Evolutionary Super-Resolution

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ABSTRACT

Super-resolution increases the resolution of an image. Using evolutionary optimization, we optimize the noise injection of a super-resolution method for improving the results. More generally, our approach can be used to optimize any method based on noise injection.

CCS CONCEPTS

• **Theory of computation → Optimization with randomized search heuristics**.

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1 INTRODUCTION

Noise injection is widely used in deep learning: it consists in adding noise for robustifying the training. Noise is usually added only at training time - we show that we can also inject noise at inference time, at least when we have a proxy for the performance. For example, we can use quality estimation by supervised deep learning [6], or the discriminator of a GAN, for estimating the quality of GAN outputs: we do this in the case of super-resolution GAN.

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2 METHODS

2.1 Noise injection in machine learning

Noise injection [17] consists in robustifying a training in machine learning by adding noise at training time. The noise is typically set to 0 at inference time for optimal results.

2.2 Generative adversarial networks (GANs)

Recently, GANs became prevalent in generative machine learning. They are currently the main tool for generating images similar to a given dataset.

2.3 Super-resolution (SR)

SR is the art and science of generating high resolution images from low resolution data. SR is ubiquitous in medical imaging [4, 11], security [9, 14] and other computer vision tasks [3, 5, 10, 16]. SR-GAN with noise injection is presented in Fig. 1.

2.4 Quality estimation

Various measures exist for measuring the quality of images [2, 13, 19]. It was recently proposed to use supervised deep learning [6]. Such a tool allows estimating the quality without any higher quality reference - therefore, it can be used for estimating if adding a given noise injection improves or deteriorates an image, without having such a target image available.

2.5 SR-GAN

Noise injection was applied to GAN and their super-resolution variants [8, 12, 15, 19], leading to the state of the art [13].

3 OUR ALGORITHM

Our method is as follows:

(1) Parameters: a super-resolution GAN, a quality estimator q.
(2) Train the super-resolution GAN as usual [13]. Get a mapping $HighResolution : LR \mapsto HR(LR) = g(LowResolutionImage = LR, z = 0)$, which creates a high resolution image HR given a low resolution image LR.

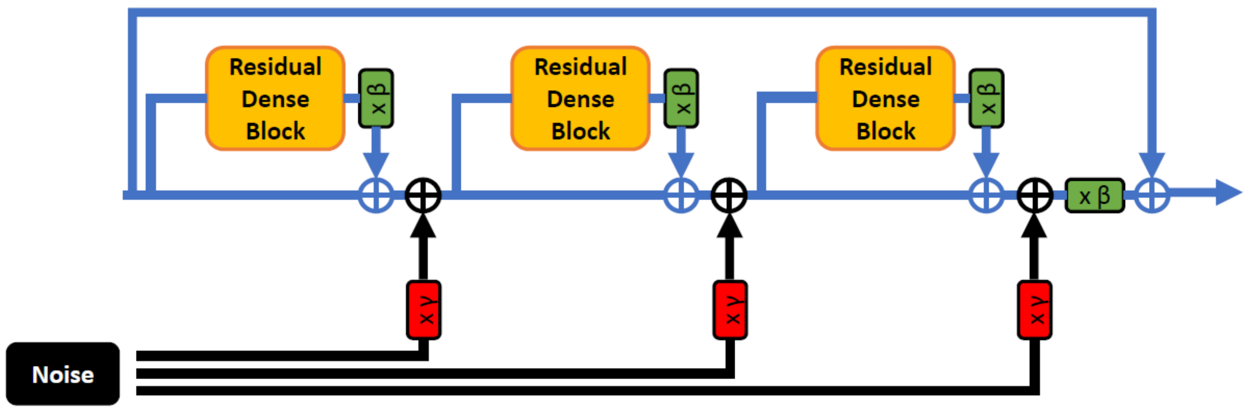

Figure 1: nESRGAN+: Gaussian noise is added after each residuals along with a learned scaling-factor.

(3) For each target image LR, Optimize z_{LR} such that $q(g(LR, z_{LR}))$ is approximately maximum.
(4) Return $g(LR, z_{LR})$, which is typically better than the classical $g(LR, 0)$.

4 EXPERIMENTAL RESULTS

We run our experiments on widely used super-resolution datasets: Set5 [1], Set14 [20], the PIRM Validation and Test datasets [2], Urban100 [7], and OST300 [18]. We validate our results using PIRM, which is not used in any of our criteria. For example, we get PIRM score 2.67 on Set5 (Enhanced Net gets 2.93, nESRGAN+ 3.31) and 2.66 on Set14 (Enhanced Net gets 3.02 and nESRGAN+ gets 2.80).

5 CONCLUSIONS

We propose a generic method for applying noise injection at inference time, as opposed to the classical method at inference time. This is easy with an evolutionary algorithm. This requires that we have an objective function, i.e. a proxy for quality. In the case of images, quality estimators, based on supervised deep learning, do exist. We performed experiments in super-resolution GANs. Our results outperform the state of the art.

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