International Journal of Research in Advent Technology, Vol.7, No.2, February 2019
E-ISSN: 2321-9637
Available online at www.ijrat.org

A Morphological Operation-Based Approach For Lung Nodule Detection With High Accuracy From CT Images Using Edge Detection

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Abstract: The pulmonary nodule detection is a frequent circumstance in daily radiology practice. Sub-Pleural nodules are connected directly to the pleural border and have consequently open contours. There is a challenging and a computer aided diagnosis system extraction is, hence, indispensable. In this research work, an automatic segmentation approach of sub-Pleural lung nodules from Computed Tomography (CT) scans based on morphological operations is proposed for high accuracy using edge detection. This process is divided into three steps: Initial detection of sub-Pleural lung nodule, pre-processing and post-processing and Edge detection.
First, extraction and conversion of a region of interest containing the nodule, using an adaptive thresh-holding algorithm.Second, we use morphological operations to create a mask for the lung lobe and segment sub-Plural nodule. Finally, connect small structures to the border of the segmented image are removed and final nodule regions are detected. The proposed method is evaluated on 40 CT scan images (17 in axial acquisition and 23 in coronal reconstruction) and gives accuracy at a good rate which proves the effectiveness of our approach.

Key words:Lung nodules, Computed Tomography, Edge detection, Segmentation , etc…,

1. INTRODUCTION

A small growth of soft tissue (less than 30 mm) in the pulmonary parenchyma is the lung nodule[7]. Lung cancer accounts for about 20% of all nodules' cases [1]. Lung nodule presents an im-portant radiological indication for early diagnosis of lung cancer. It is necessary to identify Cancer in lung nodule at early to increase the 5-year survival rate by 70% [9].The malignancy of lung nodules varies bet-ween 1% and 80% for nodules with a diameter varying between]5mm, 20mm[,according to the Early Lung Cancer Action Project (ELCAP) database [3].
Segmentation and detection of nodules have become a major challenge in lung nodules, these are charact-erized by their densities, location, size and inner content. Several works have been developed from CT images to overcome this challenge such as those based on active contour [10] [11] [2], region growing [4], watershed algorithm [5] [12]… The majority of them rely on highly advanced segmentation and learning methods.
The gold standard for detecting and character-rizing small pulmonary nodules as well as for diagnosing and monitoring their progress is the Computed tomography (CT).Small nodules with their diameters are less than 5 mm can miss sometimes.Hence, a computer aided detection (CAD) system is essential. The aims of CAD is to solve some difficulties in the detection of lung nodules and to improve the radiologists' perfo-rmancein screening and diagnosis.

We find the mathematical morphology based approaches among these methods. It is a mathematical rules and computer theories based image processing technique used to analyze geometric structures and topological shapes. Most researchers to improve the input image quality as a pre-processing step or to touch up their segmentation results as a post-processing step [6] [13] [8] [14] apply morphological operators.Only a few researchers have thought a basic method for lung nodule segmentation from CT images is by using morphological operators.

2. RELATED WORKS

Sun et al. [15] implemented three deep learning methods : CNN, deep belief network (DBN), and SDAE in order to analyze its ability to extract automatically generated features in the diagnosis of

CT images of pulmonary nodules, and to compare its performance with traditional computer aided diagnosis (CAD) systems. The results showed that deep algorithms achieve desirable performance in the diagnosis of lung nodules with a preference from CNN to DBN and SDAE.

In [16], an end-to-end deep learning architecture of Multicrop Convolutional Neural Networks was proposed to classify suspicion of nodules malignancy from CT images.The proposed method was able to integrate nodule characteristics into a hierarchical network without segmentation procedure, which simplifies the conventional classification.

In [17], the authors used two end-to-end learning architectures that are massive formation artificial neural networks (MTANN) and convolutional neural networks (CNN) to detect and distinguish benign and malignant lung nodules from CT images. Their results indicated that MTANN's performance was significantly higher than CNN's.

Recently, deep learning methods have gained a lot of attention by researchers because of their promising results in solving complex learning problems. These methods have widely proven their performance in various disciplines especially in medical image analysis field. Several deep learning architectures such as artificial massive neural networks (MTANN) [17], convolutional neural networks (CNN) [17,15], stacked de-noising auto encoder (DSAE) [15, 21], Multicrop Convolutional Neural Networks [16], ... were used to detect and classify lung nodules from CT images.

S.Biradar et al. [18] proposed a segmentation approach based on mathematical morphology to detect circumscribed lung cancer in the early stages from 2D CT images. After enhancing acquired image by median filter, the authors applied Otsu method, as a preprocessing step, to convert input

Gray scale images to binary images. Then, they applied morphological opening operation using three different structuring elements as a segmentation process in order to extract the nodular region features such as shape,boundaries… Finally, they applied inversion and clear border operations, as post-processing step, to get the segmented image.

Mokhled S. et al. [19] proposed a morphological segmentation and Gabor filter approaches for lung cancer detection from 2D CT images. First, the authors used Gabor filter in order to enhance the input image and to improve its information’s inter printability. Second, they extracted the lung area as ROI using diffusion and morphological erosion. Thirdly, after filling holes and removing small objects from the extracted ROI, the authors applied four steps to locate lung nodule and its boundaries.

(1) They calculated an overall threshold level.

(2) They converted image to binary based on threshold level.

(3) They eroded twice the binary image by the same Structure elements.

(4) They found perimeter of nodule and lung lobes in eroded image.

Finally, they imposed perimeter into ROI image and the selected objects are detected.

J.Kuruvilla et al. [20] proposed to develop a CAD system based on mathematical morphology operations for the detection of lung cancers from 2D CT images. The authors proposed four algorithms to segment four types of nodules.The lung nodules were classified according to their location in pulmonary parenchyma. First, they segmented lung lobesusing Otsu thresh holding and morphological opening to remove small objects from the foreground. Morphological opening was applied using a new structuring element which was created by a three different structuring elements combination.Then they reversed the image and performed a clear border operation to remove small structures connected to the border .For juxta pleural nodule segmentation, the authors proposed to split the segmented image from the first algorithm and flipped the right half of the lung into the left side. Then, in each row of the image, they noted the first '1', calculate and store the difference between its adjacent values as a vector. Connect and fill starting and ending points. Finally, they combined the two halves again to obtain the cancerous part. To evaluate the proposed method's performance, the obtained sensitivity, specificity and accuracy for the segmented images are respectively 88.24%, 93.33% and 90.63%.

3. MATERIALS AND METHODS USED

A. Edge detection:

Edge detection technique for finding the boundaries of objects within images is an image processing technique. It works by detecting discontinuities in brightness. The use of edge detection is for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.

The algorithms for Common edge detection include Sobel, Canny, Prewitt, Roberts, and fuzzy logic methods

Image segmentation usingSobelmethod

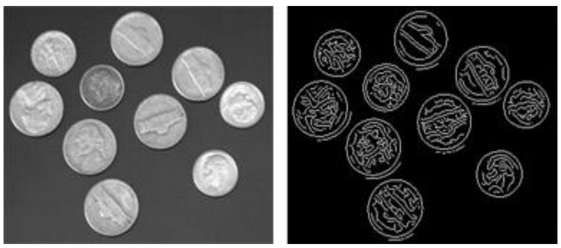

Image segmentation using the Cannymethod.

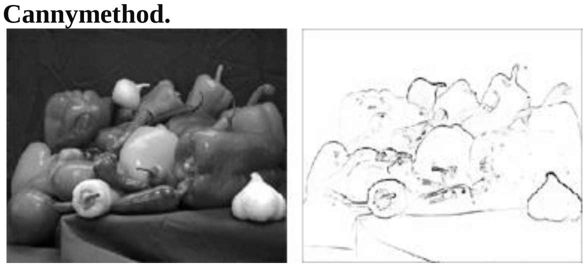

Image segmentation using Fuzzy Logic method.

B. CT lung acquisition:

We used a dataset of lung CT scans from the Radiology department of Abderrahmen Miami Hospital Ariana– Tunis, for the evaluation. The data-base contained 40 CT images in sharp filer and lung windowing of a sub-Pleural nodule (17 in axial acquisition and 23 in coronal reconstruction).Our algorithm is implemented in MATLAB (R2017a) programming language based on its Math works bibliography.

C. Pre-processing:

As input image, we choose a region of interest (ROI)containing the nodule. Then, the gray scale image is converted into a binary image by adaptive thresholding based on Otsu method (Fig.2 (b)).

D. Nodule localization:

In this step, we use mathematical morphology to isolate lung nodules. First, the lung lobe holes are filled to remove small structures corresponding to blood vessels and bronchioles. A hole is a surrounded background region by a connected border of fore-ground elements. Let A denotes a binary image that a background region (holes)is enclosed, which have to be filled and bm denotes a marker image which is settled 1-A in the image border, and 0otherwise:

bm(x,y)={1-A(x,y) if(x,y) is on the border of A
0 otherwise }…(1)

Then

$$B = \left[R_{A^c}(b_m) \right]^c \quad \ldots(2)$$

B has the effect to filling all the holes in A. These holes correspond to blood vessels and pulmonary bronchioles.

Secondly, a morphological closing operation by means of a structuring element is used to integrate the tumor region such as shape and boundaries in the lung region. The morphological closing operation is the erosion of the dilation using the same structuring element (ES). It is noted by:

$$A \bullet ES = (A \oplus ES) \ominus ES \quad \ldots.(3)$$

Morphological closing operation is used to create a mask for the lung lobe (Fig.2 (a)). Unlike other works [15] [16] that resorted to combine more than one structuring element, we used only one element. The morphological closing operation is applied on binary image using a structuring element ES1 for images in axial acquisitions and a structuring element ES2 for images in coronal acquisitions with:

- ES1 is disk with radius 10.
- ES2 is line of length 20 and degree 70.

Thereafter, we applied a simple subtraction of the resulting image after morphological closing operation and the preprocessed input image. The result is the pulmonary nodule (Fig.2 (c)).

E. Post-processing

As a post-processing step, we removed small structures attached to the image's border.

Let A denotes a binary image with small structures in the border and a marker image bm is defined as:

bm(x,y)={1-A(x,y) if(x,y) is on the border of A
0 otherwise }…(1)

Then

B=A-RA(bm)…(5)

The set difference B is a binary image of the same size at the original image A containing only the objects from A that do not touch the border (Fig.3 (a)). The steps involved in the segmentation process are represented by Alg-orithm.1

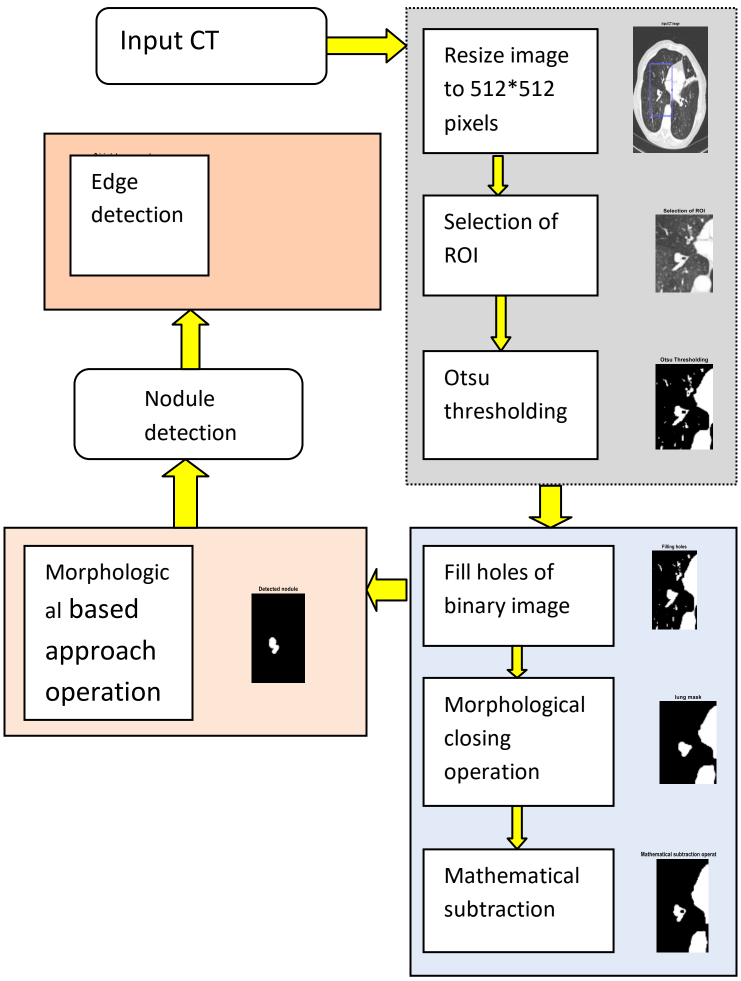

Fig.1. Block diagram of proposed method:
(a) Pre-processing steps ,
(b) localization steps,
(c) post processing,
(d) edge detection.

Algorithm.1:Detection of sub-pleural lung nodule using morphological operations

Input: Medical CT image of lung.
Output: Segmented sub-pleural lung nodule.
Begin
STEP 1. Reading input image.
STEP 2. Conversion to grayscale image.
STEP 3. Selection of region of interest ROI
STEP 4. Conversion to binary image
STEP 5. Filling holes in the lung lobe
STEP 6. Apply morphological operations
a- Applying a morphological Closing operation to create lung mask.
b- Applying a mathematical subtraction operation to extract the lung nodule.
STEP 7. Apply clear border operation
STEP 8. Segmentation output
STEP 9. Apply edge detection.
End

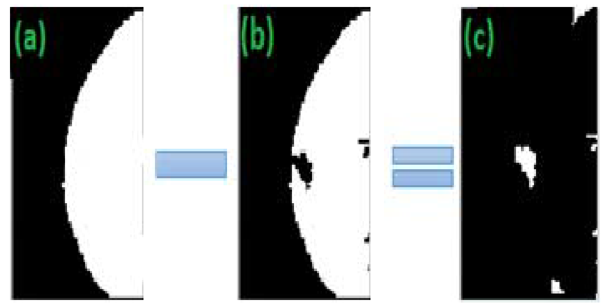

Fig.2. Localization steps:
(a) creating a lung mask by morphological closing;
(b)pre-processed image;
(c) lung nodule detected after subtraction operation

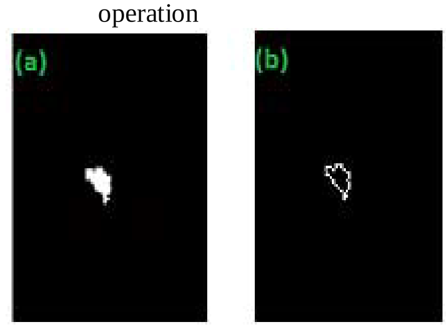

Fig.3: Final segmentation of the sub-pleural Lung nodule:
(a)detected nodule and
(b) Original shape preserved

4. RESULTS AND DISCUSSIONS:

To evaluate the method performance, we used several statistical measures which are: sensitivity, specificity, accuracy, precision, F-measure, receiver operating characteristic (ROC) curves and area under the curve (AUC). We briefly describe this statistical analysis in the following paragraphs.

Sensitivity: It measures the percentage of nodule areas in the analyzing chest CT scan correctly identified.

Sensitivity=[TP/(TP+FN)]*100 …(6)

Specificity: It measures the percentage of non-nodule areas correctly identified as non-nodule areas.

Specificity=[TN/(TN+FP)]*100 …(7)

Accuracy: It measures the proportion of true detected nodule areas with respect to the totality of areas.

Accuracy=[TN+TP/(TN+TP+FN+FP)]*100 …(8)

Precision: It measures the proportion of positives in the analyzing chest CT image which are correctly identified.

Precision=[TP/(TP+FP)]*100 …(9)

Where:

- **True positive (TP):** Predicts an area as a real part of the nodule.
- **True negative (TN):** Predicts an extra-nodular area as a real extra nodular one.
- **False negative (FN):** Predicts a nodular area as an extra-nodular one.
- **False negative (FP):** Predicts an extra-nodular area as a nodular one.

TABLE 1: Statistical Analysis: Evaluation of the proposed method performance compared with the other methods.

	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	Fm
Kurulla et al. [16]	88.24	93.33	90.63	–	–
Otsu method [17]	76.75	97.56	96.51	90.68	82.20
Our proposed method	69.25	98.93	98.88	93.54	85.56

F-measure(Fm): It represents the harmonic mean of the recall and precision values.

Fm=2*(sensitivity*precision)/(sensitivity+precision) …(10)

ROC curve: ROC curve a graphical plot between false positive rate (1- specificity) on X-axis and sensitivity on Y-axis.

AUC: It is a numerical measure of the area under ROC curve that represent the performance of the system. More the value is close to 1, more the system is efficient.

To demonstrate the efficiency of the proposed segmentation approach, we made a quantitative comparison between our method and the technique proposed by Kuruvilla et al. [20]. The performance results are presented in Table 1.

5. DISCUSSION

The proposed method has an acceptable sensitivity rate of 0.692 that proves its ability to correctly identify the nodule parts. Also, it improves specificity and accuracy from 98.88% and 90.63% to 98.57% and 97.52% respectively (compared to Kuruvillaet al. [20] method). Moreover, we can notice that our technique proves its detection efficiency with a precision rate close to 93%. In addition to that, these averages indicate the ability of our presented method to correctly find the nodule regions in the processed image. In this work, F-measure (Fm) is considered as the major metric because it is specifically interested in the lung nodule area.

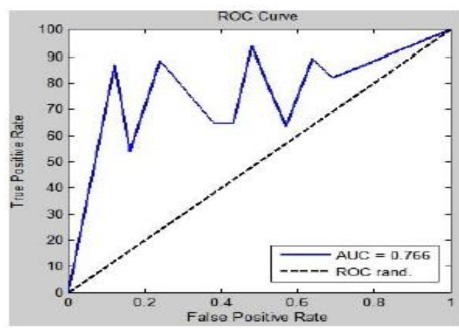

Fig.4: ROC curve of the proposed method

The proposed method showed a significant gain of run time of 7.53 seconds as well as its stability and ability to properly detect sub-pleural nodules obtaining an average Fm over 85 %.

The ROC curve for the proposed system is shown in Fig.4 and represents an AUC estimated at 0.766. From preliminary results, our algorithm can be implemented in clinical applications to help physicians in the detection and diagnosis of lung nodules.

Fig.5 and Fig.6 present some examples of the segmentation results in axial and in coronal acquisitions respectively. Here, we show the efficiency of our method for detecting sub-pleural nodules from CT image in axial and coronal acquisitions. Unlike other methods that have used mathematical morphology to detect nodules [14] [15] [16], our proposed method can retain the actual shape of the nodule (Fig.3 (b)) which provides information about most works, currently the cancer evolution, its malignancy degree and its stage. In detected nodules are spherical or ellipsoidal which reflects the structuring element effect during the application of the morphological operation.

So we can conclude that our proposed algorithm is much more efficient to count good perspective compared to others methods. The proposal of a good method for detection of lung nodule from CT image based only on mathematical morphology is mainly based on a good segmentation algorithm and that is what we are trying to prove by the proposed approach.

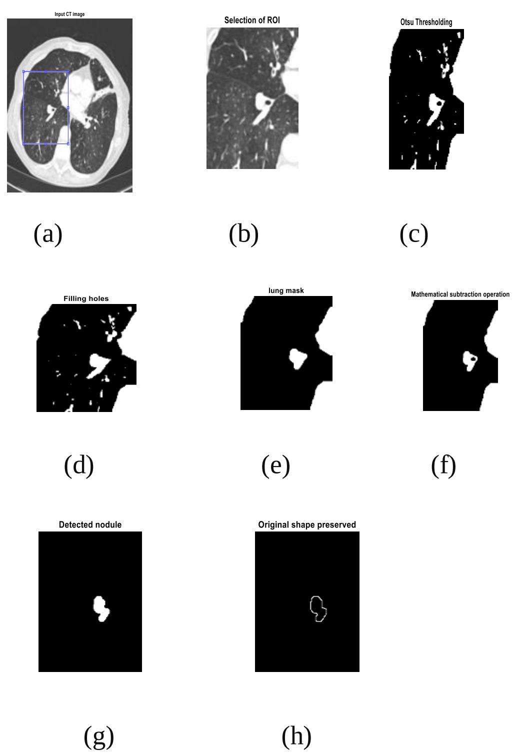

Fig.6: Examples of segmentation results of the CT images in coronal acquisitions:
(a)Image aquisation;
(b) Selection of ROI;
(c) Otsu thresholding;
(d) Filling holes of binary image;
(e) lung mask creation(morphological closing);
(f) Mathematical subtraction;
(g) detected nodule;
(h)Original shape preserved.

6. CONCLUSION

In this paper, a fast automatic segmentation method hasbeen proposed to detect sub-pleural lung nodule based on morphological operators approach. This work aims to solve the problem of open contour since sub-pleural nodules are directly connected to the boarder of pleural sheet. More over, our method retain the concavities and the original shapes of these nodules which give an important information of their malignity degree.

The proposed method was tested on a database of 40 CT scans with sub-pleural nodules, from radiology department of the Abderrahmen Mami Hospital - Ariana - Tunisia. The proposed method shown many advantages such as low computational cost, robustness, easy implementation, accuracy, stability and its ability to overcome the limitations of some advanced approaches. It can reliably be used as an additional tool to assist radiologists in the cancer diagnosis process.

In the future, parameters that characterizes the lung nodules will be selected to classify them as benign and malignant. In addition, we will correlate these different parameters to other histological types of lung tumors.

REFERENCES:

[1] Yuan, et al. "Hybrid-feature guided lung nodule Type classification on CT images. " Computers Graphics, (2017).
[2] RebouçasFilho, et al. "Noveland powerful 3D adaptive crisp active applied contour method in the segmentation of CT lung images."Medicalimage analysis 35 (2017): 503-516.
[3] Valente Igor Rafael, et al.,"Asurvey of automatic 3Ddetection of pulmonary nodule in CT images". Computer methods and programs inbiomedicine 124 (2016): 91-107.
[4] Emaminejad, et al. "to improve prognosis asse-ssment of early stage lung cancer patients,Fusion of quantitative image and genomic Bio-markers is used."IEEE Trans on Biomedical Engineering 63.5 (2016):1034-1043.
[5] Avinash.S, et al., "An improved image process-sing analysis for the lung cancer detection using Gabor filters and watershed segmentation Techn-ique.", IEEE- ICICT Vol. 3, 2016.
[6] Gangireddy, et al., "A Novel Approach for LungCancer Detection Using Morphological Operations", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 12, 2016.

[7] Mayo, John R., and Stephen Lam. "Computedtomography and the lung nodule secretes." Canad-ian Association of Radiologist Journal, (2015).
[8] Gupta Anindya, et al. "Methods for increasedsensitivity and automatic Segmentation scopeand lung nodules detection in CT images.", IEEE- ISSPIT, 2015.
[9] Camarlinghi, Niccolò. ": training and validationof algorithms using Public research databases detection of automatic lung nodules incomputed Tomography images." The European Physical Jou-rnal Plus 128 (2013): 1-21.
[10] FaragAmal A., et al., "A novel approach forlung nodules segmentation in chest CT using level sets", IEEE Trans on Image Processing22.12 (2013):5202-5213.
[11] SunShanhui, et al.,"Automated 3-Dsegmentati-on of lungs with lung cancer in CT data using a novel robust active shape model approach." IEEE transon medical imaging 31.2 (2012): 449-460.
[12] Chaudhary Anita, et al., “Detection of lung can-cer by using image Processing on CTimages.", IEEE- ICCS, 2012.
[13] C. Karthikeyan and B. Ramadoss, "Segmentati-on Algorithm for CT Image Using Morphological Operation and Artificial Neural Network", International Journal of Computer Theoryand Engineering, Vol. 3, No.4, August 2011.
[14] Zhao Yu-qian, et al. "Medical images edge detection based on mathematical morphology", IEEE-EMBS, 2006.
[15] W. Sun, et al., “Feature of automatic learning Using multi channel ROI based on deep structured algorithms for computerized lung cancer diagnosis”. Computers in biology and medicine, vol.89, p. 530-539, 2017.
[16] W. Shen, et al., “Convolutional multi-crop neural networks for lung nodule malignancysuspiciousness classification,” Pattern Reco-gnit., vol. 61, pp. 663–673, 2017.
[17] N. Tajbakhsh and K. Suzuki, “Two classes of end-to-end machine-learning models are compared in lung nodule detection and classification: Mtanns vs. cnns,” Pattern Recognit., vol. 63, pp. 476–486, 2017.
[18] Biradar, et al., Agalatakatti. "Identification oflung cancer Using CT Images." International Journal Of Engineering And Computer Science4 (2015): 13022-13025.
[19] Mokhled S. et al.., "Lung Cancer DetectionusingMorphologicalSegmentation and GaboFiltration Approaches", IJERT, Vol. 3 Issue 7, July – 2014.
[20] JinsaKuruvilla, Dr.K.Gunavathi, "Detection of Lung Cancer using Morphological Operations", IJSERVolume 4, Issue 8, August-2013.