ESTRO

Abstract

Title

Synthetic-CT generation from T1w brain MRIs with a cascaded GANs ensemble approach

Authors

Aurélien Lombard[1], Kumar Shreshtha[1], Charlotte Robert[2,3], Thais Roque[4], François Fauchon[5], Georges Noël[6], Nikos Paragios[7,8], Eric Deutsch[2,3]

Authors Affiliations

[1]Therapanacea, Artificial Intelligence, Paris, France; [2]Gustave Roussy Cancer Campus, Université Paris Saclay, Molecular radiotherapy and innovative therapeutics, INSERM UMR1030, Villejuif, France; [3]Gustave Roussy Cancer Campus, Department of radiation oncology, Villejuif, France; [4]Therapanacea, Research & Partnerships, Paris, France; [5]Centre des Hautes Energies, Department of radiation oncology, Nice, France; [6]Centre Paul Strauss, Department of radiation oncology, Strasbourg, France; [7]Therapanacea, CEO, Paris, France; [8]CentraleSupelec, University of Paris Saclay, Center for visual computing, Gif-sur-Yvette, France

Purpose or Objective

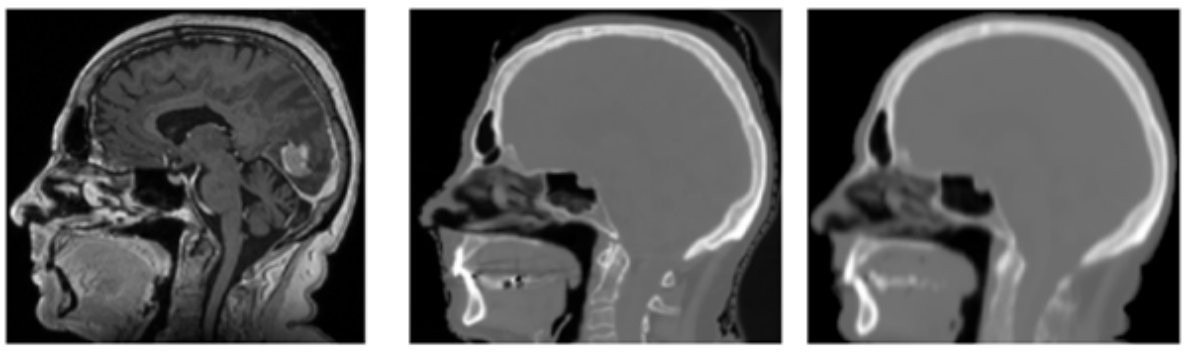
Magnetic resonance (MR) imaging is a growing modality in terms of use in radiation therapy. Used mainly in the past as secondary images for brain tumor and organs at risk annotation as for optic chiasm or hippocampus, there is now a real interest to use it as primary image for dose planning. However, in order to determine the optimal treatment plan, information related to the tissue properties are still necessary. Therefore, Computed Tomography (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 MR images that can learn from unaligned MR-CT pairs. Our approach can generate synthetic CTs from T1 weighted brain MRIs (including gadolinium enhanced scans) in real-time and thus seamlessly integrates to the MR-Linear accelerator workflow.

Materials and Methods

A dataset of 1242 T1 weighted brain MRI scans and the corresponding CT scans from multiple devices and manufacturers was collected from various sites. We deployed a two phase learning pipeline involving three key steps: (i) Conditional generative adversarial deep learning based weakly supervised 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. Multiple networks were trained using different whole body scans as reference space. Each of them relied 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 the training and validation data. Mean absolute error (MAE) on the patient head was computed for performance evaluation.

Results

We report a test MAE of 77.22 ± 17.19 HU on the patient body. For 39 cases from the test set, MAE was specifically computed for bone, air and water regions, giving 31.57±2.37 for water, 189.87±19.58 for bones and 206.56±16.08 for air. We are also planning a dosimetric impact study on these 39 patients. For qualitative assessment an example of the input MRI, the corresponding CT and the generated synthetic CT is shown in the figure.



Conclusion

We introduced an innovative ensembling AI-driven strategy for synthetic CT generation that fights the use of multi modal registration with a cascading approach. It helps to generate synthetic CTs that are 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.