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Research progress in digital auscultation: equipment and systems, characteristic parameters, and their application in diagnosis of pulmonary diseases and syndromes

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ABSTRACT

Traditional Chinese medicine (TCM) auscultation has a long history, and with advancements in equipment and analytical methods, the quantitative analysis of auscultation parameters has determined. However, the complexity and diversity of auscultation, along with variations in devices, analytical methods, and applications, bring challenges to its standardization and deeper application. This review presents the advancements in auscultation equipment and systems, auscultation characteristic parameters, and their application in the diagnosis of pulmonary diseases and syndromes over the past 10 years, while also exploring the progress and challenges of current digital research of auscultation. This review also proposes the establishment of standardized protocols for the collection and analysis of auscultation data, the incorporation of advanced artificial intelligence (AI) auscultation analysis methods, and an exploration of the diagnostic utility of auscultatory features in pulmonary diseases and syndromes, so as to provide more precise decision support for intelligent diagnosis of pulmonary diseases and syndromes

1 Introduction

Auscultation is an important part of "auscultation and olfaction diagnosis" in the four-method diagnosis of traditional Chinese medicine (TCM). By listening to the patients' respiratory sounds, speech, coughs, hiccups and so on, the nature of the disease such as cold and heat, deficiency, and excess can be assessed [1]. According to the oracle bone inscriptions, as early as the Yin Dynasty, there was a term known as "sick language", indicating that auscultation in TCM has a long history [2]; *Nanjing* (《难经》, *Classic of Questioning*) states, "To know through hearing is called sage", establishing the prominent role of auscultation. *Huangdi Neijing* (《黄帝内经》, *Inner Canon of Huangdi*) divides the tone into "Gong (宫), Shang (商), Jue (角), Zhi (徵), and Yu (羽)", and believes that the five tones are closely related to the viscera function of the human body [3]. Based on the long-term medical practices of predecessors, successive generations of TCM physicians have summarized their experiences and developed diagnostic methods with a profound theoretical foundation.

Modern medical analysis of sound signals focuses more on coughs, respiration, heartbeats, etc. Many scholars have researched sound production principles and the technical methods for analysis, providing a solid foundation for the clinical diagnosis of respiratory and cardiovascular diseases. For example, ASIAEE et al. [4] analyzed auscultation parameters to screen patients infected with Corona Virus Disease 2019 (COVID-19). ZHANG et al. [5]

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used wearable devices to observe and analyze the heart audio spectrum of patients with mitral regurgitation, aiming to monitor their left ventricular function.

The research on auscultation in TCM primarily focuses on pulmonary diseases, such as pulmonary nodules, pneumonia, and asthma, as well as TCM syndrome types, including lung Qi deficiency and lung Yin deficiency. Incorporating analytical methods such as wavelet packet decomposition and neural networks, the auscultatory parameters of pulmonary diseases have been initially revealed, providing a digital basis for the auscultatory parameters in the diagnosis and screening of pulmonary diseases, thereby promoting the further development and application of auscultation in pulmonary disease diagnosis [6].

2 Auscultation equipment and systems

In recent years, advancements in microphone-based speech signal acquisition and processing technology have facilitated the compression coding, efficient transmission, and storage of speech signals, providing crucial technical support for the digital research of TCM auscultation. As analytical requirements evolve, the types of equipment and systems are transitioning from early microcomputer systems and speech analyzers to the widespread application of microphones, electronic stethoscopes, and audio processing systems today. The collection and measurement of features such as speech, cough sounds, and heart murmurs lays the foundation for the subsequent data analysis and application.

LU et al. [7] utilized SONY A10 linear PCM recording device to collect the speech samples from patients with pulmonary nodules (Figure 1A). They employed Praat speech analysis software to extract stable and consistent audio signals, and OpenSMILE toolkit to derive acoustic parameters, with the aim of exploring the differences in acoustic features between healthy individuals and patients with pulmonary nodules of various TCM syndrome types. The faint heart sounds are difficult to detect by human ears, whereas the electronic stethoscope employs specific sensors to capture these heart sounds and convert them into digital signals. WANG et al. [8] utilized the cardiac auscultation diagrams obtained by this device to diagnose pulmonary hypertension and investigate abnormal heart sounds of patients in a more intuitive and multidimensional way (Figure 1B).

SÁNCHEZ MORILLO et al. [9] employed a piezoelectric microphone integrated with a coupled cavity to record the breath sounds in patients with chronic obstructive pulmonary disease (COPD) (Figure 1C). This device could be self-placed by the patients on the trachea, just above the sternum notch. The computer system was utilized to detect changes in breath sounds during acute exacerbation of COPD, which facilitated analysis of various causes of COPD acute exacerbation. RAMÍREZ et al. [10] analyzed voice parameters and electroglottographic data in patients with laryngopharyngeal reflux. Voice recordings were obtained using a microprocessor laryngoscope, while additional voice data were collected through a microphone and electrodes positioned anterior to the thyroid cartilage. This process allowed for the acquisition of detailed information regarding vocal cord function and vocal performance. CAVALCANTI et al. [11] conducted a preliminary study to investigate the acoustic correlation between microphones of varying quality and audio with different compression rates. The results indicated that both microphone quality and audio compression level may have an impact on the measurement outcomes (Figure 1D). DING et al. [12] proposed a high-sensitivity electronic monitor utilizing a piezoelectric micromachined ultrasonic transducer. This monitor is capable of achieving long-term, real-time bowel sound monitoring and capturing faint bowel sounds, thereby providing an innovative approach for auscultation research in digestive tract diseases. WEI et al. [13] also designed a device to monitor bowel sounds, which adopts bone conduction sensor to collect signals and can be transmitted to the phone application via Bluetooth, with advantages of low power consumption and portability (Figure 1E and 1F).

Although current auscultation equipment and systems have achieved significant advancements in precision and variety compared with previous versions, it remains necessary to consider the adaptability of these devices for capturing different sound characteristics, such as coughs, belches, and hiccups. Furthermore, it is crucial to transcend the conceptual confines of pulmonary diseases and pursue a more comprehensive development approach.

Figure 1 Auscultation equipments

A, SONY A10 linear PCM recording device. B, medical electronic stethoscope. C, piezoelectric microphone with a coupled cavity. D, microphone DPA 4066-B. E and F, portable bowel sound monitor back view and its electrode patch, respectively.

3 Auscultation characteristic parameters

3.1 Characteristics of audio data

Audio data exhibits typical time-series characteristics, primarily manifested in continuity, sequence, frequency components and so on. Therefore, in acoustic research, the time-series characteristics of audio data are usually utilized for processing and analysis. The most commonly employed acoustic characteristic parameters include fundamental frequency (F0), pitch priority jitter (PPJ or Jitter), amplitude perturbation quotient (APQ or Shimmer), and harmonic-to-noise ratio (HNR or SNR). These parameters not only reflect the physical characteristics of abnormal voices associated with conditions such as vocal cord polyps, vocal cord nodules, and glottal insufficiency [14], but also resonate with some fundamental theories of TCM. For example, the utilization of formant frequency parameters to analyze the speech of patients with pulmonary nodules can effectively reveal the characteristics of their vocal organs. Furthermore, it has been observed that these parameters are correlated with tongue position and vocal mode, which aligns with the description in *Yizong Jinjian* (《医宗金鉴》, *The Golden Mirror of Medicine*): "The throat serves as the pathway of sound, the epiglottis as the gateway, the tongue as the mechanism of sound, while the lips and teeth assist in its production" [15, 16]. XU et al. [17] conducted time-varying spectrum analysis on vesicular breathing sounds, tracheal breath sounds, wheezes and stridor, and presented the pulmonary sound information in time domain, frequency domain, and amplitude dimensions. Their analysis confirmed that vesicular breathing sounds and tracheal breath sounds exhibited time-varying characteristics, while the power spectrum of wheezes and stridor demonstrated discrete linear patterns. ZHANG [18] analyzed lung sounds, including large wet rales, wheezing sounds and bubble sounds, using wavelet transform across different frequency bands and different time points. The study determined the response position and amplitude depth of the lung sound waveforms. By combining this analysis with an artificial neural network, the lung sounds were successfully decomposed, leading to improved pathological recognition.

In addition, certain features, such as adventitious sounds and voice tremor, are also crucial for disease prediction and speech quality analysis. Adventitious sounds refer to abnormal sounds arising from conditions affecting the lungs or pleural cavity, distinct from normal breath sounds. PRAMONO et al. [19] conducted the studies on automatic adventitious respiratory sound, indicating that detection or classification of automatic adventitious respiratory sound is helpful for monitoring related diseases and predicting the outcomes. GILLIVAN-MURPHY et al. [20] employed acoustic analysis to assess vocal tremor in Parkinson's patients and neuro-healthy control groups. They explored the correlation between vocal disability and disease variables, and discussed the understanding of vocal tremor in Parkinson's patients from the aspects of frequency, amplitude, periodicity, and other relevant factors. ENGLERT et al. [21] analyzed the impact of varying voice sample lengths (VSLs) on the degree of voice quality deviation and voice quality index. They prepared three voice samples, VSL_long, VSL_cust, and VSL_short. The results showed that voice quality varied with different VSLs, and shorter VSLs exhibited a stronger correlation with acoustic analysis.

3.2 Specific meaning of audio data

Based on diverse fundamental theories, tailored to specific research objectives and diseases, researchers identify appropriate characteristic parameters for statistical analysis. This not only enriches the study of acoustic diagnosis, but also sheds light on the internal mechanisms of the diseases. However, as interdisciplinary research continue to evolve, it becomes increasingly necessary to integrate human physiological structure with physics in order to identify the most suitable and effective characteristic parameters for studying various diseases. This integration enables a deeper understanding of disease mechanisms, thereby improving the accuracy of auscultation. Based on the feature parameters mentioned above, this review summarizes commonly used feature parameters and their meanings in Table 1 [7, 22, 23].

4 Diagnostic research on pulmonary diseases and syndromes based on auscultation

4.1 Research on risk warning for pulmonary diseases

The lungs govern the Qi (vital energy) throughout the body; when Qi moves, it generates sound. Abnormalities in sound are closely associated with disruptions in lung Qi. Additionally, the lungs serve as the primary driving force of vocalization, making auscultation particularly pertinent in lung diseases [1, 24]. By integrating the equipment system, acoustic features and analytical methods, researchers have achieved significant advancements in the diagnosis and classification of pulmonary diseases such as COPD, asthma, and pneumonia. These efforts have made valuable contributions to the clinical diagnosis and treatment of pulmonary diseases.

LU et al. [25] proposed an intelligent auscultation application program based on Matlab deep learning. They selected Google Net for model transfer in deep learning, and employed the linear power spectrum method for analysis following Fast Fourier Transform (FFT). Finally, the program achieved remote and visual auscultation of patients' cardiopulmonary sounds, offering significant

Table 1 Characteristic parameters of auscultation diagnosis

Parameter type	Name	Implication
Frequency parameter	F0	Fundamental frequency, the lowest natural frequency when the vocal cords vibrate
	Jitter	The frequency difference between adjacent vocal cord vibration cycles
	F1 frequency	Center frequency of first format
	F2 frequency	Center frequency of second format
	F3 frequency	Center frequency of third format
	F1 bandwidth	Bandwidth of first format
	F2 bandwidth	Bandwidth of second format
	F3 bandwidth	Bandwidth of third format
Energy/amplitude parameter	Shimmer	The amplitude difference between adjacent vocal cord vibration cycles
	Loudness	The intensity of the signal obtained from an auditory spectrum
	HNR	Ratio of harmonic energy to noise energy
	H1-H2	Ratio of energy of the fundamental harmonic to the second harmonic
	H1-A3	Ratio of energy of the fundamental harmonic to the highest harmonic within the third octave above the fundamental
	F1 amplitude	Amplitude of first format
	F2 amplitude	Amplitude of second format
	F3 amplitude	Amplitude of third format
Spectral parameter	Alpha ratio	Ratio of summed energy in the 50 – 1 000 Hz and 1 – 5 kHz
	Slope 0 – 500 Hz	Linear regression slope of logarithmic power spectrum in 0 – 500 Hz band
	Slope 500 – 1 500 Hz	Linear regression slope of logarithmic power spectrum in 500 – 1 500 Hz band
	MFCC	Mel frequency cepstral coefficients, simulating human ear perception of sound and indicating timbre
	Spectral flux	Difference in spectrum between two consecutive frames

application prospects. WANG et al. [26] employed acoustic-based imaging techniques to capture and analyze respiratory sounds across the entire respiratory cycle. This approach is crucial for the differential diagnosis of congestive heart failure, acute exacerbation of asthma, and COPD, which may all exhibit the symptom of dyspnea clinically. By mapping the distribution of respiratory sounds onto a two-dimensional grayscale image seque nce, these diseases can be more accurately distinguished. MOSCHOVIS et al. [27] recorded the coughs of the tested children using the built-in microphones of smartphones and automatically identified them using the ResAppDx algorithm. This method can aid in diagnosing respiratory diseases in children, and has potential applications in asthma severity classification, airway obstruction detection and COPD diagnosis in the future. CHEN et al. [28] employed FFT to analyze respiratory sounds in both time and frequency domain for healthy individuals and patients with COVID-19. Subsequently, they applied these features to k-nearest neighbor (kNN) and convolutional neural network (CNN) classifiers to determine COVID-19 infection status. The results demonstrated an accuracy rate exceeding 85% for kNN classifier and 97% for the CNN classifier, respectively. Based on the patients' speech characteristics and clinical data, LU et al. [29] developed a lung cancer prediction nomogram model using indicators selected through least absolute shrinkage and selection operator (LASSO) regression. They evaluated the model using reciever operating characteristic (ROC) curve and calibration curve analyses. The results showed that the nomogram model could serve as a non-invasive screening tool to assist in predicting the risk of lung cancer. Figure 2 shows the research procedure of digital auscultation, including pre-collection preparation, collection process, characteristic parameter extraction, and data analysis [7].

Pulmonary diseases frequently result in alterations in cough and breathing patterns, which are routinely utilized as diagnostic indicators in clinical practice. Future research in auscultation should further explore its application in differential diagnosis and early risk assessment, while also assessing the severity, progression, and prognosis of diseases.

4.2 Research on classification of pulmonary diseases syndromes

In TCM theory, it is often stated that "treatment should be based on syndrome differentiation". Prior to initiating the corresponding treatment, if the pulmonary diseases can be further classified from the perspective of TCM diagnosis, that is, to distinguish among different syndromes, this will provide a more effective reference for subsequent treatment, thereby making the prescription more targeted.

SONG et al. [15] investigated the voice formant characteristics of patients with pulmonary nodules. They classified the patient's syndrome into deficiency syndrome, excess syndrome, and a blend of excess and deficiency

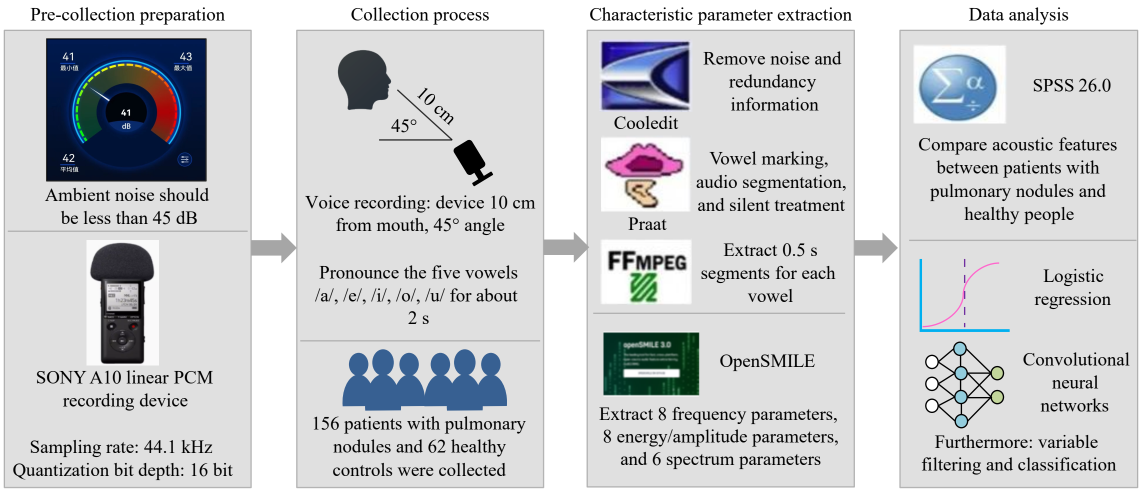

Figure 2 Research procedure of digital auscultation

syndrome, and identified the differences in the voice formant frequencies among these groups. For example, the mean F3 frequency of phonetic vowel [e] in patients with excess syndrome was 2768.74 Hz, compared to 2934.83 Hz in those with the blend of excess and deficiency syndrome. Combined with imaging examination, this analysis can assist in the diagnosis of pulmonary nodules. CHENG et al. [30] conducted a study on the voices of COPD patients. They applied artificial intelligence (AI) analysis to explore their auscultation characteristic parameters of these patients, classified them into syndrome differentiation categories based on clinical conditions, and incorporated TCM symptoms and signs to establish a decision tree model. However, there was no statistical significance between the parameters of different major symptoms. In contrast, the analysis based on disease location demonstrated statistical significance. It still shows that some parameters can reflect the condition of stable COPD patients. CHEN et al. [31] recruited 342 patients with pulmonary diseases and categorized them into four groups based on syndrome types: lung Qi-deficiency, kidney Qi-deficiency, lung Qi and Yin-deficiency, and excess syndrome. They employed wavelet packet transform and approximate entropy methods to process and analyze sound signals, extracting wavelet packet energy and Shannon entropy characteristics. Subsequently, support vector machine (SVM) and backpropagation (BP) neural network algorithms were utilized to classify and recognize the samples from different syndrome types. The results showed that the recognition accuracy achieved 83.67% and 71.95% for SVM and BP neural network, respectively. LU et al. [7] explored the acoustic differences of patients with pulmonary nodules, categorizing 156 of them into Qi deficiency syndrome, Yin deficiency syndrome, phlegm dampness syndrome, and other syndromes. Based on the variations in formant frequencies between patients with Qi deficiency syndrome and those with phlegm dampness syndrome, researchers inferred the impact of different internal mechanisms on the speech.

In research focusing on auscultation for syndrome diagnosis, data mining and machine learning methods are frequently utilized to compare acoustic signals, thereby facilitating the distinction and classification of syndromes to enhance the accuracy of diagnosis. However, such studies remain relatively scarce, necessitating further in-depth exploration in the realms of diagnostic model establishment and classification standard formulation.

5 Discussion

5.1 Establishing standardized auscultation collection and analysis protocols

Standardizing the collection and analysis of auscultation data is crucial for diagnosing pulmonary diseases and syndromes. However, auscultation technology is still in its nascent stages, facing numerous challenges, including standardized collection methods, equipment, and analytical algorithms. The Phoniatrics Committee of European Laryngological Society (ELS) recommends that auscultation collection should be conducted in a soundproof room where ambient noise is kept below 50 decibels, and that a constant distance of 10 cm should be maintained between the mouth and the microphone [32]. EYBEN et al. [23] have proposed basic standard acoustic parameters for automatic speech analysis. Additionally, several factors should be fully considered during speech collection, including gender, age, vocal organ structure changes, smoking habits, alcohol consumption, long-term exposure to dust or toxic gases, and medical history (such as hyperlipidemia) [33-35]. To enhance the clinical diagnosis of pulmonary diseases, it is crucial to summarize large-scale auscultation studies and establish standardized protocols for collection and analysis.

5.2 Introducing intelligent analytical methods for auscultation features

In the aforementioned studies, the primary focus has been on wavelet packet transform (WPT) technology and data mining. WPT excels in processing non-stationary signals, facilitating detailed analysis of local signal characteristics. Data mining extracts association rules from vast datasets, aiding in the identification of potential disease biomarkers [36]. However, both methods have their limitations, particularly in terms of data preprocessing and algorithm selection.

To enhance analysis efficiency and accuracy, advanced AI techniques tailored to the acoustic characteristics and objectives of the study must be introduced. AI methods for processing speech signals include deep learning, machine learning, natural language processing (NLP), and recurrent neural networks (RNN). Deep learning, which leverages multi-layer neural networks, excels in complex feature extraction and pattern recognition. The integration of deep learning with signal processing techniques significantly enhances analysis and classification of lung auscultation [37]. Machine learning methods, such as SVM and random forest, are employed for classification and regression tasks. NLP technology can process, identify, and model speech data in natural language, and further analyze emotional responses. This makes NLP well-suited for evaluating neurological disorders, such as Alzheimer's disease, which is characterized by cognitive and linguistic impairments [38]. As a specialized type of RNN, long short-term memory (LSTM) exhibits high prediction accuracy, particularly in processing time-series data and capturing sequential patterns within speech signals [39]. Additionally, multimodal data analysis enables the integration of speech signals with image data and physical/chemical indicators, thereby offering a more comprehensive perspective on understanding disease mechanisms through data complementarity. These analytical techniques are anticipated to provide stronger support for the development of auscultation and clinical diagnosis.

5.3 Exploring the value of auscultation features in the diagnosis of pulmonary diseases and syndromes

Auscultation features provide insights into lung conditions by analyzing the patient's speech signals, with different features revealing various information about the mechanisms of voice production and the status of vocal organs. For example, F0 characteristics can reflect airflow limitations in COPD patients, while formant amplitudes and HNR can assist in screening patients for pulmonary nodules. Additionally, special features such as adventitious respiratory sounds are indicative of underlying lung pathology. By exploring the potential applications of these auscultation features in discrimination, grading assessment, and prognosis prediction for pulmonary diseases and syndromes, their diagnostic value can be fully demonstrated. This contribution can facilitate future research, such as the exploration of benign and malignant pulmonary nodules, and the early screening of lung cancer.

Furthermore, the application of auscultation should not be limited to pulmonary diseases but should be more comprehensively explored in the context of various systemic conditions. Lastly, by integrating other TCM diagnostic information and western medical indicators, it will help to enhance the accuracy and efficiency of diagnosis from multiple dimensions.

6 Conclusion

This review offers a comprehensive overview of the research on auscultation over the past decade, particularly focusing on the advancements in equipment and systems, characteristic parameters, and their applications in the diagnosis of pulmonary diseases and syndromes. Precise equipment and systems have aided researchers in more meticulously capturing human body sounds; various characteristic parameters, representing different physical properties, have been utilized by researchers to investigate the intrinsic mechanisms of diseases. Ultimately, these have been applied in the diagnosis of pulmonary diseases and syndromes, exploring the sound differences between patients and healthy individuals, among different subtypes, and various syndrome types, thereby laying a foundation for intelligent diagnosis, differentiation, and early warning.

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Competing interests

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数字声诊研究进展：设备与系统、特征参数及其在肺部病证诊断中的应用

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【摘要】中医声诊源远流长，随着声诊设备与分析方法的不断发展，目前已初步实现声诊参数的量化分析。但由于声诊的复杂性和多样性，以及不同设备、方法和应用场景之间的差异，导致声诊研究在标准化和深入应用方面存在许多挑战。本文综述了近 10 年声诊采集设备与系统、声诊特征参数及其在肺部疾病与证候诊断中的应用等研究进展，深入剖析当前声诊数字化研究取得的进展及存在的问题，并提出应建立标准化声诊采集分析方案、引入更为先进的人工智能声诊分析方法、揭示声诊特征在肺部病证诊断中的价值，为肺部病证的智能诊断提供更精准的决策支持。

【关键词】数字声诊；设备与系统；特征参数；肺部病证；智能诊断