Diagnosis System for Abnormal Respiratory Sound Using Divided Pulmonary Sound Waveform

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Abstract
In this paper, we propose an automatic diagnosis system for abnormal respiratory sound using a divided pulmonary sound waveform. Our method is based on a principal component analysis-linear discriminant analysis (PCA–LDA) discriminator using spectrogram features of an expiration waveform. The discrimination accuracy of the system was examined in simulations. The sensitivity and specificity of healthy against pathological discrimination and the symptom discrimination accuracy were improved compared with a mel-frequency cepstrum coefficients–Gaussian mixture model (MFCC–GMM)-based method. Computational efficiency was also improved.

1. Introduction
An automatic diagnosis system for abnormal respiratory sound based on signal processing and pattern recognition has been investigated [1]-[7]. Auscultation of pulmonary sound is valuable for early detection of respiratory symptoms, for which a number of methods have been developed. For example, a detection method for pathological pulmonary sound in noise [1], a discrimination method based on a hidden Markov model (HMM) [2], a discrimination method based on a support vector machine (SVM) [4], a discrimination method for rhonchi and wheezing based on the wavelet transform and robust PCA (R-PCA) [5] and a discrimination method using a LRM (linear regression model) [6] have been proposed. However, the performance of model-based methods depends on the learning process and the computational load is high. Recently, SVM- and GMM-based classifiers have been applied for the diagnostic classification of pulmonary sounds, and this combination of classifiers showed high performance. However, the system configuration is complicated, and the performance depends on the sample sounds used in GMM [7].

The purpose of our research is to improve the performance of an automatic diagnosis system for abnormal respiratory sound using a divided pulmonary sound waveform. In particular, a computationally efficient method was realized. Our method extracts low-order sound features from a divided waveform using the discrete wavelet transform (DWT) and short-time Fourier transform (STFT). The discrimination method is simply based on PCA–LDA, which has a low computational load. To show the effectiveness of our method, simulation results using pulmonary sounds are given.

2. Diagnosis System for Abnormal Respiratory Sound
Figure 1 shows a general flow of a diagnosis system [3], [7]. A digitalized waveform is obtained in the measuring process. The observed signal is denoised and normalized in the preprocessing process. The signal is analyzed to extract features suitable for diagnosis. The variation of frequency components is usually extracted. Diagnosis is realized by two steps: the detection of a fault and symptom discrimination. This flow can be a model of a general diagnosis system.

3. Proposed Diagnosis Method
In this section, we explain our proposed diagnosis method based on PCA–LDA.

3.1 Configuration of proposed diagnosis system
Figure 2 shows the flow of the proposed diagnosis method. The diagnosis system has three main processes: preprocessing, feature extraction and symptom diagnosis.

First, we construct the PCA–LDA system. Normalized pulmonary sound samples are used in the construction. These waveforms are transformed by the DWT and STFT to extract features. PCA is applied to reduce the feature vector dimension. Then, LDA is applied to produce a subspace for discriminating symptoms.

When an unknown pulmonary sound is applied, its flow cycle is estimated using the autocorrelation function. Then, the expiration section is extracted by half-cycle
division of the waveform. High-frequency components are reduced in intensity and the size of the sample is reduced by the DWT. Furthermore, the waveform is transformed to a spectrogram by an STFT to extract features.

Finally, PCA–LDA is applied and the minimum-distance method is used to diagnose symptoms.

When the detected cycle interval is not uniform time length, the sample number is normalized by resampling or down sampling processing.

Furthermore, the cycle waveform is divided into two half-size waveforms. The former is the inspiration interval and the latter is the expiration interval. Figure 5 shows an example waveform and its spectrogram for a rhonchus sound. Figures 5(a) and 5(b) show the inspiration interval, while Figs. 5(c) and 5(d) show the expiration interval. The harmonic structure of the spectrogram of the expiration waveform is clearer than that of the inspiration waveform. These spectrum features are suitable for use in the discrimination of symptoms.

3.2 Waveform division and preprocessing

Figure 3 shows an example of the waveform of a wheezing sound and its spectrogram. When the waveform is that of a healthy person, the spectrogram has periodicity. However, the spectrogram of a wheezing sound shows a harmonic structure above 400 Hz, whereas the spectrogram of a rhonchus sound shows a harmonic structure under 250 Hz that continues for 250 ms.

Figure 4 shows an example of a waveform and its autocorrelation function. The autocorrelation function is used to estimate the cycle interval. The peak position of the autocorrelation function is detected to estimate the cycle interval of the pulmonary sound.

3.3 Symptom discrimination using PCA–LDA

A PCA–LDA-based discriminator is constructed using three sets of data of feature vectors corresponding to healthy, asthma and bronchial symptoms. The cycle waveform was manually selected to prepare the data. The PCA transform matrix was obtained by solving the eigenvalue problem. Furthermore, using the same data, the LDA transform matrix was obtained by solving the eigenvalue problem. Unknown sound data is
discriminated using the minimum-distance measure between the center of the cluster and the unknown vector. On the other hand, the MFCC–GMM-based discriminator is constructed by a modeling cluster using the same three data. MFCC are used as the data vector. They are calculated using the output of the mel-frequency filterbank and the discrete cosine transform (DCT) is applied to the output components. The GMM was constructed and the maximum likelihood function was calculated to discriminate the unknown vector [7].

4. Simulations
To show the effectiveness of our method, simulations were executed.

4.1 Simulation conditions
Respiratory sounds of healthy and pathological persons were prepared from pulmonary sounds in [8], [9]. Symptoms of asthma and bronchial stenosis were assumed. The numbers of persons with healthy persons from which samples were obtained was two, asthma was six and the numbers with bronchial stenosis was three. The total number of subjects was eleven. Pulmonary sounds with a duration of 3–9 cycles were used in simulations. The total number of sample data of subjects was 25. Three data were used for constructing LDA discriminator and for learning in the GMM. Twenty-two data were used for discrimination.

The original sampling frequency of the sound was 44.1 kHz. The length of each respiratory cycle was estimated by the autocorrelation function and the cycle length was normalized to 3 s. Then, a three-level discrete wavelet transform with Db3 (the Daubechies three wavelet basis) was applied. Furthermore, an STFT using a half-overlap Hanning window (length = 512 samples) was applied to three cycles of the waveform to extract features from the spectrogram. The interval between samples was 18 ms.

The number of sample data was $189 \times 3 = 567$. A 60-dimension feature vector was obtained by PCA from a 512-order spectrogram vector. LDA was applied to reduce the dimension of the second-order vector. The minimum-distance measure was used in PCA–LDA discrimination.

Furthermore, a 12 order vector was extracted from the 24-order MFCC that was calculated from the spectrogram. The order of the GMM was 64. The maximum likelihood function was used in MFCC–GMM discrimination.

4.2 Simulation results
The performance of the discrimination accuracy was examined in simulations. The accuracy was evaluated on the basis of Table 1. The sensitivity and specificity are defined by the following equations.

$$\text{Sensitivity} = \frac{\text{Number of true positive} \times 100}{\text{Total number of true positive and false negative}} [\%]$$

$$\text{Specificity} = \frac{\text{Number of true negative} \times 100}{\text{Total number of true negative and false positive}} [\%]$$

Table 1: Discrimination accuracy of diagnosis

| Exam. | Positivity | Negativity |
|-------|------------|------------|
|       | True positive | False positive |
|       | False negative | True negative |

Table 2 shows a comparison of sensitivity and specificity for healthy and pathological subjects. In this case, both the PCA–LDA- and MFCC–GMM-based methods show the same performance. High specificity was achieved using three types of waveform.

The discrimination accuracy of symptoms was also evaluated. Tables 3–5 show comparisons of sensitivity and specificity using expiration, full and inspiration waveforms, respectively. The proposed PCA–LDA method using expiration waveforms achieved more successful results than the MFCC–GMM-based method. The expiration interval was more useful than the inspiration and full-length waveforms.

We compared the computational efficiency of systems. Table 6 shows a comparison of the average computational time. Our proposed PCA–LDA-based method using the expiration interval was the most efficient. The computational load was 67.8% of that of the MFCC–GMM-based method when using the full-length waveform.
Table 3: Comparison of sensitivity and specificity (Expiration)

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| PCA–LDA | Asthma         | 89.5     | 0.0      |
| Exam.  | Bronchial stenosis | 10.5   | 100.0    |

(a) PCA–LDA based method

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| MFCC–GMM | Asthma     | 66.7     | 33.4     |
| Exam.  | Bronchial stenosis | 33.3   | 66.6     |

(b) MFCC–GMM based method

Table 4: Comparison of sensitivity and specificity (Full)

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| PCA–LDA | Asthma         | 89.5     | 33.4     |
| Exam.  | Bronchial stenosis | 10.5   | 66.6     |

(a) PCA–LDA based method

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| MFCC–GMM | Asthma     | 66.7     | 33.4     |
| Exam.  | Bronchial stenosis | 33.3   | 66.6     |

(b) MFCC–GMM based method

Table 5: Comparison of sensitivity and specificity (Inspiration)

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| PCA–LDA | Asthma         | 33.3     | 33.4     |
| Exam.  | Bronchial stenosis | 66.7   | 66.6     |

(a) PCA–LDA based method

|       | Symptom          |          |          |
|-------|------------------|----------|----------|
| MFCC–GMM | Asthma     | 16.7     | 66.6     |
| Exam.  | Bronchial stenosis | 83.3   | 33.4     |

(b) MFCC–GMM based method

Table 6: Comparison of computational time [s]

|       | PCA–LDA | MFCC–GMM |
|-------|----------|----------|
| Full  | 1.23     | 3.20     |
| Expiration / Inspiration | 1.03 | 2.70 |

5. Conclusions

In this paper, we proposed an automatic diagnosis system for abnormal respiratory sound using a divided pulmonary sound waveform. Our method is based on a PCA–LDA discriminator using spectrogram features of an expiration waveform. In simulations, the discrimination accuracy of the system was examined. Healthy and pathological discrimination accuracy as well as symptom discrimination accuracy was improved compared with an MFCC–GMM-based method. Furthermore, the computational efficiency was improved using our proposed method.

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