A STATISTICAL SHAPE MODEL FOR SEGMENTATION OF THE PELVIC BONE

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Purpose: Within the setting of a hybrid system (regional hyperthermia applicator plus MR tomograph) MR images showing the actual patient position in the applicator can be used for therapy planning. However, the segmentation of MR images is a quite difficult task. An automatic pre-segmentation via thresholding is not possible because there is no specific range of gray values for bone. In some regions the contour of the pelvic bone is hard to detect. Currently the manual segmentation of the pelvic bone is the most time consuming part of the whole planning procedure.
We propose the use of a statistical shape model for semi-automatic segmentation of the pelvic bone. From a set of training data, the typical shape of the pelvic bone and the most significant modes of variation are determined (training phase). This shape information can be subsequently used for the segmentation of new image data (segmentation phase).

Methods: *Training phase*: As a prerequisite for a statistical analysis a correspondence between different shapes must be established. In our model shapes are described by triangular surfaces. We have developed a new method for establishing correspondence by decomposing the surfaces into so-called surface patches, which must be topologically equivalent to a circular disk. The contours of the decomposition are aligned to contours with anatomical meaning or regions of high curvature. Corresponding patches from different bone surfaces are identified by mapping them onto a circular disk. Once the correspondence has been established, a statistical analysis is performed, resulting in a mean surface model and the most important modes of variation.
Segmentation phase: Initially the mean surface model is placed in the new image data to be segmented. The gray value profiles along the surface normals are analyzed. From this a normal shift is determined for each surface point. The resulting surface deformation is projected into the space of 'allowed' surface variations as determined from the training set. This projection means a smoothing of the surface deformation field and assures the robustness of the segmentation method. The analysis of gray value profiles and the deformation of the model are repeated until convergence. *Completeness* of the model is essential for its success, i.e., the number of models in the training set must be large enough to describe all possible shape variations.

Results: A shape model was created from a training set of CT scans of 10 male patients. The principal modes of variation as determined from this set can be well interpreted. For the segmentation phase a fixed gray value profile was used, based on assumptions about the gray values of bone and surrounding tissue. When the model was applied to image data from the training set (leave-it-in test), the original shape could be successfully reconstructed. However, application to new image data (leave-it-out test) was not successful, i.e., the training set is not complete.

Conclusions: We have generated a statistical shape model for the pelvic bone from a training set of 10 male patients. In future we want to extend the training set to 30 patients and create a training set for female patients as well. Then we want to establish a model for the gray value profiles in MR images and apply the model to MR data.