Accurate and reproducible semi-automatic liver segmentation using haptic interaction

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ABSTRACT

In this work, we describe and evaluate a semi-automatic method for liver segmentation in CT images using a 3D interface with haptic feedback and stereo graphics. Recently, we reported our fast semi-automatic method using fast marching segmentation. Four users performed initialization of the method for 52 datasets by manually drawing seed-regions directly in 3D using the haptic interface. Here, we evaluate our segmentation method by computing accuracy based on newly obtained manual delineations by two radiologists for 23 datasets. We also show that by performing subsequent segmentation with an interactive deformable model, we can increase segmentation accuracy. Our method shows high reproducibility compared to manual delineation. The mean precision for the manual delineation is 89\%, while it is 97\% for the fast marching method. With the subsequent deformable mesh segmentation, we obtain a mean precision of 98\%. To assess accuracy, we construct a fuzzy ground truth by averaging the manual delineations. The mean sensitivity for the fast marching segmentation is 93\% and the specificity is close to 100\%. When we apply deformable model segmentation, we obtain a sensitivity increase of three percentage points while the high specificity is maintained. The mean interaction time for the deformable model segmentation is 1.5 minutes.

We present a fully 3D liver segmentation method where high accuracy and precision is efficiently obtained via haptic interaction in a 3D user interface. Our method makes it possible to avoid time-consuming manual delineation, which otherwise is a common option prior to, e.g., hepatic surgery planning.

Keywords: Multimodal interaction, Segmentation, Visualization

1. INTRODUCTION

Liver segmentation is of great importance in hepatic surgery planning\textsuperscript{1–3} and also for monitoring liver enlargement which is correlated to disease progress for patients with liver metastases.\textsuperscript{4} Automated liver segmentation is a hard image analysis task due to mainly two reasons:

1. the high anatomical variability of the liver, often higher among patients with liver tumors, and
2. barely detectable borders between the liver and its neighboring structures in images.

On the other hand, manual delineation of the liver in high-resolution images is tedious, time-consuming, and error-prone. By instead using semi-automatic methods,\textsuperscript{3,5} an expert can provide knowledge to the segmentation algorithm through interaction and thereby facilitate the segmentation task.

Haptic interaction provides the unique possibility of simultaneous exploration and manipulation of data and it has been shown that it can improve semi-automatic segmentation.\textsuperscript{6} During recent years, we have been working on semi-automatic segmentation methods where the interaction is performed in an environment that allows for true 3D interaction with haptic feedback and stereo graphics. We use a specialized haptic display from Sense-Graphics\textsuperscript{7} that integrates haptics and graphics, see Figure 1. For this interactive framework, we have assembled...
a toolkit that contains implementations of a number of algorithms for segmentation, visualization, and haptic rendering.\textsuperscript{8–10} The toolkit is implemented in C++ and is integrated into the H3D API\textsuperscript{11} from SenseGraphics. In this work, we use parts of this toolkit for semi-automatic liver segmentation in contrast-enhanced CT images. First, we interactively create an approximate segmentation with a fast marching method.\textsuperscript{8} The fast marching segmentation is reproducible and provides an accuracy sufficiently high for robust volume measurements, but it contains leakage artifacts due to low contrast between the liver and surrounding tissue. To overcome this problem, we perform a subsequent interactive segmentation step where shape-constrained deformable models are fitted to the liver guided by the fast marching result. This way, the irregular regions caused by leaking are removed and we are able to increase the segmentation accuracy. Assessment of accuracy is made by comparing the segmentations with manual delineations performed by two radiologists.

The outline of this paper is as follows: In Section 2, we describe the fast marching segmentation and in Section 3, we present our deformable model implementation and how it is used to refine the fast marching result. Section 4 describes the framework for segmentation evaluation, and Section 5 presents our results. Section 6 concludes the paper with discussion and suggestions for future work for our open source toolkit.

2. FAST MARCHING SEGMENTATION

Fast marching methods\textsuperscript{12} are numerical schemes for solving the \textit{Eikonal} equation, i.e., the boundary value problem

$$||\nabla u(x)|| = C(x), \ u(x) = 0 \ on \ \Gamma,$$

where $u$ is the arrival time of the initial front $\Gamma$ propagating in its normal direction with speed $1/C$. The central idea behind the fast marching method is to systematically construct the solution $u$ in a downwind fashion, i.e., to propagate information outwards from the boundary condition. The algorithm is accelerated by limiting the computational domain to a \textit{narrow band} in the proximity of the front that is represented by a minimum heap data structure that allows for fast sorting and access of the elements.

In image segmentation, the initial front is represented by a set of user specified seed-points inside the object of interest and the slowness function $C$ is represented by a cost image having low values in homogeneous parts and high values at edges. Based on this input, the initial front is propagated and the time of arrival map $u$ is given as output. The final segmentation result is obtained by thresholding $u$ at a certain time value.
In Ref. 8, we present a fast and robust semi-automatic fast marching method for liver segmentation. The method involves the following steps:

1. Interactive initialization of the method (seeding) with the haptic interface.
2. Computation of a cost image by combining edge-preserving smoothing with bilateral filtering, probability mapping based on seed-point statistics, and gradient magnitude extraction.
3. Fast marching propagation of the seed-regions with automatic time of arrival thresholding.

Figure 2 illustrates the method.

The fast marching method was applied to 52 abdominal contrast enhanced venous phase CT images from patients with either carcinoid or endocrine pancreas tumor. Four users independently performed liver segmentation using the method and the results showed high reproducibility when we made pairwise comparisons of the four sets of segmented datasets. The accuracy was visually verified by a radiologist through combined examination of contour overlays and surface renderings. The method performs well, but in some cases there are problems with leakage, see Figure 2 (right) and Figure 6 (middle row).

3. DEFORMABLE MODEL SEGMENTATION

In Ref. 8, we discussed the possibility to use the fast marching segmentation as a first step towards a more accurate delineation with methods that involve shape constraints, e.g., deformable surface models. In this work, we realize that idea with a deformable model implementation based on Delingette’s discrete simplex mesh representation.

A 2-simplex mesh represents a 3D surface model where each simplex vertex $p_i$ has exactly three neighboring vertices $(p_{N_1(i)}, p_{N_2(i)}, p_{N_3(i)})$, see Figure 3. The neighboring vertices define a triangle in the tangent plane with normal vector $n_i$. The position of a vertex can be represented in terms of its neighbors with the use of the metric parameters $\epsilon_i$ and the simplex angle $\varphi_i$, i.e.,

$$p_i = \epsilon_1 p_{N_1(i)} + \epsilon_2 p_{N_2(i)} + \epsilon_3 p_{N_3(i)} + L(\varphi, \cdot) n_i.$$  

The metric parameters control the vertex projection in the tangent plane, while the simplex angle control the local mean curvature through the elevation function $L$.  

In order to deform the model to fit the underlying image data, we use a deformation engine based on Newtonian evolution. Each vertex is regarded as a point-mass influenced by internal forces, external forces, and damping. By using finite differences, the discretized differential equation for a vertex becomes

$$p_i^{t+1} = p_i^t + (1 - \gamma)(p_i^t - p_i^{t-1}) + \alpha_i(F_{\text{int}})_i^t + \beta_i(F_{\text{ext}})_i^t.$$
i.e., a force equilibrium equation where \( t \) is the time (iteration), \( \gamma \) is the damping factor, \( \mathbf{F}_{\text{int}} \) is the internal force of the model, and \( \mathbf{F}_{\text{ext}} \) is the external force based on data features and interaction. The weights \( \alpha_i \) and \( \beta_i \) control the level of the internal and external force components, respectively. The internal forces are decomposed into a tangential force and a normal force. The tangential force is based on the local mean curvature in order to adapt the mesh resolution to the object of interest. For the normal force, we use a \( C^2 \) constraint.\(^{13}\)

We use four different image-based external forces in our implementation:\(^{10}\)

- gradient magnitude force,
- inflation force,
- potential field force, and
- vector field force.

We also have an additional interaction force where the user selects parts of the mesh and pushes or pulls the selected vertices with the haptic probe, see Figure 4 (right).

In this work, we want to fit the surface mesh to the fast marching result. For this, we use the external potential field force which is based on a signed distance map of the segmented liver contour. When the deformation engine is activated, the vertices of the model are moved in the negative gradient direction of the potential field \( P \), i.e.,

\[
(F_{\text{potential}})_i = w_i (f_i \cdot \mathbf{n}_i) \mathbf{n}_i,
\]

where \( w_i \) is a weight and \( f_i = -\nabla P(p_i) \). Note that the force is applied only in the normal direction to avoid instabilities.\(^{13}\) The initial mesh is a coarse sphere, see Figure 3, which is interactively scaled and positioned in the volume, see Figure 4 (left). During deformation, the user can apply interaction forces and also globally refine the mesh through subdivision of mesh faces.

One user performed segmentation of the liver based on two of the four sets of fast marching segmentations, limited to the 23 datasets for which we have ground truth. This means that we have \( 2 \cdot 23 = 46 \) deformable model segmentations.
4. ASSESSMENT OF SEGMENTATION PRECISION AND ACCURACY

We quantitatively evaluate both segmentation precision and accuracy using the framework by Udupa et al. This framework provides tools for evaluation of segmentation efficacy, i.e., precision, accuracy, and efficiency. The framework is developed to be able to handle fuzzy segmentations where crisp segmentations become a particular case. A fuzzy segmentation of object $O$ obtained with method $M$ is denoted by $C^M_O = (C, f_O)$, where $C$ is the 3D grid and for any $x \in C$, $f_O(x) \in [0, 1]$ is the degree of belongingness to the object.

In order to evaluate the segmentation accuracy, we need a ground truth. For the 52 datasets used in this work, we have manual delineations for 23 of the datasets performed by two radiologists using the routine software of a Siemens Leonardo workstation. From these delineations, we construct a fuzzy true segmentation $C_{true} = (C, f_{true})$ by averaging, i.e.,

$$f_{true}(x) = \frac{1}{2} (f_{O_1}(x) + f_{O_2}(x)),$$

where $f_{O_i} \in \{0, 1\}$ represent the two crisp manual delineations. This means that $f_{true}(x) \in \{0, 0.5, 1\}$, see Figure 5 (left).

The segmentation accuracy is obtained by computing the sensitivity as the true positive volume fraction

$$TPVF = \frac{|C_{TP}|}{|C_{true}|} = \frac{|C^M_O \cap C_{true}|}{|C_{true}|},$$

and the specificity as one minus the false positive volume fraction

$$1 - FPVF = 1 - \frac{|C_{FP}|}{|C_{true}|} = 1 - \frac{|C^M_O - C_{true}|}{|C_{true}|}.$$

A completely accurate segmentation method will have both specificity and sensitivity equal to one. See Ref. 14 for definitions of the fuzzy set operations involved.

Segmentation precision is a measure of repeatability, i.e., how sensitive the result is to operator input. The suggested precision metric for two fuzzy segmentations $C^M_{O_1}$ and $C^M_{O_2}$ obtained with method $M$ at different...
occasions is

$$PR^M = \frac{|C^M_{O_1} \cap C^M_{O_2}|}{|C^M_{O_1} \cup C^M_{O_2}|}.$$ 

$PR^M$ represents the amount of tissue common to both $C^M_{O_1}$ and $C^M_{O_2}$, the intersection of the sets, as a fraction to the total amount of tissue found in the union of $C^M_{O_1}$ and $C^M_{O_2}$.

5. RESULTS

For the 23 manual segmentations performed by the radiologists, we obtain a mean precision of 88.9% with coefficient of variation (CV) 1.9% when using the precision metric $PR^M$ described above. For the fast marching method, we obtain a mean precision of 96.9% (CV 3.8%), which is considerably higher. For the two sets of 23 segmentations obtained with the deformable model segmentation, we obtain a mean precision of 97.8% (CV 0.5%) which indicates a high reproducibility.

The segmentation accuracy measures are reported in Table 1. For the fast marching method, the average sensitivity is 93.0% and the sensitivity is close to 100%, i.e., we have very few false positive voxels. When we apply the deformable mesh segmentation we obtain an average sensitivity of 96.2% which is an increase of about three percentage points compared to the fast marching result. The high specificity is maintained. The resulting simplex meshes were voxelized with 3D rasterization and region filling in order to be comparable with the true segmentations. See Figure 5 and Figure 6 for illustrations of the results.

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<td>92.9 (1.9)</td>
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<td>93.0 (1.7)</td>
<td>96.2 (1.3)</td>
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<tr>
<td>Specificity</td>
<td>99.8 (0.1)</td>
<td>99.8 (0.1)</td>
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The interaction time required for the manual delineation was between 5 and 18 minutes. As reported in Ref. 8, the mean interaction time for seeding of the fast marching method was 40 seconds per dataset with standard deviation (SD) 23 seconds. For the deformable mesh segmentation described here, we have a mean interaction time of 93 seconds (SD 16 seconds). This includes initialization and deformation with interaction forces and mesh subdivision.
6. CONCLUSIONS

We present a fully 3D semi-automatic liver segmentation method. The method is based on region growing from seeds with a fast marching method and subsequent fitting of a deformable simplex mesh with shape constraints. High accuracy and precision is efficiently obtained via haptic interaction in a 3D user interface. Our segmentation method makes it possible to segment livers without time-consuming and tedious manual delineation, which otherwise is a common option prior to, e.g., hepatic surgery planning.

The method works well, but prior to use in a clinical situation, we have a number of suggestions for future work. At this stage, the method is clearly divided into two steps, but it is possible to integrate the two parts more closely in order to make the segmentation more efficient. For the surface fitting part, we can avoid starting with a spherical mesh and instead produce an initial mesh from the fast marching result using, e.g., the triangulation algorithm described in Ref. 15. This would reduce the interaction time for the mesh deformation and probably increase the segmentation accuracy further. Another improvement would be to also use other image-based external forces than the potential field. In the future, we also consider to involve statistical shape constraints of the model.

The toolkit containing the methods described in this paper is publicly available. For download details, please, refer to http://www.cb.uu.se/research/haptics.

REFERENCES

Figure 6. Illustration of the segmentation results for two of the datasets. Top row: Seed-points (red) and fast marching segmentation results (blue). Middle row: Surface renderings of the fast marching results. Bottom row: Simplex mesh segmentation results. The shape constraints of the model mitigate the leakage problems.