Overview of Technical Elements of Liver Segmentation

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***Abstract*—Liver diseases are life-threatening, it's important to detect it tumor in early stages. So, for tumor detection Segmentation of the liver is a first and significant stride. Segmentation of the liver is a yet difficult undertaking in view of its intra patient variability in intensity, shape and size of the liver. The aim of this paper is to assemble a wide assortment of techniques and used CT scan dataset information for liver segmentation that will provide a decent beginning to the new researcher. There are different strategies from basic to advance like thresholding, active contour, region growing to graph cut is briefly abridge to give an outline of existing segmentation strategies. We review the concept of particular strategies and review their original ideas. Our idea is to provide information under which condition a chosen strategy will work or utilize.**

Keywords—component; CT Scan; Liver; Dataset; Segmentation technique

I. Introduction

The liver is key and biggest organ among different organs of the body and provide exceptionally crucial task to our body to keep it free from toxins and harmful substances such as alcohol and medications. Its primary vital functions are: to filter the blood coming from digestive track, it supports all other organs of the body in some way, regulate the supply of body fuel by managing glucose level in our body, cleanse the blood by metabolizing alcohol and obliterating and neutralizing destructive substances, produce bile, which helps in digestion, manufacture many primary and essential proteins which provide resistance to infection and help in blood clotting and thickening. Its direct the supply of vitamins and mineral in our body.

According to Global Cancer Statistics [26] liver cancer fifth the most commonly diagnosed and the second driving reason for death among men and seventh in women. Distinct methods for liver cancer is a blood test, screening and biopsy. A biopsy is intrusive procedure and is exceptionally painful diagnostic technique for patients. That is why researchers are attempting to develop noninvasive techniques. In this way, before the detection of the liver pathology, liver must be segmented accurately.

Liver segmentation is challenging task to develop robust strategies for liver segmentation. Researchers are coping with this challenge to automatically segment the liver; exceedingly unique shapes and volume of liver, similar intensity value among adjacent organs (stomach, spleen, Aorta and abdominal wall), complicated liver structure and contrast media injection cause liver tissue to have different grey level value. Liver segmentation is still an open problem as a result of these challenges. At the time being, researchers are dealing with challenging tasks to increase accuracy in diagnosis and maintain the strategic distance from the need for biopsy (a small tissue of tumor is removed and analyzed) and surgery. These systems do not replace the radiologist, but only provide the second opinion in diagnosis and support radiologist to settle on their choice. Segmentation methods are categorized into 2 main categories; automatic and interactive method. An automatic method has no user intervention and are fully automated and free from user error. It potentially saves the time of operators. The semi-automatic required user intervention like refinement of binary mask and in the selection of seed points. General approach to deal with follow in automated and semi-automatic CAD (Computer Aided System) system is: Pre-processing, Liver segmentation, Lesion Detection, Feature extraction, Classification, Evaluation. Some paper applies the post processing also as indicated by their prerequisite. In pre-processing phase filters are utilized to enhance the image quality and features, furthermore to remove noise and contortion from images. liver segmentation, the liver is sectioned from other encompassing organs. Lesion are detected from segmented liver. Then features are extracted from the lesion area to categorize them either benign or malignant, primary or secondary tumors.

Different modalities are utilized for the diagnosis of liver pathology (liver cancer, cirrhosis, hepatitis) such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), (US)ultrasounds. According to research CT is the most preferred modality because CT is less costly than MRI. The CT data is collected in the form of DICOM (Digital Imaging and Communication in Medicine) image. DICOM images can be converted to many types, however, for medical imaging it is ideal to utilize .PNG or .BMP. Many researchers work on Liver segmentation and propose different techniques. Each technique has its own merits and shortcomings.

The rest of the Paper is organized as follows section II Literature Review, section III we organize liver segmentation techniques overview, section IV we include conclusion to summarize our views. we place the dataset comparison table and techniques overview table at the end of paper.

II. Literature Review

*Lim et al [*2] Develop automatic liver segmentation using previous knowledge of liver position and use a deformable contour method based on morphological filtering operation. On the gradient label map Algorithm [2] perform deformable contouring. To reduce computational complexity and to decide suitable threshold histogram analysis is performed in the ELP (Estimated liver position). Proposed method uses multi scale morphological filter recursively with region labeling and clustering to detect search rang for deformable contouring. They use private dataset of 10 patients. Results are compared with manual segmentation by a radiologist. Graphical representation is shown below in Fig. 1

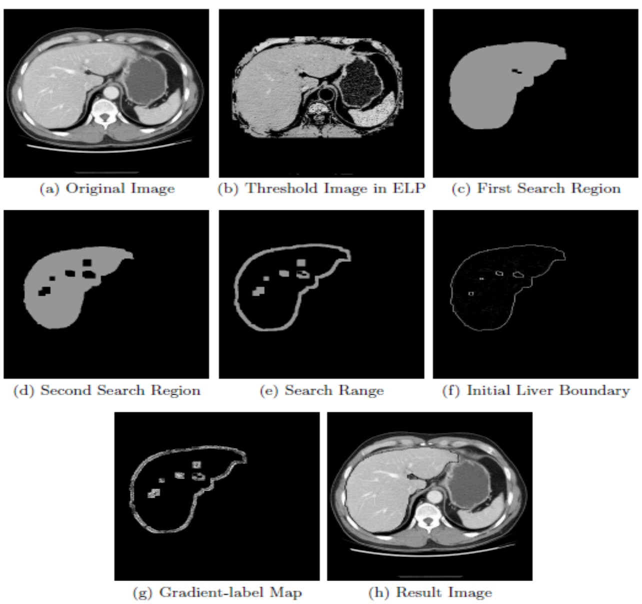


Fig. 1. Final Segmentation result

Suzuki et al [4] developed automatic liver extraction technique for contrast enhance CT images. The anisotropic diffusion filter uses for image denoising and preserving the shape of the liver. Scale specific gradient magnitude use to enhance liver boundary. These preprocessing results are passed to fast marching level set algorithm that initially refines the liver boundary and use as a rough estimate of liver shape and geodesic active contour combine with level set to extract liver shape. And estimate liver volume. Liver manually trace by the expert radiologist is use as a gold standard to compare the evaluation results of liver volume. Their local dataset consists of 15 patients. Overall accuracy is 98.4 %. Sensitivity, specificity and percent volume error is 91.1%, 99.1%, and 7.2 respectively. Limitation of the paper is small dataset. Graphical representation is shown in Fig. 2

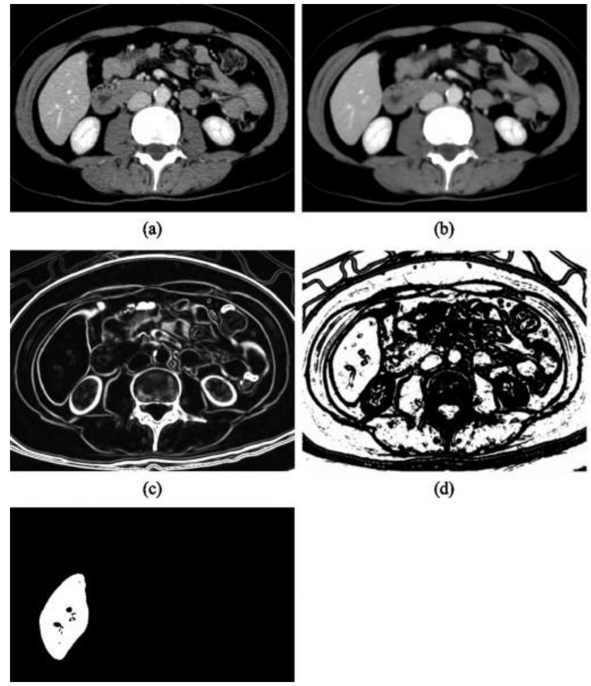


Fig. 2. (a) Original CT image (b)Anisotropic diffusion noise reduction (c) Scale specific gradient magnitude calculation (d) Non-linear grey scale conversion(e) Geodesic active contour segmentation

Massoptier et al [7] Develop innovative statistical model based approach. Active contour and gradient vector flow (GVF)are also used for hepatic segmentation. They analyzed nonlinear anisotropic diffusion and mean shift filter based on the processing time. To save processing time they follow mean shift filter. Clustering technique was used with their powerful initialization method for hepatic lesion segmentation. For lesion detection 82.6% Sensitivity and 87.6% specificity were achieved. Liver volume overlapping was evaluated by DSC (Dice Similarity Coefficient), FNR (false negative ratio), FPR (false positive ratio). They use their own private data set of 21 patient CT data set. From 46 lesions, they diagnosed different type of tumor 6 were HCC (Hepatocellular carcinoma), 2HDG (Hemangioma), 8HM (Hepatic metastases) and 5 have healthy patients.

Yussof et al [10] proposed automatic 3D liver segmentation algorithm using a hybrid technique that combines morphological operations with graph cut method. Anisotropic diffusion filter for noise removal.In liver region estimation histogram analysis was performed and give their assumption that liver, grey value always lies between 75 to 200.For liver segmentation 2D and 3D Connected Component Labeling was performed. The graph cut technique was used for the refinement of CCL segmented liver and for reconstruction of liver surface. Accuracy check is performed in 10 cases of silver07 dataset. Computation time is less than 6 min. For evaluation of segmentation results, use 5 different evaluation metrics. Volumetric overlap error(VOE), Relative volume difference(RVD), Average symmetric surface difference(SD), Maximum symmetric surface difference (MSD) and Root mean square symmetric surface difference(RMSD). On average results VOE is less than 10%, RVD is 2.99%and RMSD is close to 2mm.Limitation of their paper is, they face under segmentation problem when lesions are close to liver boundary. The dataset is very small.

Militzer et al [12] Proposed a novel system for automatically detecting and segmenting focal liver region from CT images. For classification, it utilizes a probabilistic boosting and thus provide fully automated detection and segmentation of the liver lesion simultaneously. They use hierarchical mesh-based shape representation for liver segmentation. Features selected in this paper are gray level statistical feature and Haar like features. Detection rate 77% could be achieved with the specificity of 0.93% and a sensitivity of 0.95% at the same time for lesion segmentation at the same setting.

S.S Kumar [15] presented an automatic segmentation of the liver lesion from CT radiographs. This paper utilizes medium filter, erosion, dilation, largest connected component as a pre-processing step. In post-processing, morphological operators are utilized to additionally refine the image and utilize basic region growing techniques for live segmentation and an alternate Fuzzy C-Means Clustering for tumor segmentation. He used 10 cases in his research work. The Technique result was contrasted and evaluated with the manual segmentation based on false positive rate, false negative rate, volume measurement error, spatial overlap and visual overlap. Pictorial results are shown in Figure .1 below.

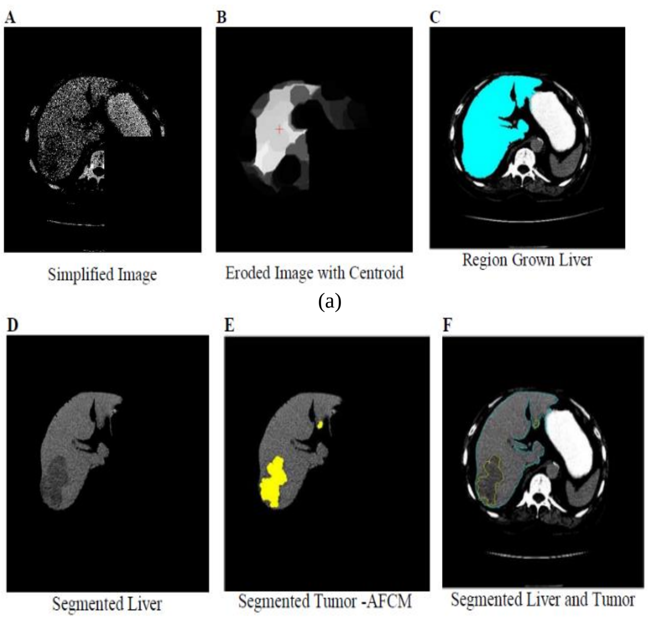


Fig. 3. (a) results of final liver segmentation using AFCM (b) results of final liver segmentation using AFCM

Belgherbi et al [17] A semi-automatic method developed for liver lesion extraction using mathematical morphology from CT images. In pre-processing for refinement of the liver they use dilation, erosion and anisotropic diffusion filter. For liver lesion, they use mathematical morphology, especially on the water shed technique. They use private data set. The proposed scheme achieves 92% Sensitivity & 99% Specificity. Brief graphical representation is shown in Fig.4. Here we focus only on the graphical representation of the liver. Pictorial representation of liver lesion is not represented here.

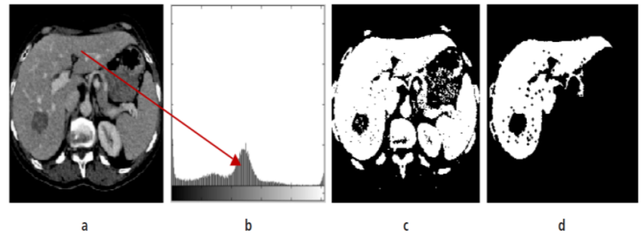


Fig. 4. Original image Histogram Thresholding Liver extraction

Marcin Ciecholewski [18] present novel method which automatically segments the liver shape. In CT scan images lumber section of the spine is utilized as seed point. After seed point selection, joint polylines are drawn to approximate the liver contour. These component polylines frames the components of two polygons eliminated from the image, which leaves only the segmented liver shape inside the image. Results are accessed on 13,30 images using Dice's similarity. Fig. 5 shows the results graphically.

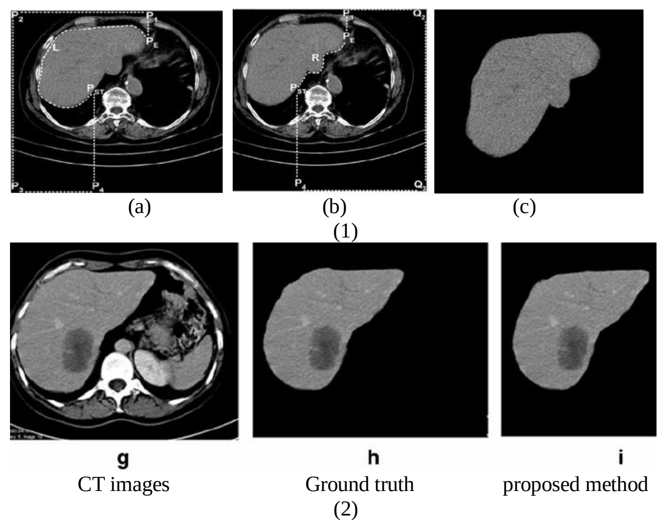


Fig. 5. (1) (a)Polygon with polyline L(b) Polygon with polyline R(c)segmented liver (2) Segmentation of liver shape using connected polylines

Anter et al [20] proposed hybrid approach using adaptive threshold and CCL for liver segmentation. For liver lesion segmentation, their method based on watershed [14] and region growing. RG algorithm has their limitation such as initial point position and its selection highly affects the segmentation result if they are not properly handling well. So, to overcome these limitations the integrate RG with watershed algorithm. Their 2 dataset consist of 112 Patients, one of radiopaedia website and aother is a local dataset collected from a local hospital. The computational time is 0.15s/slice. Overall, liver extraction accuracy is 93%. (CY) cyst (hepatocellular carcinoma), (HG)hemangioma, (HA) hepatic adenoma, (FNH) Focal nodular hyper plasma, (CC) cholangiocarcinoma, (MS)metastases achieve the accuracy 0.91, 0.90, 0.93, 0.95, 0.91, 0.94, 0.94 %respectively.

*Aldeek et al [*21] develop semiautomatic method using a Bayesian classifier for liver segmentation. In post processing, median filter and some filling operation are performed to further refine the classifier results. Dataset consists of 44 cases. Average area overlaps accuracy is over 87% They evaluate their results with the manual segmentation done by the expert radiologist. Graphical representation is shown in Fig.6.

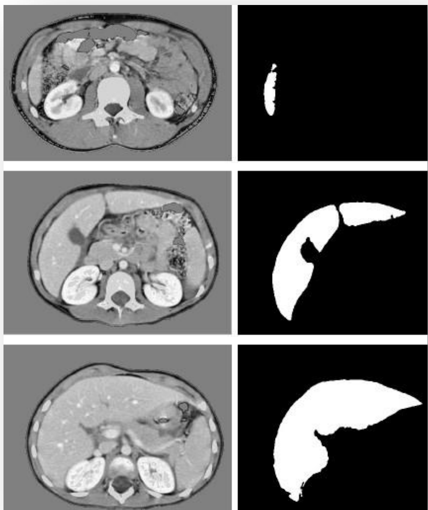
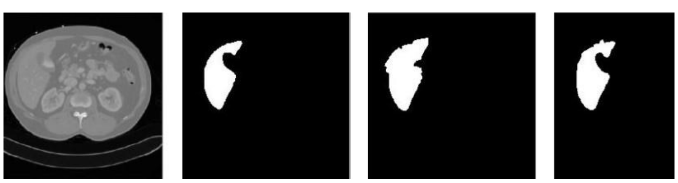


Fig. 6. Bayesian classifier segmentation results

Altarawneh et al. [30]in this paper researcher modify DLSR (Distance regularization level set) [1] method because it does not work well in case of weak or without edges of liver images. [30] overcome this issue by introducing new Balloon force that control weak and without the edges region by slowing down and controlling the evaluation process. Balloon force was created by utilizing probability density energy function to control the speed and energy of the evaluation process. Experiments were performed on 10 cases of 512*512 pixels Slices. Graphical representation of comparison are shown in Fig. 7 below.



CT Slice Ground Truth Original DSLR Proposed DSLR

Fig. 7. Comparison of DLSR with proposed DSLR with balloon force

III. LIVER SEGMENTATION TECHNIQUES

A. Active contour

Active Contour is the energy minimizing, deformable curves that moves due to the effects of internal and external object forces to detect object boundary. Internal forces prevent deformation. "The contours are classified broadly into two categories as: parametric active contours and geometric active contours. Parametric active contours are again classified into three types: Traditional snake, GVF snake and Ballon forces. Geometric active contours are Level set".

Basically, snakes use energy minimization to match a deformable model of an image.

General snake or active contour faces two problems:

- Initial model must be close to the boundary, otherwise it will show wrong result
- This model confronting issue to progress into boundary concavities.

AC [9][6][7] [13] model generally need manual initialization which is close to the image contour, otherwise it will give under or over segmentation problem. In case of liver segmentation, it causes over segmentation problem because liver share same intensity with the adjacent organs. It easily streams to the neighboring organ and cause over segmentation problem. Its performance is degraded if there should be an occurrence of irregular and higher intensities. Some of online available matlab codes are: [34] [35][36].

B. Gradient vector flow

Gradient Vector Flow [5] deal with two issues of the active contour model. It can converge into boundary concavities by calculating both concave and convex features. The traditional snake model must start close to the boundary while GVF [6][7] have the ability to start far from the boundary and till can converge to the image boundary. By and large, GVF demonstrate insensitivity to the initialization. GVF contour can handle broken object edges and subjective contour. Some of available code for GVF are in [37]

C. Level set

LS [13][16][30]semi-automatic techniques since it oblige user to select seed point.LS performance is very rely on the initial position, its performance increase when initial contour is placed close to the hepatic boundary .Its performance is degraded when the object is without edges or have weak edges[1]. The liver has the same intensity as the neighboring organs, hence cause over segmentation issues. Level set is time consuming for large computation. Level set strategy is additionally utilized for refinement of the liver segmentation. Some Matlab code accessible online is [38].

D. Graph cut

Graph Cuts, or max-flow/min-cut, is a generic technique for minimizing a specific form of energy called Markov random field (MRF) energy. In GC, image is represented using undirected weight graph. Each pixel represents every node of the graph. Each edge associated a couple of adjoining pixels. Similarity of grey level demonstrates the weight of edges between every match. Segmentation is the cut of graph. Every region speaks to a subgraph. The best cut is to make the subgraph similitude in a subgraph maximum and the closeness between the subgraph minimum. It is semi-automatic method since it requires user intervention for seed point selection which label the foreground and background. GC is not iterative method Graph cut is functioning admirably in homogenous area. Graph cut [3] can be made fully automatic using different algorithms. In case of liver tumor segmentation general active contour come up short when tumor is near liver surface, graph cut handle this kind of active contour issues extremely well.

E. Adaptive thresholding

Adaptive Thresholding [3] is additionally called local or dynamic thresholding. The principal idea of adaptive threshold is to apply different threshold on the different region of the image. Adaptive threshold divide the image into small areas and apply different threshold in different areas. On adaptive threshold value at each pixel location is depends on the neighboring pixel intensity. This type of thresholding is functioning admirably in irregular intensities and can handle the lightening condition extremely well. Adaptive threshold work on a pixel level, it sets all the pixel as foreground whose intensity value is greater than a certain threshold and all other pixels as background. Adaptive threshold work on color and grey scale image by converting it into a binary image. Adaptive threshold follow two approaches to find the threshold for every pixel: (i) the *Chow and Kaneko* approach and (ii) *local* thresholding. General online link for adaptive matlab code in [39].

F. Region growing

Region Growing [15][20][23][19]technique is semi-automatic strategy, since user interaction is required as the seed point is chosen by the user. RG method divides the image into regions according to predefine basis. This technique is initiates utilizing seed point, and examine the neighboring pixel either utilizing 4 connectivity or 8 connectivity, it iteratively adds the pixel to different region as indicated by predefined criteria. The criteria could be pixel intensity, gray level texture or color. In case of liver segmentation this technique gives great outcomes in contrast enhance images. Its effectiveness is relying on the determination of the seed point. Some of the RG code available online are [31][32][33].

G. Fuzzy clustering mean(fcm)

FCM is developed by dunn [40] is widely utilized in medical image processing. Its originate from the k mean algorithm. In k mean algorithm, each pixel is belonging to only one k cluster which is not feasible in case the of liver segmentation. FCM overcomes this issue by utilizing membership function which shows the belongings of the pixel to the cluster. FCM is fuzzy clustering technique which allows a pixel to belong to one or more clusters. FCM is a semi-automatic method. Some parameters like the selection of centroid, the degree of fuzziness and stopping criteria highly effects the performance of the FCM. In case of liver segmentation. FCM is mostly used for tumor segmentation [15] from the CT data.

H. Statistical shape model(ssm)

SSM [28][29][11]are find extremely effective in liver segmentation. The liver has an exceptionally varying shape. In this approach, probabilistic model is made to adapt to the varying shape of the liver. SSM can deal with the limitation of gray level techniques extremely well. During segmentation of liver, grey level techniques frequently appear under or over segmentation issues when the tumor is close to liver boundary. This constraint of grey level techniques can handle utilizing SSM. Utilizing the prior knowledge SSM can deal unclear boundary of the liver extremely well. SSM focus on the shape of the liver. Limitation of shape based method and classifier based method [8][23]is the they require great number of training dataset.

IV. Conclusion

The different segmentation techniques review has been done in this paper. Here the review of preprocessing, main segmentation technique, and their dataset information is provided in the form of a table. Comparative evaluation of different method is not possible in light of the fact that every author utilizes small private dataset set and different performance measure criteria are utilized. For objective comparison, for the most part acknowledge performance measures are required. From review of the techniques, it is concluded that there is still need to discover robust and efficient method for liver segmentation. As the liver is exceptionally difficult organ to handle and segment. Each existing method has its own advantage and disadvantages they are not full robust. Future work is to cover the classification techniques for liver tumor.

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TABLE I. COMPARISION OF DATASET

Ref	Author	Year	Images used	Datatypes	Image size
[2]	Lim et al	2005	10cases	Private dataset	512*512
[3]	Massoptier et al	2007	10cases	Private dataset	-
[4]	Rusko et al	2007	10cases	-	-
[5]	Gui et al	2007	4cases ,200images	Private dataset	170*170
[6]	Alomari et al	2008	13cases	Private dataset	512*512
[7]	Massoptier et al	2008	21cases	Private dataset	512*512
[8]	Mala et al	2008	105 images	Private dataset	256*256
[9]	Jiang et al	2009	5 cases	-	-
[10]	Yussof et al	2010	10cases	-	512*512
[11]	Akram et al	2010	100images	Private dataset	512*512
[12]	Militzer et al	2010	15cases	Private dataset	-
[13]	Suzuki et al	2010	15cases	Private dataset	-
[14]	Wang et al	2010	100images	Private dataset	512*512
[15]	S.S Kumar	2011	10cases	-	512*512
[16]	Li et al	2009	15cases	LTSCdataset NUHdataset	512*512
[17]	Belgerbi et al	2013	-	Private dataset	-
[18]	Ciecholewski	2014	1330 images 120 cases	Private dataset	-
[19]	Lopez-mir et al	2013	30 cases	Private dataset	512*512
[20]	M.Anther et al	2013	112cases 860 images	2 Private datasets	630*630
[21]	ALDEEK et al	2014	44cases	Private dataset	512*512
[22]	Mostafa, et al	2015	38CT images	Private dataset	-
[23]	Cheng et al	2016	800images	Open NBIA Private dataset	512*512
[24]	Sayed et al	2016	62 Images	-	256*256
[25]	Sayed et al	2016	43 images	-	256*256

TABLE II. LIVER SEGMENTATION TECHNIQUES OVERVIEW

REF NO	PRE-PROCESSING	LIVER SEGMENTATION	EVALUATION
[3]	Mean shift filter Adaptive threshold	Graph cut	Accuracy 96%
[4]	Hough transform Erosion/dilation Largest CCL	Region growing	Accuracy 76%
[5]	Canny edge detector Hermit spline curve Anisotropic diffusion filter	GGVF	-
[2]	Multilevel thresholding Morphological filter	Gradient label map K mean clustering Label based search algorithm	Accuracy 96%
[6]	Histogram analysis Markov random field	Gradient vector flow Active contour	Similarity matrix
[7]	Adaptive threshold Mean shift filter	Gradient vector flow Active contour	A volume overlap of liver 94.2% Sensitivity &specificity for tumor 82.6%& 87.5% respectively
[9]	Sobel operator Erosion/dilation	Active contour	Accuracy 94%
[10]	Opening Multiscale filtering Anisotropic diffusion filter	CCL Graph Cut	-
[11]	Median filter Adaptive Histogram Power law transformation	Closing Largest area Global threshold	Accuracy 96%
[13]	Anisotropic diffusion filter Median filter Scale specific gradient magnitude filter	Fast marching Level set Geodesic active contour	Manual tracing method
[14]	Gradient magnitude Anisotropic diffusion filter	Random walk algorithm Watershed	TP, TN, FP, FN Manual tracing method
[15]	Median filter/ Erosion Largest CCL	Region growing Alternate FCM	Manual tracing method
[16]	Morphological operations	Fuzzy Clustering Mean/ Level set Balloon force	-
[17]	LIVER: H max transform Dilation/erosion Lesion: Anisotropic diffusion filter Hmaxima transform filter	Watershed algorithm	Sensitivity & specificity 92% & 99 % respectively
[18]	-	Connected poly lines	DICE similarity co efficient 81.3%
[19]	Adaptive filter Dilation/erosion	Region Growing	-
[20]	Erosion/dilation Adaptive threshold	CCL Region Growing Watershed	Accuracy 96%
[21]	Convert intensity value into Hounsfield units Median filter	Bayesian Model	Accuracy 87%
[22]	Median filter Contrast Stretching Thresholding to separate Ribs	Artificial bee colony Optimization algorithm	Accuracy93.73%
[24]	Median filter	FCM Grey Wolf Optimization SVM	Accuracy 96%