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Assessment of ICA Algorithms for the Analysis of Crackles Sounds

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***Abstract*—Blind source separation by independent component analysis has been applied extensively in the biomedical field for extracting different contributing sources in a signal. Regarding lung sounds analysis to isolate the adventitious sounds from normal breathing sound is relevant. In this work the performance of *FastICA*, *Infomax*, *JADE* and *TDSEP* algorithms was assessed using different scenarios including simulated fine and coarse crackles embedded in recorded normal breathing sounds. Our results pointed out that *Infomax* obtained the minimum *Amari* index (0.10037) and the maximum signal to interference ratio (1.4578e+009). Afterwards, *Infomax* was applied to 25 channels of recorded normal breathing sound where simulated fine and coarse crackles were added including acoustic propagation effects. A robust blind crackle separation could improve previous results in generating an adventitious acoustic thoracic imaging.**

I. Introduction

Several pulmonary diseases are clinically described by the occurrence of discontinuous adventitious lung sounds, also known as crackles. In parenchymal lung diseases fine and coarse crackles have been found during the inspiratory and expiratory phases; for example, in fibrotic diseases fine crackles are more frequently found at the end of the inspiratory phase. The automated detection of crackles is still an open research area due to the nonstationarity behavior of both crackles and breathing sounds (BS) and the signal-to-noise ratio (SNR) between them, among others issues. Furthermore, multichannel BS acquisition systems have imposed to deal with the spatial changes of crackles and BS characteristics [1]. Recently, the acoustic thoracic imaging based on the number of detected crackles in recorded multichannel BS has been proposed [2]. In clinical settings the adventitious image may allow to identify the extent of the pulmonary areas where crackles are occurring. Therefore, providing a confident adventitious image might help to the diagnosis of pulmonary disorders. However, it is also necessary to outline the image by identify the crackle sources considering the acoustic transmission phenomenon in lung parenchyma.

In this work we assessed different independent component analysis (ICA) algorithms such as *FastICA*, *Information-Maximization* (*Infomax*), *Joint Approximate Diagonalization of Eigenmatrices (JADE*) and *Temporal Decorrelation Source Separation* (*TDSEP*) by the *Amari* index and the signal to interference ratio to separate crackles from normal breathing sounds (NBS) in simulated scenarios (1) without and (2) with crackles transmission between channels. The first step allows selecting an optimal ICA algorithm while the second permits to evaluate the selected optimal ICA algorithm considering the transmission phenomenon.

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II. Theory

A. Blind Source Separation by ICA

Blind Source Separation (BSS) by ICA is a statistical technique which works on recovering a set of unobserved signals from measured signals that are linear mixtures of unknown independent sources [3]. The statement that different sensors receive different mixtures of the sources is exploited by BSS; that is spatial diversity. Spatial diversity means that BSS looks for structures across the measured signals and not (necessarily) across time.

In the simplest BSS model, noise-free, the measured signals $x(t)$ are represented by the equation

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

where $s(t)$ are the source signals and $\mathbf{A}$ is a mixing matrix; in this mixing model, the measured signals are the product of $\mathbf{A}$ by the sources [4]. $\mathbf{A}$ is a full rank matrix, invertible and its columns are assumed to be linearly independent. Estimating the matrix $\mathbf{A}$, computing its inverse ($\mathbf{W}$), the independent components are obtained by:

$$\hat{s} = \mathbf{W}x(t) \tag{2}$$

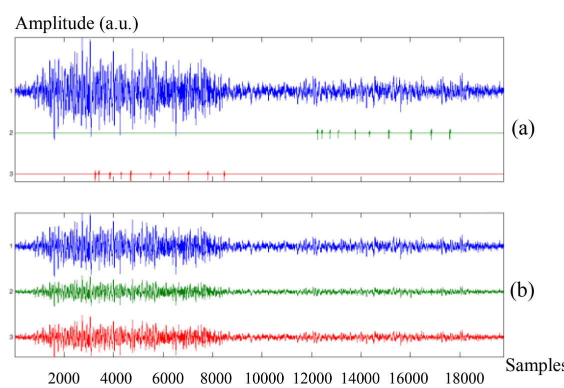

Figure 1. (a) Recorded basal NBS and simulated inspiratory (red) and expiratory (green) crackles with different time lag among them and (b) mixed sources (simulated measured signals).

B. ICA algorithms

Although a considerable amount of literature has been published on ICA algorithms, four algorithms can be classed as the most popular: *FastICA*, *Infomax*, *JADE* and *TDSEP.* Two preprocessing strategy are common in these algorithms: a) centering (subtract the mean of the mixed signal) and b) whitening, i.e. its components are uncorrelated and their variances equal unity [5].

1) FastICA is an iterative procedure which calculates the independent sources employing higher order statistics and based on a fixed-point scheme [5, 6]. Minimizing the negentropy of the mixture, uncorrelated and independent sources with non-gaussian distributions as possible are obtained. An important contribution of Hyvärinen and Oja is the way to calculate the negentropy, instead of using *kurtosis*; the authors propose the following approximation [5]:

$$J(y) \propto [E\{G(y)\} - E\{G(v)\}]^2 \tag{3}$$

where v is a Gaussian variable with zero mean and unit variance as same as the variable y. The selection of the non-linear function G (.) in (3) depends on the problem.

2) Infomax finds independent signals by maximizing the joint entropy $H(y)$ of the outputs of a neural network, minimizing the mutual information (I) between the output components [7]. In the case of two random variables, the joint entropy is defined as:

$$H(X,Y) = H(X) + H(Y) - I(X,Y). \tag{4}$$

Through maximizing the individual entropies, $H(X)$ and $H(Y)$, and minimizing the $I(X, Y)$ between the two signals, it is possible to maximize the joint entropy. *Infomax* switches between two learning rules: one for sub-Gaussian and one for super-Gaussian sources.

3) JADE determines the mixing matrix based on a joint approximate diagonalization of eigen-matrices [8]. The covariance matrix of the data $\mathbf{C_x}$ is transformed such that the second-order correlations of the data are zero by means of performing an eigen-value decomposition. A whitening matrix **M** is computed and the algorithm finds an orthogonal joint diagonalization by a unitary matrix **U.** Finally, the mixing matrix **A** is estimated as:

$$\hat{\mathbf{A}} = \mathbf{M}^{-1}\mathbf{U} \tag{5}$$

4) TDSEP minimizes temporal cross correlation between the signals [9]. This algorithm is based on several time delayed (τ) second order correlation matrices. For sources with stationary waveforms and unique power spectra, the time structure is adequately captured by temporal cross-covariances; the source covariance matrix

$$\mathbf{C}_\tau^s = \mathbf{W}\mathbf{C}_\tau^\chi\mathbf{W} \tag{6}$$

is diagonal for all time lags τ = 1,2,3, …, where $\mathbf{C}_\tau^\chi$ is the signal covariance matrix. The parameter τ must be chosen to take advantage of the temporal structure of the signals.

III. Methodology

A. Acoustic Signals Recording and Preprocessing

To generate the simulated scenarios multichannel NBS from a healthy subject were used. The signals were acquired by a microphone array of 5 by 5; the subject was seated, breathing through a calibrated Fleisch type pneumotachograph and wearing a nose clip. The sensor array and the associated nomenclature are described elsewhere [10]. To digitalize the multichannel NBS and airflow signals a 12-bit A/D card was used with a sampling frequency of 10 kHz. Signals were processed by a band pass filter with cutoff frequencies of 75 and 800 Hz.

B. Simulated scenarios for the selection of the ICA algorithm

Simulated scenarios were achieved linearly combining one NBS channel and simulated crackles by a random mixing matrix **B** (see fig. 1). Six different test conditions were considered in this paper inserting crackles during the inspiratory and expiratory phases of NBS: C1 simulated fine crackles inserted in apical NBS; C2 simulated fine crackles inserted in basal NBS; C3 coarse crackles inserted in apical NBS; C4 coarse crackles inserted in basal NBS; C5 fine-coarse crackles inserted in apical NBS; and finally, C6 fine-coarse crackles inserted in basal NBS. The idea was to assess the performance of the four ICA algorithms considering NBS spatial differences [11]. The time series of simulated fine and coarse crackles were created considering different time lags and different amplitudes among them, see Fig. 1. Fine and coarse crackles were simulated using the mathematical function proposed by Kiyokawa *et al.* [12]:

$$\begin{gathered} y(t) = 0.5\{1 + \cos(2\pi(t^{0.5} - 0.5))\}\sin(4\pi t^{\alpha}) \\ \alpha = \log(0.25)/\log(t_0) \end{gathered} \tag{7}$$

where $y(t)$ represents the simulated crackle. The mathematical model of 7 keeps the reported time domain characteristics for fine crackles as the initial deflection width (IDW) of 0.5 ms and two cycle duration (2CD) of 5ms, while for coarse crackles (CC) IDW is 1.2 ms and 2CD of 9 ms [10].

C. ICA algorithm selection by ICASSO

The selection of the optimal ICA algorithm to recover respiratory sounds was achieved using the ICASSO software [13]. Running each algorithm ten times with random initial conditions and bootstrapping the data every time, both the algorithmic and statistic reliability were assessed. ICASSO clusters the estimated components according to their mutual similarities using an agglomerative clustering with average linkage criterion. Independent components (ICs) shown on section IV corresponds to the centroids of the clusters calculated by ICASSO. Afterwards, the optimal chosen ICA algorithm was applied to a scenario of 25 channels of acoustic information where fine and coarse crackles were inserted into three NBS channels. The source channels

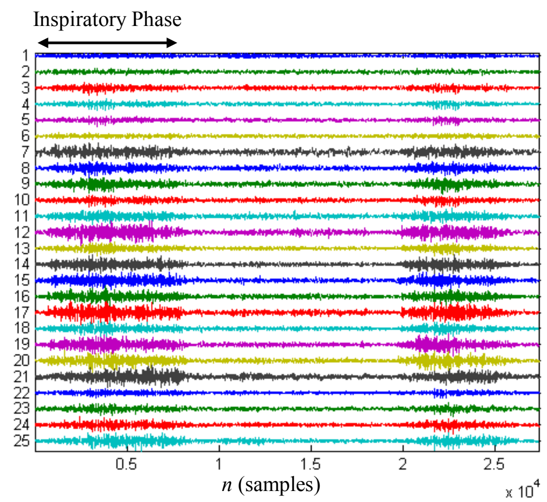

Figure 2. 25 channels of acoustic information plus simulated fine crackles into three NBS channels, 9, 17 and 19.

neighbor received an attenuated and delayed version of the three sources according to sound speed in parenchyma [14]. The signal to noise ratio was low enough to mask the crackles into NBS, see Fig. 2.

D. Performance Indexes

The performance of the ICA algorithms was evaluated by:

1) An inspection of the plots of the estimates.

2) Using the *Amari* index (*Am*):

$$Am = \sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{|p_{ij}|}{\max_k |p_{ik}|}-1\right)+\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{|p_{ij}|}{\max_k |p_{kj}|}-1\right) \tag{8}$$

where $\mathbf{P}=(p_{ij})=(\mathbf{WB})$; $\mathbf{P}$ is a permutation matrix. *Am* is an assessment of the interference of source *n* on measurement *m* [15].

3)The Signal to Interference Ratio (*SIR*) [16], defined as:

$$SIR = \frac{\left|\langle \hat{s}_i, s_i\rangle\right|^2}{\|\hat{s}_i\|^2\|s_i\|^2-\left|\langle \hat{s}_i, s_i\rangle\right|^2} \tag{9}$$

where $\hat{s}_i$ represents the estimated sources, and s_i the reference signal; the inner product is a measurement of the distance between two signals. When the estimated source is orthogonal to the reference signal, *SIR* is equal to zero; but if the estimated source is equal to a gain factor *g* of this signal, $\hat{s}_i = gs_i$, *SIR* is infinite.

IV. Results

The results in this section were obtained using the ICA parameters as follows:

1) *FastICA:* ICs were estimated by the symmetric approach and a non-quadratic functions as $G(y) = y^3$.

2) *Infomax:* the *extended* version was used assuming sub- and super-Gaussian distributions mixed sources.

3) *JADE:* the implementation to real signals was used.

4) *TDSEP:* time lags $\tau = 0, 1, 2, ..., 20$ were used.

The *Amari* indexes for the six different test conditions are listed in Table I; lower values indicate better separation. In general, *Infomax* outperforms the other three ICA algorithms as the minimum *Amari* index value was obtained in three of the six conditions. Table II includes the maximal *SIR* values in both inspiratory and expiratory phases for the six different test conditions; higher *SIR* values indicate a better estimated quality. The values listed in Table II reflect that *Infomax* is the optimal ICA algorithm for the acoustic BBS. As can be seen in Fig. 3, according to ICASSO *FastICA*, *JADE* and *Infomax* could separate correctly the three sources; however *TDSEP* mixed the inspiratory and expiratory crackles information. Furthermore, *Infomax* had the highest *SIR* values for both phases.

Fig. 4(a) shows the estimated ICs obtained by *Infomax* algorithm for the case of three fine crackles sources. The simulated sources were inserted at channels PRC4, PM4 and PLC3 during the inspiratory phase (channels 9, 17 and 19 in Fig. 2) and their information was propagated to the corresponding 8 surrounding channels of the sensor array. The number of inserted fine crackles was 10, 10 and 5, respectively. As can be seen in Fig. 4(a), the three sources were rightly separated in IC2, IC8 and IC16 while the rest of the ICs look like NBS; the ten estimated fine crackles of IC8 are shown in the zoom window of Fig. 4(b).

V. Discussion

The assessment of *FastICA*, *Infomax*, *JADE* and *TDSEP* algorithms was achieved using acquired NBS and simulated fine and coarse crackles. The simulated crackles allowed generating controlled scenarios to apply two indexes with the aim to find the optimal ICA algorithm for separate lung sounds sources. In this work the spatial differences in lung sounds was considered as NBS of 25 channels distributed on the thoracic surface. Also, transmission effects were included as the source information was propagated to others channels. The results indicate that *Infomax* represents a good choice for BBS as its *Amari* index and *SIR* value were the best. It is worthy to note the assumptions that apply to the problem at hand. In lung diseases it is assumed that crackles are added to NBS [10]; furthermore, NBS are believed to be generated by turbulences in the bronchial tree while crackles are generated by the opening of airways that are abnormally closed. Moreover, crackles sound travels through the lung parenchyma with certain speed and attenuated by thermal processes [14] before reaching the thoracic surface. Consequently, (1) crackles and NBS could be assumed as

TABLE I
Amari index

Condition	FastICA	Algorithms Infomax	JADE	TDSEP
1	0.20942	0.23478	0.20249	**0.16538**
2	0.3846	**0.10037**	0.38326	1.0868
3	0.26898	**0.21288**	0.26932	0.46549
4	0.33388	0.38021	**0.33186**	0.39507
5	**0.065303**	0.080183	0.067617	0.21828
6	0.34446	**0.1459**	0.34551	0.19031

*Numbers in bold indicate the test conditions with lower *Amari* index value independent sources since they are generated by different phenomena, (2) the spatial diversity assumption could be achieved since fine and coarse crackles are recorded by several sensors while the NBS is more local, and (3) crackles could be considered as point sources; therefore, the sensor that early records the arriving crackles could be considered as the source sensor but the rest as the neighbor sensors.

A robust blind crackle separation may improve previous results in generating an adventitious acoustic thoracic imaging (AATI) since crackles transmission between sensor channels was not considered [2]; the former may impact in the outline of the altered lung zone in AATI.

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TABLE II
SIR MAX VALUES

C	Algorithms: *FastICA*		*Infomax*		*JADE*		*TDSEP*	
	I	E	I	E	I	E	**I**	E
1	1.3645e+004	2.9347e+004	4.7543e+004	**5.4913e+008**	1.7926e+004	2.8771e+004	98.8087	95.5812
2	443.9888	7.9038e+007	5.6750e+004	**2.2902e+008**	439.8737	1.0543e+008	1.6247	1.6242
3	2.2503e+004	8.2395e+003	1.0222e+005	**5.5479e+005**	2.6559e+004	7.3529e+003	19.0319	20.9810
4	1.1330e+003	4.0603e+004	5.8647e+003	**1.4578e+009**	1.1215e+003	3.4631e+004	38.0958	51.4769
5	9.7210e+004	8.6794e+003	8.2771e+004	1.3435e+005	**1.6971e+005**	8.5139e+003	208.3684	289.9187
6	485.0772	2.2587e+004	1.0808e+004	**4.0692e+006**	479.0568	2.1627e+004	367.9525	383.5735

*Numbers in bold indicate the test condition with maximal *SIR* values. I: inspiratory phase and E: expiratory phase.

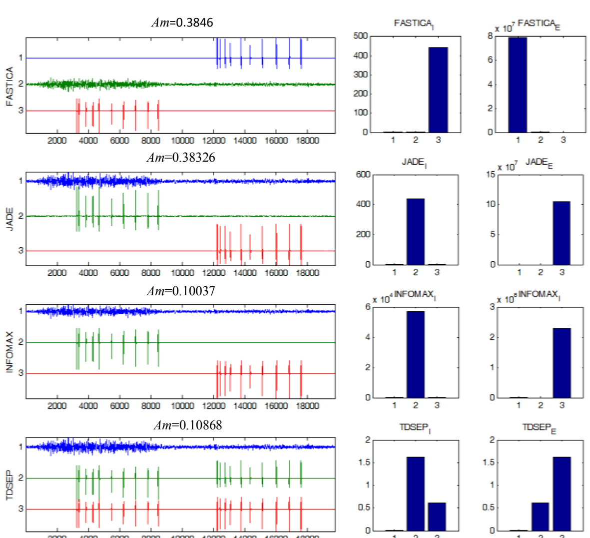

Figure 3. ICASSO results. (left) Estimated sources for simulated cases as shown in Fig. 1(b), from top to bottom *FASTICA*, *JADE*, *INFOMAX*, *TDSEP*, respectively, and (right) the associated inspiratory and expiratory SIR values.

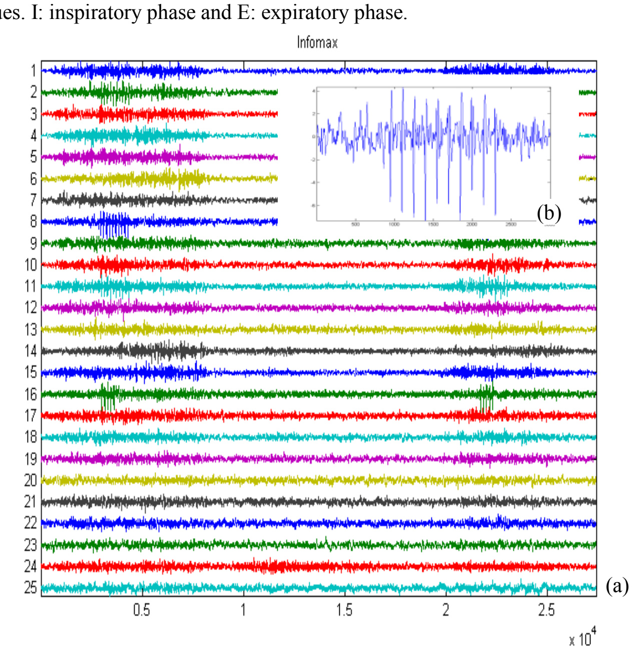

Figure 4. Infomax algorithm results, (a) The extracted 25 independent components and (b) zoom window of the component number 8.