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A Study of Effective Segmentation Techniques for Liver Segmentation

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Abstract
Segmentation of liver for transplantation planning and detection of disease remains the most challenging task in medical image processing due to high rate of inter-patient variability in liver shape, size, volume and pathologies or other diseases. Liver Segmentation helps physicians to decide whether liver disease is focal or diffused. So, determination of more efficient methods of liver segmentation to reduce the rate of errors is a vital issue among researchers. The purpose of this paper is to gather various segmentation techniques that can be used for efficient segmentation of liver. The paper provides good starting for researchers in automatic liver segmentation.

Keywords:
Image Segmentation, K-means Clustering, Level Set Method, Liver Segmentation, Watershed Segmentation

1. Introduction

Liver is an important organ with several vital functions such as for example protein synthesis and detoxification. Additionally, it regulates biochemical reactions offering the synthesis or break down of complex and small molecules and produces bile, that will be an alkaline compound aids in digestion. Yet, no technique or device can compensate for the absence of the liver. The only real available option is liver transplantation, which really is a major and risky surgery. Although transplantation from cadavers utilized to be the very first choice, transplantation from living donors has become a array of treatment as a consequence of shortage of cadaver donation in recent years. [1]. Image segmentation is really a procedure to partition a graphic into non-overlap regions, that is a significant step in the image processing area and is fundamental to the analysis and identification in image processing. Image segmentation is a significant process for every one of the medical image analysis tasks, that is basic for higher-level image comprehension and analysis. A great segmentation will benefit clinicians and patients because it gives important information for surgical planning, early disease detection and 3D visualization [4]. To be able to solve the issues of medical image segmentation, many practical methods have already been advanced in this field. These generally include watershed segmentation, thresholding method, region-growing method, fuzzy cluster method and so on. Prior to the surgical procedure, the livers that belong to the living donor and the recipient are evaluated: to recognize the liver region, to ascertain the size mismatch, to measure liver volume, and to analyze the vascular structure. Knowledge obtained by the evaluation is necessary to decide whether the donor and recipient is a great match and when the transplantation must certainly be performed.

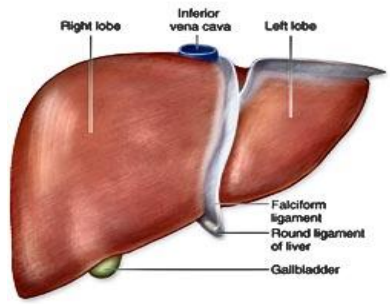

Fig: Overview of liver in human body

The success of the surgical operation and reduced quantity of complications (which may occur during or after the operation) to minimum level depends upon accuracy of anatomic information of the portal and hepatic veins, compatibility of those vessels and liver volume. Therefore, precise measurements and analysis of liver and vessels that really needs accurate liver segmentation from all image slices have vital importance for liver transplantation at pre-evaluation stage. Several automatic and semi-automatic liver segmentation methods from Computed Tomography (CT) and from Magnetic Resonance(MR)images have now been proposed to overcome problems of manual liver segmentation. A vital problem of manual segmentation is that liver boundaries may be identified differently by different radiologists and even by the exact same radiologist at an alternative solution time. Thus, segmentation results rely on

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experience and skills of radiologists. Also, it is rather time intensive and tedious task as a result of large amount of image slices and datasets.

2. Literature Survey

Militzer, A. et al. [16] proposed a novel system for detecting and segmenting focal liver lesions in CT images automatically was presented. It utilizes a probabilistic boosting tree to classify points in the liver, thus providing both detection and segmentation of the lesions at the same time and fully automatically. To make the segmentation more robust and effective, an iterative classification scheme was incorporated, that uses knowledge gained from earlier iterations into later decisions. Finally, a comprehensive evaluation of both the segmentation and the detection performance for the most common hypo dense lesions was given. Detection rates of 77% could be achieved with a sensitivity of 0.95 and a specificity of 0.93 for lesion segmentation at the same settings.

Gambino, O. and et al. [17]proposedan automatic texture based volumetric region growing method for liver segmentation was proposed. 3D seeded region growing was based on texture features with the automatic selection of the seed voxel inside the liver organ and the automatic threshold value computation for the region growing stop condition. Co-occurrence 3D texture features are extracted from CT abdominal volumes and the seeded region growing algorithm was based on statistics in the features space.

S. S. Kumar and et al. [15] proposedan approach for automatic and effective segmentation of liver and lesion from CT images needed for computer-aided diagnosis of liver is proposed. The method uses confidence connected region growing facilitated by preprocessing and post processing functions for automatic segmentation of liver and Alternative Fuzzy C-Means clustering for lesion segmentation. The algorithm was quantitatively evaluated by comparing automatic segmentation results to the manual segmentation results based on volume measurement error, figure of merit, spatial overlap, false positive error, false negative error, and visual overlap.

Ahmed M. Mharib and et al. [18]presented a review on liver segmentation methods and techniques using CT images, recent methods presented in the literature to obtain liver segmentation are viewed. Generally, liver segmentation methods are divided into two main classes, semi-automatic and fully automatic methods, under each of these two categories, several methods, approaches, related issues and problems will be defined and explained. The evaluation measurements of liver segmentation are shown, followed by the comparative study for liver segmentation methods, advantages and disadvantages of methods was studied carefully. In this paper, they concluded that automatic liver segmentation using CT images was still an open problem since various weaknesses and drawbacks of the proposed methods can still be addressed.

SuhuaiLuo and et al., [19]presented a way of summarizing the latest achievements in automatic liver segmentation. They suggested a segmentation method according to the image feature it works on, therefore summarises performance of each category and leading to finding an optimal solution for a particular segmentation task. All the methods of liver segmentation are categorized into three main classes including gray level based method, structure based method and texture based method. In each class, the latest advance was reviewed with summary comments on the advantages and drawbacks of each discussed approach. Performance comparisons among the classes are given along with the remarks on the problems existed and possible solutions. In conclusion, they pointed out that the tendency was that multiple methods will be employed together to achieve better segmentation performance.

Shi Na and et al., [23]discussed he standard k-means clustering algorithm and analyzes the shortcomings of standard k-means algorithm, such as the k-means clustering algorithm has to calculate the distance between each data object and all cluster centers in each iteration, which makes the efficiency of clustering was not high. This paper proposes an improved k-means algorithm in order to solve this question, requiring a simple data structure to store some information in every iteration, which was to be used in the next interation. The improved method avoids computing the distance of each data object to the cluster centers repeatly, saving the running time. Experimental results show that the improved method can effectively improve the speed of clustering and accuracy, reducing the computational complexity of the k-means.

3. Liver Segmentation Techniques

3.1 Region Growing

It can be classified as a pixel-based image segmentation method as it involves the choice of initial seed points. This method starts with initial "seed points" and then examines neighboring pixels (using either 4-connectivity or 8-connectivity) to find out perhaps the pixel neighbors ought to be added with the region. The method is iterated on, in the exact same manner as general data clustering algorithms. The region

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growing algorithm is described in [20] as: (i) Select several seed points. Seed point selection is dependant on some user criterion (for example, pixels in a particular gray-level range, pixels evenly spaced on a grid, etc.). The first region begins as the complete precise location of the seeds. (ii) The regions are then grown from these seed points to adjacent points according to a location membership criterion.

The criterion could be pixel intensity, gray level texture or color. Due to the fact the regions are grown on the building blocks of the criterion, the image information itself is important. For instance, if the criterion were pixel intensity, examine the adjacent pixels of seed points. If they've the same intensity value with the seed points, classify them to the seed points. It is surely an iterated process until there's no change in two successive iterative stages. The suitable choice of seed points is just a significant issue.

3.2 K-Means Clustering

K-means is one of many simplest unsupervised learning algorithms that classify a given data set into certain quantity of clusters (assume k clusters) fixed a priori. The key idea is always to define k centroids, one for each single cluster [1]. These centroids must certanly be put right into a cunning way, because different location causes different result. So, the greater choice is to position them as much as possible far from each other. The next thing is always to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early on grouping is done. Again re-calculate k new centroids of the clusters (resulting from the final step). After having these k new centroids, a fresh binding needs to be performed between the same data set points and the nearest new centroid [2]. Repeat the strategy until centroids don't move any more. In the successive loops, the k centroids change their location detail by detail. The K-mean algorithm uses the following distance formula to compute the distance of the n data points from their respective j^{th} cluster center.

3.3 Level Set Method

This method can handle topological changes and define the problem in higher dimension, but this method is time consuming and results in over segmentation. The Segmentation using level set method that evolves according to a speed image that is the result of a scanning technique based dynamic programming. The main limitations is level set method adjusts this first segmentation using a speed function obtained from a pixel classification algorithm [1]. The accuracy is only sufficient in a small number of cases. The level set method is initially proposed to track moving interfaces and has spread across various imaging domains. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner. The central idea is to represent the evolving contour using a signed function whose zero corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero level will reflect the propagation of the contour. The level set method affords numerous advantages: it is implicit, is parameter-free, provides a direct way to estimate the geometric properties of the evolving structure, allows for change of topology, and is intrinsic. It can be used to define an optimization framework. One can conclude that it is a very convenient framework for addressing numerous applications of computer vision and medical image analysis. Research into various level set data structures has led to very efficient implementations of this method.

3.4 AdaptiveThresholding

Thresholding is called adaptive thresholding when a different threshold is employed for different regions in the image. This are often referred to as local or dynamic thresholding. Adaptive Thresholding subdivide original image into small areas and utilize a different threshold to segment each sub images. Because the threshold employed for each pixel depends on the precise location of the pixel with regards to the sub images, this type of thresholding is adaptive [29]. An approach to handling situations in which single value thresholding will not work is always to divide a picture into sub images and threshold these individually Because the threshold for every pixel is dependent upon its location in a image this technique is believed to adaptive. We utilize the adaptive thresholding for segmentation of liver tumour in CT images. Threshold process convert CT image directly into binary image. The process of adaptive thresholding is the following:

1) Adaptive Thresholding divide original CT image into sub images.
2) Utilize a different threshold to segment each sub images.
3) Difficulties occur in subdivision and subsequent threshold estimation.

3.5 OTSUThresholding

The Otsu method is a popular non-parametric method in medical image segmentation, because of the ease of implementation and the relative complexity. Otsu's method is used to automatically perform histogram shape-based image

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thresholding. Its basic objective is to classify the pixels of a given image into two classes or bi-modal histogram (e.g. foreground and background), then calculate the optimum threshold separating those two classes minimizes the intra-class variance (within class variance), defined as a weighted sum of variances of the two classes.

3.6 Region Splitting and Merging

The split-and-merge algorithm is composed by two steps. First, the method subdivides the entire image into smaller regions following a dissimilarity criterion.
To divide the image, different strategies can be adopted such as a quad tree partition (where each region is subdivided into four equal regions) and a binary space partition (BSP) (where an optimal partition is selected to divide the region).[5] Second, the neighbor regions obtained from the splitting step are merged if they verify a similarity criterion.
These similarity and dissimilarity criteria can be based on an intensity range, gradient, contrast, region statistics, or texture. The combination of splitting and merging steps allows for the segmentation of arbitrary shapes, which are not constrained to vertical or horizontal lines, as occurs if only the splitting step is considered [17]. Region splitting and merging subdivide an image initially into a set of arbitrary, disjoint regions and then merge and/or split the regions in an attempt to satisfy the necessary conditions.

4. Comparison Table

The table below shows a comparison of various liver segmentation techniques along with its features and limitations:

Ref. No.	Authors	Year	Technique Used	Features	Limitations
13	Ng, H.P.	2006	K-means Clustering and Improved Watershed	92% fewer partitions than conventional Watershed Method	The K-Means Algorithm is limited to initial clusters
26	Jeongjin Lee	2007	Level Set Method	15 times faster than manual segmentation	The use of Ant Colony is Ignored
31	Laurent Massoptier and Sergio Casciaro	2008	Gradient Vector Flow and active Contour	Robust and Efficient liver segmentation in short processing time	Ineffective for colored images
32	Gang Chen	2009	Improved Level Set method	Overcomes leakage and over segmentation problems	Leads to over segmentation
14	Zhaoxiao Yuan, Yongtian Wang, Jian Yang, Yue Liu	2010	Fast Marching and Improved Fuzzy cluster Method	Accurate Segmentation of abdominal MR images.	Over segmentation leads to error in results
16	Militzer A, Hager T, Jager F	2010	Probabilistic Boosting Tree	Fully automatic detection and segmentation accurately and simultaneously	Accuracy is low
17	Gambino O, Vitabile S, LaTona G	2010	Texture Bsaed region growing	Accurate Recognition and segmentation of liver	Requires high processing time
21	EsneaultS,Lafon C, Dillenseger J	2010	Hybrid Geometrical Moments/ Graph cut method	Fast and Fully Automatic Method	Has low sensitivity and specificity
15	S.S Kumar, R.S	2011	Region Growing	Automatic and	Non effective for

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	Moni, J. Rajeesh			Effective Segmentation of liver and lesion	image matching
20	Abdalla Zidan, N. Ghalli, H.Hefny	2012	Watershed Segmentation and Artificial Neural Network	Accuracy of 92.1% could be achieved	The use of Ant Colony is Ignored
30	Amir H. Forouzan, Akira Furukawa, Yen Wei Chen	2013	K-Means Clustering and Geodesic Active Conour	Effective Segmentation in Low contrast Images	Used only for low contrast images
34	El-Masry W.H	2014	Invasive Weed Optimization	Multi-objective optimization in Computer Aided Diagnosis Applications	Computational time is high

5. Conclusion and Future Scope

In this paper, a survey on various iamge segmentation techniques has been done. It has been concluded that the ant colony optimization is also ignored in the literature. Also, the K-Means alorithm is limited to only initial number of k-clusters. Wrongly selected clusters lead to erroneous results Therefore in future, a new ant colony optimization based k- means algorithm is suggested which has ability to address initial k-clusters problem by selecting optimized clusters.

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