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LABORATÓRIO DE MÉTODOS COMPUTACIONAIS EM ENGENHARIA

UNIVERSIDADE FEDERAL DO RIO DE JANEIRO
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Fast-to-Long Acquisition Projection Learning for Denoising X-ray Microtomography

Introduction

- **Problem: Trade-off between efficiency and quality.**

- Longer acquisition times lead to higher imaging costs;
- Images acquired with shorter acquisition are noisier.

- **Proposition: Learn the mapping from fast to long acquisitions.**

- Train a model to reduce noise and improve the quality of rapidly acquired images:
  - Time (cost) reduction without compromising image quality.

Image Acquisition

▪ VTOMEX M System Scanner

- Detector settings: Parameter adjustment needed for multi-time acquisition.

	2min 35s	8min	60min
TimingVal	50	100	100
Avg	1	3	40
Skip	0	1	1

- Common to all acquisition times:
  - Raw projections (before reconstructions): 801;
  - Reconstructed volume with 2016 axial slices, each with approximately 1000×1000 pixels.

Image Acquisition

▪ Data

- 12 Brazilian pre-salt carbonate plug samples;
- Voxel size: 43 to 54 µm;
- Samples are scanned at three distinct acquisition times;
- No repositioning and fixed resolution per sample: perfect matching between the reconstructed volumes;

Sample	Voxel Size (nm)	Dimensions z	Dimensions x	Dimensions y
Sample 1	43480	2016	1232	1229
Sample 2	43480	2016	1231	1230
Sample 3	43250	2016	1235	1240
Sample 4	43480	2016	1232	1229
Sample 5	53930	2016	994	993
Sample 6	46750	2016	1146	1145
Sample 7	43480	2016	1229	1232
Sample 8	53320	2016	995	992
Sample 9	53930	2016	995	992
Sample 10	53930	2016	993	995
Sample 11	53320	2016	992	994
Sample 12	53320	2016	994	993

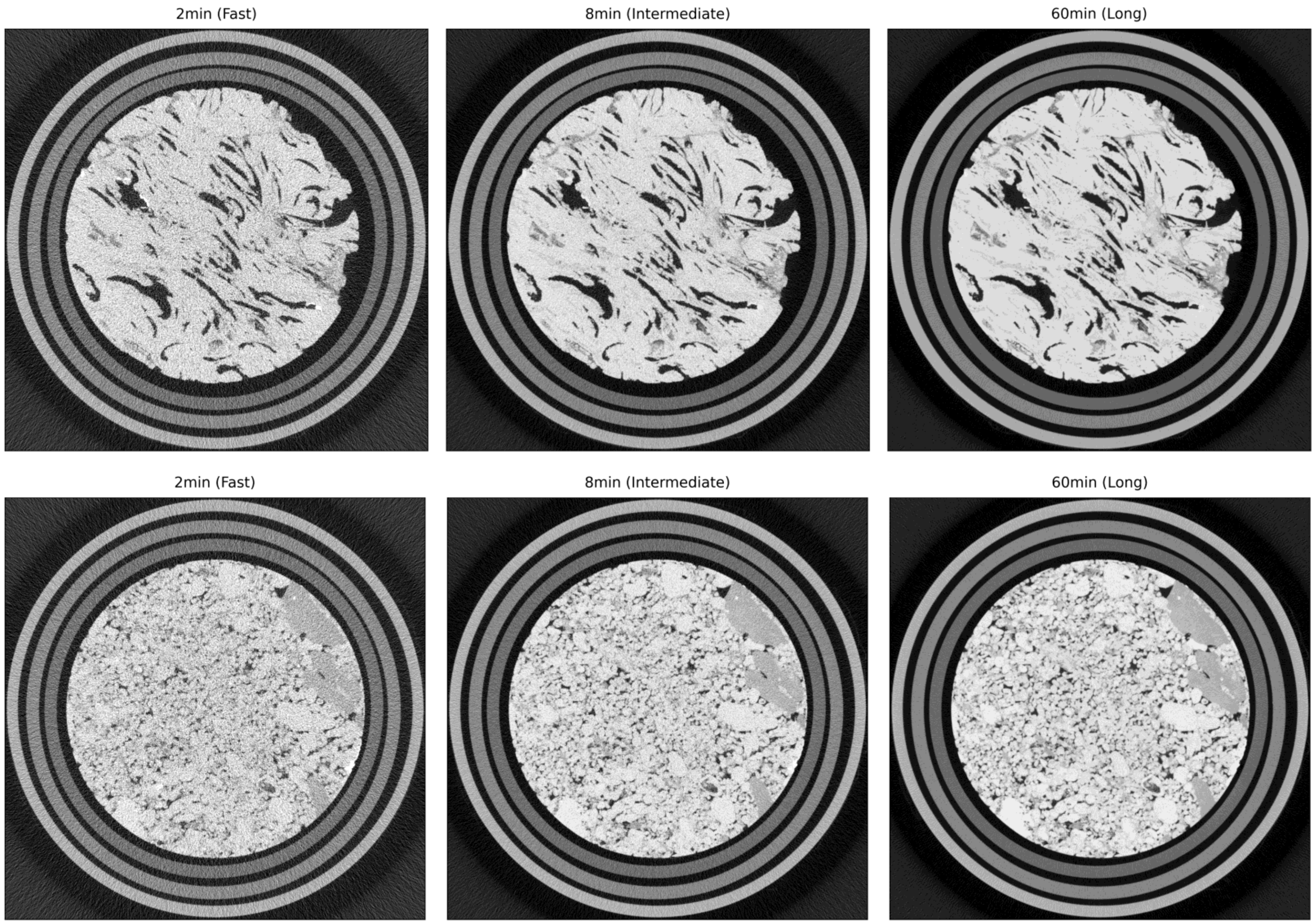
Image acquisition

- **Examples**

- 2 minutes and 35 seconds:
  - High-noise image;
  - Input to the model.

- 8 minutes:
  - Intermediate-quality image;
  - Used for evaluation.

- 60 minutes:
  - Reference image;
  - Target for training and evaluation.

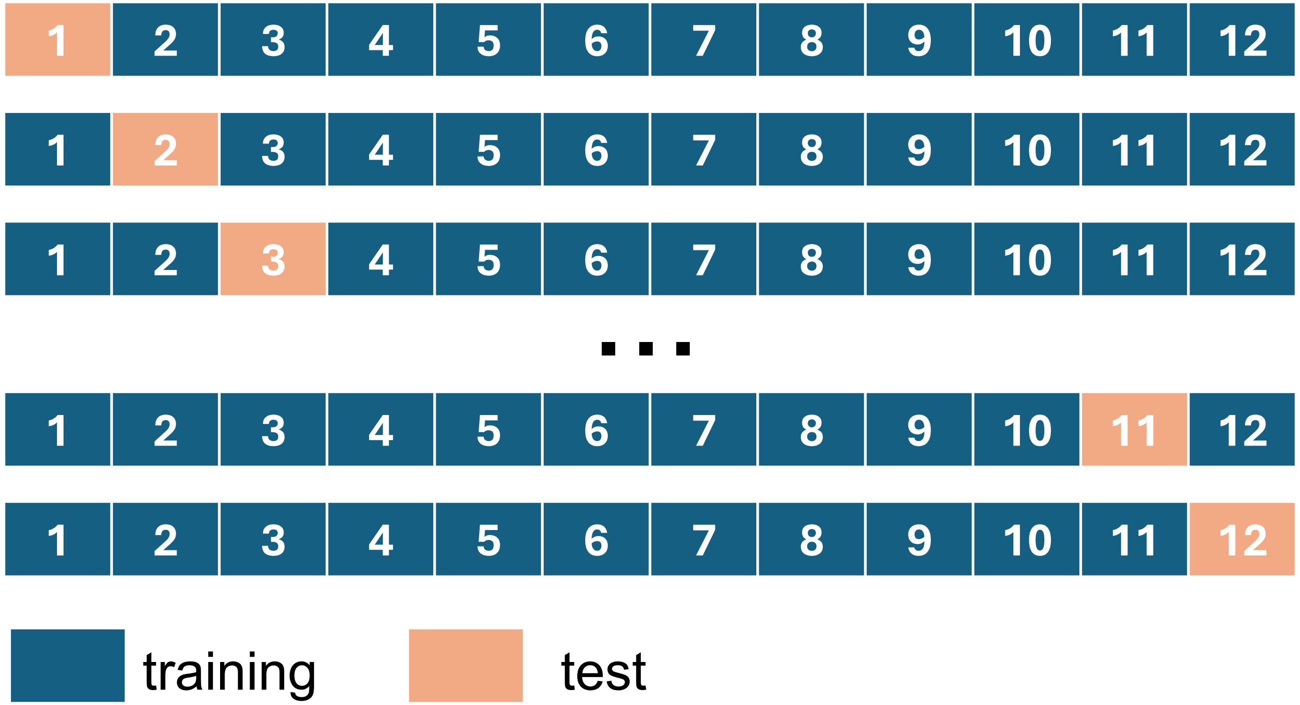


- Central z-slices of Samples 3 and 8 at different acquisition times.

Predictive Model - Training

▪ Deep Neural Network

- Supervised approach:
  - Input (x):
    - Fast acquisition (2min35s)
  - Target (y):
    - Long acquisition (60min)
- Network learns a mapping $\hat{y} = f(x)$;
- Residuals between $\hat{y}$ and y are used to update the model weights and improve output quality.



Leave-one-out: in each cycle images from a plug sample are excluded from the training data. The learned mapping is then applied to the held-out sample to generate the output.

Predictive Model - Architecture

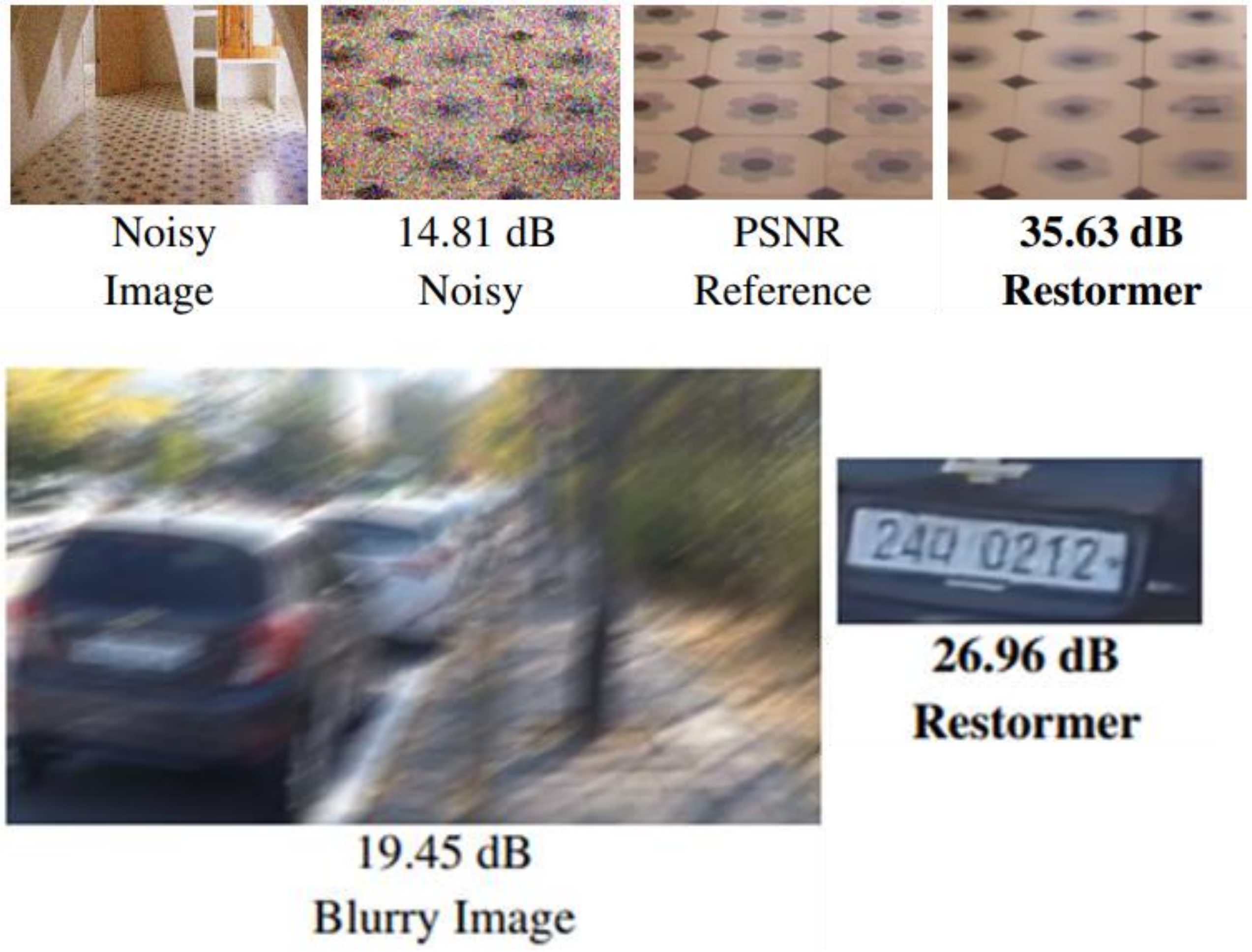
▪ Restormer

- Benchmark model for image denoising;

- Transformer-based architecture;

- Pre-trained on paired noisy/reference smartphone images from the SIDD dataset;

- Initialized with pretrained weights and fine-tuned on the micro-CT data.



Zamir, Syed Waqas, et al. "Restormer: Efficient transformer for high-resolution image restoration." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2022.

Results – Evaluation and Metrics

▪ Peak signal-to-noise ratio (PSNR)

- Higher PSNR value indicates the noise is low relative to the signal;
- Sensitive to small improvements:
  - a 3 dB increase roughly represents a doubling of the signal-to-noise ratio.

▪ Structural Similarity Index Measure (SSIM)

- SSIM values range from −1 to 1, with values closer to 1 indicating higher structural similarity;
- Combines luminance, contrast, and structural information to assess perceptual image similarity.
- Less sensitive to absolute intensity differences than PSNR.

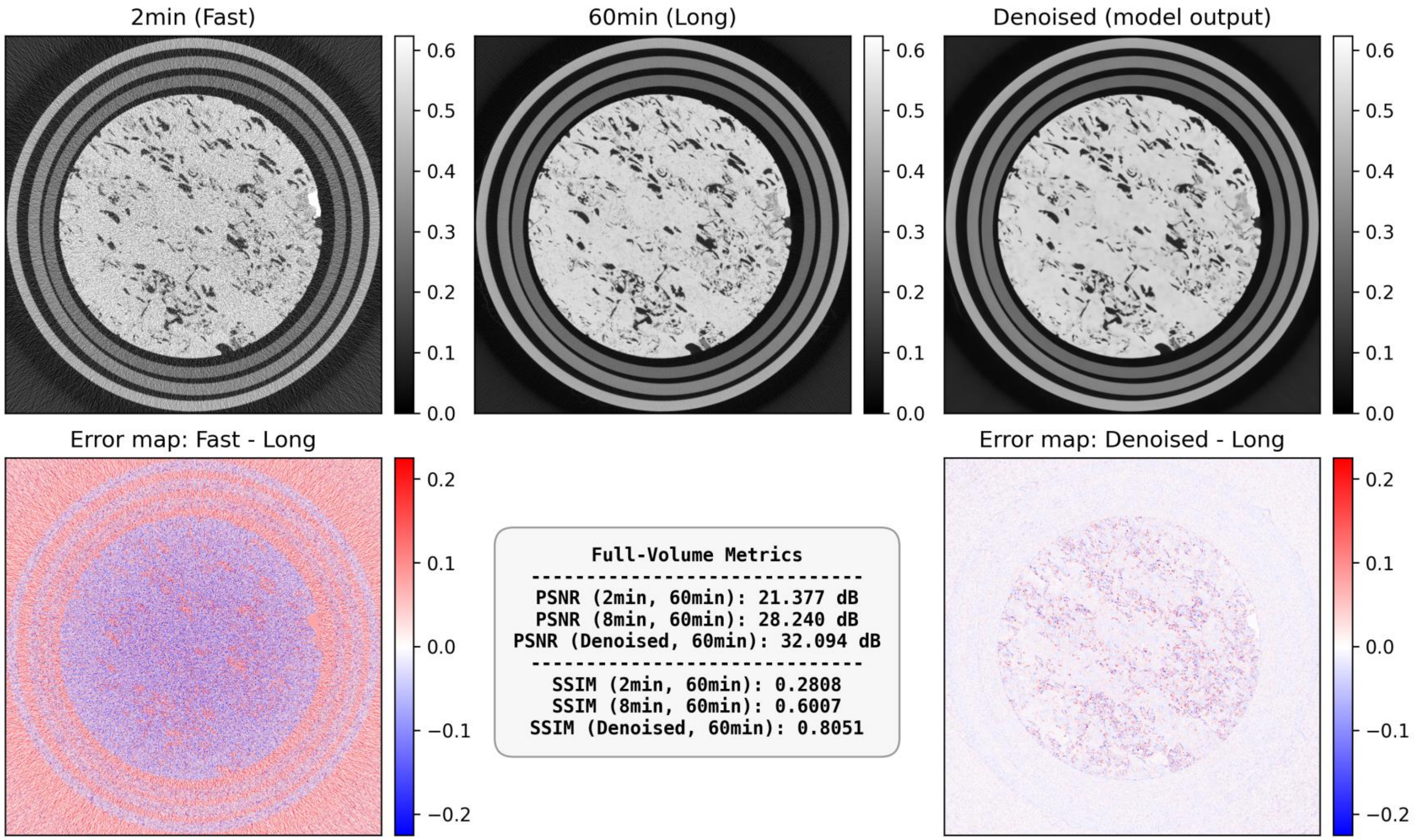
▪ Wilcoxon signed-rank test

- Non-parametric test for paired samples: equivalent to the paired t-test, without assuming normality;
- Assesses whether denoised images exhibit statistically significant improvements over fast and intermediate acquisitions.

Results - Examples

- **Sample 1**

- Grayscale images normalized to [0,1] range;
- Model reduced image noise and decreased residuals relative to the target image;
- Even though the 2min35s image was used as input, the model output was closer to the 60min target than the 8min image according to both metrics.



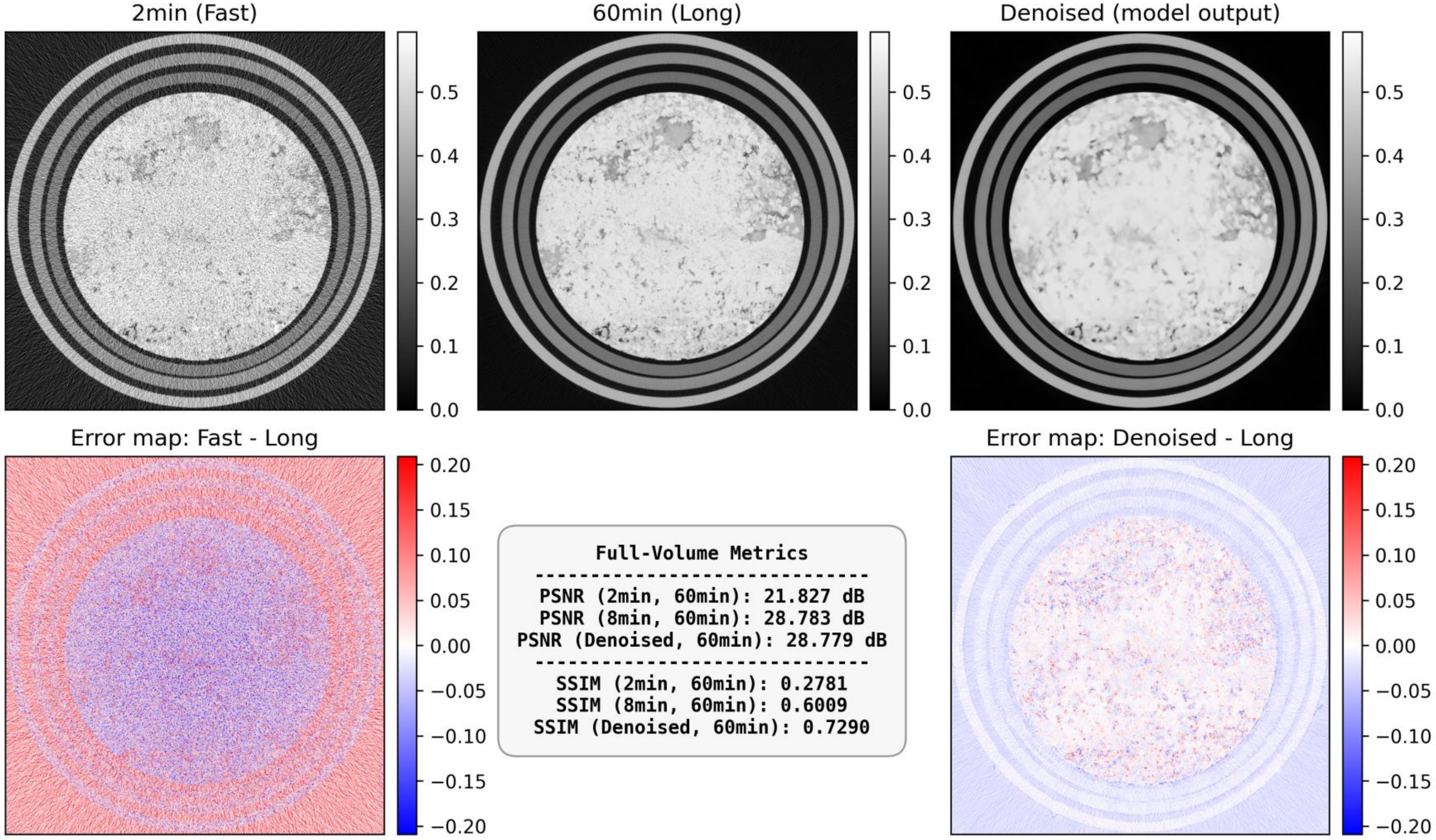
Results - Examples

▪ Sample 10

- Model also reduced image noise for Sample 10;

- PSNR between the denoised output and the 60min target was slightly lower than the PSNR between the 8min and 60min images;

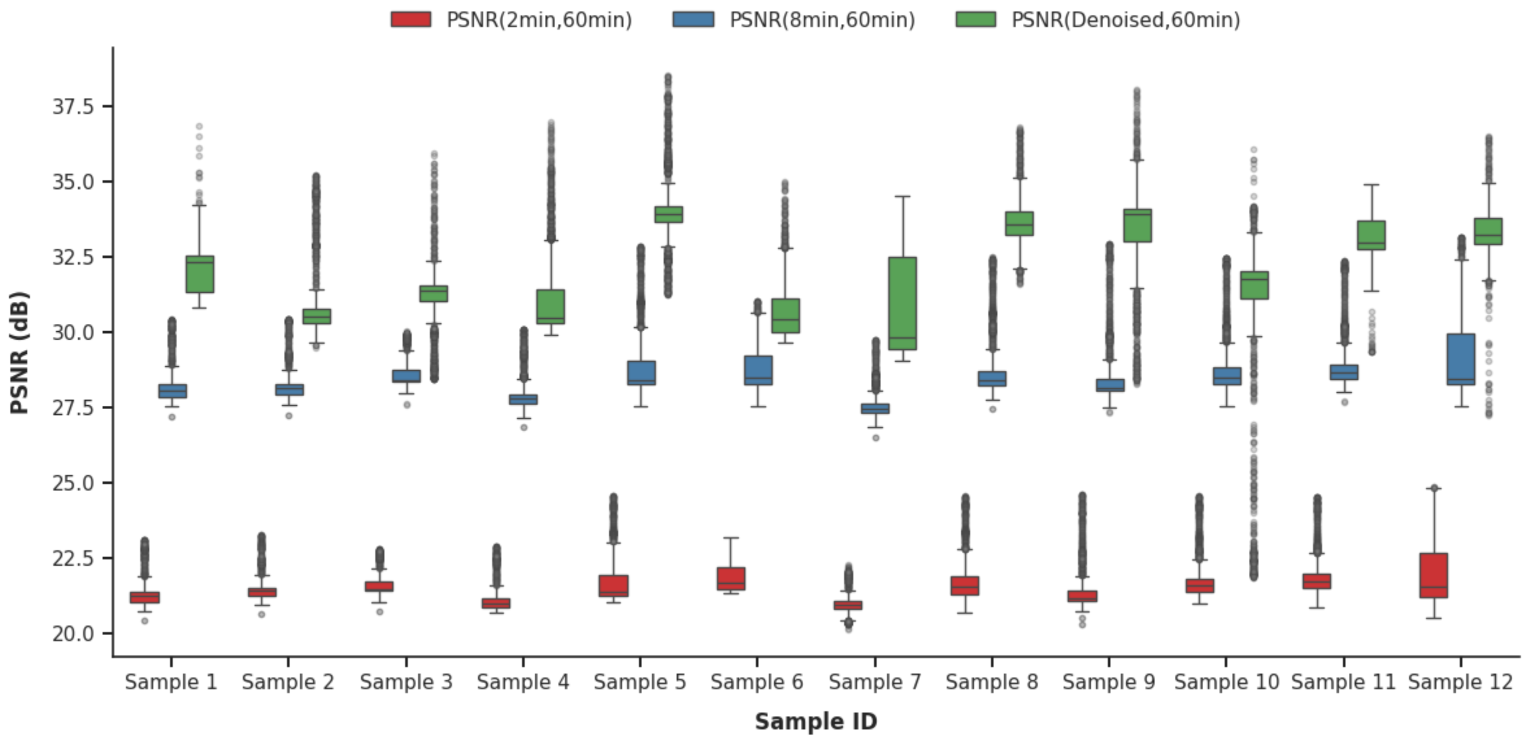
- Small pores are concealed by noise in the input image.
  - Images with finer granularity may be more challenging.



Results – Overview

▪ PSNR (axial slices metrics)

- The model consistently achieves better PSNR values against the reference than both fast and intermediate acquisitions;
- The first quartile of PSNR(Denoised, 60min) exceeds the third quartile of PSNR(8min, 60min) for all samples;
- PSNR(Denoised, 60min) usually shows heavier tails. Sample 10 (high granularity) exhibits lower-PSNR outliers.



PSNR distribution across 2,016 axial slices for each sample.

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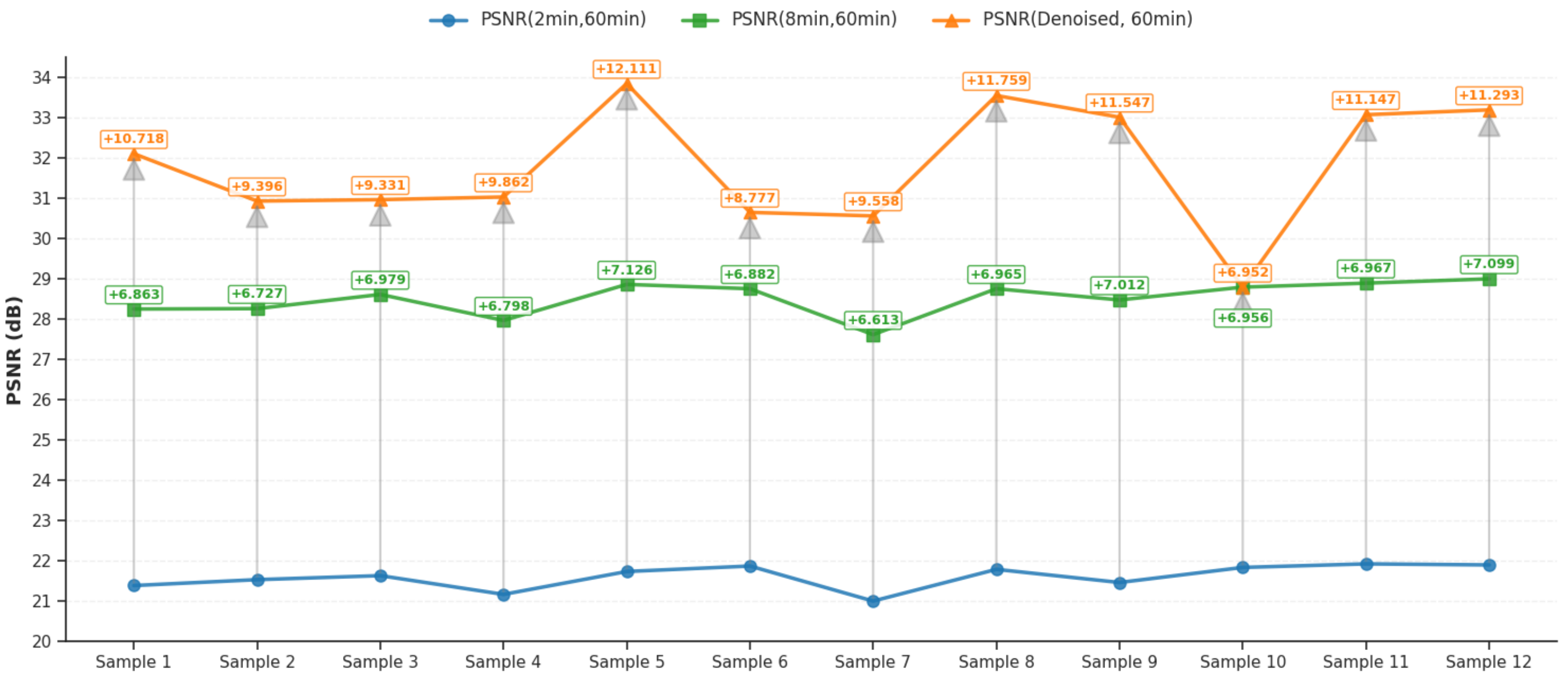
Results – Overview

▪ PSNR (full-volume metrics)

- Metrics for full-volume also show improvements over the baseline (2min35s image) for all samples.

- For 11 of 12 samples, PSNR is higher for Denoised than for the 8min acquisition (vs. reference).

- Wilcoxon signed-rank test rejects the null hypotheses that PSNR(Denoised, 60min) is less than or equal to the PSNR of the corresponding 8min and 2min acquisitions (vs. reference).



Null Hypothesis (H_0)	Alternative Hypothesis (H_1)	Statistic	p-value
PSNR(Denoised,60min) $\leq$ PSNR(8min,60min)	PSNR(Denoised,60min) $>$ PSNR(8min,60min)	77	0.00049 (2^{-11})
PSNR(Denoised,60min) $\leq$ PSNR(2min,60min)	PSNR(Denoised,60min) $>$ PSNR(2min,60min)	78	0.00024 (2^{-12})

Wilcoxon signed-rank test results for PSNR comparison.

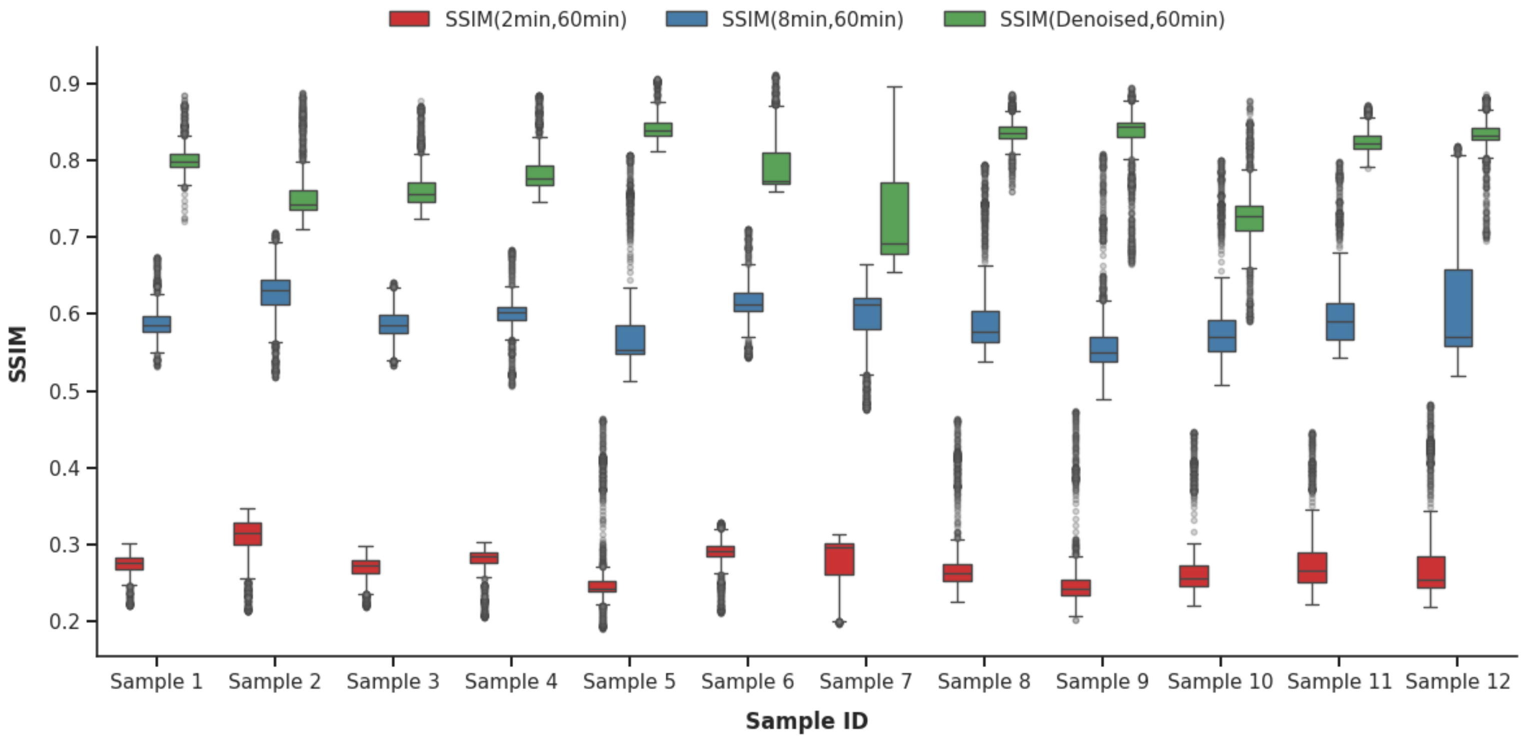
Results – Overview

▪ SSIM (axial-slice metrics)

- The model also consistently achieves better SSIM values against the reference than both fast and intermediate acquisitions;

- SSIM improvements are even more pronounced than the gains observed in PSNR metrics;

- While Sample 10 still exhibits the lowest values for the denoised images, its outliers are less severe.



SSIM distribution across 2,016 axial slices for each sample.

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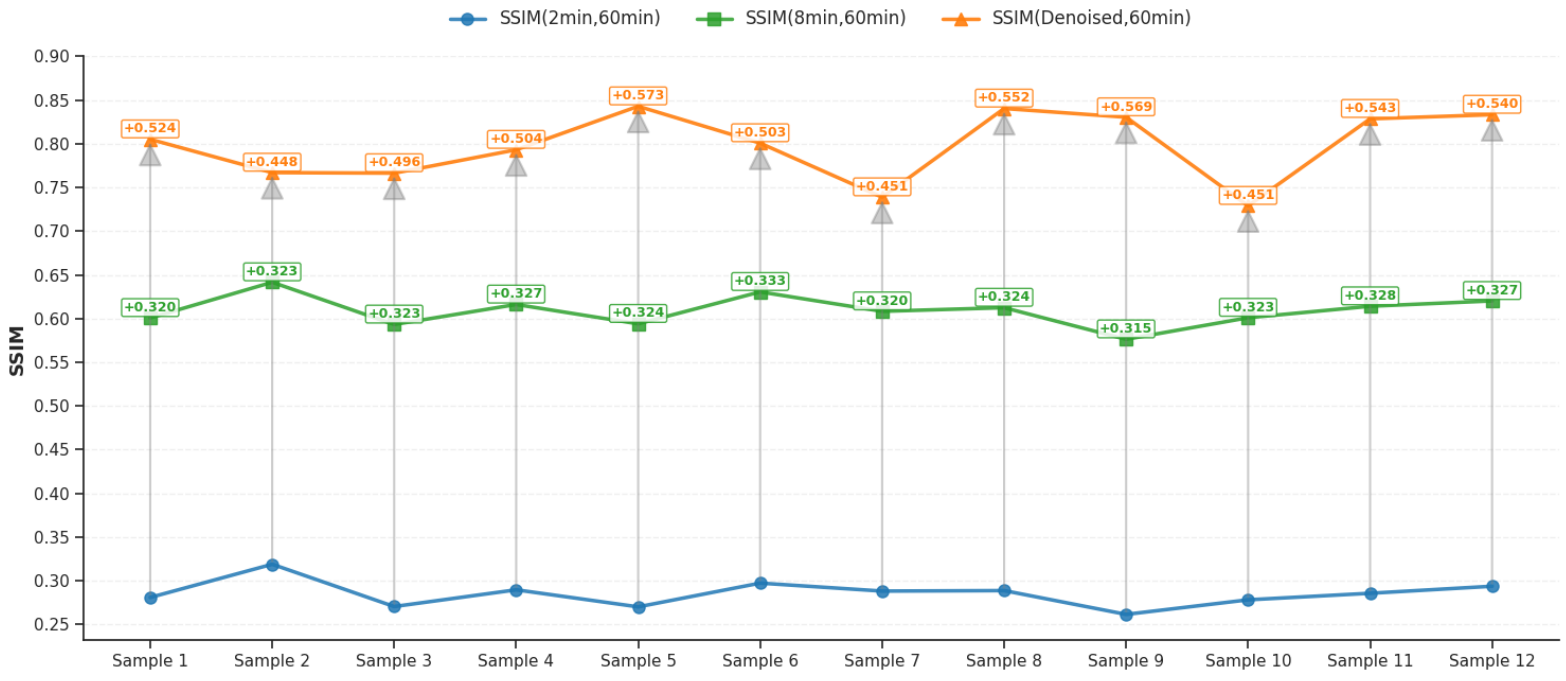
Results – Overview

▪ SSIM (full-volume metrics)

- Full-volume Denoised metrics outperforms those of 8min and 2min35s for all samples.
- Wilcoxon signed-rank test again rejects the null hypotheses.
- Stronger statistical evidence to reject the null hypothesis of the 60-minute and denoised pairs against 8-minute and 60-minute pairs.



Null Hypothesis (H_0)	Alternative Hypothesis (H_1)	Statistic	p-value
SSIM(Denoised,60min) $\leq$ SSIM(8min,60min)	SSIM(Denoised,60min) $>$ SSIM(8min,60min)	78	0.00024 (2^{-12})
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Wilcoxon signed-rank test results for SSIM comparison.

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Summary

- Restormer successfully reduced noise in fast-acquisition micro-CT images;
- Denoised outputs consistently achieved higher PSNR and SSIM values than the 2min35s baseline;
- In nearly all cases, denoised images also outperformed the 8min acquisition against the 60min reference;
- Wilcoxon signed-rank tests confirmed statistically significant improvements;
- Samples with finer granularity and smaller pores may be more challenging, as image noise can blend with pore structures.

Next steps

- Evaluate the approach on data from different scanners and acquisition protocols;
- Investigate correlations between pore size, granularity, and other laboratory-measured rock properties with denoising performance;
- Assess how denoising influences computed digital rock properties and their agreement with laboratory measurements;
- Explore even shorter acquisition times:
  - Further cost reduction;
  - Dynamic multiphase flow imaging experiments: multiple time-resolved images during fluid displacement - fast acquisitions are required.

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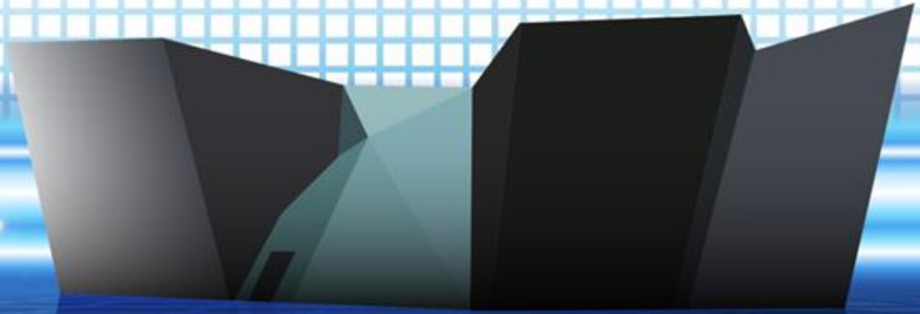
Thank you!



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