CHAPTER 6

SEGMENTATION APPROACH FOR CAD SYSTEMS USED TO DETECT LUNG CANCER FROM CHEST CT

The proposed model was tailored to improve the performance of CAD system for diagnosis of lung cancer using a novel automated approach for segmentation of lung parenchyma from the rest of the chest CT image. Segmentation of lung tissue is an important and challenging task in any CAD system that uses chest CT for diagnosis. The accuracy of the Segmentation Subsystem determines the performance of the other subsystems in any CAD system based on image analysis. Usually, the first step of a CAD system is the extraction of the lung regions. Antonelli et al (2005b) have specified that this process is crucial as it determines the success of the following stages of nodule detection and classification. This is a challenging task especially when the PBRs are in the periphery of the lung because the grayscale value of the PBR and the chest region are approximately equal. Hence, most of the nodule detection techniques do not detect the peripheral nodules or lesions that have developed from the periphery.

In this work a novel technique for segmentation of lung tissue from CT of chest has been developed. The approach involves the conventional optimal thresholding technique and operations based on convex edge and centroid properties of the lung region. This segmentation technique can be used to preprocess lung images given to a CAD system for diagnosis of lung disorders. This improves the diagnostic performance of the CAD system. This
has been tested by using it in a CAD system for detection of lung cancer from chest CT images. The results obtained show that the lungs can be correctly segmented even in the presence of peripheral PBRs and hence PBRs that cannot be detected using a CAD system that applies optimal thresholding can be detected using a CAD system that uses the proposed approach for segmentation of lungs.

6.1 CAD SYSTEM FOR DETECTION OF LUNG CANCER IN CHEST CT IMAGES USING PNN

The framework developed for the system in accordance with the proposed model is shown in Figure 6.1. The major components of the system are Image Denoising Subsystem, Segmentation Subsystem, Feature Extraction Subsystem, Image Database, Training Subsystem and Inference Subsystem.

6.1.1 Image Denoising Subsystem

The input to this subsystem is a JPEG image of chest CT scan of size 512×512 pixels. Hanson (1981) has mentioned that the ultimate source of noise in CT image is the random noise, Gaussian noise is also present in CT images. The algorithm discussed in section 5.1.1 was used for denoising the chest CT images.
Figure 6.1 Framework of CAD System for Detection of Lung Cancer from Chest CT Images
6.1.2 Enhancement Subsystem

The edges in the chest CT are enhanced to make the edges more prominent to get better segmentation results.

Input:

Denoised CT image of chest

Process:

Step 1: Laplacian operator defined by the kernel in equation (6.1) is applied to the chest CT to extract the edges.

\[
\begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1 \\
\end{bmatrix}
\]  (6.1)

Step 2: A scaled version of this edge image is added to the grayscale image as given by equation (6.2).

\[EI = I + k*LI\]  (6.2)

where \(EI\) is the edge enhanced image, \(I\) is the original image, \(LI\) is the image obtained by convolving \(I\) with the Laplacian operator and \(k\) is a constant. In this work the value of \(k\) is chosen as 0.5 based on experimentation.

Output:

Edge enhanced image
6.1.3 **Segmentation Subsystem**

The segmentation technique developed in this work involves the traditional thresholding mechanism and concepts based on convex edge to preserve the lung border.

The steps involved are as follows:

Step 1: Optimal Thresholding
Step 2: Background Elimination
Step 3: Elimination of Small Connected Components
Step 4: Separation of Left and Right Lungs
Step 5: Reconstruction of the Edge

This work focuses on Reconstruction of the Edge.

6.1.3.1 **Optimal Thresholding**

Optimal thresholding proposed by Hu et al (2001) was applied to the edge enhanced image.

**Input:**

Edge enhanced image

**Process:**

The process logic described in section 5.1.2.1.1 was applied to the edge enhanced image.

**Output:**

Thresholded image
6.1.3.2 Background Elimination

The non-body pixels obtained by optimal thresholding consist mainly of air surrounding the body, the lung tissues and a few other components. The non-body pixels connected to the border of the image were identified as background pixels. These background pixels were eliminated.

Input:

Thresholded image

Process:

Step 1: The complement of the thresholded image ($T^C$) was taken.

Step 2: The white pixels connected to the border were set to 0.

a. The thresholded image obtained from the previous stage was taken as the mask image.

b. A marker image was created with zero everywhere except along the border, where it equals the mask image.

c. Elements of the marker image connected to the outside, according to the connectivity definition were determined.

d. Elements of the marker image that were not connected to the outside were set to the lowest possible value.

Output:

Thresholded image without the background
6.1.3.3  Elimination of Small Connected Components

Small connected components with an area less than 250 pixels were identified and eliminated.

**Input:**

Thresholded image without the background

**Process:**

Small connected components with an area less than 250 pixels were identified and filled with its surrounding pixel value.

**Output:**

Thresholded image with the lung region alone without any connected components smaller than 250 pixels

6.1.3.4  Separation of Left and Right Lungs

The right and left lungs would appear connected in the thresholded image so obtained. They were separated using morphological operations.

**Input:**

Thresholded image with the right and left lungs connected

**Process:**

Morphological open operation defined by equation (6.4) was applied to the thresholded image to separate the left and right lung.

\[ I \circ Z = (I \ominus Z) \oplus Z \]  \hspace{1cm} (6.4)

where \(I\) is the image, \(Z\) is the structuring element, \(\Theta\) represents erosion and \(\oplus\) represents dilation.
Output:

Thresholded image with the right and left lungs separated

6.1.3.5 Reconstruction of the Edge

The thresholding operator identifies the nodules adjacent to the pleura (juxta-pleura nodules) as belonging to the chest and therefore suppresses them. So it is necessary to rebuild the peripheral lung tissues that have been erroneously eliminated. The goal of this phase is to reconstruct the edge in the presence of such peripherally placed PBRs.

Input:

Thresholded image with the right and left lungs separated

Process:

Step 1: The image was converted into a single connected component by applying morphological close operation using a structuring element of appropriate size; the size was determined by finding the separation between the closest pair of points in the two largest connected components.

Step 2: The convex image of this single connected component was determined.

Step 3: The centre coordinates of the single connected component and the centroid of the convex image were determined.

Step 4: The edge of the convex image was obtained using Canny operator (Canny 1986).
Step 5: The edge was aligned to the coordinate system of the thresholded image.

Step 6: The edge at the neighborhood of the lung junction was eliminated.

Step 7: A logical OR operation was performed between the edge image and the thresholded image with the right and left lungs separated.

Step 8: An image was generated with the holes filled.

Output:

Thresholded image with the right and left lungs separated and the margins reconstructed

6.1.4 ROI Extraction

The main goal of this step is to determine the ROIs in lung image. The ROIs for our system are the PBRs. The algorithm discussed in section 5.1.2.2 is used for extracting the ROIs.

6.1.5 Feature Extraction Subsystem

Majority of the medical images are generally in the gray level with few modalities containing color images. These images of different categories can be distinguished using their shape and texture characteristics. The features discussed in section 5.1.3 are extracted from the ROIs.

6.1.6 Image Database

The images in the CT image dataset were stored in the image database along with the PBRLabels, the feature vectors and the diagnostic results. In addition, the query images along with the PBRLabels, the corresponding feature vectors and diagnostic results were stored in the
database after diagnosis of each query image. After sufficient query images are diagnosed the PNN is trained again. This would result in better performance of the CAD system in the long run.

6.1.7 Probabilistic Neural Network

The PNN discussed in section 5.1.5 is used in this work. The architecture of the PNN is the same as that used in the work discussed in chapter 5, but was trained with the new set of feature vectors making it suitable for classification of cancerous and non-cancerous nodules.

6.1.8 Inference Subsystem

When a physician gives a CT chest image to the Inference Subsystem it first preprocesses the image to transform the image into a set of feature vectors, one for each PBR as discussed in sections 3.1 through 3.5. It then applies the feature vector as input to the trained neural network classifier and performs diagnosis based on the classification performed by the neural network.

6.1.9 Trained Neural Network Classifier

The CT chest image is classified using PNN. It involves deciding whether the CT image given by a physician user is cancerous or not. When the feature vector of the query image is given as input, the first layer computes distances from the input vector to the training feature vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce its net output a vector of probabilities. Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities and produces 1 for cancerous and a 0 for non cancerous lung.
Input Layer:
Input: 9 features

Process: Computes distances from the input vector to the training feature vectors

Output: A vector whose elements indicate how close the input is to a training input

Hidden Layer:
Input: Output of input layer

Process: Sums the contributions for each class of inputs to find the closeness of a pattern unit to the input vector

Output: A vector of probabilities

Output Layer:
Input: Output of hidden layer

Process: Sums the responses of the units belonging to their own class

Output: 1 for cancerous and 0 for non-cancerous image (nodule)

6.2 EXPERIMENTAL RESULTS

The system has been tested with images with PBRs at different positions in the lung, namely

i. PBRs in the interior lung region

ii. PBRs of manageable size in the periphery

iii. PBRs of very large size in the periphery.
The system was able to segment images in which the PBR was interior or on the outer border with accuracy approximately equal to that of manual segmentation by a physician as shown in Figures 6.2(d), 6.4(d) and 6.5(d). It failed in cases where a major portion of the lung was affected, i.e. in extreme cases where only a small portion of the lung was left out uninfected.

The results obtained using the proposed approach for segmentation of an image with a PBR of manageable size in the periphery is shown in Figure 6.4, an image with a PBR of very large size in the periphery is shown in Figure 6.3, an image with a PBR of an intermediate size in the periphery is shown in Figure 6.4 and that of healthy lungs is shown in Figure 6.5.

(a) Input Image  (b) Result of Optimal Thresholding

(c) Result of Rolling Ball Operator  (d) Result of Proposed Technique

Figure 6.2  Results Obtained for an Image with a PBR of Manageable Size in the Periphery
Figure 6.3  Results Obtained for an Image with a PBR of Very Large Size in the Periphery

Figure 6.4  Results Obtained for an Image with a PBR of Intermediate Size in the Periphery
Figure 6.5 Results Obtained for an Image of Healthy Lungs

The performance the CAD system was tested using 20 images with peripherally placed PBR, 80 images with internal placed PBR and 100 normal lung images. The confusion matrix for the CAD system using the proposed approach for segmentation is shown in Table 6.1.

Table 6.1 Confusion Matrix

<table>
<thead>
<tr>
<th>Actual/Predicted</th>
<th>Negative</th>
<th>Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>96</td>
<td>4</td>
</tr>
<tr>
<td>Positive</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>

The values achieved for the various performance measures are given in Table 6.2.
Table 6.2 Performance Measures

<table>
<thead>
<tr>
<th>Performance Measures</th>
<th>Values Obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimal Thresholding</td>
</tr>
<tr>
<td>Specificity</td>
<td>95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>88.5%</td>
</tr>
<tr>
<td>Precision</td>
<td>94.3%</td>
</tr>
<tr>
<td>Recall</td>
<td>82%</td>
</tr>
</tbody>
</table>

This approach increases the TP and decreases the FP and FN, thereby increasing the diagnostic accuracy of the CAD system. Comparing this system to the existing systems, the diagnostic accuracy of the existing systems is less. Heuberger et al (2005) in their work have stated that out of 141 remaining images, 59 were well segmented, small parts were missing in 57 images, big holes were visible in 32 images and 3 images were badly segmented; in some cases the right lung is removed with the background. The approach proposed in this paper is capable of extracting the lung tissue if the PBR is in the inner lung region or in the outer border of the lung. Only if the two lungs are asymmetric and vary to a large extent in terms of their convex area, segmentation remains a challenging task.

From the experimental results it could be inferred that our system outperforms the rolling ball operator, especially in case of chest CTs with PBRs of moderate size located in the periphery of the lung parenchyma. This system was able to effectively segment images with internal PBRs and peripheral PBRs of moderate size. However our system fails in cases where the PBR was very large in which case the rolling ball operator also fails. Hence this approach can be used for preprocessing of chest CT applied as input to CAD systems.