Automatic Segmentation of the Liver for Preoperative Planning of Resections

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Abstract. This work presents first quantitative results of a method for automatic liver segmentation from CT data. It is based on a 3D deformable model approach using a-priori statistical information about the shape of the liver gained from a training set. The model is adapted to the data in an iterative process by analysis of the grey value profiles along its surface normals after nonlinear diffusion filtering. Leave–one–out experiments over 26 CT data sets reveal an accuracy of 2.4 mm with respect to the manual segmentation.

1 Introduction

Individual preoperative surgical planning for resections of tumors in the liver requires segmentation of the liver tissue [1]. Reliable image segmentation is essential for the correct prediction of the blood circulation regions.
Semi-automatic methods may reduce the user interaction time for segmentation. However in the clinical routine automatic methods are desirable. 3D statistical shape models are promising for robust and automatic segmentation of medical images.
One major challenge when building a 3D statistical shape model is to establish correspondence between the points on the surfaces of different objects. We will use an approach where the geometrical distortion between two surfaces is minimized [2].
In order to match the model to the CT data, some adaption strategy must be implemented. Often statistical information about the grey values in the training data is used [3]. By filtering the data with an nonlinear diffusion filter [4] a fixed model is established, that does not depend on statistical knowledge.

2 Methods and Tools

The training set for the generation of the statistical shape model [3] consisted of 30 CT scans with contrast enhancement and a gap of 5 mm between two consecutive slices. From these CT stacks 30 liver shapes were segmented manually with the help of the visualization and volume modeling software Amira [5].
The generation of the statistical shape model is described in [2]. The statistical information is extracted from the training set by principal component analysis, resulting in a compact representation as a linear model

$$\mathcal{S}(\mathbf{b}, T) = T(\overline{\mathbf{v}} + P\mathbf{b})$$

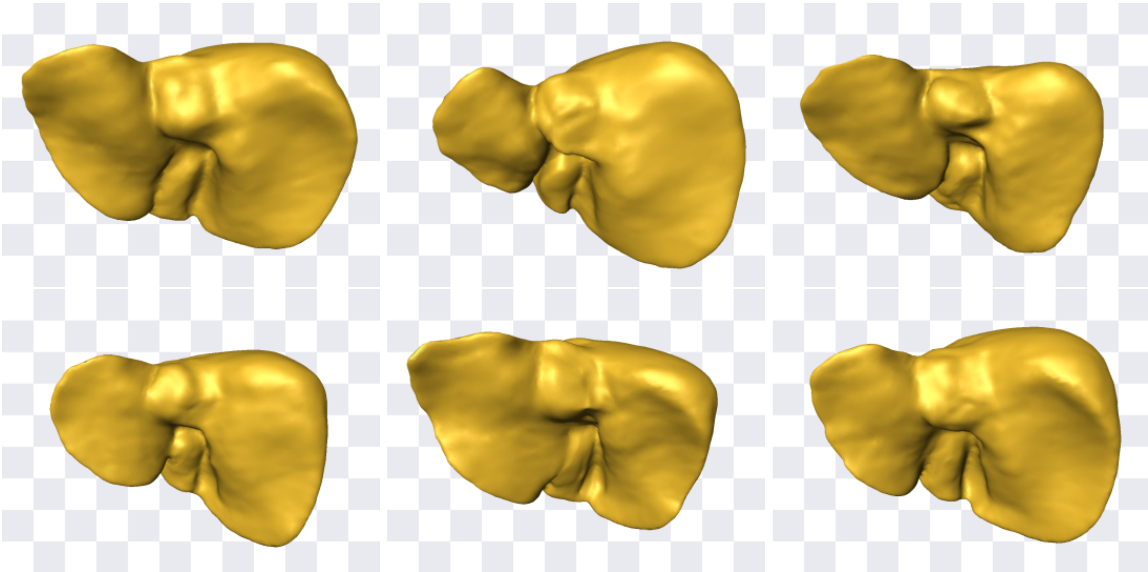

Figure 1: Visualization of the variability of a statistical model of the liver shape made from 43 training data sets: in the left column the eigenmode with the largest variance λ_1 is varied between $\pm 3\sqrt{\lambda_1}$, in the second and third column the modes with the second and third largest variance are shown respectively.

where T is a rigid transformation, $\overline{\mathbf{v}}$ the mean liver shape, P the matrix of eigenvectors of the covariance matrix of the training set and $\mathbf{b}$ are the shape weights. In figure 1 the main modes of variation of the liver shape are displayed.

The segmentation procedure consists of an iterative process, in which the coefficients of the shape modes $\mathbf{b}$ and the 3D pose parameters T of the model are optimized such that the model matches the shape of the liver in the CT stack to be segmented. In each iteration a displacement field normal to the model surface is computed from grey value profiles taken from the filtered CT data. The surface generated by this deformation is then projected back onto the shape model, resulting in a shape that is a valid representation of a liver within the space of the training data.

We adopt a multilevel approach by increasing the number of coefficients for the shape modes during the segmentation process. At each level we first compute the optimal rigid transformation and then adjust the shape coefficients of the model. Initially we start with the mean shape of the liver.

3 Results

In order to quantify the segmentation results, we measure the mean and "regional" distance between the manually segmented and automatically generated surface. We define "regional" distance by the percentage of the surface areas that differ more than X mm from each other.

We performed a leave-one-out test on each of the 30 manually segmented livers. In 4 cases the result was not acceptable, due to large deviations in the vena cava region (blood vessel that borders the liver) or very low contrast in the CT images. All other automatically segmented surfaces had a mean distance of 1.2 mm to 3.3 mm (average 2.4 mm). The percentage of the area with a distance of more than 5 mm ranged from 1 to 20% (average 11%). A typical segmentation result can be seen in figure 2.

To find out more about the residual errors we tested how well known shapes would be recov-

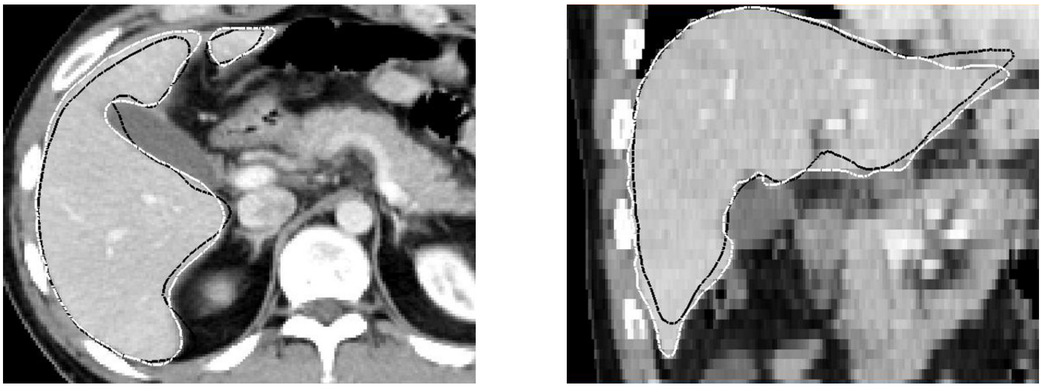

Figure 2: Visualization of the automatic segmentation in axial (left) and coronal (right) view of an exemplary data set (leave–one–out experiment).

ered with our algorithm (leave–all–in experiment). We repeated the analysis described above without leaving shapes out. On average the mean distance was 1.0 mm (0.6 mm to 1.5 mm) and the regional distance with $X = 5$ mm tolerance was 1% (0 to 5%). A similar error is also encountered in many inter– and intra–expert studies.

4 Conclusions and Discussion

It was shown that a statistical shape modeling approach works well for a robust and automatic segmentation of the liver. Besides very few cases, where our specific grey value model or bad image quality lead to unsatisfying results, most of the training data could be segmented in a leave-one-out test with a quality that is close to satisfactory for preoperative planning. Including the vena cava explicitly in the shape model should improve these results. The evaluation of the leave–all–in experiment indicates that the inaccuracies in the leave–one–out test are mainly due to the limited generalization ability of the shape model and that the adaption strategy performs very well. Due to the large variance in the liver model there is legitimate hope that increasing the number of training data sets will further improve the segmentation results.

References

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