Deep Learning Denoising of Atmospheric Lidar ATLID Data Using Noise Prediction Approach

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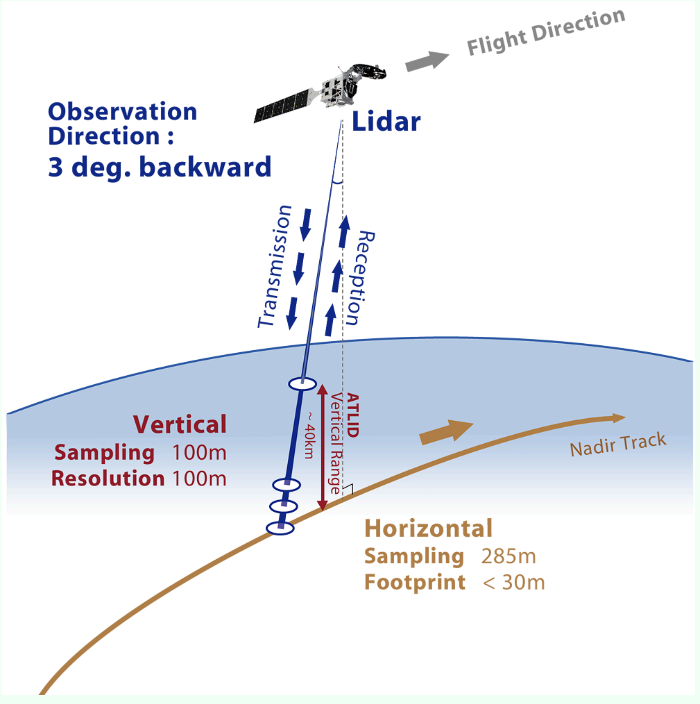
INTRODUCTION/MOTIVATION

Abstract

ATLID lidar measurements are affected by noise from solar background radiation and detector noise that degrades atmospheric feature detection. We developed a CNN-based noise prediction approach that directly predicts and subtracts noise from raw backscatter profiles while preserving atmospheric signals. Results show improved signal-to-noise ratio and enhanced detection of clouds and aerosols compared to traditional averaging methods.



The Problem :

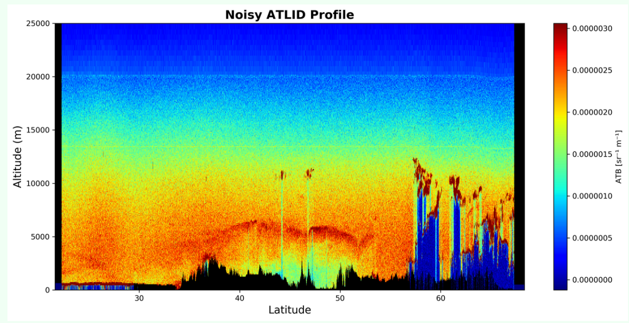
1. PLOT 1: Noisy ATLID Profile
   - Solar background noise degrades signal quality
   - Fine atmospheric features masked by noise
   - Detection accuracy significantly reduced

Current Solution Limitations:

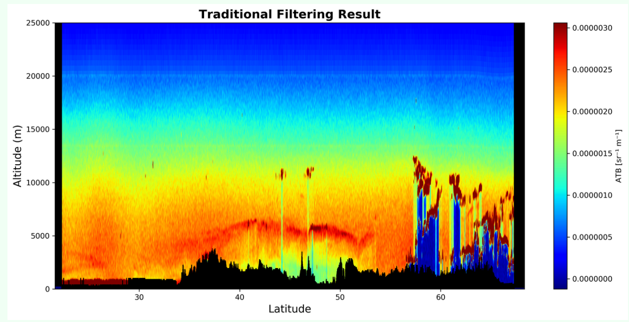
2. PLOT 2: Traditional Filtering Result
   - Spatial averaging reduces noise BUT...
   - Loss of vertical resolution
   - Fine-scale atmospheric structures disappear

🎯 **Our Goal**

Reduce noise while preserving atmospheric detail



PLOT 1



PLOT 2

METHODOLOGY

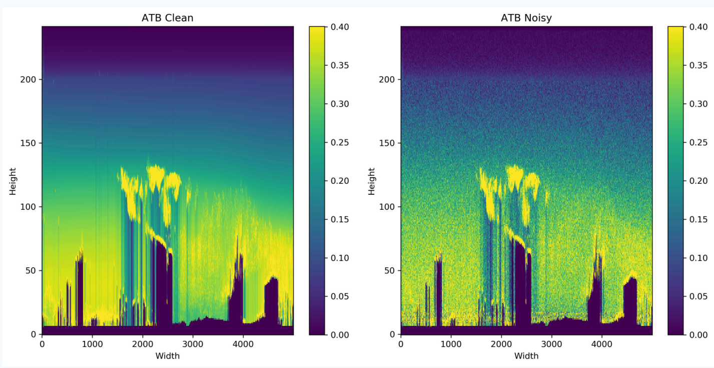
Database Creation Steps

Lidar equation:

$$ATB(\lambda, z) = (\beta_{mol}(\lambda, z) + \beta_{part}(\lambda, z)) \times e^{-2\int_{z}^{z_{top}}[\alpha_{mol}(\lambda,z')+\alpha_{part}(\lambda,z')]dz'}$$

Synthetic Dataset Generation

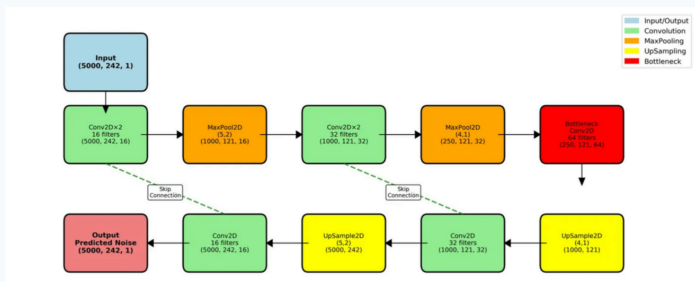
- Extract components: β_{part}, α_{part} from ATLID L2A data
- Calculate molecular: β_{mol}, α_{mol} from atmospheric density
- Synthesize clean ATB: Apply lidar equation with optical depth
- Extract realistic noise: From real ATLID measurements
- Create training pairs: (Noisy ATB, Clean ATB)
- Dataset size: 10,000 profiles (70/15/15 split)



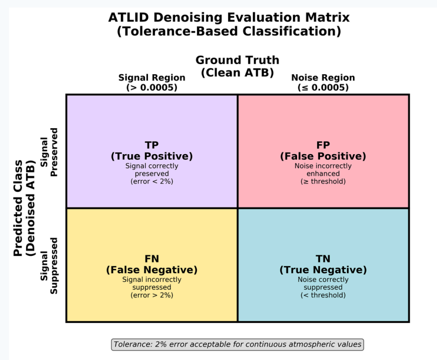
- Data Dimensions: (5000, 242) - altitude × horizontal sampling
- Normalization: Min-max scaling to [0,1] range
- Data Splitting: 70% train / 15% validation / 15% test

Input DATA

- Training Strategy: U-Net learns direct mapping (Noisy ATB → Clean ATB)
- Supervised Learning: Model trained on synthetic (noisy, clean) pairs



Model Architecture

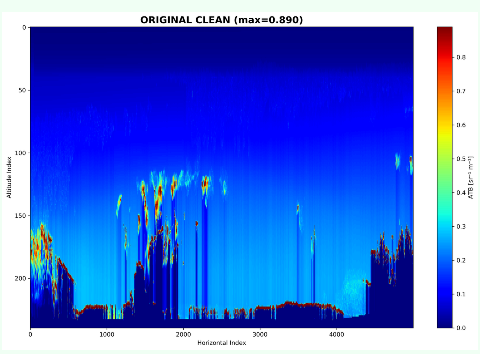


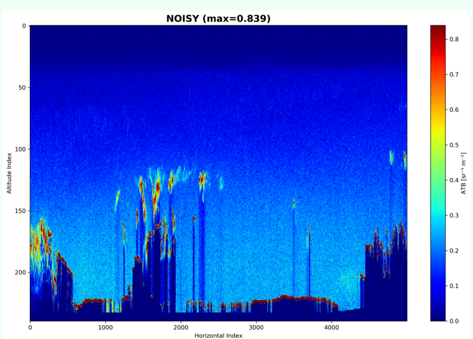
Signal-to-Noise Ratio

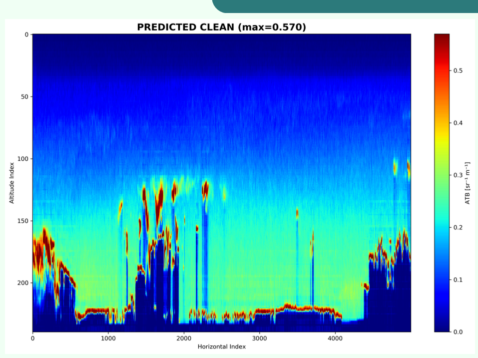
- Calculated in overlapping patches (50×500 pixels, 50% overlap)
- μ_signal: Mean of positive ATB values in patch
- σ_signal: Standard deviation of positive ATB values in patch

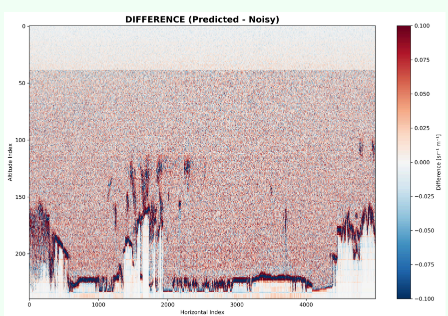
Evaluation

RESULTS

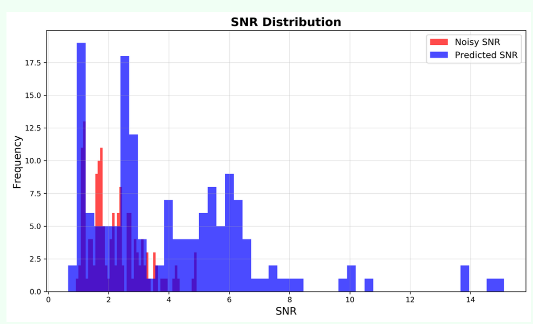






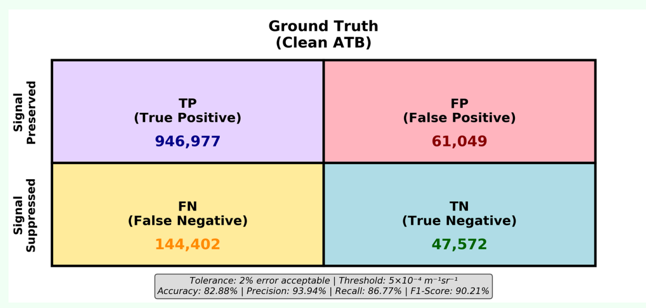


Model Performance



SNR Performance Improvement

- Noisy input SNR: 2.20
- -Denoised output SNR 4.11
- Absolute improvement: +1.91
- Relative improvement: 86.49%



Classification Performance Metrics (Tolerance: 2%, Threshold: 5×10^{-4} $m^{-1}sr^{-1}$)

Metric	Value	Formula
Accuracy	82.88%	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	93.94%	$\frac{TP}{TP+FP}$
Recall	86.77%	$\frac{TP}{TP+FN}$
F1-Score	90.21%	$\frac{2\cdot P\cdot R}{P+R}$

Denoising Results

SUMMARY AND NEXT STEPS

Summary

- U-Net denoising achieves 86.49% SNR improvement
- High precision (93.94%) with minimal false signals
- Tolerance-based evaluation suitable for atmospheric data
- Physics-based synthetic dataset ensures realistic training

Next Steps

- Improve architecture for better denoising performance
- Focus on noise prediction rather than processing entire data
- Apply to real ATLID data for operational validation
- Optimize for real-time processing

REFERENCES

[1] Selmer, P., et al. A Deep Learning Lidar Denoising Approach for Improving Atmospheric Feature Detection. Remote Sensing 2024, 16(15), 2735.

[2] Feofilov, A.G., et al. Incorporating EarthCARE observations into a multi-lidar cloud climate record: the ATLID cloud climate product. Atmospheric Measurement Techniques 2023, 16, 3363-3376.