Computer Aided Detection (CAD) System for Automatic Pulmonary NoduleDetection in lungs in CT Scans

[1]Veeresh Biradar, [2]Upasana Patil

[1, 2]*Faculty*

Dept.of Computer Science and Engg LAEC, Bidar, Karnataka, India

--**Abstract**--
The main motto of this paper is to evaluate the performance of the Automated CAD for Lung Nodule Detection using CT Scans. The CAD system is applied to CT scans collected in a Screening program for lung cancer detection. Each scan consists of a sequence of about 400 slices stored in DICOM (Digital Imaging and Communications in Medicine) format. All malignant nodules were detected and a very low false positive detection rate was achieved. The performance is evaluated as a fully automated computerized method for the detection of lung nodules in computed tomography (CT) scan in the identification of lung cancers that may be missed during visual interpretation.

I. Introduction

CT (Computed tomography) is the most sensitive and specific diagnostic modality for detecting pulmonary nodules (1 3). The reliable detection of small pulmonary nodules is crucial for the early detection of lung cancer and other nodular lung diseases (1). However, the radiologist's sensitivity for the detection of small pulmonary lesions is limited (1). Nodules may not be detected on CT images because of factors such as a failure to perform the necessary systematic search, or an understandable inability to assimilate the vast amount of information contained in the multiple images containedin a CT examination (2, 4, and5).Especially in the central lung regions, nodules can go undetected because they are confused with blood vessels imaged in cross section (1, 2). For the differentiation between spherical (nodules) and tubular (vessels) structures, contiguous slices have to be evaluated. This is a time consuming task and susceptible to error. However, the utilization of automatic nodule detection in clinical situations has recently become possible, due to the dramatic increase in computer performance that has come about over the past decade (1, 3). The purpose of this study was to evaluate the efficacy of using a computer-aided detection (CAD) workstation for the detection of lung nodules in clinically acquired chest CT examinations.

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 help to improve a radiologist's performance in the detection of pulmonary nodules [6] without which, it would become a much time consuming process for the radiologist and the CAD systems automatically.

CAD software is useful to supplement radiologists' detection performance. 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. In the future, temporal comparison should further improve the usefulness of CAD in the early detection of lung cancer.

II. extraction of pulmonary nodule

In order to extract the pulmonary nodule, we perform the following actions. First we remove the background (i.e., the pixels with the same grey level as the lungs but located outside the chest) from the image. To this aim, due to the high similarity between the grey levels of the lungs and

the image background (see Fig. 1,2), we cannot simply apply a thresholding technique. Instead we use an ad-hoc operator 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.

In the first and last groups the lungs image represents a smaller percentage of the slice than in the second group. Thanks to the thresholding operator each slice 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 (see Fig. 4).
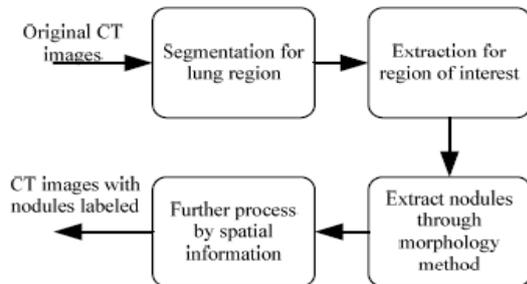
Fig. 1. The basic steps for automatical detection of pulmonary nodules

Fig. 2 A DICOM image

Otherwise, the scan is interrupted along the direction under examination and the successive row/column is analyzed in a similar way. The image produced by this operator (shown in Fig. 3) is converted to a binary image by means of a thresholding technique that uses either a static. depending on the lung zone the slice belongs to image. The detection method proposed in this paper is based on the lung anatomical structure and spatial characteristics. The image consists slices of lungs.

Fig. 3 The Image after Background Removal.

Fig. 4 The Image after Thresholding.

Afterwards, we apply the morphological opening and closing operators so as to improve the image and border definition; this allows us, in particular, to enhance the separation between distinct regions and to fill the gaps in the borders. The resulting image is shown in Fig. 5.
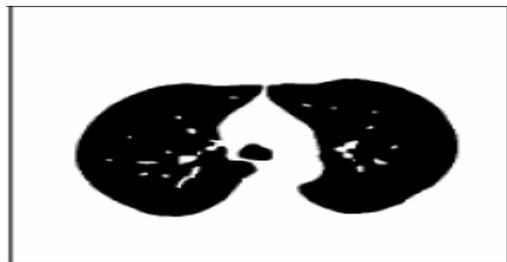
Fig. 5 The image after the opening and closing operators.

Pulmonary lobes. Then we reconstruct the pulmonary lobes borders so as to reinsert the nodules adjacent to the pleura (juxta-pleura nodules) previously suppressed by the thresholding operator.
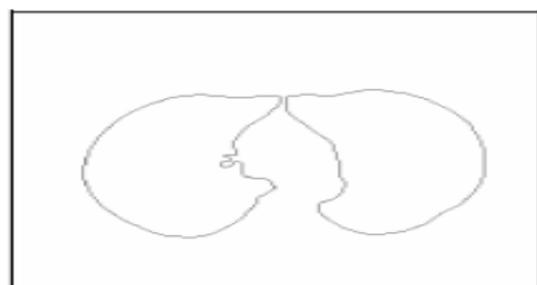
Fig. 6 Two chains representing the pulmonary lobes.

In order to rebuild the pulmonary lobes border parts that have been erroneously eliminated, for each pair of border points, we calculate two distances: the Euclidean distance d1 and the minimum distance in pixels d2 between the two points. We then compute the ratio d2/d1: if it is

greater than a given threshold the two points are candidates for a possible reconstruction.. If the condition is satisfied, then the border between the pair of points is rebuilt, i.e., the two points are connected by a line (see Fig 7).
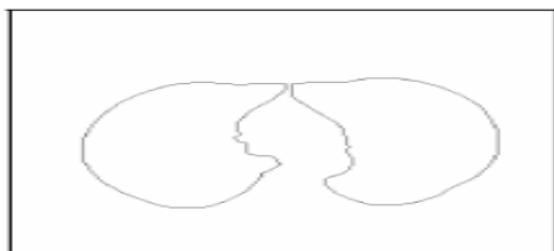
Fig.7 Reconstructed pulmonary lobes.

Finally, we apply a region filling operator to the pulmonary lobes chains in order to reintroduce the original values of grey levels inside the lungs. The resulting images (see Fig. 8), which contain only the lung regions, are input to the nodule detector. The detection method proposed in this paper is based on the lung anatomical structure and spatial characteristics. In this the image again reconstructed from original image after applying different steps as explained above. The restored image reconstruct the pulmonary lobes from original image as shown fig.8.
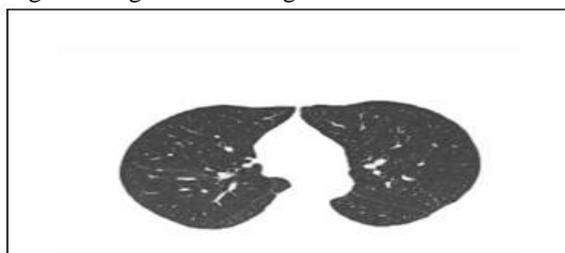
Fig. 8 Restored image.

III.   Lung Nodule Detection

Lung nodule detection is a very difficult step in a CAD system development. Actually, in CT lung images, nodules are frequently attached to blood vessels or to the pleura; further their grey tone is so similar to vessels 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. More precisely, let v(x,y,z) denote an image voxel (i.e., a 3D point) and I(x,y,z) its intensity. For each voxel we define an infinitely differentiable 3D function f(x,y,z) as the convolution of I(x,y,z) with a smoothing filter g(x,y,z): $f(x, y, z) = I(x, y, z) \oplus g(x, y, z)$. In this case we use 3D Gaussian function as smoothing filter.

IV.   Automated Lung Nodule Detection Method

The CAD system consists of CAD server and CAD workstation. The CT data are transferred from the CT scanner to the CAD server over the DICOM protocol [10, 11]. The CAD server accepts and analyzes the scans by segmenting the lung parenchyma from the vessels, mediastinum, and chest wall. Other techniques are used to include lesions that may be touching the chest wall. The CAD workstation is user controlled. The findings of CAD are presented in three windows on the monitor the original 2D axial images and a lung nodule map.

V.   Experimental Results\

CAD standalone sensitivity for the 52 solidnodules ≥ 4 mm that were present in the 25 current examinations was 65.4% (34/52). The 18 nodules missed by CAD ranged between 4.0 and 11.9 mm in size and their locations were juxtapleural (n = 4), peripheral (n = 9), and central (n = 5). As is customary when evaluating CAD algorithm performance, the CAD false-marker rate is determined on normal cases. There were 78 pulmonary nodules in the 37 scans with nodules. Their mean diameter was 7.2 mm (range 4 15.4 mm). The size distribution of the nodules was 65 (83%) in the diameter range of 4 10 mm, 12 (16%) in the range of 10 15 mm, and one (1%) in the range of 15 20 mm. The zonal distribution of the nodules was 54 (69%) in the outer third of the lung, 21 (27%) in the middle third, and three (4%) in the inner third shown in fig 9 .
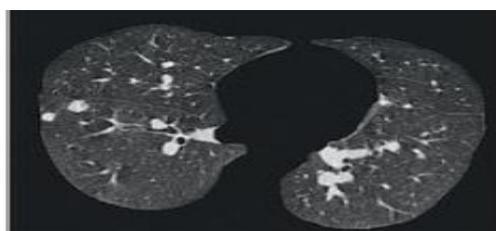
Figure 9. After a Corrected lung boundary was determined
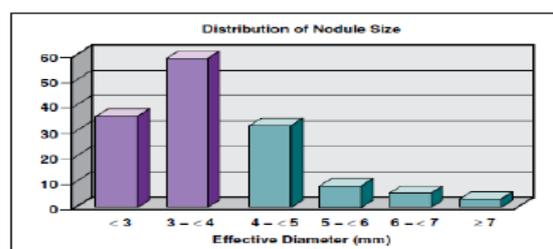
Fig.10—Histogram shows distribution of effective nodule diameters for 149 lung nodules ≥ 2 mm identified on 54 current CT examinations.

In addition to the standard 2D axial images, two other views are provided on two smaller screens. In the upper left corner, a lung map corresponding to a maximum intensity projection (MIP) view of the coronal images references the location of the CAD marks. In the lower left corner, an interactive 3D view of the CAD-detected nodule (highlighted in green) is displayed together with the surrounding pulmonary vasculature, which can be rotated in real time to permit the reader to decide if the candidate nodule is truly a real nodule and, if so, to determine if the CAD segmentation correctly includes only that portion of the nodule without adjacent non nodular structures, such as adjacent vessels and pleural surfaces shown in fig.10.

VI.   Conclusion And Future Work

We have described a CAD system for automated segmentation and reconstruction of pulmonary parenchyma, and nodule detection. The results achieved by applying the system to a database consisting of eight CT scans with a total of more than 2400 digital images have been judged definitely good by experienced chest radiologists. In particular, as regards nodule detection, all malignant nodules were detected and a very low false-positive detection rate was achieved.

In the future research, we will improve the method for excluding interference and propose an effective method to detect the nodules as many as possible. For example, we will category the possible type of the nodules and the interference structures. But we will use the enhancement way to make them up. After that a tree branch will be used to separate the different types deeply. It will cost the processing speed if we accomplish the ideas above, and we'll concern the time that consumed as well.

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