AUTOMATIC SEGMENTATION OF ABNORMAL LUNG PARENCHYMA UTILIZING WAVELET TRANSFORM

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ABSTRACT

Since several lung diseases are diagnosed based on the patterns of lung tissue in medical images, texture segmentation is an essential part of the most Computer Aided Diagnosis (CAD) systems. In this paper a novel composite method is proposed to segment the abnormality in lung tissue in pediatric CT images. The proposed approach is based on wavelet transform and intensity similarities. Our focus is on the honeycomb texture in lung tissue. After segmenting lung regions, Wavelet Transform is applied to decompose the image. The vertical subimage of lung is thresholded to extract high resolution areas. Then the regions with low pixel intensities are kept and grown to segment the honeycomb regions. The proposed method has been tested on 91 pediatric chest CT images containing healthy and unhealthy lung images. Statistical analysis shows the sensitivity of 100% along with the specificity of 94.44%.

Index Terms**—** Image segmentation, lung CT images, honeycombing

1. INTRODUCTION

Recent advances in Computed Tomography (CT) technology has enabled it to be widely used in diagnosing and quantifying different diseases. In particular, the expanding volume of thoracic CT studies along with the increase of image data, elucidates the need for CAD schemes to assist the radiologists.

Several lung diseases are diagnosed by investigating the patterns of lung tissue in pulmonary CT images, therefore texture segmentation and analysis is one of the important parts of CAD systems. In order to detect interstitial lung diseases, Uchiyama et al. [1] [2] developed a CAD scheme, in which lung regions are divided into many contiguous regions of interest with a 32x32 matrix. Six physical measures are determined for each region and artificial neural networks (ANNs) are employed to distinguish between seven different patterns including normal and abnormal lung tissue. Later same group increased the number of features and used 10 clinical parameters and 23 HRCT features to differentiate among 11 diffuse lung diseases [3]. Lung occupies at most one third of the image size, which is 512x512. Choosing the size of 32 can be a cause of loosing some abnormalities in lung, particularly small abnormal regions in pediatric CT images. Uppaluri et al. developed an adaptive multiple feature method (AMFM) which uses 22 statistical measures to classify six tissue patterns [4], [5], [6]. Edgementation is utilized in AMFM to segment different textures of lung region [7]. Edgementation is a kind of split and merge method, the split part is accomplished by edge detection and merge is done based on statistical measures. Since lung region contains an abundance of edges (vessels, air tree, air sacs, artery branches etc.), this method is time consuming for this application. Uppaluri *et al.* [4] claimed that their work is less successful for the evaluation of the honeycombing and the nodular patterns.

In this paper a novel composite method is proposed to detect the lung tissue abnormalities, which is fairly successful in pediatric CT images. The focus of this research is on a particular abnormal texture named honeycomb texture, which is the sign of several interstitial lung diseases. The proposed method is composed of a multi resolution technique and intensity similarities. Lung regions are first segmented using watershed transform [8]. Wavelet transform [9] is utilized to decompose lung image into its directional detailed subimages. The transformed image is thresholded to extract high resolution regions. Since the regions with blood vessel branches have almost the same resolution as honeycomb areas, these regions are also extracted. To separate honeycomb region from areas with vessel branches, the pixels with lower intensities in original image are kept. Morphological operations are applied on these objects to obtain accurate seeds and mask. In the last step, 2D region growing technique is used to extract the regions of interest.

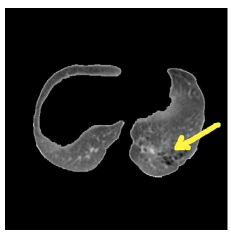
This paper is organized as follows. Section 2 gives a description of methods for lung segmentation, wavelet transform and the utilized techniques in detail. Statistical results are presented in section 3. Conclusion and the advantages of the proposed method along with the related future works are discussed in section 4.

2. METHODS

2.1. Lung segmentation

Initial lung segmentation technique is based on watershed transform [8]. Lung region is precisely marked with internal and external markers. The markers are imposed with the gradient image of the original data. Minima imposition procedure, which utilizes morphological reconstruction, is used to place regional minima only within the area of the union of the two markers. Then watershed transform is applied on the combined data to find lung borders. "Rolling ball" filter is used to smooth the contour and fill the cavities while preserving the original borders. The details of this technique are discussed in reference [8]. Figure 1-a shows a pediatric chest CT image and figure 1-b shows the segmented lung regions. Honeycomb region in lung tissue is indicated by an arrow.The honeycomb lung is composed of a porous network of fibrous walled cysts , which resembles a beehive or, more characteristically, a sponge. The cysts are filled with air, which makes them look like dark holes in CT images. Honeycombing is the sign of a variety of lung diseases [10].

(a) Chest CT image



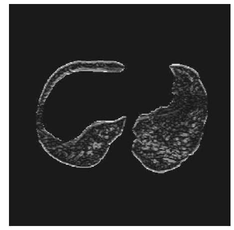
(b) Segmented Lung

Fig. 1. Lung Segmentation, arrow shows honeycomb region.

2.2. Wavelet Transform

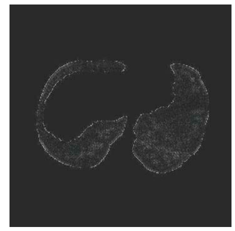
Recently, multiresloution-based approaches have drawn increasing attention in the field of texture analysis. Several successful applications of this approach to automatic texture segmentation have been proposed. Wavelet transform [9] is used in multiresolution-based approaches. Wavelet analysis is the breaking up of a signal or image into shifted and scaled versions of the original (or mother) wavelet.

In the proposed approach discrete wavelet transform is utilized to decompose lung image into its directional subimages. Discrete wavelet transform corresponds to multiresolution approximation expressions. Multiresolution analysis is carried out using 2 channel filter banks composed of a low-pass and a high-pass filter and each filter bank is then sampled at a half rate (1/2 down sampling) of the previous frequency. By repeating this procedure, it is possible to obtain wavelet transform of any order. Filtering is implemented in a separable way by filtering the lines and columns so the original image



(a) Horizontal subimage

(b) Vertical subimage



(c) Diagonal subimage

Fig. 2. Directional Details of Lung.

can be transformed into approximation, horizontal, vertical and diagonal sub-images.

Among several well known wavelets including Daubechi, Haar, and so on, which have been tested, BiorSplines 1.1 wavelet proved to have best results for this application. The horizontal, vertical and diagonal subimages obtained from applying one level wavelet transform on lung image using BiorSplines 1.1 wavelet are shown in figure 2 after upsampling. Since honeycomb region is best differentiable in vertical subimage, it is a good candidate to extract honeycomb regions.

2.3. Histogram Thresholding

To keep the high resolution regions histogram thresholding [11] is utilized. The mask of lung is used to calculate the histogram of vertical subimage (Fig. 2). The value of threshold is specified by the location of the last regional minimum in the histogram. The result of thresholding is shown in figure 3.

2.4. Extracting Honeycomb from other Textures

The areas with vessel branches have also high resolution. These areas are also extracted during thresholding. Honeycombing is a set of cysts filled with air, where as areas with vessel branches are denser than the air. In other words in a lung CT image honeycombing is seen as dark holes but vessel branches are seen as brighter area. This feature is used to distinguish honeycomb pattern from other high resolution areas. To extract the low intensity regions with high resolution the thresholded images is used as a mask on the original image.To find darkest areas of the thresholded image, the regions with pixel values less than -800 Hounsfield Unit (gray level value

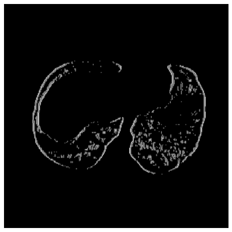


Fig. 3. High resolution regions.

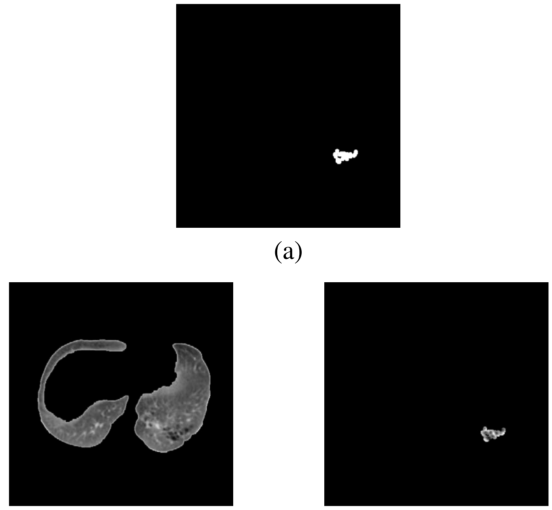
of air) are kept.
Seeded-region growing with 8-connected neighborhoods is used to extract the exact parts of honeycomb tissue. To find accurate seeds and eliminate small regions from low intensity regions with high resolution, morphological erosion with a vertical line structuring element is used (figure 4-a). The objects with the length of less than 5 are eliminated. The length of 5 experimentally proved to be the proper length to keep the seeds. To have an accurate mask for region growing the darkest high resolution objects are dilated by a disk structuring element of size 5 (figure 4-b). Since honeycomb region has circular holes a disk structuring-element is selected. With the size of 5 the cyst walls are also included in the mask. The final step is to apply region growing technique with the seed shown in figure 4-a on the mask shown in figure 4-b. The result is shown in figure 5 which shows the accuracy of this method.

(a) (b)

Fig. 4. a) Seed or marker, b) Mask.

3. RESULTS

In this section the detection of abnormal lung tissue is assessed to validate the proposed composite technique. Statistical analysis is done as an evaluation technique.
The tests have been applied on 512 by 512 by 16 pediatric Helical CT images. The images are acquired by a GE MEDICAL SYSTEMS CT scanner from the Department of Diagnostic Imaging in the Toronto Hospital for Sick Children. All approaches are implemented in MATLAB 7.0 on a Pentium IV 2.8 GHz PC with 512 MB RAM.
This method has been tested on 91 pediatric chest CT images containing healthy and unhealthy lung (with honeycomb



(a)

(b) (c)

Fig. 5. a) Result of region growing, b) Lung with honeycombing, c) Segmented honeycomb area.

Table 1. Datasets Specifications

Test Sets	Images	Healthy Images	Unhealthy Images
TST-1	57	48	9
TST-2	10	1	9
TST-3	24	24	0

patterns) images and the results revealed the accuracy of the proposed composite method. The specifications of the test datasets is tabulated in table 1. the average required time for each slice was 3-5 seconds based on the area of lung.
One approach used to define the accuracy of an imaging system is to evaluate the systems sensitivity and specificity. Sensitivity, also called true positive fraction (TPF), is the probability of diagnosing the presence of disease when it is actually present. Specificity, also called true negative fraction (TNF) is the probability of identifying the absence of disease when it is not present. This paper addresses the use of Statistical analysis to evaluate the accuracy of the new composite method, as compared to other existing methods. The statistical analysis is tabulated in table 2.

Uppaluri *et al.* [4] evaluated their method by the kappa

Table 2. Statistical Analysis of the Composite Method

Patient ID	FPs	TPs	FP (%)	Sensitivity	Specificity
TST-1	1	9	1.75	100	97.91
TST-2	0	9	0	100	100
TST-3	3	0	12.5	100	87.5

statistic of agreement between the regions and AMFM method has demonstrated to be especially successful for the detection of normal, emphysemalike, ground glass, and bronchovascular patterns of the lung parenchyma. Uppaluri *et al.* claimed that the AMFM with the sensitivity of 82.5% and specificity of 99.9% is less successful for the evaluation of the honeycombing and the nodular patterns.

Uchiyama *et al.*, who proposed an ANN method to detect different lung diseases, claimed the sensitivity of 100% for honeycombing with the specificity of 88.1% for 98 datasets. Since their method use the blocks of 32 by 32 to calculate the statistical features, it might lose small regions with abnormal texture.

In Both techniques the researchers use an abundance of statistical measures which makes the process very slow. Comparing our Composite method with Hu's and Uchiyama's techniques elucidates that the proposed technique is very promising.

The drawback of the technique is that although it detects all honeycomb areas, the boundary of the segmented abnormal area is not accurate. This issue opens an area for further research and improvement of the proposed method.

4. CONCLUSIONS AND FUTURE WORK

A novel composite technique is proposed to segment honeycomb lung tissue in pediatric CT images. In this method wavelet transform is utilized combined with intensity similarities. This technique has been tested on several datasets and compared with other methods based on speed, sensitivity and specificity. The result reveals the robustness of the proposed approach.

The proposed approach can be further improved to detect all possible abnormalities with different types of textures in lung tissue. multilevel thresholding can be utilized to separate different patterns with different resolutions. Automatic lung disease quantification is another field of research which is done on segmented abnormal region in CT images. It can also be used to monitor the healing process or the improvement of the disease. Optimization methods can also be utilized to increase the specificity.

5. ACKNOWLEDGMENT

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