

# BM3DORNL: High-Performance BM3D Denoising for Neutron Tomography

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## Summary

BM3DORNL is a high-performance Python library for denoising neutron and X-ray tomography data using a modified Block-Matching and 3D Filtering (BM3D) algorithm. The library provides two denoising modes: a generic mode for standard noise removal, and a specialized streak mode optimized for removing vertical streak patterns in sinograms that manifest as ring artifacts in reconstructed images. Built with a Rust backend and Python bindings via PyO3, BM3DORNL achieves 160× faster processing than comparable BM3D implementations while maintaining cross-platform compatibility including native Apple Silicon support.

## Statement of Need

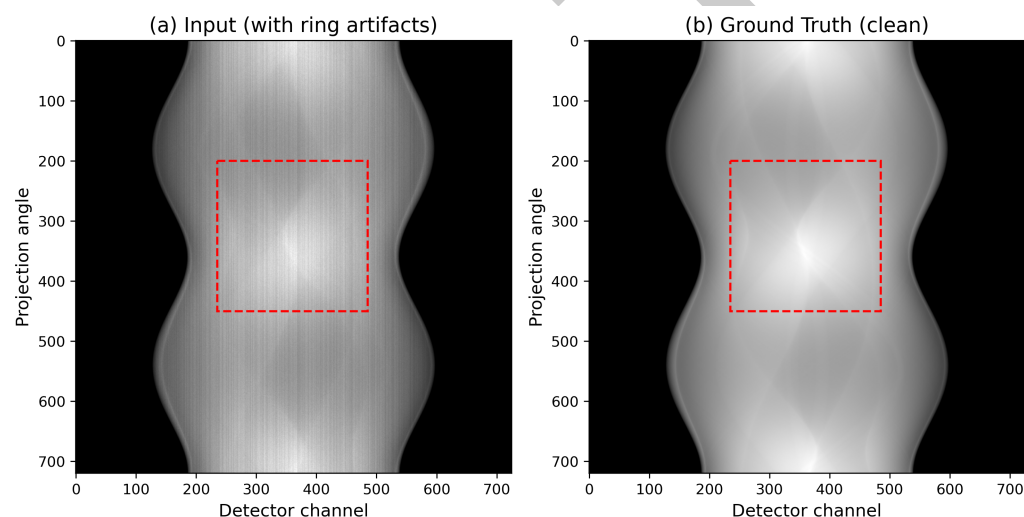
Ring artifacts are a persistent challenge in neutron and X-ray computed tomography, arising from variations in detector pixel response, beam intensity fluctuations, and systematic errors (Münch et al., 2009). These artifacts appear as concentric rings in reconstructed images, obscuring sample structure and degrading quantitative analysis. Pre-reconstruction streak removal addresses these artifacts directly in sinograms, avoiding the spatial spreading that occurs during reconstruction. Existing approaches include wavelet-Fourier filtering (Münch et al., 2009), polynomial fitting (Vo et al., 2018), and sorting-based methods (Miqueles et al., 2014), with implementations available in TomoPy (Gürsoy et al., 2014).

Mäkinen et al. (Mäkinen et al., 2021) demonstrated that applying BM3D (Dabov et al., 2007) across multiple scales achieves superior artifact removal by exploiting the self-similarity of streak patterns. However, their bm3d-streak-removal implementation is closed-source, restricted to non-commercial use, and provides only x86\_64 binaries incompatible with Apple Silicon and modern Python versions. BM3DORNL provides the neutron imaging community with an open-source, MIT-licensed, high-performance implementation that enables both high-throughput batch processing and interactive parameter tuning.

## State of the Field

Several software packages implement pre-processing streak removal for tomography: TomoPy (Gursoy et al., 2014) provides wavelet-Fourier filtering (Münch et al., 2009) and Vo's sorting/fitting methods (Vo et al., 2018); ASTRA Toolbox (Aarle et al., 2016) offers GPU-accelerated preprocessing; and bm3d-streak-removal (Mäkinen et al., 2021) implements multiscale BM3D but remains closed-source and platform-limited.

Figure 1 shows the benchmark input data: a synthetic sinogram ( $720 \times 725$  pixels) with simulated ring artifacts. We compare eight methods: four BM3DORN variants (streak, generic, multiscale, and Fourier-SVD), three TomoPy algorithms (Fourier, sorting-fitting, and sorting-based), and the original bm3d-streak-removal. The multiscale variant implements the pyramid approach from Mäkinen et al. (2021). The SVDisalightweightFFT-guided method that achieves comparable quality at  $50\times$  faster speeds.

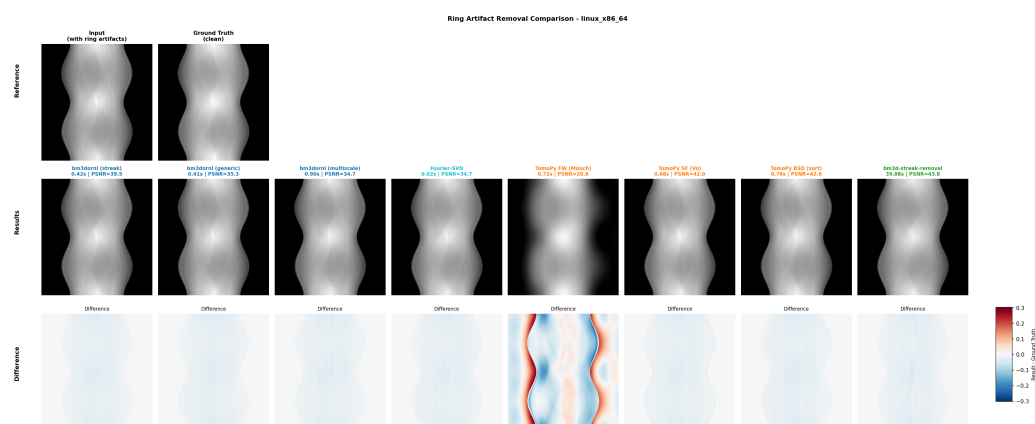


**Figure 1:** Benchmark input data. (a) Input sinogram with simulated ring artifacts. (b) Ground truth (clean sinogram). The dashed rectangle indicates the crop region shown in Figure 2.

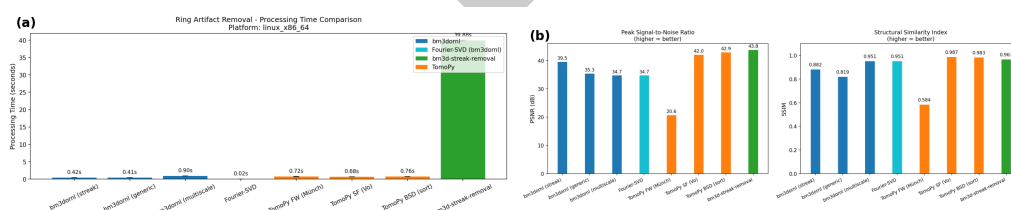
**Speed comparison:** Figure 3(a) shows processing times ( $n=100$  runs on Linux x86\_64). Fourier-SVD is the fastest method at 0.017 seconds, achieving  $2300\times$  speedup over bm3d-streak-removal (39.9 seconds). The BM3D-based methods span a performance range: standard BM3DORN processes sinograms in 0.4 seconds ( $100\times$  faster than bm3d-streak-removal), while multiscale BM3DORN takes 0.9 seconds ( $44\times$  faster) due to pyramid processing. TomoPy methods achieve comparable processing times (0.7–0.8 seconds). Cross-platform performance differs substantially: TomoPy runs  $2.5\text{--}3\times$  slower on Apple Silicon than Linux x86\_64 (likely due to unoptimized C extensions), whereas BM3DORN runs at comparable speeds (within 10%) across platforms due to its Rust backend.

**Quality analysis:** Figure 2 shows cropped results from all eight methods with their difference images (result minus ground truth). The benchmark reveals that quality metrics alone do not tell the full story. TomoPy SF achieves the highest SSIM (0.987, see Figure 3(b)), but difference image analysis shows residual vertical stripes in its output. This occurs because SSIM uses local windows ( $7 \times 7$  or  $11 \times 11$  pixels), and narrow vertical stripes affect few pixels per window. Interestingly, both multiscale BM3DORN and Fourier-SVD achieve excellent SSIM scores (0.951) while maintaining fast processing times—Fourier-SVD accomplishes this at 0.017 seconds, demonstrating that aggressive artifact removal and high-quality reconstruction are achievable without computationally expensive multi-scale processing. The difference images

70 reveal that all BM3DORNL variants produce clean vertical patterns, indicating successful  
71 artifact removal, while TomoPy methods leave faint residual artifacts.



**Figure 2:** Method comparison. Top row: Cropped results from each method with processing times. Bottom row: Difference images (result minus ground truth) using a zero-centered RdBu colormap—blue indicates artifact removal, red indicates added artifacts. Data from Linux x86\_64.



**Figure 3:** Performance metrics (Linux x86\_64, n=100 runs). (a) Processing time comparison on linear scale, showing Fourier-SVD's 2300 $\times$  speedup and standard BM3DORNL's 100 $\times$  speedup over bm3d-streak-removal. (b) Quality metrics (PSNR vs SSIM) showing trade-offs between methods. BM3DORNL variants (blue/cyan), TomoPy (orange), bm3d-streak-removal (green).

72 **Platform support:** bm3d-streak-removal is unavailable on Apple Silicon (x86\_64 binaries only),  
73 incompatible with Python 3.11+, and restricted to non-commercial use. BM3DORNL provides  
74 native performance on all platforms, supports Python 3.12+, and uses the MIT license for  
75 unrestricted commercial use.

## 76 Software Design

77 BM3DORNL employs a hybrid Python-Rust architecture: the core algorithm is implemented in  
78 Rust using the rayon crate for work-stealing parallelism, with Python bindings via PyO3 for  
79 seamless NumPy integration.

### 80 Key optimizations:

- 81 **Integral image pre-screening:** Before computing expensive patch distances, the block  
82 matching stage uses integral images to compute mean and norm bounds in  $O(1)$  time.  
83 Patches that fail these bounds are skipped, eliminating approximately 80% of distance  
84 calculations.
- 85 **Walsh-Hadamard transform:** For the default  $8 \times 8$  patches, BM3DORNL uses Walsh-  
86 Hadamard transforms instead of FFT. This is multiplication-free (only additions and

87 subtractions), cache-friendly with fixed 64-element buffers, and computed in-place  
88 without memory allocation.

- 89 ■ **Pre-computed FFT plans:** FFT plans are computed once and shared across threads via  
90 Arc, avoiding expensive plan initialization on each invocation (measured 45% speedup).
- 91 ■ **Batched stack processing:** Sinograms are processed slice-by-slice to control memory  
92 usage, ensuring each slice fits in L2/L3 cache while minimizing memory allocation  
93 through buffer reuse.

94 The library provides a minimal Python API:

```
from bm3dornl import bm3d_ring_artifact_removal

cleaned = bm3d_ring_artifact_removal(
    sinogram,
    mode="streak",
    sigma=0.0, # default to automatic noise estimation
)
```

95 **GUI application:** BM3DORNL includes a native GUI built with the egui framework for Rust.  
96 The GUI enables interactive parameter tuning, side-by-side comparison with difference visual-  
97 ization, HDF5/TIFF file loading with dataset browsing, and real-time processing feedback. At  
98 0.2–0.3 seconds per sinogram, scientists can explore parameter space interactively—something  
99 impractical with bm3d-streak-removal's 41-second processing time.

## 100 Research Impact

101 BM3DORNL is being integrated into processing pipelines at the VENUS and MARS beamlines  
102 at Oak Ridge National Laboratory. The library provides multiple performance tiers: Fourier-  
103 SVD enables real-time parameter exploration at 0.017 seconds per sinogram (2300× faster  
104 than bm3d-streak-removal), standard BM3DORNL offers robust denoising at 0.4 seconds  
105 (100× speedup), and multiscale BM3DORNL provides maximum quality at 0.9 seconds (44×  
106 speedup). For batch processing, a 1000-sinogram dataset that would take 11 hours with bm3d-  
107 streak-removal completes in 17 seconds (Fourier-SVD), 7 minutes (standard BM3DORNL), or  
108 15 minutes (multiscale BM3DORNL).

109 The hybrid Rust-Python architecture demonstrates a modern approach to scientific software  
110 development: Rust provides memory safety and performance portability (single codebase com-  
111 piles natively to arm64 and x86\_64), while Python ensures integration with the NumPy/SciPy  
112 ecosystem. This pattern is increasingly valuable as the scientific computing community  
113 diversifies hardware platforms.

114 BM3DORNL fills a critical gap: the neutron imaging community needed an open-source,  
115 actively maintained BM3D implementation that works on modern platforms. The MIT license  
116 enables unrestricted use at national facilities, and native Apple Silicon support ensures scientists  
117 can use contemporary hardware for analysis workstations.

## 118 AI Usage Disclosure

119 Generative AI tools (Claude) were used for code assistance and documentation drafting. All  
120 AI-generated content was reviewed, tested, and validated by the authors.

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