ESTRO

Abstract

Title

Automatic synthetic-CT generation from unpaired T2w pelvis MRIs using ensembled self-supervised GANs

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Purpose or Objective

Magnetic resonance imaging (MRI) is an emerging modality in terms of use in radiation therapy. On top of its conventional use for tumor and organ annotation for planning, it is now becoming part of the treatment workflow thanks to the introduction of MR-Linear accelerators where instead of using computed tomography data for treatment planning, MRI is used as an alternative modality. However, for accurate dose calculation, information on tissue properties is necessary, which is not present in MRI. Therefore, CT-equivalent representations are needed for dose calculations. To this end, we propose a novel self-supervised generative adversarial deep learning approach to generate synthetic-CTs from MRI that can learn from unaligned MR-CT pairs. The aim of this work is to generate synthetic-CTs from T2w pelvis MRIs in real-time and which may be integrated seamlessly into the MR-Linac workflow.

Materials and Methods

The dataset contains 205 1.5T T2w daily MRIs coming from the MR Linac from 42 different patients and a CT scan for each patient. We deploy a two phase learning pipeline involving three key steps: (i) cyclic generative adversarial deep learning based unsupervised cross modality image synthesis to generate synthetic CT priors from MR images, (ii) Highly accurate alignment of CT to the MRI using weak priors via mono-modal multi-metric deformable registration with a combination of intensity driven and intensity agnostic metrics to generate paired data, (iii) Synthetic CT generation with the self-paired data using deep generative adversarial networks and image similarity metrics. Multiple networks are trained using different whole body scans as reference space. Each of them relies on a different random separation between training (80%) and validation (20%) subsets. Evaluation was performed on a held out test set, 25% the size of train and validation sets combined.

Results

Mean absolute errors (MAE) on each organ and the entire patient body is computed. We report a mean absolute error of 33.1 ± 7.44 HU on the patient body. An organ-wise MAE is presented in the table.

Organ	Mean±Std Absolute Error(HU)
Anal Canal	19.88±5.67
Bladder	15.20±7.28
CTVN Prostate	33.22±4.94
Left Femoral Head	51.30±6.59
Left Iliac	59.74±7.92
Medullary Canal	39.36±13.39
Penile Bulb	14.54±4.13
Prostate	19.99±7.4
Rectum	106.14±65.5
Right Femoral Head	53.77±5.92
Right Iliac	62.94±7.45
Seminal Vesicle	34.44±8.48
Spinal Cord	34.49±11.67
Entire Patient Body	**33.10±7.44**

For qualitative assessment, here is an example of an input MRI, the corresponding patient CT and the generated synthetic CT.

MRI CT Synthetic CT

Conclusion

We introduced a first of its kind AI-driven solution for synthetic CT generation that can learn on unpaired scans and is suitable for clinical use thanks to its intensity and structure preserving learning strategy that can generate high quality, sharp synthetic CTs with accurate hounsfield values. Moreover, our approach inherits robustness and good generalization properties through an ensembling principle done on anatomically consistent sub-spaces.