ISLAMIC UNIVERSITY OF TECHNOLOGY

UNDER GRADUATE THESIS

Heuristic Search Based Parameterized Level Set For Automated Lung Parenchyma Segmentation And Nodule Extraction

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Declaration of Authorship

We, Sanjary Rahman (114409), Md. Hamjajul Ashmafee (114403), declare that this thesis titled, "Heuristic Search Based Parameterized Level Set For Automated Lung Parenchyma Segmentation And Nodule Extraction" and the work presented in it are our own. We confirm that:

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Abstract

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Heuristic Search Based Parameterized Level Set For Automated Lung Parenchyma Segmentation And Nodule Extraction

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Image Segmentation is a very important image processing technique now a days. It is greatly used in the sector of medical image processing. Segmentation for lung areas from CT images is important task on understanding tissue construction, computing and extracting abnormal areas as well as parenchyma segmentation. There are many application of the lung image segmentation in lung parenchyma segmentation, lung nodule extraction, lung tumor classification, lung cancer detection and so on. These segmentation techniques, some of them are semi-automatic and some of them are fully-automatic. Some fully-automatic techniques include thresholding, snakes, level set, region growing, bayesian network, hierarchical multi-scale, gradient descent and so on.

The main objectives of the lung image segmentation are the efficiently and accurately segment the lung parenchyma and the lung nodule. The above mentioned techniques have their strength in their own dataset to segment correctly but they cannot perform well in all kinds of dataset. Another thing which are very important here to reduce time complexity, memory space and calculation complexity. In this paper we proposed a method which use the bi-directional chain method to select the seed points near the lung parenchyma automatically. It helps our next step of the proposed method- parameterized level set method.

For level set method it is necessary to select random points in the image through which it converges to the boundary of the object(s). But in our proposed method we do not use the random seed points. Rather we use the particular seed points near the lung parenchyma got from bi-directional chain method in which we use uninformed heuristic search and memoization technique. Then we implement the level set method to get the lung parenchyma correctly in reduced computational time. It perfectly segment out the lung parenchyma along with any irregular boundary and abnormal shape. Next step of our proposed method is to segment out the lung nodule accurately even if it resides near the boundary and having any abnormal shape. Experiment is performed employing 60 CT image sets from 18 patients and satisfactory results are obtained. Obtained results are shown along with a discussion.

Index Terms- **Image segmentation, level set method, bi-directional chain encoding, memoization, uninformed heuristic search, morphological operator, nodule extraction.**

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With Regards
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Chapter 1

Introduction

1.1 Overview

Image Segmentation is the process of partitioning a digital image into multiple segments which aims to simplify and change the representation of an image into some form that is more meaningful and easier to analyze. From the segmented image we can extract the region of interest (ROI) easily based on our given features. It is a very important tool in medical image processing nowadays because it is used to segment the pathology bearing reasons (PBR) in human body by Computer Aided Design system to help the doctors in their works. In lungs tissue segmentation it is very laborious work because of its being very sophisticated to segment the lungs parenchyma without over segmentation or under segmentation. Many approaches have been proposed earlier including region growing, clustering, graph theory, active contours and so on which produce satisfactory results but in case of the noise, low contrast image, shadows, cluttering they may fail. In this case interactive segmentation is preferred vary much to avoid these issues. So development automated CAD is very important landmark in medical image processing.

There are many different approaches in the area of automated lungs image segmentation on different type of Lungs image representation such as chest radiography, CT, PET, magnetic resonance imaging (MRI) and radionuclide bone scanning. They gives different sort of feasibility to use in diagnosis system.

In automated lungs image segmentation, there are different approaches above mentioned to segment the lungs images automatically. They introduces and uses different image segmentation tools and techniques to segment the ROI efficiently and correctly. These tools and techniques have the strength in their own dataset and also have the weak points where they may fail to segment. So there are no generalized image segmentation technique in the field of image processing. Image segmentation technique varies based on the ROI, interested features, orientation of the object, color space and so on.

1.2 Problem Statement and Application

Medical Image segmentation is a very significant area of biomedical engineering. In this area we have focus on the accurate segmentation of ROI which is the key step to contribute on diseases identification, classification and further treatment. In recent year's lungs becomes a very important region of interest for medical image segmentation and extract the sub region which may help to take decision. The most significant part of the lungs is the lungs lobe parenchyma. Because lung cancer becomes one of the main causes of death in the world among both men and women, with an impressive rate of about five million deadly cases per year. The 5-year survival rate is strictly related to the stage in which the disease is diagnosed: early detection and subsequent resection of the lung cancer can significantly improve the prognosis. One of the approach in this area is nodule detection inside the lungs parenchyma which may cause to lung tumor, lung cancer and other fatal diseases. Under the classification of the nodules physicians can take decision about the patient.

So there are mainly two challenges regarding the lung image segmentation. They are accurate segmentation of lungs parenchyma and also correct segmentation of lung nodule inside the lung nodule. Both cases of segmentation are very hard to implement. Because in the lung parenchyma segmentation, the main challenge is to restrict the ROI from the other parts of the image. But normally CT images give very low contrast lung image where it is very difficult to segment the lung parenchyma correctly. In most of the cases under-segmentation or over-segmentation hinder us of efficiency. In the nodule segmentation inside the lung parenchyma, it is difficult to select the features on which we can detect the lung nodule. Because in most cases they present abnormal size, shape and density. Very often they reside at such places which cannot be detect and extract correctly for further process.

So our main challenge in the lung image segmentation is correctly segment out the lung parenchyma of the lung lobe and inside it we have to detect the lung nodule correctly and segment out them also to help the physicians for further treatment and decision. Main objective of this process is gaining high accuracy rate to segment them out.

1.3 Image Segmentation

Image segmentation is a fundamental technique used in Digital image processing and computer vision. In this method, we split image into subsets of image space or super pixels based on various kinds of features. It is also used in pattern recognition and focus on region of interest. Prerequisites for image segmentation is color space transformation, noise reduction, region extraction and merging, detecting dissimilarities and similarities.

Main objectives of image segmentation can be partitioning image into **coherent regions** or grouping image pixels into **coherent regions**. But there is no single correct answer to the question that which is the correct partitioning. In different cases of the implementation, interpretation depends on prior world knowledge. In some cases it is very difficult to represent the world knowledge.

But there are different assumptions to make a successful segmentation. They are based on the brightness or color coherence, texture coherence, motion coherence and so on. Image segmentation is a hierarchical process based on coherence where low level coherence gives lower hierarchy level and more knowledge about features such as symmetries, object models and etc. gives higher level hierarchy.

There are different techniques to segment the digital image and extract the ROI. It can be classified as edge based, region based, special theory based, based, model based segmentation.

FIGURE 1.1: Edge based segmentation.

In the **edge based segmentation** [19][20] we perform this method in gray histogram technique and gradient based method. In gray histogram technique, we separate foreground from background using conic Gaussian curve and their

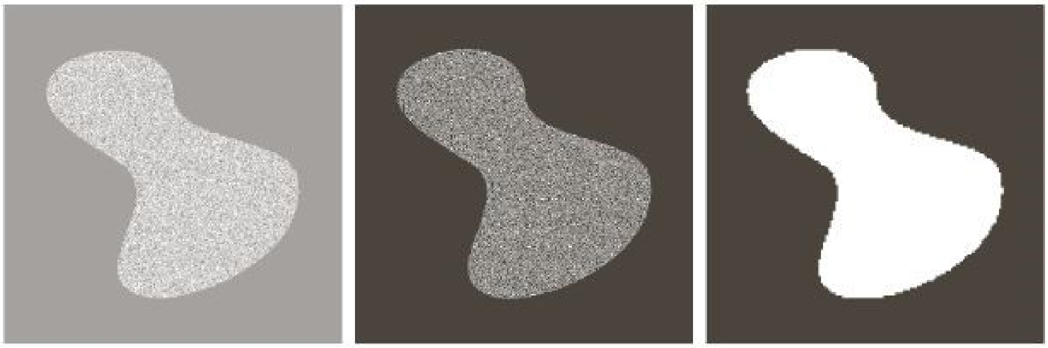

FIGURE 1.2: Region based segmentation.

intersection point. In gradient based method we use first order derivation (normal gradient method), second order derivation (Laplacian), Laplace of Gaussian or their variants. We detect the abrupt change near the edges to separate two regions. In general an image is decomposed into object and background both of constant intensity. Boundary is detected along the discontinuity. We take those pixels which are on the same side of the boundary.

Drawbacks of this method, boundary based methods fail if image is noisy or if its attributes differ only by a small amount between regions. Sometimes it needs some post processing to remove noise. Selection of relevant filter is another challenge here. Sometimes it creates problem with low contrast image like CT image.

Region based technique [12] [21] [22] is very simple and immune to noise. In this method we segment any image based on different predefined criteria. In general an image is decomposed into textured object and constant background. Discontinuity creates an intricate pattern of small edges.

In this technique, region operating method we segment any image into homogenous regions which needs iterative algorithms and computational time. In region growing, we at first select the seed the point to start and it grows based on similarities of neighboring pixels. In region splitting and merging, at first we subdivide the image into arbitrary unconnected regions and merge them according to the conditions. This technique also includes threshold based method. In global threshold technique, we only segment the image into foreground from background using single threshold depending on pixel value (f(x,y)). In local Thresholding, we divide any image into several sub-regions and various thresholds depending on pixel value (f(x,y)) and local property (p(x,y)). In dynamic Thresholding, thresholds depend on pixel value (f(x,y)), local property (p(x,y)) and spatial coordinates (x,y) because of image's different objects

FIGURE 1.3: Theory based segmentation (Clustering).

of different gray levels. Drawbacks of this method is lack of sensitivity and specificity needed for accurate classifications. Square region shape assumption in the region splitting and merging technique causes some staircase effect. It is challenge to select seed pixels for region growing. Different seed choices gives different segmentation results. During this method current region dominates the growth process which causes ambiguity around edges of adjacent regions and they may not be resolved correctly.

Theory based segmentation [23] [24] [25] depends on various fields of knowledge like genetic algorithm, wavelet algorithm, fuzzy based algorithm, neural network based algorithm, clustering based algorithm, artificial intelligence, morphology and so on. Clustering techniques in image segmentation is unsupervised learning task which divide any image space into several clusters or categories. Similarities or attributes are defined for clustering. It can be divided into several types as hard and fuzzy. In hard clustering one pixel can be categorized into only one cluster where in fuzzy clustering one pixel can be categorized into several cluster based on some information. In neural network based algorithm, image can be mapped into several neural network where each network represent one pixel. Network is trained with sample dataset to determine connection and assign weight. New image can be segmented with this trained neural network. In this technique, some drawbacks are faced. Some knowledge in beforehand is needed. In some cases initialization influences the results. Training time is another great issue here. Over-training and over fitting may causes error.

Model based learning [26] [27] [28] acts as human eye on partially visible objects. It needs geometrical knowledge about shape of the object to recreate the object. It also local information to compare with knowledge. Exact shape of the object must be in the knowledge. Drawbacks of this method are for an object

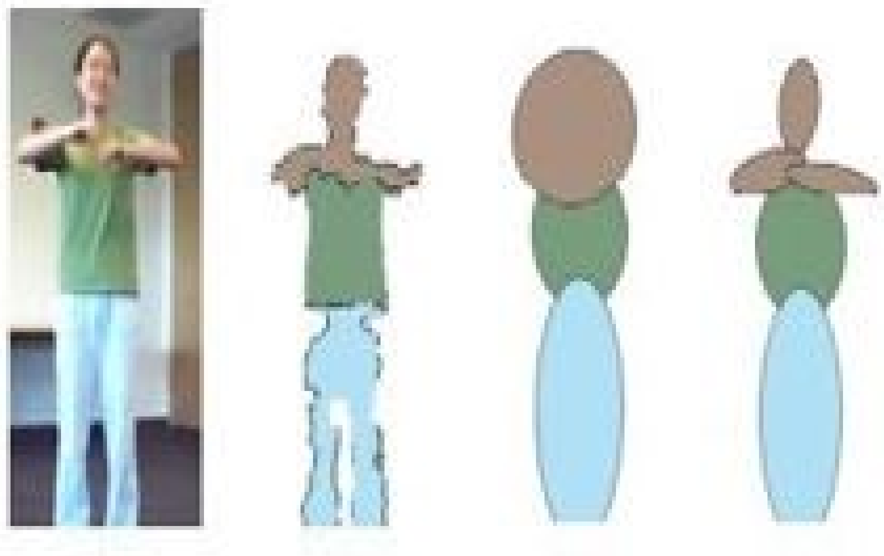

FIGURE 1.4: Model based segmentation.

we need different images from different angle for registration. A probabilistic representation is got from registered samples. It depends on the statistical inference between the model and the image.

1.4 Research Issues and Challenges Regarding Segmentation

Main challenge of the existing works of image segmentation is they are not fully automatic rather than semi-automatic. In this case the operator or the physician have select the very subjective points from the images. It needs essential training for selecting the seeds. But in recent years it becomes a vital issue of image segmentation. The next challenge is categorize and select a regularization term for the proposed algorithms to get better results. These regularization term handle the variations of the image reorientation efficiently. So main task is to tune them very well. For any medical image processing over segmentation and under segmentation is very critical issue to detect the subjective object.

It causes tremendous difference between segmented image and ground truth. Another issue is computational time for the present algorithms. It represents one of the efficiency of the image segmentation. In the recent years, main issues of medical image processing are automatic image segmentation to help the doctors to present region of interest. This automation task is very sophisticated that in some cases it needs the particular orientation, presentation method of the image for segmentation. Another higher level issue is classification of the image into different category. This classification task is based on the pattern classification by which it can categorize the objects of the image into correct cluster.

To detect and characterize any diseases in human body as well as to help the physicians in image processing accurately sometimes we have to implement image segmentation tools. It becomes a preprocessing tool for more of the CAD systems. For this work our main objective to make it fully automated as well as less parameter controlled. Sometimes intensity inhomogeneity becomes a challenge for image segmentation and more often intensity homogeneity based image segmentation is more erroneous. For large amount of data it is very hard to segment out the ROI correctly from all the images because they very prone to error and noise in the image (data). To segment out the MRI data image is very time consuming. To overcome this problem we have to discard the redundant features (dimensions) from the image. For color image segmentation we have to combine improved isotropic edge detection and a fast entropic thresholding technique. From the obtained color edges next challenge is to detect the geometric representation and select their seed for region based segmentation.

1.5 Objective and Motivation

For medical image processing accuracy is the crying need in the application. Because of relating with the human life, any kind of application needs 100% accuracy about their result and even very small amount of error can be cause of death. So main objective of the proposed method is segment out the lung parenchyma and lung nodule accurately. The objective of this paper to introduce a method that will work on CT images of lungs. The difficulty to use PET over CT images is because of wider dissemination of PET-CT and cost of producing and transporting the radio-pharmaceuticals used for PET imaging, which are usually extremely short-lived (for instance, the half-life of radioactive fluorine-18 used to trace glucose metabolism (using fluorodeoxyglucose, FDG) is two hours only. Its production requires a very expensive cyclotron as well as a production line for the radio-pharmaceuticals. So we are convinced to use CT images. This method will segment out the lung parenchyma and then lung nodules as well. Because of the textural similarities between the tumorous tissues and other soft tissues e.g. the heart, chest walls and pleura, it is difficult to distinguish between them using texture analysis alone. So our main objective is to segment out the lung parenchyma accurately. To make it accurate and certified by the physician and reduce time and computational complexity we will introduce different techniques in this field. We will reduce the search space and memory space efficiently using these techniques. This will help us to select the seed points to use level set method for segmenting out the lung parenchyma accurately. Then our next goal is to segment out the lung nodule from the lung image with the help of segmented lung parenchyma. This will help us to perform this job efficiently as the search space of the nodule detection is reduced. It will result in extracted lung nodule from the lung image. This method can also segment out the lung nodule residing along the lung parenchyma (juxtavascular or juxtapleural nodule). There are so many manual and semi-automatic method that segment out the lung parenchyma or lung nodule. We will implement this method totally automatic that needs less computational complexity, time complexity and reduced memory space. We can use this method in any kind of representation of lung CT images. It will work well in the lung images having abnormal shaped lung nodule and irregular representation of lung parenchyma.

1.6 Our Contribution

In the proposed method we have introduced several techniques that can segment out the lung parenchyma and lung nodule accurately. We have used the uninformed heuristic search and memoization technique that can reduce the search space and memory space. It also can help to select the seed points for level set method to segment out the lung parenchyma without help of any human interaction. It has reduced the computational time to carry out whole process. For heuristic search we have use 8-connectivity instead of 4-connectivity to check more points if they are corresponding to the boundary points or not. We have implemented the parameterized level set method where we have tuned the parameters for the contour function to converge to the actual parenchyma boundary. In the mean time we have used several filters that discards the redundant information from the image and makes it noise free.

Chapter 2

Literature Review

Recently, image segmentation as an image processing techniques are widely used in several medical areas for image improvement in earlier detection and treatment stages, where the time factor is very important to discover the abnormality issues in target images, especially in various cancer tumors such as lung cancer, breast cancer, etc. Image quality and accuracy is the core factors of this research, image quality assessment as well as improvement are depending on the enhancement stage where low Pre-Processing techniques is used based on Gabor filter within Gaussian rules. Following the segmentation principles, an enhanced region of the object of interest that is used as a basic foundation of feature extraction is obtained. Relying on general features, a normality comparison is made. In this research, the main detected features for accurate images comparison are pixels percentage and mask-labeling.

2.1 Lung Segmentation Using Bi-Directional Chain Encoding [2]

Computer-aided detection and diagnosis (CAD) has been widely investigated to improve radiologists' diagnostic accuracy in detecting and characterizing lung disease, as well as to assist with the processing of increasingly sizable volumes of imaging. Lung segmentation is a requisite preprocessing step for most CAD schemes. This process proposes a parameter-free lung segmentation algorithm with the aim of improving lung nodule detection accuracy, focusing on juxtapleural nodules. A bidirectional chain coding method combined with a support vector machine (SVM) classifier is used to selectively smooth the lung border while minimizing the over-segmentation of adjacent regions. This automated method was tested on 233 computed tomography (CT) studies from the lung imaging database consortium (LIDC), representing 403 juxtapleural nodules. The approach obtained a 92.6% re-inclusion rate. Segmentation accuracy was further validated on 10 randomly selected CT series, finding a 0.3% average over-segmentation ratio and 2.4% under-segmentation rate when compared to manually segmented reference standards done by an expert.

2.2 Level Set Method Based on Intensity Homogeneity [3]

Intensity inhomogeneity often occurs in real-world images, which presents a considerable challenge in image segmentation. The most widely used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the intensity inhomogeneity. This method proposes a novel region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation. First, based on the model of images with intensity inhomogeneities, we derive a local intensity clustering property of the image intensities, and define a local clustering criterion function for the image intensities in a neighborhood of each point. This local clustering criterion function is then integrated with respect to the neighborhood center to give a global criterion of image segmentation. In a level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image. Therefore, by minimizing this energy, our method is able to simultaneously segment the image and estimate the bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction). Our method has been validated on synthetic images and real images of various modalities, with desirable performance in the presence of intensity inhomogeneities. Experiments show that our method is more robust to initialization, faster and more accurate than the well-known piecewise smooth model. As an application, our method has been used for segmentation and bias correction of magnetic resonance (MR) images with promising results.

2.3 Bayesian Network Based Image Segmentation [4]

User assisted segmentation of lung parenchyma pathology bearing regions becomes difficult with an enormous volume of images. A novel technique using Bayesian Network Model Based (BNMB) Image Segmentation, which is a probabilistic graphical model for segmentation of lung tissues from the x-ray Computed Tomography (CT) images of chest, is proposed. Goal of this method is to present an automated approach to segmentation of lung parenchyma from the rest of chest CT image. This is implemented with help of a probabilistic graph construction from an over-segmentation of the image to represent the relations between the super pixel regions and edge segments. Using an iterative procedure based on the probabilistic model, we identify regions and then these regions are merged. The BNMB is evaluated on many CT image databases and the result shows higher accuracy and efficiency for both segmenting the CT image of lung and also extraction of the Region of Interest (ROI) from affected CT image.

2.4 Hierarchical Multi-scale Segmentation [1]

This segmentation technique is aimed at obtaining the statistics as a probabilistic model pertaining to the geometric, topological and photometric structure of natural images. The image structure is represented by its segmentation graph derived from the low-level hierarchical multi-scale image segmentation. We first estimate the statistics of a number of segmentation graph properties from a large number of images. Our estimates confirm some findings reported in the past work, as well as provide some new ones. We then obtain a Markov random field based model of the segmentation graph which subsumes the observed statistics. To demonstrate the value of the model and the statistics, we show how its use as a prior impacts three applications: image classification, semantic image segmentation and object detection.

2.5 Gradient-Based Boundary Detection [5]

Some methods for segmenting MRI data, especially those which employ multi-spectral data, can be very time-consuming. Hence, it is desirable to reduce the dimensionality of the multi-spectral data by eliminating regions which are of no interest. When, for example, the objective is the segmentation of the brain, it is clear that a considerable amount of the image could be discarded without compromising (in some cases even enhancing) the quality of the segmented image. This kind of technique presents an algorithm to isolate the brain from the extra-cranial tissues irrespective of the nature of the MRI brain data (sagittal, coronal or axial slices). Given a starting point, or seed, at the boundary (or near it) between the intra-cranial and extra-cranial region, the algorithm "walks" along the boundary by calculating at each point the direction of the local edge. The gradient operator chosen to calculate the edge direction was the integrated directional derivative gradient (IDDG) operator as defined by Zuniga and Haralick (1987) and is taken from the row and column directional derivatives, Dr and Dc.

2.6 Image Segmentation Based On Region Growing Method [6]

This proposed method is a new automatic image segmentation method. Color edges in an image are first obtained automatically by combining an improved isotropic edge detector and a fast entropic thresholding technique. After the obtained color edges have provided the major geometric structures in an image, the centroids between these adjacent edge regions are taken as the initial seeds for seeded region growing (SRG). These seeds are then replaced by the centroids of the generated homogeneous image regions by incorporating the required additional pixels step by step. Moreover, the results of color-edge extraction and SRG are integrated to provide homogeneous image regions with accurate and closed boundaries. We also discuss the application of our image segmentation method to automatic face detection. Furthermore, semantic human objects are generated by a seeded region aggregation procedure which takes the detected faces as object seeds.

2.7 Related Works

The segmentation of lungs from chest images is a crucial step in any CAD system that can lead to the early diagnosis of lung cancer, as well as other pulmonary diseases. The segmentation of lungs is a very challenging problem due to inhomogeneity in the lung region, pulmonary structures of similar densities such as arteries, veins, bronchi, and bronchioles, and different scanners and scanning protocols. A wealth of known publications has addressed the segmentation of lung regions from CT images and chest radio-graphs. The success of a particular technique can be measured in terms of accuracy, processing time, and automation level. Most existing techniques for lung segmentation can be classified into four categories: methods based on signal thresholding, deformable boundaries, shape models, or edges.

2.7.1 Bi-directional Chain Encoding with Support Vector Machine Approach [2]

This technique consists of 3 steps: preprocessing to generate an initial lung lobe musk using adaptive Thresholding. Detecting infection points to obtain all major concave and convex points along the lung lobe boundary, correcting the lung boundary using a Support Vector Machine(SVM) as bellow.

In preprocessing step, we use Otsu's adaptive Thresholding method to automatically obtain an initial lung mask based on the pixel intensity distribution of the input CT image. This method uses discriminate analysis to exhaustively search for a threshold value that minimizes the intra-class variance between two region s of an image.

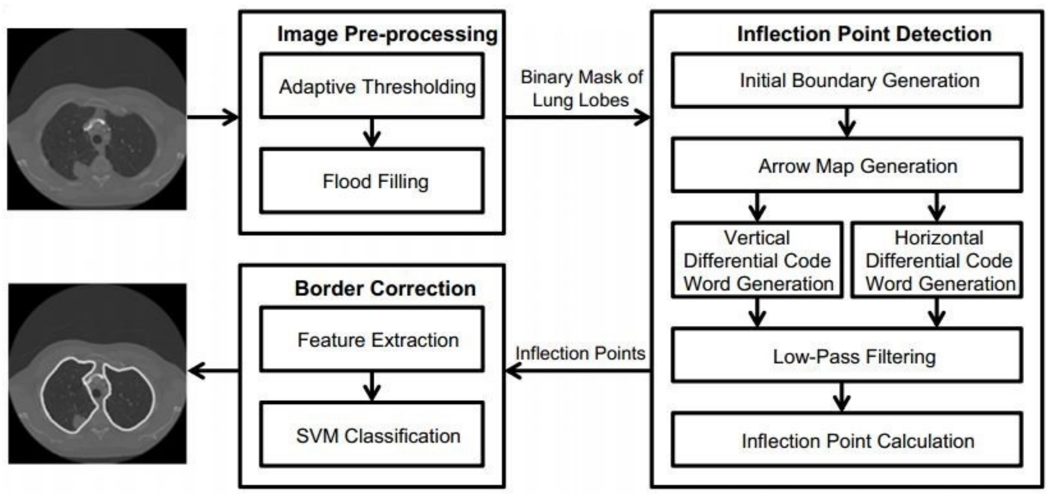

FIGURE 2.1: Overview of Bidirectional Chain Approach.

For a given image, let L represent the gray level of all the pixels [1, 2... L]. By choosing a threshold at gray level k, the pixels are divided into object class C_0 and background class C_1. Let w_0 and w_1 be the probabilities of C_0 and C_1 separated by a de fined threshold and let $(\sigma 0)^2$ and $(\sigma 1)^2$ be the variances of these two classes. The intra-class variance is defined as the weighted sum of these two variances:

$$\sigma^2_{Intra}(k) = \omega_0(k) * \sigma^2_0(k) + \omega_1(k) * \sigma^2_1 \tag{2.1}$$

The optimal threshold T is calculated as the value minimizing the following:

$$T = \underset{k\in[1,L]}{\operatorname{argmin}}\, \sigma^2_{Intra}(k) \tag{2.2}$$

After Thresholding, a flood filling method combined with 3D labeling is adopted to produce an initial lung lobe mask.

In inflection point detection, we have to include the juxtapleural nodules, boundary is characterized as bidirectional differential chain (BDC). It follows some steps:

1. An initial boundary is generated alike of lung parenchyma. The lung lobe boundary pixels are extracted from the binary mask for the left and right lobes, separately.

2. Then boundary encoding is implemented. Per lobe, both vertical and horizontal code words are obtained using the corresponding encoding coordinate systems. The encoder moves along the boundary following a (counter) clockwise path, and at each step the direction of this movement is transformed into a horizontal and vertical code word with arrow map generation.

3. Nest inflection points are calculated. A differential operation is used to generate the horizontal and vertical differential chain codes, separately. Non-zero points in the differential chain are identified as inflection points. As presented in previous figure the differential code is calculated using a clock wise differential operation based on the generated code words.

In border correction only critical point pairs are connected to correct the boundary. Three features are used to select critical points: boundary segment concave degree, relative boundary distance, relative position information. Let *EuclideanDistance (A,B)* represent the Euclidean distance between two inflection points, *A* and *B*. Let *SegmentLength (A,B)* represent shortest boundary segment

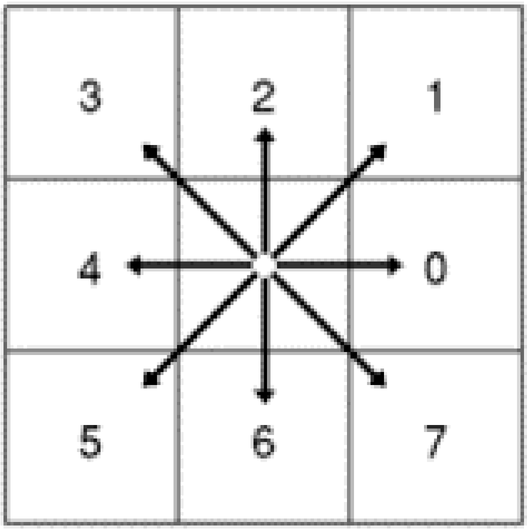

FIGURE 2.2: Encoding Process.

length between these two and *BoundaryLength* be the total length of the lung lobe. The concave feature and length feature can be obtained as

$$f_{position} = \frac{EuclideanDistance(MidPoint(A, B).CentralPoint)}{AverageDistance2CentralPoint} \tag{2.3}$$

$$\frac{SegmentLength(A, B)}{EuclideanDistance(A, B)} \tag{2.4}$$

Third feature position feature can be obtained as

$$f_{length} = \frac{SegmentLength(A, B)}{BoundaryLength} \tag{2.5}$$

Where *MidPoint(A,B)* is the midpoint between two inflection points, A and B. *CentralPoint* is the center of two lung lobe regions. And *AverageDistance2CentralPoint* is the average of all distances from lung lobe boundaries to the center. A support vector machine (SVM) classifier is used based on these three features (3, 4 and 5) to identify critical point pairs. Here is no use of threshold value or parameter tuning. SVMs are supervised, non-parametric learning models. They perform efficiently in non-linear classification tasks. SVMs map their inputs into higher dimension feature space to separate categories. These categories are based on decision boundaries learned through training data.

2.7.2 Parameterized Level Set Method using intensity inhomogeneity [3]

In any level set method we have to assign random contour functions randomly on the image. Upon each iteration this function has changed its shape towards its center (inward/outward direction) according to two parameter functions stated below:

- **Force function (Contour)** - It controls the location of contour based on the shape of object.
- **Speed function (Image)** – It controls the location of contour based on the boundary knowledge.

For segmentation, we use this value for calculating contour function

$$\gamma(t) = \{(x, y), \Psi(x, y, t) = 0\} \tag{2.6}$$

For measuring motion of the contour towards the object boundary is calculated as

$$\frac{\partial \Psi}{\partial} + \widehat{k1}.\big(F_A + F_G(\kappa)\big).\| \bigtriangledown \Psi\| = 0 \tag{2.7}$$

A segmentation of the image is achieved by finding a contour C, which separate the image domain σ into disjoint regions σ_1,σ_2,. . . ,σ_n, and a piecewise smooth function that approximates the image I and is smooth inside each region σ_i. This can be formulated as a problem of minimizing the following Mumford-Shah function

$$\mathcal{F}^{MS}(u, C) = \int_\Omega (I - u)^2 dx + \mu \int_{\Omega/C} | \bigtriangledown u|^2 dx + \nu|C| \tag{2.8}$$

As contour C is written as union of the boundaries. So it also can be written as

$$\mathcal{F}^{MS}(u_1, \dots, u_N, \Omega_1, \dots, \Omega_N) = \sum_{i=1}^{N} \int_\Omega (I - u_i)^2 dx + \mu \int_{\Omega_i} | \bigtriangledown u_i|^2 dx + \nu|C_i| \tag{2.9}$$

Where u_i is a smooth function defined on region (σ_i) known as piecewise smooth model. In this method we follow, uses variation of level set formula simplifying Mumford-Shah function as follow

$$\mathcal{F}^{CV}(\phi, c_1, c_2) = \int_{\Omega} |I(x) - c_1|^2 H\big(\phi(x)\big)dx + \mu \int_{\Omega} |I(x) - c_2|^2 (1 - H\Big(\phi(x)\Big))dx + \int_{\Omega} | \bigtriangledown H\phi(x)|dx \quad (2.10)$$

Where H is the Heaviside function and ϕ is the level set function. For contour it will be *C = x: ϕ(x)=0* which indicate the zero level set. First two terms are data term where third term with weight (v) is regularization term.

In this method it segments an image based on intensity inhomogeneity which attributed to a component of an image. It models this idea as follow.

$$I = bJ + n \quad (2.11)$$

Where j is the true image, b is the component accounts for the intensity inhomogeneity and n is additive noise. Here b is referred as bias field.
Their assumption in this method is

- The bias field *b* is slowly varying, which implies that *b* can be well approximated by a constant in a neighborhood of each point in the image domain.
- The true image *J* approximately takes *N*distinct constant values c_1,$c_2 \ldots$,c_n in disjoint regions Ω_1,Ω_2,...,Ω_n respectively

Region based segmentation relies on a specific region descriptor of intensities. But it is difficult for intensity inhomogeneity which cause region overlapping. For local intensity it will be easy with bias field, *b*. In this case we should consider a circular neighborhood with a radius ρ centered at each point *y* ε Ω as O_y*=x:* |*x-y*|< ρ. So *b(x)=b(y)* and *b(x).J(x)=b(y).*c_i. We can predict that *I(x)=b(y).*c_i + *n(x)*.

In energy formulation, neighborhood of O_y is classified in N clusters with centers m_i=*b(y).*c_i. We can apply K-means clustering to classify local intensities. For intensities *I(x)* in neighborhood of O_y, K-means is an iterative process to minimize the clustering criterion which can be written as

$$F_y = \sum_{i=1}^{N} \int_{O_y} |I(x) - m_i|^2 u_{i(x)} dx \quad (2.12)$$

Where u_i is the membership function of region Ω_i. We can simplify with region Ω_i like this

$$F_y = \sum_{i=1}^{N} \int_{\Omega_i \cap \mathcal{O}_y} |I(x) - m_i|^2 dx \tag{2.13}$$

Approximating on cluster center by m_i=*b(y).*c_i, we rewrite as below

$$\varepsilon_y = \sum_{i=1}^{N} \int_{\Omega_i \cap \mathcal{O}_y} K(y-x)|I(x) - b(y)c_i|^2 dx \tag{2.14}$$

Where *K* is the kernel function. It is flexible. It can be truncated uniform function defined as *K(u)=a* for $|u| < \rho$ and *K(u)=0* otherwise. In this method we choose *K* as truncated Gaussian function. For entire image domain it can written as:

$$\varepsilon \triangleq \int (\sum_{i=1}^{N} \int_{\Omega_i} K(y-x)|I(x) - b(y)c_i|^2 dx) dy \tag{2.15}$$

For level set formulation and energy minimization, we have two cases: *N=2* and *N>2* known as two phase and multiphase formulation. In two phase level set formulation, we have two regions Ω_1 and Ω_2. We define their membership function as $M_1(\phi)=H(\phi)$ *and* $M_2(\phi)=1-H(\phi)$ respectively where *H* is Heaviside function. For *N=2*, energy function can be expressed as

$$\epsilon = \int \sum_{i=1}^{N} \int (K(y-x)|I(x) - b(y)c_i|^2 dy) M_i(\Phi(x)) dx \tag{2.16}$$

For convenience we can constants $c_1, c_2, \ldots, c_n$ as vector *c*=($c_1, c_2, \ldots, c_n$). Thus the level set function ϕ, bias field *b* and constant vector *c* can be written as *ε(*ϕ*,c,b).*

$$\epsilon(\phi, c, b) = \int \sum_{i=1}^{N} e_i(x) M_i(\phi(x)) dx \tag{2.17}$$

Where e_i is the function defined as

$$e_i(x) = \int K(y-x)|I(x) - b(y)c_i|^2 dy \tag{2.18}$$

Their proposed variation level set formula defined as

$$\mathcal{F}(\phi, c, b) = \epsilon(\phi, c, b) + \mathcal{V}\mathcal{L}(\Phi) + \mu\mathcal{R}_p(\phi) \tag{2.19}$$

With two regularization terms that can control the shape of contour function

$$\mathcal{R}_p(\phi) = \int p(|\nabla\phi|)dx \tag{2.20}$$

$$\mathcal{L}(\phi) = \int (|\nabla H(\phi)|)dx \tag{2.21}$$

Energy minimization can be performed with respect to ϕ,c or b. In multiphase level set formula, we can use two more level set functions, ϕ_1,ϕ_2,. . . ,ϕ_i defined with N membership functions, M_i.

$$M_i(\phi_1(y), \ldots, \phi_k(y)) = \begin{cases} 0, & \text{if } y \in \Omega \\ 1, & \text{else} \end{cases} \tag{2.22}$$

Energy ε can be expressed as

$$\epsilon(\Phi, c, b) = \int \sum_{i=1}^{N} e_i(x) M_i(\phi(x))dx \tag{2.23}$$

Therefore multiphase level set formula written as

$$\mathcal{F}(\Phi, b,) \triangleq \epsilon(\Phi, b, c) + \mathcal{R}_p \tag{2.24}$$

In numerical implementation, the Heaviside function H is replaced by a smooth function that approximates H called smoothed Heaviside function H_e, which defined as

$$H_\epsilon(x) = \frac{1}{2}[1 + \frac{2}{\pi} arctan(\frac{x}{\epsilon})] \tag{2.25}$$

And derivative of H_e is computed as

$$\delta_\epsilon = H'_\epsilon(x) = \frac{1}{\pi}\frac{\epsilon}{\epsilon^2 + x^2} \tag{2.26}$$

An overview of the level set segmentation is

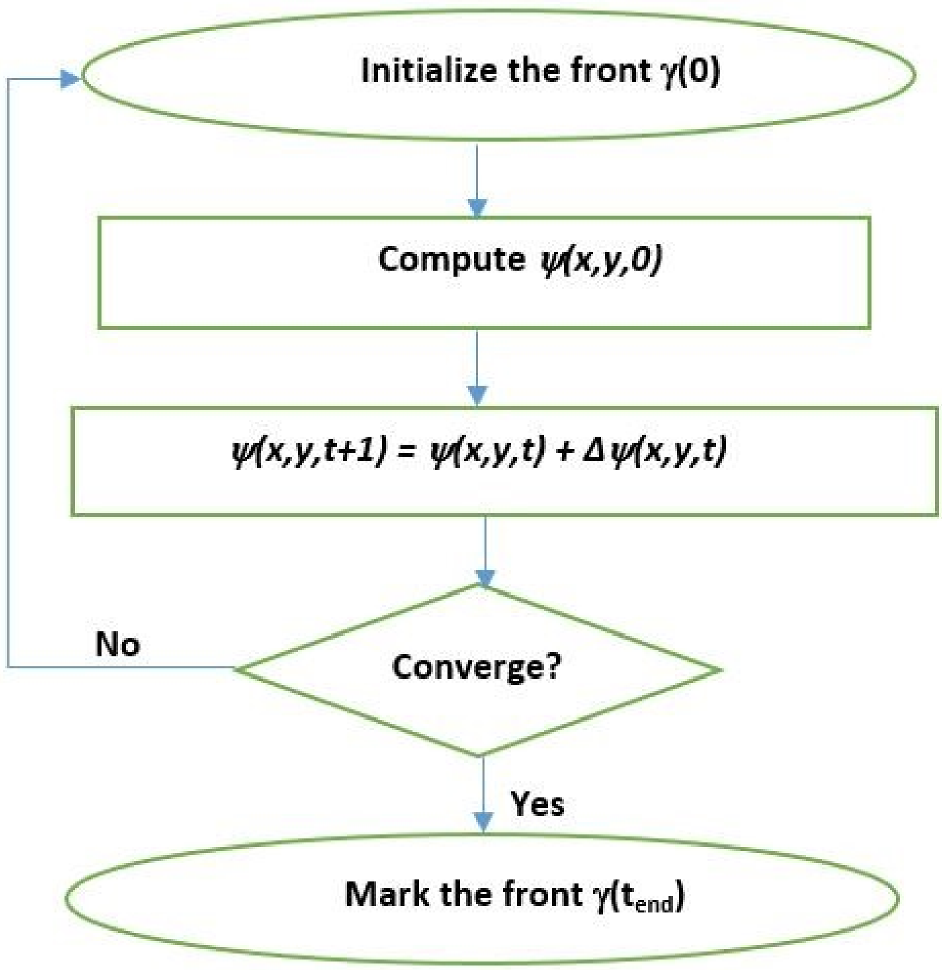

FIGURE 2.3: Overview of level set algorithm.

Chapter 3

Proposed Method

Our proposed method is completely automatic. This automated method does not required any human interaction but the image input. It automatically searches the seed points to extract the lung parenchyma and uses level set method to extract it. Then we also apply the level set algorithm inside the extracted lung parenchyma to detect the lung nodule and extract it. The whole process ends through several steps shown in the following flow chart diagram:

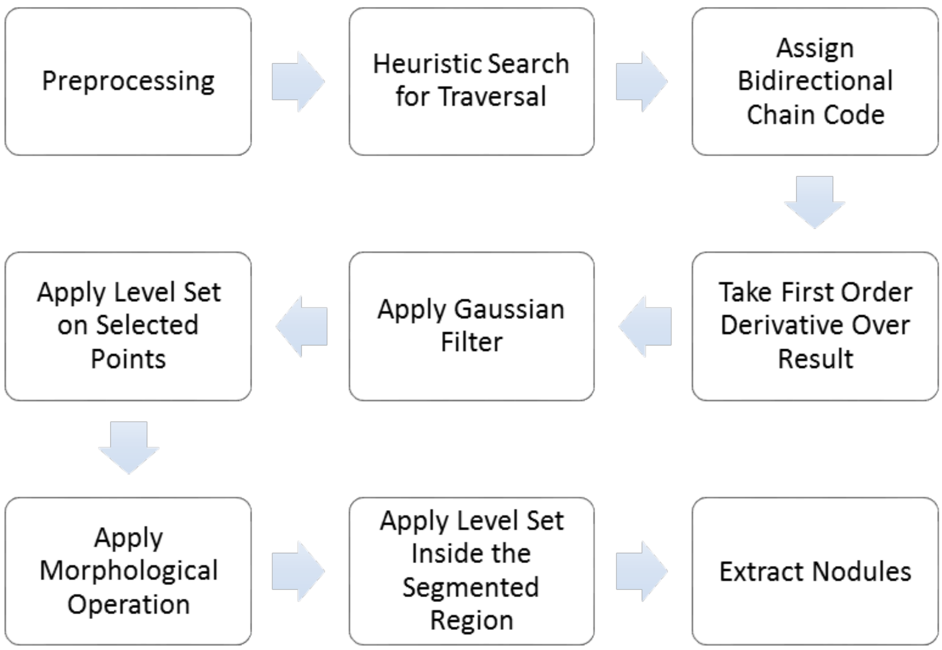

FIGURE 3.1: An overview of the proposed method.

3.1 Preprocessing [15] [16]

Adaptive thresholding is applied as a preprocessing in the lung image from the dataset. It is used to segment out the object from the background. If the background is relatively uniform, we can use the global thresholding to get binary image using pixel intensity. Because of large variation of the background intensity adaptive thresholding produce better results. Through this method we can avoid the unwanted structures.

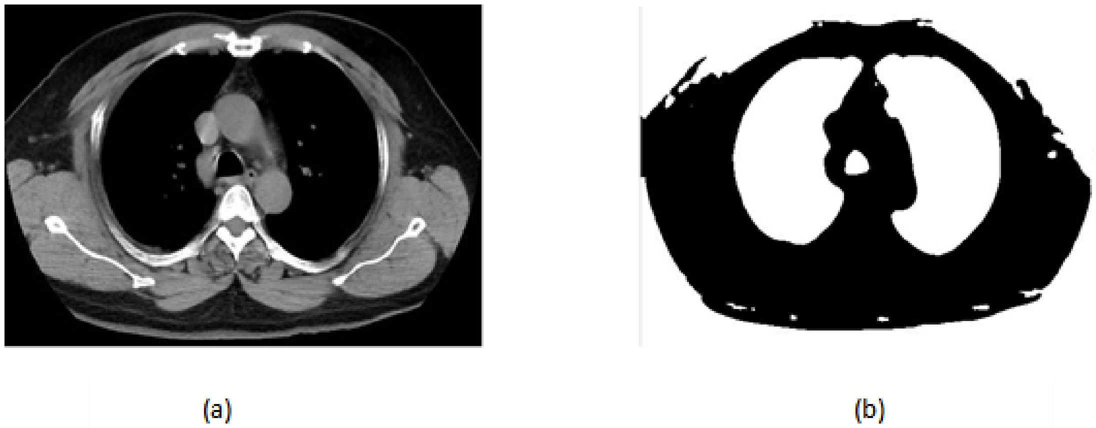

FIGURE 3.2: Original image (a) and Binary image after adaptive thresholding (b)

3.2 Inflection Point Detection [2]

From the preprocessed image our next step is to select the seed points from the image through which we implement the level set method to segment out the lung parenchyma. To select the seed points which is also known as inflection point, we have to go through some processes. Below we describe these processes.

3.2.1 Heuristic Search for Traversal [17]

We use here an uninformed search that is operated in a brute force (heuristic) way. The search space is explored without leveraging on any information on the problem. It select a random pixel as a boundary pixel and approaches towards the correct one which is actually a boundary point. In this method we use an uninformed heuristic search which works in a breadth first fashion. In the meantime, we also implement the bidirectional chain encoding method (mentioned in the following subsection) to get our desired seed point after further processing.

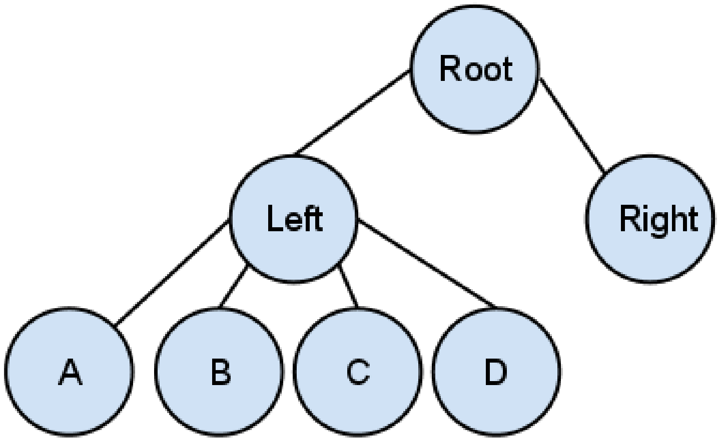

FIGURE 3.3: Model of breadth first search.

3.2.2 Assign Bi-directional Chain Code [2]

In the implemented method we use the bidirectional chain encoding. It helps to get the direction for the traversal along horizontal and vertical direction. We follow the steps mentioned below:

- At first we generate initial boundary. The lung lobe boundary pixels are extracted from the binary mask for the left and right lobes, separately.
- Then we implement the boundary encoding. Per lobe, both vertical and horizontal code words are obtained using the corresponding encoding coordinate systems. The encoder moves along the boundary following a (counter) clockwise path, and at each step the direction of this movement is transformed into a horizontal and vertical code word with arrow map generation. The encoding process is illustrated in figure.
- Then we calculate the inflection point along the calculated boundary. A differential operation is used to generate the horizontal and vertical differential chain codes, separately. Non-zero points in the differential chain are identified as inflection points. As presented in previous figure the differential code is calculated using a clock wise differential operation based on the generated code words. This differential operation is called Gaussian filtering to smooth the boundary.

3.2.3 Take First Order Derivative over Result

During the heuristic search phase, the plotted bi-directional chain code are memoized and in the same phase the derivatives between current pixel and

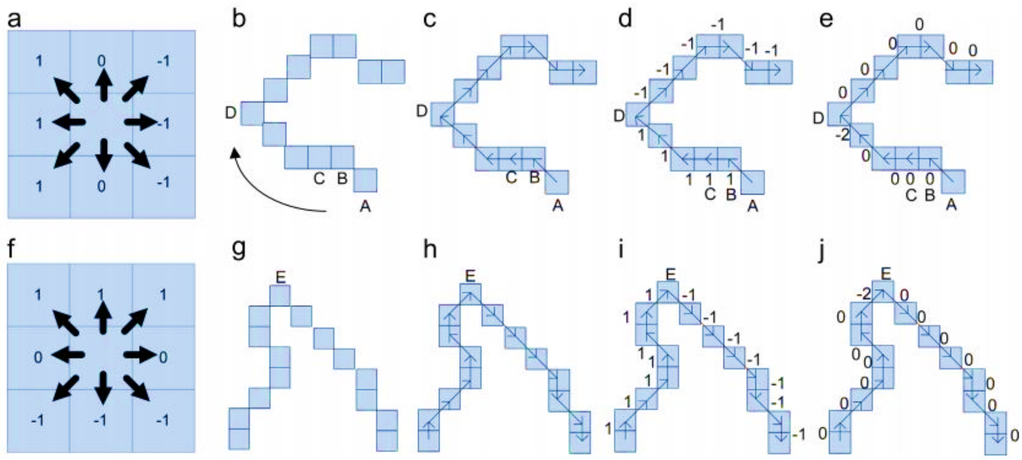

FIGURE 3.4: Encoding Process[2].

the parent pixel are taken for each pixel. This is done in both horizontal and vertical ways for better result. Then, from the calculated values, the non-zero derivatives indicates the inflection points. This points are stored and later used as seed points for level set algorithm.

FIGURE 3.5: Non Zero Derivative from Result as Inflection Points.

3.2.4 Apply Gaussian Filter

The non-zero derivatives gives us the inflection points. But, most often this gives us more than necessary points. To avoid the unnecessary points, Gaussian filter is applied on the set of inflection points. Thus we get a reduced set of inflection point after applying the filter.

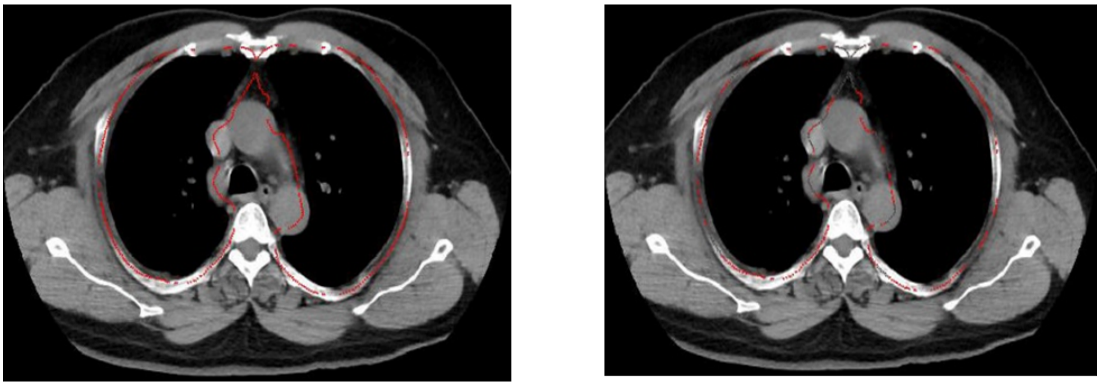

FIGURE 3.6: Extra Inflection Points Are Removed from Results From Non-Zero Derivatives.

3.3 Lung Parenchyma Segmentation

Using the selected seed points got from above mentioned processes now our actual job is lung parenchyma segmentation. For this job our main goal is to achieve accuracy to segment out it. To get a successful segmented lung parenchyma we have go through further processes given below:

3.3.1 Apply Level Set on Selected Points [3]

The inflection points that we receive using an AI based uninformed heuristic search are used as seeds for the Level Set method. This step ensures us the automation of our method. Because, selection of seed point is independent of any kind of human interaction or input. The optimal seed points are automatically selected by our proposed approach. This enables the level set procedure converge to the boundary of the parenchyma in a surprisingly fast manner. Thus time complexity is reduced due to the decreased search space.

3.3.2 Apply Morphological Operation [18]

The contour we get after applying level set is post processed using some morphological operations. The operators that are used in our case are Dilation and Erosion operators. These are used to smoothen the extracted contour if needed for abnormal cases of the data. Successive alternate use of these two operators bring noticeable smoothness to the boundary of the extracted region.

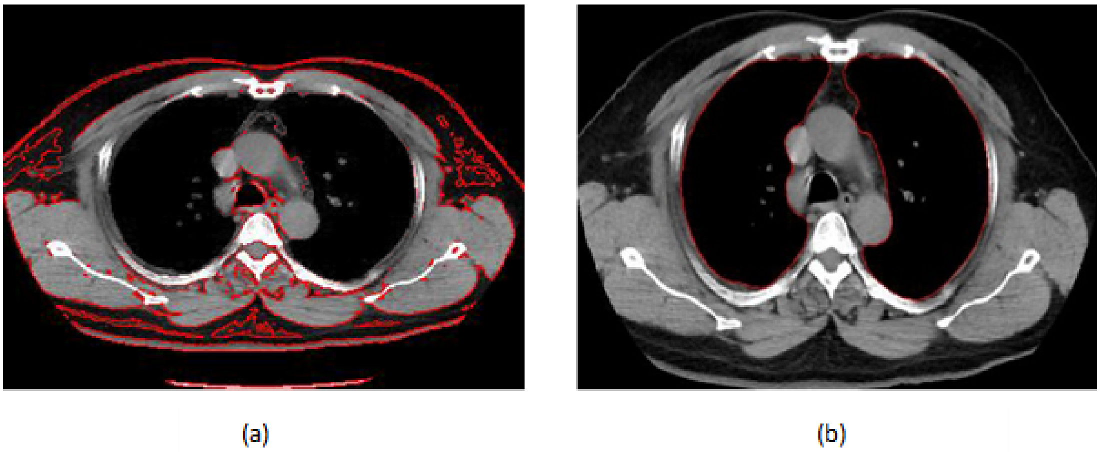

FIGURE 3.7: Selection of Seeds (a) Arbitrary, (b) Automatic.

3.4 Nodule Segmentation

Now the second job of our proposed method is to segment out the lung nodule from the lung parenchyma. From the full lung image, the search space for lung nodules is reduced. From the reduced search space we now segment out the lung nodules following the processes mentioned below:

3.4.1 Apply Level Set Inside the Segmented Region [3]

We extract our primary ROI which is the lung parenchyma successfully so far. The lung parenchyma is the source where cancer cells resides. Our next goal is to segment out the cancer nodules from inside the lung parenchyma. To achieve this goal we initiate a level set function inside our extracted primary ROI which is the lung parenchyma. The level set function converges each of the nodules inside the lung parenchyma and segment them out. Thus our final goal of the research is met.

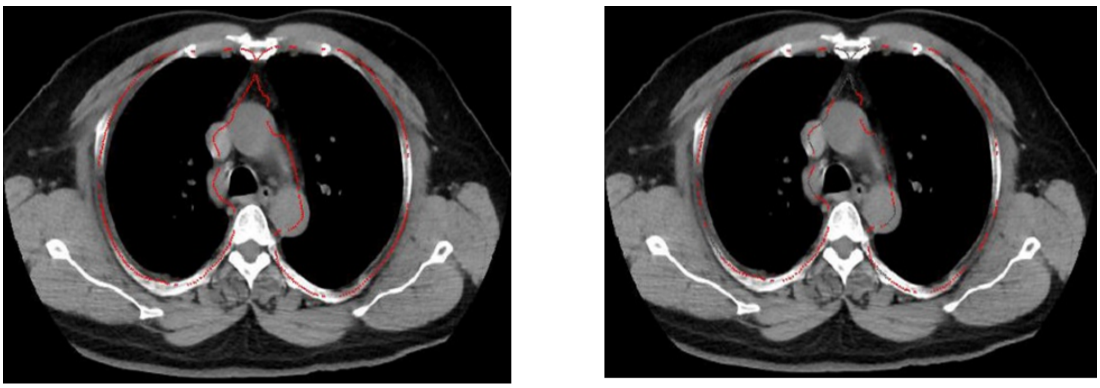

FIGURE 3.8: Applying Level Set inside the Lung Parenchyma.

3.4.2 Extract Nodules

We get the level set functions around each of the nodule inside the lung parenchyma. Next, we extract each of them out. These nodules can be further used for cancer cell detection purpose. From examining the extracted nodules, physicians can detect cancer cells or they may be evaluated using classification algorithms to detect cancer cells and followed by detection of the stage of the cancer.

There are some cases when cancer nodules are adjacent to the lung parenchyma boundary. In such cases, it is difficult to correctly detect and segment out those nodules using our approach. To overcome this situation, we used morphological operation (ie. Dilation) to enlarge the contour of the lung parenchyma to some extent. Then we applied level set on it. This approach fixes the problem and successfully segment out the Juxtapleural nodules.

Chapter 4

Result Analysis

Result analysis task for medical image processing is very tough. It needs very accurate ground truth to compare with result of the experiment. So the ground truth should be certified by a renowned expert so that the error of the proposed method can be minimized. We use the ground truth certified from an expert Pulmonary Specialist. We are concerned about the accuracy of our method.

4.1 Experimental Setup

From the dataset we categorize all data into four classes such as normal, semi-hard, hard and abnormal. We experiment our proposed method on 15 CT images from each category and in total of 60 CT images of 18 different patients.In the normal class all images have normal shaped nodule and regular lung parenchyma. And in the semi-hard class all the images have abnormal shaped nodule. Normal shaped nodule and irregular lung parenchyma exists in hard category.Abnormal shaped nodule and irregular lung parenchyma exists in abnormal category.

We can see from the above figure that our proposed method was able to segment the lungs parenchyma very efficiently and also segment the any kinds of nodule from the ROI which is even adhering the chest walls, heart and pleura. We suggest the detection all nodule from lung lobe as true positive and missing any nodule as false negative. We marked the ground truth using the help of physician.

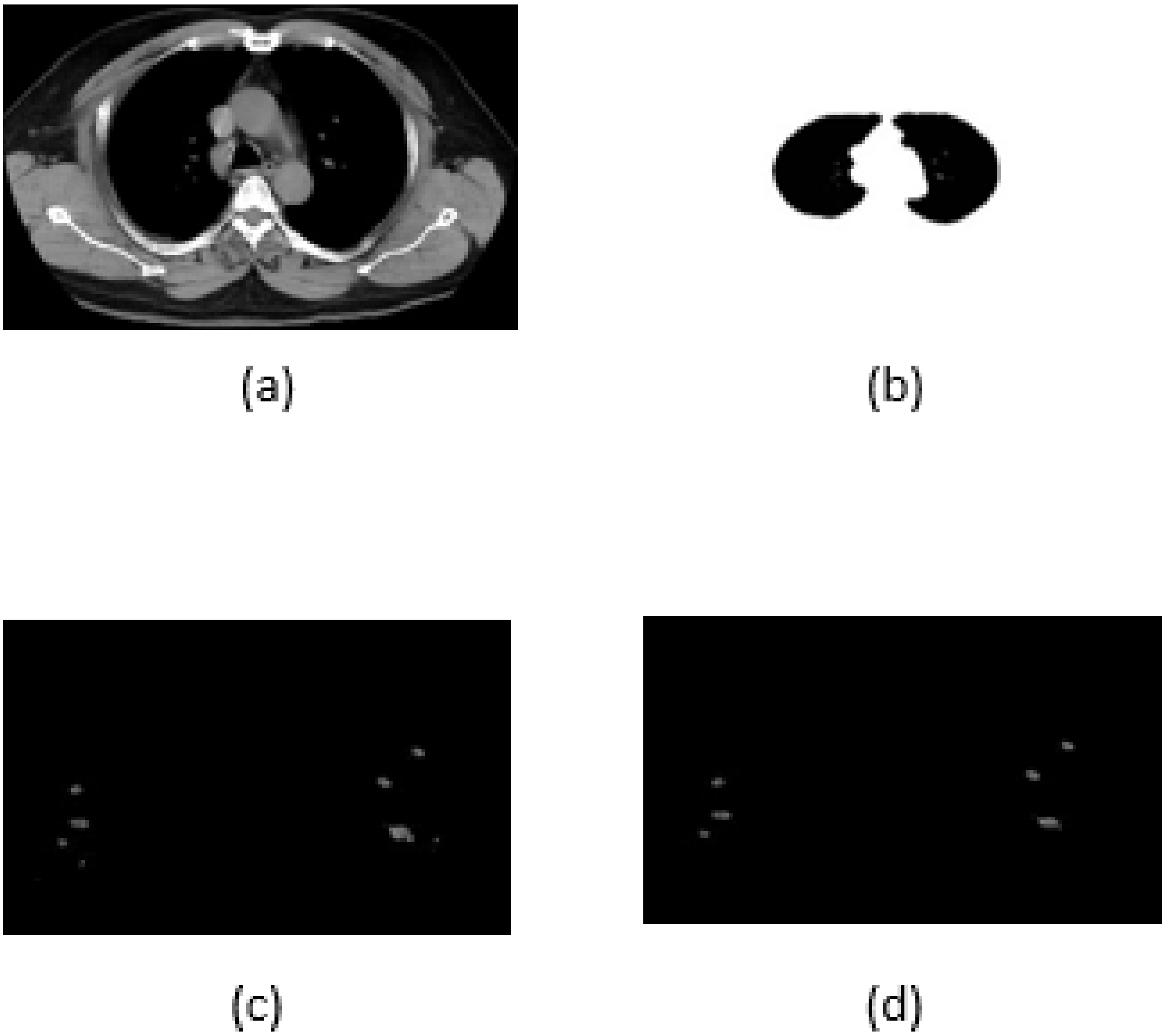

FIGURE 4.1: Original Image (Normal Category) (a), Parenchyma segmentation of proposed method (b), Nodule Segmentation of proposed method(c), Ground truth (d).

4.2 Comparison among proposed method, Snakes and Thresholding Technique

Our proposed method have compared with the SNAKES and Thresholding Technique. We describe these two methods in a nutshell here:

In the **Snakes[10]** or active contour model, it is curve defined within an image domain that can move under the influence of internal forces coming from within the curve itself and external forces are defined so that the snake will

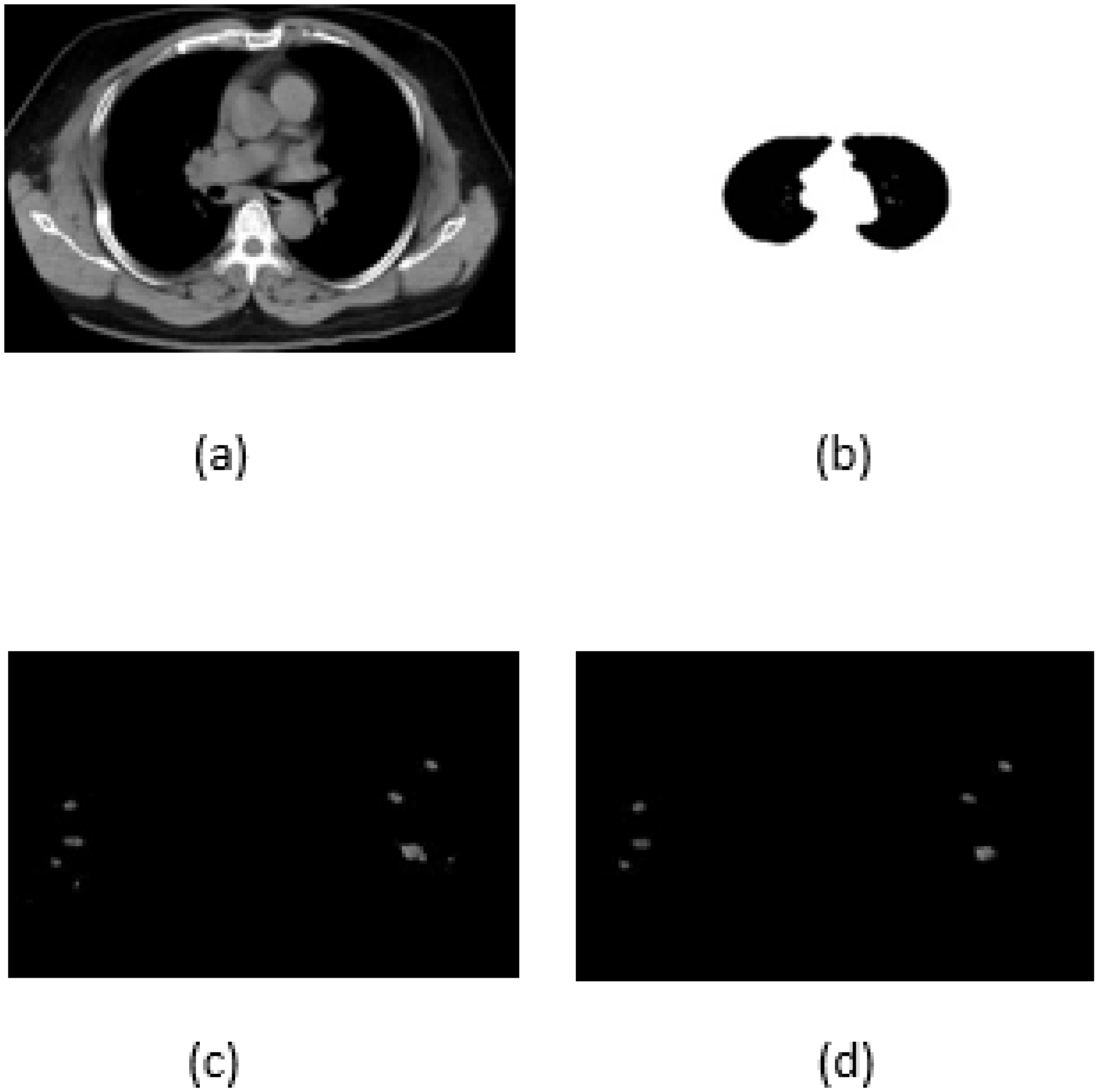

FIGURE 4.2: Original Image (Semi-hard Category) (a), Parenchyma segmentation of proposed method (b), Nodule Segmentation of proposed method(c), Ground truth (d).

conform to an object boundary or other desired features within an image. Here it focused on parametric active contour models for detail extracting from the lung areas. It extracted abnormal shadows on the lung regions by using voxel density method. Voxel is fundamental element construct 3-D image and it is defined as *V(x,y,z)*. Voxel density shows distribution of voxel in assumed local

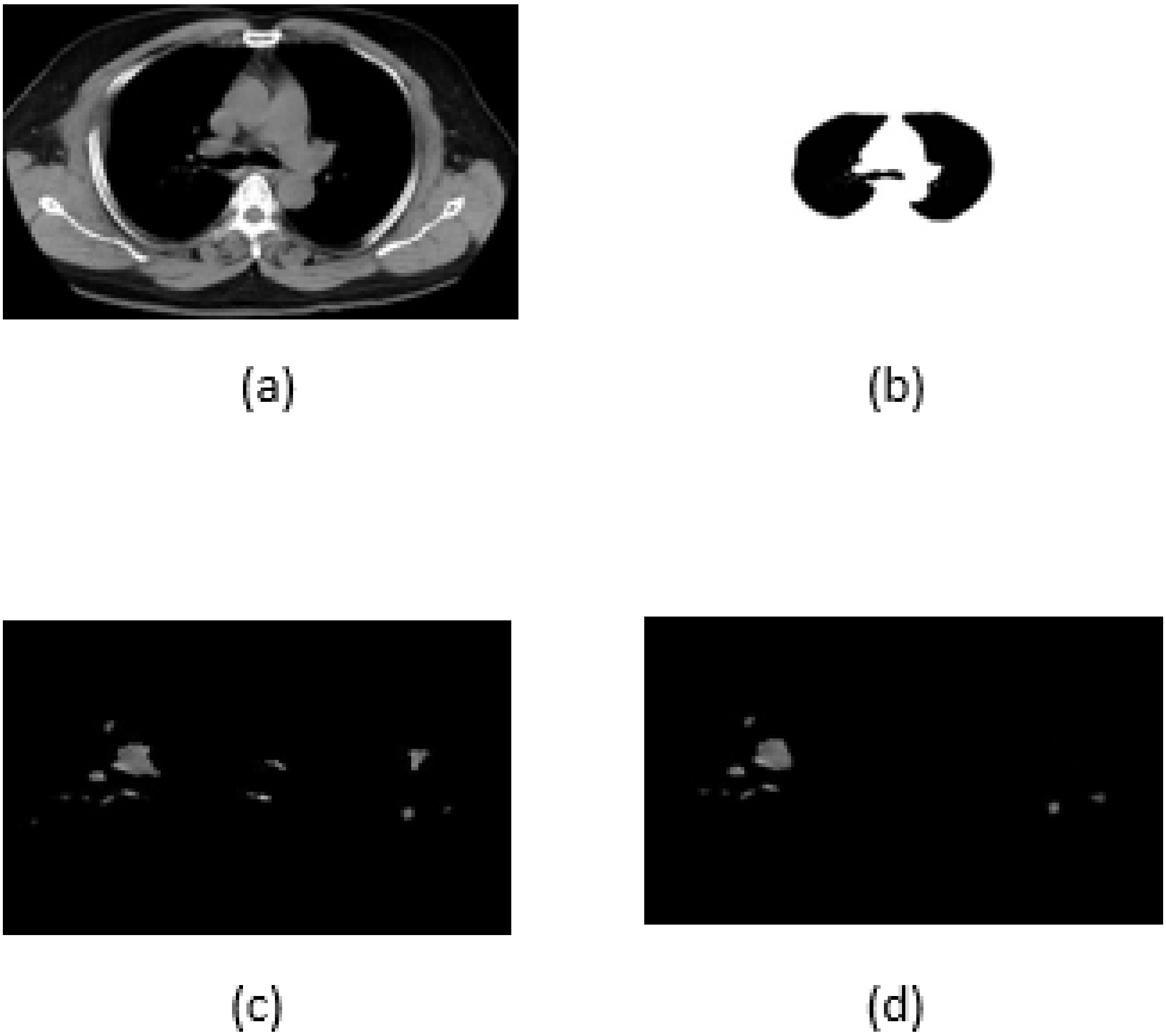

FIGURE 4.3: Original Image (Hard Category) (a), Parenchyma segmentation of proposed method (b), Nodule Segmentation of proposed method(c), Ground truth (d).

region of interest.

The applied cases were 9(3 normal and 6 abnormal cases) using threshold value is employed range of the -600 to 1000 (H.U.) to extract ground-glass opacity, lung cancer and tubercle shadows correctly. It achieved good results avoiding influence of gravity using the active contour model. The results were a true positive fraction of 0.81, false positive fraction of 0.2. This methods are not considered continuity of contour on axial direction. The method requires about 1 minute per each CT slice image.

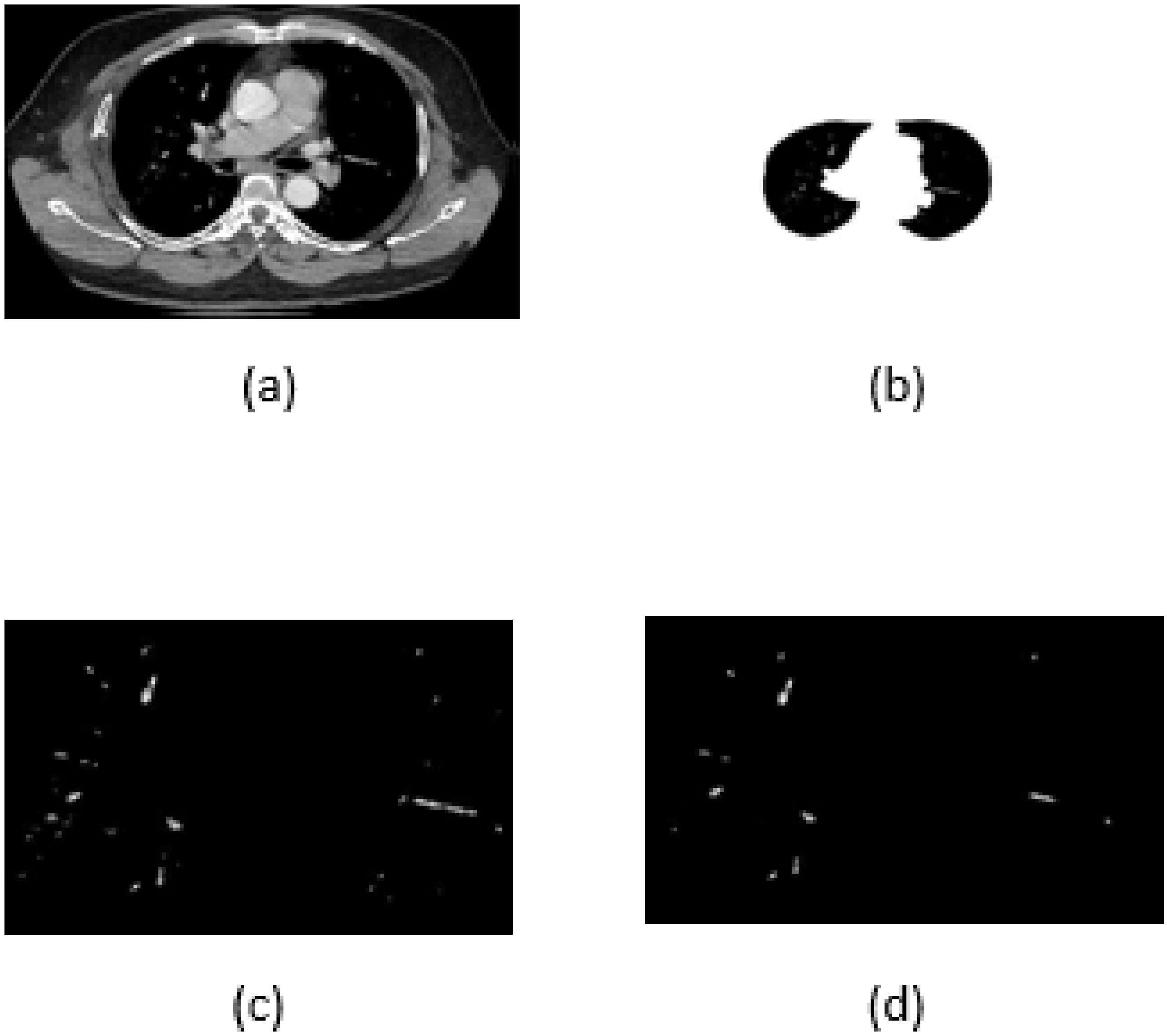

FIGURE 4.4: Original Image (Abnormal Category) (a), Parenchyma segmentation of proposed method (b), Nodule Segmentation of proposed method(c), Ground truth (d)

In the **Thresholding Technique [11]** method, it used Gaussian and anisotropic diffusion to smooth edge and removed the cross section of lung and bronchi. It derived the optimal threshold cleaning the lung and used the tracking algorithm to separate left and right lung lobe. It smoothed the edge with rolling ball technique. It toke n=10 neighborhood into account. It also applied the optimal threshold algorithm for the very weak contrast on cross-section of left and right lung. It used area overlap criteria to compare the automatic computer-based segmentation with results obtained by manual analysis. It then got the results by 2D similarity index values of 0.9946. The method is based on using anatomic information from the segmented central tracheobronchial tree, applying anisotropic diffusion applying anisotropic diffusion, optimal threshold, rolling ball algorithm, morphological smoothing for accurate segmentation of the left and right main stem bronchi and border of lung. On average, 15-20 min are required to segment a 512 X 512 X 240 data image.

Our comparison is based on the precision, recall and f-score of both the process. Let's see what precision and recall is:

Precision and Recall: In pattern recognition and information retrieval, precision (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. Precision can be seen as a measure of exactness or quality, whereas recall is a measure of completeness or quantity.

In simple terms, high recall means that an algorithm returned most of the relevant results, while high precision means that an algorithm returned substantially more relevant results than irrelevant.

For measuring accuracy tasks, the terms true positives, true negatives, false positives, and false negatives compare the results of the classifier under test with trusted external judgments. The terms positive and negative refer to the classifier's prediction (sometimes known as the expectation), and the terms true and false refer to whether that prediction corresponds to the external judgment (sometimes known as the observation). Precision and recall are then defined as:

$$Precision = \frac{TP}{TP + FP} \tag{4.1}$$

$$Recall = \frac{TP}{TP + FP} \tag{4.2}$$

F-Measure: A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score:

$$F\breve{}measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.3}$$

The proposed method was tested on 15 CT images from each category and in total of 60 CT images of 18 different patients and the following result was obtained.

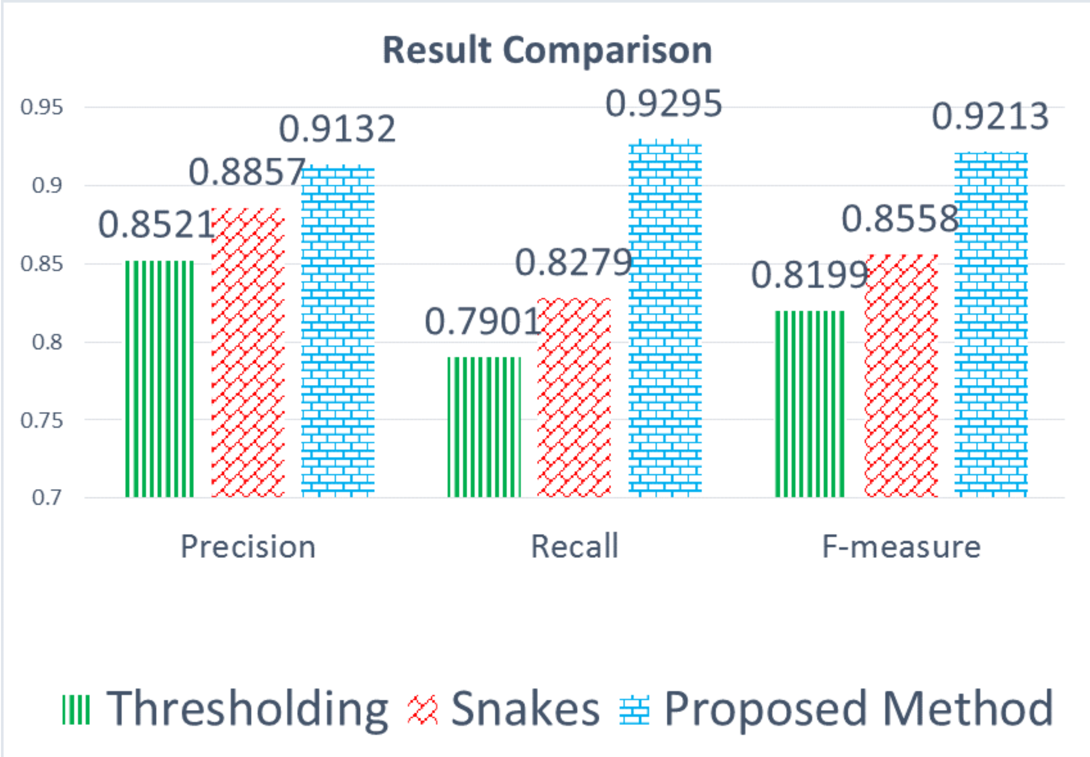

FIGURE 4.5: Result Comparison among the Thresholding Technique, Snake Technique and Proposed Technique.

The proposed method gives better result in computational time to segment out the lung parenchyma and lung nodule. The result is given below

The runtime for parenchyma segmentation without the nodule detection is taken for thresholding technique is 3.23 seconds, for Snakes it is 9.5 seconds and for proposed method it is 5.446 seconds. Though Thresholding Method takes less time without nodule extraction, but proposed method gives a much higher accuracy and smoothness in Lung Parenchyma segmentation than Thresholding.

4.3 Reason for Using 8-connectivity in Bi-Directional Chain Encoding

In the proposed method we use the 8-directional chain encoding instead of 4-directional chain encoding. The reason for using 8-directional chain encoding in the proposed method to explore the connectivity among the pixels to check that it is on the boundary or not. 4-connectivity often results in staircase effect. 8-connectivity handles it very efficiently. It explores more pixels to check the

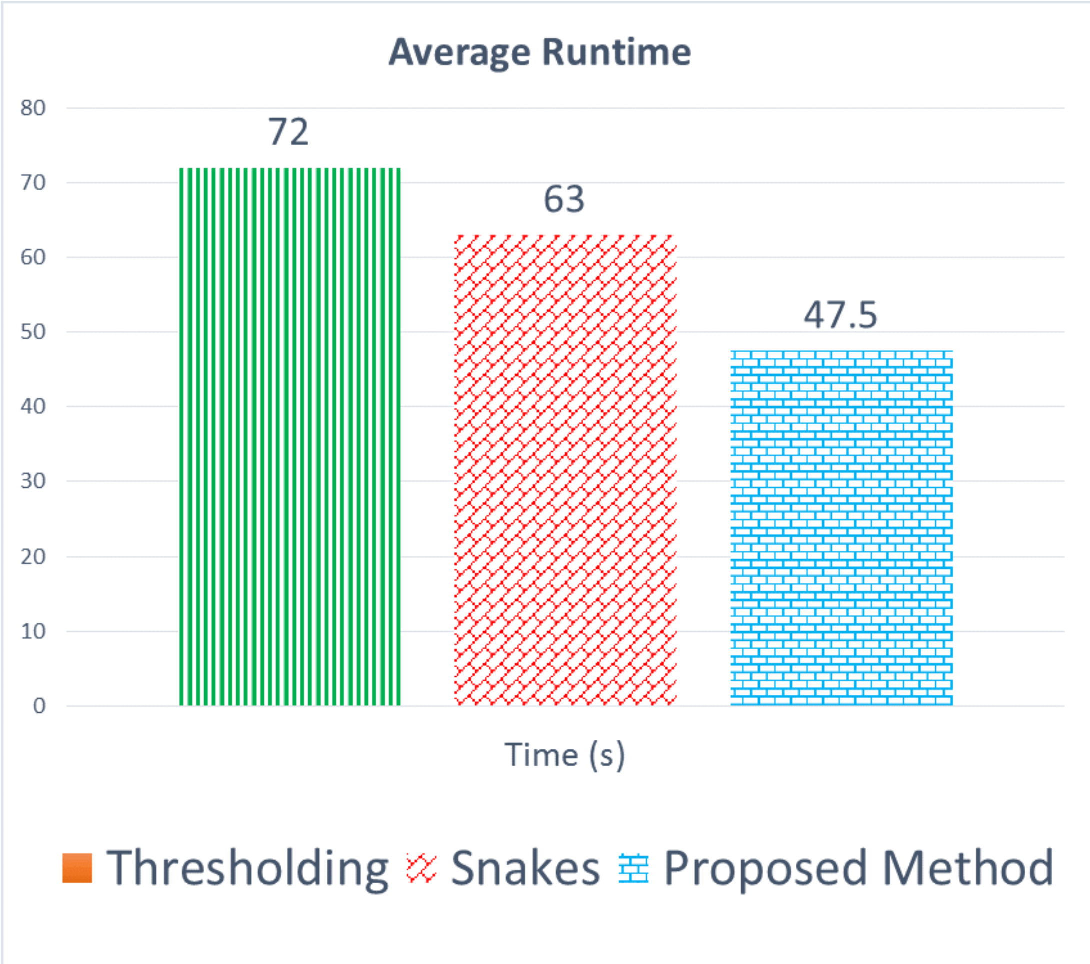

FIGURE 4.6: Average Run Time Comparison.

connectivity and it increases the probability to get the boundary pixels about 50

4.4 Importance of Using AI based uninformed Heuristic Search

In the mean time we use the AI based uninformed heuristic search (breadth first search) in the bidirectional chain encoding to reduce the computational time. Using this approach we theoretically and practically reduce the time complexity. Theoretically it becomes O(nlog(n)) from the given complexity O(n2) from the bi-directional chain encoding method. In this method at first we guess a contour like parenchyma on the image and implement the breadth first search along the points of that contour. When it converges to the lung parenchyma it stops and we get the actual lung parenchyma.

4.5 Reason for Using Memoization Technique

This memorization technique store the results of the derivative from the first operation to use it for the next operation of derivative and reduce the expensive function call and return the cached result when the same inputs invoked again. This also reduce the time complexity rather than bi-directional chain encoding. At first operation it calculates the children from each parent and save it for further calculation of first derivative. Thus using only one iteration it completes all tasks.

4.6 Reason for Using Automated Seeds in Level Set

In the classical Level Set method we use a set of arbitrary points (even all the pixels) as the seed for the image segmentation. This increases the computational time, search space, memory space and computational complexity. But when we use the seeds that we select automatically using the heuristic search we used, it dramatically reduces the convergence time to segment the lung parenchyma. Because of the search, we select optimal seed points for the level set function and so the search space for the level set function is reduced by a significant factor. This enables noticeably fast convergence of the level set function. Time complexity is thus reduced to a great extent.

4.7 Significance of using parameters (mu(μ), nu(ν), sigma(σ)) in Level Set method [3]

The level set method we used in our experiment is guided by some parameters. This parameters helps the level set function to stay in a stable shape so that, it can converge quickly. The parameter sigma(σ) is used to determine the neighborhood scaling. This implies how many neighbors should be taken under consideration while processing and updating the shape of level set function. The parameter nu(ν), determines the arc length coefficient of the level set function. It manipulates the arc length of the level set function. The parameter mu(μ) defines the distance regularization coefficient of level set function. The level set function changes it's shape as it evolves. During this process mu(μ) maintains and regularizes the distance and maintains a stable shape of the level set function.

4.8 Importance of implementing Level Set over Snakes

The capability of snakes or active contour method is to capture the ROI as a whole. If there exists more than one ROI in our domain of interest, then snakes fails to achieve its goal the grab them all individually. So, we cannot segment out each of the ROI separately using active contours or snakes.

Whereas, level set method easily overcomes this situation. In case of existence of multiple ROI in our search domain, Level Set function at first changes its shape as a convex hull for the aggregated region containing all the region of interests or nodules in our case. Then gradually it converges and shrinks it's size and more level set function evolves to contour around each of the region of interests or nodules separately. Hence, Level set method is more convenient for our work area.

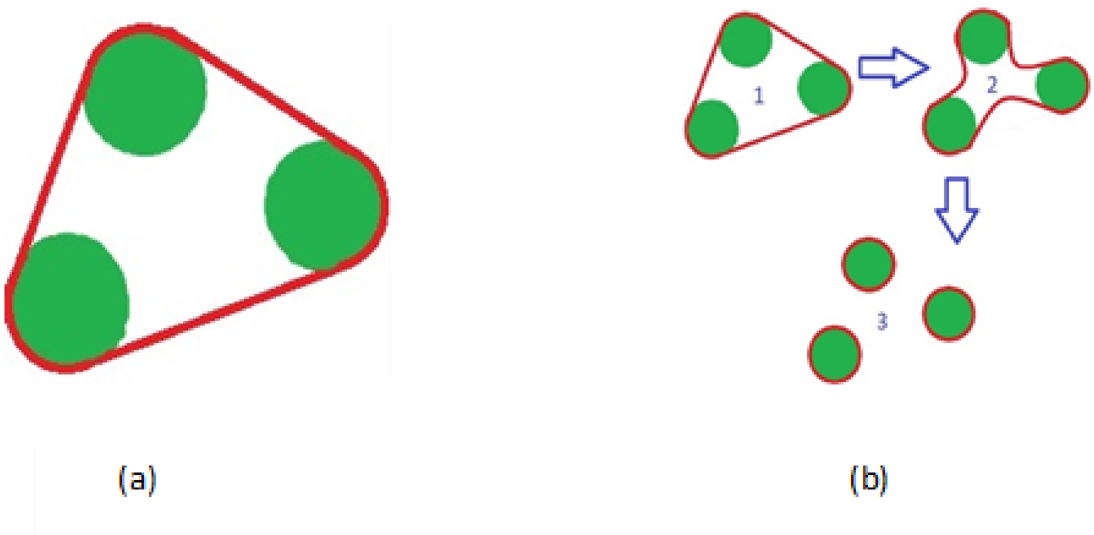

FIGURE 4.7: Comparison between Snakes and Level Set.

4.9 Causes of enlarging the area of seed points

To get the juxtapleural nodules along the lung parenchyma efficiently and correctly we have to enlarge the boundary of the seed points of the lung parenchyma segmentation. If we use the seeds as the size of the lung parenchyma there has some probability to miss some of the nodules along the boundary. So it reduces the chance the nodules residing along the lung parenchyma. Juxtavascular nodules which resides aside the vascular tissue have the problem of possibility of missing.

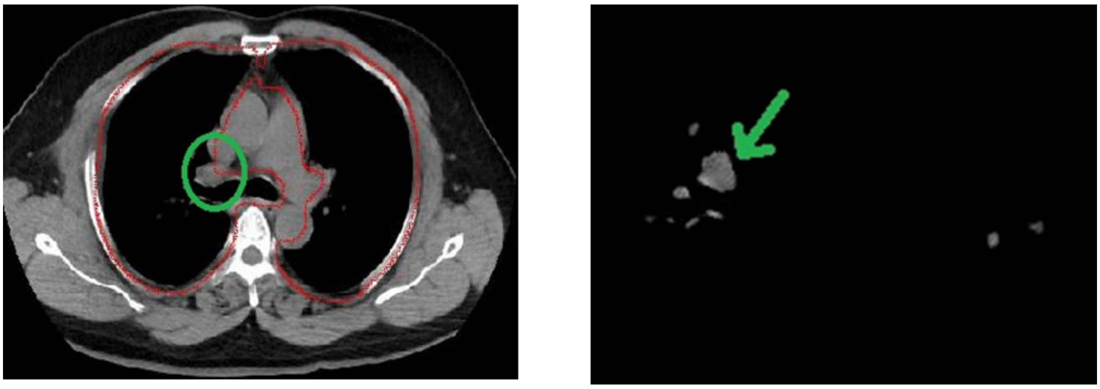

FIGURE 4.8: Juxtapleural nodule detection.

Chapter 5

Conclusion and Future Work

So far, we have segmented Lung Parenchyma in an automated fashion. No human input or any kind of interaction was required in this process. Instead of selecting arbitrary seeds for the level set function, based on an AI based heuristic search approach we selected optimal seed point automatically. These points helped reduce the search space and level set function converge in a significantly fast manner.

Thus we proposed new segmentation technique which is fully automatic. Memoization technique was used during the heuristic search to calculate derivatives to get the inflection points in a single scan of the input. We also tuned parameters of the Level Set function for better accuracy in segmentation. Using morphological operations we succeeded in detecting juxtavascular Nodules (a) and large nodules (b).

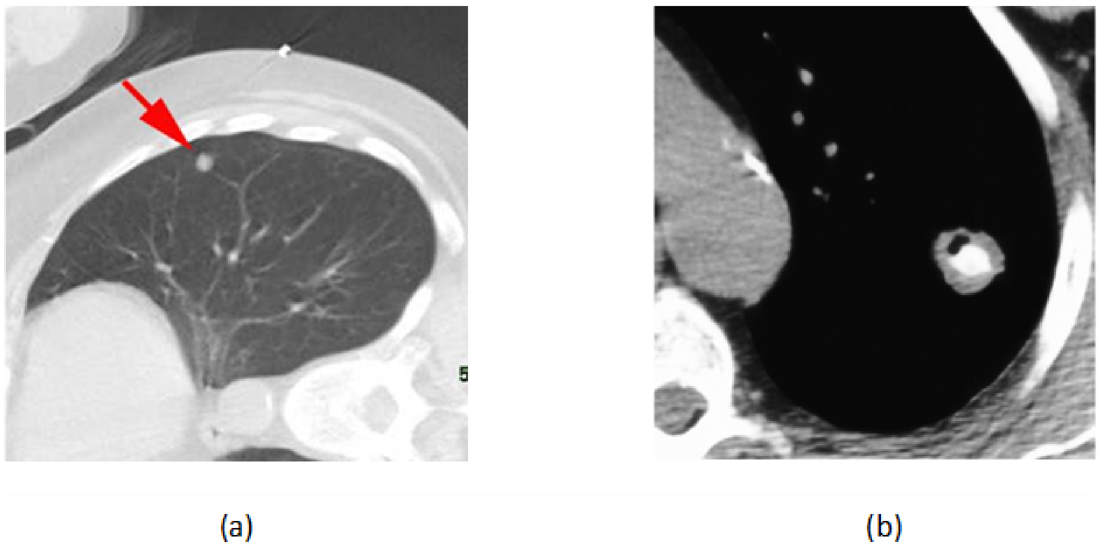

FIGURE 5.1: Juxtavascular and Big Nodule Detection.

So far we have worked on fully automated segmentation of lung parenchyma and nodules. Extracting those regions of our primary goal. In future, these segmented regions, especially the extracted nodules can be used and examined by physicians to detect cancer cells. Further plan includes, extraction of features from the segmented nodules from learn parenchyma. Then we can test those features with classification algorithms to detect cancer cell and also obtain the stage of the cancer. We hope that, this would result in a greater welfare for the mankind. A lot of life would be saved in areas of the world where efficient cancer specialists and physicians are rarely found. Human lives could be saved by early detection of cancer cells.

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