NONLINEAR ACTIVE CONTOUR MODEL FOR MEDICAL IMAGE SEGMENTATION

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR PHILOSOPHY

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY UNIVERSITY OF MALAYA KUALA LUMPUR

2016

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ABSTRACT

With the introduction of fractional calculus, this study proposes two automatic segmentation methods which are based on nonlinear Active Contour Model (ACM) for medical image segmentation. Before that, a semi-automated approach is developed which is based on Mathematical Morphology function to overcome the gap problems. Medical images are classified as having low in quality due to its level of noise and level of intensity inhomogeneity. These characteristics of medical images create problems of over segmentation and local minima during the segmentation process that leads to inaccurate segmentation. Therefore the study proposes two automated methods to overcome those problems in providing successful medical image segmentation. The first proposed method is designed using the collaboration of fractional function and sinc method. Our first method, Fractional Sinc Wave method (FSW) ACM, managed to reduce the over segmentation problem thus provide successful segmentation. The fractional function provides rapid, dynamic and bending effect capability to the contour to evolve towards the object. On the contrary, the sinc wave method with the interpolation capability, support the fractional calculus in constructing new data points within the current data points. The method shows good potential in providing an improved segmenting where the over segmentation problem is reduced However, the method did not managed to provide accurate boundary segmentation on some of the medical images. This problem is then overcome by our second method namely Fractional Gaussian Heaviside (FGH) ACM. We introduce two importance techniques which are Adaptive Fractional Gaussian Kernel (AFGK) and Fractional Differential Heaviside (FDH). The introduction of Adaptive Fractional Gaussian Kernel (AFGK), offers an excellent enhancement process where the

inhomogeneous objects in regions are now more accurately classified. The proposed Fractional Differential Heaviside (FDH) provides the nonlinear protecting capability and produce extraction of accurate local image information. The collaboration of AFGK and FDH via ACM produces a method that provides accurate boundary segmentation on four different medical image modalities. In order to access accuracy of segmentation on medical images, two types of evaluations were conducted. The first evaluation is based on quantitative evaluation where the metric of accuracy is stressed on. It was found that, the metric of accuracy for all images used in the experiments were more than 90%. The second evaluation is based on visual interpretation where the FSW ACM and FGH ACM were compared to other methods of ACM. It is noted that the accuracy produced by both methods are better than others.

ABSTRAK

Kajian ini memperkenalkan dua kaedah pembahagian keatas imej-imej perubatan secara automatic berdasarkan kaedah Nonlinear Active Contour Model dengan menggunakan konsep Fractional Calculus. Di awal kajian, konsep Mathematical Morphology telah pun di analisis dan operasi nya di guna pakai untuk pembangunan kedua kaedah ini. Dua permasaalah pada imej perubatan telahpun dikenalpasti iaitu noise and intensity inhomogeneity. Noise adalah signal yang tidak diperlukan manakala intensity inhomogeneity adalah taburan intensity yang tidak sekata pada imej perunatan tersebut. Kaedah yang diperkenalkan menggunakan teknik pencilinan yang dapat melicinkan imej dan dalam masa yang sama megurangkan jumlah noise. Kaedah yang pertama direkabentuk menggunakan teknik Fractional Sinc Wave untuk membahagikan imej perubatan dengan baik dalam masa yang sama mengurangkan intensity inhomogeneity. Ini dapat mengurangkan over sampling. Konsep fractional di reka didalam keseluruhan (global) dan sebahagian (local) pada ACM. Kekuatan fractional iaitu berulang-ulang memberikan contour bergerak lebih pantas dan berkelok-kelok. Sebaliknya, sinc wave membantu fractional calculus didalam menyediakan set data yang baru. Ini memberikan hasil pembahagian yang bagus. Walaubagaimanapun, kaedah ini tidak member hasil yang tepat pada pembahagian objek dari latar belakang nya. Kaedah kedua yang diperkenalkan masih berlandaskan konsep fractional calculus. Kaedah ini memperkenalkan dua teknik iaitu Adaptive Fractional Gaussian Kernel (AFGK) dan Fractional Differentiate Heaviside (FDH). Teknik AFGK adalah untuk pelicinan imej dan teknik FDH adalah untuk menarikan local image information. Gabungan antara AFGK dan FDH menyediakan satu kaedah yang baik di mana pembahagian yang tepat telah diperolehi. Untuk menilai

keberkesana kedua-dua kaedah yang direkabentuk, dua jenis penialaian di lakukan. Penilaian tersebut adalah penilaian kuantitatif dan penilaian perbandingan. Penilaian kuantitatif dilakukan untuk menilai metric ketepatan dimana didapati ketepatan kedua kaedah didalam pembahagian adalah melebihi 90%. Penilaian yang kedua adalah membandingkan hasil kedua-dua kaedah dengan kaedah lain. Didapati, ketepatan keduadua kaedah adalah lebih baik dari kaedah yang lain.

ACKNOWLEDGEMENT

First of all, I would like to show my gratitude to the current Dean of the faculty and the office staff for providing support in numerous ways during this research study, especially in conducting camps to provide knowledge in completing the research writing. It is an honour to me to thank the former Dean of the faculty, Prof. Dr. Siti Salwah for her initial encouragement and directions provided during this study. I would to express my warmest thanks to Dr. Rabha Al Waeil, lecturer from Institute of Mathematics of University Malaya in providing guidance to write the Mathematics equation in completing the study. A warmest thanks to Dr. Hamid Al Jalab, lecturer from faculty Science Computer and Information Technology of University Malaya in giving lesson and knowledge on Matlab programming. This thesis would not have been possible without the help from Dr. Norintan, gynecologist specialist from Columbia Hospital, Seremban on her support and knowledge in the guidance on interpreting various medical images.

Most importantly and especially, I am heartily thankful to my main supervisor Assoc Prof Dr Nor Aniza Abdullah and my previous supervisor, Prof Dr Roziati Zainuddin. Their encouragement, guidance, corrections, reviews and motivations from initial to the final thesis compilation ensure the success of the study. I would like to put forward my gratitude to my family especially my husband in understanding my responsibility in completing the thesis. Lastly, a special thanks to my father in helping me financially and all the supports throughout the study.

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LIST OF ABBREVIATIONS AND ACRONYMS

ACM	-	Active Contour Model
МоН	-	Minister of Health
WHO	-	World Health Organization
MRI	-	Magnetic Resonance Imaging
СТ	-	Computed Tomography
CAT	-	Computerized Axial Tomography
FGK	-	Fractional Gaussian Kernel
FDH	-	Fractional Differential Heaviside
AFGK	-	Adaptive Fractional Gaussian Kernel
PDE	-	Partial Differential Equation
LSM	-	Level Set Method
LSF	-	Level Set Function
GVF	-	Gradient Vector Flow
GAC	-	Geometric Active Contour
LBF	-	Local Binary Fitting
LIF	-	Local Image Fitting
FC	-	Fractional Calculus
ММ	-)	Mathematical Morphology
SE	-	Structuring Elements
CV	-	Chan & Vese
SGLACM	-	Selective Global and Local Active Contour Model
MS	-	Mumford-Shah
FGCV	-	Fast Global Minimization
LIC	-	Local Intensity Clustering
LGD	-	Local Gaussian Distribution

CHAPTER 1 INTRODUCTION

In modern medicine, utilization of medical imaging is often needed for physicians to diagnose patients' medical conditions or illness. Nonetheless, poor quality of medical images and limited number of experienced radiologists (Bhavana & Krishnappa, 2015; Caselles, Chambolle & Novaga, 2015) can lead to inaccurate diagnosis. So it is essential to have a computer system that can help radiologists to accurately interpret medical images. However, a reliable computer system for interpreting medical images normally requires an accurate and robust segmentation method.

Therefore the goal of this research is to devise a novel segmentation method that can produce accurate boundary segmentation in medical images regardless of modalities and anatomical structures involved. This chapter is dedicated to provide an overview of the intended research work. It starts with research motivation, followed by an introduction to fundamental issues in medical image segmentation in Section 1.2. A problem description is described in Section 1.3. Research aim and objectives are presented in Section 1.4, followed by a list of research questions. Section 1.6 gives an overview on the research methodology. This chapter ends with some brief descriptions of each chapter in this thesis.

1.1 Research Motivation

Modern medicine often depends on medical imaging for medical diagnosis and treatment. Medical image modalities such as Computerized Tomography (CT) scan, Magnetic Resonance Imaging (MRI) and ultrasound are non-invasive examination methods that enable physicians to examine the inner part of human body to evaluate his or her physiological condition or to identify any possible occurrence of diseases such as tumors, cancer, or cysts.

Unfortunately, every medical imaging procedure produces visual noise, and such noise tends to be more prevalent in certain imaging modalities than others, for instance, CT scan images have less noise than ultrasound images. One of the reasons for this is that procedure of ultrasound imaging produces speckle noises, resulting in blurry and unclear images. Untrained naked eye would not be able to interpret these images, and inexperienced radiologists may interpret the image inaccurately. This situation leads to unsatisfactory diagnosis and confusion among physicians involved. As a consequence, a patient needs to wait longer for a suitable medication or treatment to be prescribed by the physicians. On the contrary, an experienced radiologist will be able to interpret the image accurately despite its poor visual condition. Unfortunately, the rate of imaging utilization is far exceeded the number of qualified radiologists, for example, in the United States of America, the utilization rate increased by 6 percent each year while the number of new radiologists increased by only 2 percent each year (Bhavana & Krishnappa, 2015).

The research also found that the shortage of qualified radiologist was more apparent in developing countries. For instance, in 2004, Indonesia had fewer than 500 radiologists for its 220 million people, and Bangladesh only had one radiologist for every million people. Malaysia is also facing a shortage in the number of radiologists, as indicated by the Health Minister Datuk Seri Dr S. Subramaniam (Malay Mail Online, 2014). According to him, the shortage was due to the increasing growth of new facilities such as health clinics and hospitals throughout the country.

The increasing use of imaging facilities and the shortage of radiologist would result in a long queue of patients waiting for their medical image diagnostic report. A reliable computer system that is able to automatically detect abnormality in medical images is therefore urgently needed to speed up the diagnostic process. Such system can also alert less experienced radiologists of any possible abnormality for further inspection of the suggested area. The realization of the importance of such system is evidenced when the medical image analysis community has become preoccupied with the problems of extracting clinically useful information from medical images with the assistance of computers (Ayache et al., 2012; Hermosillo & Faugeras, 2002; Caselles, Chambolle & Novaga, 2015). This is because the primary challenge the development of an automatic system for detecting abnormalities in medical images is to design a robust and accurate segmentation algorithm that can work on any modalities and anatomical structures.

For the past decade, numerous methods have been proposed to accurately segment medical images for detecting abnormalities such as tumors or cancerous cells. Among the segmentation methods that have been developed, Active Contour Model (ACM) appears to

be the most popular for segmenting medical images (Airouche, Bentabet, & Zelmat, 2009; Zhang et al., 2013; Tingting Liu et al., 2014). ACM was initially developed by Kass, Witkin and Terpozoulos (1988) and it is classified as edge-based ACM. Even though edgebased ACM can segment some medical images, its result is hardly satisfying (Chan & Vese, 2001; Li et al., 2005). This is because the technique works on image's gradients. Therefore, its success depends on the visibility of edges in an image. Unfortunately, medical images are mostly affected by visual noises that weaken those edges. The problem becomes severe in certain medical images such as ultrasound in which the edges are too weak to actualize any objects' boundaries.

To address this deficiency, a region-based ACM was developed. The method has proven more successful than edge-based ACM in segmenting noisy medical images due to it robustness in handling noise (Bresson, 2005; Li et al., 2007). However, apart from the visual noises, many medical images such as MRI and ultrasound are also impaired with intensity inhomogeneity problem (Li et.al., 2007; Wang et al., 2009; Li et al., 2010). Intensity inhomogeneity is a problem where the distribution of intensity in an image is not homogeneous. This condition creates an interface with various levels of intensities.

Neither edge-based nor region-based ACM method alone can accurately segment medical images with intensity inhomogeneity (Zhang et al., 2010). In the attempt to resolve this problem, a combination of edge-based and region-based ACM methods were later employed by many researchers (Li et al., 2010; Zhang et al., 2010). Some of the hybrid techniques perform better than the others in segmenting certain medical images but none has yet able to accurately segment the object's boundary in the presence of intensity

inhomogeneity without producing excessive over segmentation effect. Over segmentation is the process by which the objects being segmented from the background are themselves segmented into sub-components or sub-regions. However, the regions that are segmented can be classified as non-significant areas. As medical images are created by different types of imaging modalities therefore it is important to know about these modalities and the challenges they pose to medical image segmentation. The following section provides the information.

1.2 Medical Image Segmentation

This section comprises of two sub sections. The first sub section explains about the most common medical imaging modalities. The second sub section describes the visual characteristics of medical images produced by these modalities.

1.2.1 Medical Imaging Modalities

Medical imaging is a process of creating a visual representation of the inner parts of human body including organs and bones structures for clinical analysis and medical intervention (James & Dasarathy, 2014). There are many medical imaging modalities for capturing inner parts of human body for medical diagnosis and each modality has its own strengths and weakness. Among the common modalities used are MRI, CT scan, x-ray, and ultrasound imaging.

MRI is a noninvasive medical assessment that helps doctors to diagnose and treat medical conditions. MRI uses a powerful magnetic field with radio frequency pulses to capture the inner part of human body, while a computer is used to display the captured organs, bone

and other inner body parts captured by the MRI (Maria & Sanjay, 2004). Physicians normally use MRI examination to diagnose or monitor treatment for conditions such as tumor in the chest, abdomen or pelvis, diseases of a liver, heart problems, and to determine the presence of a fetus in the womb.

Besides MRI, CT scan imaging uses special x-ray equipment to create detailed images, or scan areas of the inner parts of the body. CT scan imaging is also known as computerized tomography or computerized axial tomography (CAT). Unlike MRI, CT scan imaging provides detailed and cross-sectional views of all types of body tissues. It is known as one of the fastest and most accurate tools for examining human chest, abdomen and pelvis (Healy et al., 2011; Maria & Sanjay, 2004). CT scan is often used for detecting many types of cancers such as lymphoma and cancers of the lung, liver, kidney, ovary, and pancreas because it can provide clearer and more detailed images of organs' tissues as compared to other modalities. When compared to MRI, CT scan has higher imaging resolution and less motion artifact due to its fast imaging speed. Therefore CT scan images contain less noise and the object boundary is clearer than MRI images.

Besides MRI and CT scan imaging, an x-ray (radiograph) is another types of medical imaging. The image produced by an x-ray imaging involves exposing a part of the body to a small dose of ionizing radiation. X-ray is the oldest and most frequently applied medical imaging. It is usually used to visualize bones structures in human body.

Among all types of medical imaging, ultrasound imaging is the safest medical imaging. Ultrasound is synonyms to pregnancy where gynecologist often used to examine the growth of a fetus. However, ultrasound imaging can do more than just checking on a woman's pregnancy. For example, ultrasound is used to examine many anatomical structures such as kidneys, gallbladder and spleen. Additionally, ultrasound is also used to guide procedures such as needle biopsies and fluid drainages (Catherine, Mindy & Maria, 2012).

Ultrasound uses a device known as a transducer to send high-frequency sound waves into a human body. Sound waves emitted by the transducer will go through the body, reflect on the internal organ and are transmitted back to the ultrasound transducer to produce image on a monitor. Although ultrasound imaging is safe and can be used on several types of human body, the images it produced can only be interpreted by doctors with prior knowledge in ultrasound image reading. This is because the images are dark and severely affected with noises hence producing lots of broken edges and uneven distribution of intensity throughout the image.

Another imaging used in diagnostic is microscopic imaging. Microscopic images are normally produced by electron microscopes. Microscope images are commonly used in the field of cancer research, drug testing, cell analyses, bacteria and many more. By analyzing microscopic images, expert could count blood cells or identify type of virus or bacteria of any diseases. But, the variation of color tones and shapes in microscopy image produces quantization type of noise that made the images unclear and difficult to go through the segmentation process (Vijay & Bhupendra, 2014).

1.2.2 Medical Image Characteristics

Medical images are generally low in quality as compared to synthetic images due to their high level of noise and intensity inhomogeneity. Image noise is the 'unwanted signals' that are inadvertently produced by the imaging devices. It is sometimes referred to as image mottle that gives an image a textured or grainy appearance. The level of noise in medical image depends on the imaging device and the procedure involved, for instance, a CT scan image has less noise when compared to MRI or ultrasound images. There are many types of noise such as Gaussian noise, salt-and-pepper noise, shot noise and quantization noise. In medical images, noise leads to poor image quality which made segmentation process becomes difficult.

Among medical images, ultrasound image contains the highest level of noise, and its noise type is known as 'speckles noise'. Therefore ultrasound image usually requires preprocessing before it can be segmented to remove the unwanted noise and enhance details. Filtering and blurring techniques are among the techniques used to remove or reduce image noise. However, the use of image blurring for noise reduction can also reduce the visibility of useful image detail in an image. Figure 1.1 illustrates several example of image noise in CT scan, MRI and ultrasound images. The first column of Figure 1.1 depicts a CT scan image of an abdomen, while the second column shows an MRI image of a heart and the last column shows an ultrasound image of an appendix. Note that, each image contains different level of noise, and the ultrasound image displays the highest level of noise, followed by the MRI image and finally the CT scan image.



Figure 1.1: Level of noise in CT scan image (a), MRI image (b) and ultrasound image (c).

Another characteristic of medical images that distinguishes their quality is the degree of intensity distribution throughout the image. The distribution of intensities in medical images is often not homogeneous, a condition commonly known as 'intensity inhomogeneity'. High level of intensity inhomogeneity in medical images will create leakage at object's boundary. Boundary leakage is a problem created by weak or missing edges. Intensity inhomogeneity also creates complex texture in medical images. These problems must be addressed in order to produce accurate boundary segmentation of medical images.

1.3 Problem Description

Current methods of ACM are not able to produce accurate boundary segmentation of multimodality of medical images in the presence of intensity inhomogeneity and noises due to the following issues. First is edge-based ACM methods are sensitive to image noise therefore successful segmentation cannot be achieved due to weak or missing edges. Secondly, region based ACM methods are robust to noise but sensitive to intensity inhomogeneity which leads to over segmentation and local minima problems. Our research work aims to address these problems in order to produce a robust and accurate segmentation method for medical images.

1.4 Aim and Objectives

The aim of this study is to propose a novel method that enhances ACM ability to provide accurate boundary segmentation of medical images even in the presence of high level of noise and intensity inhomogeneity in an image. The following objectives have been formulated to gear the research work towards achieving this aim.

- 1. To develop a Fractional Gaussian algorithm for reducing image noise and preserving edge details.
- 2. To develop the Fractional Sinc Wave ACM method for solving over segmentation problem in medical image with intensity inhomogeneity.
- To develop the Fractional Gaussian Heaviside ACM method for solving the local minima problem to achieve accurate boundary segmentation in the presence of high level of intensity inhomogeneity.
- 4. To test and evaluate the proposed algorithm by measuring the accuracy, specificity and the sensitivity using the database of image Clef from the year 2010 to 2012.

1.5 Focus and Scope

This study primarily focuses on medical image segmentation for various modalities including MRI, CT scan, X-ray, microscopic images and ultrasound images. It only considers two dimensional and gray scale medical images. This study used a collection of datasets taken from image clef database from the year 2009 to year 2012. The datasets contain variety of images of human's inner parts that were captured from different angles by various medical imaging modalities. For example, there are MRI images of a heart, CT scan images of a brain, x-rays images of blood vessels, ultrasound images of a uterus, and microscopic images of cells. The purpose of using medical images of various anatomical

structures in different modalities is to enable this study to formulate an improved and robust technique that can successfully segment medical images, regardless of modalities and anatomical structures.

In regards to technique being used to segment medical images, ACM appears to be the most popular. Therefore this research work focuses on investigating the strengths and weaknesses of the key methods originated from the ACM technique and explore the potential of incorporating nonlinear mathematical concept into ACM method to improve segmentation outcome.

1.6 Research Questions

In accomplishing the stipulated research aim and objectives, the following research questions have been formulated:

- 1 Does smoothing technique contribute to a good segmentation outcome in ACM method?
 - a. Between linear diffusion and nonlinear diffusion functions, which function leads to an improved smoothness of a medical images?
 - b. Does the collaboration between nonlinear diffusion function and Gaussian smoothing lead to a better classification of inhomogeneous object in a region?
- 2. Does the collaboration between fractional calculus and sinc wave method contribute to an improve segmentation outcome in the presence of noise and intensity inhomogeneity?
 - a. Does the sinc wave method contribute to the dynamic movement of a contour in ACM?

- b. Does the fractional calculus with ACM contribute to accurate boundary segmentation?
- 3. Does the introduction of FGK with adaptive window mechanism contribute to a better classification of a region with homogeneous objects.
 - a. Does the introduction of FDH in ACM able to deliver accurate boundary segmentation of a medical image with high level of intensity inhomogeneity?
 - b. Does the benchmarking process based on human visual interpretation depict the differences among the segmentation results.
- 4. Does the outcome of the quantitative evaluation aligned with the visual interpretation outcome.

1.7 Research Methodology

Literature Investigation: Analysis and studies have been performed on various types of medical image modalities. Interviews and observations with expert doctors and radiologist have been conducted in the early stage of the research for understanding the structure, texture and interpretation of medical images. Previous methods of ACM were thoroughly studied and reviewed. Various algorithms in image segmentation were examined and experimented on various medical image modalities and anatomical structures. Observations and studies were established to analyze which methods of ACM work best on which types of medical image modalities. Based the review of the literature, research issues and problems were identified and formulated accordingly.

Design and Development: The frameworks of the proposed image segmentation methods were designed to enhance the ability of the existing ACM methods to segment medical images. Specifically, three methods are designed to address issues associated with medical images. First method is a semi-automated method. It is developed to explore the performance of mathematical morphology technique in solving the boundary leakage problem in an image. The second and third methods offer automated image segmentation process, and are designed based on nonlinear concept of fractional calculus. The second method implements the Fractional Sinc Wave method that is generalized from fractional calculus with the aim to reduce the over segmentation problem and improve segmentation outcome. However, the method cannot accurately segment medical images that are affected with high level of intensity inhomogeneity problem. To address this problem the third method is proposed and it is known as the Fractional Gaussian Heaviside. The development of the three proposed methods is executed using MatlabR(2008b) on a 2.5 GHz Intel Processor i5.

Experiment: Experiments were carried out with each of the proposed methods using several types of medical image modalities. The first experiment was conducted on the first proposed method to evaluate the strength of mathematical morphology in joining gaps along the object boundary. The second experiment was conducted on the proposed Fractional Sinc Wave ACM method to measure the effectiveness of the method in reducing over segmentation problem and improving segmentation outcome. The last experiment was conducted on the proposed Fractional Gaussian Heaviside ACM method to measure the accuracy of its boundary segmentation method on medical images of various modalities and

anatomical structures, particularly those images that are affected with high level of noise and intensity inhomogeneity.

Evaluation: The feasibility of the proposed methods is evaluated using three approaches. First is by using visual interpretation based on human perception. The evaluation results are then verified using a quantitative approach. Finally the performance of the proposed methods are compared and benchmarked against other baseline ACM methods.

1.8 Research Contributions

The specific contributions identified in the thesis are as follows:

- 1. The incorporation of nonlinear function with Gaussian filter gives good enhancement outcome by preserving the image details, and removing image noise.
- 2. The proposed implementation of sinc wave method with fractional calculus gives rapid movement and flexible bending capability of contours toward objects in an image.
- The application of Fractional Sinc Wave method via ACM improves segmentation outcome of medical images with various modalities and anatomical structures while reducing the over segmentation problem.
- 4. The introduction of Adaptive Fractional Gaussian Kernel into ACM offers an excellent image enhancement outcome, in which objects in a region are now classified with homogeneous intensity.
- 5. The proposed Fractional Differentiate Heaviside provides the nonlinear protecting capability of the image details, and has the ability to extract accurate local image information thus solve the local minima problem can be solved.

6. The collaboration between Adaptive Fractional Gaussian Kernel and Fractional Differentiate Heaviside via local ACM produces a new ACM's method, named as the Fractional Gaussian Heaviside method that has the capability to provide accurate boundary segmentation on various types of medical images in spite of the visual problems such as weak edges and intensity inhomogeneity.

1.9 Organization of the Thesis

This thesis presents three methods of medical image segmentation using ACM method to address pertinent issues in medical images such as weak edges and intensity inhomogeneity. Details for the methods are discussed in each chapter 4, 5 and 6. Overall, this thesis contains seven chapters. The outlines of each chapter are described below.

Chapter 2 presents survey results on ACM based methods in segmenting images particularly medical images. The survey reveals the strengths and weaknesses found in each of the methods. The chapter also provides intensive literature coverage on both edge-based, region-based, and hybrid ACM with sufficient highlights on their advantages and disadvantages in segmenting medical images. The chapter ends with summaries on the ability of each classification methods of ACM in producing a satisfactory segmentation result on medical images with various characteristics and modalities.

Chapter 3 gives the overview on the methodology of the three proposed methods that are able to improve the performance of the existing ACM methods in segmenting more challenging medical images such as those with severe boundary leakage and intensity inhomogeneity problems. The chapter provides the descriptions on the framework and flow process of the three methods. Chapter 3 ends with the summary of each proposed methods highlighting their relationship.

Chapter 4 introduces the first proposed method that improves ACM segmentation method using morphological technique. The technique uses mathematical approach to fill up gaps or holes in an image edges to overcome the leakage problems found at the boundary of meaningful object to be segmented. The implementation of the proposed method enables a better understanding of the process used in the morphological technique when joining gaps at an image boundary.

Chapter 5 describes the proposed method that uses Fractional Sinc Wave ACM method to enhance ACM capability for automatically segmenting medical images in the presence of high level of noise and intensity inhomogeneity. The chapter explains the strength of FSW ACM method in giving the contour the capability of flexible bending and rapid movement toward an object to be segmented. Relevant equations and procedures involved in the development of the method are also discussed. The chapter also describes the experiments conducted on four medical image modalities for measuring the performance of the proposed method against other baseline ACM methods in segmenting medical images with intensity inhomogeneity problem, and the experimental results are reported accordingly. A benchmarking process is also conducted with another two methods of ACM. To support the benchmarking process, quantitative evaluation is conducted which is based on accuracy metric to measure the percentage of accuracy of the method. Chapter 6 proposes a new ACM method that uses fractional calculus to achieve accurate boundary segmentation even though for image with severe intensity inhomogeneity problems. The method applies adaptive fractional function in its Gaussian kernel for image enhancement, and the Heaviside function for local image information extraction. Details about the design and implementation process of the proposed method are thoroughly explained in this chapter. Several experiments have been conducted to demonstrate the effectiveness of the method against other baseline ACM methods. Benchmarking process and quantitative evaluation is conducted to measure the accuracy of the segmentation methods.

Chapter 7 concludes the research work and provides suggestions for future work. It mainly highlights the accomplishment of the research aim and objectives. The chapter also gives some insights on the future direction for the research work.
CHAPTER TWO SURVEY METHODS OF MEDICAL IMAGE SEGMENTATION

This chapter surveys methods of image segmentation including methods for segmenting medical images. The chapter begins by reviewing the earliest segmentation methods to the most recent ones. Section 2.2 describes methods on medical image segmentation including those common methods of Active Contour Model. The smoothing technique of Gaussian which been used in ACM is also discussed in Section 2.3. Section 2.4 briefly describes about nonlinear diffusion function, an alternative to nonlinear mathematical concept for segmentation. This chapter ends by summarizing the findings from the survey.

2.1 Image Segmentation Methods

In past decades, a great variety of segmentation methods has been proposed. Most of the segmentation methods in the early days begin with the segmentation on synthetics images such as buildings, geometrical objects and so forth. Image segmentation later evolves to solve a more challenging problem such as medical images (Pham, Xu & Prince, 2000). Some of the earliest and common methods in image segmentation includes threshold based methods, edge-based methods, region-based methods, watershed transformation and energy based methods. The following sub-section describes several methods of image segmentation.

2.1.1 Threshold-based method

Threshold-based method is among the earliest method in image segmentation that acts as a tool to separate objects from the background. Some examples of thresholding applications are document image analysis where thresholding is used to extract the printed characters, logos, lines, colors and other elements of the image (Chen & Leung, 2004; Yan, Zhang, & Kube, 2005; Raju & Neelima, 2012). Threshold-based method is the simplest segmentation method. It transforms gray-scale image into binary format to obtain a threshold value in an image. Once the image is transformed into binary format, the image will be segmented into two segments, with values 0 and 1 respectively. This method is very useful to segment an object which only has two regions with homogeneous intensity (Orlando & Seara, 2002). In other words, both the object and background has distinctive intensities (Al-Amri, Kalyankar, & Khamitkar, 2010). However, threshold method is not suitable for segmenting images with high level of noise (Yan, Zhang, & Kube, 2005). To address this problem the method is often been used with other algorithm such as Otsu algorithm, entropy method and K-means clustering. Later, edge detection technique is introduced for segmenting specific objects in an image.

2.1.2 Edge-detection Technique

Edge-detection technique is introduced to overcome problems created by previous methods (Patil & Deore, 2013). Edges are local changes in the image intensity and it typically occurs on the boundaries between two regions (Dhankhar & Sahu, 2013; Senthilkumaran & Rajesh, 2009). It is used to identify object boundaries in an image where it focuses on the localization of significant variations of the grey level in the image.

Generally, edge detection process filters out unimportant information while preserving the structural image details (Dhankhar & Sahu, 2013; Lakshmi & Sankaranarayanan, 2010). In terms of image segmentation, edge detection works well with images that have good contrast between regions. The edge-based segmentation method does not produce successful outcome on images that are low in gradient or contain missing edges at the object's boundary. This is because the method only depends on the visibility of edges in an image. Both the threshold-based and edge based methods aim to extract boundaries of meaningful objects in an image, therefore image with unclear objects boundaries will not be successfully segmented by this method. This includes images that contain lots of noise. To solve this problem, region based segmentation method is introduced.

2.1.3 Region-based method

This method operates iteratively by grouping together neighboring pixels that have similar values, and splitting groups of pixels with non-similar values (Gu et al., 2009; Saini & Sethi, 2013; Qing & Yizhou, 2003). Region-based segmentation method has been identified to be better than the edge-based method because it covers more pixels value than the edge-based method (Rai & Nair, 2010; Saini & Sethi, 2013). This is because, region-based method uses pixel's intensity and image's gradient in its segmentation process. In the contrary, the edge-based method only uses image's gradient for segmenting an image.

The first region-based method was known as region growing method where the method uses seed pixels as input to accumulate and grow similar pixels in an image in iterative cycles (Kamdi & Krishna, 2011, Muhammad et al., 2012). The choice of seed will

determine the segmentation outcome. However, this method is sensitive to image noise where noise in the image can cause the seeds to be placed incorrectly. This issue has led to the modification of the algorithm which does not require explicit seeds.

Watershed region-based method was later developed where it does not require an explicit seeds. The basic idea of watershed method is to create a basin-like landform defined by highpoints and ridgelines that descend into lower elevations and stream valleys. The idea was introduced by Beucher & Meyer (1993) by placing a water source in each regional minimum in the relief, to flood the entire relief from sources, and build barriers when different water sources meet. Normally, watershed segmentation is applied to the gradient of an image, rather than to the image itself (Salman, 2006; Roerdink & Meijster, 2000). The aim of the watershed transform is to find the 'watershed lines' in an image in order to separate the distinct regions. Although watershed transform is robust to image noise but it provides many over segmentation regions because the method is sensitive to intensity inhomogeneity interface. Over segmentation happens when objects being segmented are again segmented into sub-regions. Research in image segmentation continued to develop another type of image segmentation method that is based on curve propagation or evolution.

2.1.4 Curve evolution-based method

Segmentation methods that are based on curve evolution are developed to address problems associated with the edge-based and region-based segmentation methods. This technique depends on an energy model which is defined by partial differential equation (PDE). PDE, in mathematics is a differential equation that contains multivariable functions and their partial derivatives. PDEs are used to formulate problem involving functions of several variables and can be used to create a relevant computer model (Tsai & Yezzi, 2001).

Among the popular techniques used in the PDE's category is the used of curve evolution with numerous applications for object extraction, object tracking and stereo reconstruction (Paragios, 2006, Maragos, 1996). The central idea of the curve's propagation is to evolve an initial curve towards an object. In image segmentation, the initial curve is placed on an image where the curve will evolve towards the object boundary. One of the famous mathematical equations on curve evolution was proposed by Osher and Sethian, and it is known as level set method (LSM) (Osher & Sethian, 1988). This method has been embedded in numerous segmentation methods for a more dynamic and smooth curve evolution outcome. In LSM, the evolving contour is represented using a signed function, where its zero level corresponds to the actual contour (Osher & Sethian, 1988; Osher & Fedkiw, 2001). The LSM encodes numerous advantages: it is implicit, parameter free, provides a direct way to estimate the geometric properties of the evolving structure and able to segment multiple regions in an image. Based on the LSM, many methods arose and this includes Active Contour Model which was later known to have the potential in medical image segmentation. Detail on LSM is discussed in Section 2.2.2. The following section explores in detail methods of ACM which are derived from partial differential method.

2.2 Medical Image Segmentation Methods

The earliest methods of segmentation are mainly focused on segmentation of images with low level of noise, such as synthetic images. Image segmentation on medical images is not suitable by those methods, because medical images are categorized as low quality images. Therefore segmentation methods such as edge detection are not applicable to segment objects in medical image. The introduction of ACM by Kass, Witkin & Terpozoulus (1988) provides improved performance in extracting objects from medical images. The initial ACM was then refined resulting in many methods and each was introduced to address some pertinent segmentation problems and challenges posed by various types of medical images. The first ACM was developed in 1988 and was named as Snake model. Detail on ACM is discussed in the following sub sections.

2.2.1 Active Contour Model

Inspired by the edge detection technique, Snake model was first developed and introduced by Kass, Witkin & Terpozoulus and gained popularity since then (Kass, Witkin & Terpozoulus, 1988). However, the idea of the snake is derived from the development of deformable models introduced by Terpozoulus in the late eighties. The idea behind the model is to deform a contour for extracting image features (Terzopoulos & Fleischer, 1988; McInerney & Terzopoulos, 1996). In ACM, first the deformable contour is placed on an image and its position is depends whether it is edge-based or region-based ACM. ACM is classified as edge-based ACM and region-based ACM (Lei et al., 2008). For edgebased ACM, the contour placement is dependent on the image and can only be at one position at a time, whereas for region-based ACM the contour placement is independent and it can be more than one position at a time. Next, the contour starts to move based on the Snake's movement with the ability to extract objects' boundaries in an image through the evolution of contour(s) (Kass, Witkin & Terpozoulus, 1988; Xu & Prince, 1998). The evolution of the contour depends on the external and internal energies of the Snake model which acts as pull and push actions. Once the contour reaches the object boundary, the movement of the snake must minimize the energy provided by the model (Kass, Witkin & Terpozoulus, 1988). Once the energy is minimized, the contour movement stops resulting in the visibility of contour along the object boundary. In stopping the contour at the correct position, the edge-based methods use the edge-detector based stopping function whereas, in the region-based ACM the stopping term is based on the global image information (Li et al., 2005). In understanding how ACM works, Section 2.2.1.1 depicts the design algorithm of the first ACM method namely the Snake model.

2.2.1.1 The concept of the Snake model

The first ACM known as snake implemented the edge-based concept and minimized its contour by iterative gradient descent. This means the contour of the Snake model is highly depending on the gradient in the image without considering the intensity of the image (Kass, Witkin, Terpozoulus, 1988). Snake flexibly moves to locate sharp image intensity variations by deforming a contour C toward the edge of an object's boundary in iterative cycles until it completely 'shrink-wraps' around the boundary of the object. Snake is the

energy minimizing based on the sum of two energies which are internal and external energy as shown in equation (2.1):

$$E_{snake} = E_{internal} + E_{external}$$
(2.1)

The external energy evolves a contour C toward the boundary of the object whereas the internal energy acts to smooth and bend the contour toward the object to be segmented. The internal energy is the total sum of elastic and bending energies. The elastic energy is treated as elastic rubber band whereby it discourages stretching by introducing tension. On the other hand, the bending energy aims to smooth out the contour. The complete equation of the internal energy is given by:

$$E_{\text{int}} = E_{\text{elastic}} + E_{\text{bending}} = \int_{s} \frac{1}{2} (\alpha |v_{s}|^{2} + \beta |v_{ss}|^{2}) ds$$
(2.2)

where α and β are weighting parameters that control the Snake's tension and rigidity, respectively. In the equation above, V_s is referring to a set of V points where s = 0, ..., s - 1. The external energy generated by processing an image I(x, y) is used to drive a Snake towards lines (regions) and edges in an image. This means, the image forces guided by the internal energy push the Snakes toward the image features such as lines and edges. On the other hand the external energy is responsible to put the Snake at a point nearby the gradient in an image. As Snake represent the edge-based ACM, the external energy will be extracted at the high gradient in an image in order to extract the boundary of the target object. This is how Snake wraps around the object boundary. The equation of the external energy is given by:

$$\int_{0}^{1} f^{2}(I_{0}(C)) ds$$

(2.3)

where the f function presents the edge-detection. The function f is given by:

$$g|\nabla I(x,y)|) = \frac{1}{1+|\nabla G_{\sigma}(x,y) \otimes I(x,y)|^2}$$
(2.4)

where g represents the stopping function for terminating the contours at edges and $G_{\sigma}(x, y) \otimes I(x, y)$ is the smoother version of I(x, y). The Gaussian function G_{σ} with the standard deviation σ , $I(x, y) * G_{\sigma}$ is a smoothed version of the original image I(x, y). Details on Gaussian filter will be discussed in Section 2.3. When a contour evolves closer to the edge, the gradient value is at the maximum level and the edge detector function approaches close to zero. At the edge, the evolved contour attains a zero speed and stop at target edge. The complete snake equation is given as follows:

$$E_{snake} = \int_{s} \frac{1}{2} (\alpha(s) |v_{s}|^{2} + \beta(s) |v_{ss}|^{2}) + E_{image}(v(s)) ds$$
(2.5)

where α and β are the weighting parameters. To understand the bending movement of the Snake model, Figure 2.1 illustrates the contour movement. The Figure 2.1 shows an initial contour and the final contour after the bending force is embedded to the contour. Image on the left side of Figure 2.1 is the initial contour placed on the image. During the evolution of the contour, the contour will bend smoothly by the internal energy towards the object. The bending contour is shown on the right side image in Figure 2.1.



Figure 2.1: On the left is the initial contour and on the right is the final contour with the accomplishment of bending energy.

There are several drawbacks of Snake model. For instance, it is very sensitive with image noise and contains small capture range. For example, consider image U as shown in Figure 2.2(a). The small capture range as shown by the arrow forbids Snake to detect concave boundary because the external energy is not attracted to the points at the boundary concavity. This is shown in Figure 2.2 (b) where the contour did not move toward the concavity area of the object 'U'.



Figure 2.2: Illustration on U shape. (a) is the U shape with the concave problem, (b) is the outcome from Snake model and (c) is the outcome from Gradient Vector Flow

To overcome the concavity problem created by the Snake model, Xu & Prince (1997) introduced the improved Snake model called as Gradient Vector Flow (GVF). This method introduced the third type of energy besides the internal and external energy introduced by the Snake model. By introducing the third energy, the contour is now able to move through a concave as shown in Figure 2.2 (c).

However, both models still facing the problem of topological changes where more than two objects in an image could not be detected or segmented. Snake provides a fast numerical algorithm but in the case of closed curves, it is not able to segment more than one object in an image or when the topology of the image changes. To overcome the limitation of the changes of topology, Osher and Sethian (1988) have proposed the powerful level set method (LSM) in year 1988. In LSM, the contour C is implicitly represented by a function of higher dimension called the level set function. After the introduction of LSM, almost all development of subsequent methods of ACM are based on LSM. Detail regarding this method is discussed in the following section.

2.2.2 Level Set Method

Level set method (LSM) is a powerful mathematical function that has been used in many applications from physics to graphics, image processing, computer vision, control, and many others (Osher & Sethian, 1988; Malladi, Sethian, & Vemuri, 1995). This section discusses the application of the level set method in active contour model. As mentioned earlier, the Snake model has contour that is not dynamic enough to segment more than two objects in an image. Level set function provides an efficient and stable algorithm to solve this problem. Interface created by the level set method is more dynamic wherein it allows a contour to move at sharp corners, break apart and merge again when necessary.

The basic idea of level set method is to place a closed contour on the surface and allow the contour to move perpendicular to itself at a prescribed speed (Osher & Sethian, 1987; Osher & Paragios, 2003). Level set method is frequently used in image segmentation through propagation of a contour. Since its introduction, the level set function has been

implemented in the subsequent methods of the active contour model such as geometric/geodesic active contour, active contour model without re-initialization, and active contour model without gradient (Paragios & Deriche, 2002).

Specifically, level set method works in a given closed contour C. The function becomes zero when the pixel is on the contour itself, otherwise the pixels are distributed outside or inside the contour C where it is known as minimum distance from the pixel to the contour C. If the pixels are distributed outside the contour C, the distance is regarded as negative value. On the other hand if the pixels are distributed inside the contour C, the distance is regarded as positive value. The level set function ϕ of the closed front C is defined as:

$$\phi(x,y) = \pm d((x,y),C)$$
(2.6)

where d((x, y), C) is the distance from point (x, y) to the contour C. The plus and minus symbol of d are chosen if the point (x, y) is inside or outside of C. Apart from solving the topological changes, level set method also has the numerical approximation advantage whereby it can be used either in a fixed discrete grid of the spatial domain or temporal derivatives. In additions, level set method can be extended to any dimension. However in two dimensional space, the level set method represents a closed curve η (such as the shape boundary) using an auxiliary function, called the level set function. η is represented as the zero level set ϕ by the equation:

$$\eta = \{ (x, y) | \phi(x, y) = 0 \}$$

(2.7)

The level set method manipulates η implicitly through the function ϕ . This function ϕ is assumed to take positive values inside the region delimited by the curve η and negative values when outside the region. In general if the curve η moves in the normal direction with a speed \boldsymbol{v} , then the level set function ϕ satisfies the level set equation:

$$\frac{\partial \phi}{\partial t} = v | \nabla \phi |.$$

(2.8)

where |.| is the Euclidean distance from the object to the contour and t is representing the time. Level set method is applied on both edge-based but region-based methods of ACM which later extend to hybrid methods of ACM. Therefore it is important to understand how does level set method works. In the subsequent section the classification of ACM, the edge-based and region-based ACM methods are described in detail.

2.2.3 Edge-Based Active Contour Model

Since the development of Snake model, researchers tend to develop methods with various functions to solve different characteristics found in medical image modalities. After the development of Snake and GVF method, the first ACM that embeds the LSM is named as Geometric ACM (GAC). This method was proposed by Caselles, Kimmel and Sapiro (1993). Generally, the method is based on the theory of contour evolution of the Snake model and the geometric flow of GAC. The method proposed a new energy that utilized the localization property and energy minimization simultaneously.

The idea behind GAC is the incorporation of the minimal distance calculation into its equation, and this calculation is derived from the image (Caselles et al., 1993, Caselles, Kimmel & Sapiro, 1997). Besides, GAC method also implemented a technique called re-

initialization. Re-initialization technique is a technique for periodically re-initializing the level set function to a signed distance function during the contour evolution. Its goal is to maintain the contour stability and to ensure potential results. The energy proposed in GAC method is given by:

$$\varepsilon^{GAC} = \int_0^1 f(|\nabla I_0(C(p))C_p|dp = \int_0^{L(C)} f(|\nabla I_0(C(s))|)ds$$
(2.9)

where *ds* in the Equation (2.9) is the Euclidean element of length and L(C) is the Euclidean length of the curve C defined by $L(C) = \int_0^1 |C_p| dp = \int_0^{L(C)} ds$. The *ds* function is the new length proposed by geometric ACM and is obtained from the edge-detecting function *f* that was discussed in Equation (2.4). The direction for which the GAC curve decrease will lead to the given minimization flow of:

$$\frac{\partial c}{\partial t} = \kappa f - (\nabla f, \mathcal{N}))\mathcal{N}$$
(2.10)

where \mathcal{N} is the unit normal to the contour C and κ is the mean curvature. The first term is the smooth function, also called as contour shortening flow, weighted by the edge detecting function $f(\mathbf{x})$. The term imposes smoothness constraints on the contour and the constant κ makes the detection of non-convex objects easier, increases the speed of convergence. The strength of GAC is derived from its geometrical function. However as its distance measurement is based on the explicit Euler scheme, thus limits the stability in the model. As a result, GAC does not manage to segment medical images that are affected with high level of noise due to weak or missing edges. Although GAC has several disadvantages but the method has been proven able to segment certain types of medical images (Airouche, Bentabet, & Zelmat, 2009; Xu & Prince, 1998). Therefore, the subsequent edge-based segmentation methods are primarily focused on refining GAC to address its limitation. After the development of GAC, Caselles again proposed a method called Geodesic Active Contour (1997) which inherits the advantages of GAC. Geodesic Active Contour combines the strength of the Snakes model and GAC for improved segmentation outcome. However, its limitation is that it could not successfully segment an object which has large gaps at its boundary.

One of the methods that yield good potential to overcome GAC limitations is the Active Contour Model without re-initialization developed by Chumning Li (2005). It is an extension of Snake and GAC models. The method was designed to speed up the segmentation process by eliminating the re-initialization technique which is considered as the main idea behind this method. Re-initialization technique has been extensively used as a numerical application in LSM model. The standard re-initialization technique is to solve the following re-initialization equation:

$$\frac{\partial \phi}{\partial t} = sign\left(\phi_0\right)\left(1 - |\nabla \phi|\right)$$
(2.11)

where ϕ_0 is the function to be re-initialized, and sign ϕ is the sign function. So far, this technique has been used extensively for maintaining stable curve evolution and to ensure desirable results. However, some opinions beliefs that the re-initialization technique may move the function ϕ incorrectly and lead to incorrect results in segmentation. Due to some facts, the re-initialization technique was eliminated in Li's method (Li et al., 2005; Li et al.,

2009). In Li's method, in order to maintain the level set function as an approximate signed distance function during the contour evolution, Li has proposed the following integral:

$$u\wp(\phi) = \int \frac{1}{2} \left(|\nabla \phi| - 1 \right)^2 dx dy$$
(2.12)

where $u_{\mathscr{O}}(\phi)$ is the new proposed distance that eliminates the re-initialization technique in the previous level set method. The complete equation for active contour model without reinitialization is as follows:

$$\varepsilon(\phi) = u \wp(\phi) + \mathcal{E}_{\mathfrak{m}}(\phi)$$
(2.13)

where $\mathcal{E}_{m}(\phi)$ is a certain energy that would drive the motion of the zero level curve of (ϕ) . However, as this method falls under the classification of edge-based model, it inherits the weaknesses of the model such as sensitive to image noise and the contour placement is dependent and not flexible. This is illustrated in Figure 2.3 where the initial contour could not move exactly at the boundary of the object when the image was affected with high level of noise.

Figure 2.3(a) is a synthetic image with less noise, and 'A' and 'S' are the objects to be segmented. Both objects have different intensity from the background (bright intensity). However, both alphabets have anti-alising effect obtained from digital processing along their boundaries resulting in unclear edges and numerous existences of local minima along the boundary. These conditions make segmentation process difficult because they forbid a contour from getting to the exact boundary of the alphabets. Similar segmentation outcome of a CT scan image of brain is shown in Figure 2.3(b). The intensity in the interior part of the brain is non-homogeneous which hinders this method to segment the image successful

particularly in the brain's inner parts. Finally, Figure 2.3(c) represents a MRI image of a heart. The image has high level of noise and intensity inhomogeneity. Both conditions make it impossible for any edge-based approach to segment the image successfully. These experimental results demonstrate that edge-based approach is unable to successfully segment low quality medical images.



Figure 2.3: Experiments and results on medical images using active contour model without re-initialization. (a) is the synthetic image, (b) is the CT scan image of brain and (c) is the MRI image of heart.

To conclude, there are several drawbacks of edge-based ACM segmentation especially when dealing with medical images. First of all, edge-based ACM is sensitive to image noise. Noise is common attribute in any medical images. In some medical images such as ultrasound, the level of noise is very high resulting in blurred images and objects' boundaries is difficult to be seen. Secondly, the placement of contour in an image is dependent and not flexible because it can only be placed once in an image, therefore the contour may located far from the object boundary. Lastly, as the level set formulation of the final contours are always closed contour, the inner objects will not segmented. Section 2.2.4 discusses the region-based ACM methods that are able to the solve some of these problems.

2.2.4 Region-Based Active Contour Model

Apart from noise that degrades the low quality of medical images, distribution of intensity that is not homogeneous in the image is also an important issue to be solved. Medical images with homogeneous regions and less noise can be easily segmented using the edge-based ACM. Unfortunately there are only a handful of them. The fact is, many medical images hardly have any regions with homogeneous intensity (Zhang et al., 2013). The condition leads to complex image texture with hardly any apparent anatomical structure can be seen. As a consequence, any possible abnormality in the image could be missed and the image cannot be segmented due to very weak or missing edges. Due to these weaknesses of the edge-based method, region-based curve evolution technique is introduced.

The first known region-based method was developed by Mumford-Shah (1989) that approximates an image into a piecewise smooth representation. The concept forms the basis of various region statistics based segmentation which allows image segmentation without depending only on the image's gradient. Influenced by Mumford-Shah method, Chan-Vese (C-V) has developed a mean-curvature flow in which the mean intensity inside and outside the curve are used as a smooth approximation function of the image (Chan and Vese, 2001).

C-V's ACM is a region-based method that is not sensitive to image noise (Zhang et al., 2010). The method which is named as 'Active Contour Model Without Edges' permits the movement of a contour either on gradient or without gradient. The method becomes a popular method among researcher as it shows great potential in segmenting noisy medical images. If a medical image does not have strong gradient due to noise, the method moves

its contour based on pixels intensity in a region to extract object's boundary in the image. The idea of C-V method is based on the assumption that an object has distinctive intensity from its background and contains homogenous intensity. C-V method considers only two regions, Ω_{in} and Ω_{out} and both regions have homogeneous intensity. In general, the object to be segmented is represented by the regions with value of u_0^1 and let denote this boundary by C. Then the method has $u_o \approx u_0^1$ inside the boundary and $u_o \approx u_0^o$ outside the boundary. Then the following equation is given as the fitting energy of the method.

$$\mathcal{F}(C, c_1, c_2) = \mu. length(C) + v. area(inside(C)) + \lambda_1 \int ||u - c_1|^2 dx dy + \lambda_2 \int ||u - c_2|^2 dx dy$$

$$u - c_2 ||u - c_2|^2 dx dy$$

$$(2.14)$$

Here, let C be the evolving curve in which c_1 and c_2 are two constants representing the average of u_0 'inside' and 'outside' curve C. On the other hand, $\mu > 0, \nu > 0, \lambda_1, \lambda_2 > 0$ are fixed parameters. When these parameters are fixed, μ controls the smoothness of the zero level set, ν increases the propagation speed and λ_1, λ_2 control the image data force inside and outside the contour, respectively. In order to minimize the fitting energy, C-V add some regularizing terms, in this situation the length of C and the area inside C as represented by the first two terms in the equation (2.14). With the level set function, the model assumed that the object and the background have homogeneous intensity as given in the equation below.

$$C = \{x \in \Omega : \phi(x) = 0\},\$$

inside(C) = $\{x \in \Omega : \phi(x) > 0\},\$
outside(C) = $\{x \in \Omega : \phi(x) < 0\}.\$

(2.15)



Figure 2.4: Experiments and results on synthetic image of alphabets (a), CT scan image of brain (b) and MRI image of heart (c) using C-V method.

Figure 2.4 demonstrates the outcome of the C-V method when segmenting medical images. The experimental results on three different types of images using C-V method are shown in Figure 2.4. Figure 2.4 (a) is a synthetic image that contains several alphabets. The alphabets have brighter intensity than the background, in accordance with the assumption made by the method. Unlike the edge based method, this region based method successfully extracts the boundary of all the alphabets. Figure 2.4 (b) and (c) display the segmentation outcome on CT scan image of a brain and MRI image of a heart. In (b), the outer part of the brain contains different levels of intensity compared to its outer part. However, the method could successfully segment both the outer and inner part of the brain.

The success of the C-V method in Figure 2.4 is influenced by the independent contour placement that allows the contour to be near to the object boundaries. In (c), the MRI image of heart has intensity inhomogeneity and complex texture. The texture becomes complex due to the creation of many small regions with different levels of intensity throughout a

region to be segmented. As the model works on the assumption that both the inside and the outside of region C must have homogeneous intensity, it produces over segmentation problem when attempting to segment image with intensity inhomogeneity. Intensity inhomogeneity occurs in many medical image modalities including MRI, CT scan, x-rays and ultrasound as shown in Figure 2.5. Figure 2.5 (a) is the x-ray image of blood vessels, Figure 2.5(b) is the MRI image of a heart and Figure 2.5 (c) shows the microscopic image of cells. Due to the presence of intensity inhomogeneity in these images, segmentation using the region-based ACM method produces over segmentation problem, as shown in Figure 2.5(d), Figure 2.5(e) and Figure 2.5(f).



Figure 2.5: Examples of medical images with intensity inhomogeneity problem. In (a) is the x-ray image of blood vessels, (b) is the image of MRI heart and in (c) is the image of microscopic of cells.

In summary, the edge-based and the region-based ACM methods have their own strengths and weaknesses. Table 2.1 illustrates the strengths and weaknesses of methods of ACM.

Main characteristics of ACM	 Energy based minimization Contour initialization with Gaussian smoothing Stopping function 						
Types of ACM methods	Characteristics	Chronology of methods	Strengths	Weaknesses			
Edge-based ACM	 Based on local properties in the image. Use edge-detector based stopping function. 	Snake, GVF, GAC.	 Better segmentation capability than edge detection technique Able to segment images with clear and high level of gradient. 	 Sensitive to image noise Trap at the local minima along object boundary. 			
Region-based ACM	 Based on global properties in the image. Based on inside and outside regions. Use the stopping function to terminate contour's movement. 	ACM without edges (CV), Piecewise constant.	 Provide robust segmentation. Able to segment noisy images. Potential in medical image segmentation 	• Sensitive to images with high level of intensity inhomogeneity.			

 Table 2.1: Strengths and weaknesses of edge-based and region-based ACM.

As the region-based methods process only the global property of an image, they are unable to successfully segment medical images with intensity inhomogeneity problem. In this situation, a combination on both edge-based and region-based would be a better solution. In the next section, the hybrid methods of ACM are discussed.

2.2.5 Hybrid Model of Active Contours

Previously, ACM methods are either classified as edge-based or region-based. Both of the classifications utilized the energy minimization concept in its contour evolution. Edge-based segmentation methods provide a better precision along the object boundary provided that the image does not suffer from high level of noises. On the other hand, region-based methods are less susceptible to noises as it highly utilizes the global properties of an image, but it will not work successfully if the image contains problem of intensity inhomogeneity.

Recent trend in medical image segmentation research shows the growing interests to apply the combination of both classifications of active contours models to improve segmentation outcome (Huang & Zeng, 2015). Some methods start with the edge-based approach at the beginning and proceed to region-based approach in their development while others use the region-based with the integration of local properties of the edge-based active contour. Paragios et al. (1997) combined a probability based active region model with the classical edge-based model, and Chakraborty et al. (1996) developed a game-theory based approach to combine region and edge-based models in an attempt to exploit the benefit of both approaches.

Shawn Lankton (2008) conducted experiments that enabled region-based energy to be localized in a fully variational manner. His work significantly improved the accuracy of heterogeneous image segmentation. Zhang et al. (2010) proposed an ACM with selective local or global in his implementation which is based on LSM. The method improves the LSM by avoiding the calculation of signed distance function and re-initialization. The method allows the segmentation process to take place by using the local or global selection.

However, if the selection is based on global, it create the over segmentation problem when dealing with images that contains high level of intensity inhomogeneity. In the later trend, many region-based ACM applied the localization strategy in achieving accurate segmentation by embedding the local image information. Some of the known methods are Local Binary Fitting Energy (LBF), Local Image Fitting Energy (LIF), Local intensity Clustering (LIC) and many more. Brief description on these methods is presented in Chapter 6.

In summary, generally the hybrid ACM that combines both local and global properties of ACM shows good potential in medical image segmentation. Since then, many methods of ACM move to the combination of local and global ACM in providing a successful outcome of segmentation. Table 2.2 provides some chronologies of hybrid ACM with its capability in segmenting various types of medical images.

Methods of ACM normally used the smoothing technique called Gaussian filter. It is used to support the smooth movement of the contour toward the object in the image. Therefore, in the next section we present the Gaussian filter as the smoothing technique used in most ACM methods.

Hybrid methods of ACM	Objectives	Findings	Drawbacks	Medical Imaging	Anatomical structure
Local Binary Fitting Energy (LBF)	Proposed a region-based ACM that utilized the local information in local regions.	Able to segment images with the presents of intensity inhomogeneity.	The method ignore the region variance information that lead to inaccurate segmentation.	MRI	Blood vessels and brain images
Local Image Fitting Energy (LIF)	A novel method based on Gaussian filtering for variational level set.	Able to segment images with intensity inhomogeneity.	The method highly utilized the local properties and did not consider the global properties that lead to inaccurate segmentation.	MRI	Blood vessels and brain images
Local Gaussian Distributi on Fitting Energy (LGD)	A novel method that defined the local image intensities as Gaussian distributions which is based on mean and variance.	Enable in segmenting medical images with noisy and texture images.	The used of local means and variance to control the noise level and intensity inhomogeneity trapped a contour from moving further towards object in the image.	MRI, ultrasound	Blood vessels, brain images and heart, liver.
Local Intensity Clusterin g (LIC)	A novel region-based ACM that derives the local intensity clustering properties in an image properties.	Enable in segmenting medical images within intensity inhomogeneity with robust to initialization.	The method did not consider the clustering variance that lead to inaccurate segmentation.	MRI, CT scan, x-ray, ultrasound	Blood vessels, breast cysts, bones, prostate.

Table 2.2: Several methods of hybrid ACM with it objectives and findings in medical image modalities.

2.3 Smoothing Technique: Gaussian Filtering

As mentioned earlier, pixels intensity in most medical images are non-homogeneous throughout an image. Intensity inhomogeneity in medical images leads to non-smooth texture in the image. Smoothing technique is therefore required to remove noise and other fine-scale structures in an image (Zhang et al., 2010; Li & Acton, 2007; Spann & Nieminen, 1988). One of the best methods for smoothing image texture is called the Gaussian smoothing. This technique is widely used in active contour model. In most ACM's methods, the Gaussian technique uses the concept of linearity diffusion.

The Gaussian smoothing technique is the two-dimensional convolution operator. The idea behind Gaussian filtering technique is achieved by its convolution operator whereby it uses the two-dimensional distribution as its "point-spread" function (Gedraite & Hadad, 2011; Spann & Nieminen, 1988). However, before the convolution is performed, the image which is stored as a collection of discrete pixels is first transformed into a discrete approximation to the Gaussian function. Once a suitable kernel has been calculated then the Gaussian smoothing can be performed using a standard convolution method. The standard equation of Gaussian smoothing technique is given by:

$$G_{\sigma}(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$
(2.16)

where σ is the size of the window or the convolution. The size of the window must be proportional to the image size and normally it depends on the application. In order to smooth the image, the Gaussian smoothing will locate the pixel weight in an image and then determine all the related pixels with similar intensity. In the application of segmentation, the related pixels or the pixel weight can be viewed as the edges or boundary of desired object to be segmented. This means the edges or boundary is enhanced during the Gaussian smoothing process while other unrelated pixels are ignored, as illustrated in Figure 2.6.



Figure 2.6: Graph for Gaussian smoothing technique.

Many works in image processing have been using the Gaussian smoothing as a filter to remove or reduce noise in an image. In most active contour models, Gaussian smoothing technique is also applied for smoothing process during the evolution of the contour towards the boundary of the object to be segmented. However, many methods of ACMs have recently been using Gaussian smoothing to regularize the level set method for stability of the contour during the evolution (see detail in Section 2.5). For example, work by Zhang et al (2010) uses the Gaussian smoothing kernel to regularize the level set function. Work by Li Wang et al. (2009) utilizes the local Gaussian distribution as the fitting energy with difference means and variance in order to control contour movement. Recently, work by Bo et al. (2013) proposes an expression of simple energy function with the fractional order of Gaussian kernel embedded within its region-based geometric active contour. However, as

the Gaussian is based on linear function, the image will become unclear once the parameter is increased with a bigger value.

Most ACM methods that utilize the linear Gaussian filter cannot produce satisfactory segmentation outcome when dealing with medical images that contained high level of intensity inhomogeneity and high level of noise. This is because linear Gaussian will eliminate some unimportant structures that will affect the continuity of the smoothing process. In addition, Gaussian smooth an image across the edge where it only considers the image's gradient is covered but not its local properties. Furthermore, the local image properties in the image are difficult to locate with linear Gaussian as the flux in Gaussian tends to follow one direction.

The solution of linear Gaussian can be overcome by using nonlinear Gaussian. Nonlinear Gaussian smooth an image around the edge to preserve local image details and allows Gaussian's flux to have flexible direction in finding local image properties. Moreover, the nonlinear Gaussian will smooth an image based on the diffused image and not the original one for better smoothing result when compared with linear Gaussian. Further description on the nonlinear function is provided in the following section.

2.4 Nonlinear Diffusion Function

Image smoothing is part of image enhancement process that plays an important role to improve visual appearance of an image as well as facilitate image analysis process. It is essential to smooth an image prior to segmentation process. This section introduces the role of a nonlinear diffusion function in image smoothing process.

Linear function is used to smooth an image in a controlled way and usually it is convolved with Gaussian filter to provide a better smoothing effect (Chad & Karen, 2013). Gaussian filter works directly with image gradients. In Gaussian, enhancing an image is to smooth the image by adjusting or modifying the gradient's levels of the neighboring pixels. Linear Gaussian filter can smooth image texture for improved segmentation outcome. However, linear diffusion can dislocates edges when moving from strong edges to weak edges (Wang, Xu & Wei, 2005). As a consequence the dislocated edges will not represent the right object boundary of the original image (Weickert, 1999; Weickert, 1994; Barenblatt & Vazquez, 2003).

On the other hand, the nonlinear diffusion reduces image noise and enhances the edges without dislocating them (Junmo et al., 2005). Nonlinear diffusion function is one of the image smoothing techniques that are based on the physical notion of diffusion where it can be locally controlled with the diffusion tensor (Catt'e et al., 1992; Erdem, 2012). Diffusion tensor denotes the variety movement of molecules that is able to locate the pixel intensity in solving the problem of intensity inhomogeneity (Weickert, 1998).

There are several advantages of nonlinear diffusion over the linear diffusion. First the noise is smoothed locally within regions defined by object boundaries. Secondly, local edges are enhanced and this provides an advantage when dealing with boundary leakages problem along an object boundary. The nonlinear diffusion function has been widely used over the past decade as the enhancement technique. The first application of the nonlinear concept in image segmentation process is done by Perona & Malik (1990). The following

sub-section discusses the application of nonlinear diffusion with the contour evolution in ACM.

2.4.1 Contour Evolution via Nonlinear Diffusion

Image segmentation can be achieved by approaches based on contour or curve evolution. In image segmentation, contour evolution has been developed into an important tool in computer vision and has been applied to a wide variety of problems such as smoothing of shapes, shape analysis and shape recovery (Zhanbing & Haishen, 2005).

The ACM provides an effective way for segmentation in which objects' boundaries are detected by evolving curves. According to this model, the easiest way to implement the contour evolution is by embedding the initial contour using the LSM method in a surface and let the contour evolve simultaneously. As ACM embedded the powerful LSM in its moving contours, the topological changes in an image are automatically handled by simplifying the data structure (Xu & Prince, 1998). In the region-based ACM which utilizes global information in an image, the stopping term is used to slow down contour evolution when it comes near the object boundaries. In the edge-based ACM where it utilizes local information in an image, the contour becomes dependent on the image's gradient, therefore the models are more sensitive to image noise. The evolution equation that is normally used in most methods of active contour is given by (Li et al, 2007):

$$\frac{\partial \phi}{\partial t} = g(\nabla I) \| \nabla \phi \| (c + \kappa)$$

(2.17)

where ϕ is the embedding surface of contour evolution representing the level set function, ∇ is the gradient and *I* is the given image, and the equation $g(\nabla I)$ is as follows:

$$g(\nabla I) = \frac{1}{1 + \|\nabla (G_{\sigma} * I)\|^2}$$
(2.18)

where the equation above is based on Gaussian and the stopping term is applied in the contour evolution and the mean curvature κ of the level set ϕ is given by:

$$\kappa = div \left(\frac{\nabla \phi}{\|\nabla \phi\|}\right) \tag{2.19}$$

and c in equation (2.17) is a constant speed evolution term. The main idea behind the curve evolution is to apply a smooth technique in the contour evolution and provide a quality noise removal from an image during the segmentation process. There are also several works related to contour evolution that enhance image structures such as edge lines, curve and so forth. For example, works by Wickert (1998) uses the anisotropic diffusion which utilized the tensor diffusivity parameters to enhance the image structure. Works by Shah (1996) developed a common framework for contour evolution, in which a new segmentation functional was developed with a coupled of partial Difference Equation (PDEs). One of the methods performed a nonlinear smoothing of an input image and the other method smoothed the image using an edge-strength function (Shah, 1996).

Previously, there are applications of image segmentation methods including ACM that embedded or uses the technique of linear or nonlinear diffusion. The equation of linear diffusion is closely related to the Gaussian smoothing scale-space. The resulting linear scale-space for $t: 0 \mapsto +\infty$ is in the form of:

$$u(x, y, t) = u_0(x, y) * G(x, y, t)$$
(2.20)

where u(x, y, t) has coarser resolution as *t* marching to infinity. As linear diffusion gave shows good relationship with the convolution of Gaussian, the equation is given by:

$$\frac{\partial u(x,y)}{\partial t} = \nabla^2 u(x,y)$$
(2.21)

where ∇^2 denotes the Laplacian operation. The equation of the linear diffusion as shown in (2.21) is normally used for noise removing from the initial image of u_0 . However, in this situation the noise and edges are equal, thus the edges have the possibility to be eliminated, displaced or blurred. To solve this problem, Perona & Malik (1990) have proposed a nonlinear diffusion in their work. The equation of their work is given by:

$$\frac{\partial u}{\partial t} = div(c(\|\nabla u\| \nabla u) \quad on \ \Omega \ X \ (0, +\infty)$$
(2.22)

subject to the boundary and the initial conditions

$$\frac{\partial u}{\partial t} = 0 \qquad on \ \partial \ \Omega \ X \ (0, +\infty),$$
$$u(x, y, t) = f \quad on \ \Omega \qquad (2.23)$$

where *f* is a noisy image, $\partial u/\partial n$ is the derivative of an image to the image boundary $\partial \Omega$, $\|.\|$ and *div* denote the L2 - norm and divergence respectively. The main theory behind nonlinear diffusion is to use nonlinear to create a scale space representation that consists of gradually simplified images where some image features such as edges are maintained or even enhanced.

2.8 Summary

Distinctive levels of noise and intensity inhomogeneity across multimodality of medical images are among the primary issues that continuously challenge the advancement in medical image segmentation process. These issues produce high possibility of images with missing edges, and very complex texture, making it extremely difficult to successfully obtain accurate boundary segmentation of objects. In this chapter, we investigate several methods of ACMs that are popularly used in segmenting medical images. These methods can be categorized into edge-based active contour, region-based active contour and the combination of both models.

The first generations of ACM are classified as edge-based, and the first method of edgebased is popularly known as the Snake model. It is based on the concept of energy minimization and utilizes local image's property to move a contour towards object's boundary in an image. However, it is sensitive to image noise and the placement of contour is not flexible. Due to that, medical images with high levels of noise cannot be segmented successfully by this generation of active contour. The introduction of the second model focuses on the utilization of global image's property in an image, thus it is classified as region-based active contour. Based on the idea of Mumford-shah model, the first regionbased method was developed by C-V. This method provides better segmentation outcome than the edge-based method as it is more robust to image noise. However, as most medical are also affected with intensity inhomogeneity problem, the method cannot segment them successfully because it produces over segmentation effect. To overcome the problem of image noise and intensity inhomogeneity in most medical images, the third generations of ACM methods that combined the strength of both edgebased and region-based was introduced. This combination method embeds the local image's property of edge-based into the region-based, and produces better segmentation performance than the earlier methods. The hybrid ACMs' methods are to solve over segmentation problem of images with intensity inhomogeneity. However, when the intensity inhomgeneity problem becomes severe or the level of intensity inhomogeneity is high, the combination method is also not capable to produce good segmentation outcome of these images. There are many other functions that are used to improve the capability of ACM in providing an improved and accurate segmentation. One of the techniques that often applied is the introduction of the smoothing techniques for ease of contour evolution.

In this chapter, we also discuss the used of Gaussian filter applied in most ACM methods. Currently, the Gaussian filter uses the concept of linear diffusion function. The literature shows that Gaussian is among the best technique to remove noise and at the same time enhances image details in medical images. However, in certain cases the image detail may loss once the parameter of Gaussian is increased to a certain value. To address this problem, we introduce the used of nonlinear Gaussian to protect the loss of image detail when the Gaussian parameter increases. In this research work, a semi-automated approach and two automated approaches of ACM with nonlinear Gaussian have been developed to smooth images and enhance image details. Our proposed methods are discussed in Chapter 4 to 6.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter presents the research methodology implemented in the thesis. The chapter is divided into three main subsections. Section 3.1 presents, the methodology used in the literature investigation. The framework, design and development of proposed methods are provided in Section 3.2. Section 3.3 describes the experiments and the evaluation process deployed in this study.

3.1 Literature Investigation and Data Gathering Process

In the early stage of this study, reviews on medical image analysis have been carried out to determine research problems. Our early investigation denotes that, interpretation of medical images by experts is important. Hence, several interview sessions and observation were conducted to learn how to interpret medical images. Appointments with two gynecologists from the Columbia Hospital and KPJ Tawakkal were conducted. During the interview sessions, information on types of medical imaging and its importance were obtained. Sessions for interpreting medical images were conducted several times to understand image texture and anatomical structures underneath those medical images.

Information collected from literature and interviews is than analyzed. Our investigation found that the main problems that hinder the interpretation of medical images are the level of noise and intensity inhomogeneity. The investigation also found that Active Contour Model (ACM) has good potential in segmenting various types of medical images. The investigation proceeds by analyzing the problems associated with ACM methods when segmenting medical images. It was found that two main problems that may lead to inaccurate segmentation of medical images are over segmentation and local minima problem (Li et al., 2005, Zhang et al., 2010).

To resolve these problems, investigation on ACM was conducted and it is identified that one of the factor that lead to an improved segmentation is to use the Gaussian filter as the smoothing technique. The current ACM is using the linear Gaussian in its implementation and it is identified that the accuracy of the methods is still unsatisfied. Therefore, we implement the used of nonlinear Gaussian in determining its efficiency as the smoothing mechanism. Three framework of the proposed method have been design. The first method is based on a semi-automated approach. This method implements the Mathematical Morphology (MM) operations and is name as Binary Morphological (BM) ACM. MM is a nonlinear and its function such as the dilation and erosion is easily executed using Matlab programming. The aim of the method is to identify the technique in solving the missing edges along the object boundary.

The study continued to solve the over segmentation problem by producing the automated approach. Based on the concept of nonlinear, the fractional calculus function is collaborated with ACM method in producing a successful segmentation outcome while solving the over
segmentation problem. The fractional function is applied on the contour to get a dynamic, rapid and bending capability to overcome the over segmentation problem. To support the capability of fractional function, sinc wave method is implemented in the method to provide the successful segmentation outcome and the method is named as Fractional Sinc Wave (FSW) ACM.

The third approach is later designed to overcome the problem created by the second approach. This automated approach is designed to solve the local minima problem faced by most methods of ACM. The design of the third proposed method is still depending on fractional function. Two techniques have been introduced which are the Adaptive Fractional Gaussian Kernel (AFGK) and Fractional Differentiate Heaviside (FGH). We named the method as Fractional Gaussian Heaviside (FGH) ACM. Both FSW ACM and FGH ACM methods are discussed in Section 3.2.2 and 3.2.3 respectively in terms of the their flow process and design development.

3.2 Design and Development

This section describes the design and development of the proposed methods.

3.2.1 Binary Morphological Active Contour Model

Prior to the design and development of the proposed methods, we have implemented the MM with ACM to gain clear understanding on ACM's operations and how MM can be used with ACM to address the problem of missing edges in an image. The MM operations such as dilation and erosion can be applied to expand and shrink the value of image pixels to close any gaps along the object boundary. Figure 3.1 illustrates the implementation

framework of the Binary Morphological ACM method where the input to this method is the output from LBF method (Li et al., 2007).



Figure 3.1: The framework of the first method which is based on semi-automated segmentation.

The input image for the method is a segmented image obtained from the execution of the Local Binary Fitting energy (LBF) method (Li et al., 2007). The input image contains many weak and broken edges, producing many gaps along the object boundary. Using the method, seeds will be inserted manually at the gaps. Once this process is completed, the dilation and erosion operation will expand or shrink the seeds to close the gaps. As a result, new lines are created to complete the boundary. Details explanation on the method is discussed in Chapter 4.

3.2.2 Fractional Sinc Wave Active Contour Model

The purpose of the second method is to solve the over segmentation problem. The second method is designed to perform an automated segmentation process on medical images. The concept of fractional function is used to implement nonlinear function in ACM. The fractional function is applied within the global and local ACM to inherit the advantages of the both local and global properties. The concept of fractional function is used to benefit its exponent behavior for the contour to move dynamically and rapidly. On the contrary, the sinc wave method is seen to produce high accuracy in the segmentation outcome once collaborated with fractional function. The advantage of both the fractional function and the sinc wave could produce an improved medical image segmentation outcome. Figure 3.2 illustrates the framework of the proposed FSW ACM method. The input to this framework is a medical image regardless its modalities. Once the image is read, the contour placement is initialized based on region-based ACM. A nonlinear Gaussian filter is applied as the enhancement technique to smooth the image texture, protect and enhance any edges.



Figure 3.2: The framework of the proposed Fractional Sinc Wave ACM method.

The nonlinear Gaussian is used to prepare a smooth image texture by enhancing and removing the image noise. The fractional function behavior gives advantage in providing the rapid, dynamic and bending capability to the contour in evolving toward the object boundary. The distance is measured from the current position of the contour to the nearest object boundary. The application of Fractional Euler Lagrance is used in the distance measurement. Once the energy is minimized, the segmentation outcome is generated. Detail explanation on the method is discussed in Chapter 5.

3.2.3 Fractional Gaussian Heaviside Active Contour Model

The third proposed method is designed is the aim to solve the local minima problem created by the second method, thus provides accurate boundary segmentation. Our third method is named as Fractional Gaussian Heaviside (FGH) ACM and two terms is introduced; the Adaptive Fractional Gaussian Kernel (AFGK) and Fractional Differentiate Heaviside (FDH).

Figure 3.3 illustrates the main processes of FGH ACM with medical image as the input. Firstly, the contour placement is initialized based on region based approach. The placement of the contour can be more than one and it can be placed anywhere in the image. The AFGK as the enhancement technique provides an effective method for edge enhancement and has good noise immunity. An adaptive window mechanism with various sizes and orientations is deployed to maintain and enhance the image details especially at an object's curves and angles. On the other hand, the FDH with the operator of fractional order gradient is implemented for effective and accurate extraction of the object boundary. The energy is minimized and the process is terminated with an outcome of segmented medical image. Detail explanation of the method is discussed in Chapter 6.



Figure 3.3: Framework of the proposed Fractional Gaussian Heaviside ACM method.

3.3 Experiments and Evaluation

The experiment process is conducted to measure the feasibility of the three proposed methods. Two medical images are used in the first method in showing how the dilation and erosion operations joint the gaps along the object boundary. The two images are the microscopic images of cells and MRI image of heart. The results and discussion are presented in Chapter 4.

In order to measure the effectiveness of the FSW ACM method in reducing the over segmentation problem, several experiments were conducted on four medical image modalities which are MRI, CT scan, microscopic and ultrasound images. The organs involved in the images vary, for example, the brain images, heart image, and blood cells. During the experiments, the capability of the proposed method to segment the following

anatomical structures will be evaluated: outer and inner parts, long and winding structures, and structure outlining in an interface with high level of noise and intensity inhomogeneity. On the other hand, experiment process on the third method is executed on four medical image modalities and they are MRI, CT scan, x-ray and microscopic images. The aim is to solve the problem by the second method which is to achieve the accurate boundary segmentation.

Besides the experiment process, benchmarking with other methods of ACM is also conducted. Two baseline methods are used for performance comparison with the FSW ACM method, and they are Chan-Vese (C-V) and Selective Global Local ACM method (SGLACM). Three baseline methods are used to benchmarks with the FGH ACM methods and they are Local Binary Fitting energy (LBF), Local Gaussian Distribution (LGD) and Local Intensity Clustering (LIC). To support the benchmarking process, a quantitative evaluation is carried for each experiment. The evaluation is based on the metric of accuracy, as explained in the following section.

3.3.1 Quantitative Evaluation Method

This section presents a discussion on the quantitative evaluation which is based on evaluation metrics (Abbas et al., 2014). In the paper, the main metric used is to measure the accuracy of the contour to the object boundary during the segmentation process. However, to measure the accuracy metric, it involved the evaluation on specificity and sensitivity. Therefore, in this study we concentrate on the accuracy metric as the computation of the accuracy metric is involving the computation on the specificity and sensitivity as well. The statistical metric of accuracy of the evaluation metric is computed as follows;

Specificity
$$= \frac{TN}{TN + FP}$$
,
Sensitivity $= \frac{TP}{TP + FN}$,
Accuracy $= \frac{TN + TP}{TP + TN + FN + FP}$
(3.1)

where TP (True Positive) is the number of overlapping pixels inside the region, TN (True Negative) is the number of overlapping pixels outside the region, FP (False Positive) is the number of overlapping pixels between the automatically labelled object and those outside the manually labelled object of interest and FN (False Negative) is the number of overlapping pixels between the manually labelled object of interest and those outside the automatically labelled object of interest. To conduct the evaluation, two images of the same medical image are used where the first image is the image with segmentation based on selected ACM method and the second image, is the medical image with manually drawn border/boundary. To evaluate the accuracy of the segmentation is to measure the distance of the manually drawn border/boundary to the automatic border/boundary created by the ACM method. Let B be the automatic border, H be the manually drawn border and d is the distance between B and H. Thus the equation of d (distance) is given as;

$$d(B,H) = argmin(b_s, h_t), b_s \in B, h_t \in H$$
(3.2)

To get the percentage of the segmentation accuracy metric q is computed as the rate of minimum distance between both manual and automatic borders. The metric q is computed as;

$$q = \frac{nd}{s} \times 100\% \tag{3.3}$$

where *nd* is the number of pixels in the image. The evaluation metric is used in chapter 5 and chapter 6 to evaluate the segmentation accuracy. The higher the percentage of accuracy depicted that the border of the segmentation is near at the object boundary.

3.4 Summary

Survey on the best medical image segmentation methods had been conducted and problems in achieving accurate segmentation had been identified. Based on the literature findings, three methods of ACM have been designed with the introduction of nonlinear function. First of all based on nonlinear function, the method of mathematical morphology is applied to join gaps along the object boundary which is based on manually inserted seeds. The method of FSW ACM is applied in the aim to achieve improved segmentation within the intensity inhomogeneity interface while reducing the oversampling problem. The third method is later designed and developed to achieve accurate boundary segmentation with the method of FGH ACM. The three proposed methods are later measured in several experiments, and the result obtained on several medical image modalities is evaluated based on visual interpretation and benchmarking. To further evaluate the potential of the proposed method, quantitative evaluation is also applied.

CHAPTER 4

BINARY MORPHOLOGY OF ACTIVE CONTOUR MODEL

This chapter reports the investigation on the strength of Mathematical Morphology (MM). The main purpose is to study the advantages of MM and to collaborate it with Active Contour Model (ACM) to solve the gaps problems identified in most medical images due to the noise and intensity inhomogeneity problem. The chapter begins with a brief introduction on Mathematical Morphology in image segmentation. Section 4.2 explained the operations of MM that can be used in image segmentation. This included the operations of dilation and erosion. The design and development of the proposed method is presented in Section 4.3. The experiments and results of the proposed method are depicted in Section 4.4. We end the chapter by summarizing the overall method developed.

4.1 Mathematical Morphological Operations in Image Segmentation

The term Mathematical Morphology (MM) is basically about dealing with shapes and structures which in image segmentation it is significant as a tool in extracting an object in an image. The aim of morphology operation is to simplify the image, eliminate irrelevant objects and preserve the useful characteristics in an image. Morphology is an operator which is constructed with operations on a set of pixels in binary image in order to extract useful component in representing an image (Álvarez, Baumela & Márquez, 2010; Ahmad

& Nasri, 2012). Therefore, there is a growing interest to apply morphological operations in image segmentation with ACM due to its low computational complexity in minimizing the energy involved in the segmentation process (Amer, 2002; Sun, Chen, & Jiang, 2012).

There are two main operations of morphology; dilation and erosion. Other operators are opening and closing, hit and miss transform. These operators use a binary image and a structuring element as an input (Parvati, 2008; Ahmad & Nasri, 2012). As the mathematical morphology take a binary image as an input, understanding on pixel connectivity is important. Pixel connectivity is the way in which pixels in 2D or 3D images relate to their neighbors. For example, 4 connectivity means 4-connected pixels are neighbors to every pixel that touches one of their edges. In addition, a diagonal pixel exist when once would like to join any two corners of the rectangular pixels which are not already joined which is called as edges. The morphological operations of erosion can be used to get the diagonal pixel in getting an accurate boundary. On the other hand, a structuring element with a determined shape is used to interact with a given image. The structuring element (SE) acts as an agent or a mask that moved in the image based on the morphological operators applied. The purpose of a SE is to fit the SE shape to the shape of the object in the image. Usually, the structuring element has a size of 3×3 and its origin is at the center pixel (Krishan & Rajender, 2013). When the structuring element or the mask is gradually shifted across an image, every pixels of the image are compared with the underlying pixels of the mask and need to meet certain condition defined by the morphological operators. If the pixels match the condition defined by the set operator of the morphological operations, the pixel underneath the structuring element is set to a predefined value (0 or 1).

In the edge-based ACM, the morphological operations of dilation and erosion are done by comparing the gradients in the image. On the other hand, the region-based ACM the dilation and erosion operations are completed by comparing of the pixels intensity in each region (Sun, Chen, & Jiang, 2012). Work by Francoise and Hel-Or (1991) embedded the mathematical morphology as an energy formulation in active contour model to solve the lung contour problem in CT scan images. The work expressed the external energy functional as a combination of conditional-gradient and anatomical structure as a prior knowledge that is expressed in term of distance function. The Mathematical Morphology operation of dilation and erosion is used as the expanding and shrinking deformation process to provide an improved segmentation. Unfortunately, the method is sensitive to noise and having difficulty to be applied to other types of medical image modalities (citation). The research performed by Victoria et al (2013), introduces a new morphological multiphase active contour model. The work is based on the multiphase implementation of Active Contour Model Without Edges (Chan & Vese, 2001). The implementation of morphological operations shows efficient and robust segmentation result on the trial vascular images. Besides, the method shows good outcome on watershed model and fuzzy c-means method. However, the method is sensitive to intensity inhomogeneity problem. In addition, one of the disadvantages of MM in image segmentation is that it does not provide smoothing effect during the curve evolution. Section 4.3 presents the new development of ACM which is based on Mathematical Morphology.

4.2 New Morphological Based Method in Active Contour Model

In this section, discussion on the proposed method of ACM with MM is presented (Norshaliza et al., 2012). As medical images are low in quality, segmenting the object from the background can be difficult. For example, the microscopic image of two cells. The characteristics of microscopic images that made it difficult in the segmentation process are noise that lead to missing edges at the boundary of the cells and intensity inhomogeneity in the image. Due to the intensity inhomogeneity problem, some ACM methods such as active contour model without edges (Chan & Vese, 2001) failed to successfully segment the cell from the background. On the other hand, the LBF method (Li, Kao, Gore, & Ding, 2007) can partially segment the boundary of the cell due to weak or missing edges in the image, as shown in Figure 4.1 below.





Figure 4.1: (a) A cell image with missing edges; (b) The close up view of the missing edges.

The aim of the proposed method (Binary Morphology model) is to improve the output image derived from the segmentation using the LBF method by the implementation of MM function. The proposed method implements the MM on binary image to overcome the boundary leakage problem. It adopts morphological closing operator using the diamond-shape SE in order to expand or to fill in the holes at the disjoint regions (Sun, Chen, & Jiang, 2012; Ahmad & Nasri, 2012; Francisco, Mar & Ramón, 2007). Morphological closing operator consists of a dilation operation followed by erosion operation. The

morphological closing operator adopts the dilation operation to expand and merge the separate region in order to build/construct the missing edges. In other words, dilation process fills in holes found at the boundary. Subsequently, the erosion operation is applied to smooth and remove any unwanted pixels from the image before an outline function is applied to create an outline of possible shape in the image. This operation is also called as morphological connectivity, and here the implementation of the 4x4 connectivity is carried out in horizontal followed by vertical movements or vice versa of the structuring element with the shape of diamond.

As mentioned earlier, morphological operation works better on binary image than grayscale image. Therefore, gray-scale microscopic image of a cell is first converted into binary image prior to the execution of the closing morphological operation on the image. The advantage when working with binary image is the speed on the evolving contour is faster when compared with image based on gradient. Moreover, the accuracy of segmentation is also higher (Sun, Chen, & Jiang, 2012; Ahmad & Nasri, 2012; Victoria et al., 2013). Figure 4.2 illustrates the microscopic image that was converted into binary image using Matlab R2008b. Note that pixels with value of 1 are denoted as object to be segmented and are called as structuring elements. Pixels with value of 0 are considered as the background. Assume that B is the binary image of the original image, the equation is given by;

$$\mathcal{E} = \mathbf{B}(\mathbf{x}) - [\mathbf{B} \ \mathbf{\hat{o}} \mathbf{A}](\mathbf{x})$$

(4.1)

where A is the structuring elements (SE) and ô denotes morphological closing operator. Eq. (4.1) represents the dilation process where the SE will expand the pixel value from 0 to 1. In other words, the pixel is added up to the neighboring pixels to fill up the gaps. Here, the

proposed method implemented the morphological closing operation with flat linear SE with proper length and degree. This measurement Eq.(4.1) is in a counter-clockwise direction with horizontal and vertical SE. In the sub sequence section, each operations of MM applied on the proposed method are presented.



Figure 4.2: The original binary image of microscopic image of cell and the dilation process.

4.2.1 Dilation Operation

This section presents the dilation process in MM. In binary morphology, dilation is a shiftinvariant operator. To understand the process, assumed that SE is labeled as S and the image is labeled as B. Therefore, the dilation operation is performed by laying the structuring element S on image B, and sliding it across the image in a manner similar to convolution. In a standard dilation operation, the structuring element S is moved over the binary image B. In general the equation is given by;

$$A \oplus B = B \oplus A = \bigcup_{a \in A} B_a$$
(4.2)

If *B* has a center on the origin, then the dilation of *A* by *B* can be understood as the locus of the points covered by *B* when the center of *B* moves inside *A*. Take note that either A and B is having the value of 0 and 1 and vice versa which means A can be white and B can be black or vice versa.

In the proposed method, the origin B (having value of 0 which is white) intersects with pixels value in A (black). The current respective pixel's value of A (black) need to cover all pixels underneath its region which is white (the gaps) to black. This means the dilation process is expanding the black pixels to other pixels the region. At this point, the binary gradient mask is dilated using the vertical SE of B followed by the horizontal SE of B. Dilation operation is used to increase object in the image. In terms of binary image in the proposed method, the equation is given by:

$$\varepsilon_A(B) = \{x | A_x \cap B \neq \phi\}$$
(4.3)

where A is translated with x, and as SE have the maximum pixel value with 1, x is translated from value 0 to value 1. The equation (4.3) above can be rewritten into the unions of the translated set I_{-a} :

$$\varepsilon_A(B) = \bigcup_{a \in A} B_{-a}$$
(4.4)

Figure 4.2(b) illustrates the dilation process using the vertical followed by the horizontal movements. This process is normally named as region filling and is discussed in section 4.2.2.

4.2.2 Region filling

Region filling process is done based on a set of dilation operations. In the dilation process, region is filled to close any small gaps or to connect the disjoint regions repeatedly. The proposed method applied the dilation operation to fill in holes at disjoint regions, and after the filling process is completed, the gap is filled and connectivity is established. Let A denote a set with a 8x8 connected boundary. Let X_o be an initial point in the boundary. Therefore, the equation of region filling is given by;

$$X_k = (X_{k-1} \oplus B) \cap A^c$$
(4.5)

A problem with dilation process is some critical part within the same region (same value) is not properly filled. As a result, there are part is the region is having pixel value of 0 (white). Therefore, the region filling is used to fill up the gap with value which is the same with the current region's value. Assumed that the process start with a point t inside the boundary of the SE with the value of 1 (black). The current pixel value for the region is also 1 (black). The SE with value of 1 will move on the current pixel value of the region with the value of 1 to overcome the disjoint. Once the SE is working by moving horizontally and vertically in the region, it will fill up any region with value of 0 (white) and converted them to value of 1 (black) to have a connected region. The proposed method will perform a contour evolution and is achieved by performing substitutions of 4x4 pixel patterns on the region boundary.

4.2.3 Erosion Operation

The erosion morphological operation with a structuring diamond element is applied to smooth the image, remove noises or unwanted pixels, and finally create the outline of possible shape in the image. The function returns a binary image containing only the perimeter pixels of object in the input image. A nonzero pixel is part of the perimeter, and it is connected to at least one zero-valued pixel. Our proposed Binary Morphological operation is explained in the following section.

4.3 Binary Morphological Model

This section presents the design and development of the proposed method named binary morphological model. In order to execute the method, segmented medical image is needed as an input to the method. The input medical image must be executed from any segmentation method to get the result and the result must depict the gaps / holes problem along the object boundary. In this study, Local Binary Fitting (LBF) energy is used to produce an input to the method. The LBF method has the potential to segment medical images with intensity inhomogeneity. However, it could not manage to segment medical images that have missing edges. The Binary Morphology model will join the gaps / holes that have been identified from the output image of LBF. Therefore, the equation of the proposed method depending on the morphological closing operation is given by;

$$[A \oplus B (X_{k-1} \oplus B) \cup A] \ominus A$$

(4.6)

A and B are the image with value of either 1 or 0 and vice versa. The first part of the algorithm shows the dilation process whereby the SE of A is expanded with pixel B. After

the dilation process, the translated pixels are filled with region. This measurement is given by;

$$X_k = (X_{k-1} \oplus B) \cup A \tag{4.7}$$

where k is the size of a window and k = 2,3,4. This algorithm terminates at iteration step k if $X_k = X_{k-1}$ and A contains the filled set and its boundary. The last step in completing the whole process is to smooth and erode the image. This is represented by A. The complete algorithm is given by;

$$\varepsilon = LBF + [A \oplus B(X_{k-1} \oplus B) \cup A] \ominus A$$
(4.8)

where the first part is the LBF method and the equation is the same as shown in (4.2). Once the LBF method deliver the output image, the binary morphological model will perform the morphological closing operation to close the gaps between the separate regions. The complete equation of LBF method is given as follows;

$$\varepsilon^{LBF}(\phi, f_1, f_2) = \int_{\Omega} \varepsilon_x^{LBF} \left(\phi, f_1(x), f_2(x) \right) dx$$

$$= \lambda_1 \int \left[\int K_{\sigma}(x - y) |I(y) - f_1(x)|^2 H(\phi(y)) dy \right] dx$$

$$= \lambda_2 \int \left[\int K_{\sigma}(x - y) |I(y) - f_2(x)|^2 (1 - H \phi(y))) dy \right] dx$$

(4.9)

where λ_1 and λ_2 are positive constants, and K is a kernel function with a localization property. Both the $f_1(x)$ and $f_1(x)$ are two numbers that fit image intensities near the point x. The point x is the center point of the above integral, and the above energy the local binary fitting (LBF) energy around the center point x. In the next section, experiment on binary morphological model is presented.

4.5 Experiment and Result

This section reports the experimental setup and results obtained based on the binary morphological model. The purpose of these experiments is to observe the capability of the mathematical morphology in joining the gaps problems along the object boundary. The algorithm is implemented using MatlabR (2008b). Two medical images are used in the experiments and they are microscopic image of two cells and MRI image of heart. In brief, below are the steps in implementing the binary morphological model.

- 1. Obtained an input image from the execution of LBF method.
- 2. Identify any gaps along an object boundary.
- 3. Insert some seeds at the gaps as many as possible.
- 4. Execute the dilation operation to expand the seeds.
- 5. Execute the erosion operation to remove unwanted pixels.
- 6. New lines/contours are created to join the gaps.
- 7. Segmentation outcome is generated.

Figure 4.3 depicts image of two cells from the modality of microscopic. Note that, along the boundary of the two cells, several gap/hole are identified. This is due to the problem of noise and intensity inhomogeneity that leads to missing/weak edges at the object boundary. The aim of binary morphological model is to use the morphological operations in joining these gaps. To get the results of binary morphological model, an input image which is segmented from LBF is executed. Figure 4.3(a) shows the results obtained when executed

with the LBF method. Figure 4.3(b), 4.3(c) and 4.3(d) shows the sequence results when applied the binary morphological model on the microscopic image of two cells based on dilation and erosion operations.



Figure 4.3: The sequence results obtained from the experiments using microscopic image;(a) shows the result obtained from LBF method (b-d) show the results obtained in sequence when implemented using the binary morphological model.

The result obtained from LBF method shows several gaps at the boundary of the two cells Figure 4.3(a). This is one of the drawbacks with LBF method as the initial positions create two contours whereby it passes at the weak edges and creates gap. The proposed model uses the closing morphological operation where it starts with the dilation operation process. Before the dilation process can be implemented, several seeds need to be placed manually by the user between regions with gaps problem. The seeds need to be inserted at several points where the dilation process needs to expand or shrink to join the gaps at the object boundary. At this point, the dilation process will merge and join gaps at the boundary of the cell which is based on the inserted seeds. The seeds can be placed as many as possible and at any positions along the object boundary. For the microscopic image of two cells, Figure 4.4 shows sample of the inserted seed shown by the dotted points.



Figure 4.4: The inserted seeds to support the dilation process whether to expand or shrinking.

The dilation process is shown in image at Figure 4.3(b). At this point, the connectivity in joining the gaps is created and implemented as discussed in section 4.2. However, from the result obtained, the image is still having unneeded regions (over segmentation) that are still being segmented by the process (shown by the arrow). To overcome the problem, the image needs to be smooth by applying the erosion morphological operation. The function of erosion morphological was set to 4 pixels in removing all diagonal connections (4-connected). The erode operation is used to erode the binary image and returning the erode image again. This is shown in Figure 4.3(c) where the image is now smooth the oversampling regions are removed. To complete the whole process, a mapping of the result obtained on Figure 4.3(c) is done on the original image of the two cells. The mapping process will return a binary image containing the perimeter pixels of objects in the input image as shown in Figure 4.3(c). The complete result is shown in Figure 4.3(d). The result depicted that the gaps problem is now solved. It is shown that the operations of dilation and erosion having the capability in creating the connectivity in joining the gaps problem along the object boundary.

To support the finding in this chapter, MRI image of heart is used to evaluate the binary morphological model. MRI image of heart suffered from noise and intensity inhomogeneity

that leads to weak at edges. The purpose of the experiment is to segment only the hole of the heart which is situated at the center of the heart image. Figure 4.5 illustrate the experiment conducted on MRI image of heart using binary morphological model. Figure 4.5 (a) is the input image to the method executed from LBF method. Note that, the contour did not perfectly segment the hole of the heart image. The binary morphological model is applied where the dilation operation is used to expand and shrink depending on the placement of the inserted seeds. Figure 4.5(b) shows the result obtained from the dilation process. Based on the results, several unwanted regions are segmented as well and this is removed by applying the erosion process. The result obtained is shown in Figure 4.5(c). Now, the output from the erosion process is become the outline or mapping on the original image of MRI of heart and the finalize result of the segmentation is shown in Figure 4.5(d).



Figure 4.5: The sequence results obtained from the experiment using MRI image of heart;(a) shows the result obtained from LBF method (b-d) show the results obtained in sequence when implemented using the binary morphological model.

From the two experiments conducted in Figure 4.4 and Figure 4.5, it is shown that mathematical morphology with its operation of dilation and erosion could be used to overcome the problem of missing or weak edges. Section 4.6 summarizes the work on binary morphological model.

4.6 Summary

The binary morphological model is designed and developed to observe the strength of mathematical morphology in joining gaps along the object boundary. Medical images are known to have low quality that made it difficult to be segmented. Due to the level of noise and intensity inhomogeneity, regions in medical images are suffered from weak or missing edges. At this situation, the contour of ACM has difficulty in recognizing or extracting the intensity in order to create the connectivity among the pixels. If there is no connectivity, this means segmentation produced is incorrect. The study observed the morphology operations in joining gaps along the object boundary of medical images. The LBF method is used to produce segmented medical image but with several identified gaps. Experiment using the dilation operation shows that the gap is joined based on the placement of inserted seeds. To get the complete segmentation, the output from erosion process is map on the original image. As the binary morphological model is based on semi automatic, the efficiency of the model is not satisfactory. Additionally, the inserted seeds may give problems especially when it passes the diagonal pixels. Therefore, two automatic segmentation methods are developed to overcome the semi automated method and this is discussed in Chapter 5 and Chapter 6 respectively. Both automated method is based on fractional calculus which is generalized from nonlinear diffusion function.

CHAPTER 5 FRACTIONAL SINC WAVE METHOD WITH ACM

This chapter describes our first approach in automatic segmentation of medical images. The approach introduces a novel implementation of fractional calculus with sinc wave method in the hybrid ACM. This implementation is proposed to address current issues of intensity inhomogeneity problem in medical images that creates inaccuracy in image segmentation (Zhang et al., 2013; Wang, Li, Sun, Xia, & Kao, 2009; Li, Xu, Gui, & Fox, 2005). This chapter begins with a brief introduction to fractional calculus and sinc wave method. In Section 5.3 we propose our algorithm and highlight its advantages in enhancing the segmentation outcome of medical images. Section 5.4 describes the strategy and issues involved in implementing the proposed algorithm. In Section 5.5 we report our experiments and their results. Section 5.7 discusses on the benchmarking results emphasizing on the performance of the proposed method against other methods of ACM. This chapter ends with a conclusion about the capability of the proposed method in addressing current problem of medical image segmentation.

5.1 Introduction

Calculus is a system of calculating or reasoning that finds the derivatives or integrals of a function. Derivatives or integrals are the fundamental tools in calculus where derivatives is a process of measuring the sensitivity to change the function value or dependent variable which is determined by another independent variable. Integral on the other hand, covers the accumulations of quantities such as areas under a curve. Fractional is a numerical value that is not a whole number where fractional is less than one. Therefore, fractional calculus is a function that takes any real number powers in differentiates or integrating a function once, twice or many times. Real number of fractional calculus is a value that represents a quantity along a continuous line whereas the term 'powers' here is referred to an iterative application. Fractional calculus can be described in many scientific phenomena such as in physics, biomedical engineering, statistics, image processing and others (Alkan & Secer, 2015).

Fractional calculus is a nonlinear mathematical function. Nonlinear function is viewed not as a straight line in a given graph and it contains a variable with an exponent other than one. In mathematics, exponent behavior is referred to a repeated multiplication of a numerical value. In nonlinear function, the data is modeled by a combination of parameters and it depends on one or more independent variables (B. J. West et al., 2003; K. S. Miller and B. Ross, 1993). Nonlinear function has the capability in enhancing and preserving image details. It also provides the most flexible contour-fitting functionality in an image (Amadori& Vazquez, 2005; Secer et al., 2013). Contour-fitting functionality is a process to construct a curve or contour in an image made from a series of data points. The nonlinear function provides the smoothing effect of this contour over the data points. In the ACM's image segmentation method which utilizes the contour evolution, the data obtained from nonlinear function is fitted to form a contour in order to wrap around an object in a given image.

In image segmentation where contour minimization is utilized, the lower bound of fractional calculus derivative does not coincide with the lower bound of the fractional calculus integral when the energy is minimized (Baumann & Stenger, 2015; Diethelm et al., 2005). This leads to difficulty in finding the local image properties thus hinders accurate boundary segmentation. Through several studies, sinc wave method or sine function is employed to determine and solve the boundary value problem. This is investigated in work by El-Gamel (2012). The advantage of sinc wave method is on its consistent movement, the ability to retain its shape in a given time. In image segmentation, sinc wave method can be applied to a contour in order to obtain a smooth and repetitive contour's movement across the time. The method therefore supports the functionality of fractional calculus and nonlinear function in order to achieve high accuracy in image segmentation outcome.

5.2 Fractional Sinc Wave Active Contour Model

Fractional sinc wave (FSW) ACM is a new hybrid ACM that integrates the strengths of fractional calculus and sinc wave method in order to enhance the capability of the existing model to accurately segment images even in the presence of intensity inhomogeneity. In this study, we proposed a method that uses the FSW within the global and local ACM. The integration of fractional calculus in both global and local ACM enables its contour to evolve in a nonlinear movement along pixels intensity so that it can be as near as possible

to an object's boundary. The exponential behavior of fractional calculus which is nonlinear provides a contour evolution that is dynamic and rapid, yet stable.

Besides giving an excellent smoothing effect on an image surface, nonlinear function provides flexibility in contour fitting function, incorporation of fractional calculus further improves the bending effect capability of the contour. Additionally, the collaboration of sinc wave method with fractional calculus has the capability of interpolation in constructing a new data point along the contour. This gave efficient contour bending flexibility to permit it to reach even at difficult angles. Furthermore, the sinc wave method provided high accuracy in finding the local image properties at the object boundary. Therefore, improved segmentation outcome is achieved.

However, the contour augmentation with fractional calculus is still not able to bring the contour to stop correctly on the object boundary especially for those complex objects with sharp curves and weak edges. In this research, we alleviate this problem by applying sinc wave method on the augmentation. The sinc wave method bends the contour flexibly, forward and backward at critical angles along the object boundary (El-Gamel, 2012; Dan Tian, 2012). With its capability of interpolation technique in constructing and placing new data points in a given sets of current data points, the sinc wave method managed to close any gap or weak edges along the object boundary. The gaps are the resultant of local minima problem that occur along an object boundary particularly in images with intensity inhomogeneity (Aydin et al., 2013). Our proposed FSW ACM offers the following advantages.

First is the implementation of nonlinear function smoothed image texture while preserving its edges and enhancing the inhomogeneous object classification in the affected regions. Secondly, the augmentation of fractional calculus with sinc wave method on contour evolution of both global and local energy has resulted in rapid contour movement with flexible bending capability to quickly segment object with sharp curves and difficult angles. Finally, apart from its ability to produce accurate segmentation even in the presence of intensity inhomogeneity, the proposed method can also resolve over segmentation, a problem commonly occur in many region-based ACM methods.

5.3 Algorithm Design of the Fractional Sinc Wave ACM

In the proposed method, the fractional sinc wave is embedded with the global and local ACM because the former is more robust to image noise while the latter allows the extraction of image's gradient along an object boundary. However, the global or region-based ACM is sensitive to intensity inhomogeneity which would produce segmentation of many unwanted regions or better known as over segmentation. In getting a satisfying result, the proposed method embedded the fractional sinc wave method within the global and local ACM. In explaining the algorithm design of the proposed method, we first present the fractional integral and derivative used in the proposed method by the definition of the Riemann-Liouville. The equation is given by;

$$D_x^{\alpha} f(x) = \frac{1}{\Gamma(\alpha)} \int_a^x f(t) (x-t)^{\alpha-1} dt$$

(5.1)

$$D_{x}^{\alpha}f(y) = \frac{1}{\Gamma(1-\alpha)} \int_{a}^{y} f'(y-u)(u-x)^{-\alpha} \, du$$
(5.2)

where Eq.5.1 represents the fractional integral and Eq.5.2 represents the fractional derivatives. The symbol of α in both equations is the positive real number, Γ is the gamma function and α is an arbitrary fixed based point. As the proposed method is using the sinc method, in general, the *sinc(t)* of order α , (*sin_{\alpha}*), is defined by (Dan Tian, 2013; Gerd Baumann and Frank Stenger, 2011) as follows:

$$sync_{\alpha}(t) = \frac{sin_{\alpha}(t)}{t}, \quad t \neq 0$$
$$= \sum_{n=0}^{\infty} \frac{(-1)^n t^{(2-\alpha)n}}{\Gamma((2-\alpha)n+2)}$$
(5.3)

where

$$\sin_{\alpha}(t) = \sum_{n=0}^{\infty} \frac{t^{n-\alpha}}{\Gamma(n-\alpha+1)} \sin((n-\alpha)\frac{\pi}{2})$$
$$= \sum_{n=0}^{\infty} \frac{(-1)^n t^{(2-\alpha)n+1}}{\Gamma((2-\alpha)n+2)},$$
(5.4)

where in Eq.(5.3), Γ is the gamma function, *t* is a variable and $\alpha \in (0,1)$ is a parameter. The sinc_{α} (t) function also called as the sampling function, it is a function that arises regularly in the theory of Fourier transforms and signal processing (El-Gamel, 2012). This function inherits the singularities strength and has the capability in supporting the fractional calculus for better bending effect capability as well as a rapid and dynamic movement. The sinc wave method has the similarities with the Heaviside function where Heaviside function is a discontinuous function and is used in operational calculus for the solution of differential equation. The Heaviside function is normally defined by a limit of the sinc wave method and is given by;

$$\lim_{t \to 0} \operatorname{sinc}(t) = H(t) = \begin{cases} 1 & t \ge 0 \\ 0 & t < 0 \end{cases}.$$
(5.5)

The value zero of Heaviside function is for negative arguments and one is for positive arguments. As the proposed method utilizes the generalization of nonlinear which are the fractional calculus and the sinc wave method, the general procedure for nonlinear FSW function is defined by the following recursive equation:

$$S_n = \alpha I_n + (1 - \alpha) S_{n-1};$$
 $0 \le \alpha \le 1$

(5.6)

where $\{I_n\}$ is the image to be processed, S_n is the processed result for the n^{th} step, and α is the smoothing coefficient. The nonlinear function has the capability in preserving image detail and reducing image noise. To support the use of the Eq. (5.6) for several iterations, Eq. (5.7) is represented using the following equation:

$$S_n = \alpha \sum_{i=1}^n \beta^{n-i} I_i + \beta^n S_0, \qquad \beta = 1 - \alpha$$
(5.7)

where the processing result is a weighted sum of all samples with exponential decreasing weights. Eq. (5.7) has a parameter of α that meets the algorithm requirements regardless of the number of inputs. This gives rapid and dynamic movement of contour in evolving in an image's surface and this is done iteratively. Eq.5.8 illustrates the complete equation of the proposed FSW ACM method.

Let *C* be a contour in an image Ω . The complete energy for FSW ACM is defined as follows:

$$F(C, d_{1}, d_{2}) = \lambda_{1} \int_{in(C)} G(x) |I(y) - d_{1}(x)|^{\alpha^{x*y}} dx dy$$

+ $\lambda_{2} \int_{out(C)} G(x) |I(y) - d_{2}(x)|^{\alpha^{x*y}} dx dy$
+ μ . Length(C) (5.8)

where λ_1 and λ_2 are the two positive parameters, G(x) is the Gaussian filter function as discussed in Eq.(2.22). The two numbers d_1, d_2 shown in Eq. 5.8 are defined by;

$$d_{1}(\phi) = \frac{\int_{\Omega} I(x) \sin c_{\alpha}(\phi) dx}{\int_{\Omega} \sin c_{\alpha}(\phi) dx},$$

$$d_{2}(\phi) = \frac{\int_{\Omega} I(x) \cdot (1 - \sin c_{\alpha}(\phi)) dx}{\int_{\Omega} (1 - \sin c_{\alpha}(\phi)) dx}$$
(5.9)

Accordingly, d_1 , d_2 in Eq.(5.9) do not have constant values as the proposed method applies the nonlinear Gaussian (Ghamisi, 2012; Perona & Malik, 1990; Erdem, 2012; Barenblatt & Vazquez, 2004). As the proposed method is embedded within the level set framework, the new equation is given as follows:

$$F(\phi, d_1, d_2) = \lambda_1 \int_{in(\phi)} G(x) |I(y) - d_1(x)|^{\alpha^{x*y}} sinc_\alpha(\phi) dx dy$$
$$+ \lambda_2 \int_{out(\phi)} G(x) |I(y) - d_2(x)|^{\alpha^{x*y}} (1 - sinc_\alpha(\phi)) dx dy$$
$$+ \mu. Length(\phi)$$

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(5.10)

where $sinc_{\alpha}(\phi)$ is based on Heaviside function. The elaboration of $sinc_{\alpha}(\phi)$ in Eq. (5.10) is presented in Eq.(5.3) and Eq.(5.4) for constructing a contour. To provide a contour with rapid and dynamic movement, the study proposes a technique by applying the Gaussian filter with fractional sinc wave method in each contour movement. This technique provides a rapid and dynamic movement, which speeds up the segmentation process. The computational requirement for separating inhomogeneous objects within regions is simplified by applying the FSW method in Gaussian filter modification. This is given by;

$$l(x) - (d_1 + d_2)^{\alpha^{x * y}}$$
(5.11)

where d_1 and d_2 are the two regions, and I(x) is the original image. For a successful segmentation outcome, the overall equation is applied to the image to improve the image intensity distribution in each region. The power of α is the control parameter of sinc wave method with two variable numbers which is based on exponential regression. If a large number is given to the α , the contour will move further towards the segmented object boundary. If a small number is used, the contour will move nearer the segmented object. This is shown in the experiments conducted in Section 5.4. The choice of input for α depends on the distribution severity of the image intensity. This input needs to be properly tuned. The contour did not stop at the exact object boundaries when only the global energy is utilized. To solve this problem, the energy function need to be minimized where the level set contour must be on the object boundary even in order to ensure the contour stop exactly on the object's boundary in the presence of intensity inhomogeneity, we have implemented distance measure that is based on fractional Euler Lagrance within the level set function. As the proposed method is based on fractional sinc wave method, the equation for distance measure as stated in the third line of Eq.(5.10) as follows;

$$Length(\phi) = \mu L_{f\alpha}(\phi)$$

(5.12)

where $L_{f\alpha}(\phi)$ is the distance measure based on fractional sinc function and is given by;

$$F_{\alpha}(\phi) = \int_{\Omega} |\nabla^{\alpha} \phi(x, y)|^{\alpha} sinc_{\alpha} dx dy$$
(5.13)

To minimize the energy function, $F_{\alpha}(\phi) = 0$ to make sure these contour is placed exactly on the object boundary. The implementation of this equation is presented in section 5.3.1.

5.3.1 Algorithm Implementation

This section describes the implementation of the proposed method. The method is implemented in MatlabR (2008b) on a 2.5 GHz with Intel Processor i5. There are two primary issues that need to be considered in the implementation of the proposed method. First is about the initial placement of a contour in an image. According to the literature, there are two implementation strategies to set the initial contour placement in an image. The first strategy automatically initializes the placement of a contour in an image. This strategy does not require a segmentation method to decide on how or where to place a contour in an image therefore segmentation methods that implement this strategy will have the same type of contour initialization. On the other hand, in the second strategy, the initial placement of a contour is determined by the segmentation algorithm therefore contour initializations can be different across different ACM methods. Our proposed method implements the second strategy therefore the initial placement of a contour is according to the region-based ACM that utilizes the global energy to achieve the contour placement flexibility during its evolution.

Another issue that needs to be considered in implementing the proposed method is in regards to use a nonlinear Gaussian filter for the smoothing technique. The nonlinear Gaussian filter requires some controlled parameters to allow a contour to rapidly move towards an object. If the values of a controlled parameter are large, the contour will move further from an object's boundary; otherwise, the contour will move nearer towards the boundary. The controlled parameter used in the algorithm is $sinc_{\alpha}$ where α is the parameter that needs to be adjusted for improved bending effect and contour fitting capability. Another parameter used is sigma σ that permits the Gaussian filter to also enhance image details including the edges. Its value can be adjusted according to the level of noise and intensity distribution in an image. The values of input for both α and σ parameters will be later explained during the execution of experiments in the following section.

The stopping function is also an issue that must be considered to ensure that the contour stops on or near an object boundary. In order to bring a contour as near as possible to an object boundary, our proposed method implements the fractional sinc method along with a distance measurement term that utilizes the local energy within the level set framework. During this process, the level set property is kept equal to $|\nabla \phi| = 1$. This value is used to stabilize and to stop the contour movement when it reaches an object boundary. The value indicates that the contour is exactly on the boundary of the segmented object boundary. The contour stability during the evolution is maintained until the segmentation process is completed. The summarization of the algorithm of the proposed method is presented below:

1. A contour is initialized based on the curve evolution

$$\mu = \begin{cases} d_1 x \in \Omega_{in} \\ d_2 x \in \Omega_{out} \end{cases}$$

where d_1 and d_2 are not constants in order to implement the nonlinear function and the initialization is based on inside and outside regions.

- 2. d_1 and d_2 in step 1, are computed based on Eq. (5.8).
- 3. The Gaussian filter is applied for providing the smooth effect on an image with the strength of nonlinear function.
- 4. The contour evolves based on the FSW ACM method represented by $sinc_{\alpha}$, $\alpha > 0$.
- 5. The controlled parameter α is applied in Eq.(5.8) to control the movement of a contour.
- 6. To minimize the energy function, $F_{\alpha}(\phi) = 0$ to make sure a contour is placed exactly on an object boundary as shown in Eq. (5.11). Otherwise, repeat step 2.

In step 3, x and y are the control parameters of α which are adjusted to obtain an efficient contour bending effects and a rapid movement toward the boundary of an object of interest. Giving a larger number of x and y parameters (i.e., more than 0.7) will move the contour far from the boundary. Too small values input for the (i.e., less than 0.4) draws the contour near or flat at the boundary of objects of interest. The nonlinear function applied on the contour has the capability of the fractional sinc wave function hence it will move the contour increasingly and decreasingly towards an object boundary and stops when the energy is minimized or when the level set property is equal to $|\nabla \phi| = 1$. The FSW ACM method works well when the local energy is efficiently adapted at the area with high gradient level. Section 5.4 presents the experimental results on multimodality of medical images.

5.4 Experiments and Results

Several experiments have been conducted to evaluate the feasibility of the proposed method to automatically perform accurate boundary segmentation of medical images in the presence of intensity inhomogeneity. Additionally, the experiments aim to demonstrate that the proposed method works well regardless of imaging modalities and anatomical structure of the images. For this reason the datasets used for these experiments comprises of medical images from various modalities namely CT scan, MRI, microscopic and ultrasound images, and representing various types of human organs or anatomical structures. This section describes the medical datasets used and reports the experiments that have been carried out on these datasets and their results. This section includes the ground truth data medical images so that detail of areas that need to be segmented.

5.4.1 Dataset

Medical images of various modalities and anatomical structure used in these experiments were taken from the database of image Clef from the year 2010 to 2012 (www.imageclef.org). The medical images used in the experiments are MRI, CT scan, microscopic and ultrasound images. Table 5.1 presents the characteristics of the medical images used in the experiments.
Imaging	Organ	Criteria	Level of noise	Level of
modalities	captured			Intensity
CT scan	 Brain Chest Heart Abdomen include kidney liver, spleen, pancreas Pelvic include ovaries, bladder Lymph nodes 	 Object to be segmented consist of the inner and outer parts, for example, brain, heart and abdomen. Different shapes and brightness are used to represent anatomical structure, for example, the white flare to represent the outline of the brain tissues. 	• More severe in the inner part compared to the outer parts.	Inner parts contains high level of intensity inhomogenei ty
MRI	 Brain Chest Heart Abdomen include kidney liver, spleen, pancreas Pelvic include ovaries, bladder Blood vessels 	 Object to be segmented consist of the inner and outer parts, for example, brain, heart and abdomen. Images appeared to be darker than CT scan images and images such as heart appeared to be difficult in visual. 	• Level of noise is higher than CT Scan	• High level of intensity inhomogenei ty throughout the image
Microscopic	Blood cellsBacteria	• Consist of a collection of individual cells that are small in size and scattered throughout the image.	 Moderate. Often dependent on anatomical structure. 	 Moderate. Often dependent on anatomical structure.
Ultrasound	 Appendix Liver Heart Breast tumor/cancer Kidney Uterus Bladder 	 The lowest image quality among all modalities. Images are dark with unclear objects' outline. 	• Severely affected by noise	• High level of intensity inhomogenei ty throughout the image.

Table 5.1: The visual characteristics of medical images used in the experiments.

5.4.2 Experimental Procedures and Results

This section presents the procedures used in the experimental process and reports the experimental results. The experiments are conducted using MatlabR (2008b) on a 2.5 GHz with Intel Processor i5. The execution of the experiments involved several types of medical images with various anatomical structures. The main purpose of these experiments is to observe the capability of our method in segmenting multimodal medical images with various anatomical structures in the presence of noise and intensity inhomogeneity. In the experiments, two parameters are used that is the sinc α and sigma of σ . Both of these parameters need to be appropriately tuned to get a satisfying result. The values of these medical images.

The reporting of the experimental results is presented in the following sub-sections. The first sub section (Section 5.4.3.1) presents the experimental results on medical images with inner and outer parts such as brain, abdomen and heart. MRI and CT scan images of these anatomical structures are used in this experiment to demonstrate the capability of the proposed method to successfully segment the inner and outer parts of medical images of different anatomical structures and imaging modalities.

The second sub section (Section 5.4.3.2) reports the experimental results on sets of medical images that contain collection of individual cells that are small in size, for example, the microscopic images of cells or bacteria. Separating each of the individual cells is indeed a challenging process as most of the cells' images are affected with intensity inhomogeneity. The final sub section 5.4.3.3 reports experimental results on ultrasound images that are

commonly known as images with the lowest quality among the current modalities. Ultrasound images contained high levels of noise and intensity inhomogeneity, and appear darker than other modalities. In some cases, it becomes difficult to visually recognize the object to be segmented in an ultrasound image.

To measure the effectiveness of the proposed method in segmenting four types of medical images, twelve images of CT scan, twelve images of MRI, eight images of microscopic and four images of ultrasound were used in the experiment and their results are reported in the thesis. However, the experimental evaluation is based on visual interpretation where the evaluation is based on human eye ability in looking at the segmentation outcome. Therefore a quantitative evaluation using metric of accuracy is needed to support the findings.

Prior to the experiments, the ground truth data for the segmented medical images need to be built. The ground truth data of the segmentation outcome for the medical images is based on the medical experts' opinion. They were asked to manually drawn the segmented regions on the raw medical images. The outcome must be based on the objective of the proposed method. For instance, the objective of our FSW ACM is to segment regions within the noise and intensity inhomogeneity interface while solving the over segmentation problems. Figure 5.1 presents two images of medical imaging which are the MRI image of heart and the ultrasound image of breast cysts, along with their ground truth images.



Figure 5.1: Images of MRI image of heart (a) and its ground truth image in (b); Breast cysts of ultrasound in (c) and its ground truth image in (d).

Figure 5.1(a) shows the MRI image of a heart that was affected with noise and its distribution of intensity is non-homogeneous. The ground truth for the image is shown in Figure 5.1(b). For this image parameter α is chosen as 0.5 and the value of sigma σ is chosen as 1.0. As the level of noise and intensity inhomogeneity is not considered as very high, the smoothness of a contour cannot be too smooth, otherwise the movement of the contour will be unstable.

On the other hand, the ultrasound image of breast shown in Figure 5.1(c) was affected with high level of noise and intensity inhomogeneity. Therefore, the value of α is chosen as slightly smaller which is 0.1 and the value sigma of σ must be larger for example 3.0 in order to provide smoother effect to the contour. The optimum value for α is 1.0 and σ is 5.0. The ground truth image for ultrasound of breast is shown in Figure 5.1(d). The experiments' results are presented in the next sub-sections.

5.4.2.1 Medical Images with Inner and Outer Parts

This section reports our experimental findings on the capability of the proposed method in segmenting both the inner and outer parts of several human organs (brain, heart, abdomen, breast) which were represented in both CT scan and MRI images. Our first experiment with the FSW ACM method presents a collection of images from CT scan modality as shown in Figure 5.2(a – l). Figure 5.2(a - i) presents images of abdomen at different angles. The inner part of the abdomen contained object such as bladder, kidney, liver and others. Figure 5.2(j) represents an image of a brain, Figure 5.2(k) presents an image of a heart and Figure 5.2(l) shows an image of lungs. These images contain anatomical object that has inner and outer parts. The outer part contains a round or sphere anatomical structure. The object situated at the inner part depicted various anatomical structures of sizes and shapes. The parameters used in the experiments are $\alpha = 0.7$ and $\sigma = 1.0$. Note that, small numbers are chosen for both parameters due to the low level of noise and intensity inhomogeneity in the CT scan images. As the characteristics of visual features among the images appear to be similar therefore the experimental outcomes are more or less equivalent.



Figure 5.2: Images of CT scan modality comprises of abdomen at different angle, brain, heart and lungs.

Generally, the proposed method can successfully segment the outer part of the target object from the background for all images shown in Figure 5.2(a - 1) and the segmentation outcome is shown in Figure 5.3(a - 1). However, the segmentation results on the inner part of the objects varies for example, images shown in Figure 5.3(i), 5.3(k) and 5.3(l) displays better segmentation outcomes as compared to the rest of the images. The successful outcomes are attributed to low level of intensity inhomogeneity in the areas within the inner part of the object in Figure 5.3(i), Figure 5.3(k) and Figure 5.3 (l), and the distribution of intensity in those areas appear to be more distinctive. These outcomes have proven that the proposed nonlinear Gaussian filter can reduce noise and enhance edges for fast and smooth segmentation process. The implementation of the fractional sinc wave method can further increase the efficiency of a contour to rapidly move along edges and flexibly bend at any difficult curves and angles of an object to ensure accurate boundary segmentation outcome. In comparison, the inner parts of objects in other images suffer from intensity inhomogeneity problem as the areas appear bright with various intensities and high illumination. However, some components in the inner parts of these objects particularly in images Figure 5.3(a), Figure 5.3(c), Figure 5.3(d) and Figure 5.3(e) can still be segmented by the proposed method despite the problem. These results demonstrated that the proposed method has the capability to reduce the impact of the intensity inhomogeneity problem on medical images.



Figure 5.3: Experiments and results on twelve images of CT scan modality with $\alpha = 0.7$ and $\sigma = 1.0$.

The same experiments were repeated on a set of MRI images to observe the performance of the proposed method in segmenting both the inner and outer parts of an object in MRI images shown in Figure 5.4. The images have more noise and inhomogenous intensity as compared to the CT scan images. Among these images, images of a heart from various viewing angles (Figure 5.4(e)-(h)) and a liver (Figure 5.4(l)) have suffered from high level of intensity inhomogeneity throughout the image, resulting in unclear object boundary. Also noteworthy that the MRI's brain images (Figure 5.4(a-d)) and heart images consist of outer and inner parts. The outer part of the brain consists of bone structure while the inner part contains the brain tissues or muscles. There are high level of intensity inhomogeneity in the region of brain tissues and muscles which can create weak or missing edges along objects boundaries as shown in Figure 5.4(d), (f) and (h). Therefore a successful segmentation of the inner part of the brain is indeed a challenging process.



Figure 5.4: MRI images of heart, breast, abdomen and lung.

Figure 5.5 displays the experimental outcomes of our proposed method on MRI images. This experiment uses $\alpha = 0.7$ and $\sigma = 1.0$. The segmentation outcomes of the proposed method on MRI brain images are shown in Figure 5.5(a-d). Generally the method can successfully segment both the outer and inner parts of the images. However the accuracy of the segmentation result of the brain tissues is still lacking due to high level of intensity inhomogeneity in that areas. In Figure 5.5(a) and (c), the white flare of the brain tissue appears darker with similar intensity therefore the method is not able to properly segment the boundaries of the brain tissues. The best segmentation result of the inner part of the brain tissue appears darker with similar intensity therefore the method is not able to properly segment the boundaries of the brain tissues. The best segmentation result of the inner part of the brain image would be those presented in Figure 5.5(b). This is perhaps due to a more distinctive level of intensity throughout the inner regions.

Figure 5.5(e – 1) presents the results obtained on MRI images of a heart, abdomen, breast cancer and lung. As these images are unclear due to high levels of noise and intensity inhomogeneity, α is set to 0.5 and σ is set to 1.0. Our segmentation method can successfully segment both the outer and inner parts of a heart object in Figure 5.5(e - g). In Figure 5.5(h) however, only the outer part can be properly segmented because its inner part contains high level of intensity inhomogeneity which leads to many broken edges. Look at image shown in Figure 5.5(1) which is the image of a liver. The proposed method managed to separate the liver object from the background but may not be that accurate due to the level of intensity that is high. However, the method managed to segment the object. For images shown in Figure 5.5(i), (j) and (k), both the outer and inner parts of the objects are successfully segmented by the proposed method.

As the results of the experiments are mainly based on visual interpretation, a quantitative evaluation is carried out to further support the findings. As mentioned in chapter three, the percentage of the accuracy is measured based on the difference between the automatically created border by the proposed method and the border that is drawn manually by expert (the ground truth image). Table 5.2 illustrates the results after conducting the evaluation metric. Note that, the evaluation metric used in this study is based on work by Abbas et al.(2014) as explained in Chapter 3 of the thesis.



Figure 5.5: Experiments and results on MRI images of brain with $\alpha = 0.5$ and sigma of $\sigma = 1.0$.

CT scan images /	Fig. 5.3 (a)	Fig. 5.3 (b)	Fig. 5.3 (c)	Fig. 5.3 (d)	Fig. 5.3 (e)	Fig. 5.3 (f)	Fig. 5.3 (g)	Fig. 5.3 (h)	Fig. 5.3 (i)	Fig. 5.3 (j)	Fig. 5.3 (k)	Fig. 5.3 (l)
Accuracy metric	96.33	94.67	95.79	94.43	96.54	96.21	95.11	94.68	96.69	96.64	96.23	96.88
MRI images /	Fig. 5.5 (a)	Fig. 5.5 (b)	Fig. 5.5 (c)	Fig. 5.5 (d)	Fig. 5.5 (e)	Fig. 5.5 (f)	Fig. 5.5 (g)	Fig. 5.5 (h)	Fig. 5.5 (i)	Fig. 5.5 (j)	Fig. 5.5 (k)	Fig. 5.5 (l)
Accuracy metric	90.12	96.67	94.79	95.43	92.67	96.21	95.11	93.68	95.69	96.64	95.23	93.88

Table 5.2: Evaluation metrics based on accuracy obtained for CT scan images.

The evaluation metric is applied on twelve images of CT scan and MRI. According to the statistical metric of accuracy, the average accuracy obtained on twelve CT scan images is 95.85%. On the other hand, the average metric for the accuracy of segmentation on MRI images is 94.61%. The accuracy metric shown in Table 5.2 are aligned with the segmentation outcome which is based on visual interpretation as shown in Figure 5.3 and Figure 5.5. For example, Figure 5.3(a) shows a successful segmentation where the inner and outer part of the abdomen is segmented. In accordance, the quantitative evaluation shows the metric accuracy of 96.33% which is aligned with the segmentation outcome. Figure 5.5(a) shows an image of MRI brain. The contour did not accurately segment the white flare of the brain. Therefore, the metric of accuracy is just 90.12%. From the percentage of accuracy displayed in Table 5.2 the accuracy produced by the FSW ACM method on the CT scan images and MRI images are satisfactory.

5.4.2.2 Medical Images with Collections of Individual Cells

Microscopic images are medical image that are normally used to capture images of bacteria or blood cells. The images often comprise of a collection of individual cells that are adjacent and resemble to each other. Each individual cell is having the same size but separating between one individual cell to another can be unsuccessful. For a bacteria image, some image has unique anatomical structure and contains outer and inner part. Experts used microscopic images to determine the type of bacteria or to calculate the number of cells in human blood.

This experiment employs eight images of microscopic that consist of four images of bacteria and four images of blood cells. Figure 5.6(a - d) depicts images of bacteria in a collections of individual cells whereas Figure 5.6(e - h) displays close shot images of cells in a form of a single object, in order to have a clearer view on its anatomical structure. The aim of the experiment is to separate each individual bacteria successfully and to accurately segment the unique anatomical structure of the cell.



Figure 5.6: Images of cells and bacteria images of microscopic images.

As the images of the cells in Figure 5.6(a – d) have average noise, α is set to 0.7 and σ is set to 1.0. In some parts of the images, the distribution of intensities are not homogeneous thus influenced segmentation accuracy along an object boundary. Based on the results shown in Figure 5.7(a - d), the proposed method managed to segment the four images successfully. Image shown in Figure 5.6(a), has a clear background and the objects have different intensities from the background. Therefore, the proposed method do not faced problem in successfully segmenting the object in 0.5 seconds. In Figure 5.7(c), as the object of bacteria has brighter intensity and high illumination, the outlines of the bacteria are not successfully segmented. Look at the image shown in Figure 5.7(b) and Figure 5.7(d), the textures of both image backgrounds have slightly different intensity inhomogeneity. Due to that, the contour segmented the regions at the background but, it did not affect the segmentation made on each of the bacteria.



Figure 5.7: Experiments and results on microscopic images of cells and bacteria where images in (a - d) is using $\alpha = 0.7$ and $\sigma = 1.0$ and images in (e - h) is using $\alpha = 0.5$ and $\sigma = 1.0$.

Microscopic images shown in Figure 5.6(e - h) represents object of blood cells. Figure 5.6(e) shows image of microscopic of two cells. The image is considered as dark image and part of the boundary of the image is missing. Therefore, the parameter of α is set to 0.5 and the sigma σ is set to 1.0. From the result obtained in Figure 5.7(e), the proposed method managed to segment the outer and the inner parts of the two cells although part of the boundary is not accurately segmented. This is due to the missing edges at the boundary of the image. Figure 5.7(f) and Figure 5.7(g) show images of blood cells. In Figure 5.7(g) the contour managed to segment the blood cells but in Figure 5.7(f) some part of the boundary was not properly segmented. However its inner part was well segmented. Figure 5.6(h) shows an image with clear background but its inner part contains intensity inhomogeneity. Based on the result obtained in Figure 5.7(h), the contour managed to segment the object inside the blood cell successfully and managed to reduce segmenting the unwanted regions. The average percentage of accuracy on eight microscopic images is 95.64%. Due to the characteristic of microscopic images which is having low level of noise, the accuracy shown is higher than images of CT scan and MRI. However, the metric of accuracy shown for Figure 5.7(h) shows the lowest accuracy due to the level of intensity inhomogeneity which is slightly higher than other images in Figure 5.6 which is 92.02%.

Microscopic images	Fig. 5.7 (a)	Fig. 5.7 (b)	Fig. 5.7 (c)	Fig. 5.7 (d)	Fig. 5.7 (e)	Fig. 5.7 (f)	Fig. 5.7 (g)	Fig. 5.7 (h)
Accuracy metric	97.12	96.56	95.89	97.02	92.12	95.56	96.89	92.02

Table 5.3: Evaluation metrics based on accuracy obtained for microscopic images.

5.4.2.3 Outlining Object in Ultrasound Medical Images

Ultrasound modality is used to capture human organ which consists of muscle such as breast tumor, cysts ovary, lung and many more. Ultrasound images are darker than other modalities and have the highest levels of noise and intensity inhomogeneity. This experiment will test the ability of our proposed method to segment object boundary in ultrasound images. Figure 5.8(a - d), presents four images of ultrasound used in this experiment which are the liver, appendix and two images of breast cancer respectively.



Figure 5.8: Images of ultrasound of liver, appendix and two images of breast cancer.

Due to ultrasound characteristics, both parameters are set with values of α is set to 0.1 which is smaller and σ is set to 3.0 which is larger to give more smoother effect to the contour. Figure 5.8(a –d) shows the segmentation outcomes when the proposed method is applied on these images. Figure 5.8(a) shows ultrasound image of a liver. The dark area on the center of the image is the liver object that should be segmented. The distribution of intensity in its surrounding area is inhomogeneous. Similar conditions are reflected in Figure 5.8(c) and (d), both represent the image of breast cysts. Despite the aforementioned conditions, the proposed method can successfully segment both the liver and the cysts in the images. The success is due to the ability of nonlinear Gaussian filter to appropriately

smooth the intensity inhomogeneous regions and enhance the relevant edges in order to permit a contour to rapidly move along the objects boundaries. The application of sinc wave method can further improve the capability of the contour to flexibly bend at difficult curves and angles to ensure boundary segmentation of both objects can be achieved. A slightly different anatomical structure of an appendix is shown in Figure 5.8(b). The location of the appendix is indicated by label 'A'. It is surrounded with masses of body tissues or muscles with high level of noises and intensity inhomogeneity. It is indeed a difficult image to segment. However, the proposed method managed to segment the appendix and the over sampling problems are reduced. Over segmentation problems are referring to segmentation of unwanted regions. This is proven by the percentage of accuracy where the average on four ultrasound images is 93.42% as shown in Table 5.4.



Figure 5.9: Experiments and results on ultrasound images by the proposed method with $\alpha = 0.1$ and $\sigma = 3.0$.

Among the medical images, ultrasound images are having the lowest quality with high level of noise and intensity inhomogeneity. The metric of accuracy is also low where images in Figure 5.9(b), Figure 5.9(c) and Figure 5.9(d) show around 92%. This is because the contour segment several unwanted regions besides only segment the correct outlining of the object in ultrasound images.

Ultrasound images	Fig.5.9(a)	Fig.5.9(b)	Fig.5.9(c)	Fig.5.9(d)
Accuracy metric	97.12	92.08	91.80	91.23

Table 5.4: Evaluation metrics based on accuracy obtained for ultrasound images.

5.5 Benchmarking Evaluation on FSW ACM

The earlier sections have shown the feasibility of the proposed method to successfully segment medical images in the presence of high levels of noise and intensity inhomogeneity, regardless the modalities and anatomical structures. In this section we compare the performance of the proposed method with other baseline methods to prove its performance is equivalent to other ACM methods or even supersedes some of those methods. The medical images of various modalities and anatomical structures that are used in this experiment include CT scan, MRI, microscopic and ultrasound images. The baseline methods involved in this experiment are as follows: Chan-Vese (C-V, 2001) method and Selective Global and Local (SGLACM) method by K.Zhang (2010). The C–V method is a region-based ACM that endures high computational cost and produces over segmentation in dealing with intensity inhomogeneity. The SGLACM method manages to address the C–V method's deficiencies but does not provide contour stability during its evolution. To support the benchmarking process, an evaluation metric is used in accessing the accuracy of the segmentation outcomes among the evaluated methods.

5.5.1 Experimental Results

The experiments expects the outcome as a clean image with the initial contour wrap around the object of interest. A clean outcome of segmentation in this study is where only the object of interest is segmented without segmenting other unwanted regions regardless the intensity inhomogeneity problems. The images used in the experiments are MRI images of a brain and a heart, a CT scan image of a brain, ultrasound images of a heart, appendix and breast cyst and x-ray images of blood vessels. The C–V method is among the popular methods currently used in medical image segmentation. The SGLACM method, meanwhile, combines both edge-based and region-based ACMs by using a hybrid concept similar to the proposed method. Hence, the C–V and SGLACM methods were used as the baseline methods in this study.

The first experiment begins with the segmentation of an MRI image of a brain which later supported by two CT scan images of brain. Both MRI and CT scan images had less noise. However, images present are darker and had many sub-regions except for the second image of CT scan that focusing on the inner part of the white flare which result in a brighter environment. The inner part of brain images are suffered from the intensity inhomogeneity problem that create a challenging situation in segmenting the white flare. The segmentation results are shown in Figure 5.10, Figure 5.11 and Figure 5.12 respectively.

In experiments conducted in Figure 5.10 to Figure 5.12, the parameter of α that represents the $sinc_{\alpha}$ function (Eq.5.7) is adjusted to 0.5 and the parameter of sigma σ is adjusted to 1. If the sigma is chosen as a big number the initial contour may move dynamically and may disappeared without segmenting the object of interest. This is due to the smooth effect on the image texture which is high that may push the contour to move rapidly thus disappear from the image. On the other hand, the parameter α of $sinc_{\alpha}$ function is given as 0.7 due to the level of noise which is less when compared to the microscopic image of cell. Figure 5.10(a) shows that the C–V method successfully segmented the image. The method highly utilized the global energy. Hence, in inner part with intensity inhomogeneity, the method tended to also segment unwanted regions and produced over segmentation. The SGLACM method only segmented the outer part of the brain image shown in Figure 5.10(b). The segmentation result of the proposed method in Figure 5.10(c) illustrates a smooth segmentation outcome. Both the outer and inner parts of the brain were successfully segmented.

Application of the FSW ACM method in the Gaussian filter also improved the image's appearance. The region was smoother, the edges were clearer, and the image structure was preserved. As a result, the proposed method successfully addressed the intensity inhomogeneity problem in the inner part of the image and alleviated the over segmentation problem. Accordingly, the MRI brain was segmented in 50 iterations within 0.66 s. The proposed FSW ACM method segmented the image with a lower computational cost compared to the baseline methods. The C–V method made 300 iterations within 7.28 s. The SGLACM method completed the segmentation in 120 iterations within 1.03 s.



Figure 5.10: Brain MRI image segmentation. The final results using the C–V in (a), SGLACM in (b) and proposed FSW ACM in (c) respectively with α =0.5 and σ = 1.0 for our method.

On the contrary, Figure 5.11 illustrated the segmentation outcome conducted on a CT scan image of a brain. The image is used as to support the first experiment of MRI image of brain where the image also contained numerous sub-regions which lead into over sampling or the initial contour may segment the unwanted regions as well. However, unlike the MRI image of a brain, the inner parts of its sub-regions were surrounded with a bright intensity (Figure 5.11). The C–V method produced the segmentation of unwanted regions and completed the segmentation in 50 iterations within 2.77 s and this is shown in the first column of Figure 5.11(a). The SGLACM method revealed a similar outcome, where only the outer part of the brain was segmented in the MRI image as shown in Figure 5.11(b). The method completed the segmentation in 120 iterations within 1.6 s. The proposed FSW ACM method produced a cleaner outcome with a segmentation of both the outer and inner parts in 40 iterations within 1.01 s.



Figure 5.11: CT scan image of brain segmentation. The final results using the C–V in (a), SGLACM in (b), and proposed FSWACM in (c) respectively with $\alpha=0.7$, $\sigma = 1.0$, for our method.

The experiment proceeded on another CT scan image of a brain but this time the image is focusing at the white flare of the brain. The aim is to show the accuracy of segmentation provided by the proposed FSW ACM method in segmenting each of the white flare existed in the brain image. The texture of the image is smooth but, the classification of the intensity levels happen in the image are challenging where the initial contour may not correctly moved toward the white flare and segment each of the white flare in the image. The values for $\alpha = 0.7$ and $\sigma = 1.0$ is same as used in Figure 5.10 as the characteristics of the images are similar.

Among the results obtained, the FSW ACM method presents outcome which situated in Figure 5.12(c) shows better accuracy when compared to the outcome by C-V method in Figure 5.12(a) and SGLACM method in Figure 5.12(b). The FSW ACM method did not produced any unwanted segmented regions and the thin long white flare shown in Figure 5.12(c) is excellently segmented when compared to other methods where the white flare is not successfully segmented. C-V method due its intensity inhomogeneity problem, did not segment the white flare in the image successfully. On the other hand, SGLACM method produced a segmentation which is not complete. In terms of speed, FSW ACM method managed to complete the segmentation process within 40 iterations in 0.8 s whereas C-V method took 300 iterations in 6.2 s and SGLACM method took 60 iterations in 0.9 s.



Figure 5.12: Segmentation of a second CT scan image of a brain that focus on the white flare. The final results using the C–V in (a), SGLACM in (b) and proposed FSW ACM in (c) respectively with α =0.7 and σ = 1.0 for our method.

The experiment using the MRI image of a heart was then conducted. Two MRI images of heart with different angle and texture is produced. Both images revealed a slightly different texture than the earlier images. It also suffered from a high noise level with severe intensity inhomogeneity leading to weak edges. The hole in the center revealed a similar gradient level to the background with a dark intensity, which made the segmentation process more challenging.

Due to the texture of both images which are unclear and having more intensity levels which is not homogeneous, the $sinc_{\alpha}$ parameter is adjusted to be bigger which is 0.084 and the sigma σ is maintain to 1. In this situation the interpolation process of FSW ACM method will better classify the non-homogenous objects in a region. The experimental results on the MRI image of a heart are shown in Figure 5.13 and Figure 5.14. The segmentation results using the C-V, SGLACM and proposed FSW ACM methods are shown in (a), (b), and (c) respectively in both Figure 5.13 and Figure 5.14. The segmentation outcomes were similar in the C-V and the proposed FSW ACM methods for both images in Figure 5.13 and Figure 5.14. The proposed FSW ACM method demonstrated a cleaner and more defined segmentation outcome without any oversampling. This result indicated a significant reduction of the intensity inhomogeneity in the image. For image in Figure 5.13, the C-V method made 100 iterations within 3.68 s to complete the segmentation, whereas the proposed FSW ACM method segmented the heart object from the MRI image with only 40 iterations in 1.7 s. On the other hand C-V method complete the segmentation of image in Figure 5.14 within 70 iterations in 2.11 s and the FSW wave ACM method complete the segmentation within 60 iterations in 1.2 s. The SGLACM method, which made 120 iterations in 0.95 s for image in Figure 5.13 and 60 iterations in 1.1 s for image in Figure

5.14, only segmented the outer part of the heart object and did not segment the hole in the image center.



Figure 5.13: Experiment on the MRI image of a heart. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c) respectively with $\alpha = 0.5$ and $\sigma = 1.0$ for our method.



Figure 5.14: Experiment on another MRI image of a heart in different angle. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c) respectively with $\alpha = 0.5$ and $\sigma = 1.0$ for our method.

The experiment continued with three ultrasound images that represent an image of a liver in Figure 5.15, image of an appendix in Figure 5.16 and image of a breast cyst in Figure 5.17. Ultrasound images are known as the noisiest images among medical images. To conduct the experiments on these ultrasound images, the $sinc_{\alpha}$ is adjusted to 0.1 which is much smaller and sigma σ as 3.0 which is larger for more smoother effects. This is due to the image nature which is rough and having severe intensity inhomogeneity. Moreover, its

intensity distribution is not homogeneous, its object boundary is very weak, and it has many missing edges. Besides, the liver image is particularly dark with complex and rough texture, which poses a challenging situation for any segmentation process.

The segmentation outcomes obtained from this experiment are depicted in Figure 5.15. As expected, the C–V method displayed many overlapping pixels in the image's regions with 250 iterations in 7.28 s. The SGLACM method only segmented the image exterior with 120 iterations in 0.82 s. Although the selective global was applied, the contour did not segment the liver object because of the complex image texture. The proposed FSW ACM method demonstrated an impressive outcome in Figure 5.15(c). Without any over segmentation, the method accurately segmented the ultrasound image of a liver with 50 iterations in 0.78 s.



Figure 5.15: Experiment of an ultrasound image of a liver. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c), respectively with the parameter of α =0.1 and σ is 3.0 for our method.

The experiment was repeated on an ultrasound image of an appendix to further support the consistency of the experimental findings on ultrasound images. This appendix image was more challenging to segment because its texture was more complex and darker than the previous images. The appendix object was labelled "A". Much noise and overlapping pixels surrounded the object, and the quality of this ultrasound image was very low. Hence, the σ

values of the proposed method were set larger than usual with $\sigma = 3.0$ as mentioned earlier. The segmentation results of the appendix object are shown in Figure 5.16. The C–V method produced severe over segmentation effect, which made its segmentation result less successful. The SGLACM method only segmented the outer image border, ignoring the segmentation of the appendix object.

A successful appendix object segmentation was demonstrated by the proposed FSW ACM method in Figure 5.16 with a significantly less over segmentation effect than the C–V method. In terms of the time taken to complete the segmentation, the proposed method took the least time among all the methods. The proposed FSW ACM method took only 40 iterations within 1.21 s, whereas the C–V method completed the segmentation in 140 iterations within 3.23 s. The SGLACM method took about 120 iterations within 1.68 s.



Figure 5.16: Experiments on ultrasound image of appendix. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c) respectively with the parameter of $\alpha = 0.1$ and $\sigma = 3.0$ for our method.

The experiment demonstrated another ultrasound image which represented the image of breast cyst in Figure 5.17. The reason is to support the experiments conducted earlier and to observe the efficiency of the proposed method. As the nature of the ultrasound image is the same as previous ultrasound images, both parameters of α and σ used are the same as used

in Figure 5.15 and Figure 5.16. Based on the outcome obtained as shown in Figure 5.17, the FSW ACM method produced a cleaner outcome with reduced intensity inhomogeneity and managed to successfully segment the cyst within 40 iterations in 1.2 s. On the other hand, C-V method segments the cyst object within 250 iterations in 8 s but produced segmentation of unwanted regions. SGLACM only segmented the outer part but did not managed to segment the cysts object and this is done within 50 iterations in 1.31 s.



Figure 5.17: Experiments on ultrasound image of breast cysts. The final results using the C–V in (a), SGLACM in (b), and FSW ACM in(c), respectively with the parameter of $\alpha = 0.1$ and $\sigma = 3.0$ for our method.

The final experiment was conducted on x-ray images of blood vessels in Figure 5.18. Unlike the other images, these images were distinctive with a long and winding structure. The background of both images had slightly brighter intensity than the interior region of the vessels. The texture of the image is smooth and the intensity level that represent the background to the vessel object are slightly similar where the intensity level is difficult to be identified. Thus, the parameter α is adjusted to 0.3 and the σ is adjusted to 3.



Figure 5.18: Experiments on X-ray images of thin and winding blood vessels. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c), respectively with the parameter of $\alpha = 0.3$ and $\sigma = 5$ for our method.

The segmentation results on these images are shown in Figures 5.18 and 5.19. The boundary of the long and thin vessels suffered from the intensity inhomogeneity problem, which made the segmentation arduous. The SGLACM method (Figure 5.18 (b)) did not accurately segment the blood vessel. In this case, the contour did not stop on the exact blood vessel boundary. To complete the segmentation process, the method made 120 iterations within 2.02 s. The C–V method did not successfully segment the vessel and failed to identify the area badly affected with the intensity inhomogeneity problem. This area is indicated by an arrow in the first column. To complete the segmentation, the C–V method made 300 iterations within 2.68 s. Using the proposed FSW ACM method, an accurate segmentation outcome of the blood vessel was achieved with lower computational cost. The method made only 40 iterations within 1.1 s. A similar experiment was repeated on another blood vessel for consistency purposes (Figure 5.19).



Figure 5.19: Experiments on the second type of blood vessel x-ray images. The final results using the C–V in (a), SGLACM in (b), and proposed FSW ACM in (c), respectively with the parameter of $\alpha = 0.3$ and $\sigma = 5$ for our method.

The image in Figure 5.19 illustrates an intensity inhomogeneity problem along with some subsequent pixels weak in intensity in the vessel. All the methods successfully segmented the blood vessel, albeit with different computational times. The C–V method completed the segmentation process in 50 iterations within 8.4 s. It also encountered some segmentation difficulties along the vessel boundary because of the intensity inhomogeneity effect. On the contrary, the SGLACM method made about 40 iterations in 6.8 s to complete the vessel segmentation. The proposed FSW ACM method completed successful blood vessel segmentation in just 30 iterations within 5.4 s. This computational time was the shortest completion time achieved among the methods. Speed, aside from improving the segmentation, was also important in completing the segmentation process. The FSW ACM method produced a satisfactory segmentation process. Table 5.4 summarized the time taken in completing the segmentation process for all experiments conducted earlier. On the other hand Table 5.5, summarize the evaluation executed based on the segmentation accuracy.

 Table 5.5: Summarization and comparison on time in seconds took in completing the

Medical Image	Object	Time taken				
Modalities		FSW ACM method	C-V method	SGLACM method		
MRI	Brain	0.66s	7.28s	1.03s		
MRI	Heart	0.95s	3.68s	0.82s		
MRI	Heart (different angle)	1.25s	2.11s	1.15s		
CT SCAN	Brain	1.01s	2.77s	1.6s		
CT SCAN	Brain	0.85s	6.2s	0.95s		
ULTRASOUND	Liver	0.78s	7.28s	0.82s		
ULTRASOUND	Appendix	1.21s	3.23s	1.68s		
ULTRASOUND	Breast Cysts	1.25s	8s	1.31s		
X-RAY	Blood Vessel	1.1s	2.68s	2.02s		
X-RAY	Blood Vessels	5.4s	8.4	6.8s		

segmentation process.

 Table 5.6:
 Summarization and comparison on time in seconds took in completing the

Methods	Medical Images	Chan-Vese	SGLACM	FSW ACM
Accuracy	MRI Brain	95.55	93.23	95.9
Accuracy	MRI heart 1	92.52	90.11	92.87
Accuracy	MRI heart 2	92.91	90.07	93.68
Accuracy	CT Scan Brain 1	89.34	90.23	96.67
Accuracy	CT Scan Brain 2	89.12	92.34	95.43
Accuracy	Ultrasound Liver	92.34	88.12	96.55
Accuracy	Ultrasound Appendix	89.34	86.12	95.64
Accuracy	UltrasoundBreast Cysts	93.23	88.67	96.23
Accuracy	X-Ray bloodVessel 1	93.23	90.56	94.23
Accuracy X-Ray bloodVessel 2		96.04	96.2	96.37

segmentation process

From the results obtained as shown in Table 5.6, the metric of accuracy shown by the FSW ACM method is more than 90% for medical image modalities used in the experiment. The metric of accuracy obtained by each medical images produced by FSW ACM method shows higher accuracy than accuracy obtained from C-V and SGLACM method. This show FSW ACM provides an improvement of the segmentation outcome.

5.6 Discussion

This section discusses the analysis conducted based on results gained from the experiments on four medical image modalities. Most of the images used in the experiments suffered from the intensity inhomogeneity problem and noise. The only different is the level of intensity inhomogeneity and noise. Hence, some critical edges along the object boundary became weak or missing and led to gaps at the object boundary. Among the medical images used in this paper, the CT scan image has the least noise, especially at the outer part of the object from the background. Other images, such as those from MRI, microscopic imaging and ultrasound imaging have much noise, which leads to the intensity inhomogeneity problem. The proposed method aims to reduce the intensity inhomogeneity problem, thereby improving the object segmentation in medical images in a shorter processing time.

This study introduces the use of FSW method of order α with hybrid ACM because it removes noise in an image while maintaining the edges of the image structure. The use of sinc wave method along with the fractional calculus is further introduced for a flexible contour movement with improved bending effect capability during its evolution. This bending flexibility enables the contours to easily move forward and backward the object of interest and to quickly segment the object. Moreover, the sinc wave method with fractional function has the strength to rapidly move the contour within the intensity inhomogeneity interface efficiently. It further moves the contour slower when it is near the object boundary with the support of local energy. Consequently, the contour locally adapts at the boundary interface for improved segmentation result.

Based on several experiments conducted, it is shown that the proposed FSW ACM method managed to provide an improved segmentation while reducing the over sampling created by the intensity inhomogeneity problem. Segmentation executed on CT scan images depicted a satisfying result. The contour managed to separate the object in the image perfectly from the background. Regarding the inner part, the contour managed to move toward the multiple objects without any over segmentation. On the other hand, segmentation on MRI images produced successful results. Due to the texture the parameters applied is chosen as slightly highly. Although the MRI images depicted as images as dark and having more noise, the FSW ACM method managed to segment the object excellently. This is proven that, the FSW ACM method applied managed to deals with weak pixels in the image.

Microscopic and ultrasound images are shown as an image in having soft and rough texture respectively. Some microscopic image is having severe intensity inhomogeneity until it made the contour difficult to wrap around the object of interest. On the other hand, the ultrasound image is dark and the intensity distribution is not homogeneous. Detecting the object of interest is difficult thus made the segmentation crucial. In conducting the experiments on these images, both parameters of α and σ is chosen to be higher. Based on the results obtained, FSW ACM method had proven that the collaboration of fractional function with FSW method managed to overcome the intensity inhomogeneity problem and provide improved segmentation. The potential of FSW ACM method in segmenting several modalities of medical images is supported by conducting the evaluation metric which is based on the accuracy of segmentation. It is shown that in most experiment, the accuracy is more than 90%. This means the distance of the contour to the object boundary is near and the segmentation achieved its goal.

However, based on several experiments conducted, the method having drawback where it fail to produce accurate boundary segmentation. Details discussion and illustration on the drawback will be discussed in the chapter 6 and the proposed Fractional Gaussian Heaviside (FGH) ACM will overcome the problem created by the FSW ACM method. This will be discussed in Chapter 6 of the thesis.

5.7 Summary

This chapter presents a combination of global and local ACMs that uses the FSW ACM method of order α , with exponential regression to speed up the contour evolution. This method provides improved bending effects for contour movement forward and backward during its evolution and enhances the object boundary edges. This study proposes the application of fractional sinc wave method on the contour during its evolution using both global and local energies. The Gaussian filter is modified with the FSW ACM method to smooth the image and enhance its edges, thereby preserving the image structure. The filter is also used to reduce the oversampling issue produced by the region-based ACM on images with intensity inhomogeneity. The contours embedded with the FSW ACM method actively moved forward and backward to be closer to the object boundary. A distance measurement based on fractional Euler Lagrance with local energy is implemented to

accurately segment an object at its correct boundary within the level set framework. The energy function is minimized as the level set curve meet exactly on the object boundary. Regardless of the image modalities, the proposed method provides improved segmentation of the object of interest at a lower computational cost than the other common ACM methods. In addition, the measurement of accuracy metric is more than 90% is all types of medical image modalities.

CHAPTER 6

FRACTIONAL GAUSSIAN HEAVISIDE ACTIVE CONTOUR MODEL

This chapter proposes the second approach in automatic segmentation of medical images. We proposed a novel region-based ACM with fractional calculus concept and namely Fractional Gaussian Heaviside (FGH) ACM. In the proposed method, we introduce two important terms; Adaptive Fractional Gaussian Kernel (AFGK) and Fractional Differentiate Heaviside (FDH). The aim of the implementation is to address the problem encountered in the first approach; Fractional Sinc Wave (FSW) ACM in achieving the accurate boundary segmentation within the intensity inhomogeneity interface. The chapter begins with a brief introduction of the proposed method in providing the accurate boundary segmentation while Section 6.1.1 presents brief information on hybrid ACM methods that utilized the local image information. Section 6.2 discusses the FGH ACM method in general. The design and development of the proposed method; FGH ACM method is discussed in Section 6.2.1 where Section 6.2.1.1 presents the discussion on AFGK and Section 6.2.1.2 presents discussion on FDH. The energy minimization of FGH ACM is presented in Section 6.2.1.3. Implementation of the proposed method is presented in Section 6.3 with demonstration of the proposed method in showing its strength to overcome the problem created by FSW ACM method. We report our experiments and their results followed by some experiments for benchmarking evaluations to compare the performance of our

proposed method with the previous FSW ACM method and other well-known segmentation methods in Section 6.4 and Section 6.5 respectively. Section 6.6 discusses on the benchmarking results emphasizing on the performance of the proposed method against other methods of ACM. This chapter ends with a conclusion about the ability of the proposed method in addressing the current problem of medical image segmentation.

6.1 Introduction

The FSW ACM method discussed in Chapter 5 contributed to a method that reduced the over segmentation problem thus produced successful segmentation on four types of medical image modalities. However, it is discovered that FSW ACM method has several drawbacks. First, the method was trapped at local minima problem along the object boundary. Second, the method does not have the capability in recognizing regions with least gradient in the image. Due to these factors, accurate boundary segmentation is not achieved. Our investigation found that, medical images with long, winding and spiral structures gave challenges to FSW ACM in guiding the contour to move along the winding and spiral structure in order to provide successful segmentation. Moreover, images with object boundary that is affected with high level of intensity inhomogeneity until it leads to missing edges also gave effect to the contour of FSW ACM in providing an accurate boundary segmentation. This chapter presents our novel contribution in solving the local minima problem by introducing the FGH ACM in providing accurate boundary segmentation.

Through investigation, embedding the local image information will have the probability in solving the local minima problem. Additionally, losing of edges in an image need to be avoided to make sure there is no gap along the object boundary. Previously, the hybrid methods of ACM embedded the local image information in their method to solve the local minima problem which leads to accurate segmentation. Several techniques are used by these methods in providing accurate to segmentation.

6.1.1 Hybrid methods with Local Image Information

In medical images, local minima are frequently encountered when the initial contour is far from the object that needs to be segmented (Bresson et al., 2005; Li et al., 2010). Local minima problem is more crucial for small anatomical structures of medical images such as object of white flare (brain), boundary of bacteria object and many more. This is because when a contour stuck in a local minima problem, the gradient or nearest intensity value among the neighboring pixels becomes invisible (Li et al., 2010). The local minima problem often occurs in medical images with high level of intensity inhomogeneity. Embedding the local information at the critical area in medical images is one way to solve the local minima problem in order to extract the object boundary (Li et al., 2007; Zhang et al., 2010).

Several studies on ACM have attempted to solve the local minima problem to achieve the accurate boundary segmentation within the high level of intensity inhomogeneity. Many local region-based ACM methods are currently attempting to solve the local minima problem. The idea began with work of Brox and Cremers (2009), who have extended the Mumford-Shah (MS) model by embedding the local energy as the first-order approximation
(Mumford & Shah, 1989). The work provided smoother regions by modeling each region with an estimated mean into a local Gaussian neighborhood. Shawn Lankton (2008) conducted experiments that enabled region-based energy to be localized in a fully variational manner. His work significantly improved the accuracy of heterogeneous image segmentation.

Li et al. (2007) analyzed the localized energy and developed a method called local binary fitting energy (LBF). Their work introduced local energy with a kernel function (Li et al., 2007) to extract the local image information and achieve accurate segmentation in the presence of intensity inhomogeneity. Their method yielded good performance in the segmentation process, especially on medical image segmentation. However, the method required high computational cost, especially in handling severe intensity inhomogeneity images, because it had to be performed in four convolution operations. Furthermore, it sometimes did not reveal accurate segmentation at the desired object boundary (Li et al., 2007; Chan & Vese, 2001).

Li et al. (2011) again developed a novel region-based ACM that derived a local intensity clustering property of the image intensities and namely Local Intensity Clustering (LIC). Based on the image intensities, a local clustering criterion function is defined for the image intensities in a neighborhood of each point. The local clustering criterion function derived earlier is then integrated to the neighborhood center to give a global criterion of image segmentation. The LIC method can be considered as a locally weighted *K*-means clustering method. The method does not consider the clustering variance, which may cause inaccurate segmentation.

Wang et al. (2009) developed a new region-based ACM that utilized the local image intensities. The local image intensities are then described by Gaussian distribution with different means and variance as its variables. The means and variances of local intensities are considered as spatially varying functions to handle intensity inhomogeneities and noise of spatially varying strength. As the method highly depending of the means and variances of the Gaussian distributions, small intensities within the image is not extracted that leads to inaccurate segmentation. In addition, the method provides high computational cost and leads to slower segmentation speed.

Lastly, Darolti et al. (2008) proposed a method called local region descriptor (LRD) to characterize the entire image region that had overlapping pixel intensity. The method aimed to solve the problem of overlapping pixels leading to the difficult extraction of the local image information at the object boundary. However, the LRD method showed several drawbacks. One example was its level set evolution that acted locally because the Dirac function used was restricted to neighborhood pixels around the zero level set, thereby easily trapping the contour at the local image details (C. Darolti et al., 2008). Moreover, the region descriptor used in the LRD method did not consider the region variance, which led to inaccurate segmentation.

6.2 Fractional Gaussian Heaviside Active Contour Model

The second automatic approach of the thesis is still based on the fractional calculus concept. Two important techniques are formed which are; the Adaptive Fractional Gaussian Kernel (AFGK) which is used to enhance the image and the Fractional Differentiate Heaviside (FDH) is applied to extract the local image information. The goal of the FGH ACM method is to provide the accurate boundary segmentation.

6.2.1 The Design of Fractional Gaussian Heaviside

The design of FGH ACM method is based on the application of AFGK and FDH techniques. The Gaussian filter in previous FSW ACM method that is nonlinear is now replaced with FGK in AFGK. The new FGK which is also nonlinear shows the capability in merging and grouping the inhomogenuous object that belongs to the same intensity level (Yunmei et al., 2003; Miller & Ross, 1993). The capability of nonlinear function in enhancing and maintaining the image structure while reducing the image noise is also inherit by AFGK. Additionally, an adaptive window is applied where it has the capability in adaptively change according to the gradient magnitude changes in an image. This gave excellent result of a smoother image texture especially at the critical area along the object boundary.

The FDH technique is introduced to extract the local image information. The integer-order gradient operator implemented in most ACM methods is now generalized to FDH function which is based on energy formulation regulations. The FDH function uses the fractional-order gradient operators which weigh both image gradient and intensity to mitigate the local minima problem and improve the object boundary segmentation outcome. The FDH

function offers a nonlinear protecting capability to maintain the image structure and has the ability in the extraction of local image information. The proposed FDH function works within the level set framework, thereby stopping the contour when its energy is minimized at the object boundary. The algorithm design of the proposed method is reported in Section 6.2.1.1 and Section 6.2.1.2.

The proposed FGH ACM shows several advantages. First, the AFGK technique introduces a new method of enhancing the image quality within the environment of high level intensity inhomogeneity. The enhancement is carried out by reducing the noise and enhancing the image details. Besides, the FGK have the capability in merging and grouping the inhomogeneous object in a region. Second, the FDH function extracts the image gradient and its various intensities for an accurate boundary segmentation outcome. Lastly, the implementation of fractional-order gradient all throughout the proposed model ensures contour stability when maneuvering every object boundary within the difficult intensity inhomogeneity image. Furthermore, it also forbids the contour from stopping until the segmentation process is successfully completed.

6.2.1.1 Adaptive Fractional Gaussian Kernel

The application of adaptive window mechanism with FGK has shown a significantly better smoothing process than the previous Gaussian filter. The flexibility of the window mechanism that can be adapted perfectly based on changes of the image texture gave motivation to the study in applying the window mechanism concept. The window sizes will be adjusted to move increasingly and decreasingly in such a way to smooth most in the direction of least gradient. As the FGK is used, the edges are preserved and enhanced, however at critical area some local image details are invisible and difficult to be detected. Therefore, the AFGK provide the capability to embed the local image information for extraction process to take place.

One of the critical parts of segmentation process is to find the exact location of contour C on the object boundary to achieve accurate boundary segmentation. The role of fractional calculus in the proposed window mechanism makes the window narrower and smaller, such that it can adapt to the object boundary angle as it moves closer to the boundary. This technique prevents the loss of critical information and improves the classification of objects in the inhomogeneous interface. Furthermore, the proposed adaptive window with fractional calculus prevents the merging of information on the two sides of the boundary, thereby keeping the intensities sharp in this area. The smoothing process is based on Gaussian kernel as discussed in Chapter 2 in Eq. (2.22). In this situation, the Gaussian kernel is classified as nonlinear function with a scale parameter of $\alpha > 0$. The two-dimensional FGK is decomposed into two of one-dimensional Gaussian kernels in the proposed method, where the adaptive window is implemented. The resulting equation is given as follows:

$$G_{\alpha}(x,y) = G_{\alpha}(x) * G_{\alpha}(y)$$
(6.1)

The standard deviation of the one-dimensional fractional Gaussian at a pixel should be inversely proportional to the minimum and maximum of the fractional gradient magnitude at the image pixel; thus, the standard deviations of σ_x and σ_y are represented as:

$$\sigma_x = \alpha/2(G_n + 1) \tag{6.2}$$

and

$$\sigma_y = \alpha/2(G_m + 1) \tag{6.3}$$

Near the object boundary, when the value of the gradient magnitude increased, the Gaussian kernel will becomes smaller. Otherwise, it becomes narrower near the edge along the object boundary. This is because the value of local gradient magnitude across the edge of the object boundary is larger than the value of local gradient magnitude along the edge of the object boundary. The value of parameter α of the Gaussian kernel in the proposed method needs to be user-tuned depending on the image characteristics to achieve an effective result.

Furthermore, parameter α enables the user to increase the smoothing effect when image noise is presented but decrease its value with low image noise. In addition, the coordinates on both sides of the object boundary are computed to calculate the FGK with the adaptive window for an improved smoothing effect and obtain the relation between the points of the two sides. This computation is conducted to achieve the rotation invariance of the window using fractional calculus. The equation for this computation is given as follows:

$$R_{\alpha} = \Gamma(1 + \alpha) \begin{pmatrix} \cos(\alpha \pi/2) & \sin(\alpha \pi/2) \\ -\sin(\alpha \pi/2) & \cos(\alpha \pi/2) \end{pmatrix}$$
(6.4)

where α represents the fractional power derivatives for the FGK. The preceding equation is further explained as follows:

$$D^{\alpha} \sin(t)$$

$$=\sin\left(\frac{\alpha\pi}{2}\right)\cos_{\alpha}(t) + \cos\left(\frac{\alpha\pi}{2}\right)\sin_{\alpha}(t)$$
(6.5)

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$$D^{\alpha}\cos(t) = \cos\left(\frac{\alpha\pi}{2}\right)\cos_{\alpha}(t) + -\sin\left(\frac{\alpha\pi}{2}\right)\sin_{\alpha}(t),$$
(6.6)

where D^{α} denotes the Riemann–Liouville fractional differential operator of the order $0 \le \alpha \le 1$.

$$D^{\alpha}f(t) = \frac{d}{dt} \int_{a}^{t} \frac{(t-\tau)^{-\alpha}}{\Gamma(1-\alpha)} f(\tau)b\tau = \frac{d}{dt} I_{a}^{1-\alpha}f(t)$$
(6.7)

The following equation corresponds to the fractional-order gradient operator for a continuous function f(t) of the order $\alpha > 0$:

$$I_a^{\alpha} f(t) = \int_a^t \frac{(t-\tau)^{\alpha-1}}{\Gamma(\alpha)} f(\tau) d\tau.$$
(6.8)

The rotation invariance of the adaptive window is achieved on the basis of Eqs. (6.6) and (6.7). We define the following axes by considering the fractional trigonometric function:

$$x = \Gamma(1+\alpha)[X\cos(\alpha\pi/2) - Y\sin(\alpha\pi/2) + X]$$
(6.9)

and

$$y = \Gamma(1+\alpha) \left[X \sin\left(\frac{\alpha\pi}{2}\right) - Y \cos\left(\frac{\alpha\pi}{2}\right) + Y \right],$$
(6.10)

where *X* and *Y* are the usual axes. The preceding relationships determine the corresponding image pixels. Furthermore, the values of the image pixel and the window are multiplied and added to obtain the smoothed image intensity. The advantage of using fractional calculus is obvious on the image edges and angles, which are ignored when normal calculus is employed. Correspondingly, the inhomogeneous object and the image local information

found in a given region are now effectively classified. In addition, the sharp edges at the boundary are maintained to extract information better with the use of the contour during the segmentation process. The section that follows discusses the fractional-order gradient for the image segmentation process and the complete algorithm description of the proposed FGH ACM method.

6.2.1.2 Fractional Differentiate Heaviside

The FDH function is generalized using the region-based ACM method to solve the local minima and the intensity inhomogeneity problems. We assume that a dependency exists between different image pixels, and that each pixel value is related to its neighbor in a region. The energy is minimized within the level set framework. We derived the following complete algorithm for the proposed method on the basis of fractional calculus:

$$\varepsilon_{\alpha}^{F}(d_{1}(x), d_{2}(x), \phi)$$

$$= \mu \int \delta(\phi(x, y)) |\nabla^{\alpha} \phi(x, y)| dx dy$$

$$+ \lambda_{1} \int_{in} G_{\alpha}(x - y) |I(y) - d_{1}(x)|^{2*\alpha} dy \qquad 0 < \alpha < 1$$

$$+ \lambda_{2} \int_{out} G_{\alpha}(x - y) |I(y) - d_{2}(x)|^{2*\alpha} dy \qquad 0 < \alpha < 1$$
(6.11)

where G_{α} is the FGK, ∇^{α} is the fractional-order gradient operator, and $d_1(x)$ and $d_2(x)$ are the two fitting numbers placed to extract and spot the intensity belonging to the same class:

$$d_1(\phi) = \frac{\int_{\Omega} I * H_x^{(\alpha)}(\phi) dx}{\int_{\Omega} H_x^{(\alpha)}(\phi) dx}$$

(6.12)

and

$$d_{2}(\phi) = \frac{\int_{\Omega} I * (1 - H_{x}^{(\alpha)}(\phi)dx)}{\int_{\Omega} (1 - H_{x}^{(\alpha)}(\phi)dx)}$$
(6.13)

Note that:

$$\nabla^{\alpha}\phi(x,y) = \phi_{x}^{(\alpha)} + \phi_{y}^{(\alpha)}$$
(6.14)

The following equation is obtained using *I* as the image and H^{α} as the fractional differential Heaviside function:

$$H^{(\alpha)}(t-\varsigma) = H(t-\varsigma)\frac{(t-\varsigma)^{-\alpha}}{\Gamma(1-\alpha)}, \quad t > \varsigma.$$
(6.15)

The two fitting numbers are responsible in classifying and combining the inhomogeneous intensity. Besides, the two fitting numbers are placed near the intensity of the object of interest and used to extract the local image information embedded earlier by the Gaussian kernel. The AFGK decomposes the two-dimensional Gaussian into one-dimensional Gaussian kernels. The adaptive window is horizontally and vertically moved across the image to multiply the window and image values and produce a smooth image texture. The process is pre-calculated, saved, and reused to speed up the computations.

Parameter α in Eq. (6.11) represents the order of the FDH function. This stage is applied within the level set framework, where stabilizing the level set is possible. The proposed method uses the fractional-order gradient instead of the integer-order gradient operator used in the previous ACM methods. The integer-order gradient operator term stands for the changing rate of the level set curve length, which is used to control the speed of the level set from shrinking. The fractional-order gradient of FDH function implemented in the proposed method enables us to control the speed of the level set from shrinking, thereby improving stability. The energy is minimized to obtain the accurate boundary segmentation because the proposed method works within the level set method. The complete algorithm of the proposed method is discussed in Section 6.2.1.3.

6.2.1.3 Energy minimization and Level Set Method

One of the aims of ACM is to minimize energy when the level set contour is on the object boundary. In this study, the fractional-order gradient operator was used to obtain a stable contour to realize energy minimization. In any ACM method, the energy of the level set is minimized on the object boundary. For example, in the C–V method, the energy is minimized when the parameters are equal to zero, whereas the two fitting values in the LBF method are optimally chosen to minimize the energy of the level set method. The proposed method also minimizes the energy when contour C is placed on the object boundary, with the condition that $d_i(x) \approx 0, i = 1,2$. The fractional gradient flow equation that corresponds to the FDH function and the minimization energy is defined as follows:

$$\phi_{t} = \delta(\phi) \{ \mu [D_{x}^{\alpha*}(|\nabla^{\alpha}\phi(x,y)|^{-1}D_{x}^{\alpha}\phi) + D_{y}^{\alpha*}(|\nabla^{\alpha}\phi(x,y)|^{-1}D_{y}^{\alpha}\phi) -\lambda_{1}(I(y) - d_{1}(x))^{2} + \lambda_{2}(I(y) - d_{2}(x))^{2}$$
(6.16)

where $D_x^{\alpha*}$ and $D_y^{\alpha*}$ are the adjoints of the usual fractional differential operator, satisfying the condition that the fractional derivative on the boundary of Ω for the function φ is vanished. The contour stops when the energy is minimized and accurate segmentation is achieved. Based on the discussion in Sections 6.2.1.1 and 6.2.1.2, the proposed FGH ACM is summarized in the following steps.

- 1. Initialization of contour.
- 2. Updating the fractional Gaussian kernel by tuning the parameter of α , $0 < \alpha < 1$ through Eqs. (6.5) and (6.6).
- 3. Updating the window sizes and shapes according to the interface of intensity inhomogeneity by adjusting the α using Eqs. (6.9) and (6.10).
- 4. Updating the fitting numbers, $d_1(x)$ and $d_2(x)$ optimally using Eqs. (6.12) and (6.13), respectively.
- 5. Evolving the level set function according to Eq. (6.16).
- 6. Regularizing and minimizing the energy of the level set function.
- 7. When the condition of $d_i(x) \approx 0, i = 1, 2$ is met, the contour movement is stopped; otherwise, return to step 2.

6.3 Implementation and Demonstration

This section presents several demonstrations based on the implementation of the proposed FGH ACM method. The demonstration and the implementation is executed using Matlab R(2008b) on a 2.5 GHz Intel Processor i5. The main aim is to observe the performance of FGH ACM method in solving problem created by the FSW ACM method in providing accurate boundary segmentation. In illustrating the problem created by the FSW ACM method, Figure 6.1(a) presents a synthetic image that was affected with intensity inhomogeneity problem along the object boundary thus made it difficult in getting accurate boundary segmentation. Figure 6.1(b), presents the outcome obtained from the segmentation executed based on FSW ACM method. The contour was stuck at the local minima problem thus accurate segmentation in not achieve. This problem is then solved by FGH ACM method in providing accurate boundary segmentation. The operator of FDH; the fractional order gradient has the capability in extracting the local image information thus accuracy along the object boundary is achieved. Figure 6.1(c) denotes the outcome gained.



Figure 6.1: Demonstration on synthetic image of a star. (a) is the original image. (b) is the outcome from FSW ACM and (c) is the outcome from FGH ACM.

Another synthetic image is executed in supporting the first experiment. Figure 6.2(a) presents the image of a star where the intensity level is decreasing from top to bottom, until the intensity level at the bottom of the star is hardly seen. Figure 6.2(b) depicts the outcome

obtained using the FSW ACM method. Unfortunately, the method failed to accurately segment the object as the contour did not recognized the low intensity level at the bottom of the star.



Figure 6.2: Demonstration on another star image with decreasing of intensity where (a) is the original image, (b) is the outcome from FSW ACM and (c) is the outcome from FGH

ACM

This problem is solved by FGH ACM method as shown in Figure 6.2(c). The method managed to complete the segmentation and produced accurate boundary segmentation as the application of FDH managed to extract the local image information at the location where the gradient magnitude is low. To better shown that the FGH ACM method in provides better accuracy than FSW ACM method, Figure 6.3(a) demonstrates a flower image within a solid dark and Figure 6.3(d) illustrates an image with decreasing gradient from left to right. To observe the potential of FGH ACM, comparison with the FSW ACM method is presented. It is obviously depicted that the FSW ACM method failed to accurately segment both images. This is clearly shown in Figure 6.3(b) and Figure 6.3(e) respectively where the contour did not accurately segment both boundary of the object.



Figure 6.3: Demonstration on two synthetic images, (a) is the original image of a flower. (b) is the outcome from FSW ACM, (c) is the outcome from FGH ACM, (d) is the original image of another synthetic image, (e) is the outcome from FSW ACM, (f) is the outcome from FGH ACM.

With the introduction of FDH in the proposed FGH ACM method, the contour managed to extract the local image information thus solved the local minima problem existed in both images. The fractional-order gradient, protect the edges and maintain the contour stability. In addition, the application of window mechanism works perfectly at the angle of the object boundary in creating a smoother texture and enhancing the important edges from disappearing. Figure 6.3(c) and Figure 6.3(f) show both images that are accurately segmented by the proposed FGH ACM method thus solved problem created by FSW ACM method. Section 6.4 presents several experiments conducted on four medical image modalities and they are MRI images, CT scan images, x-ray image and microscopic images.

6.4 Experimental Result and Discussion

Based on the implementation and demonstration in the earlier section, several experiments were conducted to evaluate the efficiency of the FGH ACM algorithm in performing the segmentation on multimodal of medical images. The medical image modalities involved in the experiments are MRI and CT scan brain, CT scan image of brain skull and heart, microscopic image of bacteria or cell and x-ray images of blood vessels. These medical images are having characteristics of high level of intensity inhomogeneity that made the contour stuck at the local minima problem where accurate segmentation at object boundary is not achieved.

The goal of FGH ACM method is to provide the accurate segmentation at the object boundary. Therefore, the ground truth in the experiment is different from the ground truth executed with FSW ACM method. Figure 6.4 demonstrates two medical images that we used as sample in showing the ground truth of the segmentation outcome. Figure 6.4(a) is the image of CT scan brain. The segmentation outcome should cover the lowest intensity level in an image. Therefore, the ground truth for CT scan image of brain is shown in Figure 6.4(b). On the other hand, Figure 6.4(c) shows the image of blood vessel using the X-ray modality. This image is affected with high level of noise and intensity inhomogeneity that affected the edges along the blood vessel. The ground truth for the image is shown in Figure 6.4(d).

In executing the experiments based on FGH ACM method, the value of α need to be tuned to achieve accuracy at the object boundary. For image of CT scan of brain, the value of α is chosen as slightly higher which is 5 but for x-ray image of blood vessel, the value of α is tuned as 1 which is smaller as the interface is highly affected with intensity inhomogeneity problem. The optimum value of α for FGH ACM method in the experiments is 10 which is depending on the characteristics of the medical image itself.



Figure 6.4: Demonstration for the ground truth images where in (a) is the image of CT scan brain and the ground truth is in (b). (c) depicts the x-ray image of blood vessel and the ground truth is in (d).

6.4.1 Experiment on medical image modalities

Figure 6.5 depicts the experiments conducted on the three MRI images of brain, three MRI images of heart, three CT scan images of brain skull and three CT scan image of brain. The focus of the segmentation is to accurately segment the anatomical structures of the object with different sizes and shapes allocated at the inner part of the image. The images are highly affected with intensity inhomogeneity and noise. On the other hand, Figure 6.6 depicts the experiments on three images of MRI vessels, three images of x-ray blood vessels and three images of microscopic of bacteria. These images are highly affected with

intensity inhomogeniety until the object boundary is difficult to be identified. The anatomical structures are long, thin and winding that gave difficulty for the segmentation process.

Figure 6.5(a – c) shows the result obtained from MRI images of brain by using the FGH ACM method. The white flare situated at the inner part of the image made the segmentation process challenging due to the presence of high level of intensity inhomogeneity and noise, but FGH ACM method managed to wrap around the white flare accurately. Due to the nature of the image, the parameter of FGH ACM method is set to $\alpha = 5$. The experiment proceeded with another three images of CT scan brain ((Figure 6.5(j – l))). The white flare in the image is having low level of noise and intensity inhomogeneity where the boundary of white flare is clearly seen. With parameter of $\alpha = 2$, all the three images are successfully and accurately segmented by FGH ACM method.

The CT scan image of brain skull is another set of images to be segmented. FGH ACM method managed to provide the accurate boundary segmentation for all the three images as shown in Figure 6.5(g - i). This shows that the AFGK managed to smooth the image texture by preserving and enhancing the image details which made the FDH easier for extracting the local image information. However, as the image is dark and having lots of noise, the parameter of α is set to 8 that is considered high. Another set of images used are the MRI images of heart. One of the image was affected which high level of intensity inhomogeneity where the object boundary is missing. With parameter of $\alpha = 5$, the FGH ACM method managed to accurately segment the object boundary. This is shown in Figure 6.5(d – f). To conclude, the contour of FGH ACM method have the capability in moving through the

winding and spiral structures of the white flare and produced accurate segmentation. On the other hand, the soft boundary of heart with high level of intensity lead to missing or weak edges, but the contour had success in recognizing the pixel value thus solve the local minima problem.



Figure 6.5: Segmentation outcome by FGH ACM method on MRI of brain (a - c) with parameter of $\alpha = 5$, CT scan images of heart (d - f) with parameter of $\alpha = 2$, MRI images of brain skull (g - i) with parameter of $\alpha = 8$ and CT scan images of brain (j - l) with parameter $\alpha = 5$.

The experiments continued on medical images that are having independent object such as the blood vessels and bacteria or cells images. These images are having low intensity level at the object boundary. Figure 6.6 presents the experiment conducted on three images of MRI vessels, three images of x-ray blood vessels and three images of microscopic bacteria. Figure 6.6(a – c) depicts images from MRI vessel where FGH ACM method managed to accurately segment the vessels object with parameter of $\alpha = 3$. Figure 6.6(d – f) presents images of x-ray blood vessels which is thin and long. The level of intensity is moderate. But with the introduction of AFGK and FDH, the proposed method managed to segment the object with the parameter of $\alpha = 3$.

The last images are images of microscopic image of bacteria as shown in Figure 6.6(g – i). The object to be segmented is having high level of intensity that lead to weak at edges. The FGH ACM managed to wrap the contour along the object boundary although part of the boundary is hardly recognized with parameter of $\alpha = 5$. This concluded that the collaboration of AFGK and FDH leads to accurate boundary segmentation. Meanwhile, the quantitative evaluation is presented and the results are shown in Table 6.2 for image shown in Figure 6.5 which is based on metric of accuracy. On the other hand, Table 6.3 listed the evaluation metric executed on the nine medical images (Figure 6.6) which is also based on metric of accuracy.



Figure 6.6: Segmentation outcome by FGH ACM method on MRI vessels (a - c) with parameter of $\alpha = 3$, CT scan images of blood vessels (d - f) with parameter of $\alpha = 3$, and microscopic images of bacteria/cell (g - i) with parameter $\alpha = 5$

 Table 6.1: Summarization of accuracy percentage on MRI and CT scan images using FGH

 ACM method.

Images	Fig.											
	6.6(a)	6.6(b)	6.6(c)	6.6(d)	6.6(e)	6.6(f)	6.6(g)	6.6(h)	6.6(i)	6.6(j)	6.6(k)	6.6(l)
Metric of Accuracy	94.21	96.82	94.32	93.45	94.82	93.32	94.63	93.54	95.11	94.66	96.89	96.34

 Table 6.2: Summarization of accuracy percentage on x-ray and microscopic images using

 FGH ACM method.

Images	Fig.								
	6.7(a)	6.7(b)	6.7(c)	6.7(d)	6.7(e)	6.7(f)	6.7(g)	6.7(h)	6.7(i)
Metric of Accuracy	94.63	93.54	95.14	94.21	96.45	95.97	94.07	95.17	96.51

Based on the quantitative evaluation displayed in Table 6.1 and Table 6.2, the metric of accuracy is aligned with the outcome of the segmentation which is based on human perception. For example, MRI image of heart that shows a dark images where the boundary is hardly seen. However, based on visual interpretation FGH ACM managed to accurately segment the object and the metric of accuracy show 94.82% of accuracy. The average metric of accuracy for images in Figure 6.5 is 94.83% and the average metric of accuracy for images in Figure 6.6 is 91%.

6.5 Benchmarking on Fractional Gaussian Heaviside Method

Benchmarking process is conducted on FGH ACM in this section. The experiment in this section was also designed using Matlab R(2008b) on a 2.5 GHz Intel Processor i5 according to the implementation framework. The benchmarking will be divided into two subsections where in Section 6.5.1 the benchmarking process is done with FSW ACM methods. On the other hand, Section 6.5.2 presents the benchmarking with Local Binary Fitting Energy (LBF), Local Intensity Clustering (LIC) and Local Gaussian Distribution (LGD) methods. Subsequently, several experiments were conducted to evaluate the efficiency of the algorithm to perform accurate boundary segmentation of the object in the presence of intensity inhomogeneity.

6.5.1 Benchmarking with Fractional Sinc Wave method.

The aim of the experiment is to observe the potential of FGH ACM method in solving the accuracy problem at object boundary which did not achieved by FSW ACM method. Twelve images of medical image that included three images of MRI brain, three images of CT scan heart, three images of x-ray blood vessels and three images of microscopic image

of bacteria or cell are used. The images listed are having intensity that is not homogeneous and the gradient magnitude at the object boundary is low until the edges could not be recognized.

The first experiments will be conducted on three images of MRI brain as shown in Figure 6.7(a – c). The result obtained is observed to verify that FGH ACM method could accurately segment the white flare of the brain image. The white flare of brain is having the anatomical structure which is winding and spiral. In this situation, separating and accurately segment the white flare can be difficult due to the local minima problem. In conducting the experiment, the parameter of α Gaussian kernel is tuned to 5 for FGH ACM method. Figure 6.7(a - c) presents the outcome executed from the FSW ACM method and Figure 6.8(a – c) depicts the outcome from FGH ACM method. From the outcome (Figure 6.7(a - c)), it is obvious that the contour of FSW ACM method, did not extract the white flare boundary accurately where the contour did not manage to wrap around the winding and spiral structure of the white flare. This may due to the missing of local image information which is then overcome by the FGH ACM method where the segmentation outcome shows accurate segmentation. The FDH proposed in the FGH ACM method managed to extract the local image information and overcome the local minima problem thus provide accurate boundary segmentation as shown in Figure 6.8(a – c).

The experiment proceeded with three images of CT scan of heart. As heart images are made from muscles, the level of intensity inhomogeneity is seen as high level that leads to missing edges along the object boundary. In addition, some images of heart is having tiny vessel allocated at the internal part of the heart. Segmenting this anatomical structure is challenging. Due to this factors, the parameter of α is set to 3 for a better segmentation outcome. To show the effectiveness of the FGH ACM method in providing accurate segmentation, Figure 6.8(d - f) show the outcome of CT scan images of heart based on execution of the FGH ACM method. On the other hand, Figure 6.7(d - f) depicts the segmentation outcome on CT scan image of heart based on the FSW ACM method. The idea is to compare the problem created by the second method could overcome perfectly by the third method.



Figure 6.7: Segmentation outcome depicted from the FSW ACM method. MRI images of brain is situation at (a - c), CT scan images of heart is shown at (d - f), images of x-ray blood vessels is at (g - i) and images of microscopic bacteria is shown at (j - l).

Noted that, the three images shown in Figure 6.7(d - f) did not well segmented by the FSW ACM method in terms of providing an accurate segmentation at the object boundary. This may due to the local minima problem that diverted the contour from accurately stop on the correct boundary. To overcome the problem, the FDH proposed in the FGH ACM method efficiently extract the local image information along the object boundary in providing accurate boundary segmentation. Figure 6.8(d - f) shows the perfect outcome by FGH ACM method. Notice that the tiny vessel at the heart image Figure 6.8(e - f) is also segmented by the contour. The contour managed to stop exactly on the correct position along the object boundary.

Based on the two experiments conducted on brain and heart images, the experiment continued to segment the blood vessels from an x-ray modality and bacteria/cell image from microscopic modality. Images of the blood vessels are having the anatomical structure which is long, thin and winding. In addition, the intensity level of both images is lower from the object to the background which made the contour have difficulty in recognizing the intensity of the object boundary. Figure 6.7(g - i) presents the outcome of x-ray images of blood vessels after an experiment using FSW ACM is executed.

Note that, the contour could not accurately move along the object boundary especially on images that are unclear. To overcome the weaknesses by FSW ACM method, FGH ACM method embed the AFGK to enhance the edges to be seen and extract by the FDH. As the image is unclear, the parameter α is set as a small number which is 1. This is because if a large number is used, the movement of the contour will be fast and accurate segmentation

could not be achieved. With the parameter α is set as 1, an accurate boundary segmentation is achieved to all three images of x-ray (Figure 6.8(g - i)).



Figure 6.8: Segmentation outcome depicted from the FGH ACM method with α =5 for MRI images of brain (a – c), CT scan image of heart are shown at (d – f) with α =3, images of x-ray blood vessels are shown at (g – i) with α =1 and images of microscopic bacteria is shown at (j – l) with α =1.

To support the experiments conducted on x-ray images of blood vessel, we conducted another experiments on three images of microscopic of bacteria/cell which is taken as an individual object. The images of bacteria/cell have a unique shape of boundary. The intensity level from the object to the background is low until some of the edges along the object boundary are missing. The contour may have difficulty to recognize the low intensity in order to get the accurate boundary segmentation. In observing the potential of FGH ACM in segmenting microscopic images, we compare the outcome with FSW ACM method. Figure 6.7(j - 1) display the outcome obtained on three images of microscopic using FSW ACM method. Due to the characteristics of the images, the contour could not successfully stop exactly on the correct boundary of the object to be segmented. For images which is dark and having least gradient, the contour is diverting to other area in the image. This problem is overcome by the FGH ACM method is providing an improved and accurate segmentation. With parameter of α that is set to 1, the FDH managed to move along the object boundary and provide an accurate segmentation. This is shown by the images shown in Figure 6.8(j - 1). Three microscopic images are well segmented along the object boundary.

To support the benchmarking process conducted earlier which is based on visually interpretation, the evaluation metric is applied as used in chapter 5. Recall back, the evaluation metric is based on the metric of accuracy. Table 6.3 illustrated the metric of accuracy for MRI images used in the demonstration. The metric presents the metric of accuracy between the FSW ACM method and FGH ACM method. The aim is to observe the pattern of the accuracy metric of FGH ACM that should show incremental of percentage from the FSW ACM method.

From the metric of accuracy listed in Table 6.1, the percentage accuracy for both FSW ACM method and FGH ACM method is more than 90%. The FGH ACM method managed to improve the percentage accuracy from the FSW ACM method. The average percentage

for MRI images based on FGH ACM method (Figure 6.8(a - c)) are 97.45%, while the percentage of CT scan images based on segmentation outcome by FGH ACM method are 95.07%. On the other hand, the x-ray images accuracy percentage are 96.12% and microscopic accuracy percentage is 98.14%. The percentage for all images shown in Table 6.1, shows improvement of the segmentation from the FSW method to FGH ACM method.

Images/ Method	Fig. 6.7 (a)	Fig. 6.7 (b)	Fig. 6.7 (c)	Fig. 6.7 (d)	Fig. 6.7 (e)	Fig. 6.7 (f)	Fig. 6.7 (g)	Fig. 6.7 (h)	Fig. 6.7 (i)	Fig. 6.7 (j)	Fig. 6.7 (k)	Fig. 6.7 (l)
Sinc Wave ACM	92.31	94.34	93.12	91.12	91.23	92.03	91.54	90.05	90.33	93.12	92.32	94.16
Images/ Method	Fig. 6.8 (a)	Fig. 6.8 (b)	Fig. 6.8 (c)	Fig. 6.8 (d)	Fig. 6.8 (e)	Fig. 6.8 (f)	Fig. 6.8 (g)	Fig. 6.8 (h)	Fig. 6.8 (i)	Fig. 6.8 (j)	Fig. 6.8 (k)	Fig. 6.8 (l)
FGH ACM	96.21	97.82	98.32	94.12	95.54	95.57	96.7	96.54	95.12	98.63	98.47	97.32

 Table 6.3: Summarization of accuracy percentage on MRI, CT scan, x-ray and microscopic images by FSW ACM method and FGH ACM method.

The experiment was carried out to evaluate the performance of the FGH ACM method in achieving accurate boundary segmentation within the interface of severe intensity inhomogeneity against other ACM methods that utilize local image information in their segmentation process. The methods used for the comparison are the Local Intensity Clustering method (LIC) (Li et al., 2011) Local Gaussian Method (LGM) (Wang et al., 2009), and Local Binary Fitting Energy (LBF) (Li et al., 2007). In addition, the evaluation metric is also applied to support the benchmarking process.

6.5.2 Benchmarking with methods using local image information

This section reports the experimental finding on various characteristics of medical image modalities. This experiment was conducted to measure the effectiveness of the proposed FGH ACM method in handling segmentation process within severe intensity inhomogeneity interface to accomplish the accurate boundary segmentation. The performance of the proposed FGH ACM method is compared with three different methods of ACM that rely on local image information for their segmentation process. The methods include Local Gaussian Distribution Method (LGD), Local Intensity Clustering (LIC), and Local Binary Fitting Energy (LBF). The experiment begins with an MRI image of brain. The internal part of the brain image contains white flares with inhomogeneous intensity. Unlike other images, the white flare is thin, with long and winding structure.





Figure 6.9 presents the result obtained from the experiment conducted on the MRI image of brain. Figure 6.9(a) shows the segmentation outcome using the LGD method, followed by the LIC method in Figure 6.9(b), the LBF segmentation outcome in Figure 6.9(c), and FGH ACM method in Figure 6.9(d). The LGD method did not manage to segment the inner part of the brain. Its contour failed to be placed along the object boundary of the white flare areas, thereby hindering inaccurate segmentation. Likewise, the LIC method was also not

successful in accurately segmenting the brain structure within the white flare area. The LBF method is sensitive to the initial placement of its contour; hence, the object boundary of the white flare is also not well segmented. This failure may be due to the two contours on the image. Some parts of the object boundary were not segmented as shown in Figure 6.9(c). In addition, the method also shows slight over segmentation effect in its outcome. In this situation, accurate segmentation could not be achieved. Meanwhile, the proposed FGH ACM method managed to produce a comprehensive and accurate boundary segmentation outcome successfully even in white flare areas with parameter of α is set to 4. The capability to maneuver segmentations along complex brain structure, which is long and winding with sharp curves, is mainly attributed to its novel AFGK and FDH function. The AFGK technique provides a smooth and preserves critical information, such as the edges at some critical part, namely, the white flare. The adaptive windows applied supported the Gaussian kernel by moving towards critical angles along the boundary of the white flare, thereby enabling the FDH function to extract the intensity at that position and regularize the level set.



Figure 6.10: Segmentation results on another MRI image of brain from the top view where (a) shows the result by LGD method (b) shows the result by LIC method, (c) is the results obtained by LBF method, and (d) the result obtained on the basis of our method for α =5.

The same experiment was repeated on another slice of MRI image that shows the top view of the brain, with more focus given to the white flare areas. This experiment was conducted to support the previous experiment. Better and clearer segmentation outcome was obtained with the second experiment as compared with the first. As expected, the segmentation result was consistent with that of the previous experiment for all tested methods. The LGD method still failed to complete the segmentation process successfully because of severe intensity inhomogeneity in the image as shown in Figure 6.10(a). The LIC method produced a better segmentation outcome, but failed to segment the brain structures situated in the white flare areas, as indicated in Figure 6.10(b). Meanwhile, the LBF method managed to segment almost all the brain structure, but with less accuracy and has slight tendency to also segment unwanted regions. FGH ACM method showed satisfactory results and achieved accurate boundary segmentation with $\alpha = 5$, similar to the outcome depicted in Figure 6.9.

The results obtained based on the proposed FGH ACM on two MRI images of brain shown earlier depicted an excellent outcome with cleaner and accurate segmentation especially along the boundary of the white flare. To show a good collaboration of AFGK and FDH, the next experiment is conducted on CT SCAN image of a brain but the brain image is affected with a tumor indicated by the white round object. Figure 6.11 illustrates the outcome obtained based on the experiment conducted using the four methods of ACM including FGH ACM method.



Figure 6.11: Segmentation results on another brain image but using CT SCAN modality. (a) shows the result by LGD method, (b) shows the result by LIC method, (c) is the results obtained by LBF method, and (d) is the result obtained on the basis of FGH ACM method for α =5.

Figure 6.11(a) depicts the outcome based on LGD method, followed by the outcome using the LIC method at Figure 6.11 (b), outcome by the LBF is presented at Figure 6.11(c) and Figure 6.11(d) is the outcome based on the proposed FGH ACM. This time, the image of brain by the modality of CT scan shows a dark area at the inner part of the brain with least intensity. Most white flare was affected with least intensity until the white flare boundary is unseen due to the darkness of the image texture. Due to the darkness factor, LGD method did not managed to complete the segmentation where the contour could not segment the white flare area situated at the inner part of the brain.

LBF method managed to move the contour at the inner part but the contour did not manage to produce an accurate segmentation and this is shown in Figure 6.11(c). This may due to the sensibility of the two contour placement of the method. On the other hand, the LIC and FGH ACM method managed to segment the inner part of the brain. However, LIC method have inaccuracy in the segmentation where it produced over segmentation problems (Figure 6.11(b)). FGH ACM method managed to provide accurate segmentation with lessen over segmentation with parameter of α = 5. This shows that the collaboration of AFGK and FDH provide an accurate boundary segmentation of the FGH ACM method.



Figure 6.12: Segmentation results on a heart image of CT SCAN. (a) shows the result by LGD method, (b) shows the result by LIC method, (c) shows the results obtained by LBF method, and (d) shows the result obtained by our method for α=3.

Next the finding report on a CT scan image of a heart which is then followed by another image of heart using the modality of MRI. Both heart images have soft texture with severe inhomogeneous intensity. The objects to be segmented in Figure 6.12 have lighter intensity and are located in the sub-region of the object. Figure 6.12 (a) shows the result obtained using the LGD method, followed by those obtained through the LIC, LBF and the proposed methods. Among the presented results, the proposed FGH ACM method shows significant improvement in the segmentation outcome, accurately segmenting the boundary of the two objects successfully for α =3. Other methods, such as the LGD method, did not manage to segment the object where only one object is segmented. The objects are not well segmented by LBF because of the sensibility problem of the contour. The LIC method managed to show some segmentation; however, the result obtained was neither accurate nor satisfying, demonstrating some over sampling effects. To show the effectiveness of the proposed FGH ACM method, another image of heart from the modality of MRI is used. Its texture is soft but the image is darker than one in CT scan image. The boundary of heart is affected by

lots of noise which leads to intensity inhomogeneity thus made the segmentation process crucial.



Figure 6.13: Segmentation results on a heart image of CT SCAN. (a) shows the result by LGD method, (b) shows the result by LIC method, (c) shows the results obtained by LBF method, and (d) shows the result obtained by our method for α=3.

Figure 6.13(a) shows the result obtained using the LGD method, followed by those obtained through the LIC, LBF and FC ACM methods. Similar as previous outcome, the FGH ACM depicted the most perfect outcome with better accuracy at the object boundary and cleaner outcome for α =3. The LGD and LBF method did not managed to segment some part of the object boundary. On the other hand, LIC method managed to complete the segmentation but produce over segmentation.

The next experiment presents images by x-ray modality of blood vessels. It is known that the object of blood vessels is long, thin and winding. The image is having high level of noise and the distribution of intensity is not homogeneous. In addition the level of intensity of the object of interest is at least until it made it difficult to be separated from the background. This is shown in Figure 6.13. On the other hand, another x-ray image of blood vessel is shown in Figure 6.14 depicts an object of blood vessel which is dark with noise and intensity inhomogeneity. The pixel intensity within the neighborhood pixels inside the blood vessel has similar levels which lead to over segmentation during the segmentation process.



Figure 6.14: Segmentation results on blood vessel from x-ray modality. (a) shows the result by LGD method, (b) shows the result by LIC method, (c) is the results obtained by

LBF method, and (d) shows the result obtained on the basis of our method for $\alpha=1$.

Results obtained by the four methods denote various segmentation outcomes and this is shown in Figure 6.14. Both the LGD and LIC methods completely failed to segment the object in this image, indicating the inability of their contours to evolve in the environment severely affected by intensity inhomogeneity problem. Meanwhile, the LBF method and FGH ACM method were able to move the contour along the blood vessel and produce better segmentation outcomes. Nonetheless, the outcome of the proposed FGH ACM method for α =1.



(a) (b) (c) (d) **Figure 6.15:** Segmentation results on blood vessel of an eye taken from x-ray modality. (a) shows the result by LGD method, (b) shows the result by the LIC method, (c) is the results obtained by LBF method, and (d) shows the result obtained on the basis of our method for $\alpha=1$

Result obtained from the second x-ray blood vessel image is depicted in Figure 6.15. The results obtained shows slightly different outcome from those in Figure 6.14. This is due to the image texture which is darker and having intensity inhomogeneity at the foreground. As the blood vessels is having similar intensity in the pixel neighborhood, LGD method shown at Figure 6.15(a) and LBF method at Figure 6.15(c) shown over sampling at the inner part of the blood vessels. This means both methods does not managed to provide a successful segmentation. On the other hand, the proposed FGH ACM method and LGD method show good segmentation results. Nonetheless, the outcome of the proposed FGH ACM method is more complete and accurate than those produced by the LGD method.

The last experiment conducted in this section will be on microscopic images of bacteria. Both images are shown in Figure 6.16 and Figure 6.17 respectively. Noted that, microscopic images of bacteria are having bacteria object with least intensity yet the background is also having similar intensity as the one in the object. The intensity distribution is not well distributed which made the segmentation failed to be completed or produced over sampling. The object of bacteria as shown in Figure 6.16 is having several level of intensity that leads to over segmentation. This is shown by the outcome of the image using the four methods mentioned earlier.



Figure 6.16: Segmentation results on microscopic image of bacteria. (a) shows the result by LGD method, (b) shows the result by LIC method, (c) is the results obtained by LBF method, and (d) shows the result obtained on the basis of our method for α =2.

Figure 6.16(a) depicts the outcome using the LGD method, outcome from LIC method at Figure 6.16(b), outcome from LBF method at Figure 6.16(c) and FGH ACM method at the Figure 6.16(d). Notice that LGD method and LIC method could not produce satisfying segmentation, where the exact object of bacteria is not really segmented. On the other hand, both LBF and FGH ACM method managed to complete and perfectly segment the bacteria object from the background, but some over segmentation is created. Nonetheless, the outcome by the FGH ACM method is better than other methods without any over segmentation at the background of the image than the other methods for α =2. To support the outcome as in Figure 6.16, another image of microscopic image of bacteria is used with similar characteristic as above and is shown in Figure 6.17. This time, the object of bacteria was affected with intensity inhomogeneity along the object boundary until the boundary is having gaps along the boundary.


Figure 6.17: Segmentation results on microscopic image of cell. The first column shows the result by the LGD method, the second column shows the result by the LIC method, the third column results obtained by the LBF method, and the last column shows the result obtained on the basis of our method for α =2.

Figure 6.17 depicts the results gained from the experiment conducted. Figure 6.17(a) is the result obtained from LGD method, Figure 6.17(b) is the result obtained from LIC method, Figure 6.17(c) is the result from LBF method and Figure 6.17(d) is the result obtained from the proposed FGH ACM method. From the results presented, it is obvious that, the contour of LGD and LIC method could not move toward the object of interest, thus the segmentation failed. The method by LBF and FGH ACM managed to move the contour toward the object of interest and provide satisfying result. However, LBF produce some over sampling. To support the benchmarking findings, the evaluation metric which is based on the metric of accuracy shows that the FGH ACM method provide accurate boundary segmentation on most of the medical images. Based on the experiments, FGH ACM method provide the average accuracy of 94.85%, LGD method provide the average accuracy of 75.09% and LBF method provide the average accuracy of 91.75%. The metric of accuracy shown in Table 6.5 is aline with the segmentation outcome which is based on visual interpretation.

Medical images	Metric of Accuracy			
	LGD	LIC	LBF	FC ACM
MRI image of brain 1	72.23	89.48	90.23	97.51
MRI image of brain 2	70.86	92.49	94.31	97.88
CT SCAN image of brain	71.45	94.04	94.92	96.11
CT SCAN image of heart 1	65.48	92.08	93.44	95.71
CT SCAN image of heart 1	86.76	91.89	91.11	94.23
X-ray image of blood vessel 1	23.11	21.07	91.87	93.49
X-ray image of blood vessel 2	90.41	86.01	88.09	91.88
Microscopic image of bacteria 1	67.12	87.72	89.16	92.45
Microscopic image of bacteria 2	22.23	21.1	92.63	94.39

Table 6.4: The evaluation metric comparison for medical images among LGD, LIC, LBFand FGH ACM method.

In concluding the experiments executed, the proposed FGH ACM managed to segment accurately at the object boundary on various medical image modalities with various characteristic. Section 6.6 presents a discussion based on the result gained by the FGH ACM method when compared with other three baseline ACM methods.

6.6 Discussion

This section provides a brief discussion on the experiments conducted using FGH ACM method. Previously in chapter 5, several experiments using four medical images modalities have been carried out on the FSW ACM method. However, it is later discovered that, the FSW ACM method has a drawback which it cannot provide an accurate boundary segmentation. This may be due to the lacking of technique in extracting the local image information which produced the local minima problem.

The proposed FGH ACM method is using an excellent enhancement process which is called as AFGK (Adaptive Fractional Gaussian Kernel). The fractional calculus used here is known as having the nonlinear capability in preserving and enhancing the image details. The collaboration of fractional and Gaussian Kernel managed to classify and merge the intensity level in a region in a better way. To give a perfect enhancement result, the adaptive window is applied to move along the critical angle to better preserve and enhanced the edges. Once the image texture is enhance, the FDH with the fractional-order gradient operator is applied to extract the local image information and avoid the local minima provide. This is to provide an accurate segmentation along the object boundary. Demonstration have been carried out on several synthetic images which having a low gradient to illustrate the capability of the proposed method in extracting the object boundary.

Later, four medical image modalities were used during the experiment with different characteristics. Noticed that the parameter of Gaussian of α is used and need proper tuning in getting a good result. On images with dark and smooth texture the parameter of α used is seen as smaller when compared to images with difficult structure of object and severe intensity inhomogeneity. However, the FGH ACM method managed to provide good potential in segmenting different type of medical image modalities with various characteristics. The quantitative evaluation using the evaluation metric is performed on FGH ACM method to observe the metric of accuracy achieved in the segmentation process. It is shown that the FC ACM method managed to produce more than 90% of segmentation accuracy even though medical images with severe intensity inhomogeneity.

6.7 Summary

In this study, a novel local region-based active contour model with fractional calculus for image segmentation in the presence of intensity inhomogeneity was presented namely fractional Gaussian Heaviside (FGH) ACM. The method introduced the adaptive fractional Gaussian kernel to avoid redundant information or pixels in the image from merging together, thereby providing better regions with homogeneous object. The fractional calculus used has the capability to maintain image structure and reduce random noise; the sizes and orientation of the adaptive rectangular window adapt with the changes in the local image details for better smoothness of the image texture. In this situation, the intensity inhomogeneity interface is handled properly and the edges are enhanced and ready for boundary extraction. Later, the fractional differential Heaviside function will have the capability in protecting the edges and lower frequency, especially at the object boundary for better feature extraction. In addition, the FDH function has the capability to extract the gradient and the intensity of the image. After the boundary condition is met within the level set framework, our proposed method may provide a satisfaction segmentation yet accurate boundary segmentation. Comparison with the FSW ACM method using several synthetic images and several medical image modalities are presented. The aim is to show the capability of FGH ACM method in providing accurate boundary segmentation thus solve the drawbacks by the FSW ACM method. The proposed method showed potential capability in classifying the inhomogeneous object in a better manner, thereby providing accurate segmentation, especially at the boundary of the object that need to be segmented.

CHAPTER 7 CONCLUSION

This chapter mainly concludes the research findings. It highlights our contributions in designing methods for accurate medical image segmentation even in the presence of high levels of noises and intensity inhomogeneity. Both methods introduce the use of fractional calculus and sinc wave method in a Hybrid ACM. The chapter ends with some suggestions for future work which includes possible enhancement to the proposed method.

7.1 Research Findings

In modern medicine, diagnosis and examination of diseases can be more efficient with the assistance of medical imaging. Medical imaging is one of the techniques used by experts to examine the condition of internal parts of human body for medical diagnostics and interventions. Among the commonly used medical imaging modalities are MRI, CT scan, ultrasound and x-ray. However, medical images produced by these modalities contain many visual problems such as high levels of noise, and inhomogeneous distributions of intensities. These characteristics make it impossible for untrained human eye to understand the visual contents of those images. High dependency on the experienced radiologists would slow down any diagnostic process due to huge production of medical images to be examined by a small number of available radiologists each day. Having a computer aided

diagnosis (CAD) system can therefore facilitate to speed up the examination process and alert radiologist of any possible abnormalities in those images.

However, the CAD system's ability to detect any abnormalities in medical images is heavily dependent on the accuracy of its segmentation algorithm. Among the most commonly used algorithms for segmenting medical images are those derived from the Active Contour Model (ACM) (Casseles, 2003, Li et al., 2005). ACM is based on the concept of energy minimization and contour evolution. The energy is minimized once the contour meets the correct object boundary which can be easily achieved in images with no apparent visual problems. The strength of ACM is based on its contour evolution, its stopping function, and its smoothing strategy. However, ACM is still facing several problems that hinder its successful execution for an accurate boundary segmentation of multimodal medical images in the presence of noise and intensity inhomogeneity. These problems will forbid the contour from accurately wrap around the object in an image. Therefore these problems need to be removed or reduced.

Smoothing process can reduce noise and improve image texture (Zhang et al., 2013). ACM methods use the Gaussian filter as their smoothing techniques, and its execution is based on a linear concept. In our investigation, the ACM methods with linear Gaussian are not able to perform accurate boundary segmentation on medical images in the presence of intensity inhomogeneity (Li et al., 2010; Zhang et al., 2010). The straight line movement of linear Gaussian increases the probability of losing image details (Wang et al., 2009). In this study the linear Gaussian is replaced with nonlinear Gaussian. Our experimental finding shows that nonlinear Gaussian has better capability than linear Gaussian in reducing noises,

preserving medical image details and enhancing its edges. In addition to that, nonlinear function with its contour fitting functionality makes it more convenience for the ACM contour to evolve due to smoother interface. The design and development of the nonlinear Gaussian filter for medical image enhancement is the first contribution of this research. The second contribution of this study is in regards to a novel design of the Fractional Sinc Wave FSW ACM method which is capable to reduce over segmentation problem when segmenting medical images with noise and intensity inhomogeneity. To recall, the proposed method is based on a combination of edge-based and region-based ACM in order to harness the strengths for both of the approaches. The strength of the edge-based approach is that it can produce a precise boundary segmentation outcome provided that the image has less noise but this is not possible for medical images. Unlike the edge-based approach, the region-based approach is more robust to noise hence it has high tendency to successfully segment medical images. Nevertheless, both approaches have their weaknesses that impede a successful implementation of accurate boundary segmentation of medical images with high level of noise and intensity inhomogeneity.

Among the weaknesses of an edge-based ACM method is its sensitivity to image noise because low quality medical images has high tendency for weak and missing edges in the images (Lakshmi & Sankaranarayanan, 2010). On the other hand, a region-based ACM method produces satisfactory segmentation outcome on noisy medical images but not on images with intensity inhomogeneity (Lankton, 2008). This is because intensity inhomogeneity in an image would create many small regions with inhomogeneous intensities even within the object in the image. As a result, the region-based segmentation approach would produce islands of segmented regions including the unwanted regions as well, a condition known as over sampling in segmentation. The proposed FSW ACM method should therefore need to address these weaknesses in order for it to successfully segment medical images that contain lots of noises and non-homogeneous distributions of intensities.

The FSW is a method in the ACM that is based on the concept of fractional calculus and sine wave method. The nonlinearity nature of the fractional calculus enables a contour to have flexible bending movement and rapidly evolve through the intensity inhomogeneity interface towards objects to be segmented in an image. The implementation of the nonlinear Gaussian filter in the proposed method improves image texture, enhances its edges and protects them from disappearing. The sinc wave method with its interpolation capability can construct new data points along the contour's path close to an object boundary to enable the contour to move as near as possible to the boundary hence increases the segmentation success.

The feasibility of the proposed method is evaluated in our experiments on several medical images with various modalities (MRI, CT scan, microscopic and ultrasound) and anatomical structures, taking into account the occurrence of noise and intensity inhomogeneity in those images. The justification of using multimodality of medical images is that different modalities produce medical images with different levels of noises and intensity inhomogeneity. The ability to segment images from these common modalities increases the robustness of the proposed methods in segmenting medical images. The robustness and significance of the methods is further proved by using medical images on various anatomical structures such as human heart, brain, blood vessels and cells, hence

making our work unique against many research work in medical image segmentation that are often dependent on a specific anatomical structure. The performance evaluation of the proposed segmentation methods is carried out in three ways. Firstly is the segmentation outcomes from the experiments are evaluated via visual interpretation by human perception Second, by using quantitative measurement based on metric of accuracy by Abbas et al. (2014). The metric accuracy is done by creating the correct segmentation contour on the medical image which is later compared with the segmentation outcome depicted by the proposed method. Finally, benchmarking evaluation is used against some baseline ACM methods.

To ease the understanding on the capability of the FSW ACM method, we provide the discussion of our experimental results based on the following three categories of medical images. The first category contains different modalities of medical images of various anatomical structures that have both inner and outer parts to be segmented, for instance, human heart, abdomen, and blood cells. Having this specific category is important because our experimental results show that the inner part is the mostly affected area by intensity inhomogeneity problem. Additionally, the inner part normally composed of unique anatomical structures such as long, winding and spiral. Meanwhile the quantitative evaluation of our experimental findings denotes around 95.2% success rate of the proposed FSW method in segmenting medical images in this category, as reported in Section 5.4.2.1. The benchmarking evaluation against the baseline ACM methods shows that the proposed method produces an improved segmentation outcome as compared to C-V and SGLACM methods.

The purpose of the second category is to determine the ability of the proposed FSW method to successfully segment a collection of individual cells in medical images that are usually captured by microscopic modality. Among the challenges in this category is the collection of objects often comprises of tiny cells structure. In the presence of noise and intensity inhomogeneity, the border of each tiny cell would encounter leakage problem thus complicate the process of accurately segmenting each individual cell. The application of nonlinear Gaussian filter in the proposed method helps to alleviate this problem, as explained in Section 5.2. Further, the implementation of the FSW method gives the contour the strength to rapidly evolve and effectively maneuver through curves and angles of tiny cells, for a successful segmentation outcome. The quantitative evaluation of our experimental findings indicate around 92% success rate of the proposed method in segmenting medical images in this category, as reported in Section 5.4.2.2. The benchmarking evaluation also demonstrates that the proposed segmentation method supersedes the performance of the two baseline ACM methods.

Finally the third category concerns on handling segmentation on the lowest image quality among modalities which is the ultrasound images. Due to its poor quality, the image shows dark surfaces with unclear edges therefore object outlining can hardly be traced. As noise and intensity inhomogeneity level in ultrasound image appeared to be the highest among medical image modalities, it becomes a great challenge to obtain successful segmentation. Even though region-based ACM methods can segment some medical images, it produces over sampling problem especially when involving images with high level of noise and intensity inhomogeneity. The nonlinearity of the FSW method alleviates this problem by smoothing the image texture and providing rapid and dynamic contour movement through the image. The sinc wave method has proven its capability in giving high segmentation accuracy when it is being integrated with fractional calculus. In our experimental results, the novel FSW method had shown its ability to successfully segment ultrasound images with various anatomical structures.

As a conclusion, the segmentation outcomes of the FSW ACM method demonstrates a better accuracy from the baseline methods with obvious reduction on the over sampling problems. Additionally, the applied quantitative evaluation denotes that the metric accuracy of the proposed methods appears to be relatively higher than the C-V and SGLACM methods. However, the proposed method still lacks of boundary segmentation accuracy when the image is affected with high level of intensity inhomogeneity. Figure 7.1 shows an image of a MRI heart where the inner and outer boundaries of the heart object are not accurately segmented by the FSW ACM method.



Figure 7.1: Segmentation on MRI image of heart with intensity inhomogeneity problem.(a) is the original image, (b) is the segmentation outcome by FSW ACM, (c) the correct segmentation outcome.

Figure 7.1(a) shows an example of a MRI heart image with intensity inhomogeneity problem. In reference to Figure 7.1(b), the contour of the FSW method did not accurately segment the inner and outer boundaries of the heart although it has reduced the over

sampling problem. The correct boundary that should be segmented by the proposed method is as indicated in Figure 7.5(c). In our investigation, the applied smoothing technique must have the capability to preserve the local image information besides enhancing the edges in order for the contour to extract object boundary accurately.

The lacking in the FSW ACM method is sufficiently addressed in the novel design of our second ACM method, named as the Fractional Gaussian Heaviside FGH ACM. This is the third contribution of our research work. The proposed method improves the extraction of local image information in order to achieve accurate boundary segmentation on multimodality of medical images that contain high levels of noise and intensity inhomogeneity. The proposed FGH ACM method comprises of two important components: Adaptive Fractional Gaussian Kernel (AFGK) and Fractional Differentiate Heaviside (FDH).

Due to the problem of local minima in medical images, accurate boundary segmentation is not achieved. A local minima is a problem where the contour could not locate any appropriate pixel value among the neighborhood in a region. This leads to leakage problem along an object boundary. The local image information is needed to improve the related pixel value to overcome the problem. The first component of FGH ACM is the introduction of AFGK as the image enhancement mechanism. The AFGK is comprises of fractional Gaussian Kernel (FGK) and adaptive window mechanism. Our investigation shows that the collaboration between the fractional calculus and nonlinear Gaussian Kernel (FGK) extends the capability of the nonlinear Gaussian in preserving edges in an image through the process of merging and grouping the homogeneous object in the same regions. In addition, the capability of an adaptive window mechanism further preserves and enhances image edges. The window mechanism with its sizes and shapes vary depending on the changes of the image texture, will smooth the image by moving increasingly and decreasingly at direction of least gradient. The FGK at this situation will protect the edges for easy extraction by the fractional Differentiate Heaviside (FDH) function.

The proposed FDH as the second component with the operator of fractional order gradient is responsible for extracting the local image information as it weighs not only the gradient but also the intensity of the image. Additionally, the fractional order gradient of FDH is capable in controlling the speed of a contour from shrinking thus maintain its stability. The collaboration of AFGK and FDH provides excellent result in producing accurate boundary segmentation on multimodality of medical images with different anatomical structures even in the presence of high level of intensity inhomogeneity.

The feasibility of the FGH ACM method is tested on four types of medical image modalities (MRI, CT scan, X-ray and microscopic) with complex structures. The first experiment focuses on medical images that contain objects with long, winding and spiral structures for instance, the white flare areas of brain images, and blood vessels. These structures create challenges in providing accurate boundary segmentation as the interface produces high level of intensity inhomogeneity. In addition to that, the topology of the white flare and the blood vessels always changes due to the winding and spiral structures. The second experiment worked on the MRI image of a heart and microscopic images of cells. The objects' boundaries in these images are highly affected with intensity inhomogeneity that leads to missing edges. Noteworthy that the boundaries of these objects were not accurately segmented using the FSW ACM method.

Our experimental results have demonstrated that the proposed FGH ACM method can alleviate the problem faced by the FSW ACM method. The quantitative evaluation of our first experimental denotes around 94% of success. The benchmarking evaluation shows that the proposed method produces accuracy of segmentation along the object boundary when compared to the Local Binary Fitting energy (LBF), Local Gaussian Distribution (LGD) and Local Intensity Clustering (LIC) methods. The quantitative evaluation of our second experiment also demonstrates a successful segmentation outcome that is around 96.1% Details of the experimental results and discussions can be obtain in Section 6.4. These satisfactory segmentation outcomes are the results of the implementation of the following components. First is the AFGK produces excellent smoothing technique in preserving the edges along complex structures, and allows the FDH to extract the local image information. Furthermore, the application of an adaptive window smoothed the edges along object boundary to enable the FGK to classify and merge the inhomogeneous object in the same region. The FDH with the fractional order gradient that weigh not only the gradient but the intensity is capable to extract and spot the image details thus solve the local minima problem. Besides, it could control the speed of level set from shrinking and maintain the stability of the contour.

We also conduct a benchmarking evaluation to compare the performance of the FGH method against the FSW method. Several medical images are used in the experiment which denotes the limitation of FSW method in providing the accuracy at the object boundary.

The FGH method had proven its capability in extracting the local image information and this has solved the problem created by the earlier method. In addition to that another benchmarking evaluation is conducted with three other ACM methods (Local binary Fitting energy, Local Gaussian Distribution and Local Intensity Clustering) to demonstrate the capability of the proposed method in providing boundary segmentation accuracy against the other three methods. Additionally, the applied quantitative evaluation denotes that the metric accuracy of the proposed method appears to be relatively higher than LBF, LGD and LIC methods.

7.2 Future Enhancement

This research has introduced the concept of fractional calculus in ACM method for image segmentation. The introduction of nonlinearity concept through fractional calculus would give an insight for improving the accuracy of segmenting medical images. This is because both of our proposed ACM methods that are based on fractional calculus concept are able to segment various anatomical structures in medical images of multi-modalities even though in the presence of high level of noise and intensity inhomogeneity. In fact our second method can produce accurate boundary segmentation for medical images that are affected with high level of intensity inhomogeneity. This accomplishment is very significant indeed because almost all medical images are affected with intensity inhomogeneity and different types of noise.

Having a robust segmentation algorithm with good accuracy for medical images with various modalities and anatomical structures would encourage a development of a reliable CAD system to assist doctors in their diagnosis and alert them of any potential abnormalities in the images. As the scope of this research is only to produce a robust and accurate segmentation method for medical images, further work is required to build a CAD for detecting any abnormalities in medical images.

Additionally, during the evaluation of our proposed methods we have experienced that the proposed methods have the capability to complete a successful segmentation within a shorter timeframe as compared to other baseline methods of ACM. However, it is beyond the scope of this research to produce a segmentation method with low computational cost. Therefore, our future work also includes further research and experiments to prove that the proposed methods are computationally cost effective hence suitable to process huge collections of medical imaging data. Finally, we aim to extend the capability of these robust algorithms for segmenting colored and three-dimensional medical images.

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