Group 6

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

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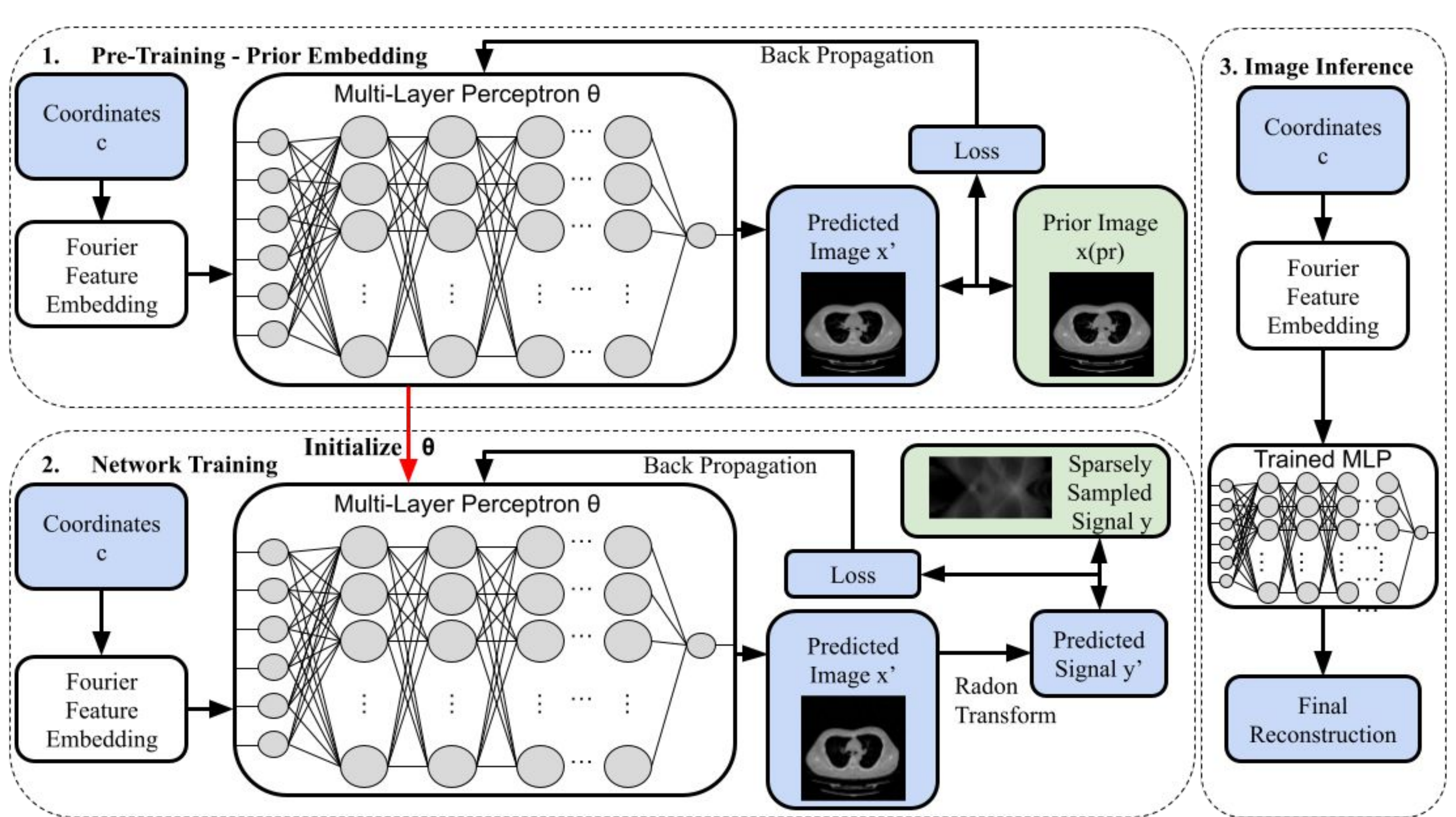
Introduction & Motivation

- **Problem:** High-quality CT scans are crucial for diagnoses and treatment, but traditional recon methods require dense sampling (1000+ projections), leading to increased acquisition time and radiation exposure.
- **Solution**: ***NeRP****: Implicit Neural Representation Learning With Prior Embedding for Sparsely Sampled Image Reconstruction* [1]
  - High-quality recon with **sparsely sampled** data (~20 projs)
  - State-of-the-art performance
  - Learns a **patient-specific** neural representation with a **prior**
    - Non-reliant on big training sets (like conventional DL methods)
    - Generalizable to various imaging modalities & body sites
- **Research Gap**: The impact of **lower-quality prior images** on recon performance has not been extensively studied.
- **Objectives of Our Project**:
  - **Replicate** NeRP for the task of 2-D CT reconstruction.
  - Evaluate NeRP's **robustness** with lower-quality priors.

Methodology

- **Implicit Neural Representation Learning**: A **Multi-Layer Perceptron** learns a continuous function that maps coordinates to intensities.
- **Prior Embedding(Initialization)**: A previous CT scan of the same patient is used for pre-training in the image domain.
- **Network Training**: Sparse measurements of the target CT are used to fine-tune the MLP's weights through back propagation.
- **Image Inference:** By feeding coordinates into the MLP, the final reconstruction can be retrieved for performance evaluation.

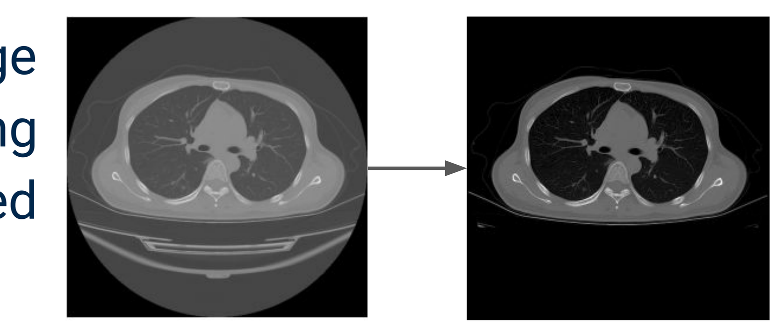


Computed Tomography (CT) Reconstruction

- Attenuated X-rays captured as projections from different angles.
- An inverse problem formulated as $\mathbf{y = Ax + e}$.
- **Goal**: retrieve **x (the CT scan)** from **y (the projection signals)**.
- **A** - Radon Transform; **e** - acquisition noise.

Dataset & Pre-Processing

- Publicly available chest CT image data from The Cancer Imaging Archive (TCIA) [2], preprocessed manually to remove device bed.



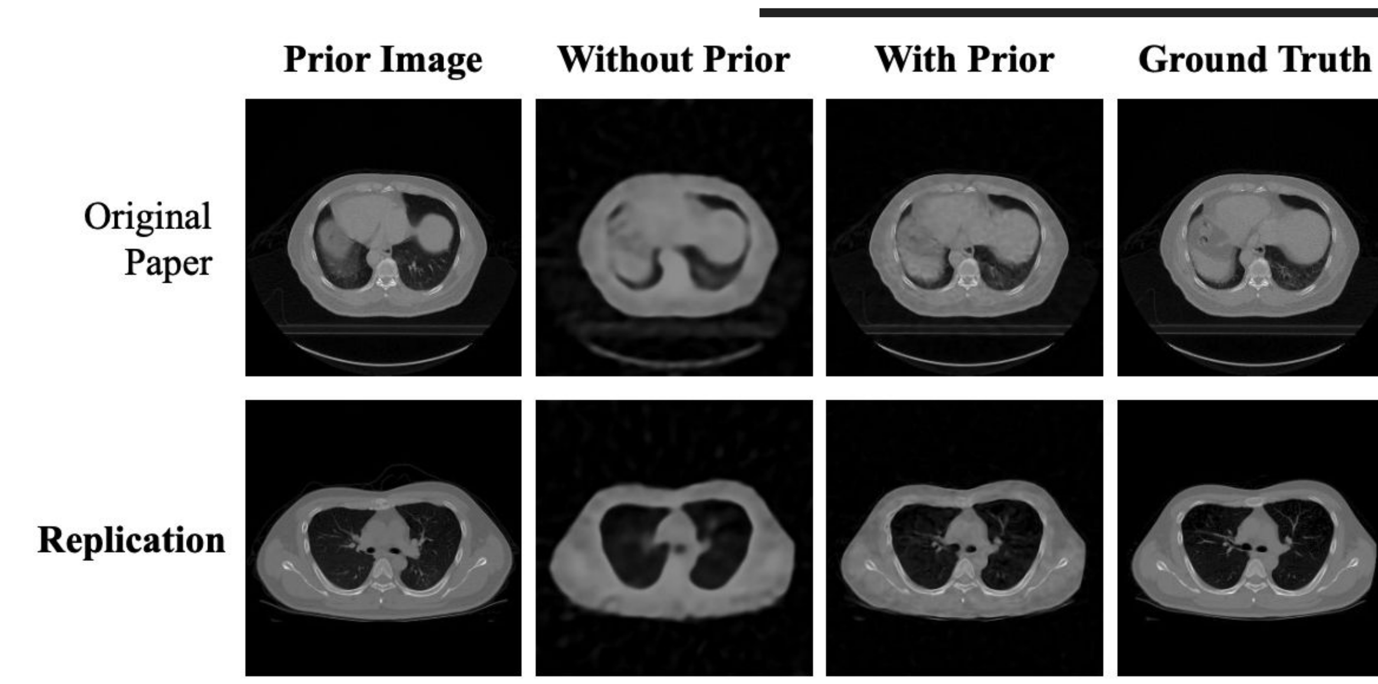
Evaluation Metrics

- **Peak Signal-to-Noise Ratio (PSNR)** quantifies the ratio of the maximum possible power of a signal to that of noise. Higher means better.
- **Structural Similarity Index Measure (SSIM)** evaluates the quality by comparing luminance, contrast, and structural similarity. 1.0 means perfect similarity.

Replication Results

- Results of 2D CT image recon in NeRP and our replication using 20 projections.

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

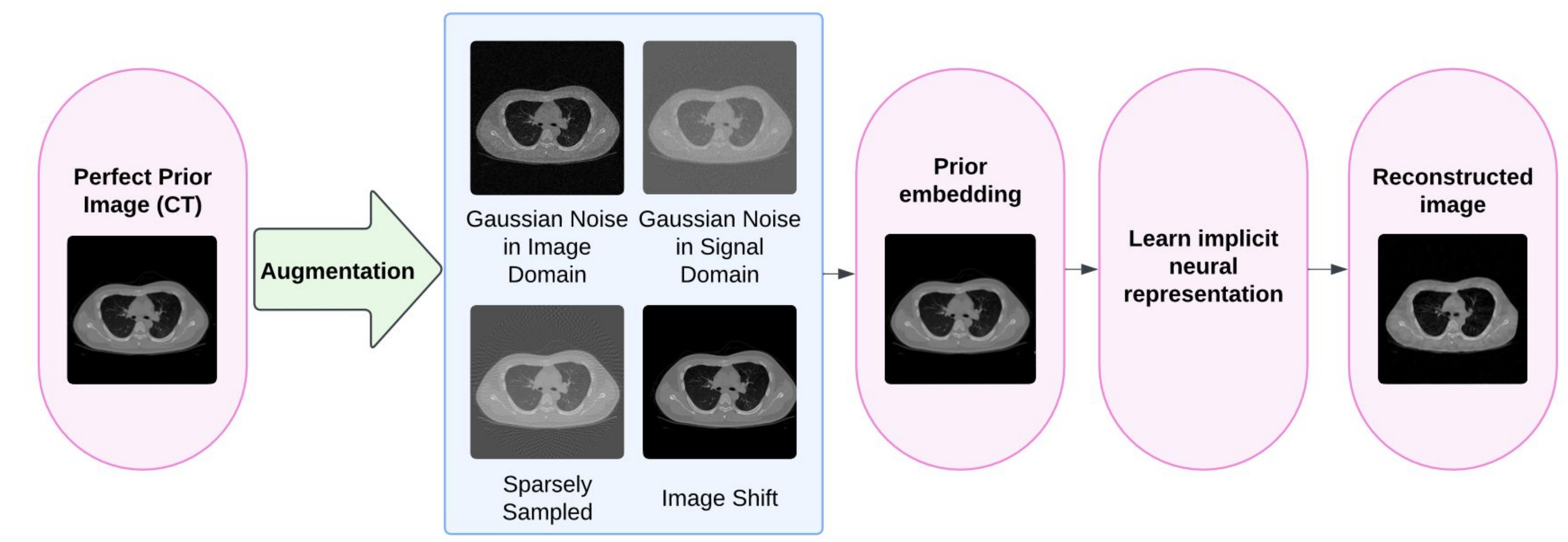


References

[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.
[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.; Turkbey, B. T.; and Wood, B. J. 2020. CT Images in COVID-19 [Dataset].

Extension

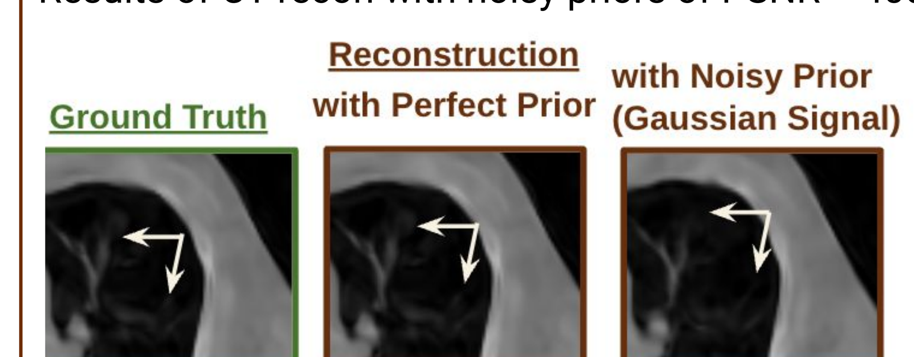
- **Motivation:** High-quality priors may not always be available due to noise, misalignment, or sparse sampling.
- **Goal:** Test NeRP's **robustness** by evaluating the effect of lowering the quality of priors through gaussian noise, sparse sampling, and spatial misalignment.

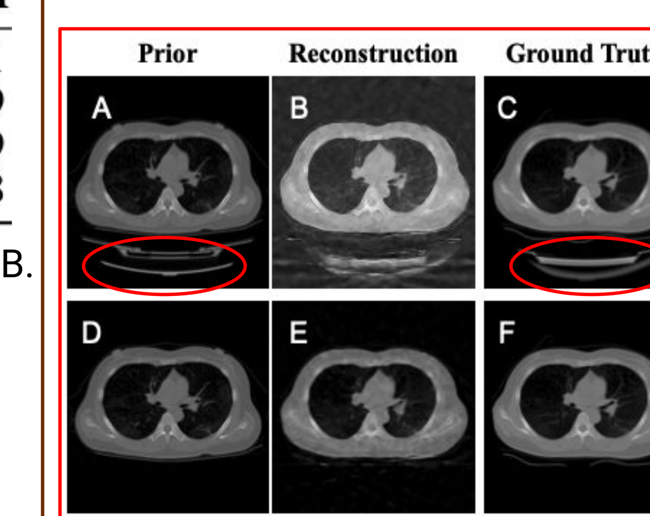


Extension Results

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

Results of CT recon with noisy priors of PSNR ≈ 40dB.



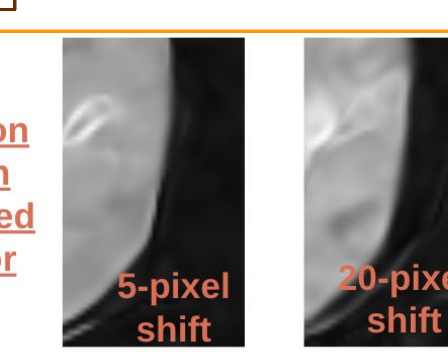


Device bed inconsistency

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

Results of CT Recon w/ Shifted Priors

Recon with Shifted Prior



Conclusions & Societal Impact

- **Robustness**: NeRP proves robust against various types of noise, indicating more potential applications in clinical settings.
- **Guidance for Application**: Spatial misalignment and device bed inconsistency have a negative effect on reconstruction quality.
- **Towards Efficient CT Reconstruction**: Reduced scanning time and radiation exposure for the benefits of patients.
- **Broad Implication**: New opportunities for effective imaging solutions in healthcare.