CS270B-Advanced Digital Image Processing
ShanghaiTech University
Spring 2025

Homework 2 Image SR & Denoising

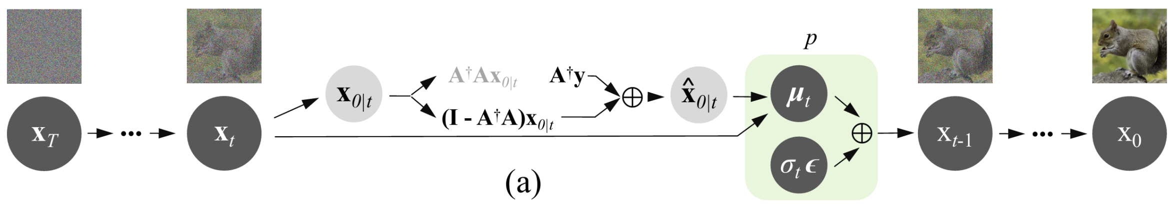
Submission DDL: 2025/04/03 23:59

Please complete the code in the attachment to accomplish the following tasks. Submit a brief report in English detailing your implementation and experimental results. The report should be in **PDF format**, using any template, but **not exceeding 10 pages**.

1 Image Super-resolution

1.1 Diffusion Model (20 points)

Consider diffusion-based models for image super-resolution work. Here We provide a Diffusion Model **(DDNM)** [1]. It utilizes the ability of the diffusion model to generate high-quality samples, while constraining the generation process by introducing a zero-space projection, allowing it to better solve inverse problems such as image denoising and super-resolution.



(a)

In this section, Please complete the following tasks:

- Implement **DDNM** framework according to the sample code, and consider how to validate the effectiveness of the model.(Hint: You should perform unconditional denoising and calculate metrics like **PSNR/SSIM**.)
- Leverage its capabilities to achieve image super-resolution at multiple scaling factors, including **2×, 4×, 8×, and 16×**, and report the quantitative and qualitative results of super-resolution and compare them with **one** traditional interpolation method (*e.g.*, `nearest`, `cubic`, `bilinear`, etc.).

  (Hint: You might find some assistance from github.com/yinboc/liif and `OpenCV` package.)

2 Image Denoising

2.1 Noise Type (20 points)

Consider our discussions about image noise modeling in the lecture. Here we use $\mathbf{x}$ to represent a clean image and $\mathbf{y}$ to denote the noisy image after being corrupted by noise. Please answer the following questions.

- ***Gaussian noise***. Please give a formulation of a noisy image corrupted by Gaussian noise with noise level σ. Then implement it in your code.

- ***Poisson noise***. Please give a formulation of a noisy image corrupted by Poisson noise with noise level λ. Then implement it in your code.

- ***The difference***. As observed, Gaussian noise and Poisson noise differ significantly. Please explain the primary differences between the two.

2.2 Noise2Noise [2] (30 points)

In our previous class discussion, we touched upon the Noise2Noise framework, a novel approach to training denoising neural networks. This methodology allows for the training of a denoising model using pairs of independently noisy observations of the same scene, eliminating the need for clean images. Please implement and train a denoising network following the Noise2Noise framework. You may utilize the example Set12 dataset or any image of your preference.

- Evaluate the denoising performance of your model on the Set12 dataset (or any image you like), which has been artificially corrupted with both additive Gaussian noise ($\sigma = 25$) and Poisson noise ($\lambda = 30$). Your assessment should encompass both quantitative (PSNR/SSIM) and qualitative analyses.

- Compare the denoising results with those from conventional denoising methods, such as BM3D and Non-local Mean (implementations of both methods can be easily found on the Internet).

2.3 Blind Spot Network (30 points)

Consider the self-supervised denoising methods we discussed in class. Noise2Void [3] proposed a blind spot network (BSN) denoising method based on the assumption that pixel signals in the image are spatially correlated in the image, and noise signals are spatially independent with zero-mean. Noise2Self [4] shared the same idea. In the training schedule, they first mask a few random pixels of the masked noisy image, and the network takes the masked noisy image for input. The loss function is computed on the masked pixels between the network output and the unmasked noisy images.

- Implement the Noise2Self framework according to the sample code. Specifically, you only need to implement the function for masking pixels with zero value.

- Report the quantitative and qualitative results of the denoising result with Noise2Noise.

References

[1] Y. Wang, J. Yu, and J. Zhang, "Zero-shot image restoration using denoising diffusion null-space model," *arXiv preprint arXiv:2212.00490*, 2022.

[2] J. Lehtinen, J. Munkberg, J. Hasselgren, S. Laine, T. Karras, M. Aittala, and T. Aila, "Noise2noise: Learning image restoration without clean data," in *International Conference on Machine Learning*, pp. 4620–4631, International Machine Learning Society, 2018.

[3] A. Krull, T.-O. Buchholz, and F. Jug, "Noise2void-learning denoising from single noisy images," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2129–2137, 2019.

[4] J. Batson and L. Royer, "Noise2self: Blind denoising by self-supervision," in *International Conference on Machine Learning*, pp. 524–533, PMLR, 2019.