Semi-automatic Liver Segmentation From Computed Tomography (CT) Scans based on Deformable Surfaces

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Abstract—This paper presents a semi-automatic segmentation method to extract the liver volume from CT scans, based on discrete deformable surfaces with a priori shape and intensity information. A shape model of the liver, represented as a triangular mesh, is built and is manually located in the region of interest, to be iteratively deformed in function of the intensities and the edges. In the deformation process, the distances between the vertices of the mesh are evaluated to maintain a homogeneous distribution of the surface points, while a low-pass filter is applied to assure surface smoothness. Some experimental results of the proposed segmentation method are presented to illustrate its performance.

Index Terms—liver segmentation, deformable surface model, boundary extraction, computed tomography.

I. INTRODUCTION

In clinical practice, liver volume measurement is an important parameter for follow-up under medical treatments and planning of hepatic resections [1], [4], [12]. Generally, this measurement is done by manual delimitation of liver boundaries from CT images at each axial slice. However, this is a time-consuming procedure, which depends on the expertise of the specialist and is usually not reproducible. On the other hand, automatic liver segmentation from CT images is still a challenging problem, due to the similar intensities present in surrounding organs and tissues, the varying shape of the liver, and the presence of tumors and large blood vessels in the hepatic tissue. In this paper, we propose a semi-automatic liver segmentation method based on discrete deformable surfaces [9]–[11], [15], which incorporates a priori shape and intensity of the liver in order to adjust the parameters of the deformation model on these particular images.

II. MATERIALS AND METHODS

A. CT images and reference segmentations

Liver CT images and their respective reference segmentations were obtained from the dataset available on the web1 [5], [6]. These images were acquired in different machines, at different resolutions, and using a contrast material. Pixel size in these images varies from 0.55mm to 0.8mm in x/y direction, while the inter-slice distance varies from 1mm to 3mm. The reference segmentations were performed manually by experts in more than 20 livers with both healthy and pathological tissue.

B. Semi-automatic liver segmentation method

The proposed approach consists in deforming an initial surface based on intensities and edges information, until it reaches the liver boundaries. A diagram of the proposed segmentation method is shown in Figure 1. Initialization of the deformable model is done by using a surface with the average shape of the liver, represented as a triangular mesh. This surface was built using a method similar to [16], on images obtained with a multi-classifier combination technique [14], which was applied to 19 reference segmentations, with the same orientation and the same point of reference in function of their centers of mass.

Information of the liver intensities was extracted from an image sample (manually defined from a representative region of the hepatic tissue to be segmented), and was used both to establish the initial location of the surface on the images, and to define the deformation parameters.

The surface deformation is governed by the following motion equation [7], [8]:

$$x_{i}^{t+1} = x_i^t + w_1 f_{tension} + w_2 f_{fib} - w_3 f_{edge}$$  (1)

where $x_{i}^{t+1}$ is the next position in time of vertex $i$, given its current position $x_i^t$ and a set of forces ($f_{tension}$, $f_{fib}$, and $f_{edge}$), while $w_1$, $w_2$ and $w_3$, are weighting parameters. The tension force ($f_{tension}$), defined as

\begin{align*}
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initially segmented region \[18\]. Finally, the edge force (according to the distribution of the liver intensities in the initially segmented region) [18]. Finally, the edge force \(f_{eb}\), based on the balloon force [3]

\[ f_{eb} = B(I)\mathbf{n}_i, \]  

moves each vertex in the normal direction \(\mathbf{n}_i\), and with magnitude \(B(I)\) (see Figure 2), to inflate or deflate the mesh according to the distribution of the liver intensities in the initially segmented region [18]. Finally, the edge force \(f_{edge}\)

\[ f_{edge} = \left[ \nabla \left( \frac{1}{1 + k} \right) \cdot \mathbf{n}_i \right] \mathbf{n}_i, \]  

is defined as

\[ k = \left[ \frac{\left| \nabla (G_\sigma * I) \right|}{\text{median}_R(\left| \nabla (G_\sigma * I) \right|)} \right]^2. \]  

This \(f_{edge}\) stops the surface vertices at the strong boundaries of the image [2], using a Gaussian function \((G_\sigma)\), with standard deviation \(\sigma\), that smoothes the image \((I)\), and the median of the gradient magnitude distribution \((\text{median}_R(\left| \nabla (G_\sigma * I) \right|))\) in the manually segmented hepatic tissue region. The effect of the \(k\) function is to enhance strong edges and decrease weak edges, both of them present in the hepatic tissue. After each vertex \(\mathbf{x}_i^t\) has been moved to its new position \(\mathbf{x}_i^{t+1}\), a low-pass filter (smoothing) is applied [17], together with an evaluation of distances between neighboring vertices [13], merging closest vertices (see Figure 3) or inserting new points in order to break up long edges (see Figure 4), while the low-pass filter allows to obtain a smoothed surface at each iteration of the deformation process.

### C. Definition of the Deformable Model Parameters

Optimal values of \(w_1\), \(w_2\), and \(w_3\), that weight the deformation forces, were adjusted experimentally. Defining \(w_1\) as 0.9 reduce the effect of \(f_{tension}\), allowing flexibility in the mesh deformation to follow the variability of the liver morphology, and at the same time, controlling the appearance of outlier vertices on the surface. The maximum distance (in the normal direction) that a vertex can move at each iteration is controlled by the parameter \(w_2\), that has been setted at \(mdv\) (minimum distance between voxels). Finally, a value of 1.5\(mdv\) has been selected for \(w_3\) (slightly higher than \(w_2\)), allowing that \(f_{edge}\) counteract \(f_{eb}\) when the vertices are on the object edges.

The range of the edge lengths of each triangle in the mesh was defined between 2\(mm\) and 5\(mm\). This range was set both to capture the details of the liver surface in the images and to avoid mesh self-intersections in the deformation process. Hence, at every iteration step, a subdivision operation breaks the triangles with an edge longer than 5\(mm\), while a trimming task removes the triangles with an edge smaller than 2\(mm\), without affecting the topology of the mesh. The surface is deformed iteratively whereas a fixed number of iterations was reached.

### III. Results and Discussion

For evaluate the results of the proposed liver segmentation method, it is not enough just a comparison of the volume estimation results, other metrics are also needed to compare voxel by voxel and between generated surfaces. Therefore, we used the metrics described in [5], [6], that measure the Volume Difference (VD), the Volumetric Overlap Error (OE), the Average Distance (AD), the RMS Distance (RMSD) and the Maximum Distance (MD) between surfaces. Quantitative results regarding the performance of the proposed segmentation method on all 20 training cases from the dataset available at www.sliver07.org are presented in Table I. In all of these metrics, the best score possible is 100 (equal to the reference...
segmentation), 0 the worst, and a score of 75 is comparable to a human observer.

From the results presented in Table 1 and Figure 5, can be notice the adaptability of the surface deformation to the shape variability of the liver, based on information of the average shape of this organ and the intensities range of the hepatic tissue. Nevertheless, the model did not take into account the pixel intensities of the tumors, neither of the large blood vessels (as hepatic and portal veins) when these are enhanced by contrast material, causing that these structures are not included, in most of the cases, in the segmented region. However, extending the intensities range did not solve this problem, because this includes also in the segmentation those tissues closer to the liver, such as the subcostal muscles and fat of the rib cages, the heart and the stomach.

Although the performance of this method is similar for slight variations of the initial position of the average shape of the liver, it is important that in this stage this surface covers most of the region to be segmented, avoiding to touch the heart, the muscles between the ribs or the kidneys, and to include the blood vessel ramifications within the liver.

IV. CONCLUSION

A semi-automatic liver segmentation method was proposed, based on discrete deformable surfaces with a priori shape and intensity information, in order to limit model deformation degrees of freedom, adjusting it to the particular liver features in the images. A low-pass filter and a remeshing method were included in order to preserve the surface smoothness. Depending on the manual initialization, this segmentation method works properly; although improvements are expected for automatic positioning of the initial surface, and the inclusion of the large blood vessels and tumors in the segmentation.

REFERENCES


RESULTS OF THE COMPARISON METRICS AND CORRESPONDING SCORES FOR ALL 20 TRAINING CASES.

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Average: 8.4, 67, 5.7, 71, 1.2, 70, 2.8, 61, 23.3, 69, 68
Fig. 5. From left to right, a sagittal, coronal and transversal slice from a relatively easy case (12, top), an average case (10, middle), and a relatively difficult case (16, bottom). The outline of the reference standard segmentation is in blue, the outline of the segmentation of the method described in this paper is in red. Slices are displayed with a window of 400 and a level of 70.