An Effective Automatic Detection of Lung Tumor Based on Novel Optimized Chan-Vese Algorithm

Lim J Seelan, Dr. L. Padma Suresh

***Abstract*: One of the severe health hazards is lung cancer. United States alone bears approximately 25% lung cancer burden. This type of cancer is cured if it is detected in an earlier stage and reduces mortality rate. With the rapid rising of lung cancer patients, the CAD (Computer Aided Detection) method plays a significant role in the field of automatic recognition for medical images. This method focused on automatic identification of lung nodule using optimized chan-vese algorithms. The computer automatic system consist of following steps: - image acquisition, image preprocessing, and image segmentation. This method is mainly helpful for automated finding of lung nodules that are appended to the chest wall. The final output shows the application of the proposed method in the medical field will bring great progress for medical development.**

***Index Terms*: Histogram equalization, Curvelet transform, adaptive concave hull, optimized chan-vese**

I. INTRODUCTION

Segmentation is an important procedure in digital image processing that has found wide application in several areas. In a biomedical application image segmentation is plays an important role. This method is most widely used by radiologist because of its accurate results. Here the input image is partition into meaningful region. The exact purpose of this method is to detect the tumor region by segmenting the abnormal CT input image. The medical images can be segmented manually or automatically. But the accuracy of image segmentation using the segmentation algorithm is more when compared with the manual segmentation. For segmenting and identification of lung nodules from the medical images vast of time was spent by radiologist and doctors[1], [2]. However, accurate classification of lung tumors is a time-consuming process, and large difference is observed between physicians. Consequently, over the last decade, from different study results it is being identified that accurate labeling is very time consuming method but if we use image processing techniques this labeling is simple and faster. Various literatures are discussed here based on the image processing techniques. Wei et. al1 [2] Presented improved chain code process for detection of juxtapleural nodule. In a final conclusion the author reported inclusion rate is 100%. But, for the evaluation of result only 32 Juxtapleural nodules are considered. Zhou et al [16] anticipated the lung division and smoothing model for the advancement of nodule. The main drawback of this method is, it might miss the little juxtapleural nodules at the sharp edge result because of weighted averaging. Shen et al. [10] projected a bidirectional chain code and SVM classifier method for segmenting the lung tumor. In this scheme, for identifying nodule the inflection points on the lung limits are recognized. This is the greatest test in this strategy because these points are extremely delicate to noise. As well as, based on the scan quality, versatile edge, SVM execution and the over and under-segmentation proportion is determined. Singadkar et al. [9], planned a novel component extraction and unsupervised learning for a programmed lung division. This procedure performs well when typical scope of abnormalities appears in the lung, however in the final result it neglects to incorporate the juxtapleural nodules. Tong et al. [6] proposed a three stage method for identifying lung nodules. At first, for a division procedure the versatile edge calculation was utilized. At that point to evacuate lung vessel active contour model (ACM) was utilized and ultimately a Hessian lattice (selective shape filter) was utilized to recognize the suspicious knobs. The general discovery rate of this technique is 85%. Marten et al. [8] proposed the assessment of highlights, for example, nodule measure, position, edge, lattice attributes and vascular and pleural connections which are compared with best quality level. In these correlations a portion of the creators utilize physically fragmented sore as the best quality level and some different users use master references as the best quality level. Azimifar et al. [14] developed active contour modeling for division of lung tumors. It acquires a general recognition rate of 89%. Dehmeshki et al. [15] clarified volumetric estimation for recognizable proof of lung injury. Here new region growing strategy is utilized for division process. In this technique it was discovered this calculation is exceedingly reproducible for different kinds of nodules from different information conventions. The primary point of the aggregate work is to identify lung nodules automatically from CT pictures.

In this proposed work for the noise removal and contrast enhancement the curvelet transform and histogram equalization models are used. Here the curves and shapes of the lung regions are enhanced. After the preprocessing procedure the image binarization and lung border corrections are performed using various algorithms. Finally using the optimized chan-vese algorithm the lung segmentation is performed and the tumor region is identified.

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The role of the proposed method is described as below:

- This model does not require any user interaction because it is fully automatic.
- For recognizing right essential point along convex and concave territory on the lung edge this proposed plan uses curvature data.
- By joining precise arrangement of prevailing points the developed algorithm can exactly correct lung boundary.
- By limiting the over division and under division it effectively incorporate the juxtapleural nodule and pulmonary vessels close to the mediastinum.

This paper is structured as pursues: Section 1 focuses the introduction & literature survey. Section 2 explains the methodologies, Section 3 deals with results and discussion and Section 4 shows the conclusion of the work.

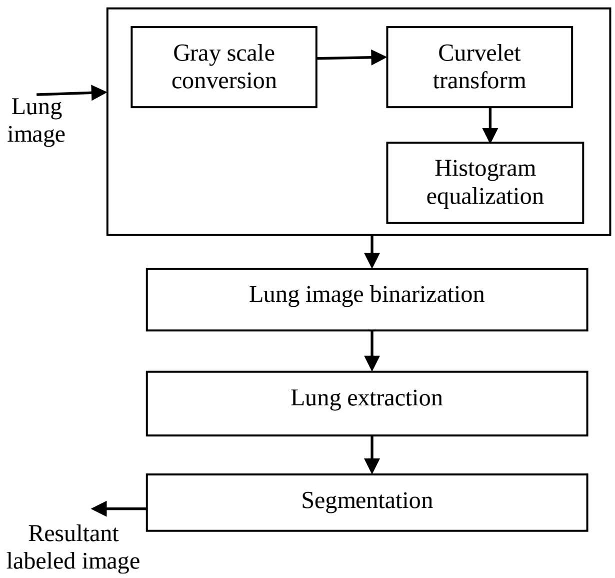

Figure 1: block diagram of proposed model

II. METHODOLOGY

For improving the detection quality and to reduce the load the Automatic nodule detection scheme utilizing CT examines are helpful for the doctors. The procedure for the location of lung nodule comprises of, the CT lung acquisition, preprocessing, image binarization, lung extraction and the segmentation of lung nodules. The principle point of this procedure was to expel the undesirable parts of CT image other than lung lesion. Fig. 1 demonstrates the block representation of segmentation scheme.

A. Image Acquisition

In this medical image acquiring process Computed Tomography (CT) examine images are mostly used because it has low noise and improved transparency compared to another imaging technique images. The lung images are obtained from NIH/NCI Lung Image Database Consortium (LIDC) which is an on-line CT image dataset available in the "Cancer Imaging Archive". Here the images are available in the DICOM format using image converters this images is convert into JPEG format. Normally, the size of the image is 512 x 512 and then it converted to 256 x 256 to obtain superior feature. In this proposed method there is 60 images is used for processing which consist of tumor and non-tumor images.

B. Preprocessing

Noise is an unwanted component present in the images. During processing, the obtained information is may be pretentious because of noise and it does not obtain accurate result. This component affects the feature of the image which results in image blurring. Therefore, noise should be removed to get the clear result. Different de-noising methods can be used for eradicate the noise.

Initially the input image is changed into grayscale image. Normally the medical image is in gray scale format in order to avoid the hardware level error occurred during the processing the gray scale conversion is performed. Next both curvelet transform and adaptive median filters are applied to the gray scale conversion image. The curvelet transform is used for representing the clear shapes and edge. This transform mainly focuses the sharpening of curves and de-noising the images.

The adaptive median filter eliminates the impulse noise presented in the image. Here the adaptive median filter detects the noise pixel based on the value of neighbourhood pixel and threshold. If the pixel exceeds the threshold value this filter classifies the pixel as noise pixel. Then the noise pixel value is replaced by neighbourhood pixel median value. Finally the compared with the adaptive median filter output the curvelet transform result is used for further processing because if the curves in the images are enhanced then automatically the appearance of the image will be improved. To obtain the high contrast image the histogram equalization is performed for the result of the curvelet transform.

C. Image Binarization

Following noise deduction process, a fuzzy thresholding technique is applied for CT image binarization process this is an accurate binarization process and it helps to eliminated all the distinct areas in the lung region. The main aim is to add the important areas of the lungs that are useful for lung segmentation.

- **Fuzzy Thresholding**

Fuzzy thresholding is the structure of clustering in which each data point will form more than one cluster. This method includes some several processes such as

- Choose a number of clusters.
- Allocate coefficients indiscriminately to every data point for there in the cluster.
- Compute centroid for each cluster.

D. Lung extraction

Next the pre-processing models the morphological operations and canny edge detector is applied for indicate the shapes and margins of the related components. A new adaptive concave hull algorithm is used to achieve accurate original lung masks for a region based active contour model.

a. Morphological Operation

This model is based on the image shape. This method needs two inputs; original image and structural element. Dilation and erosion operations are involved for the morphological transformation.

Dilation: Dilation on binary images is to make wider the areas of center pixels at their boundaries of image.

Erosion: Erosion on a binary image is to erode away the limits of center pixels. This will shrunk the area of center pixels and larger the holes within those area.

b. Canny edge detection

The Canny technique marks boundaries of original image by looking for local maxima of the gradient. Here using derivative of a Gaussian filter the value of gradient is computed. To detect the strong and weak boundaries this method uses two thresholds, and finally includes only the weak edges in the output if they are linked to strong edges.

c. Adaptive concave hull method

It calculates the envelope of a collection of points in a plane, this algorithm produce convex or non-convex hulls to characterize the area occupied by the given points. This model is performs based on the following steps:

- To determine the initial apex of the polygon with minimum value.
- The recent points K-nearest points are choose and the candidate points are to be next point of the polygon.
- The procedure is continued until the chosen candidate is the initial apex. For the initial apex to be selected as a candidate, it must be inserted again into the data set following the earliest four points of the polygon are calculated.
- By the ending process, the polygon is closed with the initial and the end point being identical.

E. Image Segmentation

Image segmentation implies the dividing, the image into numerous regions. The fundamental point is to remove valuable data from image in medical imaging applications. This depends on one of the two key properties such as discontinuity and similarity. It is a very challenging task for extracting the features from the images and these features are useful for classifying the images into anatomical parts like tumors, cells, tissues, blood vessels and so on.

a. Optimized chan-vese algorithm

Optimized chan-vese algorithm is one of the popular segmentation techniques. This algorithm is based on region based active contour model, this active contour model do not use image gradient rather uses statistical information for controlling the contour inside and outside the object boundary throughout the evolution. Region based models are less sensitive to weak edges, noise, in-homogeneity, poor con-trast etc. To avoid these problems a novel technique is proposed. It accurately identifies the object boundaries. It allows the outline to deform so as to reduce a known energy function in turn to generate the accurate segmentation. The classical optimization techniques are useful in finding the optimum solution. Here combine two optimization algorithms to obtain better results. This hybrid method gives optimum value accurate. There are three major changes have been made into the classical BFO which is emerged as proposed Hybrid BF-GWO algorithm.

. Chan-Vese stated an energy function $F(c_0, c_1, C)$ which is defined as

$$F(r_0, r_1, R) = \mu.Length(R) + v.Area\big(inside(R)\big) + \lambda_0 \int |u_0(x,y) - r_0|^2 dxdy + \lambda_1 |u_0(x,y) - r_1|^2 dxdy \quad --- (1)$$

Here R is the evolving curve,
r_0 *and* r_1 are the values of u surrounded by R,
$\mu \geq 0, v \geq 0, \lambda_0 \lambda_1 > 0$ are the values used as constants,
u_0 is an input image.

Using the level set algorithm the minimization problem is avoided and it is explained by the following expression

$$\inf_{r_0, r_1, R} F(r_0, r, R) ------(2)$$

$$R(t) = \{(x,y) | \phi(x,y) = 0\} --(3)$$

Where,
"t" is an artificial time.

For $t = 0$, $\phi(x,y,0) = \phi_1(x,y)$. The gradient flow Chan-Vese is defined as based on the following equation.

$$\frac{\partial \phi}{\partial t} = \delta_\epsilon(\phi)\left[\mu\, div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_0(u_0 - r_0)^2 + \lambda_1(u_0 - r_1)^2\right] = 0 \text{ in } \Omega \text{ -------------- (4)}$$

$$\frac{\delta_\epsilon(\phi)}{|\nabla\phi|}\frac{\partial\phi}{\vec{n}} = 0 \text{ in } \partial\Omega \text{ ----------------- (5)}$$

b. Algorithm

Input: computed tomography (CT) lung image,
Output: Segmented tumor region and its parameter values such as area, perimeter, centroid, diameter.
Step 1: Start the procedure
Step 2: Set $\varphi = \varphi_1$
Step 3: for k=1:no.of outside contour procedure
Step 4: compute c_0 and c_1 for the current φ
Step 5: for l=1:no.of inside contour procedure
Step 6: update φ
Step 7: reinitialize φ to signed distance function
Step8: find the local best (pbest) using BFO
Step 9: find the global best (gbest) using GWO
Step 10: calculate Step size c(i) = α (rand – ½)
The values lies in between [0, 1], α is the randomization variable
Step 11: update optimized result, segmented image, labeled image
Step 12: calculate performance parameter like area, perimeter, centroid, diameter for an obtained result.
Step 13: stop the procedure.

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III. RESULTS AND DISCUSSION

In this part, the experimental results for the proposed techniques are discussed. In a lung CT image the optimized hybrid chan-vese algorithm is applied to detect the lung lesions. This algorithm is helpful for obtaining accurate segmentation result.

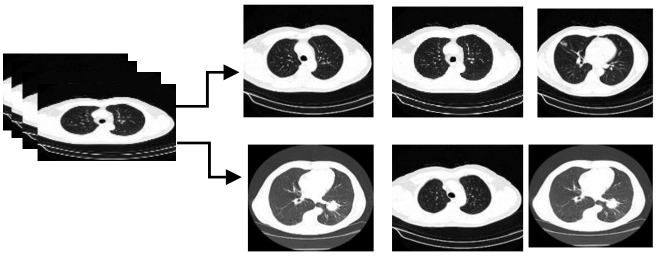
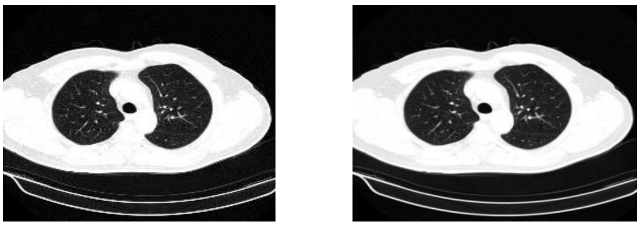


Figure 2: Dataset Samples

Here for the implementation the MATLAB 2016a software is used. The Lung CT images was obtained from LIDC database, for further procedure totally 60 images are used it includes both benign and malignant images which are analyzed and examined to obtain the better results of the proposed scheme.

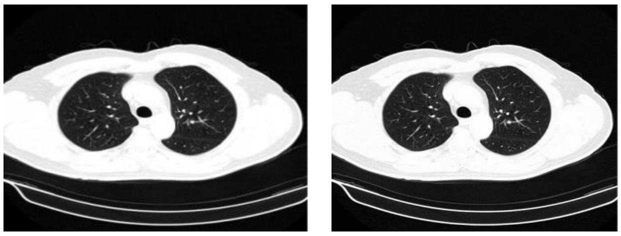


(a) (b)

Figure: 3. (a) Input image (b) Gray scale image

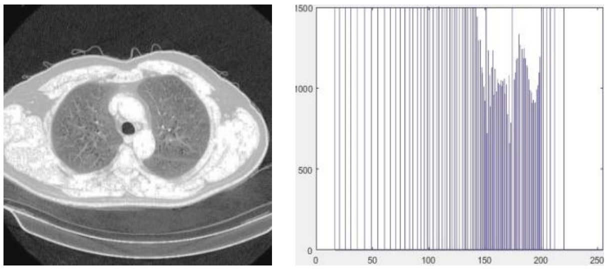
Figure.2 shows the sample datasets both benign and malignant images obtained from LIDC database. Some samples (sample 1, sample 2) are taken to show that it is been used for analyzing the result of the proposed model.

An image is given as input to preprocessing techniques to remove the unwanted component and improve the quality. In this method initially the input image is altered into grayscale image Figure 3 shows the preprocessed image, here 3(a) represents the input image of proposing method, 3(b) represents the grayscale conversion image,. After alteration the adaptive median filter and curvelet transforms are used for de-noising. Both techniques remove the noise, but curvelet transform effectively removes the noise because it sharpens the edges and shapes if the edge in the images improves then image quality will be automatically improved. Figure 4 (a) & (b) shows the comparison of curvelet and adaptive filter image. Then histogram equalization is performed for obtaining high contrast image. The plots are generated for the resultant equalized images it is shown in figure 5(a) & (b)



(a) (b)

Figure: 4. (a) adaptive median filter image (b) Curvelet transformed image



(a) (b)

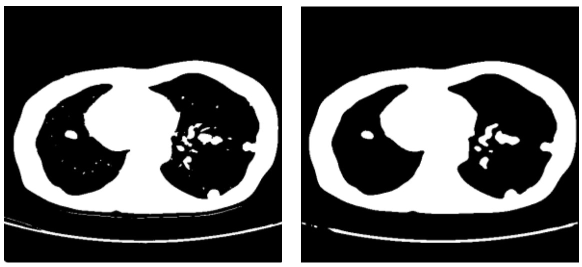
Figure5: (a) Histogram equalized image, (b) Histogram equalized plot

The performance measures such as PSNR, MSE, SNR, and SSIM are analyzed and the values are obtained. This is shown in table 1.

A fuzzy thresholding and Otsu thresholding technique is helpful for CT image binarization. Here all the unrelated components are removed. Figure 6(a) and 6(b) shows the result of image binarization. The result of fuzzy output is compared with the Otsu thresholding technique. Compared with the Otsu thresholding technique the fuzzy thresholding techniques give better outputs.

Table: 1. Performance values of the database images

Metrics	MSE	PSNR	SNR	SSIM
Sample 1	59.1	35.66	30.41	0.9756
Sample 2	38.57	36.17	32.26	0.9735
Sample 3	69.76	35.45	29.69	0.9733
Sample 4	25.07	36.66	34.13	0.9766
Sample 5	43.17	36.04	31.77	0.9740
Sample 6	40.91	36.10	32.01	0.9742



(a) (b)

Figure 6: image binarization result (a) fuzzy thresholding (b) Otsu thresholding

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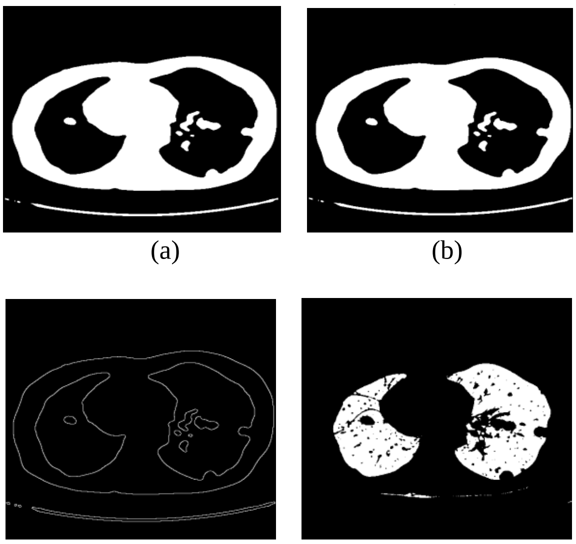
Next the pre-processing models the morphological operations and to identify the shapes and margins of the related components the canny edge detector is used. In morphological operation Dilation and erosion operations are involved. Canny edge method uses two thresholds for detecting strong and weak boundaries, and finally includes only the weak edges in the output if they are linked to strong edges. The resultant output is displayed in 7(a) - 7(d).



(a) (b) (c) (d)

Figure 7: (a) eroded image, (b) dilated image, (c) canny detector output, (d) border cleared image

A new adaptive concave hull algorithm is used to achieve exact original lung masks for a region based active contour model. This algorithm produces convex or non-convex polygons to characterize the lung area occupied by the given points. Output of concave hull algorithm is displayed in figure 8.

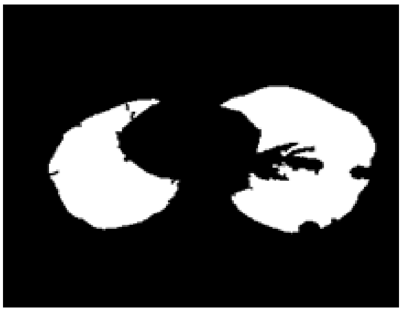
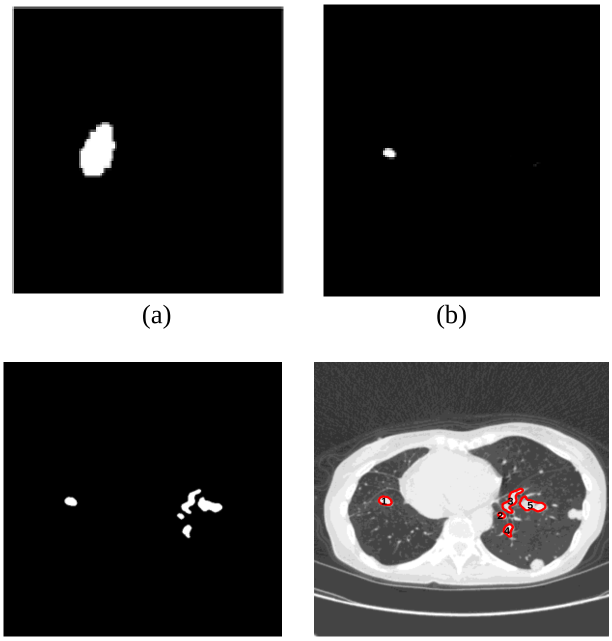


Figure: 8. adaptive concave hull output

The segmentation technique mainly used for isolating the cancerous region from the input CT images. Here optimized chan-vese algorithms used for segmentation. This will provide better results. The resultant segmented image is compared with the output of k-means clustering and region based active contour model. Both techniques are provides same results and it was miss some minutes nodules, over segmentation problem occur in the k-means result. It is shown in figure 9(a) & (b). So to avoid this the optimized techniques used.



(a) (b) (c) (d)

Figure 9: segmented images of (a) k- means segmentation, (b) region based active contour model, (c) optimized chan-vese, (d) labeled image of optimized chan-vese algorithm

Table II: Parameter Measures

Region	Area (mm^2)	Perimeter (mm)	Centroid (mm)	Diameter (mm)
1	1680.0	148.7	125.5	46.2
2	60.0	25.7	206.6	8.7
3	56.0	24.4	320.6	8.4
4	42.0	22.1	243.8	7.7
5	20	12.1	199.3	5.9

This technique easily identifies any sizes of the nodules and precisely smooth's the pulmonary vessels. For exact and vigorous lung field division with the nodules this proposed strategy can be utilized. It doesn't require any user cooperation. It gives right predominant points along convex and concave region on the lung limit and reduces over division and under division.

IV. CONCLUSION

The lung cancer is the deadliest diseases. The early detection is one of the challenging tasks. It is easily diagnosed by medical image processing techniques. In this proposed image processing technique the pre-processing for Lung cancer CT images was done by curvelet transform and was enhanced by Histogram equalization. Using this shapes and curves are correctly identified. The borders and boundaries are extracted.

From the final result of segmentation, it concludes that optimized chan-vese technique gives the better results compared to other techniques such as k-means clustering and region based active contour model. Future developments will include using an optimization method for finding the accuracy and stages of tumor in the classification process and will performs the subsequent steps of image processing models using various algorithms and classifiers.

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