Liver Segmentation: A Survey of the State-of-the-art

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***Abstract* - With tremendous technological development in all ways of life, it has become necessary to develop the medical fields, including the diagnosis on which treatment is done; where the successful treatment depends on the preoperative. Examples for the preoperative such as planning to understand the complex internal structure of the liver and accurately localize the liver surface and its tumors; there are numerous algorithms proposed to do the automatic liver segmentation. In this survey paper, we analyze critically some of different published works for liver segmentation algorithms since 2007 till 2016. This paper also compares and contrasts the methods, datasets, results and limitation for each work. A comprehensive comparative analysis is conducted.**

Keywords—Liver Segmentation, Computed Tomography, Convolutional Neural Network, Supervoxel, Graph Cuts

I. INTRODUCTION

The liver is a wedge-shaped organ on the right side of upper abdomen; it is biggest gland in body and responsible for carrying out some very important functions to keep the body pure of toxins and harmful substances [1]. Modern surgeries rely on Computer Aided Diagnosis (CAD) systems to assist doctors in the diagnosis of medical images and surgical planning. CAD it is one of the major research topic because it is part of the routine clinical work in medical imaging and diagnostic radiology[2]. Liver pathologies such as cirrhosis, liver cancer and fulminant hepatic failure can be diagnosed by using non-invasive techniques (Medical imaging) such as computed tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), Positron Emission Tomography (PET) or Single-Photon Emission Computed Tomography (SPECT). one of the advantages of CT images it is their higher signal to noise ratio, better spatial resolution and they provide a more accurate anatomical information about the visualized structures;therefor, the diagnosticians are preferred to use a CT image[3]. Because of complexity of liver shapes and variable liver sizes among patients the segmentation of the liver from medical images is very difficult and also due to low contrast between the liver and surrounding organs like stomach, pancreas, kidney and muscles[4]. Moreover challenge is presence large tumors and other liver pathologies because the livers with pathologies are different from healthy one and that result either under segmentation or over segmentation. In the last few decades, a large variety of semiautomatic and fully automatic approaches have been proposed to improve the liver segmentation procedure, such as: region growing, clustering, deformable models or level sets, statistical shape models (SSMs), probabilistic atlases, graph cuts and recently, deep convolution neural networks[5][6].There are many efforts to survey the methods for liver segmentation and each one of them divides and categories the methods based on different point of view, such as in [7]; which they use the image feature to categories the methods into three main classes including gray level based method, structure based method and texture based method as shown in Fig. 1.

II. LITERATURE REVIEW

There are many semiautomatic and fully automatic approaches have been proposed to improve the liver segmentation procedure. In[8], a fully automatic framework was proposed for liver segmentation based on 3D convolutional neural network (CNN) and globally optimized surface evolution. Firstly, the deep 3D CNN gives the initial liver surface after it was trained to learn a subject-specific probability map of the liver. Then, refining the initial liver segmentation by using the prior information about novel energy function; Finally, propagated the initial liver surface to the optimal position by minimized the energy function using a global optimization-based approach.

A novel method was proposed in[9] , for automatic segmentation of liver using supervoxel based graph cuts. They were automatically extract the Liver Volume of Interest (VOI) and the foreground/background seed points for graph cuts.Firstly, they were determining the region of abdomen by using the Maximum Intensity Projection (MIP) and thresholding methods. And extract the specific liver VOI from the region of abdomen according to prior knowledge about locating of liver organ and by using a histogram based adaptive thresholding method and morphological operations.They generated the supervoxels of the liver VOI by using the Simple Linear Iterative Clustering technique. Secondly, foreground/background seeds for graph cuts were selected on the largest liver slice, and the graph cuts algorithm was applied to the VOI supervoxels.

The authors in [10] proposed a novel 3D liver segmentation method based on multi-region appearance and graph cuts approach in order to reducing user interaction and improving the accuracy and efficiency.

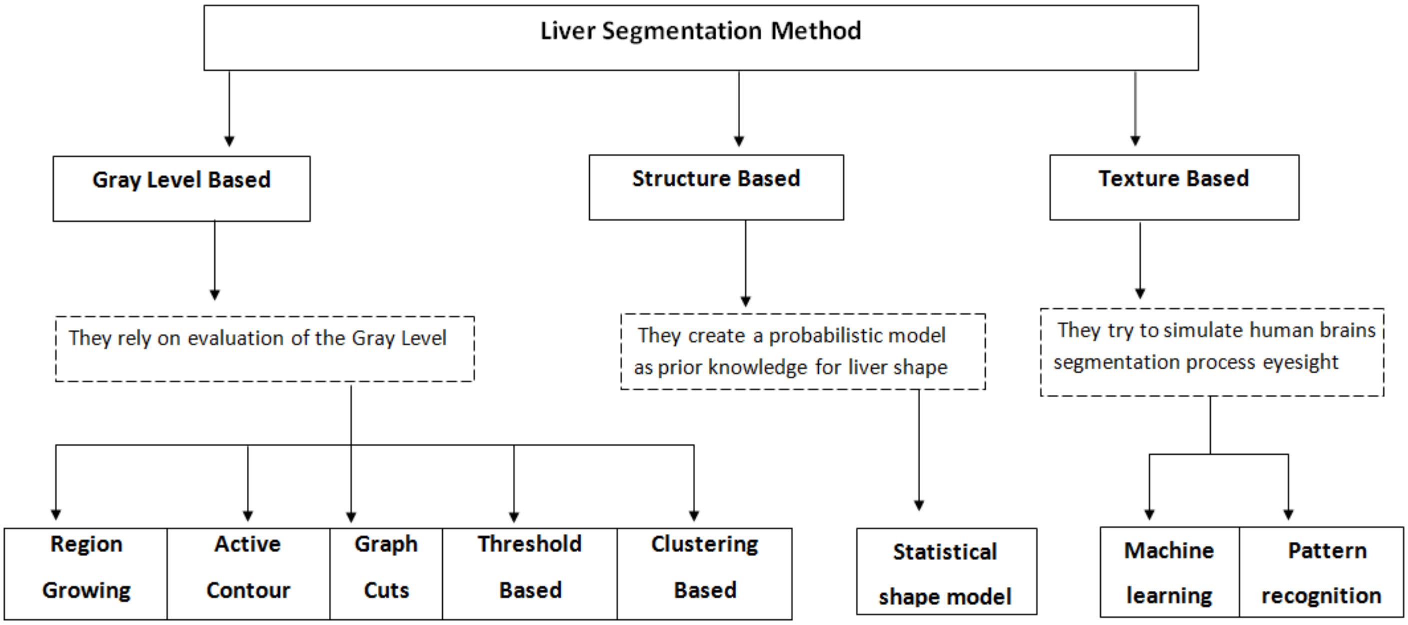

Fig.1 Categorization of Liver Segmentation Methods [7]

The liver could contain tumor or metastasis which it result liver with multiple sub-regions, for such case they introduced a novel multiregion-appearance model and appearance selection scheme to segmenting the target multiregion object. The graph cuts approach was used to optimized the proposed energy function. They had compare their work with other graph cuts based methods, state-of-the-art semiautomatic and interactive methods and with prior model based methods. They found that the proposed model needs only initial seeds in the liver when compared with the other graph cuts methods and it required low interactive compared with the other semiautomatic and interactive methods and also the proposed model can be applied to livers with any shape because it was not restricted by specific training data when compared with prior model based methods.

A Fully automatic CT liver segmentation using a novel statistical shape model approach was presented by [11] that combine learned local shape constraints with observed shape deviation during adaptation.

[12]Presents a new hybrid fully automatic method for fast segmentation of the liver and the lesions inside the liver by using statistical model-based approach and active contour technique. There is no required interaction with the user. The role of statistical model approach was to distinguish the liver tissue from other surrounding abdominal organs. In the other hand the active contour technique used in order to obtain more natural and smoother liver surface segmentation. They compared length of processing time of their work with and the accuracy with manual contour-drawing approach made by an expert radiologist who delineated each liver slice using a public-domain image processing program (ITK-SNAP[17]). The assessment expressed a good result but the algorithm faced some limitations in special pathological and anatomical situations, such case is when the heart and the liver were in close contact, so difficult to distinguish the limit between these two organs, as result of that part of the heart included into the liver segmentation.

A single-block linear detection algorithm (SBLDA) for automatic liver segmentation from abdominal CT images was proposed in [13] ,they successfully reveals satisfactory segmentation results in abdominal CT images with low contrast, also in decreases the computational time because it does not require iteration and initialization. Mainly their proposed method consist of three major parts: image preprocessing, liver edge extraction with SBLDA, and image post-processing. They compared their proposed algorithm with Shi's method (MLR-SSC [18]) ; where their method not affected by initial shapes and saves considerable runtime ,on the contrary the Shi's method affected the by initial shapes which result leading to significant segmentation error.

A supervised learning algorithm for liver segmentation in CT image is presented in [14], it was extension of the method in [19], which is the minimal cost path segmentation method; and also it is similar to Active Shape Model segmentation methods in the sense that it modeling the object as a set of landmarks (vertices) and connections between neighboring landmarks (edges); but it differ in applying multiple local shape models instead of using a global shape model. For the local shape and gray-level appearance a statistical models were built based on a set of training images and corresponding surface meshes. The proposed work was demonstrates the potentially of segmenting the liver in contrast enhanced CT images when validated in the first implementation and it was participated in the Grand Challenge on 3D segmentation (MICCAI 2007) [20].

Liver tumors detection and segmentation method was developed in [15], using fast learning algorithm Extreme Learning Machine (ELM). Two-class ELM classifier used to detected and segmented the suspicious region of tumor which it firstly was learned for voxel classification using the tumor/non-tumor samples selected by the user, followed with erosion and dilation operation to morphological smoothing. They also proposed one-class ELM for tumor detection where the user only needs to select healthy liver samples; and compared it with two-class ELM. A semi-automatic approach used to extract the boundary of a tumor by randomly selecting samples within a limited region of interest for classifier training where each voxel is associated with a set features such as entropy, Law's features [21] and sum-and-difference histograms [22]. Their proposed kernel based ELM achieves an encouraging results when compared with traditional ELM, and it also faster than SVM [23] [24]. And because of the available more tumor information in two-class ELM; it shown a relatively higher accuracy when compared with one-class ELM, but not in the case of unknown tumor.

A semi-automatic method to identify tumors from 3D CT scans based on 2D region growing with knowledge-based constraints was proposed by [16]. Firstly,they decompose the 3D scan image into component slices.Then, theyapply 2D region growing with knowledge-based constraints on each slice. Finally,they load up the individual segmented lesions together to generate a 3D volume. The region-growing approach used to calculate the seed point and feature vectors and also to label the voxels. The Knowledge-based constraints were used to ensure that the segmented region size and shape is within acceptable parameters. The method was require a minimal user involvement in order to define an approximate region of interest around the lesion in each slice image which improved the performance of region growing, as well as reduces computational requirements.

III. Discussion

Table I shows a summary of various liver segmentation works that discussed in the literature review along with its used methods, result and limitations of each one. These works are varying on the segmentation algorithms, the number and types of metric used for evaluation, dataset and level of user interaction. The authors in[9] and[13] reduce the computational time by constructing the graph over supervoxels instead of the voxels in [9]and it does not require iteration or initialization in [13]. The algorithm in [12] fails to separate the liver from the heart. In contrast, the authors in [9] they succeeded in separating the liver from heart and kidney and also when the tumors are presence in the liver. But, there were still some small segmentation errors occurring near the liver boundaries at the tip of the liver and at the place of vena cava. On other hand, the work of [8], automatically generate additional foreground seeds on both the liver and tumor regions; therefore, they successfully segmenting livers with tumors near the boundary and inhomogeneous appearances. Instead of modeling the liver and tumor independently as some other algorithms, the authors of [10] introduce a novel multiregion-appearance model in order to segment the target multiregion object; also they needs only initial seeds in the liver. The main advantages of the framework of [13], is to overcome the problem of weak edge areas and also the artifacts cases. The underlying technique for their proposed framework was used to segment retinal blood vessels. But, there was much segmentation error exists in small liver regions and it fail to extract the tumor at the edge of the liver. The work of [16], have some limitation in that there is a poor lesion segmentation result due to low contrast visibility and non-uniform lesion texture.

IV. CONCLUSION

The liver segmentation is faced challenging problems such as: shape variations of the liver, inhomogeneous appearances, existence of metastasis, subregions livers. In addition, must separate the liver from surrounding organs and tissues with similar intensities and more important is livers with tumors reside near the boundary. The problem of automatic liver and tumor segmentation is still open based on the review of the state of the art described in this paper. Although there are a great deal of effort to develop the liver segmentation algorithms, but there is still some algorithms fail to segment special cases due to the complex liver shape, while the others still require the user interaction. And some other they do not segment both liver and tumor. The works of [15] [16] segmenting the tumor only, and the works of [8] [9] [10] [11] [13] segmenting the liver only, the only work segmenting both liver and tumor is [12], but it fail to separating the liver from heart which is successfully done in work of [9]. Some of the works faced some limitations such as when the liver contains tumor at the edge; the authors of [9] and [13] fail to segment small part of the liver due to either the liver has tumor in the boundary or in the liver tip area which it is a challenging area in the liver. On the other hand, the authors of [8] successfully deal with tumor at the edge. The area of vena cava is miss segmented by [9] and not mention in other works. Generally, the observed advantages of large number of works from the literature tend to be in using a dataset from different data sources. In another hand, they are lacking in the small dataset size where the range of the dataset size is between 10 and 86 image.

TABLE I. OVERVIEW OF LIVER SEGMENTATION METHODS: VOE = VOLUMETRIC OVERLAP ERROR, RVD =RELATIVE VOLUME DIFFERENCE, ASD=AVERAGE SYMMETRIC SURFACE DISTANCE, RMSD= ROOT MEAN SQUARE SYMMETRIC SURFACE DISTANCE, MAXD=MAXIMUM SYMMETRIC SURFACE DISTANCE, VO=VOLUME OVERLAPPED, VD=VOLUME DIFFERENCE, ACCU_ LIV_SURF_ SEG = ACCURACY OF LIVER SURFACE SEGMENTATION, SENSI_TUM_SEG= SENSITIVITY FOR TUMOR SEGMENTATION, SPECI_TUM_SEG =SPECIFICITY FOR TUMOR SEGMENTATION ,DIFFHOS = FROM DIFFERENT HOSPITALS, SLIVER07 = MICCAI 2007 LIVER DATASETS.

Authors	Year	Used Method	Datasets	Result	Limitations
Hu P et al. [8]	2016	3D Convolutional Neural Network (CNN) and Globally Optimized Surface Evolution.	Sliver07 + local hospitals	VOE = 5.35±1.23% RVD = - 0.17 ±1.34% ASD = 0.84±0.25 mm RMSD = 1.78 ±0.56 mm MSD = 19.58± 3.07 mm overall score = ±80.34.5	Spent 80% of computation time on calculation data term.
W. Wu [9]	2016	Supervoxel Based Graph Cuts	Sliver07	VOE = 7.87% RVD = 1.31% ASD = 1.286 mm RMSD = 2.498 mm MaxD = 23.563 mm	-Small segmentation errors occurring near the liver boundaries at the tip of the liver and at the place of vena cava.
L. Huang et al. [13]	2016	Single-Block Linear Detection Algorithm (SBLDA)	3D-IRCAD	-sensitivity =96.59% -accuracy= 98.65% -specificity = 99.03%	-segmentation error in case of small liver regions - fail to extract tumor in the edge of the liver
Peng J et al. [10]	2015	A Novel Region-Appearance And Graph Cuts.	MICCAI + MICCAI 2007 + local hospitals	VOE = 4.58%±0.51% RVD = 1.08%±0.80% ASD = 0.68±0.14 mm RMSD = 1.45±0.36 mm MSD = 16.89±3.69 mm computation time = 2–3 min overall score = 83.4±3.1	-------------
W. Huang et al. [15]	2013	fast learning algorithm Extreme Learning Machine (ELM),	DiffHos	mean VO =67.15% mean VD =14.16% mean ASD =2.27mm mean RMSD=2.47mm mean MSD= 8.46mm	-------------
Erdt et al. [11]	2010	learned local shape constraints with observed shape deviation	3D-IRCAD	-average mean surface distance =1.3---1.85 mm - processing time =45 s	-------------
Massoptie et al. [12]	2008	Statistical Model-Based Approach And Active Contour Technique	DiffHos	-VO = 94.2% -Sensitivity= 82.6% -specificity =87.5%, -accuracy of liver surface segmentation = 3.7 mm - processing time = 11.4 s for a 512×512-pixel slice	-Fail to separating the liver from heart
D. Wong et al. [16]	2008	2D region growing with knowledge-based constraints	DiffHos	Ave Overlap Error =39.40 % Ave Volume Difference= 24.20% Ave Surface Distance=2.20mm RMS Surface Distance =3.02mm Max Surface Distance=12.69mm Total Score =64	-Have some poor lesion segmentation result due to low contrast visibility and non-uniform lesion texture
Hermans et al. [14]	2007	Supervised Learning Algorithm	Sliver07	the method has potential to result validated segmentation	-Too small search regions during segmentation

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