Computer Aided Detection of Lung Nodules in Multislice Computed Tomography

P. Korfiatis , C. Kalogeropoulou , L. Costaridou

***Abstract*— Early detection may be of critical importance in lung cancer prognosis. Multi-detector Computed Tomography (CT) increases sensitivity in early lung cancer detection by potentially identifying nodules of smaller size. A Computer Aided Detection (CAD) system for automatic identification of lung nodules is proposed. The system is multistage, including segmentation of lung boundaries, initial nodule pick up and False Positive (FP) reduction. The system is targeted to improve lung boundary identification by an automatic thresholding a approach, capable of dealing with juxta pleura nodules. A selective enhancement filter was implemented in combination with minimum error thresholding for initial nodule pick up to deal with vessels abutting small nodules. FP regions were subsequently removed using a Support Vector Machine (SVM) classifier employing morphological features extracted from corresponding nodule candidate regions of the enhanced and the original images. The proposed automated scheme was tested on a slice data set containing 279 nodules from 21 cases available by the Lung Image Database Consortium. System performance on a slice basis provided sensitivity of 81%, with an average of 5 FPs per slice. Further analysis of the slice dataset with respect to size, contrast and location of nodules provided sensitivities of 81%, 83% and 85% for nodules of small size, low contrast and near pleura. The proposed CAD scheme may be a useful tool in assisting radiologists in lung nodule detection.**

I. Introduction

LUNG cancer is the leading cause of cancer-related death in both men and women, accounting for approximately 30% of all cancer deaths. Early detection and treatment of lung cancer can improve chances for survival [1].

Multislice computer tomography has demonstrated improved lung nodule detection sensitivity in comparison to classical radiography but is associated with the disadvantage of large number of CT slices that have to be reviewed by radiologists when searching for lung nodules. Thus, Computer Aided Diagnosis (CAD) schemes are introduced aiming to assist radiologists in the lung nodule detection task.

Several methodogical approaches have been proposed in lung nodule Computer Aided Detection (CAD) systems utilizing image processing and classification techniques. One of the pioneer methods in this area was proposed by Giger et al. [2]. Gurcan et al. [3], Armato et al. [4- 7] and Arimura et al. [8], have recently reported the most representative for lung nodule detection systems on helical Computed Tomography (CT) images.

These studies indicated that computerized detection in helical CT is promising. However, their performance may be limited by the size of collimation of 5 or 10 mm.

Recently, multi-detector helical CTs with thin slice thickness are available for lung cancer screening, capable of detecting smaller nodules, free of partial volume effect as compared to thick slice helical CT. Newer CAD systems are developed with thin slice single-[9] or multi-detector row CT images [10]. Further investigation is needed in thin slice CT regarding CAD system applicability and performance, especially with respect to False Positive (FP) reduction.

In this paper, a lung nodule computer aided scheme is reported utilizing thin slice CT data. This method emphasizes on automation of the pre-processing stage and use of a Support Vector Machine (SVM) classifier for final nodule detection. The detection scheme is demonstrated using a reference dataset provided by Lung Image Database Consortium (LIDC), a cooperative effort of National Cancer Institute (NCI) [11].

II. Materials and methods

A. Data set

The thin slice thoracic CT database available by LIDC consists of 21 nodules and boundary definition of the nodules from case overlays. The 21 scans in the database comprise considered consist of a total of 798 slice images, with the number of slices per scan raging from 28 to 62, with mean of 38 slices per scan. The 21 nodules were found in 279 slices of a total of 798 slices. 219 slices were used to test system performance. Each CT slice has an image matrix of 512 x 512 pixels. Pixel size was raging between 0.625 and 0.742 mm with mean value of 0.692 mm, depending on the physical size of the patient. Slice thickness was 0.625 mm.

In addition for each nodule a thoracic radiologist has indicated it's location with respect to lung parenchyma or pleura. Furthermore based on nodule boundary definitions available on LIDC nodule effective diameter and contrast were quantitatively calculated for the 279 nodules. Figure 1 represents the distribution of effective diameter for the 279 nodules. Nodule size ranged from 3 mm to 25 mm, with the

Manuscript received June 30, 2006.

P. Korfiatis is with the University of Patras, School of Medicine, Department of Medical Physics, 265 00 Patras, Greece (korfp@upatras.gr)

C. Kalogeropoulou.,is with University of Patras, School of Medicine, Department of Radiology, 265 00 Patras, Greece

L. Costaridou is with is with the University of Patras, School of Medicine, Department of Medical Physics, 265 00 Patras, Greece (phone: +30-2610-969111; fax: +30-2610-969113; e-mail: costarid@upatras.gr).

majority of nodules having size less than 10 mm and intermediate contrast.

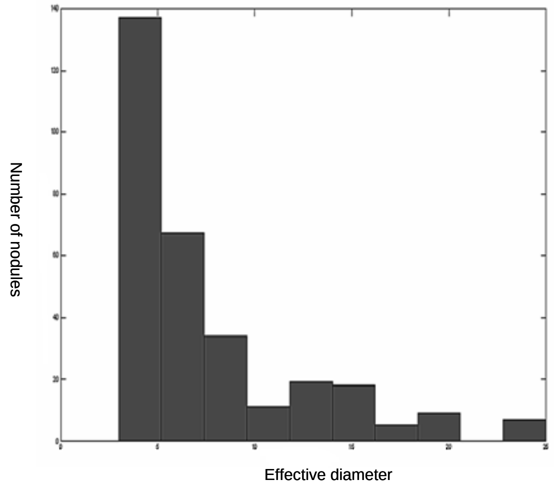


Fig.1. Distribution of lung nodule effective diameters.

B. Lung field segmentation

The overall scheme for automated lung nodule detection in thin slice CT images is shown in figure 2.

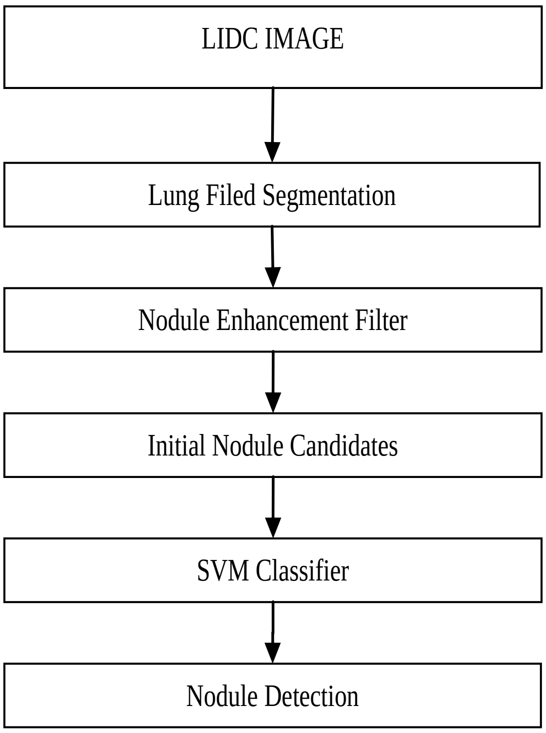
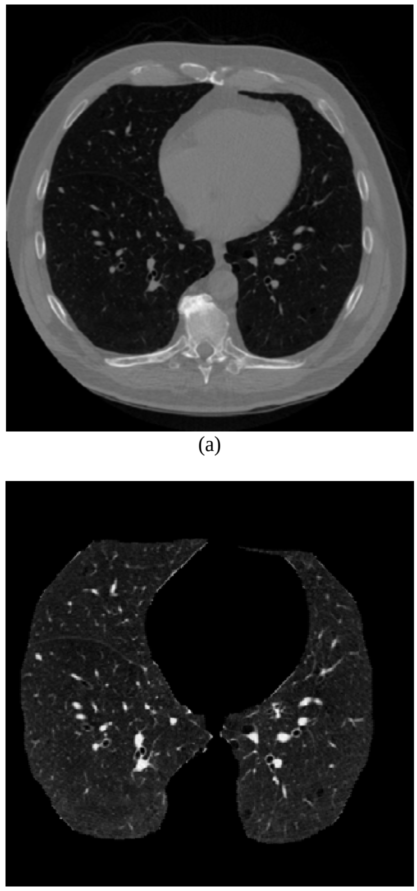


Fig.2. The overall scheme for automated lung nodule detection.

The first step is segmentation of lung regions. One important issue in lung region segmentation is that of juxta-pleural nodules, as nodules adjacent to the pleura may be excluded during segmentation of lung regions.

In this study an automated segmentation approach is adapted to deal with experimentally set thresholds for lung boundary detection [2 -5 8 10]. Segmentation is performed with minimum error thresholding, according to Kittler et al. [12] applied on an edge enhanced image, using Canny filter [13]. In case of exclusion of a juxta-pleural nodule a morphological closing operation was applied for smoothing the outline of the segmented lung region and to include this type of nodule. A disk with varying radius was used for this purpose, followed by region filling [4 13].

Figure 3b demonstrates the result of application of lung field segmentation on the original image 3a.


(a)

(b)

Fig. 3. a)Original image b)Final segmentation result

C. Nodule candidate identification

A variety of techniques have been proposed for initial nodule identification, including thresholding, k-means clustering as well as selective enhancement filters. In the present study a selective nodule enhancement filter was applied to the segmented lung region for identification of initial nodule candidates.

This filter, proposed by Li at al. [14] is targeted to distinguish nodules, blood vessels and airway trees. It is based on eigen value analysis of the Hessian matrix at each pixel of an image. The effect of nodule enhancement filter is shown in figure 4.

Nodule enhancement filtering generates several areas, which are considered as "initial" nodule candidates and represented by their centroids.

Fig. 4. Result of nodule enhancement filter at the segmented lung region image.

D. *False positive reduction*

Several approaches have been proposed for FP reduction in CAD systems for lung nodule detection. Most common approaches used are rule based schemes, Linear Discriminant Analysis (LDA), and neural networks [4, 6, 15].

In this study, categorization of nodule candidates as ‘nodule’ or ‘non-nodule’ is based on a pattern recognition approach employing an SVM classifier [16, 17]. The SVM classifier used morphological features generated from both enhanced and original image data. Two training sets were constructed using original and enhanced ROIs each one cropped from 60 slices. The cropped ROIs correspond to 60 nodule patterns, representative of the spectrum of morphology of nodules contained in the dataset, as well as 100 structure noise patterns. For each pattern morphological features described in the next paragraph, were calculated.

A ROI with size of 41 x 41 pixels was selected corresponding to the maximum nodule size encountered in this study. Lung nodule regions were segmented with the use of an automated region growing algorithm.

III. RESULTS

A data set was constructed from LIDC database, considering nodules in individual slices of the above data set. Thus, a database containing 279 slices, each one containing one nodule, was generated. The system was tested on 219 nodules, excluding the 60 nodules used in order to train the classifiers.

The system's performance on this database is summarized in table 1. In the initial step, 98% (215/219) of initial nodule candidates were detected, with an average of 95 FPs per slice. The average size of the four nodules missed was 4 mm. After the application of the first classifier the FPs were reduced to 53 per slice and the sensitivity was reduced to 96% (211/219). Following, the application of the second classifier, sensitivity was reduced to 81% (178/219) with the number of FPs per slice reduced to 5. The 41 nodules missed had an average size of 6,2 mm.

Furthermore, an effort was made to analyze detection performance with respect to size, contrast and location of nodules shown in table 2. Nodule detection performance with size below 15 mm and over 15 mm was 81% (142/162 and 43/54 respectively) and 5 FPs in both cases. The low contrast nodule subset contained 41 of the available 219 nodules, with contrast ranging between 0.1 and 0.4. The detection sensitivity for this sub category of nodules was 83% (34/41) and the FPs were 6 per slice. Increased sensitivity of nodules with low contrast is probably attributed to the increase sensitivity of the nodule enhancement filter.

TABLE 1. PERFORMANCE OF EACH STAGE OF THE AUTOMATED NODULE DETECTION METHOD ON SLICE BASIS.

	SENSITIVITY (%)	FPS/ SLICE
INITIAL PICK UP	98	95
SVM CLASSIFIER-ENHANCED IMAGE	96	53
SVM CLASSIFIER - ORIGINAL IMAGE	81	5

Nodules positioned near pleura have great interest in the evaluation of a lung nodule detection scheme; these are mostly high contrast nodules and could be missed at the segmentation stage. Using a subset of 37 nodules attached or located near pleura the proposed method achieved detection of 85% (29/34) with 5.3 FPs per slice

TABLE 2. PERFORMANCE OF THE AUTOMATED NODULE DETECTION METHOD ON SLICE BASED SUBSETS.

	SENSITIVITY (%)	FPS/SLICE
NODULE SIZE >15mm	81	5.0
NODULE SIZE <15mm	81	5.0
LOW CONTRAST	83	6.6
NODULES NEAR PLEURA	85	5.3

IV. DISCUSSION

In this paper, we have described a CAD scheme for the automated detection of lung nodules on thin slice CT.

The system is based on an automated detection approach utilizing a classifier rather than a rule based scheme.

Specifically a SVM scheme was implemented aiming to maximize classification accuracy. Two approaches were explored for FPs reduction, utilizing morphological features extracted from both original and enhanced image data. The system was trained with nodule patterns, representative of the spectrum of morphology of nodules contained in the dataset, as well as structure noise patterns.

Automated delineation of lung boundaries is considered another advantage of he proposed system. The anticipated effect of alteration of lung region boundary shape introduced by closing and opening operation, following minimum error thresholding is minimized due to the small size of disk radius used. The potential use of other segmentation techniques, such as classifier based segmentation, could potentially deal with more accurate lung boundary delineation.

The performance of lung CAD systems appears to be highly associated with the section thickness and seems to be better on thin-section than on thick section CT images. In this study 98% (table 1) of nodules are detected in the initial pick up stage, while Arimura et al. reported 91% pick up using slice thickness of 10mm.

The performance of the proposed system yielding over 80% sensitivity, but as expected increased number of FPs (5 per slice) could be potentially attributed to the partial CT data used characterized by luck of continuity of the 3D vessel structure. Recently Bae et al. reported an automated detection system using 2D approach for the pre-processing stage and 3D features for classification yielding sensitivity over 90% with number of FPs varying (4-6.4) depending on nodule size.

Improved design of the presented CAD scheme requires the use of data set covering the entire lung volume and increased number of cases. Furthermore use of additional expected to increase system performance, while reducing the number of FPs.

Analysis of the performance of the proposed scheme has demonstrated encouraging results, with respect to nodule size, contrast and position (table 2). Finally, it is felt that automated lung nodule detection may be useful tools in assisting radiologists in lung nodule detection in low dose multislice CT.

V. CONCLUSION

A fully automated lung nodule detection scheme has been developed and evaluated with a small size database of multi-detector thin slice CT, publicly available from LIDC. A combination of automated preprocessing and classification methods were used achieving 81% detection of nodules with 5 FPs per slice on a slice-based sample. Further analysis of the proposed system with respect to nodule size, position and contrast has demonstrated promising performance of the proposed scheme.

REFERENCES

[1] American Cancer Society, “American Cancer Society Cancer factys and figures 2005”, www.cancer.org 2005.

[2] M.L. Giger, K.T. Bae, H. MacMahon, Computerized detection of pulmonary nodules in computed tomography images, Invest. Radiol. 1994; 29 459– 465.

[3] Gurcan MN, 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.

[4] Armato SG III, Roy A, Macmahon H, Li F, Doi K, Li S, Altman MB. Evaluation of Automated Lung Nodule Detection on Low-dose Computed Tomography Scans From a Lung Cancer Screening Program1, Acad Radiol 2005; 12:337–346.

[5] Armato SG III, Giger ML, MacMahon H. Automated detection of lung nodules in CT scans: preliminary results. Med Phys 2001; 28:1552–1561.

[6] Armato SG III, Altman MB, Wilkie J, et al. Automated lung nodule classification following automated nodule detection on CT: A serial approach. Med Phys 2003; 30:1188–1197.

[7] Armato SG III, Altman MB, LaRivière PJ. Automated detection of lung nodules in CT scans: effect of image reconstruction algorithm. Med Phys 2003; 30:461–472.

[8] Arimura H, Katsuragawa S, Suzuki K, Shiraishi J, Li S, Doi K. Computerized scheme for automated detection of lung nodules in low-dose computed tomography images for lung cancer screening, Acad Radiol 2004; 11:617–629.

[9] Brown MS, Goldin JG, Suh RD, McNitt-Gray MF, Sayre JW, Aberle DR. Lung micronodules: automated method for detection at thin-section CT-initial experience. Radiology 2003; 226:256-262.

[10] Bae KT, Kim JS, Na YH, Kim KG, Kim JH. Pulmonary nodules: automated detection on CT images with morphologic matching algorithm-Preliminary results Radiology 2005; 236:286-294

[11] The Lung Image Database Consortium. Available at http://imaging.cancer.gov/programsandresources/InformationSystems/LIDC

[12] Kittler J., Illingworth J. Minimum Error Thresholding. Pattern Recognition 1986; 19:41-47.

[13] Gonzalez, Rafael C . Woods , Richard E., Digital image processing. Addison-Wesley , 1992.

[14] Li Q, Sone S, Doi K. Selective enhancement filters for nodules, vessels, and airway walls in two and three-dimensional CT scans. Med Phys 2003; 30:2040–2051.

[15] Suzuki K, Armato SG 3rd, Li F,Sone S , Doi K. Massive training artificial neural network (MTANN) for reduction of FPs in computerized detection of lung nodules in low-dose computed tomography. Med Phys 2003; 30:1602–1617.

[16] Ruiz F.V., Nasuto J.S., Biomedical-Image Classification Methods and Techniques In: Medical Image Analysis Methods, edited by L. Costaridou (Taylor & Francis Group LCC, CRC Press: Boca Raton, FL, 2005), pp. 137- 183.

[17] Papadopoulos N.A., Plissiti E.M., Fotiadis I.D., Medical-Image Processing and Analysis for CAD Systems In: Medical Image Analysis Methods, edited by L. Costaridou (Taylor & Francis Group LCC, CRC Press: Boca Raton, FL, 2005), pp. 51-86.