Database-guided detection and segmentation of organs in MR FastView localizers for automatic scan planning

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Purpose: Automatic planning of MRI scans has gained attention as a means to increase scan reproducibility and operator efficiency. In this work, we investigate automatic multi-organ localization in large FoV localizer datasets acquired using a fast continuously moving table technique (*syngo* TimCT FastView, Siemens AG, Erlangen, Germany). To this end, we developed a fast learning-based detection and segmentation method for 6 organs including liver, heart, lungs, and kidneys. The automatically identified anatomical information allows for precise automated scan planning based on an organ or structure of interest. We compare the accuracy of our detection and segmentation routines on ground truth annotations from 196 full body MR scout scans with 5 mm isotropic resolution.

Methods: To achieve a fast, robust detection and segmentation algorithm for multiple organs, we use a learning-based hierarchical detection network (HDN) [1]. In this framework, the localization and segmentation of each organ is done in a sequential manner by leveraging spatial dependencies among the organs. Statistical variation of each organ surface is represented with a point distribution model, meaning the unknown state of an organ in a volume is the position, orientation, and scale, as well as the coefficients that describe the organ surface. The spatial dependencies between organs allow for efficient organ localization through the use of sequential Monte Carlo estimation. Robustness is achieved through discriminatively trained classifiers, which model the appearance of each organ given an input image using larger collection of Haar and steerable features [2]. Fine-scale organ structure is obtained by performing a surface boundary refinement, where mesh surface points are displaced locally to the most likely region (given by a classifier) and the result is regularized using the shape model. In our detection network, the kidneys are predicted from the liver, and the left and right lungs are predicted from the heart. After all of the organs are segmented, a final post-processing step is performed on a signed distance function representation of the object to remove overlap between organs (see Figure 1 for an overview of the complete detection pipeline).

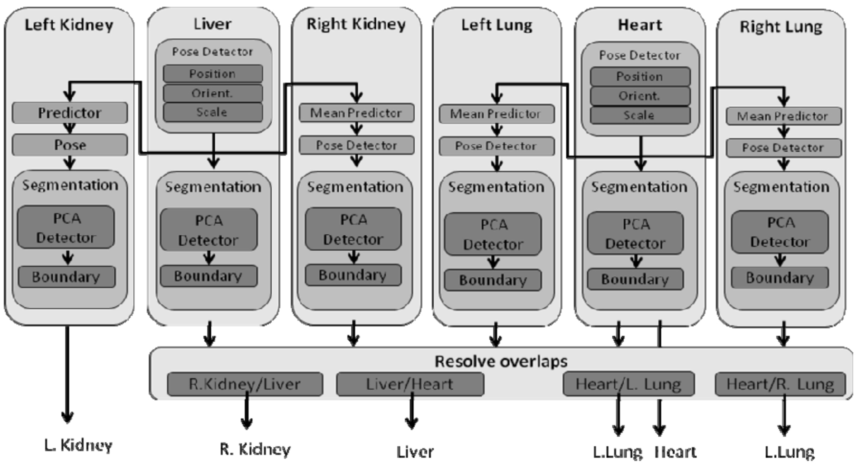

Figure 1: Processing pipeline for multi-organ detection and segmentation

Results: We trained and evaluated our system using 4-fold cross validation on a total of 196 *syngo* TimCT FastView localizer scans (sequential TurboFLASH sequence; all axial slices are acquired at isocenter while the table is moving; 5 mm isotropic resolution, 5 cm/s table velocity). Table 1 illustrates the average surface-to-surface deviation computed in mm on the detection results and the 80th percentile of this distance. Figure 2 gives a qualitative impression of the resulting segmentation quality. On a dual processor Intel® Xeon® CPU X5650 @ 2.67GHZ, the detection and segmentation of all the organs takes 8 s on average.

Discussion: Overall, the achieved accuracy within the voxel resolution, and the processing time of 8 s, would make it possible to use the computed semantic information in automatic scan planning. As we also have correspondence between our shape models and the automatic segmentation results, it would be easily possible for an operator to specify precise location information on organ surfaces and utilize that information in subsequent scan steps. Adding extra organs is also possible and would come at limited computational cost due to the efficiency of the HDN.

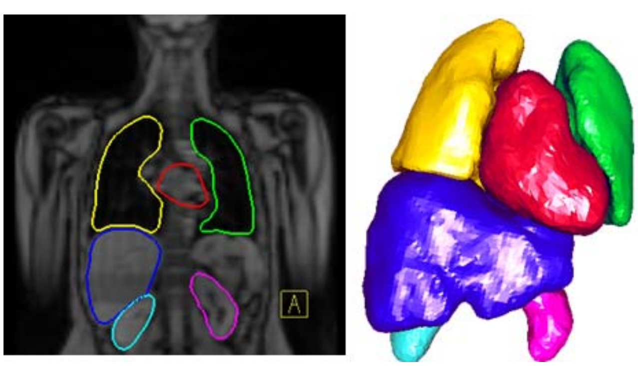

Figure 2: Result of multi-organ segmentation

Table 1: Accuracy of segmentation (surface-surface distance, mm)

Organ	Mean	80%
Right lung	3.35 ± 0.91	4.12
Left lung	3.19 ± 0.87	3.77
Heart	4.23 ± 1.33	5.33
Liver	3.99 ± 2.33	4.54
Right Kidney	2.97 ± 3.63	2.94
Left Kidney	3.18 ± 4.25	2.63

References: [1] Sofka *et a*l. Multiple Object Detection by Sequential Monte Carlo and Hierarchical Detection Network, CVPR '10. [2] Zheng *et al.*, Four-chamber heart modeling and Automatic Segmentation for 3D Cardiac CT Volumes Using Marginal Space Learning and Steerable Features, IEEE TMI, '08