Lung Nodule Detection using a Neural Classifier

M. Gomathi and Dr. P. Thangaraj

Abstract—**The exploit of image processing techniques and Computer Aided Diagnosis (CAD) systems has demonstrated to be an effectual system for the improvement of radiologists' diagnosis, especially in the case of Medical Image Processing. The main intention of this paper is to estimate the performance of the Computer-Aided Detection (CAD) system for nodule detection in lungs in screening computed tomography (CT). The automated extraction of the pulmonary parenchyma in CT images is the most crucial step in a computer-aided diagnosis (CAD) system. All malignant nodules were detected and a very low false-positive detection rate was achieved. This paper discusses a dot-enhancement filter for nodule candidate selection and a neural classifier for false-positive finding reduction. The performance is evaluated as a fully automated computerized method for the detection of lung nodules in screening CT in the identification of lung cancers that may be missed during visual interpretation.**

Index Terms—**Computer Aided Diagnosis (CAD), Dot-Enhancement Filter, Medical Image Processing, Nodule Detection, Neural Classifier.**

I. Introduction

The Lung cancer is the second most commonly diagnosed cancer and the lung is a most frequent site of metastasis from other cancers that manifest as pulmonary nodules. The Chest computed tomography (CT) is the most sensitive diagnostic imaging modality for the detection of lung cancer and the resolution of any equivocal abnormalities detected on chest radiographs. Recently, CT techniques have been applied to screening for the detection of the lung cancer in high-risk populations and have been shown to be promising for detection of early lung cancers. Thin-section three-dimensional CT of the thorax may allow us to evaluate small lung nodules automatically at early stages. With sequential follow-up CT scans, early changes in nodule size and number can be assessed.

Computed Tomography (CT) is the most recently used diagnostic imaging examination for chest diseases such as lung cancer, tuberculosis, pneumonia, and pulmonary emphysema. A survey result reveal the truth that more than 9 million people worldwide die annually from chest diseases [1]. Interestingly CT scans have been used for detection of lung cancer [2] because there is some evidence suggesting that early recognition of lung cancer may allow a favorable diagnosis [3].

The thin-section CT scan generally generates a large data set, with typically 250–350 images of 1-mm section thickness, and it requires radiologists to spend a considerable amount of time interpreting the images to produce the appropriate results

As a means to reduce radiologists' workload, computer-aided detection (CAD) systems may be used. The automatic CAD systems also helps to improve a radiologist's performance in the detection of pulmonary nodules [4] without which, it would become a much time consuming process for the radiologist and the CAD systems automatically. In the field of medical diagnosis an extensive diversity of imaging techniques is presently available, such as radiography, computed tomography (CT) and magnetic resonance imaging (MRI). The Chest computed tomography (CT) is the most sensitive diagnostic imaging modality for the detection of lung cancer and the resolution of any equivocal abnormalities detected on chest radiographs [5] [6].

The main distinguishing attribute to diagnose malignant nodules is their growth over time. In order to support radiologists in the identification of early-stage pathological objects, researchers have recently begun to explore computer-aided detection (CAD) methods in this area. Algorithms are previously being developed to do temporal comparisons on follow-up studies. All the detected nodules would be automatically assessed to see if they have increased in volume and at what rate. This feature probably will greatly enhance the diagnostic value of CAD systems in CT screening for early lung cancer.

This paper explains an approach for lung nodule detection in screening CT. A dot-enhancement filter is utilized effectively for the selection of nodule candidate. In addition a neural classifier is employed to reduce the false-positive rates. The experiments are conducted on real time collected data set (CT scan) to prove the efficiency of our approach. The remainder of the paper is organized as follows. Section 2 provides an overview on related research works in medical image processing. Section 3 explains the extraction of pulmonary parenchyma. Section 4 discusses on CAD system. Section 5 illustrates the experimental results and Section 6 concludes the paper with discussions.

II. Related Work

This section of the paper provides an overview on the related research work carried on medical image processing.

Kenji Suzuki et al. in [7] presented an image processing technique using Massive Training Artificial Neural Networks (MTANN). Their approach resolve the problem faced by radiologists as well as computer-aided diagnostic (CAD) schemes to detect these nodules in case when the lung nodules overlaps with the ribs or clavicles in chest radiographs. An MTANN is extremely a non-linear filter that can be trained by use of input chest radiographs and the equivalent "teaching" images. They used a linear-output back-propagation (BP) algorithm that was derived for the linear-output multilayer ANN model in order to train the MTANN. The dual-energy subtraction is a technique used in [7] for separating bones from soft tissues in chest radiographs by using the energy dependence of the x-ray attenuation by different materials.

A robust statistical estimation and verification framework was proposed by Kazunori Okada et al. in [8] for characterizing the ellipsoidal geometrical structure of pulmonary nodules in the Multi-slice X-ray computed tomography (CT) images. They proposed a multi-scale joint segmentation and model fitting solution which extends the robust mean shift-based analysis to the linear scale-space theory. A quasi-real-time three-dimensional nodule characterization system is developed using this framework and validated with two clinical data sets of thin-section chest CT images. Their proposed framework is a combination of three different but successive stages. They are model estimation, model verification and volumetric measurements. The main issue of the approach is a bias due to the ellipsoidal approximation.

Segmentation-by-registration scheme was put forth by Ingrid Sluimer et al. in [9]. In the scheme a scan with normal lungs is elastically registered to a scan containing pathology. Segmentation-by-registration scheme make use of an elastic registration of inclusive scans using mutual information as a similarity measure. They compared the performance of four segmentation algorithms namely Refined Segmentation-by-Registration, Segmentation by Rule-Based Region growing, Segmentation by Interactive Region growing, and Segmentation by Voxel Classification. The comparison results revealed that refined registration scheme enjoys the additional benefit since it is independent of a pathological (hand-segmented) training data.

Xujiong Ye et al. in [10] presented a new computer tomography (CT) lung nodule computer-aided detection (CAD) method. The method can be implemented for detecting both solid nodules and ground-glass opacity (GGO) nodules. Foremost step of the method is to segment the lung region from the CT data using a fuzzy thresholding technique. The next step is the calculation of the volumetric shape index map and the “dot” map. The former mentioned map is based on local Gaussian and mean curvatures, and the later one is based on the eigen values of a Hessian matrix. They are calculated for each Voxel within the lungs to enhance objects of a specific shape with high spherical elements. The combination of the shape index and “dot” features provides a good structure descriptor for the initial nodule candidate generation. Certain advantages like high detection rate, fast computation, and applicability to different imaging conditions and nodule types make the method more reliable for clinical applications.

A novel approach for lung nodule detection was described by M. Antonelli et al. in [11]. They described a computer-aided diagnosis (CAD) system for automated detection of pulmonary nodules in computed-tomography (CT) images. Combinations of image processing techniques are used for extraction of pulmonary parenchyma. A region growing method based on 3D geometric features is applied to detect nodules after the extraction of pulmonary parenchyma. Experimental results show, that implementation of this nodule detection method, detects all malignant nodules effectively and a very low false-positive detection rate was achieved.

III. Extraction Of Pulmonary Parenchyma

The extraction methodology of the pulmonary parenchyma can be regulated by removing the background as an initial step (i.e., the pixels with the same grey level as the lungs but located outside the chest) from the image to avoid confusion. This is intended, due to the high similarity between the grey levels of the lungs and the image background, which cannot be simply applied by using a Thresholding technique. Instead an ad-hoc operator is used which, starting from the four corners of the image, moves along the four directions identifying as background pixels, those pixels whose grey level is within a pre-fixed range. Figure 1 show an original image from CT before removing the back ground.

When a pixel value is found outside the range (out pixel), then it analyses for few more pixels in the scan direction. If any such of the pixels have values within the range then both these pixels and the out pixel are marked as background pixels and the scan goes on to be continued. If not, the scan is interrupted along the direction under examination and the successive row or the particular column is analyzed in a similar way. These images produced by the operator are converted to binary images by means of some specific technique like Thresholding technique that uses either a static or a dynamic threshold depending on the lung zone the slice that belongs to the zone in the lungs.

Figure 1.Image before back ground removal

More specifically, after discarding the first few initial and last slices of a CT scan that do not contain lung images the remaining slices are classified into three groups corresponding to the upper, middle and lower parts of the lung volume. In the first and last groups the lung image represents a smaller percentage of the slice than in the second group. Therefore a different thresholding technique is applied depending on the group the given slice belongs to. By using a dynamic threshold determined through an iterative procedure for the slices of the middle part of the lung, a threshold is determined empirically for all other slices. The Thresholding operators produce each slice which is transformed into a binary image where the foreground, i.e., the object we are interested in, consists of the lungs and all the rest is background. Figure 2 and Figure 3 represent the image after removing the background and after the implementation of thresholding process respectively.

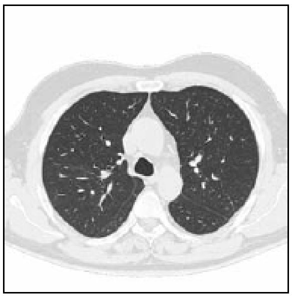

Figure 2.Image after background removal

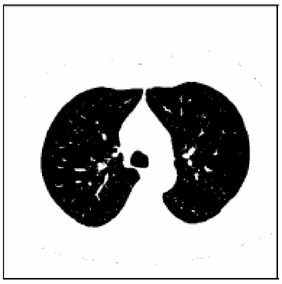

Figure 3.Image after Threshold processing

Afterwards, the morphological opening and closing operators is applied so as to improve the image and border definition to enhance the separation between distinct regions and to fill the gaps in the borders. Fig 4 shows the resultant image after applying the morphological operators

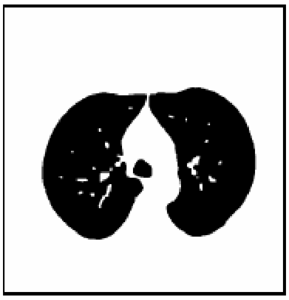

Fig. 4 The image after the opening and closing operators

Then we detect the image borders through a tracking algorithm that uses the Sobel operator and reduce the border size to one pixel using thinning algorithm. In this algorithm, a pixel is considered a border pixel if at least one of its neighbors is white. The algorithm starts building all the border pixels chains and then eliminates the excess pixels producing a one-pixel contour image. Fig 5 shows the resultant image with thinned borders

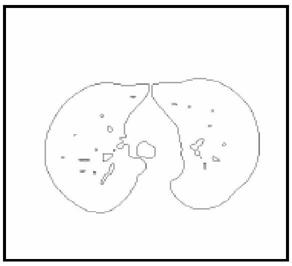

Fig. 5 The image with thinned borders

IV. NODULE EXTRACTION AND CAD SYSTEM

The Lung nodule detection is a very difficult step in every CAD system development. Actually, in CT lung images, nodules are frequently attached to blood vessels or to the pleura; and also the grey tone is so similar to vessel sections that traditional intensity-based methods are inappropriate. Instead, an effective nodule detection algorithm must take both the grey level and the object shape into account. In our CAD system we adopt a method that uses 3D shape information to identify spherical regions with a given grey level. The idea is to distinguish spherical from cylindrical (typically blood vessels) shapes analyzing a shape index (SI), defined in terms of 3D characteristics, extracted from sets of voxels with grey level in the range of the nodule intensity.

In the past decade, various CAD systems have been proposed for the detection of pulmonary nodules on CT images. The majority of CAD systems were developed and evaluated on single–detector row CT images with 5–10-mm section thickness, while more recent systems were assessed with thin-section single or multi–detector row CT images. The sensitivity for detecting nodules with reported CAD systems varied from 38% to 100%, and the false-positive detections per case ranged from 1 to 75. The performance of CAD systems appears to be highly associated with the section thickness (or reconstruction interval) and seems to be better on thin-section than on thick-section CT images.

Pulmonary nodules may be exemplified by very low CT values and/or low contrast, may have CT values similar to those of blood vessels and airway walls or may be strongly connected to them. This section primarily focuses on detection of nodule candidates by means of a 3D enhancing filter emphasizing spherically-shaped objects. This process is regarded as a first and foremost step of the technique in lung nodule detection. The second step relies on reducing the false-positive findings by employing a voxel-based neural approach. These two steps of the analysis are then applied on the lung volume identified by means of a segmentation algorithm, which defines the internal region [12].

The main aim should be that the automated nodule candidate detection should be characterized by a sensitivity value close to 100%. This assists us to avoid setting an a priori upper bound to the CAD system performances. On the basis of this proposal lung nodules are modeled as spherical objects and a dot-enhancement filter is applied to the 3D matrix of voxel data. The dot-enhancement filter endeavor to resolve the local geometrical distinctiveness of each voxel, by calculating the Eigen values of the Hessian matrix and estimating a magnitude and a likelihood functions that are exclusively configured to differentiate between the local morphology of linear, planar and spherical objects, the latest modeled as having 3D Gaussian sections [13], [14].

A multi-scale approach as proposed in [8] can be followed to improve the sensitivity of this filter to nodules of different sizes. Then Gaussian smoothing is implemented as directed in [13]. In meticulous, the Gaussian smoothing and the calculation of the Hessian matrix were pooled in a convolution between the original data and the second derivatives of a Gaussian smoothing function. The assortment and the number of intermediary smoothing scales must be resolute empirically on the basis of the dataset of available CT scans. After finding the filtered images, each voxel of the space matrix is assigned the maximum magnitude x likelihood value obtained from the different scales, multiplied by the relative scale factor. Then, the local maxima in the 3D space matrix are detected by applying a peak-detection algorithm to the filter output. The final filter output is a list of nodule candidates sorted by the value the filter function assigned.

Most False Positive findings that are crossings between blood vessels have to be reduced. To reduce the amount of FP per scan, voxel-based neural approach (VBNA) is developed. Each voxel of a region of interest (ROI) is characterized by a feature vector constituted by the grey level intensity values of its 3D neighbors (Figure 6) and the eigen values of the gradient and the Hessian matrices [15]. A feed-forward neural network is trained and tested by assigning each voxel either to the nodule or normal tissue target class. Finally a candidate nodule is characterized as "CAD nodule", in case if the number of pixels within its ROI is labeled as "nodule" by the neural classifier if it exceeds some qualified threshold.

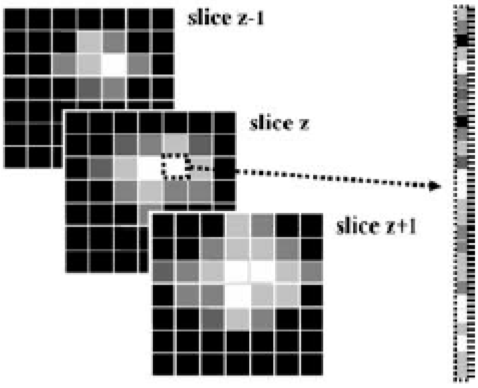

Figure 6 Voxel-based neural approaches for reduction of false-positive

V. Experimental Results

The CAD system was tested on a dataset of low-dose CT scans with reconstructed slice thickness of 1.25 mm. The performance of the CAD system was evaluated in terms of nodule detected (especially additional nodules detected) and the number of false-positives per CT study. There are several cases where the radiologist would have missed to find the lung nodule without using the CAD system. The database used for this study consists of 33 CT scans, containing 74 internal nodules with diameter between 5 and 12 mm. Each scan is a sequence of about 300 slices stored in DICOM (Digital Imaging and COmmunications in Medicine) format. Once the internal region of the lung has been recognized and the 3D dot-enhancement filter has provided the lists of nodule candidates, the VBNA is functional to reduce the amount of FP findings. Five three-layer feed-forward neural networks were qualified on five different random partitions of the teaching set into train and test sets.

The performances accomplished in each trial for the correct classification of individual pixels are reported in Table I, where the sensitivity and the specificity values obtained on the test sets and on the whole teaching set in the best three trials are shown. Among the results reported in Table I, the second one was more balanced with respect to sensitivity and specificity on the test set and achieved the best performance on the teaching set.

TABLE 1 Sensitivity & Specificity of Test & Teaching Set

Test Set		Teaching Set	
Sensitivity [in %]	Specificity [in %]	Sensitivity [in %]	Specificity [in %]
78.6%	83.4%	85.3%	85.9%
79.8%	81.5%	87.2%	86.4%
77.3%	85.2%	81.5%	86%

VI. Conclusion

This paper presented an approach using dot-enhancement filter for nodule candidate selection and a neural classifier for false-positive finding reduction. This paper presents and discusses the results of the method applied to computed-tomography (CT) examinations performed in a screening program for early detection of lung cancer. The results achieved by applying the system to a database, which is the information collected from a real time environment of hospital, of CT scans for digital images have been judged definitely well by experienced chest radiologists. The dot-enhancement pre-processing is a suitable tool for the identification of nodule candidates. VBNA implemented in this approach is an effective approach to the problem of false positives reduction.

In the future, enhanced techniques can be used in segmentation, feature extraction and classification phases of lung nodule detection to improve the performance. Further, the temporal comparison could improve the usefulness of CAD in the early detection of lung cancer. Lung Nodule Detection in CT Scans is an active area of research which is continuously emerging and there are many enhancements that can be included to make more efficient. Now-a-days, CAD software is useful to supplement radiologists' detection performance, without which many of the positive nodules may go undetected. However, at present, it is not adequate as a stand-alone procedure. Furthermore, all suspected lesions detected by CAD must be interpreted by radiologists to rule out false-positives.

References

[1] C. J. Murray and A. D. Lopez, "Mortality by cause for eight regions of the world: global burden of disease study," Lancet, vol. 349, no. 9061, pp. 1269–1276, 1997.

[2] C. I. Henschke, O. S. Miettinen, D. F. Yankelevitz, D. M. Libby, and J. P. Smith, "Radiographic screening for cancer. Proposed paradigm for requisite research," Clinical Imaging vol. 18, no. 1, pp. 16–20, 1994.

[3] B. J. Flehinger, M. Kimmel, and M. R. Melamed, "The effect of surgical treatment on survival from early lung cancer. Implications for screening," Chest, vol. 101, no. 4, pp. 1013–1018, 1992.

[4] H. MacMahon, R. Engelmann, and F. M. Behlen, "Computer-aided diagnosis of pulmonary nodules: results of a large-scale observer test," Radiology 2004, 213, pp. 723–726, 2004.

[5] E. R. Heitzman, "The role of computed tomography in the diagnosis and management of lung cancer: an overview," Chest 1986, 89 (suppl 4), pp. 237S–241S.

[6] M. A. Howe, and B. H. Gross, "CT evaluation of the equivocal pulmonary nodule," Computer Radiology 1987, vol. 11, pp. 61–67.

[7] Kenji Suzuki, Hiroyuki Abe, Heber MacMahon, and Kunio Doi, "Image-Processing Technique for Suppressing Ribs in Chest

Radiographs by Means of Massive Training Artificial Neural Network (MTANN)," IEEE Transactions on medical imaging, vol. 25, no. 4, pp. 406-416, 2006.

[8] Kazunori Okada, Dorin Comaniciu, and Arun Krishnan, "Robust Anisotropic Gaussian Fitting for Volumetric Characterization of Pulmonary Nodules in Multi-slice CT," IEEE Transactions on Medical Imaging, vol. 24, no. 3, pp. 409-423, 2005.

[9] Ingrid Sluimer, Mathias Prokop, and Bram van Ginneken, "Toward Automated Segmentation of the Pathological Lung in CT," IEEE Transactions on Medical Imaging, vol. 24, no.8, pp.1025-1038, 2005.

[10] Xujiong Ye, Xinyu Lin, Jamshid Dehmeshki, Greg Slabaugh, and Gareth Beddoe, "Shape-Based Computer-Aided Detection of Lung Nodules in Thoracic CT Images," IEEE Transactions on Biomedical Engineering, vol. 56, no. 7, pp. 1810-1820, 2009.

[11] M. Antonelli, G. Frosini, B. Lazzerini, and F. Marcelloni, "Lung Nodule Detection in CT Scans," World Academy of Science, Engineering and Technology, 2005.

[12] J. Heuberger, A. Geissbühler, and H. Müller, "Lung CT segmentation for image retrieval using the Insight Toolkit (ITK)," Medical Imaging and Telemedicine (MIT), August 2005.

[13] Q. Li, S. Sone and K. Doi, "Selective enhancement filters for nodules, vessels, and airways walls in two- and three-dimensional CT scans," Med. Phys., vol. 30(8), pp. 2040-2051, 2003.

[14] P. Delogu et al., "Preprocessing methods for nodule detection in lung CT," Computer Assisted Radiology and Surgery, Proceedings of the 19th International Congress and Exhibition, International Congress Series, vol. 1281, pp. 1099-1103, 2005.

[15] I. Gori, M. Mattiuzzi, "A method for coding pixels or voxels of a digital or digitalized image: Pixel Matrix Theory (PMT)," European Patent Application 05425316.6.

[16] ArmatoSG 3rd, McLennan G, McNitt-Gray MF, et al. Lung image database consortium: developing a resource for the medical imaging research community. Radiology 2004; 232: 739–748.

[17] GurcanMN, Sahiner B, Petrick N, et al. Lung nodule detection on thoracic computed tomography images: preliminary evaluation of a computer-aided diagnosis system. Med Phys 2002; 29: 2552–2558.

[18] ormanns D, Fiebich M, Saidi M, Diederich S, Heindel W. Automatic detection of pulmonary nodules at spiral CT: clinical application of a computer-aided diagnosis system. Eur Radiol2002; 12: 1052 -1057.

[19] GurcanMN, Sahiner B, Petrick N, et al. Lung nodule detection on thoracic computed tomography images: preliminary evaluation of a computer-aided diagnosis system. Med Phys 2002; 29: 2552–2558

[20] HeitzmanER. The role of computed tomography in the diagnosis and management of lung cancer: an overview. Chest 1986; 89(suppl 4): 237S–241S.

M. Gomathi, Member of IACSIT, received the Master of Computer Applications degree in 1998 from Bharathiar University. Her Masters Thesis research was on "Handwritten Character Recognition", and has completed her M. Phil, in Computer Science at Bharathiar University in the year 2004. Currently she is working as an Assistant Professor in Velalar College of Engineering and Technology and a research scholar at Kongu Engineering College, Anna University. Her area of research is in Medical Imaging.

Dr. P. Thangaraj received the Bachelor of Science degree in Mathematics from Madras University in 1981 and his Master of Science degree in Mathematics from the Madras University in 1983. He completed his M. Phil degree in the year 1993 from Bharathiar University. He completed his research work on Fuzzy Metric Spaces and awarded Ph.D degree by Bharathiar University in the year 2004. He completed the post graduation in Computer Applications at IGNOU in 2005. His thesis was on "Efficient search tool for job portals". He completed his Master of Engineering degree in Computer Science in the year 2007 from Vinayaka Missions University. His thesis was on "Congestion control mechanism for wired networks". Currently he is designated as Dean of School of Computer Technology and Applications at Kongu Engineering College, Autonomous institution affiliated to Anna University. His current area of research interests are in Fuzzy based routing techniques in Ad-hoc Networks.