Image Deblurring and Super-Resolution by Learning from Blurry and Low-Resolution Images Only

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July 9, 2024

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A bit of context

1st internship in Lyon

- worked out[1] a new method for image super-resolution

2nd internship in Edinburgh

- extended it to non-blind image deblurring

3rd internship back in Lyon

- looking for a new method for blind image deblurring

[1] thanks to my advisors' brilliant insights

Image deblurring

Goal

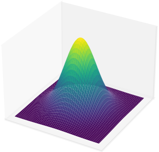
- Deblurring a dataset of blurry images $\{y_i\}_{i=1}^N$

Applications

- Astronomical imaging
- Microscopy
- Remote sensing
- Handheld camera photography

Imaging model

Blur Kernel

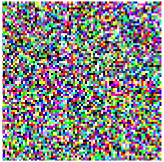


$*$

Sharp Image

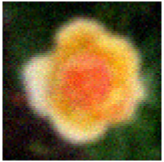
$+ \ \sigma \ \cdot$

Noise



$=$

Blurry Image



Or with symbols

$$y = k * x + \varepsilon \tag{1}$$

Constraints

- Known blur kernel (non-blind deblurring)
- Unknown blur kernel (blind deblurring)

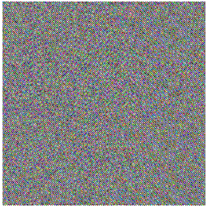
Ill-posedness of deconvolution

(Noiseless)

$$\hat{X} = K^{-1} \odot Y$$

(Slightly noisy)

$$\hat{X} = K^{-1} \odot Y$$



Different regularization approaches

The distributions must match

$$\hat{\mathcal{X}} = \mathcal{X} \tag{2}$$

- Consistency with blurry images is not enough!

Approaches

- Using a Bayesian prior on image distributions
- Using data for supervised learning
- Finding a way to do self-supervised learning
  - Equivariant imaging

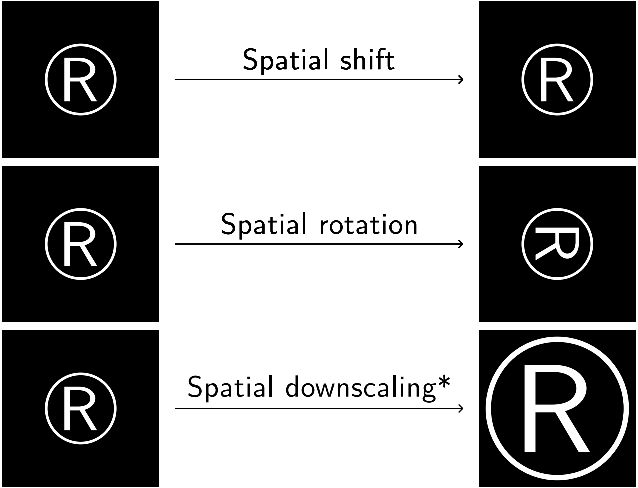
Invariance to scale

- Rescaled images of a rose remain images of a rose.

Or leaving pretty flowers aside...

$$T_g x \in \mathcal{X}, \ \forall x \in \mathcal{X}. \tag{3}$$

Spectral effect of spatial transforms



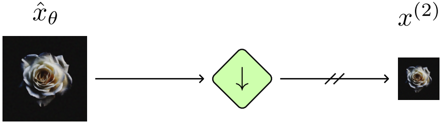
* (sic)

Scale-equivariant imaging

Every training epoch

- All the blurry images y are deblurred using the neural network f_θ

$$\hat{x}_\theta = f_\theta(y) \tag{4}$$



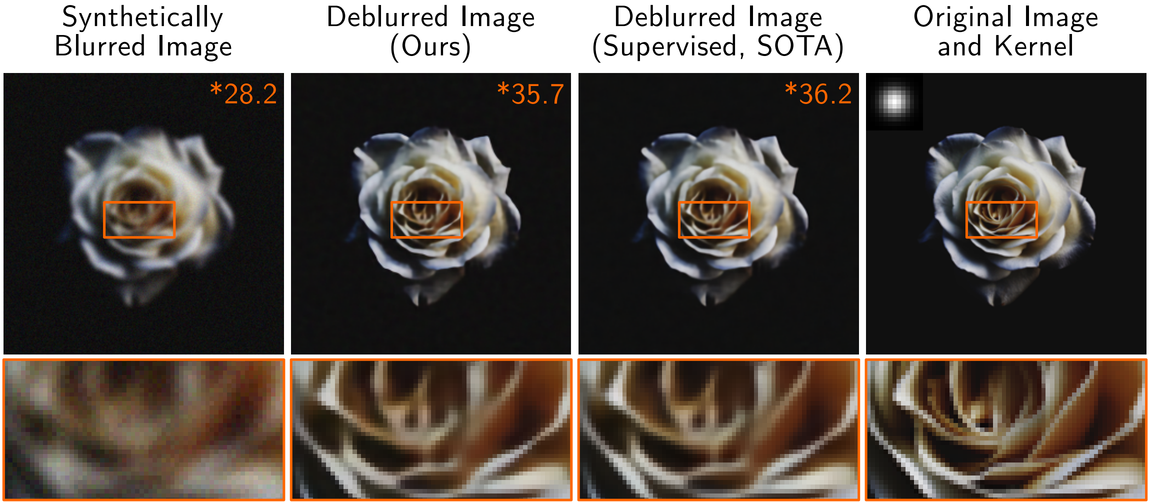
- Blurry images are synthesized from $x^{(2)}$ ...

$$y^{(2)} = k * x^{(2)} + \tilde{\varepsilon} \tag{5}$$

- ... and are then deblurred using f_θ

$$\hat{x}_\theta^{(2)} = f_\theta(x^{(2)}) \tag{6}$$

Results on Gaussian deblurring



Kernel: Gaussian (s.d. = 2px)

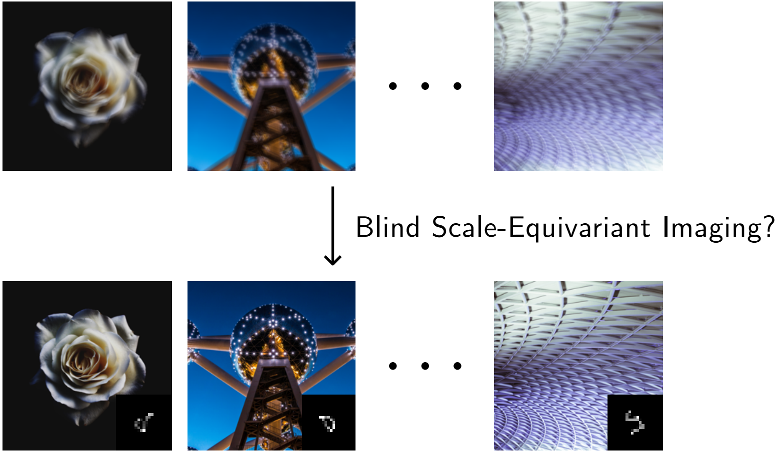
* PSNR

Results on Gaussian deblurring

	Kernel standard deviation (px)		
Deblurring method	1	2	3
Supervised learning (SOTA)	30.9	25.9	23.6
Self-supervised learning (ours)	30.3	25.9	23.7
No processing	26.4	22.8	21.2

Average PSNR between deblurred and reference images (dB)

What's coming next?



References

- Self-Supervised Learning for Image Super-Resolution and Deblurring, **Scanvic**, Davies, Abry and Tachella, arXiv, 2024
- Robust Equivariant Imaging: a fully unsupervised framework for learning to image from noisy and partial measurements, Chen, Tachella, Davies, CVPR 2022
- Equivariant Imaging: Learning Beyond the Range Space, Chen, Tachella, Davies, ICCV, 2021

Credits

Results for bicubic super-resolution

Super-Resolved Images

Bicubic	Ours	Supervised (SOTA)	High-Resolution Image

Sampling rate: 2

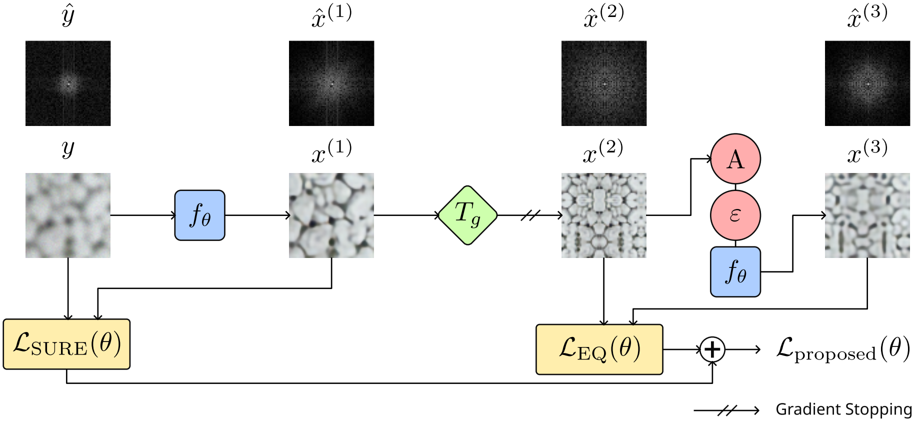
* PSNR

Results for bicubic super-resolution

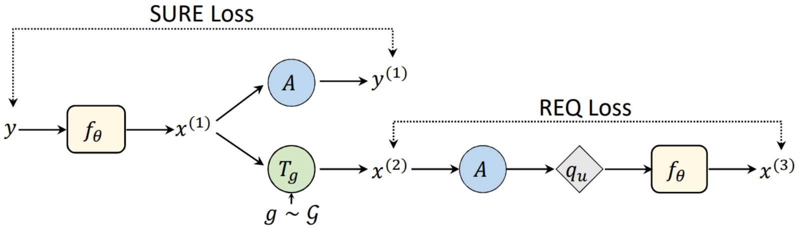
	Sampling rate		
Upsampling method	2	3	4
Supervised learning (SOTA)	29.2	24.3	22.7
Self-supervised learning (ours)	29.1	24.4	22.9
Bicubic upsampling	27.4	23.3	21.9

Average PSNR between upsampled and reference images (dB)

Scale-equivariant imaging



Equivariant Imaging



$$\mathcal{L}_{\text{REQ}}(\theta) = \sum_{i=1}^{N} \|x_i^{(3)}(\theta) - x_i^{(2)}(\theta)\|^2 \quad (4)$$

- Robust Equivariant Imaging, Chen, Tachella, Davies, CVPR 2022