Deblurring Using Conditional Generative Networks

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Project Statement

We aim to generate a high-quality sharp image from the given non-uniform blind blurred image. As the family of deblurring problems mainly go into two types: blind and non-blind deblurring, this project focuses on the former one, which means blur kernels or functions are unknown and can hardly be derived. Meanwhile, we do not assume the potential blur is partially uniformed or locally linear since most of blurring cases in reality are complex.

Approaches

Early work mainly focused on deriving and estimating the blur functions and then performing the deconvolution operation on the image to get that target output. Later on, with the help of CNNs, people can have more choices to approximate the blur functions. Recently, some kernel-free end-to-end approaches were proposed, of which some of it are based on special designed multi-scale convolutional neural networks, and some are based on generative adversarial networks (GANs). GANs are known for the ability to preserve texture details in images, create solutions that are close to the real image manifold and look perceptually convincing.

In this project, inspired by recent work on image-to-image translation by conditional GANs, we treat deblurring as a special case of such image-to-image translation. Thus, we want to address this problem based on the conditional GANs, and potentially provide some positive modifications when implementing and training the models.

Conditional GANs are generative models derived from GANs. Different from learning a mapping from random noise vector z to output image y, conditional GANs learn a mapping from observed image x and random noise vector z, to y, which is G: (x, z) -> y. In our case, the generator G is trained to learn how to produce the deblurred image corresponding to the input non-uniform blind blurred image that cannot be distinguished from ground truth images by an adversarial trained discriminator D, which is trained to do as well as possible at detecting the generator's fake images.

Evaluations

When doing deblurring tasks, there are typically three ways to evaluate the performance:

1. Compare with benchmarks using some criteria, such as PSNR or SSIM
2. Evaluate the improvement of precision of object detection in the images
3. Undertake image Turing test, which is to ask human whether they can distinguish the generated deblurred images and the realistic sharp images.