Synthetic CT generation from T2 weighted MRI using a hybrid regression and multi-atlas approach

S. Ghose[1], D. Rivest Henault[1], J. Mitra[1], J. Sun[2], P. Pichler[3], P. Greer[3], and J. Dowling[4]

[1]Australian e-Health Research Centre, CSIRO Digital Productivity Flagship, Herston, QLD, Australia, [2]University of Newcastle, NSW, Australia, [3]Department of Radiation Oncology, University of Newcastle, NSW, Australia, [4]Australian e-Health Research Centre, CSIRO Digital Productivity Flagship, QLD, Australia

Introduction: Magnetic resonance imaging (MRI) with a better soft tissue contrast compared to computed tomography (CT) images is used for tumor delineation in MR guided radiation therapy planning. Generation of the dose plan in radiation therapy is however dependant on tissue specific electron density that can be directly obtained from CT images. There is a direct relationship between CT image intensities or Hounsfield units (HU) and tissue electron densities unlike MRI. Currently, in MR guided radiation therapy planning both MR and CT images for a patient are acquired and co-registered to obtain tissue specific HU map. Obtaining both CT and MR images for every patient is however expensive and the cancer patient is exposed to a certain degree of radiation during CT image acquisition. In recent years a number of approaches have been proposed that can directly generate tissue specific HU from MR images. These methods may be broadly categorized into regression-based methods[1] and atlas-based methods[2]. In this work, we propose to use a hybrid atlas and regression-based method to generate synthetic CT images from MRI for radiation therapy planning of prostate cancer treatment. Compared to a pure regression-based method[1], an additional UTE sequence is not required to segment the bone, thereby reducing the cost of the treatment and facilitating clinical acceptability. Also in comparison to a pure atlas-based method[2], we use regression-based soft tissue modeling, producing better soft tissue estimation. The proposed hybrid approach achieves a 0.6% dose difference compared to the use of original CT in the dose plan.

Method: Clinical MR and CT scans of 15 patients aged between 61 to 78 years who had prior intensity modulated radiation therapy (IMRT) were retrospectively chosen to validate the proposed method. For each patient, a whole-pelvis T2-weighted (T2w) MRI and a CT for dose calculation were available. The hybrid approach can be broadly divided into two parts: (a) an expectation maximization (EM) based clustering of the soft tissues followed by polynomial regression based prediction of CT intensities and (b) a multi-atlas based segmentation and prediction of the bone intensities generated in a leave-one-patient-out validation framework.

The MRIs were co-registered to the corresponding CT images[3] to build tissue specific regression models and to generate synthetic CT information of the bone in multi-atlas framework. An EM based clustering was performed on the co-registered MRI to identify the muscle, fat, water and dense bone/air class to form the posteriors. The bladder label from manual segmentation was used to accurately identify the water class, as in few cases water class was found in fat tissue. The bladder label was however only used to build the model and not used during validation. For each of the soft tissue class i.e. muscle, fat and water the corresponding CT and MRI intensities were sampled from the co-registered CT/MRI images to build tissue-specific regression models. A regression model of a second degree polynomial was selected after experimenting with a small cohort of five patients for the prediction of CT intensities given the MR intensity of a tissue class. Thus three regression models each corresponding to fat, muscle and water were created during training. The bone and air could not be well-separated with EM since both usually have similar intensities in T2w MRI and hence similar posteriors. This problem was however solved using the multi-atlas based method discussed in the following paragraph.

During validation, given a new patient MRI image, an EM based clustering identified the soft tissues muscle, fat and the bladder/water. Tissue specific regression models of the muscle and the fat generated in the training stage were used to convert MR intensities to CT values. A multi-atlas based segmentation scheme[4] was used to segment the bone and bladder of the test patient image using a leave-one-patient-out framework. In short, all patient MRI images were non-rigidly registered to the test image using diffeomorphic demons. The labels of the bladder and the bones were transformed, fused and a patch based local weighted voting was performed to generate the final segmentation. MR intensities of segmented bladder were transformed to synthetic CT with the regression model of water. Co-registered CT images of the training cases were transformed to the test image space with the transformation obtained during registration. The CT images were fused to generate the synthetic CT image for the test case. Bone intensities of the generated synthetic CT image were directly used as predicted CT values for the test image. Finally the predicted muscle, fat, water and bone intensities were fused to generate the complete synthetic CT image. The adopted approach of EM-based clustering provided better segmentation accuracies of soft tissues compared to atlas-based approach. Further, while building regression models the CT intensities could be controlled with the prior knowledge of the HU range of the respective tissue type to achieve an accurate HU estimation. For example all values outside the range of 10-40 HU and their corresponding MR values may be rejected while modelling muscle regression. Generation of a synthetic CT image is illustrated in Figure 1.

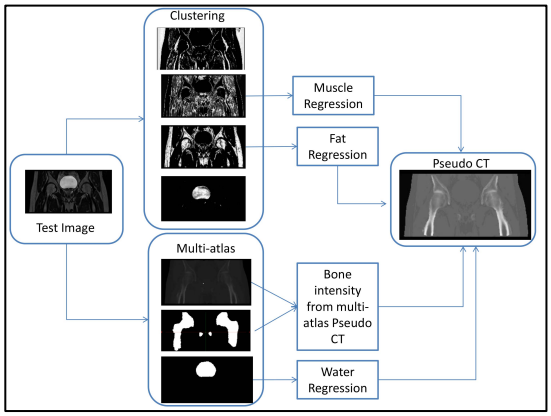

Fig. 1. Pseudo-CT generation framework.

Results: Synthetic CT of a patient was generated in a leave-one-patient-out validation framework. Fiducials implanted in the prostate during the course of the treatment were used to co-register the synthetic CT and the original CT images for comparing the dose. The co-registered images were sent to Pinnacle where the IMRT plan was copied and the dose was calculated. Compared to 7990.7±73.33 cGy a mean dose of 8040.4±101.19 cGy was achieved with synthetic CT for 15 patients (Table 1). The mean difference between the original dose and dose from synthetic CT was 0.6%. The Student's *t*-test p-value between the dose from planning CT and synthetic CT is 0.1345 indicating that the dose difference is not statistically significant. As observed in Fig. 2, there is an excellent coherence between the planning CT and predicted synthetic CT. Comparing our hybrid approach of generating synthetic CT with our previous average atlas-based method[2], the dose difference was reduced from 2% to 0.6%.

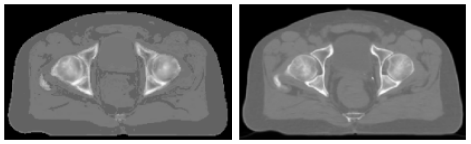

Fig. 2. Planning CT (left) and generated synthetic CT (right) of the same axial slice. Good visual coherency between the two images are observed.

Table 1. Dose difference comparison between synthetic CT and planning CT

	Planning CT (cGy)	Synthetic CT (cGy)	Dose Differ. (%)	Student's *t*-test *p*-value
Mean Dose	7990.7±73.33	8040.43±101.19	0.6	0.1345

Discussions : The observed mean dose difference of 0.6% is statistically insignificant and there is an excellent agreement between the dose computed from planning CT and synthetic CT generated in a hybrid approach. In some cases however, a positive bias is observed in dose estimation. We hypothesise that there is a slight under estimation of the skin tissue in T2w MRI compared to CT causing such difference. More experiments are however required to validate our assumption. The hybrid approach is also suitable for attenuation correction in MRI-PET.

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