Accelerating Neutron Tomography Ring Artifact Removal Using BM3DORNL

Chen Zhang, Dmitry Ganyushin, Jose Borreguero-Calvo, Pete F Peterson

Computing & Computational Sciences Directorate, Oak Ridge National Laboratory

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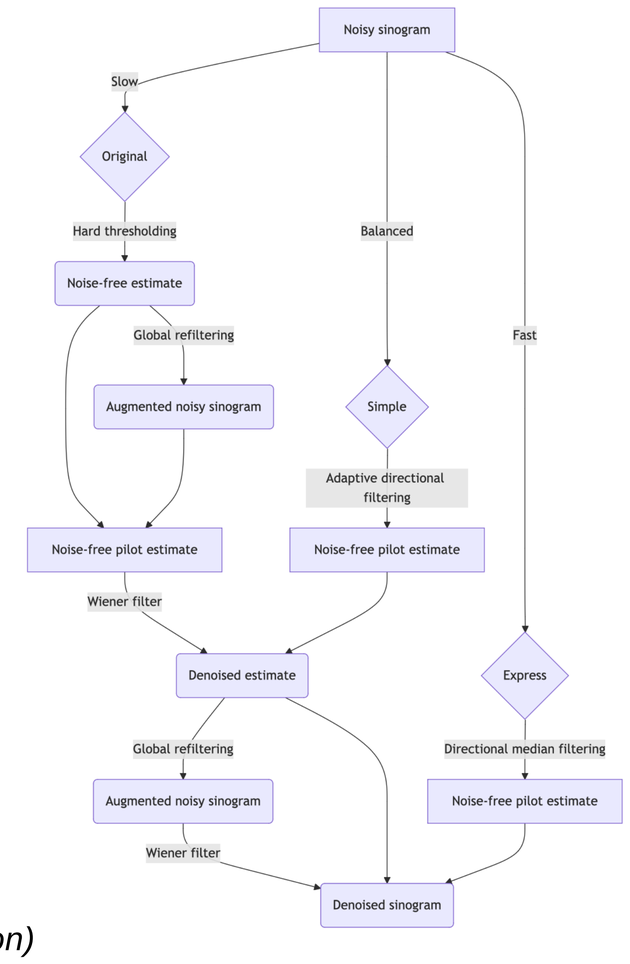
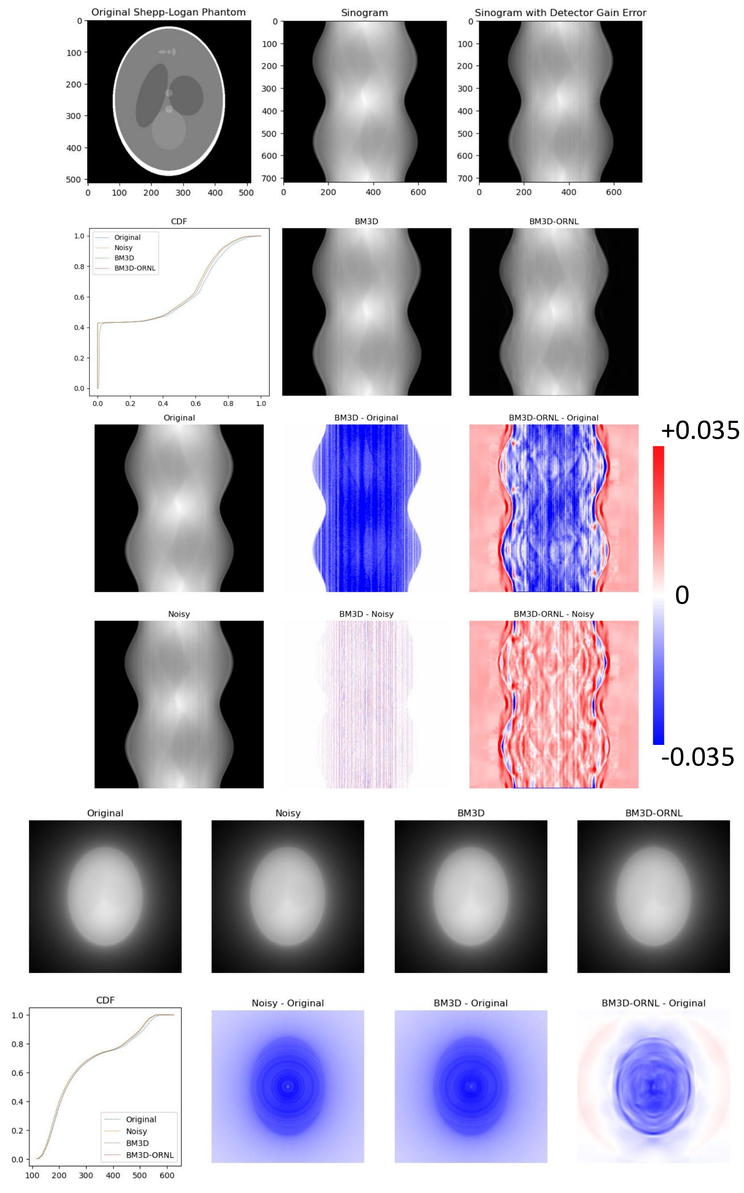
Motivations

- Ring artifacts in tomography significantly impact data quality and hinder analysis. It is caused by vertical streak type artifacts in the corresponding sinograms.
- These artifacts often coexist with other noise types, complicating removal.
- Traditional intensity-based methods struggle due to minimal impact on overall intensity distribution (see the Cumulative Distribution Function plot, CDF on the right).
- Current state-of-the-art BM3D algorithm is:
  - CPU-bound
  - Closed-source
  - Time-consuming for large datasets
- BM3DORNL addresses these limitations with:
  - GPU acceleration
  - Open-source implementation
  - Improved processing speed

How it works



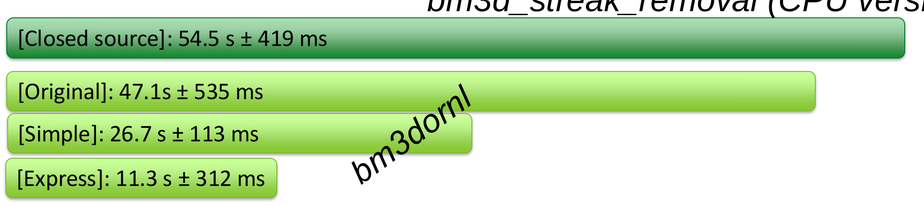
This flow chart illustrates three processing routes in BM3DORNL for ring artifact removal. The "**Original**" path faithfully re-implements collaborative BM3D filtering, prioritizing accuracy over speed. The "**Simple**" path balances efficiency and quality, using directional median filtering for initial estimation. The "**Express**" path offers the fastest processing with a quick noise-free estimate and single BM3D pass, suitable for rapid preliminary analysis.



*This composite figure demonstrates the performance of BM3D [closed-source] and BM3DORNL[**Simple**] on a 2D Shepp-Logan phantom with added vertical streak artifacts, simulating ring artifacts in tomography **without** using the multi-scale method.*

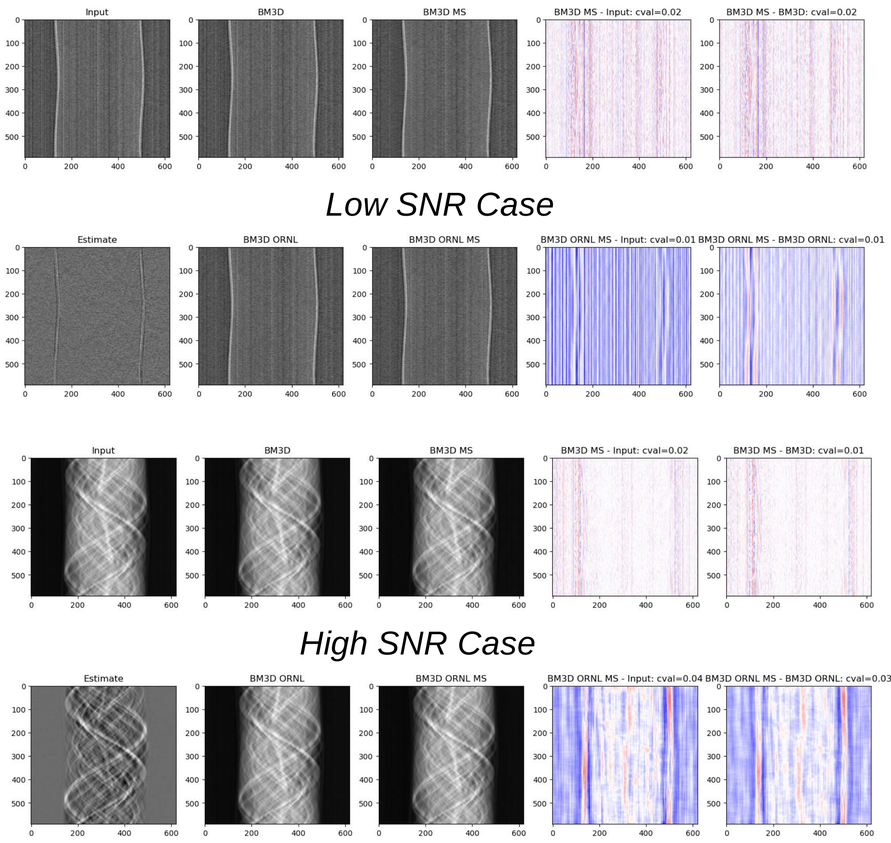
Performance boost

bm3d_streak_removal (CPU version)



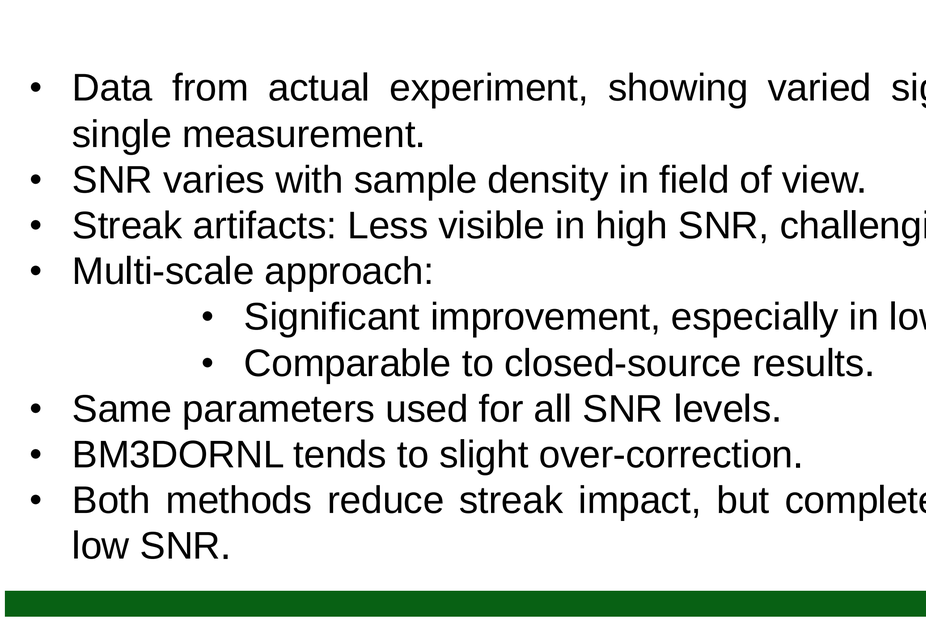
Benchmarks performed on a 2D Shepp-Logan phantom, using Jupyter's timeit magic for consistent timing. All tests conducted on the same system. BM3DORNL's "Express" mode achieves up to ~5x speedup compared to the closed-source implementation, with "Simple" mode offering a balance of speed and accuracy.

With Multi-scale enabled



Low SNR Case

High SNR Case



- Data from actual experiment, showing varied signal to noise ratio (SNR) in single measurement.
- SNR varies with sample density in field of view.
- Streak artifacts: Less visible in high SNR, challenging in low SNR.
- Multi-scale approach:
  - Significant improvement, especially in low SNR.
  - Comparable to closed-source results.
- Same parameters used for all SNR levels.
- BM3DORNL tends to slight over-correction.
- Both methods reduce streak impact, but complete removal difficult in extreme low SNR.

Future work

- **Multi-GPU Processing:** Develop a load balancer to partition sinogram stacks into chunks for distributed processing across multiple GPUs, significantly enhancing processing speed for large datasets.
- **Machine Learning-Based Estimation:** Implement ML models for noise-free estimates, expanding BM3DORNL's application areas and potentially improving accuracy.
- **Enhanced Documentation:** Improve documentation and provide more comprehensive usage examples to facilitate adoption by the scientific community.
- **Continuous Community Engagement:** Foster active community involvement to drive ongoing improvements and adaptations to emerging needs in tomography research.

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