

Discrimination of Lung Sounds using a Statistics of Waveform Intervals

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Abstract In a lung auscultatory sounds diagnosis, the diagnosis result would be affected by the skill of the doctor, that is, the doctor should discriminate a lung sounds by own subjective, since standard diagnosis procedure with objectivity has not been established yet. In many cases of the lung sounds diagnosis, the existence of features, which are called adventitious sounds, are important key. The adventitious sounds is roughly classified into two class; one is called coarse crackles, and the other is called fine crackles. Thus, we construct a computer aided diagnosis (CAD) system for classifying a lung sound into three types, that is, coarse crackle, fine crackle and normal breath sound. We aimed with the waveform time intervals for discrimination. Our CAD system calculates average histograms of intervals for each class, and discriminates a input histogram into these three types by the distance between each average histogram.

Keyword: Computer Aided Diagnosis, Respiratory Sounds, Peak interval analysis

1 Introduction

In the field of clinical medicine, auscultatory method is one of a basic skill for medical doctors, since the method is the easiest and the cost for the method is the lowest one. Moreover, since the auscultatory discrimination is not invasion method, the doctors would use this method repeatedly. However, in order to diagnose objectively, the auscultatory discrimination requires good skill and experiences for the doctor.

In order to diagnose of lung disease from the respiratory sounds, the existence of ab-

normal sounds becomes a key point for discrimination. From the clinical point of view, the abnormal sound that has greater than 250 [msec] duration is called a "continuous rale" and one that has less than about 20 [msec] duration is called a "discontinuous rale" or "crackle". The sound pitch of crackles depends on the process of the disease. However, obvious criteria for evaluating the pitch of crackles in a practical examination has not been discovered yet, because inter-examiner disagreement often occurs, that is, the respiratory sounds would not be generated by a stationary process and reproduction of the sounds is not occurred in periodic. Because of the difficulty for objective evaluation, a discrimination procedure using respiratory sounds has not been established yet.

In these decades, evolution of computer ability carried revealing the detail crackle characteristics in several studies, which was based on the time-expanded waveform analysis (TEWA) [1][2][3].

The waveform of a crackle expanded in time can be regarded as two parts, which are called, initial deflection width (IDW) and two-cycle duration (2CD), respectively. IDW is the time from the onset of the crackle until the first deflection returns to baseline. 2CD is the time from the onset of the crackle to the point where the waveform of the crackle has completed two cycles. The ratio between IDW and 2CD is considered as the good feature for analysis of crackles, so that finding starting points of crackles are a important for measuring the IDW and 2CD. However, finding accurate these crackle starting points are hard to carry out for the computer.

In this study, we developed a computer aided diagnosis (CAD) system for auscultatory sounds discrimination, based on the TEWA. We considered the essence of IDW

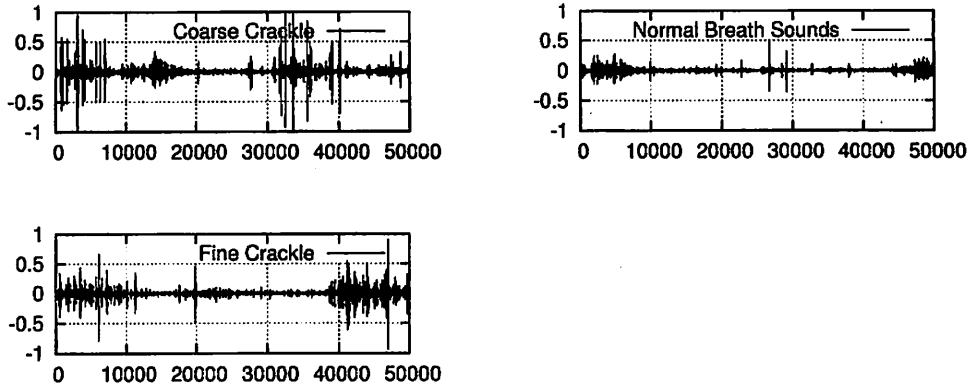


Figure 1: Typical sound wave forms: the horizontal axis represents time scale using sampling ticks, and vertical axis represents the amplitude of sounds. Left top shows coarse crackle, left bottom shows fine crackle, and right top shows normal breath sounds.

and 2CD method is involved in the intervals of peaks on crackle signal, so that our system calculate the statistics of the peak intervals, and apply the statistics for abnormal sounds recognition. Roughly speaking, the crackle can be classified as two types, that is, one is called “fine crackle” and the other is called “coarse crackle”. The features of the fine crackle are low amplitude, high pitch, and short duration time. On the other hand, the features of coarse crackle are high amplitude, low pitch, and long duration time. In order to support diagnosis for lung disease, our CAD system try to classify the respiratory sounds into three types, that is, normal breath sounds, fine crackle, and coarse crackle.

In sec.2, we explained the method and materials, and next in sec.3, we showed the recognition result of our system.

2 Method

Figures 1 show typical waveforms of the respiratory sounds which involved several noise and heartbeat sounds. In figures 1, Each vertical axis shows the amplitude of sounds, and each horizontal axis shows the time scale counted by the sampling ticks. In our data, the sampling rate is 11025 [Hz], and the each figure shows about 5 [sec] waveform. In those figures, left top shows coarse crackles waveforms, left bottom involves fine crackles, and right top shows normal breath sounds wave-

forms. In figures 1, we can observe that both crackles are occurred with high initial deflection (IDW), which indicates high amplitude in the waveform. And we can see that each crackle does not occurred in periodic. The American Thoracic Society reported the major frequency band of each respiratory sounds as follows: the fine crackle has two major frequency bands, one is 200~500 [Hz] and the other is 700~1000 [Hz]. the bands of coarse crackle is around 250~ 500 [Hz], and that of the normal breath is 150~600 [Hz]. Since these major bands are overlapped, discrimination using naive frequency filtering is not effective for discrimination of these sounds[4].

Fig.2 shows a magnification of the coarse crackle waveform in fig. 1 around time count 33600. and the waveform of this figure shows a typical coarse crackle. The coarse crackle occurred around 33600 counts and duration time is around 300 counts (about 27[msec]). Also fig.3 shows a typical fine crackle in fig.1 around 6000 counts. The fine crackle occurred around 6050 counts and duration time is around 50 counts (about 5[msec])

Comparison of these figures, we can find the coarse crackle has long duration time, so that we can discriminate these crackles if we can find the initial time of occurring crackle. However, the accurate finding of initial time of crackle occurring would be hard to carry out, and the result would be too much sensitive to the accuracy of the initial time of

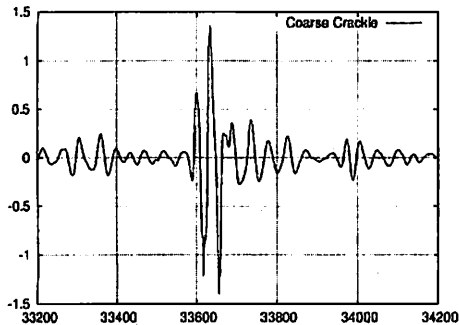


Figure 2: Typical coarse crackle waveform: the coarse crackle occurred around 33600 counts, and its duration time is about 300 counts

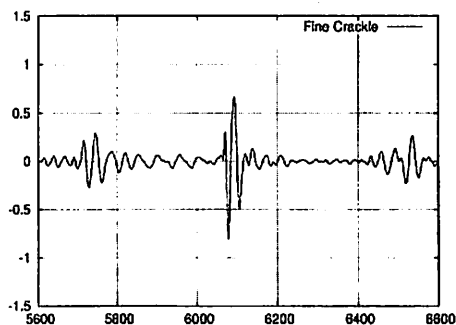


Figure 3: Typical fine crackle waveform: the fine crackle occurred around 6050 counts, and its duration time is about 50 counts

crackle occurring. Thus we use the statistics of the waveform intervals around the crackle for discrimination. In order to find the rough position of the crackle, we apply the thresholding to the waveforms, after that detection of waveform peak is carried out. Then, we can obtain several intervals of peak to peak for the waveforms. Fig.4 shows a schematic representation of the waveform intervals.

In order to use statistics of crackle waveforms, we calculate the histograms of waveform intervals for each subject, and after that, we calculate the average of the histograms for each class. When we describe the i -th subject histogram data, which belongs to the class c , as $\mathbf{d}_i^c = (d_{i1}^c, d_{i2}^c, \dots, d_{im}^c)^T$ where superscript T means transpose. Each element d_{ij}^c means the frequency of j -th histogram bin. The number of each class element as N^c , we

can describe the average histogram as

$$\mathbf{m}^c = \frac{1}{N^c} \sum_{i=1}^{N^c} \mathbf{d}_i^c. \quad (1)$$

Also covariance matrix V^c can be described as

$$V^c = \frac{1}{N^c - 1} \sum_{i=1}^{N^c} \mathbf{d}_i^c (\mathbf{d}_i^c)^T. \quad (2)$$

We aimed average mean histograms for crackle discrimination in our CAD system. These histograms can be regarded as the vector whose elements are frequency, so that we adopt a simple method for discrimination, that is, the system measures the distance between each mean histogram and that of the test datum. For measuring the distance, we adopt the Maharanobis distance. The Maharanobis distance is usually used to normalize the data in the meaning of the variance. When we obtained \mathbf{x} as the test data histogram, the Maharanobis distance M^c for the center of the class c is denoted as

$$M^c = (\mathbf{x} - \mathbf{m}_c)^T (V^c)^{-1} (\mathbf{x} - \mathbf{m}_c), \quad (3)$$

where $(V^c)^{-1}$ means the inverse matrix of the covariance matrix for class c .

In order to discriminate the test data, the system select the class c^* which have the minimum distance to the test datum:

$$c^* = \underset{c}{\operatorname{argmin}} M^c. \quad (4)$$

3 Experiment

To evaluate the discrimination ability of our CAD system, we prepared 36 examples for

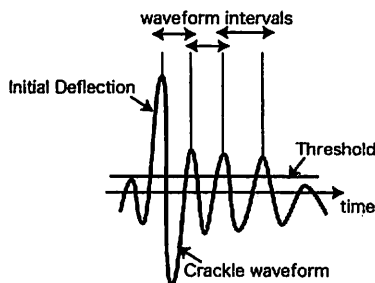


Figure 4: Schematic diagram of intervals of crackle waveform

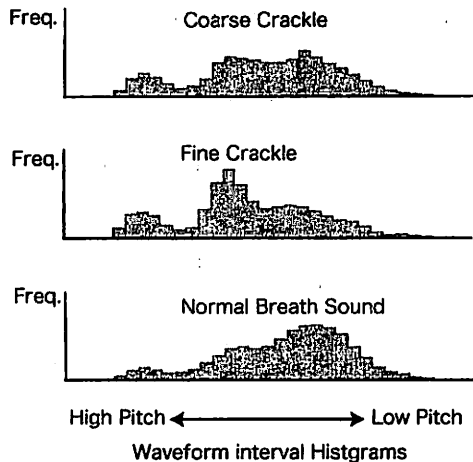


Figure 5: Average histograms of intervals of waveforms for crackles and normal breath

coarse crackles, 44 examples for fine crackles, and 140 examples for normal breath sounds, provided by Yamaguchi University hospital. Each datum are digitized by the digital stethoscope with voice recorder made by the Starkey Japan and Sony Inc. (Sampling Freq.:11025[Hz], 16[bits], 1[ch], and 5.0[sec]). To reduce the sampling noise, we apply the low pass filter whose cut off frequency is 2000 Hz. The threshold for finding the crackle position would be set at the 0.05 % point of the maximum amplitude. We set the number of the histogram bins as 26, which is decided by experimentally.

Fig.5 shows a typical example of the mean histograms m^c for coarse crackle, fine crackle, and normal breath sounds classes. In the histograms, at high pitch area, we can find the characteristic peak for both crackles, and moreover, we can also find that fine crackle histogram has another peak in the middle pitch area.

Table.1 shows the classification ability result to the Yamaguchi University hospital data. We can see the number of true-negative misclassification is 2 examples for coarse crackle class, and 1 example for the fine crackle class. From the clinical point of view, keeping the low true-negative ratio is important requirement for CAD system. In such meaning, we conclude the performance of our system may be good for classification.

4 Conclusion

In this study, we developed a CAD system for respiratory sounds classification. The system classified the input respiratory sounds into 3 classes, that is, coarse crackle class, fine crackle class, and normal breath sound class. In order to classify the breath sound, we apply waveform intervals for the feature extraction, and a naive statistical pattern recognition mechanism. In the result, we obtained good performance for the Yamaguchi University hospital data.

In our future work, we should evaluate the system performance to the other origin data, and improve the system performance.

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Table 1: Classification ability

	Classification result			Corre
	Coarse	Fine	Normal	
Coarse(36)	34	0	2	94%
Fine(44)	5	38	1	86%
Normal(140)	14	9	119	86%