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Iterative mesh transformation for 3D segmentation of livers with cancers in CT images

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ABSTRACT

Segmentation of diseased liver remains a challenging task in clinical applications due to the high inter-patient variability in liver shapes, sizes and pathologies caused by cancers or other liver diseases. In this paper, we present a multi-resolution mesh segmentation algorithm for 3D segmentation of livers, called *iterative mesh transformation* that deforms the mesh of a region-of-interest (ROI) in a progressive manner by iterations between mesh transformation and contour optimization. Mesh transformation deforms the 3D mesh based on the deformation transfer model that searches the optimal mesh based on the affine transformation subjected to a set of constraints of targeting vertices. Besides, contour optimization searches the optimal transversal contours of the ROI by applying the dynamic-programming algorithm to the intersection polylines of the 3D mesh on 2D transversal image planes. The initial constraint set for mesh transformation can be defined by a very small number of targeting vertices, namely *landmarks*, and progressively updated by adding the targeting vertices selected from the optimal transversal contours calculated in contour optimization. This iterative 3D mesh transformation constrained by 2D optimal transversal contours provides an efficient solution to a progressive approximation of the mesh of the targeting ROI. Based on this iterative mesh transformation algorithm, we developed a semi-automated scheme for segmentation of diseased livers with cancers using as little as five user-identified landmarks. The evaluation study demonstrates that this semi-automated liver segmentation scheme can achieve accurate and reliable segmentation results with significant reduction of interaction time and efforts when dealing with diseased liver cases.

1. Introduction

Liver cancer is the third most common cause of death from cancer worldwide [1], and liver is the most common metastatic spread sites of cancers after the lymph nodes, which have been found in 30–70% of patients who are dying of cancer [2]. With the technical advances of computed tomography (CT), hepatic CT scanning has become one of the major routinely-performed clinical imaging modality in cancer diagnosis, staging, and treatment evaluation because of the relatively low cost and wide availability [3]. Segmentation of liver in CT images is crucial for liver-related clinical applications. However, accurate and reliable liver segmentation continues to be a challenging task especially for diseased livers because of the deformation of the liver shape caused by large tumors, the complexity of the diseased liver pathologies, the variability of image presence of different hepatic diseases (such as hypodense or hyperdense lesions), and the fuzzy boundaries between liver and the adjacent organs (such as heart and stomach). Therefore, liver segmentation attracts continuously researchers' attentions in medical imaging and graphics community [4,5].

Numerous automated, semi-automated and interactive methods for liver segmentation have been developed, including statistical shape model [6–8], atlas matching method [9–11], deformable model [12,13], level-set method [14–17], and other hybrid methods based on user-interaction [18], graph-cut [19], region-growing [20], machine-learning [21], etc. With regard to segmentation accuracy and reliability, there is a clear tendency that interactive methods outperform semi-automated methods, which in turn outperform fully automated approaches. However, user interaction time and efforts tend to have a reversed tendency: interactive segmentation of a liver on CT images is labor-intensive,

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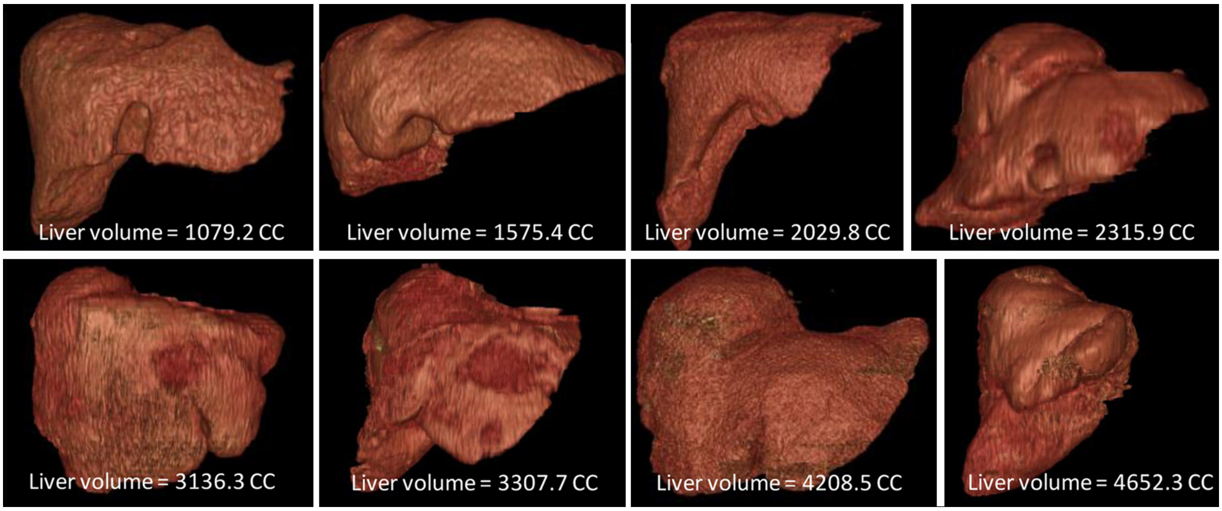

Fig. 1. Examples of the inter-patient variability in sizes and shapes of diseased lives from patients with cancers or metastasis. All the patients were scanned by the same protocol at supine position. All the resulting images are displayed in the anterior viewing orientation. The sizes of livers vary significantly with more than four times of difference and more importantly the shapes vary substantially too. The CT intensities of liver parenchyma and cancerous tissues are apparently different.

time-consuming and prone to inter-operator variability. Clinical applications seek an accurate and reliable segmentation method for diseased livers with minimum amount of required user interactions.

The technique challenges of the segmentation of diseased livers result from the high inter-patient variability in liver shapes, sizes and pathologies as well as the longitudinal intra-patient variability. It is not uncommon that cancers and metastases change the liver size and deforms the liver shape, and thus result in a very large range of variations among patients. Fig. 1 demonstrates the inter-patient variability in shapes and sizes of diseased livers from patients with cancers or metastases. The sizes of livers vary significantly with more than four times of difference. More importantly, the shapes of livers show substantial difference caused by cancers or metastases or treatments: (1) liver shapes may be bended or twisted or deformed severely due to the growing or shrinking of tumors; (2) different hepatic lobes may be shrunk or expanded extraordinarily; and (3) tumor tissues show substantially different CT intensity compared to normal liver parenchyma. This inter-patient variability makes the modeling of a statistic shape for liver segmentation an extremely challenging task. To deal with the complex shape variations of diseased livers, sparse shape composition model [22] and auto context multi-atlas model [23] were proposed to handle errors or outliers of statistic models and preserve local details for different shapes of liver. These atlas-based or shape-prior-based automatic methods require learning from available shapes of segmented livers, which may be itself a difficult task.

As long as fully-automated segmentation methods fail to produce satisfactory segmentations on these diseased cases, certain amounts of user interaction are still required. Deformable models offer the essential options of interactive control over the segmentation process via interactive manipulating of a deformable surface [24]. Traditional mesh deformation methods simulate the mechanism behavior of a surface by minimizing the stretching and bending energies of the surface, such as active geometric deformed models [25] and active contour models or snakes [26]. However, one limitation of these energy-based mesh deformable methods is that the difference between the initial mesh and resulting mesh must be sufficiently small, which may turn out a large amount of interactive manipulations. Motivated by the deformation transfer model [27], which transfers the mesh deformation using deformation gradients instead of local energies, mesh may be deformed efficiently using a small set of targeting points while allowing accurate detail-preserving interactions.

In this paper, we proposed a multi-resolution mesh segmentation algorithm, called *iterative mesh transformation* that deforms the mesh of a region-of-interest (ROI) in a progressive manner by iterations between mesh transformation and contour optimization. The initial constraint set for mesh transformation can be defined by a very small number of targeting vertices, namely *landmarks*, and progressively updated by adding the targeting vertices selected from the optimal transversal contours calculated in contour optimization. This iteration between 3D mesh transformation and 2D transversal contours optimization provides an efficient solution to a progressive approximation of the targeting ROI mesh with minimum user interactions. By using this iterative mesh transformation algorithm, we developed a semi-automated image segmentation scheme for diseased livers with cancers. This scheme can effectively segment the diseased livers with cancers using as little as five user-identified landmarks. It achieves accurate and reliable segmentation results when dealing with these diseased liver cases, and reduces significantly the interaction time and efforts. The resulting 3D liver mesh provides the meta-data for quantitative image analysis of diseased livers in different clinical applications.

The major contributions of the proposed method are twofold.

- Technical contributions: Diseased livers tend to have high inter-patient variability of shapes and sizes, which makes the modeling of a statistic shape for liver segmentation an extremely challenging task. The transformation optimization in iterative mesh transformation provides an effective solution for the global approximation of a diseased liver, which is superior to those of energy-based mesh deformation that tends to converge to a local boundary caused by the inhomogeneity in diseased regions. On the other hand, the transversal contours optimization provides the local refinement for detecting the precise boundaries of a liver. As a result, the combination of 3D transformation optimization and 2D contour optimization provides an accurate and efficient technical solution for the segmentation of diseased livers.
- Clinical contributions: Manual contouring remains the major clinical procedure for segmentation of diseased livers with pathologies, which is labor-intensive, time-consuming and prone to inter-operator variability. The proposed iterative liver segmentation scheme is easy-of-use and reduces the interaction effort as