BIL 717
Image Processing
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Image Deblurring

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Acknowledgement: The slides are adapted from the course “Recent Advances in Image Deblurring” given by Seungyong Lee and Sunghyun Cho @ Siggraph Asia 2013.

Introduction

Blind Deconvolution

Non-blind Deconvolution

blur [blɜ:(r)]

- Long exposure
- Moving objects
- Camera motion
  - panning shot

blur [blɜ:(r)]

- Often degrades image/video quality severely
- Unavoidable under dim light circumstances

Various Kinds of Blurs

Camera shake (Camera motion blur)

Object movement (Object motion blur)

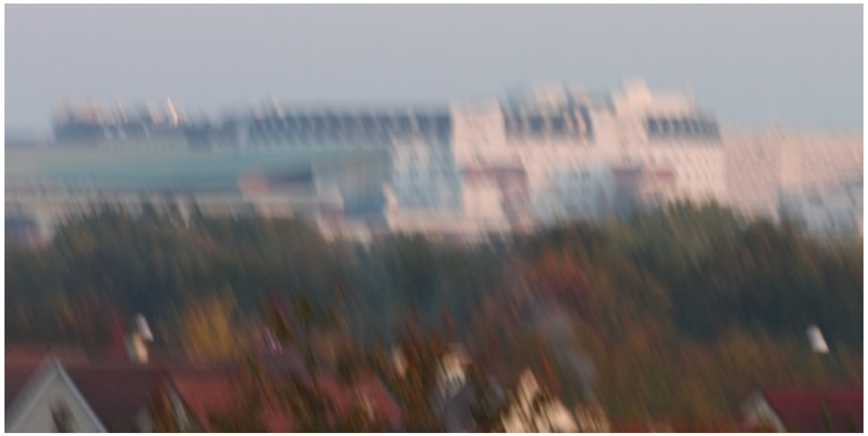
Out of focus (Defocus blur)

Combinations (vibration & motion, …)

Camera Motion Blur

SIGGRAPH ASIA 2013 HONG KONG

- Caused by camera shakes during exposure time
  - Motion can be represented as a camera trajectory

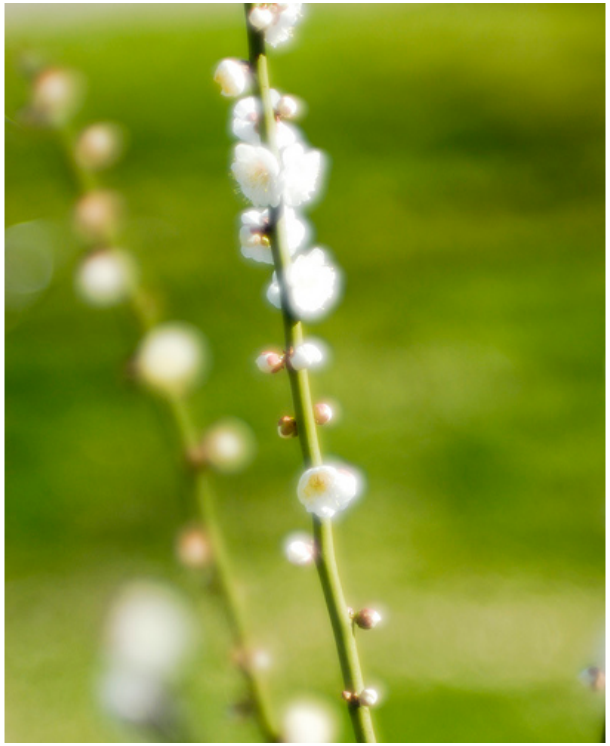


Object Motion Blur

- Caused by object motions during exposure time

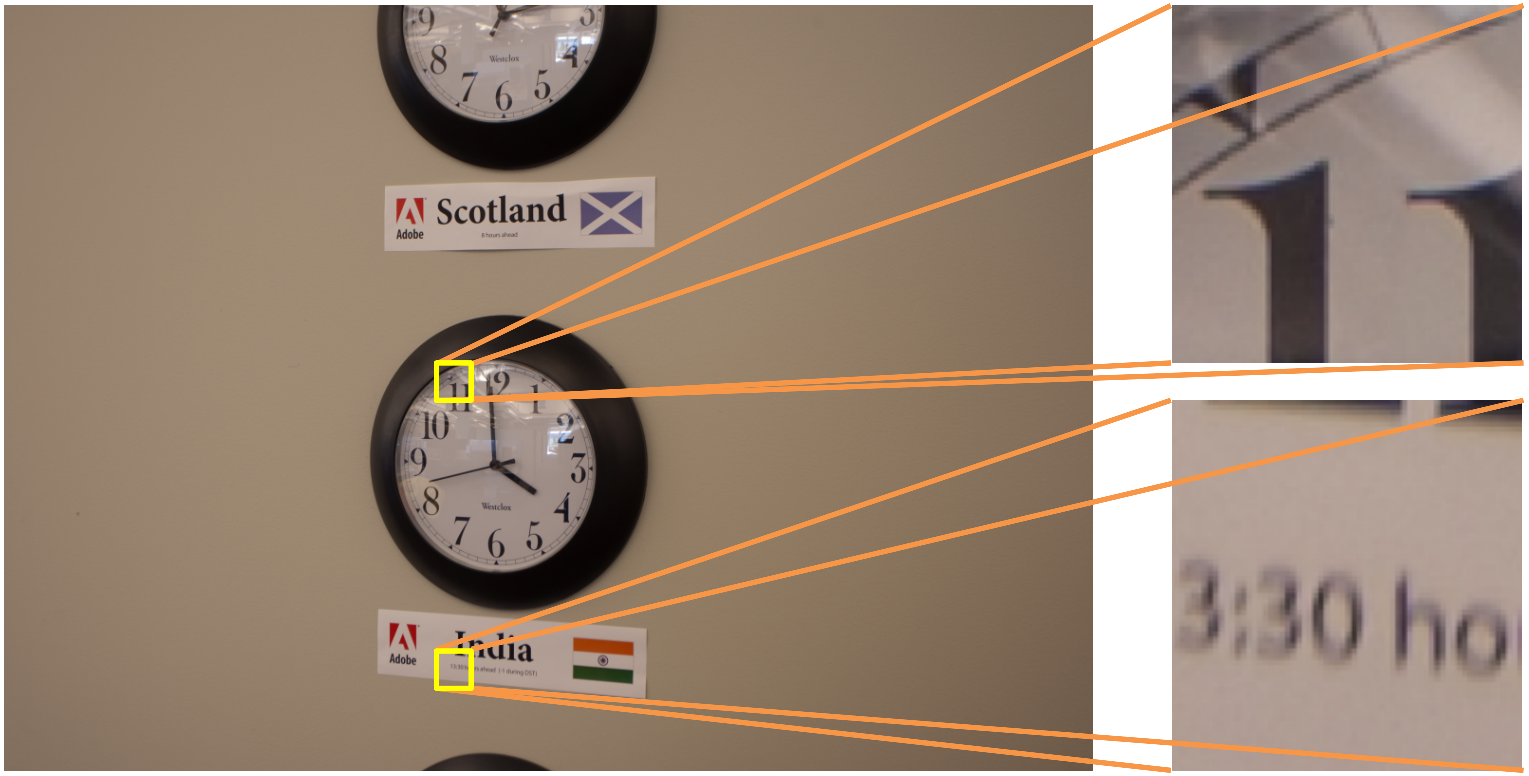
Defocus Blur

- Caused by the limited depth of field of a camera



Optical Lens Blur

- Caused by lens aberration



Deblurring?

- Remove blur and restore a latent sharp image

from a given blurred image

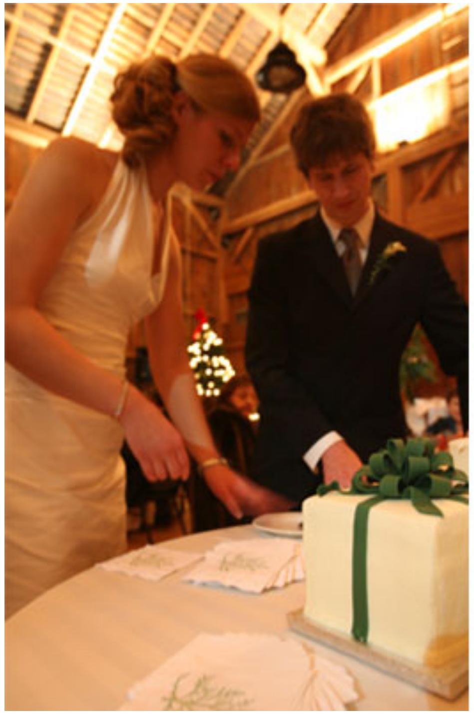
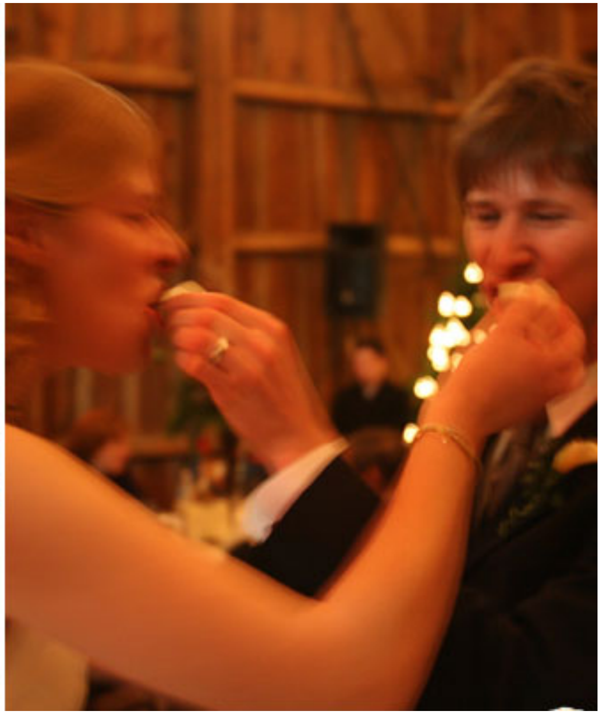
find its latent sharp image

Deblurring: Old Problem!

- Trott, T., "The Effect of Motion of Resolution", *Photogrammetric Engineering*, Vol. 26, pp. 819-827, **1960**.
- Slepian, D., "Restoration of Photographs Blurred by Image Motion", *Bell System Tech.*, Vol. 46, No. 10, pp. 2353-2362, **1967**.

Why is it *important*?

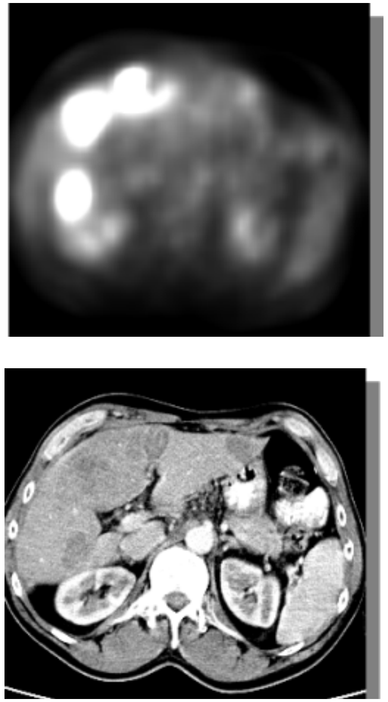
- Image/video in our daily lives
  - Sometimes a retake is difficult!

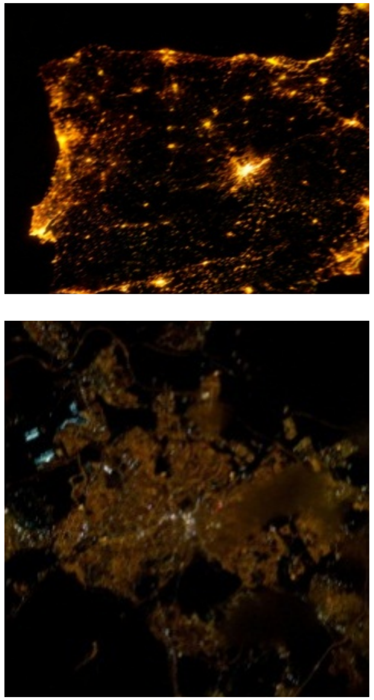

Why is it *important*?

- Strong demand for high quality deblurring

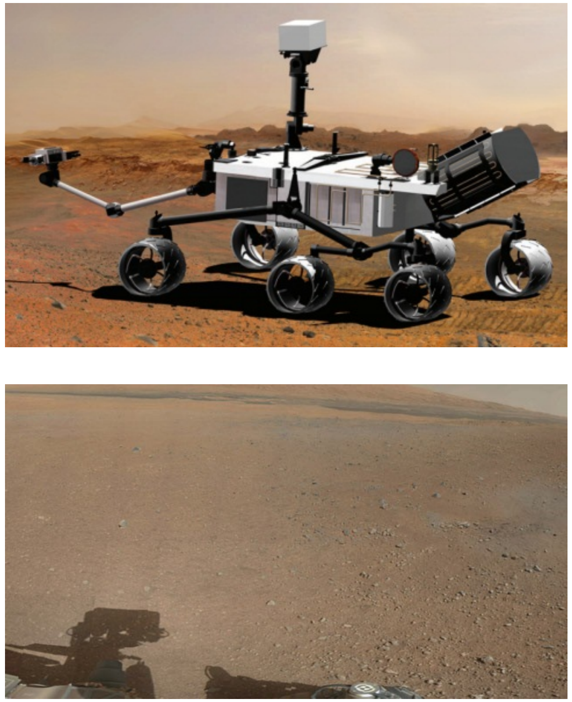
CCTV, car black box



Medical imaging



Aerial/satellite photography



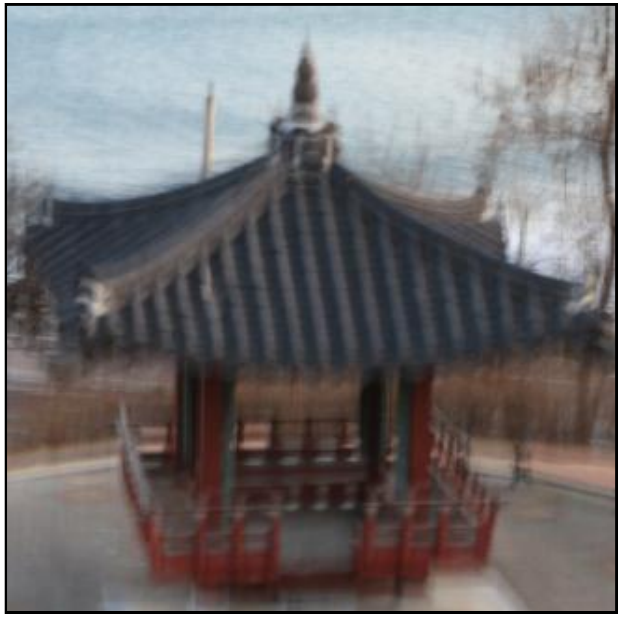
Robot vision

Deblurring

from a given blurred image

find its latent sharp image

Commonly Used Blur Model



Blurred image

=

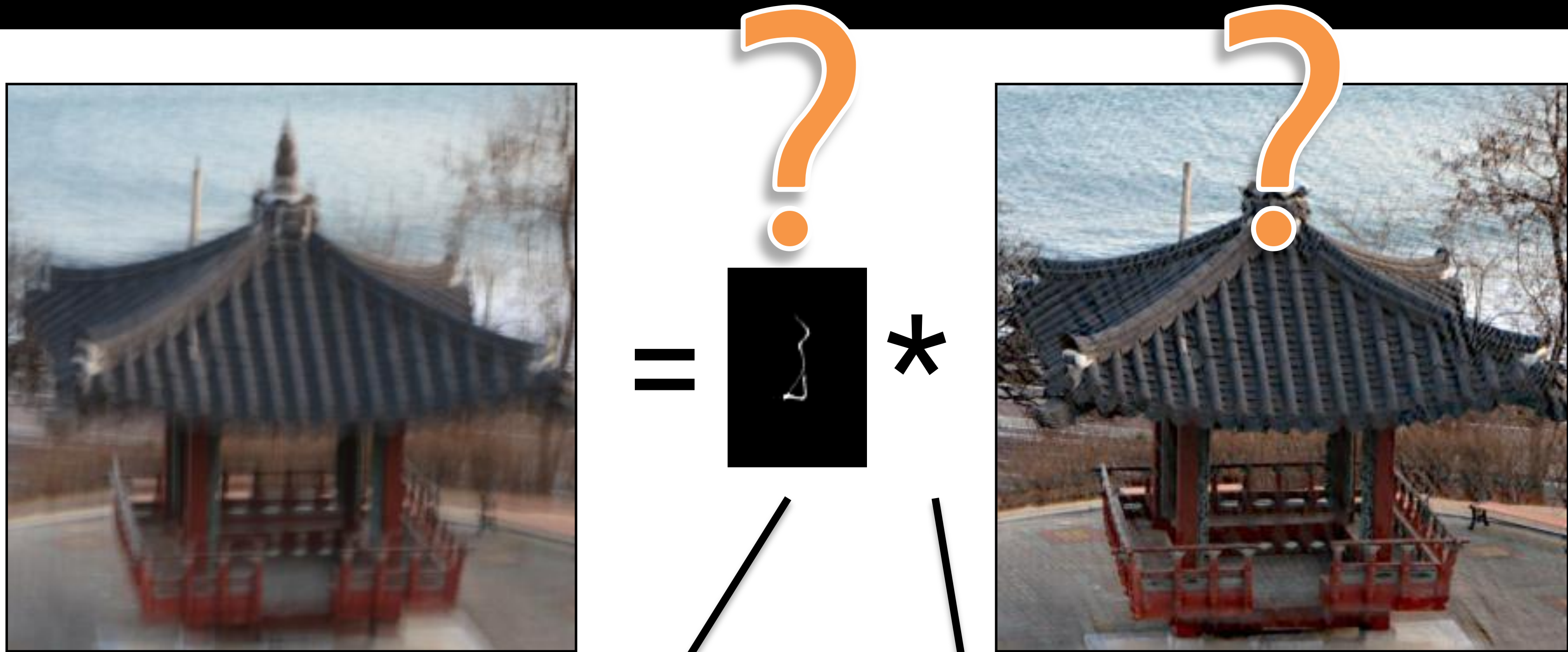
*

Latent sharp image

Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

Blind Deconvolution



Blurred image

Latent sharp image

Blur kernel
or Point Spread
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Convolution
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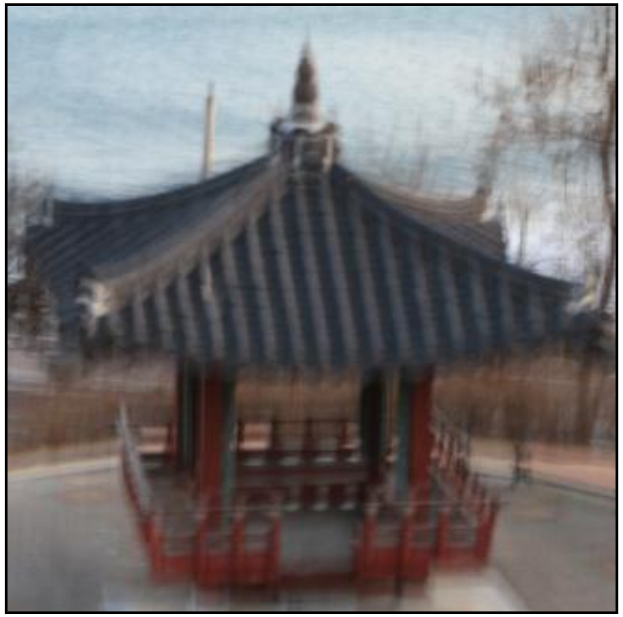
Non-blind Deconvolution



Blurred image

=

Blur kernel
or Point Spread
Function (PSF)

*

Convolution
operator

Latent sharp image

Uniform vs. Non-uniform Blur

Uniform blur

- Every pixel is blurred in the same way
- Convolution based blur model

Uniform vs. Non-uniform Blur

Non-uniform blur

- Spatially-varying blur
- Pixels are blurred differently
- More faithful to real camera shakes

Most Blurs Are Non-Uniform

Camera shake (Camera motion blur)

Object movement (Object motion blur)

Out of focus (Defocus blur)

Combinations (vibration & motion, ...)

Introduction

Blind Deconvolution

Non-blind Deconvolution

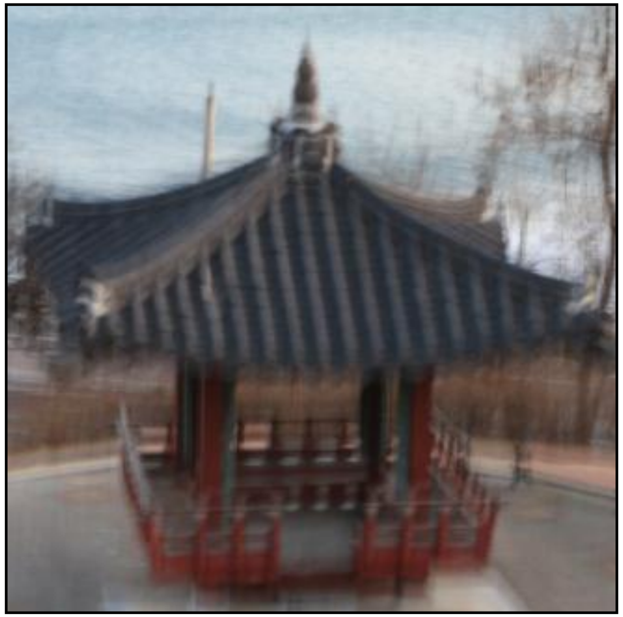
Introduction

Blind Deconvolution

Non-blind Deconvolution

- Introduction
- Recent popular approaches
- Non-uniform blur

Blind Deconvolution (Uniform Blur)



Blurred image

=

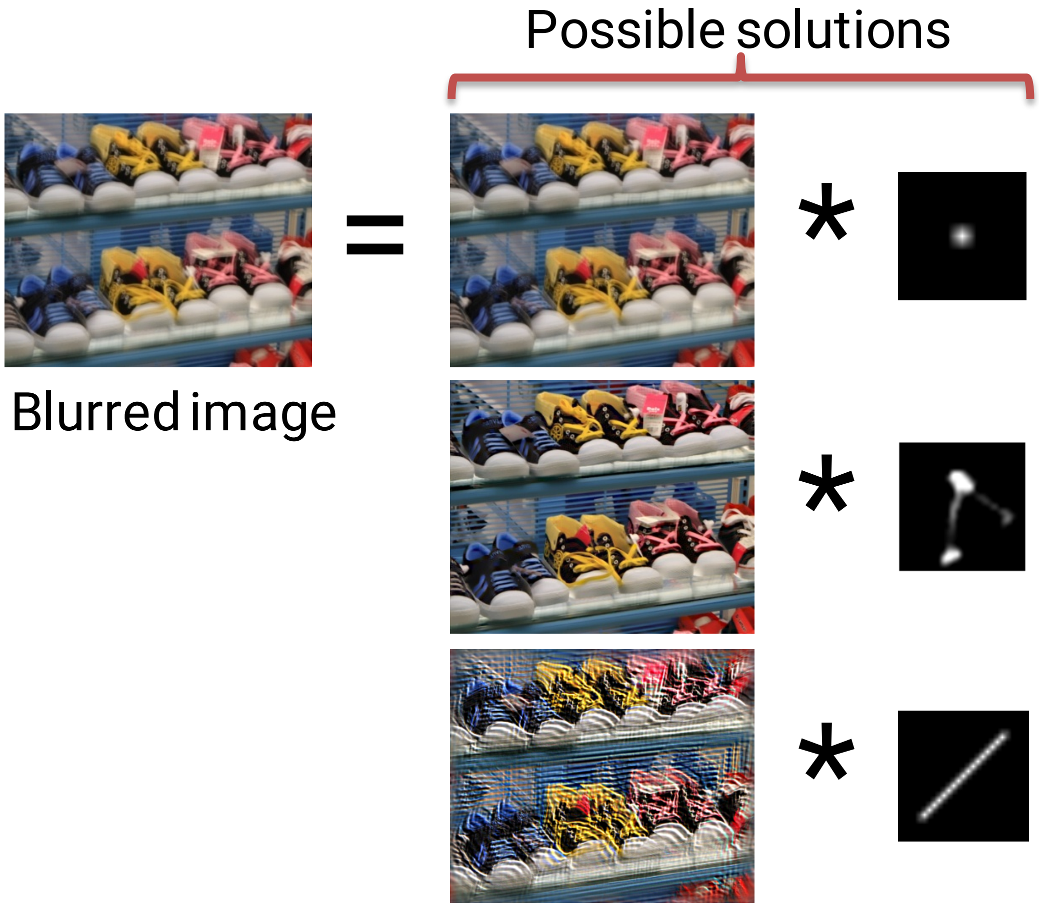
*

Latent sharp image

Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

Key challenge: Ill-posedness!



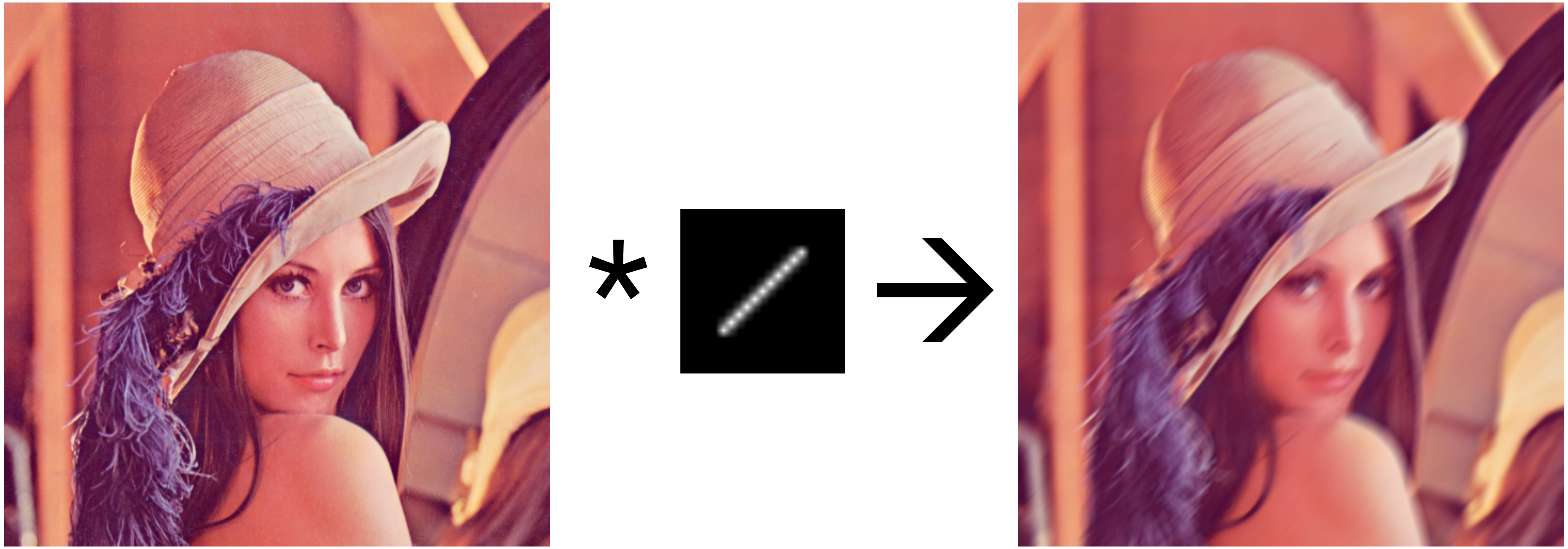
- Infinite number of solutions satisfy the blur model

- Analogous to

$$100 = \begin{cases} 2 \times 50 \\ 4 \times 25 \\ 3 \times 33.333\ldots \end{cases}$$

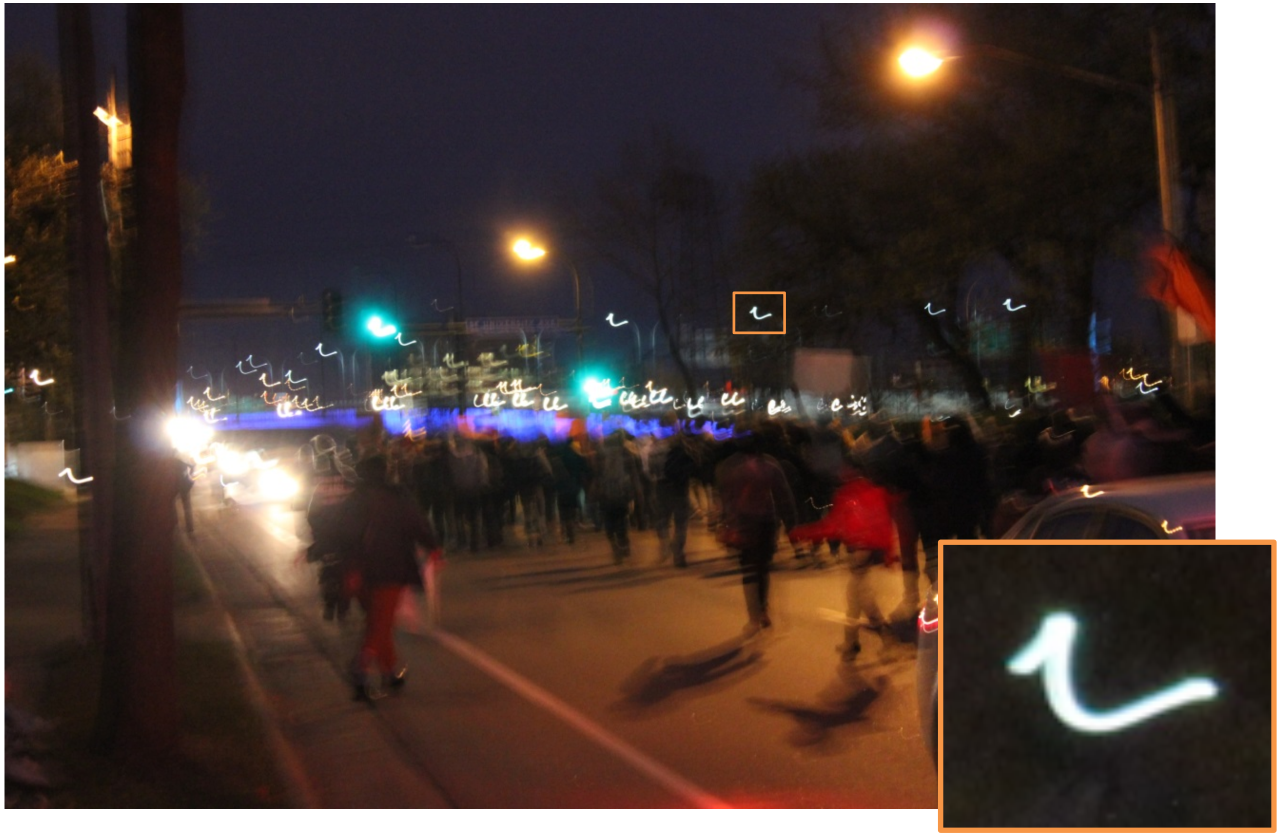
In The Past…

- Parametric blur kernels
  - [Yitzhakey et al. 1998], [Rav-Acha and Peleg 2005], …
  - Directional blur kernels defined by (length, angle)



In The Past…

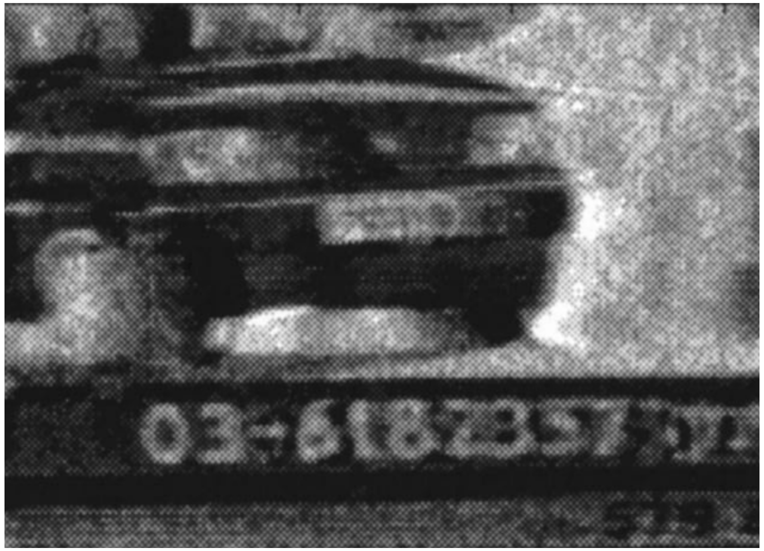
- But real camera shakes are much more complex



In The Past…

- Parametric blur kernels
  - Very restrictive assumption
  - Often failed, poor quality

Blurred image



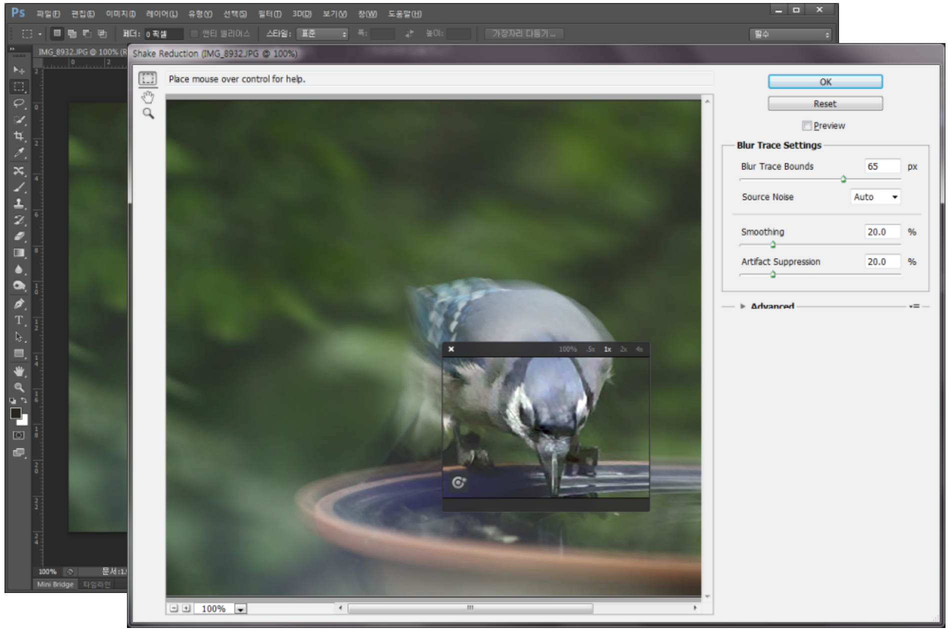
Latent sharp image

* Images from [Yitzhaky et al. 1998]

Nowadays…

- Some successful approaches have been introduced…
  - [Fergus et al. SIGGRAPH 2006], [Shan et al. SIGGRAPH 2008], [Cho and Lee, SIGGRAPH Asia 2009], …
  - More realistic blur kernels
  - Better quality
  - More robust

- Commercial software
  - Photoshop CC Shake reduction



Introduction

Blind Deconvolution

Non-blind Deconvolution

- Introduction
- Recent popular approaches
- Non-uniform blur

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

- [Shan et al. SIGGRAPH 2008], [Krishnan et al. CVPR 2011], [Xu et al. CVPR 2013], …

- Seek the most probable solution, which maximizes a posterior distribution
- Easy to understand
- Convergence problem

Recent Popular Approaches

Maximum Posterior (MAP) based

- [Fergus et al. SIGGRAPH 2006], [Levin et al. CVPR 2009], [Levin et al. CVPR 2011], …

Variational Bayesian based

- Not seek for one most probable solution, but consider all possible solutions
- Theoretically more robust
- Slow

Edge Prediction based

Which one is better?

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Which one is better?

- [Cho & Lee. SIGGRAPH Asia 2009], [Xu et al. ECCV 2010], [Hirsch et al. ICCV 2011], …

- Explicitly try to recover sharp edges using heuristic image filters
- Fast
- Proven to be effective in practice, but hard to analyze because of heuristic steps

Recent Popular Approaches

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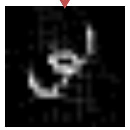
MAP based Approaches

Maximize a joint posterior probability with respect to k and l

Posterior distribution

$$p(k, l \mid b)$$



Blur kernel k

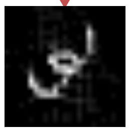
Latent image l

Blurred image b

MAP based Approaches

Bayes rule:

$$\overset{\text{Posterior distribution}}{p(k, l \mid b)} \propto \overset{\text{Likelihood}}{p(b \mid l, k)}\ \overset{\text{Prior on } l}{p(l)}\ \overset{\text{Prior on } k}{p(k)}$$



Blur kernel k

Latent image l

Blurred image b

MAP based Approaches

Negative log-posterior:

$$-\log p(k, l|b) \Rightarrow -\log p(b|k,l) - \log p(l) - \log p(k)$$
$$\Rightarrow \underbrace{\|k * l - b\|^2}_{\text{Data fitting term}} + \underbrace{\rho_l(l)}_{\text{Regularization on latent image } l} + \underbrace{\rho_k(k)}_{\text{Regularization on blur kernel } k}$$

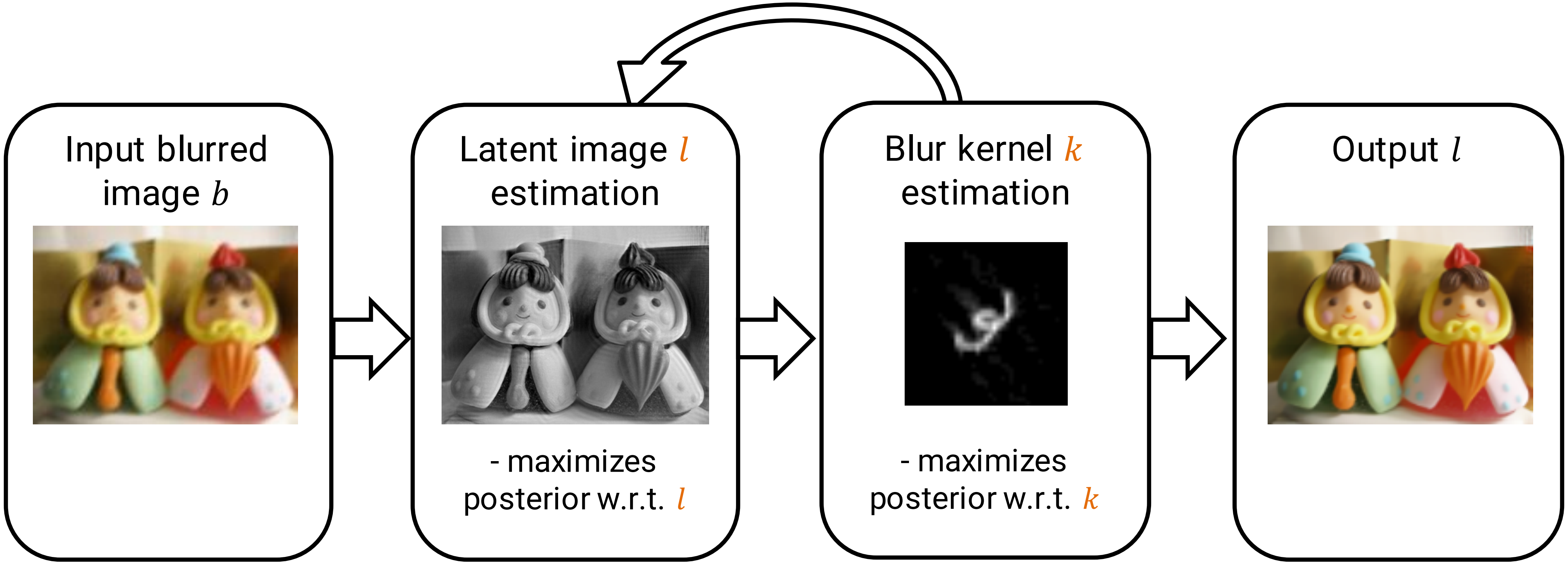
MAP based Approaches

Negative $\log$-posterior:

$$-\log p(k,l|b) \Rightarrow -\log p(b|k,l) - \log p(l) - \log p(k)$$
$$\Rightarrow \underbrace{\|k * l - b\|^2}_{\text{Data fitting term}} + \underbrace{\rho_l(l)}_{\text{Regularization on latent image } l} + \underbrace{\rho_k(k)}_{\text{Regularization on blur kernel } k}$$

Alternatingly minimize the energy function w.r.t. k and l

MAP based Approaches



MAP based Approaches

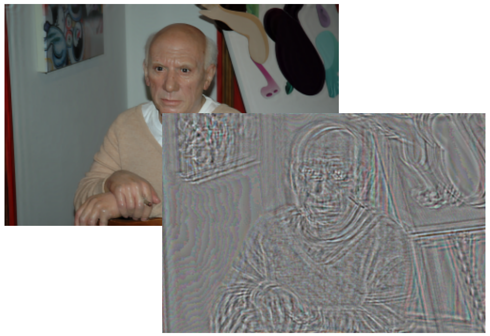
- Chan and Wong, TIP 1998
  - Total variation based priors for estimating a parametric blur kernel
- Shan et al. SIGGRAPH 2008
  - First MAP based method to estimate a nonparametric blur kernel
- Krishnan et al. CVPR 2011
  - Normalized sparsity measure, a novel prior on latent images
- Xu et al. CVPR 2013
  - L0 norm based prior on latent images

Shan et al. SIGGRAPH 2008

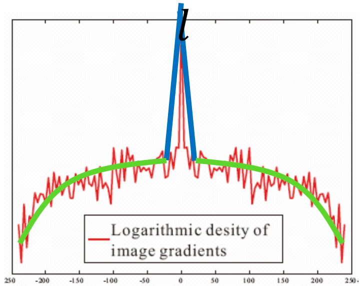
- Carefully designed likelihood & priors

$$\color{orange}{p(k, l|b)} \propto \underbrace{p(b|l,k)}\,\underbrace{p(l)}\,\underbrace{p(k)}$$

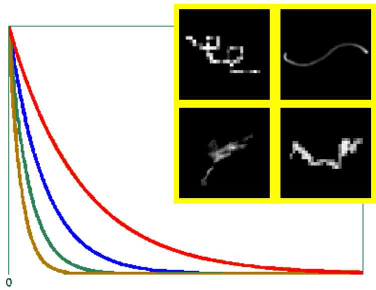
Likelihood based on intensities & derivatives



Natural image statistics based prior on l



Kernel statistics based prior on k

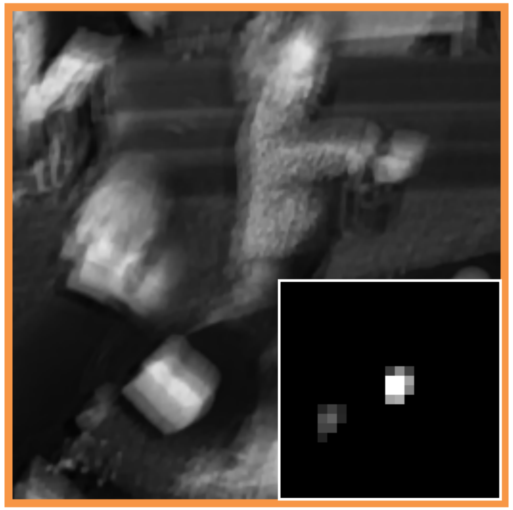


Shan et al. SIGGRAPH 2008

- A few minutes for a small image
- High-quality results

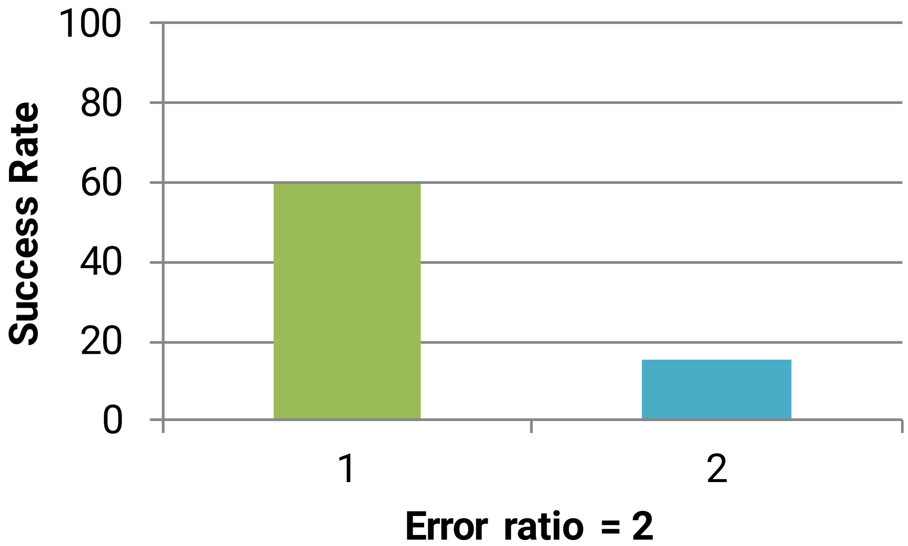
Shan et al. SIGGRAPH 2008

- Convergence problem
  - Often converge to the no-blur solution [Levin et al. CVPR 2009]
  - Natural image priors prefer blurry images



Shan et al. SIGGRAPH 2008

Fergus et al. SIGGRAPH 2006
(variational Bayesian based)



Recent Popular Approaches

Maximum Posterior (MAP) based

- [Fergus et al. SIGGRAPH 2006],
  [Levin et al. CVPR 2009],
  [Levin et al. CVPR 2011], …

Variational Bayesian based

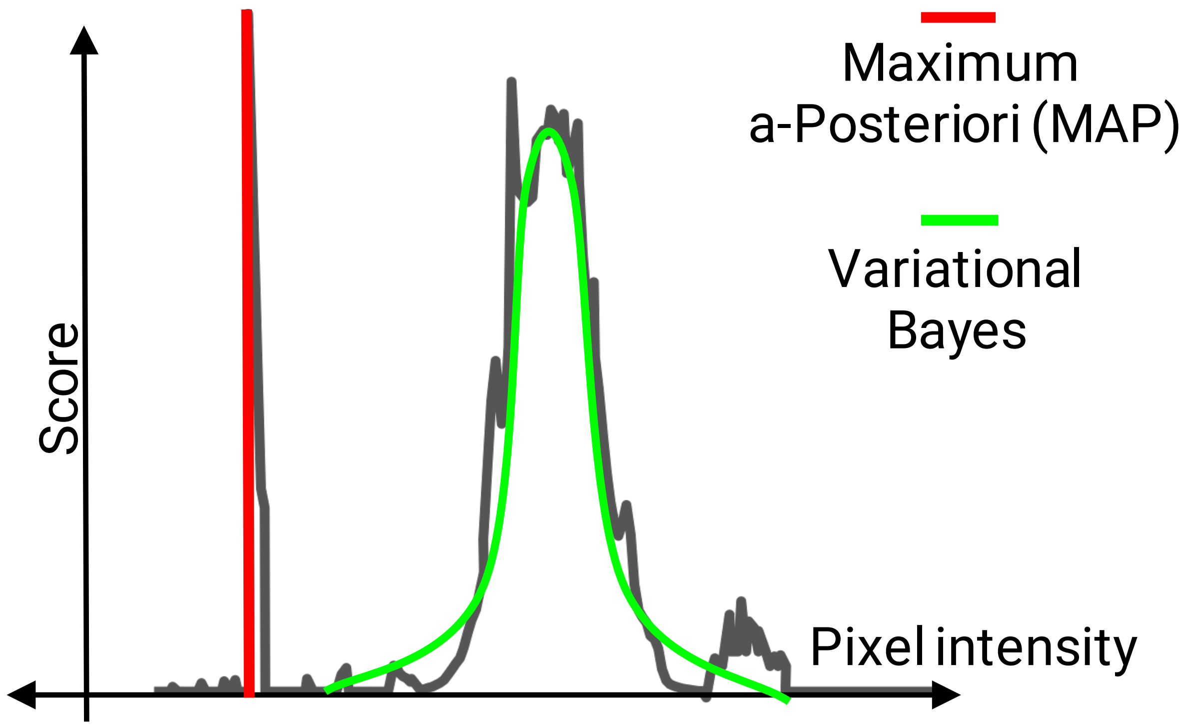
- Not seek for one most probable solution, but consider all possible solutions
- Theoretically more robust
- Slow

Edge Prediction based

Which one is better?

Variational Bayesian

MAP v.s. Variational Bayes



- MAP
  - Find the most probable solution
  - May converge to a wrong solution
- Variational Bayesian
  - Approximate the underlying distribution and find the mean
  - More stable
  - Slower

Variational Bayesian

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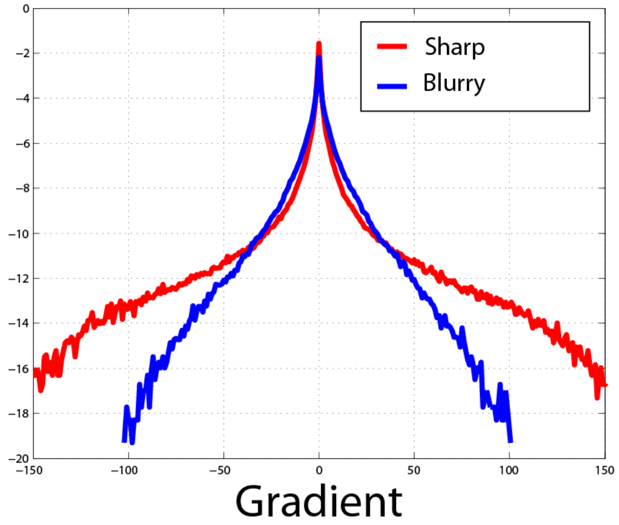
- Fergus et al. SIGGRAPH 2006
  - First approach to handle non-parametric blur kernels
- Levin et al. CVPR 2009
  - Show that variational Bayesian approaches can perform more robustly than MAP based approaches
- Levin et al. CVPR 2010
  - EM based efficient approximation to variational Bayesian approach

Fergus et al. SIGGRAPH 2006

- Posterior distribution

$$p(k, l|\mathrm{b}) \propto p(b|k, l)p(l)p(k)$$



Fergus et al. SIGGRAPH 2006

- Find an approximate distribution by minimizing Kullback-Leibler (KL) divergence

$$\underset{q(k),q(l),q(\sigma^{-2})}{\arg\min} KL\left(\underbrace{q(k)q(l)q(\sigma^{-2})}_{\substack{\text{approximate distributions for blur kernel } k,\\ \text{latent image } l, \text{ and noise variance } \sigma^2}} \middle\| p(k,l|b)\right)$$

- cf) MAP based approach:

$$\underset{k,l}{\arg\min}\, p(k,l|\mathrm{b})$$

Fergus et al. SIGGRAPH 2006

- First method to estimate a nonparametric blur kernel
- Complex optimization
- Slow: more than an hour for a small image

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

- [Cho et al. SIGGRAPH Asia 2009], [Xu et al. ECCV 2010], [Hirsch et al. ICCV 2011], …
- Explicitly try to recover sharp edges using heuristic image filters
- Fast
- Proven to be effective in practice, but hard to analyze because of heuristic steps

Edge Prediction based Approaches

- Joshi et al. CVPR 2008
  - Proposed sharp edge prediction to estimate blur kernels
  - No iterative estimation
  - Limited to small scale blur kernels
- Cho & Lee, SIGGRAPH Asia 2009
  - Proposed sharp edge prediction to estimate large blur kernels
  - Iterative framework
  - State-of-the-art results & very fast
- Cho et al. CVPR 2010
  - Applied Radon transform to estimate a blur kernel from blurry edge profiles
  - Small scale blur kernels
- Xu et al. ECCV 2010
  - Proposed a prediction scheme based on structure scales as well as gradient magnitudes
- Hirsch et al. ICCV 2011
  - Applied a prediction scheme to estimate spatially-varying camera shakes

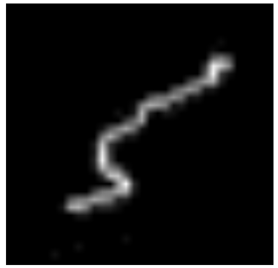
Cho & Lee, SIGGRAPH Asia 2009

- Key idea: blur can be estimated from a few edges

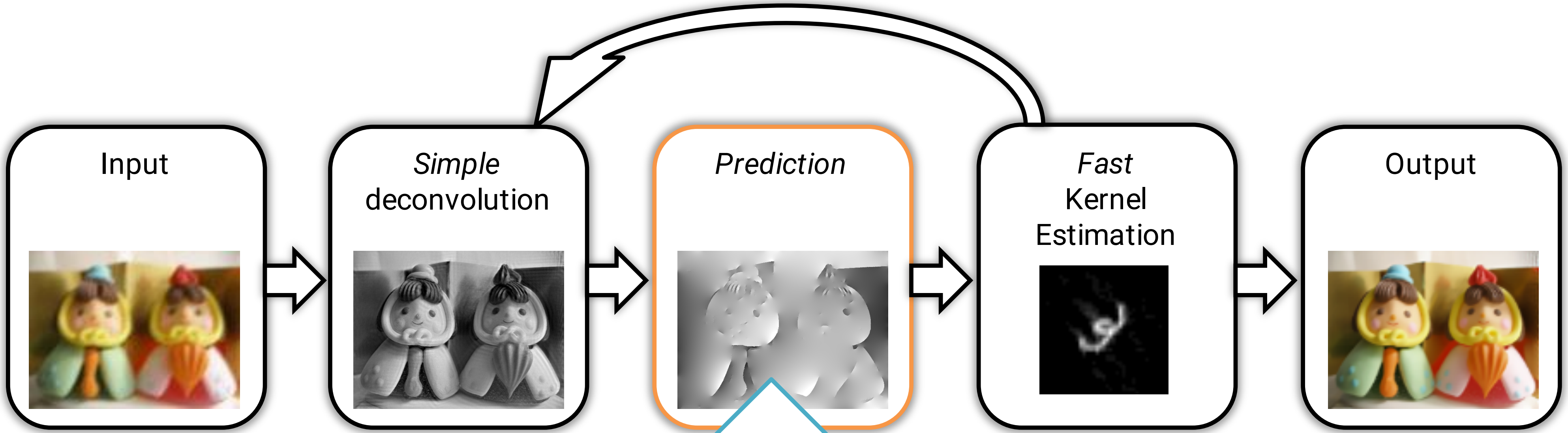
➔ No need to restore every detail for kernel estimation

Blurred image

Latent image with only a few edges and no texture

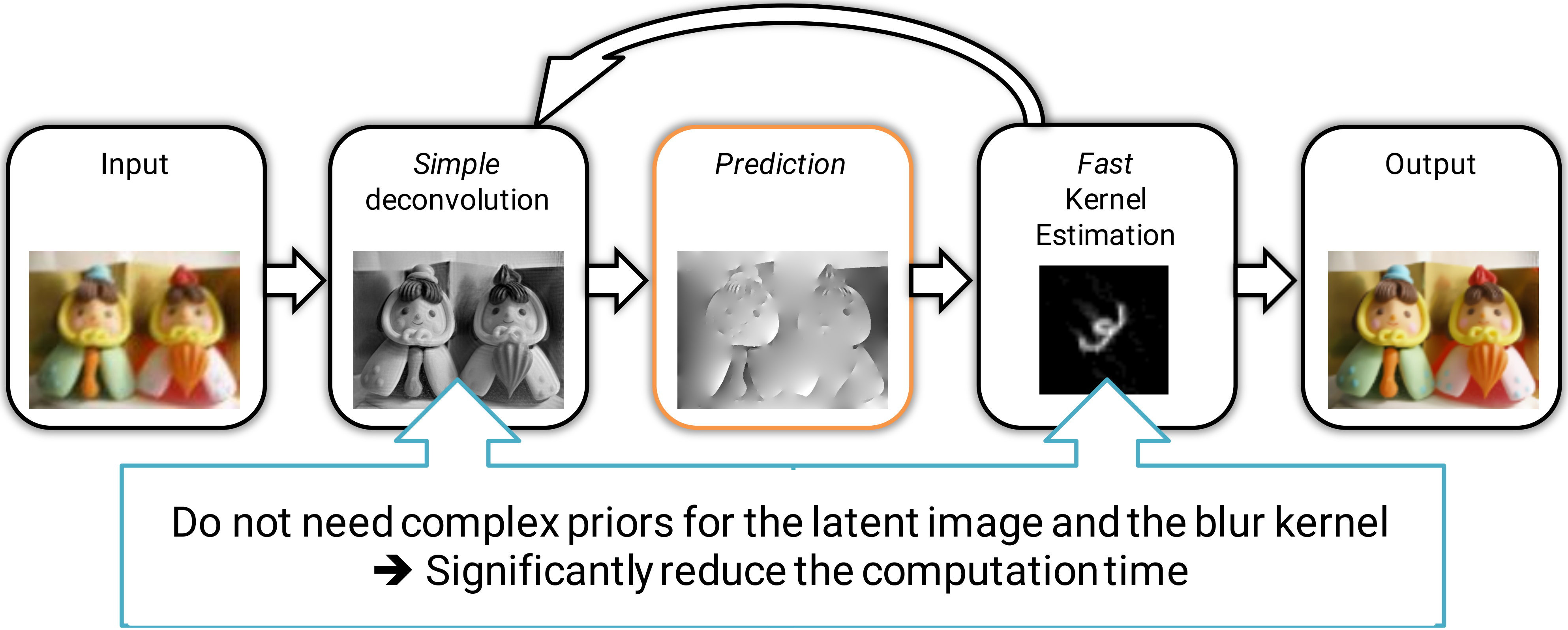


Cho & Lee, SIGGRAPH Asia 2009

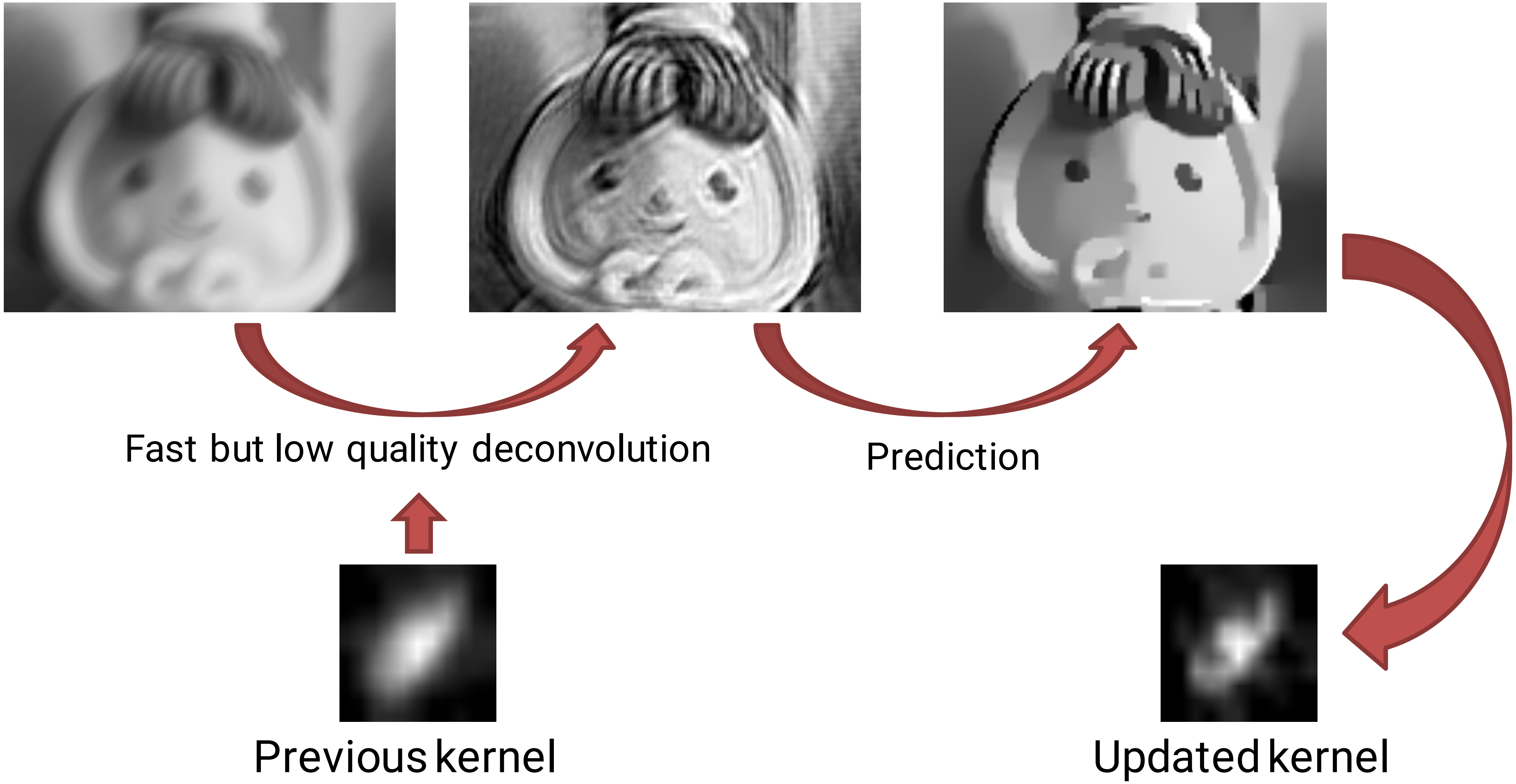


Quickly restore important edges using simple image filters

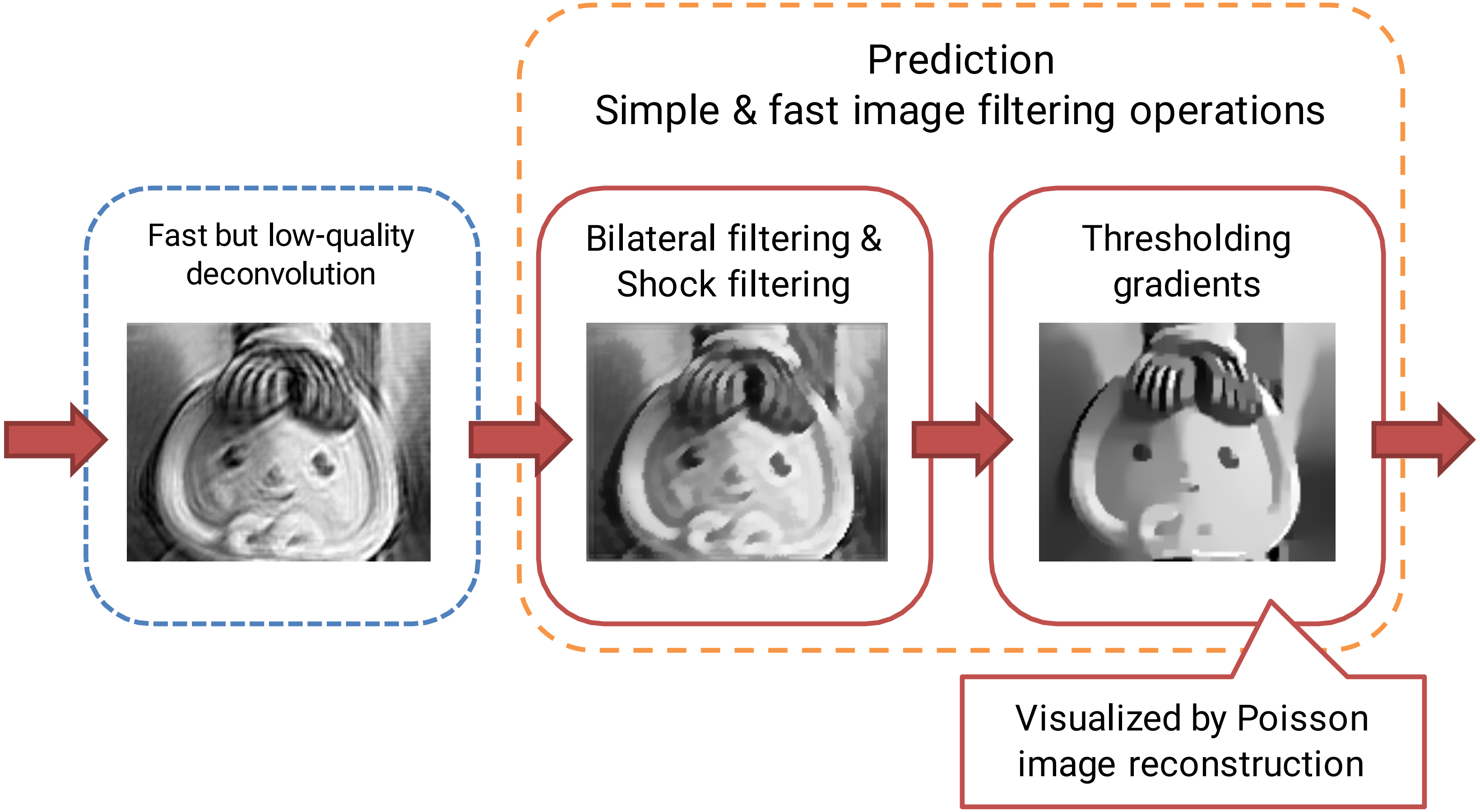
Cho & Lee, SIGGRAPH Asia 2009



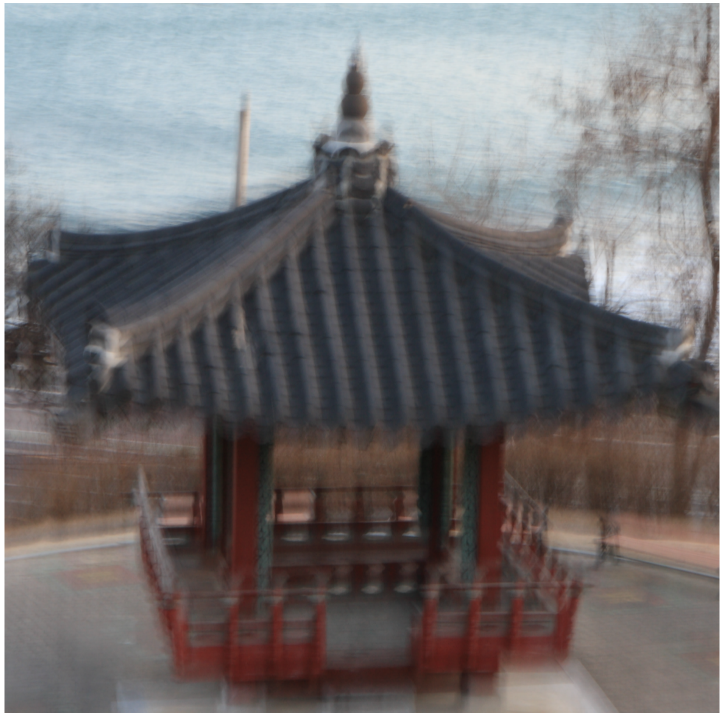
Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009



Blurry input

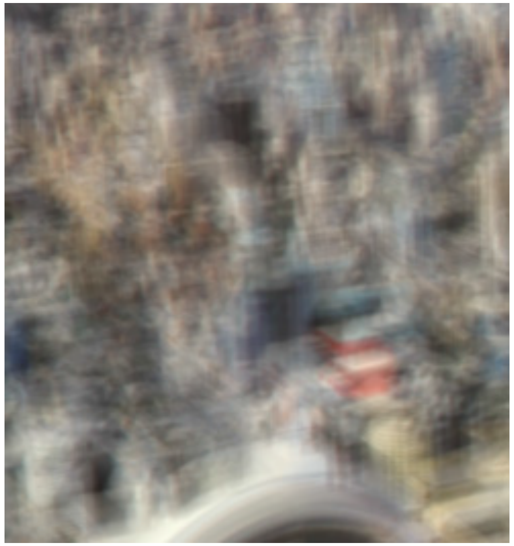
Deblurring result

- State of the art results
- A few seconds
- 1Mpix image
- in C++

Blur kernel

Xu & Jia, ECCV 2010

- Extended edge prediction to handle blur larger than image structures



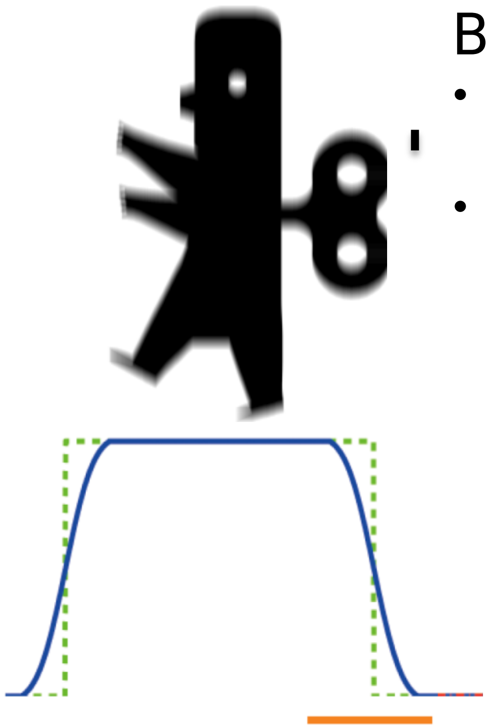
Blurred image

Fergus et al.
SIGGRAPH 2006

Shan et al.
SIGGRAPH 2008

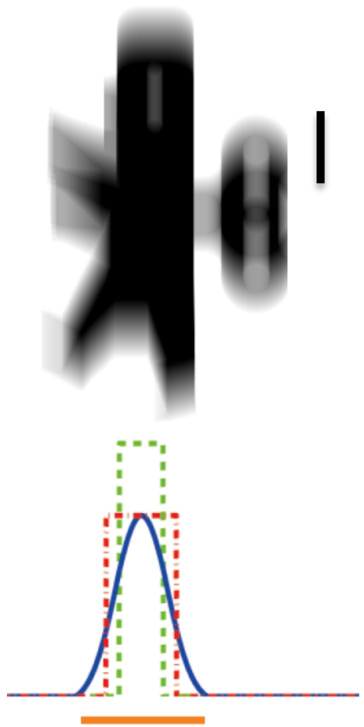
For this complex scene, most methods fail to estimate a correct blur kernel. Why?

Xu & Jia, ECCV 2010



Blur < structures

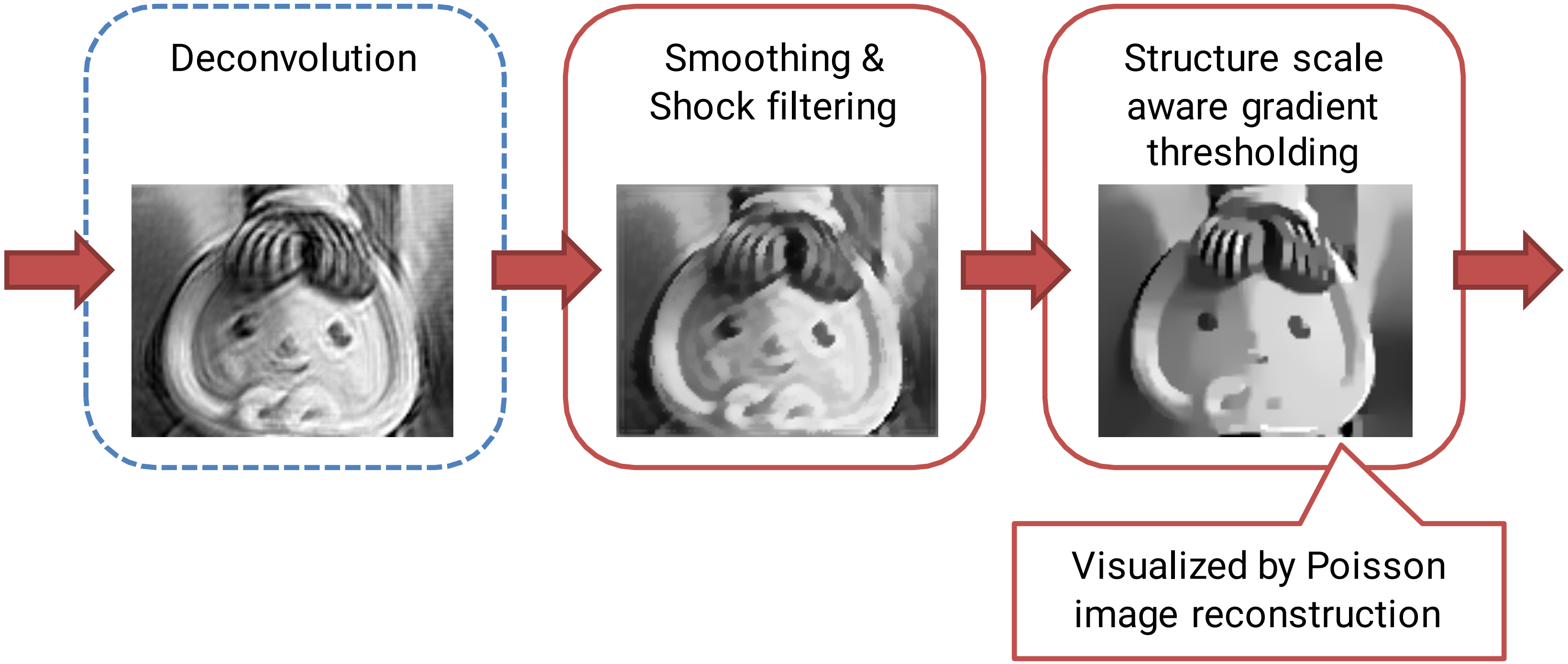
- Each blurry pixel is caused by one edge
- Easy to figure out the original sharp structure



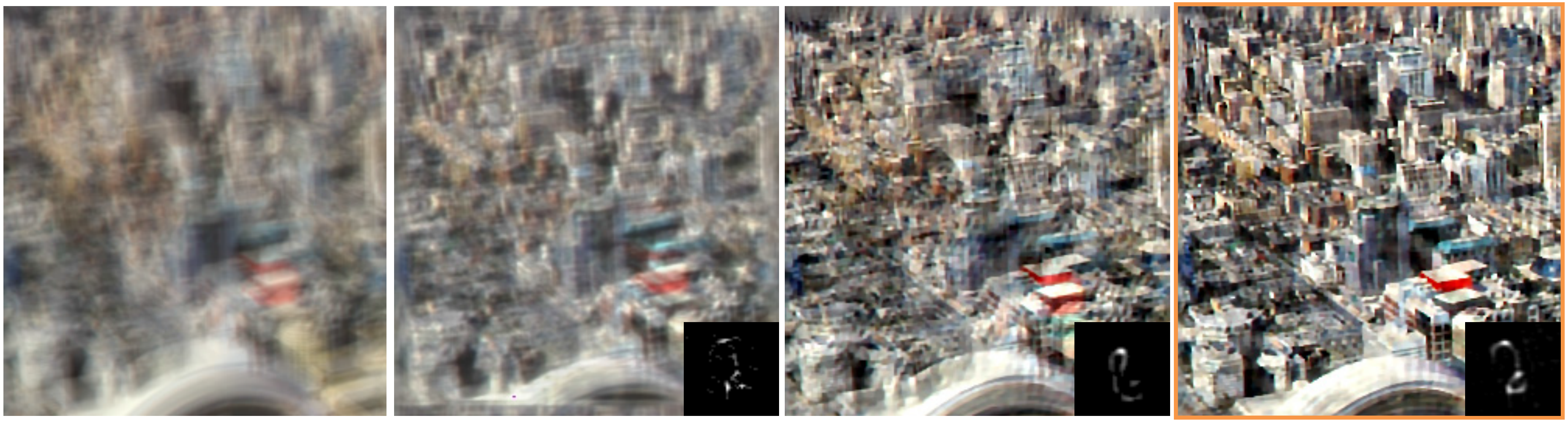
Blur > structures

- Hard to tell which blur is caused by which edge
- Most method fails

Xu & Jia, ECCV 2010



Xu & Jia, ECCV 2010



Blurred image	Fergus et al. SIGGRAPH 2006	Shan et al. SIGGRAPH 2008	Xu & Jia, ECCV 2010

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

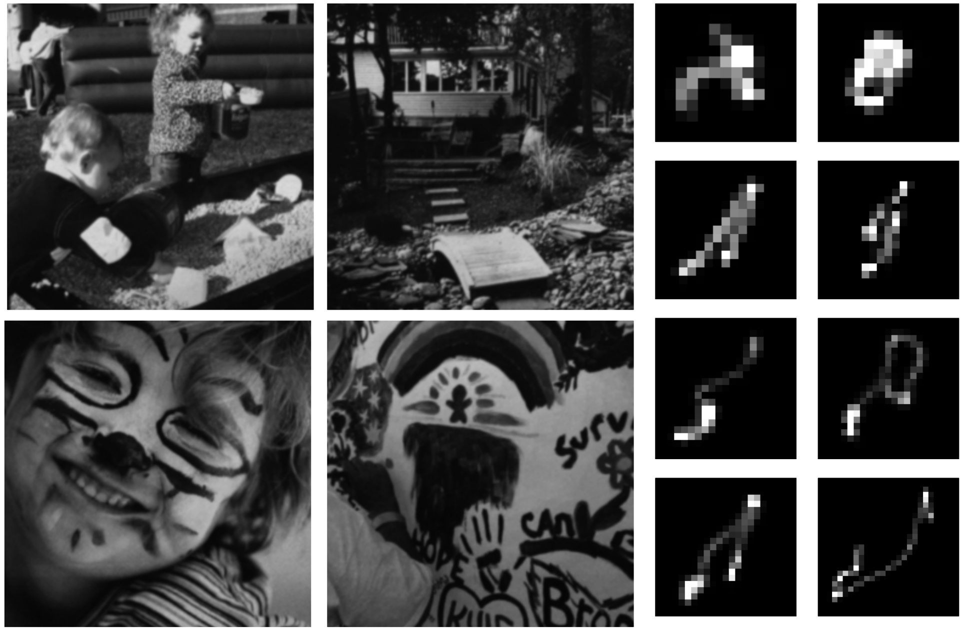
Which one is better?

Benchmarks

- Many different methods…
- Which one is the best?
  - Quality
  - Speed
- Different works report different benchmark results
  - Depending on test data
  - Levin et al. CVPR 2009, 2010
  - Köhler et al. ECCV 2012

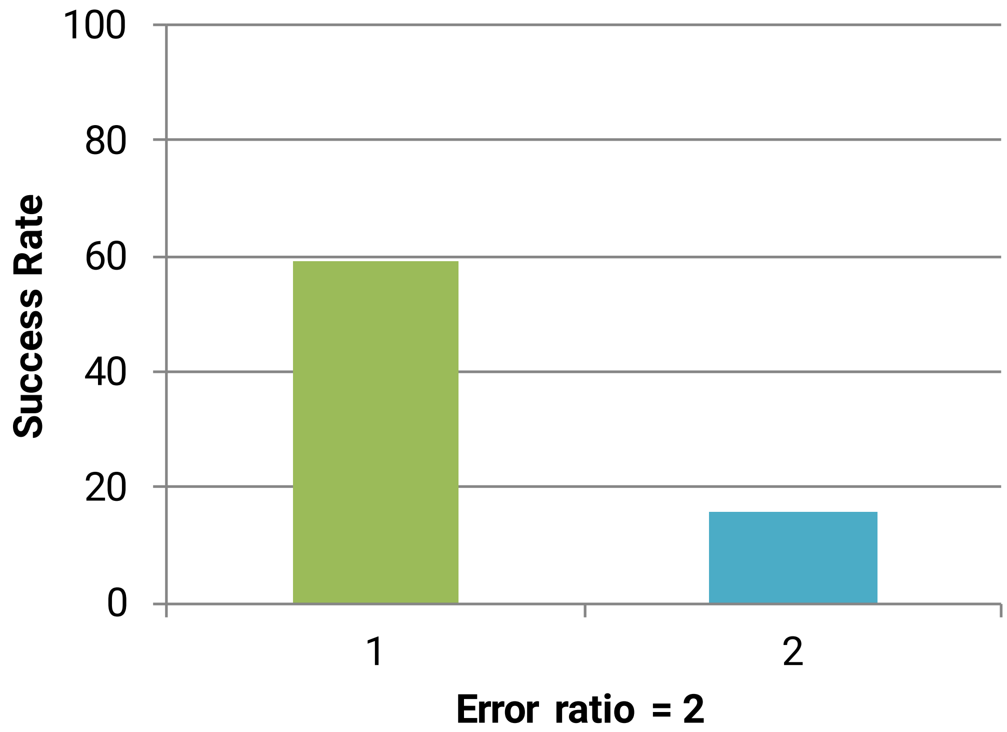
Benchmarks

- Levin et al. CVPR 2009
  - Provide a dataset
    - 32 test images
    - 4 clear images (255x255)
    - 8 blur kernels (10x10 ~ 25x25)
    - One of the most widely used datasets
  - Evaluate blind deconvolution methods using the dataset



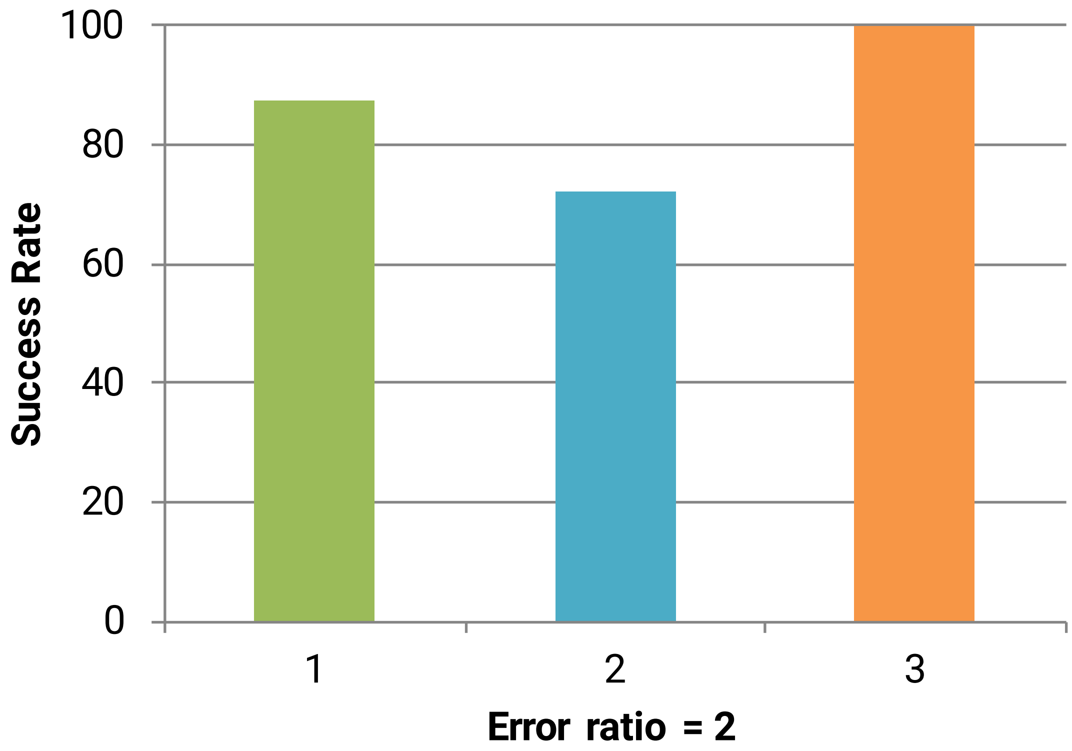
Benchmarks

- Levin et al. CVPR 2009
  - Counted the number of successful results



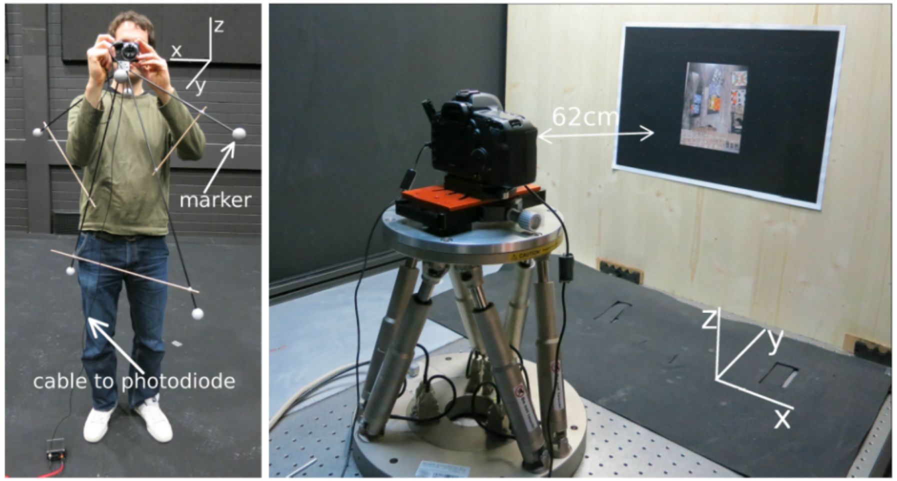
Benchmarks

- Cho & Lee, SIGGRAPH Asia 2009
  – Comparison based on Levin et al.'s dataset
  – Slightly different parameter settings



Benchmarks

- Köhler et al. ECCV 2012
  - Record and analyze real camera motions
    - Recorded 6D camera shakes in the 3D space using markers
    - Played back camera shakes using a robot arm
  - Provide a benchmark dataset based on real camera shakes
  - Provide benchmark results for recent state-of-the-art methods

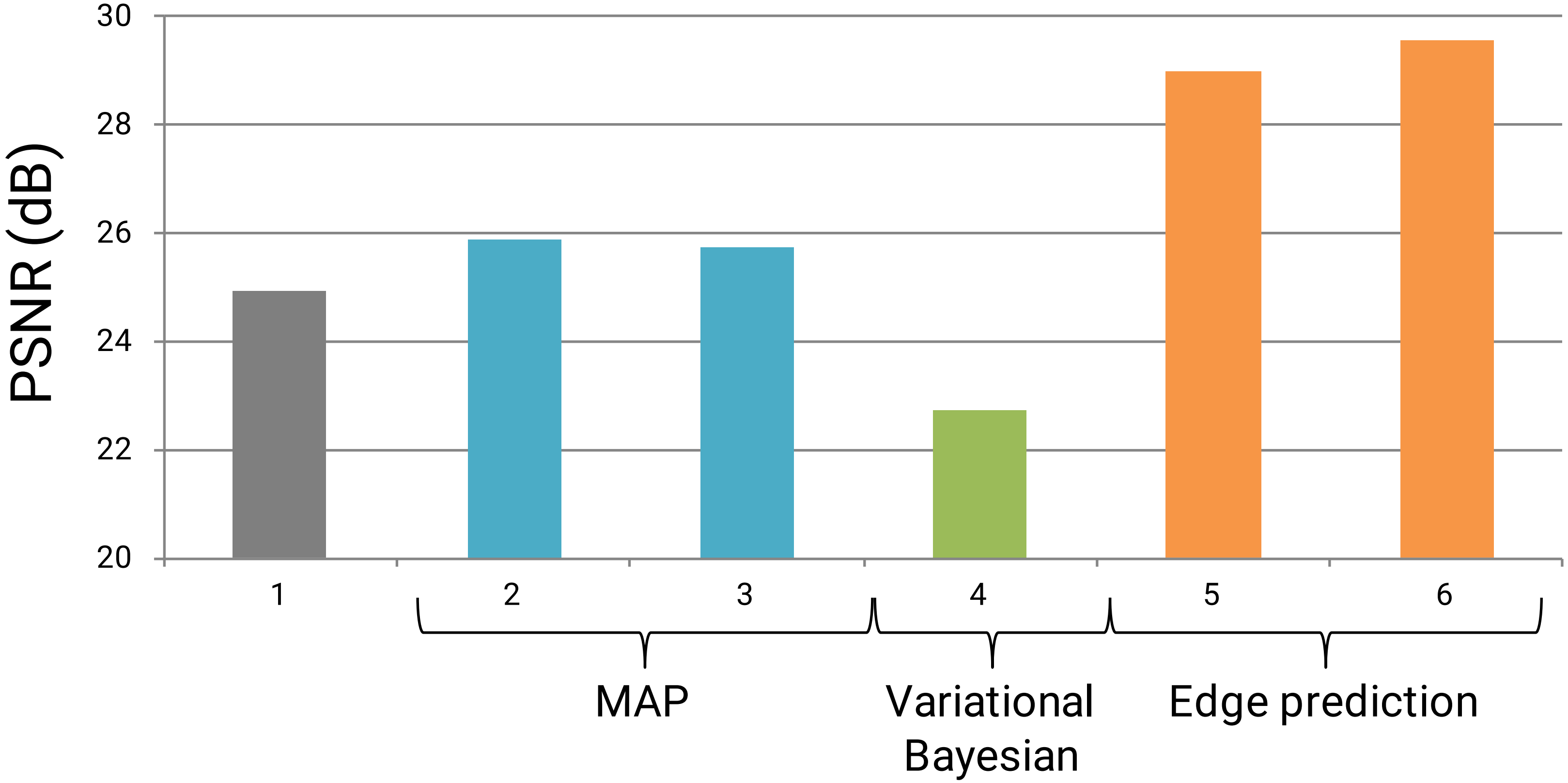


Benchmarks

- Köhler et al. ECCV 2012
  - Dataset
    - 48 test images
    - 4 sharp images
    - 12 non-uniform camera shakes

Benchmarks

- Köhler et al. ECCV 2012



Benchmarks

- Benchmark results depend on
  - Implementation details & tricks
  - Benchmark datasets
  - Parameters used in benchmarks

- But, in general, more recent one shows better quality

- Speed?
  - Edge prediction > MAP >> Variational Bayesian

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

- Introduction
- Recent popular approaches
- Non-uniform blur

Convolution based Blur Model

- Uniform and spatially invariant blur

Real Camera Shakes: Spatially Variant!

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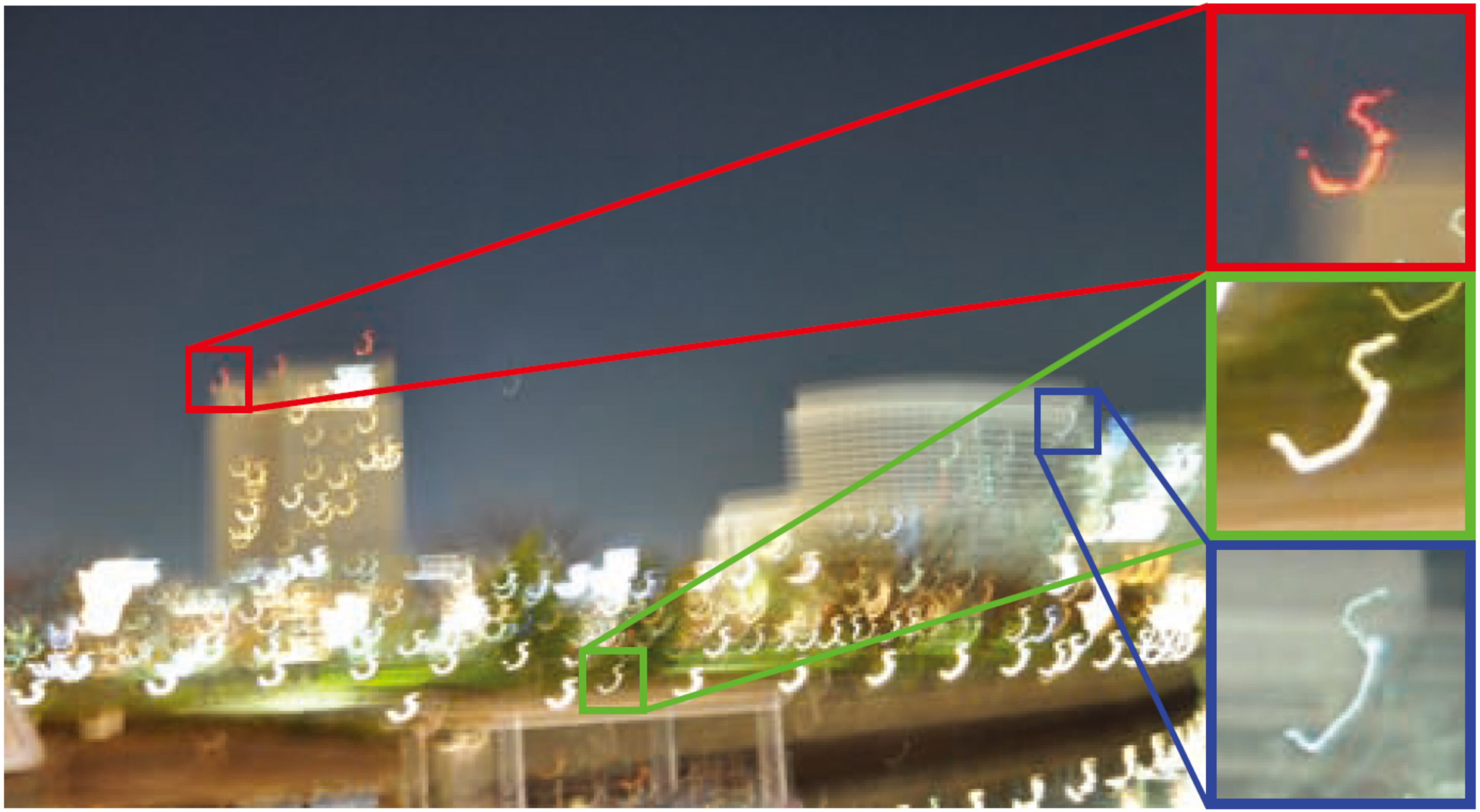


Uniform Blur Model Assumes

x & y translational
camera shakes

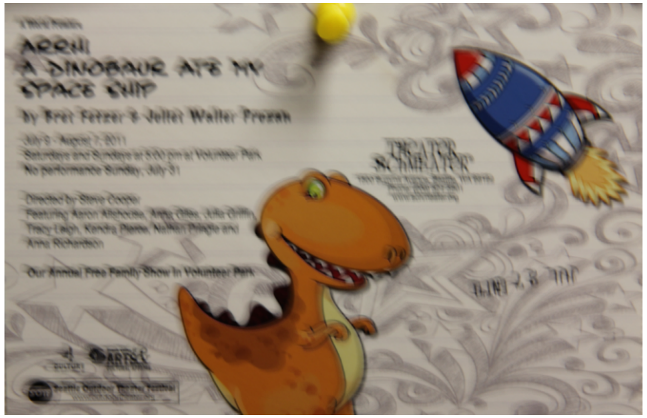
Planar scene

Real Camera Shakes

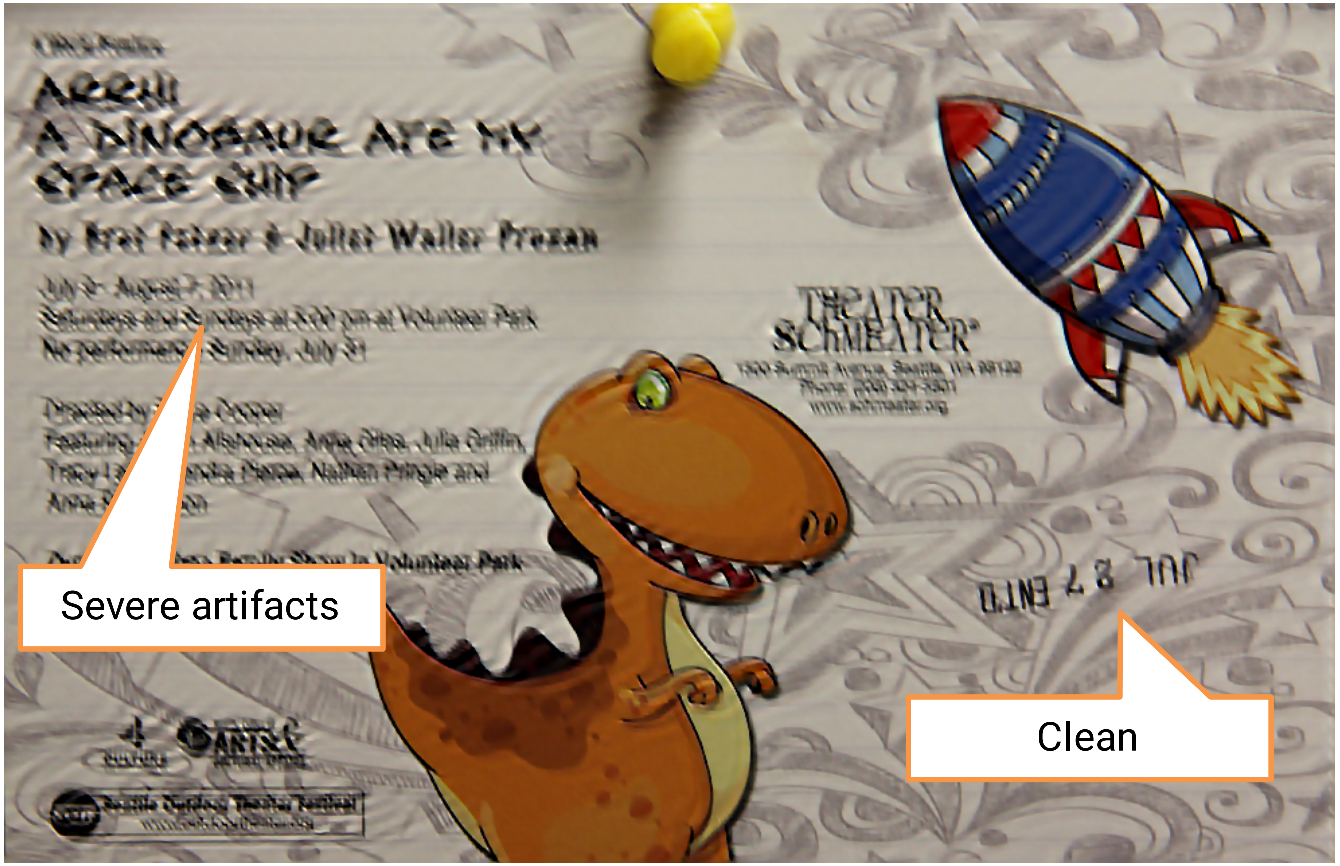
6D real camera motion

Different depths

Real Blurred Image



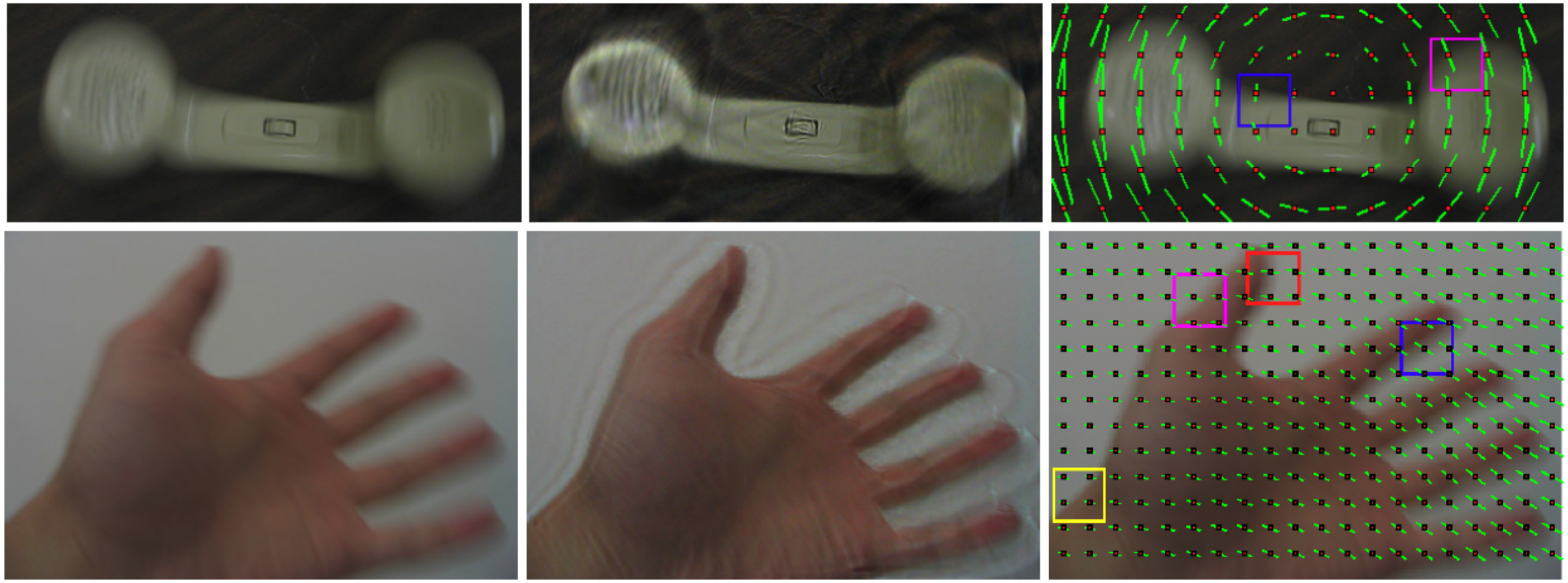
Non-uniformly blurred image



Uniform deblurring result

Pixel-wise Blur Model

- Dai and Wu, CVPR 2008
  - Estimate blur kernels for every pixel from a single image
  - Severely ill-posed
  - Parametric blur kernels



Pixel-wise Blur Model

- Tai et al. CVPR 2008
  - Hybrid camera to capture hi-res image & low-res video
  - Estimate per-pixel blur kernels using low-res video

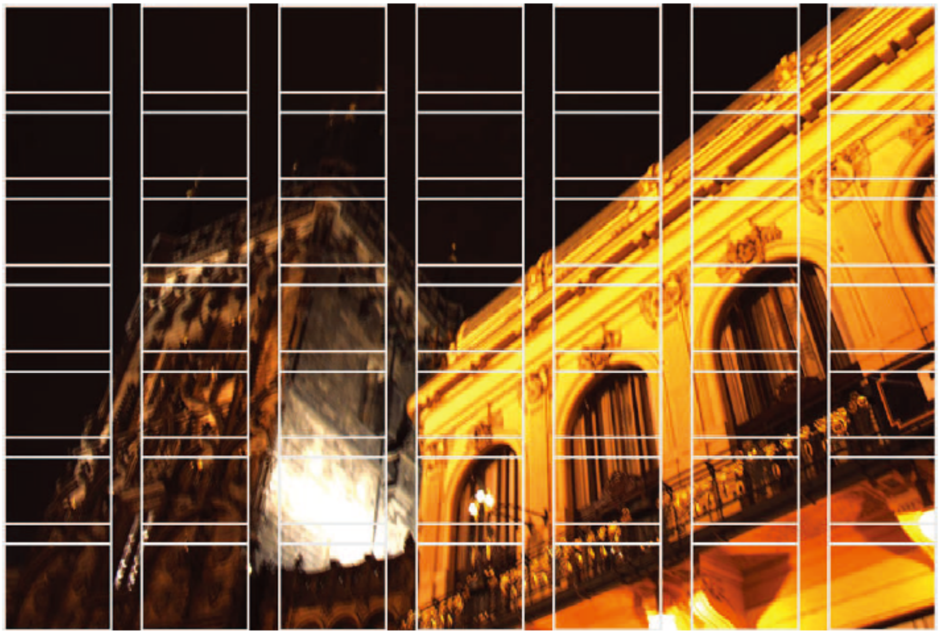
Hi-res.
image

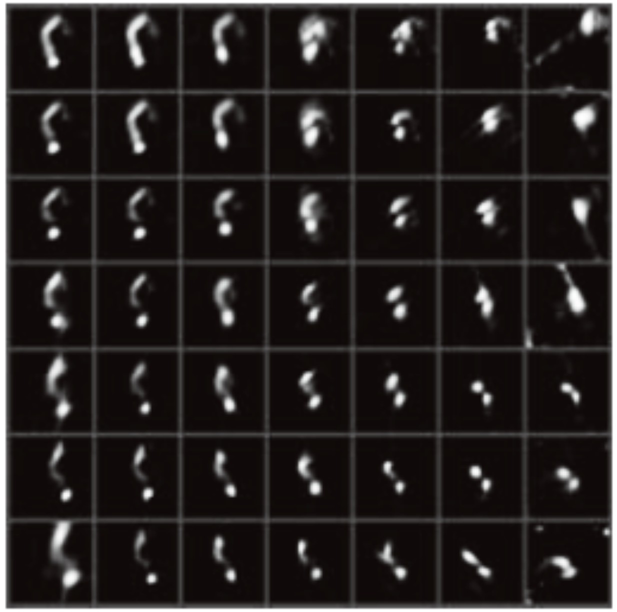
Low-res.
video

time

Patch-wise Blur Model

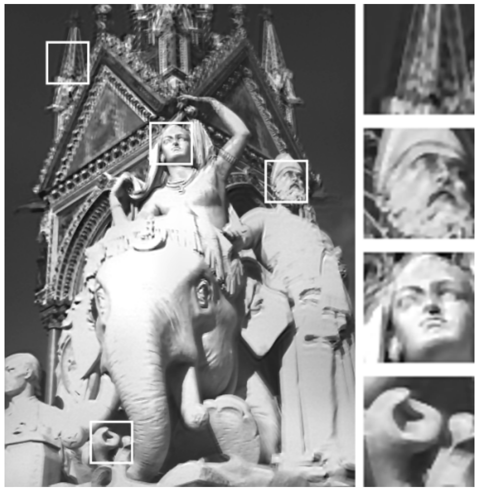
- Sorel and Sroubek, ICIP 2009
  - Estimate per-patch blur kernels from a blurred image and an underexposed noisy image





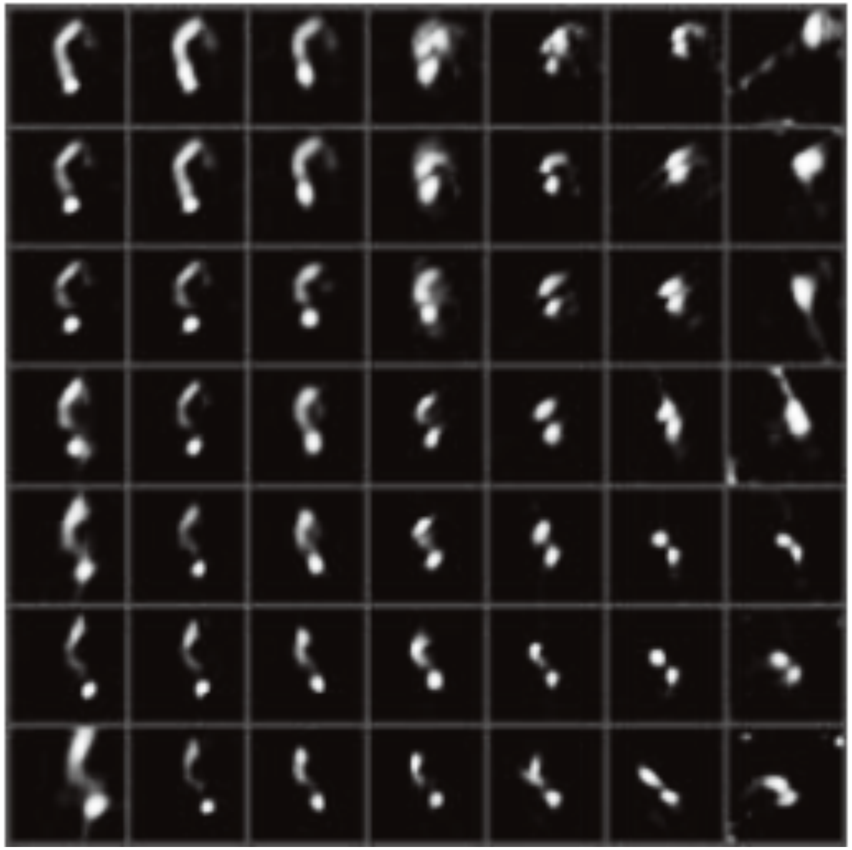
Patch-wise Blur Model

- Hirsch et al. CVPR 2010
  - Efficient filter flow (EFF) framework
  - More accurate approximation than the naïve patch-wise blur model
- Harmeling et al. NIPS 2010
  - Estimate per-patch blur kernels based on EFF from a single image

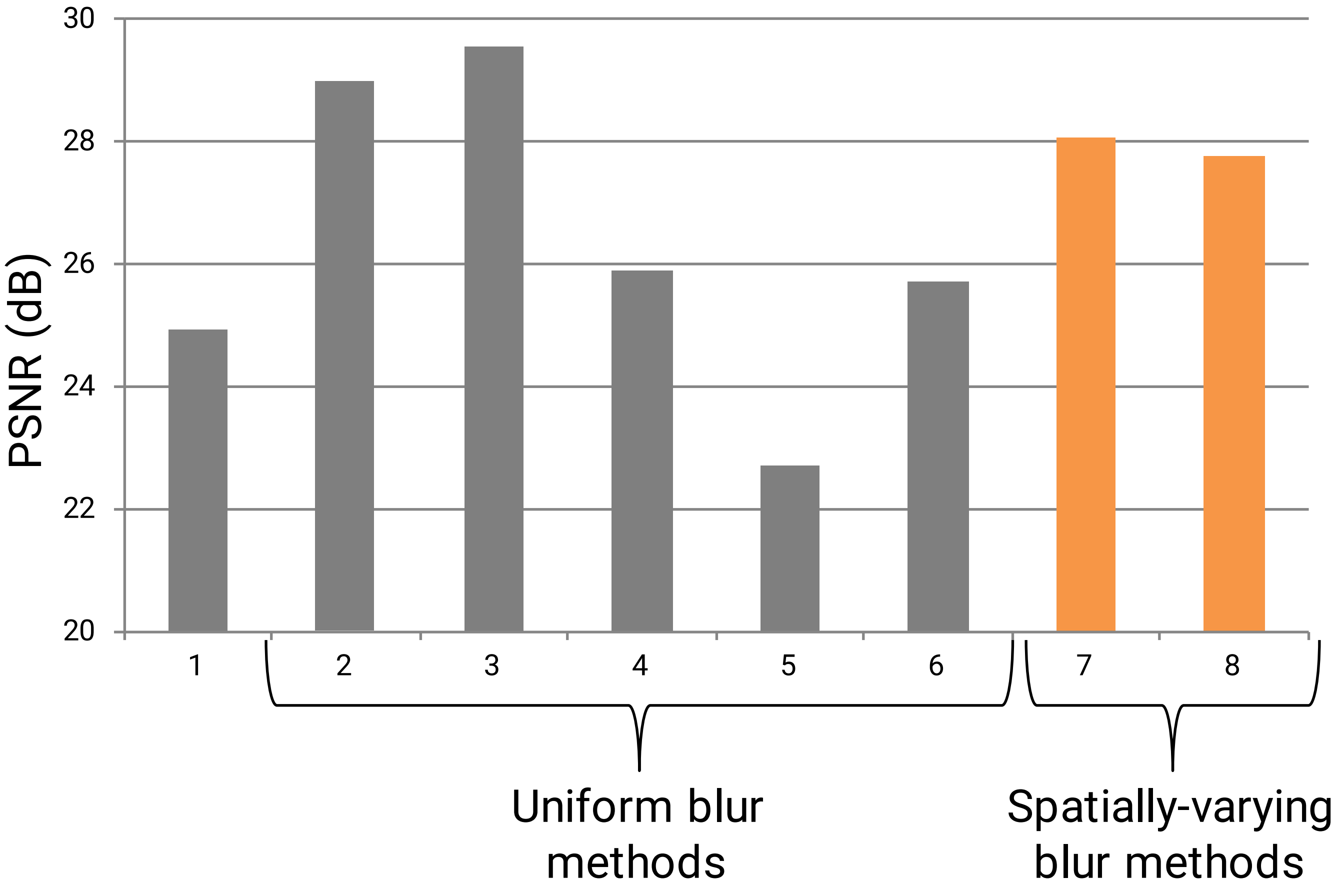


Patch-wise Blur Model

- Approximation
  - More patches → more accurate
- Computationally efficient
  - Patch-wise uniform blur
  - FFTs can be used
- Physically implausible blurs
  - Adjacent blur kernels cannot be very different from each other



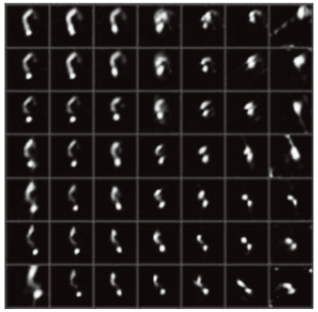
Benchmark [Köhler et al. ECCV 2012]



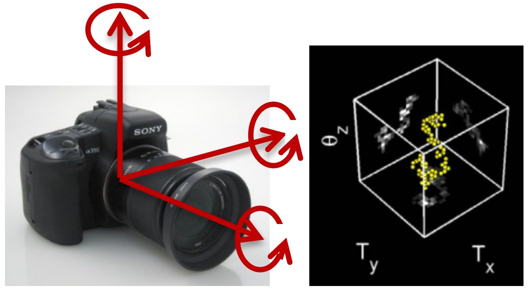
Due to high dimensionality, spatially-varying blur methods are less stable.

Summary

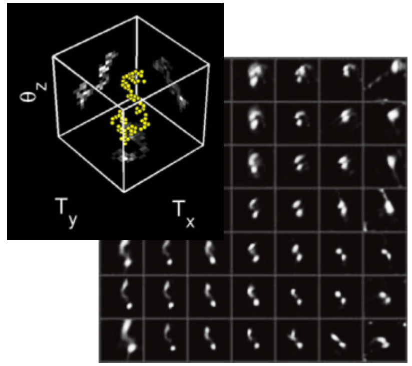
- Different blur models



Patch based
Efficient but no global constraint



Projective Motion Path
Globally consistent but inefficient



Hybrid
Efficient & globally consistent

- More realistic than uniform blur model
- Still approximations
  - Real camera motions: 6 DoF + more (zoom-in, depth, etc…)
- High dimensionality
  - Less stable & slower than uniform blur model

Remaining Challenges

Failure example of Photoshop Shake Reduction

- All methods still fail quite often
- Noise
- Outliers
- Non-uniform blur
- Limited amount of edges
- Speed…
- Etc…

Introduction

Blind Deconvolution

Non-blind Deconvolution

Introduction

Blind Deconvolution

Non-blind Deconvolution

- Introduction
- Natural image statistics
- High-order natural image statistics
- Ringing artifacts
- Outliers

Non-blind Deconvolution (Uniform Blur)

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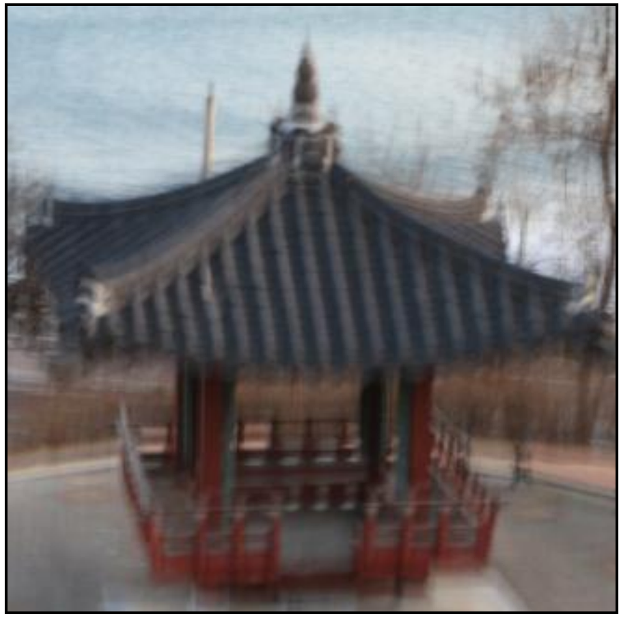


Blurred image

=

*

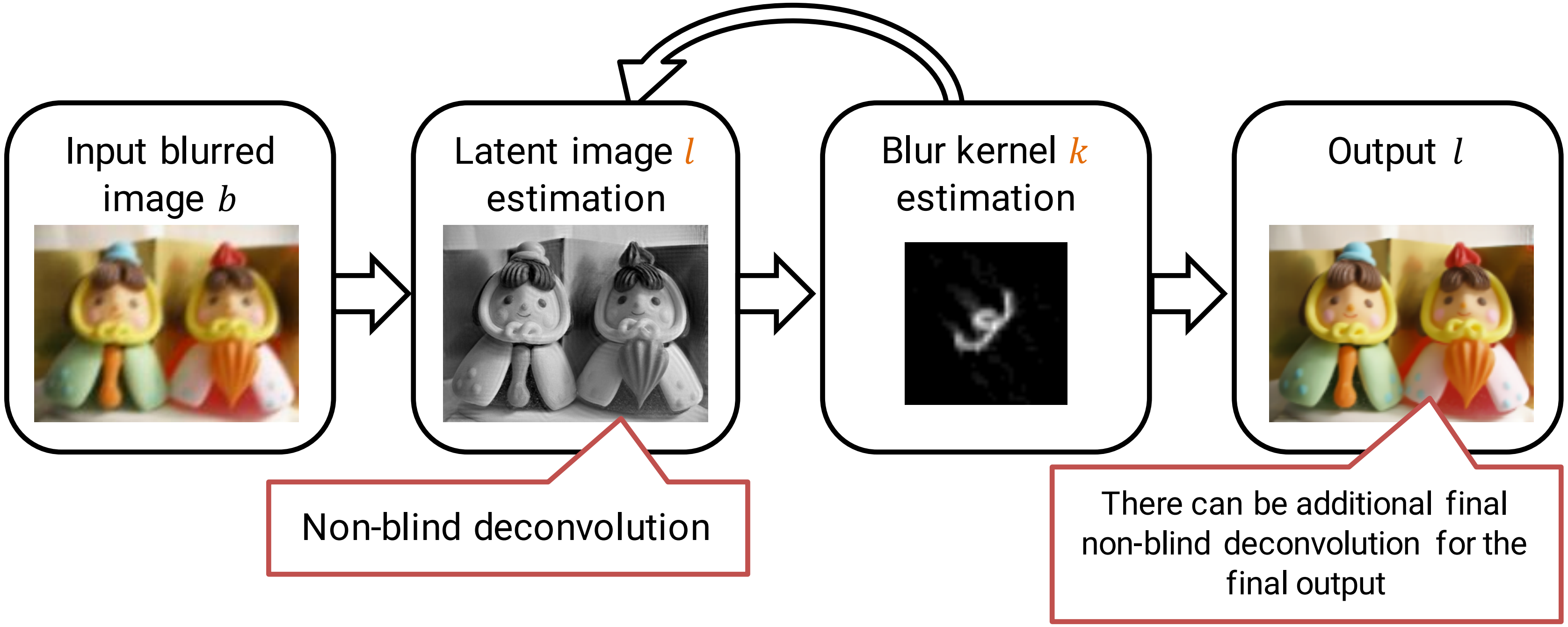
Latent sharp image

Blur kernel

Convolution operator

Non-blind Deconvolution

- Key component in many deblurring systems
  - For example, in MAP based blind deconvolution:



Non-blind Deconvolution

- Wiener filter
- Richardson-Lucy deconvolution
- Rudin et al. Physica 1992
- Bar et al. IJCV 2006
- Levin et al. SIGGRAPH 2007
- Shan et al. SIGGRAPH 2008
- Yuan et al. SIGGRAPH 2008
- Harmeling et al. ICIP 2010
- Etc…

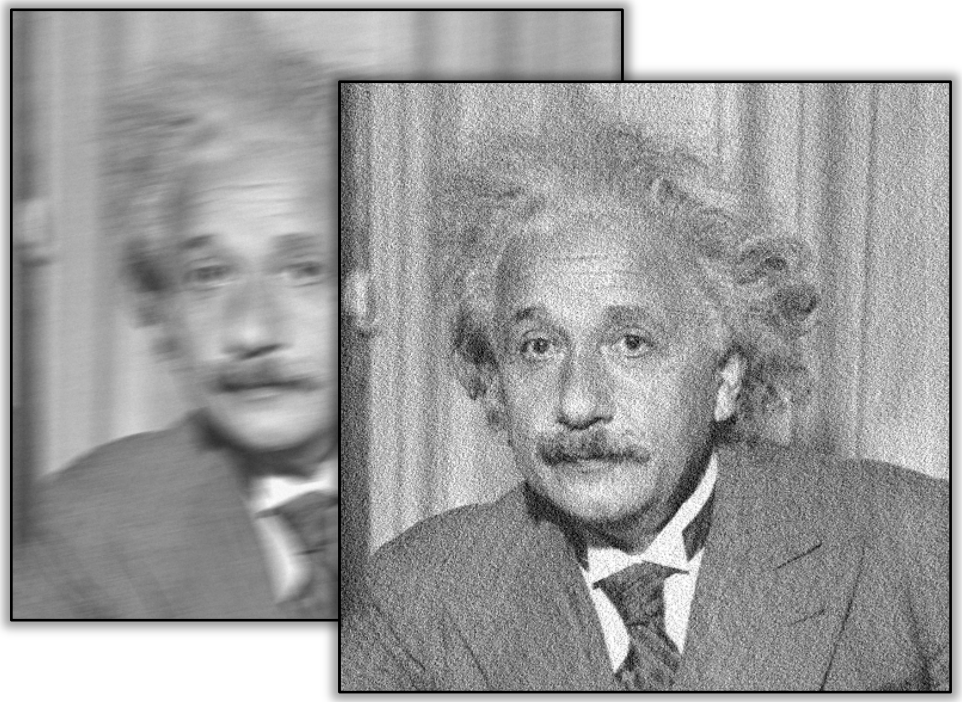
Ill-Posed Problem

- Even if we know the true blur kernel, we cannot restore the latent image perfectly, because:

- Loss of high-freq info & noise ≈ denoising & super-resolution

Ill-Posed Problem

- Deconvolution amplifies noise as well as sharpens edges



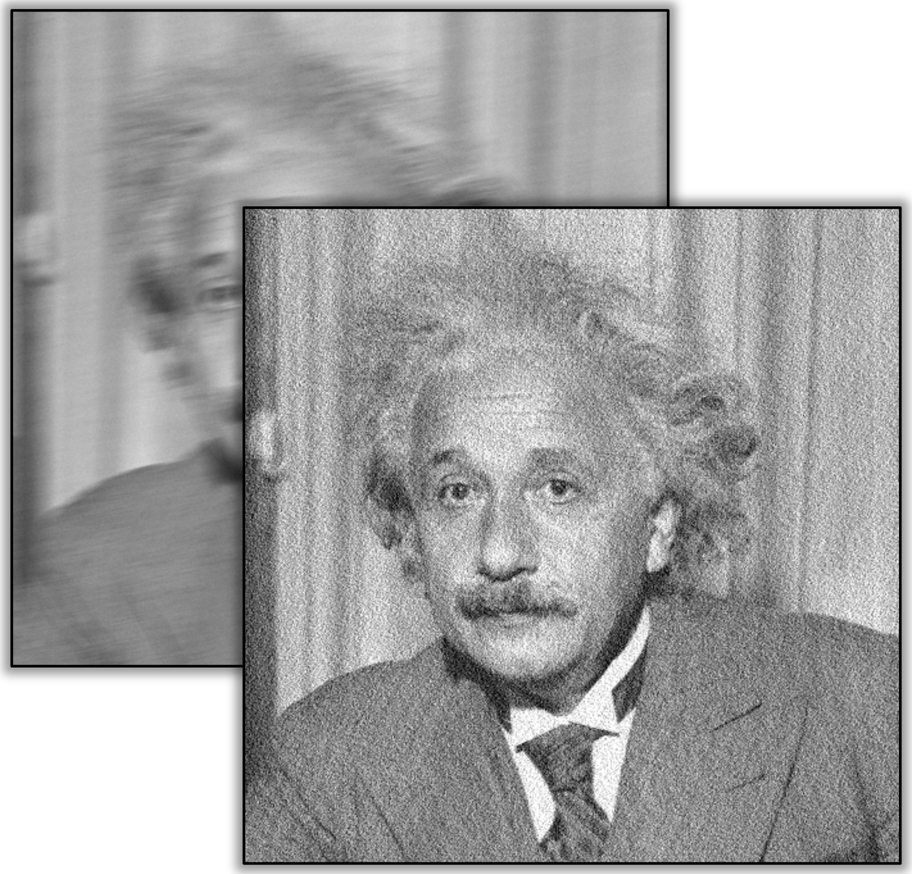
- Ringing artifacts
  - Inaccurate blur kernels, outliers cause ringing artifacts

Classical Methods

- Popular methods
  - Wiener filtering
  - Richardson-Lucy deconvolution
  - Constrained least squares

- Matlab Image Processing Toolbox
  - deconvwnr, deconvlucy, deconvreg

- Simple assumption on noise and latent images
  - Simple & fast
  - Prone to noise & artifacts



Introduction

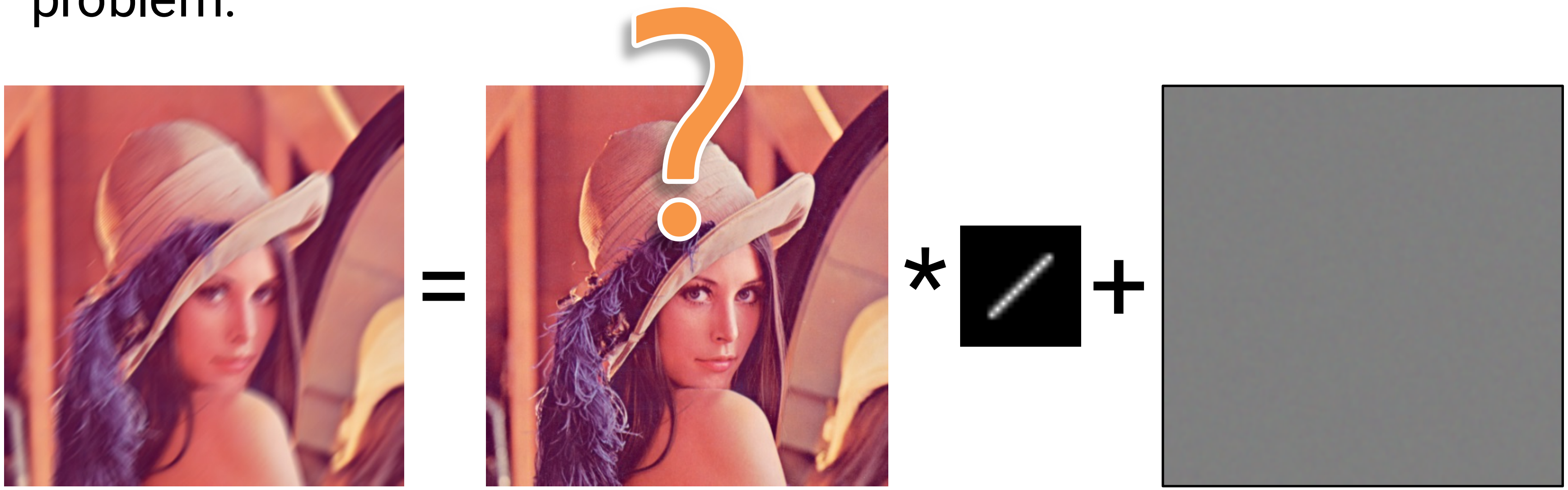
Blind Deconvolution

Non-blind Deconvolution

- Introduction
- **Natural image statistics**
- High-order natural image statistics
- Ringing artifacts
- Outliers

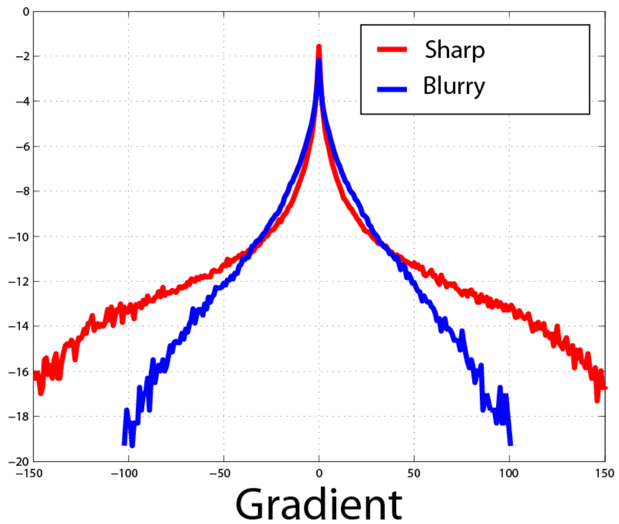
Natural Image Statistics

- Non-blind deconvolution: ill-posed problem
- We need to assume something on the latent image to constrain the problem.



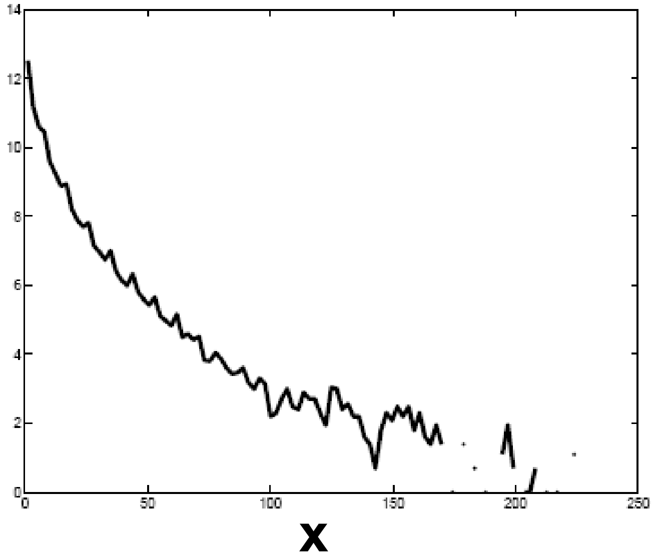
Natural Image Statistics

- Natural images have a heavy-tailed distribution on gradient magnitudes
  - Mostly zero & a few edges
  - Levin et al. SIGGRAPH 2007, Shan et al. SIGGRAPH 2008, Krishnan & Fergus, NIPS 2009

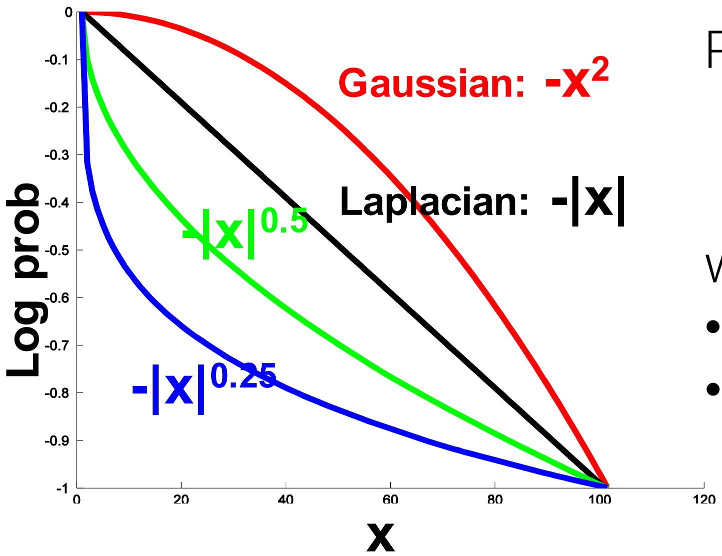


Natural Image Statistics

- Levin et al. SIGGRAPH 2007
  - Propose a parametric model for natural image priors based on image gradients



Derivative histogram from a natural image



Parametric models

Proposed prior

$$\log p(x) = -\sum_i |\nabla x_i|^\alpha$$

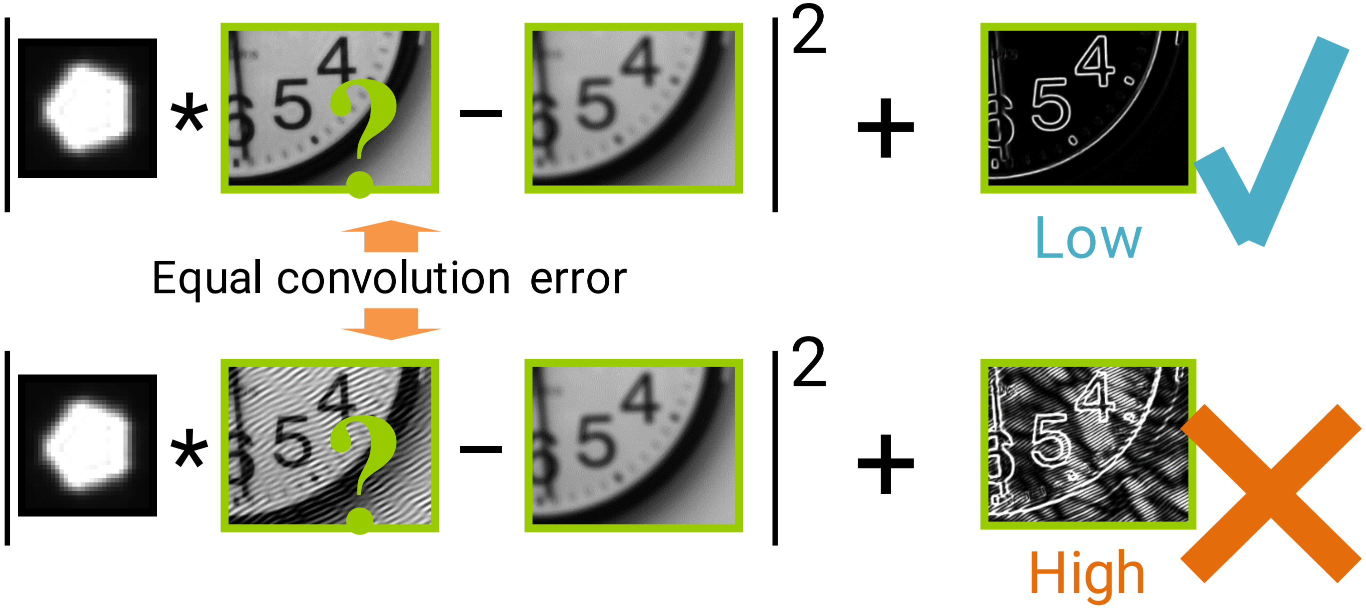
where:

- x: image
- α: model parameter, $\alpha < 1$

Natural Image Statistics

- Levin et al. SIGGRAPH 2007

$$l = \arg\min_{l} \{ \underbrace{\|k * l - b\|^2}_{\text{Data term}} + \underbrace{\lambda \textstyle\sum_i |\nabla l_i|^{\alpha}}_{\text{Prior}} \} \qquad (\alpha < 1)$$



Natural Image Statistics

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- Levin et al. SIGGRAPH 2007

Input

Richardson-Lucy

“spread” gradients

Gaussian prior

$$\sum_i |\nabla l_i|^2$$

“localizes” gradients

Sparse prior

$$\sum_i |\nabla l_i|^{0.8}$$

Introduction

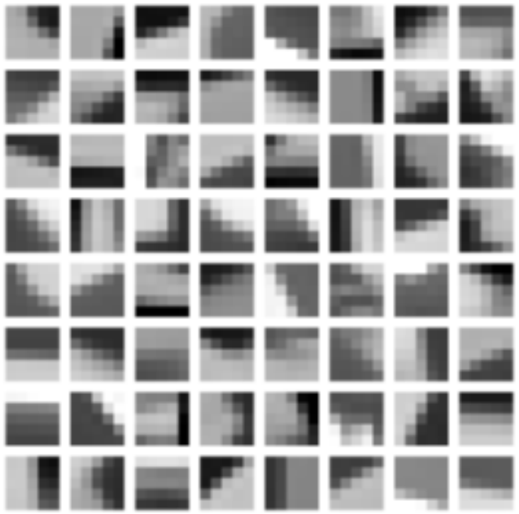
Blind Deconvolution

Non-blind Deconvolution

- Introduction
- Natural image statistics
- **High-order natural image statistics**
- Ringing artifacts
- Outliers

High-order Natural Image Priors

- Patches, large neighborhoods, …
- Effective for various kinds of image restoration problems
  - Denoising, inpainting, super-resolution, deblurring, …

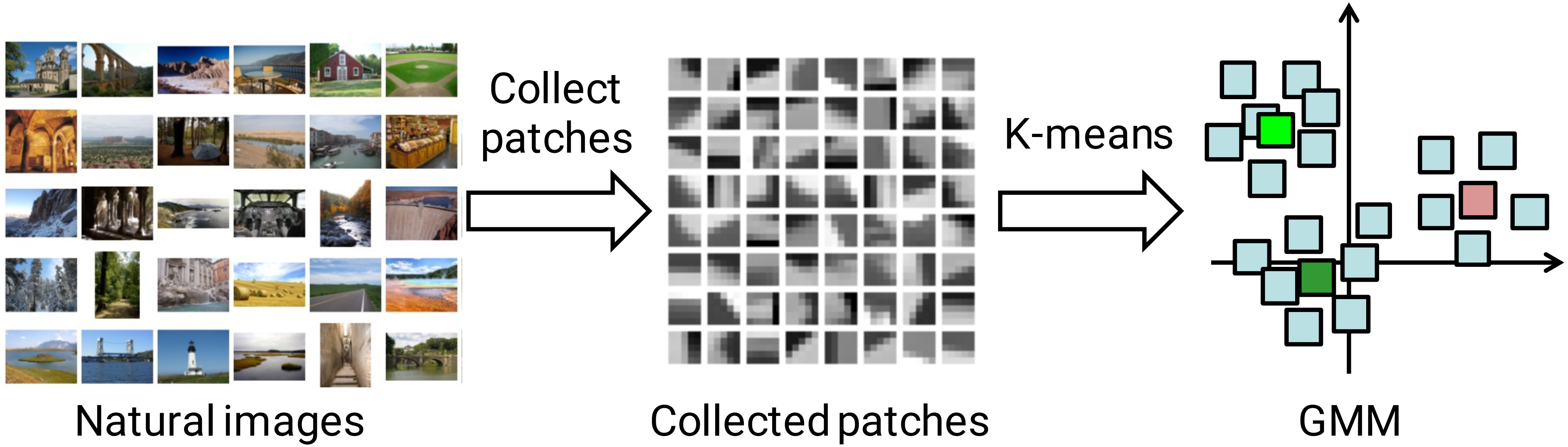


High-order Natural Image Priors

- Schmidt et al. CVPR 2011
  - Fields of Experts
- Zoran & Weiss, ICCV 2011
  - Trained Gaussian mixture model for natural image patches
- Schuler et al. CVPR 2013
  - Trained Multi-layer perceptron to remove artifacts and to restore sharp patches
- Schmidt et al. CVPR 2013
  - Trained regression tree fields for 5x5 neighborhoods

High-order Natural Image Priors

- Zoran & Weiss, ICCV 2011
  - Gaussian Mixture Model (GMM) learned from natural images



High-order Natural Image Priors

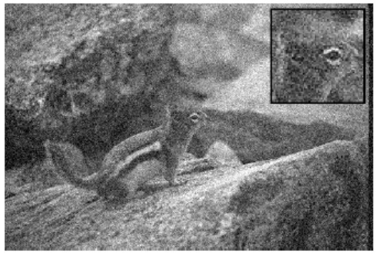
- Zoran & Weiss, ICCV 2011
  - Given a patch, we can compute its likelihood based on the GMM.
  - Deconvolution can be done by solving:

$$\arg\min_{l} \left\{ \|k * l - b\|^2 - \lambda \sum_{i} \underbrace{\log p(l_i)}_{\text{Log-likelihood of a patch } l_i \text{ at } i\text{-th pixel based on GMM}} \right\}$$

High-order Natural Image Priors

- Zoran & Weiss, ICCV 2011

Denoising



(a) Noisy Image - PSNR: 20.17

(b) KSVD - PSNR: 28.72

(c) LLSC - PSNR: 29.30

(d) EPLL GMM - PSNR: 29.39

Deblurring

Blurred image

Krishnan & Fergus
PSNR: 26.38

Zoran & Weiss
PSNR: 27.70

Introduction

Blind Deconvolution

Non-blind Deconvolution

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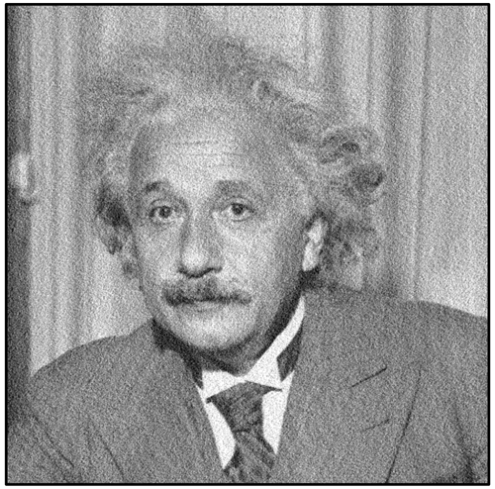
Ringing Artifacts

- Wave-like artifacts around strong edges
- Caused by
  - Inaccurate blur kernels
  - Nonlinear response curve
  - Etc…

Ringing Artifacts

- Noise
  - High-freq
  - Independent and identical distribution
  - Priors on image gradients work well



- Ringing
  - Mid-freq
  - Spatial correlation
  - Priors on image gradients are not very effective

Ringing Artifacts

- Yuan et al. SIGGRAPH 2007
  - Residual deconvolution & de-ringing
- Yuan et al. SIGGRAPH 2008
  - Multi-scale deconvolution framework based on residual deconvolution

Blurred image

Richardson-Lucy

Yuan et al. SIGGRAPH 2008

Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

Blurred image

Guide image

Residual deconvolution result
with *less ringing artifacts*

- Relatively accurate edges, but less details
- Obtained from a deconvolution result from a smaller scale

Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

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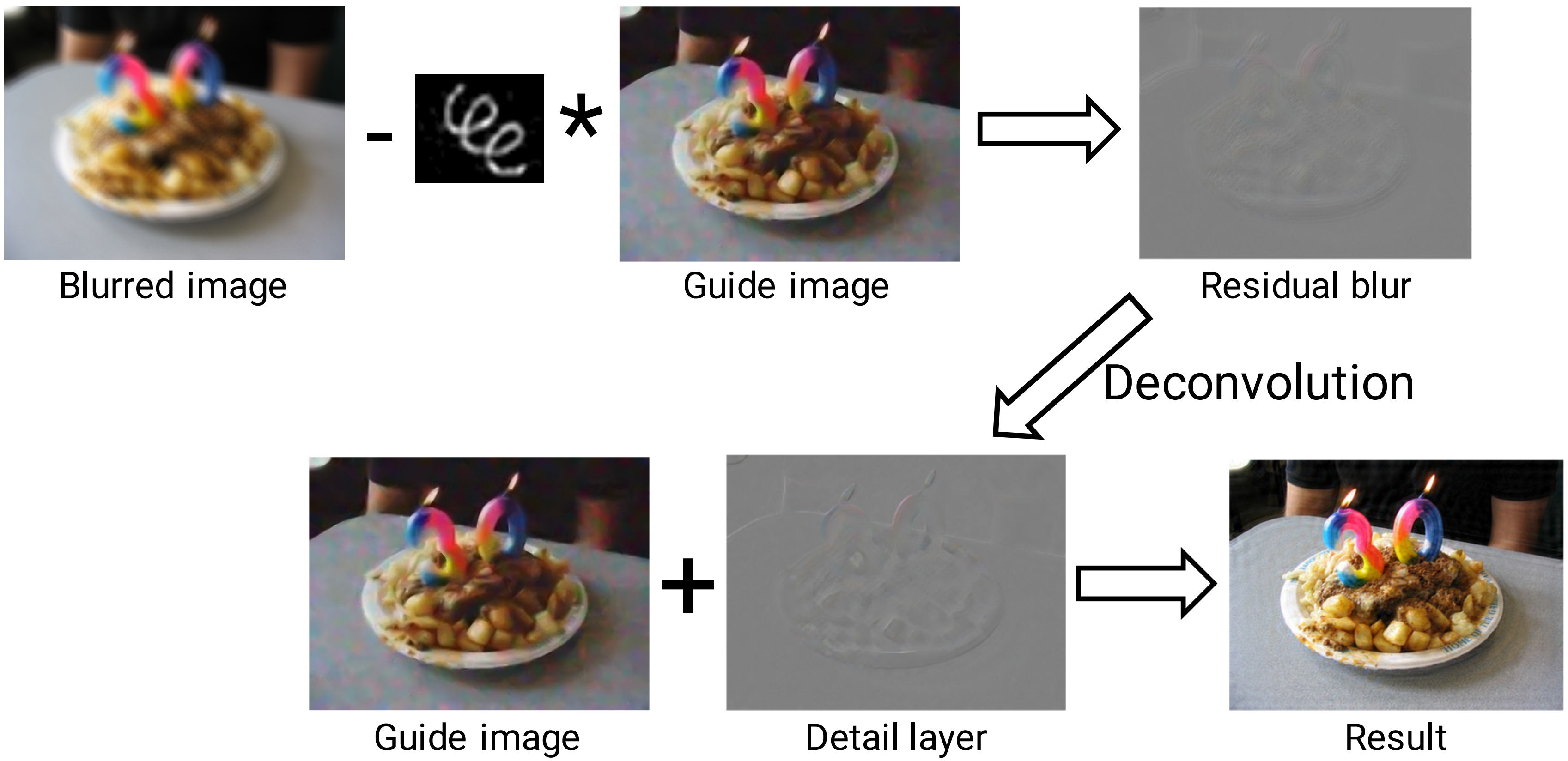

Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

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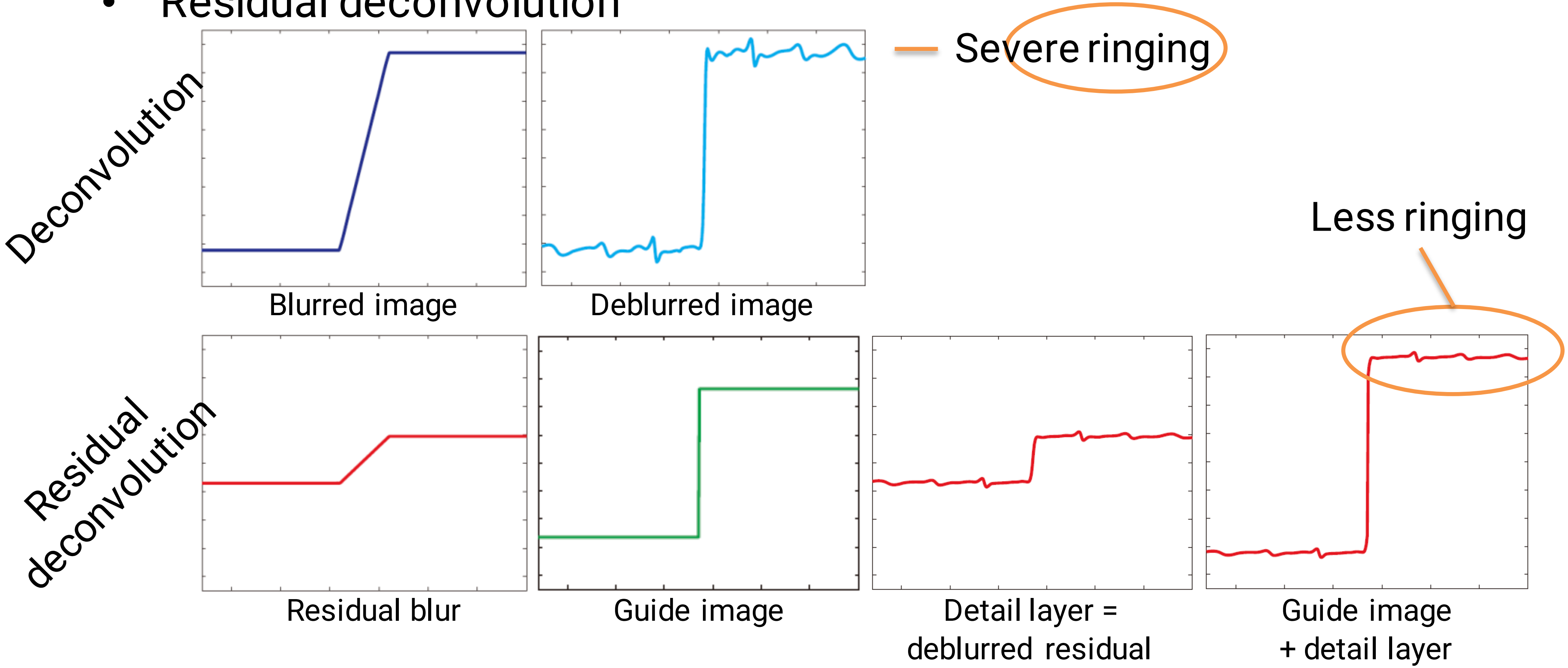
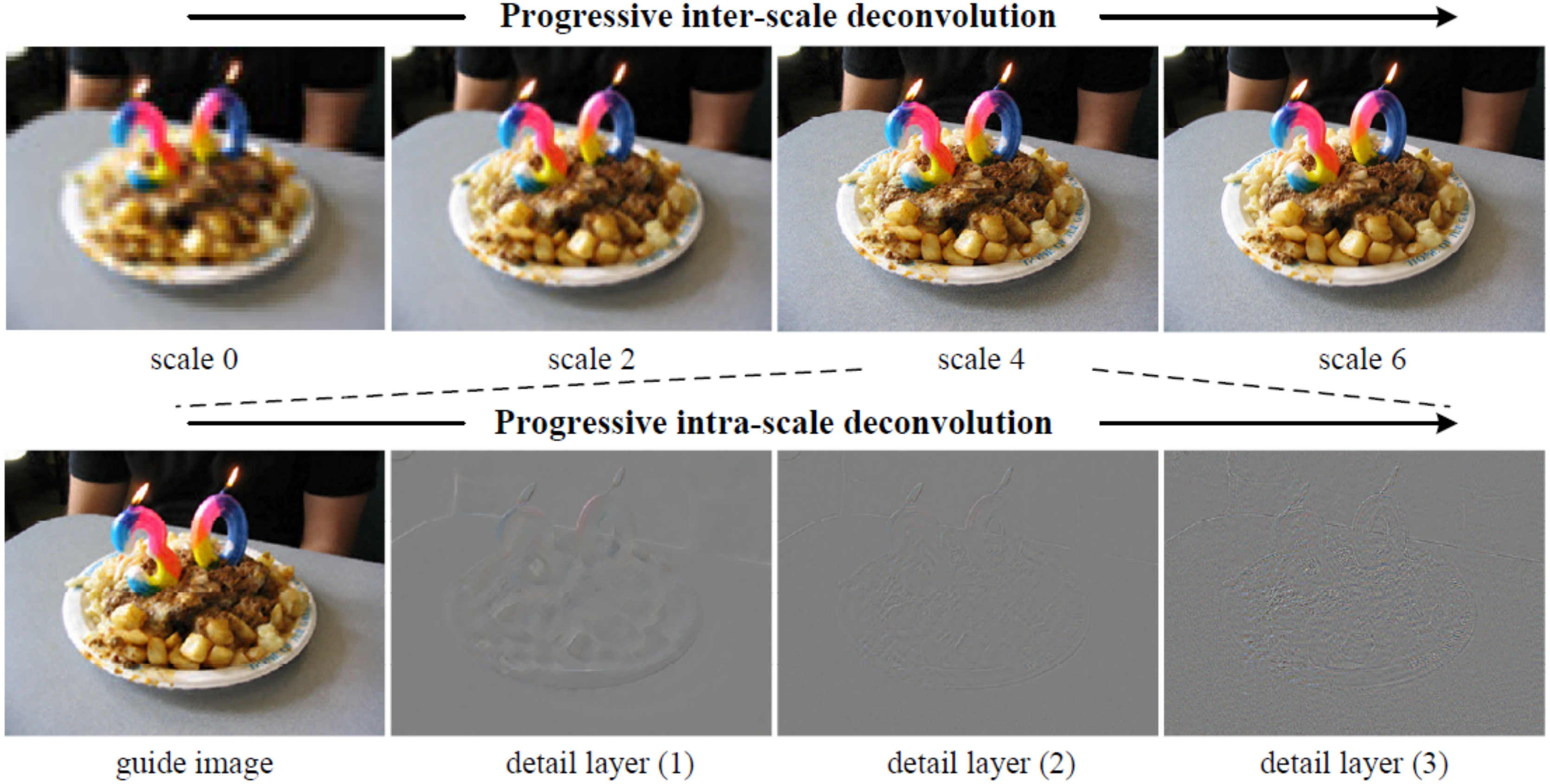
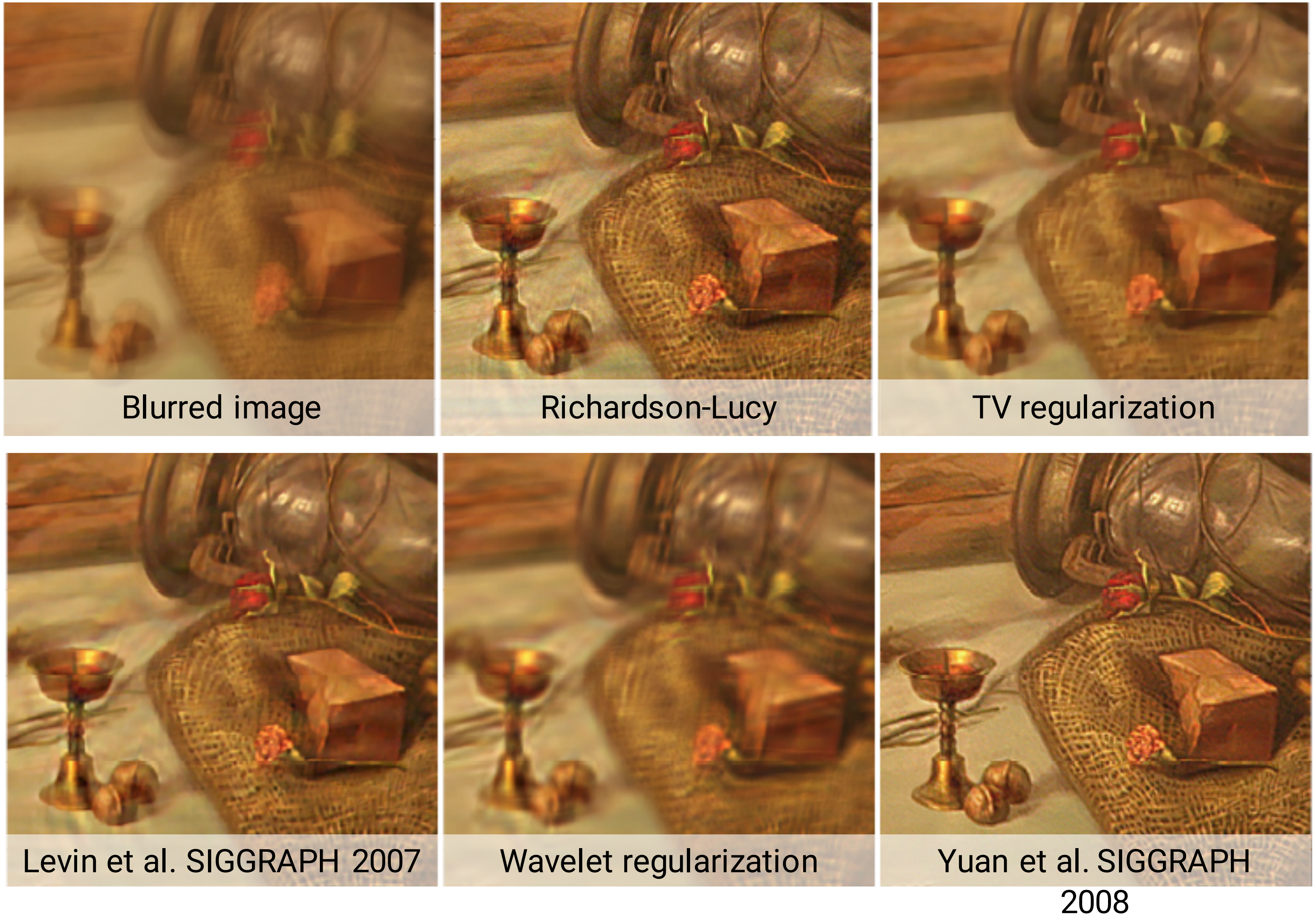
- Residual deconvolution



Progressive Inter-scale & Intra-scale Deconvolution [Yuan et al. SIGGRAPH 2008]

- Progressive inter-scale & intra-scale deconvolution




Blurred image
Richardson-Lucy
TV regularization
Levin et al. SIGGRAPH 2007
Wavelet regularization
Yuan et al. SIGGRAPH 2008

Introduction

Blind Deconvolution

Non-blind Deconvolution

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Outliers

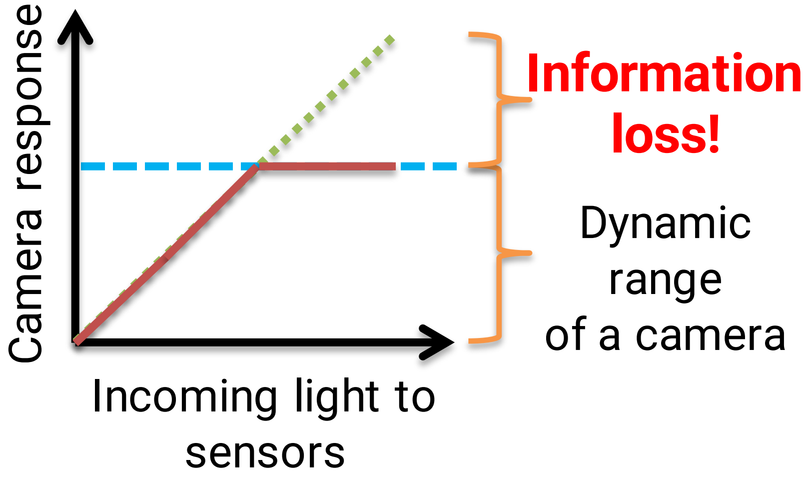
- A main source of severe ringing artifacts

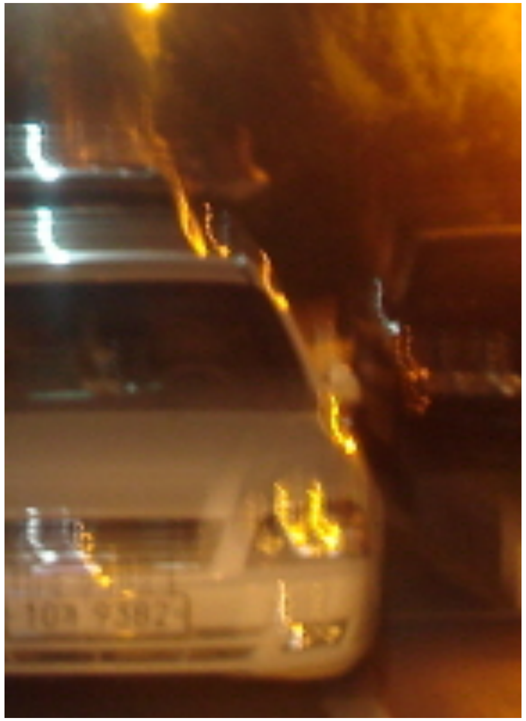
Blurred image with outliers

Deblurring result
[Levin et al. SIGGRAPH 2007]

Outliers

- Saturated pixels caused by limited dynamic range of sensors





Blurred image

[Levin et al. 2007]

Outliers

- Hot pixels, dead pixels, compression artifacts, etc…

Hot pixel

Blurred image with outliers [Levin et al. 2007]

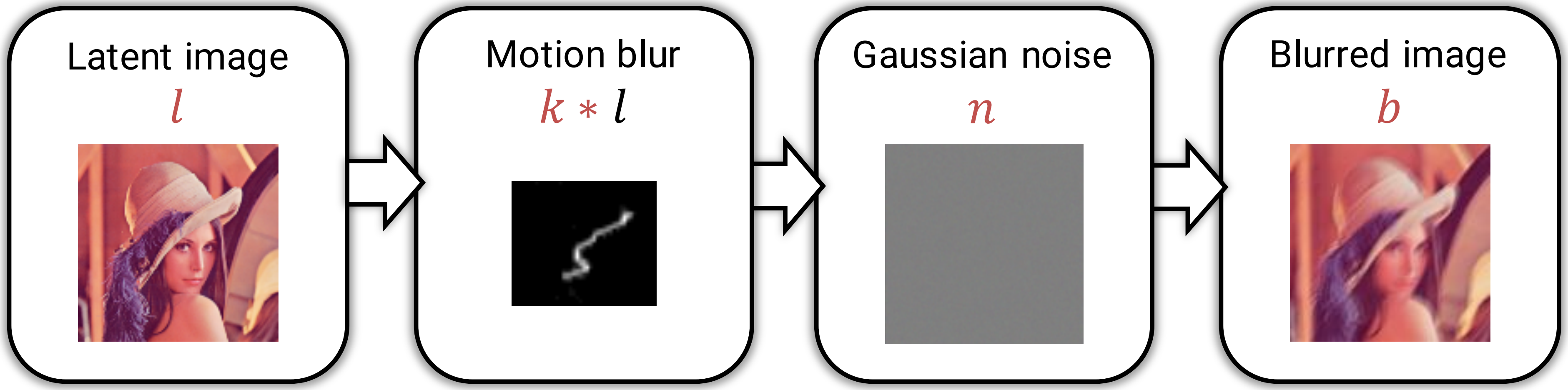
Outlier Handling

- Most common blur model:

$$b = k * l + n$$

small amount of Gaussian noise

Equivalent to



Outlier Handling

- An energy function derived from this model:

$$E(l) = \underbrace{\|k * l - b\|^2}_{\substack{L^2\text{-norm based data term:}\\ \text{known to be vulnerable to}\\ \text{outliers}}} + \underbrace{\rho(l)}_{\substack{\text{Regularization term on}\\ \text{a latent image } l}}$$

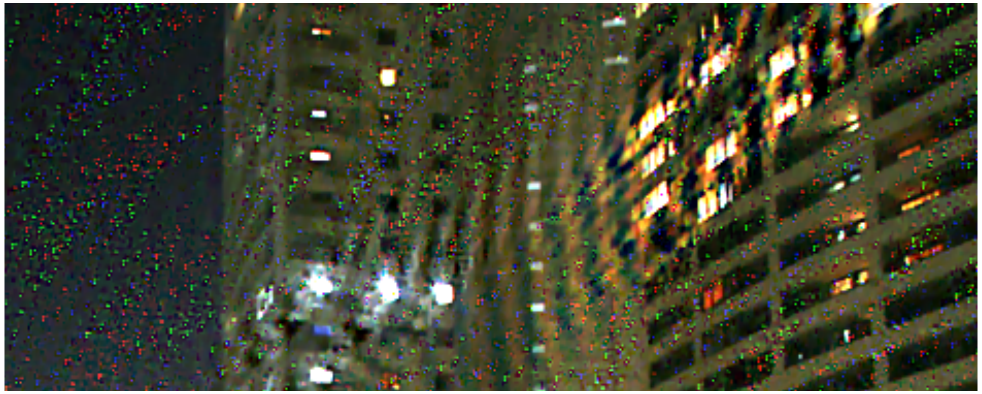
- More robust norms to outliers
  - L^1-norm, other robust statistics…

$$E(l) = \|k * l - b\|_1 + \rho(l)$$

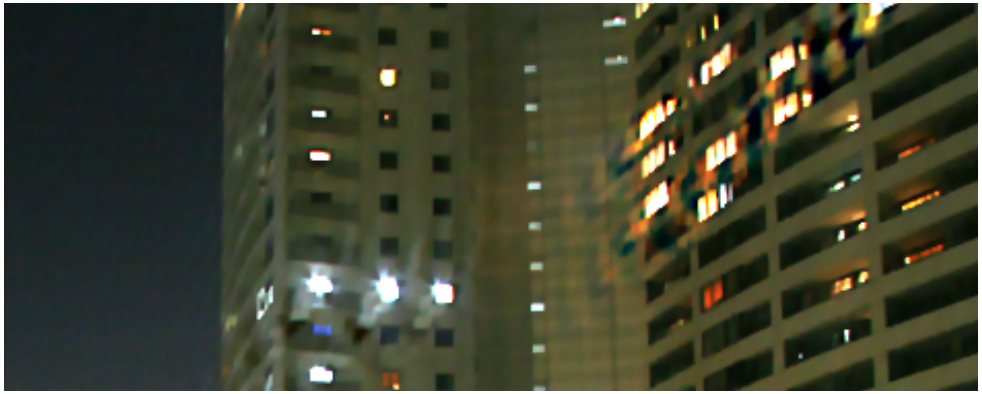
  - Bar et al. IJCV 2006, Xu et al. ECCV 2010, …

Outlier Handling

- L^1-rm based data term
  - Simple & efficient
  - Effective on salt & pepper noise
  - Not effective on saturated pixels



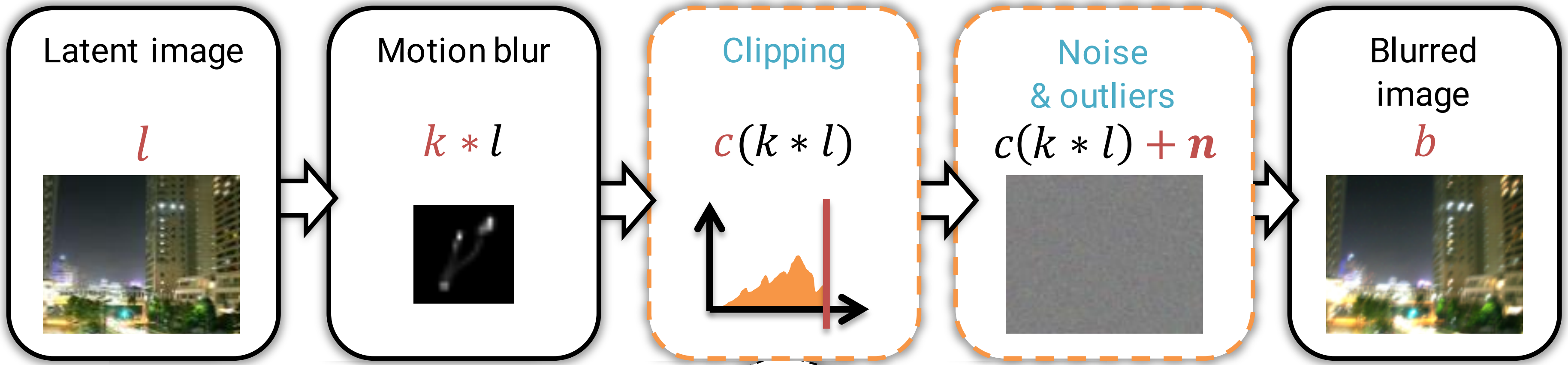
L^2-norm based data term



L^1-norm based data term

Cho et al. ICCV 2011

- More accurate blur model reflecting outliers

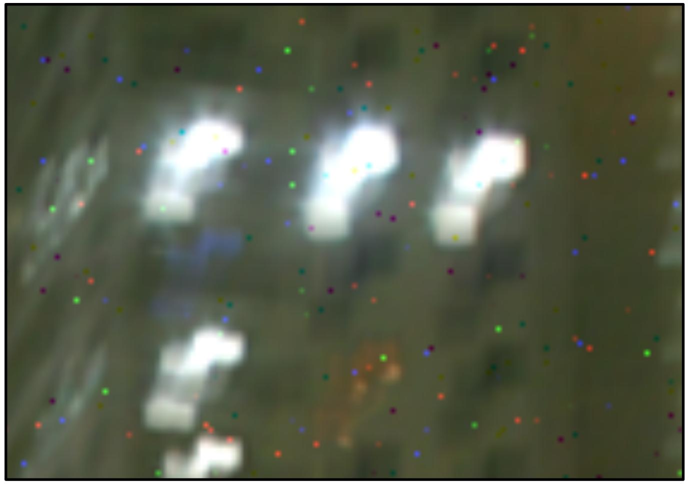


$$c(u) = \begin{cases} u & \text{if } u \in \text{DynamicRange} \\ \text{LowerBound} & \text{if } u < \text{LowerBound} \\ \text{UpperBound} & \text{if } u > \text{UpperBound} \end{cases}$$

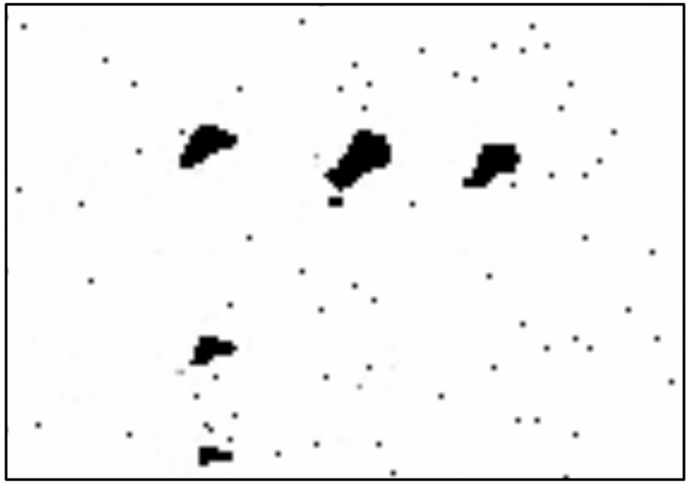
Cho et al. ICCV 2011

- Classification mask

$$m(x) = \begin{cases} 1 & \text{if } b(x) \text{ is an inlier} \\ 0 & \text{if } b(x) \text{is an outlier} \end{cases}$$



Blurred image b



Classification mask m

Cho et al. ICCV 2011

- MAP estimation

Classification mask m

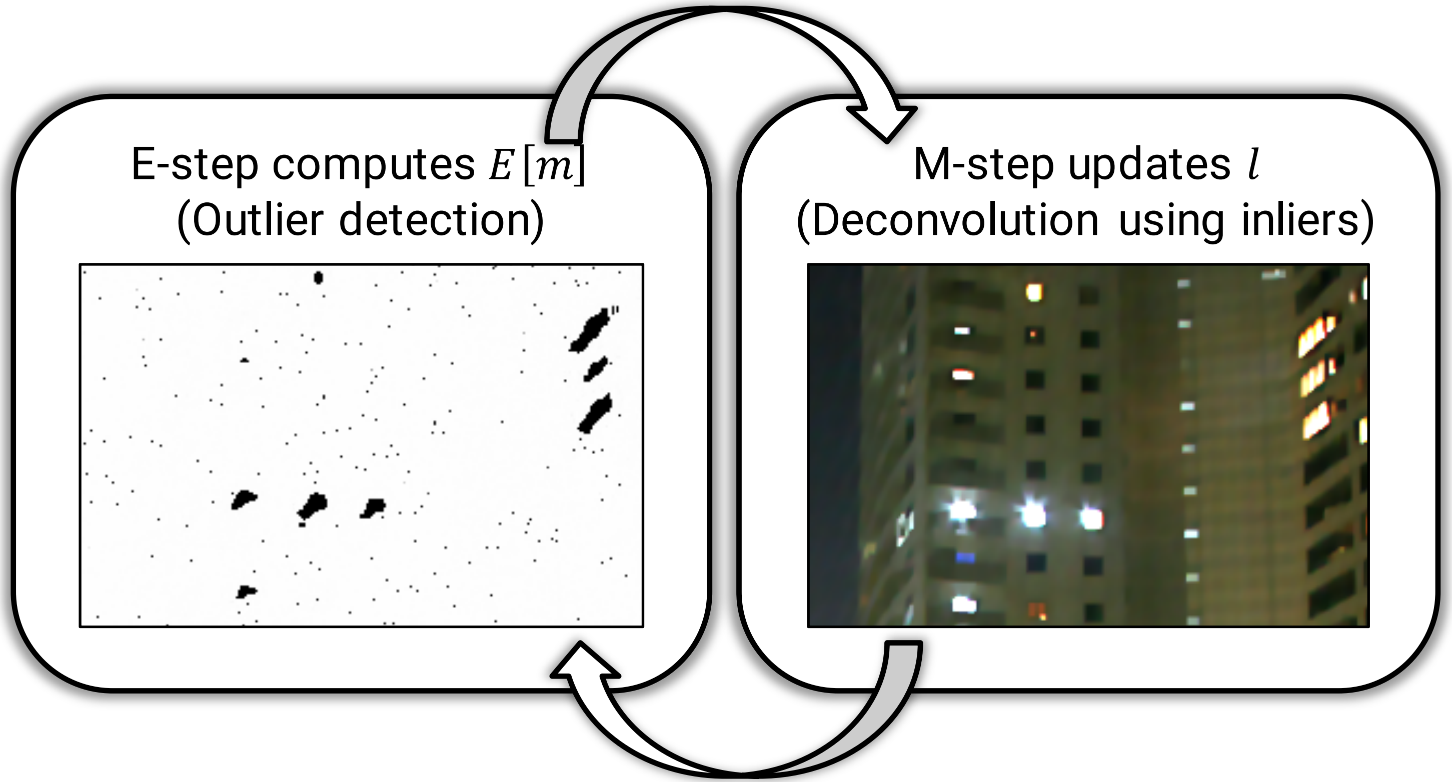
Given b & k, find the most probable l

$$l_{MAP} = \arg\max_{l} p(l|b,k)$$

$$= \arg\max_{l} \sum_{m \in M} p(b|m,k,l)\,p(m|k,l)\,p(l)$$

Cho et al. ICCV 2011

- EM based optimization



Blurred image

Blurred image

[Levin et al. 2007]

L1-norm based deconv.

[Harmeling et al. 2010]

[Cho et al. ICCV 2011]

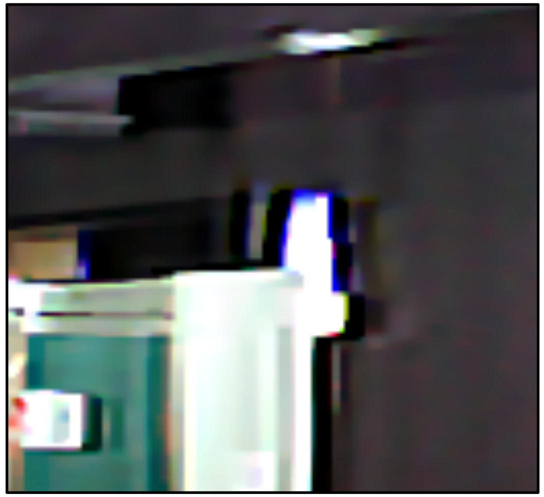
Blurred image

Blurred image

[Levin et al. 2007]

L1-norm based deconv.

[Harmeling et al. 2010]



[Cho et al. ICCV 2011]

Summary & Remaining Challenges

- Ill-posed problem - Noise & blur
- Noise
  - High-freq & unstructured
  - Natural image priors
- Ringing
  - Mid-freq & structured
  - More difficult to handle
- Outliers
  - Cause severe ringing artifacts
  - More accurate blur model
- Speed
  - More complex model → Slower
- Many source codes are available on the authors' website