A Simple Two-stage network For MR-CT Translation

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Abstract. CT is currently the main reference image for radiation therapy, which contains electronic density information and displays clear bones. However, its disadvantage is that soft tissue imaging is not clear and needs to be guided by MR images. We propose a simple two-stage convolutional neural network for generating CT images from MR images. We obtain the enhanced CT (eCT) by adjusting the window width and window level of the CT, highlighting bones and soft tissues. The eCT serves as the target of the first stage and CT is the target of the second stage. We use a residual block-based UNet to learn the mapping between MR and CT stage by stage. With this proposed method, we achieved an advanced place in the validation phase and of SynthRAD Challenge.

Keywords: MR-to-CT translation · Two-stage · UNet.

1 Introduction

Magnetic resonance imaging (MRI) guided radiation therapy is one of the current research hotspots, however, the ionizing radiation from CT scans can affect the health of patients, and simultaneously scanning CT and MRI increases the economic burden on patients. Existing registration-based methods[1] introduce systematic errors, while GAN-based methods[2] fabricate artifacts. To address the above issues, we propose a simple two-stage convolutional neural network for generating CT images from MR images.

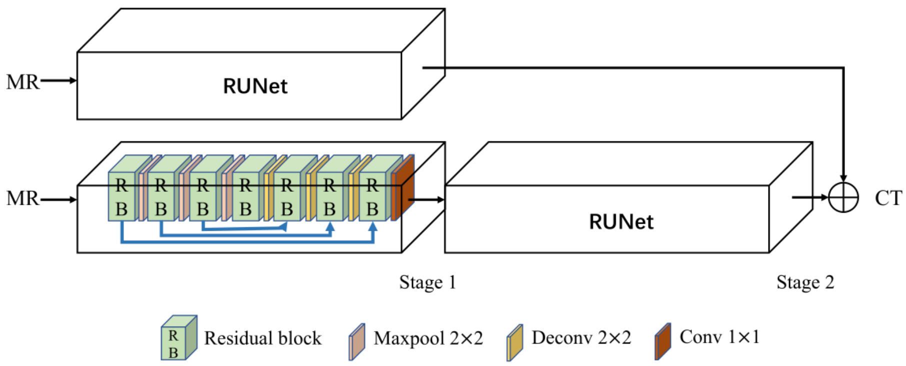

Fig. 1. A residual block-based UNet (RUNet) is used to learn the mapping between MR and CT stage by stage.

2 Method

We obtain the enhanced CT (eCT) by adjusting the window width and window level of the CT, highlighting bones and soft tissues. The eCT serves as the target of the first stage and CT is the target of the second stage. As shown in Fig. 2, we use a 2.5d residual block-based UNet (RUNet) to learn the mapping between MR and CT stage by stage. Specially, we use 5 adjacent MR slices as the first-stage input.

2.1 Loss Function and Training Strategy

We use the joint loss of l1 and ssim as the loss function for each stage. We train the first-stage network, the second-stage network, and the residual branch in sequence. The parameters of the trained part are frozen.

3 Experiments

3.1 Datasets

We use the synthesizing computed tomography for radiotherapy challenge (SynthRAD 2023) dataset to evaluate the efficiency of our method. The following pre-processing steps were performed on the data: 1. Conversion from dicom to compressed nifti. 2. Rigid registration between CT and CBCT. 3. Anonymization (face removal, only for brain patients). 4. Patient outline segmentation (provided as a binary mask). 5. Crop MR/CBCT, CT and mask to remove background and reduce file sizes. For brain and pelvis, we resized the image sizes to 288 * 288 and 492 * 516, respectively.

3.2 Experiment Settings

All experiments in this section are performed on Ubuntu 20.04.5 LTS, with Intel(R) Xeon(R) Gold 6330 CPU @ 2.00GHz. All models are run with NVIDIA GeForce RTX 3090 using PyTorch.

3.3 Metrics

The metrics measuring the accuracy of the algorithm are masked Peak Signal-to-Noise Ratio (PSNR), Mean absolute error (MAE), and Structural similarity index (SSIM) between sCT and CT.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |CT_i - sCT_i| \tag{1}$$

where n is the number of voxels in the mask.

$$PSNR = 10\log_{10}\left(\frac{Q^2}{\frac{1}{n}\sum_{i=1}^{n}(CT_i - sCT_i)^2}\right) \tag{2}$$

where n is the number of voxels in the mask, and Q is the typical range of voxel intensities in the CTs (3000 HU).

$$SSIM = \frac{(2\mu_{CT}\mu_{sCT} + C_1)(2\delta + C_2)}{(\mu_{CT}^2 + \mu_{sCT}^2 + C_1)(\delta_{CT}^2 + \delta_{sCT}^2 + C_2)} \tag{3}$$

where μ is the mean pixel value, δ is the variance . $C1 = (0.01Q)^2$ and $C2 = (0.03Q)^2$ are two variables to stabilize the division with weak denominators, where Q is the typical range of voxel intensities in the CTs (3000 HU).

3.4 Results

As shown in , we'll present the performance on synthrad challenge and visualize our results of synthesized CT (sCT).

4 Conclusion

In this paper, we investigated a simple two-stage convolutional neural network for generating CT images from MR images. The proposed method shows promise in capturing relevant visual features and producing accurate CT images. Further research and refinement of the methodology could lead to improved MR-to-CT synthesis techniques with significant clinical implications.

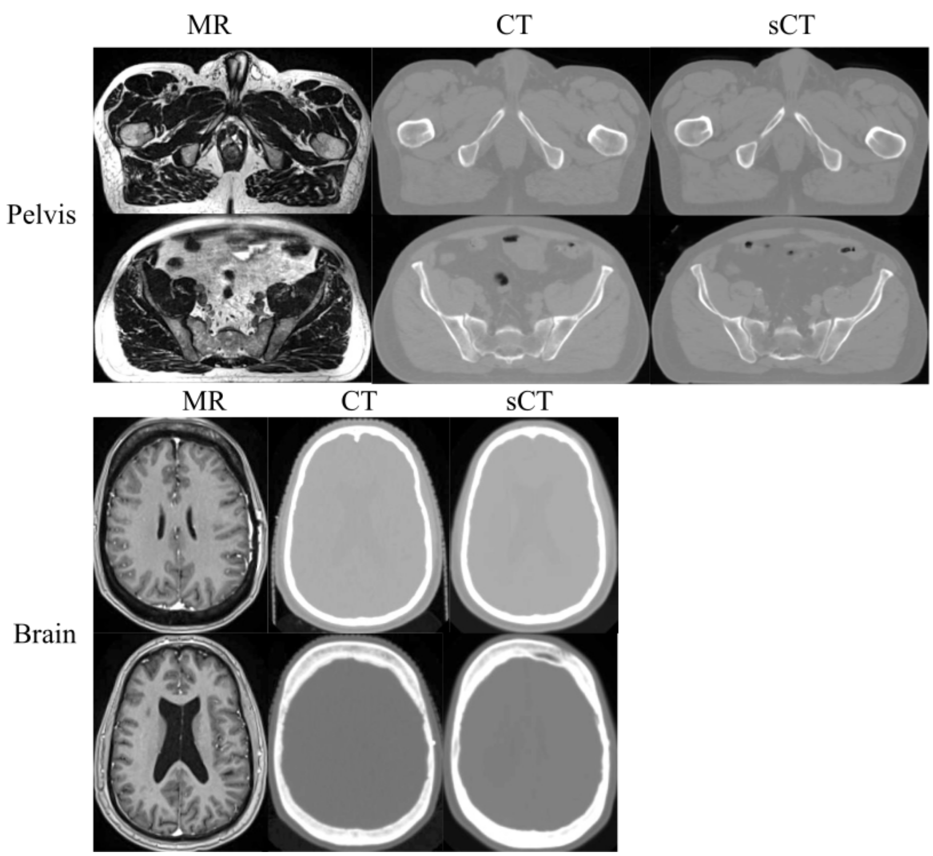

Fig. 2. Some results of our proposed methods.

References

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