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An Enhanced Framework for Automated Segmentation of the Pulmonary Lobes from Chest CT Scans using Level Set Approach

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Abstract*-- Segmentation of the pulmonary lobes is relevant in clinical practice and particularly challenging for cases with severe diseases or incomplete fissures. Automatic segmentation of the separate human lung lobes is a crucial task in computer aided diagnostics and intervention planning, and required for example for determination of disease spreading or pulmonary parenchyma quantification. In this work, a novel approach for lobe segmentation based on multi-region level sets is presented. In a first step, interlobular fissures are detected using a supervised enhancement filter. The fissures are then used to compute a cost image, which is incorporated in the level set approach. By this, the segmentation is drawn to the fissures at places where structure information is present in the image. In areas with incomplete fissures (e.g. due to insufficient image quality or anatomical conditions) the smoothing term of the level sets applies and a closed continuation of the fissures is provided. The approach is tested on nine pulmonary CT scans. Lobe segmentation can be a very challenging task if images lack in quality or if anatomical anomalies occur. Using level sets for image segmentation has many advantages. First of all, level sets yield a nice representation of regions and their boundaries on the pixel grid without the need of complex data structures. This considerably simplifies optimization, as variational methods and standard numerics can be employed. Furthermore, level sets can describe topological changes in the segmentation, i.e. parts of a region can split and merge.

Index Terms—**Computed tomography (CT), fissures, lobes, lungs, segmentation, Level Set Approaches.**

I. INTRODUCTION

The human lungs are divided into five anatomic compartments called lobes. A lobar fissure separates the lung lobes. The left oblique or major fissure separates the left lungs into upper and lower lobes. The right lung consists of upper, middle, and lower lobes where the upper and middle lobes are separated by the horizontal or minor fissure; the middle and upper lobes and alienated from the lower lobe by the right oblique which is also known as major fissure [see Fig.1][1]. Relative lobar rotation of fissures to one another is allowed to adapt shape changes in the thoracic cavity. Each lobe is served by separate airway and vascular networks mostly in the case of incomplete fissures. In specific anatomic regions of the lung some pulmonary diseases are more common. For example, tuberculosis and silicosis are completely upper lobe diseases, while interstitial pulmonary fibrosis is usually present in the lower lobes. Pulmonary emphysema is commonly present in the upper lobes, but in the case of lower lobes there is a rare genetic variant deficiency related with alpha-1 anti-trypsin. Thus, clinical important for disease classification and understanding the tissue and functional distinctiveness of the lobar parenchyma is more significant which leads to the segmentation of lung lobes for effective identification of lung disease.

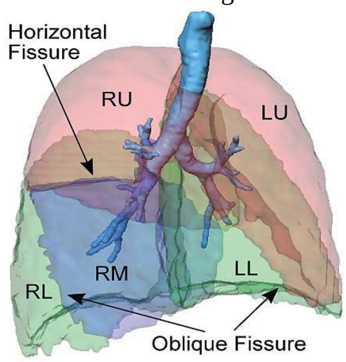

Fig.1 Lung Lobes

Lobar analysis is valuable in treatment selection, planning, and review [1]. For example, there are emerging therapies for emphysema that use full lobar segregation. These therapies rely on computed tomography (CT) images for identifying the airway and lobar allocation. Moreover, it may be important to identify incomplete fissures, since it is supposed to get collateral ventilation between lobes because of incomplete fissures. Lobar anatomy can be studied from CT imaging. Because of low contrast and uneven shape and appearance in CT imagery, it is a foremost challenge to the automatic detection of the fissures which occasionally makes it difficult even for manual analysts to mark their exact location. Usually, the fissures partition the lungs into two parts which appear as a thin bright sheet. Some pulmonary diseases can modify the appearance of the fissures on CT images which is given by Hayashi et al. [10]. Also, considerable fissure disintegration is observed—fissure disintegration is the nonexistence of the fissures at their predictable location, leading to incomplete fissures.

II. RELATED WORKS

Previous approaches to lung segmentation have been divided into direct and indirect. Based on gray-level information present in the data, we classify direct approaches, while the indirect approaches consist of methods that use information from other anatomical

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structures to approximate the location of the fissures. Both this methods have need of placing markers on lobes manually to guide the segmentation. Various direct method approaches are given by Rikxoort et al. [4], Zhang et al. [5], Wang et al. [6], Wiemker et al. [7]. Recently anatomy guided lung segmentation has been given by Soumik et al. [12]. Indirect methods are proposed by Kuhnigk et al. [8], Zhou et al. [9], Beichel et al. [11]. Therefore, specific algorithms have been tried. Pu et al. [13] presented computational geometry method to detect and segment fissures. To enhance the pulmonary fissures Laplacian smoothing is applied. The disadvantage is that it detect the fissures incorrectly. Kuhnigk et al. [14] presented lobe segmentation based on watershed transformation. The reliability can be increased due to high resolution images. But detecting the visible fissures is inaccurate. Lassen et al. [15] proposed three algorithms for segmenting the lobes. The main advantage is reducing the processing time. The disadvantage is inaccuracies arise due to lobar boundaries with an extremely angular shape. Wei et al. [16] presented the recognition of major fissures. The algorithm uses three steps to identify the major fissures in the human lungs. The algorithms are texture analysis, fissure region analysis and fissure identification. It requires longer computation time and manual segmentation. In the existing system marker based watershed algorithm is used for image segmentation [1] .In the watershed transform, a gray scale image is represented as a terrain, and the height of each point in the terrain gives the intensity level. A watershed transform identifies the minima, in the terrain, and the watersheds, or merges, unraveling the basins. Vincent et al. [2] presented an algorithm for watershed transforms. Hahn et al. [3] proposed a two-step process based on the original algorithm by Vincent et al. But Watershed is extremely sensitive to the change in intensity. A slight distinction in lighting or other forms of noise would result in a severe dysfunction. This phenomenon is known as over segmentation. The results are frequently inaccurate, even in the vicinity of clearly visible fissures, and often require manual correction. Other methods must be applied in order to overcome this. And not all enhancement schemes can be applied with Watershed to all types of images in general. In the proposed system marker based watershed algorithm used for segmentation of ROI is replaced by level sets to segment the pulmonary lobes because of the advantages over the former as well the increase in performance of segmentation. Here, fissure-enhancing techniques are used to define an additional force term that draws the level set to the fissures. In image regions with insufficient fissure information, a smooth completion of the fissures is estimated by the level sets and thus closed objects are guaranteed.

III. LEVEL SET APPROACHES

A. Overview

Fig.2 shows a flow diagram of the overall process, beginning with the segmentation of the lungs. The CT scan lung image is pre-processed for the removal of noise. Median filter is applied to reduce noise. The lungs are extracted from the original image by applying basic morphological operations and histogram equalization. Level Set Approach is used to construct a region of interest (ROI) encompassing the fissures. Next, a multi channel splitting and masking is computed on the segmented region. This image will be given as input to the watershed transform. After the watershed analysis is completed, we obtain an approximate segmentation of the lobar fissures.

B. Steps

1) Image reading:

In this section, Image for Processing is read so that the image properties can be easily obtained.

2) Preprocessing:

In this section, raw data of the image is being handled to obtain complete information about the physical properties of the image. That includes image format, size and other typical description about the system.

3) Supervised Enhancement:

In this module section, in order to increase the performance of the segmentation, supervised image enhancement is applied, that includes the enhancement of brightness and noise removal aspect of the image.

a) Multiregion- level- set:

A domain of the image can be split into multiple parts by the region segmentation framework. A set of regions can evolve, minimising the energy, if the number of regions is fixed and reasonable initialisations for the regions are available.

4) Feature extraction:

a) Level-set approach extraction:

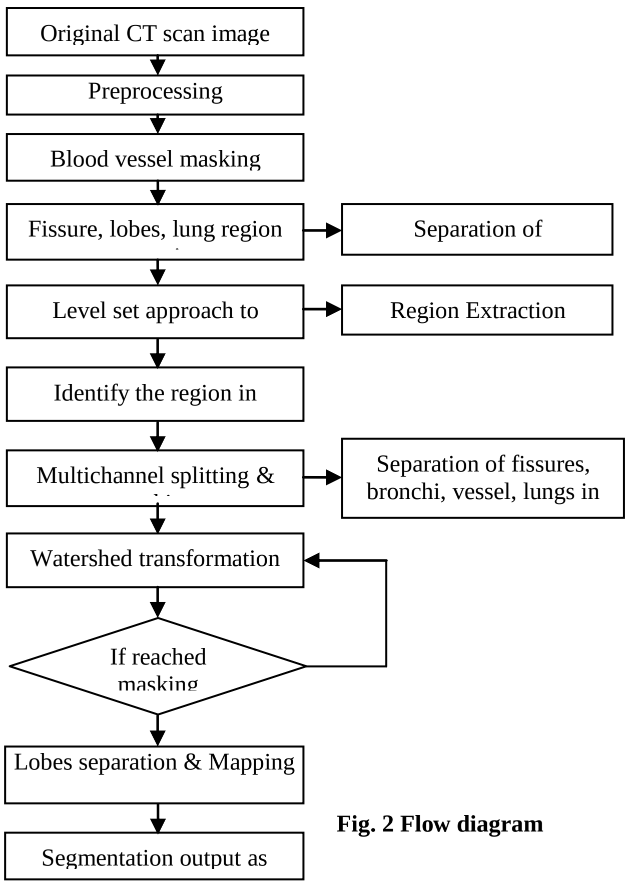

Fig. 2 Flow diagram

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Suppose you are given an interface separating one region from another, and a speed F that tells you how to move each point of the interface. A black curve separates a dark blue inside from a light blue outside, and at each point of the black curve the speed F is given. This speed can depend on a variety of physical effects. Imagine that the dark blue is ice and the light blue is water. Then the boundary can shrink as the ice melts, or grow as the ice freezes; the speed then depends on the temperature jump between the two. Imagine that the dark blue is honey and the light blue is tea. Then the boundary moves as the heavy fluid falls into to the light one, and the speed depends on gravity, the ratio of the fluid densities, and the surface tension between the two. Most numerical techniques rely on markers, which try to track the motion of the boundary by breaking it up into buoys that are connected by pieces of rope. The idea is to move each buoy under the speed F, and rely on the connecting ropes to keep things straight. The hope is that more buoys will make the answer more accurate. Unfortunately, things get pretty dicey if the buoys try to cross over themselves, or if the shape tries to break into two; in these cases, it is very hard to keep the connecting ropes organized. In three dimensions, following a surface like a breaking ocean wave is particular tough

b) Fissure marking automated:

To perform segmentation, the limit of the fissures boundary is to be defined. In this section, fissure is automatically tracked and partitioned for segmentation approach.

c) Lobar boundaries:

This module is used to confirm the boundaries of the segmented region. Once the fissures are marked, then lobar boundaries are overlapped of the given image section. Lobar are the final limits for the given fissure boundaries. The algorithm works on a gray scale image. During the successive flooding of the grey value relief, watersheds with adjacent catchment basins are constructed. This flooding process is performed on the gradient image, i.e. the basins should emerge along the edges. Normally this will lead to an over-segmentation of the image, especially for noisy image material, e.g. medical CT data. Either the image must be pre-processed or the regions must be merged on the basis of a similarity criterion afterwards.

a) A set of markers, pixels where the flooding shall start, are chosen. Each is given a different label.

b) The neighboring pixels of each marked area are inserted into a priority queue with a priority level corresponding to the gray level of the pixel.

c) The pixel with the highest priority level is extracted from the priority queue. If the neighbors of the extracted pixel that have already been labeled all have the same label, then the pixel is labeled with their label. All non-marked neighbors that are not yet in the priority queue are put into the priority queue.

d) Redo step 3 until the priority queue is empty.

5) Fissure segmentation:

Once the feature such as the boundary, thickness and other combinational feature are tracked then, segmentation is applied. Feature is identified and the obtained values are to perform fissure segmentation.

6) Watershed Transformation:

A grey-level image may be seen as a topographic relief, where the grey level of a pixel is interpreted as its altitude in the relief. A drop of water falling on a topographic relief flows along a path to finally reach a local minimum. Intuitively, the watershed of a relief corresponds to the limits of the adjacent catchment basins of the drops of water. In image processing, different watershed lines may be computed. In graphs, some may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. Watersheds may also be defined in the continuous domain. There are also many different algorithms to compute watersheds. For a segmentation purpose, the length of the gradient is interpreted as elevation information.

7) Lobe segmentation:

The mean and maximum distances were calculated for each lobar border in 3-D by computing the distance between each voxel in the reference standard and the closest voxel in the lobar segmentation. For cases with a poor lung segmentation, the volumetric overlap can be low even if the detection of the lobar border is completely correct.

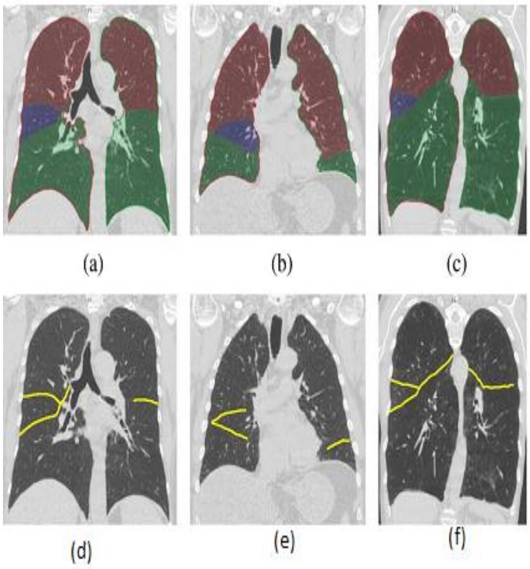

Fig.4.(a)Original image,(b)Blood vessel masking,(c)Level set approach,(d)Middle lobe segmentation,(e)Lower lobe segmentation,(f)Upper lobe segmentation

IV. RESULTS AND DISCUSSIONS

In fig.4 the fissures are tracked automatically using the level set approach. This will increase the overall performance and computation of the system during result execution. Analyses based on sensitivity, Mean distance from center, median distance are done with level set approach which is compared with existing method and the result is given below.

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TABLE.I Comparison ratio of Sensitivity and Mean Distance from center

Sensitivity and Mean Distance from Center	Watershed Approach	Level Set Approach
Fissure Left	0.7	0.9
Fissure Right	0.85	1.24

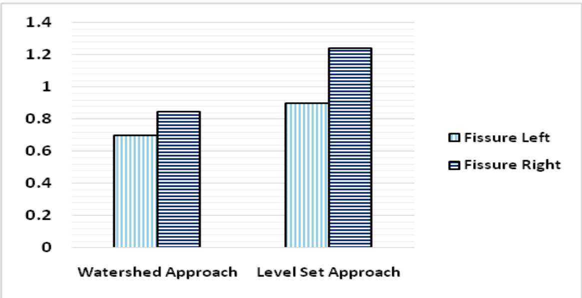

Fig.5. Comparison ratio of Sensitivity and Mean Distance

TABLE.II Comparison ratio of Median Distance

Median Distance	Watershed Approach	Level Set Approach
Fissure Left	9.97	11.2
Fissure Right	9.02	11.34

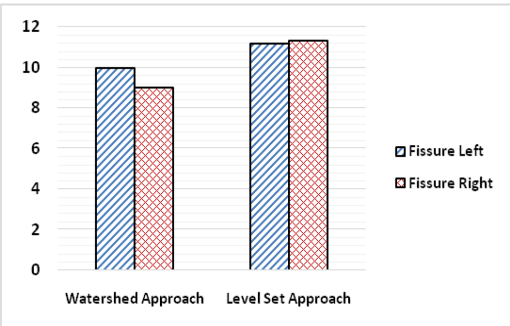

Fig.6 Comparison ratio of Median Distance

Fig.5 shows the comparison ratio of sensitivity and mean distance from center for the watershed and level set approach and Fig. 6 shows the comparison ratio result of median distance for both watershed and level set approach. From this result the level set approach gives accurate result than watershed approach.

V. CONCLUSION

In this paper, we propose an alternative approach based on level sets to segment the pulmonary lobes. Here, fissure-enhancing techniques are used to define an additional force term that draws the level set to the fissures. In image regions with insufficient fissure information, a smooth completion of the fissures is estimated by the level sets and thus closed objects are guaranteed. In Future, the System can be focused for CT Sets of Lung Images where the feature information can be more effectively identify and understandable. The CT sets can be processed to reveal extra information about lobe segmentation.

REFERENCES

[1] Bianca Lassen, Eva M. van Rikxoort, Michael Schmidt, Sjoerd Kerkstra, Bram van Ginneken, Jan-Martin Kuhnigk, “Automatic Segmentation of the Pulmonary Lobes From Chest CT Scans Based on Fissures, Vessels, and Bronchi,” IEEE Transactions on medical imaging, vol. 32, no. 2, February 2013.

[2] L. Vincent and P. Soille, “Watersheds in digital spaces: An efficient algorithm based on immersion simulations,” IEEE Trans. Med. Imag., vol. 13, no. 6, pp. 583–598, Jun. 1991.

[3] H. Hahn and H. O. Peitgen, “IWT—Interactive watershed transform: A hierarchical method for efficient interactive and automated segmentation of multidimensional grayscale images,” in Proc. SPIE Conf. Med. Imag., 2003, vol. 5032, pp. 643–653.

[4] E. M. van Rikxoort, B. van Ginneken, M. Klik, and M. Prokop, “Supervised enhancement filters: Application to fissure detection in chest CT scans,” IEEE Trans. Med. Imag., vol. 27, no. 1, pp. 1–10, Jan. 2008.

[5] L. Zhang, E. A. Hoffman, and J. M. Reinhardt, “Atlas-driven lung lobe segmentation in volumetric X-ray CT images,” IEEE Trans. Med.Imag., vol. 25, no. 1, pp. 1–16, Jan. 2006.

[6] J. Wang, M. Betke, and J. P. Ko, “Pulmonary fissure segmentation on CT,” Med. Image Anal., vol. 10, no. 4, pp. 530–547, 2006.

[7] R.Wiemker, T. Bülow, and T. Blaffert, “Unsupervised extraction of the pulmonary interlobar fissures from high resolution thoracic CT data,”in Proc. 19th Int. Congress Exhibition—Computer Assist. Radiol. Surg.(CARS), Berlin, Germany, 2005, pp. 1121–1126.

[8] J. M. Kuhnigk, H. K. Hahn, M. Hindennach, V. Dicken, S. Krass, and H. O. Peitgen, “Lung lobe segmentation by anatomy-guided 3-D watershed transform,” in Proc. SPIE Conf. Med. Imag., 2003, vol. 5032, pp. 1482–1490.

[9] X. Zhou, T. Hayashi, T. Hara, and H. Fujita, “Automatic recognition of lung lobes and fissures from multislice CT images,” in Proc. SPIE Conf. Med. Imag., San Diego, CA, 2004, vol. 5370, pp. 1629–1633.

[10] K. Hayashi, A. Aziz, K. Ashizawa, H. Hayashi, K. Nagaoki, and H.Otsuji, “Radiographic and CT appearances of the major fissures,” Radiographics,vol. 21, pp. 861–874, 2001.

[11] R. Beichel, T. Pock, C. Janko, R. B. Zotter, B. Reitinger, A.Bornik, K.Palágyi, E. Sorantin, G.Werkgartner, H. Bischof, and M. Sonka, “Liver segment approximation in CT data for surgical resection planning,” in Proc. SPIE Conf. Med. Imag., 2004, vol. 5370, pp. 1435–1446.

[12] Soumik Ukil and Joseph M. Reinhardt, “Anatomy-Guided Lung Lobe Segmentation in X-Ray CT Images,” IEEE Transaction on medical imaging, vol. 28, no. 2, February 2009.

[13] J. Pu, J. Leader, B. Zheng, F. Knollmann, C. Fuhrman, F.Sciurba, and D. Gur, “A computational geometry approach to automated pulmonary fissure segmentation in CT

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ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 9, March 2014

examinations," IEEE Trans. Med. Imag., vol. 28, no. 5, pp. 710–719, May 2009.

[14] J.-M. Kuhnigk, V. Dicken, S. Zidowitz, L. Bornemann, B. Kuemmerlen, S. Krass, H.-O. Peitgen, S. Yuval, H.-H. Jend, W. S. Rau, and T. Achenbach, "New tools for computer assistance in thoracic CT—Part I: Functional analysis of lungs, lung lobes, and bronchopulmonary segments," Radio Graphics, vol. 25, no. 2, pp. 525–536, 2005.

[15] B. Lassen, J.-M. Kuhnigk, M. Schmidt, S. Krass, and H.-O. Peitgen, "Lung and lung lobe segmentation methods at fraunhofer mevis," presented at the 4th Int. MICCAI Workshop Pulmonary Image Anal., Toronto, Canada, Sep. 2011.

[16] Q.Wei, Y. Hu, J.MacGregor, and G. Gelfand, "Automatic recognition of major fissures in human lungs," Int. J. Comput. Assist. Radiol. Surg., vol. 7, no. 1, pp. 111–123, 2012.

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