1aSCb10. Modeling occurrence tendency of adventitious sounds and noises for detection of abnormal lung sounds
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Diagnosis of pulmonary emphysema by using a stethoscope is based on the common knowledge that abnormal respiratory (adventitious) sounds usually appear in patients with pulmonary emphysema. However, the spectral similarity between adventitious sounds and noises at auscultation makes highly accurate automatic detection of adventitious sounds difficult. In this paper, we have proposed a novel method for distinguishing between normal lung sounds in healthy subjects and abnormal sounds, including adventitious sounds in patients, taking into account the occurrence tendency of adventitious sounds and noises. According to our investigation results, adventitious sounds occur repeatedly in successive inspiratory/expiratory phases of patients. On the other hand, noise sounds mix at random in lung sounds of both patients and healthy subjects. In our method, the occurrence tendency of these sounds is described using Gaussian distribution of a random variable obtained by subtracting the acoustic likelihood for abnormal respiration from the likelihood for normal respiration. The spectral likelihood calculated using hidden Markov models and the validity score of the occurrence tendency of the adventitious/noise sounds are combined to derive the classification result. Our method achieved a higher classification rate of 94.1% between normal and abnormal lung sounds than that achieved using the conventional method (87.4%).
INTRODUCTION

The auscultation of lung sounds is one of the most popular medical examination methods used for identifying respiratory illnesses because it does not cause any physical strain to patients. Abnormal respiratory sounds usually appear in patients. These abnormal sounds are caused by abnormalities in the lungs and in the bronchial tubes and are termed as “adventitious sounds.” However, the accurate detection of adventitious sounds requires in-depth experience and knowledge in medicine. The automated identification of respiratory illnesses through the detection of abnormal respiratory sounds using a stethoscope at home would be beneficial because that way, appropriate medical treatment can be administered to patients at an early stage.

Several studies have been conducted on the acoustic analysis of respiratory sounds for detecting specific adventitious sounds [1-4]. We have developed some classification procedures for distinguishing between normal and abnormal respiratory sounds based on a maximum likelihood approach using hidden Markov models (HMMs) [5, 6]. These procedures have used spectral features as acoustic parameters. Through these procedures, we demonstrated the effectiveness of employing a stochastic approach for detecting of abnormal respiratory sounds. Many respiratory sounds include a few noises that are similar to the adventitious sounds. However, such sounds, which may not necessarily be adventitious, were classified as abnormal. To address this problem of false positives, we proposed a classification method using not only the spectral features but also the durations of noises and adventitious sounds [7]. This method improved the classification performance for normal respiratory sounds. However, there was room for improvement in the accuracy of abnormal respiration detection.

In our previous studies, we distinguished between normal and abnormal respiratory sounds using only one inspiratory/expiratory phase. However, it is desirable that we use a series of respiratory sounds. This is because it can be assumed that the occurrence of noise in respiratory sounds is random, whereas adventitious sounds occur repeatedly in successive inspiratory/expiratory phases. Therefore, we proposed a classification method considering the occurrence tendency of adventitious sounds and noise in a series of respiratory sounds. We add the term that expresses the occurrence tendency into the maximum likelihoods that were used in our previous methods. The validity of our proposed method is confirmed through a classification experiment between normal and abnormal respiratory sounds. In addition, we also carried out a classification experiment between healthy subjects and pulmonary emphysema patients.

LUNG SOUND DATA

Recording

We prepared 126 lung sound samples, 63 from patients with pulmonary emphysema and 63 from healthy subjects. Our recording point was the second intercostal space on the subjects’ front right. Each lung sound sample consisted of successive respiratory phase segments, and the average number of respiratory phase segments was around 10. In the case of recording, a sampling frequency was 44.1 kHz, and the recorded data was downsampled to 5 kHz. In this dataset, 372 abnormal respiratory periods that contained the adventitious sounds recorded from the patients and 351 normal respiratory periods from the healthy subjects, which did not include any adventitious sounds, were used for distinguishing between normal and abnormal respiration. All datasets of 1068 respiratory periods were used for distinguishing between healthy subjects and patients with pulmonary emphysema.

Manual Segmentation

We manually divided an abnormal respiratory period into successive acoustic segments. To model the adventitious sounds from the subjects with pulmonary emphysema, 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 \( w_i \) \((1 \leq i \leq N)\),

\[
W = w_1 w_2 \cdots w_{i-1} w_i
\]

where the start time of segment \( w_{i+1} \) is the end time of segment \( w_i \). In our dataset, an abnormal respiratory period comprised several segments, and a normal respiratory period comprised one breath segment \((N=1)\). Each adventitious sound type was labeled with a continuous sound segment (coarse crackle, fine crackle, and so on) or a
discontinuous sound segment (rhonchus, wheezing, and so on). For these two classes of adventitious sounds and some classes of breathing segments, we generated acoustic models using HMMs.

**DETECTION OF ABNORMAL LUNG SOUNDS**

**Baseline Formulation**

In our classification approach, for each respiratory period \( X \) in an input respiration sample, the likelihood \( L_{ab}^{X} \) for an abnormal respiration candidate and that \( L_{no}^{X} \) for a normal respiration candidate were calculated. If the likelihood for an abnormal respiratory candidate was higher than that for a normal candidate, the input respiratory period was regarded as abnormal respiration containing adventitious sounds. To calculate the probability \( P(W \mid X) \) of a normal/abnormal segment sequence \( W \) for a respiratory period \( X \), we used an acoustic likelihood \( P(X \mid W) \) and a segmental sequence likelihood based on the Bayes’ theorem:

\[
P(W \mid X) \approx P(W)P(X \mid W),
\]

where \( P(W) \) is the occurrence probability of a segment sequence. In this study, we used a segmental bigram to calculate \( P(W) \) [6];

\[
P(W) = \sum_{w_{1}w_{2} \ldots w_{N}} P(w_{1} \mid w_{N} = 1).
\]

The total likelihood, composed of the acoustic likelihood \( \frac{\log P(X \mid W)}{g_{12}} \) derived from HMMs and the segmental sequence likelihood \( \frac{\log P(W)}{g_{12}} \) derived from equation (3), was calculated using a weight factor \( \frac{1}{g_{12}} \). The diagnostic state (normal/abnormal) that yielded the segment (sequence) \( \hat{W} \) with the highest likelihood was the classification result, as given by the following expression:

\[
\hat{W} = \arg \max_{W} P(W \mid X) = \arg \max_{W} (L(X \mid W)),
\]

where \( L \) indicates the likelihood \( L_{ab}^{X} \) for an abnormal respiration candidate \( \hat{W}_{ab}^{X} \) or the likelihood \( L_{no}^{X} \) for a normal respiration candidate \( \hat{W}_{no}^{X} \) (a period comprising one breath segment). The weight factor \( \alpha \) was constant, and it controlled the contribution of the segmental sequence’s occurrence probability. The value of \( \alpha \) was determined experimentally to achieve the best performance. In our previous classification method [6], referred to as the baseline, the classification criterion \( C_{M1} \) for the \( i \)-th respiratory period between normal and abnormal respiration was described as follows:

\[
C_{M1} = L_{i}^{no}(X_{i} \mid \hat{W}_{i}^{no}) - L_{i}^{ab}(X_{i} \mid \hat{W}_{i}^{ab}).
\]

**Occurrence Tendency of Adventitious Sounds**

To capture the differences between the occurrence features of noises and adventitious sounds, we investigated the occurrence counts of these two sound types. We observed obvious adventitious sounds in 67% of the inspiratory periods of the patients and in 64% of the expiratory periods of patients. Furthermore, in 64% of the patients, lung sounds were of the adventitious type in two or more respiratory periods. Therefore, we assumed that adventitious or similar sounds occurred repeatedly in respiratory cycles of the patients. However, 80% of all the respiration sounds contained some noise in the case of both the patients and the normal subjects.

Next, the likelihood of each respiratory period obtained from healthy subjects and that from patients were investigated. First, for each respiratory period, the likelihoods \( L_{ab}^{X} \) and \( L_{no}^{X} \) were calculated according to equation (4). Then, the difference \( x_{i} \) between the two likelihoods of the \( i \)-th period

\[
x_{i} = L_{i}^{no}(X_{i} \mid \hat{W}_{i}^{no}) - L_{i}^{ab}(X_{i} \mid \hat{W}_{i}^{ab})
\]

was calculated. To calculate the occurrence tendency score \( X_{i} \) of normal respiration for the \( i \)-th respiration period \( (1 \leq i \leq M, \ M \) is the number of respiratory periods for each lung sound sample) as follows:
where \( N_k \) was the number of analysis frames for the \( k \)-th respiratory period. In this definition, \( x_i / N_i \) was not considered in calculating \( X_i \). According to our assumption, a low (negative) value \( X_i \) indicates that the preceding or the following respiratory periods likely includes some adventitious sounds and that the occurrence probability of adventitious sounds in \( i \)-th period is high as well. Figure 1 shows the histogram of the occurrence tendency score \( X \) for healthy subjects and patients. The horizontal axis indicates the occurrence tendency score \( X \), and the vertical axis indicates the ratio of the occurrence number of each score. For normal subjects, the score of each respiratory period was distributed in the positive value region (average 172 and standard deviation 130). On the other hand, the patients’ scores were distributed broadly (average -284, and standard deviation 448). These investigation results show that the proposed tendency score considering the likelihoods of the surrounding respiratory periods is useful for detecting abnormal respiratory periods.

Detection of Abnormal Respiratory Period Considering Occurrence Tendency of Adventitious Sounds

We formulated a procedure for detecting abnormal respiration considering the occurrence tendency of adventitious sounds. First, a Gaussian distribution was adopted for modeling the distribution of tendency score \( X \) for normal subjects and patients as \( N^{no} = N(172, 130^2) \) and \( N^{ab} = N(-284, 448^2) \), respectively. Then, the cumulative distribution function \( F(X) \) for healthy subjects was generated using the Gaussian distribution \( N^{no} \), and \( G(X) = \int_{-\infty}^{\infty} N^{ab} dX \), which was cumulated in the opposite direction, was used for patients. These two functions are shown in FIGURE 1. Using these functions, we defined the classification criterion for normal respiration and abnormal respiration considering the occurrence tendency of adventitious sounds as follows:

\[
C_{M3} = L^{mo}(X_i | \hat{X}_i^{mo}) - L^{ab}(X_i | \hat{X}_i^{ab}) + \beta(F(X_i) - G(X_i)) + \gamma.
\]

In our experiments, the weight \( \beta \) and offset \( \gamma \) were constant, and they were experimentally determined to ensure that the classification rate was the maximum. If the value obtained using equation (8) was positive, the input respiratory period was considered normal, and if the value was negative, the respiratory period was considered abnormal.

![FIGURE 1. Histogram of occurrence tendency score and cumulative distribution functions](image)

**EXPERIMENT**

Experimental conditions

Our classification procedure comprises a training process and a test process. The acoustic models for normal respiration were generated using normal respiratory sounds from healthy subjects, and those for abnormal respiration were generated using abnormal respiratory sounds from patients. In our experiments, we assumed that the respiratory phase and respiratory boundaries are known. As such, if the test sample was expiratory sound,
acoustic models generated with the expiratory sounds were used. Further, an input lung sound sample was divided into several respiratory periods using the given boundaries. For lung sound samples, at every 10 ms, a vector of 6 mel-warped cepstral coefficients and power was computed using a 25 ms Hamming window. HMMs with three states and two Gaussian probability density functions were used.

Classification between Normal and Abnormal Respiration

To confirm the classification performance of the proposed method, we carried out four classification experiments between normal respiration and abnormal respiration using methods M1, M2, M3, and M4. M1 was the baseline method, and its classification criterion is given by equation (5). Method M2 is a previously proposed approach [7] that considers duration distribution for adventitious sounds and noises. In this method, the segment sequence with the highest likelihood is given as follows instead of equation (4) in baseline:

$$
\hat{W} = \arg \max_{W} (\alpha \log P(W) + \log P(X|W) + \lambda D(W)),
$$

where the term $D(W)$ indicates duration validity score derived from the distribution functions of the durations of adventitious sounds and noises, and weight $\lambda$ is a constant value. The classification criterion is same as that given by equation (5). M3 is the method proposed in this paper, and it considers the occurrence tendency of adventitious sounds and noises. The classification criterion is described in equation (8), and the segment sequence with the highest likelihood is given by equation (4). Method M4 combined methods M2 (duration distribution) and method M3 (occurrence tendency). In this method, the segment sequence with the highest likelihood is given by equation (9), and the classification criterion is equation (8).

The classification performance is summarized in Table 1. It is shown that M3 enhanced the classification performance to 94.1% from the baseline performance of 87.4%. According to the results of a significance test, there was considerable difference in the classification rate between M1 and M3 at less than 1% of the significance level. The performance of the proposed method was superior to that of the previously proposed M2. M3 achieved the best performance for both normal respiration and abnormal respiration detection among M1, M2, and M3. However, the classification performance of the combination method M4 (M2 + M3) is almost same as that of M2. This is a subject for future work.

<table>
<thead>
<tr>
<th>Method</th>
<th>Normal</th>
<th>Abnormal</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1 (Baseline)</td>
<td>86.0</td>
<td>88.7</td>
<td>87.4</td>
</tr>
<tr>
<td>M2</td>
<td>92.6</td>
<td>86.8</td>
<td>90.0</td>
</tr>
<tr>
<td>M3 (Proposed)</td>
<td>93.0</td>
<td>95.2</td>
<td>94.1</td>
</tr>
<tr>
<td>M4 (M2 + M3)</td>
<td>90.3</td>
<td>89.9</td>
<td>90.1</td>
</tr>
</tbody>
</table>

Classification between Healthy Subjects and Patients

Three classification experiments for distinguishing between healthy subjects and patients were carried out using the methods M1, M2, and M3. In these experiments, as a classification strategy, the total likelihood for healthy subjects or patients was calculated by summing the likelihood of all normal respiratory candidates or all abnormal respiratory candidates in a lung sound sample, respectively. When the total likelihood for abnormal respiratory candidates is higher than that of normal respiratory candidates, the input subject is regarded as a patient:

$$
\sum_{i=1}^{M} L_{i}^{no}(X_{i} | \hat{W}_{i}^{no}) - L_{i}^{ab}(X_{i} | \hat{W}_{i}^{ab}) = \sum_{i=1}^{M} x_{i}^{p} < 0, \quad \text{(M1 and M2)}
$$

$$
\sum_{i=1}^{M} L_{i}^{no}(X_{i} | \hat{W}_{i}^{no}) - L_{i}^{ab}(X_{i} | \hat{W}_{i}^{ab}) + \beta(F(X_{i}) - G(X_{i})) + \gamma \sum_{i=1}^{M} x_{i}^{p} < 0. \quad \text{(M3)}
$$
We carried out the classification experiments using all the lung sounds in our dataset. Classification performance for each method is summarized in Table 2. The average performance of the baseline method and the proposed method vary negligibly. This is because the classification strategy adopted in these experiments used the total likelihood of all respiration periods, and this classification strategy has same ability as the proposed method, which uses the likelihood of all respiration periods as well (equations (7) and (10)). However, the classification method M2, which considers duration distribution, achieved the highest performance.

<table>
<thead>
<tr>
<th>Method</th>
<th>Healthy subjects</th>
<th>Patients</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1 (Baseline)</td>
<td>81</td>
<td>95</td>
<td>88.1</td>
</tr>
<tr>
<td>M2</td>
<td>95</td>
<td>87</td>
<td>91.3</td>
</tr>
<tr>
<td>M3 (Proposed)</td>
<td>89</td>
<td>87</td>
<td>88.1</td>
</tr>
</tbody>
</table>

CONCLUSIONS

In this paper, we proposed a new method for distinguishing between normal lung sounds in healthy subjects and abnormal sounds including adventitious sounds in patients. In our proposed method, we focused on the difference in the occurrence tendency of adventitious sounds and noises at auscultation to improve the adventitious-sound-detection performance. In many case, adventitious sounds occur repeatedly in successive inspiratory/expiratory phases in patients. However, noise sounds mix at random with the lung sounds of both patients and healthy subjects. In our method, the occurrence tendency of these sounds was described using the Gaussian distribution of a random variable as obtained by subtracting the acoustic likelihood for an abnormal respiration candidate from that for a normal respiration candidate. Each cumulative function of the Gaussian distribution for a patient and a healthy subject was used to calculate the total likelihood for identifying abnormal respiration. The proposed method achieved a higher classification rate of 94.1% between normal and abnormal lung sounds than the baseline, conventional method did without considering the occurrence tendency (87.4%). Furthermore, the performance of this method was better than that of a previously proposed method (90.0%) [7], which considered the duration distribution of adventitious and noise sounds. However, with regard to the lung-sound-based classification of healthy subjects and patients, the proposed method could not outperform the conventional method. Improving this classification performance would be the subject of our future work.

REFERENCES