DETECTION OF ABNORMAL LUNG SOUNDS TAKING INTO ACCOUNT DURATION DISTRIBUTION FOR ADVENTITIOUS SOUNDS

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ABSTRACT

In this paper, we propose a novel method for distinguishing between normal lung sounds from healthy subjects and abnormal lung sounds containing adventitious sounds from patients. The spectral similarity of adventitious sounds and noises at auscultation makes it difficult to obtain a high accuracy of the abovementioned classification. However, there is a remarkable difference between the duration of noise sounds and that of adventitious sounds. In the proposed method, the duration of these sounds is described using a Gaussian/Gamma distribution. The spectral likelihood using hidden Markov models and the validity score of the duration of the noise/adventitious sounds are combined to derive the most likely acoustic segment sequence for each respiration. Our classification method achieved a higher classification rate of 90.0% between normal and abnormal lung sounds than the conventional method (classification rate: 88.1%). Our approach to the classification of healthy subjects and patient subjects using the proposed method also achieved a higher classification rate of 84.1%.

Index Terms— lung sound, classification, adventitious sound, duration, acoustic model

1. INTRODUCTION

A diagnosis of pulmonary emphysema using a stethoscope is beneficial. This is because the auscultation of lung sounds is one of the most popular and cost-effective medical examination methods for identifying respiratory illnesses. This auscultation is based on the heuristics that abnormal respiratory sounds usually appear in patients with pulmonary emphysema. Sounds such as wheezes are caused by abnormalities in the lungs and bronchial tubes; they are termed *adventitious sounds* [1].

Several studies on the acoustic analysis of respiratory sounds for the detection of specific adventitious sounds have been conducted [2-5]. These studies used spectral features to assist doctors in hospitals to make diagnoses.

The objective of this study is to develop a home-use device for identifying a respiratory illness by detecting abnormal respiratory sounds among lung sounds. We have developed a classification procedure for distinguishing between normal and abnormal respiratory sounds on the basis of a maximum likelihood approach using hidden Markov models (HMMs) [6-8]. This procedure also uses spectral features as acoustic parameters and demonstrates the usefulness of a stochastic approach to the detection of abnormal respiratory sounds. However, the use of only power and spectral features hinders the achievement of a relatively high level of classification. This is because many respiration sounds include some noise from the stethoscope or internal organs, and the spectral features of several noises are very similar to those of some types of abnormal respiratory sounds.

To address this problem, we propose a classification method based on the detection of using not only the spectral features but also the duration of noise sounds and adventitious sounds. As a result of our investigation on the respiratory sounds, we found that there is a remarkable difference between the duration of noise and that of adventitious sounds. In our modeling of the duration distributions of these two sound types, a normal (Gaussian) distribution or Gamma distribution is adopted. The total likelihood of each respiratory sound is obtained by adding the spectral likelihood derived from HMMs and the segmental duration score calculated using the distribution functions of these sounds. The validity of the proposed method is confirmed through a classification experiment between normal and abnormal respiratory sounds. Finally, the performance of the classification between healthy subjects and patients carried out using the proposed method is described.

2. LUNG SOUND DATA

2.1. Training and evaluation data

In our recording of lung sounds, an electronic stethoscope incorporating a piezoelectric microphone was used. We

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used the second intercostal space on the subjects' front right as the recording point.

63 lung sound samples from 63 patients with pulmonary emphysema and 63 samples from 63 healthy subjects were prepared. Each lung sound sample consisted of successive respiratory phase segments, and the average number of respiratory segments was 8. Each sample from the patients contained at least one segment including the adventitious sound. The segments were tagged according to the respiratory phase (inspiratory or expiratory), diagnostic state (normal or abnormal), and the subject's health states (healthy or patient). The subject's health state was identified by a doctor based on auscultation as well as many other medical conditions.

The data could be divided into four groups according to the diagnostic state and the subject's health state as follows:

- AP (abnormal respiration from patient subjects): respiration that contains obvious adventitious sounds.
- NH (normal respiration from healthy subjects): respiration that contains neither adventitious sounds nor adventitious-like noises.
- AH (abnormal respiration from healthy subjects): respiration that contains noises from internal organs that are similar to adventitious sounds.
- NP (normal respiration from patient subjects): respiration that does not contain obvious adventitious sounds but sometimes contains adventitious-like noises.

In this study, respiration data related to AP and NH were used for confirming the ability to classify the adventitious sounds of patients and the normal respiratory sounds of healthy subjects (Section 5.1), and all respirations were used to classify the patients and healthy subjects (Section 5.2). The number of respiratory segments is listed in Table 1.

2.2. Hand labeling

We prepared two types of labels, one for the acoustic segments based on the acoustic and segmental features such as adventitious sounds and the other for specifying the period of noises.

2.2.1. Labels for acoustic segments

We assumed that an abnormal respiratory period was composed of successive acoustic segments. To model the adventitious sounds of patient subjects, we defined the segments according to their acoustic features and assigned a symbol to each segment.

Suppose a respiratory period W comprises N segments: let the i-th segment be w_i $(1 \le i \le N)$. Then,

$$W = w_1 w_2 \cdots w_i \cdots w_N \tag{1}$$

Table 1. Number of respiratory sound samples

Respiration	Patients	Healthy subjects
Normal	297 (NP)	351 (NH)
Abnormal	372 (AP)	48 (AH)

In our data, one abnormal respiratory period comprises several segments, and one normal respiratory period comprises one breath segment ($N = 1$). In this study, each adventitious sound was presented using a continuous or discontinuous sound segment; the segment sequence of an abnormal respiratory period thus consisted of one of the two types of segments and respiratory-sound segments not including adventitious sounds. Some typical examples of continuous sound segments are coarse crackle, fine crackle, and pleural friction rub. Rhonchus or wheezing sounds are examples of discontinuous segments. We included silent periods in the breath segments.

2.2.2. Labels for noise segments

In addition to the labels of acoustic segments, periods (beginning and ending times) of noise sounds in all the respiratory data were specified. The period of noises frequently overlapped with the period of adventitious sounds. In the recording using the stethoscope, the mixing of noises was inevitable, and consequently, 80% of all respiration sounds included some noises from the stethoscope or internal organs.

3. CLASSIFICATION STRATEGY

3.1. Abnormal respiration detection

Our strategy to detect an abnormal respiratory sound is based on a maximum likelihood approach. Let the occurrence probability of the segment sequence W in respiration sounds be $P(W)$.

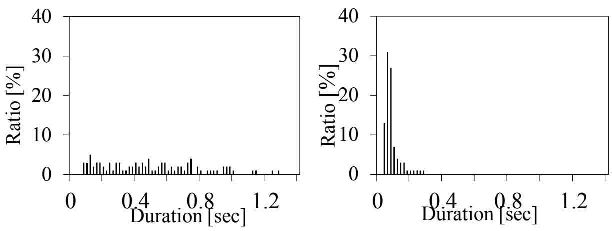
$$P(W) = P(w_1 w_2 \cdots w_i \cdots w_N), \tag{2}$$

where w_i is not a noise segment but an acoustic segment. We used a segmental bigram to calculate $P(W)$ [7].

The total likelihood is composed of the acoustic likelihood derived from HMMs, the segmental sequence likelihood, and the score of the duration validity of adventitious sounds. The derived diagnostic state (normal/abnormal) for the respiratory input that gives the segment (sequence) $\hat{W}$ with the highest likelihood $P(\hat{W} \mid X)$ is given below:

$$\hat{W} = \underset{W}{\arg\max}\, P(W \mid X) = \underset{W}{\arg\max}\left(\alpha \log P(W) + \log P(X \mid W) + \beta D(W)\right) \tag{3}$$

where X is the respiratory input and $P(X \mid W)$ is the acoustic likelihood. The term $D(W)$ indicates the score of



(A) Adventitious sounds (B) Noise sounds

Fig. 1. Histograms of duration for adventitious sounds and noise sounds

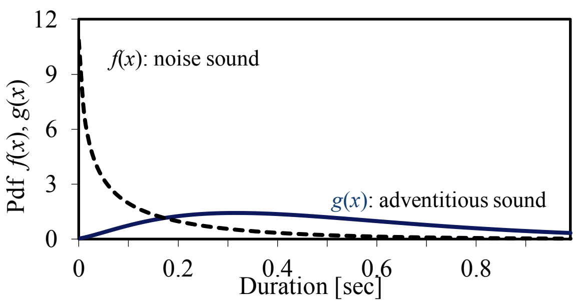


Fig. 2. Probability density functions of Gamma distribution for noise and adventitious sounds

the duration validity of adventitious sounds, and the introduction of $D(W)$ to the process of obtaining the best segmental sequence is the main topic of this paper. The weight factor α controls the contribution of the bigram, and the weight factor β controls the contribution of the duration. We describe the score $D(W)$ in Section 4.2 precisely.

3.2. Criteria for patient detection

The classification of healthy and patient subjects was carried out by using two likelihoods obtained using $P(\hat{W} \mid X)$ for normal and abnormal respiration. We examined two criteria for identifying a patient: (C1) detection of abnormal respiration, i.e., if a lung sound data sample includes at least one abnormal respiration, the subject is regarded as a patient; (C2) detection of one or more confident abnormal respirations. We proposed the idea of the "confident abnormal respiration" in a previous paper [8]. This idea is as follows: if the difference between the likelihood for the normal respiration candidate and the likelihood for the abnormal respiration candidate is larger than the threshold for the respiratory input, we regard this test respiration to be abnormal with confidence. A lung sound sample consists of several respiratory periods. Then, if the proposed method detects one or more confident abnormal respiration periods in a test lung sound sample, it classifies the subject as a patient subject.

Table 2. Mean value and standard deviation of duration for each sound type [sec]

Sound	Mean	S.D.
Adventitious sounds	0.54	0.34
Noise sounds	0.13	0.20

Table 3. Parameters for Gamma distribution

Sound	Scale θ	Shape k
Adventitious sounds	0.21	2.52
Noise	0.31	0.42

4. DURATION MODELING

4.1. Distribution of duration

We investigated the duration of the noises and adventitious sounds using the labels of the lung sound data (Table 1). The histogram of the duration of adventitious sounds including continuous and discontinuous sounds is shown in Figure 1 (A), and that of noise sounds is shown in Figure 1 (B). By comparing these two histograms, we found a consistent difference in the duration of adventitious and noise sounds. The duration of almost each noise sound is less than 300ms. On the other hand, that of each adventitious sound considerably varies from 50 to 1000ms, and there is no significant peak. Table 2 shows the mean values and the standard deviation for adventitious sounds and noise sounds. We use the difference between two duration distributions to achieve a relatively high classification performance.

In this study, a normal distribution or Gamma distribution is adopted to describe the occurrence probability of the duration for noise or adventitious sounds. We defined a scale parameter θ and a shape parameter k of the probability density function (pdf) of the Gamma distribution using the mean and the standard deviation given in Table 2 for each sound. These parameter values are listed in Table 3. The outline shape of the pdfs of the Gamma distribution for the two sound types is shown in Figure 2.

4.2. Validity score of distribution for adventitious sounds

In the proposed approach, we set the cross point of the two pdfs for the noise and adventitious sounds as the threshold T at first. If the duration of the obtained adventitious sound segment was shorter than the threshold, we assumed that the probability of misrecognition of noise sound to the adventitious sound was high. Then, we defined the validity of duration $D(W)$ using the ratio of the pdf $f(x)$ of the noise duration to the pdf $g(x)$ of the duration of the adventitious sound as follows:

$$D(W) = -\sum_{x_i \in W} d(x_i, W) \tag{4}$$

$$d(x_i, W) = \begin{cases} \log \dfrac{f(x_i)}{g(x_i)}, & \text{if } x_i \le T \text{ and } W \text{ is a abnormal respiration candidate.} \\ 0, & \text{if } x_i > T \text{ or } W \text{ is a normal respiration candidate.} \end{cases} \tag{5}$$

where x_i is the duration of the i-th adventitious sound segment in each respiration W. According to the investigation results presented in Section 4.1, the threshold T was set to 380ms or 180msec when the normal or the Gamma distribution was used, respectively.

5. EVALUATION EXPERIMENTS

We performed classification tests to evaluate the proposed method. The lung sound data were sampled at 5 kHz. Every 10 ms, a vector of 5 mel-warped cepstral coefficients and power was computed using a 25-ms Hamming window. The acoustic models (HMMs) for normal respiration were generated using the respiratory sounds from healthy subjects (NH in Section 2.1), and the models for abnormal respiration were generated using the sounds from patients (AP). HMMs with three states and two Gaussian probability density functions were used. In our experiments, we assumed that the respiratory phase and respiratory boundaries were known. As such, if the test sample was expiratory, acoustic models generated by expiratory sounds were used.

5.1. Classification of normal and abnormal respiration

To confirm the detection performance of adventitious sounds, a classification experiment for distinguishing between abnormal respiration for patients and normal respiration for healthy subjects was carried out. The evaluation samples were abnormal respirations from patients (AP) and normal respirations from healthy subjects (NH), as given in Table 1. We performed a leave-one-out cross validation on these samples. In addition, samples recorded from the same subject as the test sample were excluded in the training process so that our experiments would be subject-independent.

Table 4. Classification performance between normal and abnormal respiration [%]

Method & distribution		Healthy, normal (NH)	Patient, ab-normal(AP)	Average
Baseline (5.1.1)		86.8	89.5	88.1
Proposed (5.1.2)	Normal	92.6	86.8	89.6
	Gamma	91.5	88.7	90.0

5.1.1. Baseline performance

First, to confirm the performance of the baseline, we carried out the classification experiment using only power and spectral features. The obtained classification results are shown in Table 4. The recall rate of the abnormal respiration was 89.5%, and that of the normal respiration was 86.8%. The average classification rate weighted with the data amount was indicated as "Average" (classification rate: 88.1%).

5.1.2. Performance evaluated using validity score of adventitious sound

Next, we carried out the classification experiment taking into account the duration distributions of noises and adventitious sounds. A normal distribution or Gamma distribution was used for calculating the validity score to derive the most likely segment sequence. The obtained classification results are also shown in Table 4. According to Table 4, the classification performance of the proposed method was higher than the baseline performance because of the effectiveness realized by taking into account the difference in durations of the noises and the adventitious sounds. There was no significant difference in the classification ability between the normal distribution and the Gamma distribution.

To verify the validity of the proposed method, the classification performance for the segments that contain long noises, short noises, and no noises is shown in Table 5, where the Gamma distribution was used. The term "long"

Table 5. Detection performance for segments containing noise or adventitious sound [%]

Segments of duration x (second)		Baseline		Proposed	
		Normal	Abnormal	Normal	Abnormal
Noise sounds	Short ($x < 0.18$)	84.2	89.4	88.2	87.9
	Long ($x \ge 0.18$)	68	92	79	90
	No noise	89.8	89.3	94.6	89.3
Adventitious sounds	Short ($x < 0.18$)	-	89	-	84
	Long ($x \ge 0.18$)	-	89.7	-	90.1

implies that the duration of the noise/adventitious sound was longer than the cross point of the two pdfs $(x \geq T = 180\,[\mathrm{ms}])$. Table 5 also shows the classification performance for the abnormal segments that contain adventitious sounds.

The proposed method increased the detection performance of normal respiratory sounds, which include noises. The purpose of our method was to decrease the misrecognition of short noises as adventitious sounds, and this purpose was achieved to some extent with the increase in the classification rate of the normal respiratory sounds including short noises (from 84.2% to 88.2%). On the other hand, the detection performance of abnormal inspiration, which contained short adventitious sounds, was decreased (from 89% to 84%). This was because the proposed method misrecognized the short adventitious sounds as noises.

5.2. Classification of healthy and patient subjects

Finally, the classification experiments for distinguishing between healthy subjects and patient subjects were carried out. In these experiments, two criteria to identify a patient were examined: (C1) detection of abnormal respiration and (C2) detection of one or more confident abnormal respirations [8].

Table 6 shows the classification performance of the baseline or the proposed method using each classification criterion, respectively. The baseline performances of 64.3% (C1) and 81.7% (C2) were lower than those of 75.4% and 88.7% in reference [8], respectively. This is because the number of healthy subjects was increased from 39 to 67, and we evaluated an equal number of healthy subjects and patient subjects in this paper. Both the normal and the Gamma distributions achieved higher performance than the baseline for the two criteria. It was shown that the combination of the abnormal respiratory sound detection procedure that took into account the duration distribution of the noise and adventitious sounds and the patient detection criterion based on the confident abnormal respiration achieved a relatively high score.

Table 6. Performance of classification of between patients and healthy subjects [%] (C1: detection of abnormal respiration, C2: detection of one or more confident abnormal respirations)

Criterion	Method & Distribution		Healthy	Patients	Average
C1	Baseline [8]		29	100	64.3
	Proposed	Normal	54	97	75.4
		Gamma	44	98	71.4
C2	Baseline [8]		73	91	81.7
	Proposed	Normal	81	86	83.3
		Gamma	81	87	84.1

6. CONCLUSIONS

This paper proposed a new method for discriminating between normal respiration from healthy subjects and abnormal respiration containing adventitious sounds from patients. The key characteristic of the proposed classification method was that it took into account the duration distribution of noise and adventitious sounds, where the normal (Gaussian) or Gamma distribution was used for describing the distribution of each sound. In the proposed method, stochastic likelihoods were calculated based on the maximum likelihood approach by using HMMs for acoustic spectral features and the duration validity score obtained from the normal/Gamma distribution.

According to the classification experiments for distinguishing between normal and abnormal respiration, the proposed classification method achieved a better performance than the conventional method. Furthermore, the proposed method also achieved a better performance on the classification for distinguishing between healthy subjects and patients. It was also shown that the combination of the proposed method and the patient detection criterion based on the confident abnormal respiration achieved a relatively high performance for the classification of healthy and patient subjects.

With respect to the classification of healthy and patient subjects, however, our experiments indicated that there was considerable room for improving the performance. This is a subject for future work.

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