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An Automated Lung Cancer Detection from CT Images Based on Using Artificial Neural Network and Fuzzy Clustering Methods

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ABSTRACT

Lung cancer is a serious public health problem, as the most significant data today can indicate that its incidence continues to increase in women at 3.1% annually over the past 20 years; on the other hand in men, an annual decline of 0.8% is also observed for the past 20 years. The modalities used for capturing the images are X-Ray, Computer Tomography (CT) scans and Magnetic Resonance Imaging (MRI) and among these CT is the standard for detecting pulmonary nodules. Lung nodule detection in chest Computed Tomography (CT) images becomes very necessary in the present clinical world. Neural network has been significant in the areas of research in the past two decades. The main aim of this research is to provide a Neural network System for detection of lung cancer nodules from the Chest Computer Tomography images. The structure can automatically spot the lung cancer nodules with reduction in false positive rates and it also lessens the time taken by the radiologist for elucidation.

Index Terms— Magnetic Resonance, Lung cancer, Neural network, X-Ray, Computer Tomography

INTRODUCTION

With the name of lung cancer or lung cancer is malignant pulmonary includes those derived from tumors of the lung epithelial cells, or neuroendocrine cells. Less than 10% of bronchogenic carcinomas derived from alveolar region. Lung cancer, the most

outstanding early twentieth century disease, has become a health problem of the first order. It is the most common cancer suffered by mankind and today are diagnosed annually 2,000,000 cases. Says little in favor of humanity to think that even the most frequent cancer and causing increased mortality, it is also one of the most easily preventable as it is estimated that the snuff is directly responsible for 90% of cases . Snuff. Snuff smoke is by far the main risk factor for developing lung cancer. Snuff smoke contains 4,000 different chemicals including a minimum of 40 components included with demonstrated carcinogenic potential, such as nitro sources, and. A person of 35 years of smoking 20 or more cigarettes a day have a 13% risk of dying from lung cancer before age 75 and 28% chance of dying from a disease related to snuff. The risk of developing lung cancer increases with the number of cigarettes smoked per day, number of years smoked, age of smoking initiation, the degree and intensity of inhalation, the tar and nicotine and the use of unfiltered cigarettes. Other forms of smoking (cigar, pipe) have also been linked with lung cancer, although this relationship is not so obvious. Despite the irrefutable certainty that snuff causes lung cancer (and many other serious diseases), smoking prevalence remains high, and what is more disturbing, the population sector in which smoking is increasing more significantly it is in adolescents and lower social strata, and in less developed countries. Unfortunately, this is due in large part to the success of very aggressive advertising campaigns to promote smoking among these population groups. Passive smoking. Since the 80s were shown that nonsmoking women who lived with male smokers had a higher risk of developing lung cancer risk, the role of so-called passive smoking has been the subject of much scientific debate as both social and political. Approximately 15% of cases of lung cancer occur in non-smokers and 5% of cancer deaths are attributable to passive smoking.

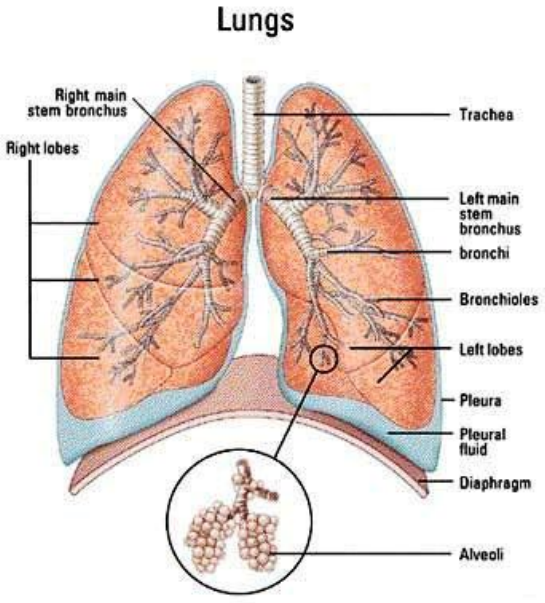

Figure 1. Structure of the Lungs

There are differences in histological type of lung cancer among men and women. In men the most common is squamous cell carcinoma and adenocarcinoma in women. Among male smokers relative to develop squamous cell carcinoma and small cell carcinoma risk is similar, while in women the relative risk for small cell carcinoma is higher than they have to develop squamous cell carcinoma. The different incidence of the various histological types between men and women suggests that factors other than snuff could influence its development. In the development of lung cancer in women has been postulated hormonal and especially the effect of estrogen. Race. The black men seem to have a greater risk of developing lung cancer than white men for the same degree of smoking. Diet. There is epidemiological evidence that eating plenty of fruits and vegetables lowers the risk of developing lung cancer.

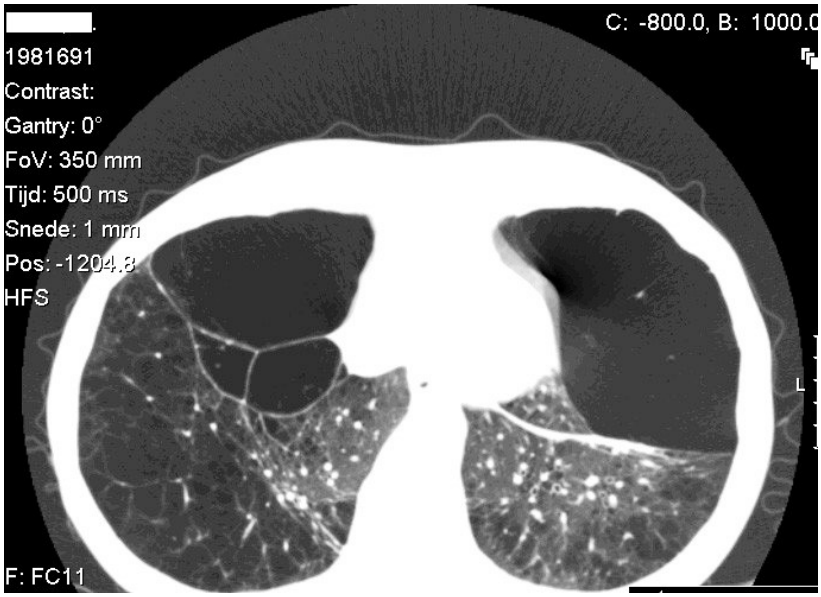

Figure 2. CT scan – Lung Image

Computed Tomography Imaging known as a CT scan (or CAT scan) is a particular type of x-ray that uses multiple x-ray beams at different angles to build up a cross section of the body's organs and tissues. The protective effect could be due to the presence in food of beta-carotene (retinoid precursor of vitamin A). However, recent studies have failed to demonstrate a beneficial effect of supplementation of beta-carotene in the diet. Other nutrients such as folic acid, selenium and vitamins C and E may also have a protective effect against the development of lung cancer. Atmospheric pollution. There is a small but consistent difference in the incidence and mortality from lung cancer among urban and rural areas suggest that air pollution may play a carcinogenic role in densely populated urban areas. Respiratory diseases. Idiopathic pulmonary fibrosis and COPD are two entities that are associated with an increased risk for lung cancer risk. Hereditary predisposition. It is shown that the genetic characteristics of the individual have a determining influence on the risk of

developing lung cancer after exposure to snuff or other carcinogens. The non-smoking relatives of individuals with lung cancer are at risk 2 or 3 times higher than develop that nonsmokers with no family history. Moreover, the ability to induce genetically determined cytochrome P450 enzymes such as aryl hydrocarbon hydroxylase involved in the metabolism of various carcinogens, it has been associated with an increased risk for lung cancer risk. Finally, and as discussed below, a relationship between specific mutations in certain oncogenes and suppressor oncogenes and development of lung cancer.

LITERATURE SURVEY

The clinical history and physical examination are essential in the evaluation of patients with suspected lung cancer. Special emphasis will be on finding guide constitutional syndrome symptoms such as cough, dyspnea or suggest demonstrations extent of local disease (chest pain, hoarseness) or systemic (headache, bone pain). Chest radiograph. Is impaired in the majority of patients when the first symptoms appear. 80% of cases of lung cancer develop in the main airway, so the most common radiographic findings are enlargement (by the tumor or by the presence of mediastinal lymph nodes) and atelectasis. The obstruction of a main bronchus or lobar image causes a partial or complete atelectasis that is often associated with a distal retention condensation bronchial secretions and secondary infectious pneumonitis. The clinical and radiographic picture is sometimes difficult to differentiate from bacterial pneumonia. Should be suspected of an end bronchial tumor when mediastinal lymph nodes seen in the chest radiograph, radiographic when condensation is not altered after 3 weeks of antibiotic therapy, or when repeated episodes of infectious pneumonitis occurring in the same anatomic location.

Kazunori Okada et al (2005) proposed a statistical estimation and validation, described in a multi-slice X-ray computed tomography (CT) images of geometric oval pulmonary nodule structure. And proposed joint segmentation and multi-scale modeling this approach suitable solution. The technology extends the average will be based on a linear scale turning powerful spatial analysis theory. And placed in near real-time three-dimensional planning illustrations nodules using this method, and check out the two sets of clinical data thin section chest CT images. This proposed approach in three different stages, but the continuous estimation model, model validation and volume measurements.

Ginneken et al (2001) described, the authors classification of different categories of lung extraction methods, rule-based classification, based on pixel category. In technology is based on the rule and using a series of steps, tests and rules, the extraction process, the most part of the proposed methods are that a class. Threshold, growing area, edge detection, edge detection, morphological operations, and the dynamic programming technique is used in some. Lung pixel classification is used, another method in which each pixel is classified in the CT image, the extraction process of the anatomical type region. Different types of neural networks, Markov random field modeling workbook for training, with a variety of local characteristics, including severity, location, texture measures.

Woten et al (2007) proposed numerical methods for detecting the use of artificial neural networks to achieve broadband planar antennas and three regional lung cancer promotion. In this method, the modified points and four antennas are used, which is able to produce different polarized waves. Wave polarization effects described fully in the method detection statistics by the author.

Provides a comprehensive proteomics-based spectrum technology can accurately diagnose various diseases. However, there exist some problems in the mass spectrometry data, such as a large volume, in the case of noise and the complexity of the data, so that very difficult proteomic profiling. In this proposed method, the system based on neural network is proposed by Xu et al (2009) for proteomic pattern analysis for prostate cancer screening. The technique is statistically significant nature of the technology, the classification of radial basis function neural network (RBF neural networks) of probabilistic neural network (PNN), and eventually led to the foundation by improving our analysis of the test, the three-stage feature selection. Display empirical observation, the method is very effective compared with the method. The proposed method has high sensitivity (97.1%) and specificity (96.8%), combined with a prostate biopsy, and are expected to help the early detection of prostate cancer.

The feed-forward neural network has trained three algorithms require the use of artificial neural network algorithm, radial basis function (RBF) network and learning vector quantization (LVQ) network and adaptive neuro-fuzzy inference system (ANFIS) regression neural network feed. Using MATLAB simulation and performance by observing indicators, such as the number of accuracy and training time, and neurons of the diagnosis, and number conventions assessment, and these standards may be very effective in the early detection of lung cancer.

PROPOSED METHOD

Artificial neural network (ANN) is a nonlinear data-driven type of self-regulation. Artificial neural network simulation is a major tool, especially when the relationship is the basis of the data is unknown. Correlation can be identified and studied the neural network model and the input data set corresponding to the target value. Training, and the results after new data input through a separate neural network prediction. Artificial neural network learning process produce human lungs, it can handle involve non-linear and complex data, even if the data is ambiguous situations. And is therefore ideally suited to those known to be complex and often non-linear modeling of data and even agriculture. An important feature of these networks is the adaptive nature. This feature makes this technology in the field of computing very attractive. Networked "Neural" may be inspired by the nerve, but not necessarily, since they are the reality of facts and biological neural or cognitive techniques. Most networks are more closely linked to the principle of mathematical models and statistical models like a traditional and non-parametric statistical regression model, which is neuroscience models. Artificial Neural Network (ANN) is based on biological neural system simulation technology. Artificial neural networks are interconnected by a group of artificial neurons, and the use of related technologies account processing information. It is a system, which will adjust its structure,

depending on the network during the learning phase flows through external or internal information. NNS is modeling products are mainly used modern methods of complex nonlinear relationship between the analog input and output data to identify patterns or statistical data. It represents the complete architecture of artificial neural networks. The algorithms were programmed in MATLAB 6.5 Worked with standard features of this language and the specific library Fuzzy Algorithm and Direct Search.

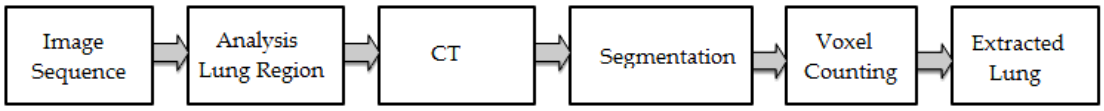

Figure 3. Existing Method

A new method for segmenting Lung cancer images is presented as in Figure 3. This system is used for detection of lung cancer by analyzing chest computer tomography (CT) images. In the first stage of this system, pure basic image processing techniques are used to extract lung regions. Long regions extracted using a mysterious and fragmented energy degrees C means (FPCM) per tablet, showing good segmentation results in a very short time. FPCM algorithms, which includes spatial information of the overall function of the members.

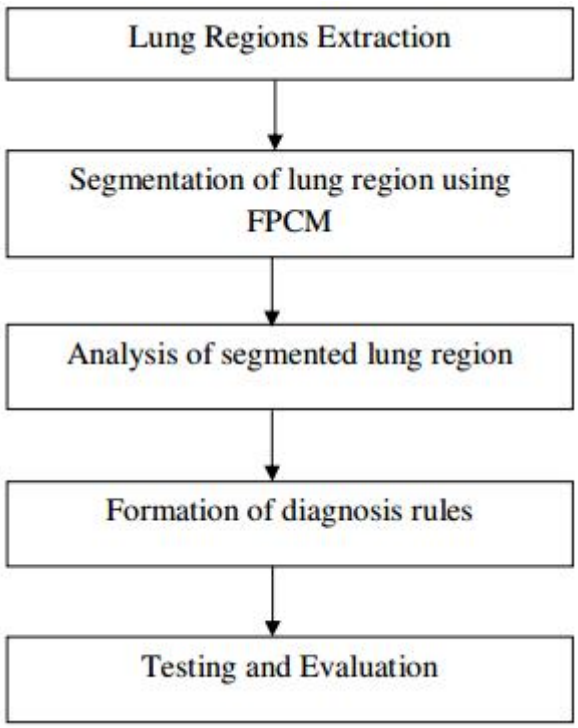

Figure 4. Proposed Method for the Lung Cancer Detection System using FPCM

FUZZY C-MEANS (FCM) ALGORITHM

The method is usually used for assembling Clustering Fuzzy C- mean (FCM). FCM of the target objective function is to find the center of the cluster and the production of organic substrates must be a member, which depends on the relative data points compared with other types of a specific category. (ie) The objective function provided by FCM is

FCM is deemed points separate statements. Therefore, one can use a program called degree C - refers to another method (PCM). Possibilistic C can be used and the type of algorithm of the Possibilistic can be described with the membership function of membership degrees. For sub-highs and representative offices as a representative membership is low which is very useful members. The intention function, which satisfies the requirements, is formulated as follows,

$$f(x_1,...,x_n)=\frac{\sum_{k=1}^{m} b^k[\prod_{i=1}^{n}\mu_{A_i k}(x_i)]}{\sum_{k=1}^{m}[\prod_{i=1}^{n}\mu_{A_i^k}(x_i)]} \tag{1}$$

where, d_{ij} represents the distance between the j^{th} data and the i^{th} cluster center, P_{ij} denotes the degree of belonging, m represents the degree of fuzziness, K_i is the suitable positive number, c is the number of clusters, and N denotes the number of pixels.

$$\frac{\partial f(x)}{\partial w_{ij}}=\frac{\partial \sigma(W_o \square \sigma(W_H \times X^T))}{\partial w_{ij}} \tag{2}$$

The standard fuzzy, c-means objective function for partitioning $\{x_k\}_{k=1}^{N}$ into C clusters is given by

$$J(U,V)=\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p}\left\|x_k-v_i\right\|^2 \tag{3}$$

Where $\{x_k\}_{k=1}^{N}$ the feature vectors for each pixel are,

$\{v_i\}_{i=1}^{c}$ are the prototypes of the clusters and the array $[u_{ik}]=U$ represents a partition matrix, namely

$$\sum_{i=1}^{c} u_{ik}=1 \mid 0\le u_{ik}\le 1, \forall k=1,2,3....N \tag{4}$$

$$0\le \sum_{k=1}^{N} u_{ik}\le N \tag{5}$$

The constrained optimization could be solved using one Lagrange multiplier then-input-1-output fuzzy neural network with simple fuzzy reasoning is defined below:

$$E^p=\frac{1}{2}[f(x_1^p,...,x_n^p)-y^p]^2 \tag{6}$$

$$b^k(t+1) = b^k(t) - \theta \left. \frac{\partial E^P}{\partial b^k} \right|_t \tag{7}$$

$$\sigma^k(t+1) = \sigma^k(t) - \theta \left. \frac{\partial E^P}{\partial \sigma^k} \right|_t \tag{8}$$

$$a^k(t+1) = a^k(t) - \theta \left. \frac{\partial E^P}{\partial a^k} \right|_t \tag{9}$$

$$\eta^k(t+1) = \eta^k(t) - \theta \left. \frac{\partial E^P}{\partial \eta^k} \right|_t \tag{10}$$

we can calculate the partial differential of the network with respect to the weight on hidden unit i that receives input j. This will us to calculate the update for the weight.

$$\frac{\partial f(x)}{\partial w_{ij}} = \frac{\partial \sigma(W_o \square \sigma(W_H \times X^T))}{\partial w_{ij}} \tag{11}$$

$$= \sigma(W_o \square \sigma(W_H \times X^T))(1 - \sigma(W_o \square \sigma(W_H \times X^T)) \frac{\partial W_o \square \sigma(W_H \times X^T)}{\partial w_{ij}} \quad \text{Chain Rule}$$

$$= (Y_o)(1 - Y_o) \frac{\partial W_o \square \sigma(W_H \times X^T)}{\partial w_{ij}}$$

$$= (Y_o)(1 - Y_o) \frac{\partial w_{o,i} \sigma(W_{H,i} \times X^T)}{\partial w_{ij}}$$

$$= (Y_o)(1 - Y_o) w_{o,i} \sigma(W_{H,i} \times X^T)(1 - \sigma(W_{H,i} \times X^T)) \frac{\partial (W_{H,i} \times X^T)}{\partial w_{ij}} \quad \text{Chain Rule}$$

$$= (Y_o)(1 - Y_o) w_{o,i} Y_i (1 - Y_i) \frac{\partial (W_{H,i} \times X^T)}{\partial w_{ij}} \quad \text{Definition of Yi}$$

$$= (Y_o)(1 - Y_o) w_{o,i} Y_i (1 - Y_i) x_j$$

To update weights on the output unit calculate is simpler:

$$\frac{\partial f(x)}{\partial w_{oi}} = \frac{\partial \sigma(W_o \square \sigma(W_H \times X^T))}{\partial w_{oi}} \tag{12}$$

$$= \sigma(W_o \square \sigma(W_H \times X^T))(1 - \sigma(W_o \square \sigma(W_H \times X^T)) \frac{\partial W_o \square \sigma(W_H \times X^T)}{\partial w_{oi}} \quad \text{Chain Rule}$$

$$= (Y_o)(1 - Y_o) \frac{\partial W_o \square \sigma(W_H \times X^T)}{\partial w_{oi}} \quad \text{Definition of Yo}$$

$$= (Y_o)(1 - Y_o) Y_i$$

The main advantage of this PCM technique is that the value of K_i can be fixed or can be changed at each iteration. The PCM is more robust in the presence of noise, in finding valid clusters, and in giving a robust estimate of the centers. The combination of FCM and PCM in Fuzzy Possibilistic C-Means could provide much better result.

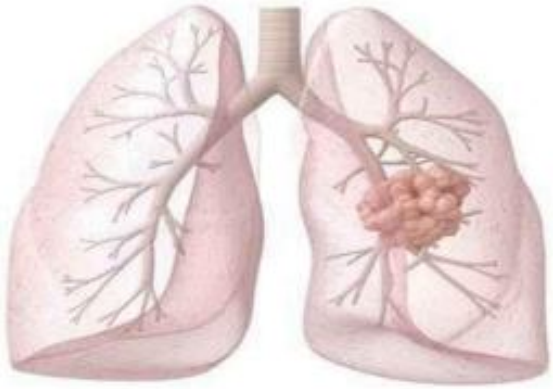

Figure 5 An example of cancerous lung image.

Because of several advantages of the fuzzy logic, the proposed system uses the Fuzzy Possibilistic C-Means (FPCM) for the segmentation purpose.

ADVANTAGES OF THE FPCM

The advantages of the FPCM method are the following:

1. Provides sections more homogeneous than other methods
2. It decreases the spurious blobs
3. It eliminates noisy spots
4. It is fewer delicate to noise than other methods.

SEGMENTATION

After the success of regional lung CT images to extract raw materials, such as described in the previous section, the CAD system second step is to propose a lung, which aims to find candidates extracted lung cancer retail area of the region - the new area of interest (Les).

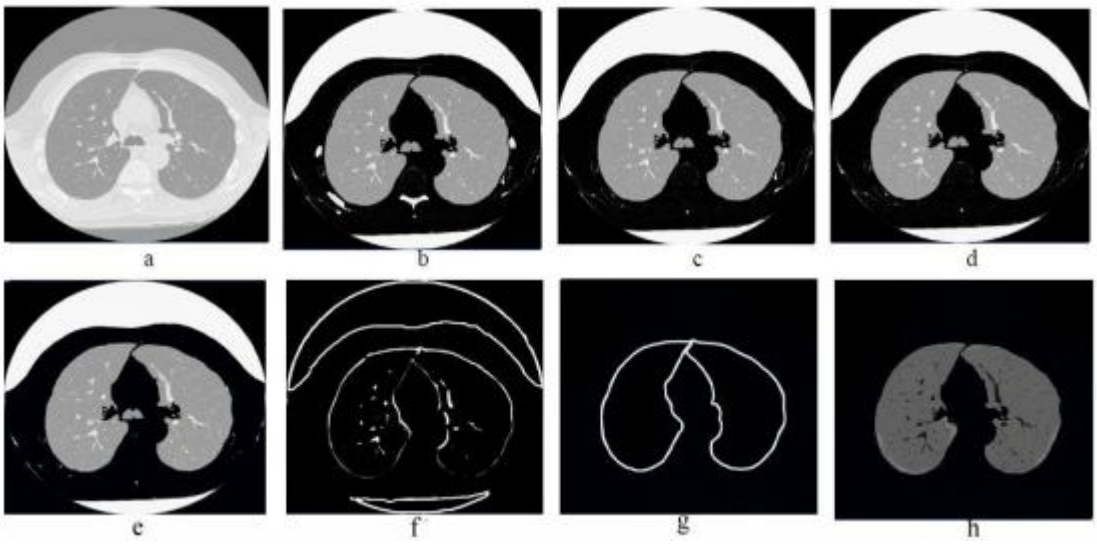

Figure 6 Lung regions extraction algorithm: a. original CT image, b. bit-plane, c. erosion, d. median filter, e. dilation, f. outlining, g. lung region borders, and h. extracted lung.

There are several segmentation methods obtainable in the literature which can be cast-off for this purpose. But FPCM is used here due to its significant performance.

METHODOLOGY

The main limitations of the earlier gray level thresholding techniques are the problem of selecting suitable and accurate threshold values. Moreover, some approaches, as in (Kanazawa et al 1998) need a post processing step to compensate the lost parts that may occur as a result of using the thresholding technique. The way to overcome the problem of the threshold, the region of the lung for the original data base have a new method to obtain bit plane technique fragmentation various functions of the automatic extraction of use. The extraction approach described in this section is fully automatic and depends on a set of basic digital image processing techniques adapted to the CT data. A CT image of chest contains different regions such as the background, lung, heart, and liver and other organs' areas. The main aim of lung region extraction step is to separate the lung regions, the regions of interest (ROIs), from the surrounding anatomical structures. Figure 4 clearly explains the method (Sammouda et al 2006) for the extraction of the lung regions from CT chest image. Initially, the bit-plane slicing algorithm (Gonzalez et al 2002) is applied to each CT image of the raw data. Bilateral section then checks the resulting bits to select the best image surface, a certain degree of extraction will help the accuracy and clarity of the original image from the area in the lung CT- data.

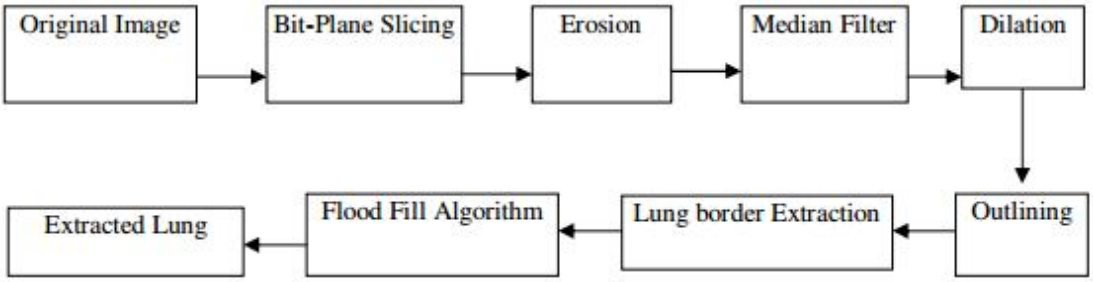

Figure 7. The Lung regions extraction method

In order to refine the selected bit-plane image, other approaches were used for different purposes in a sequence of steps. Erosion, the main purpose of the filter medium and the expansion step is to eliminate irrelevant details can add additional difficulties during the extraction process the lung borders. The outlining step mainly aims to extract the structure's borders. Lung boundaries separate step is used to extract all other structures boring structure of the lung. Finally, the method is based on the pile for the flood fill to fill the lung and the severity of the original extraction region. Figure 6 shows the results of applying step by step, the lung regions extraction method to a given CT image.

EXPERIMENTAL RESULT

FPCM clustering algorithm is able to integrate the two fuzzy degrees C mode features. Memberships and typicalities are very vital for the correct feature of data substructure in clustering problem. Thus, in this target function is determined by two members FPCM

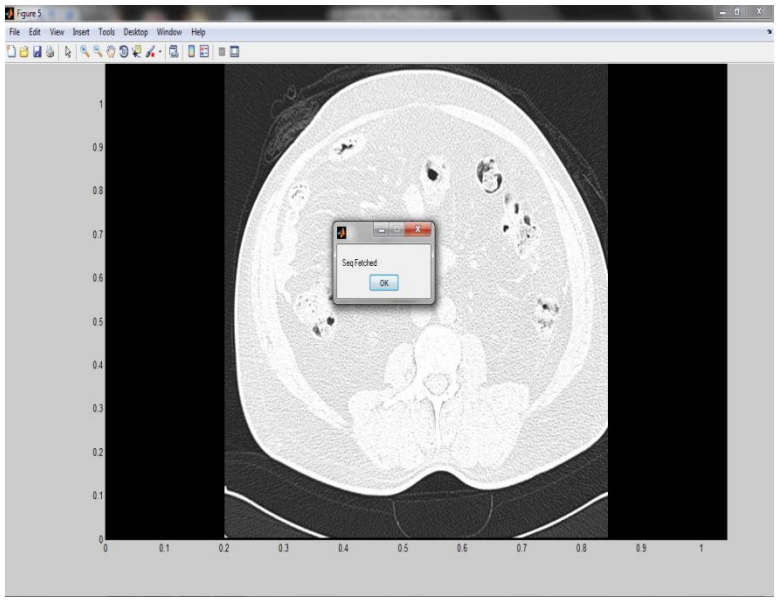

Figure 8. Sample Input CT Image Sequence

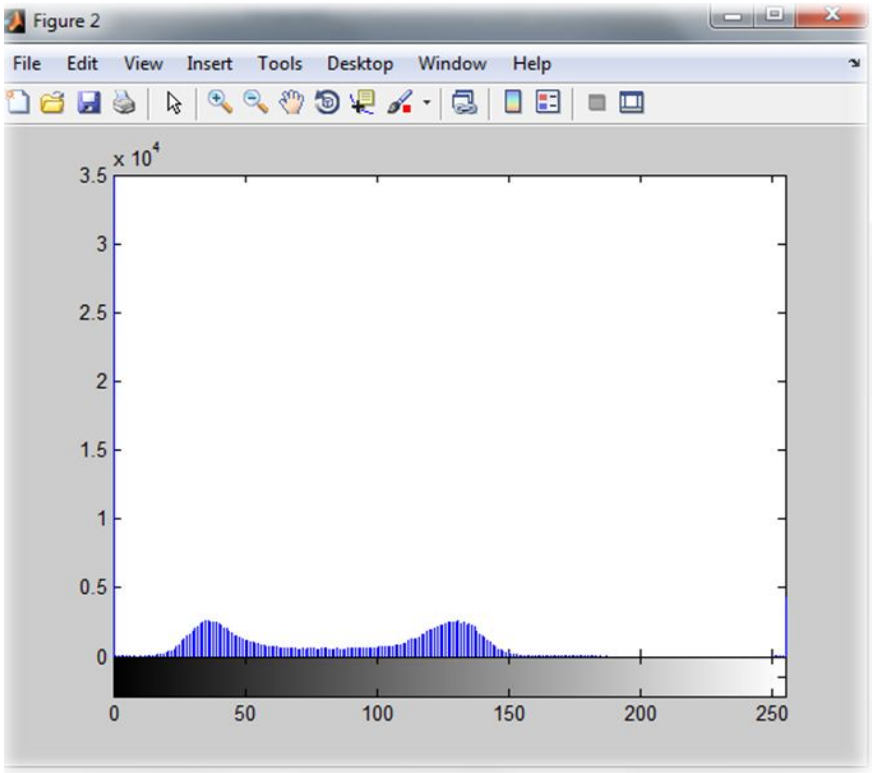

Figure 9. CT Image Sequence

Table 1.proposed nodal areas with lymph node stations

Proposed nodal zones	Nodal stations
N2 nodes	
Upper zone	Highest mediastinal (1) Upper paratracheal (2) Prevascular and retrotracheal (3a, 3b) Lower paratracheal (4)
Aortopulmonary xone	Subaortic (aortopulmonary window) (5) Para-aortic (ascending aorta or phrenic) (6)
Subcarinal zone	Subcarinal (7)
Lower zone	Paraesophageal (below carina) (8) Pulmonary ligament (9)
N1 nodes	
Hilar zone	Hilar (10) Interlobar (11)
Peripheral zone	Lobar (12) Segmental 13) Subsegmental (14

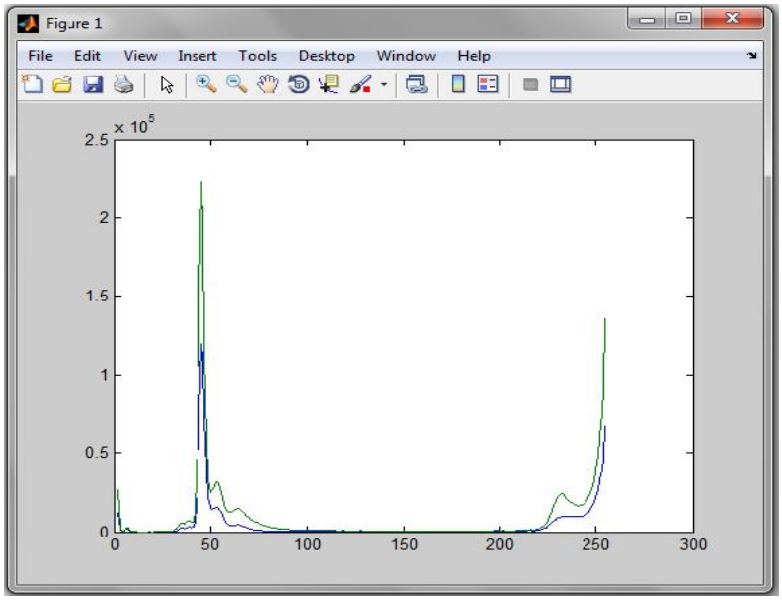

Figure 10. Combined segmentation for CT Image Sequence

The diagnosis rules formulated are very much useful in detecting the cancerous regions at the early stage. The threshold values used in the diagnosis rules helps in detecting the cancerous region at its starting stage (i.e. when the cancer region is very small). After all the rules are applied, very small numbers of cancerous candidate objects are present. These remaining candidates are marked by the CAD system as possible cancerous regions. Then the images with these regions were reported and exhibited to radiologist to take the final decision. This shows that the purpose of the proposed CAD system is not to replace the light. However, in order to help the radiologist to provide a tool to remind them of the potential distortions to facilitate their detection of lung cancer at an early stage. Moreover, the proposed approach aims at improving the accuracy of detection and minimizing the time spent by radiologists in analyzing a vast number of slices per patient.

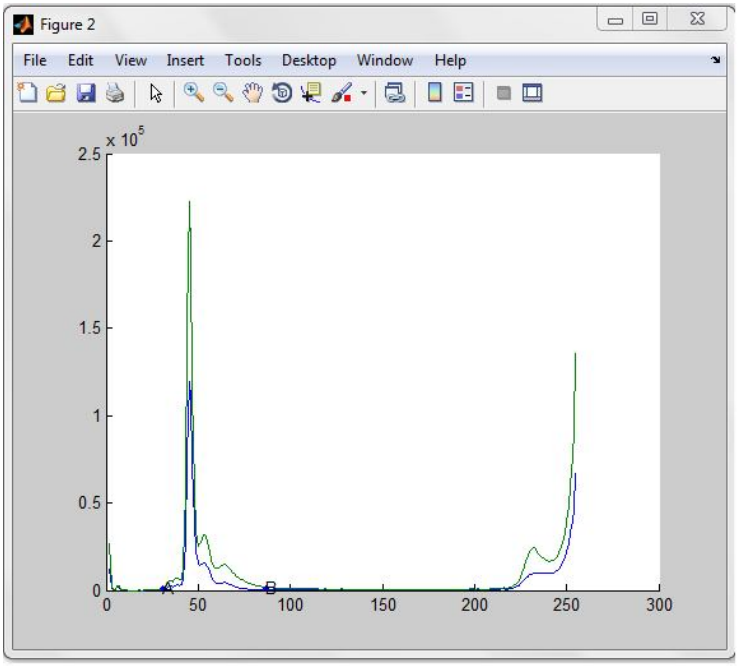

Figure 11. Convergence Points Extraction

FPCM complete data set is applied with the above specifications extracted from lungs, and keep the results of the following steps, so that each region is further processed. As a result, a uniform split FPCM minutes and that it takes to achieve the desired results in a short period of time is divided. FPCM need less than 100 repetitions to achieve results targets.

DISCUSSION AND CONCLUSION

The novel approach is the use of technology chipping away a small plane, rather than being used as a first step in the extraction process, the image is converted to new ways of CT technology threshold binary image. Bit-plane slicing technique is together faster and user-independent associated to the thresholding technique. After the extraction step, the partition has been able to use a mysterious lung degrees C means (FPCM) algorithm to extract. The results indicated a homogeneity FPCM algorithms in a very short period of time is obtained. Then, from the debris FPCM led analysis of primary pulmonary nodule candidates, extracts a set of features for use in diagnostic rules. These rules are formulated in the next step to discriminate between cancerous and non-cancerous candidate nodules. This technique is a powerful method for noisy image segmentation and is suitable for single and multi-feature data with spatial information. The extracted features in the proposed system are: the segmented lung regions, the Maximum Drawable Circle (MDC) and the average intensity value of the region.

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