



# Automatic CT-Image Segmentation for Lungs with Salient Region Detection

Chithra.C<sup>1</sup>, Kiran.P.B.<sup>2</sup>

<sup>1</sup>PG student, Department of CSE, Udaya School of Engineering, Kaniyakumari, India

<sup>2</sup>PG student, Department of CSE, Udaya School of Engineering, Kaniyakumari, India

<sup>1</sup>[chithra.smart000@gmail.com](mailto:chithra.smart000@gmail.com); <sup>2</sup>[kiranprabhakaranb@gmail.com](mailto:kiranprabhakaranb@gmail.com)

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**Abstract**— *Detection of salient image regions is useful for applications like image segmentation, adaptive compression, and region-based image retrieval. one of the important step for the earlier detection of lung disease is the computer aided diagnosis of lung images of the patient. The lung image is captured and is processed at first in order to do the segmentation process. Segmentation is done based on the part we need to do our further processing. That means, here the lung area is being segmented. Segmented part is subjected for keen observation for the detection of the lung diseases. Further steps include the measurements of parameters inside the segmented part includes tissue and air volume, density units of the tissue, contrast in the image. in the existing method, it only highlight the portion we need in the environment. But it becomes significant when it is applied in medical field for the detection of diseased part. Salient region referred here is the diseased area within lung. In this paper we present a novel method to determine salient regions in images using low-level features like Compactness and Local Contrast. The method is fast, easy to implement and generates high quality saliency maps of the same size and resolution as the input image. We introduce a Local and Global Contrast based salient object extraction algorithm, to accurately segment the lung parenchyma of lung CT images, which can help radiologist in early diagnosing lung diseases.*

**Keywords**— *computed tomography, lung segmentation, active contour algorithm, salient region detection*

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## I. INTRODUCTION

In imaging science, image processing is processing of images using the mathematical operation by using any form of signal processing for which the input is an image, such as photograph or video frame, the output of image processing may be either an image or set of characteristics or parameter related to image. Computer vision is closely related to image processing. Diagnosis of lung images is helpful from the earlier days for the detection of lung diseases. CT is preferred more compared to x-ray because CT can reveal the soft tissue and other structures that can't be seen in case of x-rays. Most of the radiologist in medical field assist the help from the computer aided diagnosis for detection of disease affected area. Segmentation is the choice for the effective detection for this purpose. It will divide the image into specific classes by comparing each images' pixel value with a number of intensity value called threshold. It is needed to highlight the portion for the further processing. So visual attention is necessary mechanism. There is a great difference between the task driven and stimulus driven mechanism where the former is based on the higher level information including emotions, previous task knowledge etc. where the latter is based on the low level visual stimuli. salient region detection is one of the mechanism mostly preferred today in order to expose the region that we need and also suppressing those unwanted. Because of this it have many applications such as adaptive compression, region based image

retrieval , object recognition , image segmentation and so on. The features of the image such as local contrast and compactness are extracted from the preferred region and is diffused to form the saliency map. Before that the super pixel is abstracted to form the graph. The different visual feature that contribute to attentive selection of stimulus are combined to one single tomographically oriented map , the salient map which integrates the normalized information from the individual feature maps into global measure of conspicuity. The saliency map will highlight the lung region which is abnormal. This paper presents the application oriented salient region detection ie, in medical field for the lung disease diagnosis.

## II. RELATED WORK

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. CT scans can show several types of tissue with great clarity such as bone, soft tissue and blood vessels and allows easy differentiation between soft tissue structures, which greatly improves on the conventional x-ray. CT scans can detect and determine the exact size and location of anatomical abnormalities such as tumours, lesions, blood clots and blood vessel defects and bone defects. The images produced are generally of cross-sectional nature, with multiple scans creating the ability to produce 3-D images of internal structures. Computed Tomography Imaging works on the same basis of an x-ray. As the x-ray beams pass through the body, they are absorbed at different levels and a profile is created of x-rays beams of different strengths. These are recorded on film as an image or in the case of an x-ray, resembling a shadow. The use of a computer in CT scanning is what differs from a conventional x-ray. A CT scanner consists of a table on which the patient lies which moves in through the ring shaped scanner. A moveable ring located is on the edge of the scanner which contains the x-ray tube and its associated detection. A CT scan involves the movable ring revolving around the patient with fine fan of x-ray beams being passed through the body from all angles into their associated detectors, with the information from each detector relating to a particular part of the body. All this information from the detectors must be compiled into a detailed image of the particular slice of the body by the computer. Every time the movable ring makes a 360 degree rotation, a slice has been acquired. These slices give such detailed images of the internal structures of the body that they have become widely used in radiology, in both the diagnosis of diseases, checking of bodily structures such as the brain, heart, liver, lungs and kidneys and also in trauma to check for injury. Major CT Techniques includes Spiral Computed Tomography and High Resolution Computed Tomography so on. Lung segmentation many of the authors greatly depends on the segmentation of the particular region of interest for detecting diseases. Computer aided diagnosis is mostly preferred today because of the expense of the manual segmentation. In this paper active contour segmentation algorithm is used for the segmentation of the lung images. A Snake or active contour model is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours. Snakes are greatly used in applications like object tracking, shape recognition, segmentation, edge detection, stereo matching. Snakes may be understood as a special case of general technique of matching a deformable model to an image by means of energy minimization. Snake is an "active" model as it always minimizes its energy functional and therefore exhibits dynamic behaviour.

## III. EXISTING SYSTEM AND PROPOSED SYSTEM

### 3.1. Existing System

The system will perform the segmentation on lung images so that it can be analysed for diseases. Region growing algorithm is one of the lastly used algorithm for segmentation of lungs. The main source of data for implementation of this algorithm is images from the Picture Archiving and Communication System (PACS), a system that is used for transferring the images from the modalities directly to servers, and is available immediately to users, regardless to their location. Salient region detection is associated with environmental image ie, in order to expose objects needed and suppress those unwanted.

### 3.2. Design Goals

In this paper we try to include a new algorithm for image segmentation which is more efficient and accurate than previous approach. So our main goals includes:

- 1) To segment image more accurately without errors.
- 2) To include the application oriented salient region detection method, especially in medical field.
- 3) To expose the region of interest using saliency map.

### 3.3 Proposed System

The proposed approach mainly focus on the application oriented area of the salient region detection. It helps the radiologist to detect the disease affected to lung using CT image as input and through further processing steps.

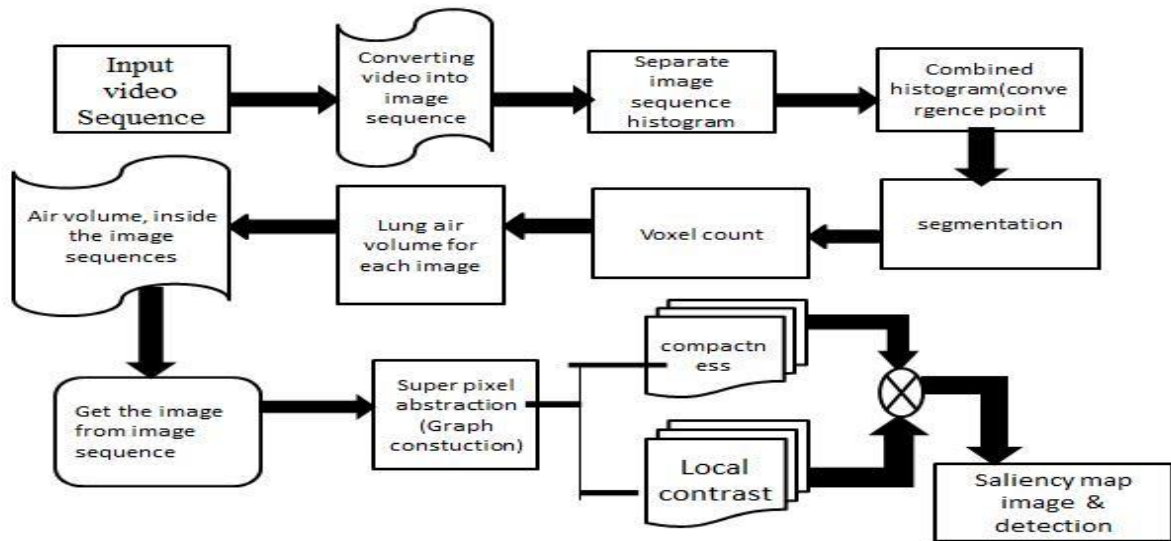


Figure 1: Architecture of proposed system

In fig 1, the input given is the CT image of the lung. Computed tomography (CT) is a radiographic inspection method that uses a computer to reconstruct an image of a cross sectional plane of an object. For this Estimation, Segmentation Process is introduced. First Histograms are calculated for the Image Sequences. Second using active contour method segment the lung air area and at last by using volume rendering method the voxels in the area are counted to estimate the lung air volume. And at last by using volume rendering method the voxels in the area are counted to estimate the lung air volume. Other parameter inside each image is found and is compared against the normal parameter measurements and thus the abnormalities are being obtained. The resulting image is obtained and is abstracted to super pixel and it is converted to graph. The features such as local contrast and compactness are extracted from image and separate saliency map is created and is combined to finalised saliency map. This Saliency map will expose the disease affected portion of the lung.

#### IV. EXPERIMENTAL RESULTS

We demonstrate our proposed system with modules of implementation. The proof of the concept empirical result are encouraging.

##### A) Extraction of convergence points

In first step CT Image sequence are to be given as input. Then histogram can be obtained for the image sequence and they are overlay to form the combined histogram. A graph that contains histogram where X axis shows number of pixels and Y axis shows voxel size of CT Image. They are combined to extract the convergence points. The combined Histogram is nothing but that the two histograms are plotted in the same surface region. The points are identified when the distances between them to reach a minimum. For this standard deviation of all the histograms within the sequence is calculated for each intensity value. Consequently, the converging areas are searched for the points with a minimum standard deviation, which are selected as the convergence points A and B. Now the histogram regions before point A, between points A and B, and after point B correspond to the background-air volume, lung's air volume, and soft-tissue volume. The histogram at nodes A and B correspond to good initial estimates to extract the lung's air volume. The convergence point A which corresponds to minimal number of voxels variation w.r.t. volume variation during respiration is the best point that represents the interface regions. After point A, intensity values will correspond to air mixed with small amount of alveoli tissue. This continues until a point B, where the lung tissue starts to be dominant with small amount of air. As such each histogram curve between points A and B provides a good approximation to the lung's air volume. Then point B, the second convergence point in the combined histogram, is another good initial position to extract the lung air area portion.

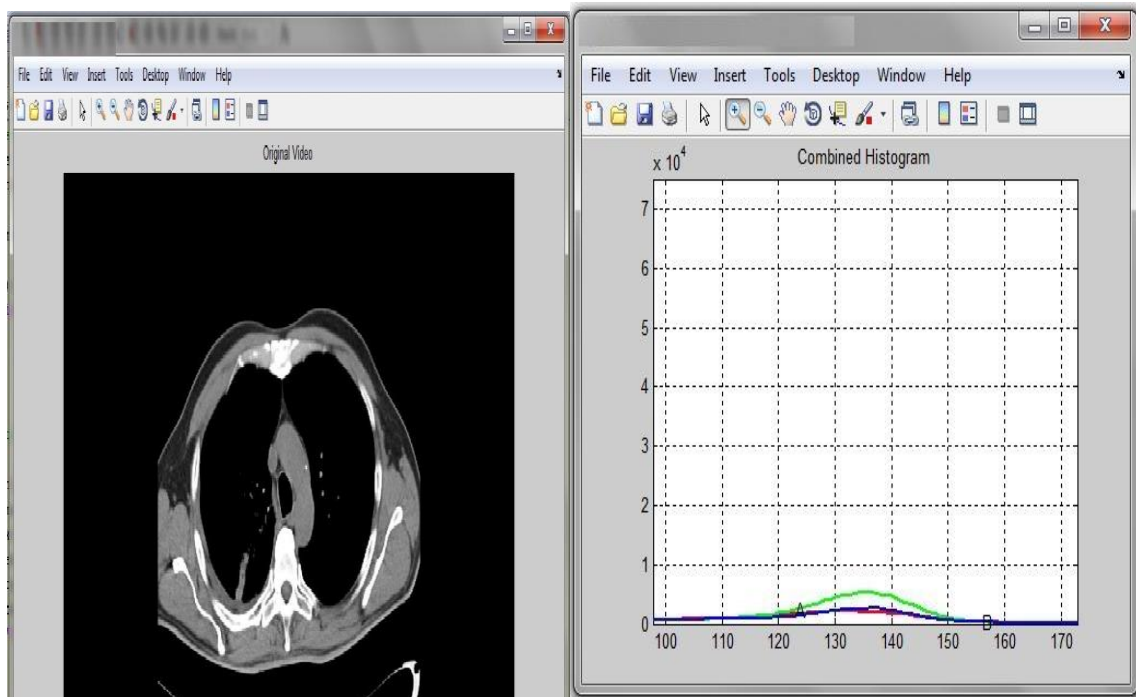


Figure 2: CT Image Sequences of Lung are to be give as input and the histograms lung air area.

### B) Segmentation

Our Segmentation having Active Contour method algorithm is proposed to detect tumour whose boundaries are not necessarily defined by gradient. Energy minimization is the major factor concentrated here. For Curve evolution Level set Segmentation does not depend on the gradient of an image but Active Contour Segmentation depends on the gradient of the image. Our approach mainly concentrates on formulating Level set equations in such a way that the dependency of active contour on gradient is minimized. Our approach is tuned to predict the interior contours automatically. The approach of active contour is to evolve a curve, subject to some constraints. In our approach these constraints are formulated using Level set equations. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object. In the classical snakes and active contour models an edge-detector is used, depending on the gradient of the image  $U_0$  to stop the evolving curve on the boundary of the desired object. The Active Contour model is represented as in equation (4.2.2.1),

$$J_1(C) = \alpha \int_0^1 |C'(s)|^2 ds + \beta \int_0^1 |C''(s)| ds - \lambda \int_0^1 |(C(s))|^2 ds \quad (4.2.2.1)$$

Here  $\alpha, \beta, \lambda$ , and are positive parameters. The first two terms control the smoothness of the contour (the internal energy), while the third term attracts the contour toward the object in the image (the external energy). By minimizing the energy, we are trying to locate the curve at the points of maxima  $|\nabla u_0|$ , acting as an edge-detector, while keeping smoothness in the curve (object boundary). Depending upon the above formulation, The minimization problem is stated as follows in equation (4.2.2.2),

$$\text{Inf}_c J_2(C) = 2 \int_0^1 |C'(s)| \cdot g(|\nabla u_0|(C(s))) \quad (4.2.2.2)$$

Solving the minimization problem in the above equation consists of finding the path of minimal new length in that metric. A minimizer  $C$  will be obtained when  $g(|\nabla u_0|(C(s)))$  vanishes, i.e., when the curve  $C$  is on the boundary of the object. Thus level set formulation is given as in equation . Because all these classical snakes and active contour models rely on the edge-function, depending on the image gradient  $|\nabla u_0|$ , to stop the curve evolution, these models can detect only objects with edges defined by gradient.

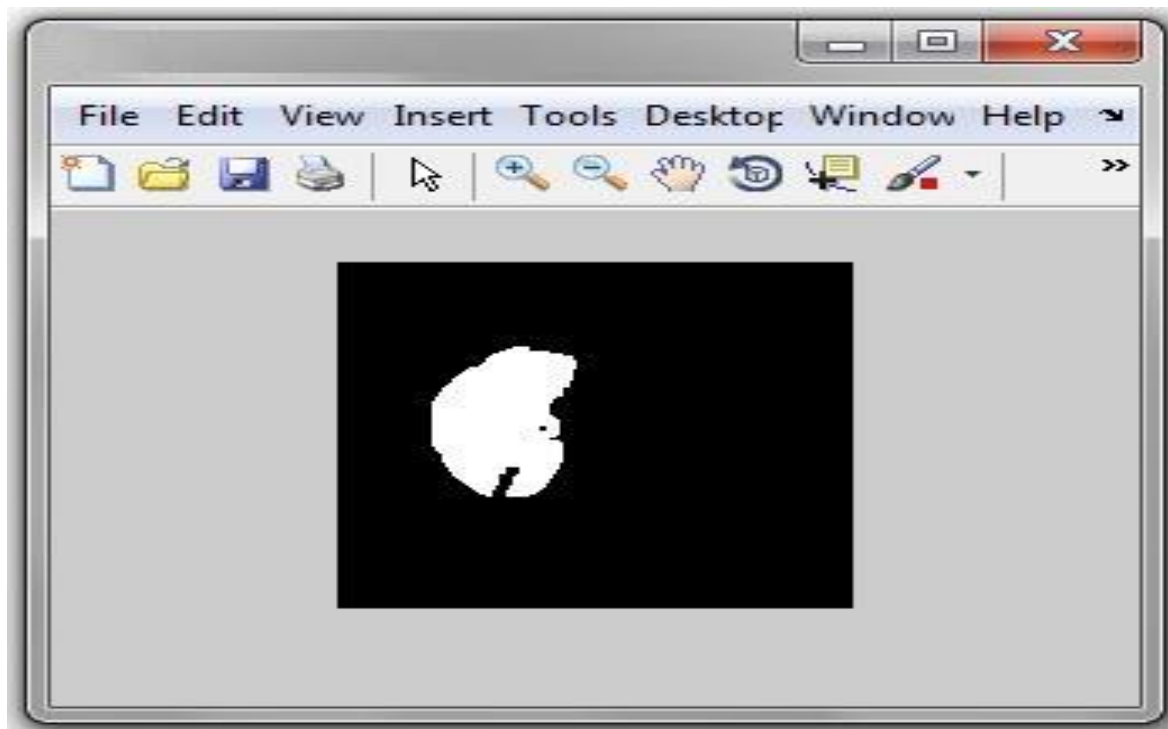


Figure 3. Segmentation Result

### C). Volume rendering

Volume is a three-dimensional array of voxels. Just the same way an image is a 2D array of pixels. 3D images produced by CT Volume rendering means rendering the voxel-based data into viewable 2D image. Volume rendering is a volume visualization method that projects the shape of objects in the data set onto the screen instead of the grey values. Volume rendering is a set of techniques used to display a 2D projection of a 3D discretely sampled data set. A typical 3D data set is a group of 2D slice images acquired by a CT, MRI, or Micro CT scanner. Usually these are acquired in a regular pattern (e.g., one slice every millimetre) and usually have a regular number of image pixels in a regular pattern. This is an example of a regular volumetric grid, with each volume element, or voxel represented by a single value that is obtained by sampling the immediate area surrounding the voxel. To render a 2D projection of the 3D data set, one first needs to define a camera in space relative to the volume. Also, one needs to define the opacity and color of every voxel. This is usually defined using an RGBA (for red, green, blue, alpha) transfer function that defines the RGBA value for every possible voxel value. This can be accomplished by calculating volume gradients in the dataset that will be used as the orientation of the object shape. A shading model is used to calculate the observed effect of a light source shining on this shape. By assigning transparency and color based on the grey-values in the dataset, the contribution of this shaded object to the value of a pixel on the screen can be calculated using a composition formula. Iso surface volume rendering has some conceptual similarity with voxel based surface rendering algorithms in the sense that both methods intend to visualize an iso-surface in the 3D data field. An iso-surface is, by definition, the surface in a (continuous) field  $F(x,y,z)$  at which the value equals a pre-defined iso-value. When an iso-value  $Iso$  is given, the equation  $F(x,y,z) = Iso$  will give a relation in  $x$ ,  $y$  and  $z$ , which describes the corresponding iso-surface. In the case of a volumetric dataset however, we have to define an iso-surface in a discrete data field  $D(nx,ny,nz)$ .

A reconstruction filter  $R(x,y,z)$ , that might be interpolating or approximating, can be used to compute the values of the discrete data field at arbitrary  $(x,y,z)$  locations. This implies that this (continuous) reconstruction filter implicitly extends the discrete data field to a continuous data field  $Dr(x,y,z)$ . Hence, it is possible to define the iso-surface in a discrete field  $D(nx,ny,nz)$  as the iso-surface in this extended continuous data field  $Dr(x,y,z)$ . This extended field, and hence the iso-surface, is determined by the data values in the discrete field on one hand and the reconstruction filter of choice on the other hand. This iso-surface is equal to the implicit surface defined by  $Dr(x,y,z)=Iso$ . It is clear that this isosurface is not the same as the 'iso-surface' extracted with the marching cubes algorithms. When a linear reconstruction filter is used, only the nodes of the triangles lie exactly on the real iso-surface. The main difference between iso-surface volume rendering and traditional volume rendering methods is that iso-surface volume rendering aims to find the intersection point of a ray with the isosurface between the re-sampling locations on this ray instead of calculating the opacity at re-sampling locations. The

opacity and gradient are calculated at the location of the intersection. When tri-linear interpolation is used, the intersection points can be found by finding the roots of a third order polynomial function. The grey-value at an arbitrary  $(x, y, z)$  location inside a basic voxel cube can be described as  $L3(A...H, x, y, z)$ , in which  $A...H$  are the voxel values. The  $x$  location on a ray through this sub-volume can be parameterized as, in which  $x_0$  is the  $x$  coordinate of the location where the ray enters the sub-volume and  $x_1$  is the  $x$  coordinate of the location where the ray exits the sub-volume. In a similar way, also the  $y$  and  $z$  locations can be written as a linear function of  $\lambda$ . These values can be used to rewrite the tri-linear interpolation function as a third order polynomial for each line segment. By calculating the roots of the difference of this polynomial and the iso-value, the exact intersection locations can be calculated. Calculating the roots of a third order function is however a extremely computational intensive operation. The iso-surface will be located between these two samples. From the data values and the iso-value, the depth can be calculated using the straight-line approximation. This approach gives the following equation (4.2.4.4)

$$f = \frac{Iso - D(x_1, y_1, z_1)}{D(x_2, y_2, z_2) - D(x_1, y_1, z_1)} \quad (4.2.4.4)$$

$$\text{depth} = k_1 + (k_2 - k_1).f$$

In these equations,  $f$  is the location in between the two samples where the intersection is found ( $\lambda$ ). Note that the 1D variant of this formula is used in the marching cubes algorithm to find the intersection points of an iso-surface with the edges of an elementary cell of the voxel-grid. In the regula-falsi iteration method, this formula is used for the calculation of the new base point. In the iso-surface volume rendering method, these problems are solved by taking samples at the intersection points of the rays with a unit cell consisting of eight voxels. In this way, even the smallest image details will not be missed as long as one of the rays intersects these details. When using a low image resolution, it is hence possible that none of the rays will hit a very small object (smaller than the pixel size). In this case, this small object will not be visible. This means that the smallest object visible is about the projected pixel size in the volume. Increasing the image resolution or zooming in on details will make even the smallest objects visible, as will be shown with the rendering of a single voxel. Because the samples are taken at the boundaries of the cell, the function on the interval between these points and the derivative of this function are both continuous functions. This makes this method more suitable for an iterative search for the root of this function. When the iso-surface location is known for all rays, true surface gradients can be calculated instead of volume gradients. In this way, the surface will be shaded in accordance with the estimated shape. When the shape is estimated accurately, this surface gradient will be equal to the congruent volume gradient at the surface.

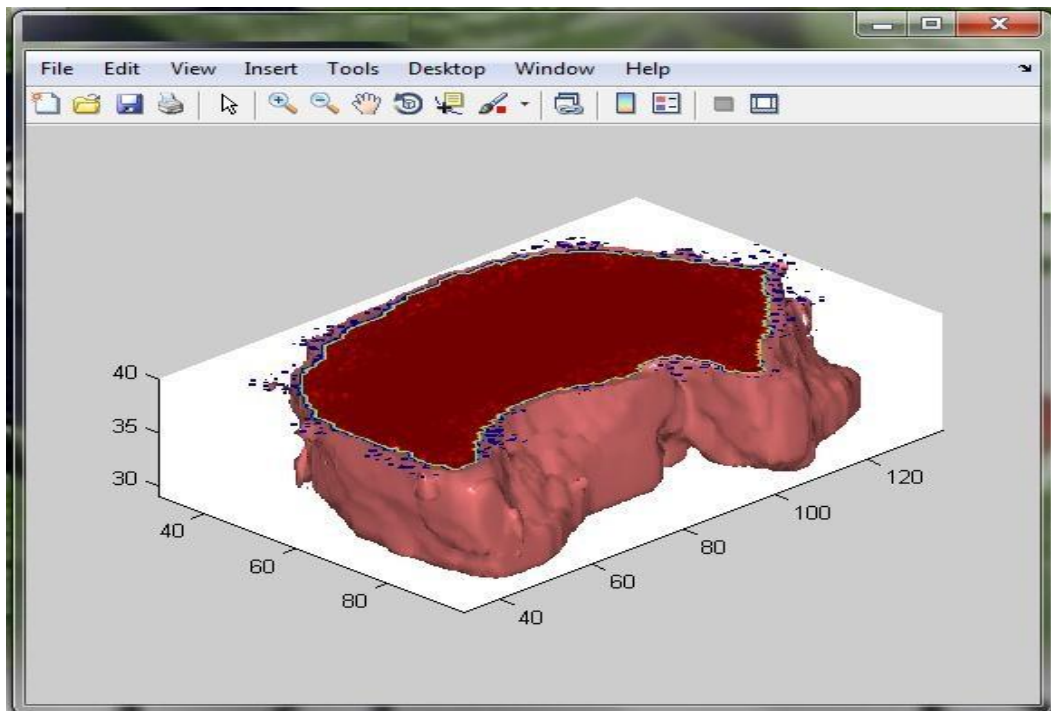


Figure 4. The volume of lung air to be rendered from the Input Image.

## V. CONCLUSION & FUTURE WORK

This research work has successively estimated the lung air volume from the CT image sequences. It would be very helpful to doctors to give medicine in right manner. This technique can be used in clinical applications, such as lung brachytherapy, where the lung's air volumes in a respiratory sequence are needed. This automatic method may improve complex semiautomatic algorithms and it is currently used for ejection fraction estimation. The method can also be used in other biomedical applications, where important physiological parameters need to be extracted. An example of such applications is estimation of the ventricle's ejection fraction from sequential cardiac images. This paper thus concludes that the lung air volume from the CT image sequences are to be estimated automatically and efficiently compared to the existing method. As this method was very useful because it need only few minutes for estimation process than the earlier methods. We present a novel method to determine salient regions in images using low-level features like Compactness and Local Contrast. The method is fast, easy to implement and generates high quality saliency maps of the same size and resolution as the input image. We introduce a Local and Global Contrast based salient object extraction algorithm, to accurately segment the lung parenchyma of lung CT images, which can help radiologist in early diagnosing lung diseases. The future work includes expanding the salient region detection to wider areas for various purposes including scientific field and other application that it is not used now a days.

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## AUTHORS



**Chithra.C**

Received the BE degree in computer science and engineering from Anna university, Chennai in 2014 and doing ME in computer science and engineering under same university. Research interest includes image processing, networking etc. she has been involved in several workshop and technical paper presentation



**Kiran.P.B**

Received the B.Tech degree in computer science and engineering from Pondicherry university (central - university ) in 2013.He currently working towards ME degree in Udaya school of engineering, Kanyakumari India, affiliated to Anna university Chennai .He is official Redhat trained administrator. He has been involved in several technical paper presentation and workshops .His research interest includes computer networks, cloud computing, image processing and mobile computing.