Deep Residual Learning for Model-Based Iterative CT Reconstruction using Plug-and-Play Framework

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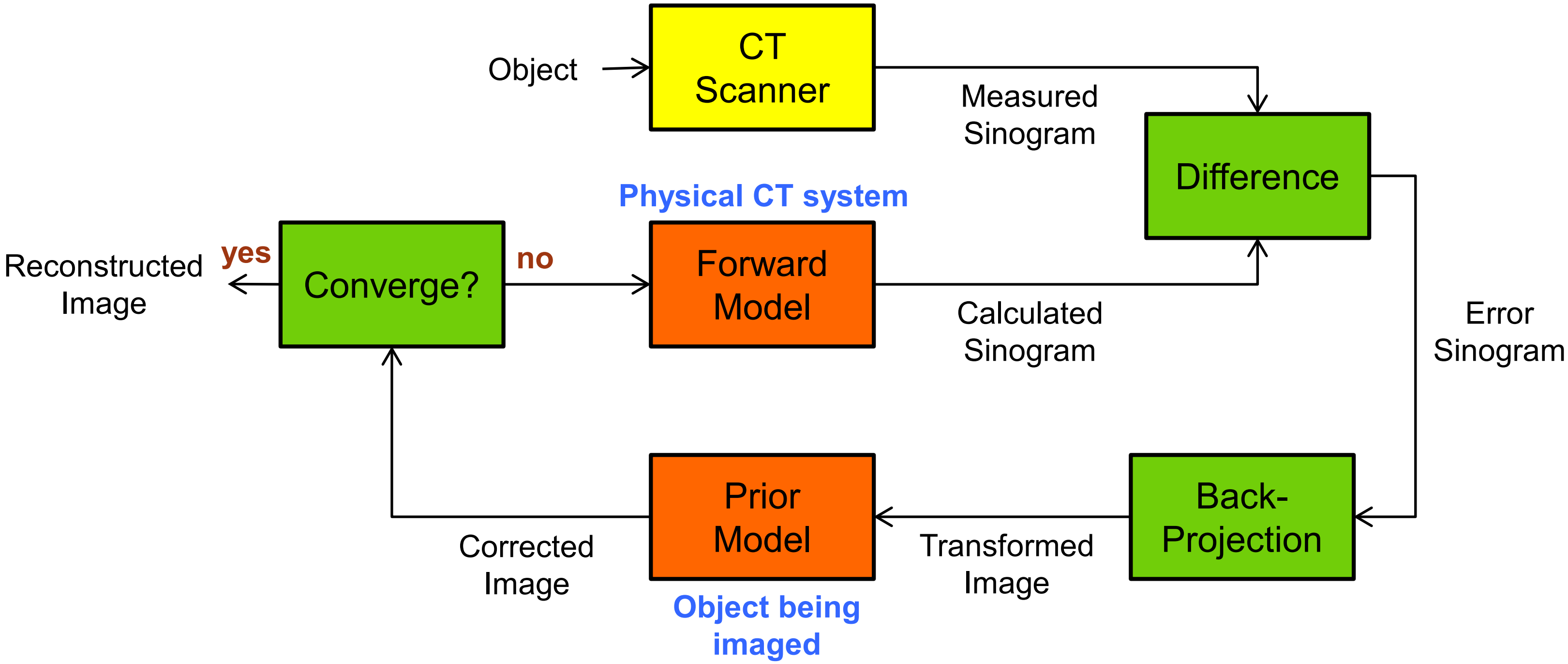
Model-Based Iterative Reconstruction (MBIR)

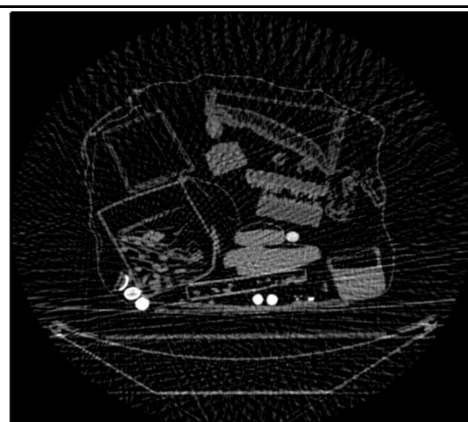
- Computed Tomography (CT) Reconstruction
  - Diagnostic Radiology
  - Additive Manufacturing Inspection

- MBIR Flowchart



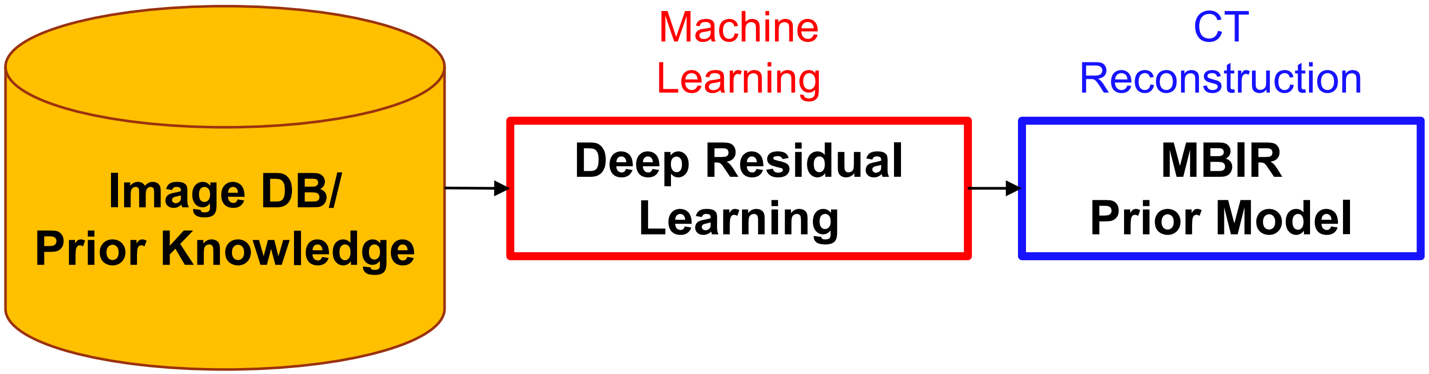
Advantage of MBIR over Filtered-Back Projection (FBP)

- Superior Image Quality: Low Noise and High Resolution

	FBP	**MBIR**
Low-dose (quarter dose)		
Sparse-view (16 views)		

Prior Model in MBIR

- Accurate prior modeling is critical to the image quality of MBIR.
- Typical Prior Model: MRF
  - Penalize intensity fluctuation in the neighborhood
  - Challenge: Noise-induced fluctuation vs. underlying object
- Solution: Prior Model from an Image Database



MBIR Optimization

- MAP Estimation

$$\hat{x} = \arg\min_{x} \left[\boxed{\frac{1}{2} \left\| \mathbf{A}x - y \right\|_{\mathbf{W}}^{2}} + \frac{1}{2\sigma^2} \boxed{\Phi(x)} \right]$$

Forward Model **Prior Model**

$x \in \mathbb{R}^N$: reconstructed image, $y \in \mathbb{R}^M$: measured CT scan

$\mathbf{A} \in \mathbb{R}^{M\times N}$: system matrix for CT scan, $\mathbf{W} \in \mathbb{R}^{M\times M}$: measurement noise variance

$\sigma \in \mathbb{R}$: regularization parameter, Φ: $\mathbb{R}^N \to \mathbb{R}$: prior model

- First-order iterative optimization
  - Iterative Coordinate Descent (ICD) / Ordered Subset (OS)
  - Prior model should be first-order differentiable.

Not flexible for Data-driven Prior

Plug-and-Play (PnP) Framework

- Variable Splitting

Separate variable

$$(\hat{x},\hat{v}) = \arg\min_{x,v}\left[\frac{1}{2}\|\mathbf{A}x-y\|_{\mathbf{W}}^2 + \frac{1}{2\sigma^2}\boxed{\Phi(v)}\right] \quad \text{s.t. } x = v$$

- Alternating Direction Method of Multipliers (ADMM)

$$L_\lambda(x,v,u) = \frac{1}{2}\|\mathbf{A}x-y\|_{\mathbf{W}}^2 + \frac{1}{2\sigma^2}\Phi(v) + \frac{1}{2\lambda^2}\|x-v+u\|_2^2$$

Augmented Lagrangian

Step 1: Reconstruction Module

$$\hat{x} = \arg\min_{x} L_\lambda(x,\hat{v},u) = \arg\min_{x}\left[\frac{1}{2}\|\mathbf{A}x-y\|_{\mathbf{W}}^2 + \frac{1}{2\lambda^2}\|x-\hat{v}+u\|_2^2\right]$$

Step 2: De-noising Module

$$\hat{v} = \arg\min_{v} L_\lambda(\hat{x},v,u) = \arg\min_{v}\left[\frac{1}{2\sigma^2}\Phi(v) + \frac{1}{2\lambda^2}\|\boxed{\hat{x}+u}-v\|_2^2\right]$$

Step 3: Update Dual Variable

$$u \leftarrow u + (\hat{x}-\hat{v})$$

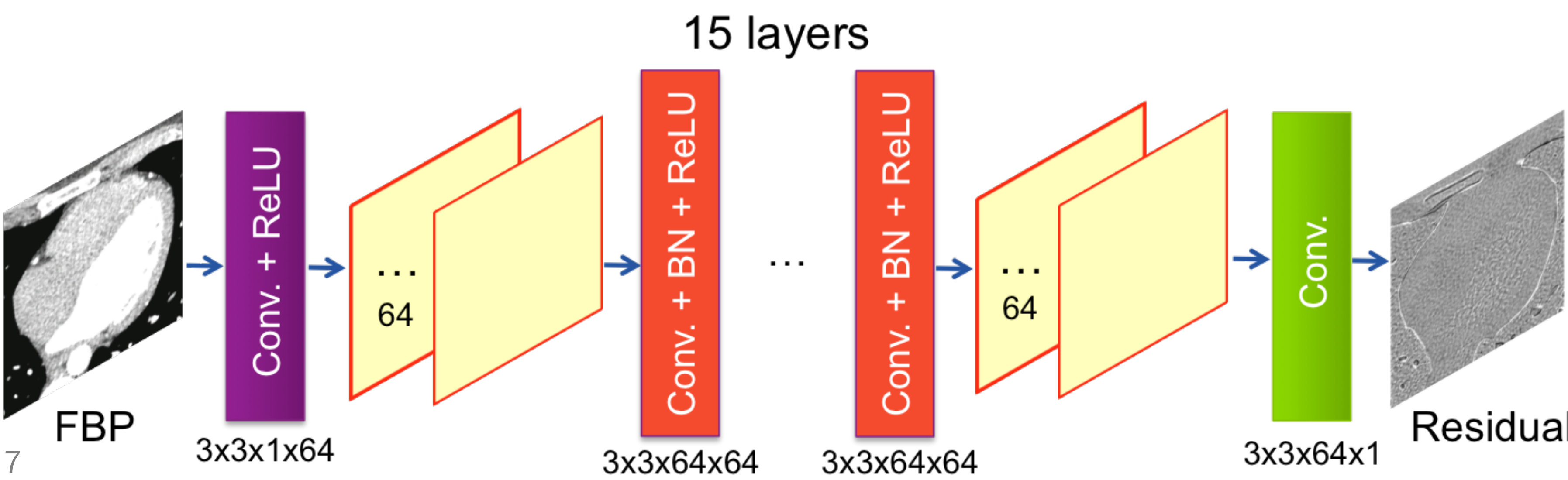
Input noisy image

Independent Module for De-noising

Deep Residual Learning for De-noising

- Deep Neural Network
  - Powerful performance for vision tasks such as de-noising
  - Weights of a neural network learned on large training dataset
  - Challenge: Long training time

- Deep Residual Learning for Efficient Training
  - Bypassing low-freq. image



Deep Residual Learning: Training

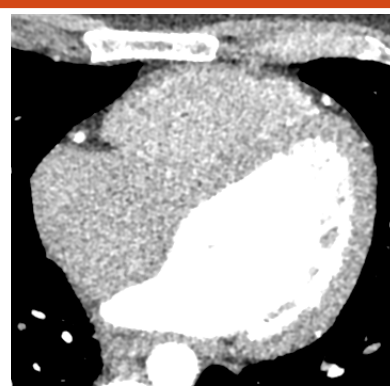
- Cost $$l(\Theta) = \frac{1}{2K}\sum_{k=1}^{K}\left\| R(\tilde{v}_k^{tr};\Theta) - (\hat{v}_k^{tr} - \tilde{v}_k^{tr}) \right\|_2^2$$

$\{\tilde{v}_k^{tr}, \hat{v}_k^{tr}\}$: noisy and clean image pairs, $R(\bullet;\Theta)$: Residual neural network

- Training Database
  - 40x40 patches for all slices, Data augmentation (flip, rotation)
  - Randomly selected 256000 patches, mini-batch size: 128

Database

FBP



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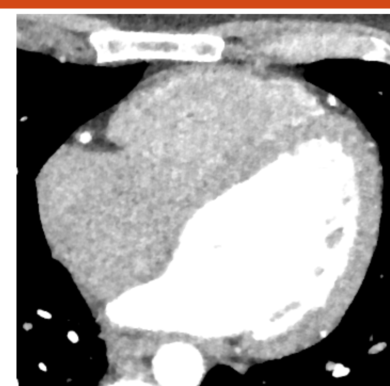
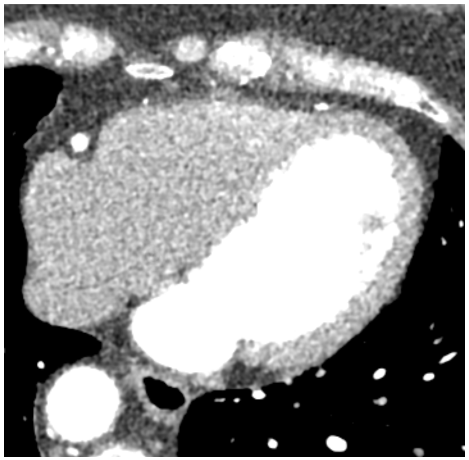
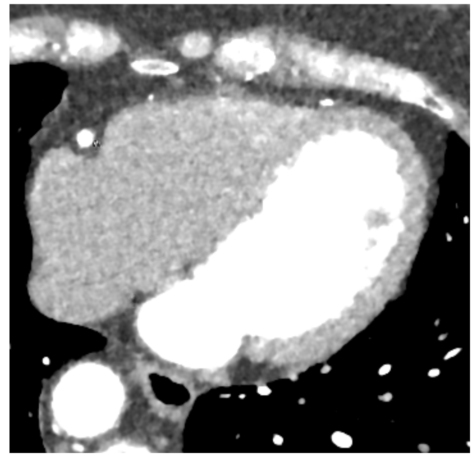
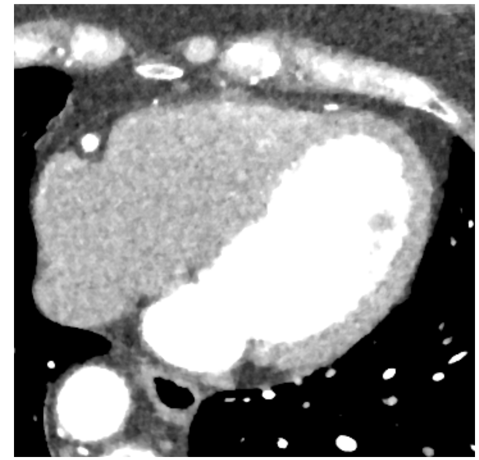
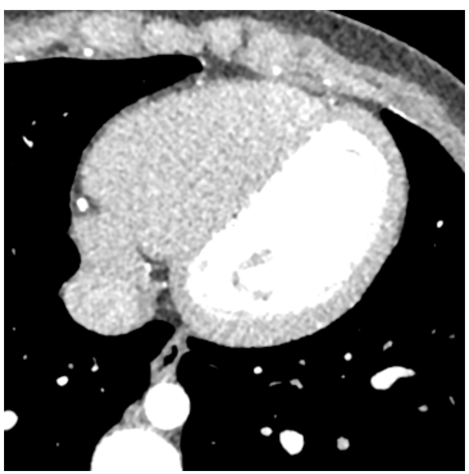
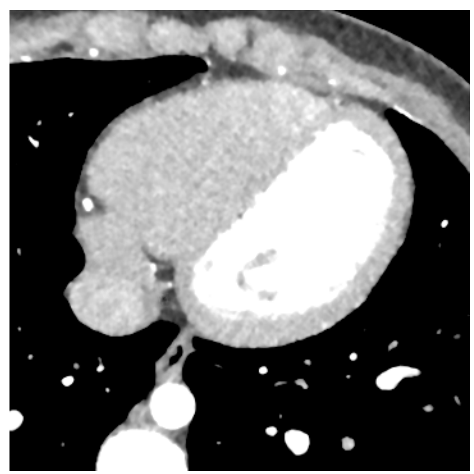
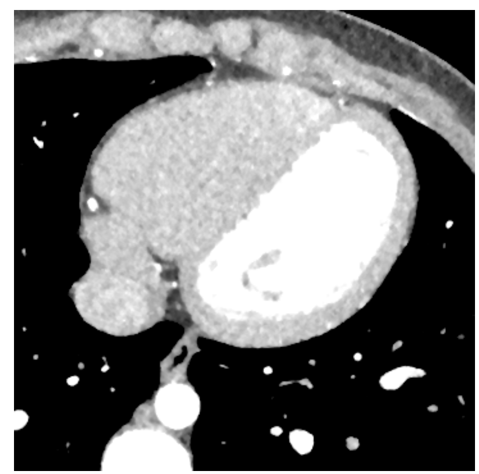
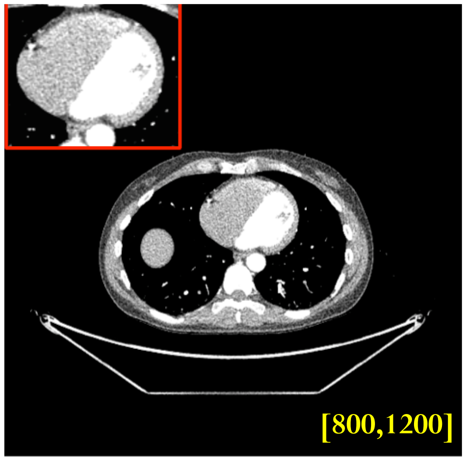
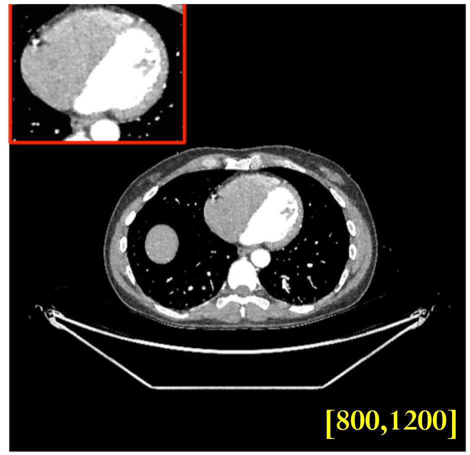
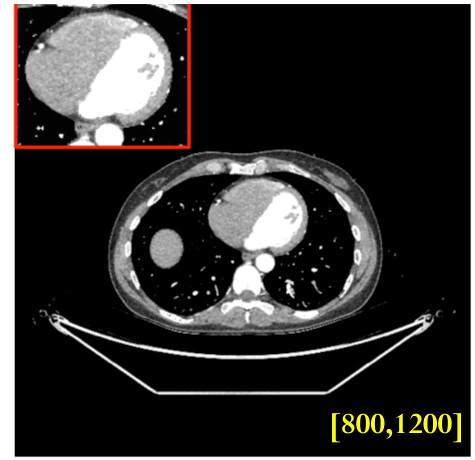
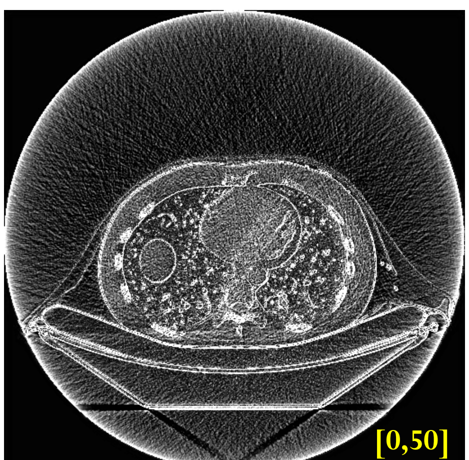
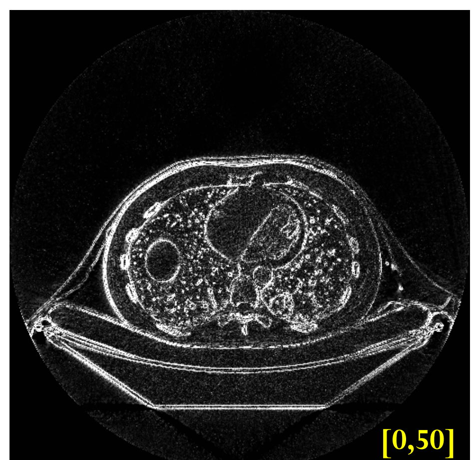


Ground-Truth MBIR (20 iter.)

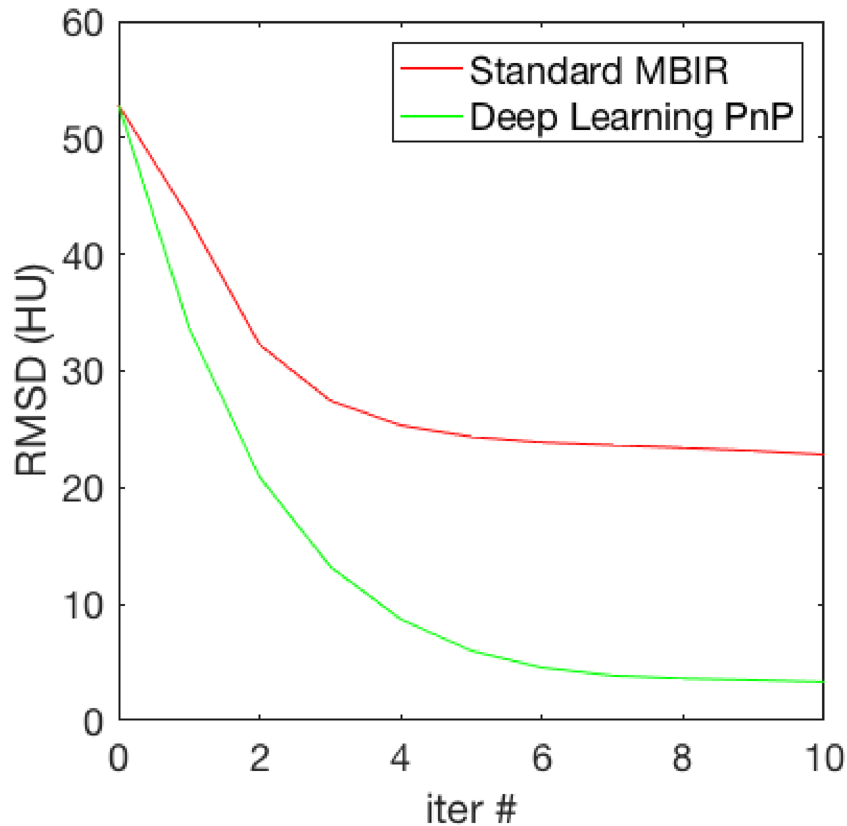
Deep Residual Learning: Testing

	FBP	Deep Residual Learning De-noising	Ground-Truth MBIR
Testing Scan #1			
Testing Scan #2			

MBIR Result: Qualitative @ 1 iter.

	Standard MBIR with MRF Prior	PnP MBIR with Deep Learning Prior	Ground-Truth MBIR
Reconstructed Image			
Difference Image			

MBIR Result: RMSD



Significant Speed-up with Faster Convergence

Computational Time

- Deep Learning Training Time
  - 4 NVIDIA Titan X GPU (12GB memory)
  - Google Tensor Flow
  - 65 minutes / 50 epochs

- Deep Learning Testing Time
  - ~10ms/slice

- Standard MBIR and PnP MBIR require similar amount of recon. time per iteration.

Conclusion

- Summary
  1. Image prior modeling from FBP/MBIR database
     - ➢ Deep Residual Learning for Image De-noising
  2. Incorporating the prior model from a database into MBIR
     - ➢ Plug-and-Play Optimization Framework

- Deep Residual Learning is effective in reducing the noise and enhancing the resolution in FBP.

- PnP MBIR with deep learning prior significantly improves the image quality compared with standard MBIR.