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Adventitious Lung Sounds Imaging by ICA-TVAR Scheme

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Abstract—**Adventitious lung sounds (ALS) as crackles and wheezes are present in different lung alterations and their automated characterization and recognition have become relevant. In fact, recently their 2D spatial distribution (SD) imaging has been proposed to help diagnose of pulmonary diseases. In this work, independent component analysis (ICA) by infomax was used to find crackles sources and from them to apply a time variant autoregressive model (TVAR) to count and imaging the ALS. The proposed methodology was assessed on multichannel LS recordings by embedding simulated fine crackles with known SD in recorded normal breathing sounds. Afterwards, the adventitious image of two patients with fibrosis and emphysema were obtained and contrasted with the classical pulmonary auscultation provided by a pneumologist. The results showed that combining ICA and TVAR leads to a robust methodology to imaging ALS.**

I. Introduction

Pulmonary disorders as pneumonia and others with fibrotic lung process are characterized by the presence of adventitious lung sounds (ALS) [1]. In particular, crackles are sounds produced by the opening of abnormally closed airways that physicians could perceive through a stethoscope depending on the severity of the disease. In clinical settings it is essential to know the extent of the pulmonary area where crackles are occurring [2]. Furthermore, knowing the number and type of crackles may be used to improve the accuracy of the pulmonary diagnosis. Consequently, in a previous effort crackle imaging based on the interpolation of the crackles counting by TVAR modeling was proposed to know their spatial distribution as well as their strength on multichannel LS recordings [3]. The results were promising; however, the proposed methodology had a limitation in the sense that in assessing its robustness none crackles transmission was considered. In fact, since the crackles counting was performed on a channel by channel basis it was plausible to obtain the crackles spatial distribution without indentifying source crackles or transmitted ones. In a further attempt blind source separation (BSS) by independent component analysis (ICA) was achieved to extract the independent component corresponding to simulated crackles scenarios that included transmission effects, different algorithms as FastICA, Infomax, JADE and TDSEP were assessed [4]. Infomax provided the best results according to performance indexes as the Amari index and the Signal to Interference Ratio (SIR). In this work, we combine ICA by Infomax and the time-variant AR modeling of selected independent components (ICs) that reflects ALS to get a more reliable 2D ALS imaging that combine two concepts: the adventitious source estimation and the crackle counting by looking for nonstationary changes in the IC time series.

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II. Theory

A. Univariate Time-Variant Autoregressive (AR) modeling

A nonstationary random process as the crackles sounds can be modeled as the output of a time-variant linear all-pole filter excited by white noise where the actual sample of the process, $u[n]$, is represented by a lineal combination of its p previous samples, $u[n-i]$, $i=1,\ldots,p$, and the actual sample of the error signal, $v[n]$. The coefficients of the linear combination $\{a_i(n),\ i=1,\ldots,p\}$ as well as the model order p need to be determined. In this work, the recursive least squares (RLS) algorithm was used to estimate the TVAR coefficients of IC time series using a constant forgetting factor λ and the Akaike criterion was employed to establish the TVAR model order at four [3].

B. ICA and the Spatial Distribution of ICs

ICA is a method for transforming a set of observation of random variables into components which are statistically independent [5]. In the most simplistic ICA model (noise free), the method assumes that observed random variables $x_1(t)$, $x_2(t)\ldots x_n(t)$, where t is the time, are generated as a linear mixture of independent sources $\boldsymbol{y}$: $\boldsymbol{x}=\mathbf{A}\boldsymbol{y}$, where $\mathbf{A}$ is named the mixing matrix with unknown sources. ICA estimates the ICs as $\hat{\boldsymbol{y}}=\mathbf{A}^{-1}\boldsymbol{x}=\mathbf{W}\boldsymbol{x}$, where the matrix $\mathbf{W}$ is the unmixing matrix [6]. By $\mathbf{W}^{-1}$ interpolated distribution maps of the ICs can be gotten to determine specific areas responsible for specific activity. The columns of $\mathbf{W}^{-1}$, give the relative projection weights and polarities from every one independent component onto each measurement point; these distribution maps indicate the physiological origin of the estimated sources [7].

III. Methodology

A. *Acoustic Signals Acquisition, Preprocessing and Subjects*

Acoustic signals from a healthy subject and patients suffering lung fibrosis and emphysema were acquired by a sensor array of 5 by 5; sensor array and associated nomenclature are described elsewhere [8]. The subjects were seated in a quiet room, breathing through a calibrated Fleisch pneumotachograph and wearing a nose clip. The multichannel sounds and airflow signals were digitalized by a 12 bit A/D card with a sampling frequency of 10 kHz. The acoustic signals were pre-processed by a band pass filter with cutoff frequencies of 75 and 1500 Hz. The healthy subject and the two patients signed an informed consent according to Helsinki guidelines. The patients were exanimate and diagnosed at the National Institute of Respiratory Diseases at Mexico City.

B. *Processing Scheme and Analyzed Cases*

Fig. 1 shows the proposed methodology to obtain the 2D crackles imaging. Independent components are extracted from 25 LS multichannel signals by Infomax. To get a crackle distribution image, the ICs were visually inspected to select only those that are associated to crackles sounds, i.e., the ICs associated to breathing and other sounds were avoided. Afterwards, TVAR modeling of selected ICs is performed; to estimate the number of crackles the procedure uses a criterion to decide the presence of a crackle that is based on the abrupt changes in the derivative of the TVAR time series coefficients $\{a_i(n),\ i=1,\ldots,p\}$. An empirical thresholding was applied to the derivatives as 0.035 times their standard deviation and if an abrupt change was above the threshold in all the TVAR coefficients, the information was considered as produced by a crackle [3]. To obtain the spatial distribution of each crackles' IC, the corresponding columns of $\mathbf{W}^{-1}$ matrix were mapped as 2D images using a color map between red and blue colors. The crackles' counting is added to the map by including the number at the maximum of the column of $\mathbf{W}^{-1}$ matrix. Also, the whole crackles spatial distribution is obtained by the spatial sum of all individual 2D images. To assess the ICA-TVAR scheme a simulated scenario was generated adding fine crackles into normal breathing sounds (NBS) during the inspiratory phase at sensors PRC4, PM4 and PLC3, see Fig. 2(a) and 2(c). The crackles information was propagated, attenuated and delayed to surrounding sensors in an anisotropic way. The number of inserted fine crackles was 10, 10 and 5, respectively. The signal to noise ratio was low enough to mask the crackles into NBS [4]. Regarding patients, a pneumologist performed the classical pulmonary auscultation using a stethoscope at the positions of the acoustic sensor array to have an image pattern to be contrasted with the 2D crackles imaging by ICA-TVAR scheme. The pattern was generated by the pneumologist in a subjective way indicating few, moderate or considerable number of crackles with 1, 2 and 3 filled circles, respectively; the inspiratory phase was represented with a positive slope line, see Fig. 3(a) and (c).

IV. Results and Discussion

A. *Simulated Case*

The results are reported using the sensor array nomenclature of Fig. 2(a) projected on the back of the subject [8]. For simulated crackles in Fig. 2(b) the estimated ICs 12, 15, 17 and 21 are depicted as well as the associated 2D spatial distribution. The estimated number of crackles for each IC was 11, 7, 10 and 15, respectively. It can be observed that the temporal morphology of the ICs 15 and 17 resembles the simulated fine crackles (10 and 5 crackles); the corresponding estimated numbers by the TVAR approach are 10 and 7. Also, it is feasible to observe that the temporal morphology of the IC 21 indicates a mixing of the 5 and 10 crackles information. In Fig. 2(c) it is shown the spatial distribution of the image pattern constructed by the number of simulated crackles while in Fig. 2(d) the sum of all the selected ICs is shown. Figs. 2(c) and 2(d) lead to the conclusion that there is a good agreement between the pattern and the crackles image by ICA using Infomax. Also, the crackles image reveals that the procedure is robust in the sense that it avoids to detect false active regions; in inactive regions the "thoracic surface" is free of crackles as indicated by a blue color in the images of Figs. 2(c) and (d).

B. *Real Cases*

For testing the ICA-TVAR scheme two real cases corresponding to patients suffering fibrosis and emphysema were used. For patient 1, Fig. 3(a) shows filtered LS signals at some of the sensors positions where the ICA-TVAR scheme detected crackles. Independently, the pneumologist found crackles at the right basal region of the lungs, i.e., at acoustic sensors PRC4, PRX4, PRC5 and PRX5, see Fig. 3(e). Also, the clinical auscultation procedure revealed the presence of a wheeze with moan quality that was mainly concentrate at sensors PM4, PRC4 and PRX4. The crackle imaging by the ICA-TVAR scheme applied to the multichannel acoustic information, filtered from 75 to 1500 Hz, is in good agreement with the subjective crackle image suggested by the pneumologist, Fig. 3(f); the advantage of the ICA-TVAR images of selected ICs is the additional information of the estimated number of crackles, see Fig. 3(b) - (d). Fig. 3(f) depicts the spatial distribution and the strength of the crackles been relevant at the lower right basal pulmonary region that resembles the pneumologist findings. It has been demonstrated the pneumologist limitation to hear crackles with low SNR and this fact could explain that ICA-TVAR image shows additional active pulmonary regions in Fig. 3(f). As previously mentioned, the pneumologist also reported the presence of a wheeze that he labeled as a moan, and by ICA it was possible to obtain an IC associated to it that is depicted in Fig 3(g). For patient 2, the pneumologist found crackles at the right and left basal regions of the lungs, i.e., at the left at PLX4, PLX5, PLC4, PLC5, at the middle at PM5, and at the right at PRC4, PRC5, PRX4 and PRX5, see Fig. 4(b). The crackle imaging by the ICA-TVAR scheme reveals the presence of crackles at both basal regions that is in agreement with the perception of the pneumologist, Fig. 4(a).

V. Conclusion

In this work, BSS by ICA and TVAR modeling was combined to obtain a reliable 2D SD of adventitious lung sounds by mapping their strength. The results showed good agreement between the information provided by the pneumologist and the crackle image obtained by the proposed method where the ICs are selected without any cue from the physician. The robustness of the proposed scheme was showed by mathematical simulation that allowed generating a reference image with known crackle number, SD, crackle type as well as SNR [3, 8]. Furthermore, the evaluation of the proposed method included the acoustic information of two patients suffering fibrosis and emphysema. This study has some limitations: first, it is necessary to validate its utility increasing the number of patients in clinical settings; second, the ICs corresponding to crackles information were selected visually from the complete set of ICs provided by Infomax, in a future work an automated method could be proposed for this task. Finally, the results are promising and the crackle imaging scheme may be help identifying pathological lung zones in a more objective and quantitative reliable way as compared to the traditional auscultation procedure.

References

[1] S. Reichert, R. Gass, C. Brandt, E. and Andres, “Analysis of respiratory sounds: state of the art”, Clinical Medicine: Circulatory, Respiratory and Pulmonary Medicine, vol. 2, pp. 45–58, 2008).

[2] J. H. Ryu, C. E. Daniels, T. E. Hartman, and E. S. Yi, “Diagnosis of interstitial lung diseases”, Mayo Clin. Proc., vol. 82, no. 8, pp. 976-86, 2007.

[3] S. Charleston-Villalobos, G. Dorantes-Méndez, R. González-Camarena, G. Chi-Lem, J. G. Carrillo, and T. Aljama-Corrales, “Acoustic thoracic image of crackle sounds using linear and nonlinear processing techniques”, Med. Biol. Eng. Comput., vol. 49, pp. 15-24, 2010.

[4] Castañeda-Villa N., Charleston-Villalobos S., González-Camarena R, and Aljama-Corrales T., “Assessment of ICA Algorithms for the Analysis of Crackles Sounds”, Proc. IEEE-EMBS Int. Conf, pp. 605-608, 2012.

[5] A. Hyvarinen, "New approximations of differential entropy for independent component analysis and projection persuit", Advances in Neural Information Processing Systems, vol. 10, pp. 273-279, 1998.

[6] A. Hyvarinen and E. Oja, "Independent component analysis: algorithms and applications", Neural Netw., vol. 13, no. 4-5, pp. 411-430, May 2000.

[7] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis", J. Neurosci. Methods, vol. 134, no. 1, pp. 9-21, Mar. 2004.

[8] S. Charleston-Villalobos, R. González-Camarena, G. Chi-Lem, and T. Aljama-Corrales, “Crackle sounds analysis by empirical mode decomposition”, IEEE Eng. Med. Biol. Mag., vol. 26, no. 1, pp.40-47, 2007.

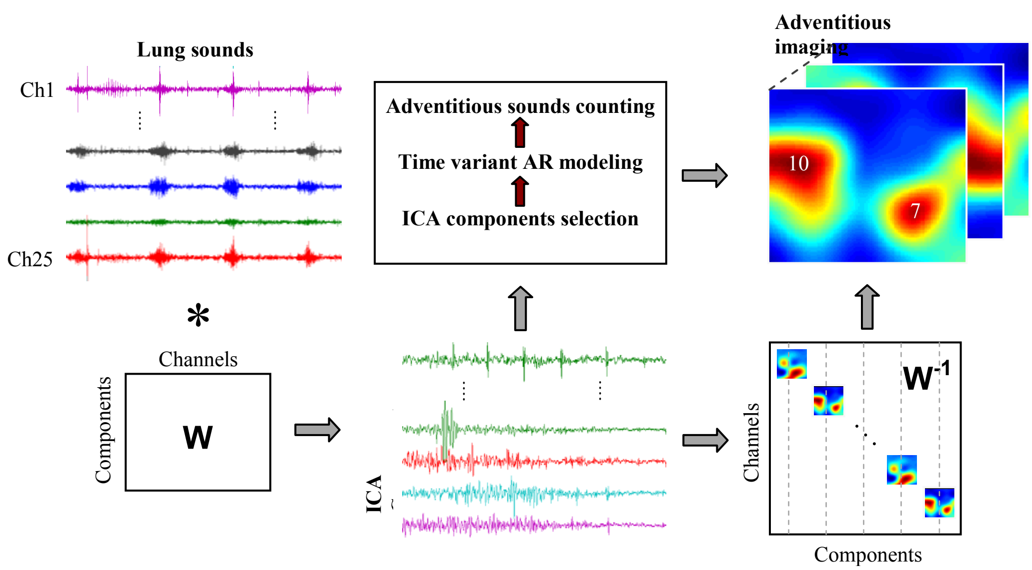

Fig. 1. Proposed methodology for discontinuous lung sound imaging. Twenty five channels of LS are analyzed by Infomax to obtain the corresponding ICs. Columns of $\mathbf{W}^{-1}$ matrix provide the spatial distribution of each IC while the TVAR modeling of visually selected ICs provides the estimated number of crackles. Finally, estimated number of crackles is shown in conjunction with the 2D spatial distribution.

L						R
	PLX1	PLC1	PM1	PRC1	PRX1	
	PLX2	PLC2	PM2	PRC2	PRX2	
	PLX3	PLC3	PM3	PRC3	PRX3	
	PLX4	PLC4	PM4	PRC4	PRX4	
	PLX5	PLC5	PM5	PRC5	PRX5	

(a)

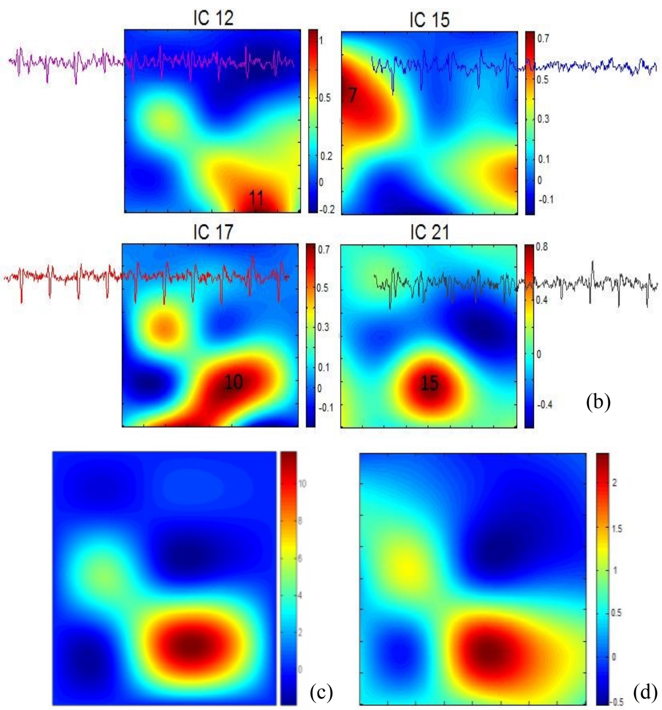

Fig. 2 2D imaging of a simulated case by the ICA-TVAR scheme. (a) sensor array nomenclature, (b) estimated crackles' ICs and their spatial distribution (SD), (c) actual 2D image of simulated crackles with the colorbar indicating number of crackles and (d) estimated image by the spatial sum of the ICs-SD in (b). L and R stand for the left and right side of the back of the subject.

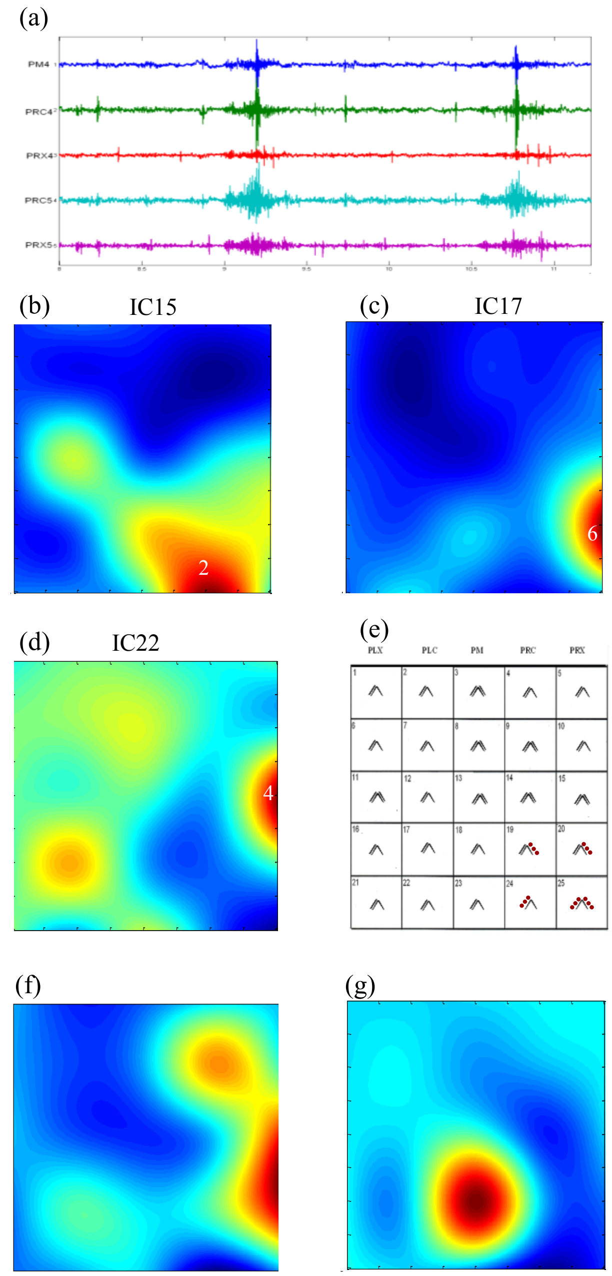

Fig. 3 Crackles imaging for patient 1: (a) filtered LS signals at different sensors; (b)-(d) spatial distribution of selected ICs with crackles counting included; (e) crackles spatial distribution by pneumologist; (f) estimated image by the spatial sum of the ICs-SD; (g) moan spatial distribution.

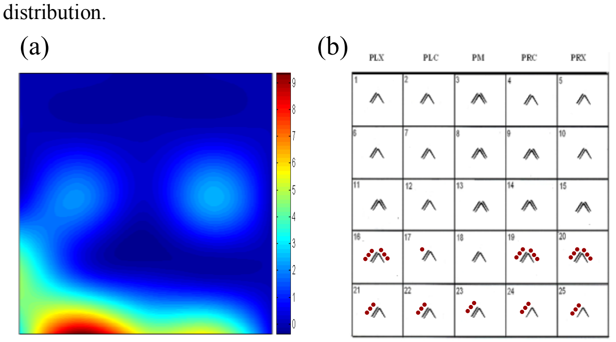

Fig. 4 Crackles imaging for patient 2: (a) crackles spatial distribution from selected ICs; (b) crackles spatial distribution by pneumologist.