Postprint: Techniques and Methods for Constructing a Lung Auscultation Sound Database

Authors: Zhang Dongying, Ye Peitao, Li Qiasheng, Jian Wenhua, Liang Zhenyu, Zheng Jinping, Zheng Jinping

Date: 2024-05-14T00:00:00+00:00

Abstract

Currently, lung auscultation results from both physical and electronic stethoscopes remain primarily dependent on physicians' professional expertise in auscultation interpretation and differential diagnosis, and have not yet achieved intelligent diagnostic interpretation. When patients suffer from pulmonary diseases at home, they are unable to self-detect pulmonary abnormalities, resulting in delayed treatment; during the treatment of respiratory infectious diseases, in-ear stethoscopes are susceptible to contamination, leading to nosocomial infections. Despite the wealth of health status information contained in auscultation sounds, the lack of standardized collection protocols, classification criteria, and analytical tools has constrained their objective analysis and practical application. This study employed unified auscultation sound collection equipment and protocols for lung auscultation sound data acquisition, curation, and database design, utilizing MatlabR2017a software for data management and analysis, to establish a lung auscultation sound database comprising both healthy populations and patients with pulmonary diseases, formulated a standardized system for auscultation sound classification, annotation protocols, and audio feature signal parameters, and constructed a system for the storage, management, and analysis of lung auscultation sound data, thereby providing crucial data support for research related to pulmonary disease screening, monitoring, and the translational application of medical artificial intelligence. This research accumulated valuable experience in constructing lung auscultation sound audio databases, offering beneficial references and insights for the management and analysis of audio databases, and laying a foundation to support subsequent applications of medical artificial intelligence-assisted auscultation in pulmonary disease screening and monitoring, thereby demonstrating significant medical value and practical application significance.

Full Text

Study of Techniques and Methods for Building a Database of Lung Auscultation Sounds

ZHANG Dongying[1,2], **YE Peitao**[3], **LI Qiasheng**[2], **JIAN Wenhua**[2], **LIANG Zhenyu**[2], **ZHENG Jinping**[2*]

[1] Faculty of Medicine, Macau University of Science and Technology, Macau 999078, China
[2] The First Affiliated Hospital of Guangzhou Medical University/Guangzhou Institute of Respiratory Health/National Clinical Research Center for Respiratory Diseases, Guangzhou 510120, China
[3] Guangdong Second Provincial General Hospital, Guangzhou 510310, China

Corresponding author: ZHENG Jinping, Chief Physician/Professor/Doctoral Supervisor; E-mail: 18928868238@163.com

Abstract

Currently, lung sound auscultation results from both physical and electronic stethoscopes still rely primarily on physicians' professional diagnostic abilities, and intelligent automated interpretation has not yet been achieved. When patients with pulmonary diseases are at home, they cannot detect lung abnormalities independently, often leading to delayed treatment. During the management of respiratory infectious diseases, in-ear stethoscopes are prone to contamination, causing nosocomial infections. Although auscultation sounds contain rich health information, the lack of standardized collection methods, classification criteria, and analytical tools has limited their objective analysis and practical application. This study employed unified auscultation sound collection equipment and protocols for lung sound data acquisition, organization, and database design. Using MATLAB R2017a software for data management and analysis, we established a lung auscultation sound database for both healthy individuals and patients with pulmonary diseases. We developed a standardized system for classifying and annotating auscultation sounds, along with audio characteristic signal parameters, and built a comprehensive system for storing, managing, and analyzing lung auscultation data. This provides crucial data support for research on lung disease screening, monitoring, and medical artificial intelligence applications. The study accumulated valuable experience in building lung sound audio databases, offering useful references for audio database management and analysis, and laying the foundation for subsequent medical AI-assisted auscultation applications in lung disease screening and monitoring, which holds significant medical value and practical importance.

Keywords: Lung diseases; Lung auscultation sounds; Audio database; Support vector machine; Feature recognition; Data analysis

1 Lung Auscultation Sound Collection

With advances in medical science and technology, pulmonary disease diagnosis increasingly relies on medical data. Lung auscultation sounds, as a critical diagnostic basis, necessitate the establishment of standardized audio databases and data analysis systems. However, building a high-quality lung auscultation sound database is challenging. Medical professionals must consider how to ensure data accuracy and reliability, how to effectively organize and store data, and how to leverage artificial intelligence and machine learning technologies for data processing and analysis. In recent years, AI and machine learning have provided new possibilities for addressing these challenges, improving the efficiency and accuracy of data collection, processing, and analysis, and enabling the extraction of more valuable information from massive medical datasets. Consequently, utilizing these technologies to construct lung auscultation sound database systems has become an important research direction.

Lung auscultation is a crucial tool for diagnosing and monitoring respiratory diseases. Lung audio signals provide valuable information such as breath sounds and adventitious sounds, assisting physicians in diagnosing disease types and severity. However, interpreting lung auscultation sounds requires extensive experience and specialized knowledge. Traditional methods rely primarily on clinical practice and accumulated experience, but these approaches are limited by strong subjectivity, individual variation, and inconsistent impacts on physician training and diagnostic agreement. To address these limitations, researchers have explored machine learning and signal processing techniques to analyze and model lung auscultation data. Through machine learning and neural network models, AI can rapidly learn from large volumes of annotated respiratory sound data to achieve automatic analysis. Automatic recognition and classification of respiratory sounds involve two steps: feature extraction and classification. However, a major obstacle in AI development for respiratory sounds is the lack of publicly available, high-quality, large-scale respiratory sound databases for algorithm research and comparison. Establishing a lung auscultation sound database can provide the foundation for automated diagnostic systems, disease monitoring, and health assessment. With the development of smart healthcare and telemedicine, establishing a public, large-scale lung auscultation sound database holds significant importance for promoting medical resource sharing, collaborative research, and improving lung disease diagnosis and treatment.

1.1 Audio Data Collection Equipment

This study utilized the 3M™ Littmann® 3200 electronic stethoscope to acquire lung auscultation sound data. This device features digital signal transmission rather than acoustic vibration for collecting respiratory sound data, enabling collection of a broader audio range with digital signal conversion. It simultaneously generates visual sound spectrograms, allowing users to see respiratory waveforms while listening, which helps adjust auscultation technique for more accurate results. Compared with conventional stethoscope heads, this model can detect lower-frequency sounds with a wider frequency range, greater loudness, and effective environmental noise reduction. Its collection frequency range is 20–2000 Hz with a sampling frequency of 4 kHz, can amplify sound 24 times, reduces probe-end noise, and improves acoustic transmission quality. Additionally, it offers recording, storage, and data transmission capabilities, can connect to computers, and supports analysis with compatible audio software, making it an ideal tool for establishing standardized lung auscultation sound databases.

1.2 Study Subjects and Recording Protocols

1.2.1 Study Subject Preparation All study subjects were recruited from the First Affiliated Hospital of Guangzhou Medical University (patients from the respiratory inpatient department, healthy individuals from hospital staff). Prior to enrollment, participants were fully informed about the lung auscultation database study, including collection procedures and required cooperation, and signed informed consent forms. Detailed information including age, sex, underlying diseases, and physical condition at collection was recorded for grouping.

This open exploratory study recruited 350 participants, divided into seven groups of 50 each for detailed comparison and analysis. This design ensured study accuracy and validity while protecting participant rights. The study was approved by the Ethics Committee of the First Affiliated Hospital of Guangzhou Medical University (Medical Ethics Review No. 82, 2017).

Inclusion Criteria: 1. Voluntary participation 2. Age $\geq$ 18 years 3. **Healthy group:** (a) No chronic lung disease, no long-term dust exposure, non-smoker, no organic cardiovascular disease; (b) No acute upper respiratory infection or respiratory symptoms (cough, sputum) within the past 3 weeks; (c) Normal chest X-ray and ECG within the past 6 months 4. **COPD patients:** (a) Dyspnea, chronic cough or sputum with risk factor exposure; (b) Post-bronchodilator FEV1/FVC < 0.7; (c) No large pleural effusion or pneumothorax; (d) Clinically diagnosed COPD (meeting criteria 1-3 or 3–4) 5. **Bronchial asthma patients:** (a) Recurrent wheezing, breathlessness, chest tightness, or cough triggered by allergens, cold air, physical/chemical stimuli, viral infections, or exercise; (b) Diffuse, primarily expiratory wheezing with prolonged expiration during attacks; (c) Symptoms relieved by bronchodilators or spontaneously; (d) Other diseases causing wheezing excluded; (e) For atypical cases, at least one positive test: (i) positive bronchial provocation test, (ii) positive bronchodilator test, or (iii) diurnal PEF variability $\geq 20\%$; (f) Clinically diagnosed bronchial asthma (meeting criteria 1–4 or 4–5 or criterion 6) 6. **Bronchiectasis patients:** (a) Childhood respiratory infection history (measles, pertussis, post-influenza pneumonia, or tuberculosis); (b) Chronic cough with purulent sputum or recurrent hemoptysis; (c) HRCT showing bronchiectatic changes; (d) Clinical diagnosis (meeting criteria 1–3 or criterion 4) 7. **Interstitial lung disease patients:** (a) Dry or moist rales in bilateral lower lung fields, more prominent at end-inspiration; (b) Diffuse shadows or unusual nodular interstitial patterns on chest X-ray; (c) Restrictive ventilatory dysfunction with impaired gas exchange; (d) BALF analysis; (e) Pathological confirmation via bronchial or surgical lung biopsy; (f) Clinical diagnosis (meeting criteria 1-5 or 2, 4, 5, 6) 8. **Pneumonia patients:** (a) Cough with sputum or worsening respiratory symptoms with purulent sputum, with/without chest pain; (b) Fever $\geq$ 38°C; (c) Signs of infection on physical examination; (d) WBC $> 10\$\times10^{\{9\}/Lor < 4\times10}\{9\}\$$/L; (e) Chest X-ray showing infiltrates; (f) Clinical diagnosis (meeting any of criteria 1-4 plus criterion 5) 9. **Lung tumor patients:** (a) Chest CT suggesting lung tumor or mass; (b) Tumor diameter $>$ 2 cm; (c) Clinically considered possible lung tumor; (d) No large pleural effusion or pneumothorax; (e) No surgical resection; (f) Clinically diagnosed lung tumor (meeting criteria 1-5 or 2, 4, 5, 6)

Exclusion Criteria: 1. Diagnosed epilepsy currently receiving medication 2. Pregnancy 3. Patients with lung resection surgery 4. Comatose or consciousness-impaired patients 5. Individuals unable to cooperate with study procedures 6. Patients in ICU or critical condition 7. Those who did not sign informed consent 8. Patients meeting two or more inclusion criteria simultaneously

1.2.2 Recording Environment Preparation Recording was conducted in a quiet, independent space with appropriate temperature and ambient noise levels not exceeding 40–50 dB.

1.2.3 Data Collection Detailed medical histories and relevant examination data were collected, including age, height, weight, primary symptoms, smoking history, respiratory diagnoses, chest CT results, and pulmonary function test data.

1.2.4 Recording Methods Participants were instructed to relax and breathe calmly for several minutes. Using the 3M™ Littmann® 3200 electronic stethoscope, auscultation was performed at nine locations according to the 9th edition of *Diagnostics* (People' s Health Publishing House): larynx, bilateral upper/middle/lower lung fields, and bilateral subscapular regions [Figure 1: see original paper]. At least 15 seconds of respiratory sounds were recorded at each point while participants remained quiet. The stethoscope probe was placed firmly against the skin, and participants were instructed to take deep breaths to ensure each recording contained 2–3 complete respiratory cycles.

1.2.5 Quality Control Two attending physicians from the respiratory department independently reviewed and diagnosed all recorded lung sounds. In case of disagreement, a third respiratory physician was consulted to resolve discrepancies before data inclusion.

2 Data Management

2.1 Data Transmission

The 3M™ Littmann® 3200 electronic stethoscope has limited memory, storing only 12 audio segments of 30 seconds each. Therefore, after recording each participant, lung sound audio was transmitted to a computer via Bluetooth using the StatAssist software, with each segment labeled according to the specific participant and lung location.

2.2 Data Storage

Audio transmitted to the computer was saved in .zsa format with automatically generated file names. To correspond with specific participants, participant names were appended to the file codes. These .zsa files served as the raw data.

2.3 Audio Export

.zsa format audio was exported to .wav format for subsequent annotation and analysis. Audio files from the same participant were imported into a single folder named with the original file name, then renamed according to body location to ensure accurate correspondence between each sound and the specific participant' s anatomical site.

2.4 Data Desensitization

Audio data containing participant names constitutes sensitive information vulnerable to leakage from device loss or computer viruses. Therefore, data were desensitized by randomly renaming all files and mapping the new names to participant information and basic data.

2.5 Cloud Database Establishment

Data stored on computers risk loss from hardware failure, making cloud storage essential. A locally accessible cloud database was established to ensure secure data storage. Unannotated, annotated, and reviewed data were saved separately in the cloud database to facilitate statistical tracking and data traceability.

3 Audio Preprocessing and Analysis

3.1 Lung Sound Noise Reduction

Preprocessing first involves removing noise from lung sounds to improve signal clarity and quality for accurate capture and recognition. Although electronic stethoscopes have noise reduction capabilities, some noise is inevitably introduced during collection, including environmental sounds, internal circuit interference, probe-skin friction, and internal body sounds like heartbeats. Without effective noise filtering, these artifacts significantly impact lung sound recognition.

3.1.1 High-Pass Filtering High-pass filtering removes low-frequency noise while preserving high-frequency components to extract useful lung sound information. Respiratory and cardiac sounds typically concentrate in higher frequency ranges, while noise is usually low-frequency. By applying a high-pass filter, low-frequency interference is suppressed, clarifying lung sound signals. The key is selecting appropriate cutoff frequencies and filter parameters to adequately remove noise while preserving useful signal components.

3.1.2 Low-Pass Filtering Based on lung sound characteristics, a low-pass filter was designed to remove high-frequency components while retaining low-frequency portions. After designing the filter, it was applied to lung sound signals to eliminate high-frequency noise while preserving low-frequency components. Filtered signals may require reconstruction to restore them to their original form.

3.2 Audio Annotation

3.2.1 Annotation Software Audacity is a free, open-source audio processing software for recording and editing audio. Its visualization tools analyze audio and other signal data, supports scripting in Python, Perl, or any command-line language, and is compatible with Mac OS X, Microsoft Windows, GNU/Linux, and other operating systems.

3.2.2 Annotator Selection Annotation accuracy significantly impacts model recognition efficiency. Respiratory physicians experienced in lung sound identification are recommended as annotators to improve accuracy. Since recorded sounds differ slightly from clinical auscultation, each annotator required professional training before formal participation.

3.2.3 Annotation Process Audio files were imported into Audacity and converted from waveform to spectrogram mode, which visually displays respiratory cycles and their inspiratory/expiratory phases, facilitating rapid selection and labeling. After selecting regions, labels were input. For precision, each respiratory cycle in the entire audio segment was first selected, then inspiratory and expiratory phases were distinguished and qualitatively labeled (normal, moist rales, wheezing, stridor, or snoring sounds) to aid feature extraction. Incomplete respiratory fragments may reduce feature extraction effectiveness, so only relatively complete cycles were annotated.

Annotation included: expiratory and inspiratory segments, locations of normal, moist rales, and dry rales (precise to milliseconds), and subtypes of dry rales. Audio quality was graded as Level I, II, or III, with Level I being optimal. Quality assessment included signal-to-noise ratio, noise duration proportion, and subjective evaluation. Annotated audio was saved in Audacity Project File (.aup3) format. All annotators used identical headphone models (Audio-Technica ATH-M20X) to ensure consistent auditory experience.

3.2.4 Label Review Controversial annotations were discussed publicly, and consensus opinions were adopted. Data that could not be resolved were excluded. After all audio annotation, senior physicians from the respiratory and critical care department reviewed all audio, corrected erroneous or non-standard labels, and excluded low-quality data (audio with excessive noise or insufficient volume). Reviewed labels were then used for AI model training.

3.3 Feature Extraction and Recognition

3.3.1 Moist Rales and Wheezing Recognition and Duration Moist rales and wheezing are common respiratory sounds identifiable via stethoscope. Moist rales are wet sounds caused by increased respiratory mucus secretions, resembling gurgling sounds from fluid movement during breathing. They may be fine and clear or coarse and loud, caused by infection, congestion, excessive secretions, or obstruction, lasting from seconds to minutes. Wheezing is high-pitched sound from airflow through narrowed airways, resembling high-velocity airflow noise through a narrow space. It may be continuous or intermittent, with varying intensity and pitch, caused by airway narrowing, bronchospasm, obstruction, or lesions, also lasting from seconds to minutes.

Based on audio analysis, moist rales are intermittent, non-continuous signals with duration generally <20 ms. The research team used MATLAB to display 16 moist rales spectrograms, with red portions indicating 20 ms signals centered on moist rales peaks [Figure 2: see original paper]. Wheezing typically fills entire expiratory or inspiratory phases, with statistical analysis showing duration generally >250 ms. This study marked 500 ms signals centered on wheezing peaks in red, which covers >80% of the respiratory phase in most cases [Figure 3: see original paper].

3.3.2 Peak Amplitude Quantitative Analysis Statistical analysis of over 1,500 moist rales revealed peak amplitudes exceeding twice the average amplitude. Using MATLAB, 16 moist rales spectrograms were displayed with red lines indicating twice the average amplitude [Figure 4: see original paper]. Testing of over 100 wheezing sounds using a 200 ms Hamming window for low-pass filtering showed that most filtered wheezing segments had 160 ms peak portions exceeding the filtered signal' s average value (red line in [Figure 5: see original paper]). This method identified all wheezing peak locations marked with green lines.

3.3.3 Support Vector Machine (SVM) Recognition SVM is a supervised learning algorithm for classification and regression, a binary classification model that maximizes the margin between classification boundaries and data points. Based on statistical learning theory, SVM finds optimal classification hyperplanes in high-dimensional space and can be applied to regression, anomaly detection, and time series prediction with high accuracy and robustness.

This study used SVM for moist rales and wheezing recognition through four components: audio database establishment, signal feature extraction, SVM training, and SVM prediction. Unlike most studies using entire audio files, our training dataset comprised preprocessed audio segments including normal and abnormal fragments. Moist rales segments consisted of 20 ms signals centered on peaks, while wheezing segments used 500 ms signals centered on peaks. This approach offered two advantages: (1) peak-centered segments have stronger signals and higher SNR, reducing background noise interference and improving accuracy; (2) smaller data volume significantly reduced processing time, enhancing real-time practicality.

During collection, we found that stethoscope probe displacement during inspiration or movement created fake moist rales that are currently unavoidable. To improve recognition accuracy, we manually annotated and identified fake moist rales, establishing a fake moist rales audio database for future automatic recognition. Each moist rales fragment was 20 ms. Using algorithmic and semi-automated methods, we established true and fake moist rales fragment libraries [Figure 6: see original paper].

For further processing, wavelet transform was applied to moist rales and fake moist rales to extract frequency domain features. These features were calculated from basic waveforms and spectra, then used as input variables for the trained SVM model. Through wavelet decomposition, feature calculation, and SVM classification, the system achieved high accuracy in distinguishing true from fake moist rales [Figure 7: see original paper].

The algorithmic process combined automatic methods with manual review. Two databases were established: one for true moist rales and one for fake moist rales. Since true moist rales typically do not exceed 20 ms, all samples were extracted at this length to capture these brief signals precisely. Key time-domain and frequency-domain features were extracted and used for SVM training and optimization, successfully distinguishing true from fake moist rales.

Signal preprocessing involved bandpass filtering (100–2000 Hz, containing diagnostically relevant information), followed by scanning with a 20 ms window to detect potential moist rales. For each detection, time-domain and frequency-domain features were extracted for SVM classification. The process included: (1) preprocessing and resampling, (2) bandpass filtering, (3) intelligent threshold calculation, (4) 20 ms window scanning, (5) feature extraction, and (6) SVM classification [Figure 10: see original paper].

Since wheezing fills entire respiratory phases, 500 ms fragments were extracted, covering >80% of the phase in most cases. Wheezing fragment libraries were established through algorithmic and semi-automated methods [Figure 9: see original paper]. The complete SVM recognition process is shown in [Figure 12: see original paper].

3.3.4 Wavelet Decomposition for Feature Extraction Wavelet decomposition is a signal analysis method that decomposes signals into different scales and frequency components for better characteristic analysis. Using wavelet functions for scaling and translation, signals are decomposed into multiple frequency components. For example, decomposed moist rales signal frequency distribution is shown in , with each component having different scales and shapes. This method can reduce noise and compress data, finding wide application in signal processing, image processing, and medical imaging.

Lung auscultation sounds are complex physiological signals containing multiple frequency components. Wavelet decomposition extracts features based on signal frequency characteristics. Using wavelet basis functions, lung sounds are decomposed into components of different scales and frequencies, reflecting temporal and spatial variation characteristics and providing richer information for feature extraction. High-frequency components may represent rapid breathing or coughing, while low-frequency components may represent respiratory rhythm, enabling classification models for disease identification.

Input sound fragments were decomposed into eight frequency bands: D1, D2, D3, D4, D5, D6, D7, and A8 [Figure 13: see original paper]. Moist rales decomposition results are shown in [Figure 14: see original paper]. For each of the eight decomposed signals, 32 features were extracted: (1) 8 absolute value means, (2) 8 absolute value variances, (3) 8 absolute value maxima, and (4) 8 ratios of adjacent values. Features 1-8 and 17-24 represent energy distribution across frequencies, while features 9-16 and 25-32 represent energy variation across frequencies .

4 Applications and Conclusions

Using the above collection procedures and database construction methods, this study collected 3,362 qualified audio recordings from 392 patients with chronic respiratory diseases, 500 audio recordings from 56 healthy individuals, and 9,469 audio recordings from publicly available databases (HF_{{{Lung}}_{{V1}}} from National Taiwan University, a respiratory sound database from the International Conference on Biomedical and Health Informatics, and the SPRSound database from Shanghai Jiao Tong University). Using MATLAB R2017a for data management and analysis, audio data were preprocessed, annotated, and analyzed via SVM recognition and feature extraction. Based on respiratory sound analysis algorithms, the software can automatically import sounds, display spectrograms, and identify normal lung sounds, dry rales, and moist rales using SVM models, with precise annotation of locations on spectrograms [Figure 15: see original paper].

Early detection, diagnosis, and intervention for respiratory diseases facilitate effective management of chronic respiratory patients. The establishment of lung auscultation sound databases and related methodological research lays the foundation for intelligent interpretation and home health management product development, can assist in clinical management of respiratory infectious diseases, and provides technical references for developing high-quality, affordable domestic intelligent stethoscopes.

Limitations

Currently, pathological lung sound fragments in this database are relatively limited, possibly due to: (1) exclusion of severely ill patients who might present more pronounced abnormal sounds; (2) failure to include patients with multiple concurrent respiratory diseases whose complex conditions could produce diverse lung sound variations; and (3) potential delays in medical record updates, meaning that during sound collection, patients' actual health status may have improved, resulting in weaker or absent abnormal sounds that do not accurately reflect active disease phases.

Acknowledgments

Shanghai Tuoxiao Intelligent Technology Co., Ltd. assisted with algorithm development.

Author Contributions

ZHANG Dongying proposed the research concept, designed the study, developed grouping protocols for auscultation subjects, directed intelligent recognition of fake moist rales, guided patent applications, and drafted and revised the manuscript. ZHANG Dongying, LI Qiasheng, LIANG Zhenyu, and JIAN Wenhua were responsible for subject screening, enrollment, study implementation, and quality control. ZHANG Dongying and YE Peitao handled data collection, acquisition, cleaning, statistical analysis, and figure preparation. ZHENG Jinping served as research advisor, guiding study design and manuscript revision.

The authors have no conflicts of interest to declare.

References

[1] SRIVASTAVA A, JAIN S, MIRANDA R, et al. Deep learning based respiratory sound analysis for detection of chronic obstructive pulmonary disease[J]. PeerJ Comput Sci, 2021, 7: e369. DOI: 10.7717/peerj-cs.369.

[2] BARDOU D, ZHANG K, AHMAD S M. Lung sounds classification using convolutional neural networks[J]. Artif Intell Med, 2018, 88: 58-69. DOI: 10.1016/j.artmed.2018.04.008.

[3] GOTTLIEB E R, ALIOTTA J M, TAMMARO D. Comparison of analogue and electronic stethoscopes for pulmonary auscultation by internal medicine residents[J]. Postgrad Med J, 2018, 94(1118): 700-703. DOI: 10.1136/postgradmedj-2018-136052.

[4] KWON A M, KANG K. A temporal dependency feature in lower dimension for lung sound signal classification[J]. Sci Rep, 2022, 12: 7889. DOI: 10.1038/s41598-022-11726-3.

[5] CHAMBERLAIN D, KODGULE R, GANELIN D, et al. Application of semi-supervised deep learning to lung sound analysis[J]. Annu Int Conf IEEE Eng Med Biol Soc, 2016, 2016: 804-807. DOI: 10.1109/EMBC.2016.7590826.

[6] YE P T, ZHANG D Y, CHEN W Y, et al. Research progress of artificial intelligence in respiratory sounds[J]. Int J Respir, 2022, 42(13): 961-966. DOI: 10.3760/cma.j.cn131368-20220120-00045.

[7] AVILES-SOLIS J C, VANBELLE S, HALVORSEN P A, et al. International perception of lung sounds: a comparison of classification across some European borders[J]. BMJ Open Respir Res, 2017, 4(1): e000250. DOI: 10.1136/bmjresp-2017-000250.

[8] HOFFMANN C, FALZONE E, VERRET C, et al. Brief report: pulmonary auscultation in the operating room: a prospective randomized blinded trial comparing electronic and conventional stethoscopes[J]. Anesth Analg, 2013, 117(3): 646-648. DOI: 10.1213/ANE.0b013e31829ec0a5.

[9] Shanghai Medical Association Pediatric Respiratory Group, Fujian Medical Association Pediatric Respiratory Group, Jiangsu Medical Association Pediatric Respiratory Group, et al. Expert consensus on high-quality respiratory sound database construction and management standards[J]. Chin J Appl Clin Pediatr, 2023, 38(7): 481-485. DOI: 10.3760/cma.j.cn101070-20230605-00436.

[10] YAO X J, WANG H, LI Y, et al. Research progress on lung sound signal analysis and recognition methods[J]. J Chongqing Univ Technol (Nat Sci), 2013, 27(12): 49-53.

[11] ZHANG K X, WANG X F, HAN F F, et al. The detection of crackles based on mathematical morphology in spectrogram analysis[J]. Technol Health Care, 2015, 23(Suppl 2): S489-S494. DOI: 10.3233/THC-150986.

[12] REICHERT S, GASS R, BRANDT C, et al. Analysis of respiratory sounds: state of the art[J]. Clin Med Circ Respirat Pulm Med, 2008, 2: 45-58. DOI: 10.4137/ccrpm.s530.

[13] SONG Q, LIN H P, ZHOU Q D. Theoretical research on support vector machines[J]. Inf Technol, 2013, 37(9): 152-154, 159. DOI: 10.3969/j.issn.1009-2552.2013.09.042.

[14] LIU G D. Research on the application of support vector machines in pathological lung sound recognition[D]. Tianjin: Nankai University, 2015.

[15] YE P T, LI Q S, JIAN W H, et al. Regularity and mechanism of fake crackle noise in an electronic stethoscope[J]. Front Physiol, 2022, 13: 1079468. DOI: 10.3389/fphys.2022.1079468.

[16] SHI L K, LIU W H, LI Z R. Lung sound feature extraction method based on LDA and wavelet decomposition[J]. Comput Eng Appl, 2017, 53(22): 116-120, 149. DOI: 10.3778/j.issn.1002-8331.1605-0330.

[17] LIU W Q. Research on lung sound signal reconstruction and respiratory cycle segmentation combining EMD and wavelet transform[D]. Wuhan: Jianghan University, 2023.

(Received: January 22, 2024; Revised: April 10, 2024)
(Editor: MAO Yamin)

Note: Figure translations are in progress. See original paper for figures.