Segmentation of Lung on CT Images Using Robust Active Shape Model (RASM) and Tumour Location Using Morphological Processing

[1]K. Kothavari and [2]S.N. Deepa

[1]Department of ECE, Dr. NGP Institute of Technology,
Coimbatore 641048, Tamil Nadu, India
[2]Department of EEE, Anna University, Regional Centre,
Coimbatore, Coimbatore - 641 047, Tamilnadu, India

Abstract: This paper presents a Computer Aided Detection method in Computed Tomography (CT) images of lungs using mathematical morphological operations, Early detection and treatment of lung cancer can greatly improve the survival rate of patient. Segmentation is one of the important step in analysing medical images, RASM segmentation is carried out in this paper. Pre-processing is carried out with the help of Gaussian filter in order to remove the speckle noise and the contrast of the image is improved by mean filter. Tumour location is performed using morphological processing

Key words: Lung Segmentation · Robust Active Shape Model · Classification · Erosion · Dilation

INTRODUCTION

Statistics showed that lung disease death rate is still on the rise. According to the latest report by the American Lung Association, death rates due to lung disease are currently increasing, while death rates due to other leading causes, such as heart disease, cancer and stroke are declining [1]. High mortality rates of lung diseases have encouraged many researchers to focus their efforts on improving their diagnosis and treatment methods. There are many techniques to diagnosis lung cancer, such as Chest Radiograph (x-ray), Computed Tomography (CT), Magnetic Resonance Imaging (MRI scan) and Sputum Cytology, In recent years the image processing mechanisms are used widely in several medical areas for improving earlier detection and treatment stages, in which the time factor is very important to discover the disease in the patient as possible as fast, especially in various cancer tumour such as the lung cancer, breast cancer. Lung cancer has been attracting the attention of medical and sciatic communities in the latest years because of its high prevalence allied with the difficult treatment.

MATERIALS AND METHODS

Fig. 1 refers to the various steps for lung cancer detection. During the scanning, the quality of image is affected by different artifacts due to non uniform intensity variations and noise. Thus the pre-processing of image aims at selectively removing the redundancy present in scanned images without affecting the details, that play a key role in the diagnostic and analysis process. The image filtering becomes the important step in pre-processing. Therefore each image is Gaussian filtered to improve its quality. In lung fields segmentation, lung field masks have been prepared manually by deriving the peripheral pixel co-ordinates. Robust active shape model matching approach is being used. The robust matching algorithm allows dealing with outliers, The RASM model is trained from manually drawn contours in training images. The RASM model finds the main variations in the training data using Principal Component Analysis (PCA), which enables the model to automatically recognize if a contour is a possible/good object contour [2]. Also the RASM modes contains matrices describing the texture of the lines perpendicular to the control point, these are used to correct the positions in the search step[3].

Corresponding Author: K. Kothavari, Department of ECE, Dr. NGP Institute of Technology,
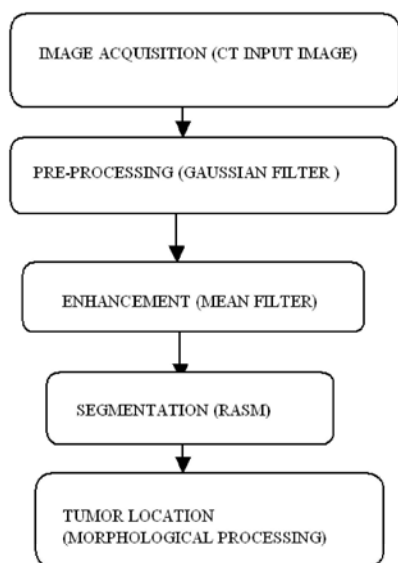Coimbatore 641048, Tamil Nadu, India.

```
┌─────────────────────────────────────┐
│  IMAGE ACQUISITION (CT INPUT IMAGE)  │
└─────────────────────────────────────┘
                   │
                   ▼
┌─────────────────────────────────────┐
│  PRE-PROCESSING (GAUSSIAN FILTER )    │
└─────────────────────────────────────┘
                   │
                   ▼
┌─────────────────────────────────────┐
│  ENHANCEMENT (MEAN FILTER)            │
└─────────────────────────────────────┘
                   │
                   ▼
┌─────────────────────────────────────┐
│  SEGMENTATION (RASM)                  │
└─────────────────────────────────────┘
                   │
                   ▼
┌─────────────────────────────────────┐
│  TUMOR LOCATION                       │
│  (MORPHOLOGICAL PROCESSING)           │
└─────────────────────────────────────┘
```

Fig. 1: Flow diagram for Lung Cancer Detection System

After creating the RASM model, an initial contour is deformed by finding the best texture match for the control points. This is an iterative process, in which the movement of the control points is limited by what the RASM model recognizes from the training data as a "normal" object contour. Properties of PCA can be used for determination of selected object orientation or its rotation too.

Denoising and Enhancement: Removing noise and increasing the contrast of the is important task before segmentation of an image, so in this paper Gaussian filter is used to remove speckle noise and histogram equalization and mean filter are used to increase the contrast

Gaussian Filter: Gaussian filter is used for removing the noise present in the image, it is a filter whose impulse response is a Gaussian function.. Therefore speckle noise have been added and removed from the input image. Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. This behaviour is closely connected to the fact that the Gaussian filter has the minimum possible group delay. Mathematically, a Gaussian filter modifies the input signal by convolution with a Gaussian function. The one-dimensional Gaussian filter has an impulse response given by

$$g(x) = P\left|xi - \overline{x}\right|2 \tag{1}$$

Gaussian distribution, or normal distribution, is really a function of probability theory. Often this function is referenced as bell-function because of its shape. Gaussian filter are a class of linear smoothening filters with the weight chosen according to the shape of Gaussian function. The Gaussian kernel is widely used for smoothing purpose. The Gaussian smoothening filter is a very good filter for removing noise from the normal distribution. Gaussian smoothening is a particular class of averaging, in which it is a 2D Gaussian. The Gaussian filter is non-causal which means the filter window is symmetric about the origin in the time-domain. This makes the Gaussian filter physically unrealizable. This is usually of no consequence for applications where the filter bandwidth is much larger than the signal. In real-time systems, a delay is incurred because incoming samples need to fill the filter window before the filter can be applied to the signal. The Gaussian function is non-zero for $x \in [-\infty, \infty]$ and would theoretically require an infinite window length. However, since it decays rapidly, it is often reasonable to truncate the filter window and implement the filter directly for narrow windows, in effect by using a simple rectangular window function. In other cases, the truncation may introduce significant errors. Better results can be achieved by instead using different window functions. The filter function is said to be the kernel of an integral transform. Fig. 2 Shows the input image, with added speckle noise and the Gaussian filters output.

Enhancement -Histogram Equalization: Histogram equalization is a method for stretching the contrast of the images by uniformly redistributing the gray values. It enhances the quality of the image and is useful when the image is intended for viewing. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The goal of image enhancement technique is to improve the characteristics or quality of an image, such that the resulting image is better than the original image. Histogram equalization is widely used for contrast enhancement.[4] However, it tends to change the brightness of an image. Preserving the input brightness of the image is required to avoid annoying artifacts in the output image. Fig. 3 Shows Mean filter's output.
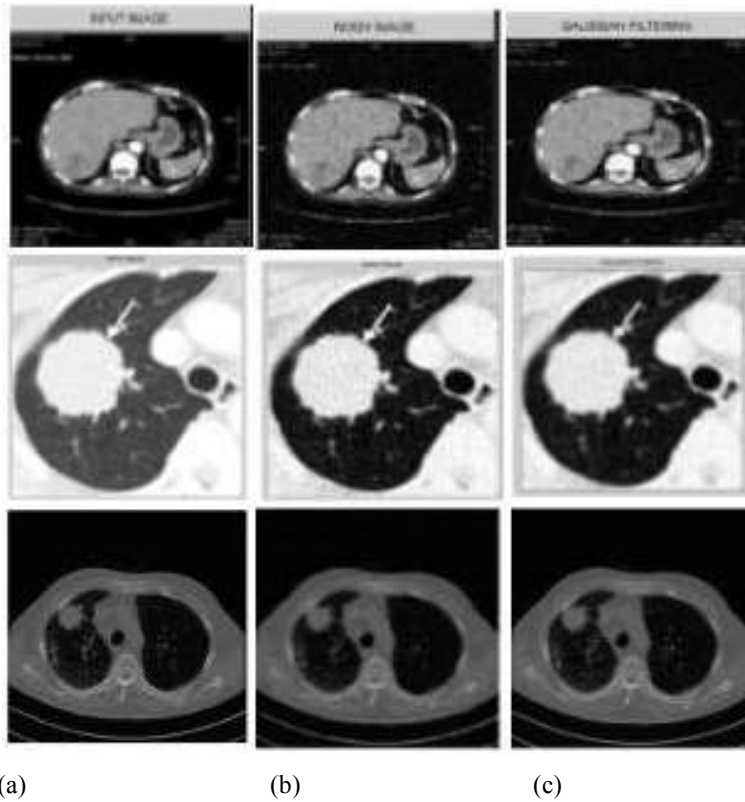
(a)   (b)   (c)

Fig. 2: Gaussian filter output, (a) Input Image (b) Noisy Image with Speckle Noise (c) Gaussian filter output

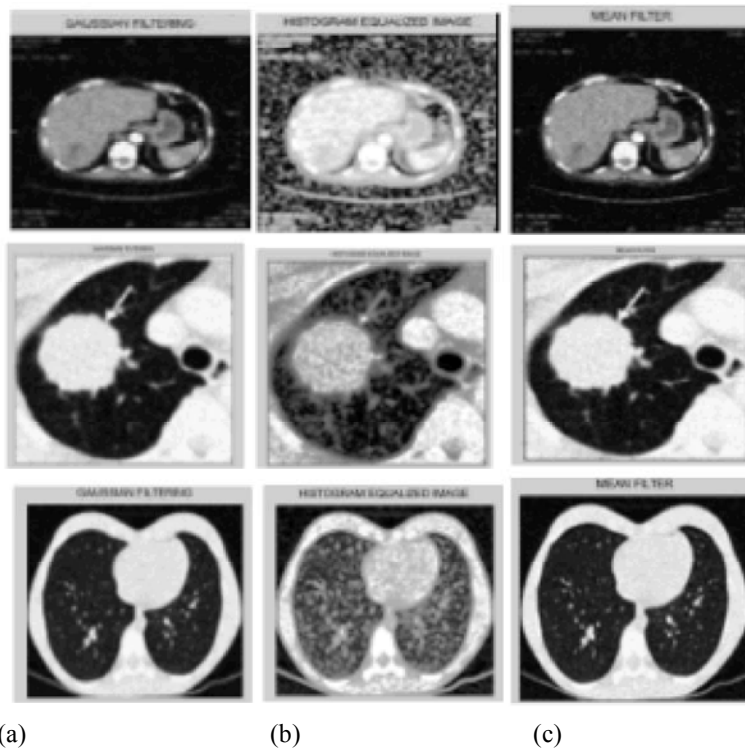(a)   (b)   (c)

Fig. 3: Image Enhancement Output,(a) Gaussian Filtered Input Image. (b) Histogram Equalized Image. (c) Mean Filter Output

Image Segmentation: Segmentation is used to simplify and/or change the representation of an image into something that is 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 visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (Edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as colour, intensity, or texture.

Robust Active Shape Models: Biomedical images usually contain complex objects, which will vary in appearance significantly from one image to another. Attempting to measure or detect the presence of particular structures in such images can be a daunting task. The RASM model is trained from manually drawn contours in training images. The RASM model finds the main variations in the training data using Principal Component Analysis (PCA), which enables the model to automatically recognize if a contour is a possible good object contour [5, 6]. Also the RASM modes contains matrices describing the texture of the lines perpendicular to the control point, these are used to correct the positions in the search step. After creating the RASM model, an initial contour is deformed by finding the best texture match for the control points. This is an iterative process, in which the movement of the control points is limited by what the RASM model recognizes from the training data as a "normal" object contour. Then PCA is used to find the mean appearance (intensities) and variances of the appearance in the training set. Robust Active Shape Models are statistical models of the shapes of objects which iteratively deform to fit to an example of the object in a new image. The shapes are constrained by a Statistical Shape Model to vary only in ways seen in a training set of labelled examples.

Building Model: To build a statistical model of appearance we require a set of annotated images of typical examples. First decide upon a suitable set of landmarks which describe the shape of the target and which can be found reliably on every training image. Good choices for landmarks are points at clear corners of object boundaries, 'T' Junctions between boundaries or easily located biological landmarks. However, there are rarely enough of such points to give more than a sparse description of the shape of the target object. The argument this list with points along boundaries which are arranged to be equally spaced between well defined landmark points.

To represent the shape we must also record the connectivity defining how the landmarks are joined to form the boundaries in the image. $\{(x_1, y_1),(x_2, y_2),...,(x_n, y_n)\}$. For a 2-D image can represent the n landmark points, $\{(x_i, y_i)\}$, for a single example as the 2n element vector, x,

where

$$x = (x_1,..., x_n, y_1,....y_n)T \tag{2}$$

If it have s training examples, it generate s such vectors x_j. Before we can perform statistical analysis on these vectors it is important that the shapes represented are in the same co-ordinate frame. The shape of an object is normally considered to be independent of the position, orientation and scale of that object. A square, when rotated, scaled and translated, remains a square. The approach is to translate, rotate and scale each shape so that the sum of distances of each shape to the mean is minimized.

Statistical Models of Shape: Suppose there are s sets of points x_i which are aligned into a common coordinate frame. These vectors form a distribution in the 2n dimensional space in which they live. If a model can act as the distribution, it can generate new examples, similar to those in the original training set. To simplify the problem, first reduce the dimensionality of the data from 2n to something more manageable. An effective approach is to apply Principal Component Analysis (PCA) to the data. The data form a cloud of points in the 2n-D space, though by aligning the points they lie in a (2n - 4)-D manifold in this space. PCA computes the main axes of this cloud, allowing one to approximate any of the original points using a model with less than 2n parameters. PCA is closely related to factor analysis. Factor analysis typically incorporates more domain specific assumptions about the underlying structure and solves eigenvectors of a slightly different matrix. Approximation of the training set x is done using

$$x \approx x + Pb \tag{3}$$

(where $P = (p1|p2|... |pt)$ contains t eigenvectors of the covariance matrix and b is a t dimensional vector given by
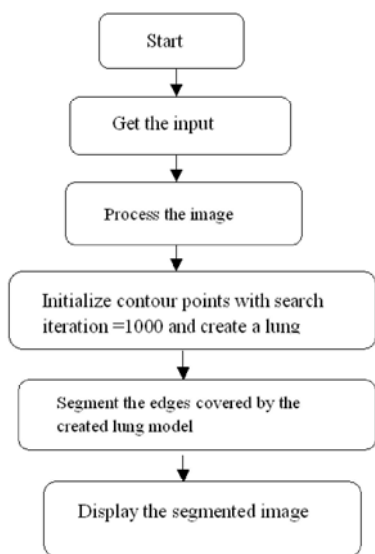
$$b=PT(x\square x^-) \tag{4}$$

Fig. 4: Flowchart of RASM

Fig 4. Flowchart of RASMThe variance of the ith parameter, b_i across the training set is given by λ_i. By applying limit of $\pm 3\sqrt{\lambda_i}$ to the parameter bi we ensure that the shape generated is similar to those in the original training set.Usually call the model variation corresponding to the ith parameter, bi, as the ith mode of the model. The eigenvectors, P, define a rotated co-ordinate frame, aligned with the cloud of original shape vectors. The vector b defines points in this rotated frame

Fitting a Model to New Points: A particular value of the shape vector, b, corresponds to a point in the rotated space described by P. A simple iterative approach to achieving this is as follows: Matching model points to target points

- Initialize the shape parameters, b, to zero (the mean shape).
- Generate the model point positions using $x = \bar{x} + P_b$
- Find the pose parameters (X_t, Y_t, s, θ) which best align the model points x to the current found points Y.
- Project Y into the model co-ordinate frame by inverting the transformation $T:y = T\text{-}1_{X_t,Y_t,s,\theta}(Y)$
- Project y into the tangent plane to $\bar{x}$ by scaling: $y' = y/(y.\bar{x})$.
- Update the model parameters to match to $y'b = PT(y'\text{-} \bar{x})$
- If not converged, return to step 2.

Fig. 4 refers to the flowchart of RASM, were the input image is taken and processed, to initialize the contour points with search iteration, to segment the edges of the created lung model,[8.9] Fig. 5 shows the segmented output, were the model of the lung is obtained from ASM segmentation, Fig. 6 shows the RASM segmented output. The basic idea behind robust ASM matching is to only use inliers components of Y to update model parameters. It is well known that the effectiveness of M-estimators strongly depends on the selection of the weighting function and its parameters. Usually, this selection is not trivial and the optimal selection might change from case to case. Random sampling techniques try to find a subset of inliers by evaluating a number of randomly sampled subset so update points

Tumour Location- Morphological Processing: Morphological processing is a set of operations that process images based on shapes. It applies a structuring element to an input image and generates an output image The most basic morphological operations are two: Erosion and Dilation. They have a wide array of uses, i.e. removing noise, Isolation of individual elements and joining disparate elements in an image, Finding of intensity bumps or holes in an image. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. By choosing the size and shape of the neighbourhood, can construct a morphological operation that is sensitive to specific shapes in the input image. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.

Dilation: Dilation is a process in which the binary image is expanded from its original shape. The way the binary image is expanded is determined by structuring element this structuring element is smaller in size compared to the image itself.the size used for the structuring element is 3 × 3,Let B_x denote the translation of B so that its origin is located at x. The *dilation* of X by B is defined as the set of all points x such that B_x hits X - that is, they have a nonempty intersection [10]

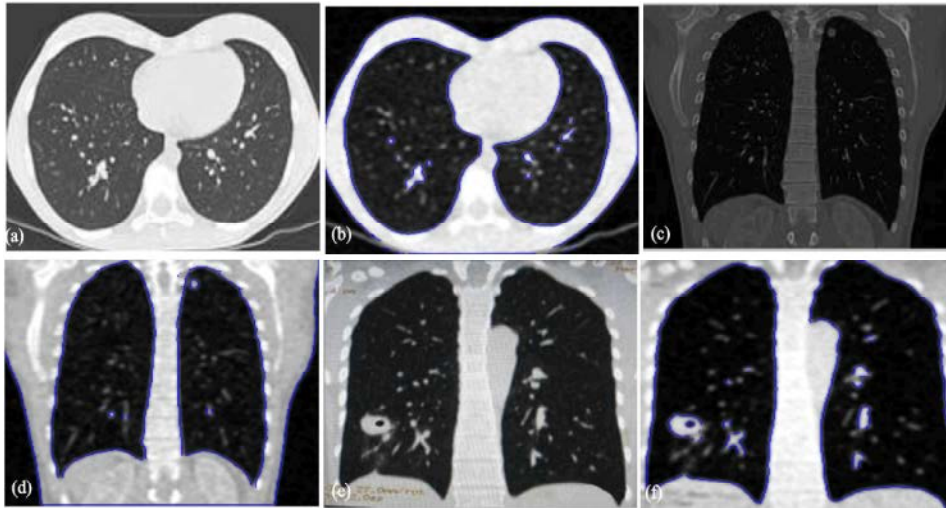$$X \square B = \{x | Bx \cap nX \neq \square\} \qquad (5)$$

Fig. 5: Examples for Segmentation using ASM (a,c,e,) Filtered CT slices (b,d,f,)   Segmented   Image
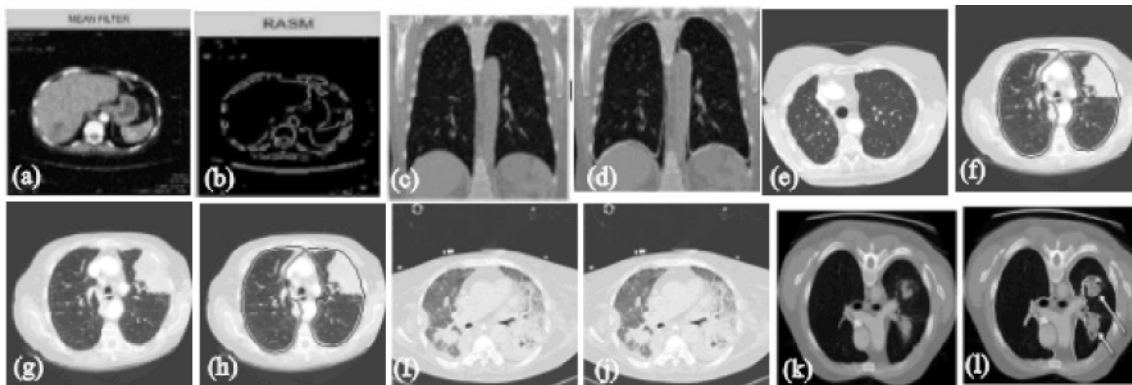

Fig. 6: Example of segmentation using RASM (a,c,e,g,i,k) Filtered CT slices, (b,d,f,h,j,l) Segmented Images
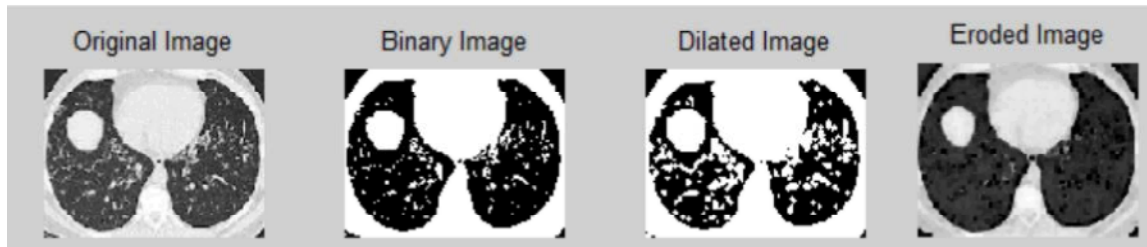

Fig. 7: Example for Dilation and Erosion

Each time the origin of the structuring element (*B*) touches a binary 1-pixel (*X*), the entire translated structuring element shape is *ORed* to the output image which has been initialized to all zeros. The Fig. 7 refers the output of dilation and erosion

Erosion: Erosion operation is the process close to dilation. What this does is to compute a local minimum over the area of the kernel. As the kernel is scanned over the image, the minimal pixel value is computed and replace the image pixel under the anchor point with that minimal value.

Fig. 8 illustrates the output of morphological operation, where the process is done by eroding away the boundaries of the RASM output in order to locate the tumour from the dilated image and the holes are being filled in the output of the dilated image to get the filled image [11,12].
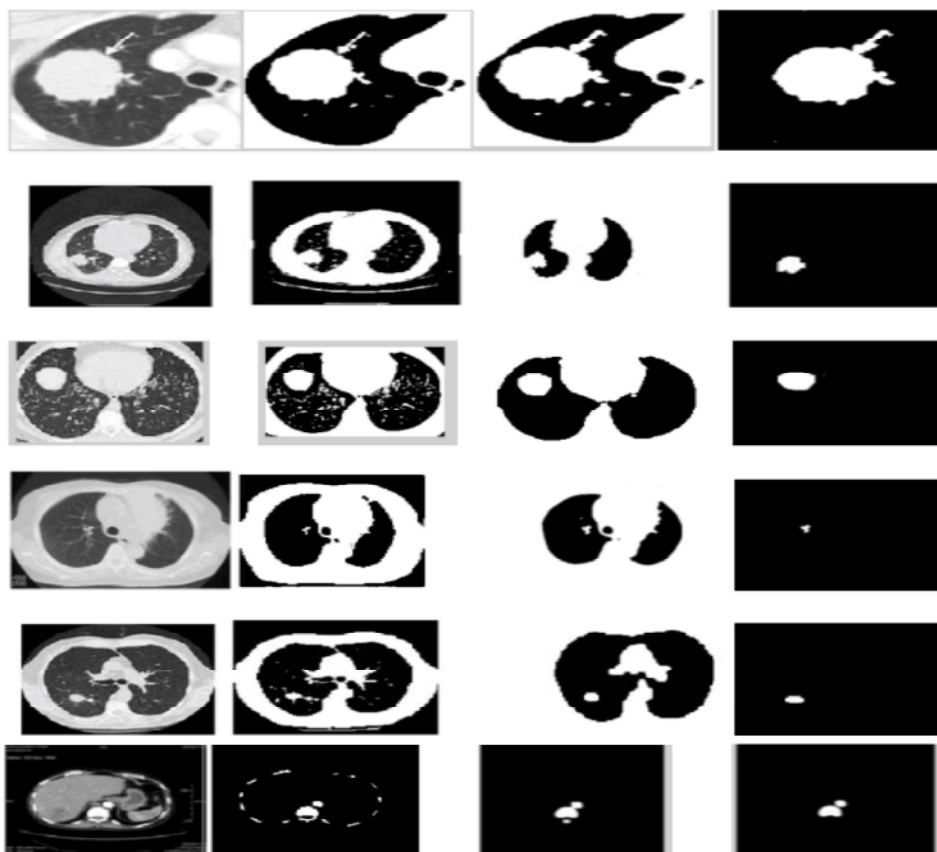
Fig. 8: Exmples for Tumour location using thresholding and morphological processing.

Centriod calculation is being done to segment the white regions alone, region props command is used for the centroid calculation process and it is used to measure the property of the binary image. Various morphological operations are 'Open' and 'Remove' 'Open' is used to perform morphological operation (erosion followed by dilation), the remove option does not change the boundary of the image pixels, but it removes the interior pixels. Fig. 8 refers to the calculated centroid output which is obtained from the output of the filled image. From the output of the filled image, the centre of mass which specifies the white regions alone are being calculated and the largest area is being segmented.

RESULTS AND DISCUSSION

A CT lung image is taken as input. As an initial step pre-processing being carried out by using Gaussian filter in order to remove the speckle noise. Image enhancement is done with the help of contrast stretching (histogram equalization) by uniformly redistributing the grey values. This is followed by segmentation using RASM (Robust Active Shape Modelling). Location of tumor is done with the help of morphological processing (erosion and dilation). Table 1 illustrates PSNR details of various filters, on comparing with the parameters, Gaussian filter found to be more efficient when compared with the other filters. Table 2 illustrates the difference between various segmentation techniques

Table 1: Comparison PSNR values of Noise Removal Filters

Filter	PSNR								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Gaussian	46.60	45.89	45.32	44.71	44.08	43.66	43.24	42.82	42.42
Median	38.63	37.57	37.12	36.82	36.59	36.43	36.02	36.20	36.05
Average	42.73	41.22	40.92	40.26	39.65	39.25	38.86	38.49	38.24
Mean	25.24	22.89	21.26	19.96	18.86	18.08	17.49	16.82	16.26

Table 2: Comparison of Segmentation Techniques

Segmentation	Mean	Standard Deviation
RBS	0.5374	0.4986
RASM	0.0326	0.1867
FCM	0.2388	0.3100
KFCM	0.8326	0.3733

79

CONCLUSION

In this proposed work the main processing step is a robust active shape model (RASM) matching method which is utilized to roughly segment the outline of the lungs. The robust matching algorithm is specifically designed to take advantage of general-purpose computation on graphics processing units, which reduces the execution time considerably. Then Tumour location was done using morphological processing and the geometric features. Each image sample is scanned and stored to a size. Generally during the scanning, the quality of image is affected by different artifacts due to non uniform intensity, variations, motions, shift and noise. Thus, the pre-processing of image aims at selectively removing the redundancy present in scanned images without affecting the details, that play a key role in the diagnostic and analysis process.

Statement of Competing Interests: The authors have no competing interests'

REFERENCES

1. Abbosh, Y.M., Yahya and A.F. Abbosh, 2011. ”A. Neural Network for the Detection and Localization of Breast Cancer.” IEEE Transactions on Biomedical Engineering., 50(2): 156-159.
2. Jiamin Liu and Jayaram K. Udupa, 2009. ”Oriented Active Shape Models”.IEEE Transactions on Medical Imaging., 28(4): 571-584.
3. Sluimer, I., M. Prokop and B. Van Ginneken, 2005. Toward "Automated Segmentation of the Pathological Lung In CT". IEEE Trans. Med. Imag., 24(8): 1025-1038.
4. Ali Sadeghi Naini, Rajni V. Patel and Abbas Samani, 2010. "CT-Enhanced Ultrasound Image of a Totally Deflated Lung for Image-Guided Minimally Invasive Tumor Ablative Procedures".IEEE Transactions on Biomedical Engineering, 57(10): 2627-2630.
5. Shanhui Sun, Christian Bauer and Reinhard Beichel, 2012. "Automated 3-D Segmentation of Lungs With Lung Cancer in CT Data Using a Novel Robust Active Shape Model Approach" IEEE Transactions On Medical Imaging, Vol. 31, No. 2, February .
6. Jan Hendrik Moltz, Lars Bornemann *et al*. 2009. ”Advanced Segmentation Techniques for Lung Nodules, Liver Metastases and Enlarged Lymph Nodes in CT Scans IEEE Journal of Selected Topics in Signal Processing”, 3: 1.
7. Xujiong Ye*, Xinyu Lin, Jamshid Dehmeshki, Member, 2009. "Shape- Based Computer-Aided Detection of Lung Nodules in Thoracic CT Images". IEEE Transactions on Biomedical Engineering, 56(7): 1810-1820.
8. Pu, J., Roos, C.A. Yi, S. Napel, G.D. Rubin and D.S. Paik, 2008. '”Adaptive Border Marching Algorithm: Automatic Lung Segmentation on Chest CT Images”. Computer. Med. Image. Graph. 32(6): 452-462.
9. Kitasaka, T., K. Mori, J. Hasegawa and J. Toriwaki, 2003. ”Lung Area Extraction From 3-D Chest X-Ray CT Images Using a Shape Model Generated by A Variable Bezier Surface," Syst. Comput. Jpn., 34(4): 60-71.
10. Jayraman, S. Esaikirajan and T. Veerakumar, 2011. "Digital Image Processing" Tata Mcgraw- Hill Education.
11. Abel Karera, Ellen Fungai Maguranyanga, Sindiso Nleya and George Chingarande”The Effectiveness of Ultrasound in Early Detection of Benign Prostatic Hypertrophy”, A Case Study of Chitungwiza, Zimbabwe World Journal of Medical Sciences 10 (2): 122-128, 2014© IDOSI Publications, 2014
12. Jemila Rose, R. and S. Allwin, 2013. " Ultrasound Cervical Cancer Based Abnormality Research Segmentation Using Adaptive Fuzzy C-Mean Clustering" Academic Journal of Cancer 6(1): 01-07, 2013 © IDOSI Publications, 2013.