Limited-Angle Computed Tomography Reconstruction using Combined FDK-Based Neural Network and U-Net

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Introduction

❖ Background

❖ Related Work

- A CT scanner produces 360-degree projection data to reconstruct CT, but much expensive
- A C-Arm scanner is much cheaper[1], but can only scan a range less than 180 degrees
- Due to incomplete projection data, the reconstructed CT contains heavy artifacts using a conventional filtered-backprojection (FBP) algorithm
- Deep learning algorithms can be considered to remove the artifacts

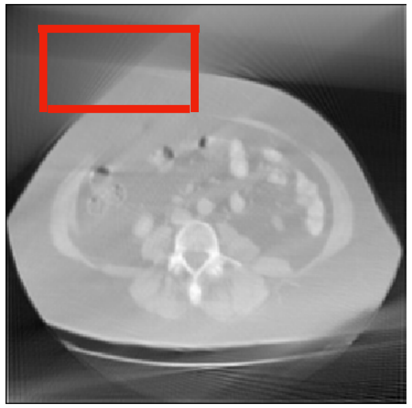


Figure 1. CT reconstruction from 145 degrees

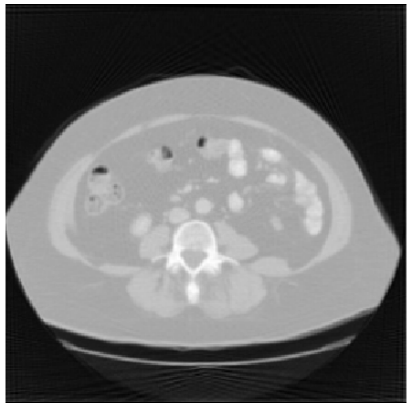


Figure 2. CT reconstruction from 360 degrees

[1] From LBN Medical and PrizMed Imaging

Introduction

❖ Background

❖ Related Work

- Schnurr et al. applied deep artifact correction to mitigate limited-angle artifacts where three U-Net-based networks and a 3D-ResNet are trained for artifact correction estimation[1]

- Dong et al. used a deep learning U-Net in projection domain of a conventional FBP method to estimate the complete projection sinogram for high-quality CT reconstruction[2]

- Würfl et al. proposed a novel method by mapping a conventional FBP method to a neural network[3]

[1] Schnurr et al., 2019
[2] Dong et al., 2019
[3] Würfl et al., 2018

Methods

❖ Würfl et al.'s Work

❖ Revised Würfl et al.'s Work

- Each layer in the FBP neural network from Würfl et al.'s work inspired by the FDK algorithm can be modeled as one matrix multiplier in terms of discrete linear algebra[1,2]

$$\mathbf{x} = \mathbf{A}^{\top}\mathbf{F}^{-1}\mathbf{K}\mathbf{F}\mathbf{W}_{\mathrm{red}}\mathbf{W}_{\cos}\mathbf{p}$$

$\mathbf{p}$ - the acquired projection data

$\mathbf{W}_{\cos}$ - the pixel-wise cosine weights of the acquired projection data

$\mathbf{W}_{\mathrm{red}}$ - the redundancy Parker weights[3]

$\mathbf{K}$ - a reconstruction filter

$\mathbf{F}$ $\mathbf{F}^{-1}$ - the Fourier transform and the inverse Fourier transform

$\mathbf{A}^{\top}$ - the adjoint system matrix

$\mathbf{x}$ - reconstructions

[1] Würfl et al., 2018
[2] Syben et al., 2019
[3] Parker, 1982

Methods

❖ **Würfl et al.'s Work**

❖ **Revised Würfl et al.'s Work**

- For our problem of limited angle 145 degrees

$$\mathbf{x} = \mathbf{A}^\top \mathbf{F}^{-1} \mathbf{K} \mathbf{F} \mathbf{W}_{\cos} \mathbf{p}$$

- Map a filtered-backprojection algorithm to a neural network[1] (The FDK neural network)
- Enable an end-to-end training (from projection to reconstruction)

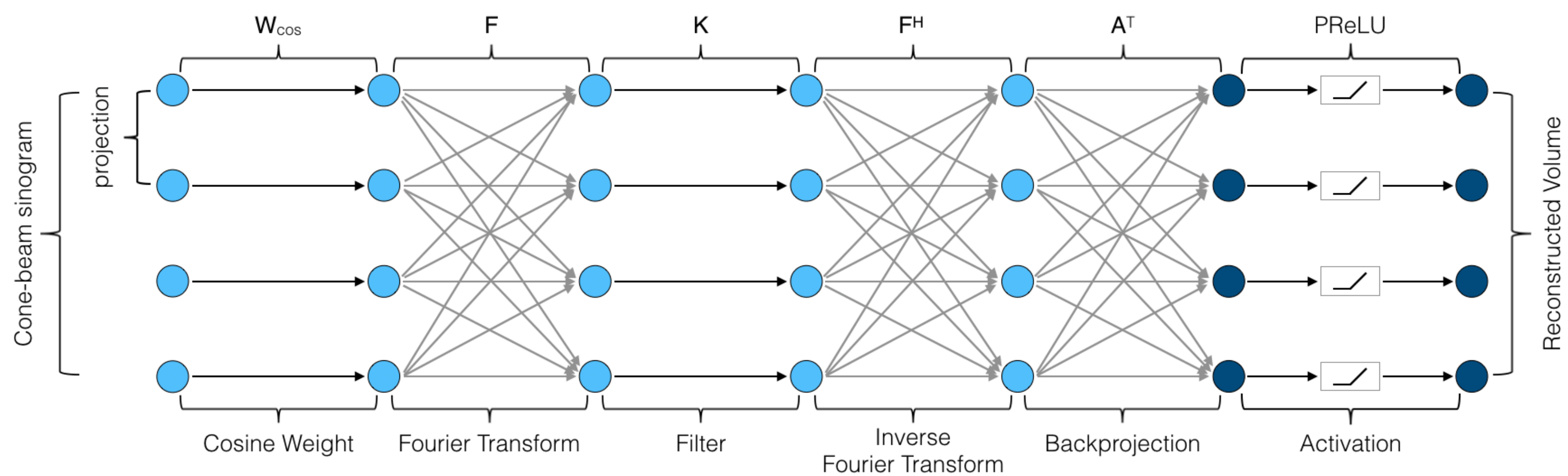


Figure 3.The FDK neural network

[1] Syben et al., 2019

Methods

- U-Net is based on Convolutional Neural Network and can help recover missing features
- Test three networks combining the FDK neural network and U-Net
  - The FDK neural network trained with a U-Net in projection domain together
  - The FDK neural network trained with a U-Net in image domain together
  - The FDK neural network trained with a U-Net in both domains together

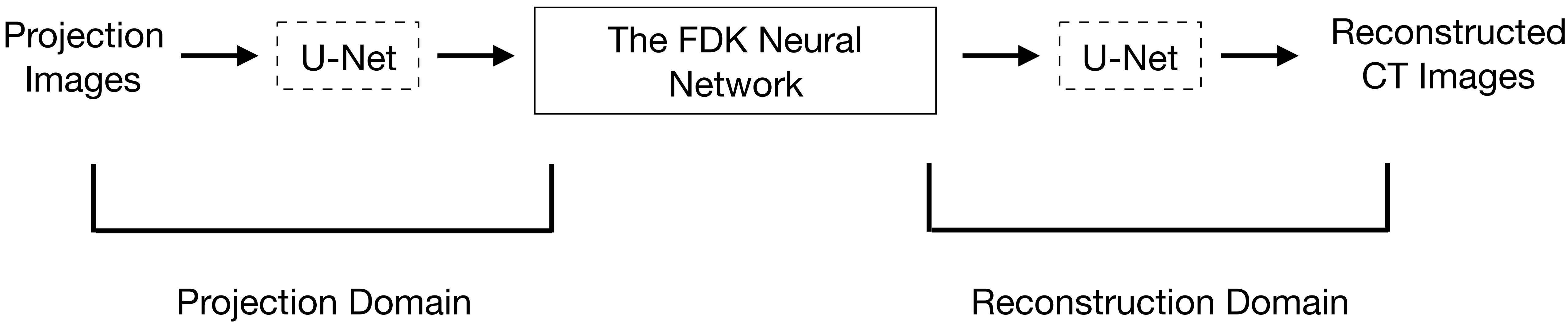


Figure 4. An overview of testing networks

Our Proposed Model

- The proposed pipeline neural networks that a U-Net is trained separately after the FDK neural network.

- Light blue nodes represent projection domain while dark blue nodes stand for image domain.

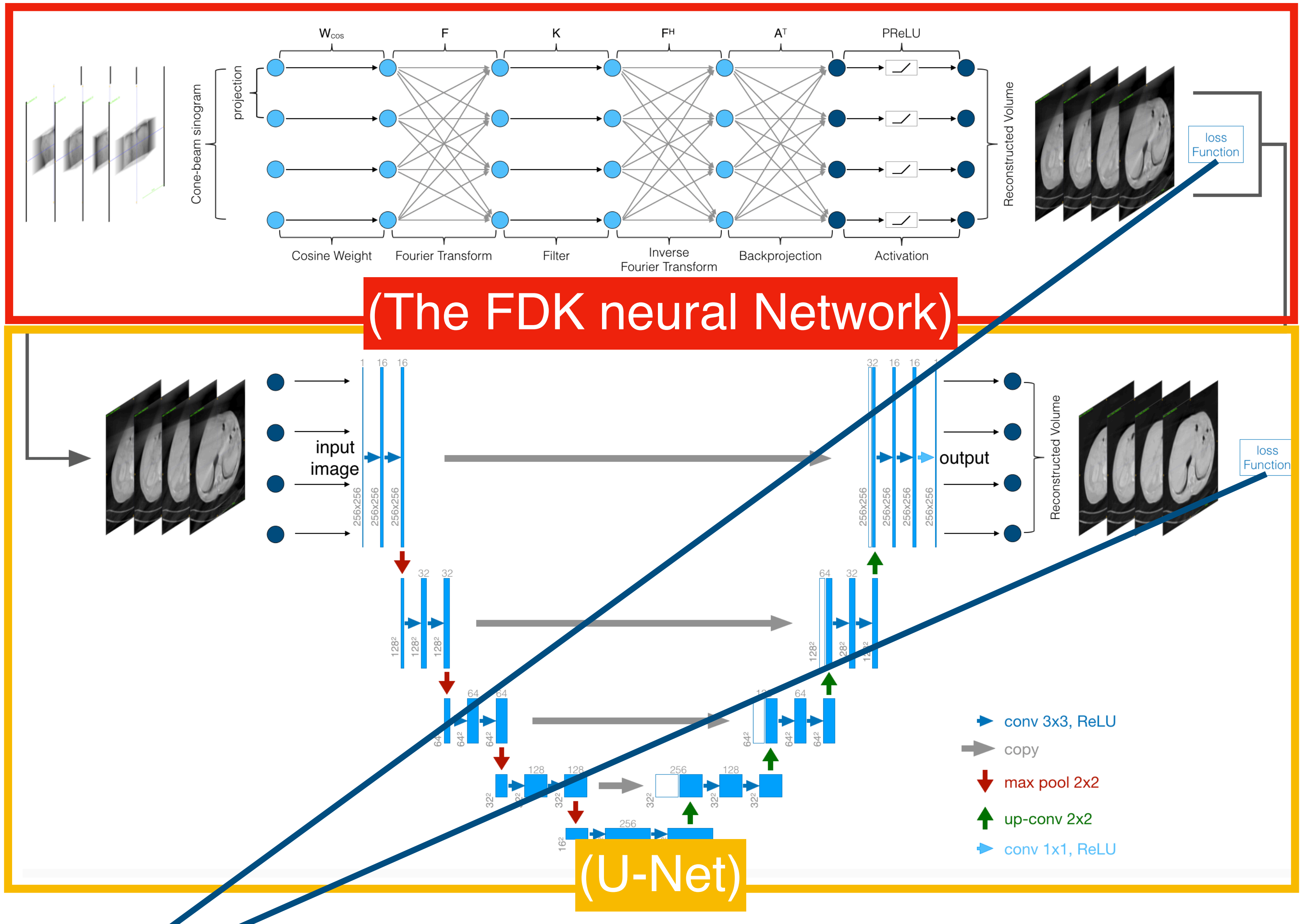
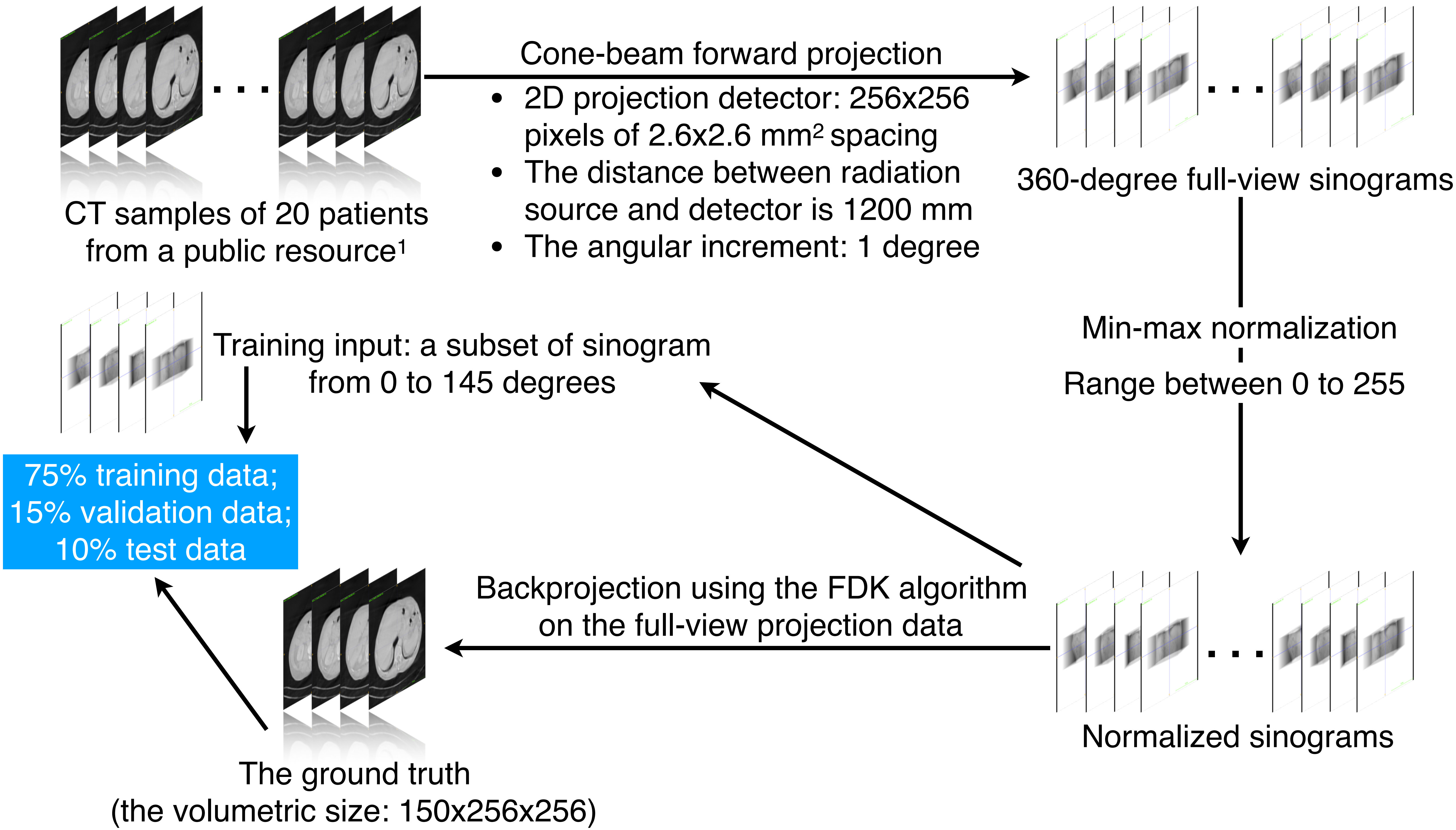


Figure 5. The proposed pipeline neural networks

Loss function: ℓ_2

Data



[1] www.ircad.fr/research/3d-ircadb-01/

Metrics

- Mean Square Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity (SSIM)

Metrics

- ❖ **Mean Square Error (MSE)**
- ❖ **Peak Signal-to-Noise Ratio (PSNR)**
- ❖ **Structural Similarity (SSIM)**

- Defined as: $\textbf{PSNR} = 10\log_{10}(\frac{R^2}{\textbf{MSE}})$

  where R is the possible maximum pixel value of the input images

- Measure the quality of reconstructed images
- A higher PSNR value generally suggests a high-quality reconstructed result

Metrics

❖ Mean Square Error (MSE)

❖ Peak Signal-to-Noise Ratio (PSNR)

❖ Structural Similarity (SSIM)

- A SSIM expression[1] used here is defined as: $\mathbf{SSIM}(x, y) = \dfrac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$

  where *x* and *y* are the two images for evaluation; μ_x and μ_y are the mean intensities of them; σ_x and σ_y are the standard deviations of them; σ_{xy} is the covariance of them; C_1 and C_2 are two constants in order to avoid instability
- Measure the similarity of two images
- Range between -1 and 1: approaching 1 meaning the two images are more identical

[1] Wang et al., 2004

Results

❖ Numerical Results

❖ Visual Results

- My approach achieved a much low mean square error, high structural similarity and high peak signal-to-noise ratio.

Model Description	*MSE*	*PSNR*	*SSIM*
The conventional FDK algorithm	0.0236	16.3539	0.7566
The FDK neural network (FDK NN)	0.0037	24.4122	0.8309
The FDK NN trained with a U-Net in projection domain together	0.0039	24.1806	0.7860
The FDK NN trained with a U-Net in image domain together	0.0030	25.5833	0.8260
The FDK NN trained with a U-Net in both domains together	0.0042	23.9518	0.7319
Our proposed pipeline neural networks	**0.0015**	**28.4647**	**0.8953**

Table 1. Numerical results of different algorithms for limited-angle CT reconstruction

Results

❖ Numerical Results

❖ Visual Results

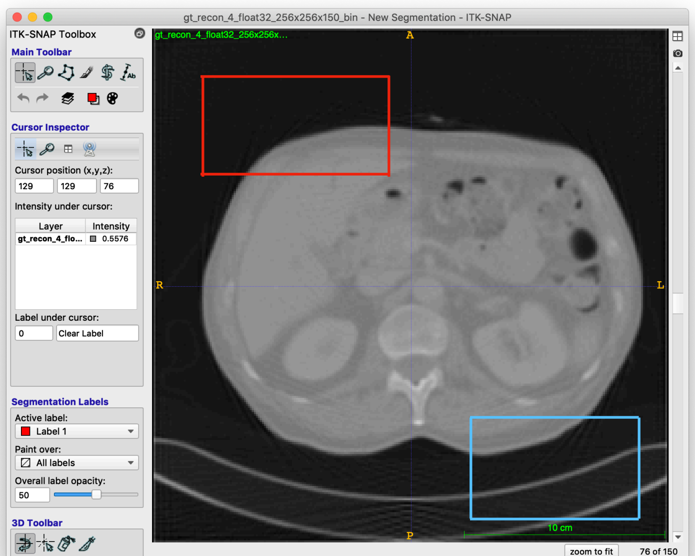


Figure 6. Ground truth

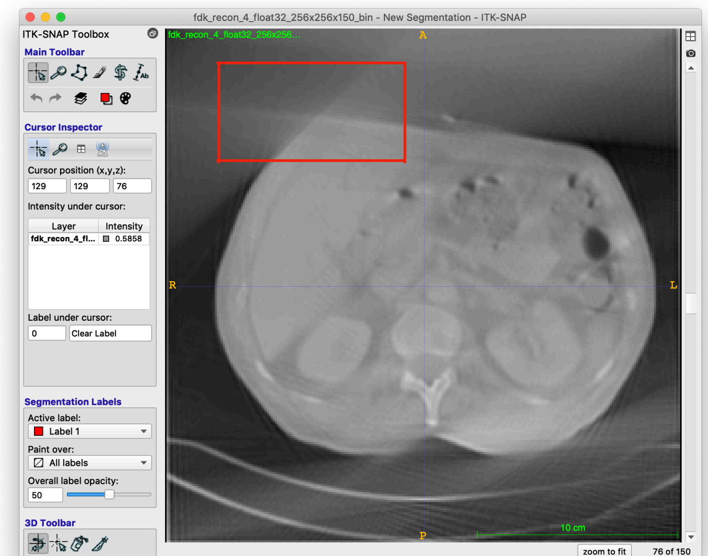


Figure 7. Conventional filtered-backprojection algorithm

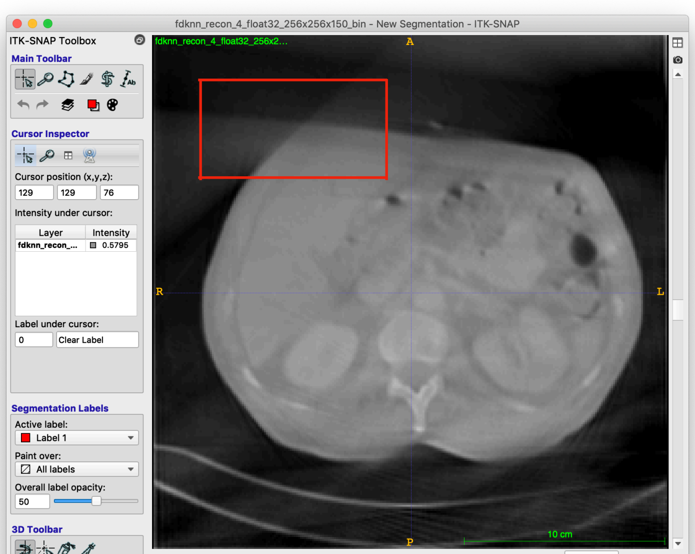


Figure 8. Filtered-backprojection neural network

Figure 9. Filtered-backprojection neural network with U-Net
(My proposed model)

Results

❖ Numerical Results

❖ Visual Results

- **Residual Results**

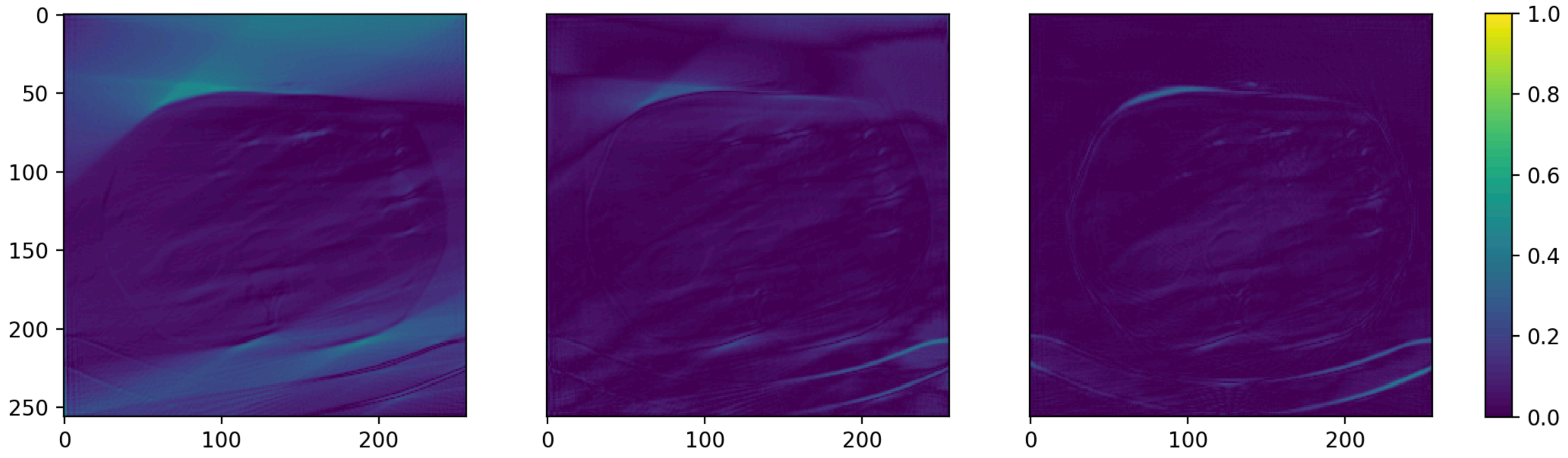


Figure 10. The residual results for the conventional FDK algorithm, the FDK neural network and our proposed model with regard to the ground truth from left to right

Results

❖ Numerical Results

❖ Visual Results

- **Limitations**

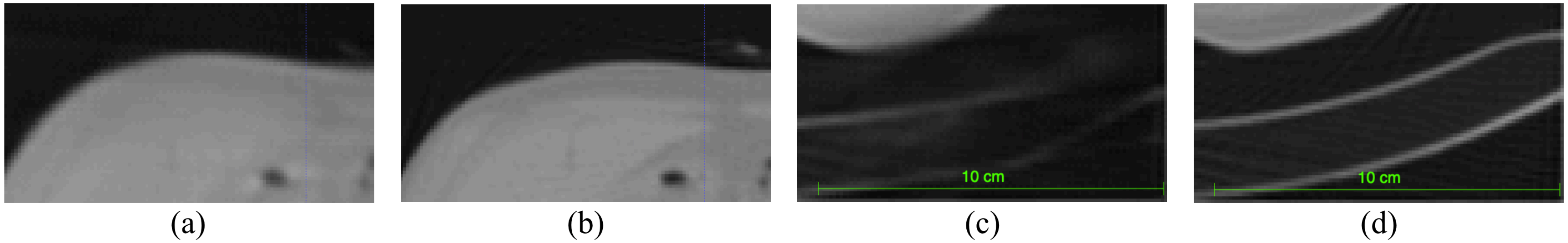


Figure 11. (a) and (b): the top left area of slice for our proposed pipeline and the ground truth from left to right; (c) and (d): the bottom right area of slice for our proposed pipeline and the ground truth from left to right

Conclusion

❖ Conclusion

❖ Future Directions

- Deep learning algorithms demonstrate encouraging results in limited-angle CT reconstruction problem
- U-Net was incorporated in different domains with FDK neural network to reduce artifacts and recover missing features
- Our proposed network pipeline that the FDK neural network followed by an image domain U-Net has achieved a significant improvement compared with the conventional FDK algorithm and the FDK neural network
- But there are still some limitations such as the areas on the top-left and bottom-right corners are still not reconstructed well

Conclusion

❖ Conclusion

❖ Future Directions

- Combining iterative methods with deep learning networks
- Adding larger training dataset
- Test the reconstruction on different anatomic data