IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 13, Issue 1 (Jul. - Aug. 2013), PP 128-133
www.iosrjournals.org

An Enhanced ILD Diagnosis Method using DWT

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Abstract : *Interstitial Lung Disease (ILD) is a group of lung diseases affecting lung parenchyma. Since the lesions can be clearly identified in the CT scan of the lung, CT analysis is best among the ways for the identification of ILD by the pathologists. The automated detection of any disease from images uses the same fact that they are diagnosed by the medical professionals by exploiting the appearance features of the image of organ under consideration. Here we are applying the same to detect Lung Diseases from CT images. Segmenting the arteries and veins from the image is one of the major steps in analyzing the medical image. We need an edge enhanced lung image to do the same, so that the vascular tree can be clearly identified. In this implementation, discrete wavelet transform is applied for edge enhancement followed by the dynamic range compression. Wavelet edge enhancement and vessel enhancement filtering comprises the first stage of the algorithm. Vessel enhancement filtering uses the Eigen values of the Hessian of the image. The second stage of the algorithm corresponds to the feature extraction and classification. Feature extraction is done from the co-occurrence matrix of the resulting vessel segmented image. The co-occurrence features of the image forms the input feature vector for fuzzy SVM classifier. The performance of the proposed scheme is evaluated for accuracy.*

Keywords – *CAD, Wavelet edge enhancement, DWT, Fuzzy SVM, ILD diagnosis, PSO thresholding, Image classifcication, Dynamic Range Compression.*

I. INTRODUCTION

Computer Aided Diagnosis or Computer Aided Detection (CAD) is the area of computer science which helps medical experts in determining or diagnosing the diseases. To diagnose a pathology in an organ or a part of the body, doctors inspects the image of it generated using the technologies such as X-Ray, computed tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET). As every field is getting automated, it will be very useful if the diagnosis can be done without any intervention of medical experts. But it is possible only if CAD methods are proven to be cent per cent accurate. But the CAD systems do not aim at replacing the pathologists, but to help them in diagnosis. The CAD system tries to see the image as through the eyes of the expert. Hence the features of the image which gives it that special appearance should be enhanced. The main such feature in an image is its edge. The edge is what forms the shape of an image.

In the case of internal organs, the automated diagnosis process is preceded by some preprocessing steps such as vascular tree segmentation. This paper aims at developing a CAD scheme to detect Interstitial Lung Diseases (ILD). ILD is a group of pathologies affecting the tissues around the alveoli. It is also termed as Diffuse Parenchymal Lung Disease (DPLD). It differs from the pulmonary obstructive lung disease that ILD will not cause obstruction in respiration. Atypical pneumonia, Pneumocystis pneumonia, Usual interstitial pneumonia (UIP) and Tuberculosis are some types of ILD which is caused by infection. The imaging techniques for the detection of lung pathologies are X-Rays, CT Scanning and Echocardiogram. Our method of diagnosis uses CT scan image. CT generates slices of specific areas of the body by passing X-rays through it.

The common steps in CAD schemes for pathologies affecting lung are image acquisition, preprocessing, feature extraction and classification. Image acquisition step chooses radiographic image and bring it to some common standards such as size, dimension etc. Preprocessing step plays an important role in the algorithm. It performs the segmentation of vessels from the image following the lung segmentation. This step crucially determines the accuracy of the method. From the segmented image, various features are extracted based on which the classification is done. The various classes and its features must be fed in the fuzzy SVM classifier system using some data sets. In addition to these basic steps, we can add various sub modules to improvise the system.

In this paper, an automated vessel tree segmentation scheme with improved accuracy rate is proposed to deal with ILD affected lung parenchyma. The method is applied to volumetric scans of patients affected by interstitial lung disease. The input to the system is a cross sectional image of the lung. In this implementation, the image of the cross section taken at the middle part of lung is used. The algorithm uses wavelet enhancement to get a clear image of vessels. The algorithm deals with a 3D multi-scale vessel enhancement filtering based on Eigen value analysis of hessian matrix.

II. RELATED WORK

Multi Detector Computer Tomography (MDCT) based identification of interstitial pneumonia (IP) is presented in [1]. The algorithms developed for the accuracy of lung field segmentation is reported in [5]. The vessel tree segmentation method which were reported in [7],[10]-[12] deals with appearance of normal lung parenchyma ,along with focal abnormalities in [12] and with pulmonary embolism [14].But the problem with this method is that they mainly rely on single or multi-scale image enhancement combined with threshold reported in literatures [7],[8] or with of volumetric data sets with almost isotropic voxels, enabling unsupervised segmentation [13] to enhance the tubular vascular structures. Following this another methods such as region growing [14], level sets[12] and fuzzy connectedness have been reported. Their drawback is their parametric nature. In case of preprocessing steps in lung image registration [2] ,airway tree [7] and lung lobe segmentation , similar vessel tree segmentation method is used. Kollar et al[12] introduced single scale enhancement filter and adopted in [9] without however capturing varying size of vessel tree segments. Multi-scale approaches which mainly based on eigen value analysis of Hessian matrix are exploited by Sato etal [8], Agam etal [2], Krissan etal[10] , Zohu etal[13] and Lo eta l [11] employing different response filter. To distinguish between vessel tree and noise components Shukta etal[1] proposed multiscale technique with connected component analysis and branch point analysis.

III. IMPLEMENTATION DETAILS

The method proposed in this paper takes the following six steps for effective diagnosis.

- Acquisition of Lung CT image
- Wavelet Edge Enhancement
- Lung Part Segmentation
- Vessel Segmentation
- Feature Extraction
- Classification

3.1 Acquisition of Lung CT image

Required number of different samples of normal and abnormal CT images needs to be collected. They must be brought to some common standards acceptable by the system so that it can treat them through common steps. The common standard includes the resolution and dimension of the image. If the image is of three dimensions, it must be brought to gray range. Fig. 2 shows the CT image of a UIP affected lung.

3.2 Wavelet Edge Enhancement

The proposed method takes advantage 2D wavelet transform as a preprocessing step. The idea of wavelet edge enhancement came from the fact that most of the information in the image is stored in the edges.

The first step in wavelet edge enhancement is the decomposition of scanned image into four coefficients: one approximation coefficient and three detailed coefficients. Approximation coefficient is the result of passing the rows and columns through a low pass filter in order. Detailed coefficients give the edges or large intensity variations and they are obtained in the following way. Horizontal detailed coefficient is the result of passing the rows and columns through a low pass and high pass filter respectively. Vertical detailed coefficient is the result of interchanging the filters mentioned in the previous arrangement.

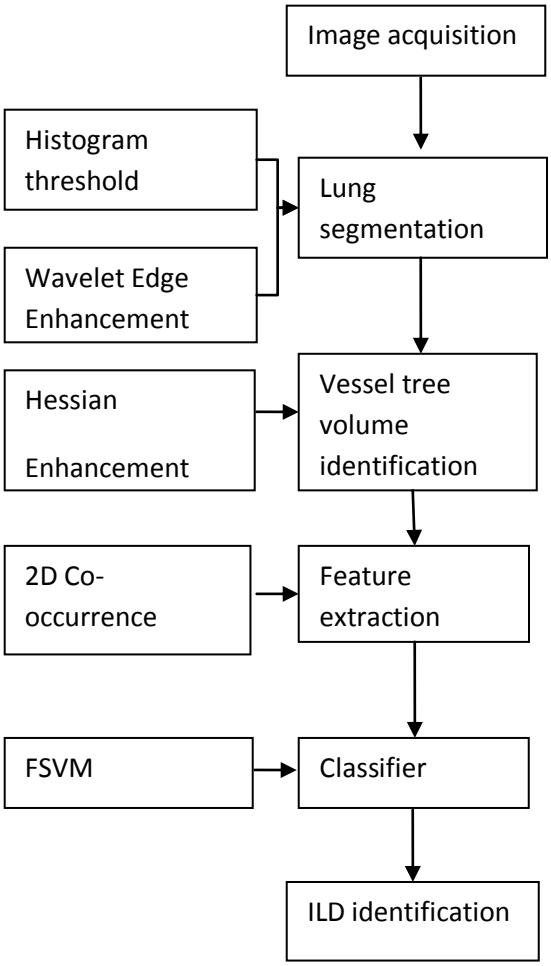


Figure 1: Implementation Flowchart

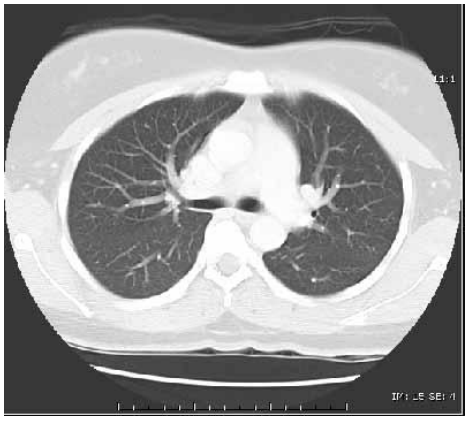


Figure 2: CT image of a UIP affected lung

Diagonal detailed coefficients are the result of using high pass filters for both rows and columns. The approximation coefficients are again decomposed in the next level. In this method, we are using four levels of wavelet decomposition for perfection. They are shown in fig . These detailed coefficients are used for the edge enhancement as explained by Farshad in [15]. The detailed coefficients at the four levels are taken for dynamic range compression as per the equation (1).

$$C_{dynamic(x,y)} = k.\log(1 + |c(x,y)|) \quad (1)$$

where c(x,y) is the pixel intensity at position (x,y) of the descrete coefficient image. The result is the logarithmic dynamic range of the image, c. k is application dependent and is found as 0.55 experimentally. The dot products of the dynamic range at four levels is taken for edge enhancement using the equation (2).

$$C_{enhanced(x,y)} = \left(1 + k.\,P(x,y)\right).C_{dynamic(x,y)} \quad (2)$$

Both strong and weak edges are highlighted in correlation images. The result is shown in fig 4.

3.3 Lung Part Segmentation

Proposed method uses the automated 3D histogram thresholding[8]. Thresholding combined with Wavelet Edge Enhancement is successfully used in lung field segmentation by Korfiatis [9]. Strong edges generate large wavelet coefficients at all levels, which is not true for weak edges.

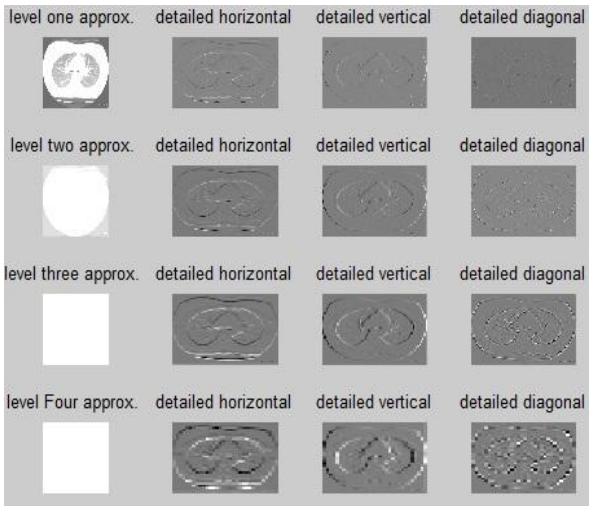


Figure 3:Four Levels of Wavelet Decomposition

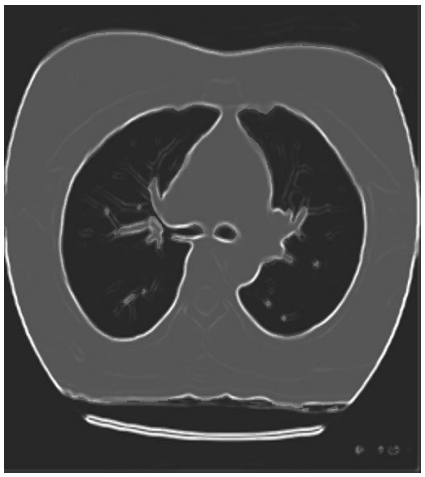
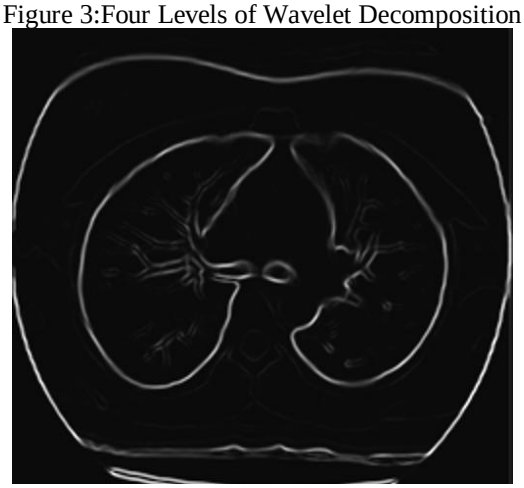


Figure 5 Lung Segmentation



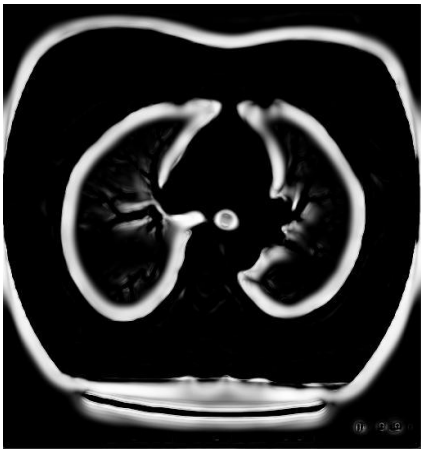


Figure 6:Vessel Tree Segmentation

As a result multiplying the coefficients across the scales enhances the large coefficients more than the smaller coefficients in the correlation image. To solve this problem we compress the dynamic range of the correlation image. Proposed method uses the automated 3D histogram thresholding[7]. Thresholding combined with Wavelet Edge Enhancement is successfully used in lung field segmentation by Korfiatis [10]. Strong edges generate large wavelet coefficients at all levels, which is not true for weak edges. As a result multiplying the coefficients across the scales enhances the large coefficients more than the smaller coefficients in the correlation image. To solve this problem we compress the dynamic range of the correlation image. However, gray level-based algorithms are insufficient in correctly segmenting lung fields in case of ILDs affecting lung borders, since ILDs are manifested as tissue texture alterations. To overcome this LF under-segmentation, a texture based border refinement step is employed mentioned by [6]. The image shown in fig.4 is the result of combining wavelet edge enhanced lung and histogram thresholded lung part. The optimum histogram thresholding is obtained using particle swarm optimization. PSO is a stochastic global optimization technique which uses swarming behaviours observed in flock of birds, school of fishes or swarm of bees, in which the intelligence is emerged.

3.4 Vessel Segmentation

To increase the effectiveness of vessel segmentation algorithm vessel enhancement procedures are first applied as a preprocessing step [12]-[13].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 (l1, l2, l3) of the Hessian matrix of each voxel, the response of the tubular structures is approximated according to Zhou et al. [13] by:

$$R(x,y,z,\sigma_s;l_1,l_2,l_3)=\begin{cases}\dfrac{(l_1+l_2)}{2}*exp\left(-\left|\dfrac{|l1|}{\sqrt{l_1^2+l_2^2+l_3^2}}-c\right|\right), & l_1,l_2,l_3<0\\ 0 & otherwise\end{cases} \quad (3)$$

A value of 0.7 is adopted for parameter c by [13]. 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 [13]. Following this step, 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. Fig 6 shows the vessel trees in the CT image shown in fig 2.

3.5 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) [15] 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. 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.

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).

3.6 Classification

Since the ILD is not a commonly found disease, the training data available for the scheme will be very less. The best classification when there is a less amount of training data is the use of support vector machines. Here we use Fuzzy SVM for the probability based classification. The input to the classifier is a feature vector. Feature vector is extracted in the previous step. FSVM defines a plane which separates the normal and abnormal images. In SVM, the plane is defined in such a way that, the distance between the support vectors are maximized. Support vectors are the points which are closer to the hyper plane. They are points at which the features of one class are close to the other one. Hence the chance of misclassification of support vectors is very high. The equation for the ith support vector in fuzzy SVM is,

If (yi=1) then Si= P(yi=1)

Else (yi= -1) then Si= 1-P(yi=1)

Hence fuzzy support vecors depends on the attitude of the sample I towards one class. The above equation considers 1 and -1 are the class representatives. FSVM reduces the effect of outliers and noises in data points.

FSVM imposes a fuzzy membership to each input point such that different input points can make different contributions to the learning of decision surface. Depending on the training data given, the classification of the input as normal and ILD affected is done.

IV. CONCLUSION & FUTURE SCOPE

The proposed method will have a better area overlap, true positive and false positive values over the existing scenarios. Extracting the exact vessel trees which in turn causes the clear lung segmentation helps the method to have error rate only in the range of small fractions. So this study brings a method for automatic segmentation of lung even the presence of ILD affected parenchyma. The measures such as area overlap, true positive fraction and false positive fraction can be computed to show its significant improvement. The segmentation accuracy of the proposed method can be evaluated quantitatively by comparing automatically derived vessel tree segments with manually defined ones. This method 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.

Acknowledgements

We wish to convey our sincere thanks to the staffs of computer science department, Government Engineering College, Thrissur for their support. We also thank the authority of Jubilee Hospital, Thrissur for their great help in collecting normal and abnormal images. The authors are grateful to all the supports and advices from the reviewers of the project.

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