Lecture 14 Image Debluring

(Introduction and Formulation)

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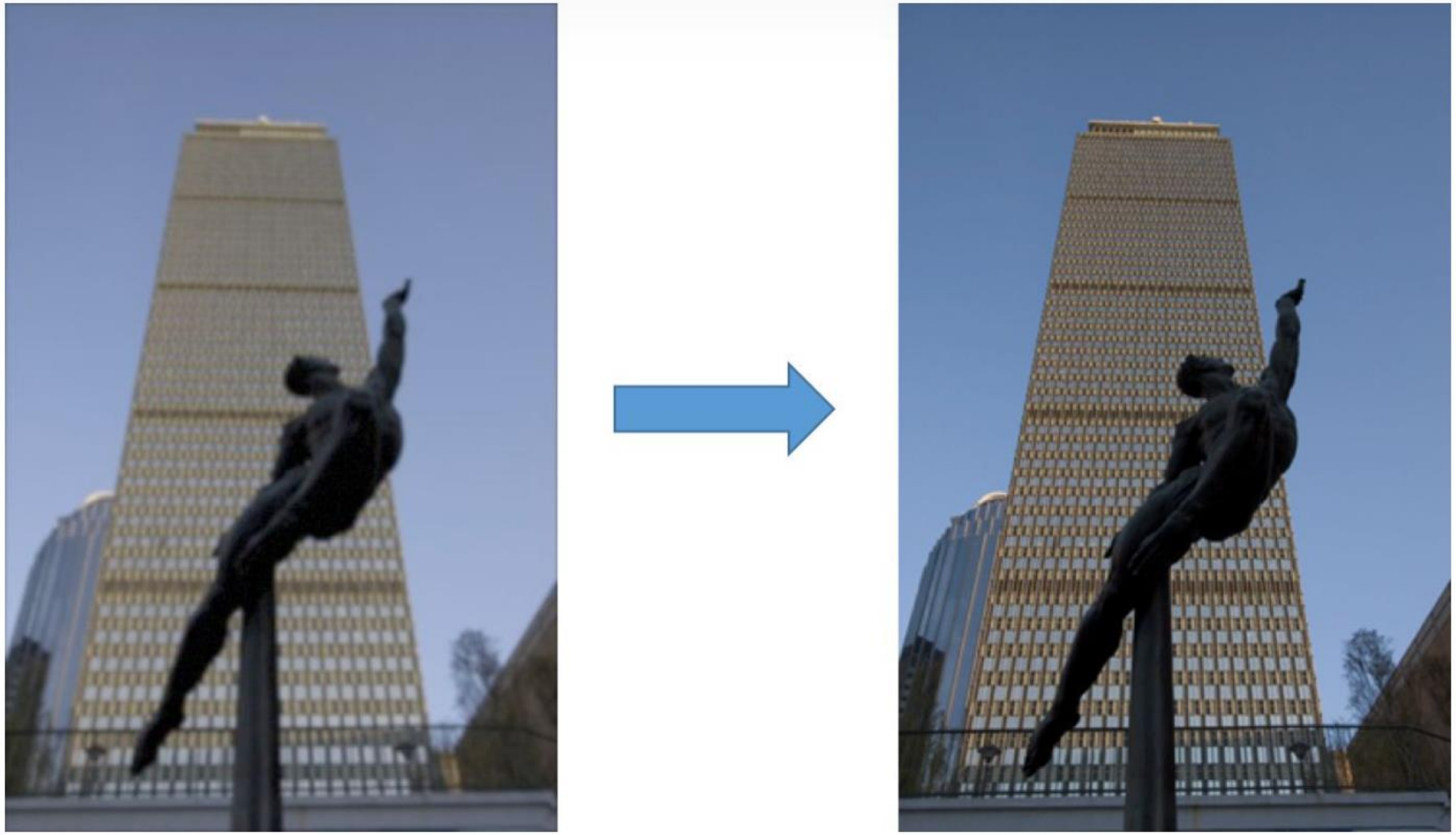
Overview-Deblur



Overview-Deblur

- original

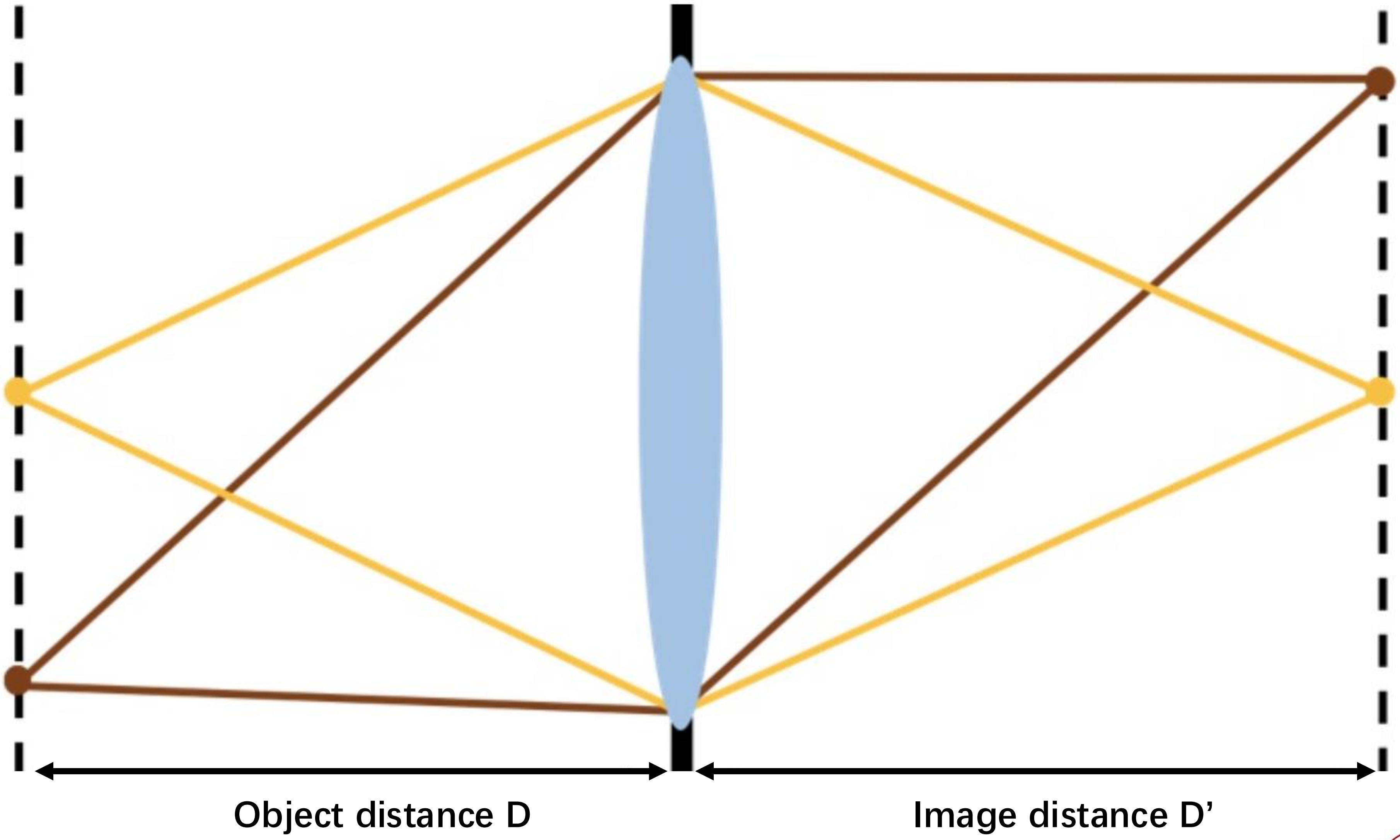
- optical blur

- motion blur

- spatial quantization (discrete pixels)

- additive intensity noise

The properties of the lens are limited



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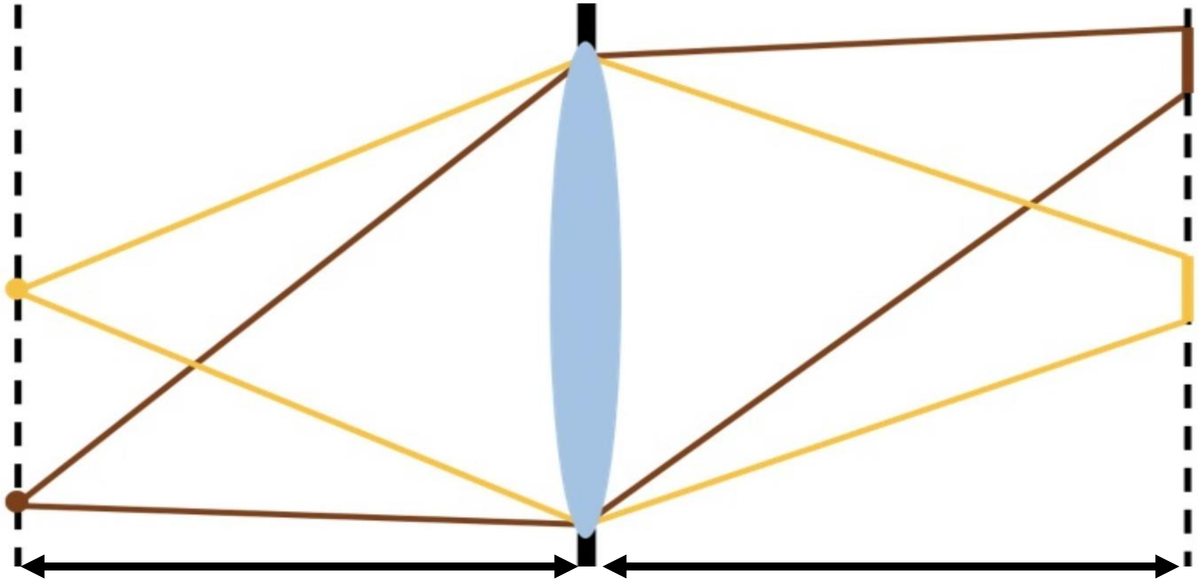
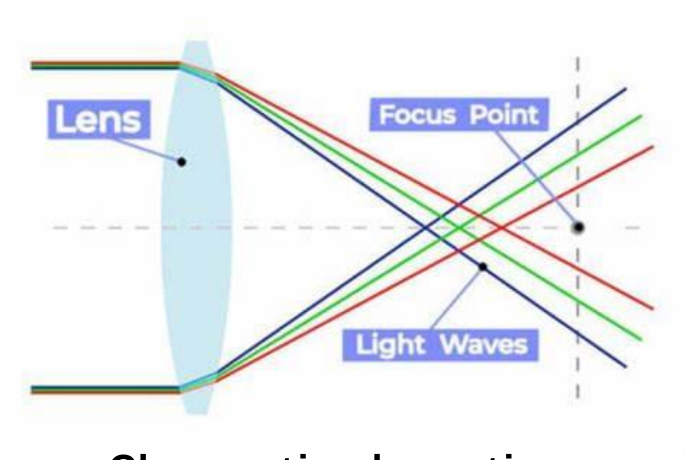
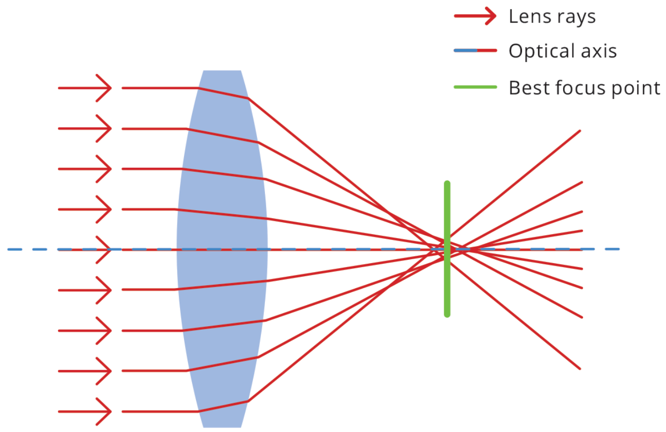
Optical Blurry





Chromatic aberration



Spherical aberration

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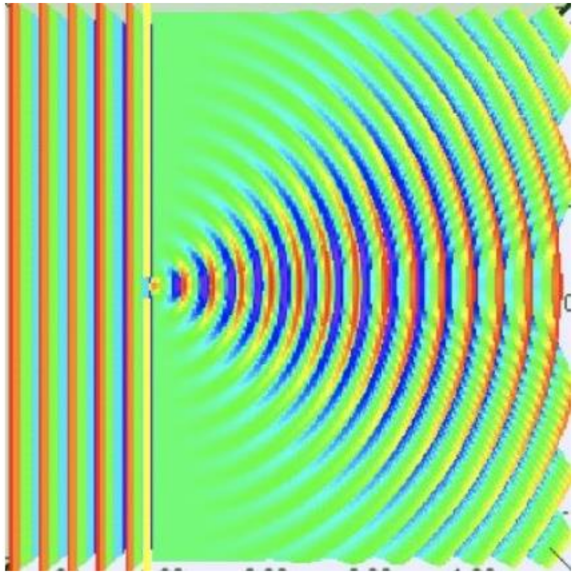
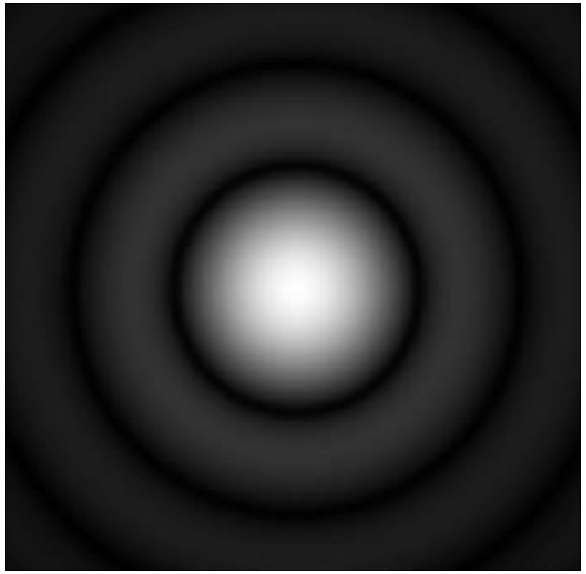
PSF



Diffraction, which is caused by the wave nature of light, as long as light passes through the aperture, diffraction occurs.



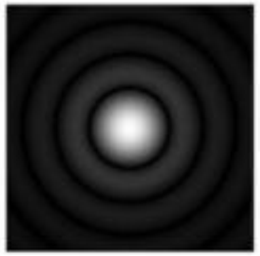
PSF, point spread function caused by the diffraction.

PSF

Reality

x

*



PSF

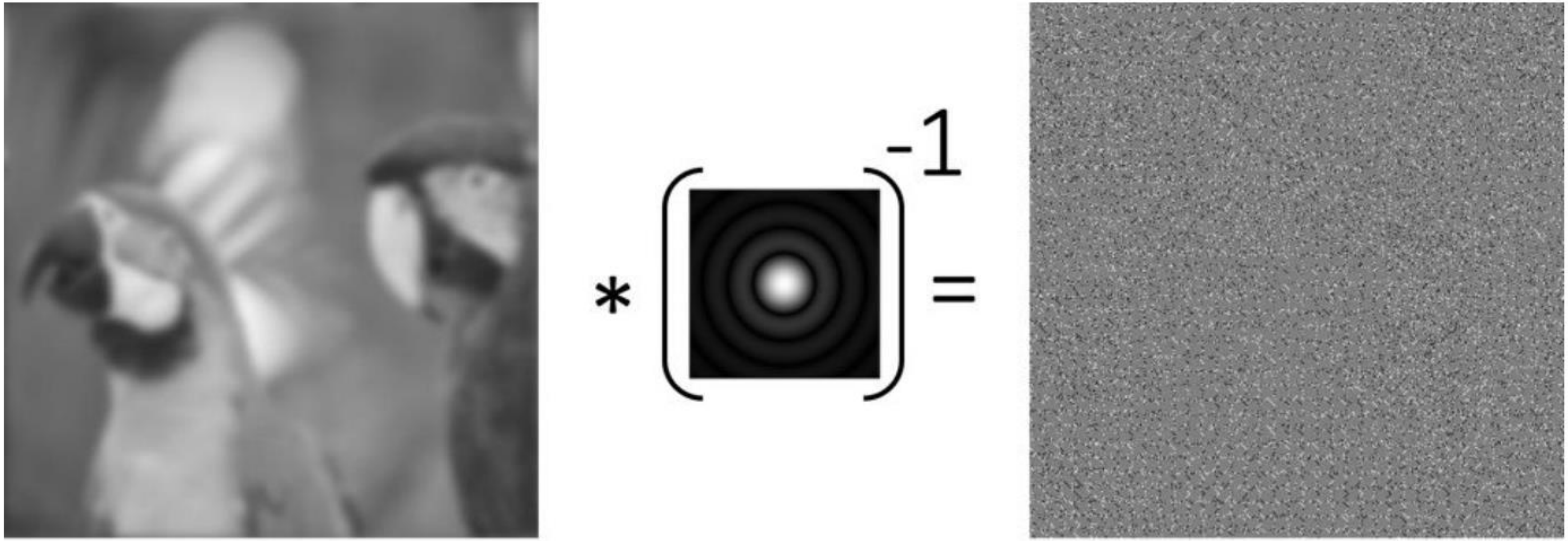
c

=

Observed image

y

Inverse Filter



Wiener Filter

Image domain $y = c * x + n$

Frequency domain $\mathrm{Y} = CX + N$

Looking for a function H that minimize expectation of error:

$$\min_{H} \mathrm{E}[||X - HY||^2]$$

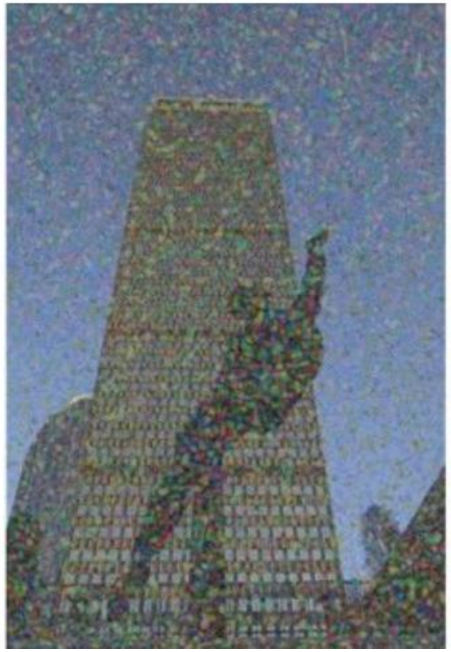
$$\min_{H} E^2[X] - HE[XY] - H^* E[Y\mathrm{X}] + H^2 E^2[Y]$$

$$H_{opt} = \frac{E[XY]}{E^2[Y]} = \frac{CE^2[X]}{CE^2[X] + E^2[N]}$$

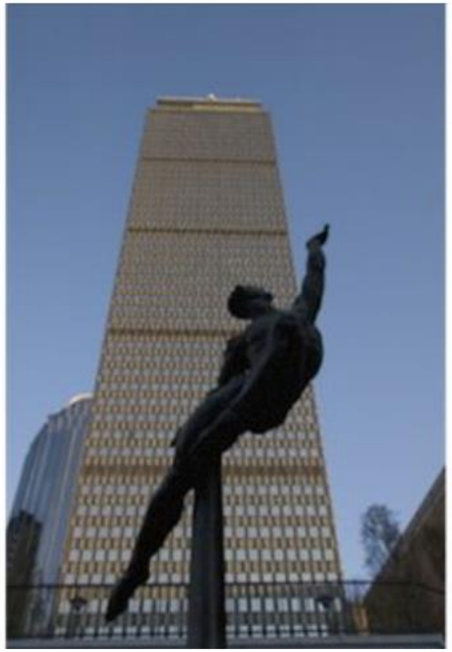
Debluring in image domain

Image domain $\min_{x} ||y - c * x||^2 + ||\nabla x||^2$

Blurred image
with noise



w/o regularization



Regularization

GT image

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Overview-Motion Blurring

- The objective is to restore a degraded image to its original form.
- An observed image can often be modelled as:

$$g(x,y) = \iint \mathrm{c}(x - x', y - y') f(x', y') dx' dy' + n(x,y)$$

where the integral is a convolution, $\mathbf{c}$ is the point spread function of the imaging system, and $\boldsymbol{n}$ is additive noise.

- The objective of image restoration in this case is to estimate the original image f from the observed degraded image g.

Maximum a posteriori (MAP) Estimation

Removing Camera Shake from a Single Photograph

Rob Fergus, Barun Singh, Aaron Hertzmann,
Sam T. Roweis and William T. Freeman

Massachusetts Institute of Technology
and
University of Toronto

Overview

Original

Our algorithm

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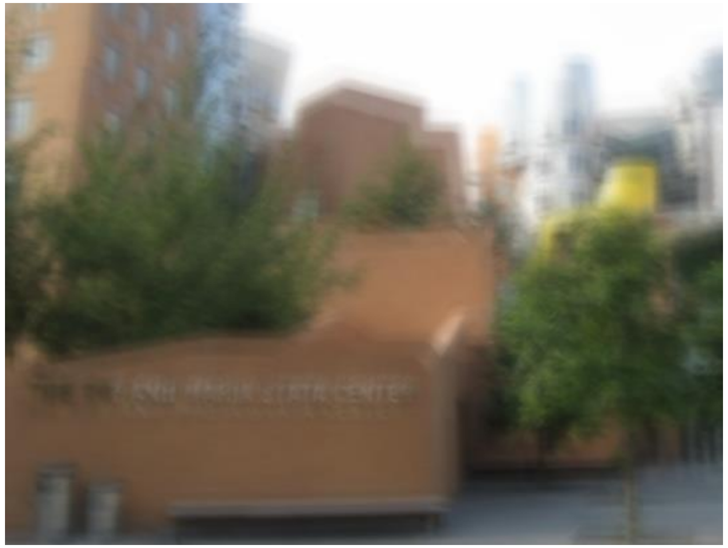
Close-up

Original

Naïve Sharpening

Our algorithm

Image formation process



=

$\otimes$

Blurry image

Sharp image

Blur kernel

Input to algorithm

Desired output

Model is approximation

Convolution operator

Why is this hard?

Simple analogy:

11 is the product of two numbers.

What are they?

No unique solution:

11 = 1 x 11

11 = 2 x 5.5

11 = 3 x 3.667

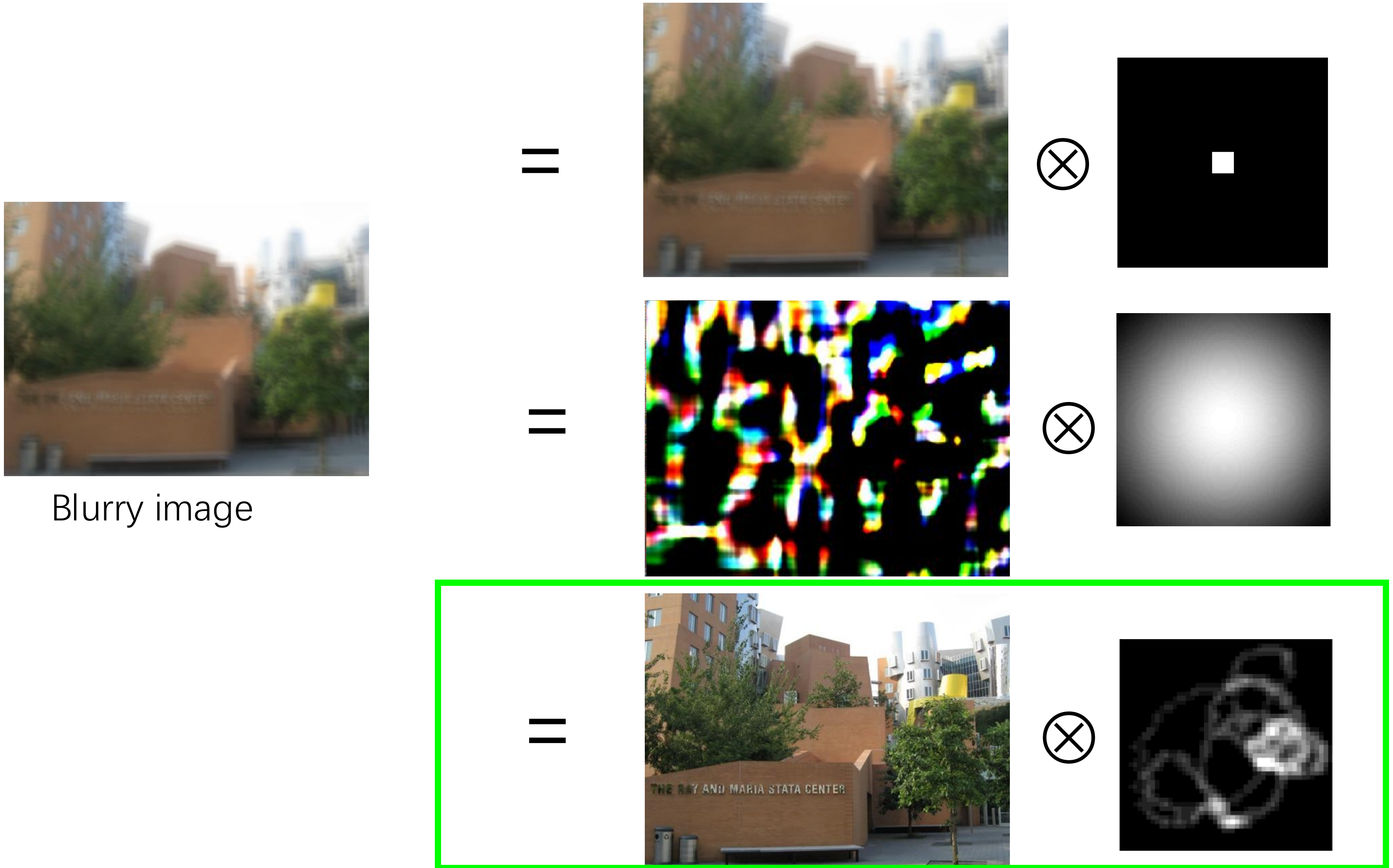
etc…..

Need more information !!!!

Multiple possible solutions

Sharp image

Blur kernel

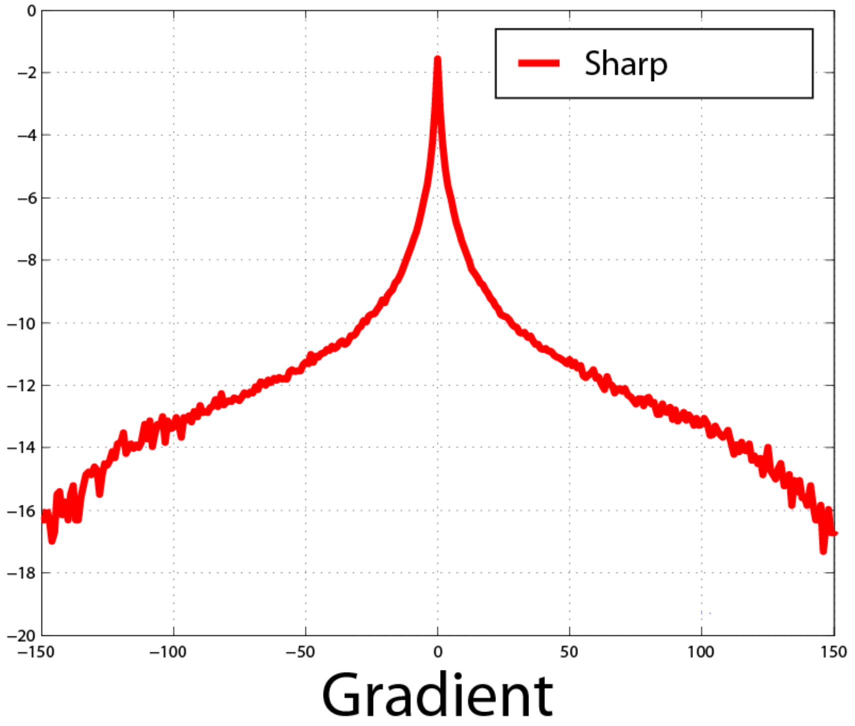


Blurry image

Natural image statistics

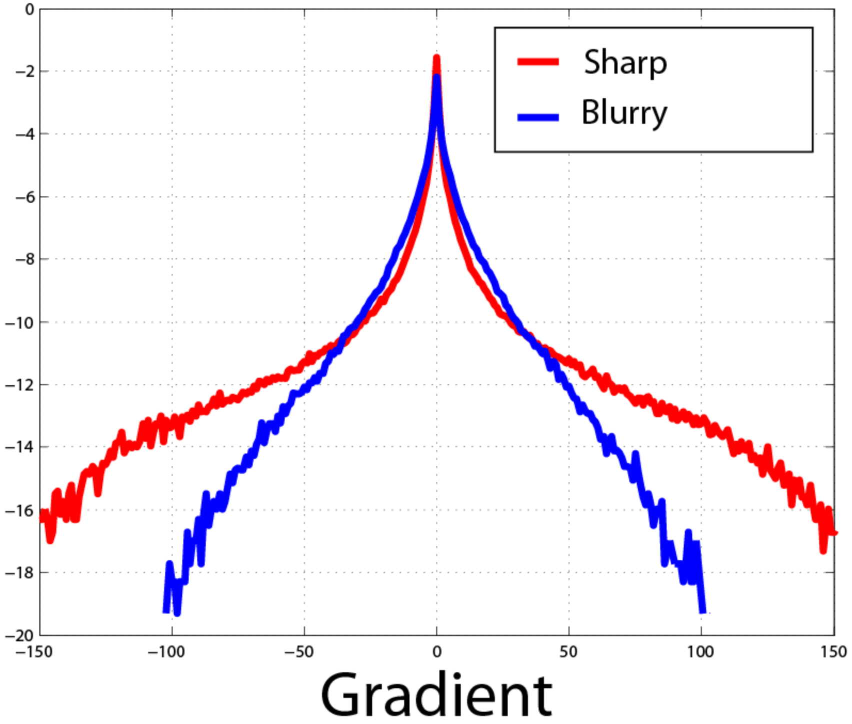
Characteristic distribution with heavy tails

Histogram of image gradients



Blury images have different statistics

Histogram of image gradients



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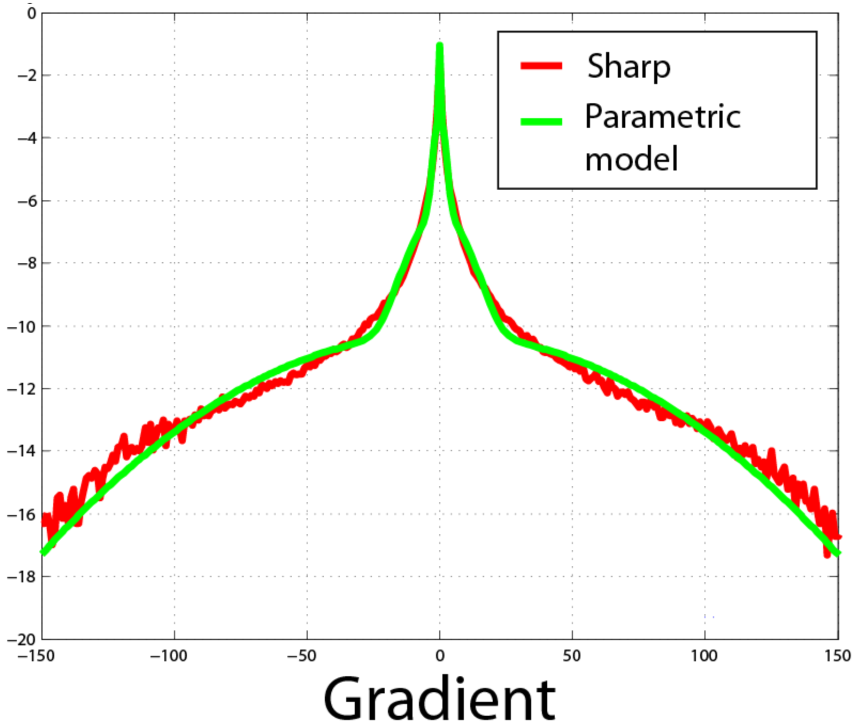
Parametric distribution

Histogram of image gradients



Use parametric model of sharp image statistics

Uses of natural image statistics

- Denoising [Roth and Black 2005]
- Superresolution [Tappen et al. 2005]
- Intrinsic images [Weiss 2001]
- Inpainting [Levin et al. 2003]
- Reflections [Levin and Weiss 2004]
- Video matting [Apostoloff & Fitzgibbon 2005]

Corruption process assumed known

Existing work on image deblurring

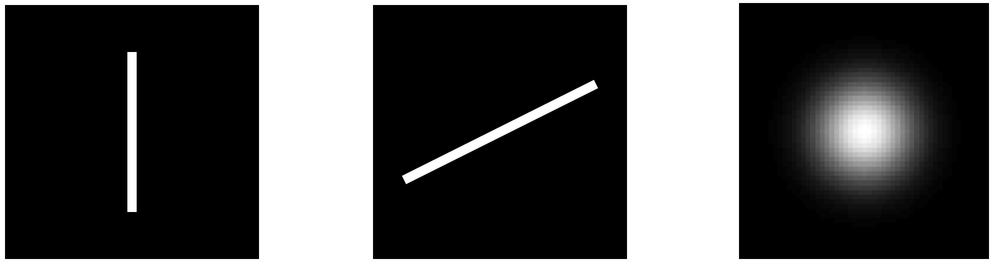
Software algorithms:

- Extensive literature in signal processing community

Mainly Fourier and/or Wavelet based

Strong assumptions about blur

→ not true for camera shake



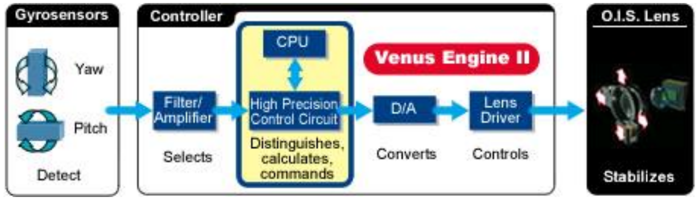
Assumed forms of blur kernels

Image constraints are frequency-domain power-laws

Existing work on image deblurring

Hardware approaches

Image stabilizers



Dual cameras

Ben-Ezra and Nayar 2004

Coded shutter

Raskar et al. SIGGRAPH 2006

Our approach can be combined with these hardware methods

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Three sources of information

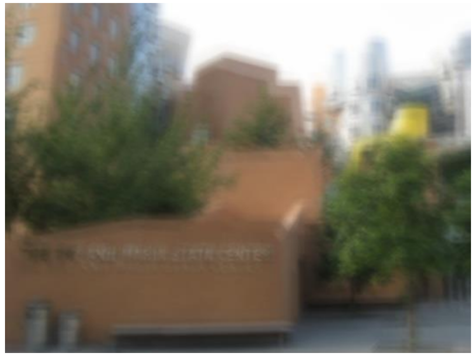
1. Reconstruction constraint:

Estimated sharp image

$\otimes$

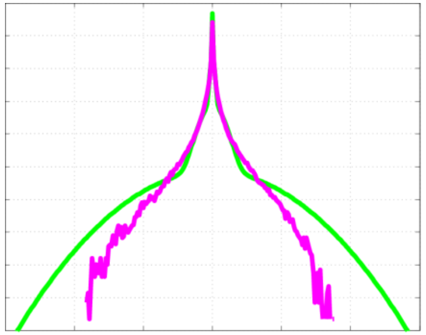
Estimated blur kernel

$=$



Input blurry image

2. Image prior:



Distribution of gradients

3. Blur prior:

Positive
&
Sparse

How do we use this information?

Obvious thing to do:

- Combine 3 terms into an objective function
- Run conjugate gradient descent
- This is Maximum a-Posteriori (MAP)

$$\max_{K,X} p(K, X|Y)$$

Kernel

Latent clean image

Observed image

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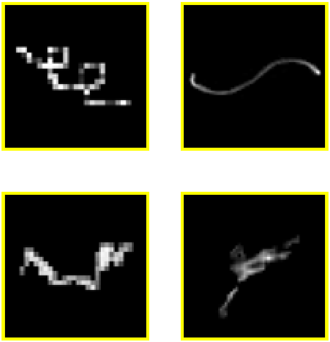
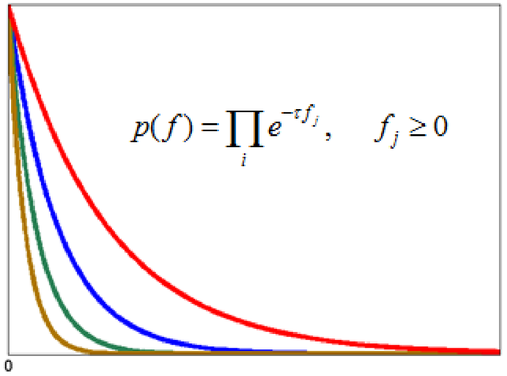
How do we use this information?

Since these statistics are based on the image gradients rather than the intensities, we perform the optimization in the gradient domain

$$\nabla Y = \nabla X \otimes K$$

Given the measured image gradients ∇Y, we can write the posterior distribution over the unknowns with Bayes' Rule:





$$p(K, \nabla X | \nabla Y) \propto p(\nabla Y | K, \nabla X) p(\nabla X) p(K)$$

$$= \prod_i N(\nabla Y(i) | \left(K \otimes \nabla X(\mathrm{i})\right), \sigma^2)$$

$$= \prod_i \sum_{c=1}^{C} N(\nabla X | 0, v_c) \prod_j \sum_{d=1}^{D} \pi_d E(K_j | \lambda_d)$$

Loss Function

- The variational algorithm minimizes a cost function representing the distance between the approximating distribution and the true posterior, measured as:

$$KL(q(K, \nabla X, \sigma^2)||p(K, \nabla X|\nabla Y))$$

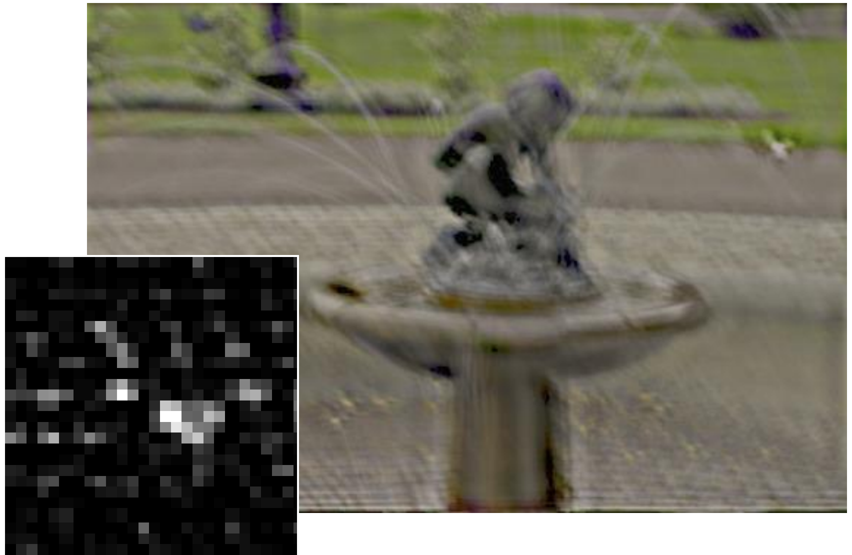
- The independence assumptions in the variational posterior allows the cost function C_{KL} to be factored:

$$\left\langle log\frac{q(\nabla X)}{p(\nabla X)}\right\rangle_{q(\nabla X)} + \left\langle log\frac{q(K)}{p(K)}\right\rangle_{q(K)} + \left\langle log\frac{q(\sigma^{-2})}{p(\sigma^2)}\right\rangle_{q(\sigma^{-2})}$$

Results from MAP estimation

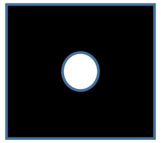
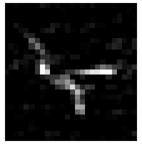
Input blurry image

Maximum a-Posteriori (MAP)

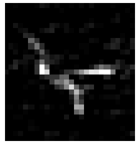


Our method: Variational Bayes

Variational Bayesian method

P( , ) > P( , )

$$p(K, \nabla X | \nabla Y)$$

  | 

#Y<#X+#K

Variational Bayesian method

$$\underset{\{K,X\}}{\operatorname{argmax}}\, p(K,X|Y) \rightarrow \underset{\{K\}}{\operatorname{argmax}}\, p(K|Y)$$

#Y>>#K

$$p(K|Y)=\int_{\mathrm{X}} \mathrm{p}(\mathrm{K},\mathrm{X}|\mathrm{Y})\mathrm{dX}$$

Overview of algorithm

1. Pre-processing

2. Kernel estimation
   - Multi-scale approach

3. Image reconstruction
   - Standard non-blind deconvolution routine

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Preprocessing

Input image

Convert to grayscale

Remove gamma correction

User selects patch from image

Bayesian inference too slow to run on whole image

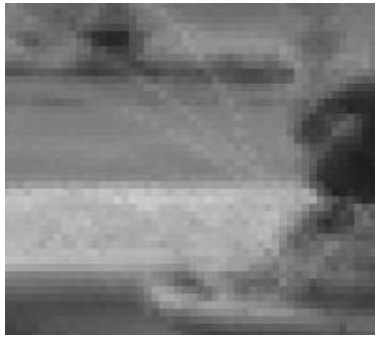
Infer kernel from this patch

Initialization

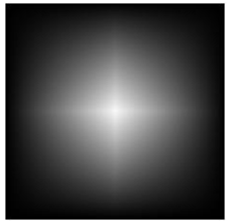
Input image

Convert to grayscale → Remove gamma correction → User selects patch from image → Initialize 3x3 blur kernel

Blurry patch



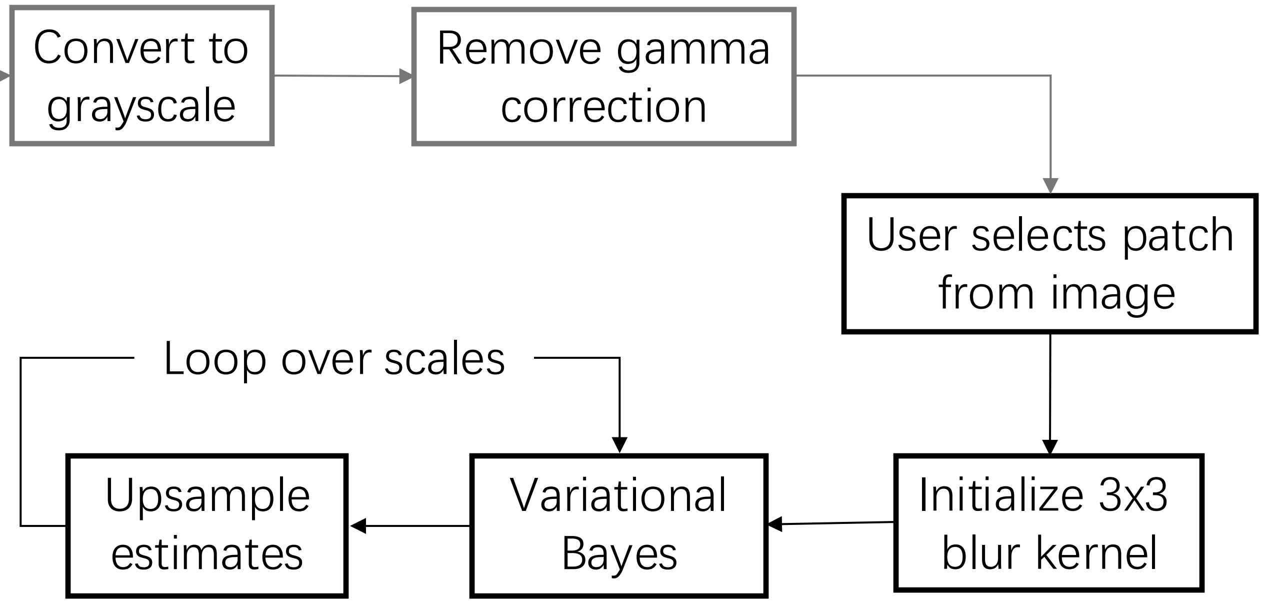
Initial image estimate



Initial blur kernel

Inferring the kernel: multiscale method

Input image



Use multi-scale approach to avoid local minima:

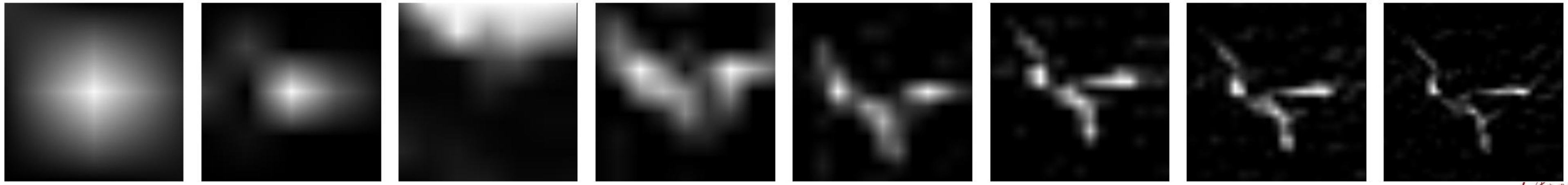
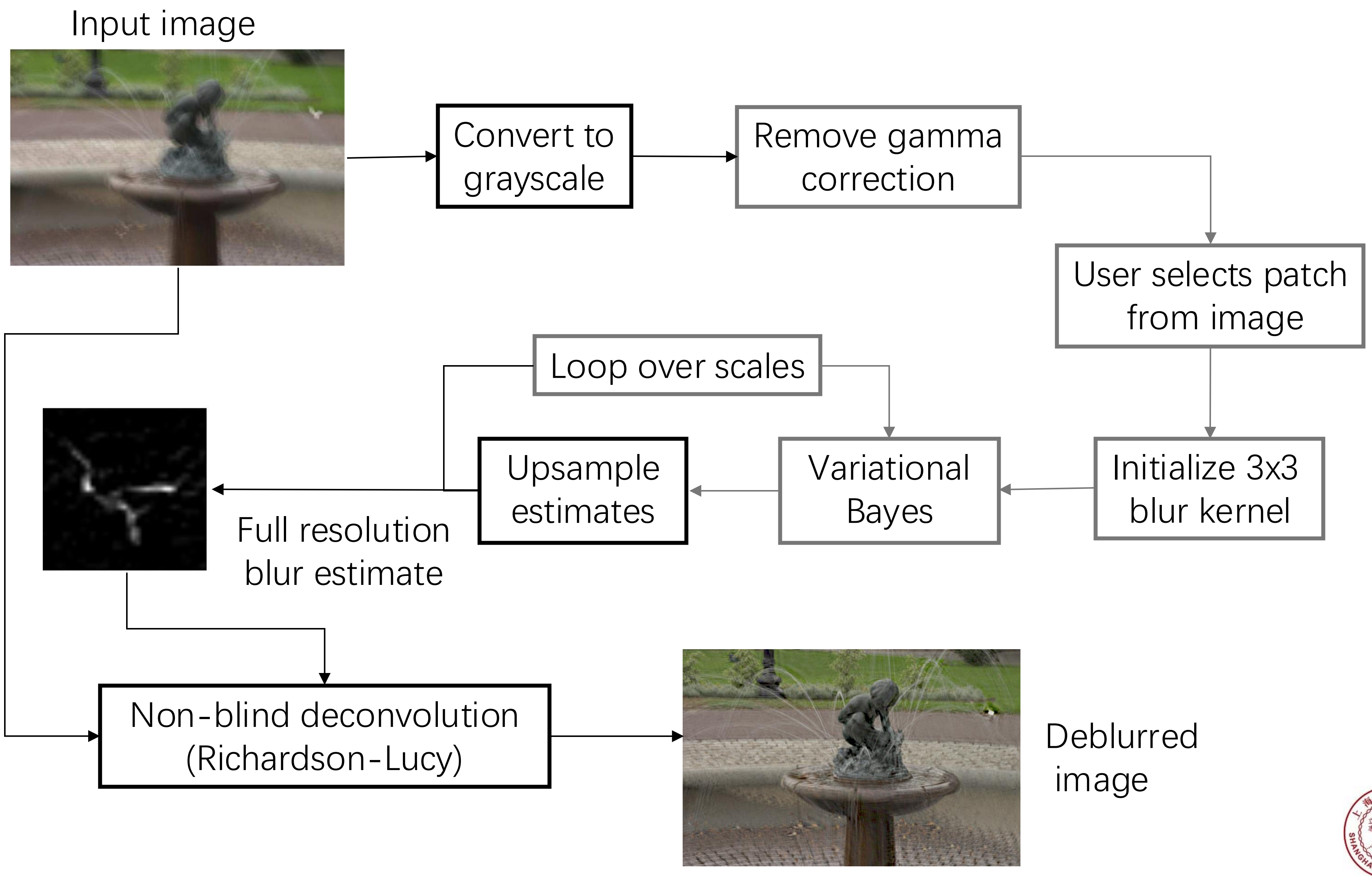


Image Reconstruction



Results on real images

Submitted by people from their own photo collections

Type of camera unknown

Output does contain artifacts

- Increased noise
- Ringing

Compares well to existing methods

Original photograph

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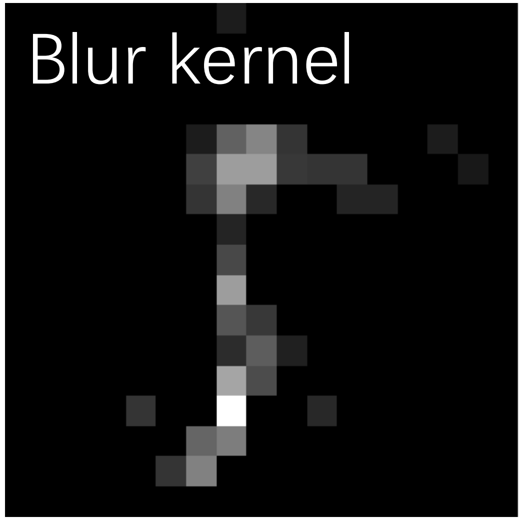

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Matlab's `deconvblind`

Close-up of garland

Original

Matlab's
`deconvblind`

Our output

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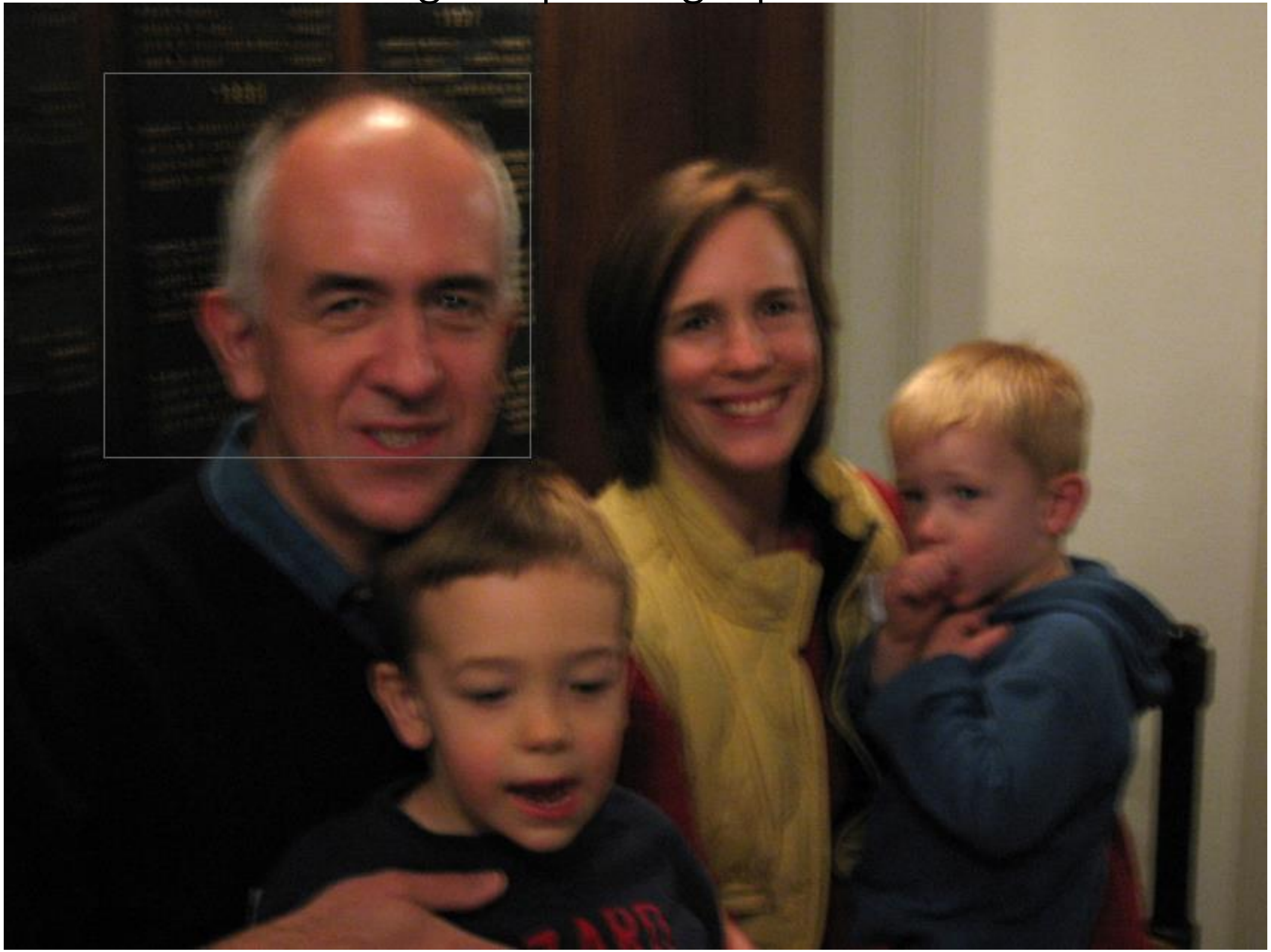
Original photograph



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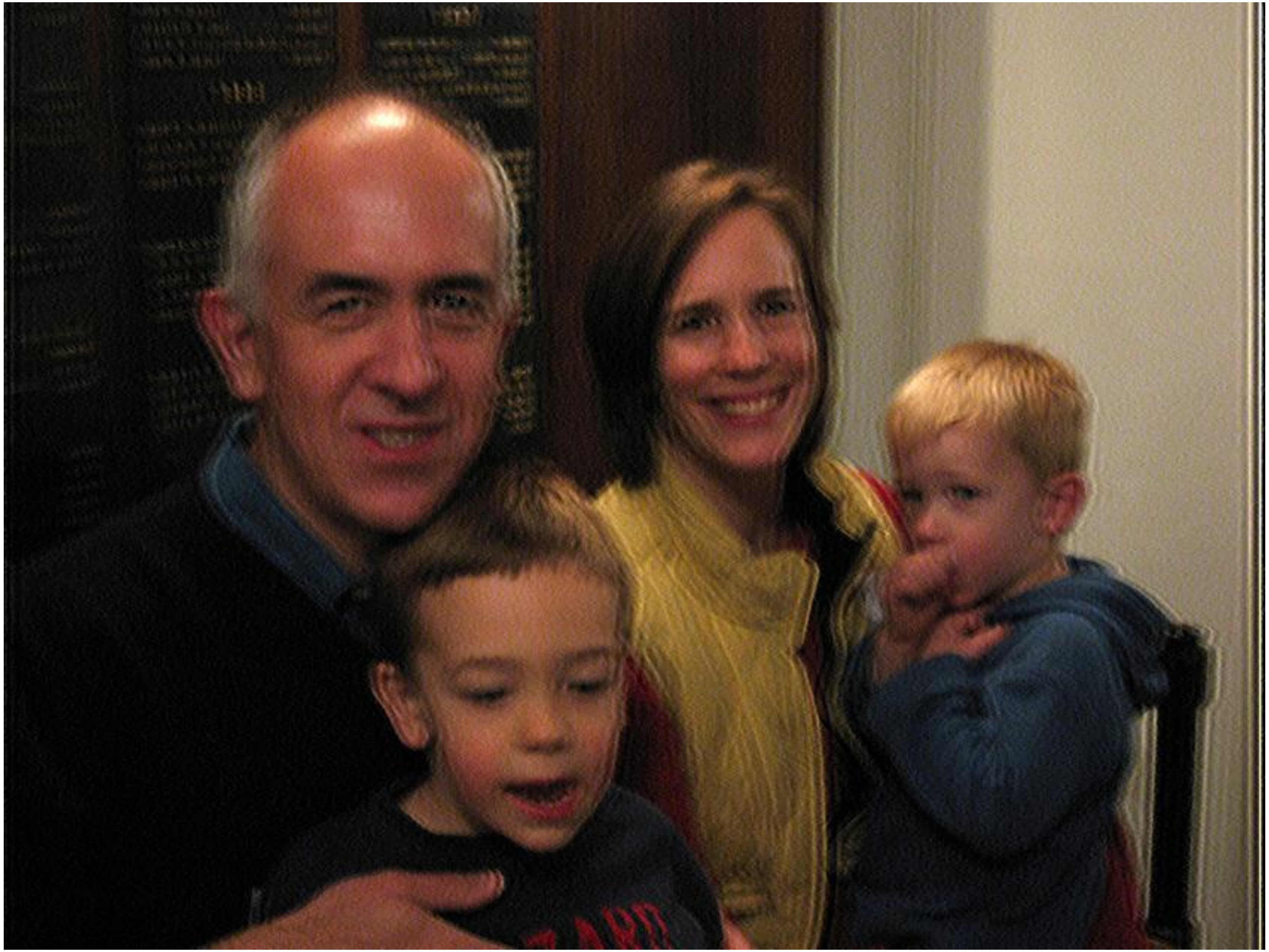
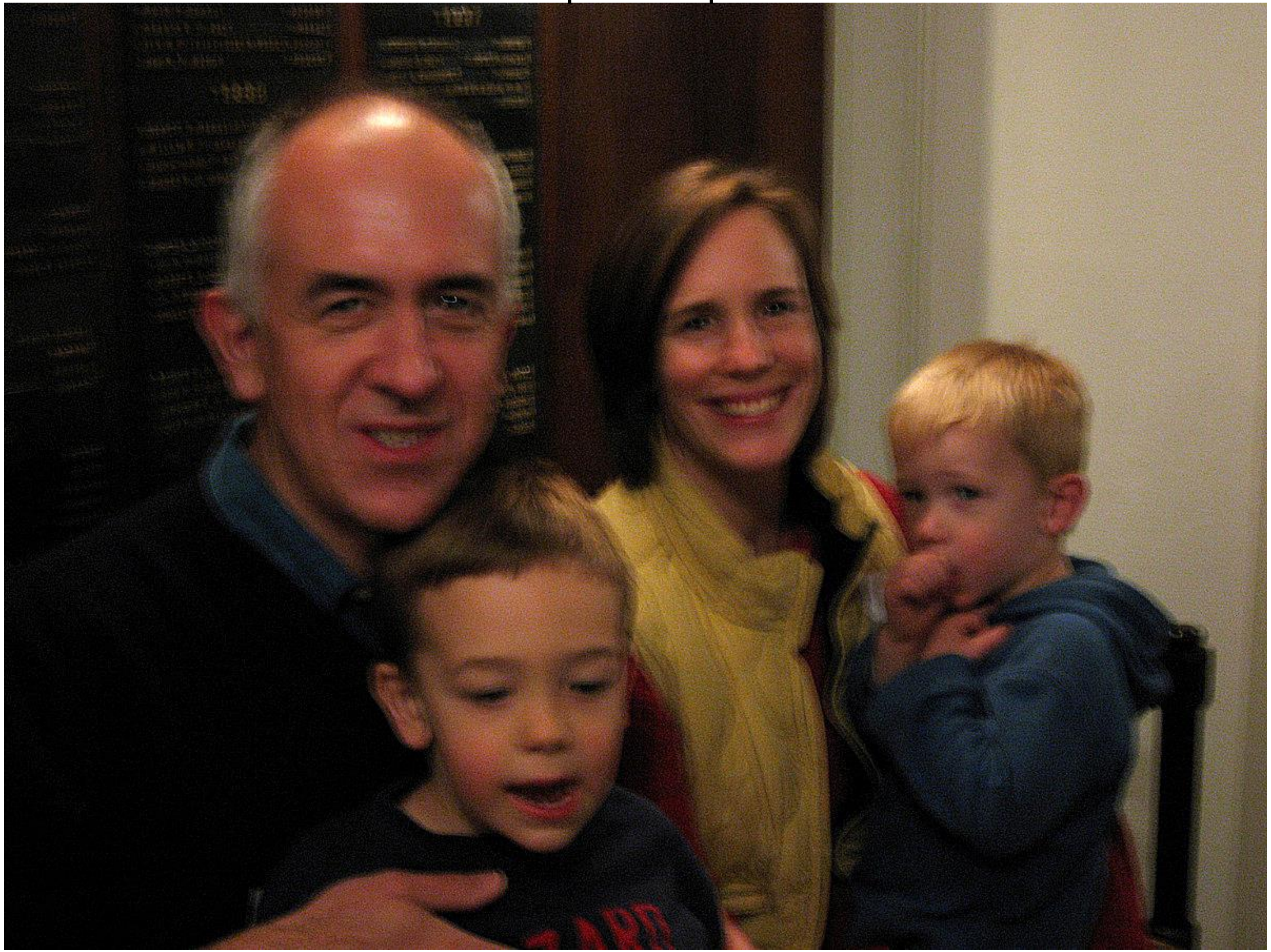
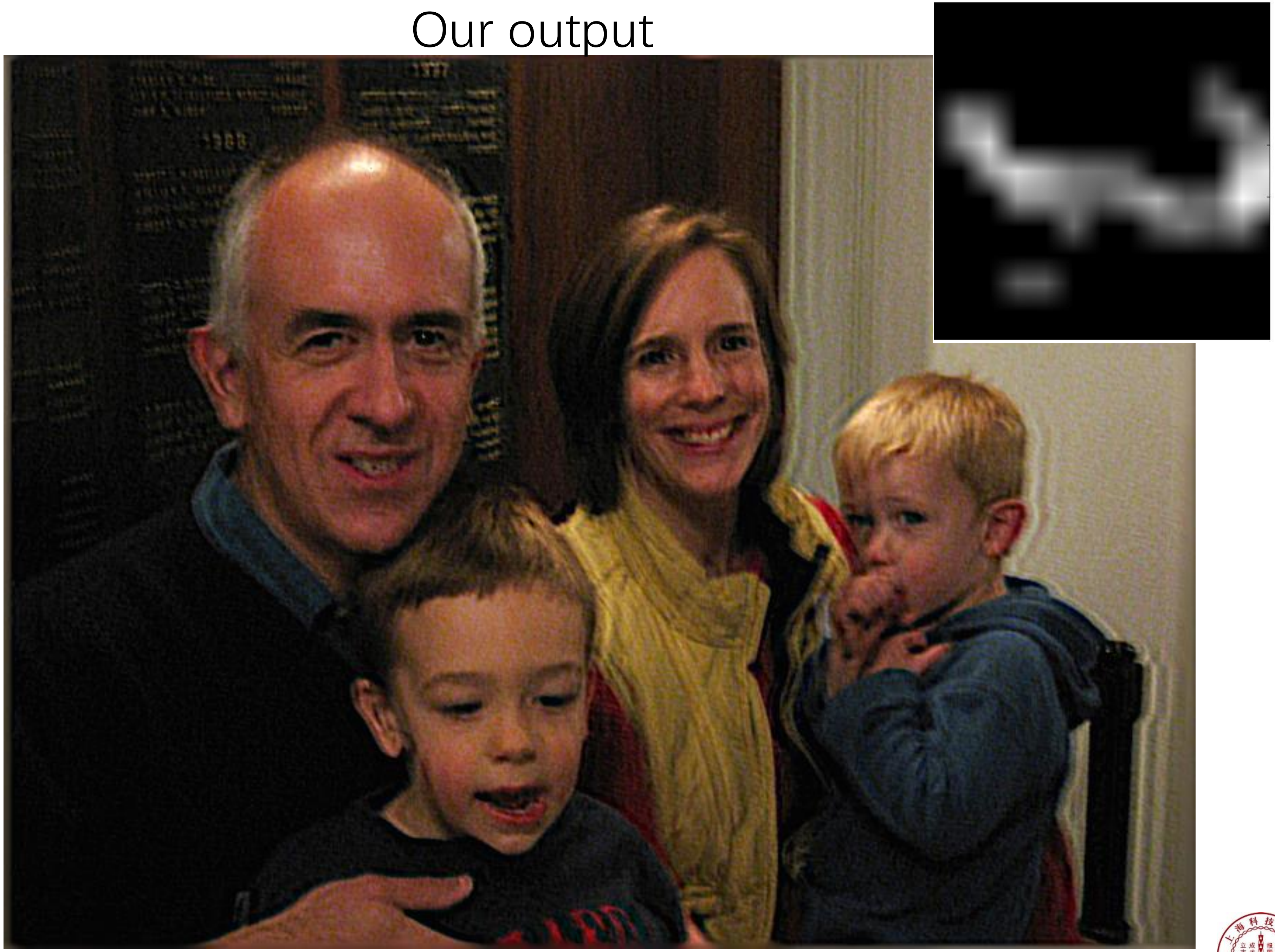


Photoshop sharpen more



Our output



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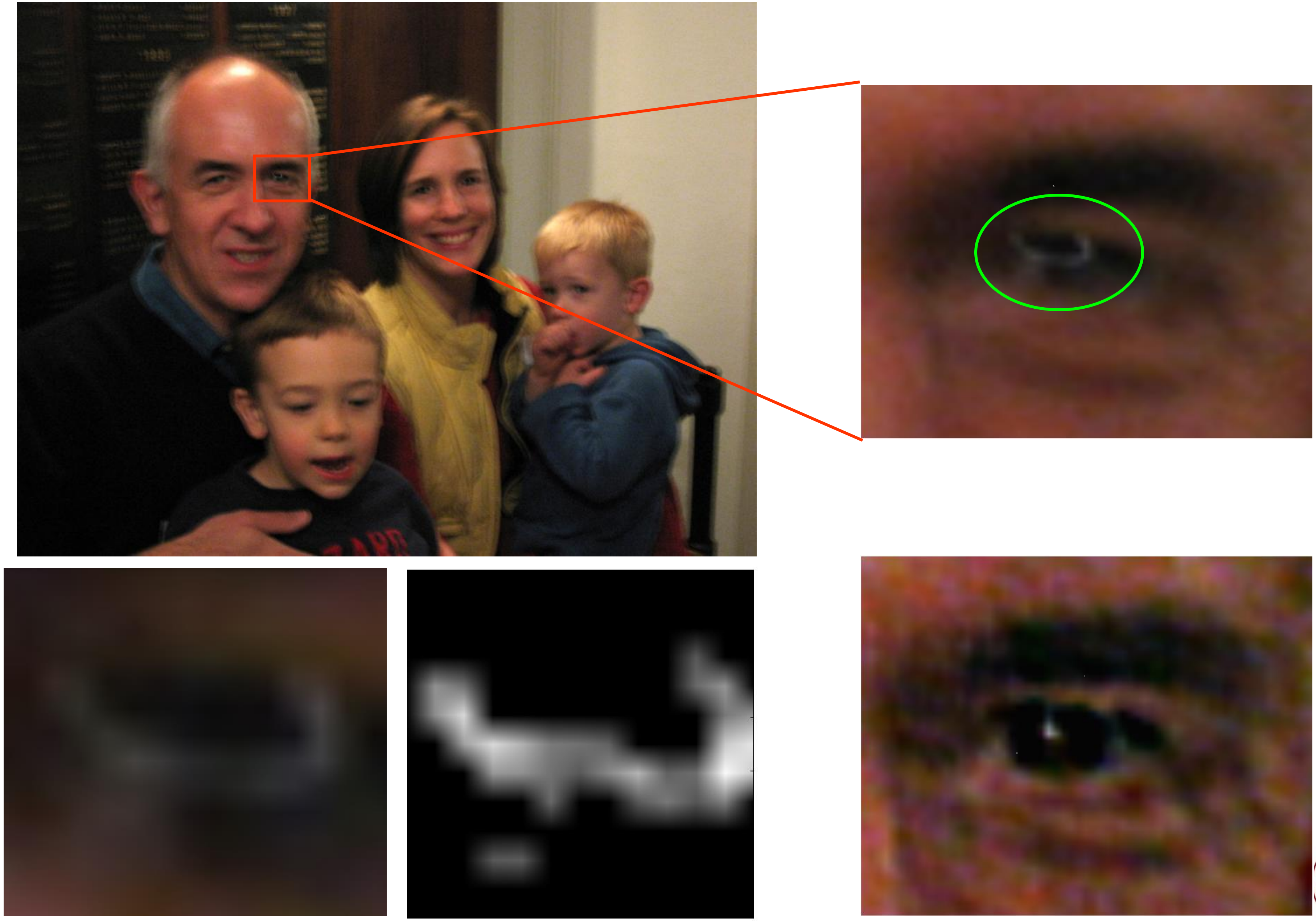

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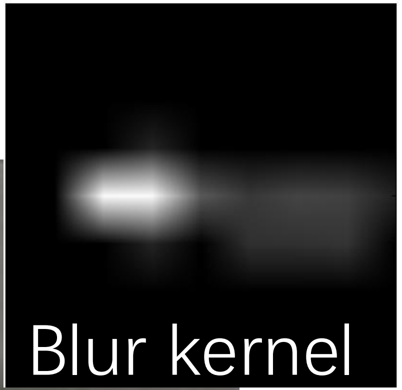
Original photograph

Our output



Original photograph

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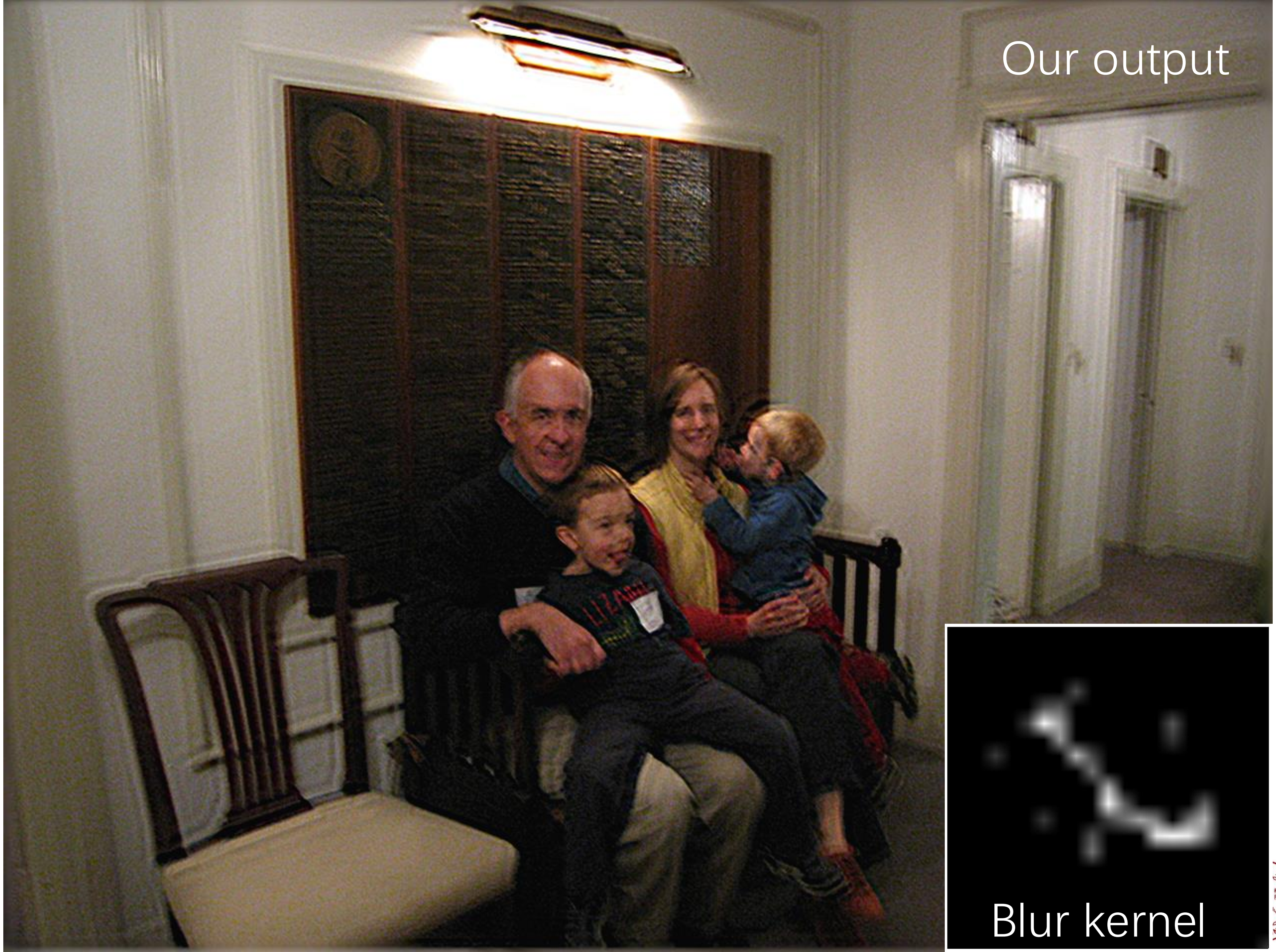
Our output

Matlab's `deconvblind`

Original photograph


Our output
Blur kernel

Close-up of child

Original photograph

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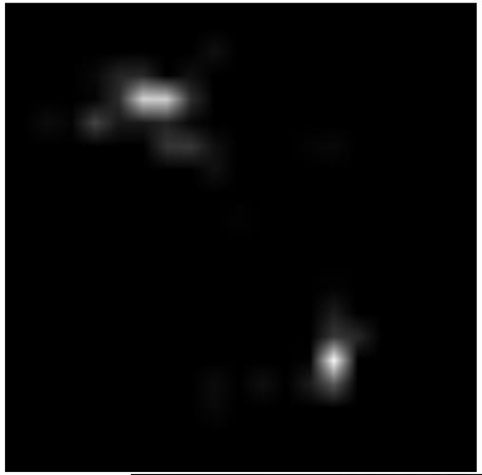
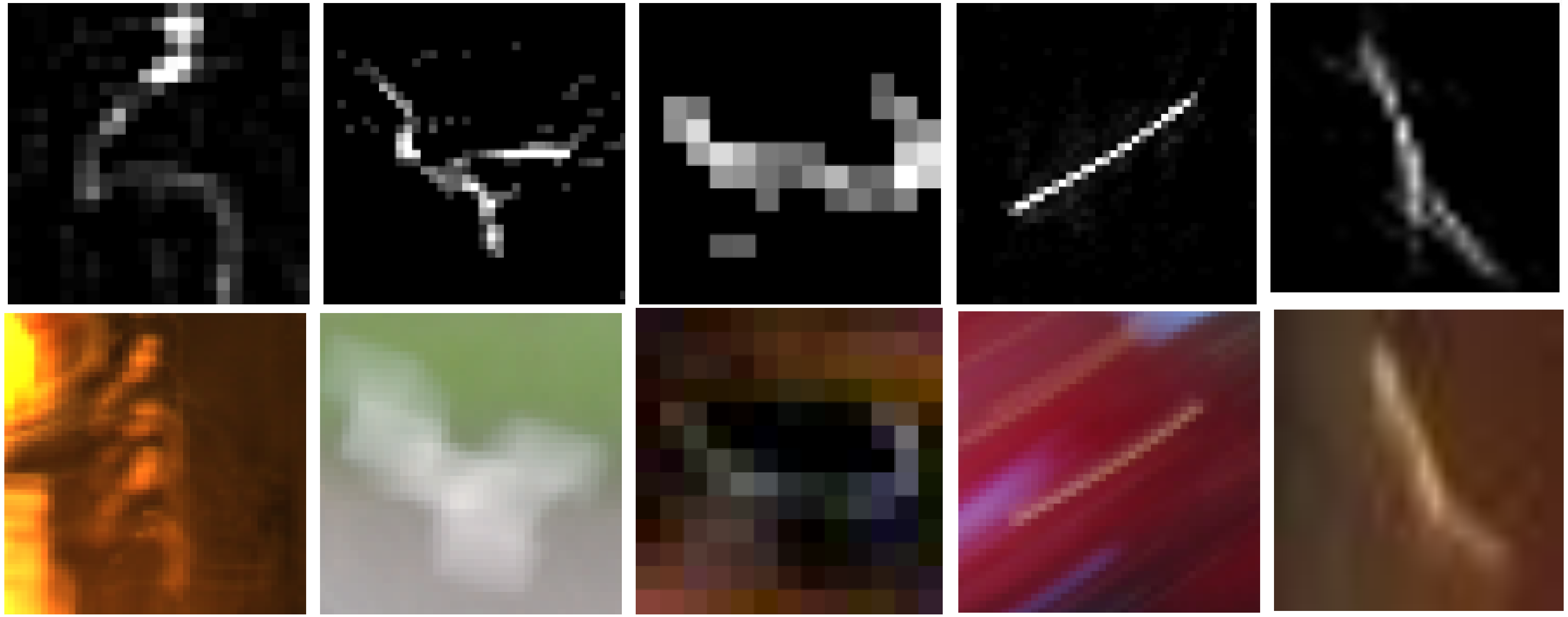
Original photograph




Our output

Image artifacts & estimated kernels



Note: blur kernels were inferred from large image patches,
NOT the image patterns shown

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Summary

Method for removing camera shake from real photographs

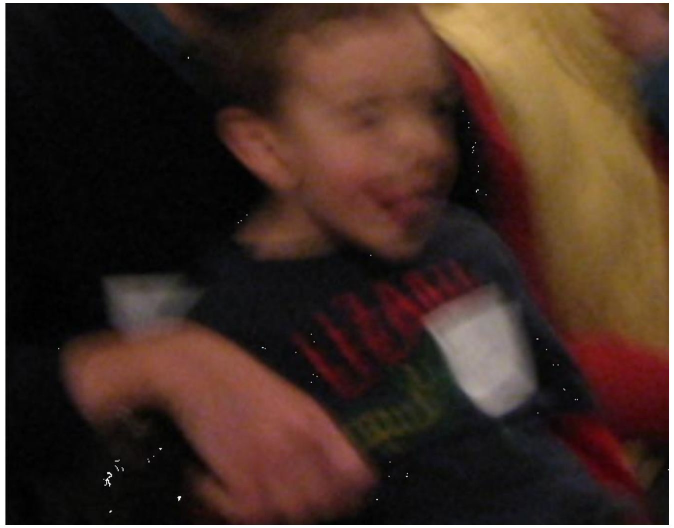
First method that can handle complicated blur kernels

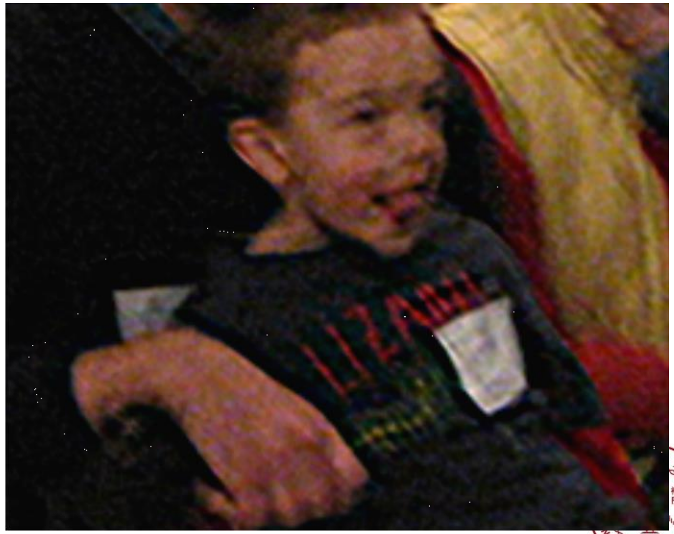
Uses natural image statistics

Non-blind deconvolution currently simplistic

Things we have yet to model:

- Correlations in colors, scales, kernel continuity
- JPEG noise, saturation, object motion





A Neural Approach to Blind Motion Deblurring

[1] Chakrabarti, A. (2016). A neural approach to blind motion deblurring. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III 14 (pp. 221-235). Springer International Publishing.

Learning a Convolutional Neural Network for Non-uniform Motion Blur Removal

[1] Jian Sun, Wenfei Cao, Zongben Xu, Jean Ponce,, Learning a Convolutional Neural Network for Non-uniform Motion Blur Removal, CVPR, 2015.

Scale-recurrent Network for Deep Image Deblurring

[1] Xin Tao, Hongyun Gao, Xiaoyong Shen, Jue Wang, Jiaya Jia Scale-recurrent Network for Deep Image Deblurring, CVPR 2018

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Uncertainty-Aware Unsupervised Image Deblurring with Deep Residual Prior

[1] Xiaole Tang, Xile Zhao, Jun Liu, Jianli Wang, Yuchun Miao, Tieyong Zeng, Uncertainty-Aware Unsupervised Image Deblurring with Deep Residual Prior, CVPR 2023

Self-supervised Non-uniform Kernel Estimation with Flow-based Motion Prior for Blind Image Deblurring

[1] Z. Fang, F. Wu, W. Dong, X. Li, J. Wu and G. Shi, "Self-supervised Non-uniform Kernel Estimation with Flow-based Motion Prior for Blind Image Deblurring," 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Vancouver, BC, Canada, 2023, pp. 18105-18114, doi: 10.1109/CVPR52729.2023.01736.

ID-Blau: Image Deblurring by Implicit Diffusion-based reBLurring AUgmentation

[1] Jia-Hao Wu, Fu-Jen Tsai, Yan-Tsung Peng, Chung-Chi Tsai, Chia-Wen Lin, Yen-Yu Lin ID-Blau: Image Deblurring by Implicit Diffusion-based reBLurring AUgmentation, CVPR 2024

Joint coil sensitivity and motion correction in parallel MRI with a self-calibrating score-based diffusion model

[1] Lixuan Chen, Xuanyu Tian, Jiangjie Wu, Guoyan Lao, Yuyao Zhang, Hongjiang Wei. "Joint Coil Sensitivity and Motion Correction in Parallel MRI with a Self-Calibrating Score-Based Diffusion Model." Medical Image Analysis,2025 Feb 21;102:103502.