DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

A STUDY ON LIVER VESSEL SEGMENTATION

by
Erdem FİKİR

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İZMİR

A STUDY ON
LIVER VESSEL SEGMENTATION

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We have read the thesis entitled **"A STUDY ON LIVER VESSEL SEGMENTATION"** completed by **ERDEM FİKİR** under supervision of **PROF. DR. CÜNEYT GÜZELİŞ** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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A STUDY ON LIVER VESSEL SEGMENTATION

ABSTRACT

Vessel segmentation is a key process for visualization, diagnosis and quantification of different segments of the medical images obtained by Computed Tomography (CT), Computed Tomography Angiography (CTA), multi-phase CT, multi-detector CT, Magnetic Resonance (MR), Magnetic Resonance Angiography (MRA) and other medical imaging techniques devoted particularly to vessels. This thesis gives an overview on liver vessel segmentation methods applied to the images obtained by any medical imaging technique. Cerebral vessel and retinal vessel segmentation methods are also studied in the thesis since the segmentation methods used have some common properties to the once for liver and so they are applicable to the liver vessel segmentation case.

Liver segmentation is a necessary step for liver transplantation and also for diagnosing liver tumors. There are many approaches for liver segmentation. One of them employs liver vessel segmentation as a tool for identifying different parts and tissues of the liver. This thesis focuses on the liver vessel segmentation methods which can ultimately be used for liver transplantation and for liver tumor diagnosis.

The body of the thesis covers liver anatomy, computed tomography angiography and medical image segmentation firstly to give a necessary background and then an overview on liver vessel segmentation methods. The thesis also presents a set of segmentation methods which are not previously used but can be used well for liver vessel segmentation.

The vessel segmentation is realized based on 1) pattern recognition, 2) image processing, 3) optimization, 4) graph analysis, and 5) partial differential equation models. The methods in the pattern recognition group can further be classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) machine learning methods including Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), 4) probabilistic methods, and 5) hybrid methods. On the other hand, image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

This thesis presents the known segmentation methods and vessel segmentation methods in particular as keeping in mind the above classifications.

Keywords: vessel segmentation, vessel extraction, liver vessel segmentation.

KARACİĞER DAMAR BÖLÜTLEME ÜZERİNE BİR ÇALIŞMA

ÖZ

Damar bölütleme; Bilgisayarlı Tomografi Anjiyografi (BTA), Manyetik Rezonans Anjiyografi (MRA) ve özel olarak damar görüntülemeye adanmış tıbbi görüntüleme teknikleriyle elde edilmiş tıbbi görüntülerin farklı bölütlerinin görüntülenmesi, tanılanması ve nicemlenmesinde anahtar bir süreçtir. Bu tez, BTA görüntülerine uygulanan karaciğer damar bölütleme yöntemleri üzerine genel bir bakış sunmaktadır. Karaciğer için verilen yöntemlerle ortak özellikleri olması ve karaciğer damar bölütlemeye uygulanabilirlikleri dolayısıyla beyin ve göz damar bölütleme yöntemleri de tezde incelenmiştir.

Karaciğerin bölütlenmesi, karaciğer nakli ve karaciğer tümörlerinin tanılanmasında gerekli bir adımdır. Karaciğer bölütlenmesi için bilimsel yazında birçok yaklaşım vardır. Bunlardan birisi karaciğerin farklı bölümlerini ve dokularını tanılamak için karaciğer damar bölütlemeyi bir araç olarak kullanır. Bu tez sonuç olarak karaciğer nakli ve karaciğer tümörlerinin tanılanmasında kullanılabilecek karaciğer damar bölütleme yöntemlerine odaklanmıştır.

Tez, öncelikle karaciğer anatomisi, bilgisayarlı tomografi anjiyografi ve tıbbi görüntü bölütlemeyi gerekli temel bilgiyi vermek üzere kapsar ve ardından karaciğer damar bölütleme yöntemleri üzerine genel bir bakış verir. Tez ayrıca karaciğer damar bölütleme için daha önce kullanılmamış ama kullanılabilecek olan genel bölütleme yöntemlerini de vermektedir.

Damar bölütleme için bilimsel yazında geliştirilen yöntemler 1) örüntü tanıma, 2) görüntü işleme, 3) optimizasyon, 4) çizgi analizi ve 5) kısmi türevli denklem modellerine dayalı olarak beş farklı kategoriye ayrıştırılabilir. Örüntü tanıma grubu içerisine giren yöntemler kullanılan öz niteliklere dayalı olarak aşağıdaki alt gruplara ayrılırlar: 1) gözelerin gri düzey şiddetine bağlı yöntemler, 2) doku tabanlı yöntemler, ve 3) geometrik yöntemler. Örüntü tanıma grubundaki yöntemler kullanılan sınıflandırıcıya bağlı olarak da aşağıdaki gibi gruplandırılabilirler: 1) bilgi tabanlı yöntemler, 2) eğiticisiz (öbekleme) tabanlı yöntemler, 3) Yapay Sinir Ağları ve Destek Vektör Makinelerini içeren makine öğrenme yöntemleri, 4) olasılıksal yöntemler ve 5) karma yöntemler. Diğer yandan, görüntü işlemeye dayalı bölütleme yöntemleri topolojik, morfolojik ve gözelerin gri düzey şiddeti-uzamsal bilgiye dayalı olarak alt gruplara ayrılabilir.

Bu tez bilinen bölütleme yöntemlerini ve özelde damar bölütleme yöntemlerini yukarıdaki sınıflamaları göz önüne alarak sunmaktadır.

Keywords: damar bölütleme, damar çıkarımı, karaciğer damar bölütleme.

CONTENTS

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CHAPTER ONE

INTRODUCTION

Liver vessel segmentation is used for determining the structure of the liver before transplantation and also for the locations of liver tumors. Liver vessel segmentation is usually implemented on images obtained by Computed Tomography (CT), Computed Tomography Angiography (CTA), multi-phase CT, multi-detector CT, Magnetic Resonance (MR) and Magnetic Resonance Angiography (MRA). Since the vascular anatomy of the liver is quite complex, then the liver vessel segmentation is still an open research area. There are many methods developed in the literature for vessel segmentation in liver, brain, eyes and other organs. A part of the segmentation methods which are not previously used for liver vessel segmentation can well be applied for liver vessel segmentation. Considering this fact, this thesis covers not only the liver vessel segmentation methods but also the other vessel segmentation methods.

The vessel segmentation is realized based on 1) pattern recognition, 2) image processing, 3) optimization, 4) graph analysis, and 5) partial differential equation models. The pattern recognition approach consists of a feature extraction stage and a classification stage applied on the extracted features usually after some transformations. The methods in the pattern recognition group can be classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) machine learning methods including Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), 4) probabilistic methods, and 5) hybrid methods. On the other hand, image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

The main purposes of the thesis is to review the methods developed in the literature for vessel segmentation in liver and also the approaches which are used for vessels segmentation in vasculatures of brain, eyes, and other organs, and to classify them according to classification types which are given and explained in chapters four. A part of these segmentation methods, which are not previously used for liver vessel segmentation, can be applied for liver vessels. The methods, which are reviewed in the following parts of the thesis, are classified according to aforementioned classification groups. The proposed classification groups for segmentation are different from the previously used ones in the literature.

This thesis can be used as a resource in studies on liver vessel examinations. The liver vessel segmentation methods are collected in the thesis. For the experts, who study on detecting tumor in liver, visualization of liver, segmenting vasculature in liver and etc., it can be useful as a resource in the extractions of the vessel trees.

For vessel segmentation, several different classifications which are quite different from the above classifications are given in the literature (Freiman et al., 2009; Kirbas & Quek, 2003; Lesage et al., 2009). The liver vessel segmentation methods, which are described in the sequel, can be a member of more than one group given above classifications.

Soler in (Soler et al., 1998) proposes a vessel segmentation method based on a histogram analysis, so it can be categorized as a pattern recognition type (probabilistic) method employing intensity feature and simple thresholding classifier. Local minima in histogram are used to define threshold parameters. The image is filtered for improving the contrast rendering before determining the thresholds. Then, the thresholded images are used to obtain the vessel structure (Soler, 1998). The method is applicable for liver vessel segmentation as a special case since it is valid for any kind of vessel system.

Dokladal et al. proposes a 3D topological based method for liver vessels extraction method in (Dokladal et al., 1999a). The efficiency of the method is examined on a raw X-Ray tomography image without applying any transformation. The method is based on a point-wise reconstruction to preserve the homotopy. The vessel tree system is obtained at a desired level of detail by adjusting a parameter which controls the level of light intensity. The method can be classified as a topological and morphological image processing based method. It is based on the hypothesis that the resulting object is simply connected, contains no holes and no cavities. The vessels are reconstructed in the following iterative way: Add simple points preserving the topology by considering their luminosity. Where, a simple point is defined as a point such that its deletion does not change the topology of the object. The method starts with a marker point that needs to be determined manually by an expert or by another image processing algorithm. Then, the object is grown in an iterative way as adding simple points next to the marker if the gray level of the considered point satisfies to the given stopping criterion. This method is reported to be superior to the histogram based method by Soler et al. (Soler et al., 1998). with the ability of giving thinner and much richer in vessel system which is also topologically correct, i.e. it does not contain any holes or cavities.

Dokladal et al. proposes in (Dokladal et al., 1999b) a thinning algorithm for extraction of liver vessels. The result of thinning is a skeleton centered in the object according to its luminosity. The proposed thinning algorithm ensures that the skeleton is topologically correct.

Hanh et al. proposes in (Hanh et al., 2001) a high quality vessel visualization and interaction technique for liver surgery planning. It provides to identify liver vascular structure from radiological data including CT and MR data. The method employs a sequence of image processing steps for deriving a symbolic model of vascular structure which reflects the branching pattern and also the diameter of the vessels. These symbolic models are visualized by concatenating truncated cones which are smoothly blended at branching points. This method aims to recognize the morphology and branching pattern of vascular systems as well as the basic spatial relations between vessels and other anatomic structures. The objectives of this work is i) to reconstruct a symbolic vascular model, ii) to visualize the reconstructed vascular model by emphasizing the topological and geometrical information as well as depth relations, and iii) to provide interaction techniques to explore these visualizations. Vessels are segmented using a fast region-growing algorithm adapted to the thin and branching vessels. So, it can be categorized as an image processing based vessel segmentation method. Herein, the used region growing algorithm starts with a user defined seed point and runs to accumulate all high-intensity voxels which are above a chosen threshold. The segmented image is further processed for obtaining a skeleton of the vessel system by applying morphologic operations such as thinning which preserve the topology and control small side-branches. The vessels are displayed as tubes after skeletonization for visualization purpose.

Doherty et al. (Doherty et al., 2002) proposes a method for 3D visualization of tumors and vessels for liver. For making the diagnostic and planning the surgery, Computed Tomography (CT) scans are used. Their objective is to find the number of tumors, their sizes and the physical and spatial relationship between the tumors and the main blood vessels. Blood vessels and liver tissue show similar contrast on the CT scans. The visualizations are being created using OpenDX and MATLAB. The data are received in the form of DICOM files and converted to the TIFF format. The images are cropped and histogram equalized, before being used in the visualization, in order to reduce the image to a convenient size and optimize the contrast. Isosurfaces, which are 3D analogue to contour lines, represent surfaces of equal density, are used in order to visualize the liver, tumor and blood vessels in 3D. The non-uniqueness of intensity values lacks to differentiate features using isosurfaces representing specific densities, as the rib cage obscures the internal organs. In order to solve this problem, Doherty et al. attempt to find a way of isolating the liver from the image by using a mask for each slice, consisting of ones in the selected section (the liver) and zeros everywhere else. The segmentation of liver is implemented by this masking operation in a semi-automatic way. Doherty et al. use an isosurface method to display the vein structures by using thresholding applied on several slices to find the density values. In order to visualize the tumors, which has the same density as the outer liver tissue, Doherty et al. specify a subset of data, or sub-volume, around the tumour and created an isosurface for this sub-volume, superimposing it on the same axes as the veins. The liver vessel segmentation method used by Doherty et al. can be categorized as a pattern recognition type (probabilistic) method employing intensity feature and simple thresholding classifier.

Saitoh et al. proposes in (Saitoh et al., 2002) segmentation of liver region through vessels on multi-phase CT. The segmentation of the liver region is primarily based on mathematical morphology and thresholding techniques. Saitoh et al. presents an automatic method for segmenting the liver region from third phase abdominal CT. First, blood vessels in the liver are extracted with a threshold. To separate two regions whose intensity levels are close, Saitoh et al. proposes a functional method by employing blood vessel streams. Herein, the liver is considered as a region governed solely by the portal vein and liver vein. These veins and their tributary streams are identified firstly, and then it is decided that the liver region is in their vicinity and also that any area far from their location is definitely not a part of the liver. Based on this technique, Saitoh et al. trace first the main vein (vena cava), a branch to leading to the liver, and then extract the blood vessels of the liver. Finally by applying a morphological dilation operation to the blood vessels, it can be roughly identify the liver region from which the final region is identified by thresholding. The method by Saitoh et al. can be considered as a hybrid method which is a combination of the mathematical morphology image processing method and the pattern recognition type method employing intensity feature and simple thresholding classifier.

Eidheim et al. proposes in (Eidheim et al., 2004) an automatic liver vessel segmentation method in MR and CT images. Eidheim et al. use matched filters to emphasize blood vessels and entropy-based thresholding to segment the vessels. Vessel interconnections are extracted and exported to a graph structure. Genetic algorithms are then used to search globally for the most likely graph based on a set of fitness functions. The presented method, which is used also clinically (Eidheim et al., 2004), can be categorized as a hybrid method which is a combination of image processing method, i.e. matched filter, and the pattern recognition type method employing a transformed intensity feature, i.e. entropy, and simple thresholding classifier.

Saitoh et al. proposes in (Saitoh et al., 2004) an automatic segmentation method for liver region based on extracted blood vessels. Saitoh et al. use four-phase CT images with resolutions as high as 1 mm. The first-, second-, third-, and fourth-phase

CT images correspond to before dye injection, the early stage, the full stage, and the wash-out stage of the injected dye. These CT data provide useful information for diagnosing hepatic cancer. The blood vessel stream in the first- and third-phase CTs is used for segmenting the liver region by tracing the portal vein and then the hepatic vein. The thresholding operation is used for separating blood vessels from liver soft tissue. The stomach and spleen regions are segmented by 3D morphological operations which are erosion and dilation. The segmented liver blood vessel region is enlarged by morphological dilation operation for obtaining an approximate liver region and then the liver region is extracted by thresholding. The presented method can be categorized as a hybrid method which is a combination of a morphological (image processing) method and the pattern recognition type method employing intensity feature and simple thresholding classifier. The main characteristic of the developed liver segmentation method relies on extracting the portal vein and then the hepatic vein in the first stage.

Charnoz et al. propose in (Charnoz et al., 2005) a robust method for the design of vascular tree matching which is also applied on liver. Charnoz et al. applies the method for intra-patient hepatic vascular system registration. The method exploits a segmented vascular system obtained by CT-scan images available from the Visible Man (The Visible Human Project). Skeletons are computed from the segmented vascular systems and then are represented as an oriented tree. The orientation symbolizes blood circulation flow. Nodes represent bifurcations and edges correspond to vessels between two bifurcations. Some geometric vessel attributes, i.e. 3D positions, radius, vessel path, are also used. The tree matching algorithm finds common bifurcations (nodes) and vessels (edges). Starting from the tree root, edges and nodes are iteratively matched. The algorithm is applied on a synthetic database containing various cases. The used segmentation method can be categorized as a skeletonization (image processing) method. The resulting skeleton is represented as a tree such that the operations implemented on the tree provide the targeted robustness against to topological modifications due to segmentation failures and against deformations.

Saitoh et al. propose in (Saitoh et al., 2005) a method for diagnosis of liver cancer based on three-dimensional hepatic blood vessel regions extracted by threshold processing. High-resolution multi-slice CT images are used in the diagnosis. The liver entrance is located by tracing the blood vessels from the abdominal aorta. The hepatic vessel region is extracted as: A temporary threshold is determined near the liver entrance, and the structure of the blood vessel is analyzed by adjusting the threshold from the temporary value in order to determine the optimal threshold. The thinning operation is applied to the blood vessel in order to construct a directed graph for representing vessel system. The existence of a loop is considered as a sign of choosing a low threshold causing over extraction of the blood vessel region. The cancer detection procedure is as follows. Cancers are found firstly in the extracted blood vessel region, and then from the rest region (Saitoh et al., 2005). The presented method can be categorized as a pattern recognition type method employing intensity feature and simple thresholding classifier. The main characteristic of the developed liver segmentation method relies on locating the liver entrance by tracing the blood vessels from the abdominal aorta.

Schmugge et al. propose in (Schmugge et al., 2006) a robust vessel segmentation method for intravital microscopy (IVM) images which enable capturing temporal changes of blood flow and vessel structure in vivo. Schmugge et al. propose a Bridging Vessel Snake (BVS) algorithm to segment a network of vessels, especially ones with less sharp boundaries. The method segments the vessels with varying diameter while imposing the structure of vessels by utilizing a ribbon snake and adding energies of width and region. The initial network of vessels is obtained by the skeletonization corresponding to mostly sharper vessels. The sharp vessels are considered as vessels of higher confidence and then new bridges among them are constructed by hypothesizing “less sharp” vessels. The method is useful for achieving accurate biological analysis of blood vessels regulation within liver and also within other organs, so for microvasculature reconstruction necessary for red blood cells flow distribution regulation analysis. The used segmentation method can be categorized as a skeletonization (image processing) method. The resulting skeleton is enlarged by BVS algorithm to obtain the network of vessels including the ones with less sharp boundaries.

Erdt et al. propose in (Erdt et al., 2008) a technique for fully automatic hepatic vessel segmentation employing graphics hardware. The technique presented enhances and extracts quickly the vascular system of the liver from CT images. The developed system consists of i) vessel enhancement on the Graphics Processing Unit (GPU), ii) automatic vessel segmentation in the enhanced images and iii) an option to verify and refine the segmentation results. The segmentation quality is assessed on 20 clinical datasets of varying contrast quality and acquisition phase. Erdt et al. reports that graphics hardware realization of the automatic segmentation provides reliable and fast extraction of the hepatic vascular system, so constitutes a beneficial technique for oncologic surgery planning.

Fei & Park, 2008 propose in (Fei & Park, 2008) an automatic liver vessel segmentation approach based on level set method for diagnosis and treatment of the hepatic disease. A flexible initialization for the level set function is implemented by segmenting the liver automatically using morphological filtering and an improved Otsu’s thresholding based on calculating the minimum within class variance corresponding to the classes of pixels each side of the threshold. The used morphological operators are performed in the following three phases: i) Removing surrounding tissues using morphological filtering, obtaining a binary image by the improved Otsu’s threshold method and tracking the location of liver, ii) Binary image of the liver where 1’s represent the tracked location image and liver boundary, and iii) Segmentation liver from the source image using the binary image of the liver. The segmented liver boundary is used as the level set initialization in the level set method used for the automatic segmentation of the liver blood vessels. Since the level set method used for liver vessels is a partial differential based method and its initialization is realized by using morphologic filtering and Otsu’s thresholding, then the method by Fei & Park can be considered as a hybrid method.

Homann et al. propose in (Homann et al., 2008) a vasculature segmentation method for CT liver images based on graph cuts and graph-based analysis. The method segments vessels using 3D graph-cuts by the utilization of probabilistic intensity information and surface smoothness as constraints. A semi-automatic graph-based technique is then employed to efficiently separate the hepatic vessel systems. The resulting vascular segmentation is assessed on 6 liver CT datasets in comparison to a manual segmentation and found reasonable in terms of robustness against to parameter choices. The basic idea of the proposed graph-cut method is to represent the image as a graph such that every voxel corresponds to a node. The edge-set consists of links connecting neighboring voxels and links connecting all voxels to the source and sink voxels. The goal is to find the optimal cut which separates the graph into two sub-sets. Where, the cost to be minimized is the sum of the weights of the cut edges which are calculated in terms of the differences of intensity values corresponding to neighboring voxels and the intensity probabilities. The method starts with performing anisotropic diffusion on the segmented liver as a pre-segmentation step. A graph cuts segmentation method is employed to detect vessels, and then the vasculature sub-trees are identified using skeletonization followed by a graph-based analysis. The anisotropic diffusion is a partial differential equation based method used in the pre-segmentation phase in order to reduce image noise while retaining significant parts of the image content, typically edges, lines and other details. On the other hand, skeletonization and then the graph analysis described above are used for obtaining liver vasculature system. So, the method by Homann et al. can be considered as a hybrid method.

Kawajiri et al. propose in (Kawajiri et al., 2008) an automated segmentation method for hepatic vessels in non-contrast CT images. The method first applies an enhancement and then extraction operation on hepatic vessels. The enhancement is performed by histogram transformation based on a Gaussian function and also multi-scale line filtering based on eigenvalues of a Hessian matrix. The candidates of hepatic vessels are then extracted by a thresholding method applied on the enhanced histogram. Small connected regions in the resulting images are removed since they could not belong to the hepatic vessels. The results obtained for two normal-liver cases one of which is obtained for plain CT images and the other for contrast-enhanced CT images of the same patient are compared for evaluating of the performance of the method. It is concluded by Kawajiri et al. that the method could enhance and segment the hepatic vessel regions even in plain CT images. Since the enhancement is implemented by thresholding applied on a transformed intensity histogram and also by a Hessian based filter, and the vessel extraction is realized again by thresholding applied on an enhanced histogram, then the method can be considered as a hybrid liver vessel segmentation method combining histogram based pattern recognition methods with an image processing method.

Doğan et al. propose in (Doğan et al., 2009) a method for extraction of the liver vessels from abdominal CTA images by a Hessian based vessel filter. The method possesses a labeling procedure for the main vessels applied after the extraction of the liver vessels. In contrast to the other Hessian filter based liver vessel segmentation methods, the method is capable of extracting all of the liver vessels not a part of them. The method can be considered as an image processing based liver vessel segmentation method.

Freiman et al. propose in (Freiman et al., 2009) a variational method for liver vessel segmentation and visualization in abdominal CTA images. The segmentation problem is posed as a functional minimization within a variational calculus framework. Where, the functional incorporates a geometrical measure for vesselness and also properties for vessel surfaces. The functional does indeed correspond to the distance between the desired segmented image and the original image. The Euler-Lagrange equations are solved by using conjugate gradients algorithm in order to find the minimum of the functional. The method is superior to the Hessian based methods in the detection of bifurcations and complex vessel structures as a consequence of the possibility of incorporating a surface term into the functional. The simulation results, which are compared to the results obtained by Hessian based method and also to the evaluations by an expert radiologist on eight abdominal CTA clinical datasets, show that the method is suitable for the automatic segmentation and visualization of the liver vessels. The method by Freiman et al. is an optimization based method formulized in the variational calculus framework.

Kaftan et al. propose in (Kaftan et al., 2009) a two-stage method for fully automatic segmentation of venous vascular structures in liver CT images. The method is useful for surgical planning of oncological resections and living liver donations. The developed hepatic vessel segmentation method is implemented in two stages. The core vessel components are detected and delineated firstly. Then, smaller vessel branches are segmented by a robust vessel tracking technique based on a medialness filter. In the first phase, major vessels are segmented using a globally optimal graph-cuts algorithm in combination with foreground and background seed detection. In the second stage, a tracking algorithm is applied locally in the areas of smaller vessels. The method is evaluated on contrast-enhanced liver CT images obtained from clinical routine and is reported promising. The method can be considered as a hybrid method employing image processing and graph analysis.

Seo & Park propose in (Seo & Park, 2009) a method for automatic segmentation of hepatic vessels in abdominal multiple detector CT images. Hepatic vessels are useful in estimating the volumes of the left and right hepatic lobes, integral for maximizing the safety of the donor and the recipient during living donor liver transplantation. The segmentation is implemented in the following steps: i) canny edge detection for determining the location of the hepatic vessel, ii) extraction of hepatic vessel candidates by threshold filtering around the detected edge, iii) addition of true negatives, defined as hepatic vessel pixels, except for the extracted vessels, as the brightness of these pixels is less than the threshold, according to the pre and post section connections, and iv) removal of false positives, defined as small connected regions smaller than nine voxels without connections to pre or post sections. The method by Seo & Park can be considered as a hybrid method implementing image processing and histogram based thresholding operations.

Chi et al. propose in (Chi et al., 2010) a method for segmenting liver vasculature in contrast enhanced CT images by using context-based voting. The liver vasculature segmentation is implemented by first extracting vessel context from input image, and then votes on vessel structures. Herein, the liver is extracted using Model-based Image Understanding Environment (MIUE) (http://www.liversuite.com/). The liver scan is next processed to be isotropic. The method is reported to be able of conducting full vessel segmentation and recognition of multiple vasculatures effectively. The vessel context describes context information of a voxel related to vessel properties, such as intensity, saliency, direction and connectivity. Voxels are grouped to liver vasculatures hierarchically based on vessel context. They are first grouped locally into vessel branches with the advantage of a vessel junction measurement, and then grouped globally into vasculatures, which is implemented using a multiple feature point voting mechanism. The proposed method is evaluated on ten clinical CT datasets. Since the method by Chi et al. employs a vessel context based voting for segmentation and for identification liver vasculatures by using region based features, such as shape and intensity, then, it can be considered as a pattern recognition type liver vessel segmentation method.

Esneault et al. propose in (Esneault et al., 2010) a fully automatic method for liver vessel segmentation by using a hybrid geometrical moments and graph cuts in CT preoperative images. The method introduces a 3D geometrical moment-based detector of cylindrical shapes within the minimum-cut/maximum-flow energy minimization framework. It exploits a data term as a constraint into the widely used Boykov's graph cuts algorithm to automate the segmentation. The method is evaluated on a synthetic dataset. The method by Esneault et al. can be classified as a hybrid method combining pattern recognition and graph analysis methods. Where, the geometrical moments are used as features in the pattern recognition.

Friman et al. propose in (Friman et al., 2010) a multiple hypothesis template tracking method for small 3D liver vessel structures. The method leads to low contrast passages to be traversed and an improved tracking performance in low contrast areas, and also a novel mathematical vessel template model providing an accurate vessel centerline extraction. The proposed tubular tracking algorithm is realized by applying 3D template matching which is based on matched filter approach of image processing. The template is an image patch containing an idealized vessel segment which is parameterized by a radius, a center location, and a direction. The used modular vessel template model is incorporated with a dedicated fitting procedure. The employed multiple hypothesis tracking for vessels, which is well established technique of signal processing and control areas, considers several possible trajectories or hypotheses simultaneously. The tracking is reported as fast enough for an interactive segmentation. The method is applied for segmenting both the liver arteries in CT angiography data and the coronary arteries in thirty-two CT cardiac angiography data sets in the Rotterdam coronary artery algorithm evaluation framework. The method by Friman et al. can be classified as an image processing and pattern recognition based hybrid method.

The thesis is planned as follows. Chapter two gives a background on liver anatomy and imaging modalities for liver. Chapter three presents a brief review on general medical image segmentation methods with a special emphasis on vessel segmentation. The liver vessel segmentation, which is the main subject of the thesis, is reviewed in detail in Chapter four. The conclusions are given in Chapter five.

CHAPTER TWO

LIVER ANATOMY AND IMAGING MODALITIES FOR LIVER

This chapter presents a description of liver anatomy and imaging techniques used for liver vessel segmentation.

2.1 Liver Anatomy

The liver is the largest gland in human. It is located on the right side of the abdominal cavity (Anthea et al., 1993; Selver, 2010). Considering surface features, the liver can be divided into four lobes each of which has unequal size and shape. The liver has two blood supplies. One of them is the hepatic artery carrying blood from aorta. The other is the hepatic portal vein carrying blood from small intestine. Herein, hepatic word, which is originated from Greek word “hēpar”, refers to liver. These two blood vessel systems branch into capillaries leading to lobules made up of millions of hepatic (metabolic) cells which further constitute the lobes of the liver. A vein passes through the centre of each lobule and then joins to the hepatic vein for carrying blood out of the liver. Ducts, veins and arteries taking place on the surface of the lobules carry fluids, i.e. bile and blood, into and from these lobules.

As depicted in Figure 2.1, the bile duct, hepatic portal vein, and hepatic artery are partitioned into left and right branches which constitute the functional left and right lobes of the liver. These functional lobes are actually separated by a plane passing the middle hepatic vein, the gallbladder fossa and the inferior vena cava. Furthermore, the right hepatic vein partitions the right lobe into an anterior and a posterior segment while the left hepatic vein partitions the left lobe into the medial and lateral segments. On the other hand, the fissure of the ligamentum teres further partitions the medial segment, i.e. quadrate lobe, and lateral segment. Couinaud system, which is also called as French system, (Couinaud, 1999) partitions the functional lobes into a total of eight sub-segments by a transverse plane through the bifurcation of the main portal vein.

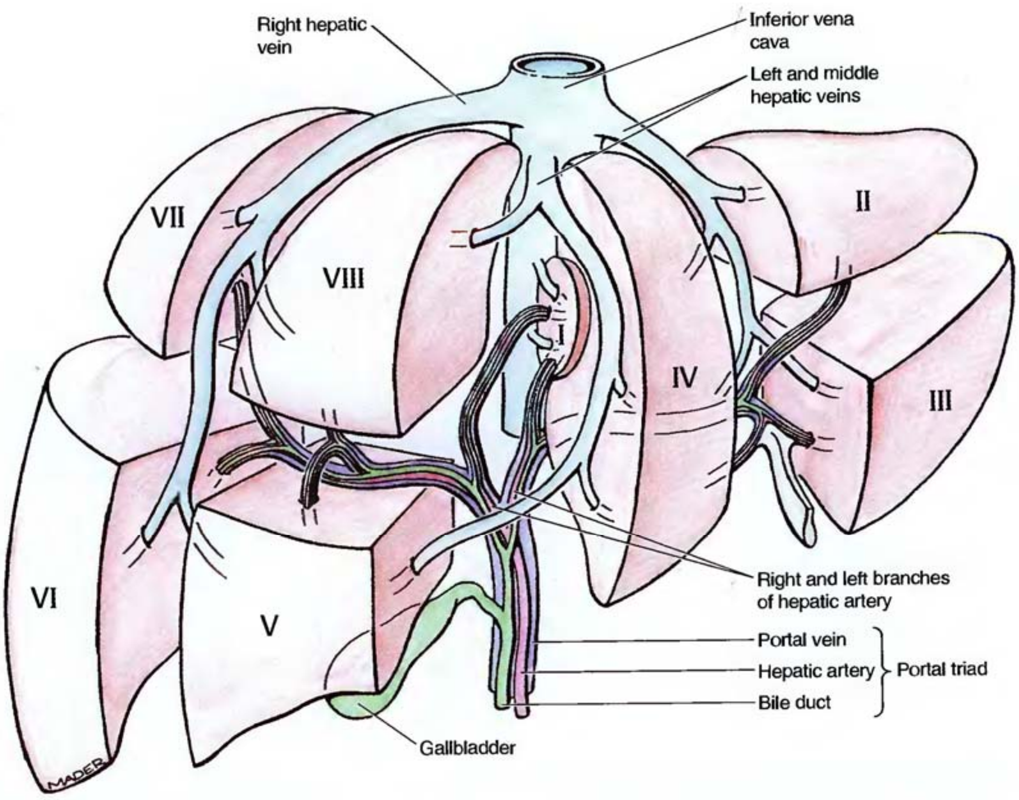

Figure 2.1 Liver anatomy and vasculature. (Moore et al., 1999).

2.2 Imaging Modalities used for Liver Vessel Segmentation

In the literature (Soler et al., 1998; Dokladal et al., 1999a; Dokladal et al., 1999b; Hanh et al., 2001; Doherty et al., 2002; Saitoh et al., 2002; Eidheim et al., 2004; Saitoh et al., 2004; Charnoz et al., 2005; Saitoh et al., 2005; Schmugge et al., 2006; Erdt et al., 2008; Fei & Park, 2008; Homann et al., 2008; Kawajiri et al., 2008; Doğan et al., 2009; Freiman et al., 2009; Kaftan et al., 2009; Seo & Park, 2009; Chi et al., 2010; Esneault et al., 2010; Friman et al., 2010), there are several different types of imaging techniques used for the liver vessel segmentation. CT, CTA, multi-phase CT, multi-detector CTA, MR and MRA are among these techniques. These techniques are briefly described below.

2.2.1 Computed Tomography (CT)

X-ray CT, which is usually called as CT, is a medical imaging technique typically requiring X-ray tube, detector and microcomputer (Herman, 2009). X-ray CT is based on ionizing radiation. X-ray sensors, which are placed at the opposite to an X-ray source rotating around the object, are used to produce X-ray slice data. A form of tomographic reconstruction is used to processes the scan data in a digital way for producing a series of cross-sectional digital images.

Image pixels are displayed based on the mean attenuation of the tissue(s). Where, Hounsfield scale is used as a standard ranging from +3071 representing the most attenuating to -1024 representing the least attenuating. For instance, water has an attenuation of 0 Hounsfield units, air is -1000 HU, and cancellous bone is around +400 HU.

2.2.2 Computed Tomography Angiography (CTA)

CT angiography (CTA) is a computed tomography technique. In order to produce detailed images of blood vessels and tissues, this technique is required to inject a contrast material into a peripheral vein (CT Angiography, (n.d.), March 13, 2011, http://www.radiologyinfo.org/en/info.cfm?pg=angioct#part_one). Injection of the contrast material to the bloodstream makes the blood vessels appear bright white. CT angiography is used to examine blood vessels especially in brain, kidneys, pelvis, legs, lungs, heart, neck and abdomen. It provides to capture of highly detailed vascular systems.

2.2.3 Multi-Detector Computed Tomography

Multi-Detector Computed Tomography (MDCT) is also called as multi-slice CT. It is used to obtain multiple slices in a single rotation. Thinner slices, which yield higher resolution, are obtained in a shorter period of time in multi-detector CT. It provides more detail and additional views. Multi-Detector CT can delineate anatomic structures in the abdomen (Lee et al., 2010). Multi-Detector CT uses a higher radiation dose as compared to single-detector CT.

2.2.4 Multi-Phase Computed Tomography

Conventional CTA, which is also called as single-phase CTA, is acquired during a short interval in the arterial phase. In contrast, multi-phase CTA images contain data related to the different time instances. Multi-phase CTA is reconstructed from raw data of thin-section perfusion CT which is used to generate parametric maps of blood flows. Multi-phase CTA is superior to single-phase CTA since it provides better vascular enhancement while having comparable image quality. However, the radiation dose of multi-phase CTA is higher than the dose of the conventional single-phase CTA (Yang et al., 2008). It should be noted that the radiation dose can be reduced by choosing large sampling interval.

2.2.5 Magnetic Resonance Imaging

In contrast to CT, Magnetic Resonance Imaging (MRI) technique is not based on ionizing radiation. MRI employs a magnetic field to align the magnetic moments of the protons with the direction of the field and employs a radio frequency transmitter for producing a varying field to change the alignment. The generated magnetic field gradients force nuclei of the atoms of the body tissues to rotate at different speeds. The protons resonate at a frequency depending on the strength of the produced magnetic field. The protons are returned back to their original lower-energy spin-down state when the field is absent. In order to understand the spinning mechanism, consider a hydrogen dipole which has a single high spin and a single low spin. Dipole and field have the same direction for low spin state while the opposite for high spin case. The energy difference, which is released as a photon, is detected by the scanner as an electromagnetic signal. This mechanism together with the fact that the protons in different tissues return to their rest states at different rates explains how to construct the MR images. Spin density, T1 and T2 relaxation times, flow and spectral shifts are used to construct images (Hendee & Morgan, 1984). 3D positions of the released photons are detected by using additional fields produced by gradient coils such that inverse Fourier transform is applied to the measured signal to extract position information hidden in the position dependent frequency spectrum.

MRI scans usually contain 5–20 sequences of images. Two basic sequences are given the sequel (Magnetic Resonance Imaging, (n.d.), May 22, 2011, http://en.wikipedia.org/wiki/Magnetic_resonance_imaging).

<u>T1 Sequence</u>: T1 sequence, which is also called as T1-weighted sequence, is obtained from a gradient echo sequence with a short Echo Time (ET) and with a short Repetition Time (TR). T1 sequences provide good contrast especially between fat and water such that fats are displayed as bright while water as dark. For liver applications, TR is hold sufficiently long to cover the entire liver in one pass with a good signal to noise ratio. In phase ET, choosing short TE minimizes magnetic susceptibility effects and permits a one breath scan to cover the entire liver.

<u>T2 Sequence</u>: T2 sequences, which are also called as T2 weighted sequences, are typically obtained from a spin echo sequence with long ET and long TR. T2 sequences display tissues, which are rich in water or other fluids, as bright and fatty tissues as dark. T2 sequences are especially useful to distinguish pathologic tissues from normal tissues. Fast spin echo combined with fat suppression is quite common T2 sequence used for liver MRI applications (Liver Imaging, (n.d.), May 22, 2011, http://www.mr-tip.com/serv1.php?type=db1&dbs=Liver%20Imaging).

MRI provides a better contrast between different soft tissues and better spatial resolution as compared to CT. In compare to CT and Ultra Sound (US), MRI is known to be more sensitive and accurate especially for detection and characterization of focal lesions in liver. A basic liver MR protocol, which consists of T2, inversion recovery and T1 sequences, requires 3-4 pulse sequences lasting normally twenty minutes (Earls, 2002).

2.2.6 Magnetic Resonance Angiography

Magnetic Resonance Angiography (MRA) requires a specific contrast agent to be injected intravenously for enhancing the appearance of blood vessels. In addition to non-specific ones such as paramagnetic contrast agent "gadolinium", liver-specific contrast agents are also available (Earls, 2002; Liver Imaging, (n.d.), May 22, 2011, http://www.mr-tip.com/serv1.php?type=db1&dbs=Liver%20Imaging; Magnetic Resonance Imaging, (n.d.), May 22, 2011, http://en.wikipedia.org/wiki/-Magnetic_resonance_imaging;).

CHAPTER THREE

MEDICAL IMAGE SEGMENTATION

Image segmentation aims to change the representation of an image in order to have a representation which is simple to be analyzed in an efficient way and more informative providing a higher recognition success. Image segmentation can be defined as the process of labeling every pixel in an image based on their visual characteristics such as intensity, color or texture (Shapiro & Stockman, 2001).

Medical image segmentation is the process of partitioning a medical image into several subsegments which are sets of pixels corresponding to certain anatomical structures, i.e. the organs such as brain, eye, lung, liver, heart, blood vessels, and normal and abnormal tissues. This chapter presents a review on semi-automated and fully automated methods for the segmentation of medical images.

Segmentation methods assist doctors in evaluating the medical images and/or automate many radiodiagnostic-medical recognition tasks. Quantification of tissue volumes, abnormal tissue diagnosis, localization of pathology, extraction of anatomical structures and partial volume correction are among the medical tasks where image segmentation (Bankman, 2009; Fitzpatrick & Sonka, 2000; Pham et al., 1999).

Medical image segmentation methods differ from the generic segmentation methods with their application-specific nature. They usually incorporate prior knowledge about the anatomical structures aimed to be segmented. A part of the methods available in the literature is based on the generic segmentation methods. However, it can be said that a specific medical segmentation problem generally requires a specific solution provided by a specific segmentation method.

The success of a segmentation method depends mainly on the anatomic structure to be segmented, the used imaging modality, partial volume effect, noise, artifacts and motion in the scan and also the patient. The segmentation of an organ-tissue requires different methods, techniques or modalities from the ones required for another organ-tissue. On the other hand, similar organs-tissues, such as tubular vessel structures of liver, brain or retina, require similar segmentation methods, techniques and modalities. This explains why this chapter presenting general medical image segmentation methods is included in the thesis whose focus is on the liver vessel segmentation.

Selection of the best segmentation method for a specific medical segmentation problem is a quite difficult problem (Pham et al., 1999). However, the performances of the available medical segmentation methods give an idea how to choose an acceptable segmentation method for a particular medical segmentation problem. To serve this purpose, this chapter is devoted to present the available medical image segmentation methods and the vessel segmentation methods of cerebral, retinal and other organs.

3.1 Overview for Medical Image Segmentation

Several different segmentation approaches are available in the medical image segmentation literature. The medical image segmentation is realized based on 1) pattern recognition, 2) image processing, 3) optimization, 4) graph analysis, and 5) partial differential equation models. The methods in the pattern recognition group can be further classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) machine learning methods including Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), 4) probabilistic methods, and 5) hybrid methods. On the other hand, image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

This subsection does not cover the entire literature; instead it is aimed to describe main medical segmentation approaches. A part of the methods used in the literature actually combines more than one approach in order to increase the success of the segmentation. Several general surveys on image segmentation exist in the literature

(Fitzpatrick & Sonka, 2000; Pham et al., 1999; Zhang et al., 2008; Cárdenes et al., 2009; Hu et al., 2009; Wirjadi, 2007).

3.1.1 Pattern Recognition Approaches

The pattern recognition approaches involve with a feature extraction stage and a classification stage applied on the extracted features usually after some transformations. The pattern recognition approaches can be classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) machine learning methods including Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), 4) probabilistic methods, and 5) hybrid methods. A part of these pattern recognition approaches is given in the following sub-sections for the sake of brevity.

3.1.1.1 Thresholding Approach

Thresholding approach can be classified as segmentation method based on histogram analysis, so they can be categorized as pattern recognition type (probabilistic) methods employing intensity feature and simple thresholding classifier. Thresholding transform images into a binary one based on pixel intensities. Figure 3.1.a shows the histogram of an image that possesses three apparent classes. The thresholding is the determination of an intensity value, called the threshold, such that the pixels having the intensity level above this threshold belong to one class while the others belong to the complement of this class. As seen from Figure 3.1.a, multi-class case needs multi-thresholding procedure which can be performed by finding the bottoms of the valleys in the histogram (Pham et al, 2000). Thresholds can also be determined by the maximum entropy method, Otsu's method based on maximum variance between classes, and k-means clustering (Segmentation (Image Processing), (n.d.), May 24, 2011, http://en.wikipedia.org/wiki/Segmentation_-(image_processing)#cite_note-computervision-0).

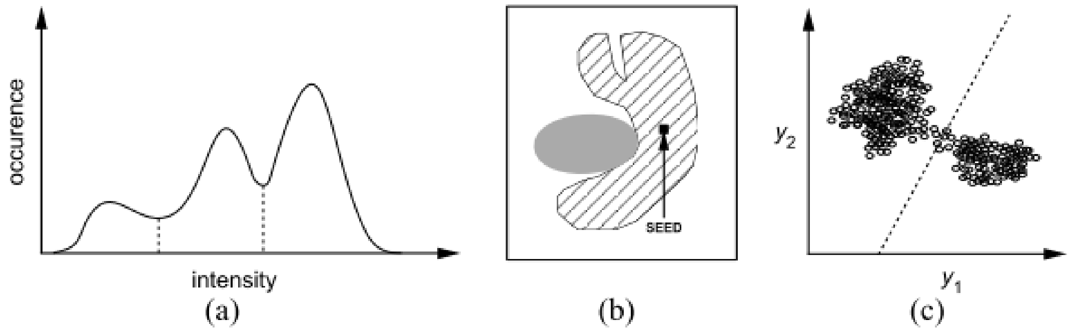

Figure 3.1 Thresholding and region growing: a) a histogram possessing three apparent classes, b) illustration of region growing, c) classification in a 2D feature space (Pham et al., 2000).

Thresholding is the simplest yet efficient segmentation method especially for images having good contrast between the pixel classes belonging to two different anatomical structures.

3.1.1.2 Clustering Approach

Clustering methods used in medical segmentation partition a data set, for instance a set of pixels' intensity vectors, into clusters each of which corresponds to a class representing an anatomical structure. After this design phase, sample vectors are assigned to clusters based on minimum distance away from the cluster centers. In this sense, clustering approach resembles to the classifier approach given next subsection. However, clustering process is unsupervised, not requiring class labels for sample vectors in the design phase in contrast to the "supervised" classifier approroaches given in the next subsection.

K-means, fuzzy c-means, and Expectation-Maximization (EM) are among the most common clustering algorithms used for segmentation purposes (Pham et al, 2000). The K-means clustering clusters data in an iterative way into k clusters by computing cluster means from the already assigned data at each step and then assigning newly considered data based on these means. So, eventually it provides a mean intensity for each class and the segmentation is realized by assigning the closest mean to each image pixel. The fuzzy c-means algorithm allows a soft segmentation. k-Nearest Neighbor (k-NN) algorithm can also be categorized as a clustering algorithm. In contrast to k-means algorithm, k-NN is a non-parametric method which does not assume a distribution for the data. k-NN assigns an (pixel) intensity to a specific class if the majority of k closest (pixel) intensity belongs to that class.

EM algorithm assumes a Gaussian mixture model for the conditional probability density function of pixel intensity data. It consequently computes the posterior probabilities and maximum likelihood estimates of the means, covariances and mixing coefficients. In contrast to other “fully unsupervised” clustering algorithms, EM algorithm requires an initial segmentation or, equivalently, initial parameters. So, the success of EM highly depends on the initialization and it requires more computational time. Clustering based segmentation methods do not directly incorporate spatial information, so they are sensitive to noise and intensity inhomogeneities. However, they are preferred for their fast computation feature (Pham et al, 2000).

3.1.1.3 Probabilistic Classifiers

Classifiers can, indeed, be classified into deterministic and probabilistic classifiers. Artificial Neural Networks (ANNs), which will be described in the next subsection, are among the deterministic classifiers. Maximum-likelihood or Bayes classifiers are examples for probabilistic classifiers which assume a mixture of probability distributions, usually Gaussion, for pixel intensities.

In both of deterministic and probabilistic classifiers, original image is transformed into a feature space such that the labels of the features are known. A common feature space in the image segmentation applications is the space of pixel intensities. Image histogram is an example for one dimensional feature space (See Figure 3.1.a) where thresholding can be used as the simplest classifier. As depicted in Figure 3.1.c, a two class classifier applied on a two or more dimensional feature space provide a separation surface.

Classifiers are supervised methods since, in the training-design phase, they use class labels which can be obtained by a manual segmentation. Most of the classifier based image segmentation methods do not incorporate spatial information (Pham et al, 2000).

3.1.1.4 Machine Learning Approaches (ANNs, SVMs)

Artificial Neural Networks (ANNs) are networks of simple processing elements, called as neurons inspired by biological neurons. ANNs can be deterministic or probabilistic, algebraic or dynamical, trainable in a supervised or unsupervised way but they are always nonlinear and parallel networks of neurons whose synaptic connection weights are the parameters storing information learned in the training phase.

Algebraic deterministic ANNs such as Multi-Layer Perceptron (MLP), Radial Basis Function Network (RBFN), are the ones used as classifiers trained in a supervised way. Such ANNs constitute semi-parametric methods since not only the connection weights, i.e. parameters, but also the number of neurons and also network topologies are also adaptable.

ANN classifiers are used for image segmentation by considering pixel intensity features as inputs to the ANN and exploting an initial segmentation in the training phase. Due to their flexibility of constructing different topological architectures and their capability of combining different kind of features, ANNs are also suited to incoroparate spatial information (Haykin, 1999; Pham et al., 2000).

ANNs, which are simulated in digital computers, can be considered as machine learning methods which cover a diverse field of methods for designing (computer) models of classification, regression and clustering based on learning from data. Support Vector Machines (SVMs) which are developed by Vapnik (Haykin, 1999) originally for decision making and then extended to solve general classification, regression and clustering problems, become the most popular machine learning approach in the last decade.

SVMs transform a given classification problem into a high dimensional space where the problem becomes a linear separation defined by a hyperplane. The optimal separating hyperplane found in the transformed space, which is, indeed, the range space of a nonlinear mapping, is determined not by all sample data but a subset of data vectors, called as support vectors. This property provides a sparse representation SVMs, so good generalization ability.

Choosing different types of classification error measures, i.e. loss functions, and different types norms for linear weights defining optimal hyperplane provide different types of SVMs each of which has its own advantageous and disadvantageous in obtaining a classification which is robust against to noise and outliers (Karal, 2011). SVMs, with their good generalization abilities and so robustness, are quite promising for obtaining robust medical image segmentation.

3.1.2 Image Processing Based Segmentation Approaches

Image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

3.1.2.1 Region Growing Approach

Region growing approach can be classified as topological and also intensity-spatial information based image processing segmentation approach since the regions are constructed from some seed pixels by considering their spatial connectivity. On the other hand, region growing can be classified as a pattern recognition approach since the pixels are assigned to the growing region depending upon their similarity to the region pixels in terms of the intensity features.

Region growing aims to extract sub-regions of the image which are homogenous with respect to a feature such as intensity or edges (Segmentation (Image Processing), (n.d.), May 24, 2011, http://en.wikipedia.org/wiki/Segmentation_-(image_processing)#cite_note-computervision-0). The simplest region growing, which can be called as seeded region growing, starts with a set of seed points which might be selected manually based on prior knowledge or by employing an automated method in the initial stage. Then, the procedure includes all pixels around the initial seeds if they have the sufficiently close intensity value with the initial seeds. The difference between the intensity of a candidate pixel and the mean intensity of the already determined part of the region is taken as the similarity measure. The procedure continues by treating a pixel, which is already included by the region, as an initial seed. An example for region growing is illustrated in Figure 3.1.b where a single region is wanted to be extracted.

Region growing is particularly useful for extracting small and relatively simple structures such as tumors and lesions. Region growing is not robust against to noise and artifacts. So, originally simply connected regions can be extracted by the region growing as having holes or being disconnected. On the other hand, originally disconnected regions can be extracted as connected. This disadvantage of the region growing is usually overcomed by a homotopic approach which ensures to preserve the topology between the initial and extracted regions.

3.1.2.2 Markov Random Field Models

Markov Random Field (MRF) is a statistical model which assumes a strong correlation among the intensities of neighboring pixels. So, it is well suited to incorporate spatial interactions among image pixels (Pham et al., 2000).

MRF assumption is also exploited in clustering based segmentation methods with a Bayesian prior model. In such methods, the segmentation is performed by the maximization of a posteriori probabilities for the given medical image usually with a global global optimization technique.

The main difficulty in MRF based segmentation methods is the selection of optimal strength of spatial interactions which may result in an oversmooth segmentation loosing of important structural details in one hand, or a subsmooth segmentation casuing many artifacts.

3.1.3 Partial Differential Equation Based Segmentation Approaches

Partial differential equations are well suited to model space-time evolution of dynamical behaviors such as wavefront evolution, deformation and diffusion. Discretization of a specific partial differential equation system with respect to spatial coordinates (and also to time) provides models for representing a specific digital image processing task. Deformable models and level set image segmentation methods described in the following subsections are two popular examples of partial differential equations based medical image segmentation.

3.1.3.1 Deformable Models

Deformable models used for medical image segmentation are model based techniques where the models are defined by partial differential equations (McInerney & Terzopoulos, 1996, 1999; Pham et al., 2000). The partial differential equations defining deformable model is, indeed, Euler-Lagrange equation whose solution minimizes a functional. Where, the functional represents the energy of a parametric contour in the two-dimensional image plane. In this sense, the deformable model is also an optimization method solved in the variational calculus framework.

The boundaries of regions to be segmented are determined by first placing the contour near the desired boundary and then by applying deformation under the influence of internal and external forces. Internal forces are used for keeping the contour smooth throughout the deformation. External forces are used for driving the contour toward the intensity extrema, edges, and other desired image features of interest which are computed from the image, for instance as the gradient of the edge map.

Deformable models produce closed and smooth boundaries for regions to be segmented, so providing robustness against to noise and spurious edges. However, they require manual interaction to choose an initial model and there is a difficulty in determining appropriate parameters.

3.1.3.2 Level Set Method

In level set method, a partial differential equation system is used to define the propagation of a contour which eventually settled down to the actual contour corresponding to the lowest level of a cost function. Where, the cost represents the image processing task addressed and imposes certain smoothness constraints (Segmentation (Image Processing), (n.d.), May 24, 2011, http://en.wikipedia.org/-wiki/Segmentation_(image_processing)#cite_note-computervision-0).

The level set method is developed by Osher and Sethian for front propagation in modeling ocean waves and burning flames (Sethian, 1999.). Malladi extends its application area to medical imaging including segmentation (Malladi, et al., 1995).

3.2 Vessel Segmentation

Vessel segmentation is a difficult problem. Because, vascular trees can have complex structures and blood vessels are usually covered by other organs. Furthermore, manual segmentation for the images generated by imaging modalities, such as CTA and MRA, is a tedious process taking even hours.

Many vessel segmentation methods are developed in the literature (Freiman et al., 2009; Kirbas & Quek, 2003; Lesage et al., 2009) which are different from the others in terms of the anatomical structures that they targeted and in terms of the segmentation approaches that they exploited. This subsection presents vessel segmentation methods applied to abdominal, cerebral and retinal organs in order to have a unified framework together with the liver vessel segmentation methods which is reviewed in the next chapter. As explained before, a part of the segmentation approaches for the vessels and tubular objects other than liver have similar characteristics with the liver vessel segmentation.

3.2.1 Abdominal Vessel Segmentation Approaches

The segmentation of organs and vasculatures in the abdominal region is a very hard problem due to their complex and highly overlapping structures.

Chen et al. propose in (Chen et al., 2000) an automatic method developed for segmentation of abdominal CT images for virtual colonoscopy in order to prepare a bowel using a low-residue diet. A contrast solution is used for enhancing the image intensities of residual colonic materials. The method applies a multistage segmentation approach consisting of a vector quantization technique for a low-level image classification and a region-growing strategy for a high-level feature extraction.

Komatsu et al. propose in (Komatsu et al., 2006) a temporal subtraction method in CT images to detect the blood vessels on the abdominal. The proposed method is applied to a set of high-resolution helical computed tomography images.

A method by Babin et al. proposes segmentation and determination of the length measurements of blood vessels in 3D abdominal MRI images (Babin et al., 2009). The method does not require contrast-enhanced images for segmentation. The approach exploits skeletonization, graph construction and shortest path estimation to measure the length of vessels.

An automatic segmentation method by Bashar et al. is proposed for abdominal vessels obtained from contrasted CT images (Bashar et al., 2010). In the initial phase, initial vessel and bone image are obtained by using multi-thresholding technique. First threshold is computed by discriminant analysis applied on a reduced CT volume. Second threshold is determined by finding the first local minimum in the histogram of the reduced CT data. In the second phase, larger vessels such as aorta are segmented by 3D region growing applied on the preprocessed CT volume. This image is subtracted from the initial bone and vessel image to obtain a new binary image without larger vessels. An experiment wiith ten cases of contrasted CT images demonstrates the potential of the proposed method on the segmentation of especially thinner vessels.

3.2.2 Cerebral Vessel Segmentation Approaches

The vascular system of human brain is a very complex 3D anatomical structure. 3D visualization of blood vessels by different imaging modalities for segmentation purposes is a very active research area. The segmentation of the brain vacular systems consists of the following four main steps i) preprocessing of digital images scanned, ii) extrating a skeleton for vascular system to have structural description, iii) matching images obtained at different sequence and time, and iv) 3D reconstruction and display (Cui et al., 2009). Segmentation of the cerebral vessel is used for visualization and also for diagnosing diseases.

Luo & Jin and Luo & Zhong present a review on cerebral vessel structure segmentation for 3D quantification and visualization of MRA images (Luo & Jin, 2005; Luo & Zhong, 2005).

A method by Lee et al. presents a reconstruction process for 3D cerebral vessel tree from a pair of Digital Subtraction Angiograms (DSAs) (Lee et al., 1996). Two different thresholding operations, one of which is local and the other is global, are used to segment the vessels from the background. After these operations, thinning is applied to obtain a skeleton for representing the structure of the vessel system.

Krissian et al. propose in (Krissian et al., 1998) an approach for segmenting vessels in 3D angiography images obtained from the brain. The method is based on a vessel model and employs a multiscale analysis for extracting the vessel network surrounding an aneurysm. The method determines points of interest around the vessel center in terms of the conditions imposed on the eigenvalues of the Hessian matrix.

Hirano & Hata propose in (Hirano & Hata, 2000) an approach for segmentation of blood vessels in CTA image exploiting fuzzy logic. In the initial phase, the method obtaines a rough image by combining raw and difference images. The difference image is obtained by applying Laplacian filter. The venae and artery are segmented by fuzzy inference for obtaining the rough image. The method applies region growing for extracting Willis Ring contacted the blood vessels.

A method by Tuduki et al. propose an automated seeded region growing algorithm for segmenting cerebral blood vessels in MRA images (Tuduki et al., 2000). In the initial phase, the method applies thresholding operation on the original MRA image to roughly obtain sturtures of blood vessels. In the second phase, the method applies thining operation for obtaining skeletons of the vessels based on the Euclidean distance transformation. In the final phase, the obtained skeletons are used as the seeds for region growing operation.

Passat et al. propose in (Passat et al., 2005) a method for brain vessel segmentation based on mathematical morphology tools. The method is applied on Phase-Contrast MRA (PC-MRA).

3.2.3 Retinal Vessel Segmentation Approaches

The retina is a layer of membrane at the back of the eye. The retina is visualized as an image by the fundus camera. The retinal images are noisy, poorly contrasted and non-uniformly illuminated. They have brightness variations within the same image and also between different images (Vlachos & Dermatas, 2010). Extraction of blood vessels in retinal images is a very hard problem also due to the facts that a large number of vessels are very thin and the local contrast is low.

The most accurate methods based on supervised classifiers incorporate with knowledge about the vessel network morphology.

An automated method for tracing retinal vasculature and analysis of intersections and crossovers is developed and applied to computer-assisted laser retinal surgery (Akram et al., 2009; Alonso-Montes, 2008; Vlachos & Dermatas, 2010).

In the literature, there are also methods for segmentation of retinal blood vessels based on i) tracing the centers of the vessels, ii) learning and classification of feature vectors, and iii) segmenting the vessel boundaries by using some set of filters or thresholds (Yedidya & Hartley, 2008).

Lam et al. propose in (Lam et al., 2010) a multiconcavity modeling approach based on the regularization framework. The method works for both of healthy and unhealthy retinas. The concavity measures are combined together considering their statistical distributions for detecting vessels.

CHAPTER FOUR

LIVER VESSEL SEGMENTATION

Liver vessel segmentation is used for determining the structure of the liver before transplantation and also for the locations of liver tumors. Liver vessel segmentation is usually implemented on images obtained by Computed Tomography (CT), Computed Tomography Angiography (CTA), multi-phase CT, multi-detector CT, Magnetic Resonance (MR) and Magnetic Resonance Angiography (MRA). Since the vascular anatomy of the liver is quite complex, then the liver vessel segmentation is still an open research area. There are many methods developed in the literature for vessel segmentation for liver. These methods, which are applied for liver vessel segmentation, are reviewed and classified as below.

4.1 Classification of the Liver Vessel Segmentation Approaches

The vessel segmentation is realized based on 1) pattern recognition, 2) image processing, 3) optimization, 4) graph analysis, and 5) partial differential equation models. The pattern recognition approach consists of a feature extraction stage and a classification stage applied on the extracted features usually after some transformations. The methods in the pattern recognition group can be classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) machine learning methods including Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), 4) probabilistic methods, and 5) hybrid methods. On the other hand, image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

For vessel segmentation, several different classifications which are quite different from the above classifications are given in the literature (Freiman et al., 2009; Kirbas & Quek, 2003; Lesage et al., 2009). The liver vessel segmentation methods, which are described in the sequel, can be a member of more than one group given above classifications.

The liver vessel segmentation methods developed in the literature are presented in the following subsections.

4.2 Liver Vessel Segmentation Approaches

In this subsection, recent algorithms, methods and approaches of the segmentation, which are proposed in the literature for liver vessels and liver vessel trees, are reviewed. The algorithms developed by authors, who are given following subsections, are overviewed, and then, they are classified as a method which is belonged to groups mentioned above and previous chapters.

4.2.1 The Method by Soler et al. – 98

Soler in (Soler et al., 1998) proposes a vessel segmentation method based on a histogram analysis, so it can be categorized as a pattern recognition type (probabilistic) method employing intensity feature and simple thresholding classifier. Local minima in histogram are used to define threshold parameters. The image is filtered for improving the contrast rendering before determining the thresholds. Then, the thresholded images are used to obtain the vessel structure (Soler et al., 1998). The

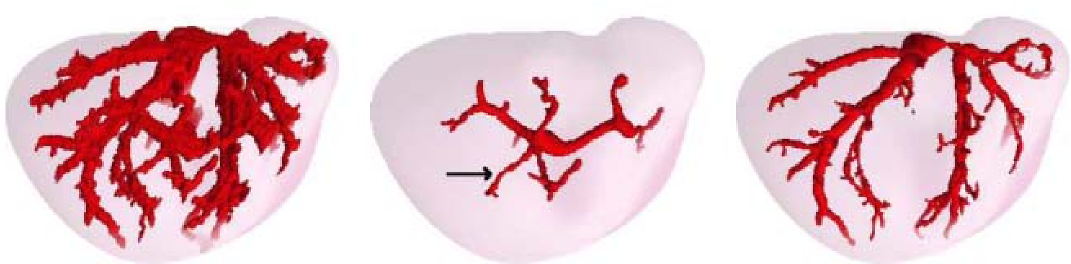

Figure 4.1 Results of the method by Soler et al. (Soler et al., 1998).

method is applicable for liver vessel segmentation as a special case since it is valid for any kind of vessel system.

According to the results which are obtained from twelve patients, it is reported that the algorithm automatically extracts the principal branches of the portal vein, enabling the delimitation of anatomical segments defined in the prevalent liver anatomy.

4.2.2 The Method by Dokladal et al. – 99a

Dokladal et al. proposes a 3D topological based method for liver vessels extraction method in (Dokladal et al., 1999a). The efficiency of the method is examined on a raw X-Ray tomography image without applying any transformation. The method is based on a point-wise reconstruction to preserve the homotopy. The vessel tree system is obtained at a desired level of detail by adjusting a parameter which controls the level of light intensity. The method can be classified as a topological and morphological image processing based method. It is based on the hypothesis that the resulting object is simply connected, contains no holes and no cavities. The vessels are reconstructed in the following iterative way: Add simple points preserving the topology by considering their luminosity. Where, a simple point is defined as a point such that its deletion does not change the topology of the object. The method starts with a marker point that needs to be determined manually by an expert or by another image processing algorithm. Then, the object is grown in an iterative way as adding simple points next to the marker if the gray level of the considered point satisfies to the given stopping criterion. This method is reported to be superior to the histogram based method by Soler et al. (Soler et al., 1998) with the ability of giving thinner and much richer in vessel system which is also topologically correct, i.e. it does not contain any holes or cavities.

4.2.3 The Method by Dokladal et al. – 99b

Dokladal et al. proposes in (Dokladal et al., 1999b) a thinning algorithm for extraction of liver vessels. The result of thinning is a skeleton centered in the object according to its luminosity. The proposed thinning algorithm ensures that the skeleton is topologically correct. The method can be classified as a topological image processing based method.

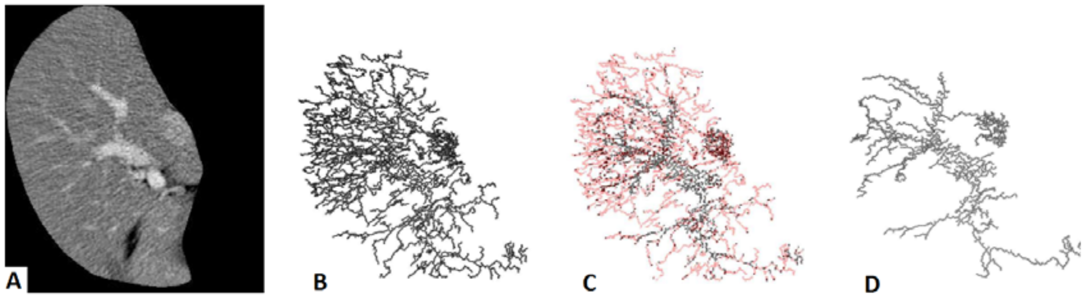

Figure 4.1 Result of the first step of thinning, insignificant segments, and sequentially filtered skeleton. A) A 2D cut of an X-Ray tomography of a liver. B) Skeleton of the vessel system. C) Skeleton segments of low mean luminosity are shown in grey. D) Sequentially filtered skleton given by (B) (Dokladal et al., 1999b).

The results of the first step of thinning, insignificant segments, and sequentially filtered skeleton are seen in Figure 4.1. A 2D cut of an X-Ray tomography of a liver is seen in “A”. Then, in “B”; skeleton of the vessel system and in “C”; skeleton segments of low mean luminosity are shown in grey. Finally in “D”, sequentially filtered skleton given by “B” is seen (Dokladal et al., 1999b).

In this study, it is reported that the proposed method contributes principally a skeletonization method of grey-scale objects with a well sensivity controlling the level of detail.

4.2.4 The Method by Hanh et al. – 01

Hanh et al. proposes in (Hanh et al., 2001) a high quality vessel visualization (HHQV) and interaction technique for liver surgery planning. It provides to identify liver vascular structure from radiological data including CT and MR data. The method employs a sequence of image processing steps for deriving a symbolic model of vascular structure which reflects the branching pattern and also the diameter of the vessels. These symbolic models are visualized by concatenating truncated cones which are smoothly blended at branching points. This method aims to recognize the morphology and branching pattern of vascular systems as well as the basic spatial relations between vessels and other anatomic structures. The objectives of this work is i) to reconstruct a symbolic vascular model, ii) to visualize the reconstructed vascular model by emphasizing the topological and geometrical information as well as depth relations, and iii) to provide interaction techniques to explore these visualizations.

Vessels are segmented using a fast region-growing algorithm adapted to the thin and branching vessels. They are skeletonized with a topology-preserving thinning algorithm which derives an exact centerline representation and the radius at each voxel of the skeleton. After that, the skeleton is transformed in a directed acyclic graph with vertices, which are representing branchings (e.g., bifurcations or trifurcations), and edges, which are representing connections between them. A list, which is recording the vessel diameters and the skeleton voxels along edge, is kept for each edge. So, it can be categorized as a hybrid based vessel segmentation method including image processing and graph analysis. Herein, the used region growing algorithm starts with a user defined seed point and runs to accumulate all high-intensity voxels which are above a chosen threshold. The segmented image is further processed for obtaining a skeleton of the vessel system by applying morphologic operations such as thinning which preserve the topology and control small side-branches. The vessels are displayed as tubes after skeletonization for visualization purpose.

In the aforementioned study, the proposed method makes two important contributions. Firstly, skeleton and vessel diameter smoothing techniques are employed to create high-quality vessel visualizations in compliance with concatenated truncated cones. Filtering techniques depending upon the Strahler scheme and interaction techniques to highlight subtrees comprise the second main respect. These interaction techniques can enable to visualize even complex vasculature in a clear way. A vascular tree reconstructed from radiological data from a living patient can be seen in Figure 4.2 (A). The vessel diameters are color-coded to emphasize discontinuities, in particular, for small vessels. Smoothed diameters in the same vascular tree is shown in Figure 4.2 (B). The inset view reveals considerable differences for small vessels (Hanh et al., 2001).

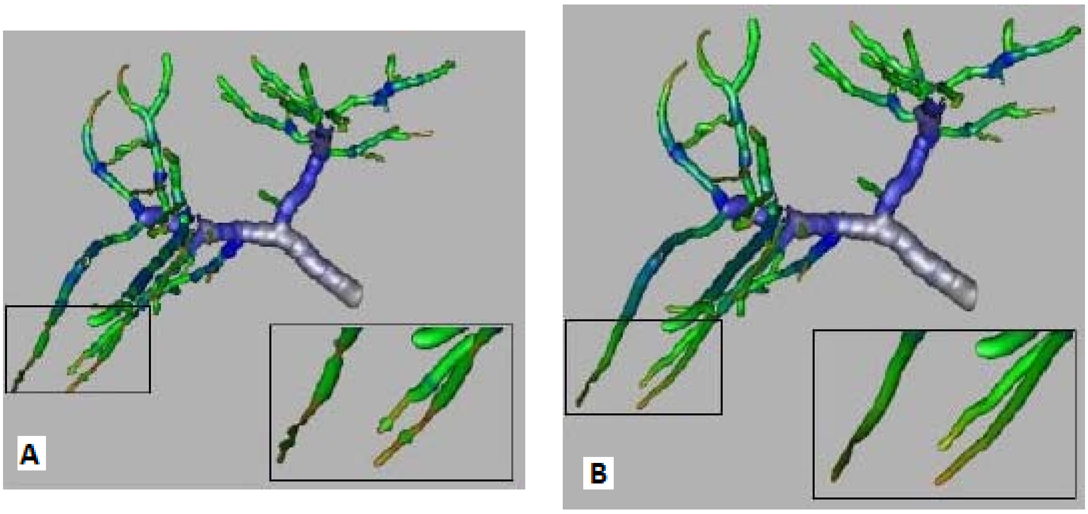

Figure 4.2 A) A vascular tree reconstructed from radiological data from a living patient. The vessel diameters are color-coded to highlight discontinuities, particularly for small vessels. B) The same vascular tree as in 'A)' is shown, but with smoothed diameters (Hanh et al., 2001).

4.2.5 The Method by Doherty et al. – 02

Doherty et al. (Doherty et al., 2002) proposes a method for 3D visualization of tumors and vessels for liver. For making the diagnostic and planning the surgery, Computed Tomography (CT) scans are used. Their objective is to find the number of tumors, their sizes and the physical and spatial relationship between the tumors and the main blood vessels. Blood vessels and liver tissue show similar contrast on the CT scans. The visualizations are being created using OpenDX and MATLAB. The data are received in the form of DICOM files and converted to the TIFF format. The images are cropped and histogram equalized, before being used in the visualization, in order to reduce the image to a convenient size and optimize the contrast. Isosurfaces, which are 3D analogue to contour lines, represent surfaces of equal density, are used in order to visualize the liver, tumor and blood vessels in 3D. The non-uniqueness of intensity values lacks to differentiate features using isosurfaces representing specific densities, as the rib cage obscures the internal organs. In order to solve this problem, Doherty et al. attempt to find a way of isolating the liver from the image by using a mask for each slice, consisting of ones in the selected section (the liver) and zeros everywhere else. The segmentation of liver is implemented by this masking operation in a semi-automatic way. Doherty et al. use an isosurface method to display the vein structures by using thresholding applied on several slices to find the density values. In order to visualize the tumors, which has the same density as the outer liver tissue; Doherty et al. specify a subset of data, or sub-volume, around the tumour and created an isosurface for this sub-volume, superimposing it on the same axes as the veins. The liver vessel segmentation method used by Doherty et al. can be categorized as a pattern recognition type (probabilistic) method employing intensity feature and simple thresholding classifier.

Initial progress is made in extraction of the tumor and vessels and visualization in a perspective. This process is accomplished by using similar methods, in both MATLAB and OpenDX. So as to examine the spatial relations of the tumor to the main blood vessels in the liver, efficient 3D models, which can be rotated and viewed from different angles, are constructed and are helpful in assisting the surgeon. In spite of the fact that manually creating a mask for each CT slice to extract the liver is necessary, there is, however, less human interaction involved in this method than it is needed for the current techniques employed in radiology.

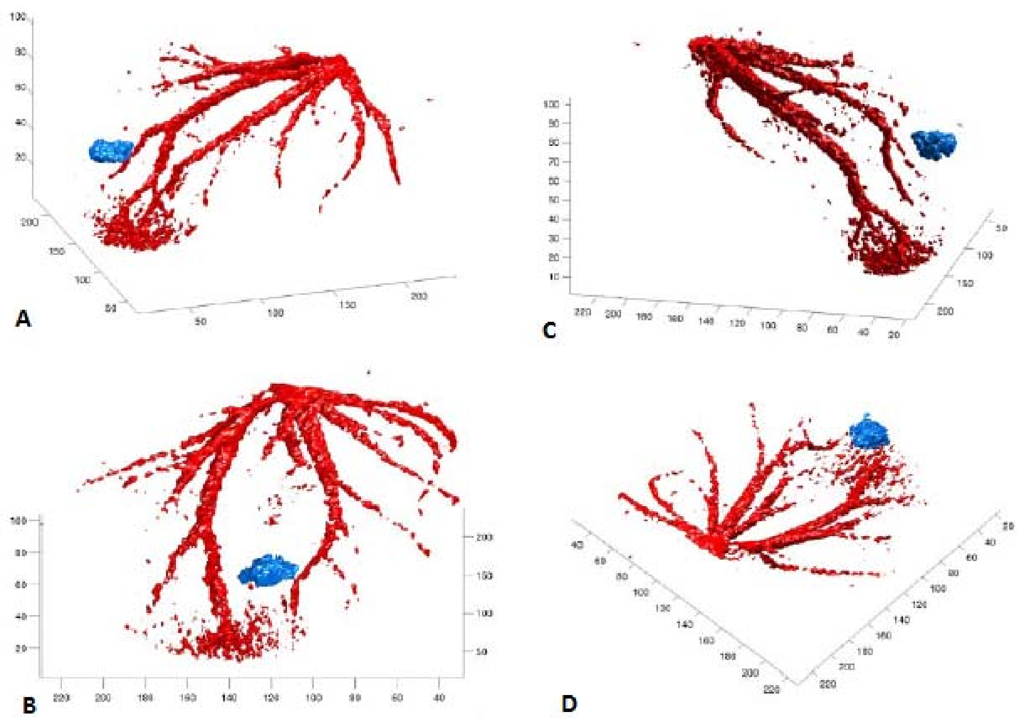

Figure 4.3 Different views of the major blood vessels with respect to the tumor, obtained using MATLAB (Doherty et al., 2002).

The visualisation of the liver and the vessels using isosurfaces relying on density values is therefore faster and more accurate than the selection processes involved in creating the images currently used by the surgeon (Doherty et al., 2002).

In visualizing the spatial relations between the liver, main blood vessels and tumor, succesful consequences are achieved via applying a mask on each CT slice to isolate the liver and using isosurfaces. Nevertheless, as to perfect to the approach, it is required to test this technique on several datasets. Notwithstanding the fact that the masking technique used here to isolate the liver is time-consuming, the rest of the procedure is automatic and based on selecting the density values with respect to the tumor and the vessels. In respect that the boundaries between organs are not well defined in many of the image slices, there is currently no way of segmenting the liver automatically.

4.2.6 The Method by Saitoh et al. – 02

Saitoh et al. proposes in (Saitoh et al., 2002) segmentation of liver region through vessels on multi-phase CT. The segmentation of the liver region is primarily based on mathematical morphology and thresholding techniques. Saitoh et al. presents an automatic method for segmenting the liver region from third phase abdominal CT. First, blood vessels in the liver are extracted with a threshold. To separate two regions whose intensity levels are close, Saitoh et al. proposes a functional method by employing blood vessel streams. Herein, the liver is considered as a region governed solely by the portal vein and liver vein. These veins and their tributary streams are identified firstly, and then it is decided that the liver region is in their vicinity and also that any area far from their location is definitely not a part of the liver. Based on this technique, Saitoh et al. trace first the main vein (vena cava), a branch to leading to the liver, and then extract the blood vessels of the liver. Finally by applying a morphological dilation operation to the blood vessels, it can be roughly identify the liver region from which the final region is identified by thresholding. The method by Saitoh et al. can be considered as a hybrid method which is a combination of the mathematical morphology image processing method and the pattern recognition type method employing intensity feature and simple thresholding classifier.

In this approach, the whole vein from the first branch of the major vein is regarded as belonging to the liver. The method involves the vein after the top of the arc, for the portal vein which forms an arc in the close vicinity of the liver. Consequently, the new method presented by Saitoh et al. segments the liver region, which utilizes the blood vessel tracing. The area extended from the recognized vessels is the liver region. This region enables to remove abutting organs employing morphological perations. For eight CT data, experiments are carried out and as results of these studies, there is perfect agreement between the automatically detected and manually detected area.

4.2.7 The Method by Eidheim et al. – 04

Eidheim et al. proposes in (Eidheim et al., 2004) an automatic liver vessel segmentation method in MR and CT images. Eidheim et al. use matched filters to emphasize blood vessels and entropy-based thresholding to segment the vessels. Vessel interconnections are extracted and exported to a graph structure. Genetic algorithms are then used to search globally for the most likely graph based on a set of fitness functions. The presented method, which is used also clinically (Eidheim et al., 2004), can be categorized as a hybrid method which is a combination of image processing method, i.e. matched filter, and the pattern recognition type method employing a transformed intensity feature, i.e. entropy, and simple thresholding classifier.

The proposed approach is used to three CT image sequences of the liver. The outcomes of 3D vessel graph demonstrate the structure of the vessels within the liver in Figure 4.4. A vessel structure is found through using the global search mechanism, and improbable vessel structures, as -that is- vessel loops, are resolved in a reliable manner. The reliability of the consequences is verified by inspection by radiologists and surgeons. The preprocessing and initialisation steps are computationally simple, whereas the global search using genetic algorithms is computationally demanding.

This is on account of the large search space resulting from a detailed vessel graph and a good number of fitness functions (Eidheim et al., 2004).

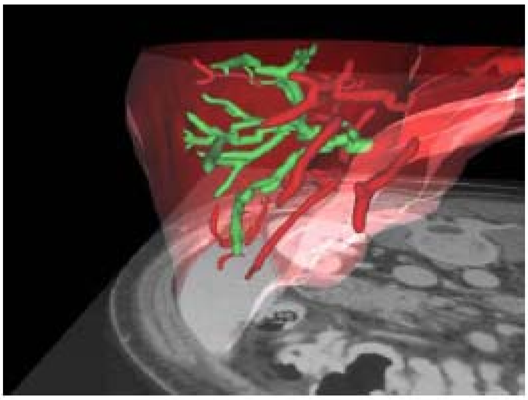

Figure 4.4 A visualised vessel graph with one continuous branch marked green. In our application, the liver contour and CT slices are visualised for verification (Eidheim et al., 2004).

The aforementioned method is developed as an application for automatically finding the most possible connectivities of vessels in the liver. Nonetheless, the masks are utilized exclude the vena cava. Noise in the CT images as well as lack of interconnections through the vena cava can bring about isolated vessel segments that should otherwise have been connected. Rendering the vessel structure of the liver in 3D images based on the interconnections is a simple task.

4.2.8 The Method by Saitoh et al. – 04

Saitoh et al. proposes in (Saitoh et al., 2004) an automatic segmentation method for liver region based on extracted blood vessels. Saitoh et al. use four-phase CT images with resolutions as high as 1 mm. The first-, second-, third-, and fourth-phase CT images correspond to before dye injection, the early stage, the full stage, and the wash-out stage of the injected dye. These CT data provide useful information for diagnosing hepatic cancer. The blood vessel stream in the first- and third-phase CTs is used for segmenting the liver region by tracing the portal vein and then the hepatic vein. The thresholding operation is used for separating blood vessels from liver soft tissue. The stomach and spleen regions are segmented by 3D morphological operations which are erosion and dilation. The segmented liver blood vessel region is enlarged by morphological dilation operation for obtaining an approximate liver region and then the liver region is extracted by thresholding. The presented method can be categorized as a hybrid method which is a combination of a morphological (image processing) method and the pattern recognition type method employing intensity feature and simple thresholding classifier. The main characteristic of the developed liver segmentation method relies on extracting the portal vein and then the hepatic vein in the first stage.

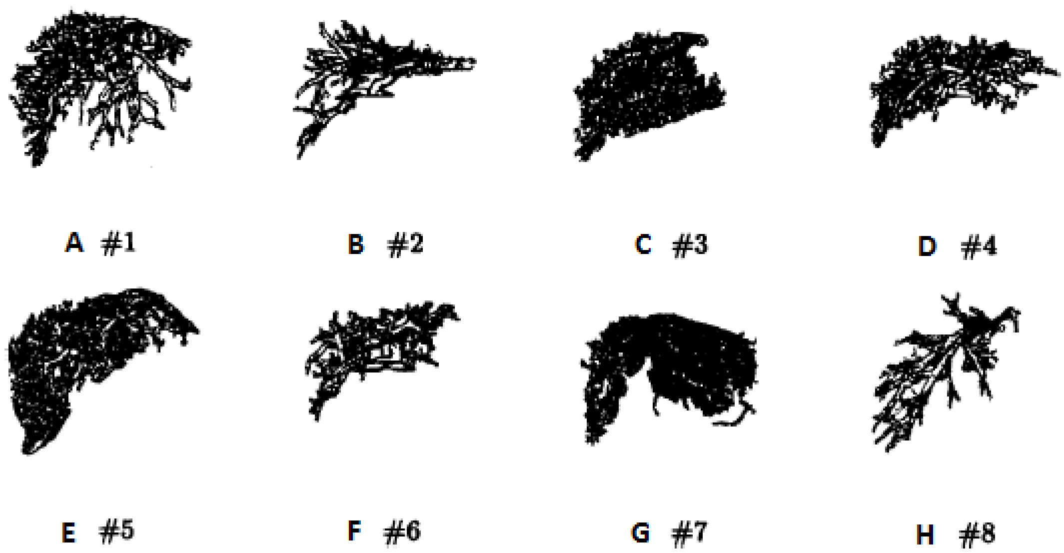

Figure 4.5 Extracted results of blood vessels (Saitoh et al., 2004).

From this study, it is inferred that segmentation of the liver region on CT images is considered as a difficult task owing to the fact that there are such touching or adjoining organs as the stomach and spleen. The proposed method exploits the function of hepatic blood flows rather than the shape alone. Adjoining organs which the blood does not flow to are separated using this property. The final liver region is accurately determined with a threshold. The method is applied to eight CT datasets and it is found that 95% of the resulting boundaries agreed well with those identified manually.

4.2.9 The Method by Charnoz et al. – 05

Charnoz et al. propose in (Charnoz et al., 2005) a robust method for the design of vascular tree matching which is also applied on liver. Charnoz et al. applies the method for intra-patient hepatic vascular system registration. The method exploits a segmented vascular system obtained by CT-scan images available from the Visible Man (The Visible Human Project). Skeletons are computed from the segmented vascular systems and then are represented as an oriented tree. The orientation symbolizes blood circulation flow. Nodes represent bifurcations and edges correspond to vessels between two bifurcations. Some geometric vessel attributes, i.e. 3D positions, radius, vessel path, are also used. The tree matching algorithm finds common bifurcations (nodes) and vessels (edges). Starting from the tree root, edges and nodes are iteratively matched. The algorithm is applied on a synthetic database containing various cases. The used segmentation method can be categorized as a skeletonization (image processing) method. The resulting skeleton is represented as a tree such that the operations implemented on the tree provide the targeted robustness against to topological modifications due to segmentation failures and against deformations.

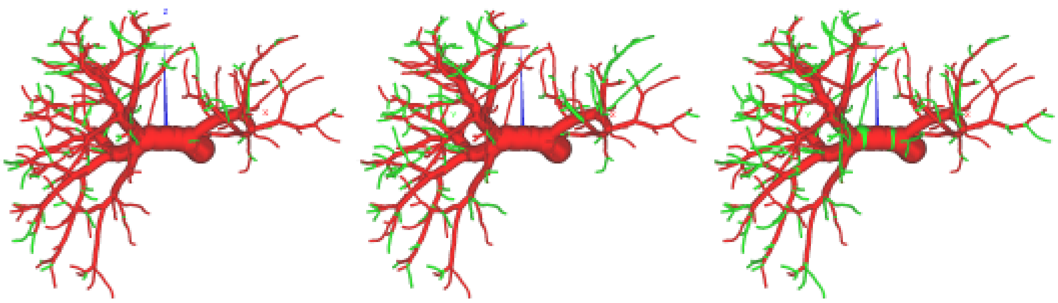

Figure 4.6 The visible Man's portal vascular system is randomly pruned to loose approximately 20%, 30% and 40% of length in both trees. Lost branches appear in green (Charnoz et al., 2005).

The aim of this study is to present the design of the original new robust method to match liver vessels between two CT/NRI acquisitions. The proposed method is well adapted, fast and robust on a complex vascular system.

4.2.10 The Method by Saitoh et al. – 05

Saitoh et al. propose in (Saitoh et al., 2005) a method for diagnosis of liver cancer based on three-dimensional hepatic blood vessel regions extracted by threshold processing. High-resolution multi-slice CT images are used in the diagnosis. The liver entrance is located by tracing the blood vessels from the abdominal aorta. The hepatic vessel region is extracted as: A temporary threshold is determined near the liver entrance, and the structure of the blood vessel is analyzed by adjusting the threshold from the temporary value in order to determine the optimal threshold. The thinning operation is applied to the blood vessel in order to construct a directed graph for representing vessel system. The existence of a loop is considered as a sign of choosing a low threshold causing over extraction of the blood vessel region. The cancer detection procedure is as follows. Cancers are found firstly in the extracted blood vessel region, and then from the rest region (Saitoh et al., 2005). The presented method can be categorized as a pattern recognition type method employing intensity feature and simple thresholding classifier. The main characteristic of the developed liver segmentation method relies on locating the liver entrance by tracing the blood vessels from the abdominal aorta.

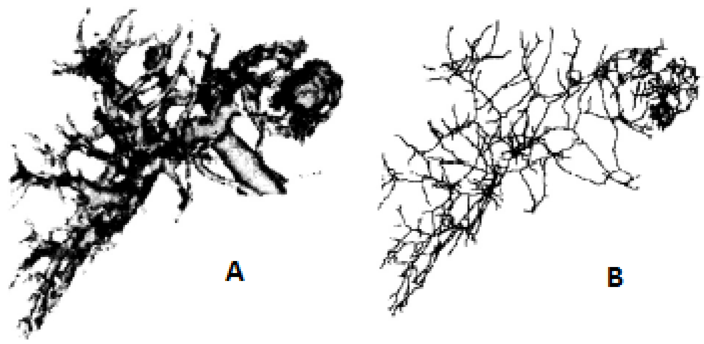

Figure 4.7 A) Extracted blood vessel and B) result of thinning algorithm (Saitoh et al., 2005).

Structural analysis of the blood vessel is performed in accordance with the basis of the 3D structure. An algorithm is proposed in which the optimal threshold is determined on the basis of the number of loops, improving the accuracy of extraction of the blood vessel region from the liver in CT images.

The study under consideration shows that the proposed approach is beneficial in detecting liver cancer on the basis of the derived blood vessel region, and a two-stage method is therefore proposed for detecting liver cancer. The detection of cancer is attempted in CT images of seven cases, including cases of early stage cancer. The cancer detection rate is 100%, with an inaccuarate detection rate of 30%, pointing the effectiveness of the proposed method.

4.2.11 The Method by Schmugge et al. – 06

Schmugge et al. propose in (Schmugge et al., 2006) a robust vessel segmentation method for intravital microscopy (IVM) images which enable capturing temporal changes of blood flow and vessel structure in vivo. Schmugge et al. propose a Bridging Vessel Snake (BVS) algorithm to segment a network of vessels, especially ones with less sharp boundaries. The method segments the vessels with varying diameter while imposing the structure of vessels by utilizing a ribbon snake and adding energies of width and region. The initial network of vessels is obtained by the skeletonization corresponding to mostly sharper vessels. The sharp vessels are considered as vessels of higher confidence and then new bridges among them are constructed by hypothesizing “less sharp” vessels. The method is useful for achieving accurate biological analysis of blood vessels regulation within liver and also within other organs, so for microvasculature reconstruction necessary for red blood cells flow distribution regulation analysis. The used segmentation method can be categorized as a skeletonization (image processing) method. The resulting skeleton is enlarged by BVS algorithm to obtain the network of vessels including the ones with less sharp boundaries.

This study presents a method to extraction of a vasculature system in intravital microscopy images. For improving performance of segmentation, in particular, on vessels with lower sharpness boundaries, a new method of bridging vessel snake is proposed. This study presents a method to extraction of a vasculature system in intravital microscopy images. For improving performance of segmentation, in particular, on vessels with lower sharpness boundaries, a new method of bridging vessel snake is proposed.

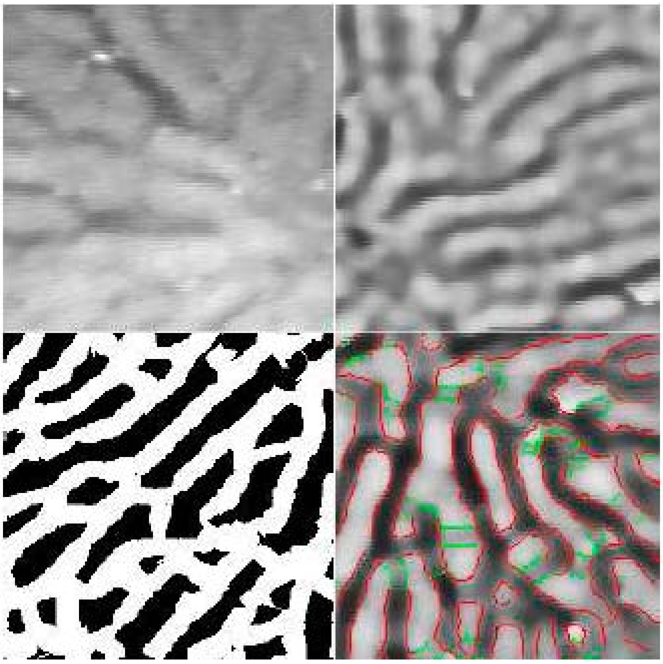

Figure 4.8 Overview of the Algorithm. (Top-left) one frame of the input sequence. (Top-right) pre-processed. (Bottom-left) binary output of segmentation. (Bottom-right) delineation of segmented boundaries of sharper vessels through skeletonization initialization (red) and less sharp vessels through bridging (green) (Schmugge et al., 2006).

The consequenes show that the algorithm improved the region under ROC curve up to 20% in dataset with low sharpness level (CLP) and increased the maximum achievable TPF by 23% with a minimal increase in FPF.

4.2.12 The Method by Erdt et al. – 08

Erdt et al. propose in (Erdt et al., 2008) a technique for fully automatic hepatic vessel segmentation employing graphics hardware. The technique presented enhances and extracts quickly the vascular system of the liver from CT images. The developed system consists of i) vessel enhancement on the Graphics Processing Unit (GPU), ii) automatic vessel segmentation in the enhanced images and iii) an option to verify and refine the segmentation results. The proposed segmentation method can be categorized as a image processing method. The segmentation quality is assessed on twenty clinical datasets of varying contrast quality and acquisition phase. Erdt et al. reports that graphics hardware realization of the automatic segmentation provides reliable and fast extraction of the hepatic vascular system, so constitutes a beneficial technique for oncologic surgery planning.

This method is an automatic hepatic vessel enhancement and segmentation approach together with a user friendly real time preview function to manually refine the resulting masks. A comparison with a manual region growing show the potential of the method to save surgery planning time while providing accurate segmentations at the same time.

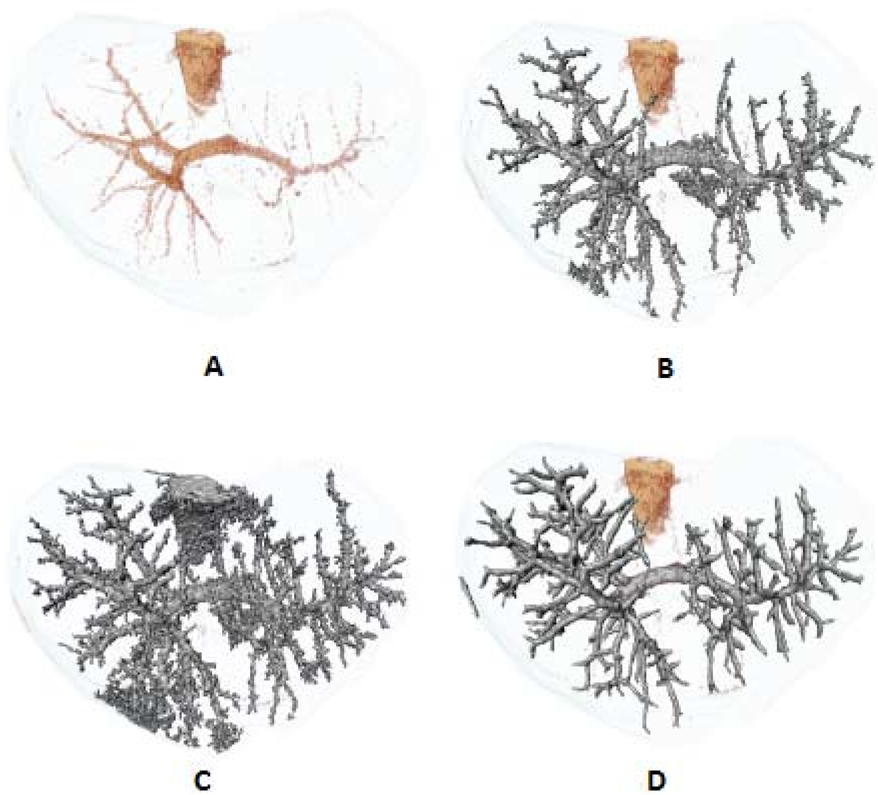

Figure 4.9 Comparison of a manual region growing segmentation with the automatic method (portal venous phase). A) Volume rendering of the original dataset, B) and C) rendered masks of region growing with different thresholds. D) The result of approach by Erdt et al. (Erdt et al., 2008).

In this study, an application on the GPU indicates that a hardware implementation can carry out the filter operations nearly fifteen times faster, even for larger neighborhoods. The overall performance can be increased by the same factor (Erdt et al., 2008). The comparison of a manual region growing segmentation with the automatic method can be seen in Figure 4.9. Firstly, volume rendering of the original dataset is given in ‘A’, and then, rendered masks of region growing with different thresholds are seen in ‘B’ and ‘C’, finally the result of approach by Erdt et al. are seen in ‘D’.

4.2.13 The Method by Fei & Park – 08

Fei & Park, 2008 propose in (Fei & Park, 2008) an automatic liver vessel segmentation approach based on level set method for diagnosis and treatment of the hepatic disease. A flexible initialization for the level set function is implemented by segmenting the liver automatically using morphological filtering and an improved Otsu’s thresholding based on calculating the minimum within class variance corresponding to the classes of pixels each side of the threshold. The used morphological operators are performed in the following three phases: i) Removing surrounding tissues using morphological filtering, obtaining a binary image by the improved Otsu’s threshold method and tracking the location of liver, ii) Binary image of the liver where 1’s represent the tracked location image and liver boundary, and iii) Segmentation liver from the source image using the binary image of the liver. The segmented liver boundary is used as the level set initialization in the level set method used for the automatic segmentation of the liver blood vessels. Since the level set method used for liver vessels is a partial differential based method and its initialization is realized by using morphologic filtering and Otsu’s thresholding, then the method by Fei & Park can be considered as a hybrid method.

Figure 4.10 3D liver blood vessels images after segmentation (Fei & Park, 2008).

The conclusion of this approach is that the liver is segmented using the morphological filtering and an improved Otsu’s threshold, then by using the liver area as the flexible initialization for automatically segmenting the liver vessels by level-set method. 2D and 3D liver and liver blood vessels efficient visualization images are supplied for surgeons to diagnose and treat the hepatic diseases.

4.2.14 The Method by Homann et al. – 08

Homann et al. propose in (Homann et al., 2008) a vasculature segmentation method for CT liver images based on graph cuts and graph-based analysis. The method segments vessels using 3D graph-cuts by the utilization of probabilistic intensity information and surface smoothness as constraints. A semi-automatic graph-based technique is then employed to efficiently separate the hepatic vessel systems. The resulting vascular segmentation is assessed on six liver CT datasets in comparison to a manual segmentation and found reasonable in terms of robustness against to parameter choices. The basic idea of the proposed graph-cut method is to represent the image as a graph such that every voxel corresponds to a node. The edge-set consists of links connecting neighboring voxels and links connecting all voxels to the source and sink voxels. The goal is to find the optimal cut which separates the graph into two sub-sets. Where, the cost to be minimized is the sum of the weights of the cut edges which are calculated in terms of the differences of intensity values corresponding to neighboring voxels and the intensity probabilities. The method starts with performing anisotropic diffusion on the segmented liver as a pre-segmentation step.

A graph cuts segmentation method is employed to detect vessels, and then the vasculature sub-trees are identified using skeletonization followed by a graph-based analysis. The anisotropic diffusion is a partial differential equation based method used in the pre-segmentation phase in order to reduce image noise while retaining significant parts of the image content, typically edges, lines and other details. On the other hand, skeletonization and then the graph analysis described above are used for obtaining liver vasculature system. So, the method by Homann et al. can be considered as a hybrid method.

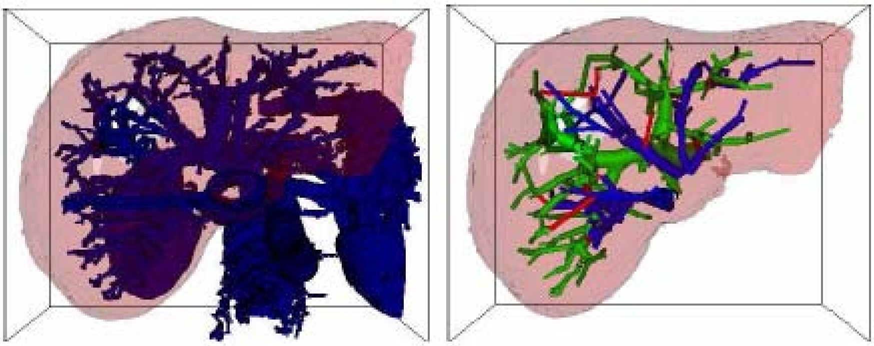

Figure 4.11 MIC2 dataset: (left) Segmentation and (right) graph representation with hepatic veins (dark-blue), portal veins (light-green), and vessels not classified (red) (Homann et al., 2008).

As a result of the study, it is reported that probabilistic intensity information and surface smoothness are used as constraints in the proposed method and an algorithm is presented to separate the different hepatic vessels as well. The segmentation step on six datasets is evaluated and the algorithm of this study is found as robust in a certain parameter range.

4.2.15 The Method by Kawajiri et al. – 08

Kawajiri et al. propose in (Kawajiri et al., 2008) an automated segmentation method for hepatic vessels in non-contrast CT images. The method first applies an enhancement and then extraction operation on hepatic vessels. The enhancement is performed by histogram transformation based on a Gaussian function and also multi-scale line filtering based on eigenvalues of a Hessian matrix. The candidates of hepatic vessels are then extracted by a thresholding method applied on the enhanced histogram. Small connected regions in the resulting images are removed since they could not belong to the hepatic vessels. The results obtained for two normal-liver cases one of which is obtained for plain CT images and the other for contrast-enhanced CT images of the same patient are compared for evaluating of the performance of the method. It is concluded by Kawajiri et al. that the method could enhance and segment the hepatic vessel regions even in plain CT images. Since the enhancement is implemented by thresholding applied on a transformed intensity histogram and also by a Hessian based filter, and the vessel extraction is realized again by thresholding applied on an enhanced histogram, then the method can be considered as a hybrid liver vessel segmentation method combining histogram based pattern recognition methods with an image processing method.

Using a Gaussian-based density transformation enhances the hepatic vessels in the liver region are enhanced and these vessels at issue are selected by using Hessian-based line filtering. The accuracy of the vessel extraction is assessed based on a quatitative comparision between the plain CT images and contrast-enhanced CT images from the same patient and a visual observation by a radiologist specialized on liver diagnosis.

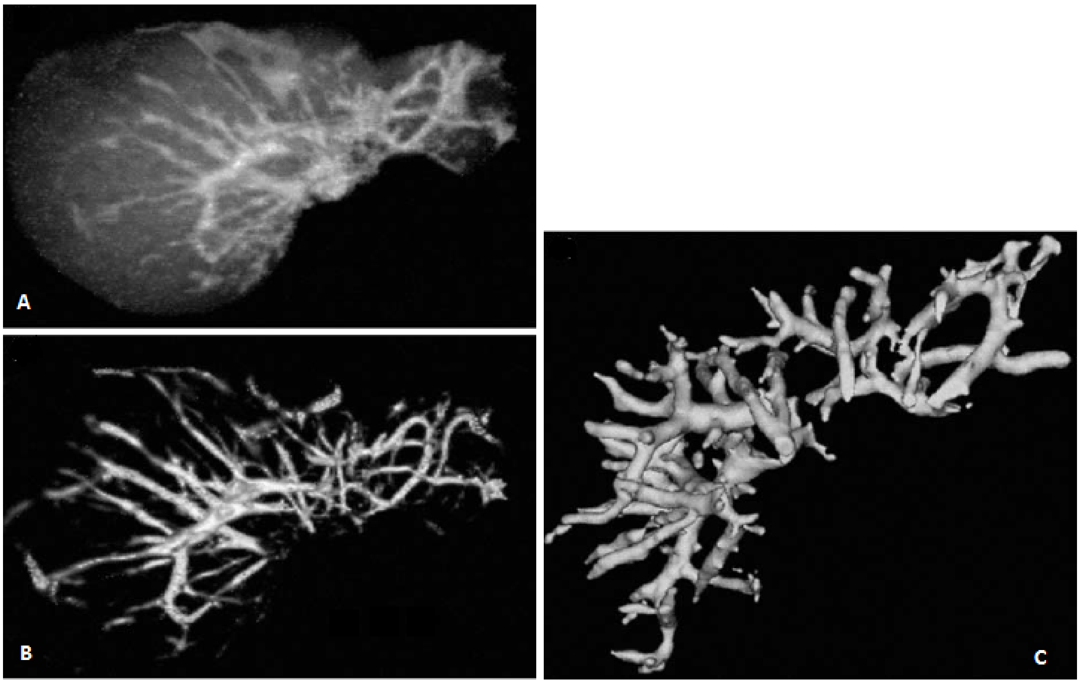

Figure 4.12 3-D view of the liver and hepatic-vessel tree. A) Volume rendering of contrast-enhanced CT images. B) Volume rendering of the hepatic vessels after the enhancement process. C) Surface rendering of the segmentation result for hepatic vessels (Kawajiri et al., 2008).

According to the proposed approach, the preliminary results indicate that even the density difference between hepatic vessels and other liver regions is very small in plain CT cases, and that most of the vessel regions can be enhanced by the proposed method as well as the human observer can. Nevertheless, on account of the noise in

CT images, many FP regions occur in the vessel identification process. It is also reported that this has to be improved in future works with the use of additional data (Kawajiri et al., 2008).

Deducing from the study, it is verified that the performance of the proposed automated hepatic-vessel identification approach is almost comparable to that of human observers. This result indicates the potential for extraction of liver lobes and liver structures (useful for the diagnosis of cirrhosis) in plain CT images.

4.2.16 The Method by Doğan et al. – 09

Doğan et al. propose in (Doğan et al., 2009) a method for extraction of the liver vessels from abdominal CTA images by a Hessian based vessel filter. The method possesses a labeling procedure for the main vessels applied after the extraction of the liver vessels. In contrast to the other Hessian filter based liver vessel segmentation methods; the proposed method is capable of extracting all of the liver vessels not a part of them. The method can be considered as an image processing based liver vessel segmentation method.

Figure 4.13 The result of vessel filter based on Hessian (Doğan et al., 2009).

In this study, it is reported that the vasculature system in the liver is extracted successfully in gray level in the fifteen datasets. The result of applying a labeling algorithm, the vessels can label correctly in eleven datasets. The reason of which the four datasets are not labeled is that the main blood vessels with dye are not thin because of they are fully unpainted. It is reported that the software has to be designed such that the interface parameters can be entered by the user. In addition, because of the fact that segmented liver image that has no venacava, which is as the initial value entered to the algorithm, vasculature system does not contain venacava in the result of extraction algorithm. It requires the venacava to be extracted by another algorithm from the original images, which are not segmented, and then it has to be added the resulting images.

4.2.17 The Method by Freiman et al. – 09

Freiman et al. propose in (Freiman et al., 2009) a variational method for liver vessel segmentation and visualization in abdominal CTA images. The segmentation problem is posed as a functional minimization within a variational calculus framework. Where, the functional incorporates a geometrical measure for vesselness and also properties for vessel surfaces. The functional does indeed correspond to the distance between the desired segmented image and the original image. The Euler-Lagrange equations are solved by using conjugate gradients algorithm in order to find the minimum of the functional. The method is superior to the Hessian based methods in the detection of bifurcations and complex vessel structures as a consequence of the possibility of incorporating a surface term into the functional. The simulation results, which are compared to the results obtained by Hessian based method and also to the evaluations by an expert radiologist on eight abdominal CTA clinical datasets, show that the method is suitable for the automatic segmentation and visualization of the liver vessels. The method by Freiman et al. is an optimization based method formulized in the variational calculus framework.

Freiman et al. conducts two evaluation studies with an expert radiologist on 3D images generated from the vessels segmentations of each dataset. In the first study, the radiologist assesses the presence of eleven vascular bifurcations, including hepatic and portal venous bifurcations. The radiologist qualitatively compares the bifurcations segmentation of the proposed method and that of Hessian-based filter method. It is defined a quantitative-qualitative visibility score indicating the quality of the segmentation, compared to the ideal visibility of the structures. The proposed approach accurately extracts 88% of the bifurcations with a visibility score of 82%, as compared to only 55% in the Hessian-based method with a visibility score of 33%. Figure 4.14 illustrates the performance of this method compared to that of Hessian-based filter method. In the second study, the radiologist assesses the individual vessels visibility on the 3D segmentation images and on the original CT slices. Ten main liver vessels are examined in each dataset (Freiman et al., 2009).

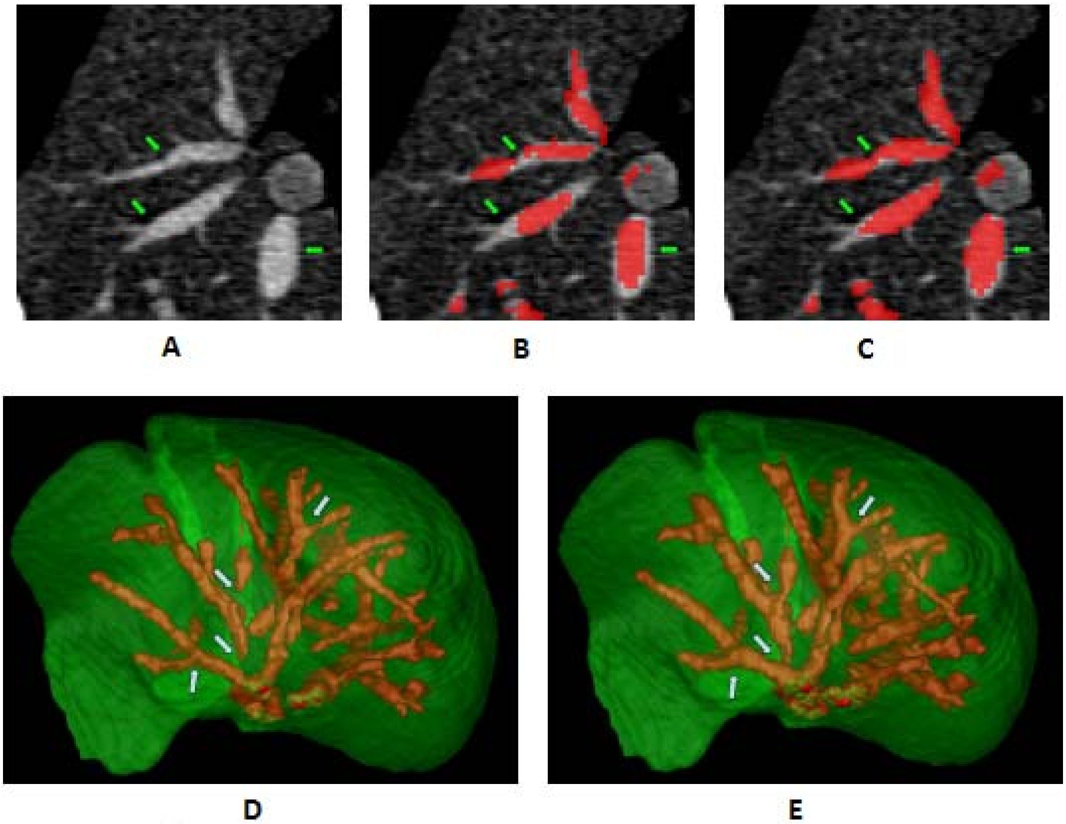

Figure 4.14 Example of the segmentation results obtained with the Hessian-based method and with the method by Freiman et al.: A-B-C) 2D axial views. The segmentation is shown superimposed on the original CTA slices; D-E) 3D visualization (Freiman et al., 2009).

In this study, it is reported that the proposed method purposes to accomplish the limitations of the Hessian-based methods in bifurcations, complex vessels structures, and pathologies by combining surface normals coupled with Hessian-based vesselness information into a variational framework. There are many advantages of the proposed method, which is fully automatic and efficient, it produces high-quality segmentations, and it performs better than existing Hessian-based methods. Two clinical evaluation studies on eight abdominal CTA datasets by an expert radiologist indicate that the proposed method successfully segments liver vasculature and their bifurcations.

4.2.18 The Method by Kaftan et al. – 09

Kaftan et al. propose in (Kaftan et al., 2009) a two-stage method for fully automatic segmentation of venous vascular structures in liver CT images. The method is useful for surgical planning of oncological resections and living liver donations. The developed hepatic vessel segmentation method is implemented in two stages. The core vessel components are detected and delineated firstly. Then, smaller vessel branches are segmented by a robust vessel tracking technique based on a medialness filter. In the first phase, major vessels are segmented using a globally optimal graph-cuts algorithm in combination with foreground and background seed detection. In the second stage, a tracking algorithm is applied locally in the areas of smaller vessels. The method is evaluated on contrast-enhanced liver CT images obtained from clinical routine and is reported as promising. The method can be considered as a hybrid method employing image processing and graph analysis.

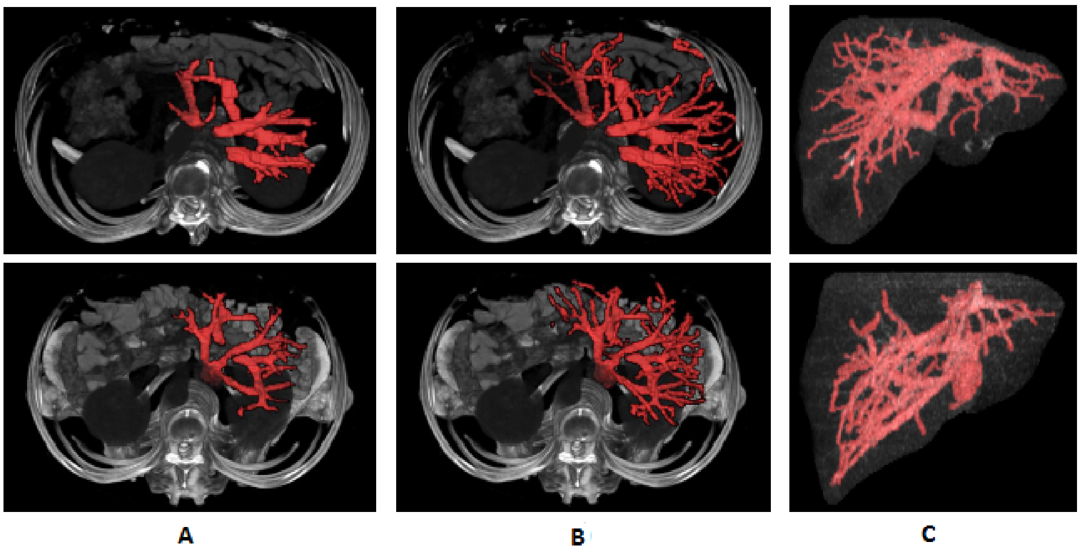

Figure 4.15 The segmentation result of the larger vessels. A) The results including the vessel tracking step, B) in top view. C) The final result is shown in red within the MIP anterior view of the segmented liver (Kaftan et al., 2009).

The figures, given in Figure 4.15, are created with a slightly different parameter setting so that both stages can be more distinctively recognized. Generally, higher significance levels during the global segmentation step will create segmentation with a higher specificity but lower sensitivity, while lower levels will result in a more complete segmentation which might also contain false positives. The centerline end-points are used for the computational more demanding vessel tracking step. Results including large and small vessels are finally shown in Figure 4.15 B and C in top view and within the MIP anterior view of the segmented liver, respectively. Depending on the application, the global segmentation results might already be sufficient (Kaftan et al., 2009).

As a result of the proposed approach, the system incorporates a globally optimal graph-cut-based segmentation with robust local vessel tracking. In intensities of vessels and their surroundings which may contain tumors, the approach is robust to variations. In addition, large and small sized vessels are acquired correctly by the using the proposed two-stage segmentation algorithm without excessive computational requirements. Besides, the vessel tracking approach can be used to add interactively missing branches or sub-trees via simplistically adding single seed-points.

4.2.19 The Method by Seo & Park – 09

Seo & Park propose in (Seo & Park, 2009) a method for automatic segmentation of hepatic vessels in abdominal multiple detector CT images. Hepatic vessels are useful in estimating the volumes of the left and right hepatic lobes, integral for maximizing the safety of the donor and the recipient during living donor liver transplantation. The segmentation is implemented in the following steps: i) canny edge detection for determining the location of the hepatic vessel, ii) extraction of hepatic vessel candidates by threshold filtering around the detected edge, iii) addition of true negatives, defined as hepatic vessel pixels, except for the extracted vessels, as the brightness of these pixels is less than the threshold, according to the pre and post section connections, and iv) removal of false positives, defined as small connected regions smaller than nine voxels without connections to pre or post sections. The method by Seo & Park can be considered as a hybrid method implementing image processing and histogram based thresholding operations.

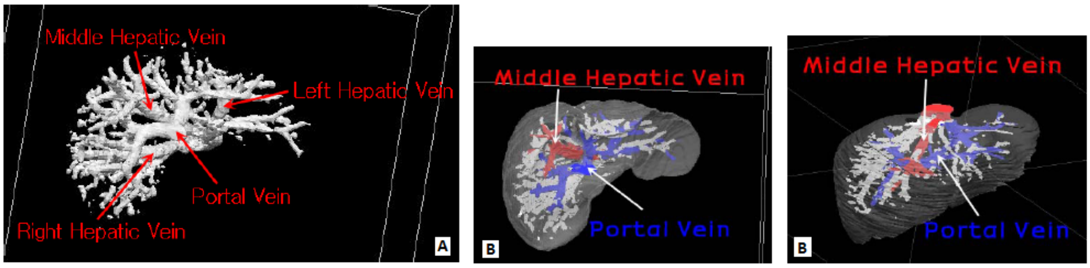

Figure 4.16 A) 3D image of the hepatic vessels segmented automatically, B) 3D images of the middle hepatic vein and the portal vein (Seo & Park, 2009).

Figure 4.16 shows the 3D of the middle hepatic vein and the portal vein, which can be used to divide the liver into two segments, left and right lobes.

Deducing from this study, it is reported that there are several variations, which are individual variations in location, size, and shape of the organs, as well as distance from and connections to other tissues. These present difficulties to automated image processing. In angiography, variable amounts and rates of contrast medium diffusion leave room for error. Notwithstanding these aberrations, canny edge detection allows processing within a narrow range of parameters. Despite aforementioned variations in the intensity of the liver structure, vessel segmentation parameters and threshold values can be automatically determined using this proposed approach. Also, it can be correctly identified the middle hepatic and portal veins from an MDCT image without based on morphological structuring elements or manually selected seeds.

4.2.20 The Method by Chi et al. – 10

Chi et al. propose in (Chi et al., 2010) a method for segmenting liver vasculature in contrast enhanced CT images by using context-based voting. The liver vasculature segmentation is implemented by first extracting vessel context from input image, and then votes on vessel structures. Herein, the liver is extracted using Model-based Image Understanding Environment (MIUE) (http://www.liversuite.com/). The liver scan is next processed to be isotropic. The method is reported to be able of conducting full vessel segmentation and recognition of multiple vasculatures effectively. The vessel context describes context information of a voxel related to vessel properties, such as intensity, saliency, direction and connectivity. Voxels are grouped to liver vasculatures hierarchically based on vessel context. They are first grouped locally into vessel branches with the advantage of a vessel junction measurement, and then grouped globally into vasculatures, which is implemented using a multiple feature point voting mechanism. The proposed method is evaluated on ten clinical CT datasets. Since the method by Chi et al. employs a vessel context based voting for segmentation and for identification liver vasculatures by using region based features, such as shape and intensity, then, it can be considered as a pattern recognition type liver vessel segmentation method.

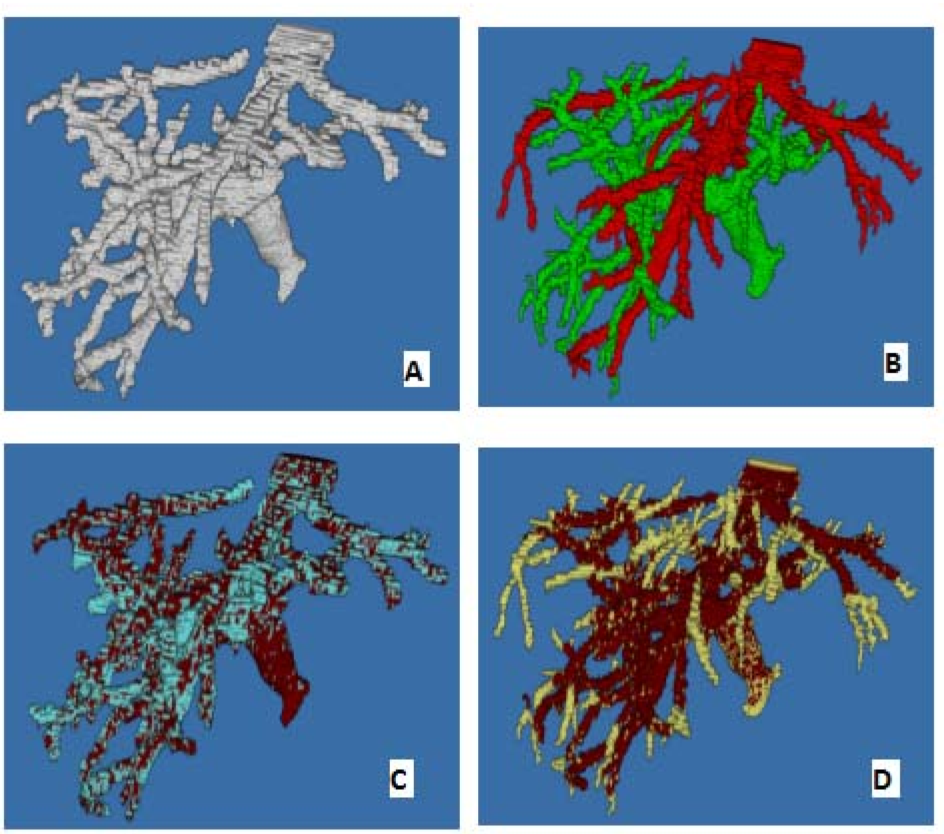

Figure 4.17 Comparison of the results: B) Liver vasculature segmented using level set based method; B) results using the proposed method. C) Veins comparison the proposed method (red: overlap vessels, blue: over-segmented vessels; D) veins comparison with the proposed method (red: overlap vessels, yellow: under-segmented vessels) (Chi et al., 2010).

In this study, the proposed approach can extract and identify liver vessel system from contrast enhanced CT images by use of region based features. The method is simple yet robust to noise and effective on segmenting the vessels. The proposed algorithm extracts liver vessel system both locally and globally relying on vasculature context, which enables its coping with vasculatures of pathologic (tumor) volumes. For classifiying vessel branches, the algorithm is computationally efficient by employing multiple feature point voting mechanism (Chi et al., 2010). The proposed algorithm is tested on ten clinical CT datasets and the obtained results are promising. The third order branches of vessel trees are segmented from the low resolution CT scans.

4.2.21 The Method by Esneault et al. – 10

Esneault et al. propose in (Esneault et al., 2010) a fully automatic method for liver vessel segmentation by using a hybrid geometrical moments and graph cuts in CT preoperative images. The method introduces a 3D geometrical moment-based detector of cylindrical shapes within the minimum-cut/maximum-flow energy minimization framework. It exploits a data term as a constraint into the widely used Boykov’s graph cuts algorithm to automate the segmentation. The method is evaluated on a synthetic dataset. The method by Esneault et al. can be classified as a hybrid method combining pattern recognition and graph analysis methods. Where, the geometrical moments are used as features in the pattern recognition.

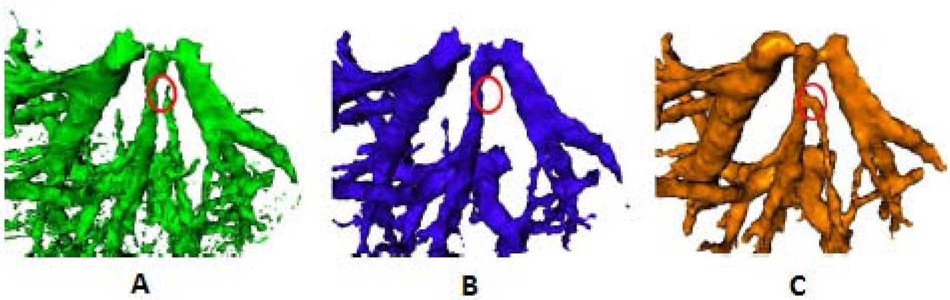

Figure 4.18 Comparison of the three segmentation methods. A) Region-growing. B) Graph cuts. C) Hybrid method. Red circles highlight the ability of the different methods to extract and connect a specific vascular branch (Esneault et al., 2010).

It can be seen differences among the applied methods in Figure 4.18. Firstly, figures shows that comparison of the three segmentation methods, which are region-growing in A, graph cuts in B and hybrid method in C. Red circles highlight the ability of the different methods to extract and connect a specific vascular branch in the figures.

Deducing from the study, the proposed method is relying on a graph-cuts technique constrained by local vessel models to take advantages of both approaches, which are global optimality of the graph-cuts technique and accuracy and robustness of the local modeling. The method is applied on synthetic data. And then, it is applied on several CT databases, which are acquired on different contrast medium diffusion phases. The acquired consequences are proved that the proposed method is robust and fast enough to be used in a clinical context. Furthermore, the method allows identifying the patient-specific vascularization surrounding a HCC. Such information is of vital importance for the definition of accurate and patient-adapted hyperthermia therapy planning.

4.2.22 The Method by Friman et al. – 10

Friman et al. propose in (Friman et al., 2010) a Multiple Hypothesis template Tracking (MHT) method for small 3D liver vessel structures. The method leads to low contrast passages to be traversed and an improved tracking performance in low contrast areas, and also a novel mathematical vessel template model providing an accurate vessel centerline extraction. The proposed tubular tracking algorithm is realized by applying 3D template matching which is based on matched filter approach of image processing. The template is an image patch containing an idealized vessel segment which is parameterized by a radius, a center location, and a direction. The used modular vessel template model is incorporated with a dedicated fitting procedure. The employed multiple hypotheses tracking for vessels, which is well established technique of signal processing and control areas, considers several possible trajectories or hypotheses simultaneously. The tracking is reported as fast enough for an interactive segmentation. The method is applied for segmenting both the liver arteries in CT angiography data and the coronary arteries in thirty-two CT cardiac angiography data sets in the Rotterdam coronary artery algorithm evaluation framework. The method by Friman et al. can be classified as a hybrid method including image processing and pattern recognition based.

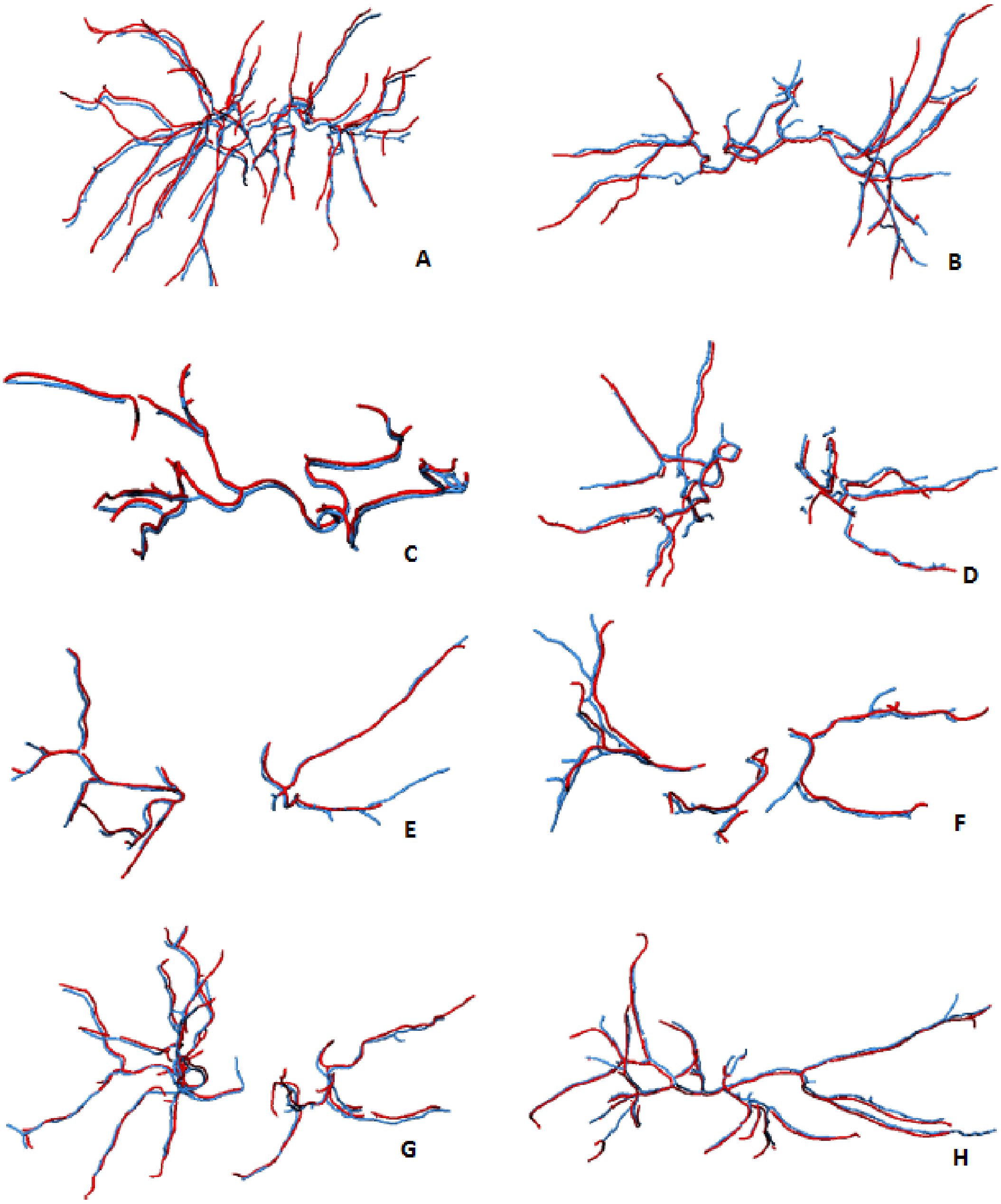

Figure 4.19 Comparison between manually and semi-automatically segmented liver arteries. A - H, show eight different liver artery systems (Friman et al., 2010).

There are significant contributions in this study. The MHT framework can be applied using many different vessel models. The specific vessel model introduced in this work is a mathematically tractable template model that can be analytically fitted to the image data. A statistically motivated criterion for evaluating the model fit has also been derived (Friman et al., 2010). Figure 4.19 provides a comparison between manually and semi-automatically segmented liver vessels. Each figure, which are A to H, shows eight different liver vessel systems. The blue vessels show the centerlines of the manual segmentation. The red vessels are the result of the hybrid region growing and tracking approach. The centerlines are intentionally shifted relative to each other to facilitate visualization.

In this study, it is reported that the proposed method achieves a high centerline detection accuracy using thirty-two cardiac CT angiography datasets in the 3D segmentation in the clinic. Furthermore, an efficient semi-automatic liver vessels segmentation is shown for the first time. Finally, the tracking algorithm is released as software which is free to provide opportunity for the future studies to use and comparisons.

CHAPTER FIVE

CONCLUSION

This thesis gives an overview on liver vessel segmentation methods which are proposed in the literature. The general segmentation methods and the vessel segmentation methods previously used for organs other than liver are also studied in the thesis since the segmentation methods used have some common properties to the once for liver and so they are applicable to the liver vessel segmentation case. This thesis focuses on the liver vessel segmentation methods which can ultimately be used for liver transplantation and for liver tumor diagnosis.

The thesis introduces the following taxonomy for liver vessel segmentation methods available in the literature. Based on this taxonomy, the liver vessel segmentation methods can be classified into the following groups: 1) pattern recognition, 2) image processing, 3) optimization, 4) graph analysis, and 5) partial differential equation models. The methods in the pattern recognition group can further be classified into the following sub-groups in terms of the features used: 1) intensity based methods, 2) textural based methods, and 3) geometric based methods. The classification of the methods in the pattern recognition group can also be done in terms of the classifiers used as: 1) knowledge based methods, 2) unsupervised (clustering) based methods, 3) Artificial Neural Networks (ANNs) supervised learning methods, 4) machine learning methods, 5) probabilistic methods, and 6) hybrid methods. On the other hand, image processing based segmentation methods can be categorized into subgroups based on topological, morphological and intensity-spatial information.

The thesis presents an overview on the known liver vessel segmentation methods based on the introduced taxonomy. It can be concluded that most of the methods developed in the literature for liver vessel segmentation are hybrid methods employing more than one method. It can also be concluded that the segmentation is realized in several steps rather than a single step. The pattern recognition based methods usually exploit intensity features together with simple thresholding classifiers applied on a transformed histogram.

The contribution of the thesis, it is as a resource in the matter of studies on liver examinations, which are about vessel segmentation in the literature. The accessible methods of liver vessel segmentation are collected in this thesis. For the experts, who study on detecting tumor in liver, visualization of liver, segmenting vasculature in liver and etc., it can be useful as a resource in the extractions of the vessel trees and it can be beneficial in terms of evaluating which method to use.

The liver vessel segmentation is still an open field for further researching, in spite of the fact that there are many promising methods, algorithms, and techniques, which are have been developed and improved. Vessel segmentation methods comprise the essence of such medical image processes as radiological diagnostic systems, creating anatomical atlases, visualization, and multimodal image registration. It is inferred that the direction of future studies of liver vessel segmentation will be towards progressing faster, more accurate and also more automated techniques.

Advances in radiological imaging modalities such as CT, MDCT, CTA, MR etc. produce high volume medical images. Fast segmentation algorithms are needed for processing of these obtained images from the imaging modalities. So as to minimize the work load, high volume of the medical image data requires more automated segmentation algorithms, even though expert knowledge and guidance is necessary in liver vessel segmentation methods.

This thesis provides a review of current liver vessel segmentation methods, which are available in the literature. It has been tried to cover not only early but also recent literature in relation to liver vessel segmentation algorithms and techniques. The main purposes of the thesis are to introduce the current liver vessel segmentation methods and to classify them according to classification types which are given and explained the previous chapters.

Finally, a table is given in Table 5.1 for general overview of the proposed approaches, which are reviewed in the chapter four. The table gives a comparison about the features of the proposed studies. The table is presented to compare the methods in terms of classification type, the number of dataset and imaging modalities, vessel tree, and user interaction.

Table 5.1 Comparison of the reviewed liver vessel segmentation methods.

Proposed Method by	**Year**	**Classification Type**	**Dataset**		**Input Type**	**Dimension**		**Vessel Tree**	**User Interaction**
			Number	**Type**		**2D**	**3D**		
Soler et al. – 98	1998	PTRG	12	Real	N/A	No	Yes	Yes	No
Dokladal et al. – 99a	1999	IMPR	1	Real	X-RAY	No	Yes	Yes	N/A
Dokladal et al. – 99b	1999	IMPR	N/A	N/A	X-RAY	Yes	Yes	Yes	N/A
Hanh et al. – 01	2001	HYBR (IMPR - GRPH)	4	Real	MR	N/A	Yes	Yes	Yes
Doherty et al. – 02	2002	PTRG	1	Real	CT	No	Yes	Yes	No
Saitoh et al. – 02	2002	HYBR (IMPR - PTRG)	8	Real	MPCT	N/A	Yes	Yes	Yes
Eidheim et al. – 04	2004	HYBR (IMPR - PTRG)	3	Real	CT	Yes	Yes	Yes	Yes
Saitoh et al. – 04	2004	HYBR (IMPR - PTRG)	8	Real	MPCT	N/A	Yes	Yes	No
Charnoz et al. – 05	2005	IMPR	20	Synthetic	CT	N/A	Yes	Yes	N/A
Saitoh et al. – 05	2005	PTRG	7	Real	MPCT	Yes	Yes	Yes	Yes
Schmugge et al. – 06	2006	IMPR	2	N/A	N/A	Yes	N/A	No	Yes
Erdt et al. – 08	2008	IMPR	20	Real	CT	N/A	Yes	Yes	No
Fei & Park – 08	2008	HYBR (PTRG - PRDF)	N/A	N/A	MDCT	Yes	Yes	Yes	N/A
Homann et al. – 08	2008	HYBR (PRDF - GRPH)	6	Real	CT	Yes	Yes	Yes	Yes
Kawajiri et al. – 08	2008	HYBR (PTRG - IMPR)	2	Real	CT	N/A	Yes	Yes	No
Doğan et al. – 09	2009	IMPR	15	Real	CTA	N/A	Yes	Yes	N/A
Freiman et al. – 09	2009	OPTM	8	Real	CTA	Yes	Yes	Yes	No
Kaftan et al. – 09	2009	HYBR (IMPR - GRPH)	30	Real	CT	N/A	Yes	Yes	No
Seo & Park – 09	2009	HYBR (IMPR - PTRG)	17	Real	MDCT	N/A	Yes	Yes	No
Chi et al. – 10	2010	PTRG	10	Real	CT	N/A	Yes	Yes	Yes
Esneault et al. – 10	2010	HYBR (PTRG - GRPH)	4	Real-Synthetic	CT	N/A	Yes	Yes	No
Friman et al. – 10	2010	HYBR (IMPR - PTRG)	32	Real	CTA	N/A	Yes	Yes	N/A

Pattern Recognition	:PTRG	X-Ray	:X-Ray
Image Processing	:IMPR	Magnetic Resonance	:MR
Optimization	:OPTM	Computed Tomography	:CT
Graph Analysis	:GRPH	Computed Tomography Angiography	:CTA
Partial Differential Equation	:PRDF	Multi-Phase Computed Tomography	:MPCT
Hybrid	:HYBR	Multi-Detector Computed Tomography	:MDCT

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