Image Reconstruction: CT Denoising

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MATH CSE Master

8 ECTS semester project

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RX Solutions

EPFL Center for Imaging

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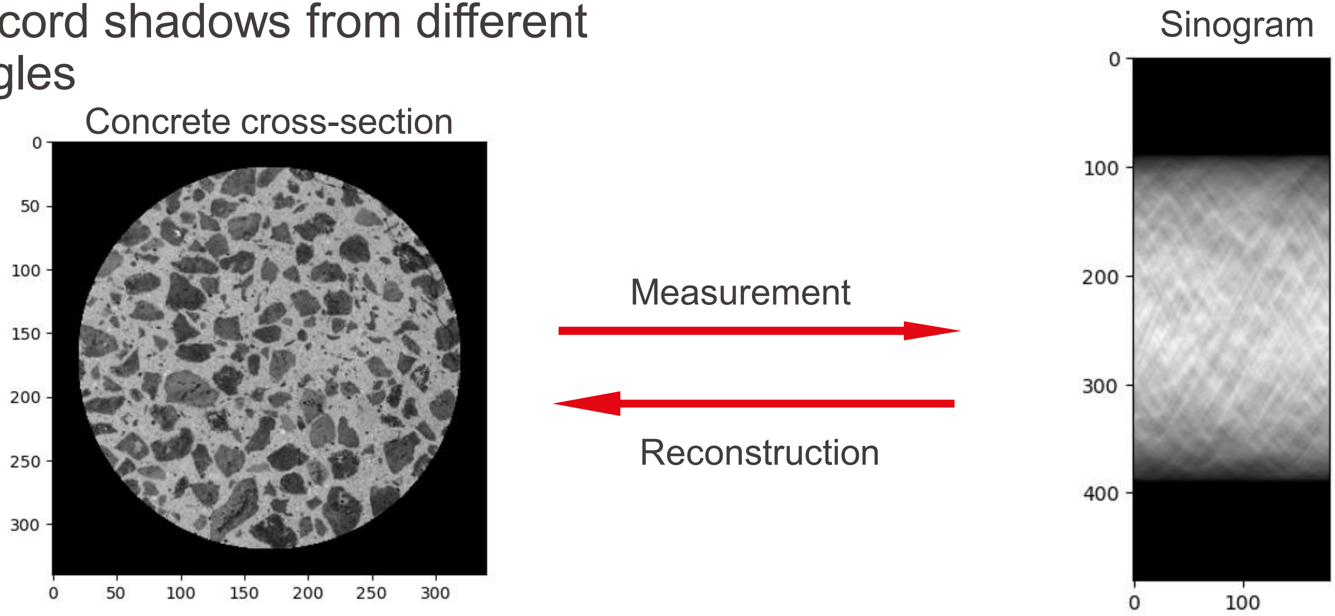
Brief overview : Computational Imaging Tomography

Determine volume absorption profile

- Project X-rays through object
- Record shadows from different angles



Popular method
Filtered Back Projection (FBP)

Direct inversion method

- Use adjoint of forward operator
- Use deblurring filter (i.e Ramp filter)

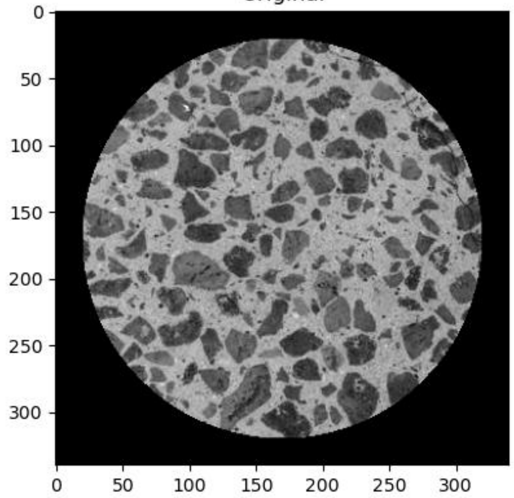
Advantages:

- Fast
- Perform well qualitatively/quantitatively upon some constraints

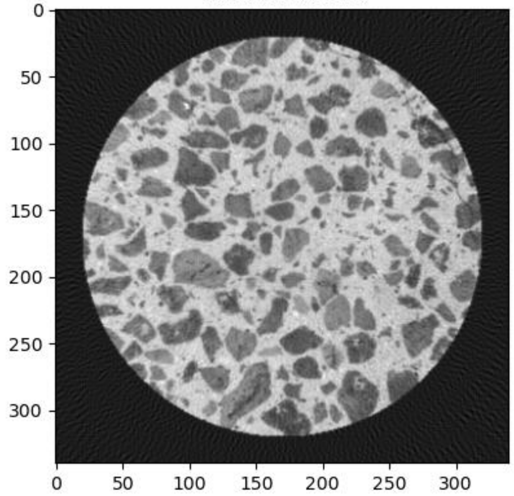
Weakness

- Noise-sensitive
- Relies on a dense angular sampling

Original



FBP with 1 projection per degree (i.e 180 proj)
No noise added



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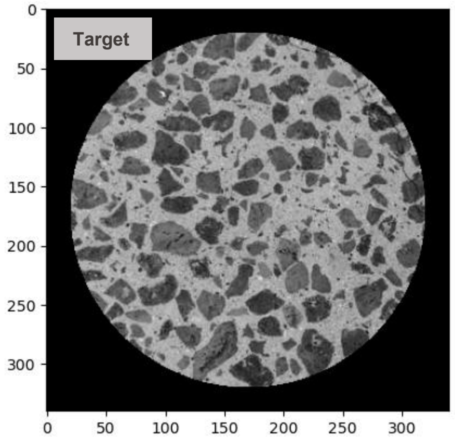
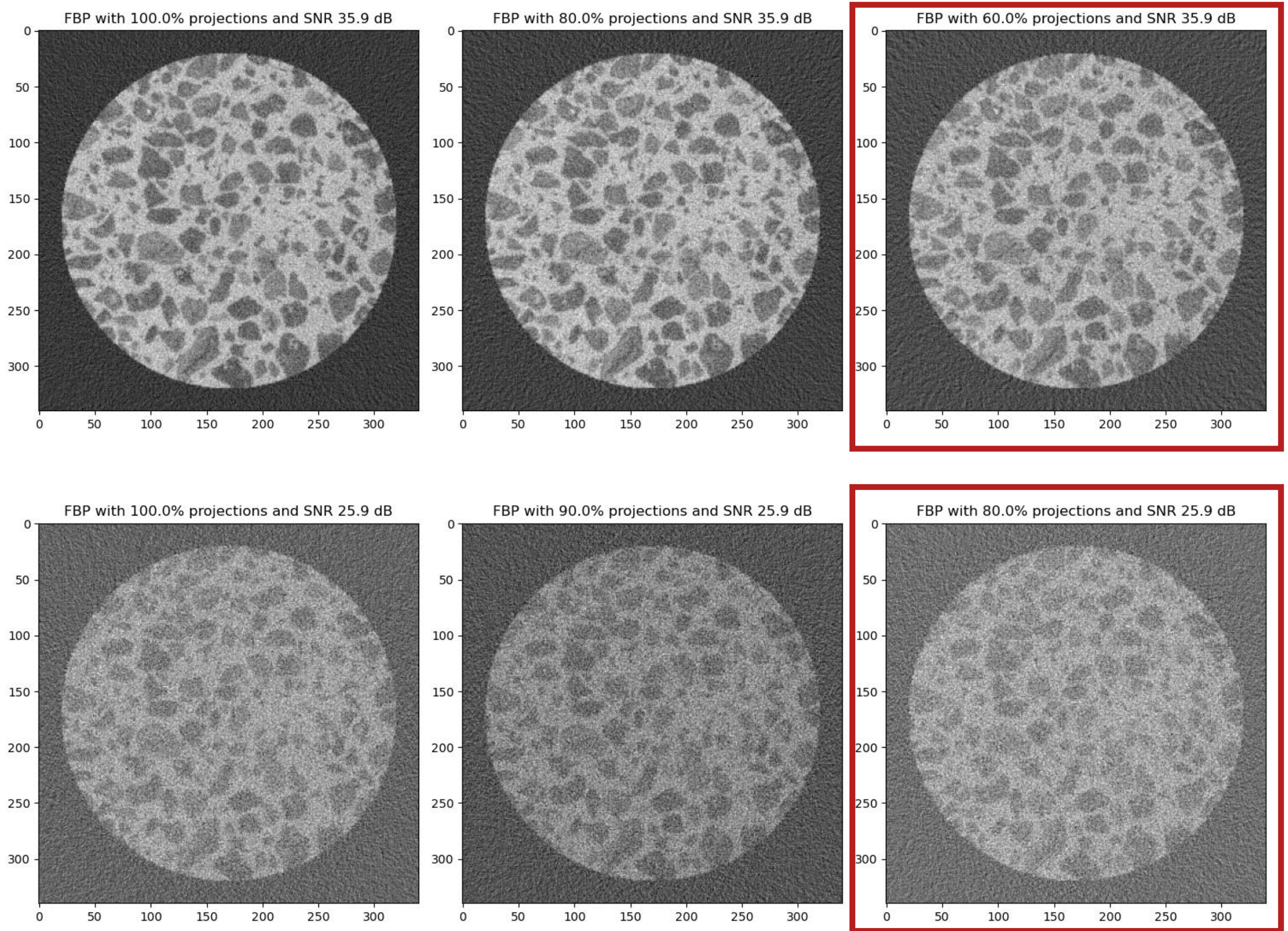
FBP Limitations

100% projections = 1 projection per degree

- Low noise level



- High noise level



Goal of the project

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Goal : Explore strategies to enhance the quality of noisy images reconstructed via FBP

Potential solutions :

- **Pre-processed FBP :** Denoise Sinograms with SP/ML methods → Apply **FBP**

  Sinogram → **Denoise** → **FBP**

- **Post-processed FBP :** Apply **FBP** → Denoise output with SP/ML methods

  Sinogram → **FBP** → **Denoise**

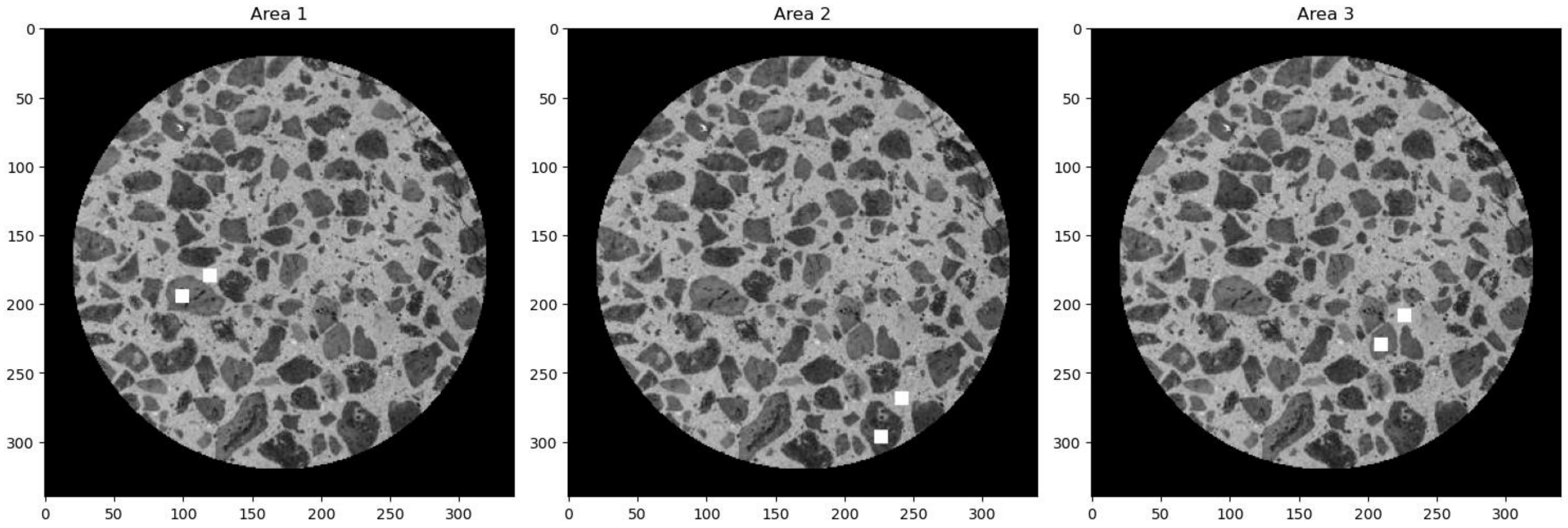
- **Model-based** → Solve optimization problem via iterative methods with **FBP** as starting point

$$\hat{\mathbf{x}}_{\text{opt}} = \arg\min_{\mathbf{x}} \|R(\mathbf{x}) - \mathbf{y}\|_2^2 + \lambda f(\mathbf{x})$$

Metrics

- Signal-to-Noise Ratio (SNR)
- Contrast-to-Noise Ratio (CNR)

$$\mathrm{CNR} = \frac{\left|\mu_{\text{signal}} - \mu_{\text{background}}\right|}{\sigma_{\text{noise}}}$$



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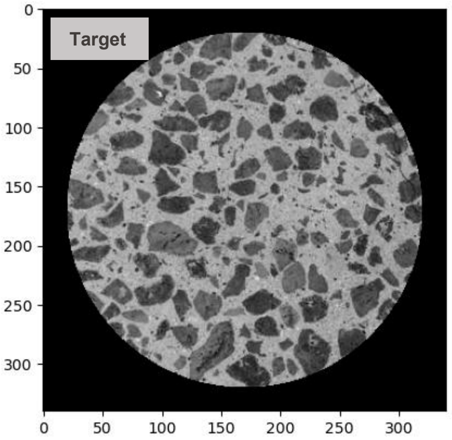
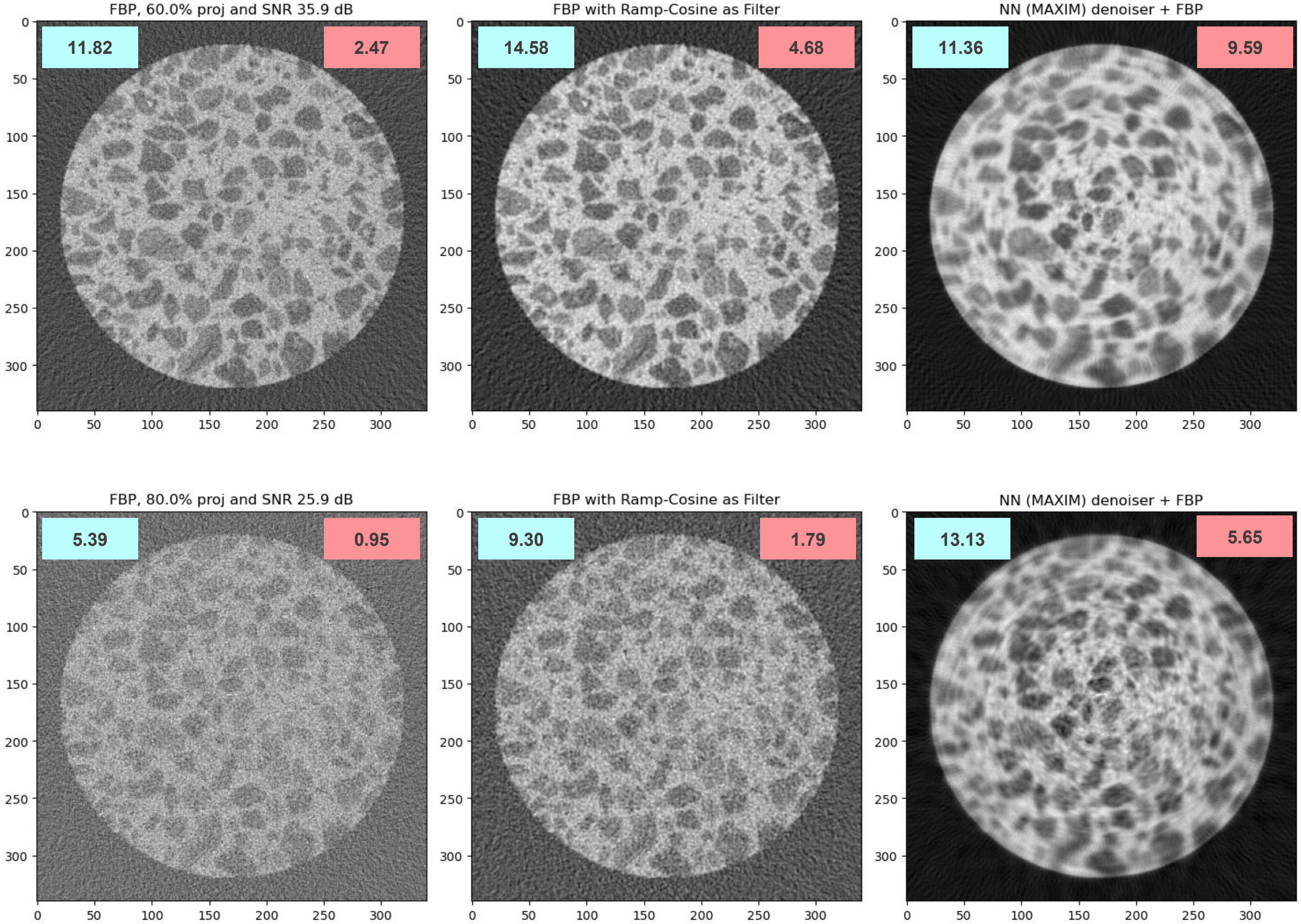
Pre-processed FBP

SNR [dB]

CNR [-]

- Low noise level





- High noise level

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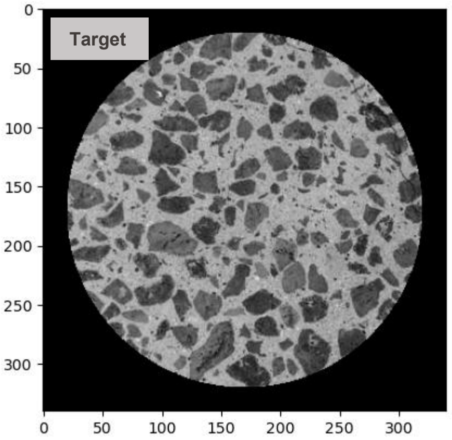
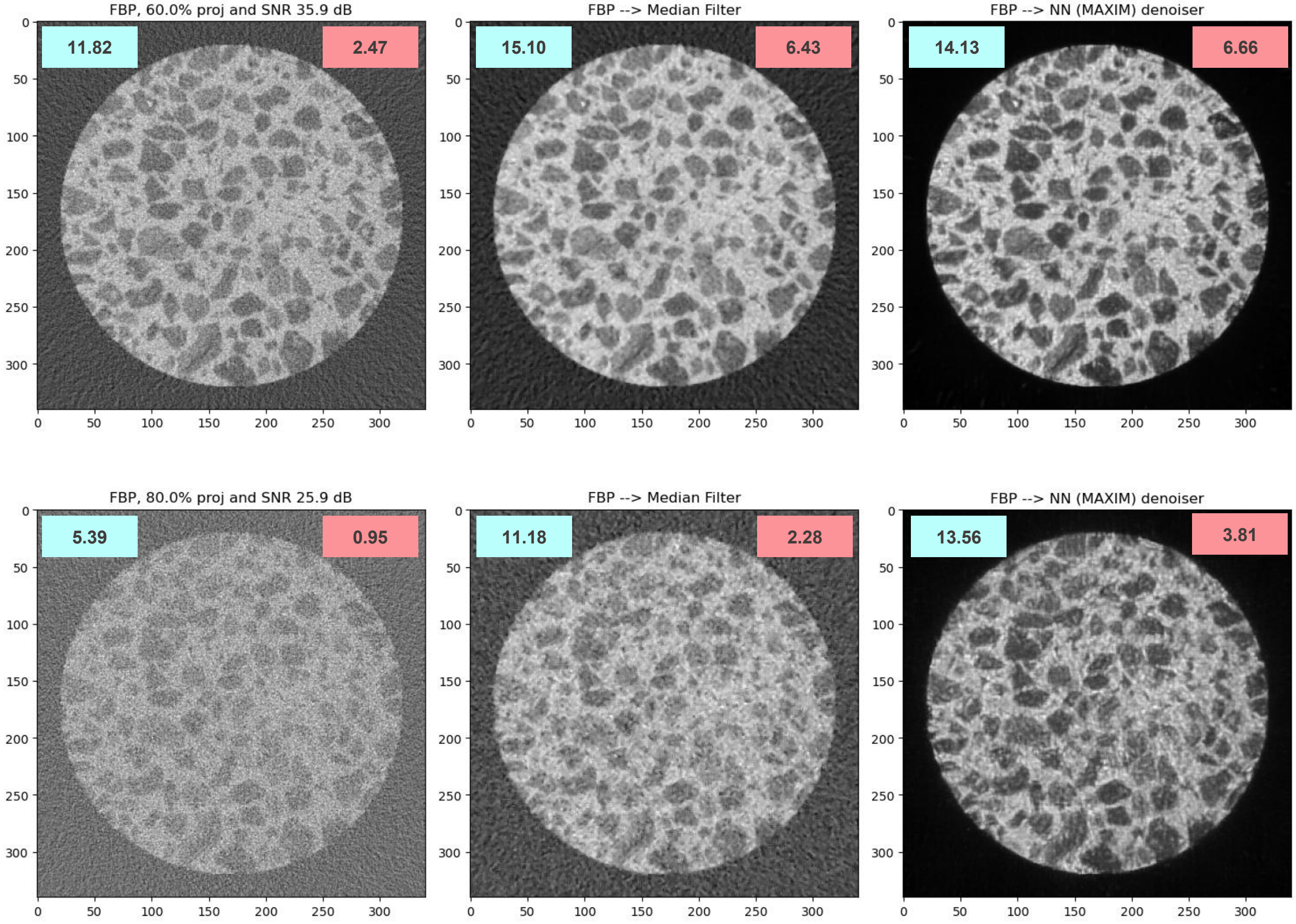
Post-processed FBP

SNR [dB]

CNR [-]

- Low noise level





- High noise level

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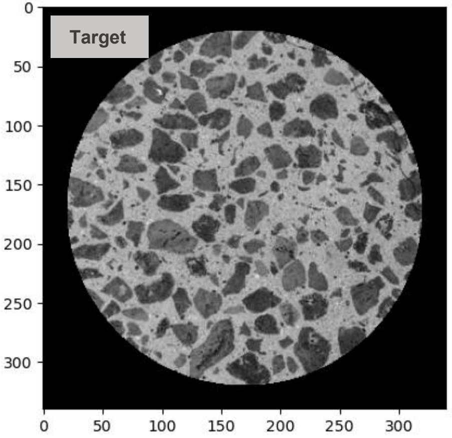
Model-based

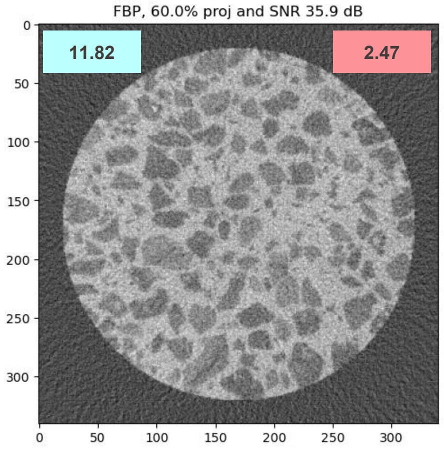
$$\hat{\mathbf{x}}_{\text{opt}} = \arg\min_{\mathbf{x}} \|R(\mathbf{x}) - \mathbf{y}\|_2^2 + \lambda f(\mathbf{x})$$

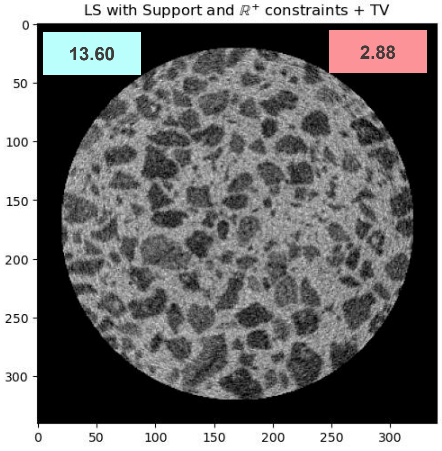
SNR [dB]

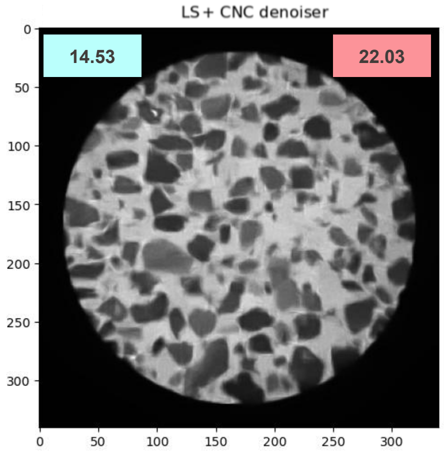
CNR [-]



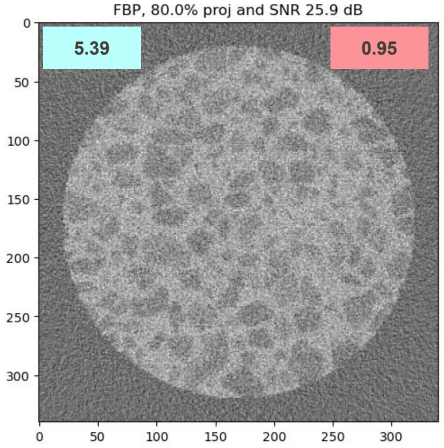
- Low noise level

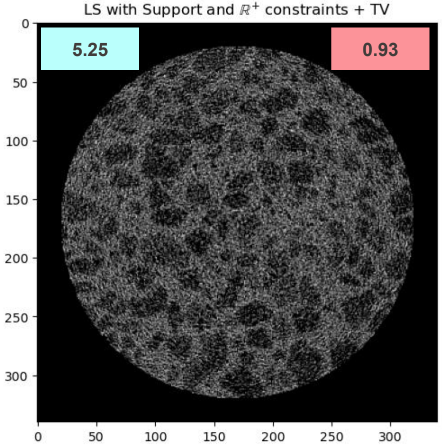


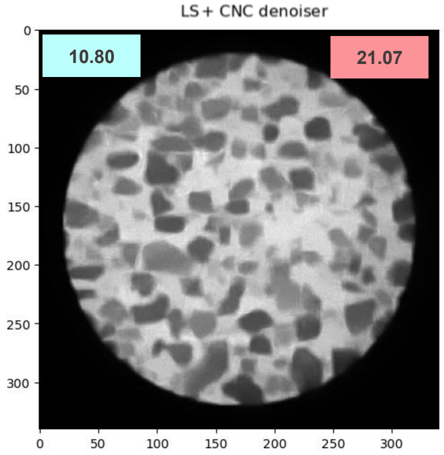




- High noise level







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Conclusion

All methods improve noise/contrast upon FBP baseline

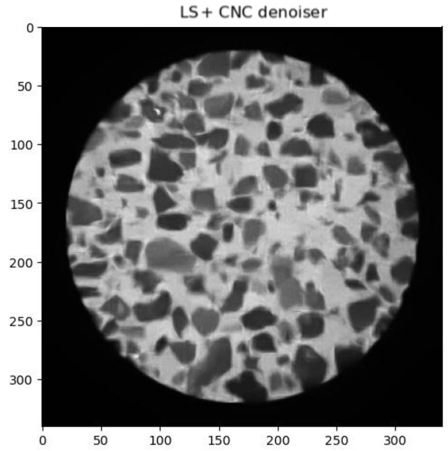
- **SP methods:**
  - Robust but offer little noise suppression / low contrast in high noise case
- **ML methods:**
  - Best contrast and better noise suppression in high noise case
- **Model-based with CNC regularizer:** → Great trade-off
  - Overall best contrast
  - Good noise reduction low/high noise cases
  - Fast runtime

To Go Further

- **Model-based with CNC regularizer**
  - Pretrained model for natural images
  - JAX conversion is still in progress.

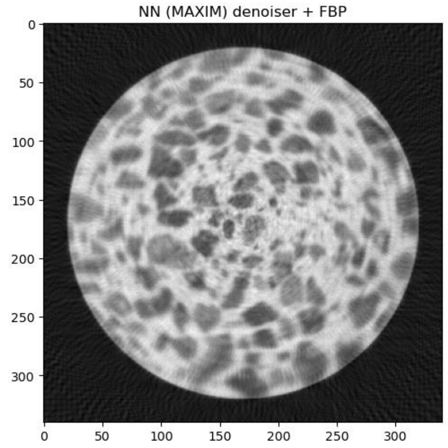
  → Finish implementation and retrain model in CT-specific dataset

  - $\hat{\mathbf{x}}_{\text{opt}} = \arg\min_{\mathbf{x}} \left\{ \|\mathbf{x} - \mathbf{z}\|_2^2 + Reg_{CNC}(\mathbf{x}) \right\}$



- **Pre-process FBP with NN**
  - Despite pretrained for 2D images, improves contrast and SNR

  → Design a 1D-dedicated ML model for sinogram denoising



Self-Assessment & Acknowledgments

- **Project outcome:**
  - Goal partially achieved → FBP can be improved, but further research is needed.
- **Personal objective:**
  - Deepen understanding of image processing and neural networks
- **Special thanks to Dr. Sepand Kashani**:

References

- **Reference work**

Sepand Kashani. Image Reconstruction 101: Computational Methods and Tools. Powerpoint. EPFL Center for Imaging, Apr. 2025.

- **Reference images**

https://ru.photo-ac.com/photo/29401522/concrete-surface-with-exposed-aggregate-cross-section

https://fab.cba.mit.edu/classes/862.19/people/erik/project.html

Thank you for your attention

Questions/Remarks