Dual compartment regression for the generation of pseudo-CT images

Schnurr A.-K, Schulz H., Nickisch H., Renisch S.

Purpose
To assess the feasibility of generating pseudo CT images of the pelvis from magnetic resonance imaging using a two-compartment regression approach.

Methods
Using a model-based segmentation of the bone structures in mDixon MR data sets of the pelvis separating the bone from the soft tissue compartment, Gaussian Process Regression is used to learn and subsequently predict Hounsfield units based on features from mDixon image sets. Features consist of patches for soft tissue, for bone prediction patches and geometry information are used.
The regression is trained on rigidly registered pairs of CT and MR data, which are affinely registered to an atlas. Samples are selected from the training images using a histogram-based scheme.

For validation the voxelwise Mean Absolute Error (MAE) between pseudo CT and the patient CT was computed in a Leave-One-Out-Cross-Validation on 17 datasets. In addition, prostate EBRT plans which were available on the original CTs were re-simulated on the pseudo CTs, and the differences were analyzed.

Results
The MAE inside the body contour was 61.5266 ± 109.3748HU. For bone structures in the pelvis a MAE of was 200.1777 ± 205.2707 achieved. The method reliably differentiates between fat and soft tissue, resulting in a MAE of 46.9416 ± 81.0603 for non-bone voxels. Excluding voxels in the patient CT, which have intensities outside of the range of fat and soft tissue [-200HU…200HU], for the comparison results in a MAE of 39.159 ± 33.16.
Re-simulated EBRT plans using the pseudo CT were evaluated using Gamma analysis. Out of the voxels receiving more than 75% of the maximum dose, 98.8% have a gamma value <1 using a 1%/1mm gamma criterion.

Conclusion
This study indicates that a combination of bone/soft tissue separation and a Gaussian Process Regression per compartment is a promising approach to improve on currently available methods using bulk density assignment or single regression.

Innovation/Impact: This method combines segmentation with a regression method to estimate continuous HU values for the generation of pseudo-CT images. By adding the segmentation and performing the regression for each compartment individually, the prediction of pseudo-CT values becomes more robust and more accurate compared to a regression using the entire body as one compartment.

Key Results:

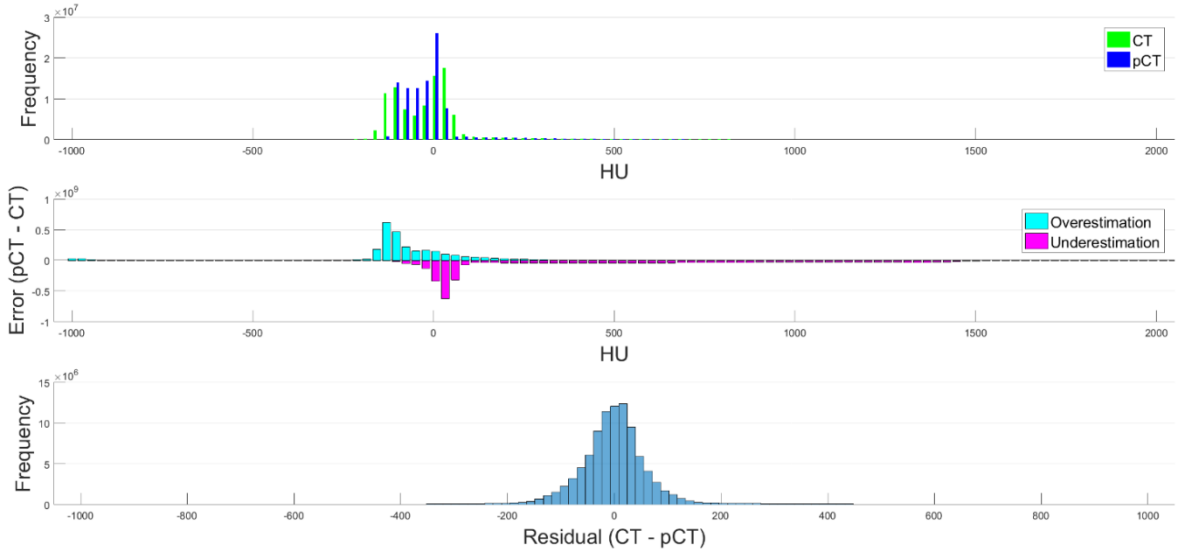

Figure 2 LOOCV on 17 data sets. From top to bottom:
1) Histogram of original CTs in comparison to pCTs
2) Distribution of prediction errors on the Hounsfield scale (As the position of rectal gases is not transferable between CT and MR data, due to the time passing in between the scans, air was excluded from the training samples. It is classified as soft tissue or fat, which leads to the error cluster around -1000 HU.)
3) Frequency of residual

$$k(\vec{f}_i, \vec{f}_j) = exp\left(\frac{-|\vec{p}_i - \vec{p}_j|^2}{2\sigma^2_{patch}}\right) \times exp\left(\frac{-|\vec{x}_i - \vec{x}_j|^2}{2\sigma^2_{position}}\right)$$

Figure 1 Covariance function expressing similarity between feature vectors (f) based on patches (p) and geometry information (x).

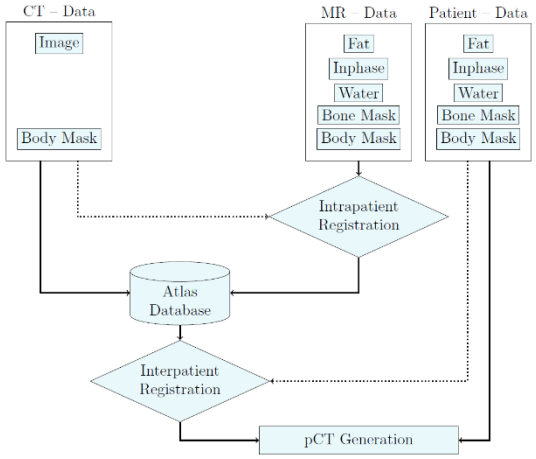

Figure 4 Registration of patient and atlas images

σ-patch_bone	0.6	0.8	1	1.2	1.4
MAE	204.347	199.53	199.996	201.801	203.504
σ-position_bone	10	20	30	40	50
MAE	200.754	198.689	199.996	201.233	202.259
σ-patch_softtissue	1	2	3	4	5
MAE	40.304	39.122	38.633	38.413	38.305

Table 1 Variation of MAE for bone of soft tissue compartments as a function of covariance parameters

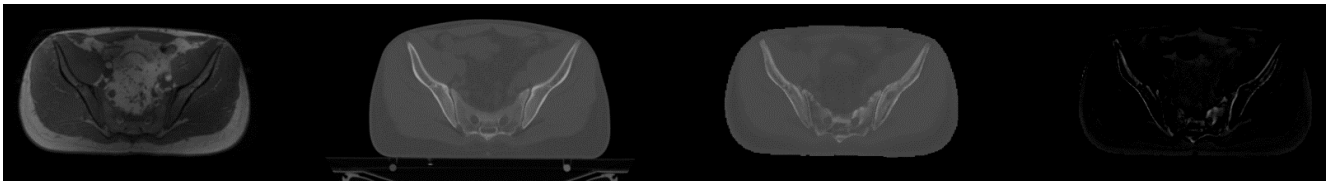

Figure 3 From left to right: patient inphase image, patient CT, generated pseudo CT and difference image