EMPIRICAL BAYESIAN PNP IMAGING WITH DENOISING DIFFUSION PRIORS

CHARLESQUIN KEMAJOU MBAKAM

Diffusion models have recently emerged as a powerful tool for addressing inverse problems across numerous field, particularly in imaging. These models mainly stem from two stochastic processes: the reverse Ornstein-Uhlenbeck process and the Langevin diffusion process. Although the solutions from these diffusion models are often impressively realistic, they sometimes lack consistency with actual measurements due to the challenges of likelihood intractability and the associated required approximations. On the other hand, leveraging a Langevin process avoids the issue of intractable likelihood but leads to lower-quality restorations and requires more computational time. In this presentation, we introduce a novel approach for image restoration tasks that circumvent the intractability of the likelihood and significantly reduces the computational expenses. This is achieved by incorporating a Denoising Diffusion Probabilistic Model (DDPM) into an empirical Bayesian plug-and-play framework. The proposed method simultaneously calibrates key hyper-parameters of the model and derives the model's posterior mean from a single measurement. Extensive experiments on image deblurring, super-resolution, and inpainting demonstrate the effectiveness and superiority of the proposed method when compared to leading state-of-the-art techniques.