An automatic virtual patient reconstruction from CT-scans for hepatic surgical planning

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An Automatic Virtual Patient Reconstruction from CT-Scans for Hepatic Surgical Planning

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Problem / Background: In order to help hepatic surgical planning we perfected automatic 3D reconstruction of patients from conventional CT-scan, and interactive visualization and virtual resection tools.
Tools and Methods: from a conventional abdominal CT-scan, we have developed several methods allowing the automatic 3D reconstruction of skin, bones, kidneys, lung, liver, hepatic lesions, and vessels. These methods are based on deformable modeling or thresholding algorithms followed by the application of mathematical morphological operators. From these anatomical and pathological models, we have developed a new framework for translating anatomical knowledge into geometrical and topological constraints. More precisely, our approach allows to automatically delineate the hepatic and portal veins but also to label the portal vein and finally to build an anatomical segmentation of the liver based on Couinaud definition which is currently used by surgeons all over the world. Finally, we have developed a user friendly interface for the 3D visualization of anatomical and pathological structures, the accurate evaluation of volumes and distances and for the virtual hepatic resection along a user-defined cutting plane.
Results: A validation study on a 30 patients database gives 2 mm of precision for liver delineation and less than 1 mm for all other anatomical and pathological structures delineation. An in vivo validation performed during surgery also showed that anatomical segmentation is more precise than the delineation performed by a surgeon based on external landmarks. This surgery planning system has been routinely used by our medical partner, and this has resulted in an improvement of the planning and performance of hepatic surgery procedures.
Conclusion: we have developed new tools for hepatic surgical planning allowing a better surgery through an automatic delineation and visualization of anatomical and pathological structures. These tools represent a first step towards the development of an augmented reality system combined with computer assisted tele-robotical surgery.

1. Introduction

One of the major stakes of computerized medical imaging analysis is to automatically identify and localize anatomical structures in 3D medical images. The tridimensional models of these isolated structures can then be used by a surgical planning tool. In the hepatic surgery, the planning requires the localization of hepatic lesions and liver vascular trees, especially the portal vein that defines the hepatic functional anatomy consisting of several anatomical segments [1,2]. There exist different definitions for dividing the liver into functionally meaningful parts. Different authors have proposed to divide the liver into two *hemilivers*, or into four segments based on the Goldsmith and Woodburne definition

[3] or into eight sub-segments based on the Couinaud definition [4] which is today the international standard [1].

In order to detect lesions and to observe vascular networks defining the anatomical segments, radiologists currently use helical Computed Tomography scan images with intravenous contrast infusion (helical CTI). Indeed, in helical CTI images, tumors appear as dark nodules within bright hepatic tissues whereas vessel trees appear as a network brighter than the liver parenchyma. However, these images are often difficult to process due to a variable image contrast between liver parenchyma and vessels, and also due to an important image anisotropy, the slice thickness being three time larger than the pixel width.

One of the goals of computerized medical imaging analysis for hepatic surgery planning is to automatically delineate liver, lesions, vessels and anatomical segments from medical imaging. Several authors proposed to delineate the liver contours from CTI images with an automatic [5,6,7,8,9], or semi-automatic process [10]. Several methods use a deformable model, either to directly delineate structures [5,7], or to improve the results of a previous delineation technique [6]. Independently of the liver delineation, vascular tree segmentation has been performed in different studies [11,12,13,10]. For instance, the method of [13] allows to extract the portal vein from abdominal CT-scan images, using a region growing technique. This technique has the advantage to give a topological information about the venous tree, which is useful for building all anatomical segments [14]. However, since it requires to manually set a threshold and an initial seed point, this technique is not automatic. Finally, there has been very few studies [15,16] about the hepatic lesions delineation. However, it can be performed by the same methods used to isolate other anatomical structures, as in [7].

Among all these studies, the work of [6] is best-suited for hepatic surgery planning since it provides a general solution allowing the delineation of the hepatic anatomy, even if the vascular system may not be clearly delineated. Also, the work described in [13] and [14] performs portal vein labeling and anatomical segments delineation, but it always reconstructs eight sub-segments even if the patient has a different number of segments.

In this article, we propose an original three steps anatomical segmentation method, based on the translation of anatomical knowledge into topological, geometrical and morphological constraints. We also present a human interface allowing an easy 3D visualization and surgical planning. This method thus allows to extract automatically and visualize *skin*, *bones*, *lungs*, *kidneys*, *spleen*, *liver*, *hepatic vessels*, *hepatic lesions* and at least the *anatomical segments* of the liver with respect to the three mainly used definitions: hemiliver, Goldsmith and Woodburne definition and Couinaud definition.

2. Tools and methods

2.1 Patients data set

This study has been performed on a set of 30 CT-scans acquired after contrast agent injection at portal phase, from an helical Siemens Somatom 4 plus CT-scan. The database is composed of 28 images with intravenous injection, and two portoscans. It includes healthy subjects, patients with lesions (Cyst or tumors), and also patients after segmentectomy. Furthermore, the rate of contrast product invasion into hepatic venous systems is really different from one patient to another, due to a difficult evaluation of the portal time.

All images have a well known noise pattern creating a kind of texture in all images. In order to remove this textured aspect, we choose to filter all images before any delineation processing. Usually, this filtering is performed with a Gaussian smoothing, but this filter implies a loss of structure boundaries. In order to solve this problem, we use an

"anisotropic diffusion", which smoothes the image only where its gradient is low. We choose a linear complexity algorithm developed by Krissian et al. [17] that allows to perfect this diffusion faster than current methods. As shown in the figure below, resulting images are much easier to process.

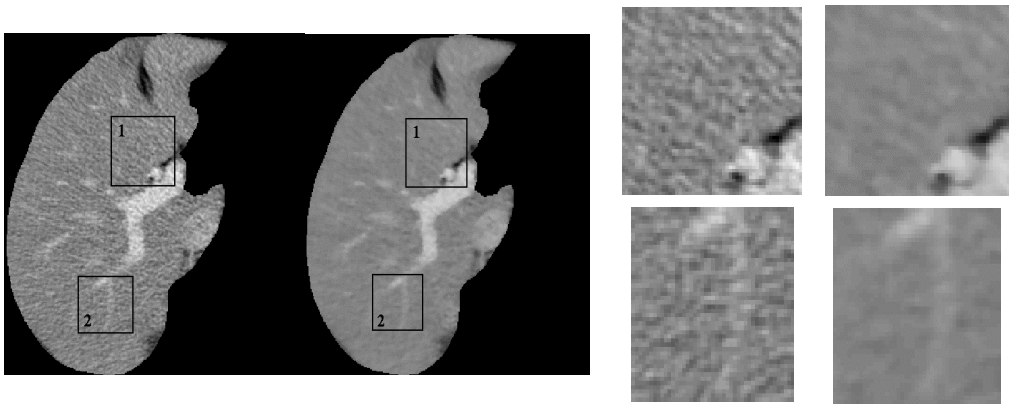

figure 1: Image before and after anisotropic diffusion. Internal boundaries are not removed by this filtering.

2.2 Automatic delineation of skins, lung, bones, kidneys, spleen and liver

This first stage of our method extracts automatically step by step, the skin, lungs, bones, kidneys, the spleen and the liver of a patient, from a CT-scan image. Our method consists in translating knowledge into medical imaging, by the way of several simple intensity, morphological, topological and geometrical constraints. The intensity in Hounsfield units of air, fat tissue, water and bones are known and are respectively -1000 HU, -120 HU to -80 HU, 0 HU, and 500 HU to 3000 HU. Air is mainly outside the patient and into the lungs (some air may be eventually found into the digestive system too). Isolating the air allows us to extract easily the skin and the lung boundaries.

A simple threshold does not allow to isolate the bones. Because of the contrast agent, others structures, such as the aorta, appear bright. To overcome this, we first isolate the fat tissue (thresholding followed by morphological operation). The bones are then characterized as the brightest structures close to the fat tissue.

Kidneys and spleen delineation is more difficult due to their intensity variation. We then propose a solution based on the gray-level histogram analysis of the image limited to regions including the spleen and kidneys. Indeed, the right inferior quarter of the image contains essentially a part of the liver and the right kidney, whereas the left inferior quarter of the image contains only the right kidneys and the spleen. Thus, a comparative analysis of the gray-level histograms allows to find the intensity range of kidneys, spleen and liver parenchyma, identically localized on both histograms. We then delineate the kidneys and the spleen by performing a thresholding followed by morphological operators.

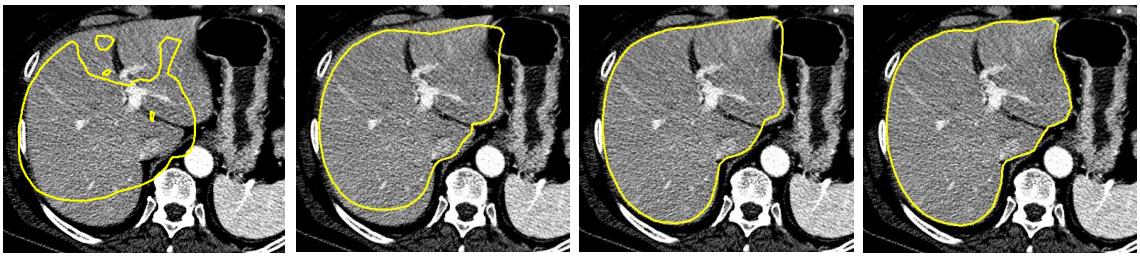

Figure 2: evolution of a deformable liver model that fits the liver outlines cut in a CTI image.

Once all these anatomical structures are removed from the original image, we finally extract the liver using Montagnat and Delingette's method [5]. It is based on a 3D reference

liver model embedded that deforms automatically towards patient liver contours by applying local and global constraints (figure 2).

2.3 Automatic delineation of internal liver structures: lesion and vascular systems

According to our knowledge, we consider that the work of [6] presents the only technique approaching a general solution for classifying internal hepatic structures by recovering the intensity distribution of hepatic lesions, parenchyma, and vessels. We improved their approach by considering that these distributions follow a normal law and by estimating these distributions with an efficient least squares minimization (Levenberg and Marquardt's [18]). Such a procedure requires an initialization of the three distributions to be estimated. However, only one peak, which corresponds to the liver parenchyma, can be seen in the original histogram. Therefore, we first fit the liver parenchyma distribution and then subtract it from the original histogram. The new histogram reveals two peaks, that correspond to respectively the lesions and the vessels tissues. We are then able to compute initial parameters for these two distributions. Finally, we adjust the three Gaussians with the initial histogram. The crossing intensities of the Gaussians define the thresholds between the three classes.

The result of this thresholding implies several misclassification. First, due to the image anisotropy, several branches are disconnected. In order to remove these mistakes, we apply a new hysteresis thresholding technique based on a distance map and thresholds computed from the Gaussian distribution parameters. Second, the final result includes false lesions, due to fat tissue appearing inside the liver parenchyma, and also wrong connections between the two venous systems of the liver, the portal vein and sus-hepatic vein. In this case, the characteristic shape of the lesions, and the topological properties of vascular systems are two information allowing the physician to detect potential mistakes. In order to use this anatomical knowledge, we have characterized the lesion shapes using axial inertia moments of the lesions and the vessels topology by the skeleton of the vascular tree. We then apply topological and geometrical constraints onto each structures removing thus nearly all misclassifications. This method allows an automatic delineation of lesions and a better topological portal vein segmentation disconnected from neighbor vascular networks.

2.4 Automatic portal vein labeling and anatomical segmentation

In practice, the current procedure for radiological delineation of anatomical segments is based on the concept of three vertical planes that divide the liver into four segments, and of a transverse scissura that further subdivides the segments into two subsegments each [2]. The three planes are defined from landmarks based on sus-hepatic veins, and the transverse scissura is defined from landmarks based on portal vein. But, as Fasel et al. [2] showed, this delineation brings too much errors and must be revised. Moreover, them results show that only procedures that account for all the portal venous distribution pattern, will result in correct depiction of the anatomic reality.

From this conclusion, we defined an anatomical segment as the influence area of a set of portal vein branches. Thanks to this definition, the anatomical segmentation becomes a labeling problem that consists to merge portal branches in two, five or height sets, with respect to hemiliver, Goldsmith and Woodburne's or Couinaud's segmentation (see figure 3). Selle et al. [15] already propose this kind of definition, but their merging method consists in considering the eight major sub-tree into the portal networks. Thus, their system will not be able to correctly label a patient's portal vein after a segmentectomy, or a patient's portal vein with some topological exception as defined by Couinaud [4].

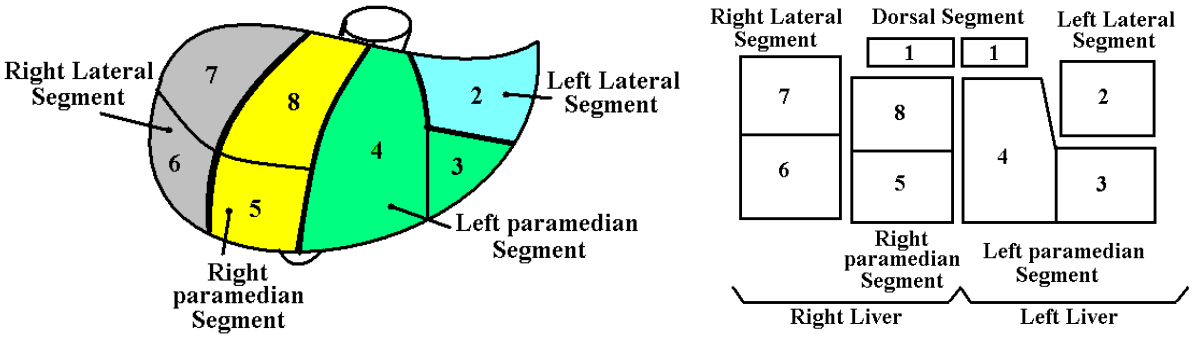

Figure 3: the three anatomical segmentations with respect to hemiliver (right and left liver), Goldsmith & Woodburne (lateral, paramedian and dorsal right or left segments) and Couinaud (numbers).

We choose to defined a new merging system that use anatomical knowledge translated into topological, geometrical and morphological constraints. This system firstly separate the liver in two hemiliver, secondly separate each hemiliver in three segments (paramedian, lateral and dorsal), and at least separate several segments in subsegment with respect to the Couinaud's definition. Each of these labeling is realized respectively with the same procedure. Firstly, we compute the influence area in the liver of all branches. We then obtain one volume of hepatic tissue per branch that corresponds to the more precise anatomical sub-segmentation. But, this precision is too important for surgeons, and does not correspond to their usual anatomical segmentation. We then merge these areas by giving the same label to branches having the same origin in the portal tree if the resulting volume of the merging areas verifies some constraints translated from definition of anatomical segmentation. These constraints allow to reduce the number of subsegments without merging two anatomical segments with respect to the usual definitions. In order to give to each subsegment the same label than the usual definitions, we register an initial segmented model onto the patient's liver using the Montagnat and Delingette's method [5]. We thus obtain a totally automatic labeling and anatomical segmentation of the patient's liver with respect to the three usual anatomical definitions.

2.5 Friendly user Interface

In order to exploit all the results provided by our method, we developed a friendly use interface that allows for a easy learning. This interface and all the available tools have been elaborated, tested and validated in collaboration with radiologist and surgeons. Thus, this interface allows easy visualization of CT-scan and all 3D anatomical and pathological structures automatically delineated, 3D navigation and zoom, view by transparency and color definition of each 3D model, a precise and automatic volume and distance evaluation, and also virtual resection (figure 4). It is a complete tool for surgical planning.

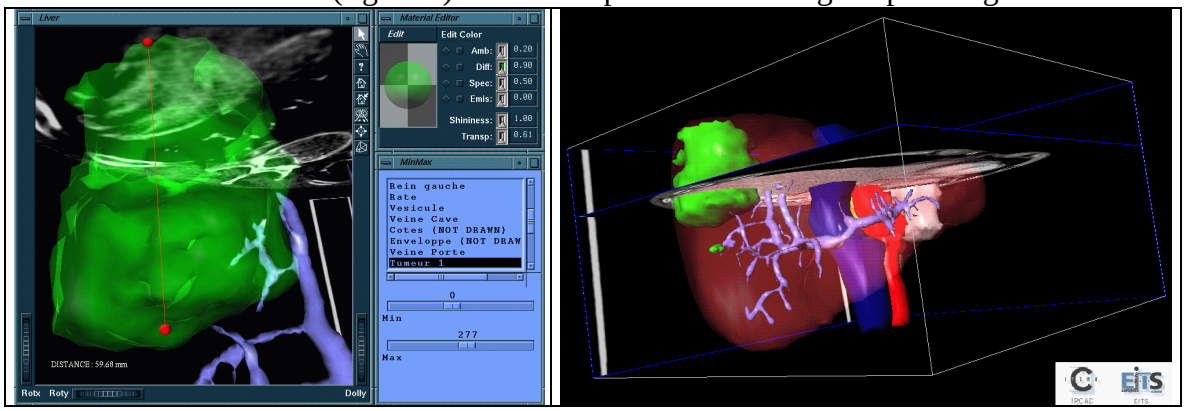

Figure 4: examples of views provides by the friendly user interface onto a patient's 3D reconstruction

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3. Results

In order to have a quantitative and objective estimation of the quality of our method, we have performed a validation by comparison of our result with a radiologist manual delineation. Firstly, where a manual delineation requires more than 11 hours to delineate portal vein and lesions, our method takes only 15 minutes. Comparison onto 5 patients shows that our method provides a precision of 2 mm for liver delineation and of less than 1 mm for other anatomical and pathological structures. Moreover, our automatic lesion segmentation has given all hypo-dense lesions over 3 mm of thickness (to be compared to the 5 mm required by the radiologist). Last, results show that the automatic portal vein labeling provides exactly the same result than a manual one, including the case of a patient after a segmentectomy.

From these first results, we have then verified on 4 different patients undergoing surgery that reconstruction results of our method before the surgery precisely guide and improve the surgical procedure. Furthermore, in one of the 4 cases, a small lesion of 5.2 mm of thickness, detected and delineated by our method but missed by the radiologist, has totally modified the initial planning (figure 5). In another of these 4 cases, our anatomical segmentation has truly localized a large tumor in three of the height anatomical segments while the standard landmark-based anatomical segmentation found the tumor in only two of these segments (figure 6): this also results in a modified surgical planning. In all cases, clinical validation during surgery has shown that results obtained by our automatic 3D segmentation were correct and add really useful information for surgical planning.

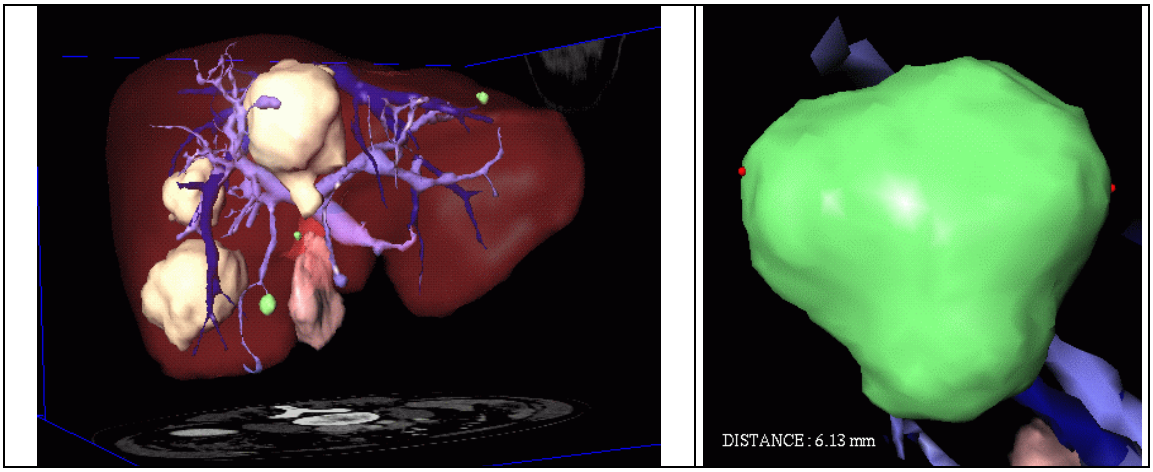

Figure 5: automatic delineation of tumors shows three tumors not detected by the radiologist (the smallest ones). Right image shows a zoom onto the left tumors and its thickness of 6 mm.

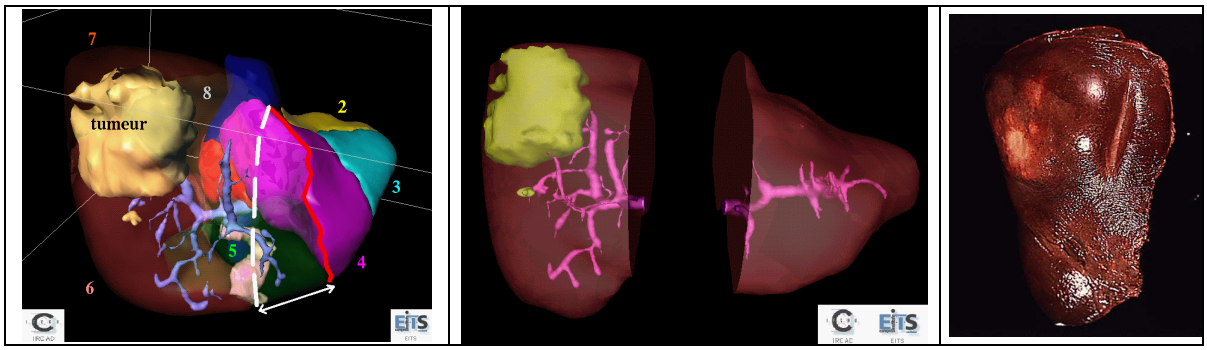

Figure 6: automatic delineation of a tumor and the anatomical segments. The result shows that the segment 8 contains a part of the tumor which was initially not visible from the CT-scan but verified after surgery.

4. Conclusion

The originality of this work lies in the full automation of the methods due to original translation of anatomical knowledge in topological and geometrical constraints. We thus offer the first fully automatic 3D reconstruction tools for liver surgery, providing not only anatomical and pathological structures visible in the CT-scan, but also invisible functional information. These original tools thus provide a real help in hepatic surgical planning through the automatic delineation and visualization of anatomical and pathological structures. Thanks to these tools which represent the first step towards an augmented reality system, computer assisted tele-robotical surgery will be available in the near future.

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