This has no effect on the end results since the preprocessing is done before feeding any data to the algorithms and thus the PSD in the denominator of the RHS of Eq. 6 does not change by replacing the lower and upper limits by 0.5Hz and 30Hz respectively. This will only result in a nonlinear rescaling of all spectral concentration coefficients due to the nominator, although no large changes can be noted if AF is extracted because the signal power linked to AF in the rejected frequencies is negligible.

III. RESULTS

A. Frequency Estimation

As a first evaluation measure the mean of the differences in estimated central frequencies are presented in table I. The upper right triangle shows the differences in frequencies for the estimation of the algorithm given in the top row versus the one in the left column based on 12 lead ECG systems, while the lower left triangle gives those values for the 8-lead (re-referenced) system. Values on the diagonal compare the results of the algorithms in their 12-lead setting versus their 8-lead setting. The table compares RobustICA + SOBI (rICA+SOBI), RobustICA + CCA (rICA+CCA), ica-sks and the combined EML (combEML) algorithm as proposed in [16] but with the decision rule in the update.

B. Spectral Concentration

The spectral concentration measure is the same as in the updating criterion. The spectral concentration is a valid measure since it's value has not directly been used to update the contrast function, but it has been used as a constraint. The results in table II show the typical values of spectral concentration for each of the methods used. The upper row gives the mean values with standard deviation for the 12 leads system, whereas the lower row show results for the 8 leads system.

C. Computational Complexity

To see the performance of the algorithms against their computational complexity, we show for each method the approximate complexity as a function of the number of samples T, the number of measurements n and the number of sources to extract m. Given that the EML based algorithms only need to estimate a single source ($m = 1$) and the RobustICA needs to do a full decomposition before the kurtosis based selection ($m = n$), the entries for RobustICA, ica-sks and combEML do not depend on m. It is worth mentioning that the n for SOBI and CCA is usually much smaller than the n taken in the other methods, since there has been done a dimension reduction through component selection based on kurtosis values. Table III gives the order of magnitude for each of the methods with the predefined lags in SOBI taken as in [5], being 17 equally spaced lags of 20ms (i.e. a range of 0 to 320 ms).

D. Graphical Results

In Fig. 1 and Fig. 2 the results are shown for the ica-sks algorithm for a simulated and a patient dataset, respectively. The simulated dataset has been constructed as to mimic cardiac electrical activity based on AF simulations as presented in [13] and ventricular activity or QRS waveforms based on a function given in [11].

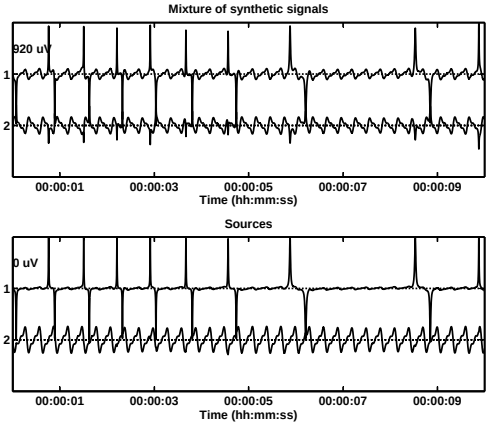

Fig. 1. Separation of a simulated AF signal from a high kurtotic QRS-like signal.

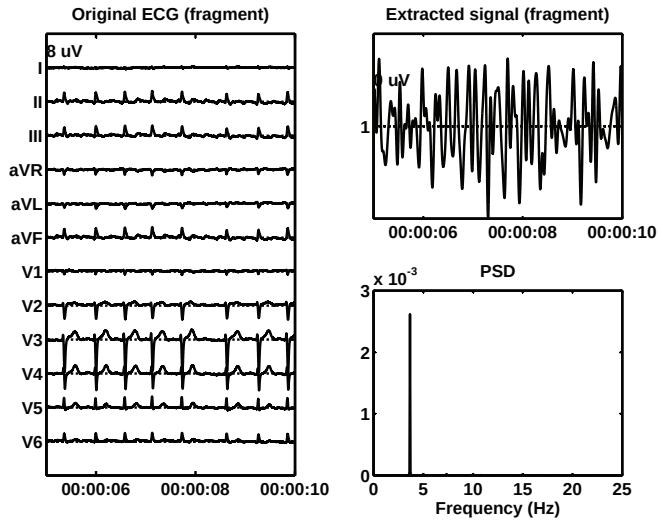

Fig. 2. Extraction of the AF from patient ECG using ica-sks.

IV. DISCUSSION

Although comparison of algorithms to solve inverse problems is not an easy task, results in this paper show that our method has acceptable results when compared to the spatiotemporal method presented in [5]. The results in table I clearly show that the used methods are comparable when the central frequency has to be estimated. However due to a lack of an objective measure of performance we do not have the possibility to make a statement about the accuracy of the estimate.

Referring to table II, we observe that the EML based methods using the constrained updating outperform the spatiotemporal methods based on a standard ICA implementation followed by a second order decorrelation method. We used the implementation RobustICA for the ICA method since it generally returned higher SC. To omit the selection procedure of the time lags introduced in SOBI, we also compared to the method of CCA, based on a single lag.

From Fig.(1) it is clear that the contrast works well on two artificial signals without using the constrained updating. Since the AF signal is generally subgaussian and the ventricular activity supergaussian [4], the contrast based on prior knowledge of the source kurtosis signs [11] is excellently suited for the two sources, two observations case. However, in the higher dimensional ECG subspace the exact prior knowledge of the sks is absent and thus we need to turn to constrained updating.

One of the most interesting features, however, is the low computational complexity of the source extraction methods based on EML (see table III). Based on a single stage only, and estimation of a single source, the flops required per iteration are heavily reduced compared to a dual stage algorithm yet yielding comparable results.

V. CONCLUSIONS

We presented a new method for extraction and estimation of the AA from the ECG of AF/AFL patients, namely ica-sks. The method is based on an ICA contrast exploiting prior knowledge about the desired source kurtosis signs and the spectral concentration in the 3-12 Hz band. As opposed to the method in [5], our method is able to exploit both properties simultaneously, resulting in an attractively low computational complexity.

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REFERENCES

[1] M. Babaie-Zadeh and C. Jutten. Semi-blind approaches for source separation and independent component analysis. In *Proceedings of 14th European Symposium on Artificial Neural Networks (ESANN) 2006*, pages 301–312, Bruges, Belgium, 2006.

[2] M. Borga and H. Knutsson. A canonical correlation approach to blind source separation. report liu-imt-ex-0062. Technical report, Department of Biomedical Engineering, Linköping University, 2001.

[3] J.-F. Cardoso and A. Souloumiac. Blind beamforming for non-gaussian signals. *IEE Proc.-F*, 140(6):362–370, 1993.

[4] F. Castells, J. Igual, J. Millet, and J. Rieta. Atrial activity extraction from atrial fibrillation episodes based on maximum likelihood source separation. *Signal Processing*, 85:523–535, 2005.

[5] F. Castells, J. Rieta, J. Millet, and V. Zarzoso. Spatiotemporal blind source separation approach to atrial activity estimation in atrial tachyarrhythmias. *Biomedical Engineering, IEEE Transactions on*, 52(2):258–267, Feb. 2005.

[6] P. Comon. Analyse en composantes indépendantes et identification aveugle. *Traitement du signal*, 7(3):435–450, 1990. Numero special non lineaire et non gaussien.

[7] P. Comon. Independent component analysis, a new concept? *Signal Processing*, 36:287–314, 1994.

[8] A. Hyvärinen and E. Oja. A fast fixed-point algorithm for independent component analysis. *Neur Comp*, 9:1483–1492, 1997.

[9] S. Makeig, A. J. Bell, T.-P. Jung, and T. J. Sejnowski. Independent component analysis of electroencephalographic data. In *Advances in Neural Information Processing Systems*, volume 8, pages 145 – 151, 1996.

[10] R. Phlypo, V. Zarzoso, P. Comon, Y. D'Asseler, and I. Lemahieu. Extraction of atrial activity from the ECG by spectrally constrained ICA based on kurtosis sign. In S. A. A. M E Davies, C J James and M. D. Plumbley, editors, *ICA 2007: 7th International Conference on Independent Component Analysis and Signal Separation*, London, UK, 2007.

[11] R. Phlypo, V. Zarzoso, P. Comon, Y. D'Asseler, and I. Lemahieu. ISRN I3S/RR-2007-13-FR: A contrast for ICA based on the knowledge of source kurtosis signs http://www.i3s.unice.fr/~mh/RR/2007/liste-2007.html. Technical report, I3S, Sophia Antipolis, France, 2007.

[12] J. J. Rieta, F. Castells, C. Sánchez, V. Zarzoso, and J. Millet. Atrial activity extraction for atrial fibrillation analysis using blind source separation. *IEEE Trans Biomed Eng*, 51(7):1176–1186, Jul 2004.

[13] M. Stridh and L. Sörnmo. Spatiotemporal qrst cancellation techniques for analysis of atrial fibrillation. *IEEE Trans Biomed Eng*, 48(1):105–111, Jan 2001.

[14] D. G. Wyse and B. J. Gersh. Atrial fibrillation: a perspective: thinking inside and outside the box. *Circulation*, 109(25):3089–3095, Jun 2004.

[15] V. Zarzoso and P. Comon. How fast is FastICA? In *Proceedings of the 14th European Signal Processing Conference (EUSIPCO)*, Firenze, Italy, September 2006.

[16] V. Zarzoso, A. K. Nandi, F. Hermann, and J. Millet-Roig. Combined estimation scheme for blind source separation with arbitrary source PDFs. *IEE Electronics Letters*, 37(2):132–133, 2001.