

# ABNORMAL-RESPIRATION DETECTION BY CONSIDERING CORRELATION OF OBSERVATION OF ADVENTITIOUS SOUNDS

Shohei Matsutake, Masaru Yamashita and Shoichi Matsunaga

Department of Computer and Information Sciences, Nagasaki University, JAPAN

## ABSTRACT

We propose a classification method to distinguish between normal and abnormal respiration by considering the correlation of the observation frequencies of adventitious sounds between auscultation points. This method is based on the fact that adventitious sounds are frequently observed in lung sounds from multiple points. We use the product of the correlation score and the abnormality score, which indicates the likelihood that a candidate is abnormal, of lung sounds from different points. When using lung sounds from eight points, the proposed method achieved a higher classification performance of 92.0% between normal and abnormal respiration compared with the baseline method not considering the other lung sounds, which achieved a performance of 84.1%. Our approach to the classification of healthy subjects and patients also achieved a higher classification rate of 90.8%.

**Index Terms**— lung sound, classification, adventitious sound, auscultation, pulmonary emphysema

## 1. INTRODUCTION

Diagnosis using a stethoscope, i.e., auscultation, is one of the most popular and cost-effective medical examination methods for identifying respiratory illnesses. Auscultation is based on the observation of abnormal respiratory sounds that are frequently observed in patients with pulmonary emphysema. These sounds, termed “adventitious sounds,” include wheezes and crackles and are caused by abnormalities in the lungs and bronchial tubes [1]. Patients can produce several types of adventitious sounds depending on the condition of the abnormal internal organs and the degree of inflammation of the organs. Physicians usually perform auscultation at several points on the patients’ chest and back. If the auscultation point is closer to the abnormal parts, the adventitious sounds will become clearer. If the physicians detect acoustic features such as adventitious sounds at one auscultation point, they auscultate at points near that point in order to confirm the sounds. The present study aims to develop an approach employing this

auscultation strategy that enables the highly accurate detection of abnormal respiration including adventitious sounds.

Several studies involving the acoustic analyses of respiratory sounds have been conducted for the detection of specific adventitious sounds [2–5]. We developed a classification procedure to distinguish between normal and abnormal respiratory sounds according to the maximum-likelihood approach using hidden Markov models (HMMs) [6, 7]. This procedure demonstrates the usefulness of the stochastic approach for the detection of abnormal respiratory sounds. However, the low intelligibility of adventitious sounds hindered the achievement of a relatively high level of classification. This low intelligibility was mainly caused by (1) the similarity of the spectral features of noises to those of some types of adventitious sounds and (2) the great distance between the auscultation point and the abnormal parts. To cope with the first cause, we devised a classification method considering the observation tendency of adventitious sounds in a series of respiratory sounds [8]. The rationale for this is that the occurrence tendency of noise in respiratory sounds is random, whereas it is observed frequently that adventitious sounds occur repeatedly in successive respiratory phases. With regard to the second cause, we showed that patient detection using lung sounds collected from multiple auscultation points is effective [9].

Adding to the previous study’s use of multiple lung sounds from different points [9], in this paper, we introduce the correlation of the observation frequencies of adventitious sounds between auscultation points to use the information from other points effectively. Therefore, the product of the correlation score and the abnormality score, which is the difference between the likelihood for an

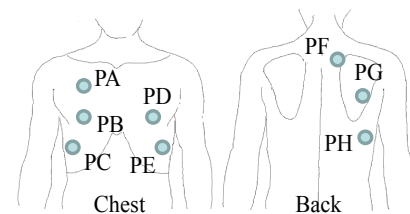


Fig. 1. Multiple auscultation points.

abnormal candidate and that for a normal candidate, of the lung sounds from other points was used in the proposed classification. The validity of the proposed method was confirmed by classification experiments involving normal and abnormal respiration, including normal subjects and patients, using lung sound samples recorded at eight auscultation points.

## 2. LUNG SOUND DATA

### 2.1. Training and evaluation data

We recorded lung sounds at eight auscultation points in patients with pulmonary emphysema and in healthy subjects in quiet clinic rooms using an electronic stethoscope that incorporates a piezoelectric microphone. The auscultation points are shown in Figure 1, where “PB” and “PD” indicate the second intercostal spaces. For each subject, one lung sound sample was recorded at each auscultation point. From this lung-sound data, we selected the patients whose eight lung sound samples included at least one sample containing at least one adventitious sound. Thus, for each auscultation point, 66 samples from 66 patients and 64 samples from 64 healthy subjects were prepared. For each subject, the eight samples were recorded not simultaneously but over a few hours. Each sample comprised successive respiratory phase segments (inspiratory and expiratory); the average number of respiratory segments was approximately 10. The average number of samples per subject—including adventitious sounds—was 4.9.

We tagged the segments according to the respiratory phase (inspiratory or expiratory), diagnostic state (normal or abnormal), auscultation point, and subjects’ health (healthy or patient). The subject’s health was determined by a doctor on the basis of auscultation and the existence of other medical conditions.

### 2.2. Manual labeling of acoustic segments

The lung sound sample  $S_{j,k}$  from the  $k$ -th subject’s  $j$ -th auscultation point comprised several successive respiratory phases  $W$  ( $j=1, \dots, J$ ,  $k=1, \dots, K$ ):

$$S_{j,k} = W_1 W_2 \cdots W_l \cdots W_{L_{j,k}}, \quad (l=1, \dots, L_{j,k}), \quad (1)$$

where  $W_{j,k,l}$  (abbreviated as  $W_l$ ) is the  $l$ -th respiratory phase in which the period was manually detected. We prepared labels corresponding to the acoustic segments based on acoustic and segmental features [6]. In our labeling process, we assumed that an abnormal respiratory phase was composed of  $N$  successive acoustic segments and that a normal respiratory phase comprised one breath segment ( $N=1$ ). Then, a respiratory period  $W$  is represented as

$$W_{j,k,l} = w_1 w_2 \cdots w_i \cdots w_N, \quad (2)$$

where the  $i$ -th acoustic segment is given as  $w_i$  ( $i=1, \dots, N$ ). In the present study, each adventitious sound was presented using a continuous acoustic segment (e.g., rhonchus, wheezing) or a discontinuous acoustic segment (e.g., coarse crackle, fine crackle).

## 3. CLASSIFICATION STRATEGY

### 3.1. Acoustic likelihood calculation

We denote the occurrence probability of the segment sequence  $W_{j,k,l}$  using Equation (2) as  $P(W_{j,k,l})$ , i.e.,

$$P(W_{j,k,l}) = P(w_1 w_2 \cdots w_i \cdots w_N). \quad (3)$$

We used the segmental bigram[6] to calculate  $P(W)$  approximately. The total likelihood is composed of the acoustic likelihood calculated from HMMs and the segmental sequence likelihood calculated from the bigram.

The segment (sequence)  $\hat{W}_{j,k,l}$  with the highest likelihood  $\log P(\hat{W}_{j,k,l} | X_{j,k,l})$  for an unknown respiratory input  $X_{j,k,l}$  is given below using Bayes’ theorem:

$$\begin{aligned} \hat{W}_{j,k,l} &= \arg \max_{W_{j,k,l}} \log P(W_{j,k,l} | X) \\ &\approx \arg \max_{W_{j,k,l}} [\alpha \log P(W_{j,k,l}) + \log P(X | W_{j,k,l})] \end{aligned} \quad (4)$$

where  $X_{j,k,l}$  is abbreviated as  $X$ . The weight factor  $\alpha$  controls the contribution of the acoustic-segment bigram and was obtained experimentally. The difference  $r$  between the likelihood  $\log P(\hat{W}_{j,k,l}^{ab} | X)$  for an abnormal respiration candidate  $\hat{W}_{j,k,l}^{ab}$  and the likelihood  $\log P(\hat{W}_{j,k,l}^{no} | X)$  for a normal respiration candidate  $\hat{W}_{j,k,l}^{no}$  is the main factor used in our classification:

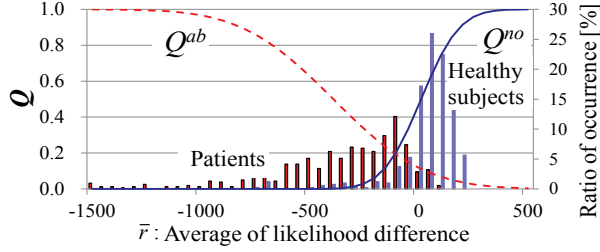
$$r_{j,k,l} = \log P(\hat{W}_{j,k,l}^{no} | X) - \log P(\hat{W}_{j,k,l}^{ab} | X) \quad (5)$$

### 3.2. Observation tendency of adventitious sounds

To calculate the correlation between the occurrence frequency of adventitious sounds at one auscultation point  $j1$  and that at an other point  $j2$  on the basis of the observed frequency of adventitious sounds from patients, we defined the average correlation score  $T_{j1,j2}$  as follows:

$$T_{j1,j2} = \sum_k C_k(j1, j2) / K, \quad (j1 \neq j2), \quad (6)$$

where  $0 \leq T_{j1,j2} \leq 1$ . If adventitious sounds were observed in both the lung sound samples at the  $j1$ -th and  $j2$ -th points for a subject  $k$ ,  $C_k(j1, j2)$  was set to 1; otherwise,  $C_k(j1, j2)$  was set to 0. This correlation score was used in the classification criteria C3 and C4 in Section 3. When  $j1 = j2$ , the correlation score  $T$  was calculated using the above equation except for the definition of  $C$ ; if adventitious sounds were observed in more than two



**Fig. 2.** Histograms of likelihood differences in other points and cumulative distribution functions  $Q^{ab}$  and  $Q^{no}$ .

respiratory periods in the sample at the  $j$ -th point,  $C_k(j, j)$  was set to 1; otherwise,  $C_k(j, j)$  was set to 0. This was used in the classification criteria C2 and C4.

Next, the average of the difference  $r$  in Equation (5) among all phases from the  $k$ -th subject's  $j$ -th auscultation point is described as

$$\bar{r}_{j,k} = \sum_l r_{j,k,l} / L_{j,k}. \quad (7)$$

We investigated the characteristics of the difference score  $\bar{r}$ . According to our assumption, if the respiratory phase  $X_{j,k,l}$  includes adventitious sounds, the value  $\bar{r}_{m,k}$  is expected to be high, where  $m$  is one of the other points. That is, some adventitious sounds are likely to be observed in lung sounds recorded at other points. Figure 2 shows histograms of  $\bar{r}$  in other points for healthy subjects and patients, using the lung sounds described in Section 2. The scores for normal subjects were distributed in the positive-value region (average 34.5 and SD 138). On the other hand, the patients' scores were distributed broadly (average -368 and SD 330). These results show that the difference likelihood  $\bar{r}$  of the respiration sounds recorded at other auscultation points is useful for detecting abnormal respiratory phases.

Next, we formulated a procedure to calculate the occurrence tendency of adventitious sounds at other points. First, each Gaussian distribution was adopted for modeling the distribution of the score  $\bar{r}$  for all normal subjects and patients as  $N^{no} = N(34.5, 138^2)$  and  $N^{ab} = N(-368, 330^2)$ , respectively. Then, the cumulative distribution function for healthy subjects was generated as  $Q^{no}(r) = \int_{-\infty}^r N^{no} dr'$ .

Conversely, the function  $Q^{ab}(r) = -\int_{\infty}^r N^{ab} dr'$ , which was cumulated in the opposite direction, was used for the patients. These functions are shown in Figure 2. We define the occurrence tendency of adventitious sounds, herein referred to as the abnormality score, in the lung sounds at another point  $m$  ( $\neq j$ ) as follows:

$$A(\bar{r}_{m,k}) = \beta(Q^{no}(\bar{r}_{m,k}) - Q^{ab}(\bar{r}_{m,k})) + \gamma, \quad (8)$$

where  $\beta$  and  $\gamma$  are experimentally determined to achieve the highest performance. In our proposed classification, the product of  $A$  (normality/abnormality score considering other sounds from different points) and  $T$  (correlation score

between auscultation points) was used.

### 3.3. Criteria of abnormal respiration detection

We examined four criteria in identifying abnormal and normal respiratory phases: C1, C2, C3, and C4. Criteria C3 and C4 considered the correlation of the observation of adventitious sounds in the lung sounds from other points that were newly proposed in this paper. A target respiratory phase is given as  $X_{j,k,l}$ .

(C1) This classification is based on a comparison of the two likelihoods for each respiration phase  $j$ , i.e.,

$$r_{j,k,l} = \log P(\hat{W}_{j,k,l}^{no} | X) - \log P(\hat{W}_{j,k,l}^{ab} | X) > 0. \quad (9)$$

This is referred to as the baseline criterion using a single respiratory phase [6]. If this inequality is true, the respiratory phase  $X_{j,k,l}$  is regarded as a normal respiration.

(C2) This classification considers the observation tendency of adventitious sounds in the preceding and succeeding respiratory phases of the test sample, i.e.,

$$r_{j,k,l} + T_{j,j} A(\bar{s}'_{j,k,l}) > 0. \quad (10)$$

The concept of this criterion is the same as that proposed in our previous paper [8]; however, the correlation score is introduced here. This criterion was examined to verify the validity of the proposed criterion C3. The term  $\bar{s}'_{j,k,l}$  is the average of the likelihood difference of other phases in the sample (Figure 3) where the target phase  $X_{j,k,l}$  was not involved;

$$\bar{s}'_{j,k,l} = \sum_{i(i \neq l)} r_{j,k,i} / (L_{j,k} - 1). \quad (11)$$

The functions  $Q^{ab}$  and  $Q^{no}$  were derived using the histograms of the average likelihood difference  $\bar{s}'_{j,k,l}$  of other phases in the target sample. The calculation of  $A'$  using the cumulative distribution function of  $\bar{s}'_{j,k,l}$  is identical to that of  $A$ .

(C3) This classification considers the observation tendency of adventitious sounds in the lung sounds of subject  $k$  recorded at other points, i.e.,

$$r_{j,k,l} + \sum_{m(m \neq j)} T_{j,m} A(\bar{r}_{m,k}) > 0. \quad (12)$$

The second term indicates the product of the correlation score and the abnormality score.

(C4) This criterion considers both the observation tendency of adventitious sounds in a series of respiratory phases of the test sample and that in lung sounds recorded at other points. C4 is a combination of C2 and C3.

$$r_{j,k,l} + T_{j,j} Q(\bar{s}'_{j,k,l}) + \sum_{m(m \neq j)} T_{j,m} A(\bar{r}_{m,k}) > 0. \quad (13)$$

### 3.4. Criteria to detect patient subjects

Three of the aforementioned criteria—C1, C3, and C4—

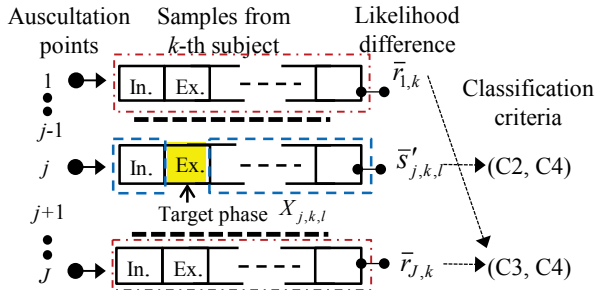


Fig. 3. Respiratory phases for calculation of the abnormality score for each classification criterion.

were expanded for identifying patients by summing the difference of the likelihoods between all normal respiratory candidates and all abnormal respiratory candidates in a test sample (respiratory phase sequence) using the equations described in Section 3.3.

(C1) For each subject, we compared the two total likelihood results (for normal and abnormal respiration) for all samples recorded at the different auscultation points. If the average likelihood for normal respiration was larger than that for abnormal respiration, the subject  $k$  was regarded as a healthy subject;

$$\sum_j \frac{1}{L_{j,k}} \sum_l r_{j,k,l} > 0. \quad (14)$$

This baseline criterion for patient detection using multiple lung sounds was proposed in [9].

(C3, C4) We compared the two likelihood results by summing the likelihood of each phase similarly to Equation (14). For example, the criterion C4 expanded for patient detection is described as follows:

$$\sum_j \frac{1}{L_{j,k}} \sum_l \left[ r_{j,k,l} + T_{j,j} A'(\bar{s}'_{j,k,l}) + \sum_{m(m \neq j)} T_{j,m} A(\bar{r}_{m,k}) \right] > 0. \quad (15)$$

## 4. EVALUATION EXPERIMENTS

### 4.1. Experimental conditions

In order to evaluate the proposed approach, we performed classification tests to distinguish between normal and abnormal respiratory phases and between healthy subjects and patients. Lung sound data were sampled at 5 kHz. For every 10 ms, a vector of five mel-warped cepstral coefficients and the power was computed using a 25-ms Hamming window. This vector was used as an acoustic feature when modeling the segment HMMs. All HMMs were generated for each auscultation point using only the lung sound samples recorded at that auscultation point. HMMs with three states and two Gaussian probability density functions were used. The respiratory sounds of healthy subjects were used to train the models for normal respiration. These models were used to calculate the

acoustic likelihood for normal-respiration candidates. The models for abnormal respiration were also generated using the sounds obtained from the patients. A segment bigram for each auscultation point was also trained using the segment labels of the training samples recorded at the same auscultation point. We performed a leave-one-out cross validation.

### 4.2. Classification of normal and abnormal respiration

A classification experiment to distinguish between the abnormal respiration of patients and the normal respiration of healthy subjects was performed using the four aforementioned criteria. The evaluation samples were abnormal respiration phases (1567) from patients and an almost equal number of normal respiration phases (1573) from healthy subjects, randomly selected. The correlation score  $T_{j,m}$ , represented by a symmetric matrix, was obtained using 101 patients. The correlations  $T_{j,j}$  at the same point (average: 0.61) were higher than those between different points (average: 0.40). If two auscultation points were near each other, the correlation tended to be high. The highest value between different points was 0.63—between PB and PC on the front right of the subjects—and the lowest correlation was 0.26: between PE (front left) and PF (back right). In our experiments, if  $T_{j,m}$  was less than 0.4, we assumed that the correlation between points  $i$  and  $j$  was negligible; therefore, we set these  $T_{j,m}$  to zero. As a result, all correlations within the sample and 46% of all correlations between different points were considered.

The obtained classification results using samples from eight auscultation points are shown in Table 1. With regard to criteria C3 and C4, experiments were performed where the number of other points was 1, 4, 6, and 7. The average classification rate weighted by the data amount was indicated as “Average.” When the number of other points was 7, the proposed criterion C3 greatly increased the classification performance to 92.04%, considering the correlation score and the abnormality score, from the 84.14% of the baseline method only using the difference of the likelihoods of the target phase. The performance of C4 was highest when the number of other points was 7. On the basis of these results, we concluded that the proposed approach is effective for the detection of unclear adventitious sounds emitted by an abnormal part that is distant from the auscultation point.

### 4.3. Classification of healthy subjects and patients

Finally, classification experiments to distinguish between healthy subjects and patients with pulmonary emphysema were performed. Here, we examined three criteria (C1, C3, and C4) to identify a patient using samples from 66 subjects

**Table 1.** Classification of performance for normal and abnormal respiration for each auscultation point [%].

Criteria	No. other points	Normal	Abnormal	Average
C1 (Baseline)	[6] 0	83.92	84.37	84.14
C2 [8]	0	86.78	88.64	87.71
C3 (proposed)	1	86.39	87.26	86.82
	4	88.40	90.58	89.49
	6	90.42	92.32	91.37
C4 (proposed)	7	90.97	93.11	92.04
	1	87.94	89.76	88.85
	4	90.04	92.09	91.06
C4 (proposed)	6	90.63	93.01	91.82
	7	91.10	93.43	92.26

with a disease and 64 healthy subjects from 1 to 8 auscultation points. For the experiment that used 7 auscultation points, 7 combinations of 6 other auscultation points per subject were examined, and the average classification rate of 910 ( $= 7 \times (66 + 64)$ ) combinations was calculated.

Table 2 shows the classification performance for each number of auscultation points. The classification performance for each criterion increased monotonically and significantly with the increase in the number of auscultation points from one to eight. This result exhibited the same trend as the C1-based experimental results obtained using the samples from the four auscultation points described in our previous paper [9]. For each number of auscultation points (from 2 to 8), the proposed criteria C3 and C4 achieved a higher performance than the conventional criterion C1, demonstrating the effectiveness of our proposed approach. However, this superiority was small compared with the improvement obtained by the increase in the number of auscultation points. This is because both our patient-classification approach and the calculation of the abnormality score were based on the same procedure of likelihood summation for all auscultation points.

## 5. CONCLUSIONS

We proposed a new method for discriminating between normal respiration and abnormal respiration. This discrimination is based on the comparison of the likelihood for normal respiration and that for abnormal respiration. The likelihood was calculated according to the maximum likelihood approach using HMMs. In this likelihood calculation, to effectively classify a respiratory phase obtained from an auscultation point, the correlation of the observation tendency of adventitious sounds between auscultation points and the difference between the likelihood for abnormal candidates and that for normal candidates in respiratory sounds obtained from other

**Table 2.** Classification of patients and healthy subjects [%].

No. aus. points	Criteria	Healthy	Patients	Average
1	C1 (Baseline) [7]	83.0	76.7	79.8
3	C1 [9]	85.38	82.03	83.68
	C3	85.55	82.03	83.76
	C4	85.66	81.93	83.76
5	C1 [9]	86.41	84.09	85.23
	C3	86.66	84.39	85.51
	C4	86.72	84.09	85.38
7	C1 [9]	88.5	90.0	89.23
	C3	90.4	90.3	90.38
	C4	90.2	90.2	90.19
8	C1 [9]	89	91	90.0
	C3	91	91	90.8
	C4	91	91	90.8

auscultation points were considered. According to the classification experiments, the proposed classification method greatly increased the classification performance compared with the baseline method, which is based on a comparison of the likelihoods of the target respiratory phase. With respect to the classification of healthy and patient subjects, however, our experiments exhibited a small improvement in performance. This is a subject for future work.

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