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Assessment of multichannel lung sounds parameterization for two-class classification in interstitial lung disease patients

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A B S T R A C T

This work deals with the assessment of different parameterization techniques for lung sounds (LS) acquired on the whole posterior thoracic surface for normal versus abnormal LS classification. Besides the conventional technique of power spectral density (PSD), the eigenvalues of the covariance matrix and both the univariate autoregressive (UAR) and the multivariate autoregressive models (MAR) were applied for constructing feature vectors as input to a supervised neural network (SNN). The results showed the effectiveness of the UAR modeling for multichannel LS parameterization, using new data, with classification accuracy of 75% and 93% for healthy subjects and patients, respectively.

1. Introduction

It is recognized that respiratory sounds comprise relevant diagnostic information for pulmonary diseases [1] and therefore, the diagnostic utility of clinical pulmonary auscultation with the acoustical stethoscope is not questionable. However, it is also recognized that pulmonary auscultation shows limitations as it depends on the experience and the hearing capacity of the physician [2] and the limited frequency response of the stethoscope [3]. In an effort to go beyond the subjective nature of clinical auscultation [4], the computerized analysis of respiratory sounds has been pursued for some time to provide a quantitative and reproducible analysis [5]. As a result, the electronic auscultation has evolved from the use of a single microphone to acoustic sensor array for multichannel respiratory sounds acquisition. The multichannel signal strategy has provided a widespread sight of the thoracic respiratory acoustic with the possibility to visualize the distribution of lung sounds (LS) as acoustic images in both temporal and spectral domains [6,7]. However, multichannel acquisition systems impose new challenges for processing and interpreting the embedded information as searching for suitable parametric representation to achieve confident automated diagnosis.

Regarding the detection of normal or abnormal respiratory sounds associated with anatomical and functional conditions of the lungs, clinicians and researchers have identified lung sounds (LS) as those respiratory sounds particularly heard on the thoracic surface [8]. Hence, LS could comprise at least two sorts of sounds, the breathing sounds related to the normal ventilatory process and the adventitious sounds usually linked to abnormal mechanisms of the pulmonary ventilation [8]. Robertson and Coope [9] proposed to classify the adventitious sounds as continuous (lasting at least 80 ms, e.g. wheezing and ronchi sounds) and discontinuous (lasting less than 20 ms, e.g. crackle sounds), all of them clinically related to different pulmonary diseases [10].

In particular, crackle sounds are short, explosive and transient adventitious LS associated with either the explosion of gas bubbles in pulmonary secretions [11] or sudden opening of abnormally closed airways [12]. Furthermore, it is thought that crackle sounds are just added to the normal breathing sounds [13]. Crackles are heard and recorded during pulmonary auscultation in subjects with cardio-respiratory pathologies such as congestive heart failure, pneumonia, brochiectasis, chronic obstructive pulmonary disease (COPD) and interstitial lung diseases (ILDs) [14,15].

ILDs are a broad heterogeneous group of about 200 of parenchymal lung diseases [16] that comprise idiopathic pulmonary fibrosis and extrinsic allergic alveolitis as the most prevalent categories in our population [17]. After some time of lung exposure to an etiologic agent, the pulmonary parenchyma

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initiates an inflammatory process, which commonly is followed by pulmonary fibrosis at the interstitial level. Usually these pathologic conditions are dispersed irregularly within the lung and they lead to an altered structure and function, characterized by a thickened interstitium of the alveolar wall, reduced lung distensibility, a spirometric restrictive pattern and a decreased oxygen exchange. As a result of these changes, the patients show clinical features that include the generation of crackle sounds in some regions of the lung [18,19]. Most of the time, in patients with pulmonary fibrosis crackle sounds appear at the end of the inspiratory phase and they likely to occur first at the basal pulmonary regions and, as the disease progresses, crackle sounds could be heard at the apical regions [20]; thus, the number, type, timing and distribution of crackles per respiratory cycle have been associated with the severity of the ILD [13].

For the diagnosis of ILDs, clinical, radiological, histopathological and functional findings could establish a definite diagnosis of the disease. Here, we hypothesize that noninvasive methodologies based on multichannel LS acquisition and digital processing techniques would provide helpful information for a confident automated detection of acoustic abnormality in some parenchymal lung diseases.

The aim of the present work is the assessment of different schemes for parametric representation of LS information to classify them as normal or abnormal sounds; the performance analysis was based on the schemes' ability to process multichannel LS information acquired at the whole posterior thoracic surface.

The paper is organized as follows. In Section 2, we review some of the more relevant efforts on LS parameterization–classification task. In Section 3, the parametric representation techniques assessed in this work are presented. The multichannel acquisition protocol, the proposed steps for constructing feature vectors and the classification procedure are described in Section 4. Afterwards, in Section 5 the main outcomes are established and the final section presents the conclusion of this paper.

2. Background and problem statement

Regarding the efforts to automatically recognize acoustic abnormal lung states, two strategies have been tried: (1) crackle sounds analysis by detecting, counting and classifying fine and coarse crackles [21], and (2) LS analysis (i.e., breathing and crackle sounds) by determining abnormality conditions using diverse parametric representations and classifiers [22–25]. Diverse studies have been done following the second strategy, but some specific methodological characteristics need to be pointed out. First, just one or a small number of microphones has been used and located at anatomical positions where physicians detect by ear evidence of acoustic abnormality [22]; second, commercial recordings of abnormal LS used for medical teaching and training were processed for classification purposes [23]; third, the univariate autoregressive (UAR) model has been used as the parametric representation of the acoustical information to be classified [24]; and fourth, the supervised neural networks (SNN) is the most used classifier [25].

This work follows the second strategy and deals with LS parameterization and classification associated with ILDs, avoiding separating crackles from breathing sounds and assuming that crackles and their number indicate the severity of the disease, and also that breathing sound features are affected by the disease. In this sense, the whole information within the inspiratory phase of the acquired multichannel lung sounds is taken into account. The mathematical model for the acquired multichannel signal assumes

$$\mathbf{x}_{LS}[n]=\mathbf{b}[n]+\mathbf{c}[n]+\boldsymbol{\eta}[n], \tag{1}$$

where $\mathbf{b}[n]$ denotes the vector for multichannel basic breathing sounds, $\mathbf{c}[n]$ is the vector for possible crackles sounds and $\boldsymbol{\eta}[n]$ is the vector associated to interference signals at time n.

Since UAR modeling has been used to build the respiratory feature vector, in this work it is used in a multichannel framework to evaluate the feature extraction task. Furthermore, for multichannel analysis of LS constructing the feature vector is a relevant task as well as its dimensionality. Consequently, this work includes the dimensionality reduction of the feature space. For this research, the selection of the appropriate feature vector for multichannel LS parameterization plays a major role rather than the choice of a classifier; therefore, for all the parameterization schemes a SNN was used to obtain the final LS classification.

3. Feature extraction techniques and neural networks

As feature extraction techniques the percentile frequencies and the UAR model have been applied to LS considering that breathing and crackles sounds are nonstationary signals [26]. The first technique has represented the classical way for LS feature extraction [14,27,28], while the UAR model has been proposed as an alternative for LS modeling and it has provided promising results for classification purposes [24,32]. Here, two additional multichannel approaches for LS parameterization are proposed for constructing the feature vector as an input to the classifier; first, the eigenvalues of the covariance matrix, and second, to take into account possible acoustical interchannel information, the multivariate AR model.

3.1. Classical percentile frequencies

The power spectral density (PSD) of the LS time series can be estimated using UAR modeling with the benefit of a more reliable PSD morphology due to its adequate frequency resolution. The estimate of the PSD, $\hat{S}(e^{j\omega})$, is obtained by

$$\hat{S}(e^{j\omega})=\frac{\sigma_v^2}{\left|1+\Sigma_{k=1}^{p}a_k e^{-j\omega k}\right|^2}, \tag{2}$$

where the UAR model coefficients a_k, $k=1,\ldots,p$, and its order, denoted by p, are determined by the Burg's method and the Akaike information criterion, respectively. The parameter σ_v^2, in Eq. (2), stands for the variance of the white noise sequence included in an autoregressive model. Afterwards, the feature vector for the acoustic information is constructed by the percentile frequencies obtained as the frequencies corresponding to some percentages of the total area under $\hat{S}(e^{j\omega})$.

3.2. Univariate AR modeling

Any second-order stationary process can be represented as the output of a linear shift-invariant all-pole filter, excited by white noise [29]. The UAR model is defined as follows:

$$x[n]=-a_1x[n-1]-a_2x[n-2]-\cdots-a_px[n-p]+v[n], \tag{3}$$

where $x[n]$, the current sample of the stationary LS time series, is modeled by a linear combination of its p previous samples plus a white noise time series $v[n]$, which is not correlated with $x[n]$. To estimate the UAR model's coefficients, $a_1,\ldots,a_p$, it is necessary to determine the order p. The Akaike information criterion defined as $AIC(p)=N\ln(\sigma_v^2)+2p$ provides a mechanism to estimate the order, where N is the number of samples and σ_v^2 is the variance of the white noise time series.