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CycleGAN based transfer learning for synthesizing CT image from MR image

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INTRODUCTION

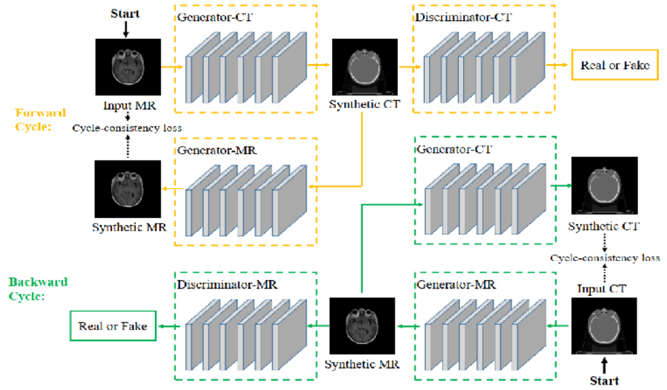
Synthesizing CT from MR is needed for dose calculation in MR-only radiotherapy planning. A lot of work has been done to use deep learning for this purpose, including CycleGAN[1,2]. However, all of these works tested the model on data acquired with the same MR protocols, so it is currently unknown how well the trained model will work for data from different hospitals and from different MR protocols. The purpose of his work is to address the model generalizability by using transfer learning to adapt the model from T2 MR to T1 MR.

METHODS

Three different types of MR images were collected, including T2 MR, T1-FLAIR MR and T1-POST MR. T2 MR dataset was acquired from Shenzhen Second People's Hospital, T1-FLAIR and T1-POST datasets were collected from University of Texas Southwestern Medical Center. We took T2 MR and corresponding CT images as the source dataset, T1-FLAIR MR and T1-POST MR as the target datasets. Four different models were investigated in this work. Including source model, target model, combined model and transfer learning based adapted model.

- Source model
  - Training with source domain dataset from scratch and testing with target domain dataset
- Target model
  - Training with target domain dataset and testing with target domain dataset
- Combined model
  - Training with source domain dataset and target domain dataset together, and testing with target domain dataset
- Adapted model
  - Using transfer learning strategy to train a model with source domain dataset and retrain the pre-trained model with target domain dataset, and testing with with target domain dataset

DEEP LEARNING ARCHITECTURE



DATASET SETTINGS

- Source model
  - 28 T2 MR data for training
  - 5 T1-FLAIR and 6 T1-POST patients for testing
- Target model
  - 14 T1-FLAIR data for training and 5 T1-FLAIR patients data for testing
  - 18 T1-POST data for training and 6 T1-POST patients data for testing
- Combined model
  - 28 T2 MR and 14 T1-FLAIR patients data for training, 5 T1-FLAIR patients for testing
  - 28 T2 MR and 18 T1-POST patients data for training, 6 T1-POST patients for testing
- Adapted model
  - 28 T2 data for pre-training and retraining on 14 T1-FLAIR data, testing on 5 T1-FLAIR data
  - 28 T2 data for pre-training and retraining on 18 T1-FLAIR data, testing on 6 T1-FLAIR data

RESULTS

Adapted model achieved best quantitative results of 74.56±8.61, 193.18±17.98, 28.30±0.83, and 0.84±0.01 for MAE, RMSE, PSNR and SSIM compared with source model, target model and combined model using T1 FLAIR dataset. Adapted model also achieved the lowest MAE (74.89±15.64), RMSE (195.73±31.29) and highest PSNR (27.72±1.43), SSIM (0.83±0.04), using T1 POST dataset. The results are shown in Table 1 and Table 2. Source model has the worst performance for all quantitative metrics, which is consistent with visual results.

Table 1: Quantitative evaluation of different solutions on model generalizability for T1-FLAIR dataset. ↑ means larger numbers are better, ↓ means smaller numbers are better.

	MAE±SD ↓	RMSE±SD ↓	PSNR±SD ↑	SSIM±SD ↑
Adapted model	74.56±8.61	193.18±17.98	28.30±0.83	0.84±0.01
Source model	126.81±14.97	230.98±29.75	26.80±1.14	0.66±0.04
p-value (source model & adapted model)	**0**	**0.01**	**0.01**	**0**
Target model	95.13±8.70	242.96±22.71	26.30±0.85	0.80±0.02
p-value (target model & adapted model)	**0**	**0**	**0**	**0.01**
Combined model	94.17±8.07	212.73±17.18	27.51±0.71	0.74±0.03
p-value (combined model & adapted model)	**0**	**0.02**	**0.04**	**0**

Table 2: Quantitative evaluation of different solutions on model generalizability for T1-POST dataset. ↑ means larger numbers are better, ↓ means smaller numbers are better.

	MAE±SD ↓	RMSE±SD ↓	PSNR±SD ↑	SSIM±SD ↑
Adapted model	74.89±15.64	195.73±31.29	27.72±1.43	0.83±0.04
Source model	109.94±5.67	232.48±14.66	25.44±0.55	0.49±0.06
p-value (source model & adapted model)	**0**	**0.02**	**0.01**	**0**
Target model	105.15±14.01	281.95±40.71	24.50±1.38	0.78±0.03
p-value (target model & adapted model)	**0.01**	**0.01**	**0.01**	**0.01**
Combined model	88.50±24.93	209.20±38.51	27.32±1.69	0.73±0.16
p-value (combined model & adapted model)	**0.03**	0.13	0.39	0.12

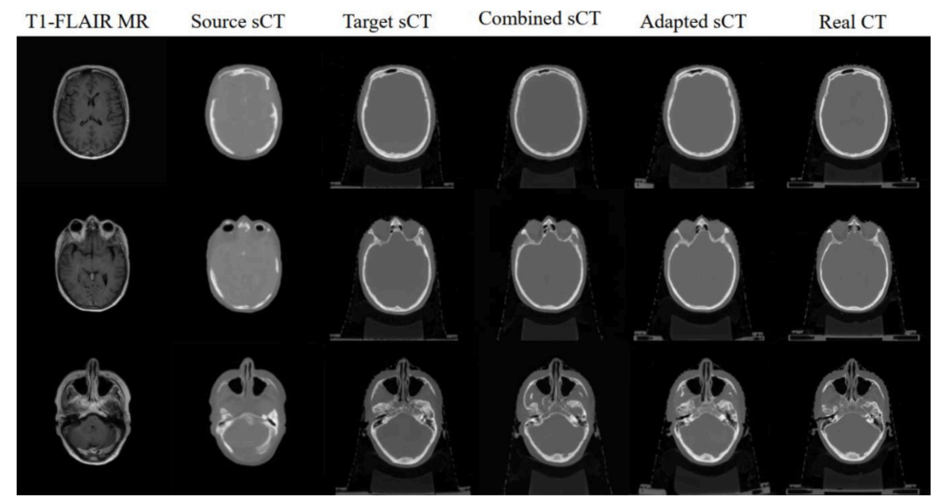


Figure 1: Visual evaluation results from one typical T1-FLAIR patient. From left to right, they are real T1-FLAIR MR, sCT images generated using source model, target model, combined model and adapted model, and corresponding real CT.

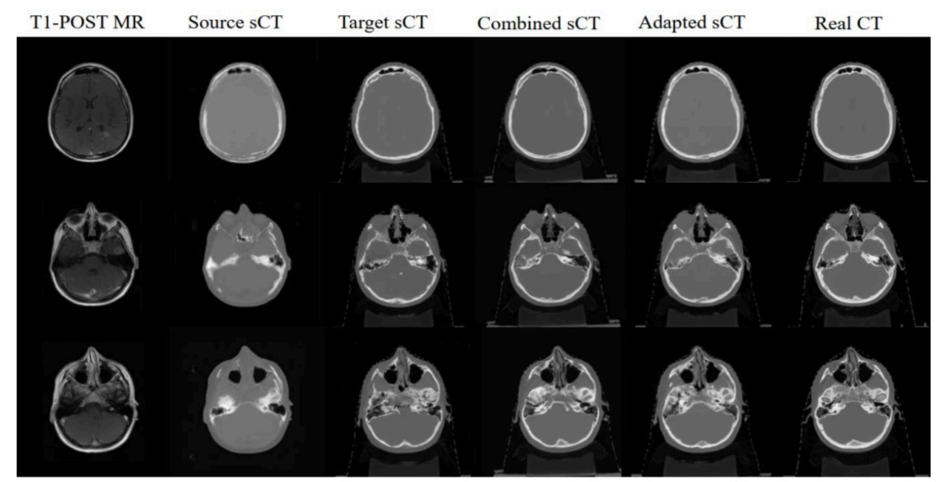


Figure 2: Visual evaluation results from one typical T1-POST patient. From left to right, they are real T1-FLAIR MR, sCT images generated using source model, target model, combined model and adapted model, and corresponding real CT.

CONCLUSIONS

This work indicates that the pre-trained CycleGAN model for MR to CT conversion can be transferred to the datasets acquired through different scanning protocols with limited data. Therefore, other hospitals could easily apply the trained model to their datasets to achieve better sCT generating performance.

REFERENCES

[1]Kearney, V., Ziemer, B. P., Perry, A., Wang, T., Chan, J. W., Ma, L., & Solberg, T. D. (2020). Attention-Aware Discrimination for MR-to-CT Image Translation Using Cycle-Consistent Generative Adversarial Networks. Radiology: Artificial Intelligence, 2(2), e190027.

[2]Yang, H., Sun, J., Carass, A., Zhao, C., Lee, J., Xu, Z., & Prince, J. (2018). Unpaired brain MR-to-CT synthesis using a structure-constrained CycleGAN. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support (pp. 174-182). Springer, Cham.