Review paper on A review on Lung Cancer Detection Using Digital Image Processing Techniques:A Comparative Study

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Abstract-Lung cancer seems to be the common cause of death among people throughout the world. Early detection of lung cancer can increase the chance of survival among people. The overall 5-year survival rate for lung cancer patients increases from 14 to 49% if the disease is detected in time. Although Computed Tomography (CT) can be more efficient than Xray. However, problem seemed to merge due to time constraint in detecting the present of lung cancer regarding on the several diagnosing method used. Hence, a lung cancer detection system using image processing is used to classify the present of lung cancer in an CT- images. In this study, MATLAB have been used through every procedures made. In image processing procedures, process such as image pre-processing, segmentation and feature extraction have been discussed in detail. We are aiming to get the more accurate results by using various enhancement and segmentation techniques.

Keywords-*CT; LCDS; Watershed Segmentation; ROI; Thresholding; Morphologic; Metastasis.*

I. INTRODUCTION

LUNG cancer is a major cause of cancer-related deaths in humans worldwide. Approximately 20% of cases with lung nodules represent lung cancers; therefore, the identification of potentially malignant lung nodules is essential for the screening and diagnosis of lung cancer. Lung nodules are small masses in the human lung, and are usually spherical; however, they can be distorted by surrounding anatomical structures, such as vessels and the adjacent pleura. Intraparenchymal lung nodules are more likely to be malignant than those connected with the surrounding structures, and thus lung nodules are divided into different types according to their relative positions. At present, the classification from Diciottiet al. is the most popular approach and it divides nodules into four types: well-circumscribed (W) with the nodule located centrally in the lung without any connection to vasculature; vascularized (V) with the nodule located centrally in the lung but closely connected to neighboring vessels; juxta-pleural (J) with a large portion of the nodule connected to the pleural surface; and pleural-tail (P) with the nodule near the pleural surface connected by a thin tail.

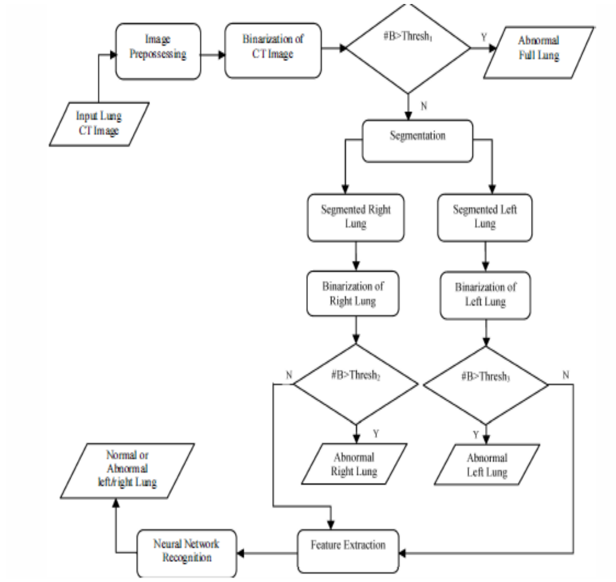
Computed tomography (CT) is the most accurate imaging modality to obtain anatomical information about lung nodules and the surrounding structures. In current clinical practice, however, interpretation of CT images is challenging for radiologists due to the large number of cases. This manual reading can be error-prone and the reader may miss nodules and thus a potential cancer. Computer-aided diagnosis (CAD) systems would be helpful for radiologists by offering initial screening or second opinions to classify lung nodules. CADs provide depiction by automatically computing quantitative measures, and are capable of analyzing the large number of small nodules identified by CT scans.

Increasingly, computed tomography (CT) offers higher resolution and faster acquisition times. This has resulted in the opportunity to detect small lung nodules, which may represent lung cancers at earlier and potentially more curable stages. However, in the current clinical practice, hundreds of such thin-sectional CT images are generated for each patient and are evaluated by a radiologist in the traditional sense of looking at each image in the axial mode. This results in the potential to miss small nodules and thus potentially miss a cancer. In this paper, we present a computerized method for automated identification of small lung nodules on multislice images.

A. Image Acquisition

Normally a special type of digital X-Ray machine is used to acquire detailed pictures or scans of areas inside the body called computerized tomography (CT). Computed tomography is an imaging procedure. The system has been collected total300 Lung CT images that are cancer and normal image of lung from the Internet and Hospital. The system used Lung CT images that are jpeg file format.

DATAFLOW DIAGRAM



B. Image Preprocessing

After Image Acquisition, images are passed through the image preprocessing steps. Fig. 1 shows the block diagram of image preprocessing steps.

1) Gray Scale Conversion

RGB image converted into gray scale image by using the Matlab function rgb2gray. It converts RGB image or color image to grayscale by eliminating the hue and saturation information while retaining the luminance.

2) Normalization

Normalize the acquired image by using the Matlab functionimre size. The system uses imre size function with the value of 150 x 140 pixels and 200 x 250 pixels. This size gives enough information of the image when the processing time is low.

3) Noise Reduction

To remove the noise the system used median filter i.e.medfilt2. Medfilt2 is 2-D median filter. Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. A median filter is more effective than convolution when the goal IS to simultaneously reduce noise and preserve edges.

4) Binary Image

Noise free gray scale image is converted to binary image, that is an image with pixels O's (white) and I 's (black). To convert gray scale image into binary image, the system use the Matlab function im2bw.

5) Remove unwanted portion of the image

Converting into binary image, we have to remove the unnecessary pixels (0) from original image. This is done because we need to develop size independent algorithm.

C. Segmentation

Image Segmentation in computer vision system, is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely ,image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. In the proposed system, segmentation processes consists of different steps.

D. Thresholding Method

Thresholding method is based on a threshold value to turn a gray-scale image into a binary image. The key idea of this method is to select the threshold value (or values when multiple levels are selected). Recently, methods have been developed for thresholding computed tomography (CT)images. The simplest method of image segmentation is called the thresholding method. The proposed system used three types of threshold value i.e. Threshlo Threshz, and Thresh3. Inbinary CT image, if the percentage of white pixels is greater than the Thresh), then full lung is affected. In segmented binary image, if the percentage of white pixels is greater than the Thresh2 and Thresh3. then the right lung and left lung respectively is affected.

E. Feature Extraction

The system has been used a rotation and size independent feature extraction method to extract the feature of the lung cancer and finally obtain 33 features for each type of lung cancer CT images.

F. Neural Network Detection

After the Thresholding method, rest of the Lung Cancer Detection System uses neural network which is very efficient and reliable. After the feature extraction process, these features are passed through the neural network to train up the system for classification purpose or detection purpose. The whole proposed training system of lung cancer detection consist of the following steps- Image Acquisition, Image Preprocessing, Segmentation, Feature Extraction, Neural Network Classification.

II. LITERATURE REVIEW

Aparna kanatte et al [1] describes Lung carcinoma is one of the most lethal of cancers worldwide. Positron emission tomography (PET) data has greater sensitivity and specificity in the staging of lung cancer than computed tomography (CT) or magnetic resonance imaging (MRI). By using knearest neighbor and support vector machines (SVM) classifiers. Wavelet features with SVM classifier gave a consistent accuracy of 97% with an average sensitivity and specificity of 0.81 and 0.99 respectively.

Yongbum Lee et. al [2] proposed novel template matching technique based on genetic algorithm(GA) template matching

(GATM)for detecting nodules existing in lung area, for Computer- Aided Diagnosis (CAD) systems to detect lung nodule in helical X-ray pulmonary computed tomography (CT) images. The GA was used to determine the target position in the observed image efficiently and to select an adequate template image from database. By using this method detection of nodule rate is about 72%.

Samuel H Hawkins et. al [3] presented on the focusing on cases of the adenocarcinoma nonsmall cell lung cancer tumor subtype from a larger data set. Comparison of classifiers for future selection approaches. Classifiers can be used to build to predict survival time.

Xing CHEN et. al [4] proposed a noninvasive detection method of lung cancer combined with a sort of virtual l SAW gas sensors and imaging recognition method. Patients breathe goes through an electronic nose with solid phase micro extraction (SMPE) and capillary column for pre concentration and separation of volatile organic compounds (VOCs) respectively.

Noha Lee et. al [5] provides insight into effectiveness of lung cancer screening and assesses the potential of computeraided design developments. CAD systems for lung tissue discrimination, nodule discrimination, and nodule characterization. CAD Technology may help radiologists alter the benefit- cost calculus of CT sensitivity and specificity in lung cancer screening.

David S et. al [6] developed CAD algorithm to detect lung nodule and polyp detection using CAD normal surface overlap method in helical Computed Tomography (CT) images.

Jyh-Shyan et. al. [7] developed a neural- digital computeraided diagnosis system (CAD) system based on a parameterized two level convolution neural network (CNN) Architecture and on a special multipliable output encoding procedure. The developed architecture was trained, tested and evaluated specially on the problem of diagnosis of lung cancer nodule found on digitized chest radio- graphs. The system performs automatic suspect localization feature extraction and diagnosis of a particular pattern class-aimed at a high degree of "true-positive fraction" detection and "low positive fraction" detection.

Freedman et al. [8] assessed the detection of signs consistent with lung cancer on chest radiographs and breast cancer on mammograms. There are systems for other diseases and other types of images under development; however, this process depends on the availability of an accurate database. The performance of a Siemens Lung Care CT CAD system against a radiologist-generated database of CT imaged nodules. CAD and individual radiologists participating in the evaluation performed similarly.

Mac Redmond R et al. [9] presented the prevalence of respectable lung cancer detected by LDCCT at baseline screening was low at 0.23%, but there was a high rate of significant incidental pathology. Low dose chest computed tomographic scanning (LDCCT) can detect early stage asymptomatic lung cancer in a high risk urban population. Four hundred forty patients underwent surgery for primary lung cancer, and 45 normal cases were selected. Eight radiologists participated in observer tests.

Basavanna et al. [11] provided guidelines for clinically relevant FPR and TPR measures [10] as well as special ROC methods for cancer screening, [15-18] and also noted that since the underlying prevalence of cancer in average risk populations is very low, the FPR should be very small for acceptable cancer screening of asymptomatic people.

Bagyasri et al. [15], the authors described a theoretical analysis on how to combine classifiers with an optimal decision rule and optimal ROC curve. To provide clinically relevant definitions for sensitivity and specificity [12-13].

Anam Tariq et al. [17] investigated the effect of a CAD scheme on radiologist performance in the detection of lung cancers on chest radiographs.

Ruchka et al. [14] reported a CAD system for nodule detection using a difference-image technique. They compared several rule-based schemes for identifying nodules. A massive-training ANN (MTANN) [34] reduced the false positives.

Danshensong et al. [18] reported on a CAD scheme to help radiologists improve the detection of pulmonary nodules in chest radiographs by focusing on false positive reduction. They could reduce the number of false positives to 44.3% with a small increase in the number of true positives of 2.3%.

Kesav kancherla et al [21-23], obtained an accuracy of 81% using 71 features related to shape, intensity and color in our previous work. By adding the nucleus segmented features we improved the accuracy to 87%. Nucleus segmentation is performed by using Seeded region growing segmentation method. Our results demonstrate the potential of nucleus segmented features for detecting lung cancer in early stage.

R. Sah et al. [24] Five year survival in stage I carcinoma was not influenced by histological type, while there was statistically significant difference in survival between adenocarcinoma (0%) and squamous cell carcinoma (46%) in stage II disease, with early stage lung cancer reported patientspecific models for detecting lung nodules for use in screening and follow-up surveillance. In the last decades, a large body of research has been reported in the field of lung nodule detection and classification [2], [16-19].

S. Sone et al [25-27] most lung cancers are not localized when first detected, but early detection is mandatory to improve prognosis. Since curable early cases are hard to visualize with conventional chest radiography, a new diagnostic means must be found. We assessed whether population-based mass screening with a spiral computed tomography scanner could contribute substantially to detection of smaller cancers, and decrease mortality.

Kramer et al. [28] described an automated method to distinguish benign and malignant solitary nodules. Fifty-five chest radiographs were discriminated using LDA and ANN for feature combination and classification. Comparisons with manual grading showed that LDA had an AUC value of 88.6%, whereas manual identification resulted in an AUC value of 85.4%.

J. C. Nesbitt et al [29-30] Reducing morphologic differences by placing patients in groups based on the TNM subset and refinement in categorization by matching TNM subsets based on histology and other factors can improve

considerably homogeneity and enhance prognostic predictability. The development of more accurate measures for predicting prognosis may serve to clarify the roles of primary and adjuvant treatment, particularly in those patients with early-stage disease associated with poor prognostic factors in whom the potential for long-term survival is reduced.

B. J. Flehinger et al. [35] 70 percent of the stage I patients in each program who were treated surgically survived more than five years, but there were only two five-year survivors among those who did not have surgery. We conclude that patients with lung cancers detected in stage I by chest x-ray film and treated surgically have a good chance of remaining free of disease for many years. Those stage I lung cancers which are not respected progress and lead to death within five years. Therefore, every effort should be made to detect and treat lung cancer early in high-risk populations.

A central concern in nodule detection is the high rate of false positives when sensitivity is increased to detect subtle nodules. A nodule is deemed a false positive result if it led to a completely negative workup or more than 12 months of follow-up with no cancer diagnosis. Reducing false positive rates while maintaining high sensitivity is still a difficult problem. Data mining techniques include LDA [34], rulebased approaches (a set of “if-then” statements),

combinations of these two [22], artificial neural networks (ANNs), and maximum-margin based discriminators such as the SVM. Novel methodologies for searching have been introduced. Matching for detection [35], unsupervised clustering techniques [33], and a local density maximum algorithm [32]. Methods to improve discrimination of nodules from lung tissue include subtraction of vessels by region-growing.

Automatic detection of small lung nodules on CT utilizinga local density maximum algorithm,Binsheng Zhao*, Gordon Gamsu, Michelle S. Ginsberg, Li Jiang, and Lawrence H. Schwartz-2003

Increasingly, computed tomography (CT) offers higher resolution and faster acquisition times. This has resulted in the opportunity to detect small lung nodules, which may represent lung cancers at earlier and potentially more curable stages. However, in the current clinical practice, hundreds of such thin-sectional CT images are generated for each patient and are evaluated by a radiologist in the traditional sense of looking at each image in the axial mode. This results in the potential to miss small nodules and thus potentially miss a cancer. In this paper, we present a computerized method for automated identification of small lung nodules on multi slice CT (MSCT) images. The method consists of three steps: (i) separation of the lungs from the other anatomic structures, (ii) detection of nodule candidates in the extracted lungs, and ~iii! reduction of false-positives among the detected nodule candidates. A three-dimensional lung mask can be extracted by analyzing density histogram of volumetric chest images followed by a morphological operation. Higher density structures including nodules scattered throughout the lungs can be identified by using a local density maximum algorithm. Information about nodules such as size and compact shape are then incorporated into the algorithm to reduce the detected nodule candidates which are not likely to be nodules. The method was applied to the detection of computer simulated small lung nodules (2 to 7 mm in diameter) and achieved a sensitivity of 84.2% with, on average, five false-positive results per scan. The preliminary results demonstrate the potential of this technique for assisting the detection of small nodules from chest MSCT images.

Quantification of Nodule Detection in Chest CT:A Clinical Investigation Based on the ELCAP StudyAmal A. Farag, Shireen Y. Elhabian, Salwa A. Elshazly and Aly A. Farag–2008

This paper examines the detection step in automatic detection and classification of lung nodules from low-dose CT (LDCT) scans. Two issues are studied in detail: nodule modeling and simulation, and the effect of these models on the detection process. From an ensemble of nodules, specified by radiologists, we devise an approach to estimate the gray level intensity distribution (Hounsfield Units) and a figure of merit of the size of appropriate templates. Hence, a data-driven approach is used to design the templates. The paper presents an extensive study of the sensitivity and specificity of the nodule detection step, in which the quality of the nodule model is the driving factor. Finally, validation of the detection approach on labeled clinical dataset from the Early Lung Cancer Action Project (ELCAP) screening study is conducted. Overall, this paper shows a relationship between the spatial support of the nodule templates and the resolution of the LDCT, which can be used to automatically select the template size. The paper also shows that isotropic templates do not provide adequate detection rate (in terms of sensitivity and specificity) of vascularized nodules. The nodule models in this paper can be used in various machine learning approaches for automatic nodule detection and classification.

Parametric and Non-Parametric Nodule Models:Design and Evaluation Amal A. Farag, James Graham, Aly A. Farag, SalwaElshazly and Robert Falk*- 2007

Lung nodule modeling quality defines the success of lung nodule detection. This paper presents a novel method for generating lung nodules using variational level sets to obtain the shape properties of real nodules to form an average model template per nodule type. The texture information used for filling the nodules is based on a devised approach that uses the probability density of the radial distance of each nodule to obtain the maximum and minimum Hounsfield density (HU). There are two main categories that lung nodule models fall within; parametric and non-parametric. The performance of the new nodule templates will be evaluated during the detection step and compared with the use of parametric templates and another non-parametric Active Appearance model to explain the advantages and/or disadvantages of using parametric vs. non-parametric models as well as which variation of nonparametric template design, i.e., shape based or shape-texture based yields better results in the overall detection process.

Computer Analysis of Computed Tomography Scans of the Lung: a Survey Ingrid Sluimer, Arnold Schilham, Mathias Prokop, and Bram van Ginneken *, Member, IEEE– 2005

In this paper, Current computed tomography (CT) technology allows for near isotropic, sub millimeter resolution acquisition of the complete chest in a single breath hold. These thin-slice chest scans have become indispensable in thoracic radiology, but have also substantially increased the data load for radiologists. Automating the analysis of such data is, therefore, a necessity and this has created a rapidly developing research area in medical imaging. This paper presents a review of the literature on computer analysis of the lungs in CT scans and addresses segmentation of various pulmonary structures, registration of chest scans, and applications aimed at detection, classification and quantification of chest abnormalities. In addition, research trends and challenges are identified and directions for future research are discussed.

Evaluation of geometric feature descriptors for detection andclassification of lung nodules in low dose ct scans of the chestamalfarag, asemali, james graham, alyfarag, salwaelshazly and robertfalk*– 2011

This paper examines the effectiveness of geometric feature descriptors, common in computer vision, for false positive reduction and for classification of lung nodules in low dose CT (LDCT) scans. A data-driven lung nodule modeling approach creates templates for common nodule types, using active appearance models (AAM); which are then used to detect candidate nodules based on optimum similarity measured by the normalized cross-correlation (NCC). Geometric feature descriptors (e.g., SIFT, LBP and SURF) are applied to the output of the detection step, in order to extract features from the nodule candidates, for further enhancement of output and possible reduction of false positives. Results on the clinical ELCAP database showed that the descriptors provide 2% enhancements in the specificity of the detected nodule above the NCC results when used in a k-NN classifier. Thus quantitative measures of enhancements of the performance of CAD models based on LDCT are now possible and are entirely model-based most importantly; our approach is applicable for classification of nodules into categories and pathologies.

III. SUMMARY OF LUNG NODULE DETECTION AND CLASSIFICATION WORK

Image processing and data mining classification techniques are useful together have shown significant improvement in medical industry in terms of prediction, detection and decision making of lung cancer in early stage.

Table 1 shows the summary of image processing and classification work, accuracy and sensitivity of various techniques.

Table.1:Summary of Lung Nodule Detection and Classification.

Author	Images	Technique		Year	Accuracy
		Segmentation algorithm	Classifier		
Aparna kanatte [1]	PET	Standard Uptake Values	KNN, SVM	2008	97%
Danshen song [18]	CT	Entropy Threshold	SVM	2000	85
Yongbum Lee [2]	CT	GATM	Classification	2001	72%
Atiyeh Hashemi [20]	CT	Region Growing	ANN	2013	95%
Basavanna [11]	CT	Max- Min cluster Algorithm	KNN, DT	2016	85%
Fatma Taher [12]	Sputum	Hopfield Neural Network(HNN)	Bayesian	2012	88.62%

Author	Images	Technique		Year	Accuracy
		Segmentation algorithm	Classifier		
Prashanth [13]	PET	Threshold Segmentation	KNN, SVM	2014	97%
Ruchika [14]	CT	Mean Shift Algorithm	Mathematical Morphology	2015	86%
Bhagyasri [15]		Marker controlled water shed Algorithm	Classification	2014	85.25%
Kesav kancherla [21]	Sputum	Speed region growing	Random forest	2013	87%
S K Vijai Anand [19]	CT	Optimal Therosholding	Back Propagation Network	2010	86.30%
S. Sivakumar [16]	CT	Weighted fuzzy probabilistic based clustering	SVM	2013	80.36%
Anam Tariq [17]	CT	Trshold segmentation	Neuro- fuzzy	2013	95%

IV. CONCLUSION

Lung cancer is one kind of dangerous diseases, so it is necessary to detect early stages. But the detection of lung cancer is most difficult task. From the literature review many techniques are used for the detection of lung cancer but they have some limitations. In our proposed method pursue approaches in which first step is binary thresholding, and then feature extraction, and then these features are used to train up the neural network and test the neural network. The proposed system successfully detects the lung cancer from CT scan images. At the end of the system can say that the system achieve its desired expectation. The proposed system test 150 types of lung CT images and obtains the result where overall success rate of the system is 96.67% which meet the expectation of system. In future this technique can be used in the detection of brain tumor, breast cancer etc.

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