AI driven feature extraction model for chest cavity spectrum signal visualization

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Abstract
Lung cancer is the most fatal cancer in the world. Early detection, diagnosis and treatment of lung cancer is an important means to improve the survival rate of lung cancer patients. The early signs of lung cancer are small pulmonary nodules, so early detection and timely treatment of pulmonary nodules are of great significance to save the lives of lung cancer patients. With the progress of medical CT technology, a large number of image data obtained by medical CT examination are increasing, which can provide more organ and tissue information, but also bring a great burden to doctors. Therefore, the detection technology of thoracic spectrum signal is a key point. The chest cavity is a non adjustable resonator with a fixed volume and space, which is located in the chest ribs and below the vocal cords. According to the principle of resonance in physical theory, the resonance characteristics are mainly related to the size of the cavity surrounded by a certain hardness of the outer wall. Therefore, some researchers believe that the volume of the chest cavity is related to the resonance of the chest cavity. Although in recent years, some teams have combined deep learning and machine learning to improve signal feature extraction, which makes signal feature extraction easier and more efficient, most of them are still based on IQ data for signal modulation recognition. Therefore, this paper studies the visual feature extraction model based on artificial intelligence and thoracic echo spectrum, and the experimental results show the effectiveness of this method compared with the latest approaches.

Keywords Artificial intelligence · Deep learning · Chest detection · Medical image · Spectrum signal · Speech analysis · Feature extraction

1 Introduction
Pleural effusion (PE) is a common sign of respiratory system, which has many causes. The commonly used diagnostic methods include routine pleural effusion and related biochemical indicators, microbiological and cytological examination, bronchoscopy and percutaneous lung biopsy. At present, 20–40% of patients are still unable to determine the cause (Abrams, 1958; Bhatnagar & Maskell, 2013; Light, 2006; Tassi et al. 2011), which is called unexplained PE. Video assisted thoracoscopy (VATS) can be used in the diagnosis and treatment of pleural diseases. Due to the need for general anesthesia, there are surgical risks. Therefore, the application of VATS in elderly patients or patients with cardiovascular and cerebrovascular diseases, diabetes and other basic diseases has certain limitations. Medical thoracoscopy (MT) is a surgical method developed in recent years, which makes up for the shortcomings of conventional examination methods and video-assisted thoracoscopy. Thoracoscopy can not only observe the whole pleural cavity including parietal pleura, visceral pleura, septal pleura and costo diaphragmatic sinus with naked eyes, but also take pathology under direct vision. Compared with PE cytology and closed pleural biopsy, it is more targeted and greatly improves the diagnosis rate of PE etiology (Adhikari et al. 2020; Benamore et al. 2006; Koegelenberg et al. 2015; Rahman et al. 2010). At present, this technique has become one of the important methods to diagnose pleural effusion of unknown origin.

Under normal circumstances, there is a small amount of liquid in the pleural cavity, which plays a physiological role in reducing the friction between the pleura during respiratory movement. The fluid in the pleural cavity is not in a static state, but in a dynamic balance process of continuous

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(1) The increase of pleural capillary hydrostatic pressure
is caused by cardiac insufficiency, increased blood vol-

(2) Low protein synthesis or excessive loss of protein
results in hypoproteinemia, which leads to the decrease
of colloidal osmotic pressure.

(3) Pneumonia, pulmonary tuberculosis, rheumatic dis-
esases and tumors involve the pleura, resulting in
increased pleural permeability.

(4) Obstruction of lymphatic vessels or abnormal drainage
of lymphatic vessels lead to obstruction of lymphatic

drainage of parietal pleura.

(5) Injury or iatrogenic factors.

The space and resonance energy of chest cavity are large,
and the sound is thick and broad. Because the resonance
part is low and the frequency is low, it is usually regarded
as a bass speaker, which is suitable for producing relatively
low tones. The multi-channel speech analysis system can
synchronously test the vibration signals of the head, mouth,
throat and chest. The surface vibration signals near the reso-
ant cavity can be obtained by high-sensitivity sensors,
and the resonance characteristics of the resonant cavity can
be obtained indirectly through microcomputer processing.
When pronouncing, the resonance characteristics of differ-
ent parts of the resonant cavity have their own character-
istics, and change with the change of pronunciation (Ding
et al. (2020); Behlau et al. 2012; Lee et al. 2013; Tajiri et al.
2021). It is found that the chest vibration energy is mainly
concentrated in the range of 1000 Hz, which indicates that
the chest mainly causes low-frequency resonance in sing-
ing. The multi-channel speech analysis system can directly
display and accurately analyze the resonance characteristics
of different voice parts. Based on the experience of hearing
and distinguishing timbre, combined with the examination of
vocal cords and the results of multi-channel speech analysis,
the vocal types of singers can be more accurately classified.
At present, there is no report on the correlation between
chest morphological data, vital capacity and thoracic reso-
nance characteristics of normal young men. According to the
statistics of the World Health Organization since 2008, about
1.37 million people die of lung cancer every year. Lung
cancer has become one of the major diseases that seriously
threaten human life, and it is also the cancer with the largest
annual death toll in the world today (Jung et al. 2014). A
large number of studies have shown that (Abe et al. 2004;
Adachi et al. 2020; Boutayeb & Boutayeb, 2005), if we can
detect lung tumor in time and take targeted and effective
diagnosis and treatment, it will have a great impact on the
growth control of lung cancer, the cure of early lung cancer
and the improvement of survival rate of lung cancer patients.
Therefore, it is an effective way to improve the detection
rate of lung diseases by studying the automatic detection
methods of plain scan and low-dose CT images, and targeted
prevention and treatment of lung diseases. For the qualitative
and quantitative evaluation of lung tumor growth, the tradi-
tional method is to use medical imaging to roughly locate
the lung tumor, and then to determine the nature of the tumor
by biopsy combined with immunohistochemical analysis.
However, biopsy methods are invasive to human body and
difficult to accurately measure tumors (Bruining et al. 2020;
Dehmeshki et al. 2007; Paik et al. 2004; Webb 1983).

Traditional medical image analysis and detection are
mostly based on the simple processing, reading or projec-
tion reading of the image by the radiologist in the PACS
terminal. The basic method is to simply observe the medical
image and make a preliminary estimation of the observed
tissue, that is to simply distinguish whether the tissue is nor-
mal or not; if it is abnormal, then carefully analyze the imaging
of the lesion tissue and make a diagnosis combined with
clinical information. Although qualitative analysis cases of
diseases in medical imaging diagnostics are the summary of
clinical experience of imaging or radiologists, it should be
said that it is a more accurate interpretation method based
on statistics, but there are also cases of interpretation errors
due to the special cases, so many factors should be taken
into account in the analysis. Experienced doctors can make
slight adjustments to the medical images, observe subtle
lesions, and correctly determine the location of organ or
tissue lesions and the impact of lesions on other tissues.
However, it is difficult to detect and analyze lung diseases
automatically by computer system, especially for the accu-
rate segmentation of pathological tissues.

Medical image research of computer aided diagnosis
(Deng, 2009; Giger & MacMahon, 1996; Que et al. 2019;
Thomas et al. 2020) mainly includes three parts: medical
image preprocessing, medical image analysis and medical
image understanding. In order to improve the accuracy of
medical diagnosis and reduce the workload of doctors, it
has become the focus of current research to assist doctors
in quantitative analysis of patients’ medical image data and
further processing of two-dimensional images of medical
images. The main research work is how to use image pro-
cessing technology, through the shape, color, texture and the
relationship with surrounding tissues and other data infor-
mation processing, to accurately analyze medical images,
and to distinguish normal and abnormal medical images.
Signal recognition is a research hotspot in the field of wire-
less communication. Therefore, wireless signal recognition
technology is a practical and indispensable technology. It
of great significance both in daily life and in the military field. Nowadays, most of the research on signal recognition is modulation pattern recognition, and the main research method is to extract different expert features for different kinds of modulation signals. Then, according to the extracted features of different experts, the collaborative voting model is constructed for classification. Because a variety of different traffic signals adopt more complex modulation methods, even many new IoT signals are obtained on the basis of traditional wireless communication signals. Therefore, single to explore the expert characteristics of each signal is not only inefficient, but also not widely applicable. If more and more signals are identified, and then the cooperative voting model based on expert features will be more complex. In the field of spectrum sensing, signal service identification can directly determine the signal type, so this paper uses artificial intelligence technology to identify it. The rest of the paper is organized as follows. In the Sect. 1, the literature review is provided, we study the state-of-the-art models. In the Sect. 2, the proposed model is designed. In the Sect. 3, the experiment is done for the verifications of the proposed model. In the Sect. 4, the conclusion and the future research plan are both studied.

2 Literature review

Medical images can be used to distinguish diseases because diseases change the distribution of physical parameters in diseased tissue regions. In general, pathological areas in medical images can be shown as grayscale abnormal areas, such as low-density or high-density areas in CT images and low-signal or high-signal areas in MRI images. Pathological areas on medical images may also show abnormalities in the size and shape of certain intrinsic tissue structures. Therefore, normal medical images and abnormal medical images can be distinguished according to whether there are morphological or gray abnormalities in the inherent structure of medical images, so as to achieve the purpose of medical image classification. After decades of development, image classification technology has gradually formed a relatively systematic theory. At present, content-based medical image classification technology is usually adopted, and the main idea is to classify images according to their content characteristics. These content features include such things as shape, texture, color, and the relationships between these spatial features. The similarity distance of feature information of image to be classified is calculated and classified according to similarity distance or by clustering.

For shape features, the edge information of image objects is mainly extracted to obtain by using the main methods such as Robert, Prewitt, Sobel operator, Laplacian edge detection operator and Canny operator. In foreign countries, Chen et al. applied Mandelbrot’s fractal theory to the classification, edge enhancement and detection of medical images in 1989, and achieved good results. In 2001, Osmar R.Zaiane and Maria-Luiza Antonie proposed to apply the related methods of data mining to the classification of medical images to improve the classification performance. In 2005, JK.Sing, D.K and Basu proposed an improved adaptive RBF neural network based on the neural network, and applied it to medical image processing, and achieved good results. In 2008, Marghny.H. Hamed and M.M. Abdelsamea proposed a medical image feature extraction algorithm based on group wise clustering algorithm to obtain high-precision texture features. In 2009, Ram REZ et al. applied the neural network technology to the classification of brain images, obtained membership functions through the learning of various features by the neural network, constructed the neural network classification model to realize classification automation, and applied this automatic classification technology to assist the diagnosis of alzheimer’s disease symptoms. In 2010, Ryoichi Komiya et al. proposed k-mean clustering algorithm and fuzzy C-mean clustering algorithm to classify and process medical images, and divided medical image samples without category markers into several categories through clustering analysis. In 2012, Batmangelich.N.K et al. applied dimension-based reduction technology to medical image classification to improve the efficiency of classification by reducing feature dimensions. In 2013, Ho Pham Huy Anh et al. proposed the application of fuzzy NARX(nonlinear regression model) technology to the classification detection of medical images, and achieved good results in the detection of brain tumors mainly through the classification of principal component analysis (PCA) of features and the NARX model of back propagation training.

3 The proposed methodology

3.1 Chest signal extraction based on deep learning

Artificial intelligence technology was first introduced into the medical field in the middle and late twentieth century to assist people to record medical history and classify diseases. As a simple statistical tool, artificial intelligence technology can improve the diagnosis efficiency. With the rapid development of modern science and technology, artificial intelligence technology has been more widely used, such as artificial neural network, simulation expert system, calculation method and hybrid intelligent system. AI helps human to process a large amount of data and knowledge in the medical field, more effectively solves the complex clinical diagnosis problems, and provides more accurate treatment plan. At present, artificial intelligence technology has become a conventional auxiliary tool for medical diagnosis and treatment,
and has been widely used in psychiatric analysis, rehabilitation treatment, medical imaging, drug research and development, disease risk prediction and so on.

The update of science and technology promotes the rapid development of artificial intelligence, showing its broad application prospects. Artificial intelligence technology is gradually applied to many medical fields, such as medical research and diagnosis, mental health and nursing, medical imaging, hospital management and supervision, drug mining and so on. Medical artificial intelligence is still in its infancy in 1970s. At first, people tried to use computer to analyze the data of chemical biology research, and began to explore the method of using computer system or program to analyze cases. In psychiatry, scientists use computer models to simulate human behavior to analyze the thinking of mental patients, assist in psychology and mental rehabilitation. Although most of the projects are in the research and development stage, the experimental results are good, laying the foundation for the application of medical artificial intelligence (Abbas et al. 2020; Ashrafian, 2015a, 2015b; Fernandez-Luque & Imran, 2018).

The imaging system allows the manipulator to enter the human body for imaging, providing the doctor with surgical vision. Compared with the traditional surgery, the surgical robot is not only less invasive, but also minimally invasive. In addition, the manipulator control is more stable, flexible and precise, with higher surgical accuracy and less surgical risk. At present, more than 3000 Da Vinci robots have been assembled in the world, and about 3 million operations have been completed. On the other hand, the application of surgical robot is limited to surgery, and its application range is limited and the operation cost is high. For patients, the financial burden is very heavy. Artificial intelligence technology is more capable than human brain in dealing with complex repetitive work, data calculation and large amount of knowledge memory. It can use complex algorithms to learn features from a large number of medical data, store and memorize a large number of the medical literature, textbooks, clinical research articles, imaging data, gene reports, etc., so as to provide clinicians with the latest medical information and help clinical practice doctors provide the best treatment for patients. In addition, artificial intelligence technology will play an increasingly important role in reducing medical errors and medical accidents. Sound signals and music signals usually have harmonic characteristics, and their timbre is usually related to the signal array relationship. Then the sound signal can be reconstructed by the filter to separate its sound and complete the function of the system. Speech features are extracted by frames, and the distribution of these features in the phoneme space represents a core person's speech information. Therefore, through the different distribution of phoneme space, we can describe the differences in human speech.

Compared with human brain, the advantage of artificial intelligence lies in its powerful computing power, which can avoid the misjudgment caused by the lack of experience of human doctors, and can also find the details that are difficult to be found by human eyes. Through in-depth research and a large number of data comparison, we can find some rules, so as to continuously improve our judgment and promote the development of precision medicine. The artificial intelligence system jointly developed by bidmc and Harvard Medical School can identify cancer cells in breast cancer pathological images with an accuracy rate of 92%, especially with the analysis of pathologists, the diagnostic accuracy rate reaches 99.5%. In China, Alibaba cloud’s et medical brain has learned 20,000 thyroid computer resources, and has successfully helped human beings improve the accuracy of judging thyroid nodules from 60–70% to 85%. After more than a year of research and training, et medical brain has been able to work as a doctor’s assistant in medical digital imaging, precision medicine and many other fields.

At present, many scholars have used deep learning model to extract intelligent features of signals. At present, with the rise of deep learning and machine learning, many teams have applied deep learning algorithms and models to the field of signal recognition. The process of signal modulation classification based on machine learning algorithm is shown in Fig. 1.

In 1989, Yann Lecun and others proposed the CNN model lenet based on back propagation algorithm. The network consists of two layers of 5×5 convolution and two layers of 2×2 pooling. The dimensions of the two layers are 500 and 10 dimensional full connection layer and softmax loss function. As a classical CNN structure, the network has the following significant characteristics:

1. A series of convolution, pooling and nonlinear activation functions are stacked to form the model structure.
2. The convolution operation is used to extract the spatial features of the input image.
Sparse connection between different layers can effectively reduce the computational cost of the model (Fig. 2).

CNN is the most representative network model in the field of deep learning. In this chapter, a classification method of thoracic images based on CNN feature representation is proposed, which is composed of CNN feature representation network and a series of CNN feature decision-making mechanisms (Figs. 3, 4).

The directed acyclic graph of CNN network is shown below.

Convolution operation is believed to be able to simulate directional selection neurons in the primary visual cortex of human brain, and convolution module is an indispensable part of CNN model. Assume that the input to the convolutional layer is the tensor x of the K channel, and that the convolutional layer consists of K multi-channel convolution kernel F with bias b. H, W, and D represent the height, width, and number of channels of input x respectively.

Then the operation of convolutional layer is:

$$y_{i'j'd'} = b_{d'} + \sum_{i=1}^{H'} \sum_{j=1}^{W'} \sum_{d'=1}^{D'} f_{i'j'd'} \times x_{i'+1,j'+1,d'}$$  

(1)

where, $i'$ and $j'$ respectively represent the height and width position indexes of the convolution kernel; i" and j" respectively represent the index of height and width of output y.

The pooling operation in the CNN model in this paper adopts the maximum pooling strategy. The maximum
pooling method chooses to calculate the maximum response value of each feature graph within the block range of the size of \( H' \times W' \). If \( x \) is the input of the maximum pooling layer and \( y \) is the output of the maximum pooling layer, the operation of the maximum pooling layer can be expressed as:

\[
y_{i'j'd} = \max_{1 \leq i' \leq H', 1 \leq j' \leq W'} x_{i'j'1}, x_{i'j'+1, j'1}, x_{i'1, j'+1}, x_{i'+1, j'+1}
\]  

(2)

We choose the modified linear unit (ReLU) as the activation function in the CNN model. The activation function has the characteristics of unilateral inhibition, relatively wide excitation boundary and sparse activation, which is proved to be more similar to the working principle of neurons. Similarly, if the input and output of the activation function are \( x \) and \( y \), the operation of this layer is:

\[
y_{ijd} = \max \{0, x_{ijd}\}
\]  

(3)

where \( i, j \) and \( d \) respectively represent the height, width and channel index of input and output.

After the network passes through a series of convolution, pooling and activation operations, in the CNN model, the feature representation of the image has been transformed from the feature map to the high-dimensional feature vector. The full connection operation of the two adjacent full connection layers is completed by matrix multiplication. Let the input of the full connection layer be \( X \) and the output be \( Y \), then:

\[
y = CX + b
\]  

(4)

where \( C \) is the connection weight of the full connection layer, and \( b \) is the bias of the full connection layer. The main function of the full connection layer is to transform the representation of eigenvectors in different eigenspaces.

Training this volume of CNN model usually needs hundreds of thousands of annotation data, but there are only a few hundred annotation images in the current common image data set. In order to effectively train CNN feature representation network, we use the method of pre training the network on large-scale natural image data set, and then transfer the training network parameters on the data set. This method is widely used in small sample deep learning and transfer learning.

The pre training process of CNN model based on single channel natural image is as follows (Fig. 5).

### 3.2 Medical signal preprocessing and feature extraction

Compared with ordinary images, medical images have different representation forms and have their own unique characteristics.

1. Medical images are multimodal. The multimodality of medical image is caused by different imaging principles of medical imaging equipment. Generally, there are two kinds of medical images, and different modes of images are used in different fields. One is the anatomical image used to describe the physiological structure of human body, such as CT image which can reflect the structural and spatial geometric information. One is to describe the functional activities of tissues and organs in different states, such as PET or SPECT images which can provide a lot of functional and physiological information, but can not reflect the anatomical structure.

2. Medical images are fuzzy in gray scale. There are two main reasons for this characteristic of medical image: one is the influence of internal factors, such as the gray value of teeth and femur will show great difference in density, which shows that the gray value of image will also change greatly in the same tissue. The second is affected by external factors, such as imaging mechanism or acquisition technology. In the process of image formation, the edge high frequency information will be blurred due to the interference of noise, which will cause the fuzziness of medical image.

3. Medical images have local effects. As long as the local effects of medical images can be reflected in the pathological state, this is mainly because some tissues are difficult to be accurately described.

4. Medical images are characterized by uncertainty. There is a correlation between the characteristics of medical
images and the characteristics of local effects, which are induced by the influence of pathological factors. Some normal tissues or parts of the structure usually do not appear with the disease, and some of the original structure and tissue will also change with the disease, such as bone spur on the surface of bone, tumor on the surface of organs.

The main modules of medical image feature extraction and classification are image preprocessing, feature extraction and classification. The key of the algorithm design is feature extraction and classification.

1. After the medical image is processed, the features of the image are extracted, and the appropriate feature information is selected to form the feature vector.
2. According to the feature information of classification, the class model between images is established.
3. The classification algorithm is designed by similarity measurement, neural network, support vector machine and other methods.
4. Input the image information data to be classified as training sample image and test sample image respectively to train classifier.
5. Output the classification results of the image.

At present, the wavelet transform, which is most commonly used in the field of image processing, is unable to effectively capture the geometric structure features of the image, especially the edge structure of the image, due to its lack of directivity. Therefore, it is not the optimal representation method in image representation, and the multi-scale geometric analysis method can make up for the lack of direction of wavelet transform to solve such problems. The Ridgelet transform, Bandlet transform, Curvelet transform and Contourlet transform are the main multi-scale geometric analysis methods proposed at present. The support space of the basis used in these transformations shows higher directional sensitivity, so they can better represent edge features than wavelet transforms.

Curvelet transformation is a multi-scale transformation proposed in 1999 in the continuous domain. This transformation is studied on the basis of the Ridgelet transformation to transform right angles and polar coordinates. It avoids the influence of boundary effect in image reconstruction by superposition each part into blocks in the frequency domain. However, the superposition operation greatly increases the redundancy of data and the computation in the transformation, and the sampling property is not obvious in the discretization.

To solve these problems, the Contourlet transform was proposed in 2002. Contourlet transform overcomes the limitation that wavelet transform has finite directions, and can reflect the three basic elements of human visual information, namely scale, space and direction. In this way, the retrieval performance of texture images can be improved effectively by making full use of the features of Contourlet transform domain. Contourlet transformation inherits the Curvelet transformation scale anisotropy and uses different technical means to reduce the data redundancy in Curvelet transformation. The support interval of the basis of Contourlet transformation is a strip structure, which presents different forms in different directions and scales, so it can effectively capture the information of edge structure in different scales. It has some advantages in describing the subband coefficients of all directions on the edge of the curve and can well express the sparsity of image information (Fig. 6).

### 3.3 Lung diseases and chest CT images

Medical CT imaging of thoracic organs is excellent, which can be used for computer system analysis of lung structure and detection of lung diseases. For lung lesions, the computer system can perform complex analysis and processing of chest CT images, including lung segmentation, airway tree, vascular tree segmentation, lung lobe segmentation and registration. The detection, classification and quantification of abnormal lesions, as well as the identification and diagnosis of signs of emphysema, lung cancer, pulmonary embolism and airway diseases. Through the analysis of chest CT images, various diseases of lung, bronchus and hilum can be found, such as benign and malignant tumor of lung, tuberculosis, inflammation, interstitial and diffuse lesions, hilar enlargement caused by structural changes of blood vessels and trachea or lymphadenopathy, and identification of subpleural bullae.

In addition, according to the location and nature of lung diseases, the lung diseases that can be identified by chest CT images are as follows:

1. Changes of trachea and main bronchus: obstructive emphysema, pneumonia and atelectasis caused by stenosis and obstruction of trachea and bronchial lumen, thickening of tube wall and cartilage calcification.
2. Pulmonary lesions: alveolar consolidation, value-added lesions granuloma, inflammatory pseudotumor, chronic pneumonia, acute and chronic pneumonia healing, diffuse pulmonary interstitial fibrosis, acute chestnut pulmonary tuberculosis, hematogenous metastasis, carcinomatous lymphangitis and sarcoidosis, allergic pneumonia, bronchiolitis, bronchiolitis, pulmonary tuberculosis, cavity and cavity lesions—cancerous or tuberculous void Cavity, pulmonary abscess, calcified lesions pulmonary tuberculosis, alveolar microlithiasis, pneumonia, etc.

3. Hilar changes: hilar enlargement lymphadenopathy, bronchial lung cancer; hilar displacement atelectasis or fibrosis.

4. Pleural lesions: pleural effusion, pleural effusion ascites, pneumothorax and hydro pneumothorax, pleural thickening, adhesion and calcification, pleural tumor, etc.

5. Mediastinal changes: space occupying lesions, pneumothorax, massive pleural effusion or benign or malignant lesions.

6. Comprehensive diseases: severe acute respiratory syndrome, pulmonary pseudotumor, pulmonary edema, acute respiratory distress syndrome, pulmonary thrombosis, pulmonary infarction, hamartoma, pulmonary metastasis, idiopathic pulmonary fibrosis, etc.

Deformation model is a new method combining region and boundary information proposed in recent decades. It combines the approximation theory of geometry, physics and mathematics, through the information contained in the image data itself and the prior knowledge based on the location, size and shape of the target to effectively segment the object in the image. Its application has been widely concerned by researchers, and has been further expanded in theory and algorithm. According to its mechanism, the current models can be divided into parametric active contour model and geometric active contour model.

Mathematical morphology medical image segmentation method. It is based on mathematical morphology processing, which uses four basic operations of expansion, corrosion, opening and closing to change or combine to produce various morphological practical image processing algorithms. The selection of structural elements has a very important impact on it. Different structural elements can complete the analysis of different image targets, and different processing results can be obtained for the same target. The basic morphological operators are simple and easy to implement, but they are sensitive to noise, so they are suitable for processing medical images with less noise.

In the segmentation of lung field, there are many problems to be solved, some of which are discussed here. The first is that the existence of lobes in the lung field leads to the lack of some areas in the segmented lung field. Because of the existence of the boundary of the lung lobes, the lobed lung field is divided into two or more regions. In this case, most of the single threshold segmentation methods based on CT value will divide a complete lung field into several separate regions. Therefore, when selecting the lung field region, the main region in the multiple regions is often selected, resulting in the partial missing of the lung field region. The second is that there is only a thin layer of pleural tissue between some left and right lung fields in the middle of the lung body. When the lung field is segmented based on global CT threshold, the contrast between the boundary of pleural tissue and lung field is greatly reduced due to the influence of partial volume effect or improper preprocessing and filtering, so that the left and right lung fields that should be separated are divided into a connected region. Some methods, such as dynamic programming, optimized threshold and watershed transform segmentation, have been used to separate the segmented and conglomerated lung fields. However, the separation process of these methods is quite complicated and requires a series of complex processing to complete the task of separating such lung fields. The third problem is the concave boundary of lung field. There are vascular, tracheal or pleural lesions in some lung fields near the hilum, which are characterized by high density, leading to the depression of the segmented lung field boundaries. Some researchers have used curvature ratio, rolling ball method, wavelet enhancement of lung field boundary and some other unsupervised segmentation methods to deal with and solve this problem. However, this problem has not been solved well.

### 3.4 Frame the thoracic segmentation process

Low-dose thoracic CT images contain a lot of high-density interference noise, and some soft tissues such as pleura, trachea wall and blood vessels also show high-density tissue characteristics. In the chest CT image, the lung field has great shape changes in different positions of the lung body, and the lung tissue structure is also more complex. If only CT threshold is used to segment the chest CT image, it is difficult to segment the correct lung field with this segmentation method. As shown in Fig. 7, the first two rows are six frames of low-dose thoracic CT images (from the Psuex image database) with the presence of complex noise, while the last two rows are chest CT images from the LIDC database.

Input: chest CT image.
Output: lung field area.

1. The low-dose chest CT images were filtered by combination, and the cross-sectional images of the human body in the chest were separated.
2. The image processing was processed by CT threshold segmentation to segment the binary region of lung field.
3. If the left and right lung fields are adhered, separate the left and right lung fields.
4. Based on the anatomical knowledge of lung field, the left and right lung field masks were selected from the segmented images.
5. If more than one mask region (with leaf crack) appears in the segmentation, the homomorphic closed operation with small radius is used to connect them respectively to form a complete lung field.
6. For the lung field near the hilum, the homomorphic operation with the radius suitable for the disk structure is used to smooth the edge of the lung field.
7. The original chest CT images were segmented by the obtained lung field mask to obtain the correct lung field.

### 3.5 Thoracic cavity segmentation based on prior shape active contour model

A reliable and robust image segmentation method should obtain meaningful results from image processing system,
and image segmentation technology is closely related to image segmentation. In a sense, image segmentation is the application of image segmentation technology in medical image. Accurate segmentation is the pre-requisite of medical image processing and analysis algorithm, and the lung field segmentation has higher requirements for lung structure analysis and disease detection in chest CT images. Because the segmentation of the lung has an important impact on the success of subsequent detection and treatment.

Firstly, the noise in the influence of chest CT is filtered, and then the images of training data are selected from the data set. The selection criteria is that the lung field images should be basically normal. The test images can select the chest CT images with pathological changes, especially those near pleural pulmonary nodules. In order to test the algorithm comprehensively, we can put in the simulation image data of the eligible nodules to test. Secondly, the training set image can be manually segmented or the method described in the previous section can be used to obtain the shape of training lung field, and then PCA feature pattern can be obtained. When the test chest CT image is segmented, the initial processing of the extrathoracic region is removed first, and then the CT threshold segmentation is performed. The active contour model was used to fit the model, and the reasonable lung field was segmented.

The analysis of lung by computer system is different from the manual depiction of interested objects, which should reflect the requirements of automatic lung segmentation. Armato et al. Demonstrated the importance of the pre-processing stage in the automatic detection of pulmonary nodules. In the environment of nodule detection, practice shows that the loss of important information contained in many processed data is due to improper pre-processing. Therefore, the evaluation standard of preprocessing is usually judged by whether these preprocessing algorithms are suitable for the core subsequent processing of specific tasks. For the model, the speech information is combined. Since the structure of each frequency spectrum is obtained by the ICA algorithm, before signal separation, it is necessary to combine the characteristics of the separated sound signal to reconstruct and inversely transform the spectrum to obtain the separated sound signal.

Spectrum situation data fusion should be established based on actual satellite images, surveyed elevation and spectrum situation data. The richer and more accurate the measured data, the more accurate the three-dimensional topographic map obtained can truly describe the spatial distribution of this information. For the different terrain data, different fusion functions need to be used. The speech rate feature is an independent subspace and has a certain correspondence with the ordinary speech rate space. Then the discriminative information of speech rate is essentially the offset of the two different subspaces.

The whole chest CT image can be divided into three regions: the non-scanned area outside the chest cavity, the external area of the scanned chest cavity and the internal region of the chest cavity. In order to eliminate the noise outside the scanning area, the method of boundary tracking is used to obtain the contour boundary of the chest cavity, and then the region segmentation is carried out based on the boundary. The results of the segmented inner thoracic region are shown as follows (Fig. 8).

4 Experiment and Verifications

In this study, 161 cases of medical thoracoscopic images were selected, including 118 cases of multiple nodules, 5 cases of single nodules, 23 cases of pleural coarseness, 9 cases of thickening, 51 cases of white necrotic material and caseous changes, 48 cases of white patches, 7 cases of carbon foam like substances, 23 cases of cellulose adhesion and 20 cases of massive adhesion. Different diseases have different manifestations under thoracoscopy (Fig. 9).

On this basis, we applied the single port thoracoscopic technique to the treatment of benign esophageal diseases. Three to
four 1 cm incisions of traditional VATS were combined into a
2-3 cm incision. There was no significant difference in clinical
efficacy between VATS group and VATS group (Figs. 10, 11).

The schematic diagram of vital capacity measurement is
shown below.

CT three-dimensional reconstruction of the chest shape is
as follows (Fig. 12).

5 Conclusion and prospect

With the wide application of artificial intelligence in the medical field, the ethical problems of artificial intelligence
in the process of diagnosis and treatment with doctors and patients are gradually increasing. At present, with the
The continuous development of digital image technology, the processing of medical signal data information to assist doctors to diagnose diseases has been widely penetrated into people’s life and work. In real life, people really feel the convenience brought by the application of artificial intelligence technology, especially in the medical field. As an important field of human life science, medicine has solved many problems that cannot be solved by human beings through the effective application of artificial intelligence technology. On this basis, this paper elaborates the basic characteristics, preprocessing, feature extraction and classification process of medical signals different from ordinary signals, and introduces the related theories of image feature extraction and image classification technology. Because the feature vector is the basis of classification, the key problem of image classification is...
feature extraction. At the same time, the selection of classification methods is directly related to the accuracy and efficiency of image classification. Therefore, this paper focuses on the image feature extraction and optimization of classification algorithm. Due to the lack of model feature representation ability and model capacity, biomedical signal analysis methods based on traditional machine learning methods are also gradually facing difficulties in data processing and analysis accuracy. In this paper, we use artificial intelligence technology and medical information feature extraction method to build a visualization feature extraction model of thoracic echo spectrum, and the experimental results show the effectiveness of this method.

Fig. 11 Schematic diagram of vital capacity measurement

Fig. 12 Three dimensional reconstruction of chest shape
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