Bachelor Thesis

Research on the automatic detection algorithm of airway based on 3D CT image

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ABSTRACT

In modern society where air pollutions are high, airway disease becomes a major cause of morbidity and mortality worldwide. Originally the CT image, airway identification was made manually, but due to its very time-consuming and laborious work, it can no longer meet society's needs for medical diagnostic. Through years of development, CT technology has progressed from single slice to multi-slice spiral CT, and its development help doctor to obtain high-resolution images by one scan, combined with advanced image processing technology for diseases analysis. Base on the above advantage CT scan imaging is considered the most used technology for diagnostic of lung disease. Identification of airway tree in CT images is the basis of lung disease analysis, pathological parameters measurement, and subsequent image configuration. But even in CT images, the airway structure is complex with poor contrast and affected by noise and volume effect. Nowadays number of computerized techniques have been developed for the automated identification of airways but still face difficulty. Therefore, how to detect the airways in 3D CT images accurately, quickly, and automatically by a computer algorithm? To realize the automatic and effective detection of airways in 3D CT image, this paper proposes an automatic detection method of airways in 3D CT image using Region growing and morphological methods to provide a good analysis of airways diseases: Firstly, the lung parenchyma in the CT sequence image is segmented using a method based on 3D connectivity and morphology method and we use the 3D region growing method to initially extract the airway tree, then use the morphological method to segment the small airway and finally used region growing method to obtain the final airway tree. The experimental results showed that the proposed method can automatically and quickly detect the airway and also build a good foundation for quantitative analysis of airways.

Keywords: CT image; Airway tree segmentation; Region growing; Morphological method

Content

Chapter1: Introduction

1.1 Background

Airways are very important for our organism, is an important place for gas exchange with the surrounding environment. Since the airways are exposed to the external environment for such a long time and are affected by external factors such as chemical emissions and air pollution, the incidence of airways respiratory system diseases has been steadily rising year after year. Malignant tumors, chronic pulmonary disease, and other chronic respiratory diseases have been the main cause of death [1-2]. Fortunately, Fast-growing medical imaging technology has become a generator of much data to facilitate faster and more detailed clinical solutions for diagnosing and treating respiratory diseases. Such as Computed tomography(CT) and magnetic resonance imaging (MRI). Computed tomography (CT) images are usually used in the diagnosis of respiratory diseases due to their good spatial resolution and imaging quality. However, due to a large number of slices in the CT image and the complex structure of the lung tracheal tree, the method of manual reading Screening or segmentation of diseased tissue is often time-consuming and laborious [8]. At the same time, manual image reading is highly subjective, and long-term image reading can easily lead to the wrong diagnostic. This clinical demand has motivated medical imaging workers and information technology practitioners to continue to research and explore image segmentation and reconstruction algorithms and technologies, hoping to automatically extract the target area of interest from the CT tomographic image sequence, and make a three-dimensional representation of the region to assist doctors to correctly understand the condition of the disease and even drive the surgical instrument to operate in real-time.

1.2 Research object

The main aim of this study is to Research automatic airways detection algorithm based on three-dimensional images to include accurate and improved diagnosis and treatment of diseases that are related to airways. This paper proposes an automatic detection method of airways in 3D CT image using Region growing based method and morphological methods: the lung parenchyma in the CT sequence image is segmented using a method based on 3D connectivity and morphology method and we use the 3D region growing method to initially extract the airway tree, then use the morphological method to segment the small airway and finally used region growing method to obtain the final airway tree.

1.3 Significance of the study

The advancement of medical imaging technologies such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound has fueled the exponential growth of two-dimensional graphic image technology. That brought great help for medical diagnosis and treatment [5]. However, the two-dimensional medical image sequence only represents the anatomical information of a certain cross-section. Doctors had to rely on their prior experience to determine the size and shape of the lesion when analyzing the images. This method relies heavily on the doctor's prior knowledge and can maybe not accurate [4]. Therefore, the data from a chest CT scan provides a lot of physiological and pathological details about the respiratory system's main organs and tissues. Doctors may observe the internal structure of the tissue or the size, shape, and location of the airways using three-dimensional visualization technology of medical images that combines computer image processing and analysis technology. The application of technology to create automated and precise three-dimensional images of the airway may have the practical significance of the following aspects:

1)Reduces the work intensity of the clinician. A CT scan of the chest usually obtains hundreds of CT images for one patient's scan. The doctor needs to identify the position, size, and shape of the patient's lesions from these images according to his own experience. This is challenging mental labor. If the patient's airway tree information can be directly reconstructed, it will reduce the work intensity and save more time.

2)Increase the accuracy of respiratory disease diagnosis. With manual images viewing for one CT scan image, we can have a different diagnosis from different doctors, but with the three-dimensional visualization, the computer automatically generates the airway tree and the patient pathological changes are clear and the diagnosis is accurate.

1.4 Research current situation

Airway detection methods based on CT images can be classified as manual, semi-automatic, or automatic airway detection methods. In the Beginning, the tracheal detection based on CT images was made manually, and doctors have to rely on their own experience, to adjust the whole window width and window level used to observe the region of interest of the trachea. There are many tracheas with low contrast, whose boundary is not obvious, and made it difficult to distinguish them through eyes. The slice thickness of CT scanning film is becoming smaller and smaller as CT technology advances, and the number of slices is growing. Each lung scanning film may be high to a hundred. Reading such a large number of CT scanning films, made it difficult for doctors to keep focused, and it is easy to have the wrong detection, and it's a time-consuming process, according to statistics, it takes about three hours to calibrate the airways in a CT scan image [11]. Due to the following factors, this method was quickly replaced by automatic methods.

Nowadays many techniques have been developed for automatic Trachea detection and segmentation. M. Sonka et al. Proposed a three-dimensional trachea tree extraction algorithm based on threshold and region growth [32].Schlatter et al. proposed several heuristic rules for detecting omissions in region growing and used the level set approach to segment and rebuild the airway tree at the same time [30]. The proposed method, however, requires preprocessing of the image's gradient information, and the algorithm complexity for detecting omissions is high. Tschirren et al. Proposed the method of keeping the active region of cylindrical objects [31], which can track the expanding direction of cylindrical objects, and then determine the candidate airway. However, this method uses affinity function to calculate the similarity and uses skeleton extraction to identify the topology of trachea structure, to avoid the omission phenomenon in region growth, which significantly increases the algorithm's complexity. Gin neken et al. to increase the robustness of the region-growing process proposed to use a multi-threshold method [24], but the threshold used by this method has a significant effect on the segmentation results. Improper selection of threshold will not only lead to long segmentation time but also easily lead to segmentation failure. Christian et al. Proposed to use the gradient vector flow to determine the growth direction of the region [25]. Lo. P et al. Determined the thin airway by calculating the shortest path from the preliminary segmentation point to a certain search range [33].Zhao Peng et al. Proposed a lung trachea tree segmentation method based on adaptive parameters [6]. This method adopts the strategy of segmented processing and the method of adaptive threshold, dynamically calculates the optimal threshold of each trachea segment, and uses the change of radius and growth wave surface to avoid omission.Jiang Huiyan et al. Proposed an improved regional growth method to segment trachea trees [35].The method adopts dynamic threshold and uses node theory to grow from 2D and 3D directions. The disadvantage is that the search range and insertion conditions of nodes in adjacent images depend on experience, and the algorithm is complex and the seed points need to be specified manually. Mori et al. [45] used a 3D rendering algorithm to removed the bronchial area by steadily increasing the growth threshold of the area until the segmented area "leaks" into the lungs. The area extracted just before the leak is identified as the bronchial area.Wood *et al.* [46], [47] used 3D seeding region growing to segment the airway and vascular trees of removed, bloated canine lungs, and airway tree branch length and cross-sectional area were measured quantitatively. To extract a gray-level image representing the distances from the seed point to all the points in the segmented image, a method known as distance tagging was used.Then, tree bifurcation points were identified at locations where two disconnected groups of voxels were separated by the same distance.The airway central axes were determined and used in the estimation process to obtain a more accurate branchpoint calculation. The methods of Mori et al. [45] and Wood et al. [46], [47] process the entire data set with a single threshold, which reduces branch sensitivity for small-diameter branches. Williams et al**.** [48] analyzed the pulmonary vascular tree structure using differential geometry-based vector fields. Using the segmented image data given by Wood et al. [10], they proposed a method for obtaining an accurate topological representation of a tubular network. Only excised lungs were used to test the technique.To detect the airway tree in CT images, Sonka et al. [52] used a rule-based approach. They used anatomical knowledge of airway structure and relationships between airways and neighboring pulmonary vessels in their approach.To identify small airways, a set of rules based on anatomical knowledge and image characteristics were applied to possible airways in each slice. To define 3D airway trees, 3 distinct combinations of airway regions from two-dimensional slices were used. The A-tree characterized all of the airway regions that were linked in three dimensions. The A-tree was combined with all large airway regions that were not 3-D-connected back to the A-tree to form the B-tree. Finally, the C-tree was identified as the union of all 2D slices detected airway regions. The data analysis revealed that the A-tree had low sensitivity, while the C-tree had more accurately classified airways, but at the cost of more wrongly observed airways. Later, Park et al. [49] improved the accuracy of the rule-based method in [52] by using a fuzzy logic approach. A fuzzy logic decision-making model was proposed using qualitative features from the images. Possible airway regions were identified using fuzzy logic marking. Only canine data was used to test the method. Pisupati [50] created a method that used gray-scale mathematical morphology to detect the 3D airway tree, pulmonary artery, and vein of isolated canine lungs.To detect different sized airways, a set of various sized structuring elements was used.The difference image between the original and reconstructed images was thresholded after processing a single slice by grayscale reconstruction. The airway tree was developed using 3D region growing. Pisupati used the wavefront propagation technique developed by Wood et al. [47] to examine the tree structure. To segment the bronchi of sheep lungs, Prêteux et al**.** [51] used a technique that combined morphological filtering, connection cost-based marking, and conditional watershed techniques. The accuracy of a quantitative study of bronchial caliber in high-resolution CT (HRCT) images was their key motivation. Since they were primarily concerned with the accuracy of their 2D airway detection system, 3D connectivity and tree reconstruction, and 3D connectivity were not taken into account.Fetita and Prêteux have recently demonstrated a 3D airway segmentation and re-construction algorithm based on mathematical morphology and connection-cost analysis, which they applied to the high resolution of human lungs [39]**.**

Their findings show that using morphological image analysis, airway branches out to generation seven can be detected.

1.5 Main parts of the paper

This article is divided into five chapters:
Chapter1:Introduction: in this section, the introduction elements such as the background of the study, research object, significance of the study, Research current situation, and finally present the main parts of the paper are presented.
Chapter2:CT image analysis, we began by introducing the CT image scan format by presenting the DICOM format, and then present the CT unit and the windowing of the CT image.
Chapter3:automatic detection methods of airways: this chapter mainly elaborate the different automated identification of airways by presenting the most used methods which are thresholding based method, region-based method, geometric-shape methods, morphological methods, machine learning methods, mathematical methods, morphology-based methods the segmentation, and repair algorithm of lung area is described in detail, and finally described the algorithm and principle of the initial segmentation of the airways tree.
Chapter4:airways tree detection using region growing and morphological method presents the initial segmentation of airways using region growing method and the fine segmentation Based on morphological method.
Chapitre5:the experimental results and analysis are presented in this chapter, which focuses on the process analysis by presenting the experimental data and segmentation method.
Chapter 6: summary and Prospects.

Chapter 2: CT image analysis

2.1 DICOM file

In the early1980s, it was extremely difficult for anyone other than manufactures of computed tomography or magnetic resonance imaging devices to interpret the images that the machines generated. To solve this problem, the American College of Radiologists and the National Electrical Manufacturers Association (NEMA) developed the DICOM (Digital Imaging and Communication in Medicine).
The DICOM format File structure is shown in Figure 2.1

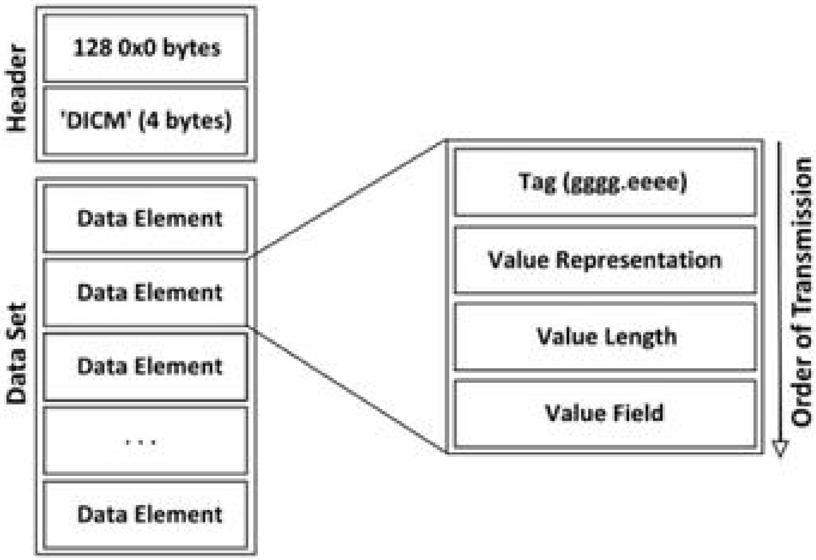


Fig 2.1 DICOM File structure

The file header contains 128byte File Preamble and 4bytes DICOM prefix (D, I, C, M) encoded in uppercase characters. The data set includes data elements, and the data elements contain the values of the object's attributes. Data elements are defined by data element Tag, VR, Value length, and a value field.

2.2 Hounsfield unit

The Hounsfield unit (HU) is a relative quantitative measurement of radio density used by radiologists in the interpretation of computed tomography (CT) images. The Hounsfield unit, also known as the CT unit, is measured using the substance's baseline linear attenuation coefficient to X-rays, where distilled water (at normal temperature and pressure) is arbitrarily defined as zero. The Hounsfield Unit for air is -1000 Hu. When studying the chest CT image, the density difference between human tissues can provide diagnostic information, but not the absolute density, so generally, The CT value is defined as follows:

$$\text{Hu}=\frac{\mu_{tissue}-\mu_{water}}{\mu_{water}}\times 1000 \tag{2.1}$$

μ_{tissue} represents the absorption coefficient of a specific tissue to X-rays, μ_{water} is the X-ray absorption value by water component of the human body.
CT images thus have values ranged from -1000HU (HU = Hounsfield unit) for air (background of the image or trachea) to 1000HU (and sometimes higher values) for bones. The following will be objectified depending on the level and width of the window in the Hounsfield absorption scale: soft tissues (muscle, heart, liver, etc.), calcium structures. The absorption coefficient measurements are calibrated to provide images at known intensities for different tissue types. The distribution of intensities in Hu units according to the types of tissue imaged is given in Tab 2.1

Tab 2.1 Average Hounsfield units

TISSUE	Hounsfield Unit (Hu)
air	-1000
lungs	-900 ～-400
fat	-100 ～-20
bone	400 ～1000
Soft tissue	20 ～70
H2o	0

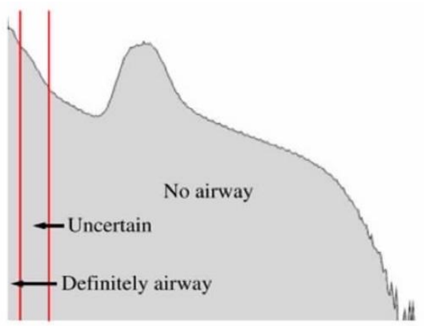


Fig. 2.2 The distribution histogram

2.3 The Windowing

Windowing, also known as gray-level mapping or histogram variation, is a technique for altering the appearance of the CT image gray-scale variable of the image using CT numbers to highlight specific structures. The brightness image is determined by the window level(wl), and the contrast is adjusted by the window width (WW). The window width (WW) refers to the total number of CT numbers in an image. A larger window can display a larger range of CT numbers. Consequently, the transition between dark and light structures will take place over a wider transition region with narrow window width. The window level (wl) is the midpoint of the displayed CT number set. as the window level is reduced; the CT image will become clearer and vice versa. To show the precise details of the target region of interest, the window can be adjusted and the CT value range of the target area is (0 ~ 255).

The window adjustment formula is:

$$\text{g(i)}=\begin{cases} 0 & f(i) < wl-0.5ww \\ \frac{f(i)-(wl-0.5ww)}{\delta} & wl-0.5ww \le f(i) \le wl+0.5ww \\ 255 & f(i) > wl+0.5ww \end{cases} \tag{2.2}$$

$$\delta = ww/256$$

g(i) is the pixel gray value after the window has been adjusted, and f(i) is the pixel value in the CT image.

Chapter 3: Automatic detection methods of Airways

3.1 Airways segmentation methods

The automated identification of airways is obtained through segmentation, which serves as a foundation for the majority of computerized lung-related analyses. Segmentation is an important step in pulmonary image processing since it uses a computer to identify the boundaries of the lung from surrounding thoracic tissue on computed tomographic (CT) images. Manual tracing, semi-automatic, and fully automated tracing are all examples of segmentation schemes. In the modern CT examination, manual segmentation was impractical due to the large data volume. When processing a CT exam with more than 100 cropped images, semi-automated segmentation schemes are subjective, repetitive, and time-consuming. The primary goal of segmentation is to simplify and transform an image representation into something more meaningful and understandable. Image segmentation is a technique for identifying structures and regions in images, such as lines and curves[36]. Several research teams have proposed and developed fully automated techniques for segmenting Airways regions in CT lung images. The majority of them are pixel-based approaches that take into account the large pixel value variation between the airways and the surrounding tissue. The existing methods for airway segmentation on CT images were discussed in this paper, with a focus on their accuracy and efficiency.

3.1.1 Threshold-based method

Threshold segmentation methods are classified as multi-level threshold methods and optimal threshold methods. When the threshold value is obtained, the infected area can be segmented using threshold-based methods, which are easy and efficient for obtaining segmentations from images with a clear distinction between the regions. The image is segmented by generating binary partitions based on image attenuation values, which are calculated by the relative attenuation of structures on CT images. Indeed, as compared to images obtained with other imaging modalities, these methods typically perform better on CT images because the attenuation values, calculated in Hounsfield units, have well-defined measurements for different tissue components on CT images. Threshold-based methods, on the other hand, generally ignore the spatial characteristics of the target objects. Kaftan J et al. used an algorithm based on threshold division because the segmentation algorithm performs a single threshold segmentation on a single CT image, and the processed data source is a two-dimensional image. Therefore, this method is the fastest, but this has a significant effect on lung texture in the lung parenchymal image sequence. It is not user-friendly, and it is frequently used in combination with other methods to obtain a complete lung parenchyma sequence. Furthermore, as opposed to other types of airways segmentation procedures, these approaches are more susceptible to noise and imaging artifacts. Since no spatial information or variability is considered during the segmentation process, the existence of irregular imaging patterns affects this class of thresholding-based segmentation methods more than other methods. Katz suggested one of the first methods using a threshold segmentation technique for the bi-dimensional case in

1964, and Weszka conducted the first survey by the end of the 1970s. After that, for the bi-dimensional case, several surveys and techniques related to threshold methods can be verified.

3.1.2 Region-based methods initial seed point

Region growing is also known as pixel-based image segmentation because it involves the initial seed points. The seed points for these regions are chosen and the regions are taken. The main idea of region-based segmentation methods is that gray levels within one region have identical values. The Region-growing method is perhaps the most well-known of these segmentation methods, in which one pixel is compared to its neighbors, and if a predefined region criterion (i.e., homogeneity) is met, the pixel is said to belong to the same class as one or more of its neighbors. Although a pre-defined region criterion is essential for the region-growing technique, it is more reliable and efficient than thresholding-based segmentation methods since it includes "region" criteria as well as spatial details.

Region-based segmentation methods (especially region growing) are useful in dealing with attenuation variations (caused by mild pathologic conditions and imaging artifacts) because of their efficiency and robustness to reinforcing spatial neighborhood information and a regional term for applications in airways segmentation on CT images. Hence, the robustness of different region-based approaches for repeatability varies. Methods for extracting homogeneous areas, such as lungs with no to moderate pathologic conditions, depend on region-based segmentation. Region-based methods produce more accurate airways segmentation results than thresholding-based methods without producing false positives in out-of-body regions with similar attenuation values. However, depending on the amount of noise and the accuracy of the neighborhood parameters, region-based methods can produce false negatives in the lung region, necessitating additional postprocessing, as demonstrated in several cases where region-based methods failed to perform well. Other region-based segmentation approaches, such as random walks and fuzzy connectedness, have been introduced in the literature in addition to region rising. The random walk and region-growing approaches to image segmentation have been shown to be less robust than fuzzy connectedness process.

3.1.3 Geometric shape analysis methods

Algorithms based on geometric shape analysis can be mainly divided into algorithms based on gradient vector flow, pulmonary tracheal tubular structure, and Marching Cubes. To extract the centerline, the automatic airways tree segmentation algorithm of gradient vector flow requires distinguishing certain structures of the trachea based on the nature of the gradient vector flow vector field and segmenting the airway tree that is similar to the tubular structure. This is done by the reverse gradient flow tracking algorithm. The reverse gradient flow tracking algorithm accomplishes this. The tubular structure of the airway segmentation algorithm works by first formulating the tubular morphology structure's filter perception function and integrating the location of the trachea centerline, and then extracting the trachea based on anatomical knowledge of the airway. Based on the Marching Cubes algorithm, first, obtain the structure database schema of the lung and trachea, and then visualize the partial distribution of the lung based on the database schema, while the structure of the trachea and other tissues needs to be distinguished in geometric space and reused The surface model calculates the main curvature and main direction, and finally extracts the airway region. Bauer et al. used multi-scale tubular structure filtering to initially extract the airway region, and used the known specific medical prior knowledge, such as branch angle, radius, etc. The tree is optimized . Pu et al. used the Marching Cubes algorithm to reconstruct the chest tissue in order to obtain a three-dimensional model of the airway tree, and then used the main curves and trajectory of the airway's surface layer, tree three-dimensional model to minimize interference in the non-airway region, and at last used the threshold Segmentation to extract the airway tree.

3.1.4 Morphological methods

Whereas an airway tree tubular composition causes it to appear as circular regions on CT image slices, identifying an airway tree can be reduced to a task of detecting two-dimensional (2D) circular structures and reconstructing them as a three-dimensional (3D) airway tree. The morphological approach is often used in nature to identify the specific shape, width, and intensity of airways., along with their spatial relationship on neighboring slices for airway recognition. This method typically consists of two primary steps the slice-by-slice identification of 2D candidate airway positions, and 3D reconstruction of the airway using various morphological operations. By Using a region-growing operation or other approaches, the first airway candidate identification can be accomplished. Aykac et al.[38] For example, identified the original airways by using a threshold to compare the restored and original images and identifying the local extrema. The most fundamental morphological processes are dilation and erosion. On the other hand, the efficiency of simple morphological operations-based reconstructions is heavily reliant on the continuous detection of identified airway candidates in space. otherwise, If the segmented 2D slices are stacked for the reconstruction of a 3D airway tree, there will be discontinuity. Rather than using a conventional morphological procedure, Fetita et al.[38]developed a mathematical morphological operator for a total airway reconstruction relying on the "link cost" concept, called selective marking, the selective marking and depth-constrained connection cost (SMDC connection cost). The connection cost takes into account three categories of airway regions: lumen, airway walls, and adjacent parenchyma tissue.

3.1.5 Machine learning based-method

Machine learning's key concept is to use a computer's processing power to evaluate and summarize existing data in order to generate more predictive rules. It is also widely used in computer vision, data mining, and medical diagnosis, and other applications., etc., so it is also called a statistical theory. lo, et al obtained the airway tree segmentation result by combining the characteristics of lung texture and regional growth and used the data set segmentation result as the training set to begin training the K-nearest neighbor (KNN) classifier [40]. Although the complexity and time are increased in the process of classification training and introduction of blood vessels, its segmentation accuracy is higher. To reduce the effect of the main trachea and main bronchi on sample collection, Meng Q E et al. first performed morphological operations on the training data and then divided it into multiple sub-areas, and then selected an equal number of regions as samples [41]. Jin D K extracts the center of the training data skeleton and makes it move randomly within 15 pixels to simulate the shape of bronchus of different orders.

3.1.6 Mathematical morphology-based method

Developed in the early 1980s by Matheron and Serra, mathematical morphology is a special analysis discipline based on morphological transformations analysis. As a mathematical tool, it can extract useful image components that express and describe the shape of a region, such as skeletons, boundaries, etc. from the image by choosing appropriate structural elements. Set theory is the language of mathematical morphology, and it can provide a powerful method for many image processing problems. The application of mathematical morphology can simplify image data, maintain its basic shape characteristics and remove irrelevant structures. Gao Dezhi et al. [42] proposed an optimal threshold lung tracheal tree segmentation algorithm based on morphological gray gradient guidance. Li Cuifang et al. [6] proposed an airway tree segmentation algorithm that combines region growth and morphology. First, the air ducts are extracted by omnidirectional region growth to avoid missing segmentation and then combined with morphological methods to extract the final Lung tracheal tree. Aykac et al. [38] proposed an algorithm to automatically segment the airway tree. Firstly, the noise is removed by a four-neighbor lowpass filter, and then the morphological grayscale reconstruction algorithm is applied to use circular structural elements on the two-dimensional axial slice the potential region of the airway is extracted, and finally, a three-dimensional tracheal tree is reconstructed according to the connectivity of the area. Fetita et al. [43] proposed a morphological synthesis method to automatically segmenting the airways tree. First, the FSD (the Flood Size-drain Leveling) morphological operator was used to determine the potential airway region, and then an iterative method was used in the airway tree to avoid leakage and reconstruct a three-dimensional airway tree.

3.2 Analysis of airways morphometry

As a conductive structure, morphological changes in the airways can significantly impact airflow and thus the lung's ability to exchange gases. Therefore, airway morphometry is extremely important. Changes in airway morphometry may also serve as an indicator of disease progression over time, as well as an indicator of treatment response. According to Berger et al., the mean airway internal area (IA) was considerably different in smokers with(chronic obstructive pulmonary disease)COPD compared to smokers without COPD. COPD is described as a lung disease characterized by the presence of chronic bronchitis and emphysema, as well as the presence of restricted airways. In theory, given an airway tree with each branch labeled, measuring global parameters such as airway generation and branch number, airway length/volume, and cross-sectional areas of the airway lumen will be relatively simple. Based on airway segmentation, Wood et al. implemented a method for measuring the branch length, angle, and diameters of an airway tree. However, additional efforts are needed to detect the outer airway wall to calculate certain parameters, such as airway wall remodeling and/or the broncho-arterial ratio. According to research, the thickening of the bronchial wall is a well-known symptom of COPD, and remodeling of the airway wall may be used to classify the seriousness of the disease, according to research. Airway wall measurements were previously done manually by changing image intensity values with window levels. Due to the large number of slices involved in a single test, performing accurate manual-tracing techniques regularly is very difficult and time-consuming. Therefore, a variety of computerized algorithms have been developed to help in the identification and measurement of airway walls depicted on CT images.

3.2.1 Full-width at half maximum (FWHM)

The FWHM method estimates the inner and outer wall positions by targeting several rays from the middle of the airway lumen outward to the parenchyma and observing intensity profiles along with these rays. As shown in Fig. 3, FWHM assumes that the outer and inner airway walls are halfway between the local minimum value within the lumen and the maximum value within the wall (i.e., the FWHM location). This approach is based purely on the gray-scale profile along a ray, which can be influenced by a variety of variables, including a partial volume effect or the blurring introduced by the reconstruction method, as well as the orientation of the airways, potentially leading to an overestimation of the airway wall steps. The half-max approach can result in an obvious estimation bias for small airways. The accuracy of this procedure, according to King et al. depends on the shape of the object and the scanner point-spread feature (PSF).

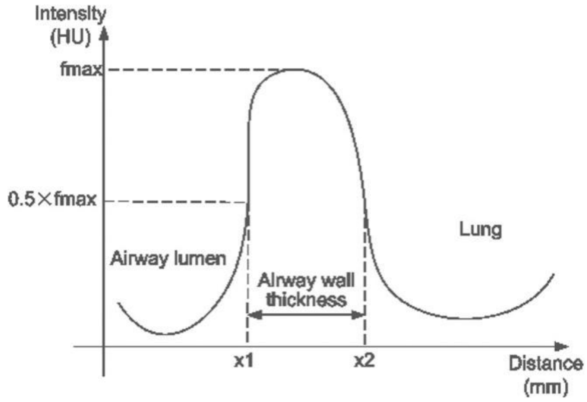


Fig 3.1 An example of the FWHM approach for identifying the airway wall.

The intensity profile from a point in the airway lumen outward is shown by the curve.

3.2.2 Contour matching method

Saragaglia et al.[53]developed an approach based on mathematical morphology combined with energy-based contour matching to solve some of the segmentation difficulties caused by vessels neighboring to airways and also wall irregularities. To reduce the reliance on pixel value variations, this algorithm first normalized the native image with the FWHM. The outer airway wall is then computed slice by slice using the airway centerlines, by gradually expanding an initial "closed" contour (e.g., a collection of connected pixels) until predefined energy reaches a state of equilibrium. The energy function is implemented as a combination of many morphological measurements, such as grayscale gradient and neighborhood distance. The inner wall contours are used as the initially closed contour to define the outer wall in this approach. Since the central axes of the airways are used to produce cross-sectional images at particular bronchial positions, the accuracy of these axes is critical to this method.

3.2.3 3D geometric deformable model

Measurements are normally restricted to airways that are largely perpendicular to the scanning plane in most of the methods mentioned above for airway morphometry study. Since the majority of airways represented on axial images are oblique to the axial plane, this may result in apparent bias in airway measurement. Furthermore, these approaches mainly concentrate on identifying regions of the airway wall that are directly connected to the parenchyma, ignoring regions between the bronchial wall and adjacent vessels. Since the bronchial wall and neighboring vessels have similar intensities, determining the boundaries between the structures is difficult. To overcome these limitations, Ortner et al.[55] proposed a novel geometric approach based on an explicit 3D triangle mesh surface model. According to simplified LaGrange dynamics, the model deforms in a force field described by gradient vector flow. The model, in particular, allows for local adaptive time phase integration, has no self-intersections during deformation, is independent of airway orientation concerning the scanning plane, and can automatically deal with adjacent vessels. However, to prevent the surface from stopping at the inner surface of the airway wall, this approach[55] involves a balloon force based on the image pressure. While the image intensity of an airway wall can vary significantly, choosing a constant parameter for the balloon force is difficult. According to Este 'par et al [54], these approaches can be divided into two categories: parametric and nonparametric, depending on whether a mechanism or model (e.g., the PSF) is used to reduce the blurring effect induced by a scanner.

Some airway features are difficult to measure accurately, and the measurement process is hampered by differences in airway caliber, wall thickness, and orientation. The process is further complicated by nonhomogeneous airway surroundings, such as neighboring airways, lung parenchyma, blood vessels, the heart, and the chest wall. Partial volume effects, which are caused by the image voxel's finite size, are also important. Fine information and small items (relative to pixel size) can be lost due to partial volume effects. Many of the techniques for determining airway wall thickness described above have been validated using phantom tests, and they all seem to function best for airways with diameters greater than 2 mm. However small airways, on the other hand, play an important role in COPD and other respiratory disorders caused by heavy smoking.

Chapter 4: Airway tree detection using region growing and morphological method

4.1 Method description

The airways tree automated identification method used in this paper consists of four major steps. The method starts with 3D segmentation of lung parenchyma from CT sequence images; next used region growing method to extract the trachea tree; Then, candidate region of small airways was selected using the morphological segmentation process; Finally, the final airway tree was extracted using the region growing method. The following chart illustrates the steps of the segmentation process used in this paper.

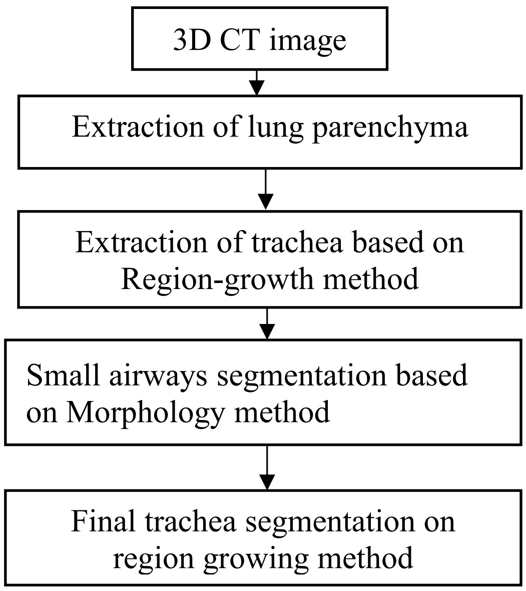


Fig.1 The flow chart of airway tree segmentation

4.2 Extraction of lung parenchyma

This paper presents a fully automatic algorithm for lung parenchyma segmentation based on thresholding, smoothing and repairing. first, the threshold method is adopted for binarization. Then three-dimensional connectivity labeling and 3D region growing are utilized to remove the main trachea.

4.2.1 Binary processing

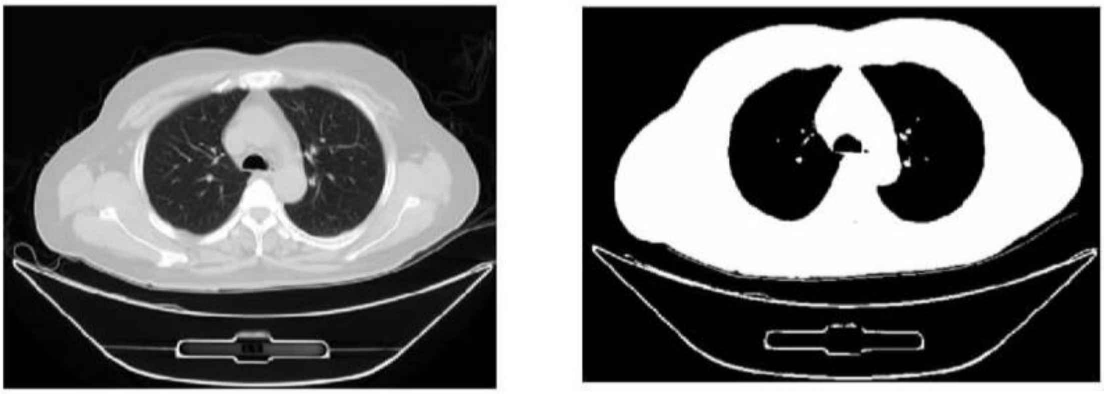
In order to binarize the input image series, the threshold Value should be chosen first. To divide the sequence input image, this paper used an adaptive threshold method. By Optimal threshold, the following formula is used to achieve the most precise results.

$$T^{i+1} = \frac{1}{2}(\mu_b + \mu_n). \quad (4.1)$$

μ_b and μ_n is the trunk and non-trunk average gray value. Here, the initial value:

$$T_0 = -500 \text{ Hu. With } T^{i+1} \approx T^i. \quad (4.2)$$

Fig 4.1.a shows the initial two-dimensional sample image used in this article. Fig 4.1.b the processing effect after binarization.



a) The original lung CT image b) The binarized image

Fig 4.1 Lung original and binarized CT image

4.2.3 3D connected component labeling

After adaptative thresholding, the background and other low gray voxels are reduced, the spot darkens and the trunk part brightens, and then the obtain binary image is inverted and labeled by 3D connected domain. The background pixels connected with the image are reversed to eliminate the background (Fig 4.3). After the above steps, only the lung (white), trachea/bronchus (white), and black cavities caused by blood vessels and nodules were left in the sequence images.in addition, the lung bottom usually includes the slice image of the stomach, and the gas part of the stomach also shows white. The amount of blood vessels and nodules in the lung tissue, on the other hand, is much smaller than the black background, and the white part of the chest is also smaller than the corresponding white part of the pulmonary parenchyma. Based on this, the amount of each connected region is measured by marking the black and white areas of the 3D image with region of interest. At the same time, the required volume threshold is set, and the pixel value in the area whose volume is less than the corresponding threshold is flipped. in this way not only, the white part caused by the stomach image can be automatically removed, but the black segment can also be correctly classified as lung parenchyma, correcting the binarization process errors.

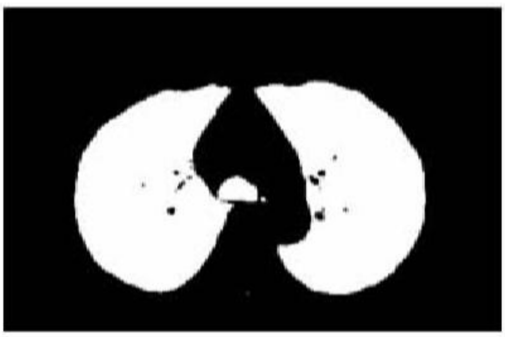


Fig 4.2 After background removal

4.2.5 Smoothing operation

There are several circular depressions on the outside of the prototype that can be seen by observation; these depressions are caused by the involvement of nodules or other high-density fibrotic lesions in the lung wall. The morphological closed operation can eliminate sharp corners in the convex image, fill small grooves better, and bridge cavities and cracks. Therefore, circular structural elements are used to close the template [13], and the final template is shown in Figure 4.4.

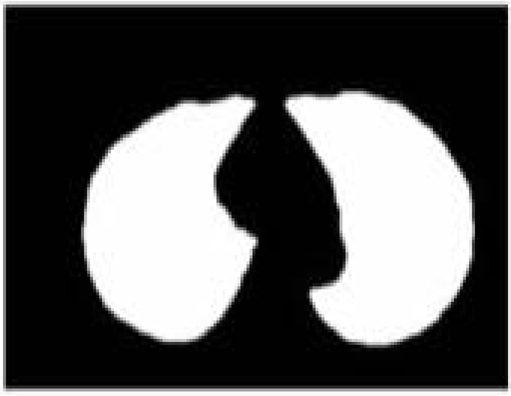


Fig 4.4 Final lung mask

4.3 Extraction of the trachea based on Region growing

The trachea and main bronchus are very easy to segment due their well-defined structure and intensity. The threshold and label filtering methods are most used to extract the airways. The trachea is localized through the image of the binary lung parenchyma. This paper used the 3D connected component labeling to extract the trachea from the lung parenchyma. The region growing method is mainly divided into three points: the selection of seed points, identification of the regional growth criteria, and then set rules for the termination of the growth process.
Here is the mathematical formula:
Assume the seed point is (x, y, z), and the interval between the two points to be divided is (4.1), and the divided region A.

$$Dist(d - A) = |d - mean(A)| \tag{4.3}$$

The point to be segmented is d = I (x, y, z), and the average value of all points in the segmented area is mean (A). The growth stops when the distance between the point to be segmented and the segmented area exceeds the preset distance threshold. which is:

$$if\ Dist(d - A) < \max dist, d \notin A \tag{4.4}$$

$\max dist$ is the maximum distance between the segmentation point and the segmented region average value.

4.3.1 Selection of seed points

Based on the traditional seed region growth method, this paper proposes a new region growing algorithm. According to anatomical knowledge, in a CT scan, the trachea appears earlier than the lung apex. Therefore, first, based on lung parenchyma segmentation, the threshold-based algorithm is applied to initialize the image segmentation to form an over-segmentation effect; then, starting from the first image of the initial segmentation result sequence, the connected region with the specified size is automatically selected as the seed region according to certain rules of seed region growth.

4.3.2 Algorithm process

The conditions of 3D region growing are some similarity criteria defined according to the CT values of each tissue. The termination criterion is defined based on the condition of the

3D region growing. If the maximum pixel value distance is $\max dist$, the region will stop growing when the distance between the segmented point and the segmented region exceeds the maximum distance $\max dist$. The pixel 26-neighborhood is used to differentiate the growing mode of the 3D region

The airway is segmented using a three-dimensional area expanding algorithm., and the preliminary airway tree is obtained.

4.4 Extraction of the trachea tree based on morphology method

By using the 3D region growing algorithm, we can only obtain the preliminary airways tree segmentation: left and right bronchi, segmental bronchi, and relatively large trachea branches. To get more detailed trachea segmentation results, this paper uses a morphology-based method to segment potential small trachea, and then link the segmentation results into three-dimensional airways region. It mainly includes the following two parts: morphological operation and trachea tree synthesis.

4.4.1 Morphological operation

In lung parenchyma, the CT value of the trachea is usually low (- 1000 Hu to - 900 Hu). Therefore, to obtain the local minimum in the image, this paper uses the gray morphological reconstruction method. According to the characteristics that the trachea is a low brightness region and is surrounded by a high brightness trachea wall, the morphological reconstruction was carried out. The low brightness area surrounded by the trachea wall is extracted as the potential airway region. Because the shape and thickness of the trachea are different with different topological directions, this paper selects a circular structure operator to do morphological operation[44]. The steps of mathematical morphology to extract potential pulmonary and tracheal regions are as follows:

1) Morphological closed operation:

$$J_1^b \text{ ==I\_source.SE.} \tag{4.5}$$

I_Source is the edge enhanced image after preprocessing, SE is the closed operation structure operator; the circular operator is selected with a 4 radius.

2) gray reconstruction operation:

$$J_{k+1}\text{=max } (J_k\Theta\text{SE, I\_Source}). \tag{4.6}$$

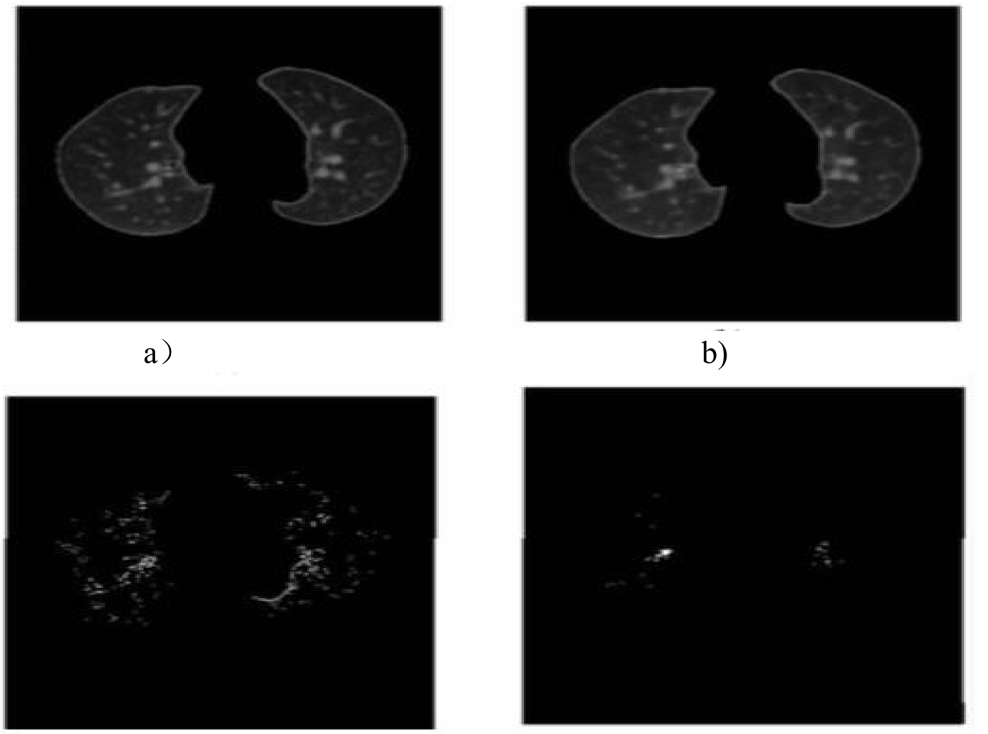
I_Source is the preprocessed edge enhancement image, j_k (k=1,2,3....) is the obtained image after the closing operation, when $J_{k+1} = J_k$, the operation end.

3) Image subtraction: Difimage = $J_{k+1} -$I_Source, J_{k+1} is the reconstructed image, Finally, the potential airway regions were obtained

4) Threshold processing of potential airway regions

The threshold value in the local minimum area is equal to 20% of the difference between the image's maximum and minimum values. After binarization, the possible lung trachea region was obtained.

In the obtained local minimum region, the selected threshold value difference between the maximum value and the minimum value of the image is 20%.This paper -200Hu. Finally, the potential lung tracheal area after binarization is obtained. The results of the above steps are shown in fig 4.4



a） b)

c） d)

Fig 4.4 The segmentation of small airway regions using morphology method

4.3.2 Synthesis of trachea tree

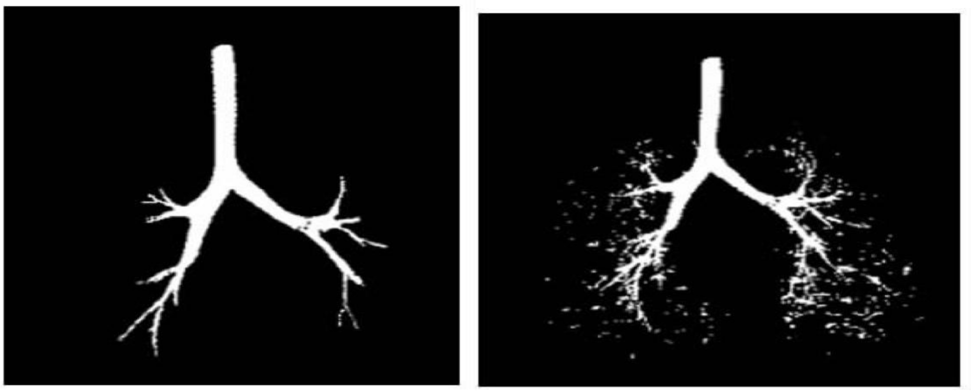
After gray-scale reconstruction, the thin airway region is obtained and the final segmentation result is displayed by MIP (maximum intensity projection).

Chapter 5: Experimental results and analysis

5.1 Experimental data

The experimental data used in this paper are all from Philips 40-slice spiral CT of Shanghai Pulmonary Hospital. A total of 20 patients' lung CT data were selected. All images are digital images in DICOM3.0 standard format with a bit depth of 12 bits. The Image layer is 512×512 pixels, and the scanning layer thickness is 2 mm. In all data sets, The minimum number of CT scans in all datasets is 240 and the maximum is 277.
In this paper, the average gray value of the region of the airway obtained from 20 groups of CT image segmentation is -950.87hu. On the x-axis is the image sequence number, and on the y-axis is the bluish gray. As shown in Fig 2.2, the gray value curve of the segmented trachea is obtained. The segmented trachea in this paper has an average gray value of about -950hu.

5.2 Segmentation results



a)Region growing b)Morphological method

Fig 5.1 3D trachea tree segmentation

Fig 5.2 3D final segmentation results of airways

5.3 chapter summary

This paper combines the 3D region growing and morphological-based method to extract the airways tree. By analyzing the segmentation results, it is found that the three-dimensional region growth method can obtain the trachea/main bronchi, Segment trachea, and main trachea branches, and the morphologically based method can effectively detect the region of the thin airway. Therefore, this article combines the segmentation results of the above two methods and applies the three-dimensional region growing method again to obtain the final airways tree. Experiments have shown that this approach can efficiently obtain the airways tree, setting a strong foundation for quantitative study of the airways in the future.

Chapter 6: Summary and Prospects

6.1 summary

This paper focuses on how to improve the rapid and high detection accuracy of airways tree using a three-dimensional CT image and a detection algorithm for airways. The following are the key research contents and associated research contents:

1) Before the extraction of airways. The lung parenchyma was segmented by binarization and 3D connected domain labeling.

2)In the stage of the airway's segmentation. This paper combines the region growing-based method and morphology-based method. in the process of airways fine segmentation, the iterative local region growing method was used, to make the details of the segmentation result more complete.

6.2 prospects

Although this paper has done some research and exploration work on the detection algorithm of airways in 3D CT images, and finally realized the segmentation and reconstruction of airways tree in the auxiliary diagnosis system of airways. Through the analysis of the existing airways automatic detection method, it can be seen that in recent years, the airways automatic detection method has attracted the attention of many researchers, and these algorithms have achieved quite good results. However, there are still some problems in the research process, which need further research. The research of airways automatic detection methods will continue to develop in the following:

1) various types Research on automatic detection of airways

2)Use large amounts of clinical data for testing and improvement

3)Adaptive determination of some parameters

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