Indirect multimodal deformable image registration using synthetic image generated by unsupervised deep learning

Blanche Texier*†[1], Cedric Hemon[2], Hilda Chourak[3], Antoine Simon[4], Igor Bessieres[5], Renaud De Crevoisier[1], Joel Castelli[6], Caroline Lafond[6], Anais Barateau*‡[6], and Jean-Claude Nunes[6]

[1]Univ Rennes, CLCC Eugène Marquis, Inserm, LTSI - UMR 1099, 35000 Rennes, France. – Université de Rennes – France

[2]Univ Rennes, CLCC Eugène Marquis, Inserm, LTSI - UMR 1099, 35000 Rennes, France. – Université de Rennes – France

[3]Univ Rennes, CLCC Eugène Marquis, Inserm, LTSI - UMR 1099, 35000 Rennes, France. – Université de Rennes – France

[4]Univ Rennes, CLCC Eugène Marquis, Inserm, LTSI - UMR 1099, 35000 Rennes, France. – Université de Rennes – France

[5]Centre Régional de Lutte contre le cancer Georges-François Leclerc [Dijon] – Unicancer – France

[6]Univ Rennes, CLCC Eugène Marquis, Inserm, LTSI - UMR 1099, 35000 Rennes, France. – Université de Rennes – France

Résumé

Introduction: In radiation therapy (RT), a current challenge lies in precise registration implying different imaging modalities and resulting in lower accuracy than monomodal registration. The aim of this study was to propose a novel deformable image registration (DIR) approach that incorporates an unsupervised deep learning (DL) based generation step of an intermediary image, to reduce the challenge of multimodal registration into a monomodal one.

Material and Methods: Two datasets from prostate RT patients were used to evaluate the proposed method: 1) Computed Tomography (CT)/ Cone Beam Computed Tomography (CBCT) pairs from 23 patients, 2) Magnetic Resonance Imaging (MRI)/CT pairs from two different care centers using different MRI devices (0.35T MRIdian MR-Linac, 1.5T GE lightspeed MRI). After a database standardization, essential to ensure DL synthesis accuracy, synthetic CTs (sCTreg) were generated with an unsupervised conditional Generative Adversarial Network (cGAN). These sCTreg from CBCT or MRI were then used to perform the sCTreg/CT registration. This intermediary step was used to guide rigid registration and DIR with the Elastix library based on BSplines. These registrations were then compared to three standard registration methods: rigid, Elastix based on BSplines, and the VoxelMorph-based (only for CBCT/CT) using multimodal pairs. Endpoints were the dice coefficient between delineated structures for both datasets. The impact of each registration on the accuracy of a

*Intervenant

†Auteur correspondant: blanche.texier@univ-rennes.fr

‡Auteur correspondant: a.barateau@rennes.unicancer.fr

supervised cGAN-based generation model was also assessed for the MRI dataset (figure 1).

Results: For both datasets, intermediary sCT generation provided the highest dice coefficients. Dices reached 0.85, 0.85 and 0.75 for the prostate, bladder and rectum for the dataset 1 and 0.90, 0.95 and 0.87 respectively for the dataset 2. When the sCTreg were not used, dices reached 0.66, 0.78, 0.66 for the dataset 1 and 0.93, 0.87 and 0.84 for the dataset 2. Furthermore, the evaluation of the impact of registration on sCTeval generation showed that best accuracy was obtained when the registration was conducted with a sCTreg.

Conclusions: For radiotherapy applications where two distinct imaging modalities are employed, an improvement in registration accuracy has been achieved using unsupervised deep learning to synthesize intermediate sCT. This method can also be used in a further dose accumulation workflow in MRI-only RT to evaluate the dose really delivered to the patient compared to the planned one.
Figure 1: Workflow of the method. A learning dataset composed of preprocessed and rigidly registered image pairs is used to synthesize a synthetic CT (sCTreg) with an unsupervised cGAN. Then, this sCTreg is used to guide the DIR with the CT. For the MRI dataset, the MRI and the registered CT are used to train a supervised 3D cGAN. The different models of sCTeval generation obtained are evaluated with the mean absolute error. The registrations (CBCT/CT and MRI/CT) were evaluated with dice coefficients.

Mots-Clés: recalage, IRM, CBCT, CT synthétique