CHAPTER 7

SUPERVISED APPROACH FOR SEGMENTATION OF LUNG PARENCHYMA FROM CHEST CT FOR COMPUTER AIDED DIAGNOSIS

The proposed model was tailored to diagnose lung disorders, namely, bronchiectasis, tuberculosis and pneumonia. In order to achieve better performance, a novel segmentation approach to segment lung parenchyma from chest has been proposed. It attempts to reconstruct the lung with peripheral PBR by using the other lung of the subject in the corresponding slice as the template. The first step is to segment the lungs using iterative thresholding followed by morphological operations. If the two lungs are not separated, the lung junction and its neighborhood are identified and local thresholding is applied. Secondly, shape features of the two lungs are extracted. The third step uses a multilayer feed forward neural network to determine if the segmented lung parenchyma is complete, based on the extracted features. Finally, in cases of incomplete segmentation, the lungs are reconstructed by exploiting the fact that in majority of the cases, even if segmentation is incomplete, one of the two lungs would be segmented correctly. Hence, the complete lung is determined based on the shape and region properties, and the incomplete lung is reconstructed by applying graphical methods namely reflection and translation. The proposed approach has been tested by using it in the CAD system that was tailored for diagnosis of lung disorders, namely Bronchiectasis, Tuberculosis and Pneumonia.
7.1 CAD SYSTEM FOR DIAGNOSIS OF LUNG DISORDERS USING BPN

The CAD system that has been developed to detect lung disorders, namely Bronchiectasis, Tuberculosis and Pneumonia by tailoring the proposed model is shown in Figure 7.1. The CAD system is composed of two major components, namely, the Training Subsystem and Inference Subsystem. The Training Subsystem and the Inference Subsystem are explained in detail with the relevant algorithms in the following subsections.

![Diagram of CAD System for Diagnosis of Lung Disorders](image)

**Figure 7.1 Framework of CAD System for Diagnosis of Lung Disorders**
7.1.1 Training Subsystem

The Training Subsystem is responsible for training the CAD System to perform correct diagnosis by teaching the system with labeled examples. The various components of the Training Subsystem are Enhancement Subsystem, Segmentation Subsystem, ROI Extraction Subsystem, Feature Extraction Subsystem, Image Database, Neural Network and KB.

The chest CT images in the dataset were enhanced by the Enhancement Subsystem. The lung parenchyma was then segmented from the enhanced image by the Segmentation Subsystem. The Regions of Interest (ROIs) were extracted from the lung parenchyma by the ROI Extraction Subsystem. Features are then extracted from the ROIs and stored in the image database. These feature vectors and the corresponding diagnoses given by an expert were used to train a BPN. Rules are extracted from the trained neural network and stored in the KB along with the feature vectors and corresponding diagnosis. The trained BPN and KB can now be used for diagnosis of a chest CT.

7.1.1.1 Enhancement Subsystem

The input to this subsystem is a JPEG image of chest CT scan of size 512×512 pixels. Hanson (1981) has discussed that the ultimate source of noise in CT image is the random noise. Gaussian noise is also present in CT images. Moreover, Segmentation Subsystem and ROI Extraction Subsystem would work effectively if the edges are sharp.

Input:

Chest CT of size 512×512
Process:

Step 1: The image was denoised using the algorithm discussed in section 5.1.1.

Step 2: A Laplacian filter (Gonzalez and Woods, 2002) defined by equation (7.1) has been used to extract the edges and these edges have been superimposed on the denoised image.

\[
g(x,y) = 5f(x,y) - [f(x+\Delta I, y) + f(x-I, y) + f(x, y+\Delta I) + f(x, y-I)]
\]  

(7.1)

Step 3: A suitable weight is used for superimposing the edges, so that the chance of values exceeding the intensity range is avoided.

Output:

Enhanced chest CT

7.1.1.2 Segmentation Subsystem

Segmentation Subsystem is responsible for extracting the lung parenchyma from the rest of the chest in the chest CT. The phases involved in the proposed segmentation algorithm are shown in Figure 7.2. The images were thresholded and the background, airways and non-lung components were removed.

The images were labeled to fall within two classes, completely segmented and incompletely segmented lung, based on the information given by a radiologist. A multilayer feed forward network comprising of 4 layers, namely, one input layer, 2 hidden layers and one output layer was created. The 26 features extracted in step 5 of process 5 in algorithm 1 correspond to the 26 nodes in the input layer. The number of layers and the number of nodes in the hidden layers was determined after several experimentations. From the
experimentation, the number of nodes was determined to be 8 in the first hidden layer and 4 in the second hidden layer. The number of nodes in the output layer was taken as 1, the value of which determines the class.

![Diagram of segmentation subsystem]

**Figure 7.2 Phases Involved in Segmentation Subsystem**

The network was trained with 183 images, 150 from class 0 (correctly segmented) and 33 from class 1 (incompletely segmented). The trained neural network is capable of classifying the segmented image between the two classes. If any of the images is classified as belonging to class 1, the lung borders are reconstructed. The detailed algorithm used for segmentation is shown in Algorithm 7.1.
Algorithm 7.1: Algorithm for Segmentation of Lung Parenchyma

Process 1: Iterative Thresholding

Input:

Enhanced chest CT

Process Logic:

Step 1: Global image threshold is computed using Otsu's method (1979). It is used as the initial threshold.

Step 2: The pixels with grayscale value less than threshold are set to 0 and pixels with grayscale value greater than or equal to threshold are set to 1.

Step 3: The mean grayscale value of pixels set to 0 is determined.

Step 4: The mean grayscale value of pixels set to 1 is determined.

Step 5: The average of the means obtained in steps 3 and 4 is chosen as the threshold for the next iteration.

Step 6: Iterate from step 2 until the threshold converges to the threshold of the previous iteration.

Output:

Thresholded image

Process 2. Background Removal

Input:

Thresholded image
Process Logic:

Step 1: The thresholded image is complemented.

Step 2: The white pixels connected to the border are set to 0 (Soille, 1999).

Output:

Binary image with the outer chest region removed

Process 3. Airways Removal

Input:

Binary image with the outer chest region removed

Process Logic:

The white pixels that are not connected to the border are set to 0. This removes the airways.

Output:

Binary image without holes

Process 4. Non-lung Components Removal

Input:

Binary image without holes

Process Logic:

Step 1: The small connected components in the outer chest region are removed.
Step 2: The connected components with an eccentricity greater than 0.98 in the outer chest region are removed because lungs have lesser eccentricity since lungs are more circular as compared to objects with an eccentricity of 0.98.

Output:

Binary image with external components in the chest region removed

Process 5. Lung Extraction

Input:

Binary image with external components in the chest region removed

Process Logic:

Step 1: The connected components are labeled based on 8-connectivity and the number of connected components is determined.

Step 2: If number of connected components is greater than 2, the two largest connected components are set to 1 and the other pixels are set to 0; the pixels which are set to 1 form the pixel positions corresponding to the parenchyma.

Step 3: If the number of connected components is 2,

a. If the area of the largest connected component is greater than 30000, the two lungs are connected and form a single component and the other component is a non lung component. This is because, the area of a single lung cannot be as large as
30000 in an image of size 512×512. Hence retain the largest component alone and go to step 4; else go to step 5.

Step 4: If the number of connected components is 1

  a. Lung junction is identified.
  b. Local thresholding is applied to the lung junction.
  c. Morphological close operation is performed.

Step 5: The shape features namely, Major Axis Length, Minor Axis Length, Eccentricity, Convex Area, Equiv Diameter, Solidity, Extent, Centroid, Bounding Box, Area of the left lung to that of the right lung and ratio of the Perimeter are extracted from each of the two lungs and a feature vector of size 26, comprising of the Major Axis Length, Minor Axis Length, Eccentricity, Convex Area, Equiv Diameter, Solidity and Extent of each lung, Centroid of the left lung - Centroid of the right lung, Bounding Box of the left lung – Bounding Box of the right lung, Bounding Box, ratio of the Area of the left lung to that of the right lung and ratio of the Perimeter of the left lung to that of the right lung is constructed.

Step 6: The extracted features are fed as input to a trained feed forward back propagation neural network.

Step 7: If the output of the neural network is 0, go to process 7.

Step 8: If the output of the neural network is 1, the severely affected lung is reconstructed using process 6.

Output:

Binary image of the segmented lungs, either complete or incomplete.
Process 6: Lung Reconstruction

Input:

Binary image of incompletely segmented lungs.

Process Logic:

Step 1: Find the height of each lung from the height of the Bounding Box of each lung.

Step 2: The lung which has lesser height is considered to be the severely affected one.

Step 3: The pixel coordinates of the other lung which is healthy or less affected are taken and reflected to get a symmetric lung in place of the severely affected lung.

Step 4: In order to cater to the difference in separation between the lungs in case of the reflected lung and the original lung,

a. The severely affected lung is segmented from the incomplete lung parenchyma.

b. The relative position of the lung from the centre of the image along the horizontal (y) direction is determined.

c. The reflected image is translated to the position obtained in step 4 b. This gives the pixel positions corresponding to the parenchyma.

Output:

Binary image consisting of the two lungs
Process 7: Lung Parenchyma Extraction

Input:

Binary image consisting of the two lungs

Process Logic:

Fill the pixel positions of the lung parenchyma by the pixel values in the input chest CT.

Output:

Lung Parenchyma

7.1.1.3 ROI Extraction Subsystem

The goal of ROI Extraction Subsystem is to extract the ROIs from the lung parenchyma. The ROIs of this system are the regions expected to bear the pathologies. The ROIs were extracted by the region growing algorithm (Gonzalez and Woods, 2002). The pathology bearing regions and bronchial walls are associated with high intensity values and the normal lung tissues have low intensity values. Hence two seed points were chosen, one corresponding the mean of the pixels below the global threshold and the other the mean of the pixels above the global threshold, in such a way that one corresponds to low intensity and the other corresponds to high intensity. Each pixel in the lung parenchyma was then analyzed for its proximity to the seed points with respect to grayscale value, and was labeled with either 0 or 1 based on whether it is close to the low intensity seed point or the high intensity seed point respectively. This is because pixels that constitute ROIs generally bear high intensity values and the normal lung tissues bear low intensity values. The regions formed were tested for connectivity and were
labeled using the algorithm proposed by Rosenfeld and Pfaltz (1966). The regions other than these ROIs were removed by morphological operations.

7.1.1.4 Feature Extraction Subsystem

The shape and texture features of the extracted ROIs are determined for quantitative analysis of the regions. Area, Euler Number, Extent, Perimeter, Solidity, Eccentricity, Orientation, Elongation and Form factor of each ROI were computed. The histogram of each ROI was generated and the first five moments were computed. GLCM was created for each ROI and the Contrast, Correlation, Energy, Homogeneity, Dissimilarity, Entropy, Inverse Difference Moment and Diagonal Moment were computed. In addition the Mean, Variance, Entropy and the same eight features from GLCM of the approximations of the level 2 wavelet decomposition of each ROI were computed.

7.1.1.5 Image Database

The image database is created in Oracle 10g and organized as two relations: IMAGE(ImageID, Image) and FEATURES(ROIID, Area, EulerNumber, Extent, Perimeter, Solidity, Eccentricity, Orientation, Elongation, FormFactor, Moment1, Moment2, Moment3, Moment4, Moment5, SpContrast, SpCorrelation, SpEnergy, SpHomogeneity, SpDissimilarity, SpEntropy, SpIDM, SpDiagonalMoment, W1Mean, W1Variance, W1Entropy, W1Contrast, W1Correlation, W1Energy, W1Homogeneity, W1Dissimilarity, W1EntropyGLCM, W1IDM, W1DiagonalMoment, W2Mean, W2Variance, W2Entropy, W2Contrast, W2Correlation, W2Energy, W2Homogeneity, W2Dissimilarity, W2EntropyGLCM, W2IDM, W2DiagonalMoment, Image ID), where the attributes with the prefix Sp represent the features extracted from the spatial domain, the attributes with the prefix W1 represent the features extracted
from the approximation of the level 1 wavelet decomposition and the attributes with the prefix W2 represent the features extracted from the approximation of the level 2 wavelet decomposition. ImageID is the primary key of the relation, IMAGE. The data type for ImageID is VARCHAR2(15). Image is stored in BLOB format. {ROIID, ImageID} is the primary key of the relation FEATURES. Image ID in the relation FEATURES references the IMAGE relation. The data type of ROIID is NUMBER(3) and that of the features is NUMBER(13,8).

7.1.1.6 Neural Network

A Multilayer Neural Network (NN) was created for diagnosis of lung disorders based on the features extracted by the Feature Extraction Subsystem. The NN used in this work consists of 44 nodes in the input layer, 32 nodes in the hidden layer and 4 nodes in the output layer. The number of input units was chosen equal to the number of features extracted from each ROI. The number of hidden units was selected after sufficient analysis. The four output units correspond to healthy region, Bronchiectasis affected region, Tuberculosis affected region and Pneumonia affected region. The NN was trained using Backpropagation algorithm with the data stored in the image database and the labels assigned to the ROIs by an expert.

7.1.1.7 Knowledge Base

The KB is constructed using the dataset used for training and the outputs produced by the trained NN for the training dataset. It is composed of facts and rules. Facts are the feature vectors used for training together with the corresponding diagnosis. Rules are generated based on the outputs of the trained NN for the training dataset.
7.1.2 Inference Subsystem

The goal of the Inference Subsystem is to generate diagnostic results. The Inference Subsystem comprises Enhancement Subsystem, Segmentation Subsystem, ROI Extraction Subsystem, Feature Extraction Subsystem, trained NN, KB and Correlation Analysis.

When a chest CT is given to this subsystem it first preprocesses the image by performing enhancement, segmentation, ROI extraction and feature extraction as discussed in sections 7.1.1.1 through 7.1.1.4. Then, the features extracted from each ROI are fed to the trained NN and the KB, each of which classifies the ROI as belonging to one of the four classes considered. The final diagnostic result is determined based on the correlation between the classification result provided by the NN and inference provided by the KB.

7.1.2.1 Correlation Analysis

Pearson’s correlation coefficient (invented by Karl Pearson) is computed between the output of the NN and the output of the KB. The output from the Neural Network is a vector of size 4, the value of each lying between 0 and 1. Hence the inference given by the KB is also converted to a vector of size 4, each corresponding to a specific class, by setting the value to 1, in case the inference corresponds to that class.

Finally, the outputs from the NN and the KB, and the correlation between the two are presented to the radiologist. This aids the radiologist in performing better diagnosis.
7.1.3 Image Repository

An Image Repository is maintained to store the details of every processed query image. It is organized in a way similar to the Image Database. After processing 100 images, the content of the Image Repository is transferred and added to the Image Database; the NN is trained again with the original data in the Image Database and the newly added data; the KB is updated. This helps in improving the performance of the system further as the collection in the Image Database increases.

7.2 EXPERIMENTAL RESULTS

The image database used by this system consists of 400 ROIs extracted from 50 images, consisting of 20 Bronchiectasis affected CT images, 20 Tuberculosis affected CT images and 10 Pneumonia affected CT images. The images are of size 512×512. Figure 7.3 shows the results of segmentation; column (a) shows a subset of the input images, column (b) shows the two lungs obtained as a result of thresholding followed by morphological operations and column (c) shows the results obtained by the proposed approach. The improvement in performance is obvious from the results shown.
Figure 7.3 Results of Segmentation
The ROIs extracted by the system using thresholding and the proposed segmentation algorithm are shown in figures 7.4 through 7.8 for a subset of images. The improvement in diagnosis is evident from the results shown.

![Input Image and Segmented Image](image)

![Regions of Interest and Labeled ROIs](image)

**Figure 7.4**  (a) Results Obtained for an Image of a Patient with Mild Bronchiectasis Using Thresholding and Morphological Operations (Number of ROIs = 1)
Figure 7.4 (b) Results Obtained for an Image of a Patient with Mild Bronchiectasis Using the Proposed Approach (Number of ROIs = 1)
Figure 7.5 (a) Results Obtained for an Image of a Patient with Severe Bronchiectasis Using Thresholding and Morphological Operations (Number of ROIs = 19)
Figure 7.5 (b) Results Obtained for an Image of a Patient with Severe Bronchiectasis Using the Proposed Approach (Number of ROIs = 19)
Figure 7.6  (a) Results Obtained for an Image of a Patient with Fluid Cavity, Pleural Thickening Multiple Nodular Lesions-TB Using Thresholding and Morphological Operations (Number of ROIs = 3)
Figure 7.6 (b)  Results Obtained for an Image of a Patient with Fluid Cavity, Pleural Thickening, Multiple Nodular Lesions-TB Using the Proposed Approach (Number of ROIs = 6)
Figure 7.7 (a) Results Obtained for an Image of a Patient with Air Space Opacity with Lobopneumonia Using Thresholding and Morphological Operations (Number of ROIs = 21)
Figure 7.7 (b) Results Obtained for an Image of a Patient with Air Space Opacity with Lobopneumonia Using the Proposed Approach (Number of ROIs = 19)
Figure 7.8 (a) Results Obtained for an Image of a Patient with Air Space Opacity with Lobopneumonia Using Thresholding and Morphological Operations (Number of ROIs = 20)
Figure 7.8 (b) Results Obtained for an Image of a Patient with Air Space Opacity with Lobopneumonia Using the Proposed Approach (Number of ROIs = 9)
The CAD System was subjected to 10-fold cross validation and the results are tabulated in Tables 7.1(a) through 7.1 (d). The average performance measures are tabulated in Table 7.2.

**Table 7.1(a) Results Obtained for 10-fold Cross Validation - Class 0**

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**Table 7.1(b) Results Obtained for 10-fold Cross Validation - Class 1**

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Table 7.1(c) Results Obtained for 10-fold Cross Validation - Class 2

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Table 7.1(d) Results Obtained for 10-fold Cross Validation - Class 3

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Table 7.2 Summary of the Results

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</tbody>
</table>

The performance of the system has been improved by a novel segmentation approach. The proposed approach is suitable for segmentation of normal lungs and lungs with severe pathology attached to the borders. Even if some additional region is segmented together with the lung parenchyma in a very few cases it does not miss any PBR and the additional regions produced are eliminated by the classifier. The proposed approach does not require a database of templates for reconstruction of the severely affected lung as it uses the shape properties of the lung which is completely segmented.

The CAD system achieved an average accuracy of 97.37442% whereas the conventional thresholding approach was unable to detect peripheral pathology bearing regions. The results obtained prove to be better than that achieved using conventional thresholding and morphological operations. The performance can be further improved by using the clinical test results as additional features. The segmentation process can be further improved by clubbing the concept of registration.