# Automatic Liver Segmentation using Multiple Prior Knowledge Models and Free-Form Deformation

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**Abstract**

In this paper, an automatic and robust coarse-to-fine liver image segmentation method is proposed. Multiple prior knowledge models are built to implement liver localization and segmentation: voxel-based AdaBoost classifier is trained to localize liver position robustly, shape and appearance models are constructed to fit liver shape and appearance models to original CT images. Free-form deformation is incorporated into segmentation process to improve the model's ability of refining liver boundary. The method was tested on IBSI 2014 VISCERAL challenge datasets and the result demonstrates that the proposed method is robust and efficient.

## 1 Introduction

Accurate and robust liver segmentation in CT images is an indispensable part in liver quantitative diagnosis and surgery planning, while variation in liver shape, appearance and fuzzy boundary remain challenging. Recently, prior knowledge models learned from big data play an important role in successful clinical image segmentation. In this study, integrating of discriminative and generative models in a hybrid scheme was presented to assist liver localization and segmentation: machine learning based voxel classifier, active shape model (ASM) [Cootes95] including statistical shape model (SSM) prior and local appearance model. Finally, the final fitted model was free-form deformed to true liver boundary under appearance model guidance. The coarse-to-fine liver image segmentation framework including liver localization, model reconstruction, model fitting and free-form deformation is illustrated in Figure 1.



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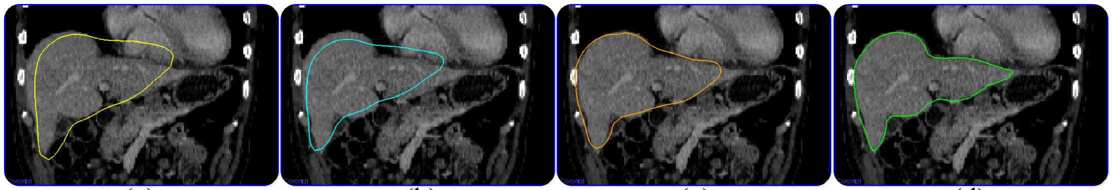


Figure 1: The four steps of liver segmentation framework: (a) liver model location; (b) registration with liver distance map; (c) shape fitting under appearance guidance; (d) free-form deformation.

# 2 Method

## 2.1 Liver localization

An atlas image based rigid registration with correlation coefficient histogram metric was used to detect the region of interest (ROI) of liver. A set of image features such as region mean intensity, variance, location, histogram and contextual features were extracted to train an AdaBoost classifier, by which a liver probability map was generated, and the position of the liver was robustly estimated.

## 2.2 Model reconstruction

The SSM of liver was constructed from training CT images and corresponding binary segmentations. Firstly, pose training described in [Huang13] was applied to resample all the images. For shape correspondence establishment, one reference mesh was obtained by marching cubes method, all other training segmentations were elastic registered to the reference mesh, landmarks were sampled equally on each training mesh. The SSM was constructed by Statismo toolkit [Luthi12] and represented by simplex mesh.

The local appearance model of liver was established by a K Nearest Neighbor (KNN)-classifier trained on both intensity and gradient profiles information inside, outside and at the true liver boundary as suggested in [Heimann07]. For each landmark, profiles perpendicular to the surface are sampled from all training volumes and stored as boundary samples. Additional non-boundary samples were acquired by shifting the profiles towards the inside and outside of the liver.

## 2.3 Shape and appearance profile fitting

For the image to be segmented, a liver probability map was derived by AdaBoost classifier, and the binary mask can be obtained at threshold 0.5. The distance map image was applied to register to the point sets of the mean shape model, and the mesh vertexes of deformed mean shape were fitted to liver boundary location with major shape variation constraints.

The appearance model is utilized to drive the model toward the precise liver boundary. Local appearance features for all landmarks are extracted at different positions perpendicular to the model surface. Previous trained KNN-classifier shifts landmarks to the optimal displacement position with maximum boundary probability.

## 2.4 Free-form deformation

Once appearance profile fitting has converged, the deformed shape model were then free-form deformed to the more accurate position. Free deformation was implemented based on deformable simplex mesh [Montagnat97] segmentation. The internal force strives to keep the deformable mesh close to the best fitting SSM, and the external forces tries to move all vertices to the locations where intensity or gradient appearance model predicts the highest boundary probability. Previous

KNN-classifier was integrated as external force to deform to conquer local specific variation of liver shape.

## 3 Result

Seven CT and seven CTce IBSI VISCERAL challenge 2014 datasets were employed to train AdaBoost classifier. Additional fifty manually segmented datasets were used to train the prior shape and appearance models. There are 1252 landmarks in the liver shape model, each landmark is sampled with 11 points in the landmark normal direction in the profile model. The experiment was tested on 8 CT and 8 CTce datasets. The four evaluation metric scores are as follows: average dice coefficient were 0.924 and 0.925, interclass correlation were 0.924 and 0.925, adjusted rand index were 0.923 and 0.920 and average distance were 0.222mm and 0.261mm for CT and CTce modality respectively.

## 4 Conclusion

In this paper, a robust and automatic liver segmentation method is proposed. The method exploits different prior knowledge to represent contextual, profile appearance and shape variation of liver, relies on different registration to construct liver model, liver localization, model fitting and refined deformation. The method has been validated on ISBI VISCERAL challenge and showed good performance. In future, we will adapt the method to other visceral organs segmentation.

## 5 Acknowledgments

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