

Score-Based Denoising Diffusion Models for Photon-Starved Image Restoration Problems

Modern computer vision systems are increasingly required to operate in extreme conditions, including ultra-fast acquisition times, low illumination, long-range and unconventional environments. This has led to the development of quantum-enhanced imaging systems that exploit the particle nature of light to exceed the limitations of classical strategies. However, measurements from these advanced sensors are photon-starved and are dominated by non-Gaussian statistics, such as low-intensity Poisson, binomial, or geometric noise as illustrated in Figure 1. Restoring photon-starved images requires specialized techniques. While conventional methods range from detail-limited variational approaches to computationally expensive deep networks, Plug-and-Play (PnP) frameworks offer a flexible alternative, combining a pre-trained data-driven prior encoded by a deep neural network, with an explicit data fidelity term specified during test time. However, state-of-the-art PnP methods using pre-trained denoising diffusion models as the prior rely on Gaussian approximation. This assumption proves highly inaccurate for the severe Poisson, binomial, and geometric statistics inherent to photon-starved imaging, resulting in poor reconstruction quality.

To address this critical gap, we introduce the first PnP denoising diffusion method for photon-starved image restoration. Instead of relying on the Gaussian approximation, our method enforces data consistency with the true physical noise model. We guide the sampling of a Denoising Diffusion Implicit Model (DDIM) with a proximal step corresponding to the negative log-likelihood. The proximal optimization problem for the non-Gaussian models lacks a closed-form solution and is subject to positivity constraints. To address this, we introduce a stabilized approximation of the likelihood, which enables the problem to be solved efficiently using any iterative solver. Crucially, our proposed proximal step is firmly nonexpansive. This guarantees better robustness and stability compared to state-of-the-art methods that rely on explicit gradient steps (e.g. Diffusion Posterior Sampling). Meanwhile, the use of DDIM breaks the standard Markovian process, resulting in a significant acceleration of the sampling efficiency.

We demonstrate the state-of-the-art performance of our method on a series of challenging photon-starved imaging experiments on the FFHQ and ImageNet datasets, with signal levels as low as one photon per pixel. For binomial denoising and geometric inpainting, our approach significantly outperforms all available alternatives across every evaluated metric (PSNR, SSIM, and LPIPS). For Poisson deblurring, it achieves higher PSNR and SSIM scores, without compromising perceptual quality.

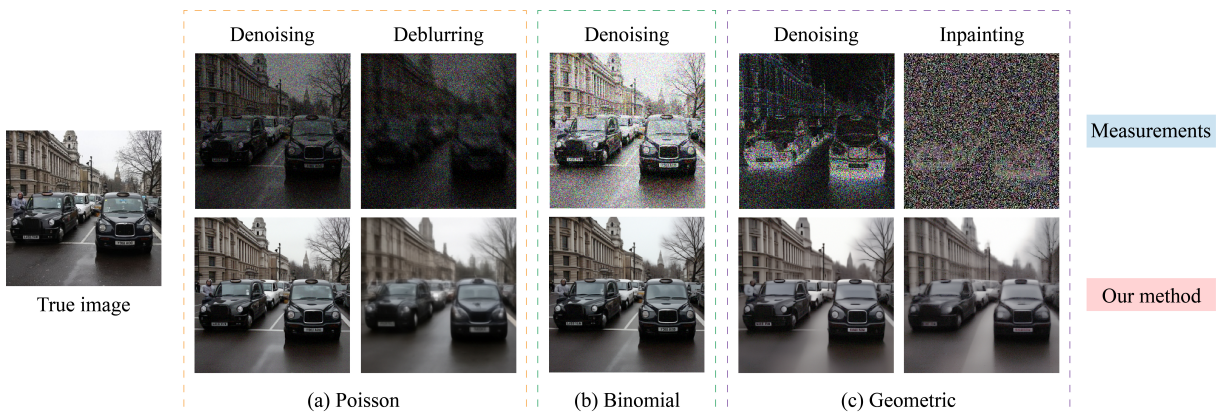


Figure 1: Restoration examples of our method: ground truth, measurements, and restored images.