Motion-Blind Blur Removal for CT Images with Wasserstein Generative Adversarial Networks

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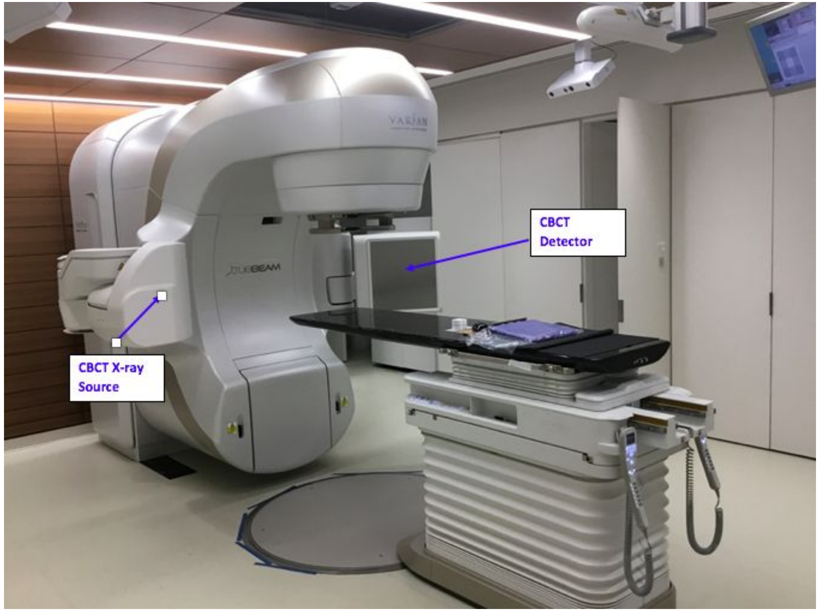
Presentation Outline

1. Introduction
2. Methodology
3. Implementation Details
4. Results

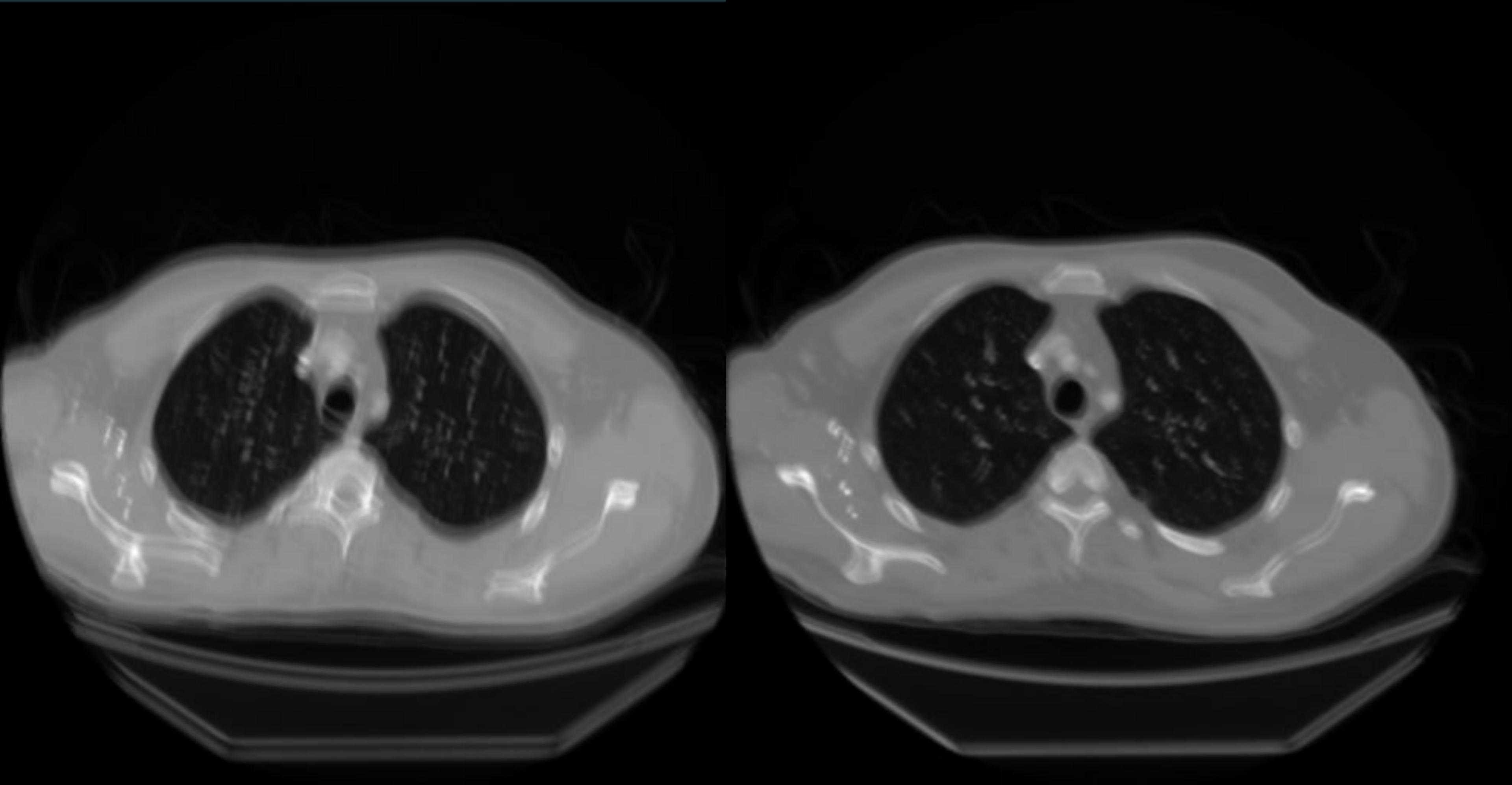
Introduction

Task

- The cone-beam **CT** (CBCT) installed on the modern medical linear accelerators requires more than 60 seconds for a full scan. Therefore, CBCT scans often exhibit pronounced **motion-induced blur** and artifacts.
- CT image deblurring is challenging because **irregular** patient body and organ motion can generate **unpredictable** blurring patterns.
- As a result, handcrafted programming is a suboptimal technique for removing blur. Creating an automated **single-image deblurring method** is therefore an important goal for radiation oncology physicists.



MSKCC CBCT on linear accelerators

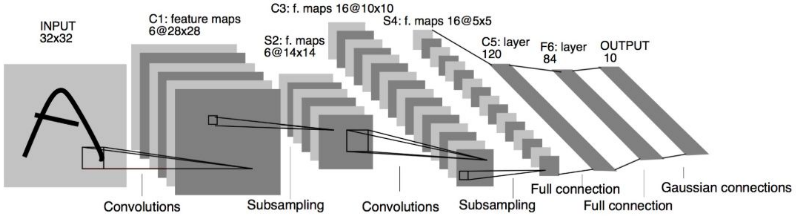


Examples of blurry CT

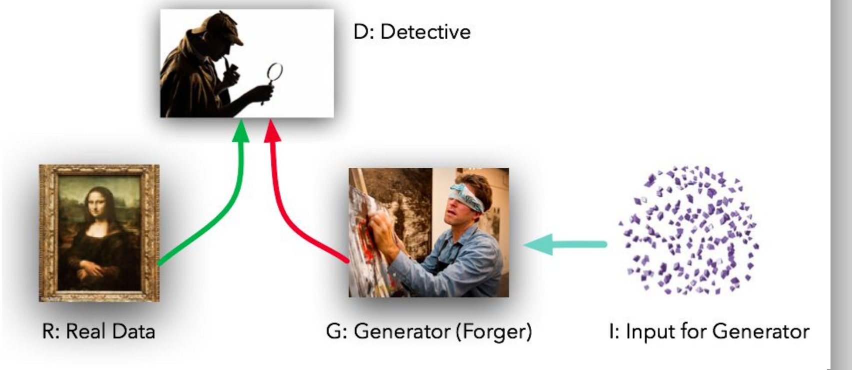
Methodology

Outline

- **Goal**: To **reconstruct** a sharp CT given only a blurry CT as the input.
- **Challenge**:
  - Note that **no prior information** about the blur was provided.
  - Only one blurry CT is fed to the model.
- **Method**: Use Deep Learning techniques to learn the **mapping** from blurry CT to sharp CT.
  - Convolutional Neural Networks (CNN)
  - Generative Adversarial Networks (GAN)



CNN



GAN

Related work

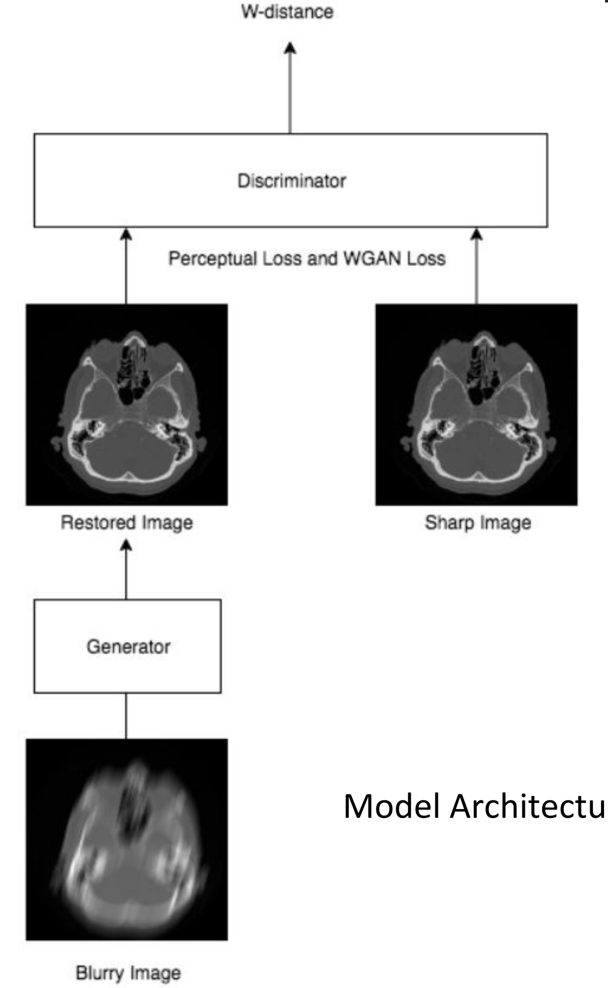
- **DeblurGAN:** Kupyn, Orest, et al. "DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks." arXiv preprint arXiv:1711.07064 (2017).

From left to right: Sharp; Blurry; Restored (Deblurred)

Model Architecture

Generator network: (ResNet)
Input: blurred image; Output: estimate of the sharp image.
Discriminator networks: (Multilayer Perceptron)
During the training time, the discriminator network takes restored and sharp image as an input and estimates a distance between them.

Training Phase: Generator Rand Discriminator are trained sequentially and adversarially.
Loss Function:
Total loss consists of WGAN loss and perceptual loss. WGAN loss is for details restoration and perceptual loss is for general content. $L = L_{GAN} + \lambda L_{Perceptual}$



Model Architecture

Paired Dataset

Original Sharp Dataset

TCIA Collections

Registered free breathing (FB) CT and deep inspiration breath hold (DIBH) CT

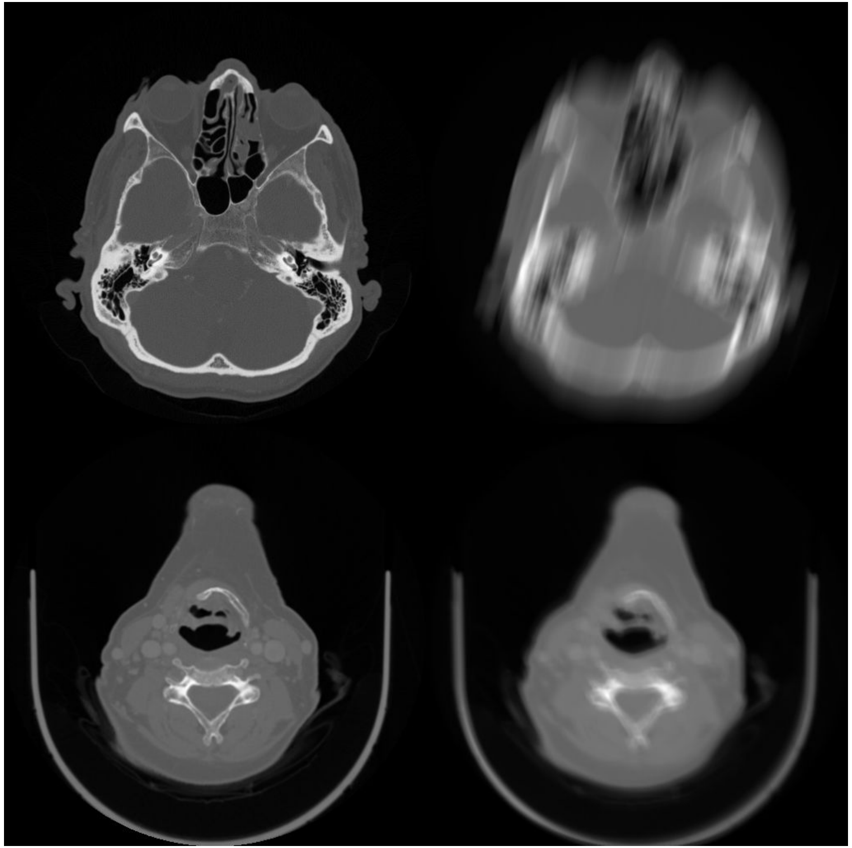
Irregular blur generation algorithm

Proposed by DeblurGAN

Randomness parameters vary

Results and examples

14,329 sharp-blurry pairs created



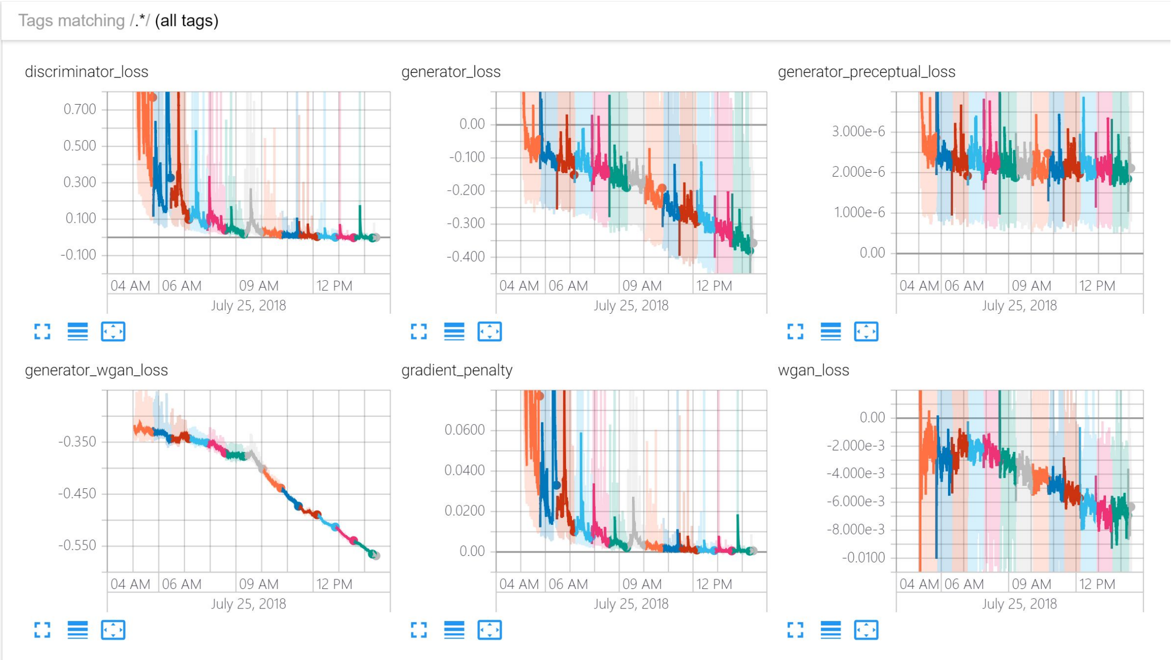
Implementation Details

Initialization Phase

- In the previous work, the author of DeBlurGAN trained the discriminator first for 5 times then train the generator for 1 time in one iteration.
- We found that, for the first few epoches, the generator cannot generate very useful example for the discriminator. Differing from regular GANs, DeblurGAN has two losses for the generator. Therefore, we could make use of this to train the generator for first few epoches by perceptual loss.After that, we introduce the WGAN-GP loss for the generator.
- This method could increase the first few epoches training speed dramatically.
- Eventually, the model converges much more faster and gained the same results.

Training Phase

- Due to the high volume of data, they are randomly split into 7 sub-dataset and are sequentially fed into the model
- The training phase took roughly 40 hours for training one proposed network.

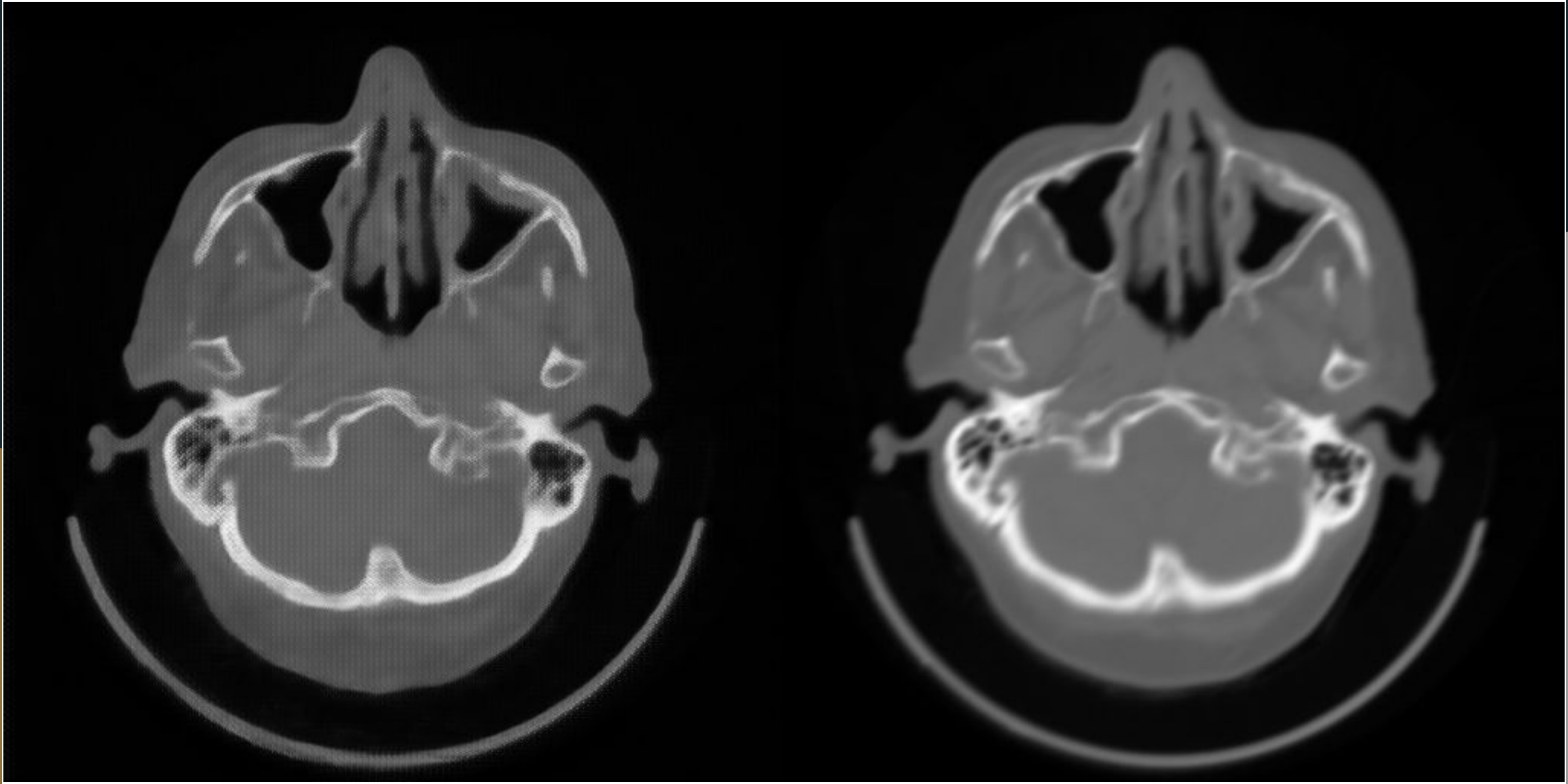


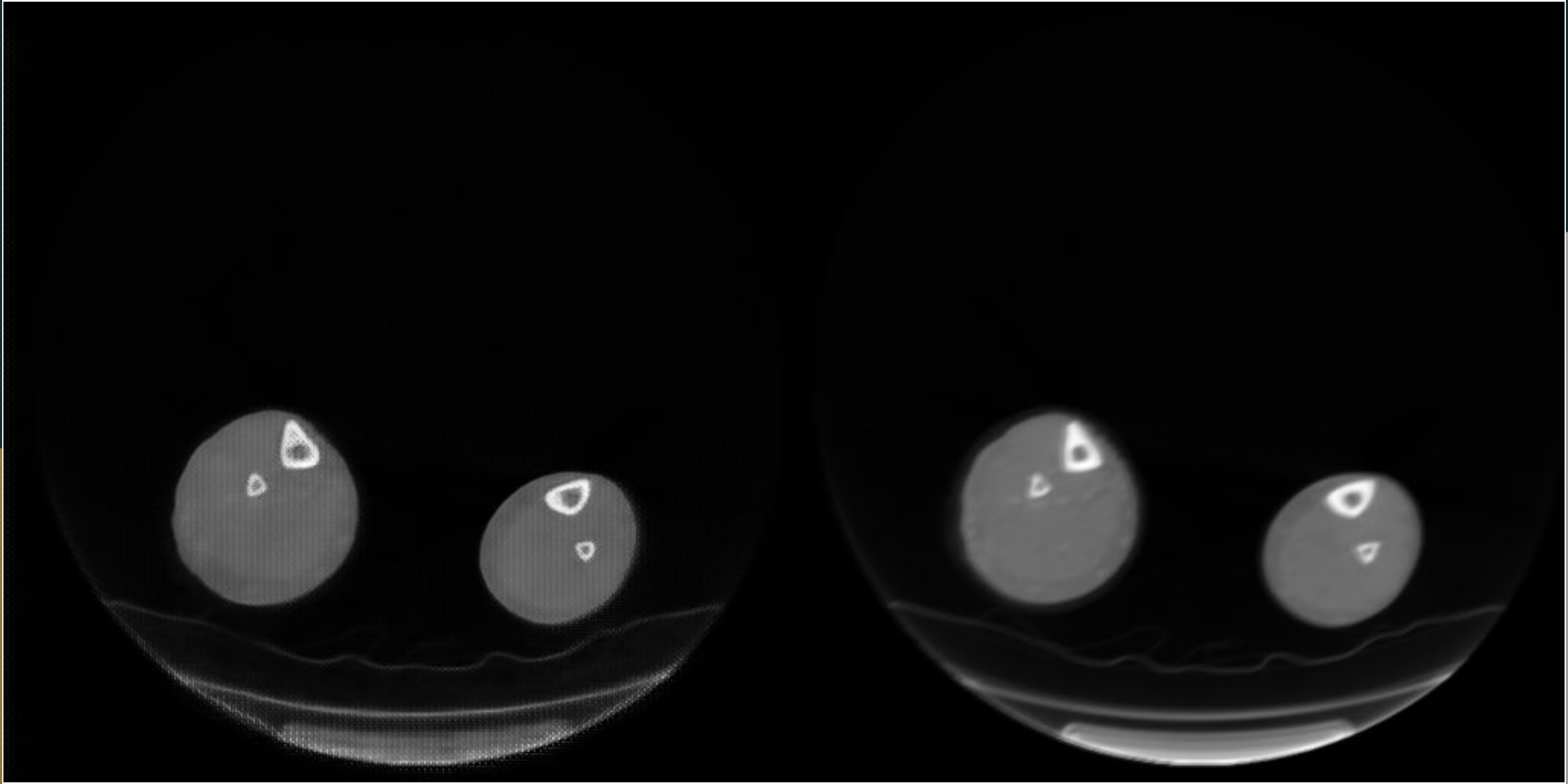
Results

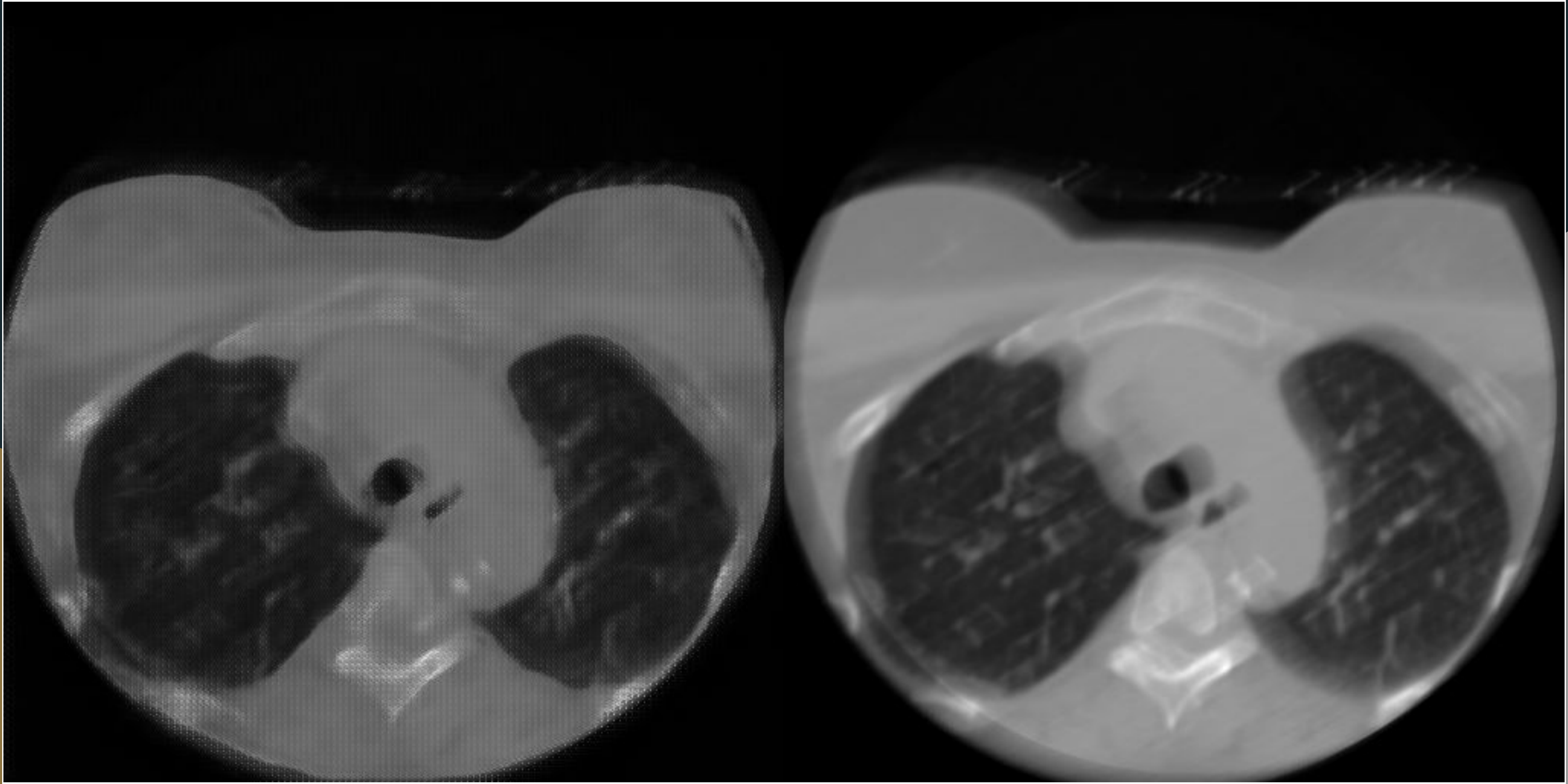
Quantitative Evaluations

	Our Method	Pixel2Pixel	DeblurGAN
SSIM	**0.94**	0.88	0.93
PSNR	**25.67**	24.72	25.22

SSIM: Structural Similarity Index
PSNR: Peak signal-to-noise ratio







Conclusion

We successfully **utilized** and **modified** a kernel-free blind motion deblurring learning approach and **improved** DeblurGAN which is a Conditional Adversarial Network that is optimized using a multi-component loss function.

Besides that, we optimized the **initialization phase** and saved much training time.

A paired dataset was created and the model was trained from scratch. This methodology has resulted in significantly **improved performance** on CT image blur removal.

Future studies include testing the **sensitivity** of the model on other medical image modalities to broaden its clinical applications.

Reference

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[2] Kupyn, Orest, et al. "DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks." arXiv preprint arXiv:1711.07064 (2017).
[3] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros. Image-to-image translation with conditional adversarial networks. arxiv,2016
[4] Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein GAN." arXiv preprint arXiv:1701.07875 (2017)
[5] Gulrajani, Ishaan, et al. "Improved Training of Wasserstein GANs." Advances in Neural Information Processing Systems. 2017.
[6] Our code on github: https://github.com/yl3832/MSKCC-Medical_Images

Thank you