A model for segmentation and detection of lung nodule from CT Scan Images using Otsu threshold

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Abstract— Lung cancer is the most prevalent and dangerous disease in the world, the percentage of people who die because of this disease becomes greater. The diagnosis which may be in the form of a segmentation of lung is one of the solutions to discover the nodule in the first stage. In this paper a robust algorithm is proposed in this paper in terms of segmentation and detection of lung nodule for computed tomography CT image. First of all, We began with acquisition of CT images and pre-processing when RGB image is converted into gray scale image. Afterwards, the noise is removed from this image using median filter. Then, an algorithm that segmented lung nodule with 2-D Otsu is proposed, this method is one of the most commonly used in automatic image segmentation, it is fast and efficient and then the detection of nodule is done from region of interest ROI. Finally, We extracted the characteristic values through GLCM features. The proposed system is implemented in MATLAB software.

Keywords— Otsu threshold, Median filter, Image segmentation, GLCM (Gray Level Co-occurrence Matrix) features , ROI (region of interest ROI), Nodule detection.

I. INTRODUCTION

Lung cancer continues to be the most diagnosed cancer type and the leading cause of for cancer related deaths worldwide. According to the American Cancer Society, the five-year survival rate is not more than 15%. To increase the chance of survival, early detection of suspicious lesions is vastly important [1].

The tumors that appear in the lung and that may be the cause of cancer can be: micro-nodules if they are less than 7 mm in diameter, nodules if their size is between 7 and 30 mm in diameter, masses if they are more than 3 cm, in this paper we are interested in the 3rd type of nodule (mass) that usually presents really lung cancer.

For detecting pulmonary nodules, computed tomography (CT) is superior to radiography, and it is now being used in many studies for the early detection and analysis of lung nodules [2]. CT scans are widely used for short-term follow up to identify nodules volumetric changes over time. The change of the volume can be used as an indicator of malignancy. Meanwhile, automatic measurements of nodule volumes has

been increasingly used as a reproducible (higher intra observer agreement) and accurate technique [3].

Image segmentation is defined by the certain principles of segmentation that divide the image into several specific and unique regions which is the key step in image processing, its segmentation results directly affect people's understanding and use of the image, therefore, image segmentation is the focus in computer image studies. The representative image segmentation method are threshold method, region growing method and edge detection method. Threshold method is simple, easy to realize, and its performance is stable, which is widely used in image segmentation [4].

Otsu method (Otsu algorithm)[5] is the most commonly used in image segmentation, the basic principle is to choose an optimal threshold which has the maximum between-class variance between the target and background that can get the best segmentation results. 1-D Otsu algorithm as one of the most traditional Otsu methods cannot handle noise in the image well because of the influence that surrounding pixels to the center pixel is not taken into account, 2-D Otsu algorithm is presented by J.Z. Liu [6], and the new method has a great improvement in image segmentation effect. That is why we used this method to segment the lungs.

The organization of this article is as follows: firstly, the detailed method for the segmentation of the lungs using an Otsu threshold model and the detection of nodule through the regions of interest followed by the extraction of the characteristics of nodule are presented in the following section (section 2). Section 3 presents the experimental results. Finally, the conclusion and direction of future work is contained in section 4.

II. PROPOSED METHOD

Here, a system for lung segmentation, nodule detection and feature extraction is proposed from CT scan images. The following figure shows the block diagram of the proposed system.

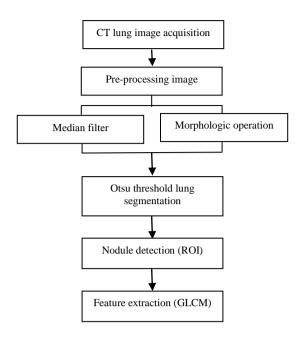


Figure 1. Block diagram of the proposed system.

A. Image acquisition

Here, the input images are chest CT scan images in JPEG format that contain tumors. The user has to select the required lung CT scan image for further processing. The images were acquired by the system and saved in a personal computer.

B. Median filter

The median filter is also the simpler technique and it removes the speckle noise from an image and also removes pulse or spike noise [14-15]. The Median Filter is performed by taking the magnitude of all of the vectors within a mask and sorting the magnitudes. The pixel with the median magnitude is then used to replace the pixel studied. The operation of median filter can be expressed as:

$$f(x,y) = median_{(s,t) \in Sxy} \{ g(s,t) \}$$
(1)

where S_{xy} represents the set of coordinates in a rectangular sub image window, centered at point (x,y), and median represents the median value of the window.

C. Morphologic operation

A binary image can be viewed as a binary valued function of x and y. Morphological theory views a binary image as the set of its foreground (1-valued) pixels, the elements of which are in Z^2 .Set operations can be applied directly to binary image sets. The operations of dilation and erosion are fundamental to morphological image processing [16,17]. Dilation is an operation that "grows" or "thickens" objects in a binary image. The specific manner and extent of this thickening is controlled by a shape referred to as a structuring element. Mathematically, dilation is defined in terms of set operation. The dilation of A by B, denoted $A \oplus B$.

$$\mathbf{A} \oplus \mathbf{B} = \left\{ \mathbf{z} \middle| \left(\hat{\mathbf{B}} \right)_{\mathbf{z}} \mathbf{I} \mathbf{A} \neq \boldsymbol{\varphi} \right\}$$
(2)

Where ϕ is the empty set, B is the structuring element. \dot{B} is the reflection of set B, is defined as

$$\hat{\mathbf{B}} = \left\{ \mathbf{w} \middle| \mathbf{w} = -\mathbf{b}, \mathbf{b} \in \mathbf{B} \right\}$$
(3)

The translation of set X by point z = (z1, z2) denoted (X)z, is defined a

$$(X)z = \left\{c\middle|c = a + z, a \in X\right\}$$
(4)

The dilation of A by B is the set consisting of all the structuring element origin locations where the reflected and translated B overlaps at least some portion of A.

Erosion "shrinks" or "thins" objects in a binary images. The manner and extent of shrinking is controlled by a structuring element. Mathematically, erosion is defined in terms of set operation .The erosion of A by B, denoted $A \otimes B$, is defined as

$$A \otimes B = \left\{ z \middle| (B)_z I A^C \neq \phi \right\}$$
 (5)

Where ϕ is the empty set, **B** is the structuring element. The set of all pixel coordinates that do not belong to set **A**, denoted A^{C} , is given by

$$A^{C} = \left\{ w \middle| w \notin A \right\} \tag{6}$$

The erosion of A by B is the set of all the structuring element origin locations where the translated B has no overlap with the background of A.

D. Otsu threshold segmentation

The principle of Otsu threshold is as follows:

Suppose the gray level of a picture is L and can be represented by a 2D gray level intensity function f(x, y), so the gray level of its neighborhood pixels is also L and can be represented by function g(x, y). Therefore, each pixel's grayscale value i and its neighborhood average grayscale value j constitute a 2-D array (i, j). Suppose M is the total

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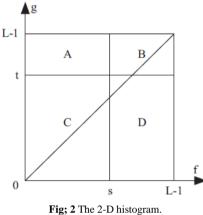
number of pixels and f_{ij} is the total number of occurrence (frequency) of array (i, j), then the expression of 2-D probability density function is [4]:

$$p_{ij} = \frac{f_{ij}}{M}$$

where $\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} f_{ij} = M$, $\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} = 1$.

(7)

Suppose the threshold pair is (s,t) then the 2-D histogram threshold is divided into four parts, as shown in Figure 2.



Now suppose that the pixels are partitioned into two classes C_0 and C_1 (background and objects) by a threshold pair (s,t) .Here, we assume when the position away from the diagonal, its probability $p_{ii}=0$. That is to say, C_0 and C_1 are in the B and C field of histogram. Then the probabilities of class occurrence are given by

$$w_0 = \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij}$$
(8)

$$w_1 = \sum_{i=s}^{L-1} \sum_{j=t}^{L-1} p_{ij}$$
(9)

The mean vectors of C_0 and C_1 are respectively:

$$\mu_{0} = (\mu_{0i}, \mu_{0j})^{T}$$

$$= \begin{bmatrix} s^{-1} t^{-1} & s^{-1} t^{-1} \\ \sum j=0 i^{p} i^{p} i^{j} & \sum j=0 j^{p} i^{p} i^{j} \end{bmatrix}^{T} (10)$$

$$\mu_{1} = (\mu_{1i}, \mu_{1j})^{T}$$

$$= \begin{bmatrix} L-1L-1 & L-1L-1 \\ \sum \sum_{i=s} \sum_{j=t}^{i} ip_{ij}, \sum_{i=s}^{L-1} \sum_{j=t}^{j} jp_{ij} \end{bmatrix}^{T}$$
(11)

Global mean vector is:

$$\mu_t = (\mu_{ti}, \mu_{tj})^T$$

$$= \begin{bmatrix} L^{-1}L^{-1} & L^{-1}L^{-1} \\ \sum \sum_{i=0}^{N} ip_{ij}, \sum_{i=0}^{N} \sum_{j=0}^{N} jp_{ij} \end{bmatrix}^{T}$$
(12)

The between-class variance matrix is defined as:

$$S = \sum_{k=0}^{1} w_k \left[(\mu_k - \mu_t)(\mu_k - \mu_t)^T \right]$$

= $w_0 \left[(\mu_0 - \mu_t)(\mu_0 - \mu_t)^T \right]$
+ $w_1 \left[(\mu_1 - \mu_t)(\mu_1 - \mu_t)^T \right]$ (13)

By using the trace of S as the measurement of betweenclass variance, there is:

$$\begin{aligned} r_{tr}(S) &= \\ w_0 \Big[(\mu_{0i} - \mu_{ti})^2 + (\mu_{0j} - \mu_{tj})^2 \Big] & (14) \\ + w_1 \Big[(\mu_{1i} - \mu_{ti})^2 + (\mu_{1j} - \mu_{tj})^2 \Big] \end{aligned}$$

The optimal threshold vector (s,t) is selected by maximizing $r_{tr}(S)$.

We used this principle of this thresholding to segment the lung and isolate it from the background to be able then to detect the nodule.

E. Nodule detection

The reconstruction of the lung border is an important step that aims to recover lung nodules that are attached to the thoracic wall [14]. The MATLAB (R2014) function is used in this work to isolate these pulmonary nodules and then to diagnose it later.

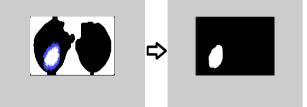
The MATLAB function is as follows:

$$BW = roipoly(I)$$

Use roipoly to specify a polygonal region of interest (ROI) within an image.

BW = roipoly creates an interactive polygon tool, associated with the image displayed in the current figure, called the target image. With the polygon tool active, the pointer changes to cross hairs when you move the pointer over the image in the figure. Using the mouse, you specify the region by selecting vertices of the polygon. You can move or resize the polygon using the mouse [13].

The following figure illustrates an extraction of region of interest in CT lung image, The result is a nodule that can be calculated their feature.



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Fig. 3 Examples of ROI extraction.

F. Feature extraction

Feature extraction is defined as grouping the input data objects into a set of features. The features extracted carefully will help to extract the relevant information from the input data in order to perform the feature matching [11].

Here, we used GLCM (Gray level co-occurrence matrix) feature, it's simply a matrix that gives the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest [12]. In this process, 4 textural features of all images in the database are extracted.

1. Contrast: It is a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\sum_{i,j} \left| i - j \right|^2 p(i,j) \tag{15}$$

2. *Homogeneity:* It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i,j=1}^{\sum} \frac{p(i,j)}{1+\left|i-j\right|} \tag{16}$$

3. Energy: It is also known as uniformity of ASM (angular second moment) which is the sum of squared elements from the GLCM. Range = [0 1] Energy is 1 for a constant image.

$$\sum_{i,j} p(i,j)^2 \tag{17}$$

4. *Correlation*: It is a measure of gray level linear dependence between the pixels at the specified positions relative to each other.

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma i \sigma j}$$
(18)

III. RESULTS OF EXPERIMENTATION

All the experiments were performed with an Intel(R) Core (TM) i5-5300U CPU with 8 GB of RAM and equipped with Matlab (R2014a) software. In this section, the results of the proposed system are shown for five images from the database.

It has been observed that the CT image of the lung is composed of a chest wall and an outer part, although just the chest wall is interesting then in our system we have to crop the image at the beginning as illustrated in Fig. 4.

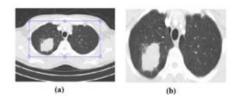


Fig. 4 Example of crop image, (a) Original image, (b) image after crop.

The original image, the image after segmentation through Otsu threshold approach and extraction of the nodule through the region of interest for 5 candidates are shown in Fig.5.

Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest. These GLCM features calculated for some of the images are shown in following table:

TABLE 1. VALUE OF GLCM FEAUTURES

GLCM features	Image 1	Image 2	Image 3	Image 4	Image 5
Contrast	0.286	0.054	0.159	0.116	0.160
Correlation	0.940	0.891	0.929	0.877	0.872
Energy	0.895	0.988	0.950	0.978	0.971
Homogeneity	0.004	0.999	0.997	0.997	0.997

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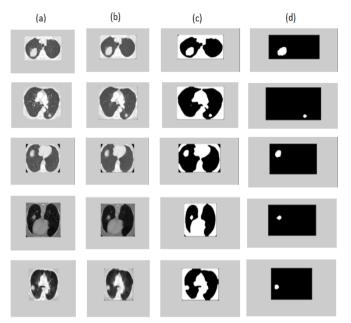


Fig. 6 Result of different subjects; (a) Input image, (b) Filtered image, (c) Segmented lungs (d) Nodule detection.

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IV. CONCLUSION

In this paper, a detailed description has been made of the different stages of our segmentation system. A method of Otsu image threshold segmentation is proposed in this paper because of the good result showing in the experiments, We extracted the regions of interest from the segmented image and finally we used GLCM feature to characterize the nodule. Thus it can be concluded that the proposed method performs well and is robust and it will assist radiologist as second opinion for the better diagnosis of lung cancer.

As a working perspective, it would be interesting to use 3D models can be to improve the performance of pulmonary nodule segmentation, furthermore it would also be interesting to work on the small nodule that are less than 3mm.

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