Digital Signal Processing 28 (2014) 18–27

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Classification and analysis of non-stationary characteristics of crackle and rhonchus lung adventitious sounds

Semra İçer *, Şerife Gengeç

Erciyes University, Engineering Faculty, Biomedical Engineering Dept., Talas, Kayseri, Turkey

ARTICLE INFO

Article history:
Available online 14 February 2014

Keywords:
Lung sounds
Feature extraction
Instantaneous frequency
Eigenvalues
Support vector machines

ABSTRACT

This paper proposed various feature extraction procedures to separate crackles and rhonchi of pathological lung sounds from normal lung sounds. The feature extraction process for distinguishing crackles and rhonchus from normal sounds comprises three signal-processing modules with the following functions: (1) $f_{\min}/f_{\max}$ was the frequency ratio from the conventional technique of power spectral density (PSD) based on the Welch method. (2) The average instantaneous frequency (IF) and the exchange time of the instantaneous frequency were calculated by the Hilbert Huang transform (HHT). (3) The eigenvalues were obtained from the singular spectrum analysis (SSA) method. In the classification process, a support vector machine (SVM) was used to distinguish the crackles, rhonchus and normal lung sounds. The results showed that the selected features positively represented the characteristic changes in sounds. The PSD frequency ratio and the eigenvalues demonstrate higher classification accuracy (between 90% and 100%) than the calculations of average and exchange time of IF. The calculated features are extremely promising for the evaluation and classification of other biomedical signals as well as other lung sounds.

1. Introduction

Auscultation is used for preliminary diagnostic and assessment of pulmonary and cardiovascular diseases. This method can be better performed through the use of an electronic stethoscope, which has been increasingly used in recent years. Follow-up examinations with an electronic stethoscope, which can measure changes in the acoustic properties on pulmonary diseases, not only provide an efficient and non-invasive method for clinical diagnosis but can be a useful tool in the computational analysis of lung sounds [1].

Generally, lung sounds that are heard with auscultation are divided into two categories: Normal breathing sounds that are heard when no respiratory disorders exist and adventitious sounds that are heard when a respiratory disorder exists [2,3]. Adventitious lung sounds can be classified as either discontinuous, which are fine and coarse crackles, or continuous, which are wheezes and rhonchus sounds. Crackles are caused by the explosive opening of small airways which were abnormally closed. Crackles are often heard in patients with pneumonia, atelectasis, bronchiectasis and pulmonary fibrosis. They are short, explosive, non-musical sounds that are evaluated according to pitch, duration, number and timing. Additionally, the frequency spectrum of crackles is between 200 Hz and 2000 Hz [4,5]. Rhonchus is caused by the interaction of air in the airway and the bronchial wall. These high-amplitude sounds produce severe airway obstruction by causing the bronchial walls to almost touch each other. According to the literature; rhonchi have a variable frequency range [6]. The two adventitious sounds that are most commonly associated with many respiratory disorders are rhonchus and crackles [2]. The preliminary data related to chronic obstructive pulmonary disease (COPD) of this study were presented at a national congress [7]. With the aid of developing computer technology and data processing methods, researchers have sought to parameterize pulmonary sounds with the aim of making auscultation a more objective and valuable diagnostic tool [8,9].

Investigation of lung sounds has been an exciting study area for many years. The research areas on pulmonary sound are numerous and diverse in literature. The papers on this subject in recent studies can be roughly examined under three groups. First, there are hardware-weighted studies that aim to establish a database for recording and processing lung sounds [10–13]. Second, there are studies that seek to filter the lung sounds from heart sounds and differentiate between various lung sounds (especially regarding the detection of crackles) [14–16]. In the last group, there are studies that analyze the time and frequency components of lung sounds, according to changes in various disease states [17–22].

* Corresponding author. Fax: +90 352 4375784.
E-mail address: ksemra@erciyes.edu.tr (S. İçer).

http://dx.doi.org/10.1016/j.dsp.2014.02.001
1051-2004/

A multivariate autoregressive model was used for feature extraction and classification of normal and abnormal lung sounds belonging to interstitial pneumonia patients. A supervised neural network was performed to obtain a correct percentage of 86% [10]. A wavelet transform was applied to lung sounds from a total of 100 individuals that included patients with asthma, pneumonia, bronchitis as well as healthy individuals. Classifications of lung sounds belonging to different groups were obtained with an average accuracy of 85% for DB5 wavelets and 88% for Sym8 wavelets using artificial neural networks [11]. The Hilbert transform was used to examine lung sounds with multi-channel sensors from 4 healthy women and 4 women that had diffuse interstitial lung disease [12]. A system was designed to evaluate the findings of auscultation more effectively. This system allowed the recording of lung sounds, playback of the recorded sounds, and display of the waveform on a monitor and archiving of the recorded sounds. The accuracy of correctly identifying the lung sounds were determined to be $26.0 \pm 14.5\%$ and $67.3 \pm 21.2\%$ with and without the system, respectively [13].

A recurrent neural filter was used for separating nonstationary adventitious lung sounds such as fine crackles, coarse crackles and squawks from vesicular sounds. The average rates of detectability were 93.90%, 98.18% and 100% for the fine crackles, the coarse crackles and the squawks, respectively [14]. The relationship between lung sound and air flow was investigated using signals from 5 healthy adults in the first group, 10 healthy children in the second group and 7 asthmatic children in the third group. The average amplitude and average air flow of the lung sounds were calculated for each segment [15]. Identification of the characteristics of crackle sounds that are non-permanent and riding up on normal vesicular sounds has been studied. At high frequencies, the parameter sensitivity of coarse crackles is higher than fine crackles [16].

A regional examination was performed with a multi-channel recording of lung sounds from 14 different lung regions on the chest wall and the trachea. The feature vectors were obtained as a time-amplitude waveform, and a multi-layer perception neural network was used for classification [17]. The time–frequency representation with HHT has been proposed as an appropriate analysis for fine and coarse crackles [18].

HHT was applied to the lung sounds for separating fine and coarse crackles, which are classified as discontinuous adventitious lung sounds. High accurate classification was obtained through this method. However, if two crackles occur successively, the method will fail to separate them due to the insignificant change in the phase [19]. Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT) techniques were aimed at obtaining the characteristics of pneumonia and wheezing sounds. The frequency range of pneumonia was determined to be between 300 and 600 Hz [20]. Classification of wheeze and non-wheeze signals was performed using features of Renyi entropy and mean-crossing. Wheeze and non-wheeze signals were successfully separated into two classes using the Fisher discriminant analysis [21]. The detection of the location of heart sounds was obtained by applying SSA, continuous wavelet transform (CWT) and entropy techniques (ENT) to synthetic and real respiratory and heart sound signals. Localization errors, correlation, false negative and positive detection rates according to these three techniques were compared. The average percentage of errors in detecting the components are similar for SSA and ENT, and the localization error of CWT is lower; SSA provides lower false negative values [22].

In clinical diagnosis, a quality auscultation is very effective in early detection of lung diseases. To distinguish from normal sounds to the crackle and rhonchi that pathological sounds heard according to the characteristics of lung disease is the most important prediagnostic process for the diagnosis of lung diseases. In addition to the studies in the literature, we aimed to classification and feature extraction using three different signal processing methods to characterize crackle and rhonchi lung sounds by quality auscultation with an electronic stethoscope. We could not find papers that used in together with the obtained features applying the traditional and non-stationary signal processing methods to lung sounds.

In this study, feature extraction and classification were performed to categorize the lung sounds into one of three categories: normal, rhonchus or crackles. The following three methods were used for feature extraction: First, power spectral density graphics of lung sounds were obtained using the Welch method based on the concept of using modified periodogram. Later, $f_{\max}$ and $f_{\min}$ frequencies were calculated from PSDs.

Second, the HHT has become more popular as a time frequency method for analyzing nonlinear and nonstationary signals. When compared with traditional methods of data processing, the main innovation of HHT is in the introduction of the empirical mode decomposition (EMD) method to filter the signal and the proposal of the intrinsic mode function (IMF) concept. HHT techniques have been applied to various fields in literature [23]. In the present study, the instantaneous frequencies of the lung sound signals were analyzed using the HHT. The mean value (IF_{mean}) and rate of change, according to the time of the normalized instantaneous frequency (ET_{IF}), for all normal, crackles and rhonchus subjects were calculated.

In recent years, SSA, a powerful technique in time series analysis has been developed and applied to many practical problems [24]. The purpose of this method is to unfold a time series into a trajectory matrix whose singular values are then determined to reconstruct a smoother time series that can be used for explaining structure and for forecasting [25]. In this study, the eigenvalues of the lung sounds were found using the SSA method. Finally, the crackles and rhonchus were classified from normal lung sounds by using SVM and the features obtained by these methods. Determining the features of crackles and rhonchus sounds is crucial for the diagnosis of lung diseases.

2. Methodology

2.1. Materials and preprocessing

In this study, the lung sounds from 20 normal and 40 patients who were receiving treatment in the Department of Pulmonary Diseases in the Erciyes University Medical Faculty were obtained with an electronic stethoscope. Crackles and rhonchus were heard and recorded during pulmonary auscultation in subjects with respiratory pathologies such as COPD, asthma, pulmonary fibrosis, pneumonia, tuberculosis, interstitial pulmonary disease, bronchitis, bronchiectasis, lung cancer and lung fungus. Fig. 1 represents a typical lung sounds acquisition system and includes two blocks: feature extraction and classification. The recording sites for the electronic stethoscope, as depicted in Fig. 1 were fixed and identical for all subjects, were determined according to the recommendation of a physician specialized in pulmonary medicine. The signals were recorded from six lung zones on the back of patients, which included the right- and left-upper, right- and left-middle, right- and left-bottom. Informed consent was taken from each subject prior to recording. Lung sounds were recorded with a 44 100 kHz sampling frequency; the recording time was automatically set for 11 s, or longer if desired. The signals, which were recorded by a WelchAllyn electronic stethoscope, were digitized using the Meditron Analyzer program. We used all the signals without splitting for the feature extraction methods. The division of the signals can lead to escape pathologies in crackle and rhonchus. We purposed to feature extraction from automatically recorded original signals. The acquired raw signals were digitally