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Feature extraction for pulmonary crackle representation via wavelet networks

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ABSTRACT

In this study, wavelet networks have been used to parameterize and quantify pulmonary crackles with an aim to depict the waveform with a small set of meaningful parameters. Complex Morlet wavelets are used at the nodes of both single and double-node networks to model the waveforms with the double-node rendering smaller modeling error. The features extracted from the model parameters have been compared with the conventional time domain features in a two-class clustering experiment with nearly 90% matching between the clusters of different parameter sets and with the model parameters forming clusters more closely distributed around their means and better separated from each other. Moreover, using simulated crackles embedded on real respiratory sounds, features extracted from wavelet networks have been shown to be more robust to background vesicular sounds compared to conventional parameters which are very sensitive to noise.

1. Introduction

Pulmonary crackles are discontinuous adventitious lung sounds that occur in pathological conditions and are superimposed on vesicular sounds. Crackles are explosive and transient in character and are considered useful diagnostic indicators in cardio-respiratory diseases [1–7]. In conventional auscultation with a stethoscope, their timing within a respiratory cycle, their regional distribution over the thorax, their number and pitch are acoustic findings that aid the physician in a preliminary assessment of the disease [8–15]. However due to its inherent subjectivity, auscultation is regarded to be of low diagnostic value and its findings are further verified by other tests.

With the advent of computer technology and data processing methods, researchers have tried to parameterize pulmonary sounds with an aim to make auscultation a more objective and valuable diagnostic tool. One area of pulmonary sound research has been in quantitative measurement, in addition to detection, of crackles. One example of a clinical study where computerized analysis of crackles has been applied can be seen in [16] where pneumonia was diagnosed using automated quantification and characterization of crackles. Criteria for a crackle waveform have been suggested by Murphy et al. [17] as being a transient containing 3–16 baseline crossings with the amplitude of its largest peak greater than twice the amplitude of the background vesicular sound. The waveform is expected to have sharp onset deflection which is followed by deflections of progressively wider baseline crossings. To quantify crackles, several parameters have been suggested, those suggested by two groups being more popular. Murphy et al. [17] have used the initial deflection width (IDW) which is the duration of the first deflection of the crackle and the two-cycle duration (2CD) which is the duration of the first two cycles of the crackle. In the study of Hoevers and Loudon [18], on the other hand, four parameters have been used to characterize crackles, namely, largest deflection width (LDW_1) which is the duration of the largest deflection of the crackle and the widths, namely durations, of its first three right and left neighbor deflections (LDW_{2-4}). The parameters associated with quantization of crackles are exclusively time domain parameters based on zero-crossings of the waveform. These parameters do not bear information on the morphology of the waveform and suffer from background noise. The Murphy parameter set, namely, IDW and 2CD, and Hoevers and Loudon parameter set, namely, LDW_1, LDW_2, LDW_3, and LDW_4, are depicted in Fig. 1 [19].

In this study, the aim is to automatically depict the crackle waveform with only a small set of meaningful parameter values as is necessary for typical discrimination tasks and to this end, wavelet networks (WNs) have been employed. WNs can be used as signal modeling tools and are based on a specific network structure where the nodes are described by wavelet functions [20–25]. They are especially useful in representing nonstationary, time-varying signals. Wavelet functions have been utilized in the studies related to pulmonary crackles, particularly in detecting these nonstationary

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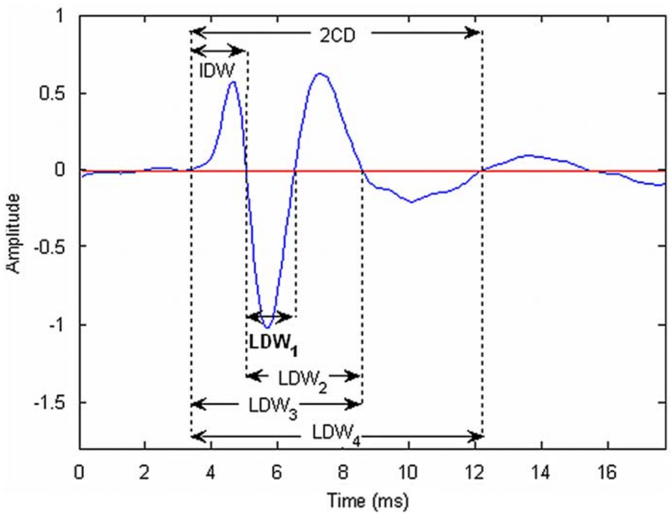

Fig. 1. Two conventional parameter sets of crackle waveform [18].

signals within the background of vesicular sounds [26–31]. In this study, however, wavelet functions, namely complex Morlet (cM) wavelet, are used at the nodes of a network to model the crackle and thus obtain parameters from that model that are relevant to the pulmonary sound research. Single- and double-node networks have been employed on a dataset of pulmonary crackles from a wide range of frequency spectrum with the double-node modeling rendering smaller modeling error. The model used has five parameters per node to represent the morphology of the crackle waveform. The features extracted from the parameters obtained from the WN have been used along with the traditional parameters in a two-class clustering experiment with a view to compare the correspondence between diverse crackle parameter sets and crackle types. Moreover, a sensitivity analysis of both conventional and WN model parameters to background noise have been realized on simulated crackles with predetermined parameters to test the robustness of these parameters in the presence of vesicular sounds.

2. Methodology

2.1. Materials and preprocessing

Pulmonary sounds and airflow were recorded synchronously using 14 air-coupled electret microphones [SONY ECM44-BPT] placed on the posterior chest and a pneumotachograph (Validyne CD379), respectively. The recording sites, as depicted in Fig. 2 [32], for the microphones which were fixed and identical for all subjects were determined according to the recommendations of a physician specialized in pulmonary medicine. The pulmonary sounds were preprocessed with low-noise pre-amplifiers, sixth order Bessel high-pass filters with 80 Hz cut-off frequency and eighth order Butterworth low-pass filters with 4 kHz cut-off frequency in order to minimize heart sound interference and frictional noise with minimal phase distortion and to prevent aliasing. The preprocessed signals were digitized at 9.6 kHz sampling rate with 12-bit resolution using an ADC card (NI-DAQ Card-6024E) and stored by means of a laptop computer. The data acquisition system is described in detail in the study of Sen and Kahya [32]. The crackle database used in this study is constructed from pulmonary sounds recorded from thirteen patients who suffered from restrictive and/or obstructive respiratory disorders. Informed consent was taken from the subjects before recordings. 2711 crackles were visually detected from the time-expanded pulmonary sound arrays by two independent researchers who are familiar with pulmonary sounds. Although the number of patients

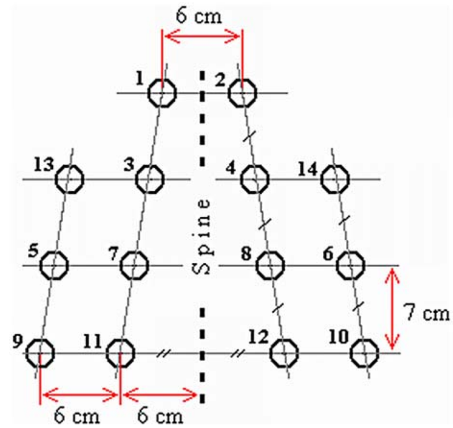

Fig. 2. The recording sites for the microphones placed on the posterior chest [32].

is thirteen, the types of disease differ and the mean frequencies of the crackles cover a wide frequency range as defined in [7].

Vesicular sounds on which crackles are superimposed distort the crackle waveforms; therefore, the elimination of the background sounds is crucial in faithful parameterization of the crackle waveform. In a previous study carried out in our laboratory, a vesicular sound elimination algorithm has been developed with a view to introduce minimum distortion to crackle parameters, the details of which are described in [19]. In summary, a region of interest with respect to a crackle is specified and a distortion metric based on the correlation between filtered and unfiltered waveforms is defined. For each crackle, an individual filter cut-off frequency based on that metric is estimated. For online applications, a regression analysis between the cumulative power spectrum of the crackle and the estimated cut-off frequency is carried out to predict an optimal cut-off frequency which results in minimum distortion of the waveform along with reduced computational cost. This algorithm to eliminate background signal which has been tested on simulated crackles embedded on different phases of real vesicular sounds with very successful results, is applied on crackles prior to the modeling analysis.

The modeling analysis is made in the MATLAB® v7.4 programming environment using a PC with 3 GHz Pentium® D CPU and 2 GB RAM.

2.2. Wavelet network modeling

A WN used for modeling has a neural network structure that performs wavelet functions as transfer functions in their hidden nodes instead of sigmoid functions that are employed in conventional multi-layer perceptrons (MLP). A wavelet, by definition, has a finite energy that is concentrated in a time interval [33]. Therefore, fewer nodes are used in the interpretation of transient signals with WN as compared to MLP, in a similar manner of radial basis functions that use Gaussian functions as transfer functions. Moreover, the wavelet function can be selected according to the characteristics of target signals to reduce the number of nodes in signal interpretation. In our application, the cM wavelet function is employed to model the pulmonary crackles due to both the similarities between the waveforms of the crackles and the cM function and the flexibility of the cM function in the modeling process. The cM function ($h(t)$) is defined as

$$h(t) = \exp(-t^2/2 + j\omega_0 t) \qquad (1)$$

where ω_0 is a constant of modulating frequency that equals to 5.33. To improve the estimation of the target signal with smaller number of nodes, the modulating frequency (ω) is not employed as a constant but rather as a variable in this study.