CHAPTER 2

LITERATURE SURVEY

The existing works on computer aided diagnosis of lung disorders, segmentation of lung parenchyma and retrieval techniques used for diagnosis are discussed in the following subsections. It provides an insight into the existing works, the achievements in this area and the problems existing in the previous works.

2.1 COMPUTER AIDED DIAGNOSIS

Rahman et al (2007) have proposed a CBIR framework for diverse collection of medical images of different imaging modalities, anatomic regions with different orientations and biological systems. They have proposed a novel machine learning based image prefiltering approach with the combination of a statistical similarity matching technique and relevance feedback scheme to update the query parameters dynamically in a medical image database. They have reduced the search space by using a Probabilistic Multi-class Support Vector Machine (SVM) and Fuzzy C-Mean (FCM) clustering for categorization and pre-filtering of images. In order to evaluate the performance of their system they have used a medical image database that includes images with ground truth corresponding to the modality, examined body region or orientation. The average recall and average precision plot show that Mahalanobis distance measure with filtered database performed much better as compared to the Euclidean distance measure. They have used a Multiclass SVM to predict the category of the query and the database images.
They have incorporated category specific parameters in the statistical similarity measures and adjusted these parameters based on the prediction. Based on the observation, they have concluded that the distance measures that utilize the category-specific feature distribution information performed better in a semantically organized database. They also assert that CBIR systems in the medical domain provide reasonable results when constrained to a single application domain.

Suzuki et al (2005a) have developed a CAD system for distinguishing malignant nodules from six types of benign nodules. They have used MTANN consisting of six expert MTANNs that are arranged in parallel, each trained to distinguish malignant nodules from one type of benign nodule. Their system provided a value proportional to the likelihood of malignancy. They have used a database consisting of 76 malignant nodules and 413 benign nodules. Their system correctly identified 100% of malignant nodules as malignant and 48% of benign nodules as benign. One of the limitations of the MTANN would be the difficulty in distinguishing malignant nodules from the benign nodules which would be similar to malignant nodules in their appearance. They consider it to be a limitation of low dose CT.

Liu et al (2001) in their work have introduced a content-based scheme for assisting collection of similar medical images, so that the collection can be used as a tutorial for differential diagnosis. The differential diagnosis technology compares and contrasts results of diagnostic measures to determine the diseases with which the patient is suffering. They have used Kohonen self-organizing network for classification which clusters the input training patterns to appropriate number of classes self-organizingly without being informed the relationship between the inputs. The system uses a Graphical User Interface (GUI) which allows the user to input an image by selecting the ROIs as fixed size rectangle. When a query image is given, the
system will retrieve a set of candidate images that are textural-similar to the query image. If there are more than one ROI, the system will perform multiple queries, one for each ROI. It will then find to which texture category each query block (ie. ROI) belongs and then identify the most likely candidate images by taking an intersection. Thus, the output is a set of candidate images that are similar to the query image(s) in texture. The experimental results show that in a simple query 96.6% of the images can be correctly retrieved with the displacement up to 22% of the size of the ROI. They conclude that the system could retrieve the correct images even when the user specifies multiple ROIs.

Dy et al (2003) in their work have developed a new hierarchical approach called the “Customized-Queries” approach (CQA) for content-based image retrieval. CQA uses multiple feature sets and a two-step approach for retrieval. First, this system classifies the query according to class labels using the features that best discriminate the classes. Then, it retrieves the most similar images within the class using the features customized to distinguish “subclasses” within a disease class. They have observed that the image features that work best to discriminate among different classes are different from the features needed to retrieve images belonging to the same subclass within each class. Hence, they customize the features accordingly. As a result, they have developed a new algorithm called Feature Subset Selection using Expectation-Maximization Clustering (FSSEM) that selects effective features for unsupervised learning algorithm. Their approach was to search through feature subset space, evaluating each subset by first clustering in the subset using Expectation-Maximization (EM) Clustering and, then, evaluating the resulting clusters in the subset. They have applied this technique to a database consisting of 312 HRCT lung images from 62 patients and found that CQA radically improves the retrieval precision over the single feature vector
approach. They have achieved a retrieval precision of 73.18% against 38.89% achieved with single feature vector approach.

Shyu et al (1999) in their work have introduced a Physician-in-the-Loop Content-Based Retrieval System for HRCT Image Databases called “Automated Search and Selection Engine with Retrieval Tools" (ASSERT). To archive an image into the database a physician first delineates the PBRs. In the meantime a lung region extraction algorithm is applied which determines the lung boundary. Then a suite of image processing algorithms are executed to create attribute vectors that characterize the PBRs individually. These attributes are subject to a Sequential Forward Selection algorithm (SFS) to reduce the dimensionality of the attribute space. Fourteen attributes corresponding to the four perceptual categories, linear and reticular opacities, nodular opacities, high-opacities and low-opacities and 12 general purpose attributes are used for image characterization. They have achieved a precision of 72.9% using a dataset consisting of 302 lung HRCT images.

Aisen et al (2003) in their work have designed and implemented ASSERT, a software system and database for computer-aided diagnosis with thin-section CT images of the chest to assist the radiologist in diagnosis of diseases with different lung opacities. This ASSERT software is designed to work with local regions of abnormal pulmonary parenchyma or PBRs and not with entire CT images. It requires the physician to first mark a PBR on an unknown query image, after which the computer identifies lung parenchyma in the PBR. Hence the diagnosis depends on the PBR marked by each of the users and is not necessarily the same for all the users. They have evaluated the system by conducting a trial with 11 volunteers who were asked to select the best diagnosis with and without software assistance. The volunteers comprised of chest radiologists and general radiologists. They have shown that the percentage of correct diagnosis increased from 29% without the aid of
any CAD system to 62% with a CAD system that retrieved four matching images that might or might not be correct; the improvement was greater for the general radiologists than that for the specialized chest radiologists. In this trial, the diseases chosen by the ASSERT software were correct in approximately 70% of cases.

Maglogiannis et al (2008) in their work have investigated the potential of Radial Basis Function Neural Network (RBFNN) for the classification of biological microscopic images displaying lung tissue sections with idiopathic pulmonary fibrosis. They have compared the results produced by the classification tool with pathology grading scores determined by three expert pathologists and with SVM. They have induced lung inflammation in mice and have used these mice for experimentation. They have used 83700 training pixels. They have achieved a sensitivity of 82% and a specificity of 88% for the mild pathology class, and a sensitivity of 100% and a specificity of 94% for the severe pathology class. They have reported a slightly higher performance than SVM. They have also reported some erroneous predictions. In case of severe illness the “ill” region has been perceived as bronchi because of similar coloring.

Garnavi et al (2005) in their work have proposed an accurate and reliable method for segmentation of lung HRCT images using a pixel based approach. The proposed method combines traditional concepts, such as global-threshold segmentation, mathematical morphology, edge detection and noise reduction, with new ideas such as, performing geometrical computations to extract the ROIs. They have applied the algorithm to images not corrupted by noise and to images corrupted by Gaussian noise. They have shown that their algorithm leads to 10% error when 25 non-uniform steps for the noise variance are introduced, which is acceptable. The work is part of a computerized system that aims at determining the severity of ILD, using
HRCT lung images. The system was tested on lung HRCT images. They have attained an accuracy of 91.33%.

2.2 SEGMENTATION OF LUNGS FROM CT IMAGES OF THE CHEST

Most of the segmentation algorithms for lung CTs discussed in literature are pixel–based methods. The works done by Iii et al (1999), Everhart et al (1994), Goo et al (2003), Gurcan et al (2002), Hu et al (2001), Ko et al (2003) and Leader et al (2003) fall under this category. Brown et al (2000) and Brown et al (1997) have done their work on knowledge–based segmentation which takes into account apriori knowledge on the structure of the lungs. In pixel–based methods, the fat tissue and bones are first eliminated. Heuberger et al (2005) suggest that as the lung parenchyma has a very low–density, it is composed of low–intensity pixels in the CT scan. This property is exploited to separate the two lungs from the surrounding tissue. Generally, the image is thresholded, either at a fixed value or based on a computed threshold.

Antonelli et al (2005a) in their work have described an automated system for detection of pulmonary nodules in CT images of lungs. In their work they have used the segmentation technique proposed by Antonelli et al (2005b) for extraction of lung parenchyma as a preprocessing step. They have used a region growing algorithm based on gray level and shape index for nodule detection. They have worked on scans consisting of a sequence of about 300 slices stored in Digital Imaging and Communications in Medicine (DICOM) format. They have showed that small juxta-pleura nodules could be identified by their system. They conclude that their approach was able to detect all malignant nodules and a very low false positive rate was achieved.
Heuberger et al (2005) in their work have proposed a technique for Lung CT segmentation for image retrieval using the Insight Toolkit (ITK), an open source image analysis tool. Their goal had been to present an algorithm that does not need manual intervention. Their lung segmentation algorithm follows five steps, thresholding, removal of surrounding air, cleaning, rolling ball operation and left and right lung separation. The approach works well when the PBR is internally placed. The algorithm is unable to track the lung border if the PBR is peripherally placed and larger than the size the rolling ball operator can handle. In some cases, wherein a lung lobe touches the border, that lobe is eliminated along with the background.

Antonelli et al (2005b) in their work have presented a method for automated identification of the pulmonary parenchyma. The method is based on a combination of either traditional or purposely-developed image processing techniques, such as threshold-based segmentation, morphological opening and closing operations, border detection, border thinning, border reconstruction, and region filling. In order to reconstruct the border for each pair of border points, they calculate two distances: the Euclidean distance and the minimum distance in pixels between the two points. They then compute the ratio of minimum distance to Euclidean distance: if it is greater than a given threshold the two points are considered candidates for a possible reconstruction. For all candidate pairs a further condition is evaluated before establishing whether the reconstruction has to be done: they verify whether the segment connecting the two points is not internal to the lung. If the condition is satisfied, then the border between the pair of points is rebuilt. They have applied this method to more than 2400 digital images. This technique also works fine only when the size of the peripherally placed node is small.
Aristofanes et al (2002) in their work have described an automatic segmentation method for the pulmonary parenchyma. The method is based on a combination of traditional techniques, such as segmentation using global threshold, morphological opening and closing operations, border detection using Sobel’s filter, thinning, representation of pulmonary structures using chain code, classification of the structures’ areas and reconstruction of the pulmonary parenchyma using rolling-ball algorithm. Their algorithm also relies on rolling ball operator for rebuilding the lung border and hence is unable to track the lung border if the PBR is peripherally placed and larger than the size the rolling ball operator can handle. They have tested the method with 150 CT images and found that for 135 images the results matched the expectation and for the other 15 the results were incorrect. In other words, the results were accurate in 90% of the images.

Hu et al (2001) in their work have presented a fully automatic method for identifying the lungs in three-dimensional (3-D) pulmonary X-ray CT images. The method involves three main steps namely, optimal thresholding, separation of the left and right lungs and a sequence of morphological operations. Optimal thresholding is first applied to extract the lung region from the CT images. Then dynamic programming is applied to separate the left and right lungs by identifying the anterior and posterior junctions. Finally, a sequence of morphological operations is used to smooth the irregular boundary along the mediastinum. This forms the basis for most of the later works in the literature. They have tested their method by processing 3-D CT data sets from eight normal subjects, each imaged three times at biweekly intervals with lungs at full inspiration. They have compared the automatic method to manually traced borders from two image analysts. Averaged over all volumes, the root mean square difference between the computer and human analysis is found to be 0.8 pixels (0.54 mm). From the literature it is found that the approach was tested only using healthy chest CT
images but was not tested using images with pathology. It is evident that the approach will not extract the complete lung if tested with images with large PBRs in the periphery, as it is based on grayscale value. Hence, it is not suitable for CAD systems for diagnosis of diseases like Tuberculosis and Pneumonia in which the PBR is on the periphery.

Pu et al (2008) in their work have presented a lung segmentation algorithm called Adaptive Border Marching (ABM). It smoothes the lung border in a geometric way and can be used to reliably include juxtapleural nodules while minimizing oversegmentation of adjacent regions such as the abdomen and mediastinum. They have compared their technique with the rolling ball approach. Their technique performs better than the rolling ball approach but tends to include a part of the non-lung tissue into the segmented lung parenchyma. They have evaluated their algorithm by applying the algorithm to 20 CT images of the lung. They have achieved an average oversegmentation volume error of 0.43% of the true volume and an undersegmentation of 1.63%. They have not tested it with CT images with large areas of heterogeneous parenchymal consolidation and mucus plugs.

Khawaja et al (2004) have proposed a method for the segmentation of lung from chest CT. The method consists of three phases, namely, Enhancement of lung CT, Elliptical Thorax Extraction and Lungs Segmentation. In the proposed approach, they have utilized the fact that the pleura membrane forms the distinguishing boundary between the lung and its surroundings. The segmentation algorithm was tested on 964 slices, belonging to six benign and three malignant cases. They claim that the proposed method of lungs segmentation performs efficiently not only on chest CT without any pathology, but also works equally well on images containing abnormality patches and nodules in any part of the lung. But the experimentation carried
out in this research work shows that elliptical thorax extraction may not work in all cases.

In the research work discussed in this thesis, reconstructing the lung borders by constructing an elliptical outline for the lungs was implemented and tested. The chest CT was first thresholded and the background was eliminated. The holes were filled with 0 and the two largest components corresponding to the two major lobes alone were retained; the other components that correspond to the non-lung region in the outer chest region were eliminated. The image was then dilated to make the two lobes a single connected component. The major axis length and the minor axis length of the connected component were estimated and an ellipse was constructed. The elliptical outline in one eighth of the region from the centre towards the left and right was eliminated and the other part of the elliptical outline was retained to form the left and right border of the lung. The results of the segmentation included a large portion of the non-lung region. Though the lung border appears to be elliptical visually, experimental results illustrate that the shape of the lung in all the CT slices is not perfectly elliptical. Hence, reconstruction of the lung border making use of elliptical concept is not a suitable approach. Hence this approach is not adapted in the work carried out in this research. The algorithms adapted from the literature in this work are discussed in chapters 4 and 5. In addition, two different segmentation algorithms have been developed in this research work and these algorithms are discussed in chapters 6 and 7.

Sluimer et al (2005) in their work have proposed a segmentation-by-registration scheme for segmentation of lung from chest CT in which an atlas based segmentation of the pathological lungs is refined by applying voxel classification to the border volume of the transformed probabilistic atlas. They have compared the performance of the proposed approach and three
other segmentation methods, namely, a conventional lung field segmentation based on thresholding and morphological techniques, a conventional segmentation employing user interaction and a voxel classification method. For their comparative study they have chosen a dataset of 10 chest CT scans that are difficult to segment by conventional methods. They have used the three measures, namely, volumetric overlap fraction, Hausdorff distance (or maximum surface distance) and mean absolute surface distance for evaluation against manual segmentations. They have inferred four results: first, “The automatic region growing method was unable to adequately segment the pathological test scans.”, second, “In segmenting high density tissues, both voxel classification and refined segmentation-by-registration outperformed the manually aided region growing method.”, third, “Refined segmentation-by-registration achieved a significant improvement upon straightforward segmentation-by-registration results.” and finally “None of the tested methods approached the performance of the second observer in segmenting the most pathological scan.”. They also state that accurate lung segmentation in the presence of PBR attached to the pleura is not possible using conventional methods based on thresholding and morphological processing and that the segmentation of pathological scans requires a different approach than the segmentation of normal scans. They add that the interactive one achieves better overall segmentation results than the fully automatic region growing method. They claim that the registration scheme has the desirable property of automatically creating segmentations with a valid lung shape due to its implicit lung model. From their experimental results they infer that the refined segmentation-by-registration scheme performs well on scans with up to a quarter of the lung volume affected by high density pathology and state that the method should be tested on a larger amount of scans before it can be reliably deployed in clinical practice. They conclude that for more severely pathological scans, the accuracy achieved is still unsatisfactory.
Chen et al (2007) in their work have proposed a method for automatic Pulmonary Parenchyma Segmentation in CT Images. They have used a mid-value nonlinear filter for noise removal. Thresholding is then applied to the denoised image to segment the lung regions from the whole CT image. Region flood filling has been used to remove artifacts outside the lung. Isolated artifacts are then removed by applying morphology and area filter approach. Finally, the obtained binary image is used as a mask to the original CT slice to extract the pulmonary parenchyma. They have evaluated the scheme using a sequence of 75 CT image slices. From the experimental results they conclude that the method is simple and easy for implementation with no complex algorithm in the steps. They claim that the proposed method is efficient enough to be used as an initial step to lung disease CAD system based on CT images but have not discussed the experimental results in case of images with peripherally placed pathologies.

Lai and Ye (2009) have proposed an Active Contour Based Lung Field Segmentation approach with prior shape to fit boundary of lung field. It fully exploits the available a priori knowledge concerning the anatomic structure of interest. They have used the boundary tracking algorithm to track the boundary of the thorax. Thorax hull has been defined and then an active contour model has been formulated. The active contour has been used for fitting to the boundary and the training set of sample contours is aligned. The mean control point vector is determined. The active contour algorithm is used to segment the lung area together with juxta-pleural nodules. They claim that, it can be used in any shape pulmonary regions, especially suitable for the segmentation of lung field with juxta-pleural pulmonary nodules due to fitting with the shape profile for pulmonary area.

Pu et al (2010) in their work have presented a “break-and-repair” strategy for medical image segmentation. They have analyzed its feasibility
by applying it to automated segmentation of lung volume and pulmonary nodule segmentation. They have used 230 chest CTs for evaluating the performance. They have stated that the evaluation in their study is still preliminary, especially for clinical applications and that it lacks a comprehensive validation using examinations with severe diseases. For the human lung segmentation, they have achieved an RMS error of $0.15 \pm 0.092$ mm and for nodule segmentation they have achieved an RMS error of $1.08 \pm 0.45$mm.

From the literature discussed in this section on segmentation approaches that can be used in CAD systems for diagnosis of lung disorders, it can be inferred that thresholding approach is incapable of segmenting the lung correctly in the presence of peripheral PBR. Registration also becomes expensive due to the fact that lung volume varies with respect to several factors and the lung shape differs between slices.

2.3 RESEARCH DIRECTION

The works discussed in the literature focus on detection of nodules and classification of benign and malignant nodules. Research is still in progress in the area of segmentation of lung parenchyma. This work involves segmenting the lungs, detecting the PBRs and analyzing the PBRs for determining the possible lung disorder.

Texture is an important feature in analyzing the detected lung nodules for possible lung disorders. Hence this work uses texture features and shape features to determine the lung disorder that the patient is suffering from. The performance of the approaches is further enhanced by employing efficient segmentation algorithms which form part of this research work. In addition the approaches developed in this research work focus on specific lung disorders to make the approach more efficient.
Comparing to the works discussed in the literature, the work carried out in this research work is different in the following ways:

First, the works discussed in the literature detect the nodules and then perform morphological operations which may tend to discard small nodules. In this research work, an approach that performs analysis of subimages of size 15×15, extracted from the lung parenchyma has been proposed. This does not involve the application of morphological operations and hence does not eliminate the PBRs of small size. Instead, it detects even small nodules but at the expense of time.

Second, the works on bronchiectasis discussed in the literature aim at detecting the radiological signs of bronchiectasis. In this research work an approach for diagnosing bronchiectasis from chest CT and for retrieving similar images from an image database has been developed. This makes use of a KB and a PNN for diagnosis and Mahalanobis similarity measure for retrieval.

Third, the segmentation approaches discussed in the literature are efficient in segmenting the lung parenchyma from healthy chest CTs and chest CTs bearing small juxta-pleural nodules. They are not effective in case of chest CTs that bear severe PBRs in the periphery. In this research work, a segmentation algorithm that applies iterative thresholding and then makes use of the convex edge and centroid properties for reconstruction of the lung border has been developed.

Fourth, a segmentation algorithm that works with all three cases, namely, lungs with internal PBR, lungs with peripheral PBR and healthy lungs has been developed in this research work. This makes use of a trained BPN to determine if the lung parenchyma segmented by thresholding and morphological operations is complete or incomplete and uses graphical
methods to reconstruct the lung parenchyma in cases of incomplete segmentation. Moreover, to improve the discrimination among ROIs belonging to different disease categories features have been extracted from the image, the histogram of the image, the GLCM and the wavelet domain.

Finally, a scheme for selection of the slice that is best suited for analysis of a nodule has been developed in this research work. This keeps track of the ROI in adjacent slices and first eliminates the ROIs that exist in less than three slices. For each ROI that is retained, the slice in which that ROI has the largest area is chosen for analysis. Application of this scheme in CAD systems for diagnosis of lung disorders reduces the computational complexity in comparison with systems that use 3-D images for analysis.