Fast Bayesian Uncertainty Estimation and Reduction of Batch Normalized Single Image Super-Resolution Network

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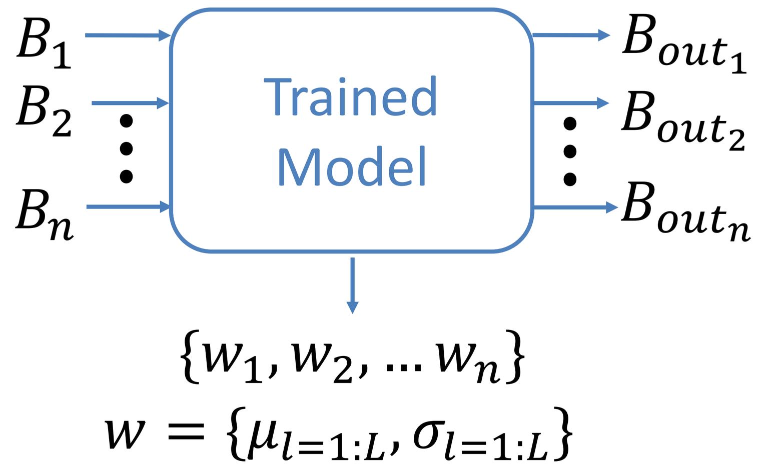
Introduction

- This paper adopts a Bayesian approach for estimating uncertainty associated with output and applies it in a deep image super-resolution (SR) model.
- We use the uncertainty estimation technique using the batch-normalization layer, where stochasticity of the batch mean and variance generate Monte-Carlo (MC) samples.
- The MC samples, which are nothing but different super-resolved images using different stochastic parameters, reconstruct the image, and provide a confidence or uncertainty map of the reconstruction.
- We propose a faster approach for MC sample generation, and it allows the variable image size during testing.
- This paper also proposes an approach to reduce the model's uncertainty for an input image, and it helps to defend the adversarial attacks on the image super-resolution model.

Uncertainty in Super-Resolution

- After training the deep super-resolution model with batch-normalization layer, calculate the stochastic parameters



- $B_1, B_2, \dots B_n$ are training batches
- $w_1, w_2, \dots w_n$ are stochastic parameters
- $\mu_{l=1:L}, \sigma_{l=1:L}$ are batch mean and batch variances respectively.
- L is the number of batch-normalization layer

- During testing, fed the low-resolution (LR) with different stochastic parameters to generate MC samples

- I_{test} is the test image
- $I_{out_1}, I_{out_2}, \dots. I_{out_n}$ are different MC samples or SR images, generated due to stochastic parameters, $w_1, w_2, \dots w_n$

Visualizing Uncertainty

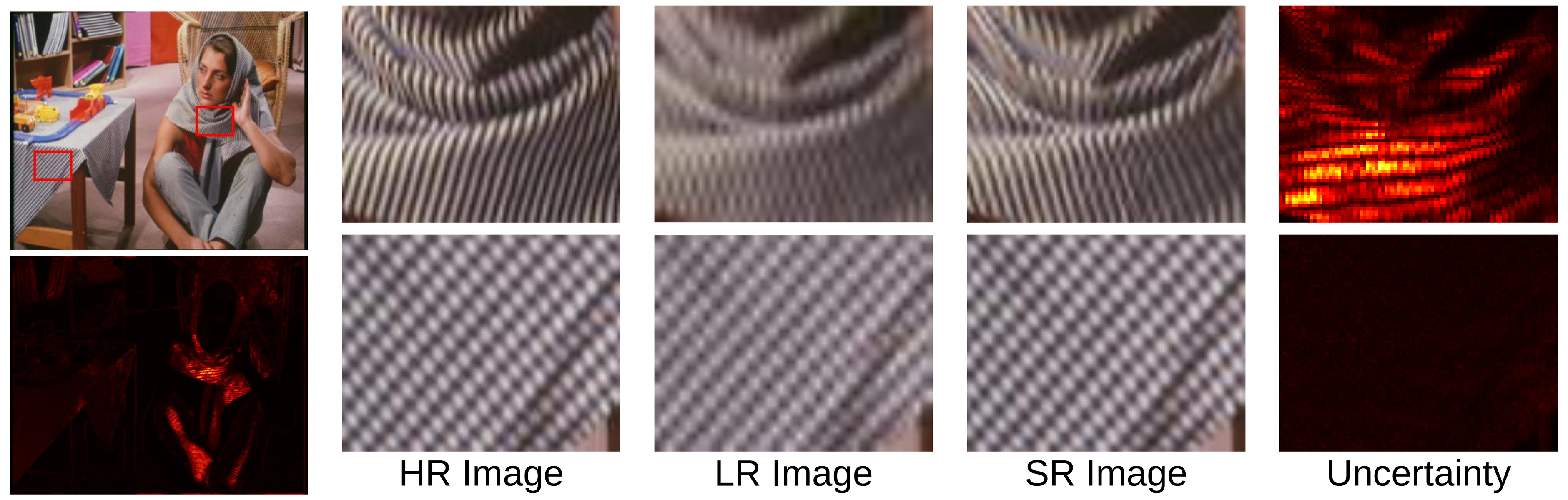


Fig. 1: Two cropped regions have different textures. We can observe from two patches that whenever the model fails to reconstruct the texture correctly, it leads to higher uncertainty.

Understanding Uncertainty

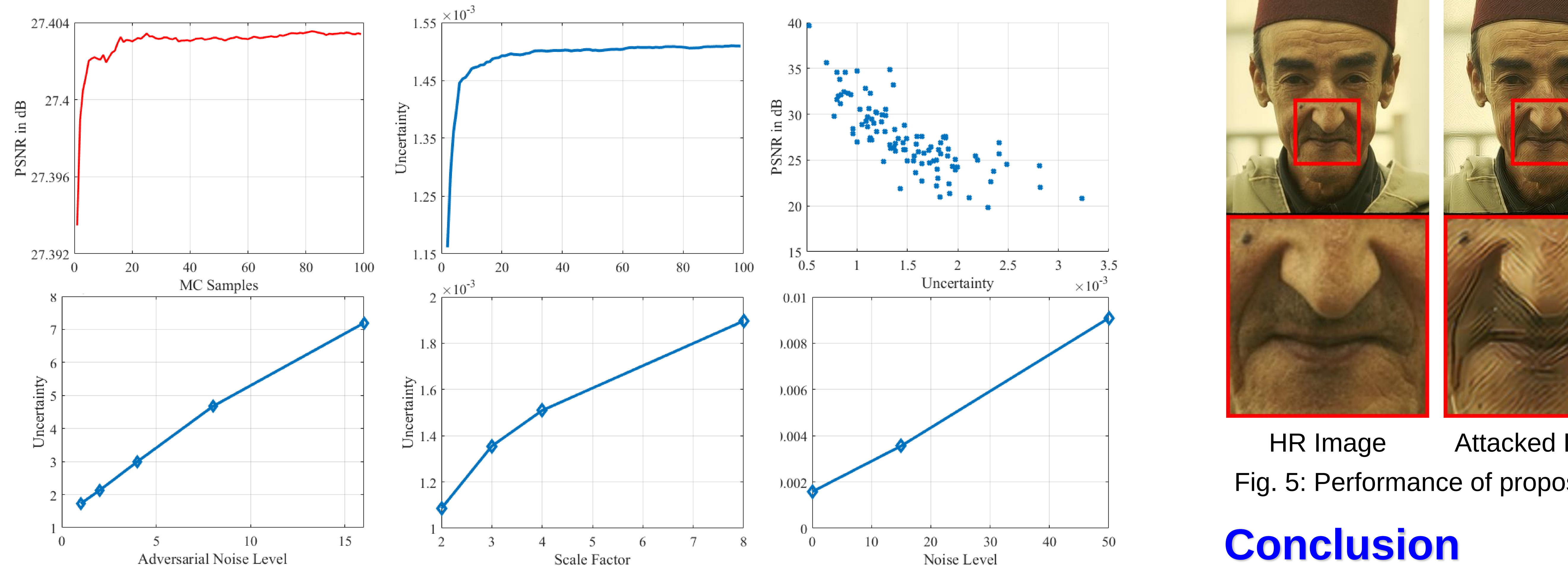


Fig. 2: Different experimental findings to understand the behaviour of uncertainty

Uncertainty Under Adversarial Attack

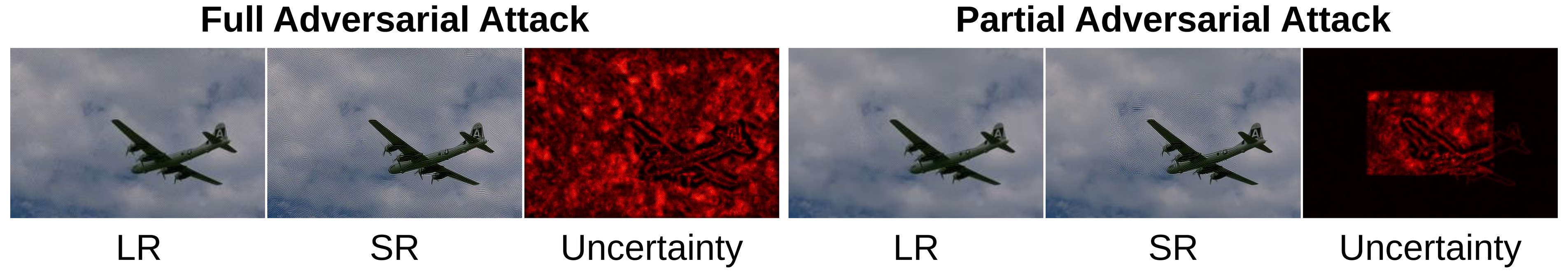


Fig. 3: Effect of adversarial attack on the deep SR model and behaviour of uncertainty

Adversarial Defense

- Error between two MC samples, $\mathcal{L} = \frac{1}{CWH} \sum (I_{SR}^{t_1} - I_{SR}^{t_2})^2$
- $\nabla\mathcal{L}$ is the gradient in each pixel of image
- $\mathfrak{N} = \mathfrak{N} + sign(\nabla\mathcal{L})$
- Do this for N number of MC sample sets
- $\frac{\mathfrak{N}}{N}$ is the average gradient sign direction for different pairs of MC samples
- $I'_{LR} = I_{LR} - m.\frac{\mathfrak{N}}{N}$
- m is the perturbation level
- I'_{LR} is the updated LR image

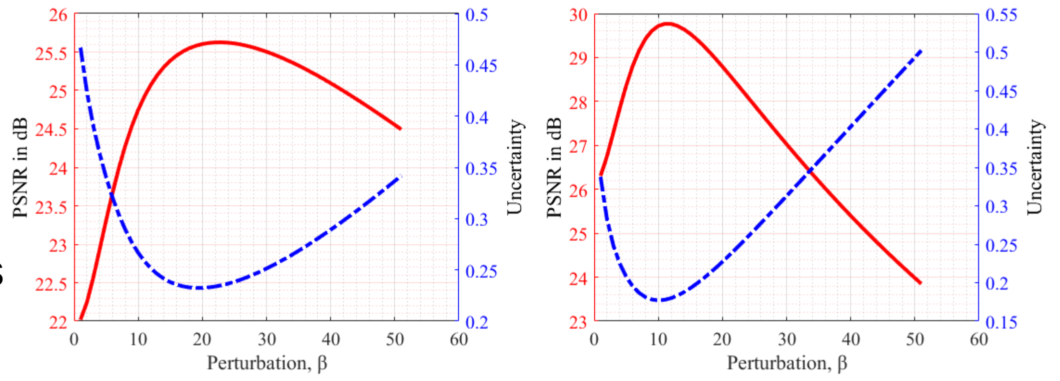


Fig. 4: Effect of perturbation level for adversarial defense on quality of the image and mean uncertainty of the corresponding image.

Visual Performance of Adversarial Defense

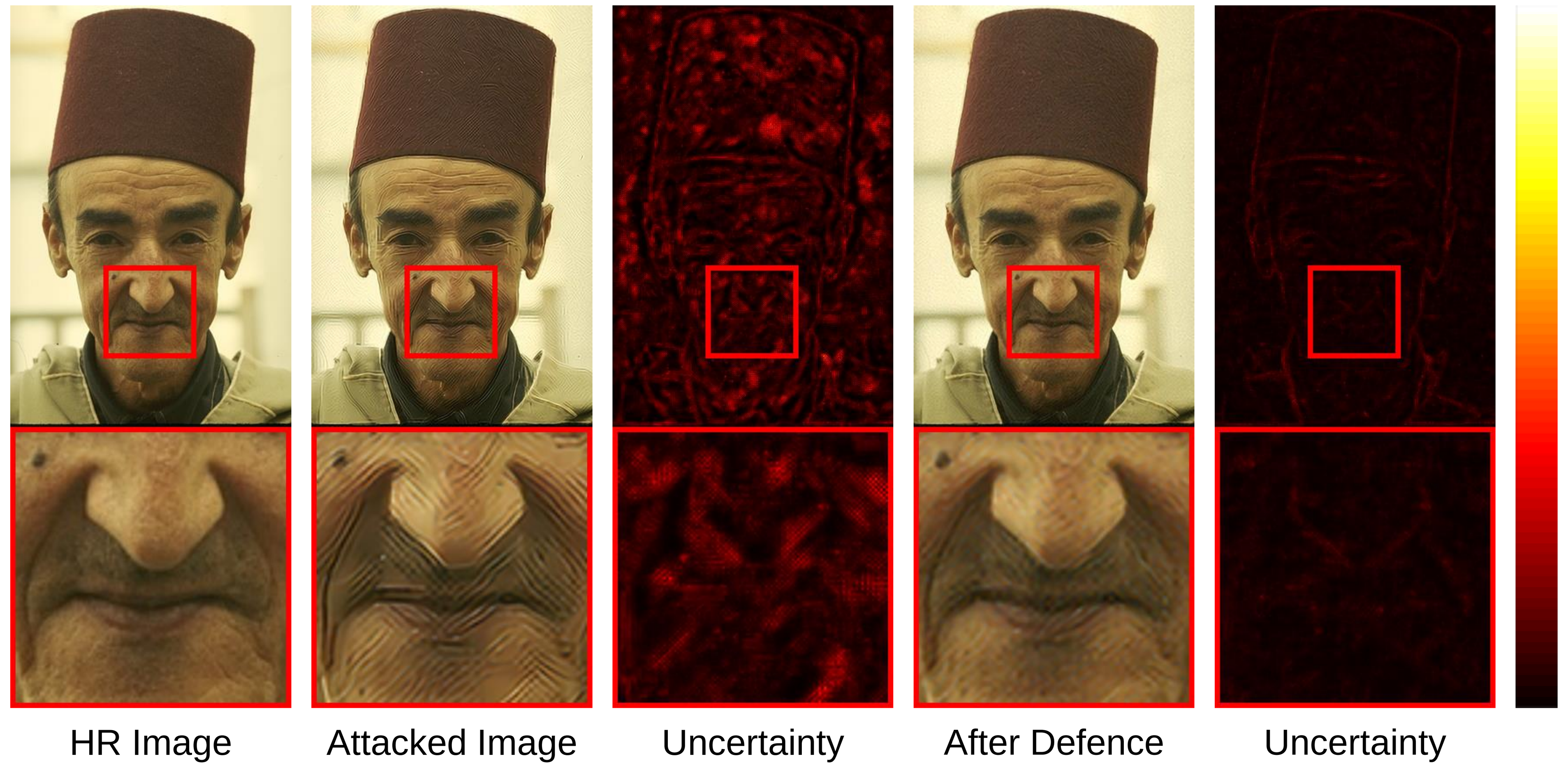


Fig. 5: Performance of proposed uncertainty reduction based adversarial defense mechanism

Conclusion

- The uncertainty map is like the signature map of the SR model, which indicates how good is the model in reconstructing images.
- The uncertainty reduction technique is useful for reconstruction performance improvement on noisy or adversarial LR images.
- A more efficient way to reduce uncertainty will make the neural network work admirably for out-of-distribution samples, and it will benefit in handling unknown image degradations.

Paper Webpage