Challenging the Necessity of a Perfect Prior:
Insights from a Replication and Robustness Study of NeRP

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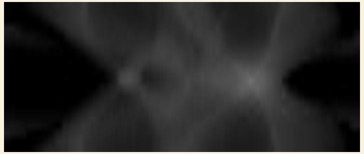
Background

Computed Tomography (CT) Scans

How Do CT Scans Work?

Scanning
with X-Rays



Multiple
2D Projections

Reconstruction

CT Scans

Essential for **diagnosis**

& **treatment** planning

Reconstruction

$$\mathbf{y} = A\mathbf{x} + e$$

Acquisition Noise

Projection Signals (from device)

Radon Transform

Ground Truth CT Image

Reconstruction Goal: Given **y**, retrieve **x** (Approximate $\mathbf{A}^{-1}$)

1000+ Projections are needed for **High-Quality Recon**

Issue

1000+ Projections Per Scan For High-Quality Recon

Multiple Scans Needed During Treatment

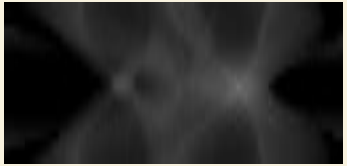
→ Frequent & Prolonged Exposure to Radiation → <u>Raised Risk of Cancer (to some extent)</u>

A Machine Learning Solution

Medical Imaging

Scan Acquisition

1000+ Projections



Reconstruction

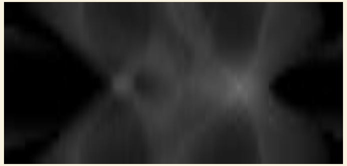
Traditional Imaging Reconstruction

Medical Imaging + Deep Learning ?

Scan Acquisition

~~1000+ Projections~~

~20 Projections



Reconstruction

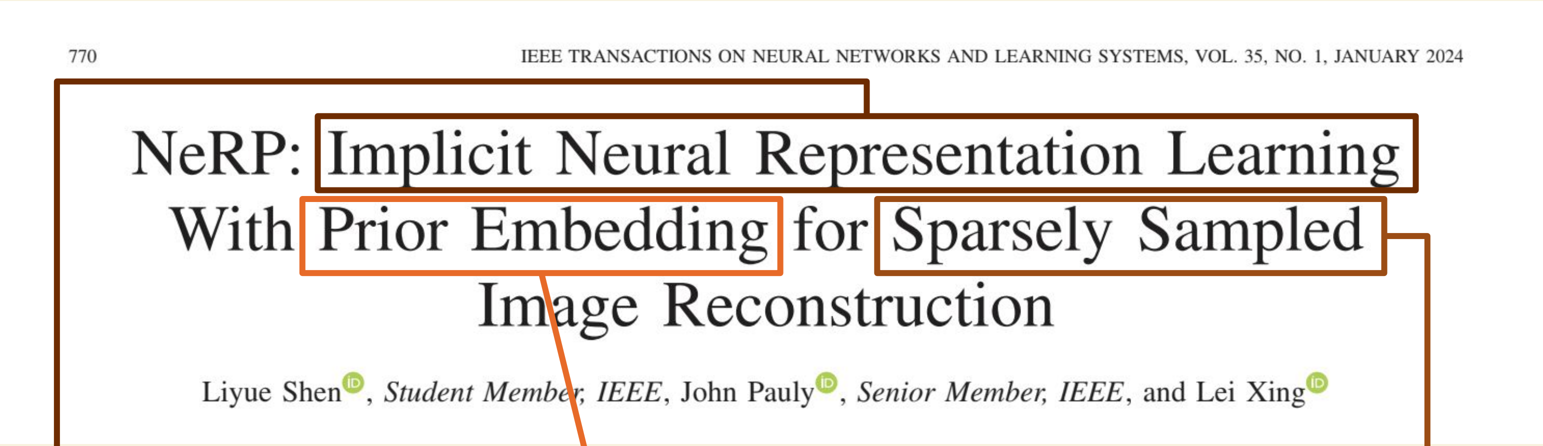
~~Traditional Imaging Reconstruction~~

Deep Learning Model

Fewer Projections → Reduced Radiation & Scanning Time

How to produce a high-quality reconstruction?

A Machine Learning Solution: NeRP[1]



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NeRP: Implicit Neural Representation Learning With Prior Embedding for Sparsely Sampled Image Reconstruction

Liyue Shen, *Student Member, IEEE*, John Pauly, *Senior Member, IEEE*, and Lei Xing

Multi-Layer Perceptron
(MLP)

Previous CT
for Pre-Training

[**Sparsely** Sampled] ~20 Projs
[**Densely** Sampled] 1000+ Projs

[1] Shen, L.; Pauly, J.; and Xing, L. 2022. NeRP: Implicit Neural Representation Learning With Prior Embedding for Sparsely Sampled Image Reconstruction. IEEE Transactions on Neural Networks and Learning Systems, 770–782.

NeRP's Contributions & Significance

Novel method for sparsely sampled medical image reconstruction

State-of-the-art performance

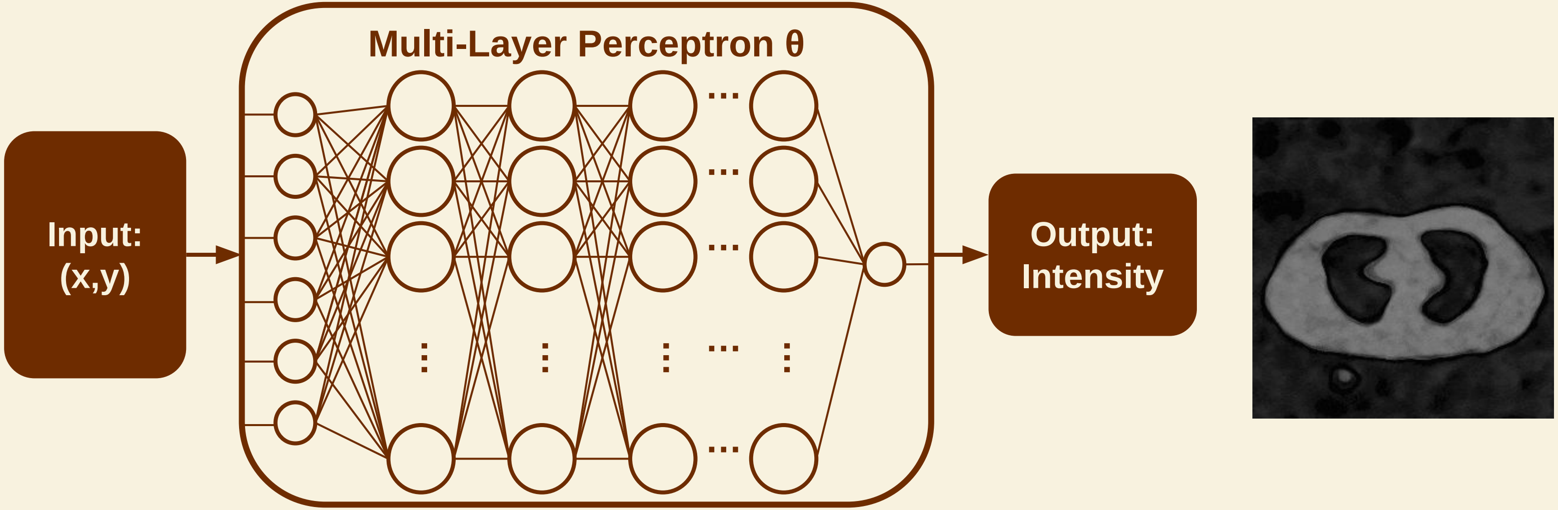
Demonstrates the importance of a prior image for pre-training

Leverages a patient's prior image for patient-specific neural representation

- Not reliant on large training datasets
- More generalizable across diff imaging modalities & anatomical sites

NeRP Replication - Technical Details

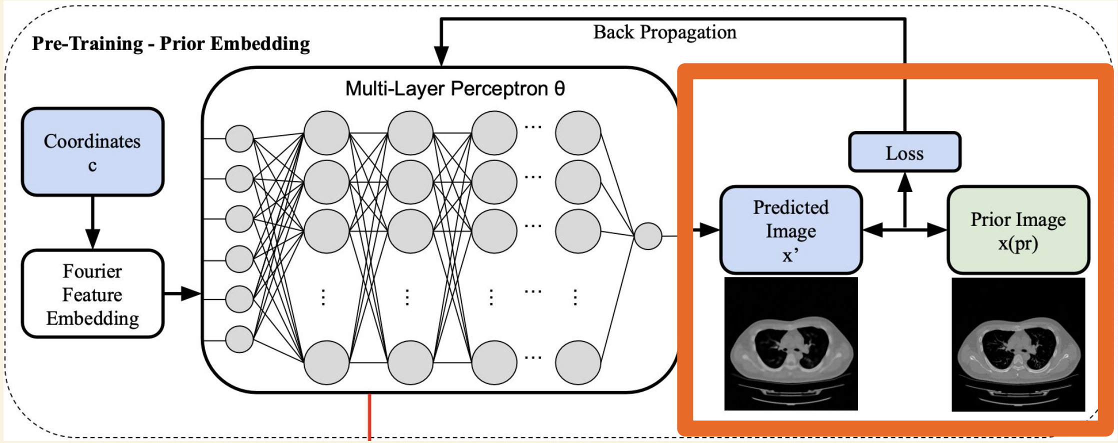
NeRP Replication: 2-D CT Reconstruction



Technical Steps

Prior Embedding

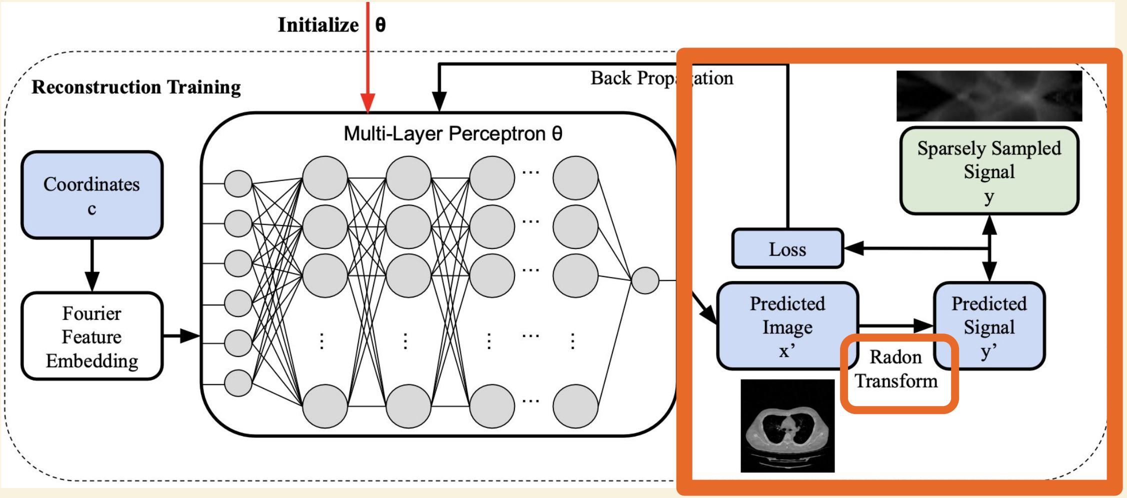
MLP learns a continuous function **M(θ)**
M(θ): maps the coordinates to intensity values of the **prior image**
Loss: between **CT Images**



Technical Steps

Prior Embedding → θ → **Network Training**

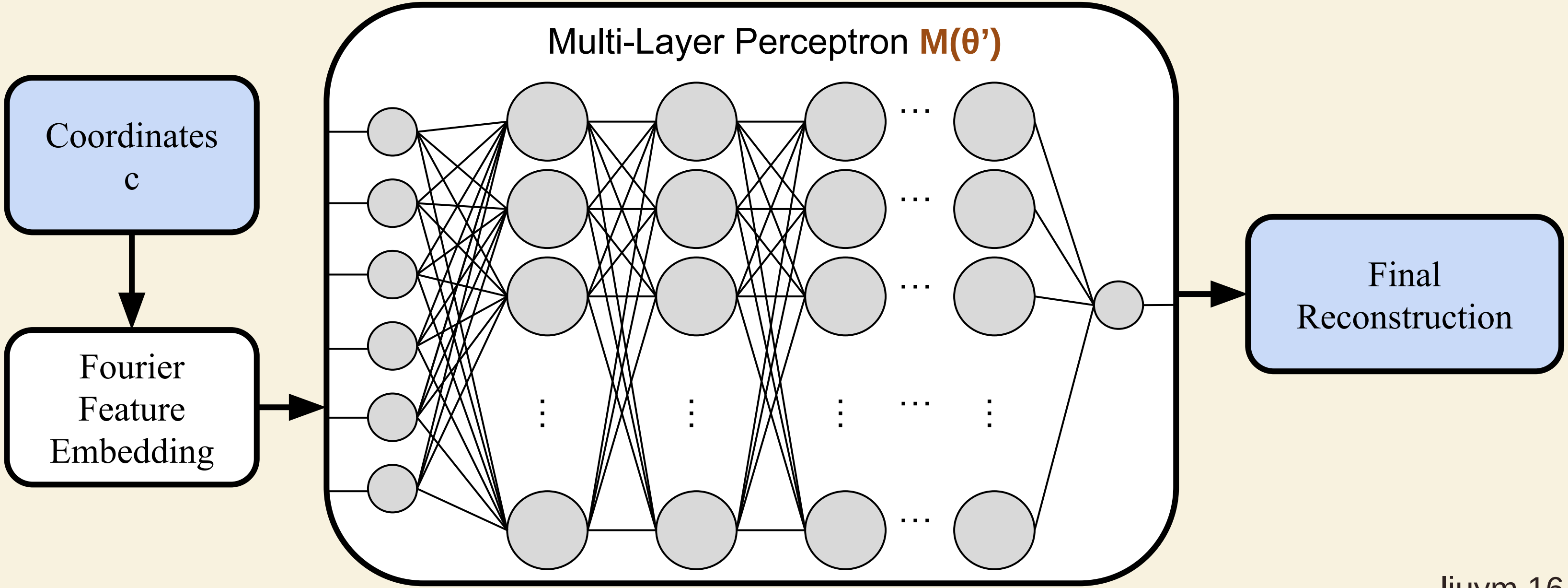
MLP is initialized as **M(θ)**
Fine-tuning with sparsely sampled projections to get **M(θ')**
Loss: between **Projection Signals**



Technical Steps

Prior Embedding θ → Network Training θ' → **Image Inference**

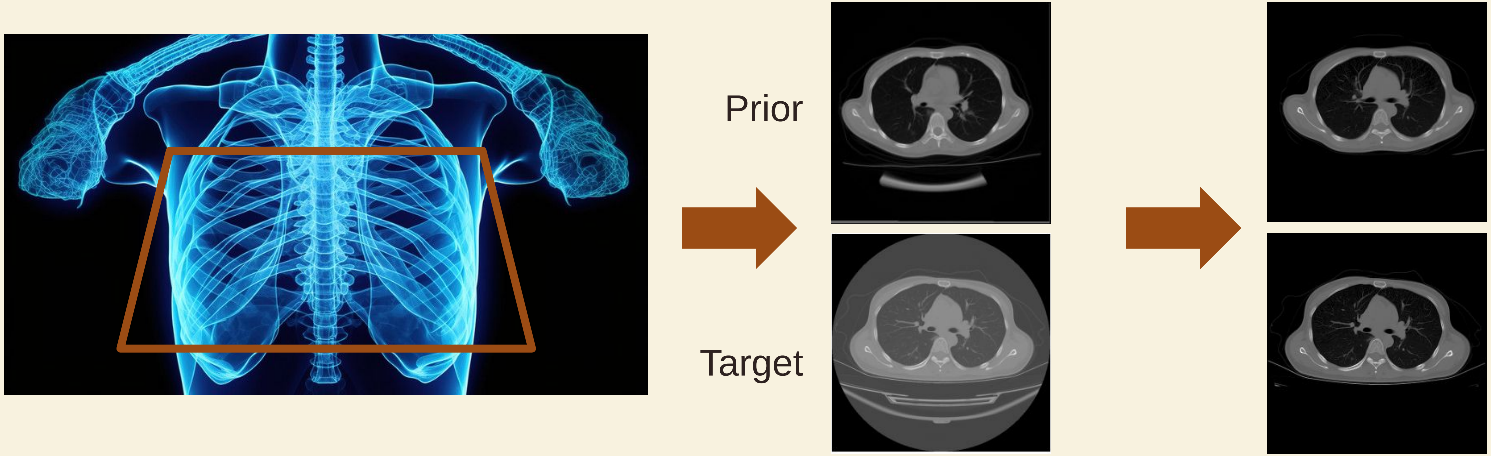
Trained MLP generates final image with **M(θ')**



NeRP Replication - Data & Result

Replication: Dataset & Pre-Processing

- 3D Chest CT scans from ‘CT Images in Covid 19’[2]
  - Each patient has **2 scans** obtained several days apart
- 2D slices preprocessed for experiments
  - Clipping & Normalization; Alignment; Device Bed Masking



[2] An, P.; Xu, S.; Harmon, S. A.; Turkbey, E. B.; Sanford, T. H.; Amalou, A.; Kassin, M.; Varble, N.; Blain, M.; Anderson, V.; Patella, F.; Carrafiello, G.; Turkbey, B. T.; and Wood, B. J. 2020. CT Images in COVID-19 [Dataset].

Replication: Evaluation Metrics

Peak Signal-to-Noise Ratio (PSNR):

- Comparing maximum signal power to noise
- Higher Value → Better

Structural Similarity Index Measure (SSIM):

- Evaluating luminance, contrast, and structural similarity
- SSIM of 1.0 → Perfect

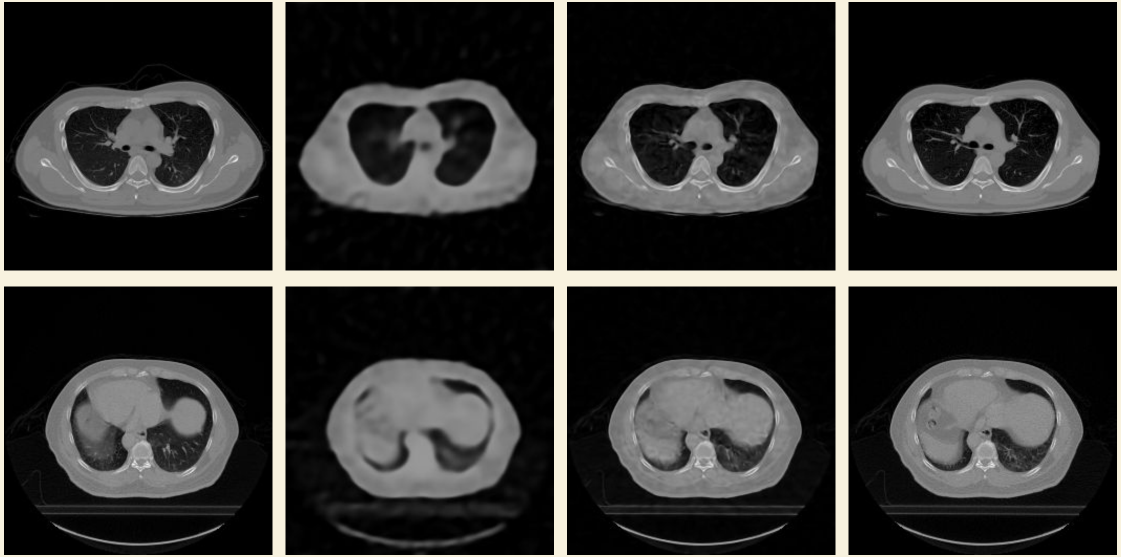
Replication Results

	With Prior PSNR/SSIM	Without Prior PSNR/SSIM
Replication	30.42/0.734	28.61/0.623
NeRP 2D	34.87/0.886	27.08/0.660

Prior Image **Without Prior** **With Prior** **Ground Truth**

Replication

NeRP 2D



Extension - Idea & Results

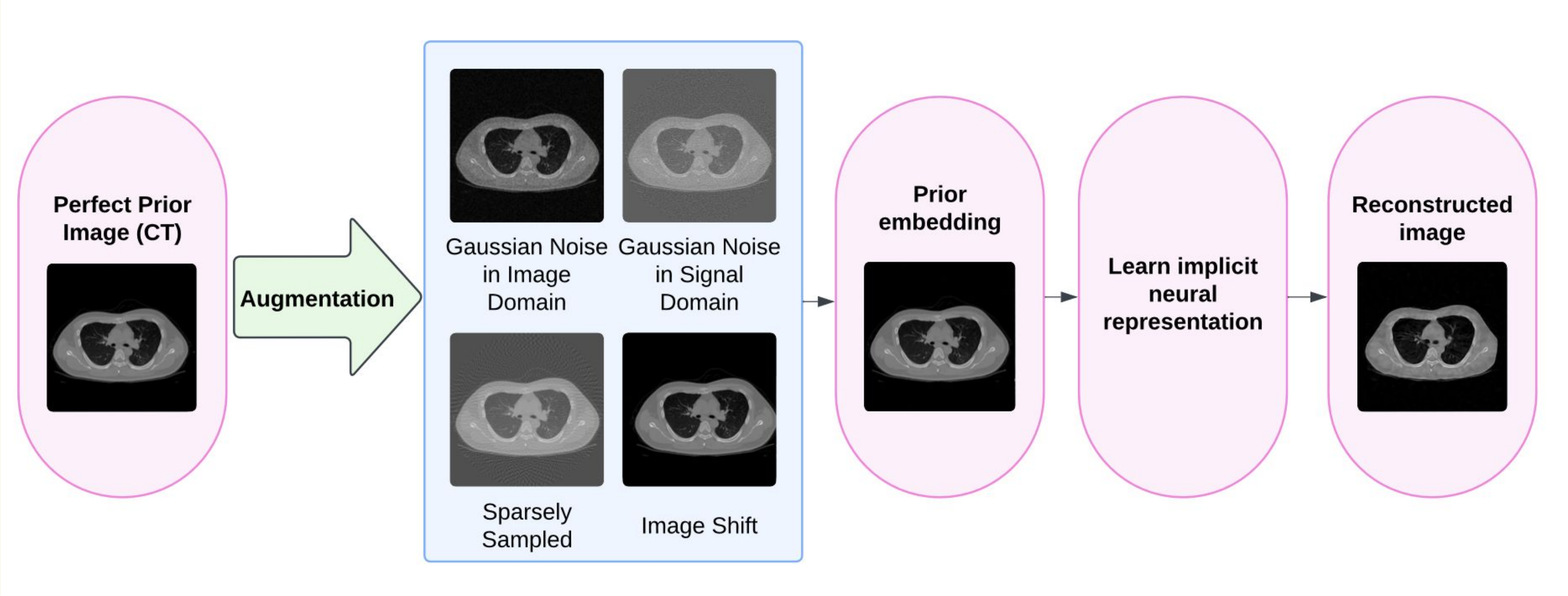
Research Problem (Extension)

Our Observation:

NeRP was only tested with a **perfect (high quality) prior** and **no prior**

How does a **reduction in the quality** of prior images impact a model's ability to implicitly learn a **neural representation** to perform image reconstruction?

Extension Pipeline



Extension Results

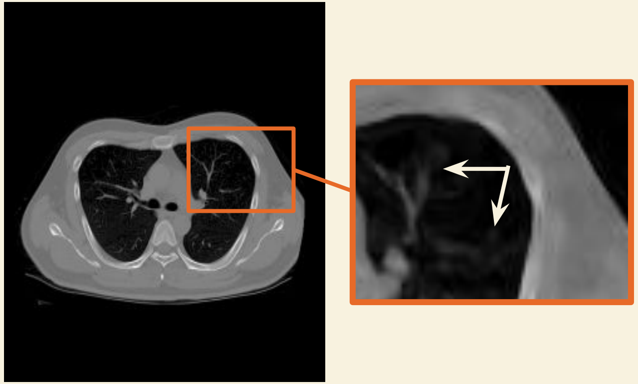
- Most noise types do not have much impact on reconstruction quality.

Prior Type	PSNR(dB)	SSIM
Perfect Prior	30.89	0.821
Gaussian Noise (Image Domain)	30.80	0.819
Gaussian Noise (Signal Domain)	31.13	0.819
Sparse Sampling	31.32	0.848

Table 2: Results of 2D CT reconstruction with priors altered with different noises; Noisy priors have a PSNR $\approx$ 40dB.

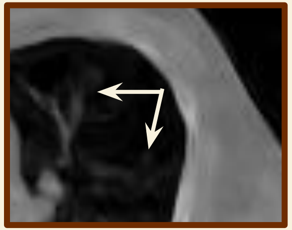
Extension Results

Ground Truth

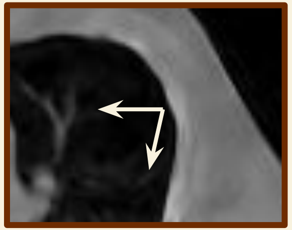


Reconstruction

with Perfect Prior



with Noisy Prior (Gaussian Signal)



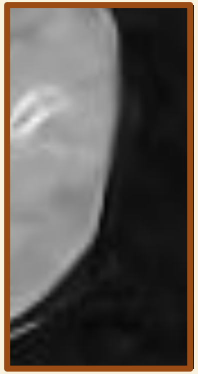
Extension Results: Shifting

- Shifting resulted in degraded reconstruction performance
- Larger shifts led to ghosting artifacts

X-Shift(pixel)	PSNR(dB)	SSIM
0	30.89	0.821
5	30.67	0.826
10	29.41	0.735
20	28.74	0.668

Reconstruction

5-pixel prior shift



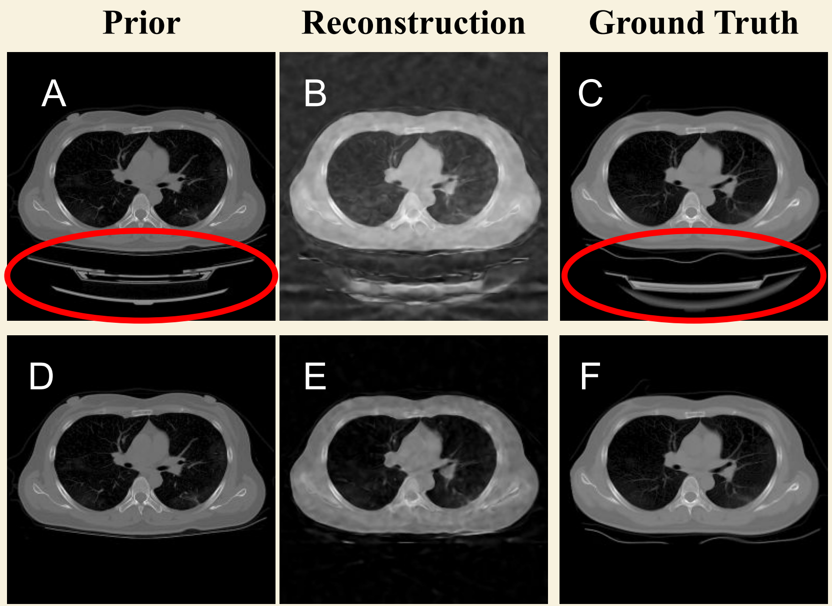
10-pixel prior shift

20-pixel prior shift

Discussion

Accidental Discovery:
Device Bed Inconsistency

- Initially getting poor results for a specific patient
- Prior and target images were taken on **different device bed shapes**



Key Extension Findings

NeRP is robust to most types of noise

⇒ produces high-quality reconstructions with noisy priors

- Noise in images and signal domain has minimal effect on reconstruction
- Spatial misalignment from shifting and device beds have a larger effect
  - Need for consistent patient positioning
  - Keep the device consistent in applications

Societal Impact

Robustness to Noisy Priors

Expands NeRP's potential application in clinical settings.

Guidance for Effective Applications

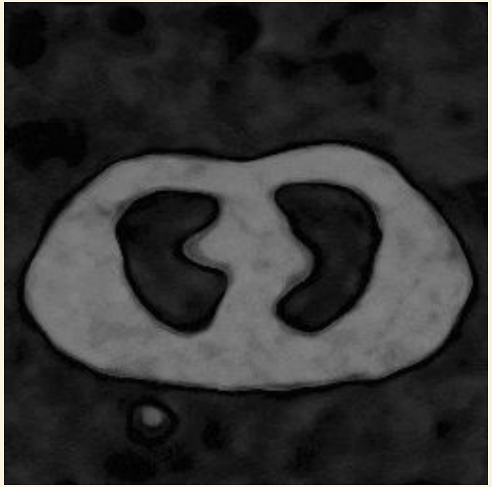
Spatial alignment and device consistency needed for optimal deployment.

Step Towards Efficient CT Reconstruction

Reduces scanning time and radiation exposure.

Broad Implication

Opens new opportunities for effective imaging solutions in healthcare.



Thanks!

Have any questions?

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