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Automatic Detection and Segmentation of Lung Nodule on CT Images

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***Abstract*—Lung nodule detection and segmentation is important for clinical diagnosis. This paper proposes a lung nodule detection and segmentation method based on a fully convolutional network (FCN), the level set method and other image processing techniques. Firstly, lung CT images are put into the FCN for lung segmentation. Secondly, lung nodules are detected inside the lung area using the threshold method and other image processing techniques. Finally, the detected lung nodules and their spiculation are segmented by the level set method and threshold method based on the coordinate system transformation. Experimental result shows that the proposed method can effectively detect and segment lung nodules with the detection accuracy of 100% and the dice overlap index of segmentation of 0.9. Therefore, this method can provide helpful references for clinical diagnosis on lung cancers.**

Keywords-detection, segmentation, lung nodule, lung CT images, deep learning

I. INTRODUCTION

Lung cancer has been the mainly threaten of health in China with its increasing incidence rate and death rate and has become one of the most serious public health problem, attracting more and more public attention. In recent years, the incidence rate of lung cancer in China has reached 733.3 thousand, ranking first in all types of cancer. With clinical data, researchers find out that the 5-year survival rate of lung cancer patients increases significantly from 14% to 49% if they get treated in the early stage of lung cancer [1]. So the early treatment plays an important role in patients' final survival rate. Since the main manifestations of lung cancer in the early stage is lung nodule, the detection and segmentation of lung nodules is important to clinical diagnosis of lung cancers.

Nowadays, the computed tomography (CT) is the most commonly used tool in clinical diagnosis for lung cancers. Lung nodule is the granulomatous lesion in lungs, which usually appears as a circle with a diameter of 3-30 mm in lung CT images. Accurate segmentation of lung nodules is of great significance for it can provide the most precise information of disease for the following clinical diagnosis [2].

Lung nodules are sometimes hard for the manual detection and segmentation for their uncertain location and low intensities. This has already become a clinical problem for its time consuming and low true positive rate (TPR). With the development of medical imaging technology, the amount of medical image data grows faster and faster. It is nearly impossible for doctors to manually segment lung nodules on lung CT images without making mistakes because a single patient can generate thousands of lung CT images. So it is necessary to develop a computer aided diagnosis (CAD) system to relieve the stress of clinical doctors and improve the detection accuracy.

Researchers have conducted series of experiments on segmentation of lung nodules based on threshold methods [3]. In clinical diagnosis, lung nodules are easy to identify because of their typical shape [4]. But in a CAD system, bone and bronchial interferences on lung CT images make it hard for the system to figure out the real lung nodule, leading to the increase of the false positive rate (FPR).

So, it is necessary to develop a method which can eliminate such interference and perform well on lung nodule detection. So that we can execute lung nodule segmentation on areas containing real lung nodules.

In this paper, a method combined with the deep learning and image processing techniques is proposed for lung nodule detection and segmentation. This method is good at eliminating the bone and bronchial interference which conventional methods may be not good at.

The rest of this paper is arranged as follows. In section II, we will introduce the LIDC database used in our experiments and each part of the proposed method including fully convolutional networks, the threshold segmentation and the level set method. In section III, we will show the result of lung segmentation, lung nodule detection and lung nodule segmentation with their corresponding images. In section IV, we discuss about the result of each part of the proposed method and make plan for the future work. Finally we conclude our research in section V.

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II. MATERIAL AND METHODOLOGY

A. *Materials for experiments*

Data used in this paper is from The Lung Image Database Consortium (LIDC) [5], which contains 1010 CT scans of lung cancer patients. The LIDC database provides not only lung CT images, but the diagnosis information about each suspected lung nodule as well. From the LIDC database, we can get the coordinate of lung nodule's outline and generate the binary image from the given coordinate as golden standard for evaluating the segmentation result of each lung nodule.

For an example, Figure 1 shows a typical lung CT image with a lung nodule at the right bottom.

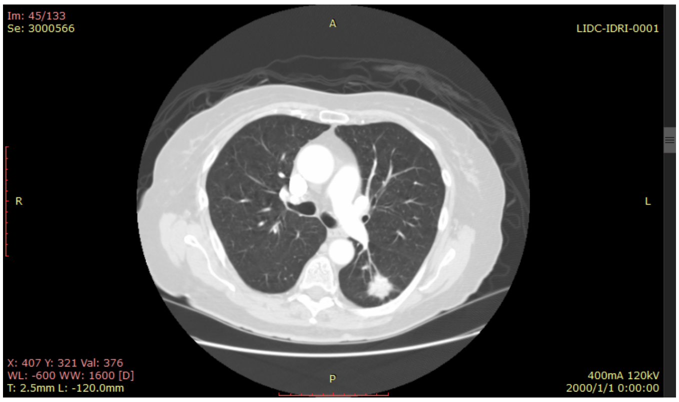

Figure 1. A typical lung CT image with a lung nodule at the right bottom.

B. *Method*

Figure 2 indicates the proposed method in diagram, which contains four steps to get the result of lung nodule segmentation.

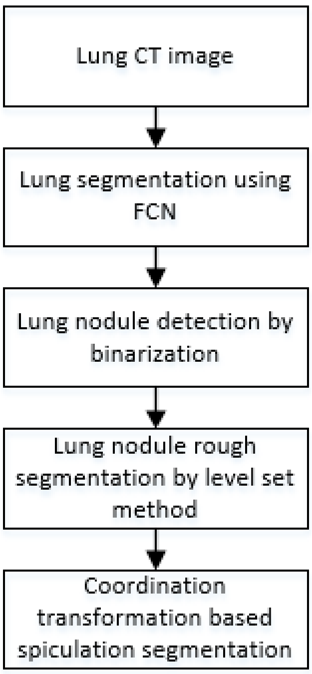

Figure 2. The diagram of proposed method.

First, the lung on a CT image is segmented using a fully convoluntional network (FCN). Then, lung nodules are detected within the lung areas using the adapative threshold method and the false positive objects are eliminated by several criterias. After that, a level set method are used to extract the main part of lung nodules in the interested regions given by the above lung nodule detection. Finally, lung nodules images are transformed into polar coordinates system for spiculation segmentation. The final result of lung nodule segmentation is combining the main part of lung nodule and spiculation together.

- Lung segmentation

The contrast between lung nodules and the background area is strong, so it is easy for doctors to separate lung nodules and the background area. But the sections of bones and bronchial in the body are also strongly contrasted with the background area on the image. This makes it hard to use the threshold segmentation to get regions of interest containing lung nodules easily. To eliminate the interference of bones and bronchial, the FCN is used for lung segmentation before lung nodule segmentation [6].

FCN is chosen for lung segmentation for several reasons. First, FCN can accept input images in any size and provide pixel-level result of lung segmentation. Second, FCN is more effective than traditional convolutional networks(CNN) because it avoids repeated storage and repeated calculation caused by sliding window in CNN.

The architecture of the FCN used in our experiment is shown in Figure 3, which contains 9 convolutional layers, 4 pooling layers and 3 upsampling layers. The network is transformed from the VGG-16 which is used for the natural image classification. We change the last three fully connected layers for classification into upsampling layers [7]. The layer before upsampling reduces the input images by 32 times. To get the output with the same size as the input images, three upsampling layers have to enlarge the output of the last pooling layer by 32 times. This is achieved by interpolation. Finally, we will have the pixel-level result of lung segmentation.

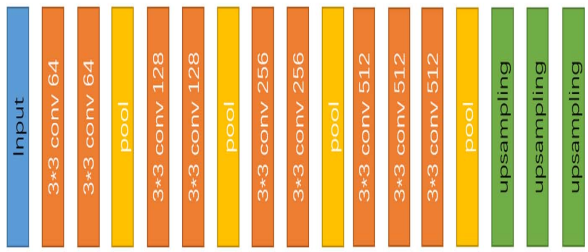

Figure 3. The architecture of the FCN used in our experiment.

- Lung nodule detection

After lung segmentation, bone interference has been removed. So lung nodules can be detected by the threshold method inside the segmented lung area. As mentioned in introduction, lung nodules should have a rounded contour and diameter of 3-30 mm. So after using the threshold method, features such as the roundness and diameter are used to eliminate bronchial interference. The roundness is defined as the ratio of the long diameter to the short one. Here the roundness of 1 means the closest circle, while the roundness of 0 means the least close to a circle.

- Lung nodule segmentation

The level set method is an extensively used method for image segmentation. In level set segmentation, an energy function is defined as a closed curve that segments the image. The energy function is minimized iteratively by the gradient descent [8]. So we choose the localized level set method for lung nodule segmentation. This method considers localized statistics to find the boundary of objects on images and get better results than traditional methods [9]. The initial contour is given by the result of lung nodule detection.

- Spiculation segmentation

Spiculation is an important clinical feature of lung nodules because it provide the important information for doctors to judge whether the lung nodule is benign or malignant. So, it is vital to preserve spiculation in lung nodule segmentation results for further diagnosis. If we exclude speculation in lung nodule segmentation, doctors may wrongly classify lung nodules.

After obtaining the main part of lung nodules, the coordinate system transformation is applied for spiculation segmentation. In the Cartesian coordinate system, the spiculation tends to radially surrounds lung nodules, which makes it hard to extract. In the polar coordinate system, spiculation approximate to be perpendicular to the outline of lung nodules. This makes it convenient to extract the spiculation from the background after image enhancement. The enhancement is achieved by applying linear filters.

Combining the spiculation and the main part of the lung nodule together, the final result of lung nodule segmentation is obtained.

III. EXPERIMENTS AND RESULTS

A. *Lung segmentation*

For 2803 lung CT images containing lung nodules wo have, we use 2000 images for training the FCN and the rest for validation. After 5000 iterations of training, the FCN proposed gets good segmentation result for lung. Although some part of outline is blurred, the overall accuracy of lung segmentation is satisfied. The accuracy reaches 90.55%. The accuracy is defined by dice overlap index.

For an example, the result of lung segmentation is shown in Figure 4. As we can see, the interference of bone is all eliminated. However, the outline of the lung is a little bit blurred and smooth because of the interpolation used in upsampling layers mentioned in the FCN architecture. The upsampling layers make the FCN insensitive to the details of the images. Considering that we just want to get lung areas containing lung nodules for the further experiment, the missing details of the outline can be ignored as long as the lung nodules are in the lung area segmented.

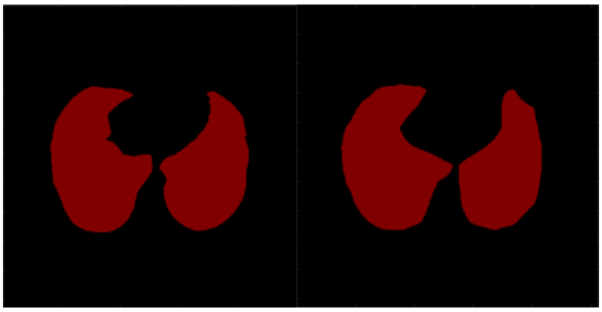

Figure 4. An example of lung segmentation result.

B. *Lung nodule detection*

Applying the threshold method inside of the lung areas obtained by the FCN, lung nodules and other non-background objects are extracted. These objects are shown in Figure 5 for an example. Regions of colors in different gray levels represent different objects including lung nodules and bronchial sections.

Figure 5. Lung nodule detection result without selection

As mentioned before, lung nodules are different from other interference in size and shape for their unique characteristic. So after selection through these two criteria, all suspected lung nodules are detected, the TPR is 100%. The final detection result is shown in Figure 6 as an example. The white part in the left image is the detected lung nodule, and the image on the right is the lung nodule image enlarged by 10 times obtained from lung nodule detection result.

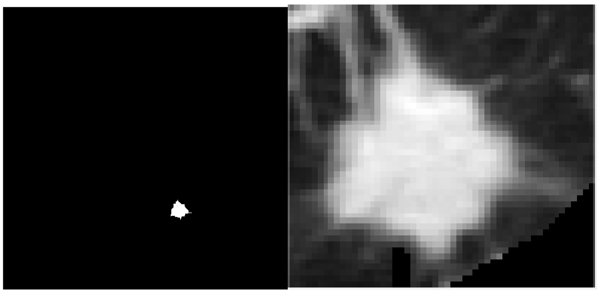

Figure 6. Result of detection and corresponding image.

C. *Lung nodule segmentation*

Based on the initial outline given by lung nodule detection, the level set method is applied to lung nodules segmentation. The segmentation result is shown in Figure 7 as an example. The image on the left is the result of lung nodule detection, and the image on the right is the result of lung nodule segmentation using the level set method. The dice overlap index reaches 0.90. In Figure 7, we can find out that we almost get the lung nodule segmentation except for its spiculation. The reason is that the level set method is good at extracting the smooth outline but not good at extracting rough edges. The spiculation is hard for the level set method to extract its rough shape.

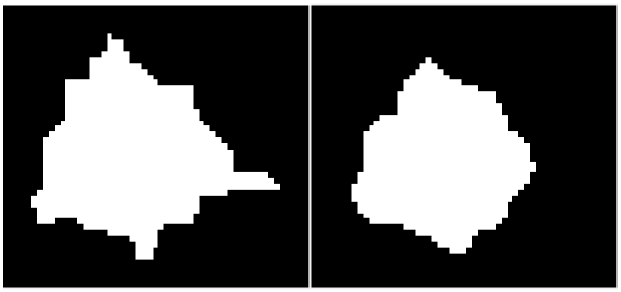

Figure 7. The initial lung nodule image the result of lung nodule detection and segmentation

D. *Spiculation segmentation*

Through the coordinate system transformation, image enhancement and threshold method, result of spiculation segmentation is obtained. The result of lung nodule segmentation using all methods mentioned above is shown in Figure 8 as an example. It is plain to see that the main spiculation is preserved but unobvious spiculation is still missing. This is because that the threshold method is applied to finally extracted spiculation after the image enhancement. The spiculation of low intensities after the enhancement is still hard to extract. This is the problem to be solved in the future research.

Figure 8. The final result of lung nodule segmentation.

IV. DISCUSSION

A lung nodule detection and segmentation method is proposed based on the deep learning, level set and other image processing techniques. As shown in section III, the proposed method effectively detects and segments lung nodules on lung CT images. The experiment results shown in Table I indicate the good performance on dice overlap index in which lung segmentation is 90.55% and lung nodule segmentation is 90%.

TABLE I. RESULT OF SEGMENTATION

Dice overlap index	**Lung**	**Lung nodule**
	0.90	*0.90*

By observing the result and corresponding images, some details can be improved in the future research. Firstly, the result of each upsampling layer can be modified to the same size as the input image and merged together to perform better on the segmentation of lungs. Secondly, the energy function of the level set method can be finetuned to better fit the characteristic of lung nodule images. Last, a more accurate spiculation detection method should be developed to get more information of lung nodules to be diagnosed.

V. CONCLUSION.

In this paper, we developed a CAD system for lung nodule detection and segmentation. For lung nodule detection, we proposed a method combined with the FCN and threshold method to detect lung nodules after lung segmentation and achieved a detection accuracy of 100%. For lung nodule segmentation, we proposed a method consists of segmentation of both main part of lung nodules and speculation and achieve a dice overlap index of 0.9. In summary, the proposed CAD system can provide valuable references for doctors and reduce the time required for clinical diagnosis.

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