Paper Review: PULSE: Self-Supervised Photo Upsampling via Latent Space Exploration of Generative Models

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About this paper

PULSE: Self-Supervised Photo Upsampling via Latent Space Exploration of Generative Models

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Abstract

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* denotes equal contribution

The primary aim of single-image super-resolution is to construct a high-resolution (HR) image from a corresponding low-resolution (LR) input. In previous approaches, which have generally been supervised, the training objective typically measures a pixel-wise average distance between the super-resolved (SR) and HR images. Optimiz-

1. Introduction







About this paper

- Published in the CVPR conference in 2020.
- Cited by 54 as of June 28, 2021
- Main goal is to create realistic high-resolution images of people's faces from very low-resolution images.

Introduction

1. Introduction



Figure 1. (x32) The input (top) gets upsampled to the SR image

Motivation

- High-resolution image data often difficult to obtain
- Consumer demand for high-resolution image capture higher than ever before
- Many downstream tasks require high-resolution images

IMAGE SUPER-RESOLUTION

Construct high-resolution (HR) images from corresponding low-resolution (LR) input

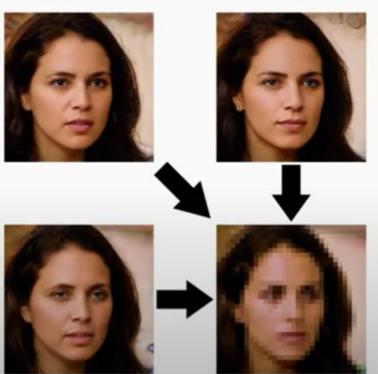
Challenges

 Problem of recovering true HR image depicted by an LR input inherently ill-posed

▶ Number of such images grows exponentially with scale factor

(Baker and Kanade 2000)

MANY HR images can correspond to same LR image



Goal

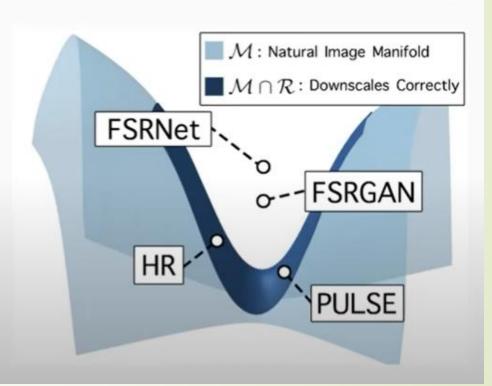
GOAL

Generate realistic images within the set of feasible solutions i.e., find points in $\mathcal{M} \cap \mathcal{R}$: points on \mathcal{M} that also downscale correctly

R: set of images that downscale correctly

Given $I_{LR} \& \epsilon > 0$, want $I_{SR} \in \mathcal{M}$ s.t. $\|DS(I_{SR}) - I_{LR}\|_p \le \epsilon$

DS(·): Downscaling operator

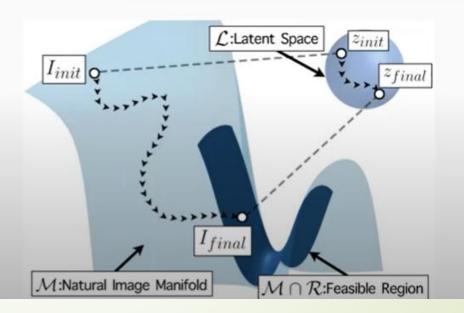


IDEA

Use generative models!

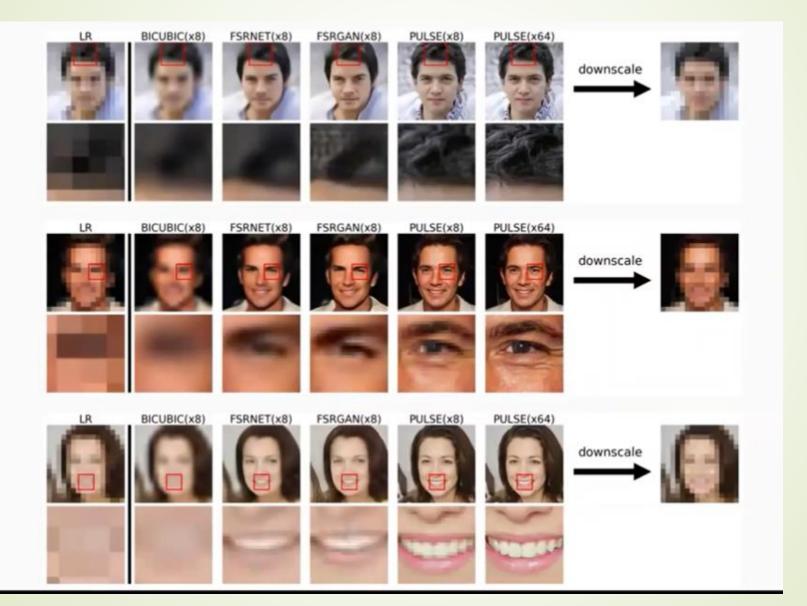
Given generator G with latent space \mathcal{L} (i.e., $G: \mathcal{L} \to \mathbb{R}^{M \times N}$), find $z \in \mathcal{L}$ with $\|DS(G(z)) - I_{LR}\|_p^p \le \epsilon$

Simply requiring $z \in \mathcal{L}$ does **NOT** guarantee $G(z) \in \mathcal{M}!$



Methods

- Used StyleGAN (Karras et al. 2019) as generative model due to capacity to generate sharp images
- Used 100 steps of spherical gradient descent with a learning rate of 0.4 starting with random initialization
- Can generate samples with global variation using new initializations and with fine-level variation using inherent stochasticity of StyleGAN



Noise Tolerence



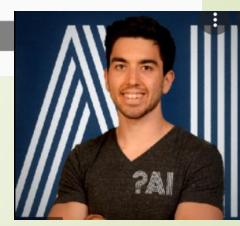
Contributions

- New problem formulation for super-resolution
- Novel algorithm for addressing the super-resolution problem
 - \triangleright Creates high-quality images at higher resolutions (1024 \times 1024 vs 128 \times 128) and higher scale factors (32 \times vs 8 \times) than state-of-the-art
 - ▶ Keeps up with advances in generative modeling without fundamental changes

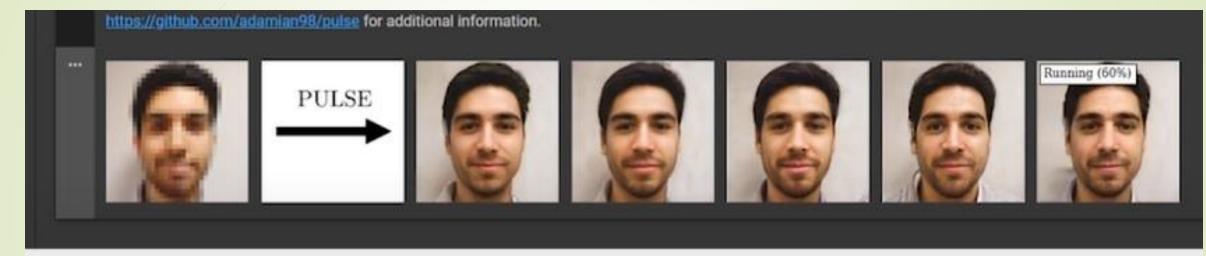
Issue with privacy and security (below is a notice from their blog page)

We have noticed a lot of concern that PULSE will be used to identify individuals whose faces have been blurred out. We want to emphasize that this is impossible - PULSE makes imaginary faces of people who do not exist, which should not be confused for real people. It will **not** help identify or reconstruct the original image.

We also want to address concerns of bias in PULSE. We have now included a new section in the paper and an accompanying model card directly addressing this bias.



Issue with privacy and security





Thank You!

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