Sudan University of Science and Technology

College of Graduated Studies

Automatic Data Extraction of Liver in Computed Tomography Images Using Segmentation Technique

استخراج البيانات التلقائي للكبد في صور الأشعة المقطعية بالكمبيوتر باستخدام تقنية التجزئة

A thesis submitted for Partial fulfillment of Academic Requirements of M.Sc. in Medical Physics

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Dedication

I dedicate my dissertation research to my family and many friends. A special feeling of gratitude to my loving parents, whose words of encouragement and push for tenacity ring in my ears, and very special to my sisters which they never left my side. Also I dedicate this dissertation to my many friends. I will always appreciate all they have done.

Acknowledgement

I wish to thank my committee members who were more than generous with their expertise and precious time . A special thanks to **Dr. Yousif Mohamed Yousif Abdallah**, my supervisor for his countless hours of reflecting ,reading, encouraging , and most of all patience throughout the entire process . I would like to acknowledge and thank to my colleagues in the Sudan Academy of science for allowing me to conduct my research and providing any assistance requested . Special thanks go to the members of medical physic department staff for their continued support. Finally I would like to thank any teachers, doctors in my loved country especially in the physics department for any advance that supported me to complete my higher study.

Abstract:

Advanced techniques of image processing and analysis find widespread use in medicine. In medical applications, image data are used to gather details regarding the process of patient imaging whether it is a disease process or a physiological process. Unfortunately, the presence of speckle noise in these images affects edges and fine details which limit the contrast resolution and make diagnostic more difficult. This experimental study was conducted in College of Medical Radiological Science and Fadil Specialist Hospital. The sample of study was included 50 patients. The main objective of this research was to study an accurate liver segmentation method using a parallel computing algorithm using image processing technique. The data analyzed by using MatLab program to enhance the contrast within the soft tissues, the gray levels in both enhanced and unenhanced images and noise variance. The main techniques of enhancement used in this study were watershed Segmentation Algorithm. In this thesis, prominent constraints are firstly preservation of image's overall look; secondly preservation of the diagnostic content in the image and thirdly detection of small low contrast details in diagnostic content of the image. The results of this technique was segmentation of liver successfully based on the methods of enhance the computed tomography images. This approach of image processing is funded on an attempt to interpret the problem from the view of blind source separation (BSS), thus to see the liver image as a simple mixture of (unwanted) background information, diagnostic information and noise.

الملخص:

التقنيات المتقدمة لمعالجة الصور وتحليلها تجد الاستخدام الواسع□طاقاً في مجال الطبي. في التطبيقات الطبية، تستخدم بيا□ات الصور لجمع تفاصيل متعلقة بتصوير المريض سواء كان لعملية مرضية او عملية فسيولو□ية. للأسف و□ود الضوضاء في هذه الصور يؤثر على الحواف و التفاصيل الدقيقة التى تحد من وضوح التباين وتجعل التشخيص اكثر صعوبة. ا□ريت هذه الدراسة في كلية علوم الأشعة الطبية، □امعة السودان للعلوم والتكنولو□يا و مستشفى فضيل التخصصي. وقد شملت عينة الدراسة على 50 مريضا .وكان الهدف الرئيسي من هذا البحث الدراسة الدقيقة لطريقة تسجيل الكبد باستخدام خوارزمية الحوسبة المتوازية باستخدام تقنية معالجة الصور .تم تحليل البيا□ات باستخدام بر□امج ماتلاب لتحسين التباين للأ□سجة الرخوة، التدريج اللو□ي في كل من الصور المحسنة وغير المحسنة وضوضاء التباين. كا□ت التقنية الرئيسية المستخدمة في هذه الدراسة هي خوارزمية مستجمعات المياه لتسجيل الصور. في هذه الدراسة واثناء ا□راء البحث كا□ت هنالك قيود بارزة متمثلة في الأتي: اولا حفظ□ظرة الصورة العامة ، ثا□يا: حفظ المحتوى التشخيصي من الصورة، ثالثا: كشف المقار□ة الصغيرة يفصل فى المستوى التشخيصي من الصورة. كا□ت□تائج هذه التقنية تسجيل الكبد بنجاح استنادا على □رق تعزيز الصور التصوير المقطعي. □ريقة معالجة الصورالتى توصل اليها من خلال الدراسة تستند على مبدأ الأفتراق المصدري الأعمى للتقليل الضوضاء والتشويش ، وهذا مهم لرؤية الكبد كخليط بسيط (غير مرغوب) ، معلومات مساعدة، معلومات وضاء تشخيصية ومعالجتها.

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Chapter One
Introduction

1.1. Introduction:

Enabled by the fast development of imaging techniques and computer hardware, there has been an explosive growth of three-dimensional (3D) image data collected from all kinds of physical sensors. The ability of a computer to properly understand and process these image data has permitted many applications to problems in computer vision and computer graphics. To achieve this ability, the first step is to extract object information from the image data, which can be characterized as an object learning procedure in machine intelligence. Examples of useful object information include: shape; color; texture; size; and its relative location to other objects in the scene. Such object information is widely used in many image processing applications including: 3D cartoon animations; video image processing; target detection in radar images; face recognition in security systems; and tumor dosimetry in nuclear medicine. For tasks geared toward object recognition and reconstruction, shape models are widely studied and used due to their insensitivity to changes in object color and surface texture, and their invariance to translation and scaling. Heavily influenced by the fast development of image acquisition equipment, medical image analysis has evolved in the last twenty years from a multiplicity of directions. Among all the techniques, image segmentation and multi-modal image registration are of special interests to us because they are intensively used to quantify tumor activity in patients being treated by radiopharmaceutical therapy. The broad, long-term objectives of the grant research are: 1) accurate tumor dosimetry from external imaging, and 2) effective and resource-conserving treatment of patients with malignant follicular lymphoma by the infusion of I-131 labeled anti-B1 monoclonal antibody (MAb) following infusion of a predose of non-radioactive anti-B1 MAb. Image segmentation is a fundamental task in medical image analysis. In segmentation, objects of interest in the image are extracted so that we can analyze their properties. Such properties can include pixel (voxel) intensities; centroid location; shape and orientation. The information from object segmentations is routinely used in many different applications, such as: diagnosis; treatment planning; study of anatomical structure; organ motion tracking; and computer-aided surgery. Object segmentation and statistical shape modeling serve and rely on each other. On the one hand, object segmentation generates noisy surface data which can be used to identify a shape model. On the other hand, statistical shape information acquired through estimated parameters in a statistical shape model can guide the segmentation procedure. Other applications, such as object registration, shape denoising and shape classification, can be enhanced by accurate object segmentation and statistical shape modeling. Due to noise and sampling artifacts in medical images, conventional edge detection and thresholding techniques either fail to locate the object boundary or generate invalid boundaries that must be removed in a post-processing step. Deformable models have been developed to address these difficulties. Deformable models are curves and surfaces defined within an image domain that can deform under different forces to locate object boundaries. Image registration is a classical procedure in image processing and analysis. It aligns two set of images so that corresponding coordinate points in the two images reflect the same physical location of the scene or 3D volume being imaged. Usually, the two set of images are obtained at different times, through different sensing systems, or from different viewpoints, so matching the two images allows us to compare or integrate the information contained in them. Due to the large diversity of data types in different applications, a wide range of techniques has been developed for different applications.

1.2. Problem of the study:

There are many problems due to absence of an accurate liver detection and segmentation which is very important for targets volumes delineation and dose delivery in radiotherapy.

1.3. Objectives of the study:

The main objective of this study is to study an accurate liver segmentation method using a parallel computing algorithm.

1.3.1. The specific objectives:

- To segment liver from adjacent organs using image processing technique .
- To design a new algorithm for accurate and fast liver volume calculation using minimal user intervention while maintaining high accuracy in volume rendering.
- To highlight the importance of MatLab image processing program in Volume delineation in radiotherapy.

1.4. Overview of study

This study consist of five chapters. Chapter one is introduction .chapter two consists of two parts; part one consist of Liver imaging using computed tomography, image processing technique for 3D visualization, image modeling and segmentation and using MatLab image processing in detection of liver. Part two consists of previous study. Chapter three is method and materials .chapter four is results. Chapter five is discussion, conclusion and Recommendations.

Chapter Two

Literature Review

2.1. Liver Imaging Using Computed Tomography:

A rapid sequence of images is acquired without table movement immediately after a bolus intravenous injection of radiographic contrast medium. The rate of enhancement in each pixel within the chosen slice can then be used to determine perfusion. The technique provides a quantifiable display of regional perfusion combined with the high spatial resolution afforded by CT. Computed tomography (CT) involves continuous patient translation during x-ray source rotation and data acquisition. As a result, a volume data set is obtained in a relatively short period of time. For chest or abdominal scanning, an entire examination can be completed in a single breath hold of the patient or in several successive short breath holds. The data volume may be viewed as conventional transaxial images or with multiplanar and three-dimensional methods. The authors review the technologic aspects of spiral CT, as well as its advantages, limitations, and current clinical applications. Computed tomography (CT or CAT scan) is a noninvasive diagnostic imaging procedure that uses a combination of X-rays and computer technology to produce horizontal, or axial, images (often called slices) of the body. A CT scan shows detailed images of any part of the body, including the bones, muscles, fat, and organs. CT scans are more detailed than standard X-rays. CT scans may be done with or without "contrast." Contrast refers to a substance taken by mouth and/or injected into an intravenous (IV) line that causes the particular organ or tissue under study to be seen more clearly. Contrast examinations may require you to fast for a certain period of time before the procedure. CT scans of the liver and biliary tract may also be used to visualize placement of needles during biopsies of the liver or during aspiration (withdrawal) of fluid from the area of the liver and/or biliary tract. CT scans of the liver are useful in the diagnosis of specific types of jaundice (yellowing of CT scans of the liver and biliary tract (the liver, gallbladder, and bile ducts) can provide more detailed information about the liver, gallbladder, and related structures than standard X-rays of the abdomen, thus providing more information related to injuries and/or diseases of the liver and biliary tract. CT scan of the liver and biliary tract may be performed to assess the liver and/or gallbladder and their related structures for tumors and other lesions, injuries, bleeding, infections, abscesses, unexplained abdominal pain, obstructions, or other conditions, particularly when another type of examination, such as X-rays, physical examination, and ultra sound is not conclusive. A CT scan of the liver may be used to distinguish between obstructive and non-obstructive jaundice. Another use of CT scans of the liver and biliary tract is to provide guidance for biopsies and/or aspiration of tissue from the liver or gallbladder.

2.2. Image Processing Technique For 3D Visualization:

Image segmentation has been a long-standing problem in computer vision. It is a very difficult problem for general images, which may contain effects such as highlights, shadows, transparency, and object occlusion. Segmentation in the domain of medical imaging has some characteristics that make the segmentation task easier and difficult at the same time. On the one hand, the imaging is narrowly focused on an anatomic region. The imaging context is also well-defined. While context may be present to some extent in segmenting general images (e.g., indoor vs. outdoor, city vs. nature, people vs. animals), it is much more precise in a medical imaging task, where the imaging modality, imaging conditions, and the organ identity is known. In addition, the pose variations are limited, and there is usually prior knowledge of the number of tissues and the

Region of Interest (ROI). On the other hand, the images produced in this field are one of the most challenging due to the poor quality of imaging making the anatomical region segmentation from the background very difficult. Often the intensity variations alone are not sufficient to distinguish the foreground from the background, and additional cues are required to isolate ROIs. Finally, segmentation is often a means to an end in medical imaging. It could be part of a detection process such as tissue detection, or for the purpose of quantification of measures important for diagnosis, such as for example, lesion burden which is the number of pixels/voxels within the lesion regions in the brain.

2.3. Image Modeling and Segmentation:

In general, the information contained in an image can be modeled in several ways. A simple approach is to record the intensity distribution within an image via a One-dimensional (1D) histogram and use simple thresholding to obtain the various segments.

2.3.1. Image Modeling:

Several variations on classical histogram thresholding have been proposed for medical image segmentation that incorporate extended image representation schemes as well as advanced information modeling. Multi-modal or multi-sequence data: Multi-dimensional are histograms formed from the intensity values produced by each of the imaging protocols. It is often the case that several acquisitions are available for the same image. Spatial information: Since intensity histograms do not preserve spatial contiguity of pixels, one variation is to add spatial position (x, y) or (x, y, z) to form a multi-dimensional feature vector incorporating spatial layout. If the medical images are in a time sequence (e.g. moving medical imagery), then time can be added as an additional feature in the representation space.

2.3.2. Segmentation:

Thus, these approaches represent each image pixel as a feature vector in a defined multi-dimensional feature space. The segmentation task can be seen as a combination of two main processes; modeling which is the generation of a representation over a selected feature space. This can be termed the modeling stage. The model components are often viewed as groups, or clusters in the high-dimensional space. Assignment which is the assignment of pixels to one of the model components or segments. In order to be directly relevant for a segmentation task, the clusters in the model should represent homogeneous regions of the image. In general, the better the image modeling, the better the segmentation produced. Since the number of clusters in the feature space are often unknown, segmentation can be regarded as an unsupervised clustering task in the highdimensional feature space.

2.3.3. Visualization:

The visualization of volumetric and multi-modal medical data is a common task in biomedical image processing and analysis. In particular after identifying anatomical structures of interest and aligning multiple datasets, a Three-dimensional (3D) visual representation helps to explore and to understand the data. Volume visualization aims at a visual representation of the full dataset, hence of all images at the same time. Therefore, the individual voxels of the dataset must be selected, weighted, combined, and projected onto the image plane. The image plane itself acts literally as a window to the data, representing the position and viewing direction of the observer who examines the dataset.

2.4. Using MatLab Image processing in detection of liver

Matlab is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include:

- Math and computation
- Algorithm development
- Modeling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics
- Application development, including graphical user interface building

Matlab is an interactive system whose basic data element is an array that does not require dimensioning. This allows operators to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar noninteractive language such as C or Fortran. Magnetic resonance imaging (MRI) has become a common way to study brain tumor. In this study the pre-process of the two-dimensional magnetic resonance images of brain and subsequently detect the tumor using edge detection technique and color based segmentation algorithm. Edge-based segmentation has been implemented using operators e.g. Sobel, Prewitt, Canny and Laplacian of Gaussian operators. The color-based segmentation method has been accomplished using K-means clustering algorithm. The color-based segmentation carefully selects the tumor from the pre-processed image as a clustering feature. The present work demonstrates that the method can successfully detect the brain tumor and thereby help the doctors for analyzing tumor size and region. The algorithms have been developed on Matlab version 7.9.0 (R2009a) platform

Jarritt et al (2010) stated in their study of Use of combined PET/CT images for radiotherapy planning: initial experiences in lung cancer that the potential role of positron emission tomography (PET) in radiotherapy still requires careful evaluation as it becomes increasingly integrated into the radiotherapy planning process. Diagnosis and subsequent radiotherapy planning based solely upon X-ray CT are known to be less sensitive and specific for disease than PET imaging in non-small cell lung cancer. The CT images may not demonstrate the true extent of intrathoracic disease. To overcome this limitation, the direct use of combined PET/CT image data in the treatment planning process has been investigated. A small pilot study of five patients was carried out at the Royal Victoria Hospital, Belfast, following the installation of a GE Discovery LS PET/CT scanner. The initial aims were to investigate the system and to make preliminary clinical evaluations. The key issues that were addressed included: verification of PET/CT alignment, patient position and reproducibility for imaging and treatment; verification of CT numbers on the PET/CT systems for dose calculation; integrity of data transfer; radiation protection of staff; protocols for target volume delineation; and the implications for physiologically-gated PET and CT acquisitions. This paper reviews our practical experience, and technical problems are described.

Kratochwil et al, (2010) mentioned in their study of PET/CT for diagnostics and therapy stratification of lung cancer that With the introduction of positron emission tomography (PET) and more recently the hybrid systems PET/CT, the management of cancer patients in the treatment strategy has changed tremendously. The combination of PET with multidetector CT scanning enables the integration of metabolic and high resolution morphological image information. PET/CT is nowadays an established modality for tumor detection, characterization, staging and response monitoring. The increased installation of PET/CT systems worldwide and also the increased scientific publications underline the importance of this imaging modality. PET/CT is particular the imaging modality of choice in lung cancer staging and re-staging (T, N and M staging). The possible increased success of surgery in lung cancer patients and also the expected reduction in additional invasive diagnostics lead to benefits for both the individual patient and the healthcare system. In this review article PET and PET/CT is presented for diagnostic and therapeutic stratification in lung cancer. The fundamentals of glucose metabolism, staging, tumor recurrence and therapeutic monitoring are presented

Jover et al (2011) stated in their study of evaluation lung cancer treatment using PET/CT scanning that PET imaging utilizes a dedicated camera system with multiple positron detector rings. PET/CT precisely aligns and combines metabolic PET mages with anatomical CT images, and is being increasingly preferred over PET scanning alone. FDG is the most widely used radiotracer in the management of cancer patients, and the prototypical PET/CT protocol used in other cancers can also be applied to the management of cervical carcinoma patients. The applications of PET/CT in cervical cancer patients include: assessing local tumor extension (information on metabolic tumor activity and possible endometrial involvement), evaluating pelvic nodal involvement (even in cases with negative CT or MRI studies), detection of distant metastases (PET/CT should be the first imaging technique used to evaluate extrapelvic disease before pelvic exenteration), radiation therapy planning (in patiens with PET scans positive for lymph nodes), identification of persistent/recurrent disease (especially in assessing response to neoadjuvant therapy and prognosis (with an inverse response-survival relationship.

Yamamoto et al, (1996) proposed a new algorithm named Quoits filter (Q-filter) to extract the isolated but low amplitude shadow located in the background which has extremely high amplitude fluctuation. Q-filter is a kind of mathematical morphology and its formulation is quite simple. This simplicity brings about a unique merit that output from this filter is analytically expressive for the case of analytical input shapes like ball, cone, or rotation of cosine function, which have characteristics of rotation symmetry and monotonic decreasing from the origin. This Q-filter is composed of two sequential operations named Q Trans. and Q Inv. Trans., Q Trans. corresponds to extracting feature parameters like a matched filter from the input image having a nonideal isolated shadow, and Q Inv. Trans. corresponds to restoring isolated images using extracted feature parameters. This filter is applied to detecting the cancer candidate shadow automatically in the CT cross sections of lung areas, aiming to reduce drastically the number of cross sections to be diagnosed by the doctor.

Cai, et al, (1999) carried out to present a validation study of CT and PET lung image registration and fusion based on the chamfer-matching method. Both anatomic thoracic phantom images and clinical patient images were used to evaluate the performance of our registration system. Quantitative analysis from five patients indicates that the registration error in translation was 2–3 mm in the transverse plane, 3–4 mm in the longitudinal direction, and about 1.5 degree in rotation. Typical computing time for chamfer matching is about 1 min. The total time required to register a set of CT and PET lung images, including contour extraction, was generally less than 30 min. They have implemented and validated the chamfer-matching method for CT and PET lung image registration and fusion. Our preliminary results show that the chamfer-matching method for CT and PET images in the lung area is feasible. The described registration system has been used to facilitate target definition and treatment planning in radiotherapy.

Sudha and Jayashree (2010) conduced study to lung cancer which is among the five main types of cancer is a leading one to overall cancer mortality contributing about 1.3 million deaths/year globally. Lung cancer is a disease and it is characterized by uncontrolled cell growth in tissues of the lung. Lung nodule is an abnormality that leads to lung cancer, characterized by a small round or oval shaped growth on the lung which appears as a white shadow in the CT scan. An effective computer aided lung nodule detection system can assist radiologists in detecting lung abnormalities at an early stage. If defective nodules are detected at an early stage, the survival rate can be increased up to 50%. This paper aims to develop an efficient lung nodule detection system by performing nodule segmentation through thresholding and morphological operations. The proposed method has two stages: lung region segmentation through thresholding and then segmenting the lung nodules through thresholding and morphological operations.

Chapter Three
Materials and Methods

3.1. Study place:

This study was performed in College of Medical Radiological Science and Fadil Specialist Hospital.

3.2. Study Duration

This study was performed in period of January to October 2014.

3.3. Methods of data collection:

Separating touching objects in an image is one of the more difficult image processing operations. The watershed transform is often applied to this problem. The watershed transform finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low. Segmentation using the watershed transform works well if one can identify, or "mark," foreground objects and background locations. Marker-controlled watershed segmentation follows this basic procedure:

1. Computation a segmentation function. This is an image whose dark regions are the objects you are trying to segment.

2. Computation the foreground markers. These are connected blobs of pixels within each of the objects.

3. Computation the background markers. These are pixels that are not part of any object.

4. Modification of the segmentation function so that it only has minima at the foreground and background marker locations.

5. Compute the watershed transform of the modified segmentation function.

Steps of liver segmentation using Matlab program:

Step 1: Read in the Color Image and Convert it to Grayscale

Step 2: Use the Gradient Magnitude as the Segmentation Function

Step 3: Mark the Foreground Objects

Step 4: Compute Background Markers

Step 5: Compute the Watershed Transform of the Segmentation Function.

Step 6: Visualize the Result

3.4. Ethical Issue:

- Permission of Radiology Department has been granted.
- No patient data published

Chapter Four

Results

This experimental study was conducted in College of Medical Radiological Science and Fadil Specialist Hospital. The sample of study was included 50 patients. The main objective of this research was to study an accurate liver segmentation method using a parallel computing algorithm.

Experimental study:

Step 1: Read in the Color Image and Convert it to Grayscale

```
rgb = imread('pears.png');

I = rgb2gray(rgb);

Imshow (I)

text(732,501,'Image courtesy of Corel(R)',...'FontSize',7,'HorizontalAlignment','right') as shown in
```

Figure 4-1.

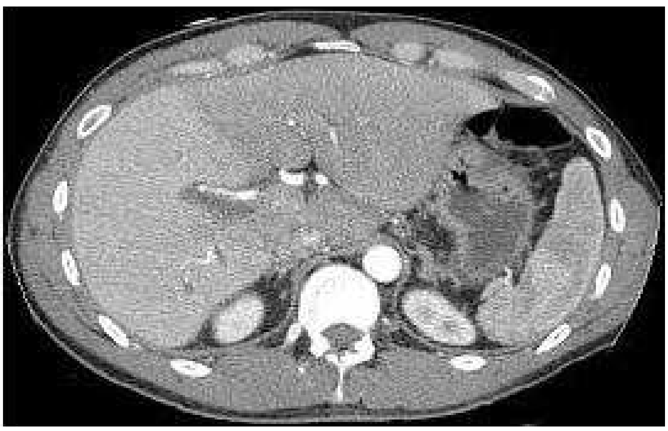

Figure 4-1. The original liver CT image

Step 2: Use the Gradient Magnitude as the Segmentation Function

The Sobel edge masks, *imfilter*, and some simple arithmetic were used to compute the gradient magnitude. The gradient is high at the borders of the objects and low (mostly) inside the objects.

```
hy = fspecial('sobel');

hx = hy';

Iy = imfilter(double(I), hy, 'replicate');

Ix = imfilter(double(I), hx, 'replicate');

gradmag = sqrt(Ix.^2 + Iy.^2);

figure, imshow(gradmag,[]), title('Gradient magnitude (gradmag)') as shown in figure 4-2.
```

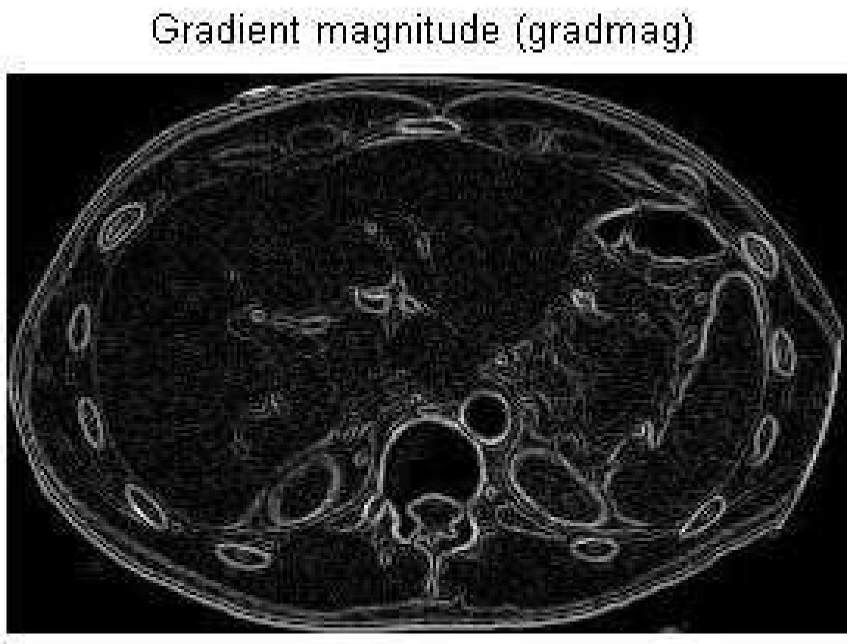

Figure 4-2. ***Gradient Magnitude as the Segmentation Function***

The image was segmented by using the watershed transform directly on the gradient magnitude using the following code:

```
L = watershed(gradmag);
```

Lrgb = label2rgb(L);

figure, imshow(Lrgb), title('Watershed transform of gradient magnitude (Lrgb)') as shown in figure 4-3.

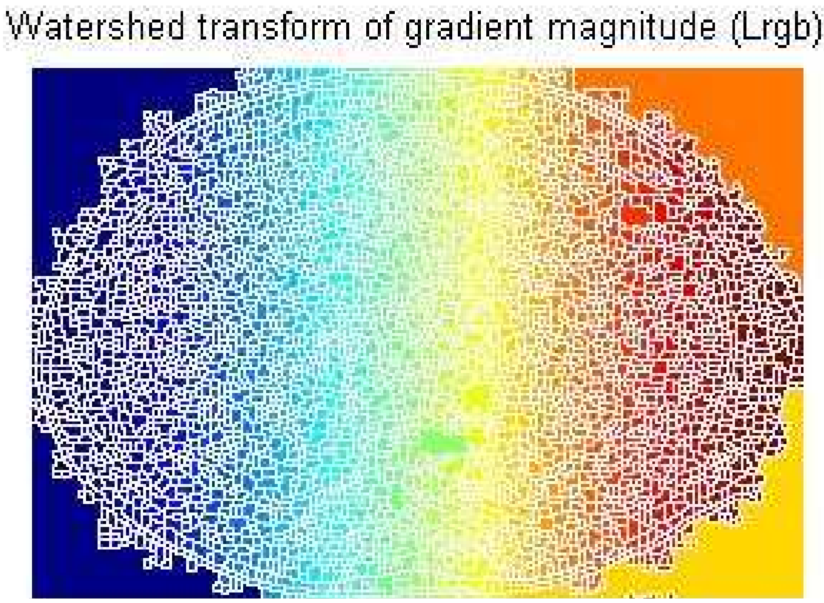

Figure 4-3. The watershed transform

Step 3: Mark the Foreground Objects

A variety of procedures could be applied here to find the foreground markers, which must be connected blobs of pixels inside each of the foreground objects. In this study morphological techniques were used and they called "opening-by-reconstruction" and "closing-by-reconstruction" to "clean" up the image. These operations will create flat maxima inside each object that can be located using imregionalmax.

se = strel('disk', 20);

Io = imopen(I, se);

figure, imshow(Io), title('Opening (Io)') as shown in figure 4-4

Opening is an erosion followed by a dilation, while opening-by-reconstruction is an erosion followed by a morphological reconstruction.

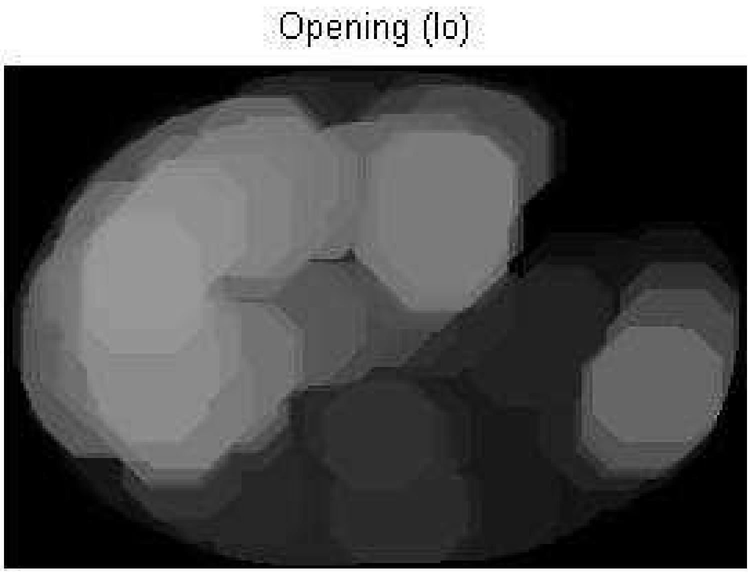

Figure 4-4. The Opening-by-reconstruction algorithm

Next the opening-by-reconstruction was computed using *imerode* and *imreconstruct* as shown in figure 4-5.

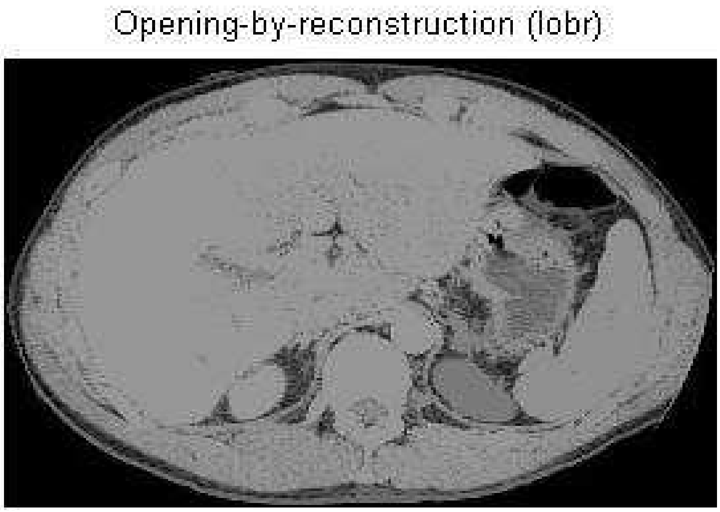

Figure 4-5. The opening-by-reconstruction was computed using *imerode* and *imreconstruct*

Following the opening with a closing can remove the dark spots and stem marks. Compare a regular morphological closing with a closing-by-reconstruction. First imclose code was tried:

Ioc = imclose(Io, se);

figure, imshow(Ioc), title('Opening-closing (Ioc)') as shown in figure 4-5.

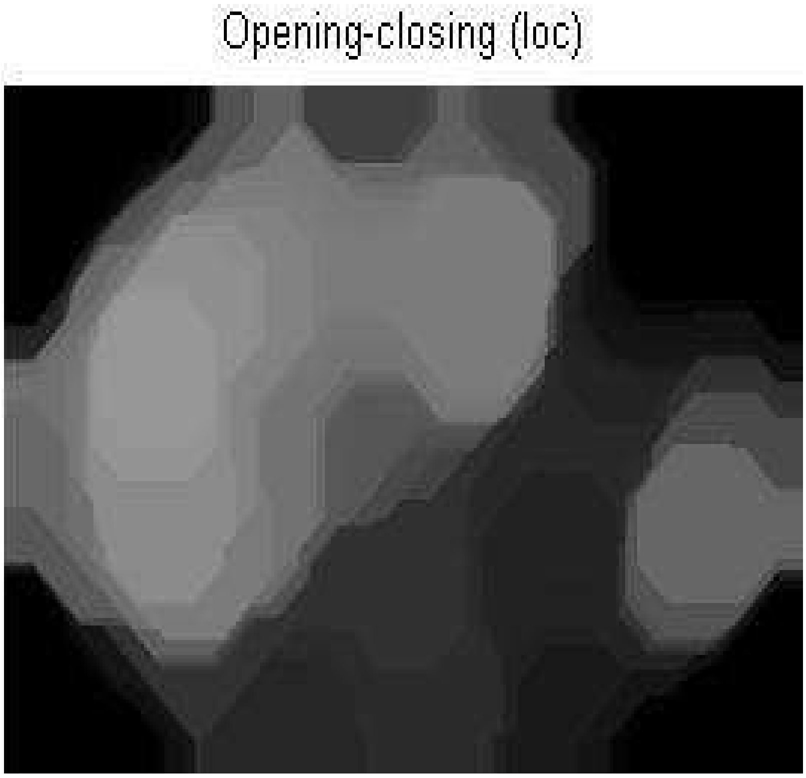

Figure 4-5. The 'Opening-closing algorithm

The imdilate code was used followed by imreconstruct. The image inputs and output of imreconstruct should complement.

Iobrd = imdilate(Iobr, se);

Iobrcbr = imreconstruct(imcomplement(Iobrd), imcomplement(Iobr));

Iobrcbr = imcomplement(Iobrcbr);

figure, imshow(Iobrcbr), title('Opening-closing by reconstruction (Iobrcbr)') as shown in figure 4-6.

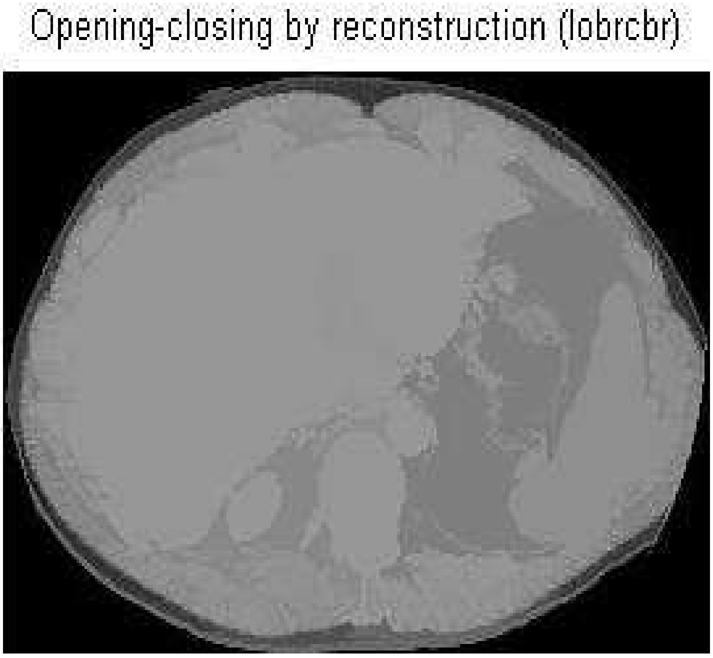

Figure 4-6. Opening-closing by reconstruction algorithm

When Iobrcbr with Ioc were compared, reconstruction-based opening and closing found more effective than standard opening and closing at removing small blemishes without affecting the overall shapes of the objects. Calculate the regional maxima of Iobrcbr to obtain good foreground markers.

fgm = imregionalmax(Iobrcbr);

figure, imshow(fgm), title('Regional maxima of opening-closing by reconstruction (fgm)') as shown in figure 4-7.

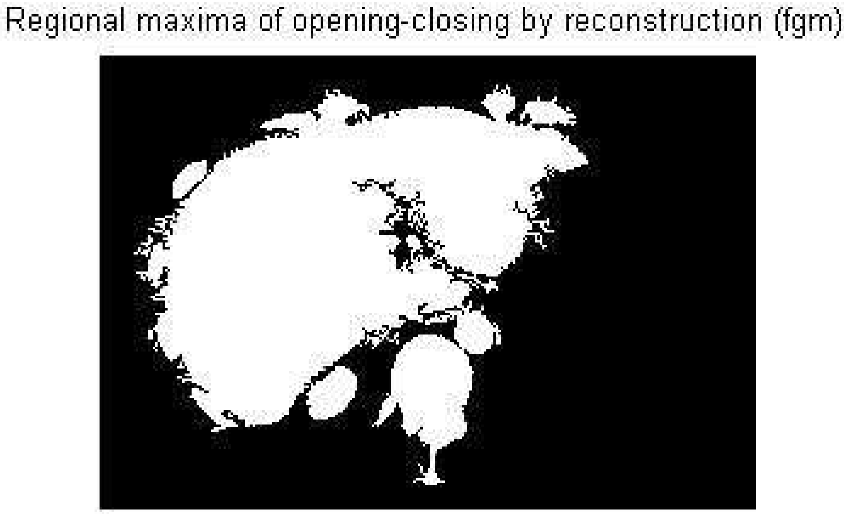

Figure 4-7. Regional maxima of opening-closing by reconstruction (fgm) filter

To help interpret the result, superimpose the foreground marker image on the original image.

I2 = I;

I2(fgm) = 255;

figure, imshow(I2), title('Regional maxima superimposed on original image (I2)') as shown if figure 4-8.

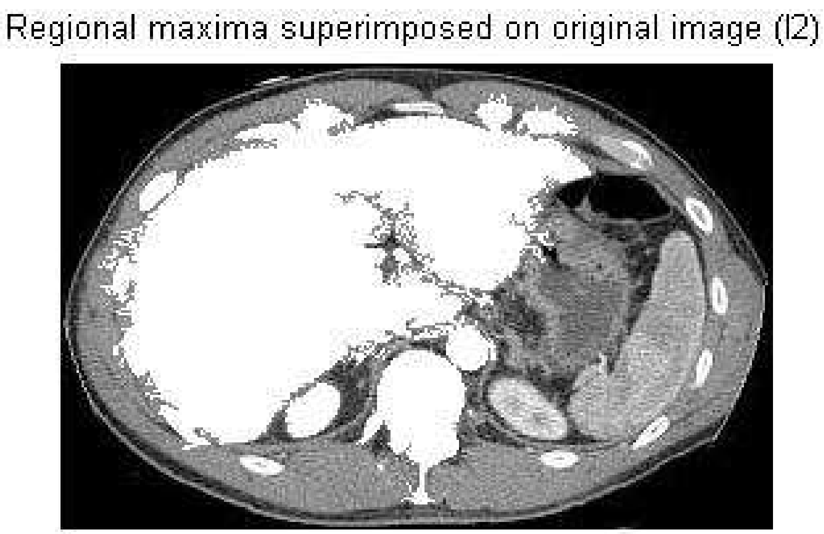

Figure 4-8. Regional maxima superimposed technique on original image

Some of the mostly-occluded and shadowed objects are not marked, which means that these objects will not be segmented properly in the end result. Also, the foreground markers in some objects go right up to the objects' edge. The edges of the marker blobs should clean and then shrink them a bit. This could be done by a closing followed by an erosion.

```
se2 = strel(ones(5,5));

fgm2 = imclose(fgm, se2);

fgm3 = imerode(fgm2, se2);
```

This procedure tended to leave some stray isolated pixels that must be removed. This could be done using bwareaopen, which removed all blobs that had less than a certain number of pixels.

```
fgm4 = bwareaopen(fgm3, 20);

I3 = I;

I3(fgm4) = 255;

figure, imshow(I3)
```

title('Modified regional maxima superimposed on original image (fgm4)') as shown in figure 4-9.

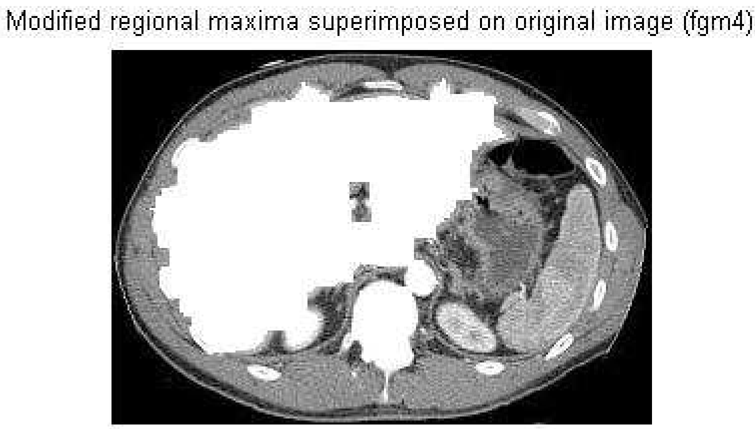

Figure 4-9. Modified regional maxima superimposed on original image

Step 4: Compute Background Markers

Now the background need to be marked. In the cleaned-up image, Iobrcbr, the dark pixels belong to the background, a thresholding operation could start with.

```
bw = im2bw(Iobrcbr, graythresh(Iobrcbr));
```

figure, imshow(bw), title('Thresholded opening-closing by reconstruction (bw)') as shown in figure 4-10.

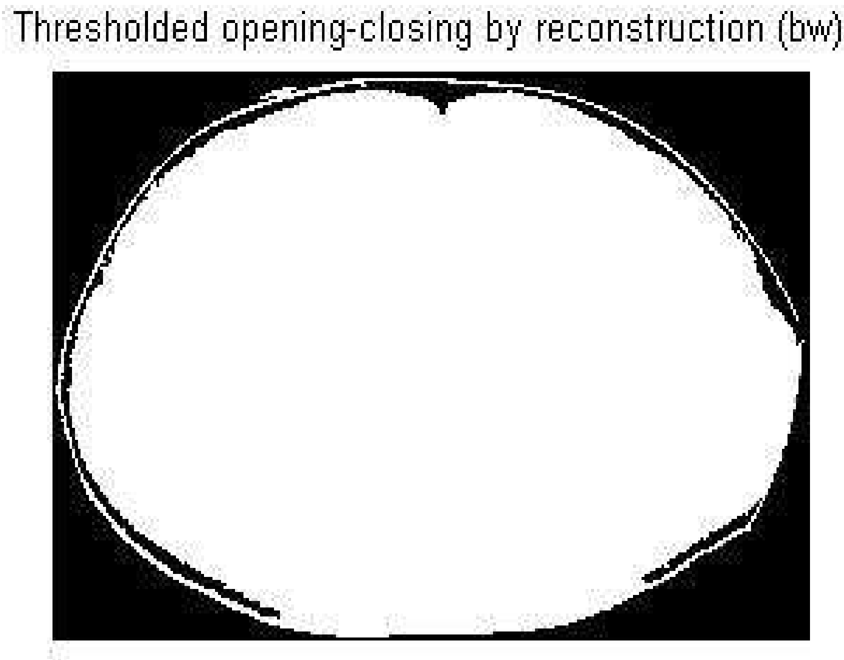

Figure 4-10. Thresholded opening-closing by reconstruction

The background pixels are in black, but ideally the background markers shouldn’t to be too close to the edges of the objects which would segment. the background would "thin" by computing the "skeleton by influence zones", or SKIZ, of the foreground of bw. This can be done by computing the watershed transform of the distance transform of bw, and then looking for the watershed ridge lines (DL == 0) of the result.

```
D = bwdist(bw);
```

```
DL = watershed(D);

bgm = DL == 0;
```

figure, imshow(bgm), title('Watershed ridge lines (bgm)') as shown in figure 4-11.

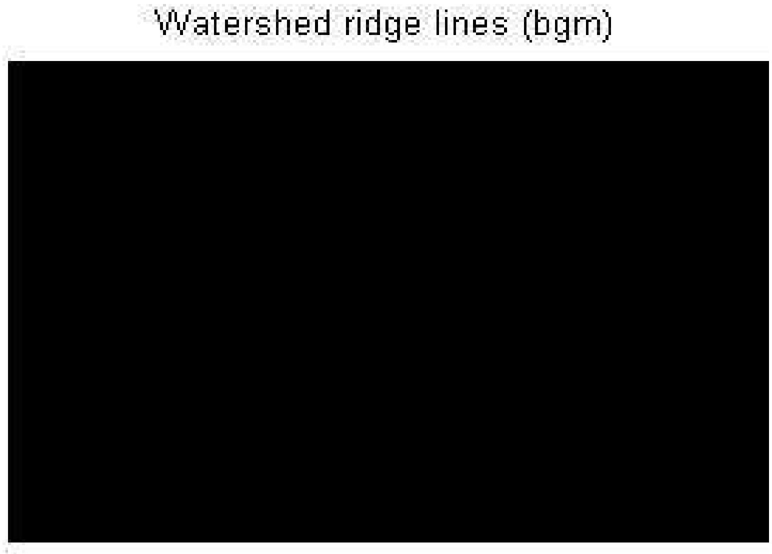

Figure 4-11. Watershed ridges of the lines

Step 5: Compute the Watershed Transform of the Segmentation Function.

The function imimposemin can be used to modify an image so that it has regional minima only in certain desired locations. Here imimposemin used to modify the gradient magnitude image so that its only regional minima occur at foreground and background marker pixels.

```
gradmag2 = imimposemin(gradmag, bgm | fgm4);
```

Finally we are ready to compute the watershed-based segmentation.

```
L = watershed(gradmag2);
```

Step 6: Visualize the Result

One visualization technique is to superimpose the foreground markers, background markers, and segmented object boundaries on the original image.

Dilation could use as needed to make certain aspects, such as the object boundaries, more visible. Object boundaries are located where L == 0.

```
I4 = I;

I4(imdilate(L == 0, ones(3, 3)) | bgm | fgm4) = 255;

figure, imshow(I4)
```

title('Markers and object boundaries superimposed on original image (I4)') as shown in figure 4-12

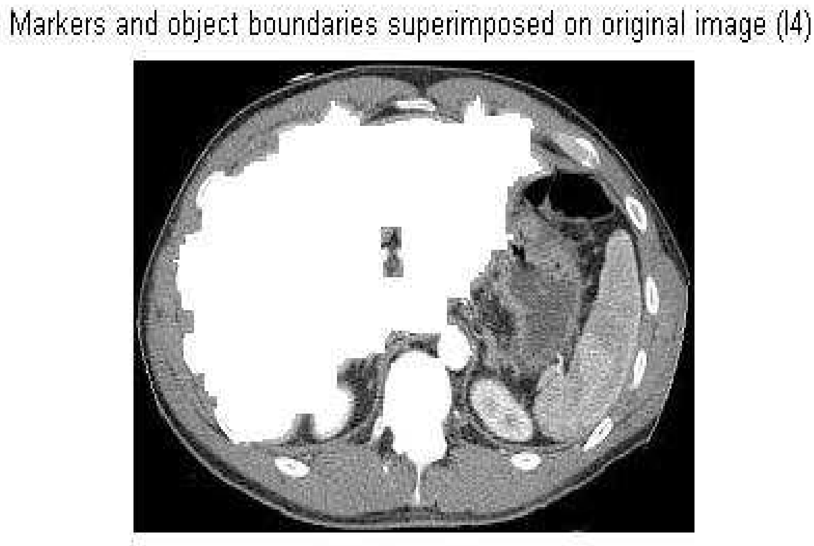

Figure 4-12. Markers and object boundaries superimposed on original image

Chapter Five

Discussion, Conclusion and Recommendations

5.1.Discussion:

Matlab is an interactive system whose basic data element is an array that does not require dimensioning. This allows operators to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRAN. Magnetic resonance imaging (MRI) has become a common way to study liver. Information provided by medical images has become a vital part of today's patient care. The images generated in medical applications are complex and vary notably from application to application. This experimental study was conducted in College of Medical Radiological Science and Fadil Specialist Hospital. The sample of study was included 50 patients. The main objective of this research was to study an accurate liver segmentation method using a parallel computing algorithm. Computed Tomography images show characteristic information about the physiological properties of the structures-organs. In order to have high quality medical images for reliable diagnosis, the processing of image is necessary. The scope of image processing and analysis applied to medical applications is to improve the quality of the acquired image and extract quantitative information from medical image data in an efficient and accurate way. The main techniques of segmentation used in this study was watershed transform. The results of this technique agreed the results of Jarritt et al, (2010), Kratchwil et al, (2010), Jover et al, (2011), Yomamoto et al, (1996), Cai et al (1999), Saudha and Jayashree (2010) who used different segmentation filtering based on the methods of enhance the computed tomography images. The anther technique was region of interest technique. Filtering is a technique for modifying or enhancing an image.

5.2. Conclusion:

This experimental study was conducted in College of Medical Radiological Science and Fadil Specialist Hospital. The sample of study was included 50 patients. The main objective of this research was to study an accurate liver segmentation method using a parallel computing algorithm. In addition to evaluate the usage of new nonlinear approach for contrast enhancement of soft tissues in computed tomography images in order to study automatic extraction of liver tissue in computed tomography. In image processing, filters are mainly used to suppress either the high frequencies in the image, i.e. smoothing the images or the low frequencies, i.e. enhancing or detecting edges in the image. Due to various factors the images are in general poor in contrast. Researchers applied image pre-processing to remove artefacts and degradations such as blurring and noise. A variety of smoothing filters have been developed that are not linear. While they cannot, in general, be submitted to Fourier analysis, their properties and domains of application have been studied extensively. For this reason researchers applied anisotropic filtering and median filtering. In study method anisotropic and median filtering algorithms were used.

5.3.Recommendations:

- The study proposed a new approach of lung tissue extraction using image processing technique (MATLAB) with limited applications and I hope from the other researchers to continue on other applications and toolbox.

- Image pre-processing techniques can easily remove artefacts and degradations such as blurring and noise so I recommended other researcher to use those techniques.

- The term contrast is used to describe these differences are small; it is difficult to identify the structure will stand out well from its surroundings and it is said the contrast is high (good). If the differences are small, it is difficult to identify the structure against its background. The contrast is said to be low (poor).

- The future work of this project is to identify the effective features for further classification. Genetic Programming-based Classifier will be used for classification of lung CT images as cancerous and non-cancerous by using the identified effective features.

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