KNOWLEDGE GUIDED AUTOMATIC CONTOUR INITIALIZATION AND SEGMENTATION OF ABDOMINAL STRUCTURES IN CT IMAGES

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by

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IN THE NAME OF ALLAH THE ALL-COMPASSIONATE, ALL-MERCIFUL

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LIST OF ABBREVIATIONS

2D	Two-Dimensional
3D	Three-Dimensional
ANN	Artificial Neural Network
ASSD	Average Symmetric Surface Distance
CAD	Computer Aided Diagnosis
CT	Computed Tomography
DC	Dice Coefficient
DICOM	Digital Imaging and Communications in Medicine
EM	Expectation Maximization
FC	Fuzzy C-means
FMA	Foundational Model of Anatomy
FN	False Negative
FP	False Positive
GLCM	Gray Level Co-occurrence Matrices
GS	Gold Standard
GTDM	Gray Tone Difference Matrix
GVF	Gradient Vector Flow
HU	Hounsfield Units
IDM	Inverse Difference Moment
JC	Jaccard Coefficient
KLT	Kanade-Lucas-Tomasi
MAP	Maximum A Posterior probability
MC	Middle Coronal

MICCAI	Medical Image Computing and Computer Assisted Intervention
MIP	Maximum Intensity Projection
MP	Maximum Probability
MRF	Markov Random Field
MRI	Magnetic Resonance Imaging
MSSD	Maximum Symmetric Surface Distance
PCA	Principle Component Analysis
ROI	Region Of Interest
RVD	Relative Volume Difference
SIFT	Scale Invariant Feature Transform
SRMSSD	Symmetric Root Means Square Surface Distance
SSM	a Statistical Shape Model
SURF	Speeded Up Robust Features
SVD	Singular Value Decomposition
SVM	Support Vector Machine
TM	Template Matching
TN	True Negative
TP	True Positive
VOE	Volumetric Overlap Error
VOI	Volume Of Interest
VTK	Visualization Toolkit

INISIALISASI DAN SEGMENTASI KONTUR AUTOMATIK BERPANDUKAN PENGETAHUAN STRUKTUR-STRUKTUR ABDOMINAL DALAM IMEJ-IMEJ TOMOGRAFI BERKOMPUTER (CT)

ABSTRAK

Imbasan tomografi berkomputer (CT) merupakan sumber yang amat berharga dalam diagnosis struktur abdominal. Di dalam pengimejan abdominal, imbasan CT bagi sesuatu bahagian anatomi biasanya menghasilkan bilangan keratan 2D yang amat banyak. CT lebih digemari bagi pengimejan abdominal berbanding dengan teknik-teknik lain yang lebih sensitif seperti MRI kerana mempunyai nisbah isyarat terhadap kebisingan yang tinggi dan resolusi ruang yang baik. Dalam bidang pemprosesan imej digital perubatan, perhatian tertumpu kepada analisa dan visualisasi automatik bahagian hati, limpa dan buah pinggang bagi membantu diagnosis, perancangan terapi radiasi dan pembedahan. Penyempadanan struktur-struktur yang masih merupakan masalah penyelidikan terbuka merupakan langkah asas pertama dalam kajian ini. Automasi proses segmentasi imej perubatan dapat mengurangkan tugasan interaktsi manual yang memakan masa, memenatkan dan subjektif, dan ini dapat membantu ahli radiologi yang biasanya terpaksa melihat beribu-ribu imej setiap hari. Oleh itu, segmentasi automatic merupakan fokus utama beberapa usaha penyelidikan. Dalam kajian ini, satu rangka kerja segmentasi berasaskan pengetahuan automatik berdasarkan kaedah-kaedah kontur aktif dicadangkan. Sistem segmentasi ini adalah generik dan menggunakan pelbagai sumber pengetahuan perubatan seperti atlas perubatan, peraturan-peraturan pakar, penglihatan pelbagai: *axial*, *coronal* dan *saggital*, ciri-ciri imej dan meta data imej DICOM. Kajian difokuskan kepada penggunaan kaedah-kaedah segmentasi kontur aktif *level set* yang menghasilkan keputusan memberangsangkan, yang mana ia teguh terhadap variasi

set data dan tidak memerlukan latihan awal yang ekstensif. Oleh itu, kaedah-kaedah ini boleh digunakan dengan penuh keyakinan untuk segmentasi struktur-struktur utama imbasan CT abdominal. Keputusan yang diperoleh amat memberangsangkan, menunjukkan peningkatan ketara berbanding dengan kaedah-kaedah lain, yang mana ralat pengukuran isipadu ialah 7% dan masa pemprosesan meningkat sebanyak 68%.

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ABSTRACT

Computed Tomography (CT) scans are becoming a priceless means of diagnosing abdominal structures. CT scans result in a huge number of 2D slices of the acquired anatomical part in abdominal imaging. CT are more preferred compared to sensitive imaging techniques such as MRI in abdominal imaging owing to their high signal to noise and good spatial resolution. In the area of medical image processing, the current interests are in the automated analysis and visualization of liver, spleen, and kidney to assist in diagnosis, radiation therapy planning and surgical planning. Delineation of these structures which is still an open research problem is the first and fundamental step in all of these studies. Automation of medical image segmentation reduces time-consuming, tedious, subjective human interaction tasks and may aid radiologists, who are normally required to view thousands of images daily. Thus, automatic segmentation is the main focus of several research efforts. In this research, we propose an automatic knowledge-based segmentation framework based on active contour methods. The proposed segmentation system is generic, and employs multiple sources of medical knowledge: medical atlas; expert's rules; multiple views: axial, coronal and sagittal; image features and image DICOM Meta data. The focus in this research is on level set active contour segmentation methods which provide promising results, robust to dataset variations and do not require extensive prior training. As such, they can be reliably used for segmentation of major structures in abdominal CT scans. The obtained results are very promising showing significant improvements over other methods where the volume measurements error is 7% and the processing time was improved by 68%.

CHAPTER 1

INTRODUCTION

Image segmentation can be identified as the process of isolating different regions in an image having homogenous features such as intensity, texture, color etc. Image segmentation is considered as an essential and crucial preliminary processing analysis and one of the most challenging tasks in any computer vision systems (Gonzalez and Woods, 2008). Image segmentation plays a major role in various imaging fields. Medical imaging is one of the mostly referred fields by the imaging community.

Medical imaging produces datasets that may require considerable amount of processing time for one particular human organ. A typical Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scan results in large number of slices of the acquired anatomical region. This stack of 2D images are referred as dataset; these images appear in gray scale color with each gray scale value corresponding to an Hounsfield Units (HU), which is a measure of radiodensity that provides an accurate absolute density for the corresponding anatomical tissues (Möller, 2009).

A typical processing of medical images includes pre-processing to remove noise and segmentation process that delineates a particular anatomy of interest. The highly complex nature of medical images makes segmentation difficult and time consuming. It also may require sophisticated segmentation algorithms to obtain reliable results.

Image segmentation plays a crucial role in medical imaging application, includes the classification of different anatomies such as bone, soft tissues and muscles; visualization of medical image; volumetric measurement; shape representation and analysis; computer guided surgery; treatments planning and human organ changes detection. Besides, there has been a growing need for segmentation in anatomical structure studies in research and teaching (Withey and Koles, 2007, O'Donnell, 2001).

Depending upon the case studies, medical image segmentation can be very complicated, tedious and time consuming. Moreover, manual delineation is a highly skilled, subjective and laborious task. Selecting each pixel manually for the desired anatomical structure in every slice of a dataset that may consist of more than 50 slices could take hours or even days (Casiraghi *et al*., 2009). As the processing resources of the computers have seen some advancement, the automation of medical image segmentation can be performed with higher accuracy, repeatability, and efficiency (O'Donnell, 2001; Straka *et al*., 2004; ChangYang *et al*., 2010). Fast and accurate segmentation would allow physicians to analyze and visualize human anatomies and assist radiation therapy and surgical planning.

1.1 Approaches in Medical Image Segmentation

Many different image segmentation methods have been developed in the past several decades in medical imaging domain. However, image segmentation remains acutely problem centric. A given segmentation method may perform well on one problem but poorly on a different application. Thus, achieving a generic segmentation method that is universally applicable for a broad range of medical applications is a very challenging task. The variety of medical applications encourages research interests on the segmentation process in order to develop, improvised and advanced methods for a given application.

One of the main factors to be considered in segmenting the desired organ is either the 2D segmentation in which each desired organ is segmented from each of the slices in the dataset individually and then construction of 3D volume from these individual slices, or a 3D segmentation in which the desired organ is segmented from the whole dataset of a volume. An important point to be noted here is that in real clinical image acquisition procedure, it is common to have limited 2D image slices with large slice spacing, to reduce patient exposure to radiation, this show the need for 2D segmentation. With the availability of high resolution 3D datasets in public databases, many researchers have ventured into 3D segmentation. Although, there are many recent research efforts in 3D image segmentation, efficient and fast 2D segmentation procedures are still the main focus. The amount of extensive research has lead 2D segmentation as a well accepted process.

Existing segmentation methods in medical domain include neural network learning methods which require training dataset to build the constraints such as intensity, texture, shape etc, that need to be given into neural network (Chien-Cheng *et al*., 2003); intensity-based methods that are based on similarity in intensity and need initialization value (Campadelli et al., 2009); rule-based recognition based on exploiting structure invariants and available features such as size, edge and location (Chien-Cheng and Pau-Choo, 2000); model-based methods that need training sets to build a model to guide the segmentation process (Heimann *et al*., 2007); active contour methods that require initialization of contour inside target structure (Lee *et al*., 2007); atlas-based segmentation which requires registration between atlas and target dataset (Furukawa *et al*., 2007) and finally unsupervised methods such as clustering techniques produces clusters belonging to many different structures. It normally combines with other methods in order to isolate specific structure (Yuqian *et al*., 2010).

Active contour segmentation methods (Liu *et al*., 2005; Lee *et al*., 2007; Martí *et al*., 2007; Furukawa *et al*., 2007; Pan and Dawant, 2001) have specific advantages over other methods, such as providing promising results, robustness to dataset variations, no prior training, and ability to capture the topology of shapes (Li *et al*., 2006). As such, they can be reliably used for segmenting structures in abdominal CT scans. However, active contour methods have some disadvantages, that is longer processing time due to the need of user interaction, to plot the contour of level set in each slice in the abdominal dataset, which is very time consuming and knowledge intensive task. In addition, performance of level set active contour methods relies heavily on having a good initialization of the contour curve close to the desired contour.

Depending on user interaction and prior knowledge, medical image segmentation algorithms can be classified as manual, semi-automatic and automatic. Automatic methods still need prior knowledge such as shape, location and texture relating to the human organ to be segmented. In addition some of these methods also require initialization. As examples, active contour segmentation methods needs curve initialization; region growing segmentation methods need seed point initialization, etc (Foo, 2006). Therefore, medical knowledge represented by variety of sources such as medical atlas, texture information, anatomical shape and location, is necessary for image processing, especially for image segmentation.

Survey indicates that there are huge demands for automating the segmentation of abdominal structures. It includes measurement of kidney volumes, which is a good pointer of common body parameters and a reliable predictor of renal function (Shin *et al*., 2009); measurement of liver volume, which is useful for liver transplantation (Nakayama *et al*., 2006); constructing volume of abdominal structures helpful in surgical planning and radiation treatment (Harms *et al*., 2005). CT scans are preferred more than sensitive imaging techniques such as MRI in abdominal imaging owing to their high signal to noise and good spatial resolution (Linguraru *et al*., 2010). But it is noted that abdominal images segmentation is complex and challenging task due to several reasons contributed by high similarities in the gray levels among different structures, the surrounding soft tissues as well as inhomogeneity in shape and texture of the same structure in different image slices (Ding *et al*., 2005).

This thesis addresses the challenges in improving the level of automation and reducing processing time while improving the accuracy of the segmentation. This thesis concentrates on adapting the medical knowledge to automate the segmentation of abdominal structures (liver, spleen, left kidney and right kidney) in CT scan using active contour segmentation methods.

1.2 Problem Statement

A major concern in image segmentation is the manual initialization of contour curve in active contour methods. Active contour methods require manual interaction from the user to initialize the contour curve inside a region of interest. In addition, more computation is required for the active contour to reach the desirable borders if the contour curve is initialized farther from its possible final position (Pan and Dawant, 2001; Lee *et al*., 2007; Martí *et al*., 2007; Lankton and Tannenbaum, 2008). Furthermore, the convergence of these methods is sensitive to the placement of initial contours. In other words, processing time of active contour methods heavily relies on the position and size of the initial curves (Li *et al*., 2006).

Critical evaluation of literature regarding past approaches and frameworks for abdominal structures segmentation in CT scan using active contour methods has led to the identification of the following issues:

1) *Initialization of contour curve in a single slice inside abdominal structure*: There are many existing active contour segmentation methods that have been applied in abdominal structures segmentation. These methods require the user to go through all dataset slices, and choose a suitable 2D slice that contains the target structure to initialize the contour curve inside the target structure, manually. These methods require a user with sufficient anatomical knowledge of abdominal structures to perform such process accurately (Lee *et al*., 2007; Pan and Dawant, 2001; Dawant *et al*., 2007).

2) *Initialization of contour curve in all abdominal structure slices*: Some of active contour segmentation methods utilizes registration process to transfer contour curve from segmented medical atlas slices and target slices (Ding *et al*., 2005). These methods face issues such as, extensive preparation of special atlas or model, sensitivity to registration process, and can be only applied to a specific structure. In addition, active contour method is adapted as a post-processing step in many segmentation approaches to enhance the segmentation results (Linguraru *et al*., 2010; Yang *et al*., 2009; Komatsu *et al*., 2008; Furukawa *et al*., 2007). These methods are considered as time consuming by performing segmentation two times, one by proposed method and one by active contour method. Some of the active contour segmentation methods require the user to go through all dataset slices, and to insert several landmark points at the topmost and bottommost slices (Lee *et al*., 2007). These points are used to specify the starting and ending of the target structure in order to reduce the number of slices, in need of processing and to know when the segmentation process should stop. Moreover, the user is required to initialize the contour curve inside the target structure in each axial slice which is a very time-consuming process and a knowledge intensive task (Lee *et al*., 2007; Martí *et al*., 2007; Dawant *et al*., 2007; Pan and Dawant, 2001).

3) *Discontinuity (multiple lobes) regions in the liver*: The disconnected regions appear in some of the axial slices because of the structure of the liver which contains multiple lobes, thus different lobes appear as different regions in a single image slice. Discontinuity regions (multiple lobes) in liver need a user

to point these regions and initialize the contour curve inside each of these regions manually (Dawant *et al*., 2007; Pan and Dawant, 2001).

4) *Intensity similarity between abdominal structure and surrounding muscles tissue*: The high similarity in intensity between liver tissue and muscles tissue affects the accuracy of segmentation results, and thus segmentation methods that are based on gradient or intensity values may not be able to differentiate the liver from its neighboring structures (ChangYang *et al*., 2010).

This research attempts to find solutions to the above mentioned problems in an automatic manner to advance and speed up active contour methods in segmenting the abdominal structures.

1.3 Significance of the Study

The significance of this study is attributed by its close association with several applications related to abdominal structures. Some examples of these applications are: organ classification, visualization of 3D abdominal structure volume, volumetric measurement, shape representation and analysis, computer guided surgery, treatments planning, changes detection, teaching and research. Medical doctors and radiologists also benefit from this study to automatically delineate the abdominal structures in CT scan. Image segmentation is considered as the heart of such applications, and the degree of success is mainly dependent upon the level of automation, segmentation results and processing speed. In many of these applications, active contour methods seem to be the most popular choice for image segmentation. However, due to shortcomings in active contour methods abdominal structures segmentation as mentioned in section 1.2, the results are still quite unsatisfactory. These methods will be a full benefit if they can produce segmentation results with higher accuracy and speed.

This study introduces a knowledge based system that integrates multiple sources of medical knowledge to automate medical image active contour segmentation method, which shall be described later. The knowledge sources include medical atlas; expert's rules; image features; multiple image views and image DICOM Metadata. It is believed that the automatic segmentation of abdominal structures in CT scans will have significant contribution in the development of a user-friendly and knowledge-guided medical image segmentation tool which may be used in Computer Aided Diagnosis (CAD) systems.

1.4 Research Objectives

The primary aim of this study is to propose a knowledge based framework that will allow the incorporation of the medical knowledge to increase the level of automation in active contour segmentation methods in isolating abdominal structures. The objectives of this research can be further summarized as follows:

- To automatically localize the desired abdominal structure and initialize contour curve inside one slice of abdominal structure slices in the CT dataset.

- To automatically propagate and initialize the curve of active contour segmentation methods in all axial slices in an abdominal CT scans dataset.

- To automatically localize discontinuity (multiple lobes) regions of liver and initialize contour curve in each region.

- To improve the segmentation and visualization of abdominal structures with faster computation time.

1.5 Research Scope

The scope of the study is outlined as follows:

1. The focus of the present research will be on 2D level set active contour segmentation methods suitable for abdominal structures.

2. The methods developed in this research are applicable to abdominal structures (liver, spleen, right kidney and left kidney) in normal CT scans without any excessive abnormalities as many appear with massive tumor or trauma cases.

1.6 Research Contributions

The main contributions of this thesis can be summarized as follows:

- This thesis introduces an efficient and simple method for abdominal structures localization based on the similarity of texture features represented by Scale Invariant Feature Transform (SIFT) feature between dataset slices and annotated atlas image. The introduced method eliminates the need for 3D atlas registration by using a simple annotated 2D atlas. This helps to overcome the problems related to possible lack of atlases especially in the abdominal part in addition selecting the optimal geometry for 3D registration and minimizing time consumption in the registration process.

- Developing an efficient method to automatically propagate the contour curve in abdominal dataset slices based on the knowledge provided by dataset images represented by multiple views (axial, coronal and sagittal) views, which lead to time reduction of active contour segmentation methods used to segment abdominal structures.

- Developing an efficient localization method for multiple lobe regions in liver structure based on Haralick texture features represented by Gray Level Co-occurrence Matrices (GLCM), Principle component Analysis (PCA) classifier and experts' rules.

- Initiating a method to eliminate muscles tissues between ribs to solve the problem of intensity similarity between abdominal structures and the muscle tissues.

- Establishing a framework to build knowledge guided medical image segmentation tool with user-friendly workflow. This knowledge guidance facility automatic initialization of contour curve determines the slices of the dataset, in each view slice, where the selected anatomical structure is present.

1.8 Organization of Thesis

This thesis is divided into five main parts as shown in Figure 1.1. Part I, which is the introductory part of this research represented in chapter 1. Following the introductory part is Part II, which presents critical review of related literature pertaining on this research as describe in Chapter 2. After this, Part III discusses the framework of proposed work, the methodology and proposed modules and algorithms as describe in chapter 3, 4, 5 and 6. Part IV contains two chapters. These two chapters are chapter 7 and 8 represent the evaluation performance of segmentation results. Part V is final part, represents the summary of this thesis including the conclusions have drawn from the research and suggests several ideas for related future work. Following this concluding chapter are the references and several appendices. Different categories of active contour segmentation methods are described in Appendix A. Appendix B shows the additional experimental results for the liver spleen and kidney structures. Appendix C contains the list of medical knowledge sources used in the thesis. Appendix D describes the parameters used to run the methods proposed in this thesis. More details in the content of these chapters as follows:

Chapter 2: This chapter provides a background to CT scan, focusing on abdominal regions and a review on medical image segmentation methods. It also provides an exhaustive description about the past abdominal image segmentation methods and medical knowledge sources.

Chapter 3: This chapter covers one of the contribution of this thesis which is the knowledge based system framework as well as the methodology of the proposed work. Detailed discussions on the modules of the proposed system and a systematic study of the overall flow of the proposed system are provided as well. Detailed information on abdominal datasets used in this research and the evaluation criteria are provided too.

Chapter 4: This chapter presents the first module of the proposed system which is abdominal structure localization. Two contributions introduced in this module are the automatic localization of abdominal structure and isolation of the muscles tissue, which is usually similar to abdominal structure. Detailed descriptions on the steps taken and results of this module are provided.

Chapter 5: This chapter provides the discussion on the second module in named contour curve propagation process. This module contributes to the automatic initialization of contour curve in all slices using multiple views. Performance of this module is presented in the results section.

Chapter 6: This chapter presents the third module of the proposed system. Multiple lobes localization module automates the initialization of contour curve inside multiple lobes in liver. Discussion on the process and obtained results is covered extensively.

Chapter 7: This chapter reports the results obtained through a set of experiments that were carried out to evaluate the performance of 2D segmentation by the proposed knowledge based system for some of the abdominal structures namely liver, spleen, left kidney and right kidney.

Chapter 8: This chapter reports the results obtained through a set of experiments that were carried out to evaluate the 3D performance of proposed knowledge based system for some of the abdominal structures liver, spleen, left kidney and right kidney.

Chapter 9: This chapter summarizes this thesis by presenting the findings and concluding this work by detailing the limitations faced by the proposed system. Suggestions on possible future extensions are also given.

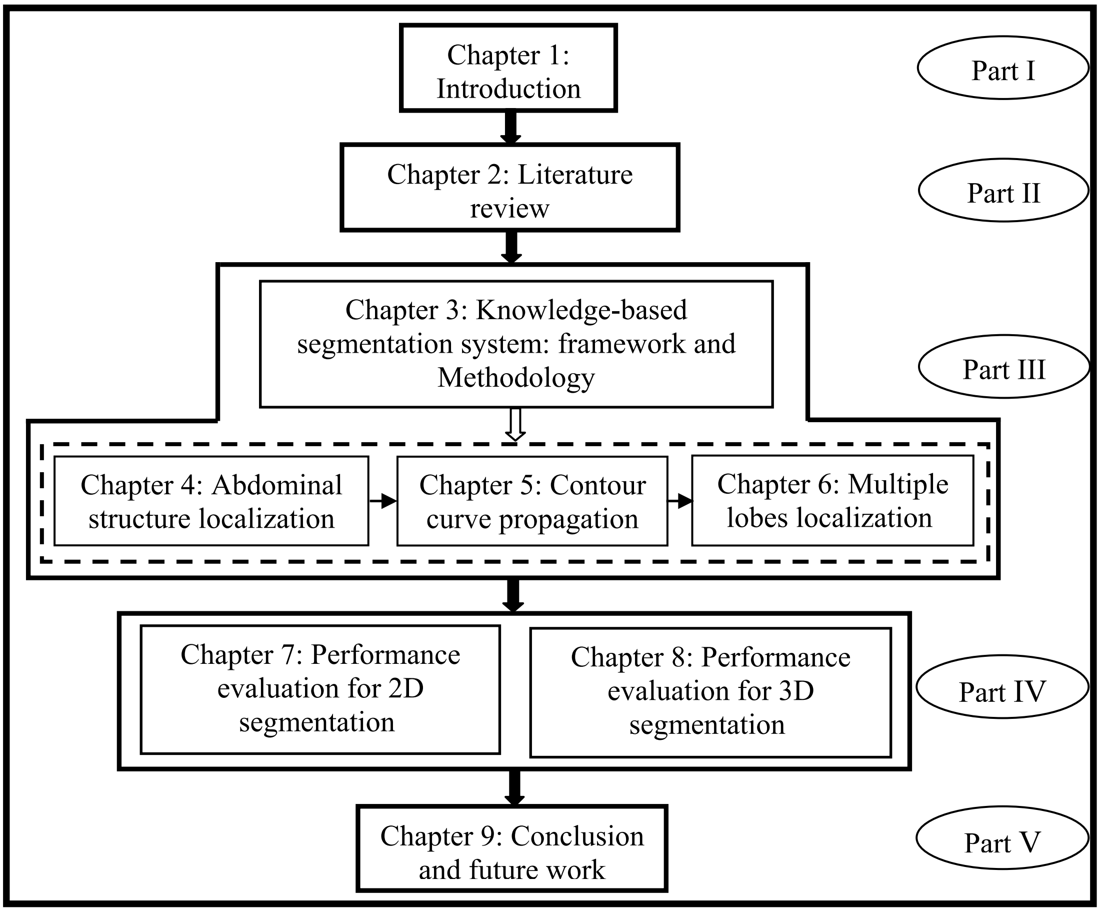

Figure 1.1: Overview of the thesis organization.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter introduces Computed Tomography (CT) imaging as a modality for medical imaging and segmentation of medical images, with emphasis on abdominal structures. A critical discussion on the related literatures is also presented, outlining the current state-of-the art in performing medical image segmentation, specifically, abdominal CT image segmentation tasks. This is followed by a discussion on how the medical knowledge sources are incorporated into image segmentation, in specific active contour segmentation methods. Based on the discussion on existing works, the chapter ends with presenting the research direction for this thesis.

2.2 Computed Tomography Imaging (CT Scans)

Computed tomography (CT) has been introduced into medical imaging in the 1970s (Hofer, 2007). Today CT scans have become an essential integral part of hospital care especially after having passed through enormous improvements in terms of technology, performance and clinical applications (Baert *et al.*, 2008). It has a wide dynamic range in use as a medical examination procedure in many specialties (Hofer, 2007). A photograph of a modern CT scan machine is provided in Figure 2.1.

CT scans depend on the technique of tomography which refers to the cross-sectional imaging of the patient’s body from either the transmission or reflection of data collected by enlightening the patient’s body from many different views. Figure

2.2 shows the various views available from a typical CT scan machine (Kak and Slaney, 1988).

Figure 2.1: Modern CT scan machine. (viamedica, 2011)

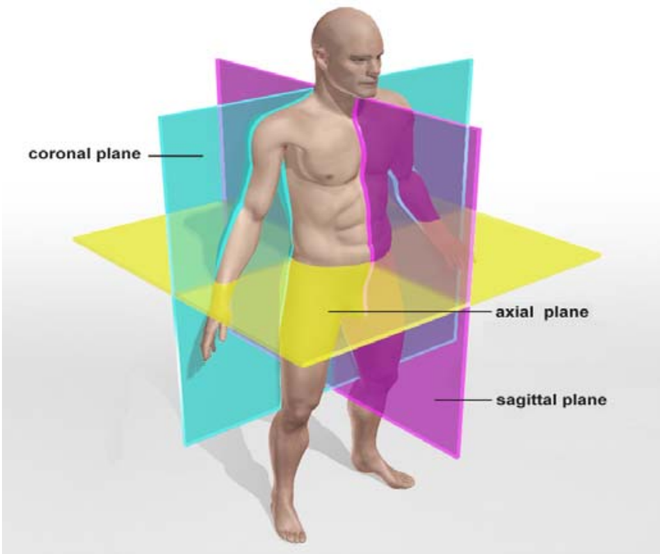

Figure 2.2: Various views of human body. (anatomy.tv, 2011)

CT is a special type of medical imaging modality procedure that involves the indirect measurement of the attenuation of the X-rays at numerous positions located around the patient being investigated to obtain structural and functional information about him (Hofer, 2007; Prince and Links, 2008). Figure 2.2 shows the various views available from a typical CT scan machine (Kak and Slaney, 1988). X-ray is used in CT scan because of its property that all tissues differ in their ability to absorb X-ray. Such property has enabled radiologists to view internal human structures with exceptional precision. Typically, bone tissues appear in white color, soft tissues such as brain or liver appear in gray color and the structures filled with air appear in black color such as the lungs (Prince and Links, 2008; Kak and Slaney, 1988) in CT images. CT scans can be used to diagnose a disease and its progress as well as compare different parts of the body in its normal state though with some disorders.

2.2.1 Abdominal CT Scanning

In general, CT scans is less costly than MRI, more readily available, and the radiologists and specialists have a relatively high degree of confidence in looking at CT scans (Linguraru *et al*., 2010). CT is a sensitive and highly-relevant method for the diagnosis of abdominal diseases (Linguraru *et al*., 2010). It is frequently used to determine stages of cancer and its progression in colon, liver and pancreas. It is also a useful test to investigate sensitive abdominal pain such as renal stones, appendicitis, pancreatitis, diverticulitis, abdominal aortic aneurysm, and lymphoma. CT is also the first way for detecting solid structure injury after a trauma (Hofer, 2007).

2.2.2 The Artifacts Present in Abdominal CT Scans

Difficulties are encountered when dealing with CT scans that have low contrast and blurred edges, due to partial volume effects resulting from spatial averaging, patient movements, beam hardening and reconstruction artifacts, as well as heartbeat and breathing (Varshney, 2002). Despite of these difficulties CT scans are extensively used in medical studies of the abdomen (Prince and Links, 2008).

2.3 Medical Image Segmentation Methods

Image segmentation in medical applications is used to delineate different human structures (bone, muscles, and soft tissues) based on features such as intensity, shape and texture. The ultimate goal of medical image segmentation is to provide richer information than which exists in the original medical images alone. Segmentation is commonly used to support tasks such as visualization and registration and to allow quantitative measurements of anatomical structures. It is also helpful in image guided surgery, tracking anatomical changes over time, assessing the progress of the anatomical structure disease and constructing medical atlases (O'Donnell, 2001; Wirjadi, 2007).

2.3.1 Categories of Medical Image Segmentation Methods

Methods for performing medical image segmentations vary widely depending on the specific application, imaging modality (MRI, CT, Ultrasound, etc.), and other factors. For example, the segmentation of brain tissue has different requirements from that of abdominal structures. This review categorizes segmentation techniques from the medical image processing point of view.

2.3.1.1 Manual Image Segmentation

Manual medical image segmentation is a difficult and time consuming task, normally used to get reference data to train a classifier, neural network or build an atlas or model. Several segmentation methods in the literature are proposed to minimize the need for manual interaction in the segmentation process (Linguraru *et al*., 2010; Kaus *et al*., 1998).

2.3.1.2 Histogram-based Segmentation

One of the simplest segmentation techniques in this category is thresholding. The threshold segmentation divides the image pixels/voxels based only on their grey-level histogram. Threshold segmentation can be defined as a filtering method that is used to label pixel/voxel whose grayscale values are in a desired range, defined by an expert user. The gray levels of pixels belonging to the object are significantly different from the gray levels of the pixels belonging to the background (Wirjadi, 2007; Gonzalez and Woods, 2008). Thresholding techniques are useful in segmenting X-ray images and CT scan images (Tian *et al*., 2001).

The success of threshold approach depends on the successful selection of a threshold value. Thresholding then becomes a simple but effective method to isolate objects from the background. However, thresholding is very sensitive to noise, intensity homogeneities and is affected by the presence of artifacts. Thresholding technique tends to produce spread groups of pixels rather than connected regions. In addition, thresholding does not typically take into account the spatial features of an image. All of these shortcomings lead to use thresholding methods only as an initial step in a sequence of image processing steps (Lee *et al*., 1998; Ramesh *et al*., 1995).

2.3.1.3 Edge-based Techniques

Edge-based segmentation methods are based on some discontinuity property of the image's pixels, detection of edges i.e. boundaries which separate distinct regions.

The result of the edge detection can be used as a pre-processing step in the segmentation process. Edge information that can be extracted by many operators such as Roberts, Laplacian, Prewitt or Sobel are integrated with other image segmentation method such as region based segmentation methods (Mohamed Ben Ali, 2009; Mueller *et al.*; 2004, Jordi *et al.*, 2002).

There are alternate edge based segmentation methods such as edge relaxation, border detection, Hough transform based, etc. However, these methods are known to be sensitive to noise, affected by the presence of image artifacts and presence of some weak edges during edge detection process. It should be emphasized that the linking process of detected edges to produce a bounded region is not an easy task (Celebi *et al.*, 2009; Sekhar *et al.*, 2008; Kalvian *et al.*; 1995, Pal and Pal; 1993, Xu and Oja, 1993; Liow, 1991; Hancock and Kittler, 1990).

2.3.1.4 Region-based Techniques

Region-based image segmentation techniques group pixels or sub-regions into meaningful regions based on a predefined homogeneity criterion. Region growing, region splitting, split and merge, and watershed methods are classified under region based techniques. Region growing works in a different manner than split/merge yet they share the elementary concept of the homogeneity test (Gonzalez and Woods, 2008). In region growing methods, a user defined seed points representing prominent image regions are followed by the growth process for each seed point until the whole image is covered (Yufei *et al.*, 2009; Sharma and Ray, 2006). Region growing methods are considered as simple methods and used to delineate small and simple structures. In split and merge methods the entire image is considered as one region and the splitting process is initiated. The homogeneity criterion (for example, intensity value) for this region is then tested. If it is not satisfied, the region is split into sub-regions and each region is tested in the same way; this process is recursively repeated until no further splitting of a region is possible. After that, the merging step takes place where all adjacent regions with similar properties may be merged following some criteria (Ng *et al*., 2008; Liow, 1991). Watershed method uses concept from mathematical morphology to partition images into homogeneous regions (Ng *et al*., 2008; Ng *et al*., 2006). Region based techniques have some disadvantages that make them not suitable as a standalone method, but by integrate them with other segmentation methods acceptable results can be achieved (Mueller *et al*., 2004). The disadvantages are summarized as follows (Pham *et al*., 2000):

a) Region growing methods require manual interaction to select the seed point for each region that needs to be isolated.
b) Under and over segmentation of regions in the image can occur.
c) Sensitivity to noise causing extracted regions to have holes or disconnected regions.
d) Difficulty to select the suitable intensity value to start the segmentation.

2.3.1.5 Visualization Techniques

Visualization techniques are demonstration of data from simulations or experiments, as geometric structure, to allow analyzing and understanding of the data. These techniques are considered as segmentation techniques due to their ability to visualize some individual human structures. In medical domain visualization techniques are used to view the medical imaging (CT and MRI) 2D slices as 3D volume and to construct the result of 2D segmentation as 3D volume. Under this category there are two methods: marching cube which is a technique to rapidly construct a 3D polygon model (David and Li, 2010; Christensen *et al*., 1997) and volume rendering which is a technique used to visualize some anatomies based on visualization functions such as raycasting and Maximum Intensity Projection (MIP) (Xiang *et al*., 2011; de Araujo Buck *et al*., 1995). Volume rendering is considered to be a superior technique to marching cube due to its ability to look through the volume. However, they need huge amount of memory to visualize the structure (Xiang *et al*., 2011; David and Li, 2010; Christensen *et al*., 1997; de Araujo Buck *et al*., 1995).

2.3.1.6 Active Contour Techniques

Active contours (also referred to deformable models) are considered as one of the most popular image segmentation methods that are used to obtain a clear boundary of the target object. This is achieved through placing closed parametric or geometric curves near object or region boundaries, followed by iterative evolution process of these curves to match with the object boundaries. The forces which change the curve's shape are external forces controlled by the image attributes to guide the curve towards the desired image features like lines, edges, intensity, texture and color and the internal forces to control the curve smoothness (Kass *et al*., 1988; Osher and Sethian, 1988).

The key advantages of active contour methods are their ability to capture the topology of shapes and their incorporation of a smoothness constraint that provides robustness to noise and spurious edges (Pham *et al*., 2000). Because of these advantages, many active contour-based segmentation methods were proposed in the literature such as (Chan and Vese, 2001; Lankton and Tannenbaum, 2008; Martí *et* *al*., 2007). However, active contour methods are not directly suitable for medical image segmentation due to several factors. Firstly, active contour methods have high computational cost. Secondly, the convergence of these methods is sensitive to the placement of initial contours. In other words, the performance of the active contour method heavily relies on the position and size of initial curves (Lankton and Tannenbaum, 2008). Generally, the performance of active contour methods is associated with performing good initialization of the contour curve. Thirdly, they lack automatic operation and require interactions from the user to initialize the contour (Li *et al*., 2006; Varshney, 2002). Further details of active contour based techniques are provided in Appendix A.

2.3.1.7 Supervised Techniques

Supervised techniques include four well known techniques such as: classification methods, artificial neural network methods, atlas based segmentation and model based segmentation. Classification is a pattern recognition technique that seeks to partition a set of features derived from the image using data with known labels (Kroon *et al*., 2008; Pham *et al*., 2000; Bezdek *et al*., 1993). Artificial neural network is composed of large number of consistent processing elements working in a harmonious manner to solve the problem in hand (Iscan *et al*., 2009; Vijayakumar *et al*., 2007; Engeland *et al*., 2006; Jain *et al*., 2000). The main advantages of classification and artificial neural network methods are their ability to learn adaptively, capability of self-organization depending upon the information received during learning time, parallel configuration capability improves the performance to work in real time. The disadvantages of classification and artificial neural network methods can be summarized as follows:

a) Sensitive to noise occurrence and training parameters.

b) A manual intervention is required to obtain and build training datasets.

c) Difficult to correctly select and label training datasets.

d) Training datasets suitable for specific type of images.

In Atlas based segmentation methods, segmentation processes is guided by previously constructed medical atlas containing information such as shape, size, and features of the anatomical structure that require segmentation. These methods deal with the segmentation process as a registration process (Xiahai *et al*., 2008; Withey and Koles, 2007). Registration is a procedure to transfer information between medical atlas and patient dataset images (Bernd Fischer and Modersitzki, 2008). Some of the weaknesses of these methods are the performance affected by the quality of the built atlas, the registration process and the human interaction required in constructing the atlas (Xiahai *et al*., 2008; Withey and Koles, 2007; Thompson and Toga, 1997; Christensen *et al*., 1997). This will be discussed in more detail in section 2.5.1.

In model based segmentation methods it is assumed that the shape of human organ has a repetitive form of geometry and the shape is modeled probabilistically from training datasets. The modeled shape can be used as a constraint while segmenting the target image or volume. The segmentation process in these methods requires registration in two phases. First phase is to build a model from training data. Second phase is to transfer anatomical information or statistical influence from constructed model to target dataset. Some of the difficulties and weaknesses of these methods are image features must be extracted first before the fitting can take place.

The performance of segmentation in model based methods depends on the number of training datasets, with more training datasets yielding more accurate results. Also the performance is affected by registration process, used for specific structure, and human interaction is required to place the initial model and to choose appropriate parameters (Vincent *et al*., 2010; Saddi *et al*., 2007; Pham *et al*., 2000; Pathak *et al*., 1998).

2.3.1.8 Unsupervised Techniques

Clustering methods are unsupervised techniques which are concerned with clustering pixels (or voxels) of a 2D (or 3D) image into regions (or volumes) of interest according to certain features of these pixels (or voxels) (Tseng and Bien Yang, 2001, Pham and Prince, 1999). Clustering methods most commonly used in the image segmentation problems in MRI images are: FCM, K-means and EM algorithms. These methods are relatively computationally efficient and do not depend on training dataset. But, similar to previously mentioned image segmentation techniques, these methods have some weaknesses such as initialization sensitivity; non-availability of the number of clusters that should be determined a priori, sensitivity to noise and outliers, and stopping criterion (Yuqian *et al*., 2010; Jiayin *et al*., 2009; Kannan, 2008).

Table 2.1 lists these categories, methods, provides a brief description on categorization of the methods based on user interaction, and discusses the advantages and disadvantages of each.