

Segmentation Of Pulmonary Lobes From Chest CT Scans And Detection Of Pnuemonia

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ABSTRACT- Pneumonia is a common lung disease. In this work an automated detection of Interstitial Pneumonia patterns by having an efficient and accurate method for vessel tree segmentation using frangifilter method and lung lobe segmentation using watershed algorithm is going to be done. Using the CT image, we segment the vessel structures and identify whether the patient is affected with pneumonia patterns or not based on the features extracted from lung lobes and do fuzzy classification. This paper aims at improving accuracy level and support medical diagnosis

Key words- Lung lobe segmentation, feature extraction, fuzzy svm

I. INTRODUCTION

The field of digital image processing refers to the processing digital images by means of digital computer. Digital images contain finite number of elements, each of which has a particular location and value. These elements are picture elements, image elements, pels and pixels. Pixels the term most widely to denote the element of digital image.

Medical imaging is the technique and process used to create images of the human body (or parts and function thereof) for clinical purposes (medical procedures seeking to reveal, diagnose, or examine disease) or medical science (including the study of normal anatomy and physiology). Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred to as medical imaging, but rather are a part of pathology.

Computed Tomography (CT), or Computed Axial Tomography (CAT: A CT scan, also known as a CAT scan), is a helical tomography (latest generation), which traditionally produces a 2D image of the structures in a thin section of the body. It uses X-rays. It has a greater ionizing radiation dose burden than projection radiography; repeated scans must be limited to avoid health effects. CT is based on the same principles as X-Ray projections but in this case, the patient is enclosed in a surrounding ring of detectors assigned with 500-1000 scintillation detectors (fourth-generation X-Ray CT scanner geometry). Previously in older generation scanners, the X-Ray beam was paired by a translating source and detector.

Tomography refers to imaging by sections or sectioning through the use of any kind of penetrating wave. A device used in tomography is called a tomography, while the image produced is called tomogram. Multidetector Computer Tomography (MDCT) – a form of computer tomography technology for diagnostic imaging

In this paper, we introduce an image processing technique named segmentation for obtaining the texture features of the chest CT scan image so that it help in comparing and classifying whether patient is affected by pneumonia or not.

The remainder of this paper is organized as follows. A description of the proposed method and a characterization of the features associated with it are presented in Section II. Section III includes performance evaluation and results

obtained. The conclusion of this paper is provided in Section IV and future enhancement in V.

II. METHOD

The Human lungs are subdivided into five lobes that are separated by visceral pleura called pulmonary fissure. There are three lobes in the right lung, namely upper, middle, and lower lobe. The right upper and right middle lobe are divided by the right minor fissure whereas the right major fissure delimits the lower lobe from the rest of the lung. In the left lung there are only two lobes, the upper and the lower lobe, that are divided by the left major fissure [see Fig. 1(a)]. A characteristic of the pulmonary lobes are separated supply branches for both vessels and airways [see Fig. 1(b)]. Lung lobe segmentation is relevant in clinical applications. In the existing system there is no provision for accessing image features for pneumonia detection. Execution time for image comparison and retrieval is very low that is some algorithm takes more time to display the output.

Fig 1 details the proposed system architecture. The affected image is preprocessed by using a median filter and the edges are detected by using a wavelet preprocessing and finally the lung fields are segmented by a combination of wavelet edge, histogram thresholding, vessel tree segmentation and watershed segmentation of lung lobes. Data cleaning and feature extraction are common for both the training set of chest images and the test set. The feature values of both set are compared using Fuzzy classifier

A. Preprocessing.

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical preprocessing step to improve the results of later processing. Median filtering is very widely used in digital image processing because under certain conditions, it preserves edges while removing noise.

The incoming data is checked and median filtering is done. In general, the median filter is proposed for impulse noise removal can be classified as lower complexity techniques and higher-complexity techniques. The lower complexity techniques use fixed size windows and simplified computations in order to achieve high-speed processing. The higher complexity techniques target excellent visual quality by

adaptively enlarging window sizes or increasing computing iterations.

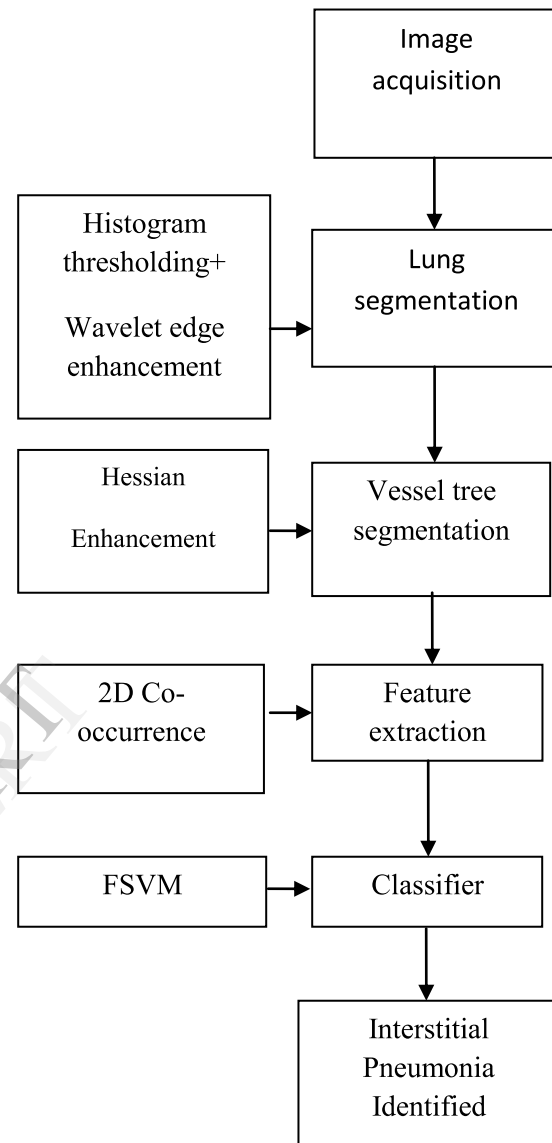


Fig.1. Flow diagram of proposed method

B. Lung Field Segmentation

The lung field segmentation comprises of thresholding and wavelet edge detection. Edge detection is an important step in pattern recognition, image segmentation and scene analysis. The conventional approaches to edge detection fail in presence of noise in images by may cause problems in many

applications. But noise is effectively reduced by wavelet filters without any significant loss in the image reduction. Unlike Canny edge detection, in which the first step is the image smoothing by a Gaussian filter to reduce the effect of noise and next step is edge detection. In wavelet, these two steps are combined into a single step and thus wavelet based techniques are computationally more efficient. It is proved that the wavelet based edge detector gives better result than traditional techniques for noisy images.

.Thresholding is a simple but effective tool for image segmentation. From a grayscale image, thresholding can be used to create binary images. The purpose of this operation is that objects and background are separated into non-overlapping sets. In many applications of image processing, the use of binary images can decrease the computational cost of the succeeding steps compared to using gray-level images. Since image thresholding is a well-researched field, there exist many algorithms for determining an optimal threshold of the image

C. Watershed Segmentation

The proposed system performs vessel tree segmentation using frangi filter method after the lung field segmentation. The resulting image is input to obtain the lobe segmented image. It is done by passing through watershed based approach. In fig 2 Watershed segmentation is performed in three stages, namely preprocessing, watershed segmenting and post processing of image

D. Feature Extraction

The refinement of the vessel tree is obtained by a classifier based on 3D texture analysis, which uses 3D co-occurrence features. 3D co-occurrence matrices are matrices that are able to capture the spatial dependence of gray-level values across multiple slices, whereas the two-dimensional co-occurrence matrices capture the spatial dependence of gray levels within a specific slice (scan). Gray level co-occurrence matrix (GLCM) [26] is a well-established tool for characterizing the spatial distribution (second order statistics) of gray levels in an image, and has been extensively exploited in lung image analysis [27]. GLCMs were generated for 13 directions and two distances ($d = 1, 2$ pixels). Thirteen second order statistics (angular second moment, contrast correlation, variance, inverse

different moment, sum average, sum, variance, sum entropy, entropy, difference variance, difference, entropy, information measure of correlation 1 and information measure of correlation 2) were extracted from each GLCM. The mean and range values of each second order statistic over the 13 directions were calculated resulting in a total of 52 features.

E. Fuzzy Classification

The classification method proposed here is the Fuzzy SVM. In conventional support vector machines, an n-class problem is converted into n two-class problems. For the i^{th} two-class problem we determine the optimal decision function which separates class i from the remaining classes. In classification, a datum is classified into class i only when the value of the i^{th} decision function is positive. In this architecture, the datum is unclassifiable if the values of more than one decision function are positive or all the values are negative. In this paper, to overcome the above type problem, we propose fuzzy support vector machines (FSVMs). Using the decision functions obtained by training the SVM, for each class, we are defining a truncated polyhedral pyramidal membership function. Since, for the data in the classifiable regions, the classification results are the same for the two methods, the generalization ability of the FSVM is the same with or better than that of the SVM.

To resolve the unclassifiable regions, we introduce the fuzzy membership functions. To do this, for class i we define one-dimensional membership functions $m_{ij}(x)$ on the directions orthogonal to the optimal separating hyperplanes $D_j(x) = 0$ as follows:

1. For $i = j$

$$m_{ij}(x) = 1 \text{ for } D_j(x) > 1$$

$$D_j(x), \text{ otherwise.} \quad (2)$$

2. For $i \neq j$

$$m_{ij}(x) = 1 \text{ for } D_i(x) < -1 \quad (3)$$

Since only the class i training data exist when $D_j = 1$, we assume that the degree of class i is 1, and otherwise, $D_j(x)$. Here we allow the negative degree of membership. For $i = j$, class i is on the negative side of $D_j(x) = 0$. In this case,

support vectors may not include class i data but when $D_i(x) = -1$, we assume that the degree of membership of class i is 1, and otherwise, $-D_j(x)$.

$$m_i(x) = \min_{j=1, \dots, n} m_{ij}(x) \quad (4)$$

In this formulation the shape of the membership function is a polyhedral pyramid.

Now the datum x is classified into the class

$$\arg \max_{i=1, \dots, n} m_i(x) \quad (5)$$

if x satisfies,

$$D_k(x) \begin{cases} > 0, \text{ for } k=i, \\ = 0, \text{ for } k \neq i \text{ and } k=1, \dots, n \end{cases} \quad (6)$$

from (2) and (3), $m_i(x) > 0$ and $m_j(x) = 0$ ($j \neq i, j=1, \dots, n$) hold. Thus x is classified into class i . This is equivalent to the condition that the condition that $D_i(x) > 0$ is satisfied for only one i .

According to above mentioned formulation, the unclassified regions are resolved and generalization ability of FSVMs is the same with or better than that of the conventional SVMs. In realizing the fuzzy pattern classification, we need not implement the membership functions $m_i(x)$ given by (4).

The procedure of classification is as follows

1. For x , if $D_i(x) > 0$ is satisfied for only one class, the input is classified into the class. Otherwise, go to Step 2.
2. If $D_i(x) > 0$ is satisfied for more than one class i ($i = i_1, \dots, i_l, l > 1$), classify the datum into the class with the maximum $D_i(x)$ (i_1, \dots, i_l). Otherwise, go to Step 3.

3. If $D_i(x) = 0$ is satisfied for all the classes, classify the datum into the class with the minimum absolute value of $D_i(x)$.

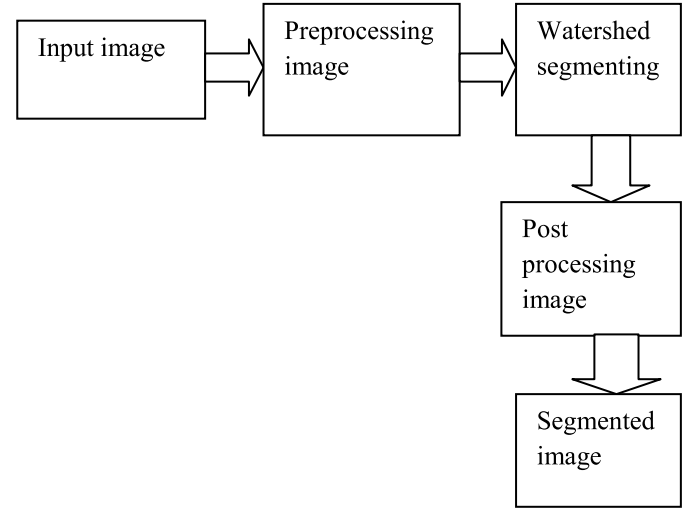


Fig 2 Block diagram for watershed segmentation

III. PERFORMANCE EVALUATION

Segmentation accuracy of the proposed method was evaluated by means of area overlap (AO), true positive fraction (TPF), and false positive fraction (FPF) metrics. Due to large volume of data analyzed, the definition of voxel-exact ground truth of the vessel tree volume, required for quantitative evaluation of the algorithm segmentation accuracy, is a tedious task. In Shikata *et al.* [11] and Zhou *et al.* [23] evaluation was performed by means of control points tracking the center lines of vessels, provided by two radiologists using a Graphical User Interface (GUI). Both studies recognized the difficulties in creating a pixel-exact ground truth attributed to the fuzziness of vessel tree segments due to partial volume effect and noise. In present ground truth can be derived by means of a GUI designed to facilitate editing of 2-D vessel segments. The GUI allowed the radiologist to review the original data in coronal, sagittal, and axial planes, and draw vessel tree segments. The development of vessel tree segmentation algorithms in case of IP-affected lung parenchyma is an open issue, challenged by the radiologic similarity of reticular patterns to vessel tree segments. While the majority of the proposed filters were limited to specific structures, this filter response has been designed in a way that enhances vessel tree segments and

vessel bifurcations and in the same time suppresses non vessel structures. Furthermore, Zhou *et al.* [23] applied their technique on non contrast patient scans, similar to the ones exploited in this study, reporting high performance

A. preprocessed CT image

The input CT image is put to median filtering to obtain a noise free and contrast improved chest CT image

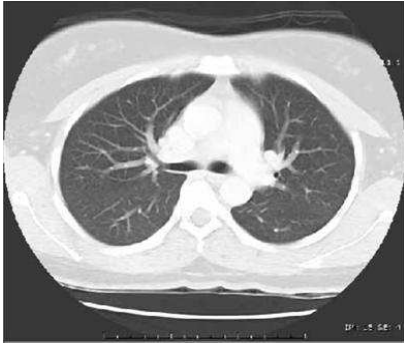


Fig 3 median filtered image

B. lung field segmentation

The lung field segmentation comprises of the wavelet edge enhancement and thresholding. This highlights the edges and also it clearly distinguishes the background pixels.



Fig 4 Lung field segmented image

Fig 5 and 6 displays the vessel segmented and watershed segmented images



Fig 5: Vessel tree segmentation

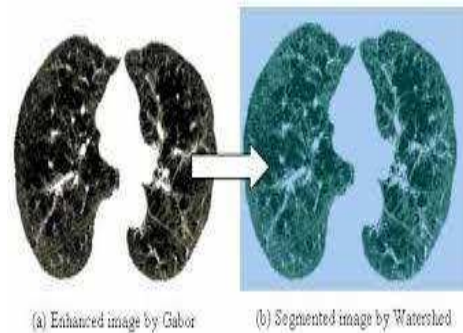


Fig 6 watershed segmented image

IV. CONCLUSION

Recently, vessel tree segmentation techniques have gained attention, since they play a key role in CAD applications aimed at nodule or pulmonary embolism detection, as well as at ILD pattern quantification. Furthermore, vessel tree segments can act as control points for lung image registration applications in case of follow-up data, as well as for guiding airway tree and lung lobe segmentation. However, the development of vessel tree segmentation algorithms in case of ILD affected lung parenchyma is an open issue challenged by the radiologic similarity of reticular patterns to vessel tree segments. In this study, an automated vessel tree segmentation scheme with high accuracy is proposed to deal with ILD affected lung parenchyma. To the best of the authors' knowledge, this is the first vessel tree segmentation algorithm that is adapted to

reticular patterns affecting lung parenchyma. This adaptation is attributed to the supervised classification mechanism incorporated in the second stage of the proposed method. The segmentation accuracy of the proposed method was evaluated quantitatively by comparing automatically derived vessel tree segments with manually defined ones, demonstrating promising results.

V. FUTURE ENHANCEMENT

Future efforts should focus on investigating additional texture features and considering performance evaluation on an augmented dataset. Robustness with respect to different image noise levels should also be investigated. Moreover analysis of the vessel tree segmentation algorithm performance should be made with respect to the disease severity (i.e. the extent of the reticular pattern). Both intra- and inter-observer variability may also be considered, which is challenged however by the difficulty in pixel-exact ground truth derivation. Formulation of pixel exact ground truth, required for the quantitative evaluation of the algorithm segmentation accuracy, is a tedious task due to the amount of data to be reviewed and the small size of vessels in lung periphery. Thus, the development of effective editing tools to aid this task is a necessity.

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