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Vascular Segmentation of Interstitial Pneumonia Patterns in Lung using MDCT

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Abstract— **Pulmonary vascular tree segmentation is gaining importance since it is one of the fundamental basis for different applications, such as the detection of interstitial pneumonia (IP), pulmonary emboli etc. Such an application will require an accurate and reliable segmentation of pulmonary vessels. The accuracy of this preprocessing stage is bound to influence the accuracy in computer aided diagnosis (CAD) of IP patterns. While lot many algorithms aimed at improving accuracy of lung segmentation, vessel tree segmentation is still an open research issue. In this paper an automated vessel tree segmentation algorithm with high accuracy is proposed in presence of pathologies affecting lung parenchyma. The initial stage accounts for a vessel enhancement filtering, which uses second order local structure of an image (Hessian) with vessel ness measure obtained on the basis of all eigen values of the Hessian. Followingly texture based refinement using 3D co-occurrence matrix, which ties all textures together (a single value per feature will take into account all texture features within a lung, finally the classification is performed to correct possible over segmentation. The proposed method utilizes Fuzzy Support Vector Machine (SVM) classifier which improves traditional SVM by adding fuzzy membership to training sample to indicate degree of membership of this sample to different class. Consequently it reduces noises and outliers in data and enhances performance and accuracy of SVM. The performance of the proposed scheme, and of the previously reported technique, in vessel tree segmentation was evaluated by means of area overlap; true positive fraction and false positive fraction of image dataset obtained from IP affected patient scans. The method is expected to improve the performance as compared to other reported techniques.**

Keywords; Pulmonary vascular tree segmentation, interstitial pneumonia, computer aided diagnosis, Fuzzy Support Vector Machine classifier, image enhancement, hessian matrix.

I. INTRODUCTION

Interstitial lung disease (ILD) refers to a group of diseases affecting the interstitium (tissue and space around the air sacs of the lungs). Usual interstitial pneumonia (UIP) is a form of lung disease characterized by progressive scarring of both lungs shown in Fig.1. UIP may be diagnosed by a radiologist using a computed tomogram of the chest, or by a pathologist using tissue obtained by a lung biopsy. Radiologically, the main feature required for a confident diagnosis of UIP is honeycomb change in the periphery and the lower portions (bases) of the lungs. For lung imaging and analyzing , computed tomography (CT) is widely used; In contrast to high resolution CT scanning, which allows only a limited portion of lung parenchyma to be sampled, MDCT(Multi Detector CT) which permits CT scanners to acquire multiple slices or sections simultaneously and greatly increases speed ,allowing acquisition visualization, characterization and quantification of the entire extend of lung anatomy, which aids in the analysis of lung malformities.

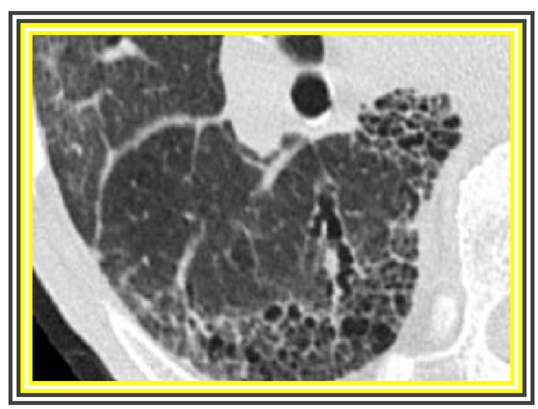

Figure1. Figure depicting honey combing in patient with Interstitial Pneumonia

Recently MDCT analysis of ILD affected has been introduced[1].These methods [2]-[5] mainly focused based on the texture analysis for identification and characterization. There are different algorithms already developed for improving the accuracy of lung fields in presence of ILD. But corresponding vessel tree segmentation is still an open research issue, due to the complexity of vessel tree, diversity of vessel size, and intensity, presence of noise etc. The previously proposed methods deals with radiologic appearance of normal lung parenchyma [10]-[16], with focal abnormalities [17]-[22] and with pulmonary embolism [23]. In another case of lung image registration [24], airway tree [11] and lung lobe segmentation [25], similar vessel tree segmentation is applied. In this paper an automated vessel tree segmentation scheme with improved accuracy rate is proposed to deal with IP affected lung parenchyma. The method is applied to volumetric scans of patients affected by interstitial pneumonia .The algorithm deals with a 3D multiscale vessel enhancement filtering based on eigen value analysis of hessian matrix and on supervised segmentation.

II. LITERATURE REVIEW

MDCT based identification of IP is reported in [1].The algorithms developed for the accuracy of lung field segmentation is reported in [7]-[9]. The vessel tree segmentation method which were reported in [10]-[16] deals with appearance of normal lung parenchyma ,along with focal abnormalities in [17]-[22] and with pulmonary embolism [23].But the problem with this method is that they mainly rely on single or multiscale image enhancement combined with threshold reported in literatures [11],[20],[22] or with of volumetric data sets with almost isotropic voxels, enabling unsupervised segmentation [23] to enhance the tubular vascular structures. Followingly another methods such as region growing[7], level sets [14] and fuzzy connectedness have been reported. Their draw back is their parametric nature. In case of preprocessing steps in lung image registration [2], airway tree [11] and lung lobe segmentation [25] , similar vessel tree segmentation method is used. Kollar [17] introduced single scale enhancement filter and adopted in [4] without however capturing varying size of vessel tree segments. Multiscale approaches which mainly based on eigen value analysis of Hessian matrix are exploited by Frangi [20], Sato [18]-[22], Li [19] , Agam [2], Krissan [12] ,Zohu [23] and Lo [13] employing different response filter. To distinguish between vessel tree and noise components Shukta [1] proposed multiscale technique with connected component analysis and branch point analysis.

III. DESIGN METHODOLOGY

The proposed method consist of five modules which are

1. Image acquisition
2. Lung segmentation
3. Vessel tree volume Identification
4. Feature Extraction
5. Fuzzy-SVM classification

The flow diagram of the method is depicted in Fig 2.

A. Image Acquisition

This module is contributed to acquire more number of samples from patients detected with IP patterns and from normal patients using MDCT scanner.

B. Lung segmentation

The proposed method exploits advantages offered by a 2D wavelet pre-processing step and core of method is automated 3D histogram thresholding [11]. Thresholding combined with Wavelet pre-processing is successfully used in lung field segmentation by Korfiatis [12]. However, gray level-based algorithms are insufficient in correctly segmenting lung fields in case of IPs affecting lung borders, since IPs are manifested as tissue texture alterations. To overcome this LF under-segmentation, a texture based border refinement step is employed mentioned by [9], [10].

C. Vessel tree volume identification

To increase the effectiveness of vessel segmentation algorithm vessel enhancement procedures are first applied as a preprocessing step [17]-[23].Here we are using a hessian-based vessel enhancement method which uses eigen value of hessian matrix to distinguish vessels from background exploiting a 3D-tubular structure associated to vessel tree**.** To meet with the wide range of vessel sizes, original images are convolved with Gaussian kernels of varying standard deviation enhancing local structures of specific sizes, followed by combination of the local maxima of filter responses at multiple scales. Calculating the eigenvalues (l_1, l_2, l_3) of the Hessian matrix of each voxel, the response of the tubular structures is approximated according to Zhou et al. [23] by:

$$R(x,y,z,\sigma_s;l_1,l_2,l_3) = \begin{Bmatrix} \frac{(l_1+l_2)}{2} * \exp\left(-\left|\frac{|l_1|}{\sqrt{l_1^2+l_2^2+l_3^2}} - c\right|\right), & l_1,l_2,l_3<0 \\ 0 & \text{otherwise} \end{Bmatrix} \quad (1)$$

A value of 0.7 is adopted for parameter c by [23].The filter responses at each scale are normalized to achieve a fair comparison among multiple scales. Considering vessel tree size varying from 2 to 24 mm, Gaussian kernels with standard deviation ranging from 1 to 12 voxels were utilized. An Expectation Maximization (EM) segmentation algorithm is then applied to the filter response volumes in order to identify the voxels with high responses associated with tubular structures [23]. Followingly we apply the EM segmentation algorithm at all scales and a hierarchical scheme is implemented to combine the results across the scales, providing vessel tree volume candidate.

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. Discriminant analysis which is used in statistics, pattern recognition etc is preferred for feature extraction process and dimensionality reduction of initial 52 features. The goal of SDA is to sequentially identify those variables (features) that widely separate the classes from one another while keeping the classes themselves as tightly clustered as possible.

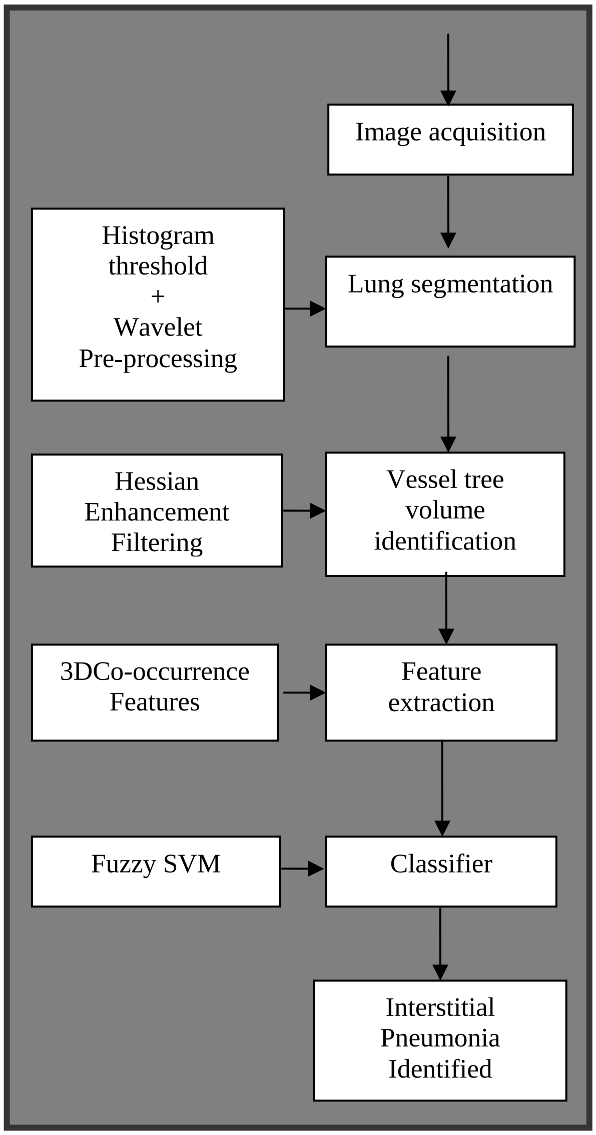

Figure2. Flow diagram of proposed method

A feature set of four features was selected consisting of: Mean of Variance (*d* =1pixels), Range of Sum Average (*d* =1pixels), Mean of Sum Entropy (*d* = 2 pixels), and Mean of Variance (*d* = 2 pixels).

E.Fuzzy SVM 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
$m_{ij}(x) = 1$ for $D_j (x) > 1$
D_j (x), otherwise. (2)
2. For i = j
$m_{ij} (x) = 1$ for $D_j (x) < -1$ (3)
$-D_i$ (x), otherwise.

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 member-ship. 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).

$$m_i(x) = \min_{j-1,\ldots,n} m_{ij}(x) \qquad (4)$$

In this formulation the shape of the membership function is a polyhedral pyramid.
Now the datum x is classified into the class

$$\arg_{i=1\ldots\ldots n} \max m_i(x) \qquad \textbf{(}5\textbf{)}$$

if x satisfies,

$$D_k(x) \begin{cases} >0, \text{ for } k=i, \\ =0, \text{ for } k=I \text{ and } k=1,\ldots n \end{cases} \qquad (6)$$

from (2) and (3), m_i (x) > 0 and $m_j(x)$ = 0 (j = i, j =1,2,...,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 , classify the datum into the class with the maximum $D_i(x)$ ($i_1, \ldots, i_l$), 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 $D_i(x)$.

IV. 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 [11] and Zhou [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.

V. Discussion

In this study, an automated vessel tree segmentation scheme is reported dealing with IP affected lung parenchyma, as depicted in MDCT as shown in Figure.3, 4, 5. 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 [23] applied their technique on non contrast patient scans, similar to the ones exploited in this study, reporting high performance.

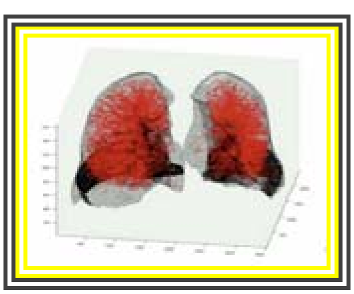

Figure3. Vessel tree segmentation 3-D representation

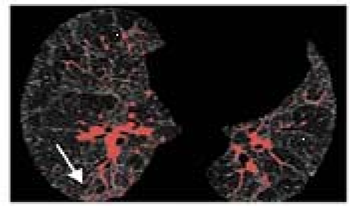

Figure 4.Vessel tree segmentation - axial slice of segmented vessels

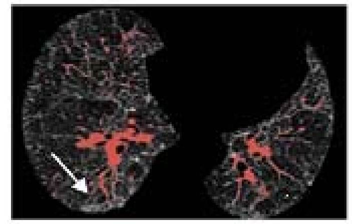

Figure 5.Vessel tree segmentation- axial slice of segmented vessels after refinement.

Segmented vessel tree is depicted by red overlay. Arrows indicate vessel tree over-segmentation example. To the best of the 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 fuzzy classification mechanism [31] incorporated in the second stage of the proposed method. The quantitative metrics area overlap (AO), true positive fraction (TPF), and false positive fraction (FPF) were considered by comparing the area of computer-derived borders to the ones derived by an expert radiologist [5]. For each accuracy segmentation metric, the mean (Mean), standard deviation (SD), minimum (Min), 1st quartile (Q1), Median, 3rd quartile (Q3) and maximum (Max) values were calculated.

VI. 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.

VII. 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.

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