On the generation of synthetic CT for a MRI-only radiation therapy workflow for the abdomen

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Abstract. MRI is an important imaging modality for contouring in radiotherapy due to its superior soft tissue contrast over CT, but it is not often used alone in a radiation therapy workflow because of the lack of electron density information which is required for dose calculations. This study investigates a method to generate synthetic CT from MRI to demonstrate the potential of using MRI alone in the radiation therapy workflow for abdominal targets. This method consists of (1) acquiring multiple MRI volumes, (2) applying intensity nonuniformity corrections to MR images, (3) identifying abdominal walls to distinguish air from bone and vertebral bodies to improve classifications between bone marrow and muscle tissues, (4) classifying tissues in each section using fuzzy c-means clustering with a spatial constraint and (5) assigning attenuation properties to individual tissue classes to generate synthetic CT. The quality of the synthetic CT was comparable to clinical CT. The proposed method allows automatic segmentation of tissue and generation of synthetic CT for the abdomen. Our results demonstrate the potential of using MRI alone to support treatment planning and image guidance for abdominal radiation therapy.

1. Introduction
MRI is increasingly being used in the radiation therapy workflow due to its superior soft tissue visualization, but it is not often used as a sole imaging modality in the planning process since the lack of electron density information precludes heterogeneity corrections. The use of multi-imaging modalities requires an imaging registration step and hence introduces uncertainties which are then propagated throughout the entire course of radiation therapy. To reduce these uncertainties, it has become of interest to streamline the workflow by implementing a planning process that is solely based on MRI. Several methods have been investigated in order to generate electron density maps from MRI for treatment planning, such as methods that manually identify tissues types and assign bulk densities [1, 2], atlas-based methods to automate the process in generating electron density maps [3, 4], and voxel-based methods to account for individual differences that are typically lacking in atlas-based methods [5, 6]. These studies have shown promising results in terms of pseudo-CT quality, and demonstrated the potential of using MRI alone in the workflow for brain and prostate radiation therapy.

Due to breathing and gastrointestinal motion [7], the registration uncertainty is likely larger in the abdomen than other body sites. Moreover, superior tissue contrast is important to identify liver and pancreatic tumours, which means that the patients with abdominal lesions could benefit greatly from
using MRI as the sole image modality throughout their treatment course. Therefore, this study investigates a method of generating synthetic CT to support the delineation of targets and organs-at-risk (OARs) for the use in treatment planning, dose calculations, and the use of synthetic CT or MRI for treatment verification towards a MRI-only radiation therapy workflow.

2. Methods and materials

To explore the feasibility of synthesizing CT from MRI to support treatment planning, diagnostic MRI scans with gadolinium (Gd) contrast were analysed. These image volumes included in-phase, fat and water images resulting from a mDixon sequence and T2-weighted images using a T2-turbo spin echo sequence (cf. Figure 1). These images were corrected for their nonuniform intensity using the N4itK algorithm implemented in SLICER (Version 4.6, surgical processing laboratory, Brigham and Women’s Hospital, Boston, MA).

Due to ultra-short T2 and T2* of cortical bone, bone cannot be easily distinguished from air on conventional MRI. To address this issue without using ultra-short echo time (UTE) pulse sequences, the abdominal wall was automatically identified using intensity thresholding and morphological processing on in-phase images, and two compartments were then created, one compartment containing air pockets and lungs and the other compartment containing bone (i.e. ribs, sternum and spine). In the outer compartment (that included bone), the MR intensity of muscle tissues were close to bone marrow on our studied MR images. Considering CT number differences between muscle and bone marrow, it may be necessary to distinguish these two tissue types. Therefore, the vertebral bodies were automatically identified based on their known spatial location in the abdominal MR images using cylindrical shapes. Hence, in this pre-processing step, four sections were created: (1) the air section from the inner abdomen compartment only containing air pockets, (2) the solid bone section from the outer abdomen compartment containing bone only, (3) the vertebral body section from the outer abdomen compartment and (4) the residual tissue section including all remaining tissues in both compartments.

A Hounsfield Unit (HU) value of -1000 was assigned to the air section with a tissue probability of 1 while a HU value of 1000 was assigned to the solid bone section with a tissue probability of 1. Using in-phase and water images a probabilistic tissue classification using fuzzy c-means clustering (FCM) with a spatial constraint as described in Hsu et al [5] was applied to the two remaining sections. The FCM algorithm assigns each voxel in an image a certain probability of belonging to a given tissue class, i.e. each voxel has a certain probability of being a member of each of the tissue classes. In the residual tissue section, four tissue probability maps were generated, which represented the classes of fat, vessels (and Gd contrast regions), muscle and internal organs. In the vertebral body section, three tissue probability maps were generated, representing the classes of bone marrow, inter-vertebral space and vessels. Corresponding CT numbers were then assigned to individual probability maps with HUs of -100 for fat, 50 for vessels, 70 for muscle and internal organs, 100 for the inter-vertebral space and 250 for bone marrow. Then, the probability-weighted sum of the attenuation properties of each voxel yields the synthetic CT.

The synthetic CT was then imported into a commercial treatment planning system (Eclipse 11.0, Varian, Palo Alto, CA). To mimic treatment planning in the abdomen, targets and OARs were contoured on in-phase images. The pancreas was contoured as clinical target volume (CTV) and the

Figure 1. (a) in-phase, (b) fat, (c) water and (d) T2-weighted MR images.
planning target volume (PTV) was generated using an isotropic 1 cm expansion with an additional expansion 0.5 cm superior/inferior directions. Planning was performed on the synthetic CT employing 2-arc volumetric modulated arc therapy (VMAT) with a total dose of 50.4 Gy in 28 fractions. Dose calculations were performed using the analytical anisotropic algorithm (AAA) with and without density corrections on synthetic CT.

3. Results
Figure 2 shows four probability images generated using FCM classification. The resulting synthetic CT is shown in Figure 3. Some misclassifications were found at tissue interface and regions with nonuniform intensities, but the quality of the synthetic CT was comparable to clinical CT. Comparing dose volume histograms (DVHs) with and without density corrections, no significant difference was found for OARs, but the dose to the 95% and 99.9% volume (D95% and D99.9%) for PTV was ~1% lower for the plan without density corrections.

4. Discussion
Our proposed method allows automatic segmentation of tissue and the generation of synthetic CT for the abdomen. In particular our method reduces the possibility of mislabelling air, bone and/or fluid and therefore yields improved CT number accuracy for bone marrow and spinal cord using conventional MRI sequences. However, there were residual nonuniform intensities within given tissue types on MR images, which resulted in tissue misclassification of voxels within those tissue types when generating the synthetic CT. The diagnostic MRI sequences used in this study have not been optimized for treatment planning purposes, so the quality of the generated synthetic CT is still limited. In addition, the CT numbers assigned to individual tissue classes were estimated based on the values of the CT dataset for one clinical case. Investigating what the adequate CT numbers for each tissue type are will be necessary to further improve the quality of synthetic CT.

Dose volume metrics only differed ~1% in target coverage between the plans with and without density corrections for the case studied. This small difference was likely due to the simulated target being far from the lungs and the use of an arc delivery technique. When abdominal targets are close to the lungs, generating synthetic CT to allow for density corrections may be more important for improving dosimetric accuracy.

Our current results clearly demonstrate the potential of using MRI alone to support treatment planning and image guidance for treatment verification in abdomen. Future work will include
improving the quality of the synthetic CT by optimizing the MR imaging sequences with sufficient tissue contrast to separate required tissue types, evaluating the robustness of the proposed method for diverse cases and its dosimetric accuracy in comparison to regular CT, determining its limitations, and exploring the proper workflow in treatment verification using synthetic CT or MRI.

Figure 3. Synthetic CT with 50.4 Gy colorwash on PTV in (a) axial, (b) sagittal and (c) coronal views. (d) DVHs for synthetic CT with density corrections (■) and without corrections (▲).

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6. References
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