Wavelet-Enhanced Deblurring Diffusion Model (WEDDM) on GS-Blur Dataset

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Background and Motivation

Why Image Deblurring Matters?

- Image deblurring is a critical task in computer vision, with applications in **autonomous driving, surveillance, medical imaging, and remote sensing**.
- Traditional deblurring models struggle with **high-noise and complex blur** seen in real-world images.

Current Limitations of Existing Models

- Many deep learning-based deblurring models are **trained on synthetic datasets** with **low noise**, which **fails to generalize** to **real-world blur**.
- High-noise environments lead to **poor performance and loss of fine textures** in restored images.

Our Approach: Using WEDDM on GS-Blur Dataset

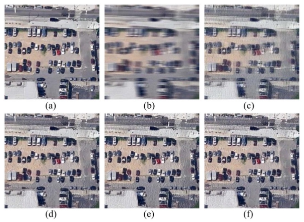
- **Wavelet-Enhanced Deblurring Diffusion Model (WEDDM)** is a **state-of-the-art blind deblurring algorithm** designed for **low-SNR remote sensing images**.
- **GS-Blur dataset** introduces **realistic, near-field motion blur** through **3D Gaussian splatting**, creating a more **complex and dynamic** representation of blur patterns.
- Our study evaluates whether **WEDDM can generalize to near-field complex blur scenarios** and outperform other models.

Research Question

How does the Wavelet-Enhanced Deblurring Diffusion Model (WEDDM) perform when trained on the GS-Blur dataset, particularly in restoring near-field images with complex blur patterns?

Previous studies have **proven WEDDM's success in removing motion blur in remote sensing**, but **its adaptability to real-world near-field blur remains unknown**.

•We explore whether WEDDM's **wavelet-based noise reduction features** improve **deblurring performance** in practical applications such as **autonomous driving, medical imaging, and consumer photography**.
•The study compares WEDDM against a **CNN-based deblurring model (MPRNet)** to **analyze the impact of dataset realism vs. model architecture**.



Note: This is adapted from "A Noise-Robust Blind Deblurring Algorithm with Wavelet-Enhanced Diffusion Model for Optical Remote Sensing Images", by Li et al., 2024, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 17: 16236–54

Application Scenarios

The findings of this study have significant implications in fields requiring **high-quality image restoration** under complex blur conditions. **Autonomous driving, surveillance, medical imaging**, and **remote sensing** all rely on clear visual data for accurate decision-making. By improving deblurring performance, WEDDM can enhance **vehicle perception in poor weather, security footage clarity, medical diagnostics, and satellite image analysis**, making image-based AI systems more reliable and effective.

Methodology

Experiment	Model	Training Dataset	Purpose
Baseline	WEDDM	Simulated Dataset	Measures WEDDM's performance on synthetic blur
Benchmark	MPRNet	GS-Blur Dataset	Tests CNN-based deblurring on realistic near-field blur
Experiment	WEDDM	GS-Blur Dataset	Evaluates WEDDM's ability to generalize to real-world blur

Experimental Design

We designed **three experimental setups** to evaluate the impact of dataset realism and model architecture. Each model is evaluated using PSNR, SSIM, and LPIPS scores to measure image quality, perceptual similarity, and noise robustness.

Data Preprocessing

To ensure **fair model comparison**, all datasets undergo **the same preprocessing pipeline**:
✅ **Resizing** images to **96×96 pixels** for computational efficiency.
✅ **Data Augmentation**: **Synthetic Dataset**: Gaussian noise + motion blur kernels.
GS-Blur Dataset: No extra augmentation needed (already includes realistic 3D Gaussian splatting-based blur).
✅ **Feature Extraction**: Using **RGB pixel values as inputs**, with corresponding **sharp images as ground truth.**

Models and Algorithms

Wavelet-Enhanced Deblurring Diffusion Model (WEDDM)
- **A diffusion-based blind deblurring model** that integrates **wavelet transformations** for **multi-scale noise reduction**.
- Designed for **low-SNR images**, adapted here for **near-field blur**.
- **Optimizer:** Adam (**lr = 1e-4**), **Loss Function:** MSE

Multi-Scale Progressive Restoration Network (MPRNet)
- A **CNN-based model** that progressively **restores images through multi-stage feature refinement**.
- Uses **spatial attention** to enhance critical regions in blurry images.

Evaluation Metrics

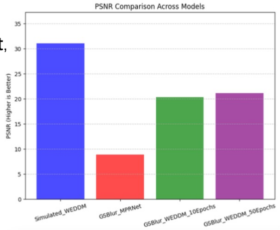
We evaluate deblurring performance using three key metrics:

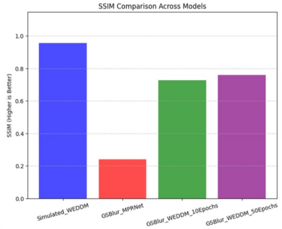
Metric	Purpose	Scale	Interpretation
PSNR (Peak Signal-to-Noise Ratio)	Image quality	0 to +∞ (Higher is better)	Higher = Less distortion, better reconstruction
SSIM (Structural Similarity Index)	Perceptual similarity	-1 to 1 (Higher is better)	SSIM > 0.8 = High-quality restoration
LPIPS (Learned Perceptual image Patch Similarity)	Perceptual distance	0 to 1 (Lower is better)	Lower = More visually similar to ground truth

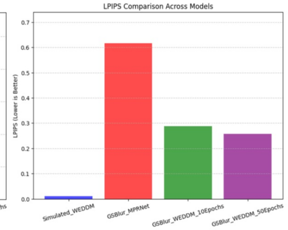
Result

Key Findings:

- **WEDDM trained on a synthetic dataset performs best**, indicating that GS-Blur introduces **more complex blur** than traditional datasets.
- **MPRNet performs poorly on GS-Blur**, confirming that **CNN-based deblurring struggles with realistic, high-noise blur**.
- **Extending WEDDM's training from 10 to 50 epochs only yields slight improvements**, suggesting the need for **longer training or hyperparameter tuning**.







Intellectual Merit and Practical Impacts

Contributions to Image Restoration Research

•Introduces **wavelet-enhanced diffusion models** to **real-world near-field deblurring**. Shows the importance of **dataset realism vs. model architecture** for training deblurring networks.

Future Research Directions

🔹 **Hybrid Models:** Combining **diffusion models with CNNs** for enhanced performance. 🔹 **Progressive Learning:** Training on simpler blur first, then increasing complexity. 🔹 **Optimization Strategies:** Adaptive learning rates, better loss functions.