

Better or Undesired? Performance of Generative Models in Denoising

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Abstract—Image denoising has been a popular topic in the field of image processing, and efforts have been made to produce higher-quality denoised images. With more generative models invented in the past decades, this paper experiments with the performance of the generative adversarial network (GAN) [1] and denoising diffusion probabilistic model (DDPM) [2] in image denoising. The performance of the models will be measured by the time cost of the denoising process, and the quality of the denoised image. Peak signal-noise ratio (PSNR) and structural similarity (SSIM) will be used as metrics to measure image quality. To further explore the performance of these models, the tests will include images with different levels of Gaussian-distributed noises, Poison-distributed noises, and mixes of the two. Images of different frequencies will also be used to test how the models perform on denoising image details.

Index Terms—Computational Photography, Denoising, Generative Models, Generative Adversarial Networks, Denoising Diffusion Probabilistic Models

1 INTRODUCTION AND MOTIVATION

IMAGE denoising is a popular topic for image processing. Its importance and popularity could be reflected in the diversity of denoising models. These models propose methods from very different perspectives. Some models mitigate noises by consulting neighbouring areas or similar areas of the image to interpolate the real value of the pixels, such as the bilateral filter [3] and the non-local means filter [4]. While these filters are efficient in denoising, the processed image could suffer from blurry artifacts as the filters discourage sharp edges.

As deep learning went viral, neural networks are also applied to the topic of denoising. For instance, Zhang et al. proposed DnCNN model [5], which uses a neural network and batch normalization to fit the noises and subtract them from the image. Still, DnCNN might also leave noticeable artifacts in the image. This problem could somehow be mitigated by the deep image prior model as it could achieve super-resolution for the image and therefore keep the image details [6]. However, the deep image prior model relies on an early stopping for the Unet fitting process, which means a deviated estimation of the number of iterations could lead to either removing image details or leaving noises in the image. In the search for a denoising model that does not suffer from any of the problems previously mentioned, we turn to the generative models to explore the possibility.

In the past decade, multiple generative models were invented to generate images based on a distribution of images [1], [2]. After appropriate training, certain generative models could generate high-quality images based on random-noise-like inputs. Since these models could generate images

from complete noises, it is intuitive to believe that these models could also generate images from noisy images with semantics. That is what this paper will experiment with - could generative models successfully denoise images while keeping the original semantics of the image?

2 RELATED WORK

The publication of generative adversarial networks (GAN) in 2014 [1] started a new fashion of generative models. GAN consists of a generative network G and a discriminative network D . While D is trained to distinguish if an image is generated by G , G is trained to generate high-quality images to confuse D . Since D is trained on certain datasets, the images generated by G are also expected to be in the same distribution as the training dataset. Following the original GAN model, multiple variants of GAN were proposed, such as InfoGAN [7] and StyleGAN [8]. However, the features extended by these models are not required for the purpose of denoising, hence we will only adopt the original GAN proposed by Goodfellow et al. [1] for this work.

Another model that is considered to outperform GAN in terms of the quality of images synthesis is the denoising diffusion probabilistic model (DDPM) [2], [9]. DDPM is trained by continuously adding noises to clear images in the dataset until the images become isotropic-like noises and then learning a distribution to find the priors of the noisy images. When a noise-only image is passed to a trained DDPM model, the model will take denoising steps in iterations and finally generate an image with semantics. Therefore, it is intuitive to believe that DDPM will also perform denoising on noisy images.

3 PROPOSED METHOD

Since this work is mainly regarding the performance of existing models instead of inventing new models, open-

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source implementations of GAN and DDPM will be adapted and cited for experiments.

The key target of this experiment is to test if these generative models actually achieve well-denoised results, so noisy images will be fed into these models. To quantitatively compare the image quality, we will prepare in-distribution noise-free images as the ground truth. Then, noises of different types (e.g., Gaussian-distributed and Poisson-distributed) and levels (e.g., varied parameters for the distribution of noises) will be added to the ground truth to produce the noisy images. After training, the models will process the noisy image and output the denoised results. Finally, the denoised results will be compared to the ground truth using several metrics (e.g., PSNR and SSIM). These two models will also be compared with other denoising methods such as the bilateral filter [3] and the deep image prior model [6].

Aside from the varied noises, there are other variables that could be manipulated to test these models from other perspectives. For example, as image denoising is a relaxation of image generation, we could reduce the size of the training dataset to test if the few-shot versions of these generative models could already perform denoising well enough. Meanwhile, we could also test if the models could handle out-of-distribution noisy images. Since many denoising models leave blurry artifacts for the high-frequency parts of the images, ground truth with different frequencies could also be used to see if these generative models are free of such undesired artifacts.

4 TIMELINE AND MILESTONES

Week 1 (Nov 13):

Complete research on DDPM and explore the application. Select the appropriate models. Adjust our plan according to the feedback.

Week 2 (Nov 20):

Prepare the ground truth and noised images. Implement, modify and train the models to meet the denoising purpose.

Week 3 (Nov 27):

Collect and compare the results of different approaches (GAN, DDPM, bilateral filter, and deep image prior model). Analyze the reason behind different performances and raise a conclusion for future improvements.

Week 4 (Dec 4):

Gather all the results and thoughts. Complete the final report, poster, and presentation.

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