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Segmentation using Sparse Shape Composition and Minimally Supervised Method in Liver Surgery Planning System

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***Abstract*—Liver surgery planning system plays an important role in achieving the optimized surgery plan in Living Donor Liver Transplantation (LDLT). Segmentation of liver is a very challenging component in liver surgery planning systems. Patient-specific shape prior is of great significance in improving the robustness of liver segmentation. However, complex liver shape variations among different patients are difficult to model, which affects the accurate segmentation in liver surgery planning. To address this problem, we incorporated the Sparse Shape Composition (SSC) in the computer assisted liver surgery planning system. The basic modules of the system consist of: (1) Segmentation module. The Sparse Shape Composition (SSC) model is employed to get a patient-specific liver shape prior and then the shape prior is combined with a minimally supervised method to segment the liver parenchyma, hepatic vessels and tumors simultaneously. (2) Approximation of liver segments. It divides the liver into several functionally independent segments. (3) Visualization module. The result of clinical experiment shows this system has a good performance in providing accurate and robust liver surgery planning.**

I. Introduction

Liver cancer has become one of the most life-threatening diseases throughout the world. For a quite large number of patients with end-stage liver cancer, the most efficient treatment is liver resection or living donor liver transplantation (LDLT)[1]. In the process of the LDLT, a portion of the healthy liver of the donor is cut off and it is used to replace a part of or the entire liver of the recipient. To achieve the best surgery strategy, surgeons must accurately calculate the volume of the liver portion that would be cut off before surgery. They also need to locate the liver portion and the distribution of intrahepatic vessels and tumors during the implementation of the surgery[2]. To accomplish these tasks, computer assisted liver surgery planning system is greatly helpful[3].

Many researchers have been making efforts to develop computer assisted planning system for liver surgery [4-6]. The architecture of the prototype of liver surgery planning systems is shown in Fig. 1. The system takes 3D abdominal image data as input and then segments the liver parenchyma, tumors and intrahepatic vasculatures including portal veins and hepatic veins. Afterwards liver can be divided into several segments that usually conform to the Couinaud liver model according to the vessel trees[7]. Finally a resection proposal is calculated based on the result of foregoing steps and all the liver components are visualized to help the preoperative planning and intraoperative guiding.

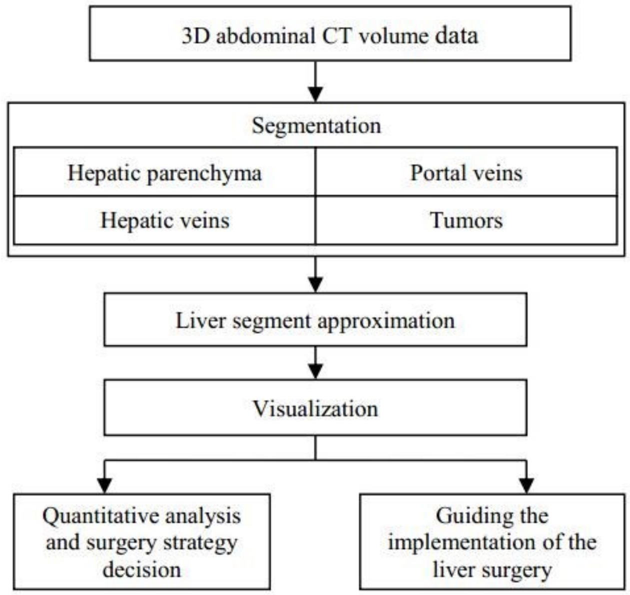

Figure 1. The framework of the liver surgery planning system

The accurate segmentation of liver parenchyma, tumors and intrahepatic vasculatures is the prerequisite for liver surgery planning, since a resection approach requires very accurate and detailed knowledge about the structures of the vascular system and the relative position between tumor and hepatic vessels. However, an excellent performance of the segmentation is hard to achieve because of the artifacts in abdominal images such as noise, partial volume effect and weak boundary information between different organs. In the past decades, a variety of efforts have been made in the field of liver image segmentation[8, 9]. It is shown that methods taking into account the shape prior knowledge could often achieve better performance than those solely rely on the appearance cue in liver segmentation [10].

Shape prior of liver is employed in the segmentation method in our system to get more accurate segmentation results. Adjoining abdominal organs such as liver, spleen and stomach might have similar gray levels, thus traditional methods such as region growing could easily lead to over-segmentation and under-segmentation. Shape-based models could effectively address this problem by providing a prior region of the liver. However, currently proposed liver

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surgery planning systems rarely take full advantage of shape priors, mainly because it is challenging to modeling the complex variations among different patients. The most widely used shape prior model is the Statistical Shape Model[11], in which a number of training shapes are required to capture all the possible shapes with robustness to noise and outlier. In our system, a sparse learning method proposed by Zhang et al. [12, 13] is employed to infer the shape prior of the liver. Afterwards, the shape prior is used as a constraint in the following accurate segmentation process. The segmentation method is a minimally supervised iterative classification approach that segments several tissues such as hepatic parenchyma, tumor, portal veins and hepatic veins simultaneously, with its ability to overcome the overlap of gray levels between these tissue classes. The liver shape prior is employed to get a more accurate segmentation result of hepatic parenchyma, which influences the segmentation of tumors and intrahepatic vessels.

In this study, we present our work on the implementation of the liver surgery planning system. We mainly focus on the two fundamental modules: one is the segmentation of hepatic parenchyma, tumors and intrahepatic vessels from clinical computed tomography (CT) scans, and the other is the liver segment approximation method. The most important contribution of this paper is addressing the complex liver shape variations from clinical patients by employing SSC model, which ensures the accuracy and robustness of the segmentation in liver surgery planning systems.

II. Methodology

A. Shape Prior Based on Sparse Representation

Sparse Shape Composition (SSC) model represents the shape prior by a sparse linear combination of shapes in the shape repository. In our liver surgery planning system, the SSC model is employed mainly because of the following challenges in the modeling of shape prior for liver. First, liver shapes from different patients have such a complex variation that a parametric probability distribution is not accurate enough to describe the variation. The SSC model addresses this problem without any assumption of parametric distribution models. Second, patient adaption of the shape prior is a critical consideration. The SSC model can preserve local details of the input shape as long as such details appear in the training data, thus it is adaptive to different patients. Third, for those a part of whose liver has been resected previously, the integrated liver could not be found in the CT scan so that a common surgery planning system could just provide the visualization of the remained part of the liver. However, the SSC model is able to infer the integrated liver benefited from its robustness against outliers, which assists surgeons in making a better understanding of the whole liver.

In our surgery planning system, a liver shape repository is constructed in advance. All the liver shapes in the repository are manually segmented by experienced experts and converted to meshes for shape modeling. For a certain patient, an initial liver segmentation based on simple region growing method is rapidly performed. The initial segmentation result is also converted to mesh and registered to shapes in the repository. The newly generated mesh serves as input of the SSC model and is approximated by an optimized sparse linear combination of a subset of the shape repository. The initial segmentation result may contain gross errors but such errors are sparse, which can be captured by SSC. The output of the SSC model is accepted as the prior liver shape for the patient, and it is employed as a constraint in the following accurate segmentation of hepatic parenchyma, tumors and intrahepatic vessels. The details of the SSC is described in [13] .

B. Accurate Segmentation

A minimally supervised classification method[14] that uses both statistical and spatial information is employed to segment several tissues in the liver region including hepatic parenchyma, portal veins, hepatic veins and tumors. It was originally proposed for 2D head image segmentation but it can be extended to 3D liver image segmentation easily. In addition, we incorporate the SSC shape prior into this classification method in our liver surgery planning system.

This accurate segmentation method is an iterative classification approach adapted from Bayesian Level Set method[15]. It can be described as a process of the growing of high-confidence (HC) points of each tissue. HC points are points with the least chance to be misclassified for each tissue class. In the first iteration, HC points are selected from the result of Bayesian classification based on thresholds of statistical intensity and the size of connected domain of each tissue class.

In the subsequent iterations, the Fast Marching Method[16] is used to compute the arrival time of the surface of HC points blobs of one certain tissue class when it marches to every unclassified point. The marching speed at each unclassified point is defined based on its intensity and the spatial relationship between that point and the liver shape prior, i.e. for one certain tissue class, the larger the difference between the intensity of the unclassified point and the average intensity of HC points, or the larger spatial distance between that point and the liver shape prior, the slower the marching speed at that point. After the marching process, arrival time could be computed and it indicates an intensity and prior knowledge weighted distance instead of the Euclidean distance. We classify each point into the tissue class with the least arrival time at that point. In the next step, new HC points are selected for each tissue class and new iteration begins. The iteration will terminate when the percentage of increase in the volume of hepatic parenchyma is below a threshold. After the iteration converges, the accurate segmentation result of liver parenchyma, portal veins, hepatic veins and tumors could be accomplished simultaneously.

C. Liver Segment Approximation Module

Liver could be partitioned into several regions based on the intrahepatic vascular system. The mostly used partitioning proposed by Couinaud et al. [7] divides liver into eight segments according to the third order branch of portal veins, and these segments could be used as ablation units in liver surgery. In the liver surgery planning system, visualization of the anatomical liver segments and their relationship to tumors is also very important, since the surgical strategy depends on the anatomical information of the related liver segment and vasculature. Besides, volumetry of the whole liver and each segment is necessary for the analysis of liver’s function.

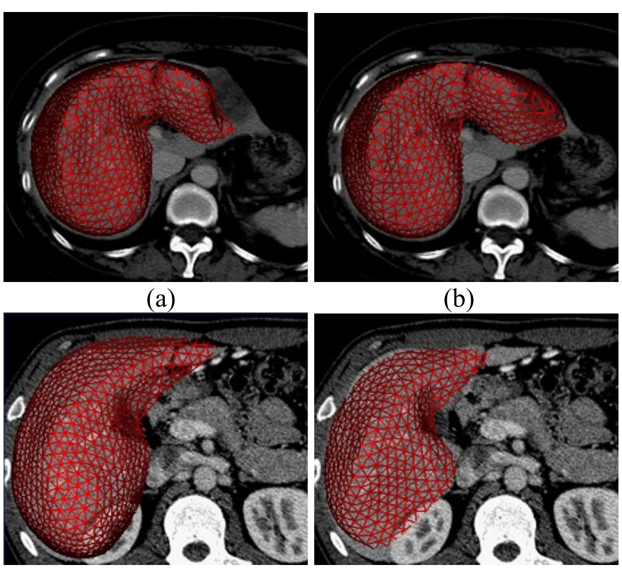
The liver segment approximation module is used to provide the knowledge of the shape and volume of the patient's individual liver segments to estimate the risks of different resection strategies. In our system, an interactive method based on the topological and geometrical structure of portal veins is used. In the first step, users label primary branches for each segment according to the anatomical structure of portal veins, and then sub-branches and terminals for each branch could be automatically labeled. In the following, the Nearest Neighbor Segment Approximation (NNSA) approach[9] is employed. This method classifies each liver voxel into the segment with the lowest Euclidean distance from its defining portal branches. Finally, each voxel of the liver will be classified into one certain segment.

D. Visualization Module

Visualization is an essential module to present the segmentation results of hepatic parenchyma, intrahepatic vessels, tumors and the results of liver segment approximation. It provides an intuitive knowledge of the structure and relative position between different tissues both in preoperative planning and intraoperative guiding process. The Visualization Toolkit (VTK)[17] is a widely used software system for 3D data visualization. In this module, we mainly use marching-cubes based surface rendering method[18] to accomplish the visualization of different tissues.

III. RESULTS

Clinical abdominal image data of enhanced CT was used in the experiments. We collected manual segmentation results of livers from 42 healthy persons to construct the shape repository and implemented the segmentation algorithm on 8 patients with liver cancer. The image resolution is 512×512 and the pixel spacing is 0.682mm×0.682mm.



(a) (b) (c) (d)

Figure 2. The initial segmentation results of two livers (a, c) and their corresponding shape priors (b, d). In (a), the tumor region is under segmented. However, the result of SSC restores that region, as shown in (b). In (c), over-segmentation occurs with the right kidney being included. The result of SSC excludes the kidney, as shown in (d).

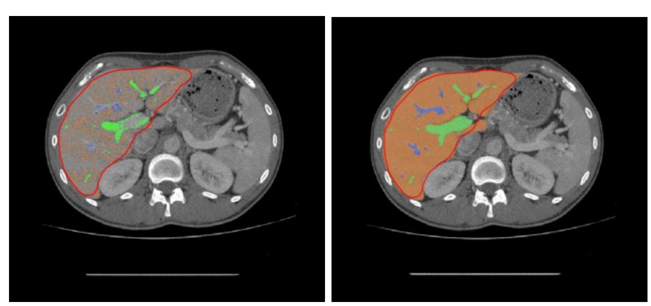
In the liver surgery application, under-segmentation of tumors and over-segmentation of kidney and others tissues are gross errors. However, they could be captured effectively by the SSC model. Fig. 2 shows the initial liver segmentation results and the output liver shape priors of two patients. In (a), tumor appears in the CT image of the patient. Since the gray level of tumor is obviously lower than that of normal liver, the region growing method fails to extract the tumor region, which leads to under-segmentation. However, the result of sparse shape representation restores the tumor region as shown in (b), so that the tumor is preserved in the segmentation result. (c) and (d) show another example. In this case, the region growing method extracts the liver together with the right kidney, as is shown in (c). The initial segmentation result is refined by the SSC model and the output shape prior excludes the kidney. The output shape prior is shown in (d).

Fig. 3 shows the HC points and segmentation result of hepatic parenchyma, portal veins and hepatic veins under the consideration of SSC shape prior. The shape prior is patient-specific and it exactly approximates the liver region, with adjoining organs such as kidney being excluded. We evaluated the segmentation algorithm in terms of sensitivity and specificity. The average sensitivity and specificity value of four tissues from the 8 patients are shown in Table I. As a result, high accuracy of the segmentation of hepatic parenchyma is achieved, which also ensures vessels outside the liver region will not be over-segmented.

Fig. 4 shows the segmentation result for a patient with liver tumor. The opacity of liver segments, intrahepatic vessels and tumors are set to less than 1.0 so that a semitransparent effect is achieved. To make an accurate surgery planning, high level branching structure of portal veins and hepatic veins should be remained in the segmentation result. As is shown in Fig. 4, the fourth-order and higher vessel branches are extracted by our

TABLE I. SENSITIVITY AND SPECIFICITY OF THE RESULTS

	Hepatic parenchyma	**Portal veins**	**Hepatic veins**	**Tumor**
Sensitivity	0.902	0.878	0.925	0.896
Specificity	0.961	0.983	0.994	0.987



(a) (b)

Figure 3. Accurate segmentation of hepatic parenchyma, portal veins and hepatic veins. (a) High confidence points of hepatic parenchyma (yellow color), portal veins (green color), hepatic veins (blue color) and liver shape prior (red curve) in the first iteration. (b) Segmentation result of hepatic parenchyma (yellow color), portal veins (green color), hepatic veins (blue color) and liver shape prior (red curve).

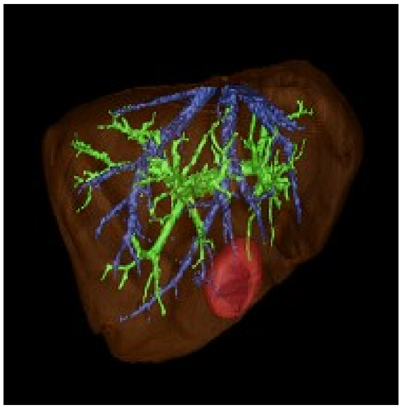
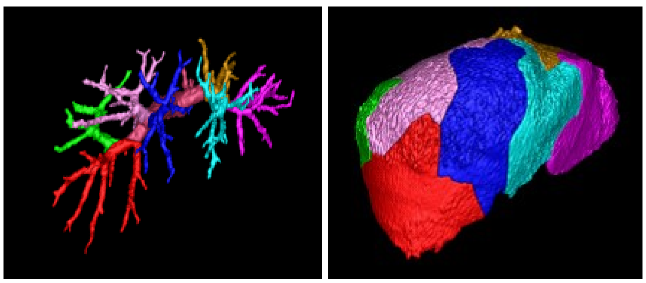


Figure 4. Visualization of the segmentation result of hepatic parenchyma, portal veins, hepatic veins and tumor.



(a) (b)

Figure 5. Result of the liver segment approximation. (a) Portal veins labeled in different colors. (b) Liver segments approximated by NNSA based on the labeled portal veins.

proposed segmentation method, with tumor being segmented at the same time, so that the accuracy of the surgery planning is ensured.

The result of the liver segment approximation is illustrated in Fig. 5. (a) shows the portal veins which are divided into eight sub-branches and each sub-branch supplies an independent liver segment. (b) shows the liver segments approximated by NNSA based on the labeled portal veins in (a). The color of each liver segment is the same as that of the corresponding portal vein's sub-branch. The volume of each segment could be measured easily, which can provide quantitative measurement of the liver. Thus, functional analysis of the liver can be performed.

IV. Discussions and Conclusions

A liver surgery planning system is introduced in this paper. It implements an accurate segmentation of hepatic parenchyma, portal veins, hepatic veins and tumors. The segmentation result is visualized to provide detailed structure and position information of the vascular system and tumors. The volume of liver segments could be calculated and analyzed based on liver segment approximation, so that surgeons can make an optimized surgery plan in LDLT.

The segmentation module in this system is mainly discussed. To achieve more stable and accurate segmentation result of hepatic parenchyma and intrahepatic vessels, a shape prior method based on SSC model is applied. The SSC model is effective in modeling complex variations of liver shapes. The local details of the input shape could be preserved by SSC so the shape prior is adaptive to different patients. The liver shape prior is incorporated with a minimally supervised algorithm in our system and hepatic parenchyma, portal veins, hepatic veins and tumors could be segmented simultaneously in a unified framework.

The main advantage of our system is the application of SSC to improve the accuracy and robustness of the liver surgery plan, which deals with complex shape variations among patients with liver cancer in clinic environment to ensure the safety of liver resection and the least waste of liver segment of the donor and recipient. Experiments have shown that the system has a good performance in the segmentation of liver, tumor and vessels, and the result is accurate and robust enough for the planning of liver surgery. Our future works will include more experiments on clinical data and improving the stability and efficiency of the system.

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