Performance Analysis for Projection-Correction Methods in Motion Deblurring Problems

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Problem Description

- The project analyzes the performance of two **Projection-Correction** algorithms for reconstructing medical images affected by **motion blur**.
- The studied algorithms are:
  - **Diffusion Posterior Sampling (DPS)**
  - **Regularization by Denoising with Diffusion (RED-Diff)**
- Both methods are based on **pre-trained diffusion models**.
- Objective: evaluate the effectiveness of these methods in recovering degraded images.

Approach to the Problem

- **Objective**: Analyze the performance of *Projection-Correction* methods **DPS** and **RED-Diff** for motion blur removal on medical images
- **Phase 1**: Dataset preprocessing (128x128)
- **Phase 2**: Data augmentation to increase dataset diversity
- **Phase 3**: Training a DDIM diffusion model on medical data
- **Phase 4**: Simulation of motion blur and its removal
- **Phase 5**: Implementation and comparison of *Projection-Correction* methods: **DPS** and **RED-Diff**
- **Phase 6**: Quantitative evaluation of performance using metrics such as **PSNR** and **SSIM**

Dataset

- We use the "Mayo Clinic CT Dataset" of low-dose CT scans.

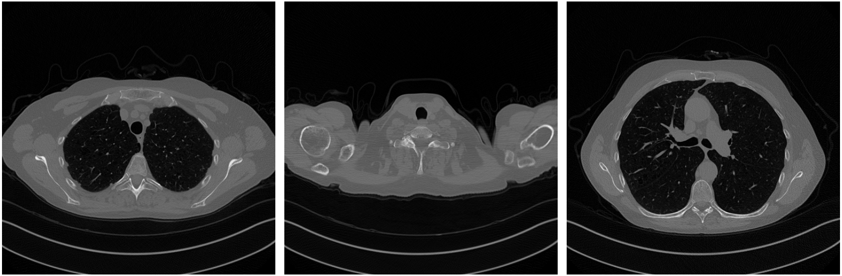


Figure 1: Examples of CT slices from the Mayo Clinic dataset

Conversion Pipeline

Before applying augmentations, each image is converted using:

1. **Grayscale**: single channel via `transforms.Grayscale(num_output_channels=1)`
2. **Resize**: to 128×128 pixels using bicubic interpolation
3. **Normalization**: values scaled to $[-1, 1]$ using mean 0.5 and std 0.5

```
base_transform = transforms.Compose([
    transforms.Grayscale(1),
    transforms.Resize((128,128), interpolation=Image.BICUBIC),
    transforms.ToTensor(),
    transforms.Normalize([0.5], [0.5]),
])
```

Data Augmentation: Types

For each clean image, we apply the following transformations:

- **Fixed rotations**: $\pm 5^\circ$ via `rotate_fixed()`
- **Horizontal flip**: `horizontal_flip()`
- **Gaussian noise**: mean 0, std 10 via `add_gaussian_noise()`
- **Salt-and-pepper noise**: probability 2% via `add_salt_pepper()`
- **Brightness adjustment**: factor 1.2 via `change_brightness()`
- **Contrast adjustment**: factor 1.3 via `change_contrast()`

Repository Organization

- raw_data/: directory containing CT slice images (train/, test/)
- checkpoints/: saved model weights (*.pth)
- scripts/: main scripts for training and evaluation
- utils.py: module with utility functions (dataset, model, checkpoint I/O)
- notebooks/: exploratory and prototyping notebooks
- result/: output images, plots, and metrics
- report/: report materials (media/, chapters/)

Diffusion Model Architecture

- **Model Type**: UNet2DModel from HuggingFace Diffusers library
- **Task**: Denoising diffusion probabilistic model for grayscale image generation
- **Input/Output**:
  - Input channels: 1
  - Output channels: 1
  - Sample size: 128×128 pixels

UNet Architecture Configuration

- **Block Configuration**:
  - Layers per block: 2
  - Block output channels: (64, 128, 256)
  - Dropout rate: 0.1
- **Downsampling Path**:
  - DownBlock2D $\rightarrow$ DownBlock2D $\rightarrow$ AttnDownBlock2D
  - Progressive feature extraction with attention in the deepest layer
- **Upsampling Path**:
  - AttnUpBlock2D $\rightarrow$ UpBlock2D $\rightarrow$ UpBlock2D
  - Symmetric architecture with attention mechanism

Diffusion Schedulers

- **Training Scheduler**: DDPMScheduler
  - Number of timesteps: 1000
  - Used for forward diffusion process during training
  - Adds noise progressively over 1000 steps
- **Inference Scheduler**: DDIMScheduler
  - Number of timesteps: 1000
  - Deterministic sampling process
  - Used for image generation and inverse problems
  - Shares beta schedule with DDPM scheduler

Model Optimization

- **Optimizer**: Adam
  - Learning rate: 1×10^{-4}
  - Weight decay: 1×10^{-5}
- **Loss Function**: Mean Squared Error *MSE*
  - Compares predicted noise with actual noise
  - Standard objective for diffusion models
- **Performance Optimizations**:
  - Model compilation with `torch.compile`
  - Mixed precision training with GradScaler
  - Cosine annealing learning rate scheduler

- **Total Parameters**: 15.722.625
- **Key Features**:
    - Attention mechanisms in deepest layers for better feature learning
    - Symmetric U-Net design for optimal information flow
    - Dropout regularization to prevent overfitting
    - Grayscale-optimized with single channel processing

Training Pipeline

- **Objective**: Train a denoising diffusion model (DDIM U-Net) on grayscale images
- **Main Components**:
  1. Data Augmentation
  2. DataLoader
  3. Model Compilation
  4. Training loop with mixed-precision

Schedulers for Diffusion

- **DDPMScheduler** for training diffusion process
  - `Timesteps` 1000
- **DDIMScheduler** for sampling
  - `Timesteps` 1000

Compiling the Model

- **Why**: optimize the model for better performance
- **Usage**:

```
model = torch.compile(model)
```

- **Benefits**: improved batch throughput

Mixed-Precision with AMP

- **GradScaler amd autocast**:
    - `GradScaler` for scaling gradients
    - `autocast` for automatic mixed precision
- Reduce memory usage and speed up training

Training Loop

1. Loss function: `MSE`
2. Start the training `model.train()`
3. For each epoch:
   - Move images to GPU (if available)
   - Generate noise and timesteps
   - Compute noise prediction on the input data
   - Prediction + MSE loss
   - Optimization + `scheduler.step()`
4. Save validation samples to visualize the model performance during training
5. Compute and log average losses
6. Save model weights each epoch

Checkpointing

- **Validation**:
  - `model.eval()` to set the model to evaluation mode
  - MSE loss on validation set
- **Checkpoint**:
  - Save the model weights to a `.pth` file
  - Update loss, PSNR and SSIM history in `history.txt`
- Monitor train vs validation loss over epochs aswell as PSNR and SSIM between the generated and original images
  - For each epoch sample 10 images from the validation set and compute the metrics

Epoch Validation

- **Metrics**:
  - PSNR: Peak Signal-to-Noise Ratio
  - SSIM: Structural Similarity Index
- **Sample Generation**:
  - Pure noise sampling using DDIM scheduler
  - Validation reconstruction:
    - Add noise to clean validation images
    - Model predicts and removes the noise
- **Quality Assessment**:
  - PSNR range: 20-40 dB (higher = better reconstruction)
  - SSIM range: 0-1 (closer to 1 = better similarity)
  - Average metrics computed over 5-10 validation samples

Monitoring Produced Samples

- **Pure Noise Sampling**:
  - Tests model's ability to generate realistic images
  - Uses DDIM scheduler for iterative denoising
  - Saves generated images as `generated_epoch_{epoch}.png`
- **Validation Reconstruction**:
  - Adds noise to clean validation images
  - Model predicts and removes the noise
  - Direct assessment of denoising performance
- **History Tracking**:
  - All metrics saved to `history.txt`
  - Enables trend analysis and model comparison

- **Loss Monitoring**:
  - Training vs Validation Loss curves over epochs
  - MSE loss
- **Quality Metrics Visualization**:
  - PSNR trends with average values
  - SSIM trends with average values
  - Both metrics computed on validation reconstructions
  - Useful to track model performance

- **Comprehensive Monitoring**:
  - Three-panel subplot: Loss, PSNR, SSIM (as shown in the Figure 2)
  - Data read from `history.txt` file
  - Enables performance trend analysis

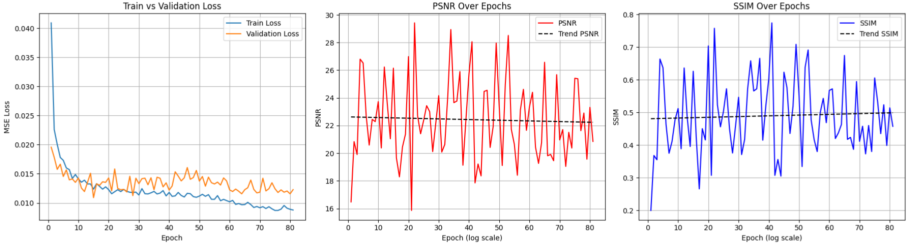


Figure 2: Training Loss, PSNR, and SSIM trends over epochs

Generated Samples from Pure Noise

- Samples generated from pure noise using the trained model
- Visualized to assess the model's generative capabilities
- Useful for understanding the model's learned features
- Figure 3 shows 10 generated samples to assess the model's performance

Generated Samples Visualization

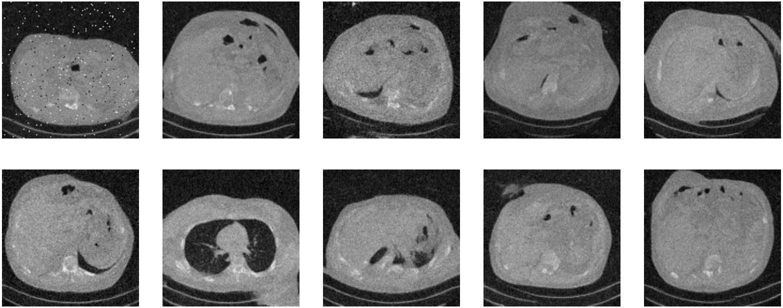


Figure 3: 10 generated samples from pure noise using the trained model at epoch 81.

- **Checkpoint Structure**:
  - Model state dictionary
  - Optimizer state dictionary
  - Current epoch number for resuming training
  - Naming: `ddim_unet_epoch81.pth`
  - `load_checkpoint()` utility function

DPS: Diffusion Posterior Sampling

- **DPS** is a method for solving inverse problems using pre-trained diffusion models
- Key idea: combine data fidelity with diffusion model prior during reverse sampling
- Modifies the standard DDIM reverse process to incorporate measurement consistency

Algorithm Overview:

1. Start with noisy initialization $x_T \sim \mathcal{N}(0, I)$
2. For each timestep t: predict x_0 using UNet
3. Apply posterior correction: $x_0^{post} = x_0^{pred} + \gamma_t \cdot K^T(y - Kx_0^{pred})$
4. Continue DDIM step with corrected x_0^{post}

Posterior Correction Weight:

$$\gamma_t = \frac{\sigma_{prior}^2}{\sigma_y^2 + \sigma_{prior}^2}$$

where $\sigma_{prior}^2 = 1 - \alpha_t$ and σ_y is measurement noise

Implementation of DPS

Algorithm Steps:

1. Initialize x_t with random noise
2. Predict noise $\epsilon_\theta(x_t, t)$ using UNet
3. Compute $x_0^{pred} = \frac{x_t - \sqrt{1-\alpha_t}\epsilon_\theta}{\sqrt{\alpha_t}}$
4. Apply DPS correction with gradient step
5. Update to next timestep using DDIM

RED-Diff: Regularization by Denoising Diffusion

- **RED-Diff** is an optimization-based method for solving inverse problems using diffusion models
- Key idea: combine data fidelity loss with regularization from denoising diffusion priors
- Uses gradient-based optimization to reconstruct images by minimizing combined objective

Algorithm Overview:

1. Initialize reconstruction μ from adjoint operation: $\mu = K^T(y)$
2. For each timestep t: sample noise and create noisy version x_t
3. Compute data fidelity loss: $\mathcal{L}_{obs} = \frac{1}{2\sigma_y^2}\|K(\mu) - y\|^2$
4. Compute regularization loss using diffusion model guidance
5. Update μ using gradient descent on combined loss

Combined Objective:

$$\mathcal{L} = \mathcal{L}_{obs} + \lambda \cdot w_t \cdot \mathcal{L}_{reg}$$

where w_t is a time-dependent weighting strategy

Implementation of RED-Diff

Algorithm Steps:

1. Initialize $\mu \leftarrow K^T(y)$ with gradient enabled
2. Sample noise $\epsilon \sim \mathcal{N}(0, I)$ and create $x_t = \sqrt{\alpha_t}\mu + \sqrt{1 - \alpha_t}\epsilon$
3. Predict noise $\epsilon_\theta(x_t, t)$ using UNet
4. Compute regularization loss: $\mathcal{L}_{reg} = w_t \cdot \|\epsilon_\theta - \epsilon\|^2$
5. Update μ using Adam optimizer on total loss
6. Repeat for all timesteps in reverse order

Weighting Strategies: linear, sqrt, square, log, clip, const

Image Degradation

- **Library**: IPPy
- **Degradation Type**: Motion Blur
- **Implementation**: Linear operator approach
- **Purpose**: Create realistic inverse problems for model evaluation

Motion Blur Configuration

- **Operator**: `operators.Blurring`
- **Parameters**:
  - Image shape: (128×128) pixels
  - Kernel type: `"motion"`
  - Motion angle: 45°
  - Kernel sizes tested: $[5, 7, 9, 11, 13, 15]$ pixels
- **Mathematical Model**:

$$y = K(x) + n \tag{1}$$

where K is the blur operator, x is the clean image, and n is noise

Evaluation Methodology

- **Dataset**: Validation set from the before-mentioned dataset
- **Degradation**: Motion blur with varying kernel sizes
- **Methods Compared**:
  - DPS (Diffusion Posterior Sampling)
  - RED-Diff (Regularization by Denoising)
- **Evaluation Metrics**:
  - PSNR (Peak Signal-to-Noise Ratio) in dB
  - SSIM (Structural Similarity Index)

Setup and Configuration

- **Motion Blur Configuration**:
  - Kernel sizes tested: [5, 7, 9, 11, 13, 15] pixels
  - Motion angle: 45°
  - Kernel type: Linear motion blur
- **Evaluation Protocol**:
  - 5 images per kernel size for statistical reliability
  - Batch size: 1 (individual image processing)

Metric Computation Process

- **For each test image**:
  1. Load ground truth image x_{gt}
  2. Apply motion blur: $y = K(x_{gt})$
  3. Reconstruct using DPS: $x_{dps} = \text{DPS}(y, K)$
  4. Reconstruct using RED-Diff: $x_{red} = \text{RED-Diff}(y, K)$
  5. Compute metrics: $\text{PSNR}(x_{gt}, x_{rec})$, and $\text{SSIM}(x_{gt}, x_{rec})$

Figure 4 shows the PSNR values for both methods across different kernel sizes.

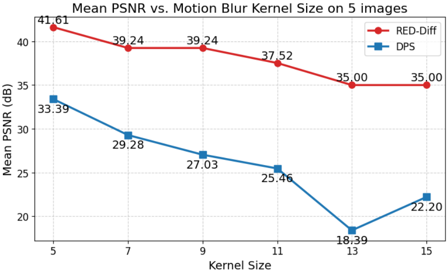


Figure 4: PSNR values for DPS and RED-Diff across different kernel sizes.

SSIM

Figure 5 illustrates the SSIM values for both methods across different kernel sizes.

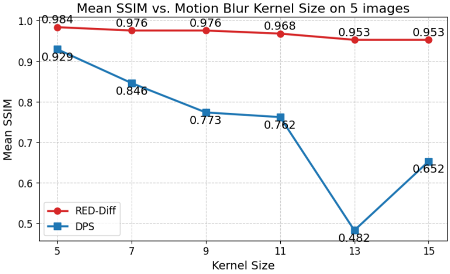


Figure 5: SSIM values for DPS and RED-Diff across different kernel sizes.

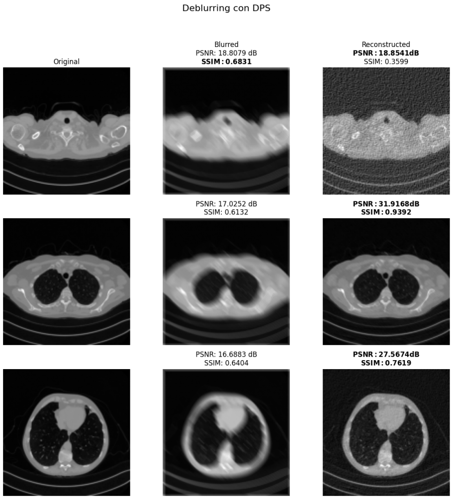
- **Trend Analysis**:
  - Both methods show performance degradation with larger kernels, even though the RED-Diff method generally outperforms DPS.
  - PSNR and SSIM correlate with blur severity

Results - Qualitative Analysis

- **Qualitative Assessment**:
  - Side-by-side comparisons: Original $\rightarrow$ Blurred $\rightarrow$ Reconstructed
  - Visual quality correlation with quantitative metrics
  - Edge preservation and artifact analysis
- **Key Findings**:
  - RED-Diff better preserves fine details
  - RED-Diff shows less artifacts compared to DPS
  - RED-Diff keeps consistent performances across different kernel sizes
  - DPS is more sensitive to kernel size variations, as shown in the PSNR and SSIM results
- **Visual Results**: To better understand the performance of both methods, we will show visual results for both DPS and RED-Diff a visual comparison had been conducted and reported on kernel size equal to 7 in the next slides.

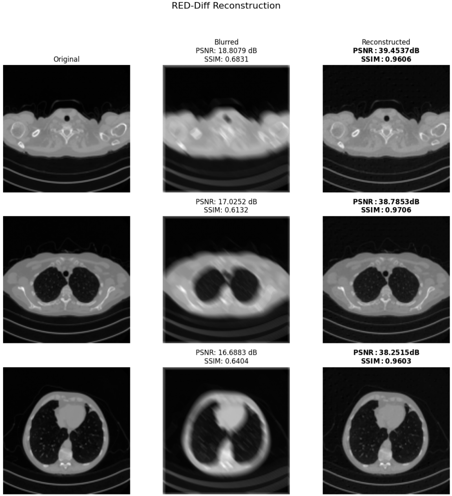
Visual Results Summary - DPS

Figure 6 presents visual comparisons of the original, blurred, and reconstructed images for both methods across different kernel sizes using DPS.



Visual Results Summary - RED-Diff

Figure 7 presents visual comparisons of the original, blurred, and reconstructed images for both methods across different kernel sizes using RED-Diff.



Scaling to 256x256

- We explored training at a larger target size of 256×256 pixels.
- Due to hardware and Colab limits, full 256×256 training proved very slow.
- We expect comparable results at 256×256 because:
  - Model architecture and training pipeline remain the same.
  - Reliable performance at 128×128 gives confidence in scaling up.
- If 256×256 runs underperform, we can still approach 128×128-level results by:
  - Leveraging our robust data augmentation to enrich the larger-scale inputs.
- The implementation is flexible, so once faster hardware or longer runtimes are available, we can re-run full 256×256 experiments with minimal changes.

Thank you for your attention