

Medical Image Translation using 3D ShuffleUNet

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1. Background/Introduction

Problem Statement

Medical image-to-image translation between different radiology modalities

- Track 1: MRI-to-sCT translation
- Track 2: CBCT-to-sCT translation ***sCT: synthetic CT

Image-to-image Translation

Learn a mapping between an input image and output image. In our study, we used 3D ShuffleUNet that maps between MRI/CBCT to sCT.



2. Challenges

- Difference between image modalities
 - MRI & CT: different protocols for obtaining image, so the contrast, texture, and highlights are very different
 - CBCT & CT: similar protocol, but CBCT has limited information in texture and quality

Image artifacts

Artifacts such as checkboard artifacts, outliers, and blurriness are very common in image translation

3. Methods

Processing

MRI: Z-score normalization

 $(x-\mu)$

CBCT/ CT: fixed-range intensity scale

 $x - voxel_{min}$ x + 1024 $\frac{1}{voxel_{max} - voxel_{min}} = \frac{1}{3000 + 1024}$

Model

We used 3D ShuffleUNet, a U-Net with

- 3D convolution layers
- Pixel-unshuffle for downsample module
- Pixel-shuffle for upsample module 3.

3D Pixel Shuffling/ Unshuffling

To address the issues of well-known artifacts such as blur and checkboard effects, we utilized pixel shuffling/unshuffling to minimize the artifacts.





4. Results									
Performance table									
Track		PSNE		SSIM		Dose MAE		DVH metric	
Track 1 (top 5)		28.70 ± 1.59		0.87 ± 0.03		0.004 ± 0.003		0.028 ± 0.053	
Track 2 (top 3)		30.58 ± 1.95		0.91 ± 0.03		0.004 ± 0.008		0.033 ± 0.154	
Track 1: MRI-to-sCT Brain Pelvis									
MRI	sCT		СТ		MRI		sCT		СТ
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Track 2: CBCT-to-sCT

5. Limitations and Future Work

For our future works,

Brain

- We will incorporate more modules such as attention to improve the translation performance.
- We will further explore in model hyperparameter for better tuning.