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Lung Tissue Extraction Using OTSU Thresholding in Lung Nodule Detection from CT Images

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Abstract—*Lung cancer mortality rate has alarmingly increased and it accounts for the major cause of cancer deaths around the globe. The presence of lung nodule can be an indicator of early stage of lung cancer. An automatic lung nodule detection system can help in timely diagnosis and thereby in reducing lung cancer mortality rate. This paper focuses on the primary phase of lung nodule detection system where the lung tissues are extracted from the lung computed tomography images taken from the Lung Image Database Consortium-Image Database Resource Initiative (LIDC-IDRI) database. The primary phase consists of 2 stages - preprocessing and segmentation. In the preprocessing stage noise removal is done by wiener filter followed by contrast enhancement using contrast limited adaptive histogram equalization (CLAHE). In the second stage, segmentation using Otsu thresholding is carried out to extract the lung tissues. The segmented lung tissues are obtained as the end result of the primary phase of the lung nodule detection system.*

Keyword — *Contrast limited adaptive histogram equalization, lung nodule, Otsu thresholding, wiener filter.*

I. INTRODUCTION

Lung cancer has been reported as the major cause of cancer deaths over the past few years [19]. The presence of lung nodules which are spherical or oval spots on lungs having a size of 1-30 mm can be considered as an indicator of early stage lung cancer. So it is very important to distinguish cancerous and non-cancerous lung nodules as early as possible. About 40 percent of lung nodules turn out to be cancerous [20]. The cancerous lung nodules are a major cause behind the increasing trend in lung cancer patients. Timely diagnosis of potentially harmful malignant lung nodules can help to increase the survival rates of lung cancer patients. However radiologists find it quite difficult to provide quantitative measurements in a fast manner. In order to deal with the lung nodule cases, it is essential to know the type and characteristics of the nodules. The diagnostic challenge lies in the proper classification of lung nodule. Nowadays computed tomography (CT) has been used as a standard diagnostic tool and for patient evaluation [19]. So it becomes necessary to develop tools to extract relevant information from these images in order to narrow the wide diagnostic possibilities. Manual diagnosis and classification of lung nodules is time consuming as well as complex. So an automatic computer aided diagnosis system to properly diagnose and classify the lung nodule is inevitable. Yongbum Lee et.al (2001) has compared newly proposed genetic algorithm based template matching with conventional lung wall template matching method. Even though the detection rate was about 72% there was difficulty in detecting low contrast apex nodules and it has exhibited high number of false positives [24]. Yang Song et.al (2013) proposed a feature based patch approximation method based on gradient and texture feature descriptors and PASA classifier has been used in order to classify the lung tissues. The proposed method was found to have promising performance and it is also extensible to other medical domains [22]. Yang Song et.al (2012) proposed a discriminative model based on support vector machine and conditional random fields using spatial, intensity and contextual features to detect and differentiate between tumors and lymph nodes. The proposed system could handle a wide and complex variety of abnormal patterns in clinical data sets [21]. Stefano Diciotti et.al (2008) proposed a fusion segregation process based on gray level similarity and object shape using geodesic distance for 3D segmentation of lung nodules and it yielded less than 6.6% RMS error in phantoms [20]. William J Kostis et.al (2003) proposed isotropic resampling of anisotropic CT data along with 3D intensity and morphology based segmentation to distinguish malignant and benign lung nodules based on the growth rate [21]. Awais Mansoor et.al (2014) proposed a pathological lung segmentation method which used fuzzy connectedness algorithm for lung parenchyma extraction and anatomy guided segmentation method using texture features. It evaluated all abnormal imaging patterns in single segmentation frame and has shown high sensitivity and specificity with an overlap rate of 95% [4]. Amal a Farang et.al (2013) utilized inhomogeneous scale in registration process to develop a prior shape model and to formulate a lung nodule segmentation process using level sets and thereby yielding a success rate of 94%.

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The proposed system was independent of the nodule size and position and it could overcome problems related to nodules attached to blood vessels and lung walls [1]. Paola Campadilli et.al (2006) presented lung field segmentation using gray level clustering method and contour following procedure which was used in order to extract nodules using simple extraction scheme. The final classification was done using support vector machines and it was found that it outperformed existing methods [19]. The Otsu thresholding method is an effective and better method to segment and extract the lung tissues from the CT images. It is suitable for lung tissue extraction. It can easily eliminate the ribs and diaphragm portions that may be present in the input image. It also retains the attached vasculature which may be needed while the classification is done. The method extracts the lung tissues by reducing the intra class variability to possible extent. Even though it could not take into consideration the local variations, it may not be an issue in case of lung tissue extraction since the variability is low when compared to the intra lung structures. Hence considering these features of thresholding the Otsu thresholding has been chosen to extract the lung tissues from the input images. The paper presents a method for efficient lung tissue extraction from the lung CT images that are obtained from LIDC IDRI database. The paper is structured as follows: Section II describes the methodology that has been used in the proposed work. Section III discusses the results of the proposed work. Section IV details the conclusions of the work and the scope for future work.

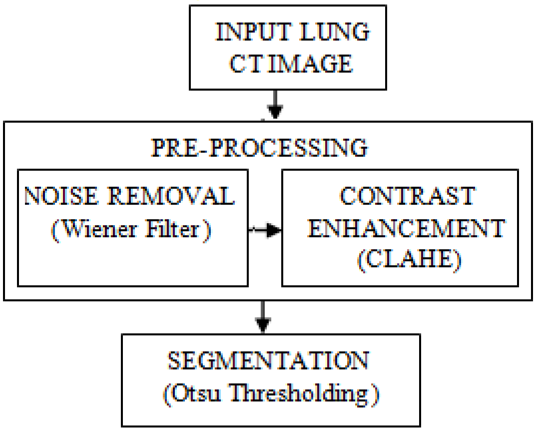

Fig.1 Proposed block diagram

II. METHODOLOGY

2.1 Block Diagram

The block diagram of the specified work is depicted in Fig.1. The detection and classification of the lung nodules from the lung CT images involves several steps. The main steps involved are pre-processing, segmentation, lung nodule detection and classification. The primary phase focuses on pre-processing and segmentation stages. The pre-processing stage involves 2 steps: noise removal and contrast enhancement. The pre-processing is followed by segmentation stage to extract the lung tissues. The images were taken from LIDC/IDRI database which is a publicly available, freely accessible database of thoracic CT image data along with the annotations of those images by experienced radiologists.

2.2 Pre processing

Image pre-processing is the technique of enhancing the data images prior to computational processing. Pre-processing of images are commonly done for removal of low frequency background noise, normalizing the intensity of the individual particles in images, removing reflections and masking portions of images. The proposed system has pre-processing stage consisting of 2 stages. They are the noise removal stage and contrast enhancement stage. Noise removal can be done using filters namely Gaussian, median, mean, wiener in order to remove the Gaussian, salt and pepper as well as additive noise. Contrast enhancement is done after the filtering to improve the contrast of images so that the visibility of structures can be improved.

1) Noise Removal using Wiener Filter

Denoising is mainly used to remove the noise that is present and retains the significant information, regardless of the frequency contents of the signal. There are many filters that are used to remove noise from digital corrupted images and in this work wiener filter is used. The Wiener filtering executes an optimal trade-off between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. Wiener filter estimates the local mean and variance around each pixel, a (n1, n2) [18].

$$\text{Mean, } \mu = \frac{1}{NM}\sum_{n1,n2\in\eta} a(n1,n2) \qquad (1)$$

$$\text{Variance, } \sigma^2 = \frac{1}{NM}\sum_{n1,n2\in\eta} a^2(n1,n2) - \mu^2 (2)$$

Where, η is the N-by-M local neighbourhood of each pixel in the image, and then creates a pixel-wise wiener filter using these estimates.

$$b(n1,n2) = \mu + \frac{\sigma^2-\nu^2}{\sigma^2}(a(n1,n2) - \mu) \qquad (3)$$

Where, $\boldsymbol{\nu^2}$ the noise variance is not given, then the average of all the local estimated variances [18].

2) Contrast enhancement using CLAHE:

Image enhancement is a process of improving the quality of image by improving its features. In the proposed system the Contrast Limited Adaptive Histogram Equalization (CLAHE) is used. It is an adaptive method to avoid the drawback of histogram equalization by block-based processing of histogram equalization. This evens out the distribution of used grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image. It optimizes the contrast enhancement on local image data in a divide and conquer mode and hence reduces the global noise [16]. In this method, image is divided into sub-images or blocks, and equalisation of histogram is performed to each one. Then, blocking artefacts among neighbouring blocks are limited by filtering approach or bilinear interpolation method. The CLAHE introduced clip limit to overcome the noise problem. The CLAHE restricts the intensification by clipping the histogram at a predefined value before computing the CDF. The slope of cumulative distribution function is limited land thereby it limits the transformation function also. The value at which the histogram is clipped (clip limit) is dependent on the histogram normalization and thereby on the size of the neighbourhood region. During the redistribution few of the pixels are added over the clip limit and it results in an effective clip limit which is larger than the predefined limit. It is to be noted that the accurate clip limit value depends on the original image. Clip limit is used to limit the maximum slope of all histograms. The algorithm of function can be summarized as [9]:

1) Calculate a grid size based on the maximum dimension of the image.
2) If a window size is not specified chose the grid size as the default window size.
3) Recognize the grid points in the given image and it has to be done from top left corner. Each one is separated by grid size pixels.
4) For each chosen point compute the histogram for the area surrounding the grid point, having area equal to window size and centered at the chosen point.
5) For predefined clip limit, trim the histogram computed above to that level and then use the new histogram to calculate the cumulative probability function (CPF).
$$P(X_k) = \sum_{k=0}^{L-1} \frac{n_k}{N} \quad (4)$$
6) for each pixel in the input image perform steps 6-8 after calculating the mappings for each grid point. The mapping of new pixel in case of uniform distribution is given by equation (5).
$$g = (g_{max} - g_{min}) * P(X_k) + g_{min} \quad (5)$$
Where, g_{max} is the maximum gray level value, g_{min} is the minimum gray value, g is the computed pixel value and $P(X_k)$ is the cumulative probability distribution.
7) Find the 4 nearest neighboring pixels for each chosen pixel.
8) Use the cumulative probability function find the mapping at 4 grid points by making use of the intensity value of the pixel as an index.
9) Interpolate among these values to obtain the mapping for the present pixel. Plot this intensity to the range [min: max] and put it in the output image.

2.3 Segmentation

The preprocessing stage is followed by the segmentation stage where segmentation using Otsu thresholding is used in this work. Thresholding is the simplest segmentation method where the pixels are partitioned depending on their intensity value. Otsu thresholding is a simple yet effective global automatic thresholding method for binarizing grayscale images such as foregrounds and backgrounds. In Otsu's thresholding method iteration is carried out for all possible values of threshold available from the image. Then measure of spread for the pixel levels each side of the threshold is computed. So it can be found whether the pixel belongs foreground or background. Finally the threshold value is found out which gives the minimum value as the sum of foreground and background spreads. In this method we exhaustively search for the threshold that minimizes the within variance, defined as a weighted sum of variances of the two classes [12].

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (6)$$

Weights $\omega_i$are the probabilities of the two classes separated by a threshold t and σ_i^2variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance.

$$\sigma_b^2(t) = \sigma^2 - \sigma_\omega^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t) \quad (7)$$

Which is expressed in terms of class probabilities $\omega_i$and class mean μ_i. The class probability $\omega_1(t)$is computed from the histogram ast.

$$\omega_1(t) = \sum_0^t p(i) \quad (8)$$

While the class mean $\mu_1(t)$ is:

$$\mu_1(t) = [\sum_0^t p(i)x(i)]/\omega_1 \quad (9)$$

The class probabilities and class means can be computed iteratively after computing. This idea yields an effective algorithm which is explained below [12]. The algorithm assumes that the image is composed of two basic classes: foreground and background. It then computes an optimal threshold value that minimizes

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the weighted within class variances of these two classes. It is mathematically proven that minimizing the within class variance is same as maximizing the between class variance [12].

1) Compute histogram and probabilities of each intensity level.
2) Set up initial $\omega_i(0)$ and $\mu_i(0)$
3) Step through all possible thresholds $t = 1$ ....maximum intensity.
   a). Update ω_i and μ_i
   b). Compute $\sigma_b^2(t)$
4) Desired threshold corresponds to the maximum $\sigma_b^2(t)$
5) We can compute two maxima (and two corresponding thresholds). $\sigma_{b1}^2(t)$is the greater max and $\sigma_{b2}^2(t)$is the greater or equal maximum desired threshold = [threshold 1+threshold 2]/2 (10)
6) Compute the new gray level using equation (11).

$$g(x,y) = \begin{cases} 1, \text{if } f(x,y) > T \\ 0, \text{if } f(x,y) \le T \end{cases} \quad (11)$$

where, x = 0,1,2,..., M-1 and y = 0,1,2,..., N-1.

III. RESULTS AND DISCUSSION

The sample images of the LIDC IDRI database are shown in the fig. 2(a). The images are low contrast images of 512 x 512 size. Prior to pre-processing the input image is converted into gray scale. The fig. 2(b) shows the gray scale image of the corresponding sample input images.

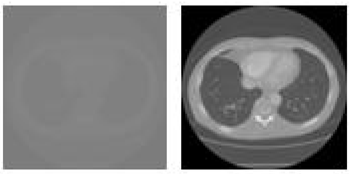

Fig. 2(a) Sample image 2(b) Gray scale image

3.1 Pre processing

The input image is pre- processed for noise removal and contrast enhancement using wiener filter and contrast limited adaptive histogram equalisation (CLAHE). The input image may contain additive noise from various sources. This may create difficulties in subsequent processing stages while retrieving features and during classification. To remove the noise components the input image is subjected to wiener filtering. The fig. 3(a) shows the wiener filtered images for sample images in which noise filtering has been done. Wiener filter is done by using a window size of 3 by 3. The filter window is slid over the input image and the pixel values are being replaced by the corresponding wiener filtered values. The wiener filtered image has removed the noise components but certain parts of the image cannot be viewed clearly due to non-uniform illumination. The contrast of the image has to be improved for better visualization. For better results in terms contrast the wiener filtered output image is subjected to contrast limited adaptive histogram qualisation (CLAHE). The method can be used to illuminate the image uniformly and to reduce the disparities in the image. CLAHE enhances the contrast of the images by transforming the values in the intensity image. It performs on individual data areas (tiles) other than operating on the entire image. Each tile's contrast is enhanced such that the output region histogram matches the required histogram. The neighboring tiles are then combined using bilinear interpolation in order to eradicate the synthetically produced boundaries. The tile used here is 8x8. The clip limit is a contrast aspect that limits over-saturation of the original image especially in homogenous areas. These areas are characterized by a maximum peak in the histogram of the considered image part due to many pixels falling inside the same gray level range. Without the clip limit, the adaptive histogram equalisation could produce the results that, in some cases, are worse than the original image. The clip limit used is 0.01. Uniform, Rayleigh or Exponential distribution is the basis for creating the contrast transform function. The distribution depends on the type of the input image. Rayleigh distribution is used so that the image appears natural.

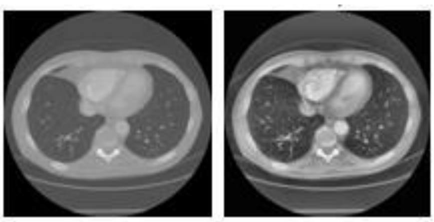

Fig. 3(a) Wiener filtered image and (b) CLAHE enhanced image

Fig. 3(b) shows the enhance image after CLAHE for the sample image. The contrast, especially in homogenous areas, can be limited in order to avoid amplifying the noise which might be present in the image. In other words, CLAHE prevents over-amplification of noises in relatively homogenous regions of the image.

3.2 Segmentation

The pre-processed image is segmented in the next stage in order to extract the lung parenchyma. The segmentation is done by using thresholding method. The extraction the lungs left and right region is done by

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thresholding. The thresholding approach uses a threshold value to convert a gray-scale image into a binary image. The threshold is used to isolate lung tissues from the rest of the original image. In this work thresholding approach used to extract the lung is the Otsu thresholding. In the first stage of the Otsu thresholding the threshold value is found and by using the threshold value the contrast enhanced image is converted to binary by using the binary thresholding. The threshold value that has been used in this is 0.4196. The fig. 4(a) depicts the binary threshold image obtained after applying the Otsu threshold.

Fig. 4 (a) Binary threshold image and (b) Complemented image

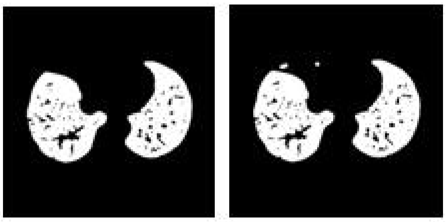

Fig. 4 (c) Border cleared image and (d) Area opened image

The complimented images obtained after thresholding is shown in fig. After the binary thresholding the result obtained is being complimented in order to provide better visualisation of the lung tissues and also to identify the attached regions. The complimenting operation inverts the binary values and so the zeros may become ones and vice versa. In the next stage the arti facts attached to the border are removed by using the border clearing operation. This will help to remove the portions of ribs and diaphragm attached to the lungs. The border cleared image is shown in fig.4(c). In the final stage the border cleared objects may have some parts of muscles attached to the lungs. So the area opening operation is done in order to remove the objects in less pixel size. The area opened image is the final segmented image having extracted lung tissues and so the same is shows in the fig. 4(d).

IV. CONCLUSION & FUTURE WORK

The paper presents the primary phase of the lung nodule detection system that aims to classify the lung nodule as cancerous or not. The primary phase constitutes the lung tissue extraction from the input lung CT images. The input images are chose from the LIDC-IDRI database and they are subjected to pre-processing. The pre-processing stage involves wiener filtering to remove the additive noise and the contrast limited adaptive histogram equalization to improve the contrast of the images. The filter- enhanced images are used for the lung tissue extraction. The lung tissues are extracted from the background using the Otsu thresholding method. The method is a global thresholding method which is efficient in extracting lung tissues. The thresholding method can easily distinguish the lung tissues from the non-lung structures. Even though the intensity similarity exists between the lung and non-lung areas it is possible to distinguish the lung tissues. The method operates on reducing the intra class variance and increasing the interclass variance. The method could eliminate the portions of ribs and diaphragm that are present in the CT images. It can retain the attached vasculature inside the lung tissue which may be useful for detecting the nodule type in subsequent processing stage. The future work is focused on extracting the lung nodules and determining the appropriate features for nodule detection. It has to be followed by the use of an appropriate classification system to distinguish the lung nodules as cancerous or not.

REFERENCES

[1]. Juan Eugenio Iglesias and, Mert R.Sabuncu, “Multi atlas segmentation of biomedical images: A survey”, Medical Image Analysis, Vol. 24, pp.205–219, September 2015.

[2]. Awais Mansoor, Ulas Bagci, Ziyue Xu, Brent Foster, Kenneth N. Olivier, Jason M. Elinoff, Anthony F. Suffredini, Jayaram K. Udupa and Daniel J. Mollura, “A generic approach to pathological lung segmentation”, IEEE Transactions On Medical Imaging, Vol. 33, No. 12, pp.2293-2310, December 2014.

[3]. Shivendra Singh, Manish Soni, Arun Patel and Ravi Sankar Mishra, “Performance evaluation of spatial domain contrast enhancement techniques for underwater images”, International Journal of Computer Applications, Vol.93,No.11,pp.41-46, May 2014.

[4]. S.Sivakumar and Dr.C.Chandrasekar, “ Image denoising for lung CT scan images”, IJETCAS, Vol.7,No.1,pp.86-91, February 2014.

[5]. Shenshen Sun, Yang Guo, Yubao Guan, Huizhi Ren, Linan Fan, and Yan Kang , “Juxta-vascular nodule

segmentation based on flow entropy and geodesic distance", IEEE Journal of Biomedical and Health Informatics, Vol. 18, No. 4, pp.1355-1362, July 2014.

[6]. Fan Zhang, Yang Song, Weidong Cai, Min-Zhao Lee, Yun Zhou, Heng Huang, Shimin Shan, Michael J Fulham, and Dagan D. Feng, "Lung nodule classification with multilevel patch-based context analysis", IEEE Transactions on Biomedical Engineering, Vol. 61, No. 4, pp. 1155-1166, April 2014.

[7]. Amal A. Farag, Hossam E. Abd El Munim, James H. Graham, and Aly A. Farag, "A Novel Approach for Lung Nodules Segmentation in Chest CT Using Level Sets", IEEE Transactions On Image Processing, Vol. 22, No. 12, pp.5202-5213, December 2013.

[8]. Anam Tariq, M. Usman Akram and M. Younus Javed , "Lung nodule detection in CT images using neuro fuzzy classifier", IEEE International Workshop on Computational Intelligence in Medical Imaging, pp. 49-53, August 2013.

[9]. Sheng Chenand Kenji Suzuki, "Computerized detection of lung nodules by means of "virtual dual energy" radiography", IEEE Transactions On Biomedical Engineering, Vol. 60, No. 2, pp. 369-378, April 2013.

[10]. Yang Song, Weidong Cai,Yun Zhou and David Dagan Feng, "Feature-Based Image Patch Approximationfor Lung Tissue Classification", IEEE Transactions on Medical Imaging, Vol. 32, No. 4, pp. 797-808, April 2013.

[11]. Yang Song, Weidong Cai, Jinman Kim and David Dagan Feng, "A Multistage Discriminative Model for Tumor andLymph Node Detection in Thoracic Images", IEEE Transactions on Medical Imaging, Vol. 31, No. 5, pp. 1061-1075, May 2012.

[12]. Amal A. Farag, Hossam Abdelmunim, James Graham, Aly A. Farag, Salwa Elshazly Sabry El-Mogy, Mohamed El-Mogy,, Robert Falk, Sahar Al-Jafary, Hani Mahdi, and Rebecca Milam, "Variational approach for segmentation of lung nodules", IEEE conference on image processing, pp.2157-2160,January 2011.

[13]. Marios A. Gavrielides, Rongping Zeng, Lisa M. Kinnard, Kyle J. Myers, and Nicholas Petrick, "Information-Theoretic Approach for Analyzing Bias and Variance in Lung Nodule Size Estimation with CT: A Phantom Study", IEEE Transactions on Medical Imaging, Vol. 29, No. 10, pp.1795-1807, October 2010.

[14]. Joao Rodrigo Ferreira da Silva Sousa, Aristofanes Correa Silva, Anselmo Cardoso de Paiva, Rodolfo Acatauassu Nunes, "Methodology for automatic detection of lung nodules in computerized tomography images", Computer methods and programs in biomedicine, Vol.98, pp.1-14, April 2010.

[15]. Lauge Sørensen, Saher B. Shaker, and Marleen de Bruijne, "Quantitative Analysis of Pulmonary Emphysema Using Local Binary Patterns", IEEE Transactions On Medical Imaging, Vol. 29, No. 2,pp.559-569, February 2010.

[16]. S.L.A. Lee, A.Z. Kouzani, G. Nasierding and E.J. Hu, "Pulmonary nodule classification aided by clustering", Proceedings of the 2009 IEEE International Conference on Systems, Man and Cybernetics, pp.906-911, October 2009.

[17]. Jan Hendrik Moltz, Lars Bornemann, Jan-Martin Kuhnigk, and Heinz-Otto Peitgen, "Advanced segmentation techniques for lung nodules, liver metastases, and enlarged lymph nodes in CT scans",IEEE Journal of Selected Topics in Signal Processing, Vol. 3, No. 1, pp. 122-134, February 2009.

[18]. Stefano Diciotti, Giulia Picozzi, Massimo Falchini, Mario Mascalchi, Natale Villari, and Guido Valli, "3-D segmentation algorithm of small lung nodules in spiral CT images", IEEE Transactions On Information Technology In Biomedicine, Vol. 12, No. 1, pp. 7-19, January 2008.

[19]. Paola Campadelli, Elena Casiraghi, and Diana Artioli, "A fully automated method for lung nodule detection from postero-anterior chest radiographs", IEEE Transactions on Medical Imaging, Vol. 25, No. 12, pp. 1588-1603, December 2006.

[20]. Ingrid Sluimer, Arnold Schilham, Mathias Prokop, and Bram van Ginneken, "Computer analysis of computed tomography scans of the lung: a survey", IEEE Transactions on Medical Imaging, Vol. 25, No. 4, pp.385-405, April 2006.

[21]. W. J. Kostis, A. P. Reeves, D. F. Yankelevitz, and C. I. Henschke, "Three dimensional segmentation and growth-rate estimation of small pulmonary nodules in helical CT images", IEEE Transactions on Medical Imaging, Vol. 22, No. 10, pp. 1259–1273, October 2003.

[22]. Yongbum Lee, Takeshi Hara, Hiroshi Fujita, Shigeki Itoh, and Takeo Ishigaki, "Automated detection of pulmonary nodules in helical ct images based on an improved template matching technique", IEEE

Transactions on Medical Imaging, , Vol. 20, No. 7, pp.595-604, July 2001.

[23]. R. Duda, P. Hart and D. Stork, Pattern Classification, 2ndEdition, Wiley, 2001.

[24]. S. G. Armato, M. L. Giger, and H. MacMahon , "Automated detection of lung nodules in CT scans: Preliminary results", Medical Physics, Vol. 28, pp. 1552–1561, January 2001.

[25]. "ELCAP public lung image database," [Online]. Available:http://www.via.cornell.edu/databases/lungdb.html

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