Efficient Liver Surgery Planning in 3D based on Functional Segment Classification and Volumetric Information

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Abstract—Anatomic hepatectomies are resections in which compromised segments or sectors of the liver are extracted according to the topological structure of its vascular elements. Such structure varies considerably among patients, which makes the current anatomy-based planning methods often inaccurate. In this work we propose a strategy to efficiently and semi-automatically segment and classify patient-specific liver models in 3D. The method is based on standard CT datasets and allows accurate estimation of functional remaining liver volume. Experiments showing effectiveness of the method are presented, and quantitative and qualitative results are discussed.

I. BACKGROUND AND RELATED WORK

Anatomic hepatectomies [3][2] (anatomic liver resections) are a procedure used for treatment of liver tumor patients and in living related liver transplantation. Such hepatectomies are represented by the resection of the left lateral segment, the right and left hepatic lobes, isolated or in association with the resection of remaining lobe segments (right and left trisegmentectomy). These are high risk procedures which must be performed by experienced surgeons. The term “anatomic” indicates that all afferent and efferent vascular elements are dissected, isolated and sectioned before the main phase of exeresis (extraction) of the compromised lobes.

An accurate evaluation of the anatomy and volume of the hepatic lobes is essential in planning hepatectomies. This is due to the presence of considerable variations in the internal distribution and volumes of the hepatic lobes [9][6]. Such careful evaluation contributes to prevent postoperative hepatic insufficiency, especially in bilobar diseases and adult living related liver transplantation, in which the volume to be resected is large [5].

Calculating liver volume involves, in addition to medical knowledge, a computational procedure which allows boundary determination of the liver on tomographic images. This process is called segmentation. Although, liver segmentation in CT has already motivated a number of research projects, its practical application still represents a major challenge. Most of the medical images segmentation techniques are based in algorithms of region growing [11][12] and active contours [13], which are computationally demanding, inaccurate or both.

Accurate and fast segmentation is crucial in liver tumor extraction as this procedure is significantly influenced by the estimation of the volume of the liver and its segments. This is a major issue because the estimated percentage of remaining liver tissue may affect the decisions made in surgery planning and even make the procedure inviable [8].

CT exams with contrast injections are often used to highlight the vessels in the images, which allows to observe the direction and caliber of the vessels in hepatectomy planning. Such exams allow to observe the inner anatomy, to define section locations and also to roughly estimate the total and partial liver volumes. However, only experienced doctors (with three years of medical residence in average) are able to interpret such images with confidence.

CT images, in the specific case of the anatomic hepatectomies, when visualized in three dimensions with the aid of computer graphics and semi-transparency, correlate more easily the anatomy of the parenchyma with liver internal structures [7]. They also correlate hepatic vessels with liver sectors and segments, allowing to identify patient-specific sizes, shapes, volumes and anatomical variations [3][9]. In such a context, surgery planning can be based on more objective data. In addition, the organ can be analyzed interactively [6][5], which reduces training time and shortens the learning curve for apprentice surgeons in the initial steps of training for hepatectomy planning [10].

While some of these techniques exist, they are implemented only in expensive workstations usually associated to the CT scanners, which are often busy with scanning activities in most hospitals, being not available for use with planning. This happens essentially because the current methods used for image segmentation and vessel classification of the liver are computationally complex and cannot run in standard desktop computers.

In this context, the general goal of this work is to propose a new methodology for liver surgery planning using computer assisted image segmentation and classification of the liver segments. More specifically, we propose an environment for CT segmentation based on a combination of image processing and computer graphics algorithms to quickly extract the liver shape and volume from a general dataset. At the same time, we propose a classification tool to interactively extract the vessel branching within the liver and define the areas affected by both the portal and venous systems. Another specific goal is to make these tools efficient enough to run on commodity personal hardware, which would increase the
chances that they are used directly by the surgeons.

In the remaining of this paper, section II describes our semi-automatic approach for image segmentation, and section III introduces our liver segments classification tool based on vessel branching. In section IV we explain how the proposed tools are applied on actual planning of liver resections, which is followed by results in section V. Finally, a discussion and our conclusions are presented in section VI.

II. LIVER SEGMENTATION WITH SmartContour

We developed the SmartContour program as a tool for semi-automatic segmentation of a CT dataset. The program has been designed to require the minimum possible user intervention. It combines automatic edge detection with parametric curves to quickly create organic contours of the segmented areas.

The input is a stack of ordinary CT images in grey scale. The program first processes the images to increase contrast. An implementation of the live-wires algorithm [1] is then used in every slice of the dataset. It is based on the algorithm of Dijkstra [4] which solves the problem of the shortest path in a graph. When applied to an image, the algorithm finds a path in which every pixel represents a graph node with weighted edges connecting the neighborhood according to the relative neighbors tonality. The lowest cost node represents a suggestion of optimal step between the two nodes. The combination of a sequence of steps is a path representing the contour of a segmented region.

In practice, a user is required to click somewhere on the liver border to define a start for the contour. After, by moving the cursor, the program automatically proposes a contour line from the starting point to the current cursor position. New clicks have to be applied when the proposed contour does not follow the organ edge. This occurs whenever a neighboring organ presents a very similar density with the liver. With standard CT images, about 10 clicks are required to define a fit contour for one slice (figure 1a).

After this contour is entered, it is sampled for control points and a Bézier spline is created which is a smooth vector information that eliminates the dent effects caused by image resolution (1b). Such curve is copied to the next slice and the live-wires algorithm is applied to its control points to fit the new contour. It is usually necessary to manually adjust a few points between slices, but rarely more than 2 or 3 points (figure 1c and 1d).

In a short time, every slice will contain a contour which is used to separate pixels inside the liver from pixels outside. These pixels are then recolored to white and black respectively. This new black-and-white dataset (1e) can be used as a mask to define a segmented liver in 3D (figure 1f) and to measure the total volume of the organ.

III. VESSEL CLASSIFICATION WITH LiverSEGMENTS

We developed the LiverSegments as a tool to classify regions of a volumetric model of the liver according to the anatomic regions defined by Couinaud [3]. Such classification is made interactively by selecting vessels directly in three-dimensions on the segmented volume data described in section II.

A. Segments

The segment classification employed here divides the liver in 8 functional segments. They are defined according to the distribution of the hepatic vessels. Such anatomy-based classification schema has been first described by Claude Couinaud [3] and is also known as Couinaud segmentation.

In general, two branches of arterial and portal blood enter the liver. They are referred as right and left as they supply the right and left sides of the organ. A simplified classification divide the liver in left and right lobe, which are supplied by each of the two main vessel branches, plus the caudate lobe, which receives blood from the two main branches and is considered separately. Such simplified view aids in understanding the Couinaud segmentation depicted in figure 2. The caudate lobe, which is in the central-posterior part of the liver, represents the segment I. The left lobe contains the segments II, III, IVa and IVb. The right lobe contains the segments V, VI, VII and VIII.

B. Classifying segments

The input to the program is the segmented data from SmartContour (sectio II) and the original CT. To increase contrast between the parenchyma and the blood vessels, a
Fig. 2: Model of the liver functional segments distribution according to Couinaud [3]. Segment I is the caudate lobe, segments II, III, IVa and IVb compose the left lobe, and segments V, VI, VII and VIII compose the right lobe.

A pipe of image filters is used: gaussian blur; noise reduction, sharpen, brightness decrease. This helps to apply transparency between the parenchyma and the vessels, making them visually more solid and uniform as in figure 3c.

Having a 3D view of the vessels, the user is required to insert points on the vessel tree to label the veins as belonging to one of the 8 segments of Couinaud. Then the system labels all voxels of the liver according to their distances to those points. We used the same strategy of a Voronoi diagram which describes a spatial decomposition by means of the proximity of the regions with a given set of points. The closest regions to given points are associated to them. In our implementation, multiple points may define a unique segment.

IV. SURGERY PLANNING

After patient specific liver segmentation and segment classification processes are done with the programs described in sections II and III, damaged areas can be identified in 3D and the doctors can decide which segments will be removed surgically. They can also plan how to make the incisions in such a way that they avoid unnecessarily sectioning of important vessels. Another important information that can be obtained is related to total and functional volumes. Total liver volume and each functional segment volumes are automatically calculated by the LiverSegments tool. These volumes, together with the identification of potential areas of ischemia and venous stasis in consequence of surgery, are taken into account to estimate the total volume of the remaining functional tissue.

A. Datasets and planning pipeline

Diagnostic and planning start with the CT acquisition. Conventional contrast injections are used, and the three phases of the liver circulation (portal, venous and arterial) can be acquired separately along time, as usual. They can also be acquired all together after a sufficient amount of contrast perfused through the 3 systems. In either case, datasets are then exported in DICOM format from the CT scanner. They can be imported into the SmarContour for segmentation.

After liver segmentation, SmartContour exports both the original images and a 3D segmentation mask. This information is the input to LiverSegments. In LiverSegments the user (radiologist or surgeon) inspects the 3D volume of the liver, showing or not the surrounding organs (Figure 3a). At this point, the total volume of the liver is also calculated and displayed. Then, interactively, the user sets the center and threshold of the density window for visualization. Selected density ranges are set to transparent allowing the vessels to be highlighted (Figure 3b). At this moment the user is able to classify the liver segments (for example, Couinaud’s) by clicking on vessel branches directly on the 3D view.

Such branch selection eventually produces a color distribution not only on the vessels but also in the neighboring regions of the parenchyma (Figures 3c and Figure 3d). Each colored region corresponds to one functional segment.
The algorithms focus on 3D imaging and can run in commodity PC, which tremendously increase the access directly to the surgeons. Moreover, the methods allow accurate volume calculation for both the liver and its functional segments, which might improve diagnostic and treatment planning.

From our preliminary tests, we concluded that the process of segmentation and classification, even for large datasets, takes less than 2 hours. Further user tests should be planned to relate operator experience, complexity of the dataset and time to complete the task. Our current tests also show that our volume calculation method is not worse than the validated methods often used with CT workstations. Further tests with real liver samples should be planned to verify the hypothesis that our method is even more accurate than the workstation ones, which we could anticipate from the more organic shape obtained.

VII. ACKNOWLEDGMENTS

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REFERENCES