PAPER

Acoustic HMMs to Detect Abnormal Respiration with Limited Training Data

Masaru YAMASHITA[†a)], ***Member***

SUMMARY In many situations, abnormal sounds, called adventitious sounds, are included with the lung sounds of a subject suffering from pulmonary diseases. Thus, a method to automatically detect abnormal sounds in auscultation was proposed. The acoustic features of normal lung sounds for control subjects and abnormal lung sounds for patients are expressed using hidden markov models (HMMs) to distinguish between normal and abnormal lung sounds. Furthermore, abnormal sounds were detected in a noisy environment, including heart sounds, using a heart-sound model. However, the F1-score obtained in detecting abnormal respiration was low (0.8493). Moreover, the duration and acoustic properties of segments of respiratory, heart, and adventitious sounds varied. In our previous method, the appropriate HMMs for the heart and adventitious sound segments were constructed. Although the properties of the types of adventitious sounds varied, an appropriate topology for each type was not considered. In this study, appropriate HMMs for the segments of each type of adventitious sound and other segments were constructed. The F1-score was increased (0.8726) by selecting a suitable topology for each segment. The results demonstrate the effectiveness of the proposed method.

key words: *hidden markov model, lung sound, patient detection, abnormal respiration*

1. Introduction

Auscultation of the lungs is used to identify respiratory sounds that may be associated with various pulmonary diseases. Although other non-invasive and inexpensive methods have been developed, auscultation using a stethoscope can obtain valuable information regarding a patient's health status. In many cases, abnormal sounds (called adventitious sounds [1]) are included in the lung sounds of a patient suffering from pulmonary diseases. Thus, even today, auscultation is an effective method to diagnose pulmonary diseases. However, doing so requires expert knowledge and experience; perceiving the difference between normal and abnormal breathing is difficult for non-medical personnel. This may be a key reason that auscultation has not been commonly adopted for household use. Furthermore, it may be difficult for elderly people or those in rural areas to visit a hospital for testing. Hence, a method to identify patients with health conditions at home could lead to early detection of pulmonary diseases.

Several studies have considered automatically distinguishing adventitious sounds from lung sounds [2]–[5]. In these works, a specific adventitious sound was detected either by using a wavelet transform, or a frame of adventitious sound was discriminated by using the short time spectrum. However, the time of occurrence and duration of adventitious sounds vary. Therefore, discriminating sounds using the features of the whole respiration and its inflection would be preferable. Furthermore, the features of adventitious and respiratory sounds depend on an individual and the degree of disease progression. Recently, convolutional neural networks [6]–[8] and recurrent neural networks [9], [10] have been used to analyze lung sounds. However, these methods require a large volume of training data to achieve good performance. To overcome these issues, in our previous studies, the features should be expressed statistically. The time series of the acoustic features of lung sounds are expressed by constructing hidden markov models (HMMs) to discriminate between normal and abnormal respiratory sounds [11]–[13]. HMM methods can express acoustic features statistically and have been applied in word recognition with limited amounts of training data [14]. Thus, HMMs can be constructed with smaller training datasets compared to deep learning methods. Therefore, HMMs were applied to detect patients with respiratory issues in the present work.

In auscultation, noise hinders the accurate detection of adventitious sounds. The sounds received often include noise from the body and rustle of the stethoscope. The sound of the heart is a typical source of noise from the body. Figure 1 shows examples of respiratory sounds, including adventitious sounds, heart sounds, and other types of noise. Because the first (S1) and second sounds (S2) could be clearly heard, S1 and S2 were marked as heart sounds. The frequency of heart sounds auscultated near the heart is high. The database used in our study includes many heart sounds; consequently, many normal respiratory sounds were identified as abnormal respiratory sounds. To distinguish adventitious sounds from heart sounds, a heart-sound model was constructed using heart sounds for training [15], [16]. As a result, normal respiratory sounds were identified correctly. However, accuracy decreased for abnormal respiratory sounds. These models were assumed not to fit. Therefore, the topology for the acoustic models has been analyzed. In our previous method [17], HMMs were constructed for heart and adventitious sounds with high accuracy by selecting a suitable number of states and mixtures. However, the classification rate was not high. This result may be attributed to two possible causes. First, despite the considerable differences between acoustic features of dis-

Manuscript received April 28, 2022.
Manuscript revised September 30, 2022.
Manuscript publicized December 19, 2022.
[†]The author is with the Craduate School of Engineering, Nagasaki University, Nagasaki-shi, 852–8521 Japan.
a) E-mail: masaru@nagasaki-u.ac.jp
DOI: 10.1587/transinf.2022EDP7068

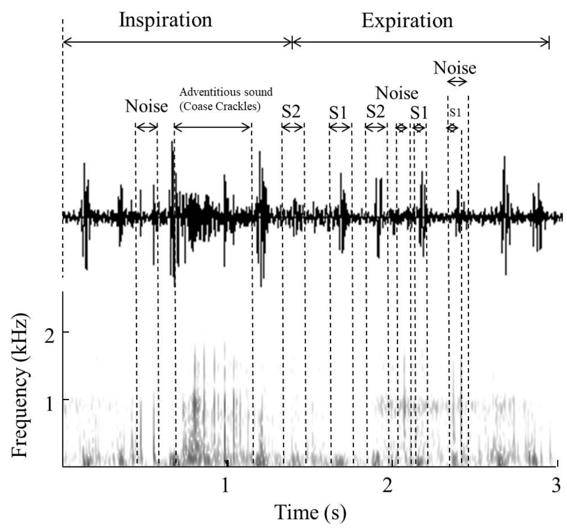

Fig. 1 Respiratory sounds, including adventitious sounds, heart sounds, and other type of noise [15].

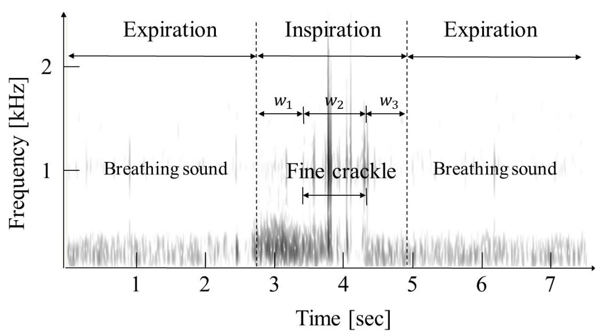

Fig. 2 Respirations, including discontinuous adventitious sounds.

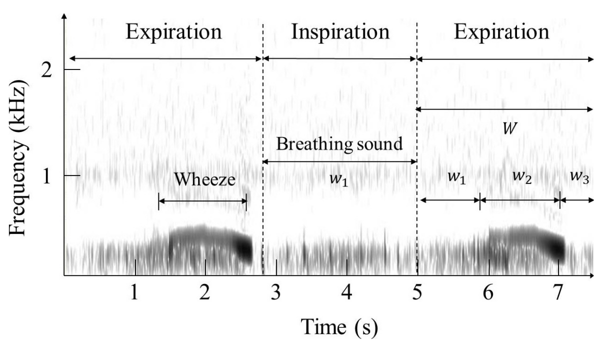

Fig. 3 Respirations, including continuous adventitious sounds.

continuous and continuous adventitious sound (Figs. 2 and 3), a single model was trained without making distinctions between the two. Second, a suitable number of states, mixtures of the HMM, and iterations of training for normal respiration was not set. Figure 2 shows the respirations, including discontinuous adventitious sounds, which are referred to as fine crackles. Figure 3 shows the respirations with continuous adventitious sounds, called wheezes. These figures show that the acoustic features of discontinuous adventitious sounds changed repeatedly and that the acoustic features of continuous adventitious sounds were unchanged in each w_2. Although acoustic features of adventitious sounds differ by type, the suitable number for each type was not selected. Furthermore, the suitable number of breathing sounds in control subjects and normal respiration was selected. In addition, although only a relatively small amount of training data are available, the models tended to overfit with a large number of training iterations. However, the number of iterations in training was not examined. Therefore, this study, focuses on the acoustic features of adventitious sounds, which can be roughly divided into two types, including continuous and discontinuous adventitious sounds. Thus, a method to construct HMMs for each sound with high accuracy was proposed by selecting a suitable number of states, mixtures, and iterations in training with a small amount of training data. The effectiveness of the proposed method was confirmed through a classification experiment.

2. Lung Sound Database

2.1 Dataset

The lung sounds were recorded by a medical doctor using an electronic stethoscope. They were recorded in WAVE format, sampled at 5 kHz, and quantized at 16 bits. The doctor judged the recording points for each subject. Therefore, the number of recording points differed between subjects. The respiratory count was 5 breaths, and the average of recorded time was 15.3 s. The medical doctor provided diagnoses and classified the subjects as control and patients. As the result, the data included 134 control subjects and 109 patients.

2.2 Manual Labeling

Segmentation was manually performed based on the recorded sounds, waveforms, spectrograms, and power. First, the lung sounds were divided into inspiration and expiration sound segments. Second, these respiratory sound segments were divided into adventitious sound segments and segments containing other breathing sounds. The adventitious sound segment was divided into continuous and discontinuous sounds. The heart-sound segments were marked on the lung sounds that were recorded from auscultation points near the heart. If the occurrence interval of adventitious and heart sounds was shorter than 100 ms, a recording is regaraded as a single segment.

2.3 Definition of Normal and Abnormal Respiration

The acoustic features of some noises are similar to those of adventitious sounds. Some respiratory sounds from control subjects include adventitious sounds. Distinguishing these sounds is challenging for non-medical personnel. Conversely, some respiratory sounds from a patient do not include adventitious sounds, but cannot be considered normal respiratory sounds. Respiratory sounds are grouped into four categories, and normal and abnormal respiration was defined as follows:

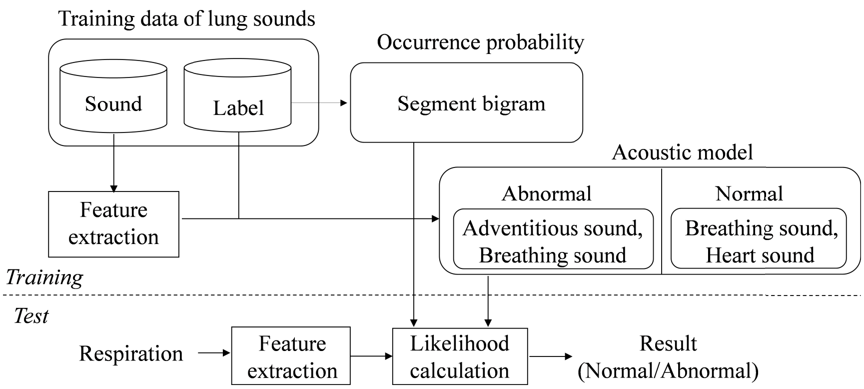

Fig. 4 Architecture of the classification system for normal and abnormal respiration.

- Abnormal respirations from patients (AP): respirations that include adventitious sounds from patients.
- Abnormal respirations from control subjects (AC): respirations that include noises resembling adventitious sounds from control subjects.
- Normal respirations from patients (NP): respirations that do not include adventitious sounds or noises resembling the adventitious sounds from patients.
- Normal respirations from control subjects (NC): respirations that do not include adventitious sounds or noises resembling the adventitious sounds from patients.

In our discrimination experiment, only NC was used as normal respiration and AP as abnormal respiration; that is, AC and NP were excluded.

3. Detection of Abnormal Respiration

3.1 Fundamental Classification Procedure

Several approaches to classification have been developed, such as methods using support-vector machine (SVM) and deep learning models. However, SVM models are more suited to analyze, e.g., flame, and are not well-suited to analyze the entire sequential signal of a sound. Deep learning methods are effective, e.g., in speech recognition. However, large-scale training databases are required. In contrast, HMMs have achieved relatively high accuracy on speech recognition tasks with small amount of training data. In this study, HMMs were used to perform classification because no large-scale database of lung sounds is available, and lung sounds should be analyzed using entirety of the sequential signal of the respiration. Generally, in speech recognition, the acoustic models of a phoneme (as the smallest unit of speech) and the occurrence probability of words are used to construct stochastic models. This technique was applied to recorded lung sounds. Figure 4 shows the architecture of the classification system for normal and abnormal respiration [13]. The system involves training and testing processes. In the training process, the HMMs are traind as acoustic and the segment-sequence models [15] that define the occurrence probability of the divided segments. In the testing process, an input respiration is classified as normal or abnormal respiration based on the maximum likelihood approach. Assuming that sample respiration W consists of N segments, it can be expressed as $W = w_1, w_2 \cdots w_i \cdots w_N$ where w_i is the i-th segment of W.

The training process can be explained as follows. First, we extract the acoustic features and train each segment. For normal respiration, if we assume that heart sounds are not included, it consists of single segment ($N = 1$). Conversely, for abnormal respiration, including adventitious sounds, it consists of at least two segments ($N \geq 2$). For example, for the case of expiration in Fig. 3, it consists of one wheeze segment and two breathing segments ($N = 3$). For the case of inspiration in Fig. 3 that does not include adventitious sounds, it consists of single breathing sound segment ($N = 1$). Training of the segment sequence model can be explained as follows. The occurrence probability of the segments $P(W)$ is calculated by using a segment bigram. $P(W)$ can be written as

$$P(W) = w_1 \times \Pi_{i=2}^{N} P(w_i|w_{i-1}) \tag{1}$$

Let $P(w_i|w_{i-1})$ be defined as

$$\begin{aligned} P(w_i|w_{i-1}) &= C(w_i|w_{i-1}) \\ &= (w_{i-1}, w_i)/C(w_{i-1}), \end{aligned} \tag{2}$$

where $C(w_i)$ is the count of w_i, $C(w_{i-1})$ is the count of w_{i-1}, and $C(w_i|w_{i-1})$ is the count of segment w_i after w_{i-1} in the training database.

The testing process can be explained as follows. The maximum likelihood calculated is found, and the corresponding segment sequence $\hat{W}$ is selected to recognize the sample respiration sound. If the sequence includes at least one adventitious sound, the sample respiration is identified as an abnormal sound. Conversely, the sample respiration is identified as a normal sound. Here, $\hat{W}$ can be written as

$$\hat{W} = \arg\max_{W}(\log P(X|W) + \alpha \log P(W)) \tag{3}$$

where X is the sample respiration, and $\log P(X|W)$ is the acoustic likelihood. The weight factor was obtained experimentally.

3.2 Detection of Patient Subjects

This section describes the detection of patients. Noises from outside the body occur irregularly. Conversely, adventitious sounds occur periodically. Therefore, for control subjects, most respirations are classified as normal even if one or a few respirations are classified as abnormal. That is, for control subjects, most of the likelihood values for normal respiration are higher than the likelihood values for abnormal respiration, even if one or a few respirations are classified as abnormal. To detect patients, we calculate the likelihood $L(W_{no})$ for the segment sequence W_{no} that does not include adventitious sounds and the maximum likelihood $L(W_{ab})$ for the segment sequence W_{ab} that includes adventitious sound segments for each respiration. If the total of $L(W_{ab})$ is greater than or equal to the total of $L(W_{no})$ then the subject is classified as patient. That is,

$$\Sigma_j L(W_{j,ab}) \geq \Sigma_j L(W_{j,no}), \tag{4}$$

where $L(W_{j,ab})$ is the likelihood for the segment sequence that includes adventitious sound segments for the j-th respiration of the subject and $L(W_{j,no})$ is the likelihood for the segment sequence that does not include adventitious sound segments for the j-th respiration.

3.3 Classification Procedure Using a Heart-Sound Model

To distinguish adventitious from heart sounds, a heart-sound model was constructed in addition to the breathing-sound model and adventitious model [15], [16]. In the training process, the acoustic models were trained. For normal respiration sounds, the normal sound model was trained using the breathing and heart-sound segments. For abnormal sound, the model was trained as in the fundamental classification procedure. In the testing process, the maximum likelihood among the calculated likelihoods was found, and the corresponding segment sequence W was selected to recognize the sample respiration sound, as in the fundamental classification procedure. The difference from the fundamental classification procedure is that, even if the sequence includes some heart sounds, the sample respiration was identified as a normal sound.

4. Construction of Appropriate HMMs

In our previous studies [11]–[16], the number of states and mixtures of HMMs for each segment was set to three, and the models were assumed to be not suitable. Therefore, we focused on analyzing the topology of acoustic models. For example, the duration of the stationary sound period differed significantly between heart and adventitious sounds. Table 1 shows the mean and standard deviation (S.D.) of the duration of adventitious and heart sounds. The duration of heart-sounds is shorter than that of adventitious sounds. Subsequently, we focused on the model for adventitious and heart sounds. To construct the appropriate HMMs for adventitious and heart sounds, suitable HMMs were constructed by selecting several states and mixtures for each segment [17]. The results showed that selecting the number of states and mixtures was effective. In [17], although we did not distinguish between the model for continuous adventitious sounds and that for discontinuous adventitious sounds, there was a significant difference in the character of the acoustic features of continuous and discontinuous adventitious sounds.

Table 1 Mean and standard deviation of duration for adventitious and heart sounds (unit in s) [15].

Source sound	Mean	S.D.
Adventitious sound	0.53	0.31
Heart sound	0.12	0.03

Thus, in the proposed approach, suitable HMMs were constructed for adventitious sound segments by selecting several states and mixtures for continuous adventitious sounds and discontinuous adventitious sounds separately. Furthermore, we construct the appropriate HMMs for breathing sounds and normal respirations.

5. Classification Experiments

5.1 Experimental Conditions

Every 10 ms, six mel-frequency cepstral coefficients (MFCCs) and power values were extracted as acoustic features using a 25-ms Hamming window. The lung sound data were sampled at 5 kHz. Figure 5 shows the auscultation points. In this study, a heart-sound model was used for auscultated lung sounds from three points near the heart (A-C). Conversely, a heart-sound model was not used for auscultated lung sounds from six points far from the heart (D-I). Table 2 shows that the number of abnormal respiratory sounds included adventitious sounds, and the numbers of patients included at least one adventitious sound. As many normal respirations or control subjects were selected randomly for each detection experiment of abnormal respirations and patient subjects. The number of each sound segment is shown in Table 3. Because there were no significant differences between the acoustic features of S1 and S2, one heart-sound model was constructed without distinctions between the two. Hereafter, a leave-one-out cross-validation was performed to construct a subject-independent model.

5.2 Classification Experiments Between Normal and Abnormal Respirations

In a previous study [17], we determined the number of states of HMMs for the heart-sound segments. We found a suitable number of states from one to five, with three mixtures and iterations in training. Figure 6 shows F1-score of detection of abnormal respiration using each number of states, mixtures and iterations in training for the heart-sound model. The F1-score was the highest when the number of states was two. Subsequently, two was selected as a suitable number of mix-

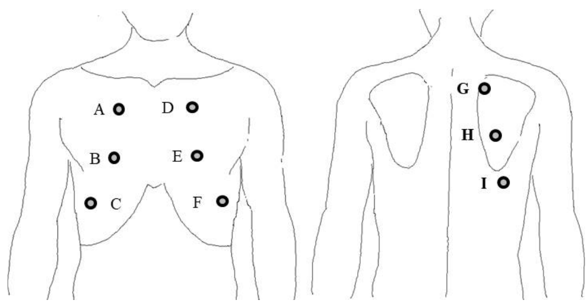

Fig. 5 Auscultation points.

Table 2 Numbers of abnormal respiratory sounds and patients.

Points	No. abnormal Respiration	No. patients
A	219	44
B	161	89
C	254	53
D	217	47
E	312	62
F	206	52
G	182	46
H	324	62
I	260	62
Total	2135	517

Table 3 Numbers of each type of sound segment.

Segments	No. segments
Heart sound	4940
Discontinuous adventitious sound	1753
Continuous adventitious sound	397
Breathing sound	4285
Normal respiration	2135

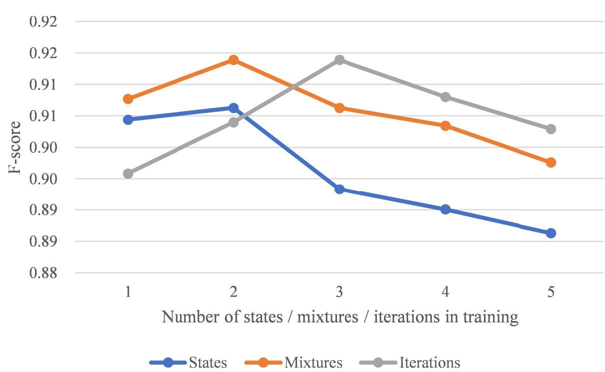

Fig. 6 F1-score of the abnormal respiration detection using each heart-sound model.

tures from one to five, with two states for the heart-sound segments. Meanwhile, three was selected as a suitable number of iterations in training from one to five with two mixtures for the heart-sound segments. Thereafter, the numbers of states, mixtures and iterations in training for each segment with this procedure were set.

For the HMMs for adventitious sounds, we first set the number of states for discontinuous adventitious sounds. We found a suitable number of states, with three mixtures and iterations in training. Figure 7 shows the F1-score of de-

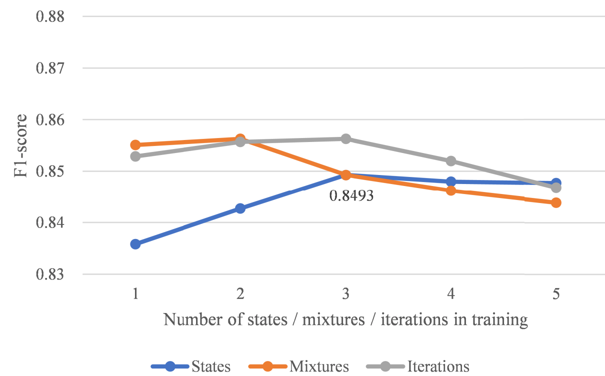

Fig. 7 F1-score of the abnormal respiration detection using each discontinuous adventitious sound model.

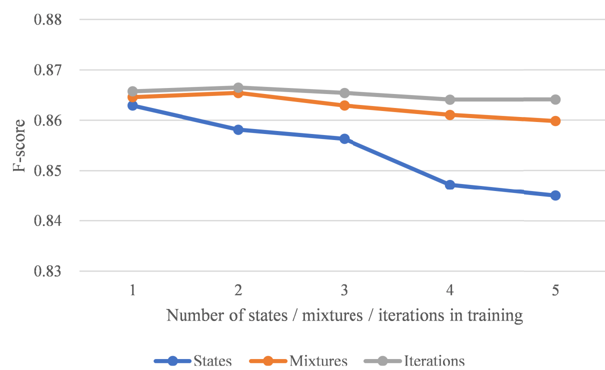

Fig. 8 F1-score of the abnormal respiration detection using each continuous adventitious sound model.

tection of abnormal respiration using each number of states, mixtures and iterations in training for the discontinuous adventitious sound model. The F1-score shown in Fig. 7 is lower than that shown in Fig. 6, because Fig. 7 was calculated using more respirations, and many veiled sounds were observed. The F1-score was the highest when the number of states was three. We then found two mixtures and three iterations in training to be suitable values.

For the HMMs for continuous adventitious sounds, we first set the number of states. Figure 8 shows the F1-score of detection of abnormal respiration using each number of states, mixtures, and iterations in training for the continuous adventitious sound model, with three mixtures and iterations in training. The F1-score was highest with a single state. We attribute this to the acoustic features of the continuous adventitious sounds being steady. Therefore, a single state was sufficient to express the continuous adventitious sound segments. We found two mixtures and two iterations to be suitable values for training. The number of states for continuous adventitious sounds was less than that for discontinuous adventitious sounds. We considered that this was the case because the change in acoustic features of continuous adventitious sounds was small. The result was the highest when we set a different number of states and iterations in training between continuous adventitious and discontinuous adventitious sounds. This result indicates the effectiveness

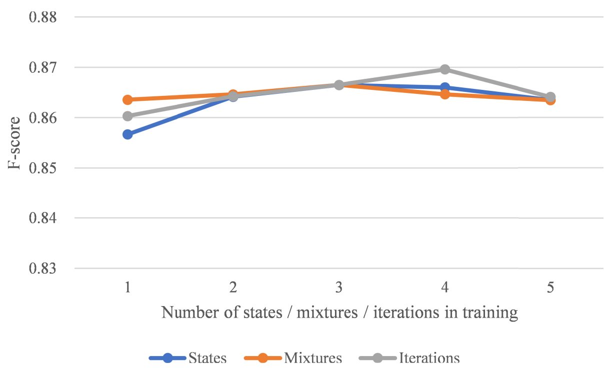

Fig. 9 F1-score of the abnormal respiration detectiion using each breathing-sound model.

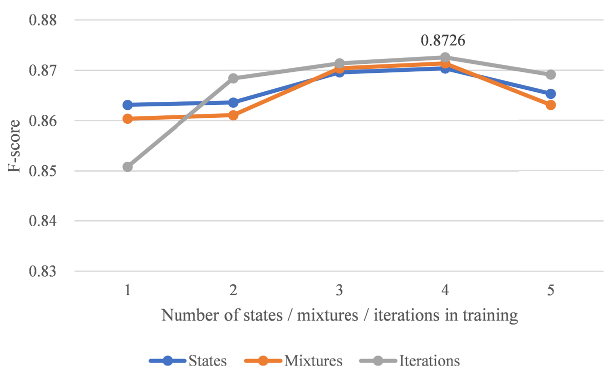

Fig. 10 F1-score of the abnormal respiration detection using each normal respiration-sound model.

of constructing the adventitious sound model for each.

For the HMMs for breathing sound segments from patients (e.g., w_1 and w_3 in Figs. 2 and 3), we first set the number of states. Figure 9 shows the F1-score of detection of abnormal respiration using each number of states, mixtures and iterations in training for the breathing sound model. The F1-score was the highest for three states. As the suitable number of mixtures was three, the model was trained in more detail than the heart-sound model or adventitious sound model. This was the case because the amount of training data for the breathing sound segments was greater than that of the heart-sound segments or the adventitious sound segments. This is because the duration of heart and adventitious sound segments was short. Then, four iterations were selected as a suitable value in training.

In the next step, we found a suitable number of states and mixtures for HMMs of the normal respiration segment. First, we set the number of states. Figure 10 shows the F1-score of detection of abnormal respiration using each number of states, mixtures and iterations in training for the normal respiration sound model. The F1-score was the highest with four states, mixtures, and iterations. The model was trained in more detail than the heart or adventitious sound model. This is because the amount of training data for the normal respiration segment was greater than that of heart or adventitious sound segments, similar to breath sounds.

Table 4 F1-score of the detection of patients.

Method	Recall	Precision	F1-score
Baseline	0.8395	0.8821	0.8603
Proposed	0.8569	0.8949	0.8755

Table 5 Comparison of the F1-scores of each method.

Method	Recall	Precision	F1-score
SVM	0.9433	0.5542	0.6982
Deep learning	0.6173	0.6346	0.6258
Baseline	0.8445	0.8541	0.8493
Proposed	0.8787	0.8598	0.8726

Conversely, we considered that, when large values were selected, the amount of training data was insufficient. That is, the model overfitted the data.

The above result shows the significant effectiveness ($p = 0.0025$) of setting the suitable states, mixtures and iterations in training.

5.3 Classification Experiments Between Control Subjects and Patients

Finally, a classification experiment between control subjects and patients is presented here. Table 4 shows the F1-score of detection of patients. In the baseline, we set the number of states, mixtures, and iterations in training as three. We selected the number of states, mixtures, and iterations in training as the best values obtained in the previously mentioned classification experiments between normal and abnormal respiration.

In the classification experiment between control subjects and patients, the results showed the possibility of improvement of the F1-score. However, the improvement was not significant because the number of test subjects was small.

5.4 Discussion

We performed classification experiments between normal and abnormal respiration using SVM and deep learning models that set parameters as in general speech recognition. In the experiment using a SVM, when abnormal flames were detected from respiration, the respiration was detected as abnormal. Consequently, although the recall rate was high, the precision was low. This was the case because noises were detected as abnormal sounds, and then respirations including noises were detected as abnormal. In contrast, in the experiment using deep learning, both the recall and precision were low. Consequently, the F1-score was not high because deep learning requires large-scale training data to achieve high performance. That is, the amount of training data was not satisfied and the model was overfitted the data. To overcome these issues, the method adopts HMMs, which are suited to express the entire sequential signal of a sound.

Then, these methods were compared. Table 5 shows the F1-score of each method. Baseline refers to a method using HMMs in which the number of states, mixtures, and iterations in training was set as three. The methods using HMMs achieved better performance than the method using SVM and deep learning. The results show the effectiveness of the method using HMMs. Furthermore, to confirm the suitable HMMs with small training data, a suitable number of states, mixtures, and iterations in training were selected. Comparing the baseline with proposed method, the F1-score of our proposed method was higher than that of the baseline method. The result shows the significant effectiveness of our proposed approach. In contrast, it does involve the drawback of some difficulty in selecting the suitable number of states, mixtures, and iterations in training without ground-truth data.

6. Conclusions

In this paper, a method was proposed to construct an appropriate HMM for heart sounds, two types of adventitious sounds, breath sounds, and normal respiration with high accuracy by selecting a suitable number of states, mixtures, and iterations in training to distinguish the sounds of normal and abnormal respiration. The result of he classification experiment confirmed an improvement in the F1-score of the abnormal respiration detection, demonstrating the effectiveness of the proposed approach. The number of states, mixtures, and iterations in training must be set according to the properties of the acoustic features and the amount of training data available. Furthermore, the resulets indicated that the suitable number of states and iterations in training differed for each type of adventitious sound. In contrast, in the classification experiment between control subjects and patients, the observed improvement was not significant owing to the small number of test subjects. In future work, we plan to clarify the number of suitable states, mixtures, and other parameters using a deep neural network, which has been shown to be effective in speech recognition.

Acknowledgments

This work was supported by The Telecommunications Advancement Foundation.

References

[1] N. Gavriely, Breath Sounds Methodology, CRC Press, Boca Raton, FL, USA, 1995.

[2] Y.P. Kahya, S. Yerer, and O. Cerid, "A wavelet-based instrument for detection of crackles in pulmonary sounds," EMBC 2001 (Conf. Proc. IEEE Eng. Med. Biol. Soc.), Istanbul, Turkey, pp.3175–3178, Oct. 2001.

[3] A. Marshall, and S. Boussakta, "Signal analysis of medical acoustic sounds with applications to chest medicine," J. Franklin I., vol.344, no.3-4, pp.230–242, 2007.

[4] S.A. Taplidou and L.J. Hadjileontiadis, "Wheeze detection based on time-frequency analysis of breath sounds," Comput. Biol. Med., vol.37, no.8, pp.1073–1083, 2007.

[5] A. Rizal, W. Priharti, D. Rahmawati, and H. Mukhtar, "Classification of pulmonary crackle and normal lung sound using spectrogram and support vector machine," Journal of Biomimetics, Biomaterials and Biomedical Engineering, vol.55, pp.143–153, 2022.

[6] F. Demir, A. Sengur, and V. Bajaj, "Convolutional neural networks based efficient approach for classification of lung diseases," Health Information Science and Systems, vol.8, no.1, p.4, 2020.

[7] T. Nguyen and F. Pernkopf, "Lung sound classification using snapshot ensemble of convolutional neural networks," EMBC 2020 (Conf. Proc. IEEE Eng. Med. Biol. Soc.), pp.760–763, Montreal, Canada, Aug. 2020.

[8] L. Pham, I. McLoughlin, H. Phan, M. Tran, T. Nguyen, and R. Palaniappan, "Robust deep learning framework for predicting respiratory anomalies and diseases," EMBC 2020 (Conf. Proc. IEEE Eng. Med. Biol. Soc.), pp.164–167, Montreal, Canada, Aug. 2020.

[9] E. Messner, M. Fediuk, P. Swatek, S. Scheidl, F.-M. Smolle-Juttner, H. Olschewski, and F. Pernkopf, "Crackle and breathing phase detection in lung sounds with deep bidirectional gated recurrent neural networks," EMBC 2018 (Conf. Proc. IEEE Eng. Med. Biol. Soc.), pp.356–359, Honolulu, Hawaii, July 2018.

[10] D. Perna and A. Tagarelli, "Deep auscultation: Predicting respiratory anomalies and diseases via recurrent neural networks," International Symposium on Computer-Based Medical Systems (CBMS 2019), pp.50–55, Cordova, Spain, June 2019.

[11] S. Matsunaga, K. Yamauchi, M. Yamashita, and S. Miyahara, "Classification between normal and abnormal respiratory sounds based on maximum likelihood approach," ICASSP 2009 (IEEE SPS), Taipei, Taiwan, pp.517–520, April 2009.

[12] M. Yamashita, K. Yamauchi, S. Matsunaga, and S. Miyahara, "An examination of constructive method of HMM considering the segmentation of respiratory sound and variety of adventitious sounds in classification between normal and abnormal respiratory sounds," J. IEICE, vol.J96-D, no.9, pp.2070–2077, 2013.

[13] H. Yamamoto, S. Matsunaga, M. Yamashita, K. Yamauchi, and S. Miyahara, "Classification between normal and abnormal respiratory sounds based on stochastic approach," 20th International Congress on Acoustics (ICA 2010), Sydney, Australia, pp.4144–4148, Aug. 2010.

[14] N.N. Oo, M. Yamashita, and S. Matsunaga, "Normal and whispered speech recognition systems for Myanmar digits," International Journal of Science and Engineering Applications (IJSEA), vol.7, no.11, pp.465–469, Nov. 2018.

[15] M. Yamashita, M. Himeshima, and S. Matsunaga, "Robust classification between normal and abnormal lung sounds using adventitious-sound and heart-sound models," ICASSP 2014 (IEEE SPS), Florence, Italy, pp.4451–4455, May 2014.

[16] M. Taguchi, M. Yamashita, and S. Matsunaga, "Detection of abnormal lung sounds considering spectral and temporal features of heart sounds," 22nd International Congress on Acoustics (ICA 2016), Buenos Aires, Argentina, pp.1858–1867, Sept. 2016.

[17] M. Yamashita, "Construction of effective HMMs for classification between normal and abnormal respiration," Proc. of APSIPA 2020, Auckland, New Zealand, pp.914–918, Dec. 2020.

Masaru Yamashita received his B.S., M.S. and Ph.D. degrees in engineering from Nagasaki University in 2002, 2004, and 2016, respectively. In 2004, he joined Nagasaki University, where he is with the Technical Staff.