Using breath sound data to detect intraoperative respiratory depression in non-intubated anesthesia

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Background

- Traditionnal Respiration monitoring in non-intubation anesthesia: SpO2; TEB。
  - SpO2: hemoglobin desaturation basically has the time lag than the occurrence of respiratory depression [4].Especially in the case of oxygen inhalation, the decrease of SpO2 is later than the occurrence of respiratory depression [5]
  - TEB: When TEB is used for respiratory monitoring, the disturbance of the blood flow of the heart and the large blood vessels in the chest is greatly disturbed; for a specific population, such as obese patients, the accuracy of using the impedance method to estimate respiratory rate is lower than that based on acoustic sound estimation [13].

- **Breath sound auscultation is one of the best ways to monitor respiration condition for its non-invasive auscultation and low cost, it is a very intuitive and valuable monitoring method.**

Background

- In general, the current research field of breath sound data processing is still fragmented, the data usage is rarely clinical data and the researches are rarely used for clinical applications.

- Many research groups study the classification of normal and abnormal breath sounds, and some research groups focus on the preprocessing of breath sound data, including de-noising filter, multi-channel data fusion and visualization of breath sound analysis results[8].

- There is basically no research publication on the application of breath sounds in non-intubated anesthesia (surgery). Some typical algorithm research works on the breath sound are listed in Table 1.

Table 1 Typical algorithm research works details

Typical Articles	[9]Datta (2017)	[10] Mondal (2017)	[11]Li (2016)	Chamberlain (2016) [12]	[13] Rizal (2016)
Main Topic	Detecting abnormal lung sounds	3 kinds respiratory Sounds Classification	Crackles detection	Detecting abnormal lung sounds	Crackles detection
Input	Spectrum Features, wavelet coefficient, MFCC	IMF mean Higher moment	Time-frequency edge signal frequency/standard deviation	Audio Signal Specific characteristics unknown	Tsallis Entropy
Output	whether normal lung sound	Normal/wheeze/crackle	whether crackles	whether wheeze/crackles	Bronchial sound /crackles
Methods	SVM	EMD+BPNN	SVM	Semi-supervised deep learning	Multilayer neuron
Performance	Acc/Se/Sp	Acc/Se/Sp	Acc/Se/Sp	AUC=0.84/0.76(wheeze/crackle)	Acc/Se/Sp
	>90 %	>90 %	>90 %	Unknown	>90 %
clinically applied	No	No	No	No	No
Hardware implementation	No	No	No	Yes	No
Self-collecting patient data	Yes	Yes	No	Yes	No

- **The signal modeling of breath sound collection is a blind source separation problem, as shown in Fig 1:**

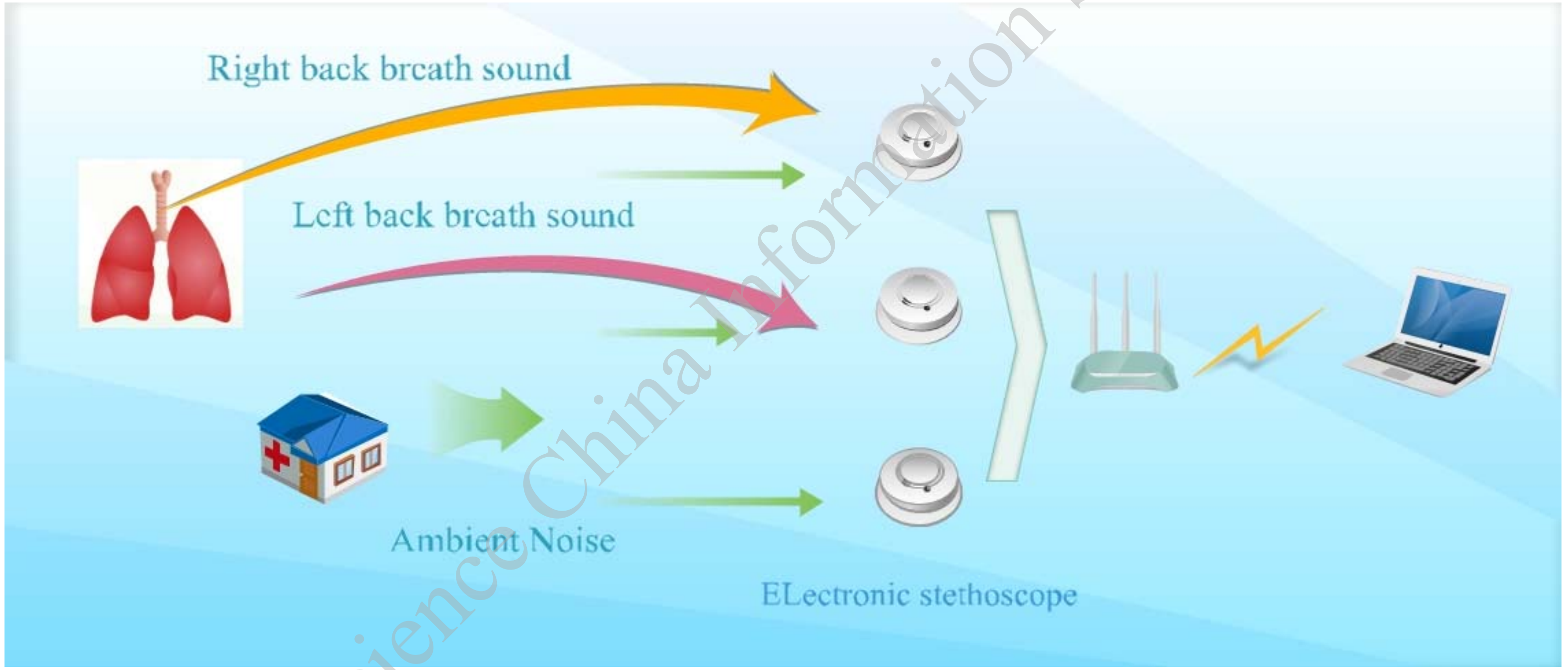

Figure 1 signal modeling of breath sound collection

Algorithm Flow

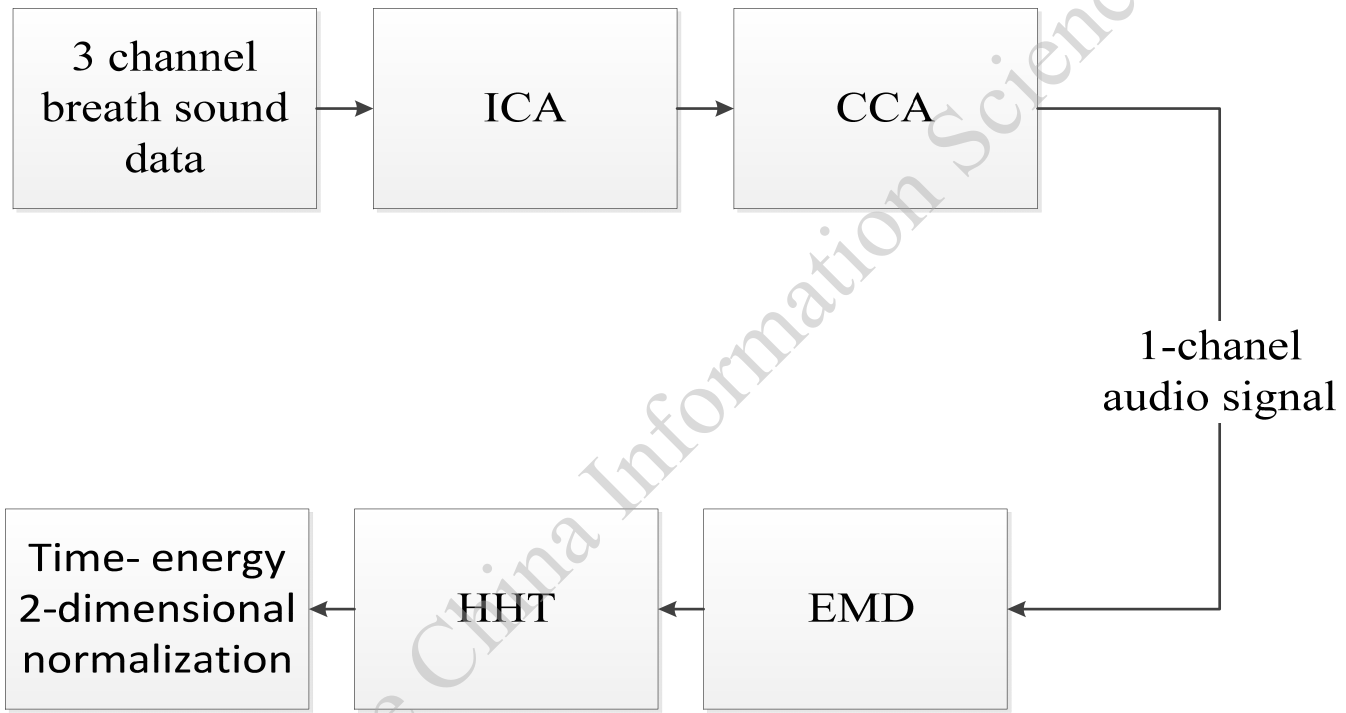

Figure 2 Algorithm Flow

Algorithm Flow

- Fig 3 shows the comparison results before and after ICA, where Fig 3 (a) is the 1-minute raw signal segment power spectrum of the breath sound collected by the selected real surgical scene, and Fig 3(b) is the simultaneous segment selected after ICA processing. Fig 3(e) is the power spectrum of the normal breath sounds template mentioned before. Fig 3(c) and Fig 3(d) show that after ICA process ,The ICA component (Fig (d)) is more similar to normal breath sound′s power spectrum (ICA process has a certain linear amplitude increase or decrease on the original signal, so power spectrum of Fig 3(d) may seem a bit bright), that is, the breath sound component is extracted or enhanced after the ICA.

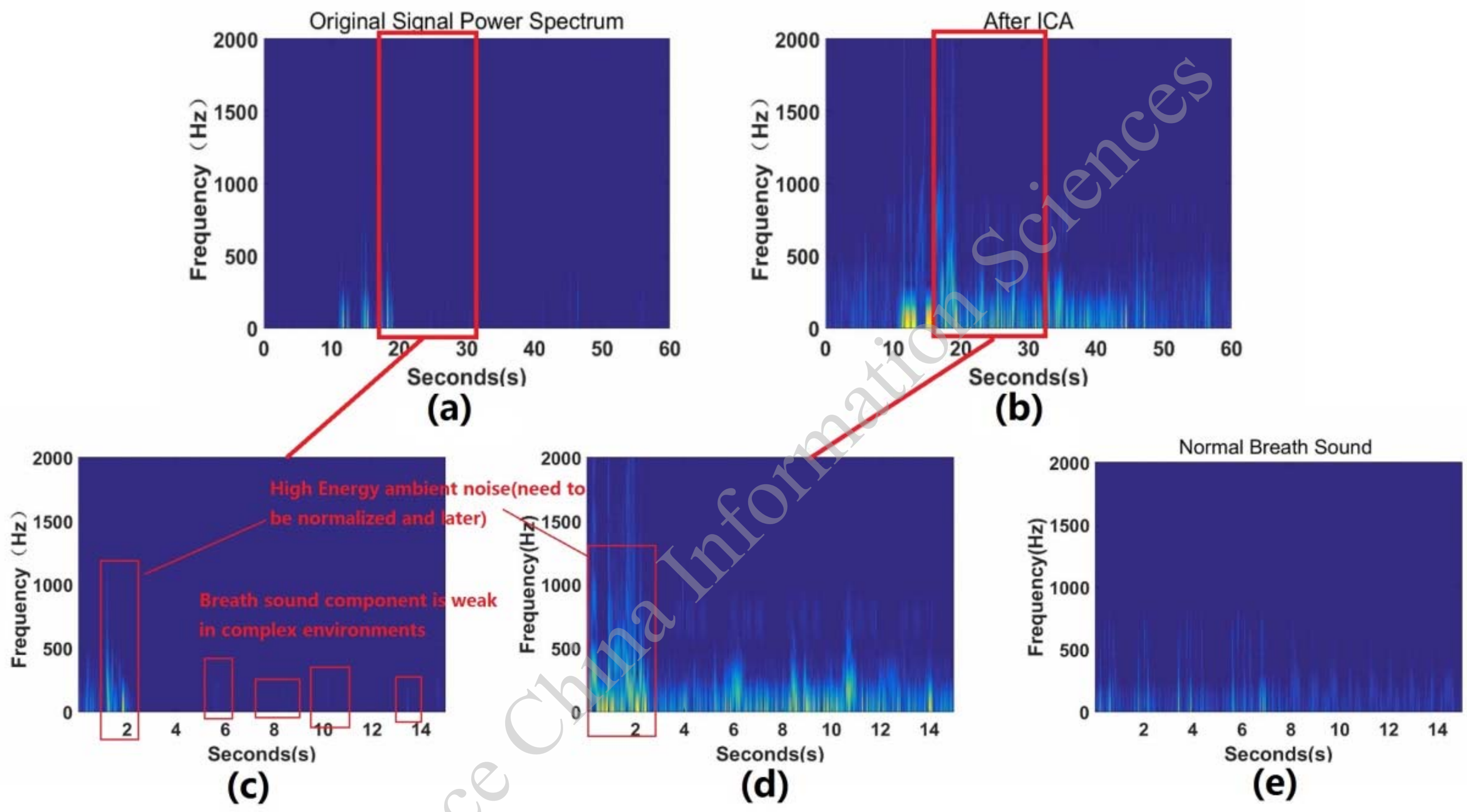

Figure 3 Comparison results before and after ICA; Fig 3(a), 1-minute raw signal segment power spectrum of the breath sound ; Fig 3(b), simultaneous segment selected after ICA processing; Fig 3(c) , Zoom in on the selected part of Fig 3(a) ; Fig 3(d) Simultaneous corresponding part of Fig 3(b); Fig 3(e), power spectrum of the normal breath sound template from [14]

Breath sound time-energy dual-scale normalization

- The normalization method in this paper is to convert the time-frequency Hilbert spectrum of a 5-minute sampling rate of 4000Hz into 150 points, with one point representing the energy average of 2s.
  - We estimate that the breath sound energy accounts for 80-90% of the entire energy of the signal. Here we remove the first 10%~15% of the energy in the whole 2s, and the corresponding time length is also removed to obtain a normalized energy value.

- **For example**, a 2s segment has a total of 8000 Hilbert spectral values, and the energy value of 200 points is within the highest 10% of the entire segment of the signal(5min) (usually burst sound or high-intensity vocals).
  - remove these 200 points.
  - Divide the sum of the remaining 7800 points of energy by 7800 to obtain a value as the energy feature point of this 2s segment.
  - The energy normalization method is to convert the above-mentioned absolute value energy into an equal ratio of energy values. The above feature extraction process can solve the problem of normalized energy characteristics caused by uneven distribution of noise interference in different time periods.

Sensor and Sensor Placement

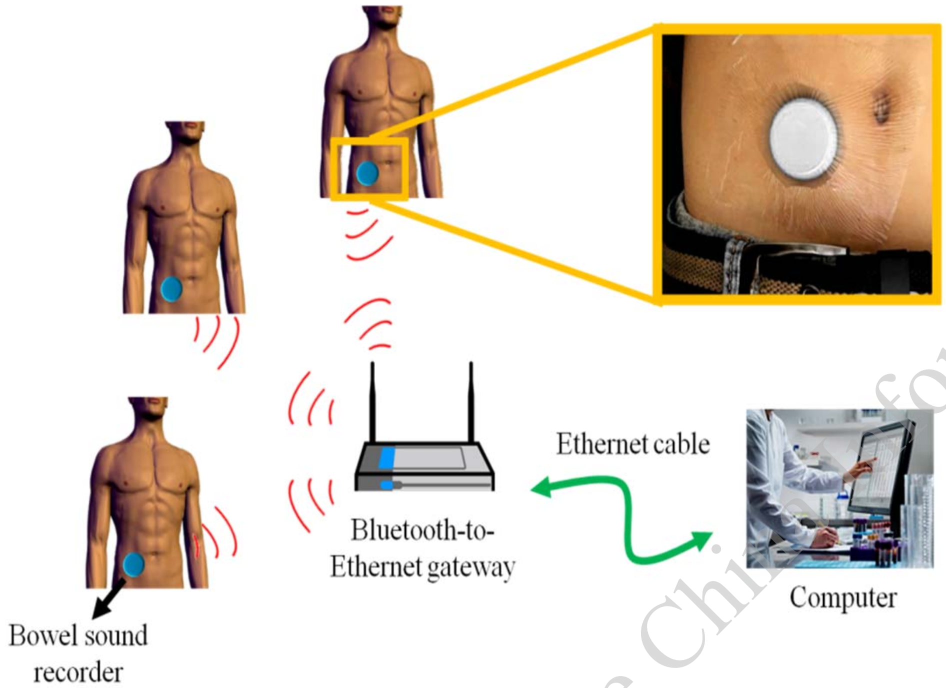

Figure 4 Monitoring system architecture[16]

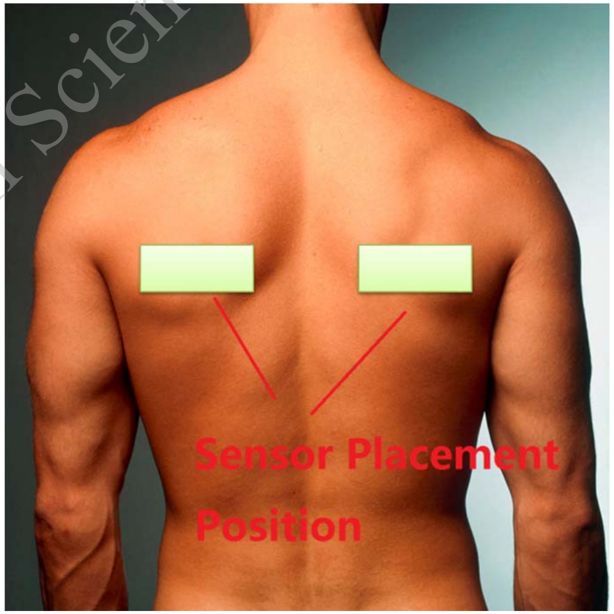

Figure 5 Sensor placement position

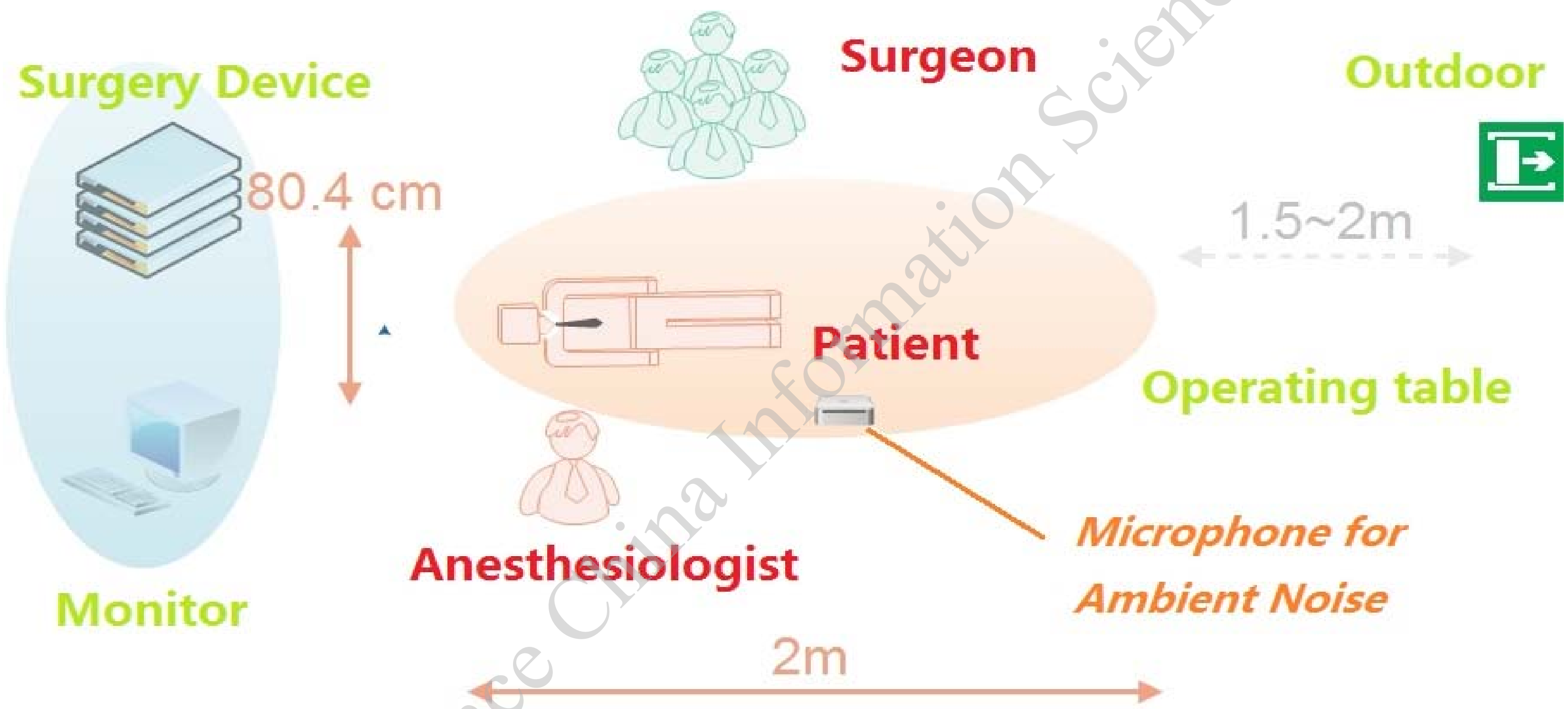

Figure 6 Schematic diagram of the collection environment

Breath sound collection process

- The collection of breath sounds is officially started at the moment when the patient takes the drug, and the collection time is 5 minutes. During this period, we have two labels recorded in one case. One is set by the assistant physician on the form, and the other one is recorded in the audio files, along with the breath sound collection by microphone.

- The doctors directly tell whether or not respiratory depression occurs during the operation, as well as the time node.

- The original intention of designing two sets of labels is to ensure the accuracy of the label and the accuracy of the time node, and reduce the probability of error caused by human records.

Table 2 Template of recording forms

Data	Name	Sex	Age	Type of surgery	
2018.6.21	Ana	Female	63	■Gastroscopic surgery	□Other________
Event	Time Point			Sample Lable	
Start injecting narcotic drugs	9:54			□No respiratory depression	■Respiratory depression
				(Negative sample)	(Positive sample)
Surgery start	10:02				
				Remarks:	
Respiratory depression Occur time	10:04				
Respiratory depression release time	10:08				
Other1________					
Other2________					
Surgery finish	10:15				

Results

- We collected data on the breath sound data of 25 patients by assistant physicians at hospital from May to August 2018.
- The type of surgery is gastroscopic surgery, and the operating room and microphone used are the same.
- Each patient's breath sound characteristics consist of two parts: one is the normalized energy characteristic result of the ICA component processed by the algorithm described before, and the other is the result obtained by the same algorithm architecture of the original respiratory sound data obtained from the left back.

Table 3 Classification Resul

the accuracy (ACC) 0.68, recall rate (Recall) 0.6

Subject	Sex	Age	Label	SVM Result
1	Female	55	1	1
2	Female	36	0	0
3	Male	48	1	0
4	Male	47	0	0
5	Female	61	0	0
6	Female	74	0	0
7	Male	58	0	1
8	Female	60	1	0
9	Male	72	0	0
10	Female	67	0	1
11	Female	37	0	1
12	Male	37	1	0
13	Female	60	1	0
14	Female	68	1	1
15	Female	56	1	1
16	Female	48	0	0
17	Female	68	0	0
18	Male	77	0	0
19	Female	35	0	0
20	Female	56	1	1
21	Female	35	0	0
22	Male	65	1	1
23	Female	67	0	0
24	Male	53	1	1
25	Female	68	0	1
ACC:	0.68	Recall:	0.6	

Discussion

- We can hardly find any article that uses intraoperative breath sound data to determine respiratory depression. Only several articles have a certain degree of relevance to the work of this article.
  - In [19],a six-channel acoustic monitoring system is used in patient monitoring and breath sound recording. However, it is just a preliminary database without further processing and classification.
- Detection of respiratory depression in non-intubated surgery using breath sounds is still a new topic. This article reproduces the results of traditional features used in other articles, and also compares the results of different classification methods, as shown in Table 3.
- Judging criteria use two parameters, Accuracy and Recall

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

TP, TN, FP and FN are, respectively, the number of true positive, true negative, false positive and false negative detected result.

$$Recall = \frac{TP}{TP + FN}$$

Discussion

ACC/RECALL		Traditional features used		
		Power Spectrum	MFCC	This work
Classification methods	KNN	0.32/0.3	0.52/0.1	0.44/0.2
	LR	0.6/0.5	0.56/0.5	0.64/0.5
	SVM-linear	0.68/0.4	0.6/0.4	0.52/0.5
	SVM-MLP	0.62/0.5	0.6/0.5	0.68/0.6

Table 4 Comparison Result

MFCC indicates Mel-Frequency Cepstral Coefficients, and the specific implementation refers to [20,21]. The Power spectrum method uses the industry-wide method of STFT(short-time Fourier transform).（sample rate=4000Hz, frame length=60 points, frame shift=15 points, FFT points=256 points ）,The FLD (Fisher's linear discriminant) method is used to reduce the dimension and then carry out subsequent classification. The selected classification methods are the traditional KNN, LR, linear kernel SVM and MLP kernel SVM.

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Information

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