A Comparison of Learning-Based Techniques for Image-Denoising and Reconstruction

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Motivation

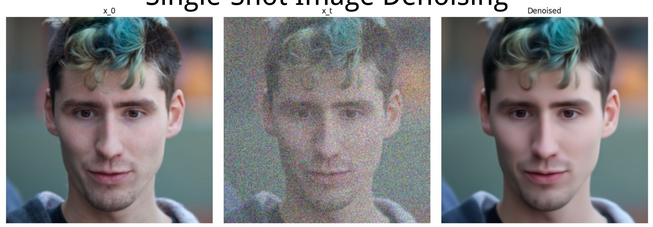
There are a variety of phenomena (thermal noise, photon noise, etc.) which can lead to corrupted image data. Thus the recovery of a clean image from corrupted data is a worthwhile problem to solve. While there exist many classical techniques for image denoising and recovery, they all have significant limitations with regards to the type of noise which can be removed as well as the quality of that removal. For this reason, this work explores learning-based methods for accomplishing the same task.

Background

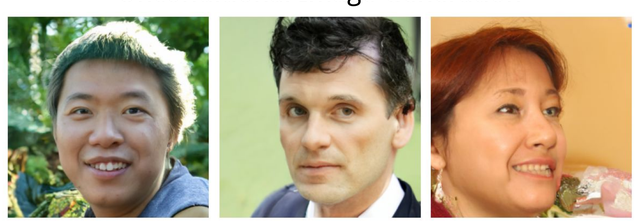
The general approaches behind all learning-based image denoising fall into two categories: image prediction and noise prediction. Image prediction methods attempt to take a noisy image, then predict what the clean image was. Noise prediction methods take a noisy image and then predict the noise which was added to the clean image. Generally, the noise prediction approach tends to work better. Additionally, the noise prediction approach allows for the opportunity to remove all the noise, add back some of the noise and then repeat. This procedure tends to produce even better results. This approach also allows for novel image generation. An image consisting of zero-mean gaussian noise can be used as input thereby yielding a novel image.

Results

Single-Shot Image Denoising



Unconditional Image Generation



ScoreALD Image Reconstruction

SDEdit Image Reconstruction

DPS Image Reconstruction

The included images are meant to allow the reader to discern the perceptual differences between various reconstruction techniques. In general, although the PSNR of an image may appear to be acceptable there may exist artifacts which significantly degrade the perceptual quality.

Quantitative Results

	Single-Shot Noise Removal	SDEdit with DDPM	ScoreALD	Diffusion Posterior Sampling (DPS)
PSNR ↑	32.59	20.38	25.00	28.38
LPIPS ↓	0.10	0.20	0.11	0.05

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