MR to CT Synthesis using U-net

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1 Introduction

In order to further optimize the MRI (Magnetic Resonance Imaging) based radiation therapy scheme and achieve results comparable to traditional CT (Computed Tomography) radiation therapy, this study adopted advanced computer synthesized image technology, aiming to generate high-quality sCT (synthetic Computed Tomography) images. By combining computer synthesized image technology with the field of medical imaging, we can bridge the information gap between MRI and CT, providing more accurate guidance for radiation therapy.

In this study, we conducted in-depth research on MRI and CT image data from 180 patients, including images of 180 brain regions and 180 pelvic regions (Data provided by SynthRAD2023). In order to achieve the goal of computer synthesized CT images, we adopted the U-net neural network architecture, which is a deep learning network that performs well in the field of medical imaging. U-net network, with its unique encoding decoding structure, can effectively capture local and global features in images, thereby generating high-resolution and detailed sCT images.

2 Method

We have adopted the U-net neural network as the core architecture, aiming to achieve the goal of generating synthetic CT images. By utilizing the U-net network, we can fully utilize its unique encoding decoding structure and outstanding performance in the field of medical imaging to generate high-quality synthetic CT images in MRI based radiotherapy. This innovative approach allows us to bridge the information gap between MRI and CT, guiding the planning and execution of radiation therapy in a more precise and accurate manner, providing patients with a better treatment experience and results.

2.1 Data processing

Normalization of pixel values. We observed that MRI values in MRI images taken by different machines would change according to different calculation models, so we normalized all MRI before input (0-1). However, in CT images, the CT values of each tissue part are close to each other, unlike the MRI values, which change with the calculation model, so we divide all CT images by a fixed number at the same time before input to speed up the convergence of the model.

3D to 2D. Since the data type of the U-net model we adopted is 2D data, it is necessary to pair and segment the 3D MRI image with the 3D CT image. So we converted the 3D image into a 2D image, where we chose to slice along the Z-axis and process it as the segmentation axis.

Random cropping. We also cropped the data to cut the 2D images to the same size(128 * 128), accelerating the training speed.

2.2 U-net model

We use a 2D U-net network, first using transpose convolution for up sampling, and then fusing the up sampling features with the corresponding down sampling layer features through the Triple Conv layer. Both the third and fourth layers use three-layer convolutional layers. The structure of the entire model is similar to a U-shaped shape, in which multiple down sampling and up sampling are used to capture and preserve feature information at different scales.

2.3 Training parameter

In the training process, the training batch size of the U-net model was set to 4, the learning rate was set to 3e-4, the total number of training rounds was set to 200, L1-loss was used as the loss function, and Adam was used by the optimizer.