An Improved Segmentation Method for Lung Cancer Detection

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ABSTRAK

Segmentasi adalah salah satu teknik memproses imej yang digunakan untuk mensegmenkan objek dari latar belakang sesebuah imej. Masalah mungkin berlaku apabila membahagikan objek dari latar belakang yang kebiasaannya disebabkan oleh kes-kes seperti “Intensity Inhomogeneity” dan lain-lain. Kajian ini mencadangkan kaedah segmentasi baru untuk digunakan dalam diagnosis atau pengesanan bahagian sel kanser paru-paru. Kaedah segmentasi imej dari setiap artikel dianalisis secara asasnya dari sudut kelebihan, ciri dan kekurangan setiap kaedah yang dicadangkan. Penyelidikan ini mengetengahkan gabungan model, yang telah dicadangkan dalam tesis atau artikel lain dengan hasilnya. Model terbaik dari artikel dikaji yang menunjukkan hasil terbaik akan dipilih, model A dan model B digabungkan dan menghasilkan hasil yang lebih baik dari segi ketepatan dan kecekapan.

ABSTRACT

Segmentation is one of the image processing technique which is use to segments an object from the background of an image. Problems may occur when segmenting an object from background normally due to cases such inhomogeneity intensity and others. This research proposed new segmentation method to be use in lung cancer diagnosis or detection purpose. Methods of image segmentation from every article are analyzed basically for advantage, features and drawbacks of each proposed method. Research suggest a combination of model, which have been proposed in other thesis or article with their results. Best model from reviewed articles which suggest best results is chosen, model A and model B to be combined and produce much better results in terms of accuracy and efficiency.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CT	Computerized Tomography
FCM	Fuzzy C-Mean
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SBPWM	Simple Boost Pulse Width Modulation
SLIVER07	Segmentation of the Liver Competition 2007
SPF	Signed Pressure Force
TCIA	The Cancer Imaging Archive

CHAPTER 1

INTRODUCTION

1.1 Background

Cancer are group of disease that undergoes an abnormal cell grows inside human that are potential to spread through body parts that if there is no any prevention or management taken it may be lethal. As for lung cancer, their presence was like circle lump within lung space which are called as lung nodule. It has been reported that there are about 1.6 million death cases out of 1.8 million lung cancer diagnoses worldwide in 2012 (Siang et al., 2016). In order to diagnose this kind of disease, technologies are required to scan through lung intersection. Years of invention and research by collaboration of scientist and engineers, there are many technologies been produced that are specifically used for cancer detection.

Computerized Axial Tomography (CT) Scan are used to scan body parts like a loaf of bread by slicing it purposely to find any abnormalities insides. However, doctors need to analyse manually all the images as the scanned images are like photos that aren’t yet filtered because CT scanner are system that only captures without going through any image processing. This process is necessary to increase accuracy and to aid the lung cancer specialist in analysing the lung for any lung nodule.

Segmentation are one of the method that are used in image processing. In shorts segmentation work by partitioning digital image into segments with same colour, intensity or texture. Thus, it is easier to analyse the image because it has already detected if there’s any specific subject. Relating with CT scan, result image can undergo segmentation process to detect any lung nodule within the lung area and highlight it so that it can be differentiate.

There are terms that will be used in this research purpose, ‘Active-Contour’ also called snakes is a framework in computer vision for delineating focus object outline which is widely used for edge detection, shape recognition and more. It describes the boundaries between focus object and possible background or other objects. Other term, Signed Pressure Force (SPF) function is formulated function that is generally used to either shrink or expand the contour. Finally, Gaussian function can be simply put to smoothen any image by using this function filter.

Below is an illustration of an example for an Active Contour, the left image shows the initial shape of the contour that shrink until it fit the target object like in the right image.

Figure 1.1: Contour shrinks fitting the object.

There’s limit to the current used method which is it can only be applied on certain cases. Problems occurred when cases aren’t appropriate with method use. Other problem the scanner alone can’t do the image processing for detecting any lung nodule.

1.2 Problem Statement

The CT scanner does not build with image processing system to determine if there is any presence of lung nodule and even though the latest segmentation method can produce a good result it is still imperfects.

Limitations of current applied methods, there are none segmentation method that can be globally applied to all various cases. Simply said, recently compose functions or methods used are limited to specified cases parameter. If used on other cases that isn't appropriate with the method, results may be inaccurate or most likely segmenting wrong parts.

Thus, the solution for this is by enhance the results of the output which is more accurate and lessen bad output by implementing Gaussian and the SPF function in Active-Contour for the segmentation method.

1.3 Objectives

The objectives are:

i. To investigate a segmentation method to enhance the result of output for lung nodule detection.

ii. To implement an improve segmentation method for automated lung cancer diagnosis using the propose method.

iii. To validate the accuracy of improved segmentation method in acquiring information on lung nodule.

1.4 Scope

The scopes of this research are:

i. Using proposed segmentation method to process the CT-Scan image.

ii. CT-Scan image processed result accurately segmenting lung nodule from others.

iii. Determine whether composed method works better than current and functioning well.

1.5 Report Organization

This report shall consist of five chapters. Chapter 1 discuss on introduction on research that explain in general about the research terms, statement of problem, objectives and scopes. While chapter 2 focus on reviews from past studies, identified problems and possible solution by others researcher. Chapter 3 will explain in details on methodologies or approach for this research. Next, chapter 4 will brief the implementing model data and testing, then show result discussion. Finally, chapter 5 concludes research results and clarification of constraint throughout the research period.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter is a summarization of all analysed related articles and thesis in image segmentation with various suggested method use. Consisting 10 reviews, each suggest for the best methods or any combination in term of segmenting an object from background. The contents of the reviews are extracted and listed according to their works, model and method used, experimental datasets and result, subject evaluated, advantages, drawback and features.

2.2 Related Work

Basic of Active Contour Method Ding et al. (2017) work on image segmentation using an active contour model. The method they are using are a combination of region-scalable fitting and optimized Laplacian of Gaussian energy. This method promotes features such improves initialization robustness, improve the efficiency and segmentation accuracy. Some synthetic and real images are used as dataset. Results from some experiments shows that good robustness initialization and better segmentation efficiency and accuracy.

A selective image segmentation done by Liu et al. (2018) using a weight variational model. Proposed method is guaranteed with uniqueness and existence of the minimizer. Experiment carried on a challenging medical images and results shows the effective and efficiency of the method.

Another work by Ding et al. (2018) on image segmentation also using an active contour. The focused method pre-fitting energy for fast image segmentation. Features from this method are it can denoise and improve image contrast. It is also improved segmentation speed and robustness against initialization. Experiment are done using images with intensity inhomogeneity as the dataset. Experiment result proved the proposed model are effective as expected but only for two-phase images.

Work of image segmentation in active contour with selective local or global segmentation by Zhang et al. (2010). In this model they are using Selective Binary and Gaussian Filtering Regularized Level Set method. Features includes in these methods are that they can locally and globally segment and also segment other than selected object. Dataset used for these methods are synthetic and real images and their founding are as stated in the.

A study on inhomogeneous image segmentation carried out by Dong et al. (2013) with their proposed method, integrating local and global intensity information adaptively. Features through this method are fast and accurately segment homogeneous and inhomogeneous image. Synthetic and real medical images are used as dataset to carry out the experiment. The purpose of this is to evaluate the efficiency and robustness of the method advantages but only in several images for local cannot be segment correctly.

An active contour image segmentation model work by Nithila and Kumar (2016) with the method used of Active contour in which it is incorporate with the fuzzy C Mean. Result from the proposed method show that it decreases segmentation rate of error while the similarity measure was increased. Experiments was performed using a synthetical image and actual images.

Zhou et al. (2016) work on active contour for medical image segmentation which are based on local and global intensity information. Features includes in this method are able to segments image with intensity inhomogeneity and has a flexibility on initialization. The experiment is done using dataset of synthetic and real images. This experiment is carried out to evaluate experiments method, the improvement significance on efficiency and accuracy.

Chartrand et al. (2017) research on Liver Segmentation on CT and MR by using Laplacian Mesh Optimization. The features found in using this method are it is reliable, efficient and can effectively be on clinical routine. Results from experiments shows that it can produce excellent segmentation with limited interaction in short time. The experiments were carried out on respiratory CT scanned images from SLIVER07 challenge.

Wang et al. (2009) work was on image segmentation using region-based active contours model. Method used in this work is a Local Gaussian Distribution Fitting energy. Features available from this method is that it can distinguish region with similar mean intensity but different variances. As for the dataset, they use texture and noisy images. Obtained from the experiments are as the expected advantage in table.

Research by Niu et al. (2017) on robust noise region-based active contour model were using a method with local similarity factor for the image segmentation. Features present from method where it can segment image or object with high noise and also with intensity inhomogeneity. It was tested using dataset from synthetic and real word image and found that the method has the better efficiency and robust to higher level of noise manifestation.

2.3 Existing Technique Comparison

Table 2.1: Summarise of each article

No	Author	Method	Features	Advantages	Drawback	Test dataset
1	Ding, Xiao and Weng (2017)	Region-Scalable Fitting and Optimized Laplacian of Gaussian energy	Smoothen homogeneous regions and edge information enhancement.	Enhance robustness of initialization, improve efficiency and accurate segmentation.	Applicable only on two-phase image.	Synthetic and real images.
2	Liu, Ng and Zeng (2018)	Weight variational model	Guaranteed existence and uniqueness of the minimizer.	Guaranteed existence and uniqueness of the minimizer.	Not Mentioned	Selective medical Image.
3	Ding, Xiao and Weng (2018)	Pre-Fitting energy	Improve image contrast and	Achieve fast segmentation, robust to initial contour, apply	Applicable only on two-phase image.	Images with intensity inhomogeneity.

			denoising the image.	denoise and improve image contrast and easily applied on others local-fitting base active contour.		
4	Zhang, Zhang, Song and Zhou (2010)	Selective Binary and Gaussian Filtering Regularized Level Set	Local/global segmentation and also segment other than selected object.	Efficient and effective than geodesic active contour (GAC) and Chan-Vese (C-V). General and robust.	Applicable only for some classical Active contour model.	Synthetic and real images.
5	Dong, Chen and Wang (2013)	Integrating Local and Global Intensity Information Adaptively	Fast and accurate segmentation on both homogeneous	Fast and accurate segmentation on both homogeneous	Local cannot segment accurately on some image.	Synthetic and real medical images.

			and inhomogeneous.	and inhomogeneous.		
6	Nithila and Kumar (2016)	Active contour with fuzzy C Mean	Segment images with intensity inhomogeneity and allow flexible initialization.	Rate of error decrease and vice versa on similarity measure	Not Mentioned	Synthetic and real images.
7	Zhou, Wang, Zhang, Liang and Gong (2016)	Active contour of local and global intensity	Able to segment image of intensity inhomogeneity and Initialization flexibility.	Intensity incorporated local and global, accurately segments small detail.	Not Mentioned	Synthetic and real images.
8	Chartrand, Cresson, Chav, Gotra, Tang and De Guise (2017)	Laplacian Mesh Optimization	Effective, reliable and effective for clinical routine.	Effective, reliable and effective for clinical routine.	Clear consensus can hardly be	30 CT-scan from SLIVER07

					established in some cases.	challenge respiratory.
9	Wang, He, Mishra and Li (2009)	Local Gaussian Distribution Fitting	Able to distinguish region with similar intensity mean but different in variance.	Local image intensities utilized efficiently. Able to deal with noise and intensity inhomogeneity.	Applied only on some texture images.	Noisy and texture images.
10	Niu, Chen, Sisternes, Ji, Zhou and Rubin (2017)	Region-based Active Contour via Local Similarity Factor	Segment object with high noise and image with intensity inhomogeneity.	Robust to higher level of noise and provide outlines of sufficient detail preservation.	It is sensitive to the active contour initialization.	Synthetic and real word images.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter cover the discussion on the methodology used in completing the research. The methodology clarifies the steps included throughout the research process. Each steps or stages are explained briefly to show what process will occur in each stage.

3.2 Methodology

This research's methodology consists of several essential steps. These steps are known as investigation of the existing method for segmentation, development of a new method, implementation of new segmentation method, verification and validation. Illustration of each steps are as follows.

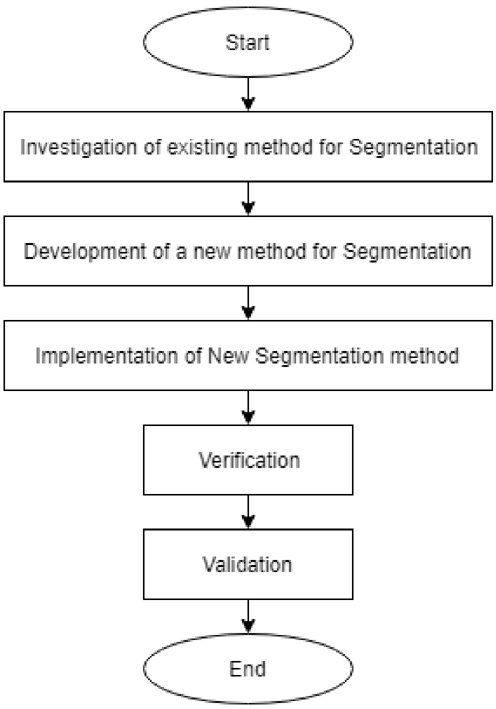

Figure 3.1: Research process flowchart

3.2.1 Investigation of existing method for Segmentation

In the earlier stage, the research literatures are reviewed and summarized. The extracted information focused on the literature works, features, advantages, drawbacks, datasets used and experimental results for every proposed segmentation method in each literature. Some of the proposed method are Region-Scalable Fitting, Local Similarity Factor for Region-Based Active Contour, Local Gaussian Distribution Fitting and more. The summarized and extracted information's have been recorded in Chapter 2.

3.2.2 Development of a new method for Segmentation

This stage proposed a new method based on reviewed literatures in Chapter 2. It is particularly to detect the presence of lung cancer. In addition, it should improve in term of performance and accuracy of the segmentation.

3.2.3 Implementation of New Segmentation method

Implementation stage will be done in the next part of this research which means it will not be discuss in this paper. As suggested in the development of new segmentation method, this phase will implement the new method by using MATLAB software to process the image information. The reason of using this software to test the new method is because it is one of well-known software that is powerful for image processing. The experimental dataset use are sets of CT scan images of lung represent medical images. These images should distinct from each of them in term of noise homogeneous factor and cancerous spot presence.

3.2.4 Verification

In this stage, the implementation will be assessed whether the proposed new segmentation method is developing by using the right tool, method prototype is able to perform the function expected to be done when processing the dataset image. Otherwise, the process should be repeat with the right one.

3.2.5 Validation

Finally, validation will be performed which is to determine and make sure that the prototype can get the input data then process and produce a segmented image. Result of the segmentation from the given CT scan image problem will be evaluate to show the performance is better and is the enhance version. This method should run smoothly without any error.

3.3 Software and Hardware Specification

The software and hardware that will be used to carry out this research are as specify with their function respectively in the tables below.

Table 3.1: Software Specification

Software	Description	Function
MATLAB	Matrix manipulation software suites for engineering and scientist programmers to carry out work.	Run the implementation of the new proposed method
Microsoft Office Word 2016	Word-processing program used for creating documents.	Write and documenting the research content
Mendeley	Elsevier programme available in for desktop and web to share articles and journals.	Cite reference into the research report

Table 3.2: Hardware Specification

Hardware	Function
Desktop	Use for developing the documentation and run related software required for the research

Printer	Print copies of documents, article and report.

3.4 Gantt Chart

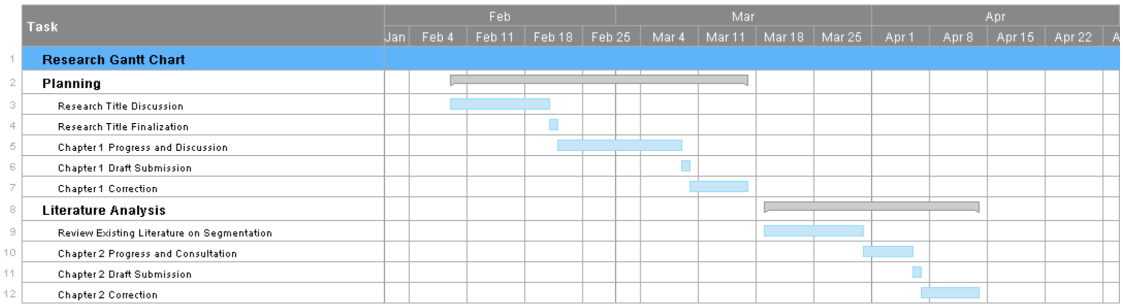

Figure 3.2: Gantt Chart (a)

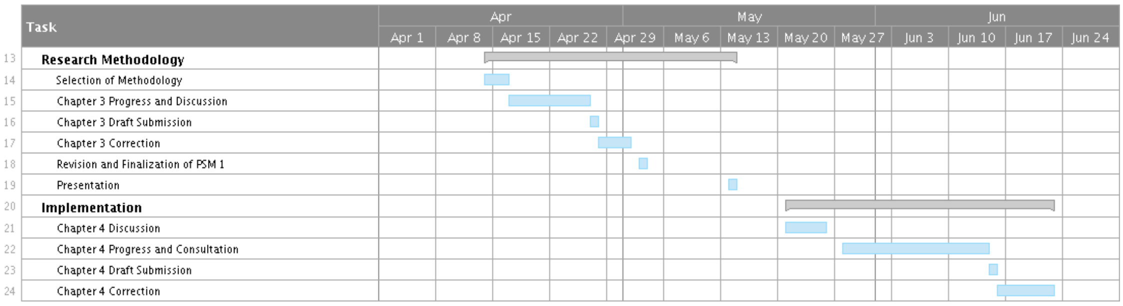

Figure 3.3: Gantt Chart (b)

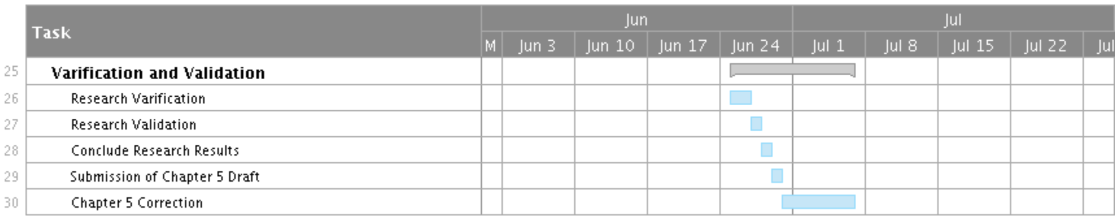

Figure 3.4: Gantt Chart (c)

3.5 Proposed Method

The proposed method consists of several important process which are pre-processing, segmentation and clustering. Figure below illustrate the process of the proposed algorithm for this study.

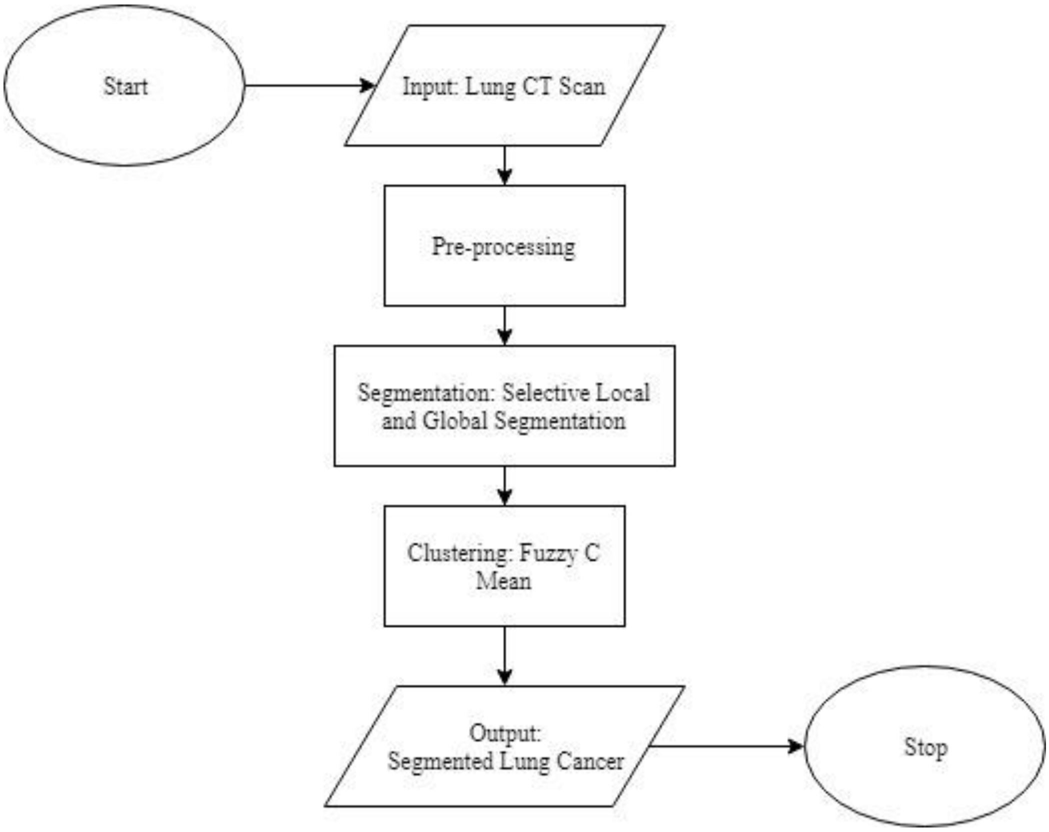

Figure 3.5: Proposed Sementation Process Model

3.5.1 Pre-processing

Using an input of actual CT Scan Image, then it undergoes a pre-processing phase before the image can be segmented. This is the initial phase for every image process which is to ensure that the noise presence intensity is not too high which might cause problem to the segmentation process.

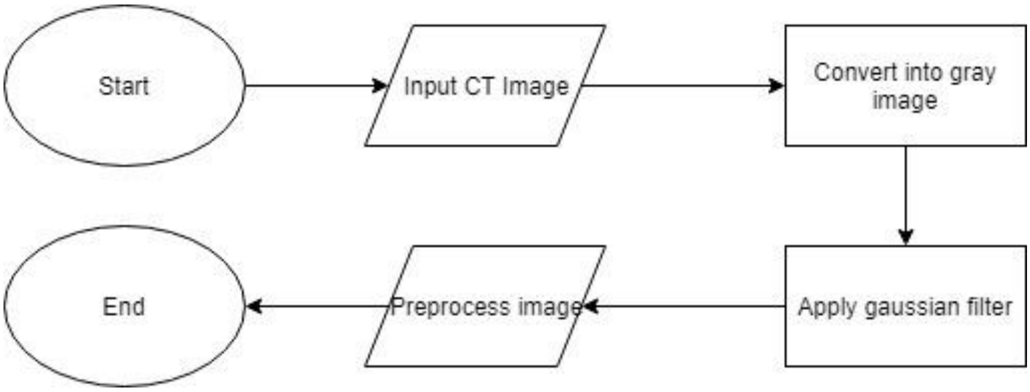

Figure 3.6: Flow of image pre-processing.

The process flow starts with reading an input image which is CT scan of the lung cancer image. The image is then convert into grayscale image to simplify the segmentation process afterwards. The syntax function ‘rgb2gray’ used to carry out the process. Then the Gaussian filter are applied to reduce the noise presence in the image.

3.5.2 Segmentation

Second to the process are segmenting the lung cancer. It is where the process of partitioning an image into several parts occur as explained in the introduction. In this research, proposed segmentation used are based on selective local and global segmentation paper (Zhang et al., 2010) by implementing active contour model of Gaussian with SPF function. The proposed algorithm procedures are as below:

Step 1: Initialize the level set function.

$$\emptyset(x, t=0) = \begin{cases} -\rho & x \in \Omega_0 - \partial\Omega_0 \\ 0 & x \in \Omega_0\partial \\ \rho & x \in \Omega - \Omega_0 \end{cases} \quad 3.1$$

Step 2: Compute $C_1(\emptyset)$ and $C_2(\emptyset)$ using equation

$$c_1(\phi) = \frac{\int_{\Omega} I(x).H(\phi)dx}{\int_{\Omega} H(\phi)dx} \qquad 3.2$$

$$c_2(\phi) = \frac{\int_{\Omega} I(x).(1 - H(\phi))dx}{\int_{\Omega} (1 - H(\phi))dx} \qquad 3.3$$

Step 3: Evolve the level set function based on equation

$$\frac{\partial \phi}{\partial t} = \mathrm{spf}(I(x)).\alpha|\nabla_{\phi}|, \qquad x \in \Omega \qquad 3.4$$

Step 4: Let $\emptyset = 1$ if $\emptyset > 0$; otherwise, $\emptyset = -1$.

Step 5: Regularize the level set function with a Gaussian filter.

$$\phi = \phi * G_{\sigma}$$

Step 6: Check whether the evolution of the level set function has converged. If not, return to step 2.

3.5.3 Clustering

After segmenting the image, cluster will be applied in order partition or cluster the pixels with strong similarity value into sets. This study proposed Fuzzy Clustering as part of the algorithm. Fuzzy clustering process is suitable for feature extraction, pattern recognition and fuzzy identification (Nithila & Kumar, 2016).

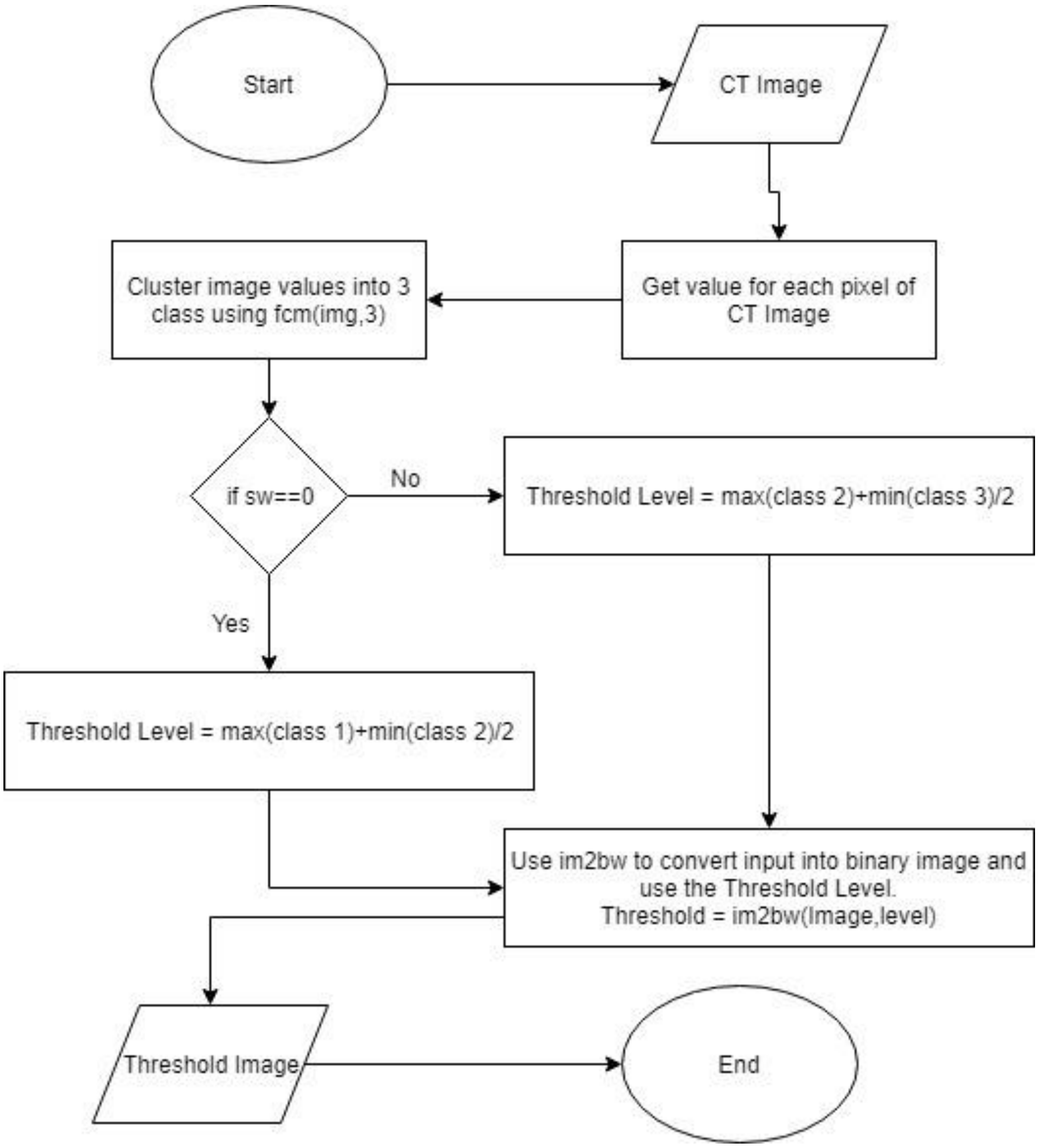

Figure 3.7: Flow of image threshold using Fuzzy C Mean Clustering

In this research, Fuzzy clustering is applied to carry out the threshold process on CT images. The process starts with get an image input of CT scan image, get each of its pixel's values and cluster all the value into 3 class. This cluster process can be done by using function syntax provided by MatLab which is "fcm" follow with "(img,3)" with image input named "img" and 3 is the number of class. Then set a condition to determine the threshold level, if condition value equal to 0, calculation is between maximum value Class 1 and minimum value of Class 2. Otherwise, calculation is between maximum value Class 2 and minimum value of Class 3. Proceed with threshold process using the syntax function ‘im2bw’ follow with ‘(img, level)’ using the obtained level value. Equation for the level of threshold are as follow:

$$\text{Level} = \frac{Max(Class\ A)+Min(Class\ B)}{2} \qquad 3.5$$

CHAPTER 4

RESULT AND DISCUSSION

4.1 Overview

This chapter present the analyses and discussions of the result that are obtained by the Selective Local and Global segmentation. The experimental result will discuss the performance of segmentation on sets of CT scan images. The last part of this summaries the findings of this experiment.

4.2 Result and Discussion

This section discussed the obtained result from the applied proposed segmentation. The study is carried out using TCIA CT Lung diagnosis as test subject or input data set. To assess the performance and accuracy of the proposed method, comparison been made between automated and manual segmentation to see each performance and accuracy by calculate Volume Error, Coefficient of Similarity, Root Mean Square Error (RMSE) Mean Absolute Error (MAE). Equations present as follows:

$$\text{Volume Error} = \frac{2(\mathrm{S}-\mathrm{GS})}{\mathrm{S}+\mathrm{GS}} \tag{4.1}$$

$$\text{Coefficient of Similarity} = 1 + \frac{(\mathrm{GS}\cap\mathrm{S})}{(\mathrm{S}\cup\mathrm{GS})} \tag{4.2}$$

$$\text{Root Mean Square Error} = \sqrt{\left(\frac{1}{2}\right)\sum e^2} \tag{4.3}$$

$$\text{Mean Absolute Error} = \frac{\sum_{i=1}^{n}|e_i|}{n} \tag{4.4}$$

Results of the calculated RMSE, MAE, Spatial Overlap and Coefficient of Similarity are shown in Table 4.1 while images of segmentation are available at the Appendix 2.

Table 4.1: Result of Volume Error, Coefficient of Similarity, RMSE and MAE.

Image	Coefficient of Similarity	Volume Error	RMSE	Mean Absolute Error
1	0.381	1.238	0.372	0.004
2	0.428	1.143	0.402	0.004
3	0.969	0.061	1.337	0.022
4	0.520	0.959	0.563	0.004
5	0.972	0.056	5.467	0.165
6	0.505	0.989	0.498	0.005
7	0.863	0.275	0.806	0.009
8	0.311	1.378	0.673	0.006

Based on previous study (Zhang et al., 2010), best Coefficient of similarity obtained was 0.914 and worst at 0.074. Compare to this study. Best obtained is at 0.974 and worst at 0.311 which is better compare to previous one. While for the Spatial Overlap obtained on previous study, the best 0.584 and worst 0.089. The results of volume error show slight improvement with average of 0.762% while previous study get 0.968%. Thus, it is appropriate for a clinical usage as it supposed to be less than 5%.

CHAPTER 5

CONCLUSION

5.1 Conclusion

Various segmentation method can be applied to carry out a lung diagnosis in segmenting cancer that is present in the lung. In this study, sets of TCIA CT Lung diagnosis with positive presence of cancer were used as input to carry out the proposed segmentation. Although result shows that it can segmented input images successfully, there is improvement need to me made. By using the MatLab R2018a, the segmentation model using SLG algorithm was applied. Based on SLG algorithm, initially begin with define its parameters of the algorithm before performing the segmentation.

5.2 Constraints

In doing this research, there are some constraint. The constraint that are present are as below:

i. Input image must be crop to only interest region (lung cavity) else segmentation would be Inaccurate.

ii. The result is not satisfied yet as it not only segments cancerous part in some cases.

iii. Unable to test on more subjects with different model due to time constraint.

5.3 Future Works

There are more possible future works can be done to achieve obtain better result in segmentation of lung cancer. Some of the possible future work are as below:

i. Improve the Selective Local and Global segmentation algorithm for better accuracy.

ii. Vary the set of input Lung Cancer images with different problems.

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APPENDIX 1

Segmentation.m

```
%PREPROCESSING
I = imread('lung7.jpg');          %get input image
d = manual(I);                    %manual segmentation
I = rgb2gray(I);                  %convert image to grayscale
figure, imshow(I);
K = medfilt2(I);                  %median filter
figure, imshow(K);


%SEGMENTATION
Img = K(:,:,1);
Img = double(Img);
[row,col] = size(Img);
phi = ones(row,col);
phi(10:row-10,10:col-10) = -1;
u = - phi;
[c, h] = contour(u, [0 0], 'r');
title('Initial contour');
% hold off;

sigma = 1;
G = fspecial('gaussian', 5, sigma);

delt = 1;
Iter = 400;
mu = 25;%this parameter needs to be tuned according to the images

for n = 1:Iter
    [ux, uy] = gradient(u);

    c1 = sum(sum(Img.*(u<0)))/(sum(sum(u<0)));%we use the standard
Heaviside function which yields similar results to regularized one.
    c2 = sum(sum(Img.*(u>=0)))/(sum(sum(u>=0)));

    spf = Img - (c1 + c2)/2;
    spf = spf/(max(abs(spf(:))));

    u = u + delt*(mu*spf.*sqrt(ux.^2 + uy.^2));

    if mod(n,10)==0
    imagesc(Img,[0 255]); colormap(gray);hold on;
    [c, h] = contour(u, [0 0], 'r');
    iterNum = [num2str(n), 'iterations'];
    title(iterNum);
    pause(0.02);
    end
    u = (u >= 0) - ( u< 0);% the selective step.
    u = conv2(u, G, 'same');
end
imagesc(Img,[0 255]);colormap(gray);hold on;
[c, h] = contour(u, [0 0], 'b');
```

```
imagesc(u,[0 255]);%displays the image on scaled axes with the min
value as black and the max value as white.
colormap(gray); %display the image in a new figure using the gray
colormap
iterNum = [num2str(n), 'iterations'];%display the iteration number by
ascending order
title(['Final contour,', iterNum]);%title that display on im
[c, h] = contour(u, [0 0], 'b', 'LineWidth',2); %contouring properties
b=ones(row,col);
hold on;
figure (4);
imshow (u);
se = strel('ball',12,12);
BW = imclose(u,se);
figure (5);
imshow(BW);

%CLUSTERING
fim=mat2gray(BW);
level=graythresh(fim);
bwfim=im2bw(fim,level);
[bwfim0,level0]=fcmthresh(fim,0);
BW2 = imclearborder(bwfim);
figure (6);
imshow(BW2);
[ jaccardIdx,jaccardDist] = coefficientOfSimilarity( BW2,d);
[ b1,b2] = spatialOverlap( BW2, d);
[err1,err2] = RMSE(BW2, d);
[mae] = meanAbsoluteError(BW2, d);
```

manual.m

```
function d = manual(Img)
subplot(2,2,1);
e=imshow(Img);
title('Original Image')
b=rgb2gray(Img);
subplot(2,2,2);
imshow(b);
title('Hand Drawing')
c=imfreehand(gca); % place a closed freehand region of interest by
clicking and dragging over an image.
d=createMask(c,e);
subplot(2,2,3);
imshow(d);
title('Manual Segmentation')
h=bwarea(d);
```

fcmtresh.m

```
function [bw,level]=fcmthresh(IM,sw)
% check the parameters
if (nargin<1)
```

```
error('You must provide an image.');
elseif (nargin==1)
sw=0;
elseif (sw~=0 && sw~=1)
error('sw must be 0 or 1.');
end
data=reshape(IM,[],1);
[center,member]=fcm(data,3);
[center,cidx]=sort(center);
member=member';
member=member(:,cidx);
[maxmember,label]=max(member,[],2);
if sw==0
level=(max(data(label==1))+min(data(label==2)))/2;
else
level=(max(data(label==2))+min(data(label==3)))/2;
end
bw=im2bw(IM,level);
```

coefficientOfSimilarity.m

```
function [ jaccardIdx,jaccardDist] = coefficientOfSimilarity( t, T2 )
% Find the intersection of the two images using '&' operatorc
inter_image = t & T2;
%figure; imagesc(inter_image); axis image; colormap gray;
%title('intersection');
% Find the union of the two images using '|' operator
union_image = t | T2;
%figure; imagesc(union_image); axis image; colormap gray;
%title('union');

%to compute the similarity between segmented manually and automated
%segmented
jaccardIdx = sum(inter_image(:))/sum(union_image(:));
jaccardDist = 1 - jaccardIdx;
fprintf('Coefficient of Similarity is %.3f\n', jaccardDist);
end
```

coefficientOfSimilarity.m

```
function [ b1,b2] = spatialOverlap( T2, t )
% Find the intersection of the two images using '&' operatorc
inter_image = t & T2;
%figure; imagesc(inter_image); axis image; colormap gray;
title('intersection');
% Find the union of the two images using '|' operator
union_image = T2 | t;
%figure; imagesc(union_image); axis image; colormap gray;
title('union');
b1= 2.*(sum(inter_image(:)));
b2 = b1./(sum(union_image(:)));
fprintf('Spatial Overlap is %.3f\n', b2);
end
```

RMSE**.m**

```
function [err1,err2] = RMSE(BW2, d)
%RMSE Root Mean Squared Error
[x,y,z] = size(BW2);            % Get Value x, y of image.
err1 = sum((BW2 - d).^2)/(x*y); % Calculate MSE
err2 = sum(sqrt(err1));         % Square Root of MSE
fprintf('RMSE is %.3f\n', err2);
end
```

meanAbsoluteError**.m**

```
function [mae] = meanAbsoluteError(BW2, d)
%get row and column size
originalRowSize = size(BW2,1);
originalColSize = size(BW2,2);
BW2 = BW2(:);
d = d(:);
mae = sum(abs(BW2 - d))/(originalRowSize*originalColSize);
fprintf('abslute error is %.3f\n', mae);
end
```

APPENDIX 2