Fully Automatic Multi-organ Segmentation based on Multi-boost Learning and Statistical Shape Model Search

Baochun He, Cheng Huang, Fucang Jia
Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences
1068 Xueyuan Avenue, Xili University Town, Shenzhen, 518055, China
Email: fc.jia@siat.ac.cn

Abstract

In this paper, an automatic multi-organ segmentation based on multi-boost learning and statistical shape model search was proposed. First, simple but robust Multi-Boost Classifier was trained to hierarchically locate and pre-segment multiple organs. To ensure the generalization ability of the classifier relative location information between organs, organ and whole body is exploited. Left lung and right lung are first localized and pre-segmented, then liver and spleen are detected upon its location in whole body and its relative location to lungs, kidney is finally detected upon the features of relative location to liver and left lung. Second, shape and appearance models are constructed for model fitting. The final refinement delineation is performed by best point searching guided by appearance profile classifier and is constrained with multi-boost classified probabilities, intensity and gradient features. The method was tested on 30 unseen CT and 30 unseen enhanced CT (CTce) datasets from ISBI 2015 VISCERAL challenge. The results demonstrated that the multi-boost learning can be used to locate multi-organ robustly and segment lung and kidney accurately. The liver and spleen segmentation based on statistical shape searching has shown good performance too.

In: O. Goksel (ed.): Proceedings of the VISCERAL Anatomy Grand Challenge
at the 2015 IEEE International Symposium on Biomedical Imaging (ISBI), New York, NY, Apr 16^{th}, 2015
published at http://ceur-ws.org

1 Introduction

Abdominal organ segmentation is an essential step in the multi-organ visualization, clinical diagnosis and therapy. Up to now, some methods [Okada12, Wang14] have been proposed, and all of them showed that information about the spatial relationship among organs is very beneficial to automatic 3D multi-organ localization. Previous studies also indicated that segmentation in a hierarchical way is more robust [Wang14, Selver14]. In our previous work [Li14], we used Adaboost and statistic shape model (SSM) prior knowledge to segment liver successfully. Now we extend this framework in multi-organ segmentation as shown in Figure 1. The differences are in two-fold. Firstly, Multi-Boost [Ben12] is employed to classify two organs one time in a top-down order. The last organ segmentation result will be used to classify the next level organs. Secondly, to acquire a customized specific shape result, free searching is directed by K Nearest Neighbor (KNN) and is constrained with voxel-based information such as probability, intensity and gradient features.

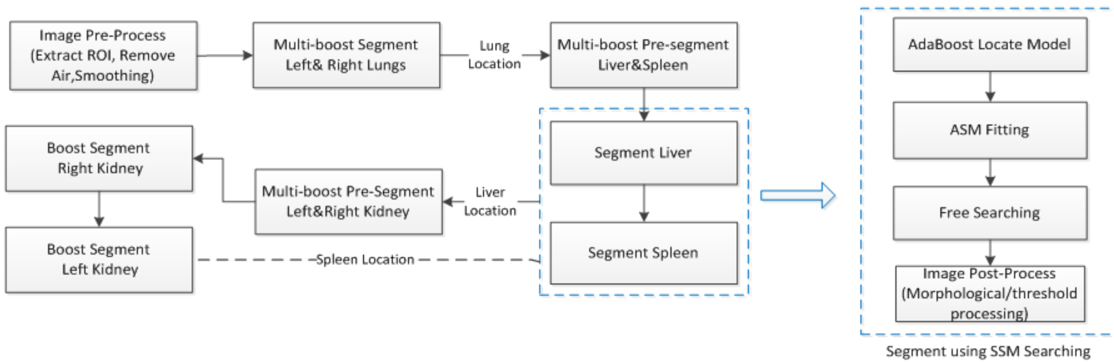


Figure 1: The framework of multi-organ segmentation

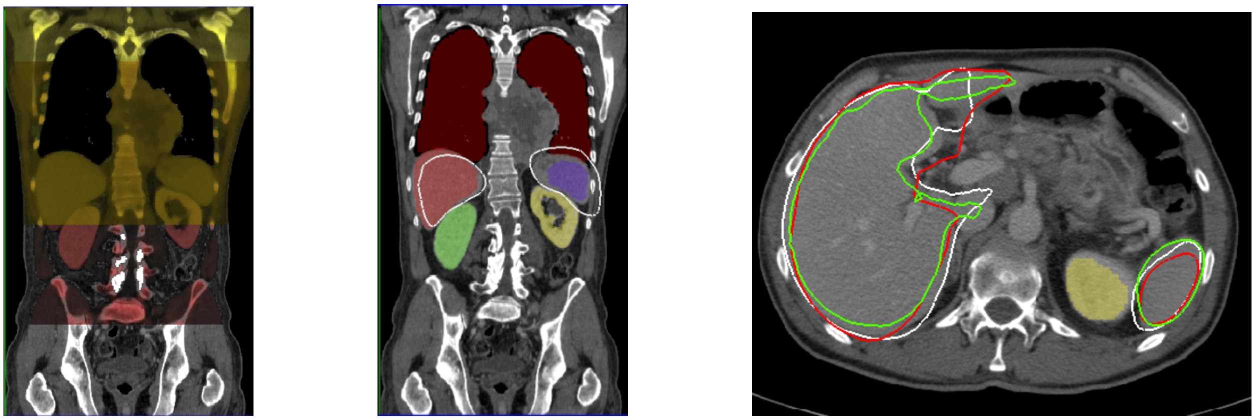
2 Method

2.1 Model Construction

SSM model was constructed from 20 CT and 20 CTce training binary segmentations. At first, reasonable region of interest (ROI) of the training binary images is extracted and generalized Procrustes aligned. Then one smooth and normal reference mesh is obtained using marching cubes method. Finally a set of corresponding shapes are created by elastic registration of the reference shape to the aligned binary images. The SSM is constructed by Statismo toolkit [Luthi12] and represented by Simplex mesh. The local appearance model of each organ is established by a KNN classifier trained on both intensity and gradient profiles information inside, outside and at the true organ boundary as suggested in [Heimann07].

2.2 Multi-organ Localization

Image features such as intensity, location and contextual information are used to train a multiboost classifier. To ensure the generalization ability of the classifierrelative location information between organs, organ and whole body were exploited. Template matching is employed to extract the organ ROI as shown in Figure 2(a). Localization and segmentation is performed in a top-down order - first left and right lung, then liver and spleen, at last left and right kidney, as seen in Figure 2(b). Thresholding was applied to the probability image of the boosting classified ROI image to get the pre-segmentation mask. Due to good boosting classification precision for lung and kidney, the pre-segmentation mask is used as the final segmentation.



(a) (b) (c)

Figure 2: Three steps in the multi-organ segmentation framework: (a) Image preprocessing; (b) Model localization and segmentation of lung and kidney; (c) Shape fitting for liver and spleen, with pre-segmentation distance map (red), continued by boundary profile search (white), finally free-searching directed by the boundary profile classifier (green).

2.3 Active Shape Model Search

Similarity and shape transform parameters are initialized first by registration of SSM shape to the distance map of the pre-segmentation image. Appearance model is utilized for accurate parameters searching [Cootes95]. Previous trained KNN-classifier shifts each landmark to its optimal displacement position, similarity and shape parameters are then calculated through matrix operations. This process is performed iteratively until the parameters converge.

2.4 Appearance Profile Classifier directed Boundary Searching

In this step, the goal is to find the optimal confidence position for each mesh vertex. Due to high accuracy of the KNN, it is still used as boundary profile classification method. However, in step 2.3, the best positions calculated by KNN may overflow or fail to reach the true boundary as illustrated in Figure 2(c). The target position around the one searched by KNN is named as KNN position for convenience. The points around the KNN position are selected as candidate points. Each candidate point is assigned by previous Adaboost probability obtained in step 2.2, where both the intensity and the gradient are scaled to [-1,1]. The point with maximum voting value will be the optimal confidence position. To preserve the smoothness of the shape, the point can only move to the computed best position in a constrained step. This process stops after iteration of user-specified numbers.

3 Results

Twenty non-contrast CT and twenty contrast enhanced CT (CTce) training volumes were used for each multi-boost classifier and KNN boundary classifier training. SSM was built on all thirty datasets. There are 2562 landmarks for the mean liver shape model and 1520 ones for the mean spleen shape model. The experiment was run on 30 unseen CT and CTce datasets and evaluated by Dice coefficient and average Hausdorff distance (AvgD). The evaluation results are shown in Table 1.

Table 1: Multi-Organ Segmentation Results

Organ	Non-Contrast CT		Contrast-Enhanced CT	
	Dice Coefficient	AvgD (mm)	Dice Coefficient	AvgD (mm)
Left Lung	0.952	0.101	0.966	0.069
Right Lung	0.957	0.094	0.966	0.078
Liver	0.923	0.239	0.933	0.203
Spleen	0.874	0.360	0.896	0.385
Left Kidney	–	–	0.910	0.171
Right Kidney	–	–	0.922	0.131

4 Conclusions

In this paper, a robust and automatic multi-organ segmentation method was proposed. The method exploits and combines different prior knowledge, such as interrelations of organs, intensity, boundary profiles and shape variation information, for robust model localization, model fitting and free searching. The method has been validated on ISBI 2015 VISCERAL challenge and showed good performance. Future work will extend the framework to more abdominal organ segmentation.

5 Acknowledgments

This work was supported by the grants as follows: NSFC-Guangdong Union Foundation (Grant No. U1401254); Guangdong Science and Technology Project (Grant No. 2012A080203013 and 2012A030400013).

References

[Okada12] T. Okada, M. G. Linguraru, M. Hori. et al. Multi-organ segmentation in abdominal CT images. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, DOI: 10.1109/EMBC.2012.6346840, pp. 3986 - 3989, 2012.

[Selver14] M. A. Selver Segmentation of abdominal organs from CT using a multi-level, hierarchical neural network strategy. *Computer Methods and Programs in Biomedicine*, 113(3):830-852, 2014.

[Wang14] C. Wang, O. Smedby. Automatic multi-organ segmentation in nonenhanced CT datasets using hierarchical shape priors. *The 22nd International Conference on Pattern Recognition (ICPR)*, pp. 3327-3332, 2014.

[Li14] X. Li, C. Huang, F. Jia, Z. Li, C. Fang, Y. Fan. Automatic liver segmentation using statistical prior models and free-form deformation. *In: Menze, B., et al. (eds.) MCV 2014. LNCS*, vol. 8848, pp. 181-188. Springer, Heidelberg (2014).

[Ben12] D. Benbouzid, R. Busa-Fekete, N. Casagrande , F. -D. Collin, B. Kgl. MULTIBOOST: a multi-purpose boosting package. *The Journal of Machine Learning Research*, 13, pp.549-553, 3/1/2012

[Heimann07] T. Heimann, H. P. Meinzer, I. Wolf. A statistical deformable model for the segmentation of liver CT volumes. *MICCAI Workshop: 3D Segmentation in the clinic: A grand challenge*, 161-166, 2007.

[Luthi12] M. Luthi, R. Blanc, T. ALbrecht, T. Gass, O. Goksel, P. Buchler, M. Kistler, H. Bousleiman, M. Reyes, P. Cattin, T. Vetter. Statismo - A framework for PCA based statistical models. *The Insight Journal*, 1:1-18, 2012.

[Cootes95] T. Cootes, C. J. Taylo, D. H. Cooper, J. Graham. Active shape models - their training and application. *Computer Vision and Image Understanding*, 61(1):38-59, 1995.