A Novel Approach toAutomatic Lung Segmentation for CT Images

BeenaUllalamata BN, Abhinandan H, Avinash Bhaskaran, Avnith A

Department of Medical Electronics, BMS College of Engineering

Bangalore -560019

bnb.ml@bmsce.ac.in

abhinandanhalemane@gmail.com

avinashbhaskaran@gmail.com

avnith.avi@gmail.com

Abstract

Cancer is one of the most serious health problems in the world. Lung cancer is the deadliest type of cancer for both men and women. Each year, more people die of lung cancer [1] than breast, colon, and prostate cancers combined. Lung Computer-Aided Diagnosis (CAD) is a potential method to accomplish a range of quantitative tasks such as early cancer and disease detection, analysis of disease progression, analysis of pulmonary function and perfusion, and automatic identification and tracking of implanted devices. Performing a chest radiograph is the first step if a patient reports symptoms that may suggest lung cancer. If there are no radiographic findings but the suspicion is high (such as a heavy smoker with blood-stained sputum), bronchoscopy and/or a CT scan may provide the necessary information. The lung segmentation is the pre-processing step in most CAD systems. However, manually segmenting the lungs is tedious and takes a lot of time for the large-sized CT databases. Here is a proposalfor a novel lung segmentation technique that can determine the threshold for each CT slice in a patient stack and automatically do the lung segmentation.

Keywords— Computer Aided Diagnosis (*CAD); Computed Tomography(CT); Thresholding; Lung*.

1. INTRODUCTION

Lung Cancer is one of the most serious health problems in the world. Lung cancer is a disease that consists of uncontrolled cell growth in tissues of the lung. It accounts for more cancer deaths than any other cancer. The incidence of lung cancer is about 60 cases per 100,000 population[2]. There are two types of Lung Cancer: Non-Small Cell Lung Cancer and Small Cell Lung Cancer [3]. The treatment and outlook vary based on the type of cancer.

Non-small cell lung cancer occurs in the airways of the lungs or the outer part of the lungs and usually grows slower than small cell lung cancers. Small cell lung cancers are typically in the bronchi, but can spread quickly to the rest of the body.Non-small cell lung cancer accounts for about 85 percent of lung cancers. Among them are Adenocarcinoma, Squamous Cell Carcinoma and Large Cell Carcinoma [4].

There can also be the growth of tumours in lungs in addition to cancer. The difference is they don't spread to other parts of the body.

There are 3 stages of Non-Small Cell Lung Cancer:

a. Stage I: Cancer is located only in lung and has not spread to any lymph nodes.
b. Stage II: Cancer has spread to nearby lymph nodes.
c. Stage III: Cancer is in lung and lymph nodes, making it Locally Advanced Disease.
d. Stage IV: Cancer has spread to both lungs, to fluid area around lungs, or to other parts of body. It is also described as Advanced Disease.

Small Cell Lung Cancer account for remaining 15 percentage. There are two stages:

a. Limited Stage: Cancer is found on one side of the chest, involving just one part of the lung and nearby lymph nodes.
b. Extensive Stage: Cancer has spread to other regions of the chest or other parts of the body.

In recent years, enormous demands for automatically recognizing complicated anatomical structures in medical images had been required on disease assessment.

With the help of medical imaging tools and computer technology, doctors can provide high-quality diagnosis for patients.

Among all the diagnostic methods, CAD has many benefits and has attracted a lot of attention. Lung CAD is also a potential method to accomplish a range of quantitative tasks such as early cancer and disease detection, analysis of disease progression, analysis of pulmonary function and perfusion, and automatic identification and tracking of implanted devices.

On a chest x-ray of someone with lung cancer, there is usually a visible mass with nodule which will looklike a white spot while the lung itself will appear

black. However, an x-ray may not be able to detect all forms of cancer or smaller lesions.

A CT scan is used to detect earlier forms of cancer. This scan takes a cross-sectional and a more detailed image of the lung. Lesions—small, abnormal areas in the lungs that might be cancerous—can be seen in a CT scan. This can be used to determine if these areas are cancerous, if the physician wants to get a sample of abnormal or suspicious tissue from the lung to make the diagnosis of cancer. In a biopsy, thenr physician will take a tissue sample from your lungs for examination. This sample may be removed via a tube placed down the throat (bronchoscopy), making an incision, or by using a needle and same sample can then be analysed to determine whether the person is suffering from cancer or not.

So CT scan plays a preliminary and important role in the diagnosis of lung cancer. In general, the volume of medical imaging data is huge. Atypical dataset of CT images may contain 500 slices or more.

For surgical planning, surgeons get a heavy workload and spendlong time to read stacks of medical images. The simplest way to achieve this is by automated analysis. A CT scan of the thorax is applied in diagnosis widely.

A fully automated approach for pulmonary segmentation is an essential pre-processing step in a lung CAD system. In pulmonary CT images, several lung region segmentation methods had been developed. In 2004, Samuel et al. applied border tracking to find region boundaries. Brown et al. adopted anatomical knowledge including expected volume, shape, relative positions and X-ray attenuation of organs to guide the segmentation process.

Hu et al. applied the optimal threshold to segment lung regions. In order to eliminate the tasks of finding an optimal threshold, Shojaii et al. presented a lung segmentation technique based on the gradient technique and the watershed transform to find the lung borders.

In 2007, Kim et al. applied a novel lung segmentation technique based on anisotropic diffusion and morphological operation.

Observing that image intensity varies in different slices of a patient's CT stack, a fixed threshold for all slices is not proper. In this paper, we propose an Adaptive Thresholding method for automatic segmentation of the lungs in CT images. For each CT slice, the proposed method will determine a proper threshold and automatically [1] do the lung segmentation.

2. THE PROPOSED SCHEME

We propose a fully automatic method based on Adaptive Thresholding [5] for segmenting the lungs in three-dimensional (3-D) Pulmonary X ray CT images. This method consists of six steps. In the first step, we read the CT image into the system. A sample original lung image data is as shown in figure 1. In the second step, a threshold is selected to convert a CT image into a binary image. The binary image is as shown in figure 2. In the third step, every component in the CT image is labelled. In the fourth step, we extract the lung area. The extracted lung area is as shown in figure 3. In the fifth step, a test is made to see if the selected threshold is right or not. If this selected threshold is not satisfactory, then it goes back to the second step.

In the first step, the algorithm will select an intensity value, called the threshold, to separate the lungs from other parts. Since pixel intensities vary from slice to slice even all these slices are in the same patient's CT stack, using a fixed threshold for all slices is not an appropriate practice.

In the proposed segmentation method, a scheme is designed to choose a good threshold for each slice. In the beginning, the threshold value is chosen to be larger than what we expect a proper threshold to be and the algorithm goes from step 1 to step 5. In step 5, a condition will be tested and if this condition is satisfied, the algorithm goes on to step 6. Otherwise, the algorithm will adjust the threshold and goes back to step 2.

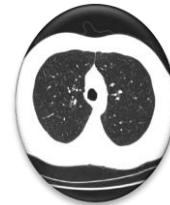The six steps of proposed method is as shown in figure 4and it is described in detail as given below.

Figure 1.Original CT Image

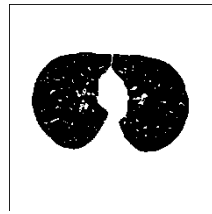Figure 2.Select a threshold and convert the CT Image into a binary image.

Figure 3.Extracted lungs

2.1. Select a Threshold and Convert the CT Image into a Binary Image.

In this step, a threshold is determined and according to this threshold, the CT image is converted to a binary image. Those pixels whose intensities are less than the threshold are converted to black and those whose intensities are greater than the threshold are converted to white.

2.2. Connected Component Labelling.

Connected component labelling [6] works by scanning an image, pixel-by-pixel (from top to bottom and left to right) in order to identify connected pixel regions, i.e. regions of adjacent pixels which share the same set of intensity values V.

Connected component labelling works on binary or Gray Level images and different measures of connectivity are possible. However, for the following we assume binary input images and 8-connectivity. The connected components labelling operator scans the image by moving along a row until it comes to a point p (where p denotes the pixel to be labelled at any stage in the scanning process) for which V={0}.
When this is true, it examines the four neighbours of p which have already been encountered in the scan (i.e. the neighbours (i) to the left of p, (ii) above it, and (iii and iv) the two upper diagonal terms).

Based on this information, the labelling of p occurs as follows:
If all four neighbours are 0, assign a new label to p, else
If only one neighbour has V={0}, assign its label to p, else
If more than one of the neighbours have V= {0}, assign the lowest adjacent label to p.
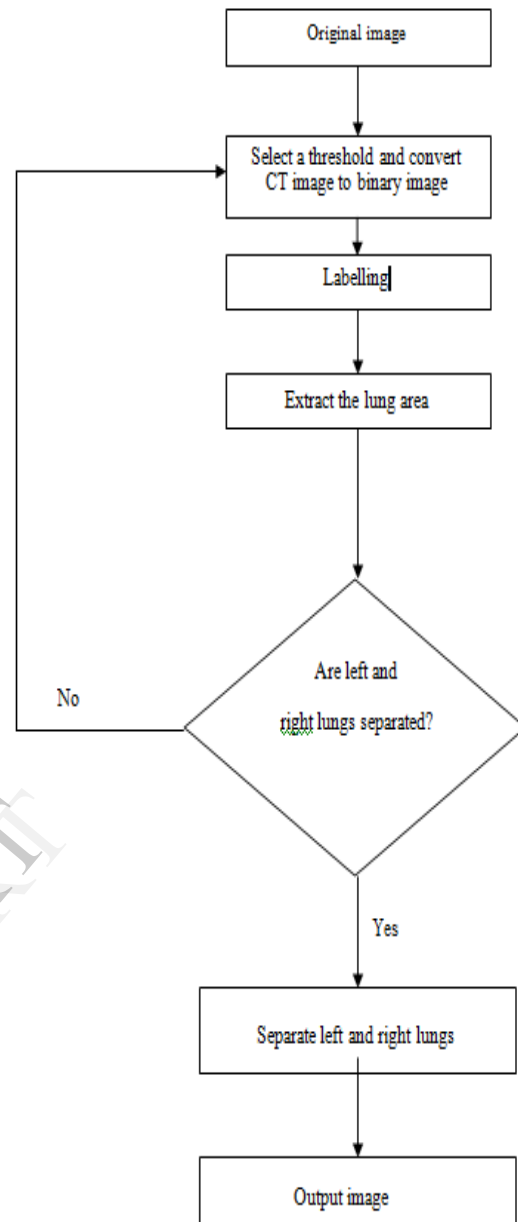

Figure 4. The flow chart of the proposed method

After the first iteration, every pixel in the image is labelled. On the second iteration every pixel's label is compared with its eight surrounding labels and the lowest label of the neighbourhood consisting of nine pixels (8 neighbouring pixels and the pixel itself) is chosen as the label for that pixel.
The third iteration is the same as the second but in reverse order to ensure that no connected component is assigned multiple labels. At this stage all connected pixels of the same intensity are assigned the same label. The total number of labels represents the number of connected components in the image.

2.3. Extract the Lung Area.

Once the labelled image has been obtained, the lung area is to be extracted. To achieve this we make use of an interesting property of lung CT images. The lungs are covered on all sides by the chest wall which appears white on the CT image. Beyond the chest wall on the CT image, lies the background which appears black.

We assume that the central row of the image will pass through both lungs. If the first pixel of the central row is black, we save its label value. Hence when we start scanning the central row from the left to right if we encounter a black pixel whose label value does not match that of the saved value, we save this label value as the lungs (right lung in the case of segmented lungs).
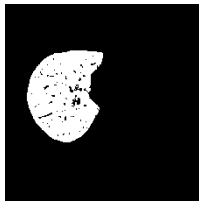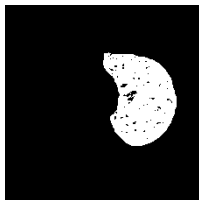

Figure 5. Extracted Right Lung
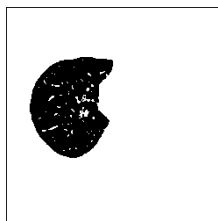

Figure 6. Extracted Left Lung
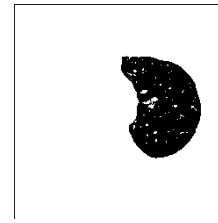

Figure 7. Complement of Right Lung

Figure8. Complement of Left Lung

We also scan from right to left in the same way. If the last pixel of the central row is black, we save its label value. Hence, when we start scanning the central row from the right to left if we encounter a black pixel whose label value does not match that of the saved value, we save this label value as the lungs (left lung in the case of segmented lungs).

After procuring the label values of the lungs (or right and left lungs in the case of segmented lungs), we set every pixel having the said label value to white and every other pixel to black. This yields an image with white lungs and black background. This method also removes the unwanted external airways, and hence there is no need to calculate the mean and standard deviation of the pixel intensities, which are otherwise required to remove the external airways.

2.4. Separation of Lungs

Separation of left and right Lungs is the final step. Once we obtain the extracted Lung Area, we test if the right lung and left lung are separated.
For this we use the concept of Labelling. We check if the label of right lung is same as the label of left Lung. If the label of right lung is same as that of the left lung, then it implies that the lungs are not separated. Thus the optimum threshold value has not been attained. So we reduce the threshold and repeat the process.
This process continues as long as, we get different labels for left and right lung.
Once we get different labels for left and right lung, we extract them separately and store in PNG format. This is done in a manner similar to the extraction of lung area.
For extraction of left lung area, wescan every pixel of the image. We keep the pixels of left lung as it is (white) based on the obtained label values and any pixel having other label values are converted to black. Thus we obtain the left lung region in white. It is then complemented.
Similarly for extraction of right lung area, we scan every pixel of the images. We leave the pixels of the right lung unaltered (white) using the obtained label values and any pixel having other label values are converted to black. Thus we obtain the right lung

region in white. It is then complemented to obtain the binary version of right lung image.

The final extracted right and left lung is as shown in figure 5 and figure 6 respectively.

3. RESULTS, CONCLUSION AND FUTURE WORK

To evaluate the performance of our method, we tested the algorithm on random CT slices.

The CT slices were converted from DICOM to JPEG using DCM Converter. The size of images was912x912.

We used Qt Creator on a PC with 2.03GHz processor and 2GB RAM. On an average, 8 seconds were required to segment an image.
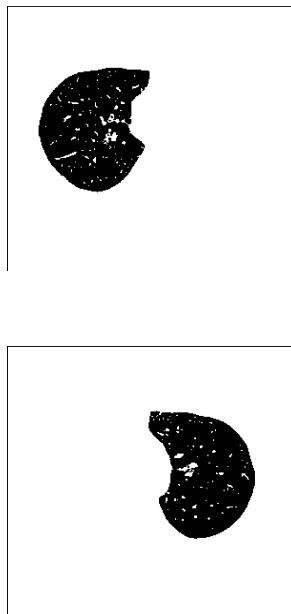
The outputs are as shown in Figure 3.

Figure 9. Right Lung and Left Lung separated.

In our method, we don't use a fixed threshold, but instead the threshold is changed as per the requirement of the slices. This enhances the segmentation of lungs. For our test images, we found the threshold usually to be in the range of 80-130.

With the extensive use of CT for most of the medical imaging purposes, having regular improvements in the processing methods is very much necessary.

We have suggested one such improvement. Further, sicne we use Qt-Creator, which is an open source, it can used with greater feasibility.

The proposed method can be enhanced by inclusion of database storage and transfer, pulmonary diseases detection. These features will take the proposed

method one step further to turn it into a complete lung imaging package.

4. ACKNOWLEDGEMENT

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