

Friedrich-Alexander-Universität **Technische Fakultät**





Swin UNETR-based MRI-to-CT and CBCT-to-CT Synthesis

Fuxin Fan¹, Jingna Qiu¹, Yixing Huang², and Andreas Maier¹

¹Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander University Erlangen-Nürnberg, Erlangen, Germany ²Department of Radiation Oncology, Friedrich-Alexander University Erlangen-Nürnberg, Erlangen, Germany

Introduction

- Synthetic CT (sCT) from MRI helps in treatment planning and accurate dose calculation. sCT from CBCT can improve the quality of image-guided radiation therapy [1].
- SynthRAD2023 incorporate 1080 paired MRI-to-CT and CBCT-

Results and Discussion

- The rankings for the quantitative results (Tab. 1) by our model are 3rd (MRI-CT) and 4th (CBCT-CT).
- The qualitative results of sCT from MRI and CBCT are shown in Fig. 3 and Fig. 4.

to-CT datasets from three institutions, making it possible for developing deep learning models [2].

Aim:

Design and optimize models for CT synthesis from MR images or CBCT images in two body regions (brain and pelvis).

Material and Methods

Swin UNETR (Fig. 1) [3]

- Structure: Cascaded Swin blocks with patch merging in encoder, CNN-based residual blocks in decoder, skip connections between encoder and decoder.
- Training: L1 loss, Adam optimizer, 4000 epochs.
- 4 models: MRI-CT (Brain or Pelvis), CBCT-CT (Brain or Pelvis). Data
- 180 paired datasets for each model.
- Random subvolumes at training $(32 \times 96 \times 96)$.

Preprocessing

- MRI: divided by 1000.
- CT: plus 1024 then divided by 2000.

Domain	Metric	MRI-CT	CBCT-CT
Image	MAE	61.72 HU	51.18 HU
	PSNR	28.83	30.40
	SSIM	0.876	0.903
Photon	Dose MAE	0.0041	0.0044
	DVH metric	0.0273	0.0317
	Gamma pass rate	98.18 %	99.06 %
Proton	Dose MAE	0.032	0.033
	DVH metric	0.215	0.171
	Gamma pass rate	97.25 %	97.09 %



Postprocessing

- Subvolume merging (Fig. 2) with overlapped length of 28, 72, 72.
- CT: multiply 2000 and subtract 1024.











[-200 HU, 200 HU]

Figure 3: Synthesized CT images from MRI. Left: Brain region; Right: Pelvis region.



Figure 4: Synthesized CT images from CBCT. Left: Brain region; Right: Pelvis region.

Conclusion

sCT

- Swin UNETR has efficacy in CT synthesis from MRI and CBCT.
- Training on subvolumes and subvolume merging help improve the synthetic image quality.

Figure 1: Illustration of the structure of Swin UNETR.



Figure 2: CT volume synthesis by subvolume merging.

References

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Contact

Fuxin Fan Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander University Erlangen-Nürnberg, Erlangen, Germany

⊠ fuxin.fan@fau.de **a** +49 9131 85 27894 SIEMENS Healthineers Uniklinikum Erlangen

