Building a patient-specific model using transfer learning for 4D-CBCT augmentation

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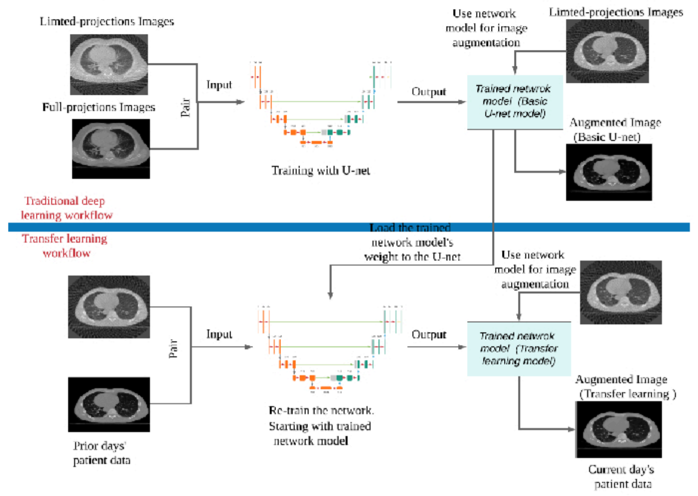
PURPOSE

- Previously we developed deep learning models to augment the quality of 4D-CBCT images. [1] However, the model was trained using a group of patients' data, and therefore may not be optimized for individual patients. [2]
- In this work, we explore the feasibility of transferring a general deep learning network trained with a group of patients' data to a patient-specific network retrained using a specific patient's data.

METHODS

- Demonstrated in Fig. 1, the network model is first trained to augment under-sampled CBCT to match with fully-sampled CBCT or planning CT images using a group of patients' data.
- Then, the model is retrained into a patient-specific model using the specific patient's CT or prior days' CBCT data with transfer learning to optimize its performance for individual patients.
- The network can be adaptively updated by adding the latest day's CBCT images in the training data. [3]



(Figure 1. Overall transfer learning workflow)

- Two transfer learning methods, including the whole-network fine-tuning method and the layer-freezing method, were investigated in our study.
- The whole-network fine-tuning method uses the new patient data to retrain all the layers in the network but lower the learning rate to make the parameter change slowly from the starting point.
- The layer-freezing method starts with the trained model as well but retrains only the bottom and final layers of the network

RESULTS

- The quantitative analysis using SSIM and PSNR (Table 1) showed that the major improvement from the transfer learning method lies in the lung area while the improvement in body area excluded lung is limited.
- The augmentation of body area from U-net is already satisfactory (Fig. 2A) with SSIM higher than 0.95.
- The augmentation by the group-based U-net in the lung area is suboptimal due to the complexity of the lung structure and the variations across patients. The transfer learning method was capable to recover more detailed anatomical structures that are lost in U-net augmentation. (Fig. 2B)

	Whole Volume	Lung Area	Body Area excluded Lung
Layer-Freezing	SSIM: 0.958 PSNR: 38.42	SSIM: 0.940 PSNR:37.28	SSIM: 0.964 PSNR: 38.89
Fine-Tuning	SSIM: 0.956 PSNR: 38.06	SSIM: 0.936 PSNR: 36.99	SSIM: 0.962 PSNR: 38.06
Basic U-net	SSIM:0.924 PSNR:33.77	SSIM: 0.839 PSNR: 34.87	SSIM: 0.954 PSNR: 35.45

Table 1. Comparison of CBCT reconstructed from simulated projections.

- The performance of transfer learning is slightly degraded due to the noises and artifacts in the fully-sampled CBCT images, which were used as the ground truth. (Table 2)
- Transfer learning had a better performance on 10% projections CBCT images for real projection data than DRR data. This may be because that the transfer learning model is better at eliminating noise and streak in the real CBCT images than basis U-net model.
- The differences map between U-net image and layer-freezing image in Fig. 3B showed that most difference were from the edge area of the lung and the area around bones that have a lot of noises.

	Whole Volume	Lung Area	Body Area excluded Lung
Transfer learning for 20% projection data	SSIM: 0.894 PSNR: 34.52	SSIM: 0.857 PSNR: 35.03	SSIM: 0.909 PSNR: 34.33
Basic U-net for 20% projection	SSIM:0.866 PSNR:32.11	SSIM: 0.793 PSNR: 33.86	SSIM: 0.896 PSNR: 31.57
Transfer learning for 10% projection data	SSIM: 0.879 PSNR: 33.96	SSIM: 0.839 PSNR:33.98	SSIM: 0.896 PSNR: 33.95
Basic U-net for 10% projection	SSIM:0.833 PSNR:30.98	SSIM: 0.738 PSNR: 31.61	SSIM: 0.870 PSNR: 30.76

Table 2. Comparison of CBCT reconstructed from real projection data.

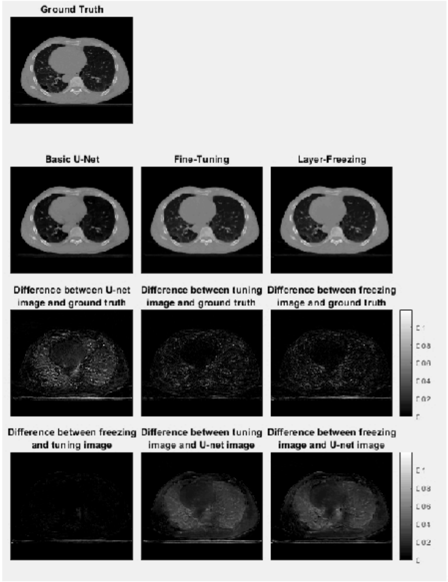


Figure 2A. Comparison between transfer learning image, basic U-net image and ground truth image

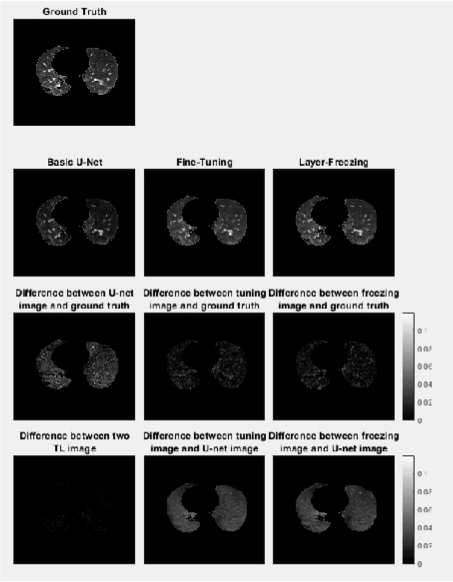


Figure 2B. Comparison between lung images extracted from Fig. 2A.

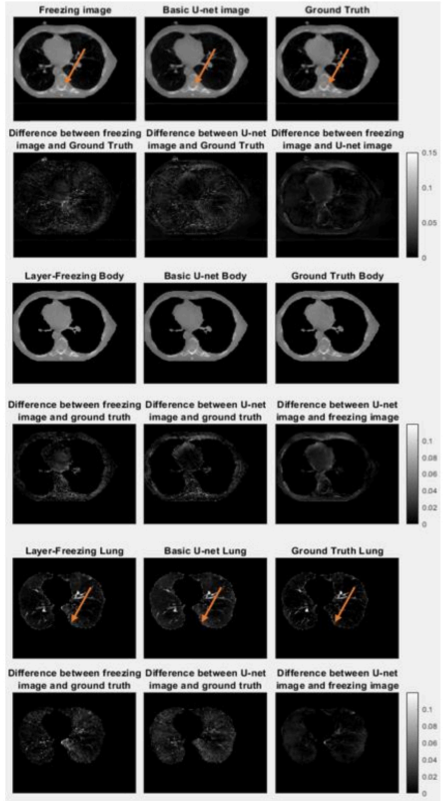


Figure 3A. Comparison of CBCT reconstructed from 179 real projections

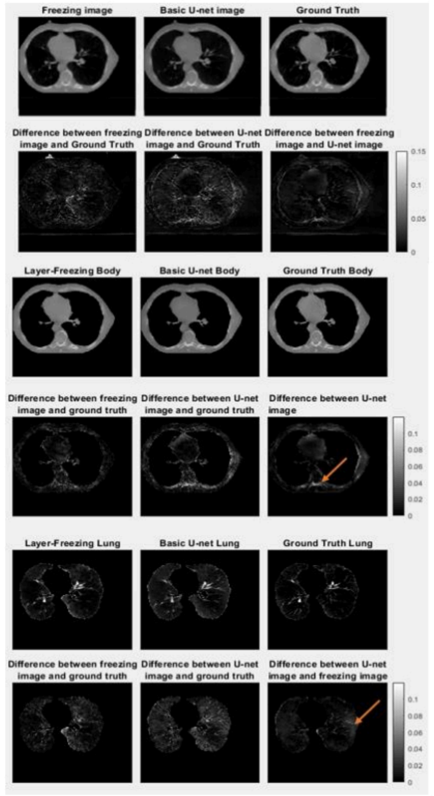


Figure 3B. Comparison of CBCT reconstructed from 89 real projections

CONCLUSIONS

- The proposed transfer learning method demonstrated its capability of augmenting the image quality of under-sampled 3D/4D-CBCT by building a patient-specific model.
- The patient-specific model further enhanced the anatomical details and reduced noises and artifacts compared to the traditional group-based deep learning model.
- The technique can be used for reducing the imaging dose or improving the localization accuracy using 3D/4D-CBCT, which can be very valuable for SBRT treatments.

ACKNOWLEDGEMENTS

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