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LETTER

Wheeze Detection Algorithm Based on Correlation-Coefficients Analysis

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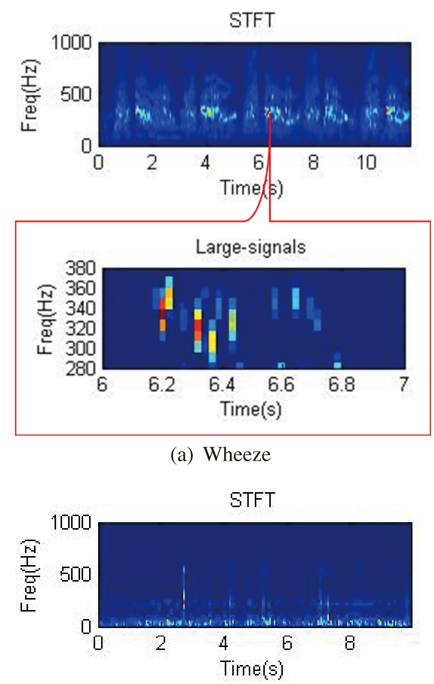
SUMMARY Wheeze is a general sign for obstructive airway diseases whose clinical diagnosis mainly depends on auscultating or X-ray imaging with subjectivity or harm. Therefore, this paper introduces an automatic, noninvasive method to detect wheeze which consists of STFT decomposition, preprocessing of the spectrogram, correlation-coefficients calculating and duration determining. In particular, duration determining takes the Haas effect into account, which facilitates us to achieve a better determination. Simulation result shows that the sensibility (SE), the specificity (SP) and the accuracy (AC) are 88.57%, 97.78% and 93.75%, respectively, which indicates that this method could be an efficient way to detect wheeze.

key words: *wheeze, large-signals, correlation-coefficients, Haas effect*

1. Introduction

Wheeze, as a type of abnormal lung sounds, is observed in patients with pulmonary diseases such as chronic obstructive pulmonary disease (COPD) or asthma. It shows a continuous sinusoidal characteristic in time domain and a significant feature of texture in spectrogram. As Ref. [1] notes, wheeze usually lasts more than 150 ms. Currently, auscultating and X-ray imaging are popular, fast methods to diagnose pulmonary diseases related with wheeze. However, both the methods are subjective and depend on the physician's experience. In addition, X-ray imaging is harmful to patients. Therefore, it is of significance to design an objective, noninvasive and efficient wheeze detection method.

As shown in Fig. 1, there are unique streak patterns in the short-time Fourier transform (STFT) spectrogram of wheeze which don't appear in that of normal lung sound. Now, some wheeze detection methods are based on analyzing the feature of time-frequency spectrograms, such as the energy [2], the power entropy [3], the tonal index [4], [5], the correlation-coefficients (CCs), etc. Nonetheless, most detection methods are with large computational complexity, or the accuracy still needs to be improved. For instance, the researchers from Nanyang Technological University (NTU) achieved a detection rate of 85% at 6dB SNR by using the method based on entropy [3], and Yu [6] proposed a method depending on correlation-coefficients (CCs) analysis whose sensibility (SE) and specificity (SP) reached 88% and 94%, respectively.



(a) Wheeze

(b) Normal lung sound

Fig. 1 Comparison of STFT spectrograms.

The objective of this study is to develop an improved wheeze detection method. First, large-signals are detected after STFT decomposition. Here, large-signals are defined as the amplitude spectrum signals whose values are greater than the empirical threshold. Then, CCs of large-signals are calculated and a procedure to determine the value and the duration of CCs is proceeded. Only when the high CCs, defined as the spectrogram correlation-coefficients whose values are greater than the empirical CCs threshold, last more than wheeze duration, can they be remained. Otherwise they will be set to zero. Different from Ref. [6], the determining of duration considers Haas effect, which is conducive to the accuracy. At last, the non-zero CCs stand for the appearing of wheeze. Simulation result proves that the sensibility (SE), specificity (SP) and accuracy (AC) are 88.57%, 97.78% and 93.75%, respectively.

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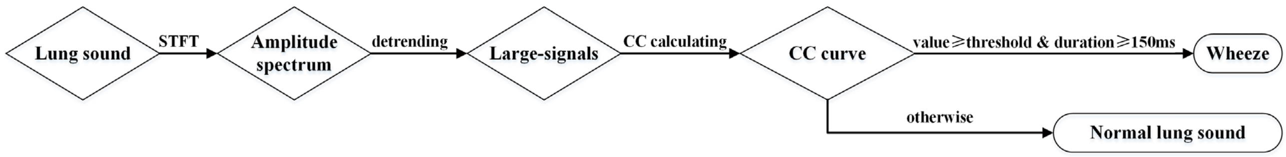


Fig. 2 The steps in block diagram of the algorithm.

2. Materials and Methods

2.1 Research Dataset

There are several databases of lung sounds used by previous researchers, such as Marburg Respiratory Sounds (MARS) [7], European project CORSA [8], etc. Unfortunately, both of them are not publicly available. The dataset in our research includes two parts: wheeze dataset (70 groups) and normal lung sound dataset (90 groups). Wheeze dataset consists of abnormal lung sounds from the American Thoracic Society (ATS), the COPD website and some other lung sound websites. Normal lung sounds gathered from healthy persons via 3M 3200 electronic stethoscope. Most of the sounds last 10 seconds, contain 3 breathing cycles approximately and the sampling frequencies are 11025 HZ, 8000 HZ, 12000 HZ, 8012 HZ and 4000 HZ.

2.2 The Proposed Method

A block diagram of the proposed method is depicted in Fig. 2. To be more specific, it is realized by the following steps:

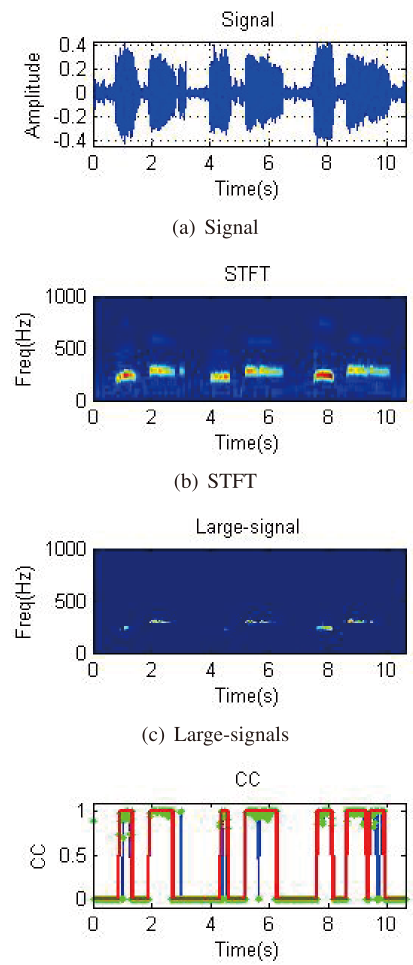
2.2.1 Decomposition by STFT

Spectrogram, a graphical representation of the way a signal's frequency contents evolving over time, is achieved by using the STFT decomposition, as defined in Eq. (1). In Eq. (1), x[n] is the signal in time domain, and w[n] denotes the window function.

$$X(m,k) = \sum_{n=-\infty}^{+\infty} x[n]w^*[n-m]e^{-j2\pi nk/N} \tag{1}$$

2.2.2 Preprocessing of Spectrogram [9]

A smoothing procedure is used first at each time instance to estimate the trend which is the basic lung sound of the spectrogram. Then detrending of the spectrogram is calculated by subtracting the trend from the original lung sound. After that, in view of the characteristic of wheezes, large-signals detecting is implemented in four respective frequency bands: B-1: 100–300 HZ, B-2: 300–500 HZ, B-3: 500–800 HZ, B-4: 800–1000 HZ. Large-signals are defined as the amplitude spectrum signals whose values are greater than the empirical threshold, as given in Eq. (2), where A_{B-k} are constants set empirically (A_{B-1}=3, A_{B-2}=3, A_{B-3}=2 and A_{B-1}=2).



(a) Signal

(b) STFT

(c) Large-signals

(d) Simulation result

Fig. 3 An detecting example of wheeze.

$$Threshold = Mean\ Value\ +\ A_{B-k} * Standard\ Deviation \tag{2}$$

2.2.3 CCs Calculating and Wheeze Detecting

There are unique stripe patterns in STFT spectrogram of wheeze which do not appear in that of normal lung sound. Therefore, wheeze provides higher CCs than normal lung sound [6]. Moreover, these high CCs will be consecutive on account of the characteristic of wheeze continuity.

Thus, the CCs of large-signals are utilized to determine the lung sound. It calculates the CCs of large-signals and then determines the duration of high CCs which are greater than the CCs threshold. If these high CCs last more than the wheeze duration (150 ms), this segment of lung sound, which the high CCs correspond to, will be judged as wheeze, as depicted in Fig. 3. The CCs threshold is empirically set to 0.9.

Particularly, better than the past method, the determining of duration is based on Haas effect, taking into account that there are some CCs less than the threshold (Fig. 4(c)) which gives rise to the discontinuity of high CCs and then causes error in wheeze detection, as the arrowhead indicated in Fig. 4(c). The Haas effect is a psychoacoustic effect which is often equated with the underlying precedence effect. The precedence effect appears if the subsequent wave fronts arrive between 2 ms and about 50 ms later than the first wave front. However, this range is signal dependent. For speech the precedence effect disappears for delays above 50 ms, but for music the precedence effect can also appear for delays of some 100 ms [10]. Hence, according to Haas effect, if the time interval between two high CCs is less than the threshold of Haas effect, these two CCs are considered continuous. It is clear from the comparison between Fig. 4(c) and 4(d) that the marking of wheeze is much more accurate with considering Haas effect. The threshold value is set 100 ms in this paper.

3. Results

3.1 Simulation Results

Figure 5 shows the simulation results of the wheeze case and normal lung sound case by using the introduced method. In particular, a red curve is obtained by replacing the continuous high CCs and the others with ones and zeros respectively, where ones indicate the occurrence of wheeze, as shown in Fig. 5(e) and 5(f). In addition, it could be observed that CCs of wheeze are larger and last for a longer time.

There are three common parameters used to estimate the accuracy of wheeze detection method named sensitivity (SE), specificity (SP) and accuracy (AC), which are calculated as Eq. (3) to (5), respectively [4], [9], [11]:

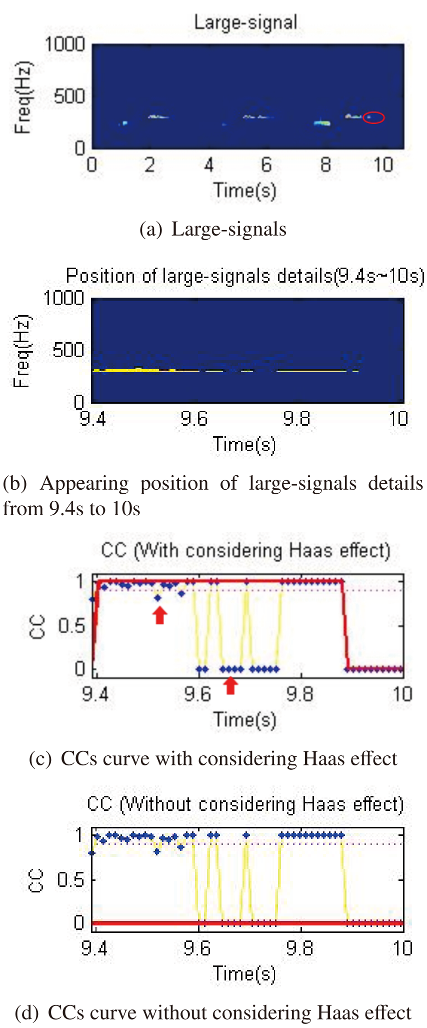
$$SE = \frac{TP}{TP + FN} \tag{3}$$

$$SP = \frac{TN}{TN + FP} \tag{4}$$

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

TP, TN, FP and FN are, respectively, the number of true positive, true negative, false positive and false negative detected results.

The accuracy of the algorithm introduced in this paper is shown in Table 1.



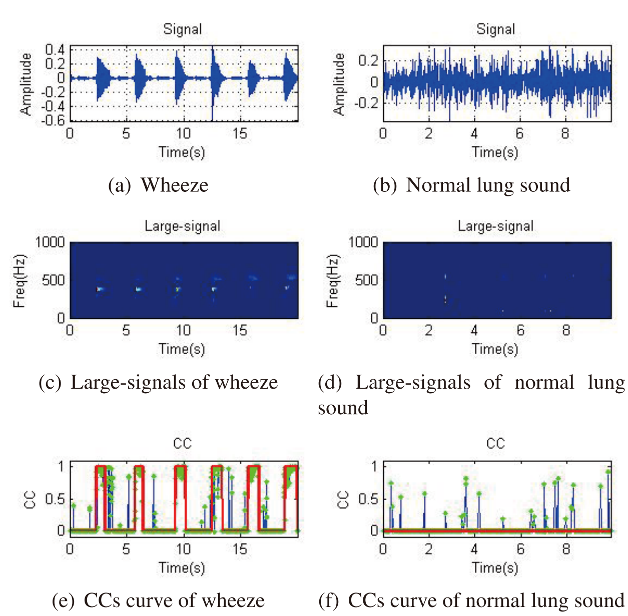
(a) Large-signals

(b) Appearing position of large-signals details from 9.4s to 10s

(c) CCs curve with considering Haas effect

(d) CCs curve without considering Haas effect

Fig. 4 Influence of considering Haas effect.



(a) Wheeze

(b) Normal lung sound

(c) Large-signals of wheeze

(d) Large-signals of normal lung sound

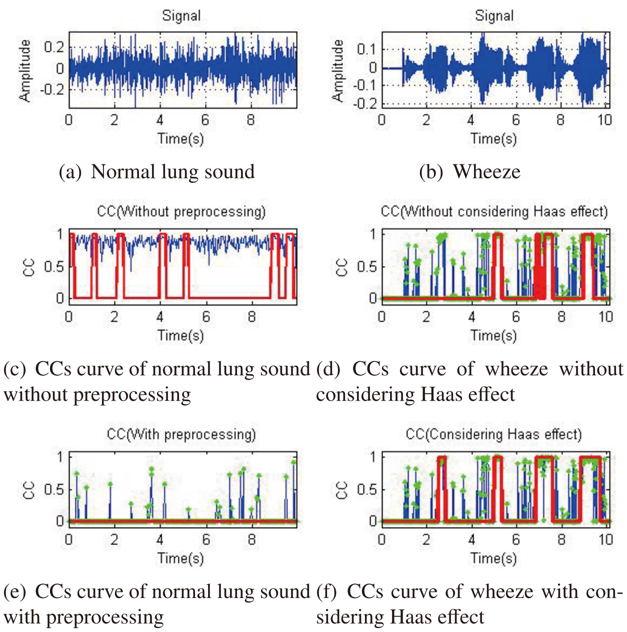
(e) CCs curve of wheeze

(f) CCs curve of normal lung sound

Fig. 5 Simulation results.

Table 1 Accuracy of the method introduced in this paper.

TP	FN	TN	FP	SE	SP	AC
62	8	88	2	88.57%	97.78%	93.75%

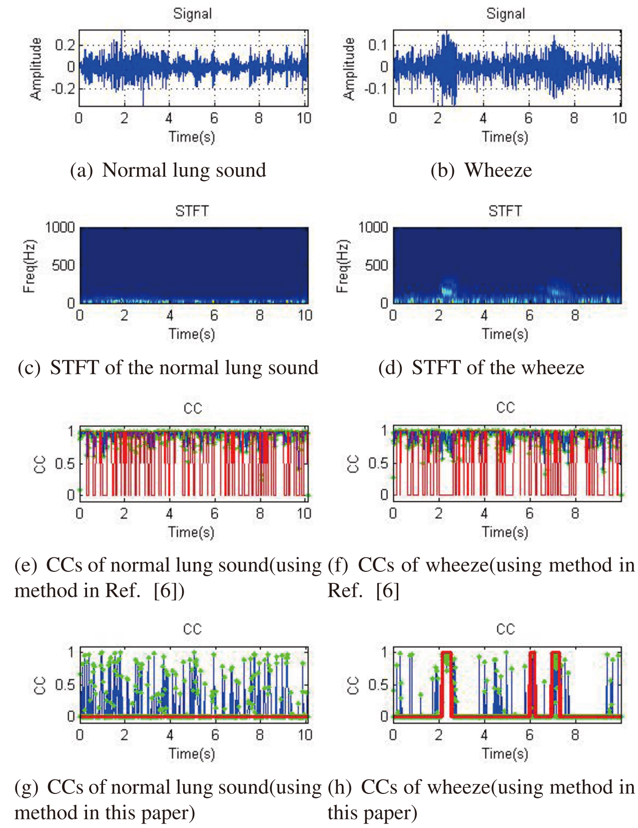


(a) Normal lung sound (b) Wheeze

(c) CCs curve of normal lung sound without preprocessing (d) CCs curve of wheeze without considering Haas effect

(e) CCs curve of normal lung sound with preprocessing (f) CCs curve of wheeze with considering Haas effect

Fig. 6 The influence of preprocessing and considering Haas effect.



(a) Normal lung sound (b) Wheeze

(c) STFT of the normal lung sound (d) STFT of the wheeze

(e) CCs of normal lung sound(using method in Ref. [6]) (f) CCs of wheeze(using method in Ref. [6])

(g) CCs of normal lung sound(using method in this paper) (h) CCs of wheeze(using method in this paper)

Fig. 7 The comparison of detecting results between the methods raised in Ref. [6] and this paper.

The simulation result in Table 1 shows that this method could be an efficient way to detect wheezes. The similar method raised in Ref. [12] gets a result that the SE and SP are 83% and 86%, respectively, while an improved one with 88% SE and 94% SP has been reported in Ref. [6]. However, both of the methods don't achieve satisfied detecting accuracies based on our dataset.

Compared with the method proposed in Ref. [6], [12], there are three aspects of improvement for the detection method. First, since most of the frequency components of wheeze are limited within a range of 100 to 1000 Hz, the CCs of the spectrogram within only this frequency band will be calculated. Therefore, the influence of most noises whose frequency are less than 100 Hz or greater than 1000 Hz, such as basic lung sound, heart sound and other noises are removed. Second, the large-signals detection removes the underlying basic lung sound which facilitates the detection of wheeze. In fact, most of the noises mentioned above, especially heart sound and basic lung sound, will bring continuous high CCs which exerts a bad influence upon the accuracy, especially FP. As shown in Fig. 6(c), there are a few of segments of normal lung sound are judged as wheeze mistakenly without preprocessing. Third, the consideration of Haas effect increase the accuracy of wheeze marking and reduces the FN. It's clear from the comparison between Fig. 6(d) and 6(f), the wheeze appearing in the first breath cycle is not marked without considering Haas effect on account of the discontinuity of CCs.

In addition, the method proposed in Ref. [6] determines wheeze by calculating the WR(wheeze ratio). However, the threshold of WR is related to the stethoscope. For example, the WR of the normal lung sound (Fig. 7(e)) and wheeze (Fig. 7(f)) from the dataset of R.A.L.E. are 55.22% and 69.05%, respectively. That is to say, if this method is applied on other stethoscopes, the threshold value should be updated by training which needs large amounts of normal lung sounds and wheezes. By contrast, the method described in this paper could be used by any stethoscope directly. Therefore, our method has a better generality and transferability. A comparison of the detecting results between the methods raised in Ref. [6] and this paper is given in Fig. 7.

3.2 Noise Testing

In order to examine noise robustness of the method proposed in this paper, Gaussian white noise is added to the dataset with different levels of SNR (from −10 dB to 40 dB, with a step of 1 dB) for testing and the change of AC is shown in Fig. 8.

It is clear that AC is a little unsatisfactory when SNR is under 0 dB. However, when SNR is greater than 0 dB, AC is higher than 90% and reaches an average value of 93.17%. This is because Gaussian white noise increases the power uniformly. Consequently, the higher the power of Gaussian white noise is, the much more difficultly large-signals can

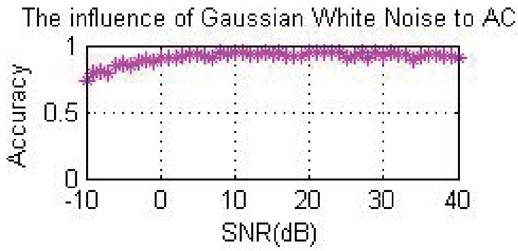


Fig. 8 Noise testing.

be detected. As a result, AC decreases with SNR reducing.

4. Conclusions

In this study, an efficient wheeze detection method is introduced which could be well used in the medical equipment and patients' health care systems. The method consists of STFT decomposition, preprocessing of the spectrogram, CCs calculating and duration determining. Particularly, the step of duration determining takes Haas effect into account, which achieves a better determination than the past method. A number of 70 wheezes from patients with pulmonary diseases and 90 normal lung sounds in total have been tested, and the result has proved that SE, SP and AC are 88.57%, 97.78% and 93.75%, respectively. This method could be used as an objective clinical diagnosis for patients with lung diseases related to wheezes, such as COPD and asthma.

Further extension of the latter, not only being tested in large scale experiments, but also reducing the complexity of computation and increasing the accuracy, will be proceeded.

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