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 [bl3:(r)]

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

blur [bl3:(r)]

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

Various Kinds of Blurs

Camera shake (Camera motion blur)

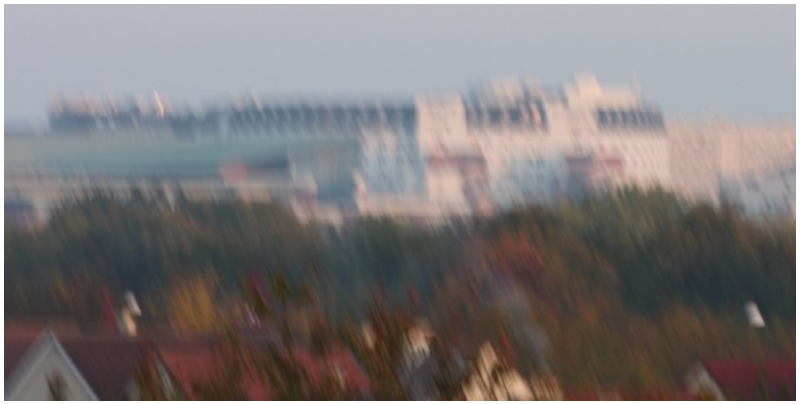
Object movement (Object motion blur)

Out of focus (Defocus blur)

Combinations (vibration & motion, …)

Camera Motion Blur

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

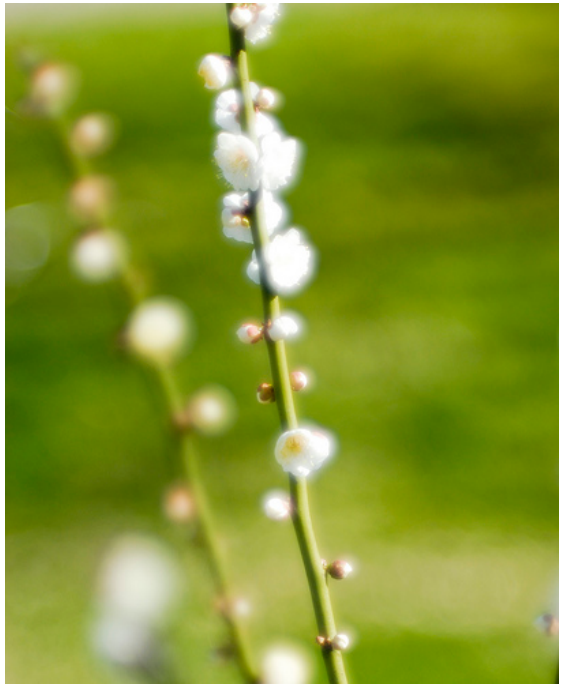


Object Motion Blur

- ***Caused by object motions during exposure time***

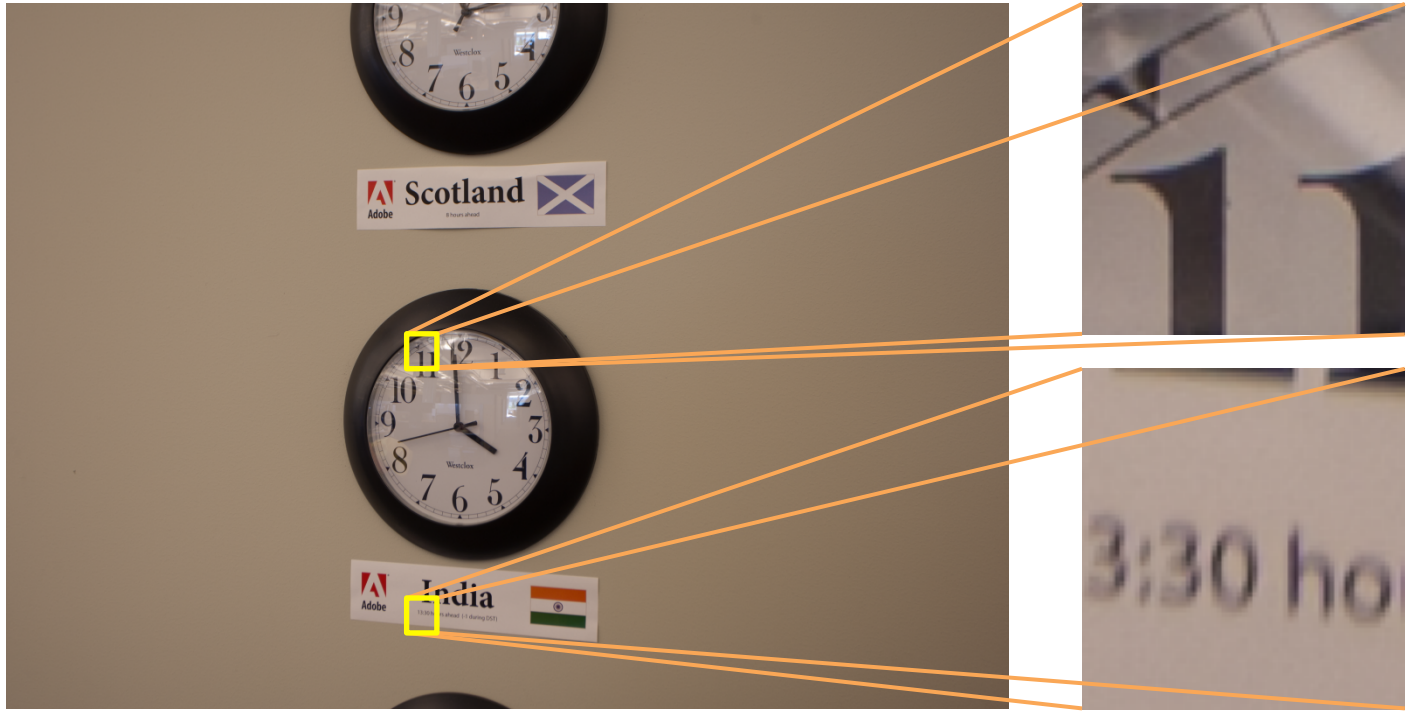
Defocus Blur

- ***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

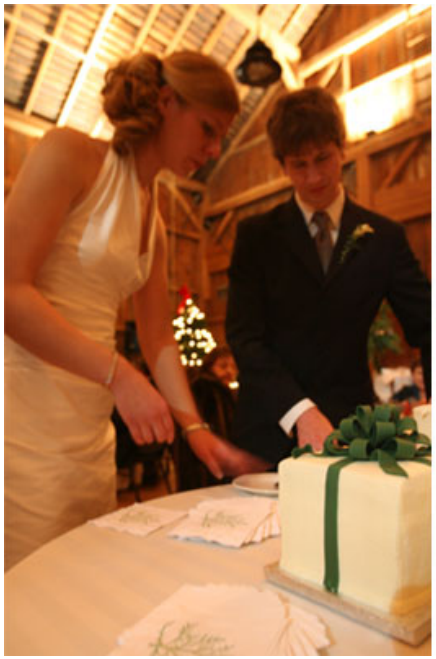
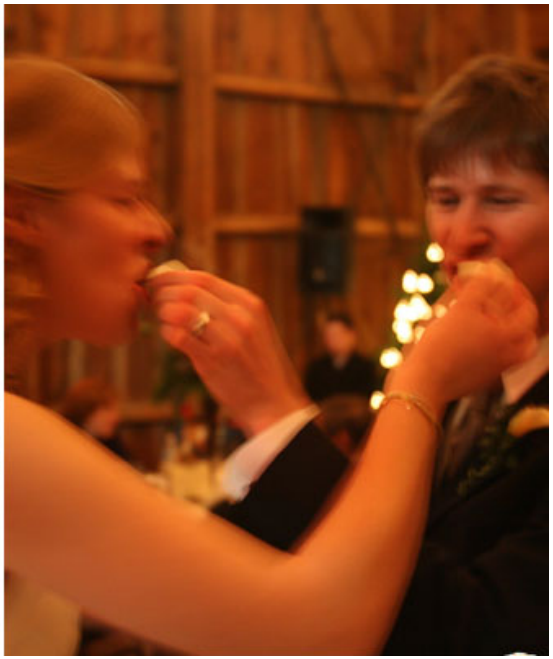
find its latent sharp image

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***?

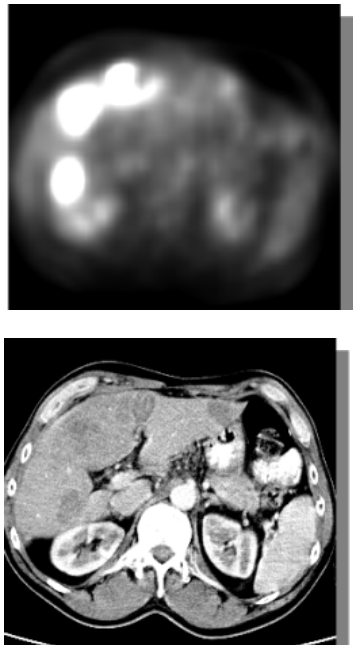
- ***Image/video in our daily lives***
  - ***Sometimes a retake is difficult!***

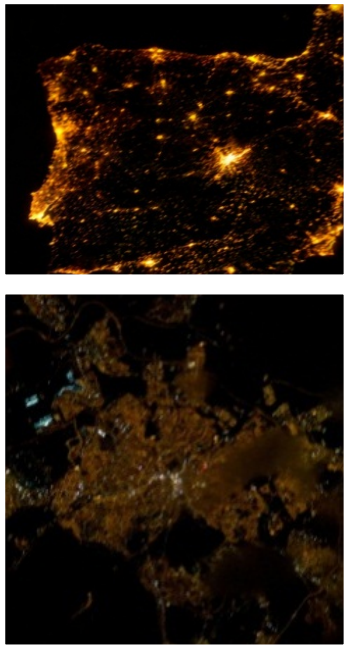

Why is it ***important***?

- ***Strong demand for high quality deblurring***

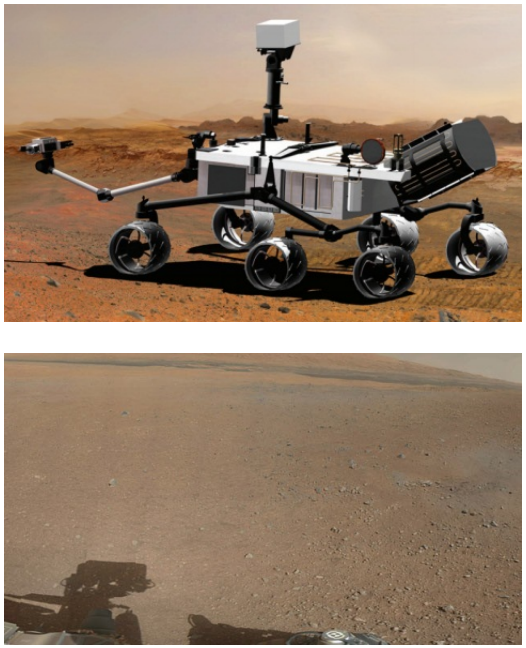
CCTV, car black box



Medical imaging



Aerial/satellite photography



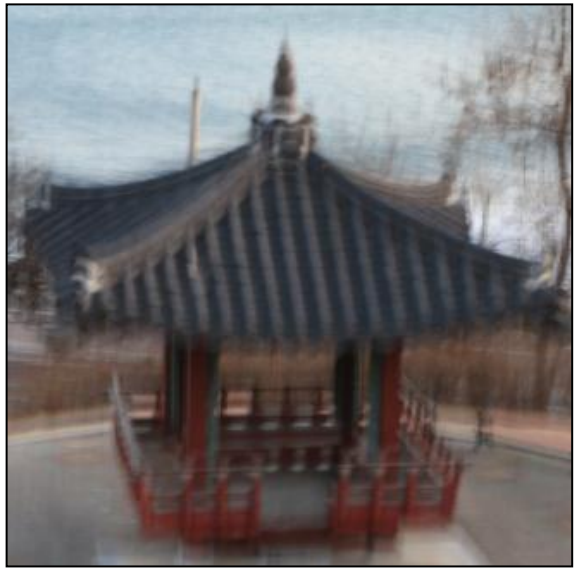
Robot vision

Deblurring

from a given blurred image

find its latent sharp image

Commonly Used Blur Model



Blurred image

$=$

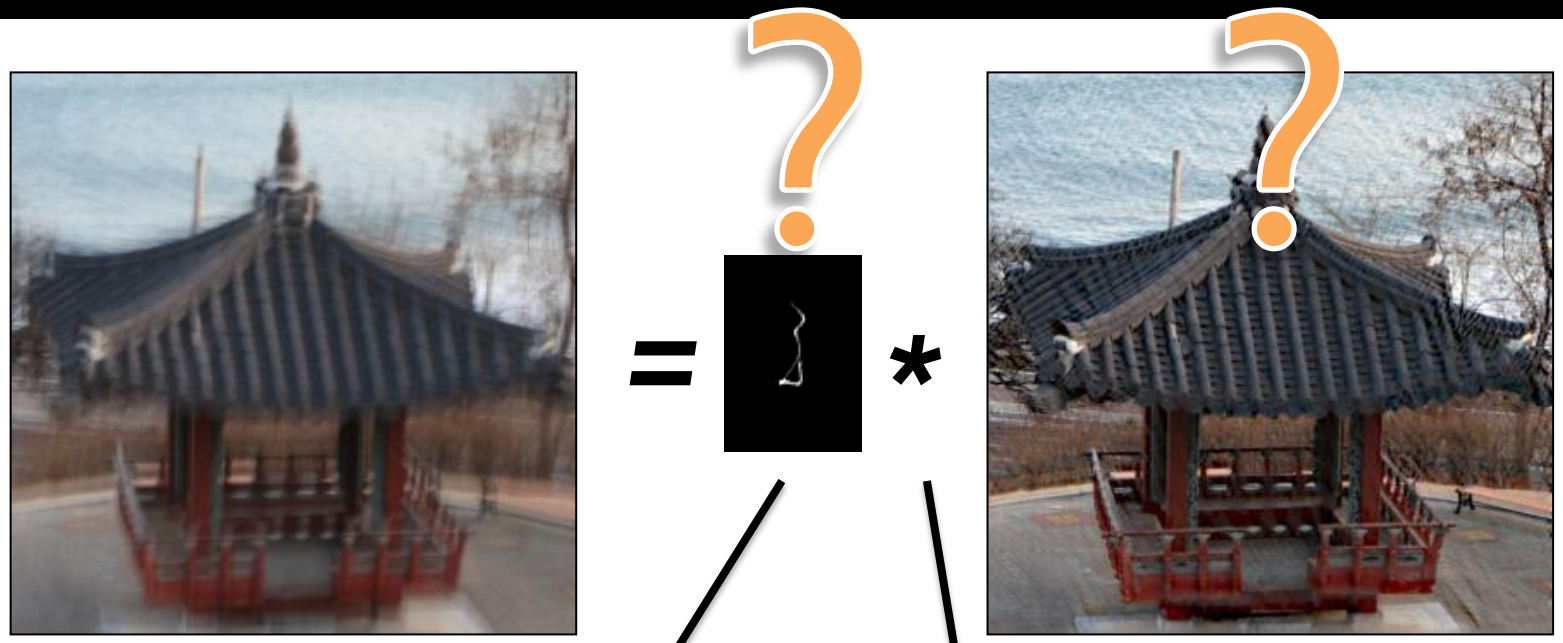
$*$

Latent sharp image

Blur kernel or Point Spread Function (PSF)

Convolution operator

Blind Deconvolution



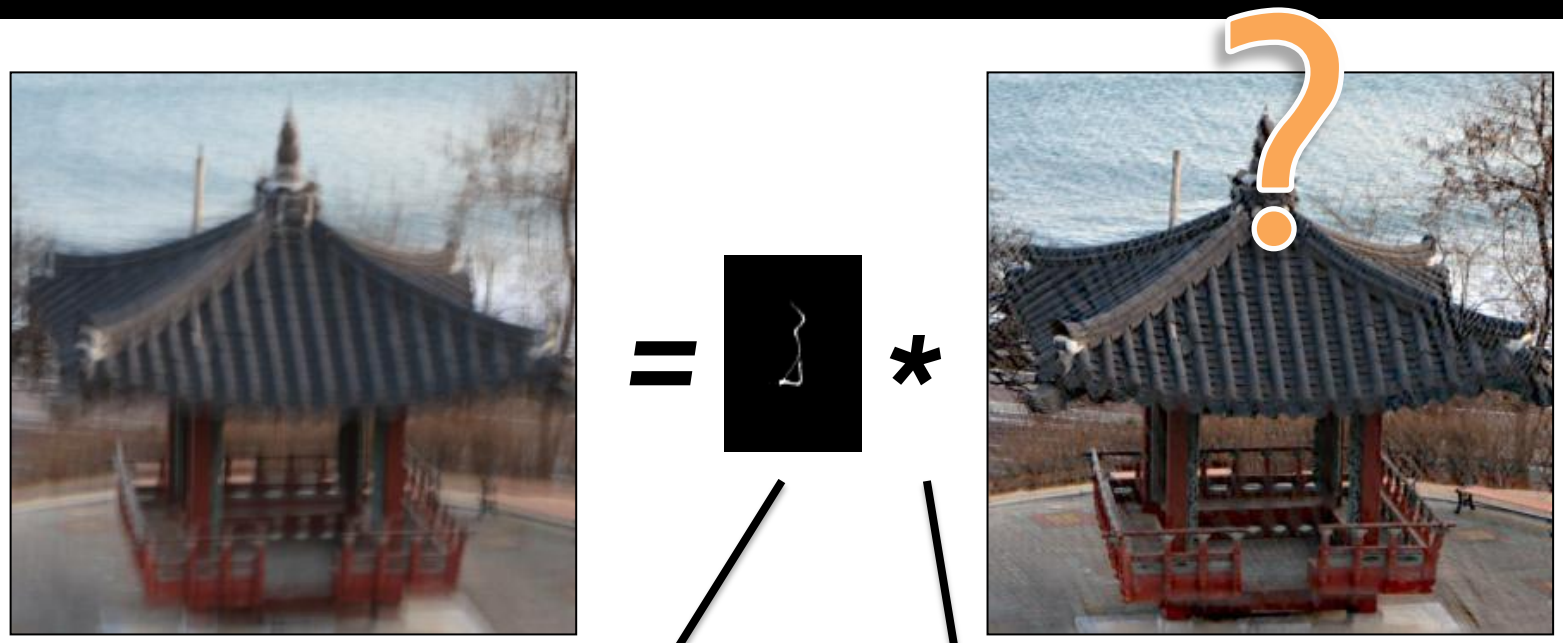
Blurred image

Blur kernel or Point Spread Function (PSF)

Convolution operator

Latent sharp image

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

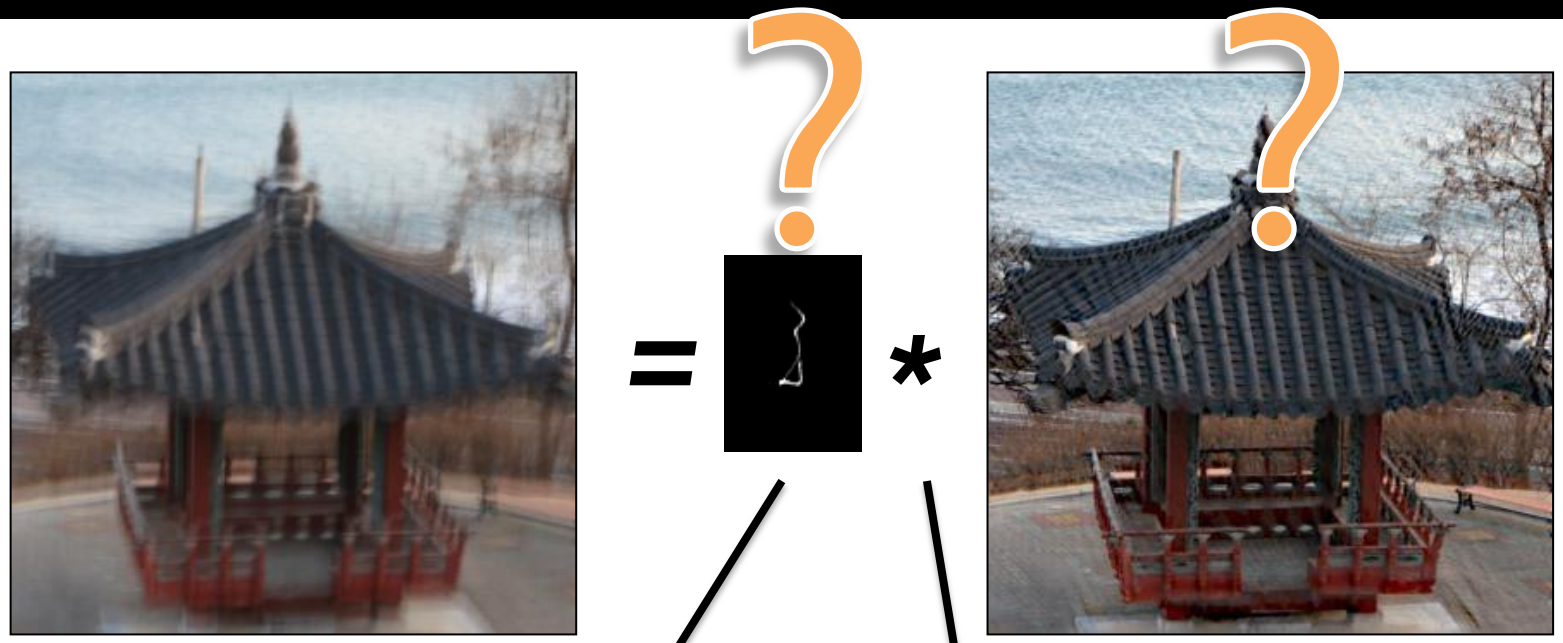
Introduction

Blind Deconvolution

Non-blind Deconvolution

- *Introduction*
- *Recent popular approaches*
- *Non-uniform blur*

Blind Deconvolution (Uniform Blur)



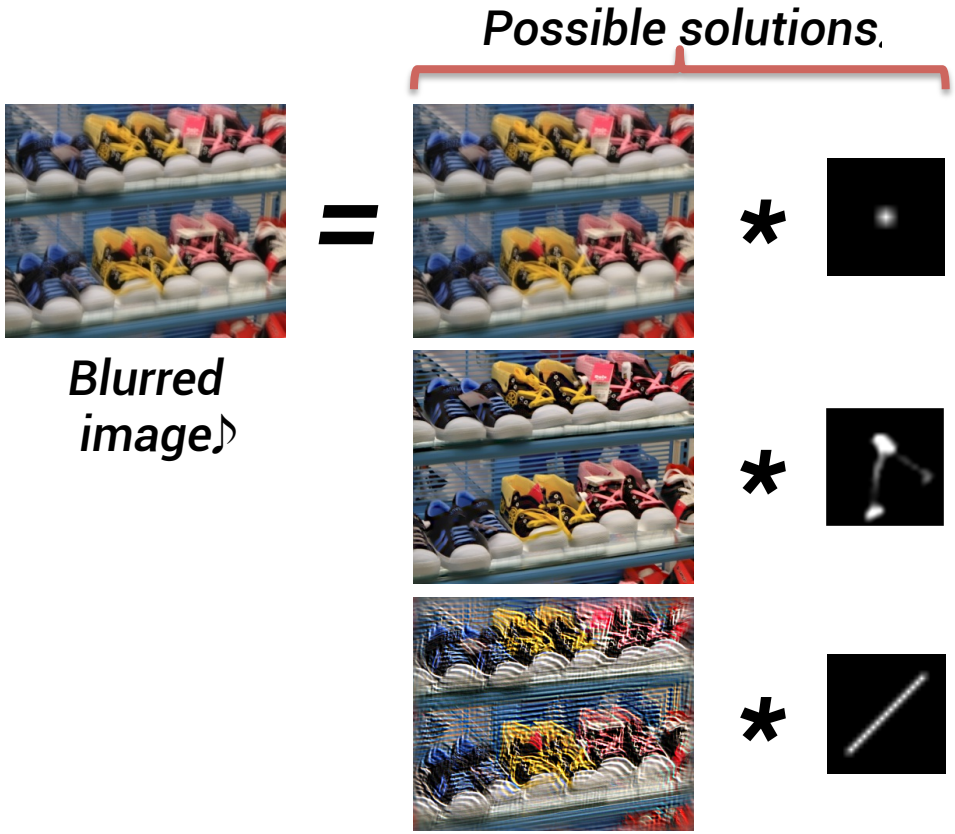
Blurred image

Latent sharp image

Blur kernel or Point Spread Function (PSF)

Convolution operator

Key challenge: Ill-posedness!



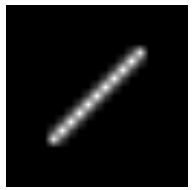
- *Infinite number of solutions satisfy the blur model*
- *Analogous to*

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

In The Past…

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

*



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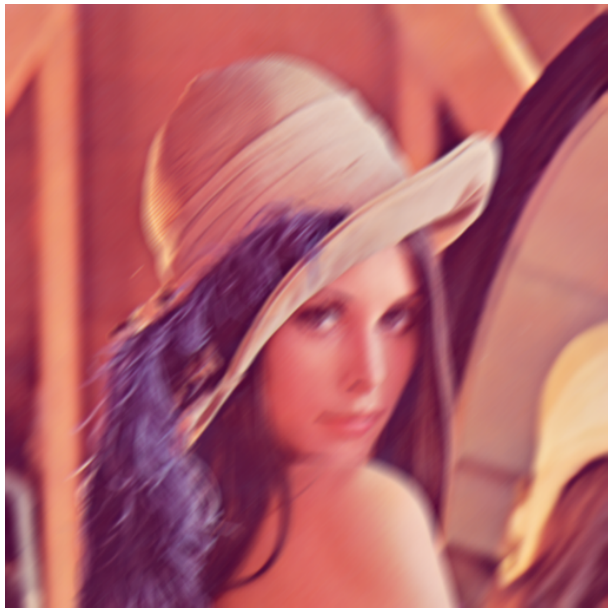


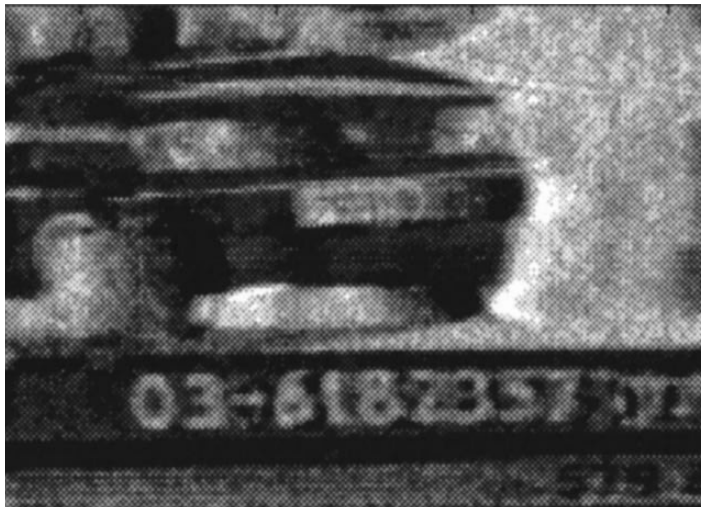
In The Past...

- ***But real camera shakes are much more complex***

In The Past…

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

Blurred image



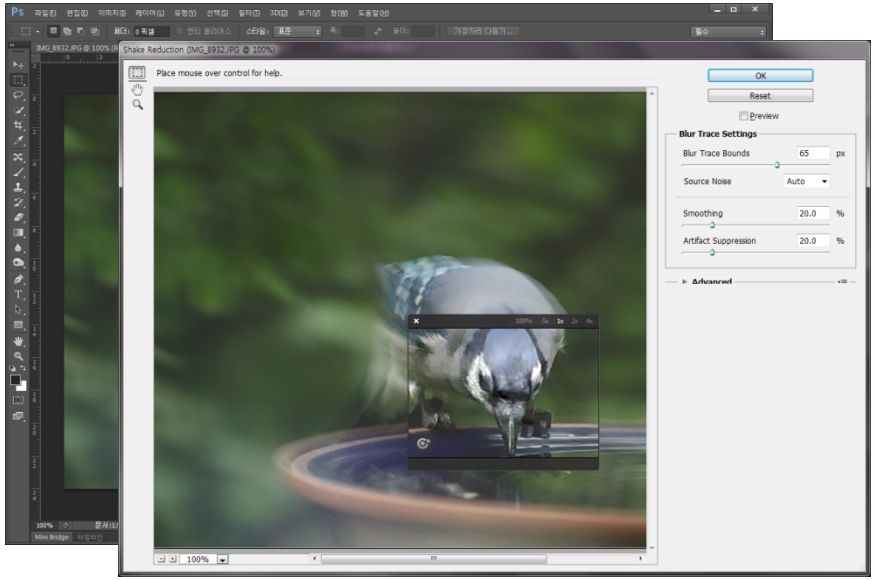
Latent sharp image

** 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

- *[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*

Variational Bayesian based

Edge Prediction based

Which one is better?

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?

Recent Popular Approaches

SIGGRAPH ASIA 2013 HONG KONG

Maximum Posterior (MAP) based

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

Variational Bayesian based

Edge Prediction based

- *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*

Which one is better?

Recent Popular Approaches

Maximum Posterior (MAP) based

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- *Seek the most probable solution, which maximizes a posterior distribution*
- *Easy to understand*
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Variational Bayesian based

Edge Prediction based

Which one is better?

MAP based Approaches

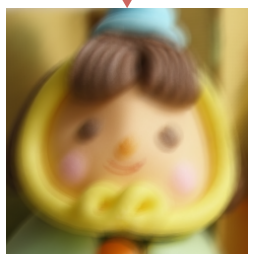
Maximize a joint posterior probability with respect to k and l

Posterior distribution

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

Blur kernel k

Latent image l



Blurred image b

MAP based Approaches

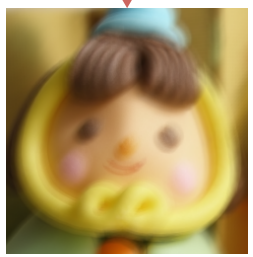
Bayes rule:

Posterior distribution *Likelihood* *Prior on l* *Prior on k*

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

Blur kernel k

Latent image l



Blurred image b

MAP based Approaches

Negative $\log$***-posterior:***

$$-\log p(k,l|b) \Rightarrow -\log p(b|k,l) - \log p(l) - \log p(k)$$

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

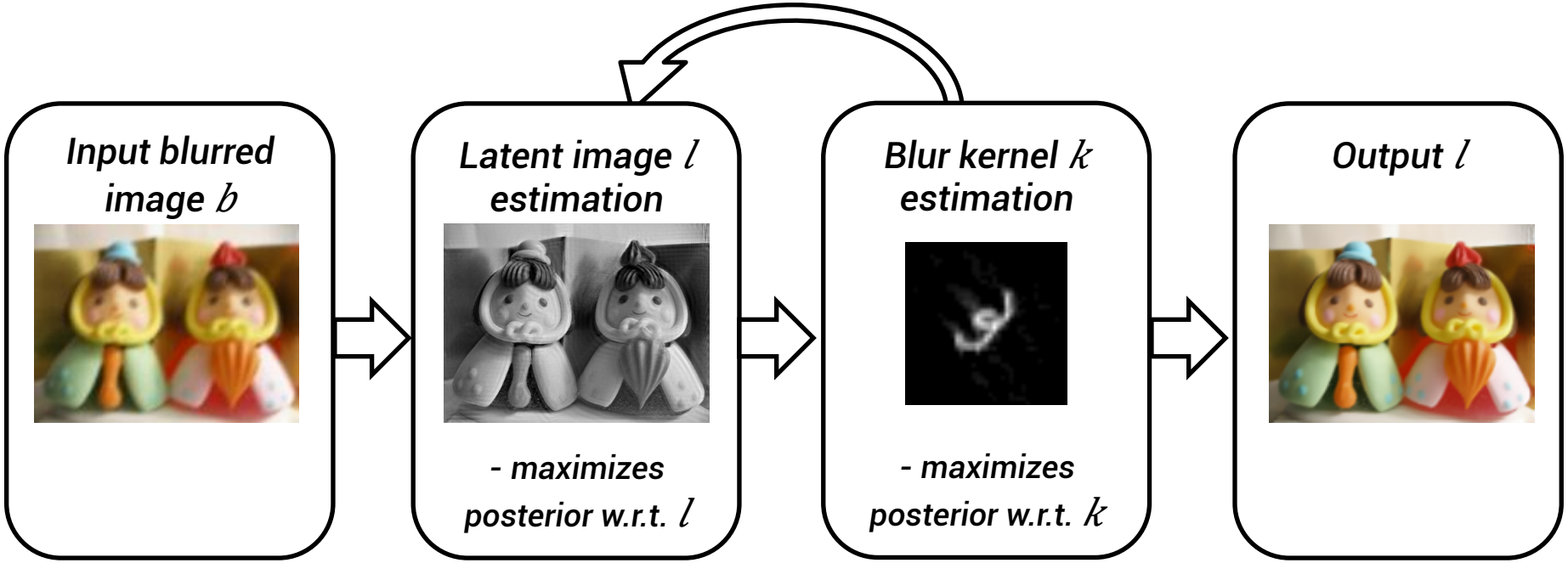
MAP based Approaches

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

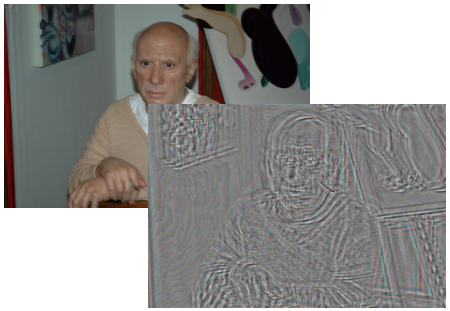
- *Chan and Wong, TIP 1998*
  - *Total variation based priors for estimating a parametric blur kernel*
- *Shan et al. SIGGRAPH 2008*
  - *First MAP based method to estimate a nonparametric blur kernel*
- *Krishnan et al. CVPR 2011*
  - *Normalized sparsity measure, a novel prior on latent images*
- *Xu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

Shan et al. SIGGRAPH 2008

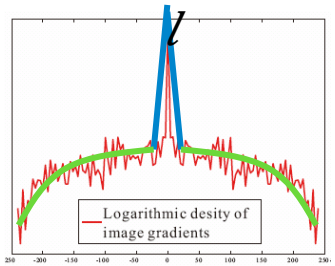
- ***Carefully designed likelihood & priors***

$$p(k, l|b) \propto p(b|l, k)p(l)p(k)$$

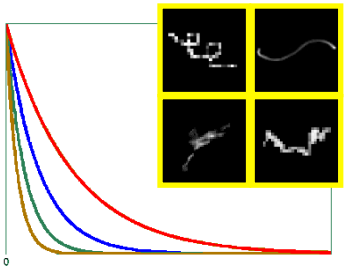
Likelihood based on intensities & derivatives



Natural image statistics based prior on l



Kernel statistics based prior on k

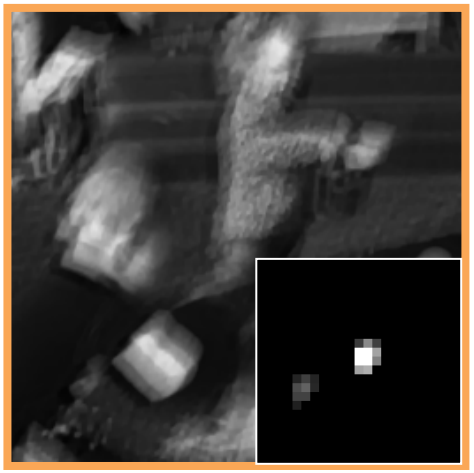


Shan et al. SIGGRAPH 2008

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

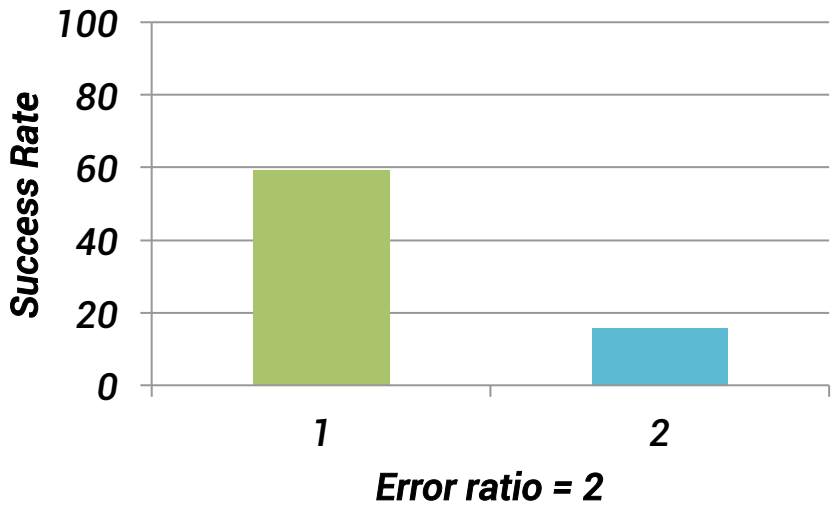
Shan et al. SIGGRAPH 2008

- *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], …*

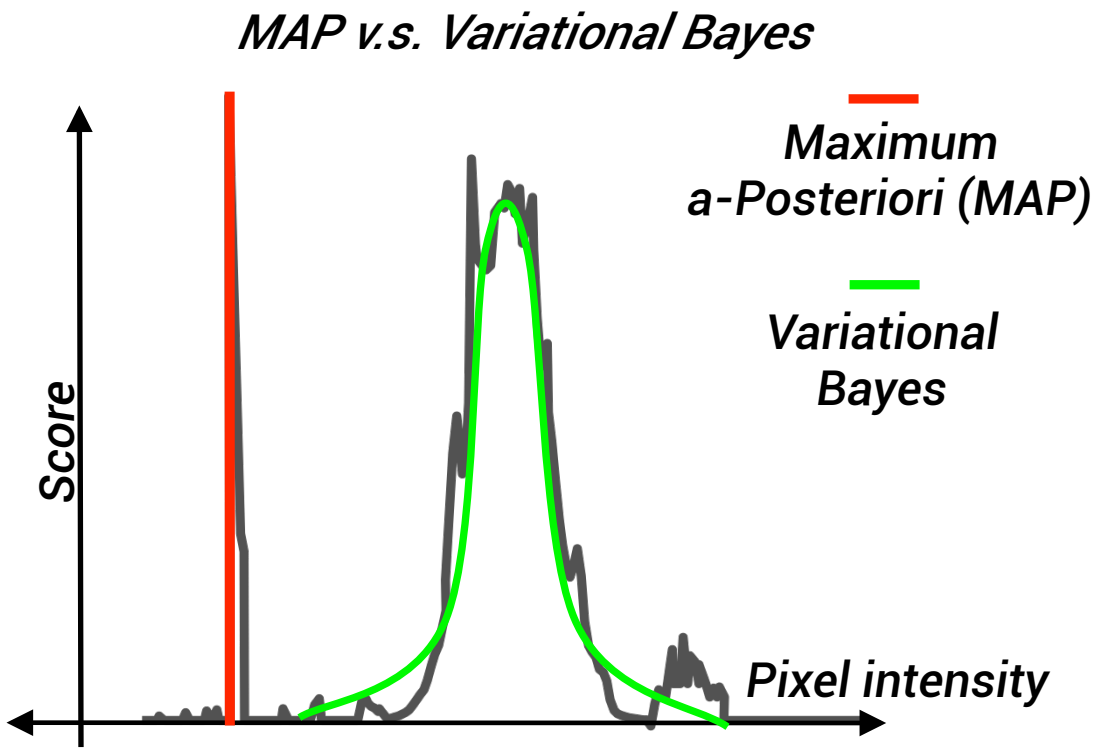
Variational Bayesian based

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

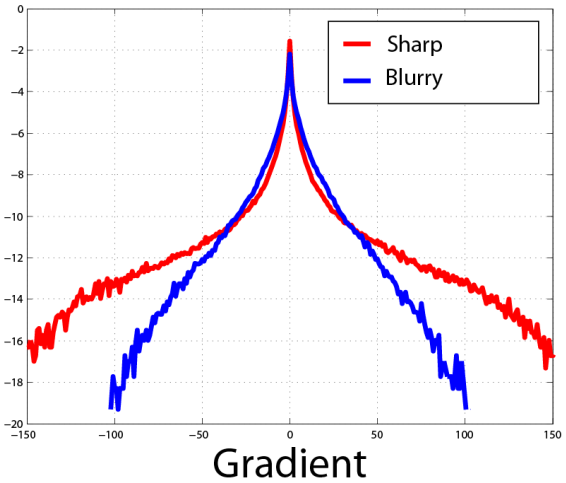
Variational Bayesian

- *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***

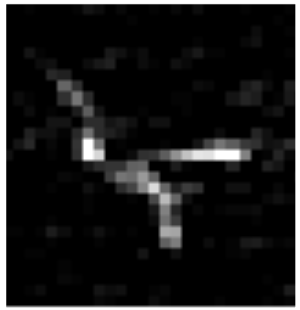
$$\arg\min_{q(k),q(l),q(\sigma^{-2})} KL\left(\underbrace{q(k)q(l)q(\sigma^{-2})}_{\text{approximate distributions for blur kernel } k\text{, latent image } l\text{, and noise variance } \sigma^2}\middle\| p(k,l|b)\right)$$

- ***cf) MAP based approach:***

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

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

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

Variational Bayesian based

Edge Prediction based

- *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*

Which one is better?

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

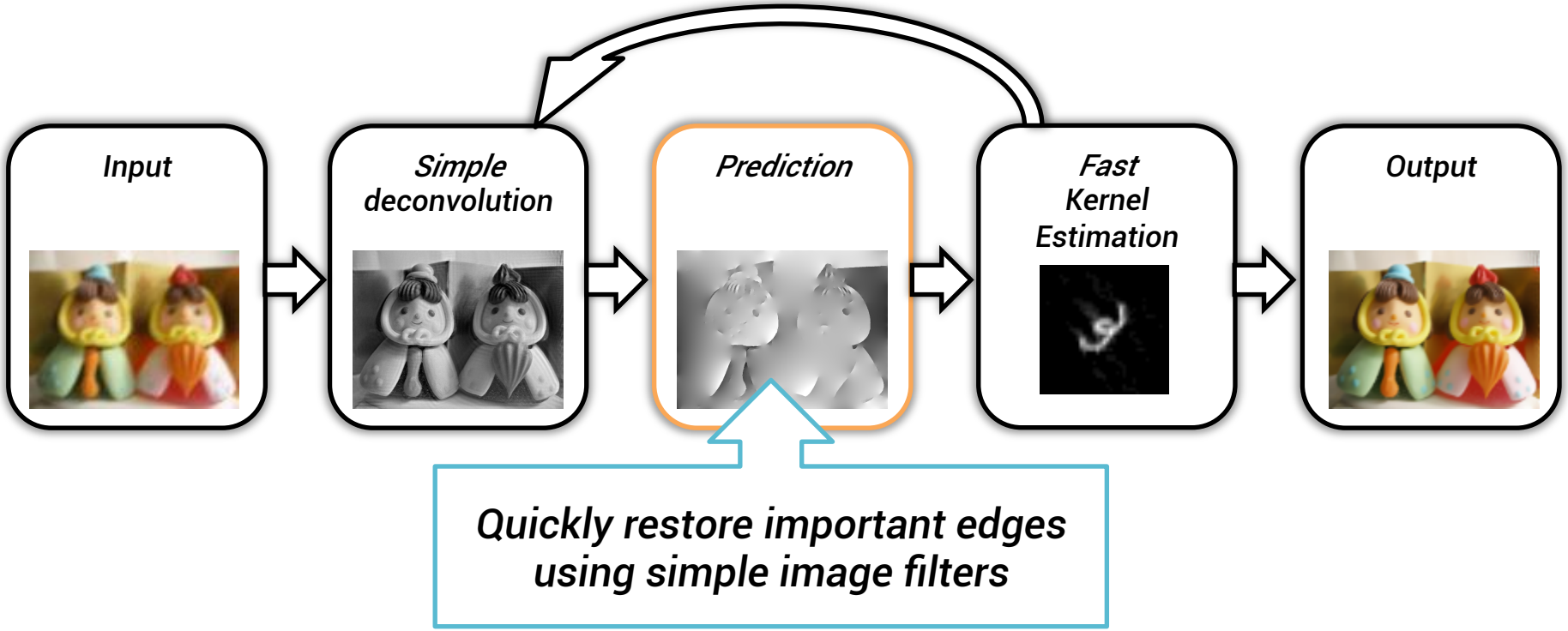
- ***Key idea: blur can be estimated from a few*** edges

➔ ***No need to restore every detail for kernel estimation***

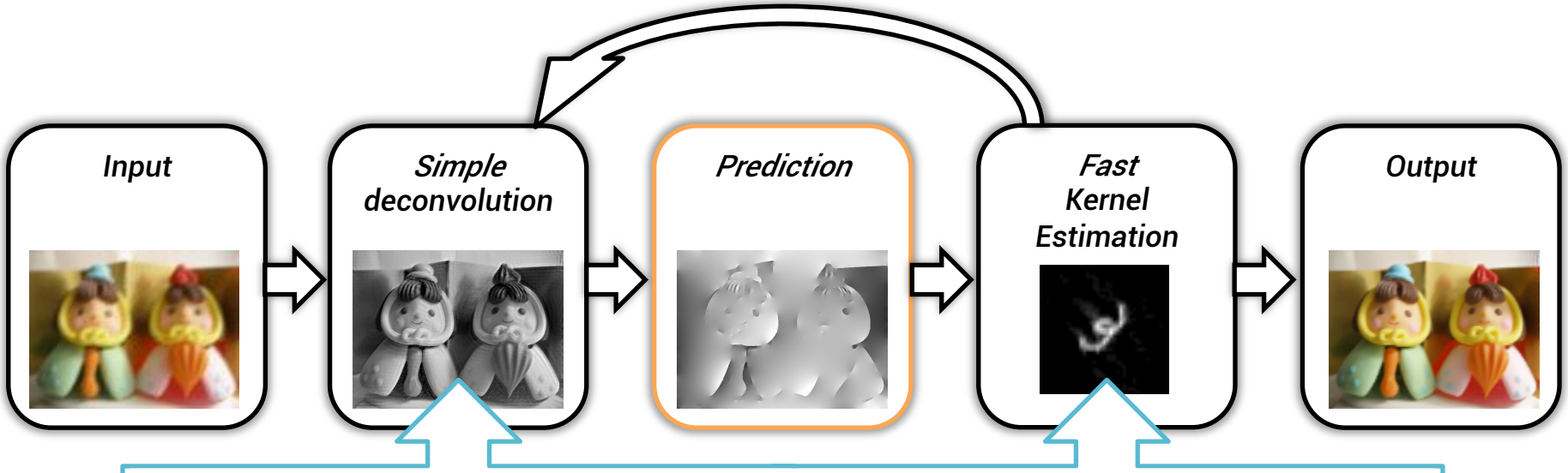
Blurred image

Latent image with only a few edges and no texture

Cho & Lee, SIGGRAPH Asia 2009

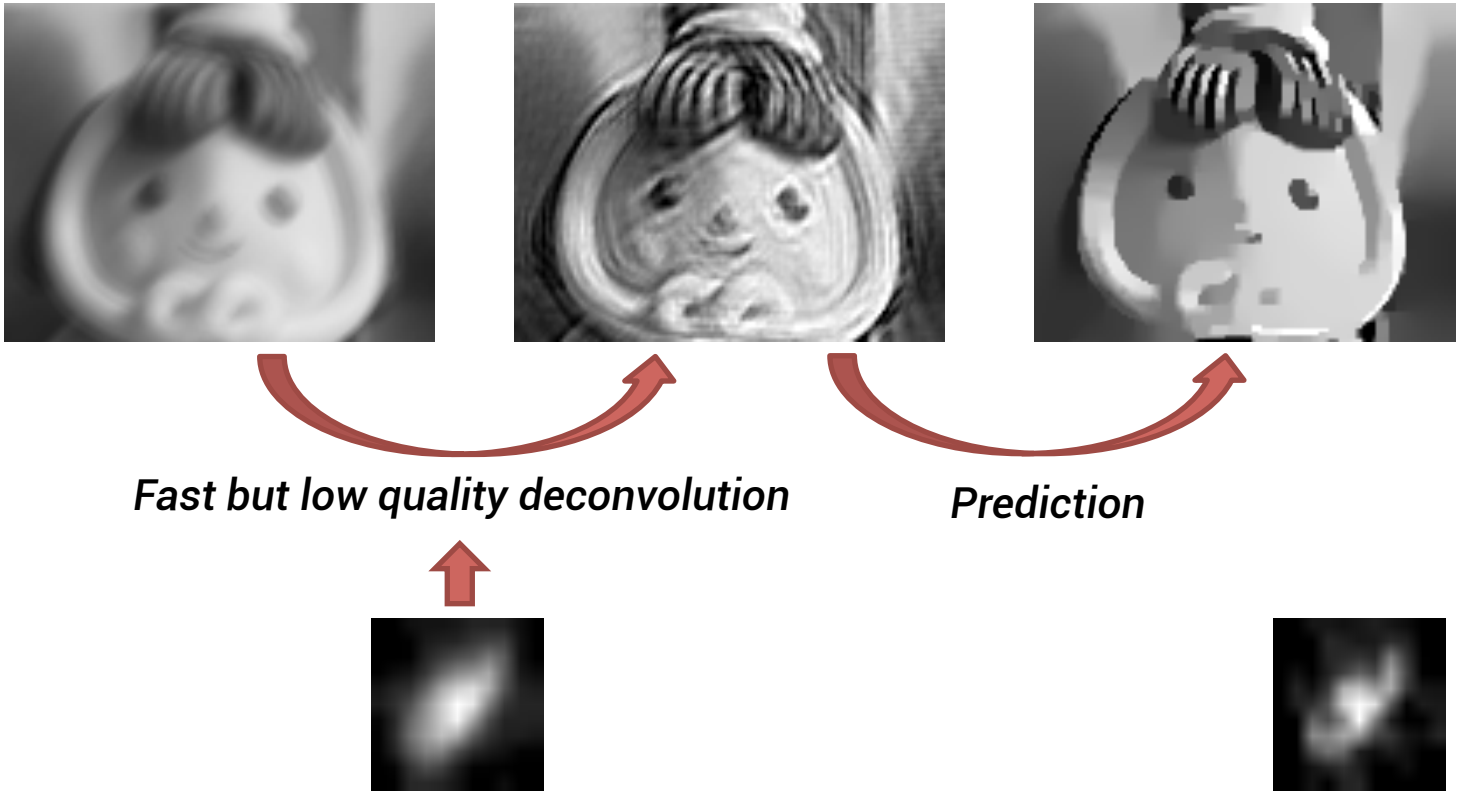


Cho & Lee, SIGGRAPH Asia 2009

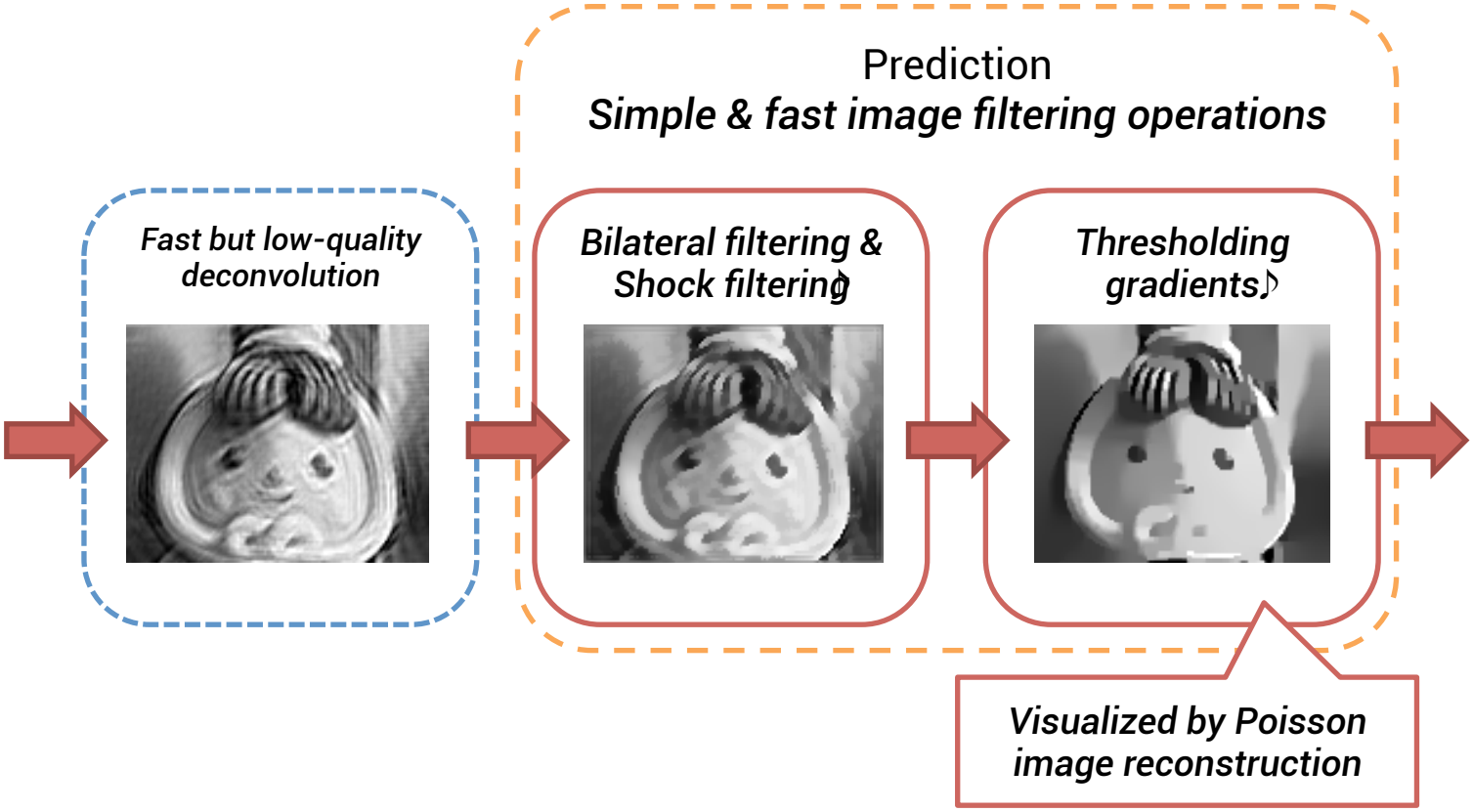


Do not need complex priors for the latent image and the blur kernel
➔ Significantly reduce the computation time

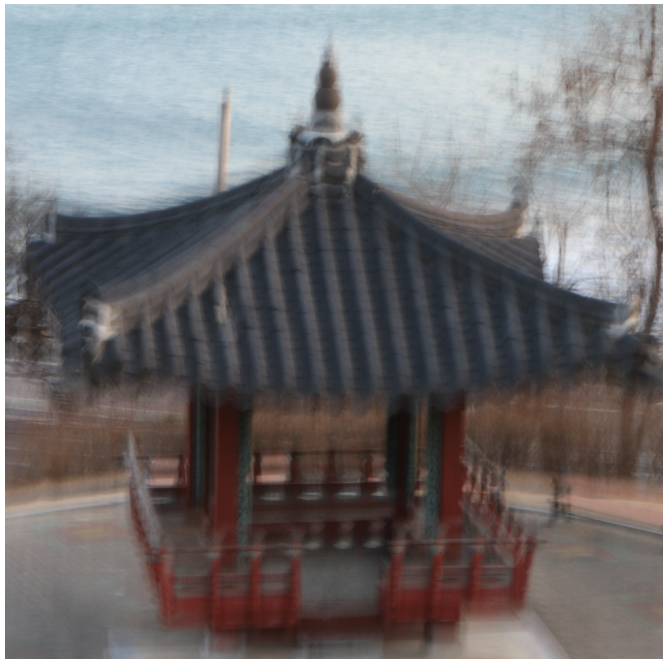
Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009



Blurry input

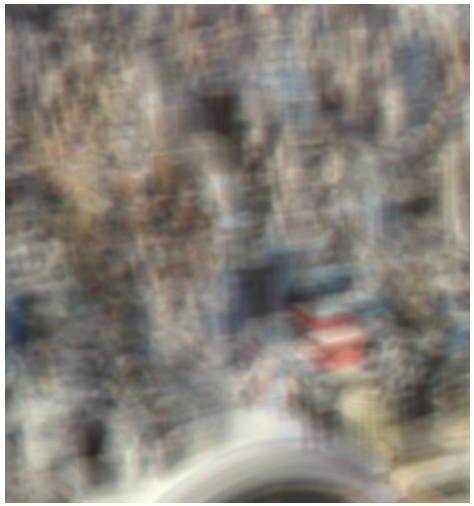
Deblurring result

- *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***



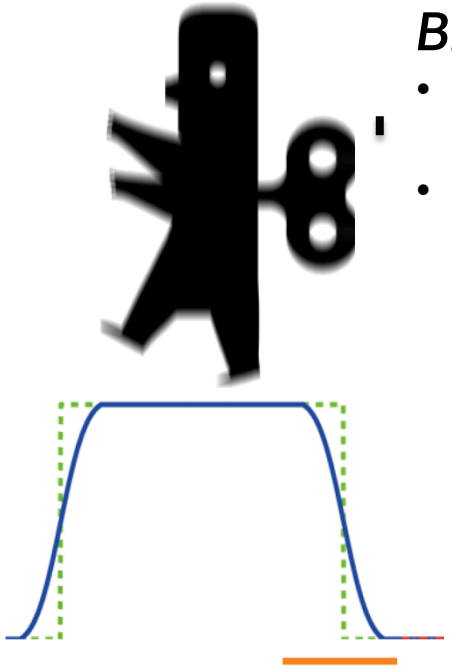
Blurred image

Fergus et al.
SIGGRAPH 2006

Shan et al.
SIGGRAPH 2008

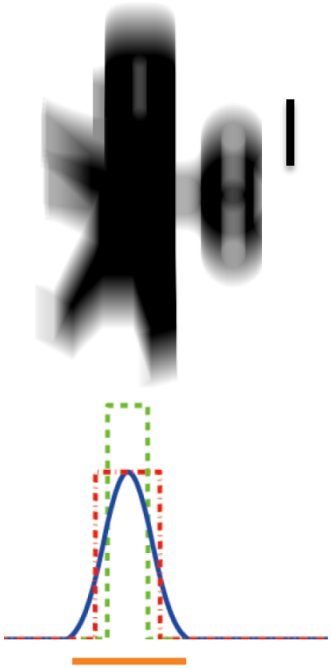
For this complex scene, most methods fail to estimate a correct blur kernel. Why?

Xu & Jia, ECCV 2010



Blur < structures

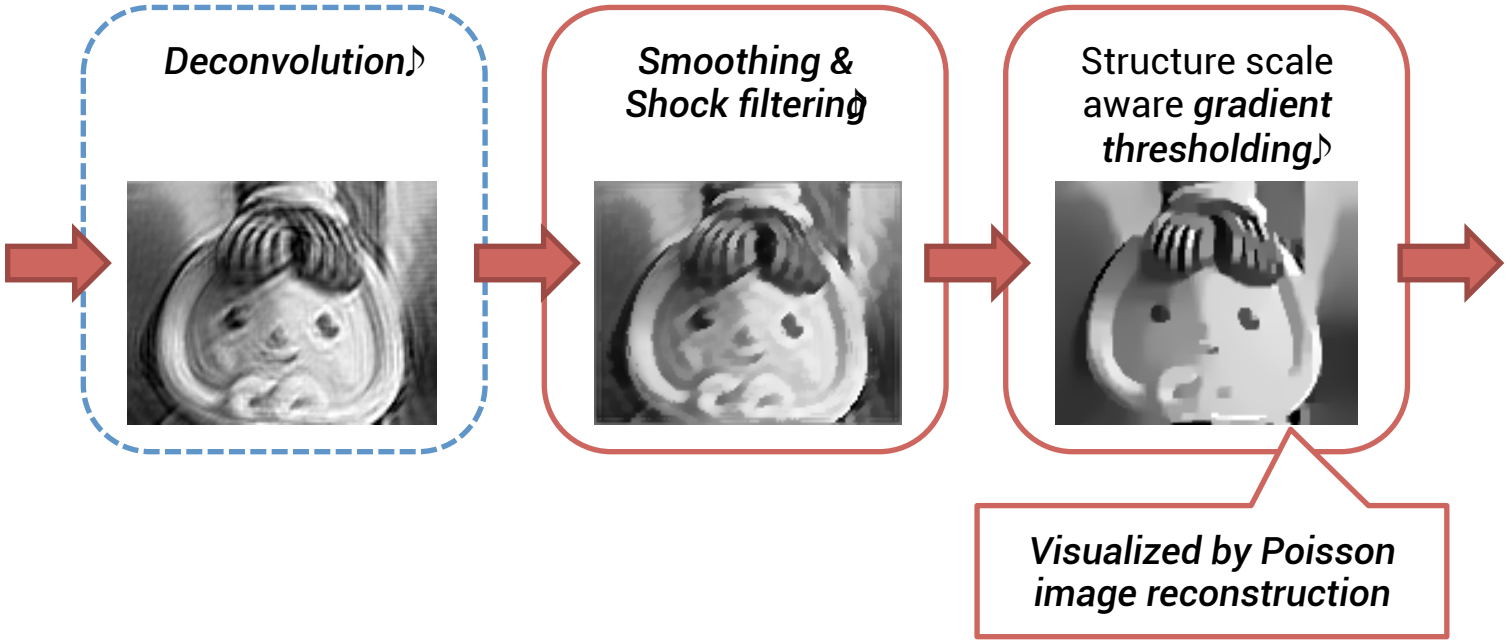
- *Each blurry pixel is caused by one edge*
- *Easy to figure out the original sharp structure*



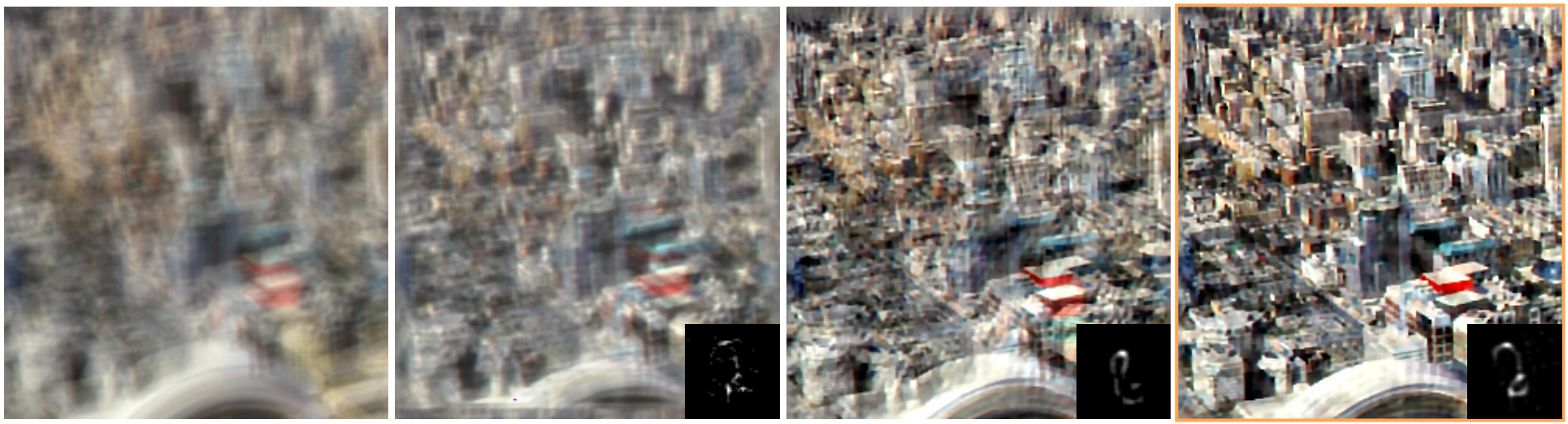
Blur > structures

- *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

SIGGRAPH ASIA 2013 HONG KONG

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

Benchmarks

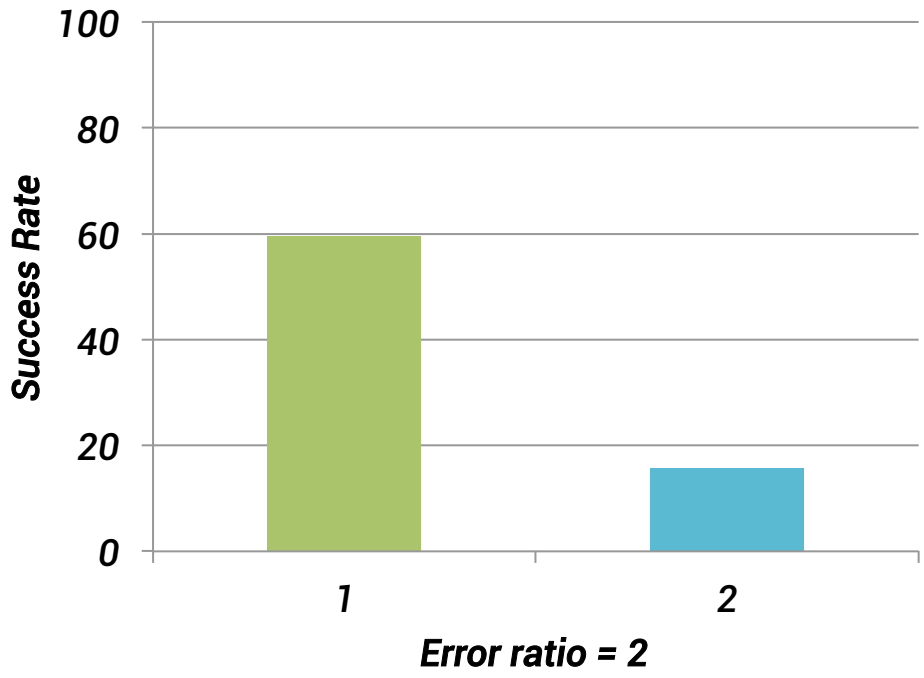
- *Many different methods…*
- *Which one is the best?*
  - *Quality*
  - *Speed*
- *Different works report different benchmark results*
  - *Depending on test data*
  - *Levin et al. CVPR 2009, 2010*
  - *Köhler et al. ECCV 2012*

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*

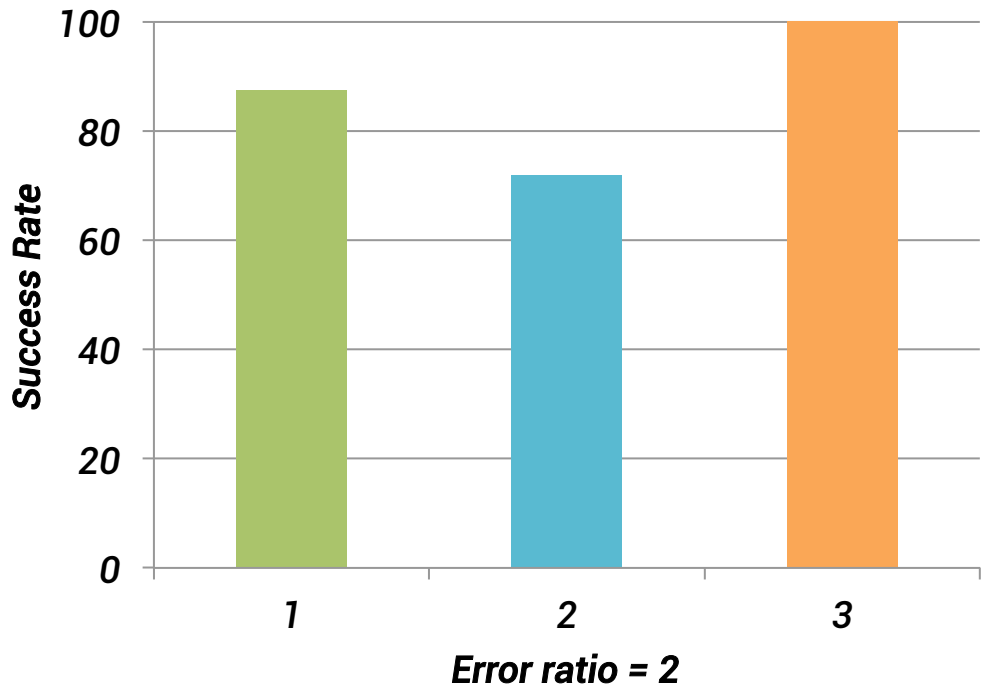
Benchmarks

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



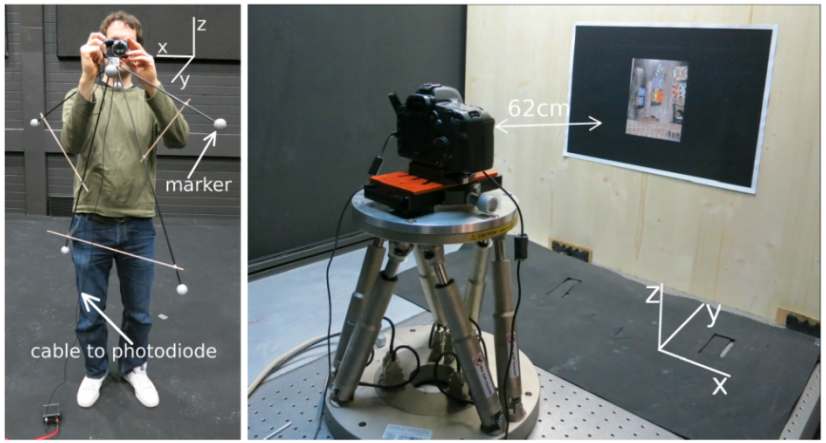
Benchmarks

- *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*

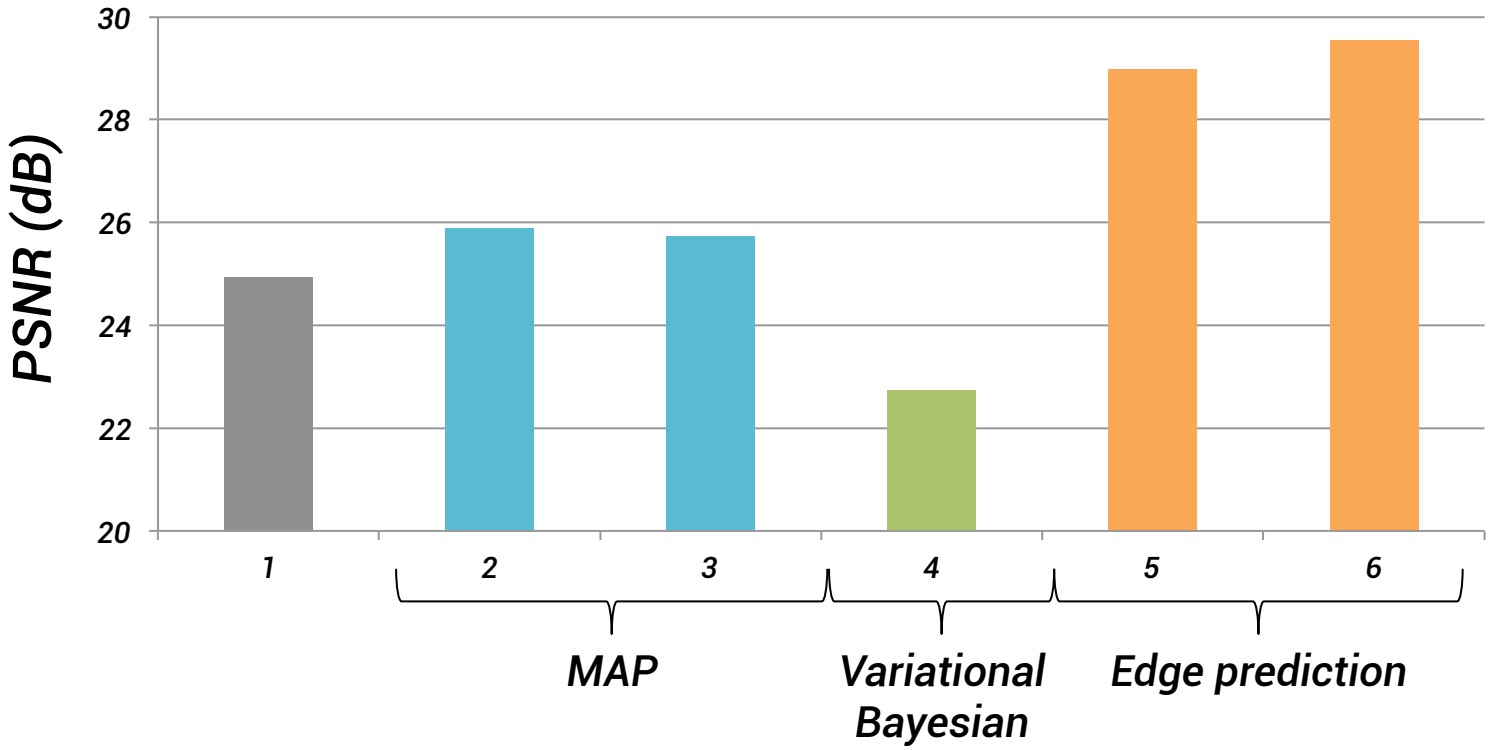


Benchmarks

- ***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

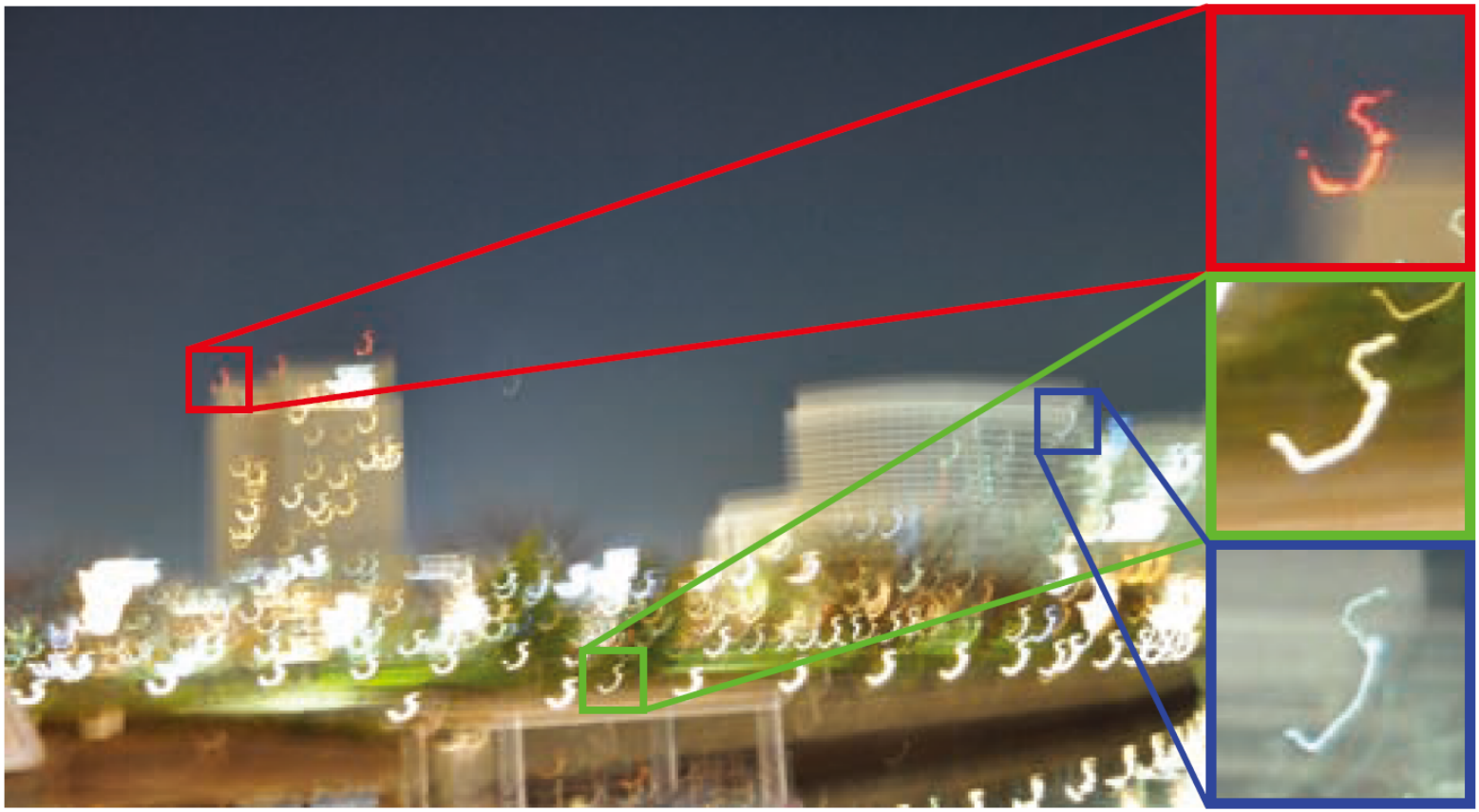
Advanced Issues

- *Introduction*
- *Recent popular approaches*
- *Non-uniform blur*

Convolution based Blur Model

- ***Uniform and spatially invariant blur***

Real Camera Shakes: Spatially Variant!



Uniform Blur Model Assumes

x & y translational camera shakes

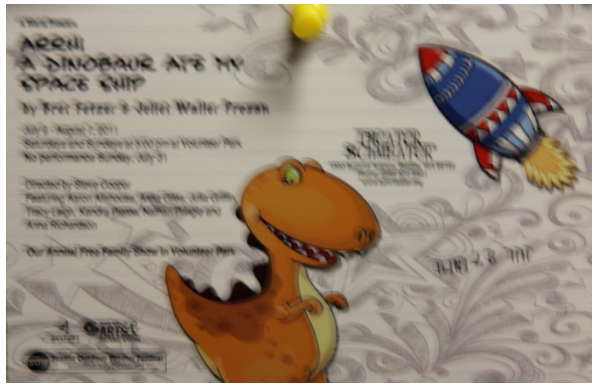
Planar scene

Real Camera Shakes

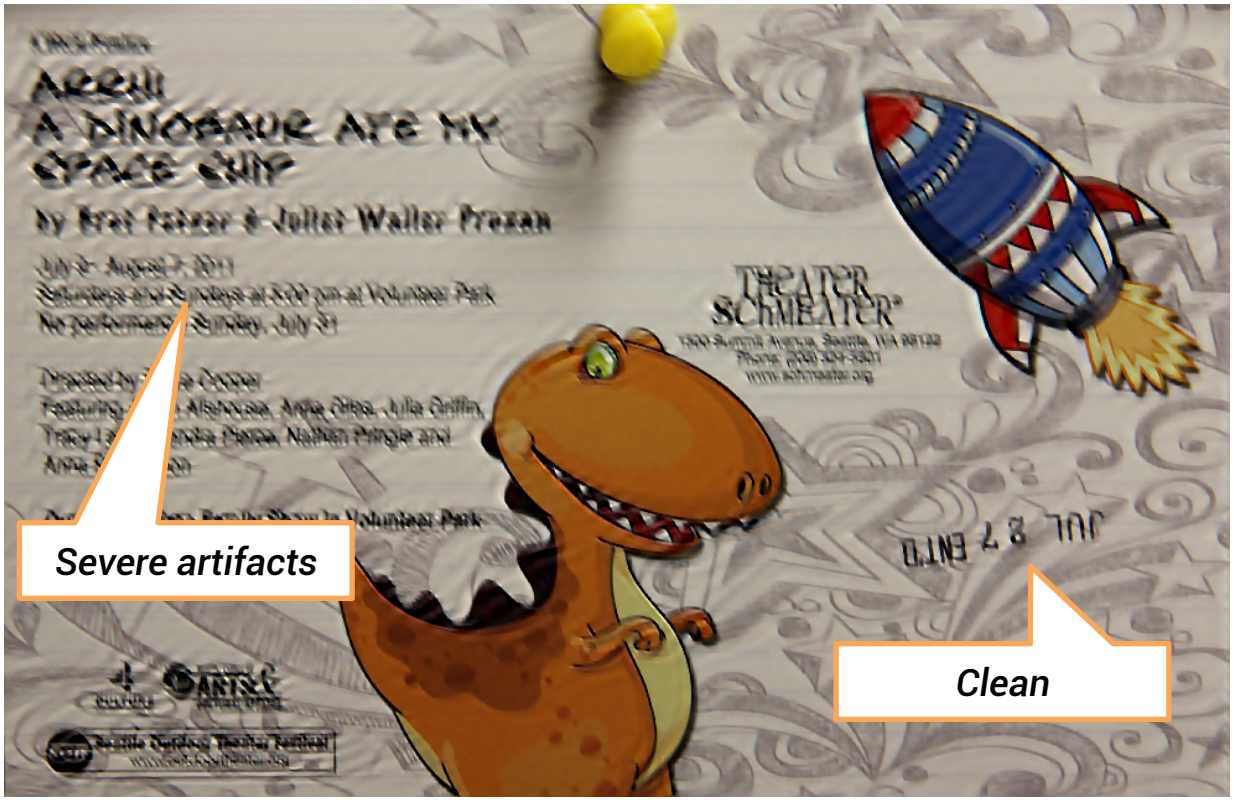
6D real camera motion

Different depths

Real Blurred Image



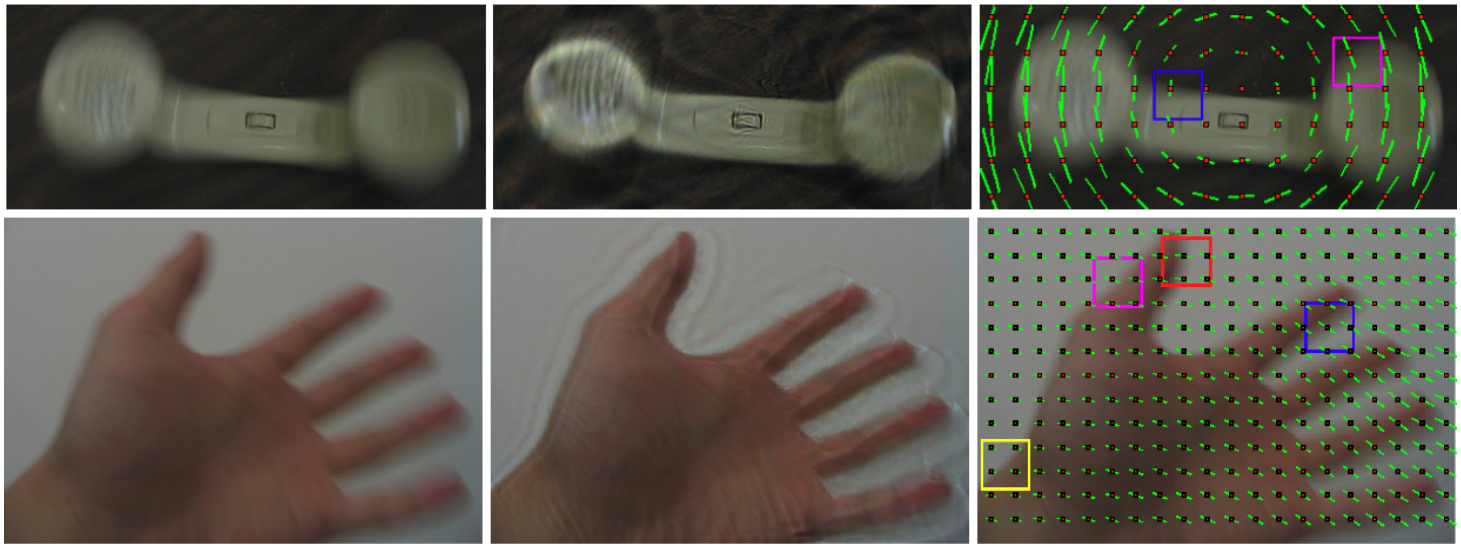
Non-uniformly blurred image



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*

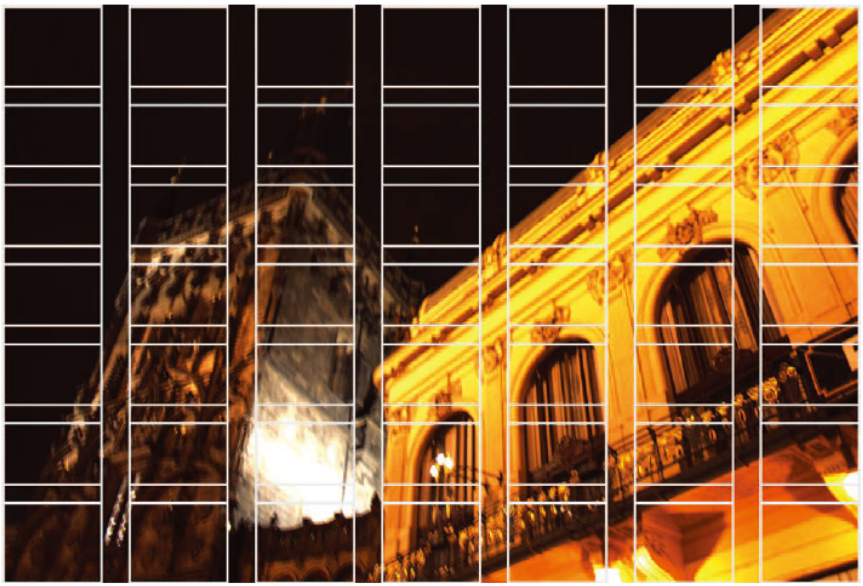
Hi-res. image

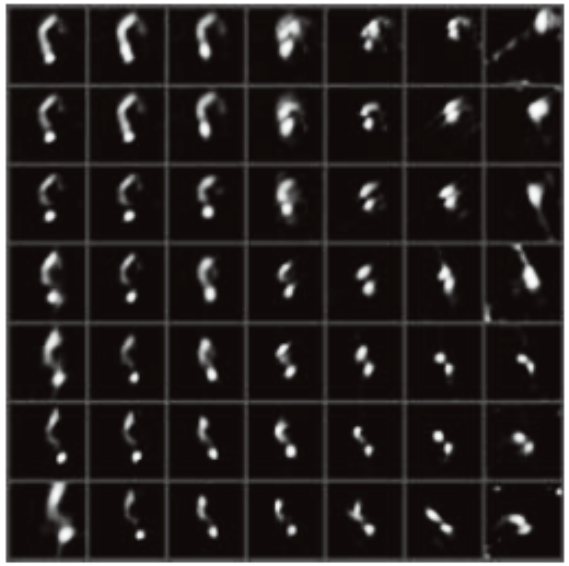
Low-res. video

time

Patch-wise Blur Model

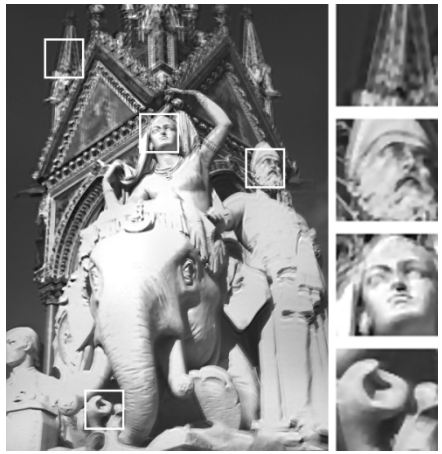
- ***Sorel and Sroubek, ICIP 2009***
  - ***Estimate per-patch blur kernels from a blurred image and an underexposed noisy image***





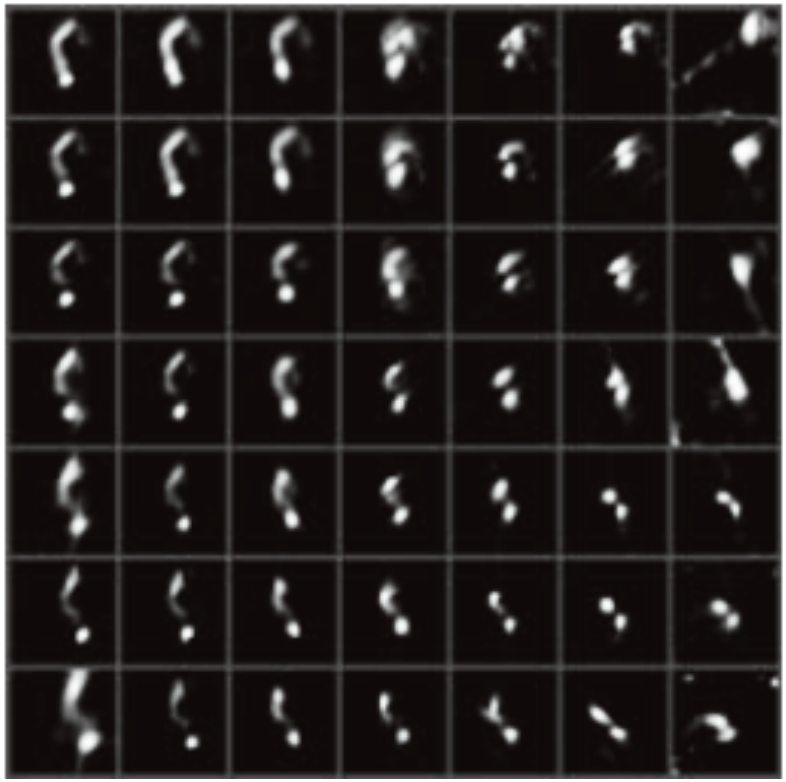
Patch-wise Blur Model

- *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*

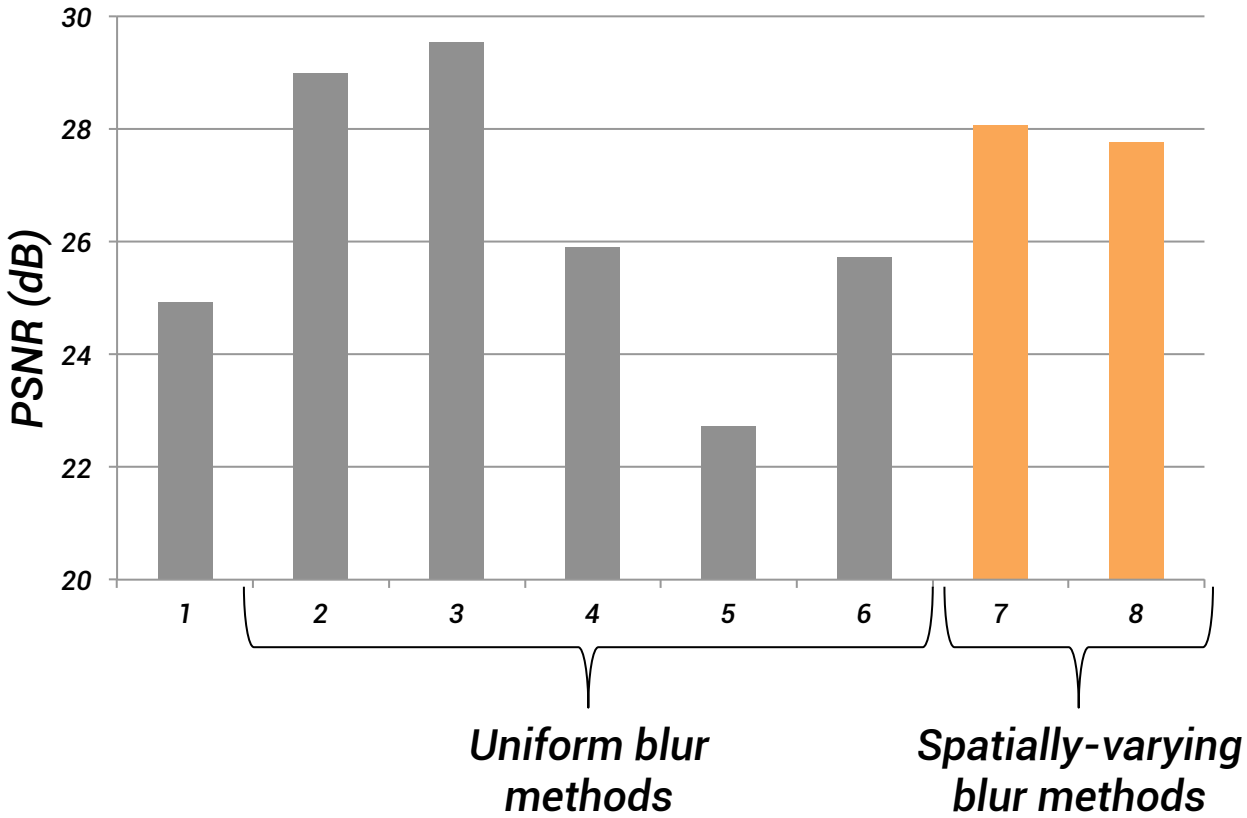


Patch-wise Blur Model

- ***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***



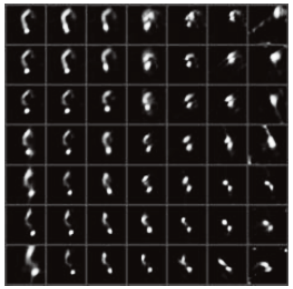
Benchmark [Köhler et al. ECCV 2012]



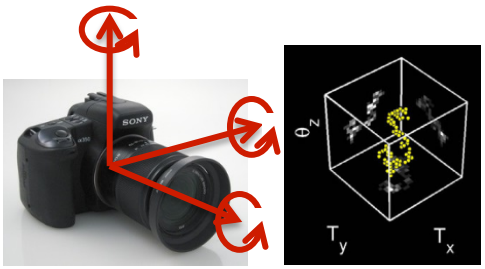
Due to high dimensionality, spatially-varying blur methods are less stable.

Summary

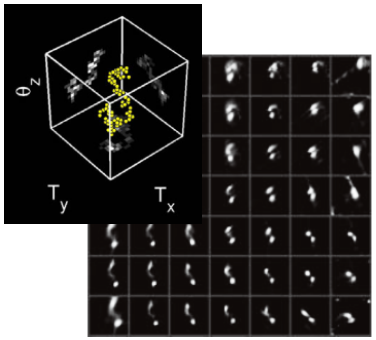
- *Different blur models*



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

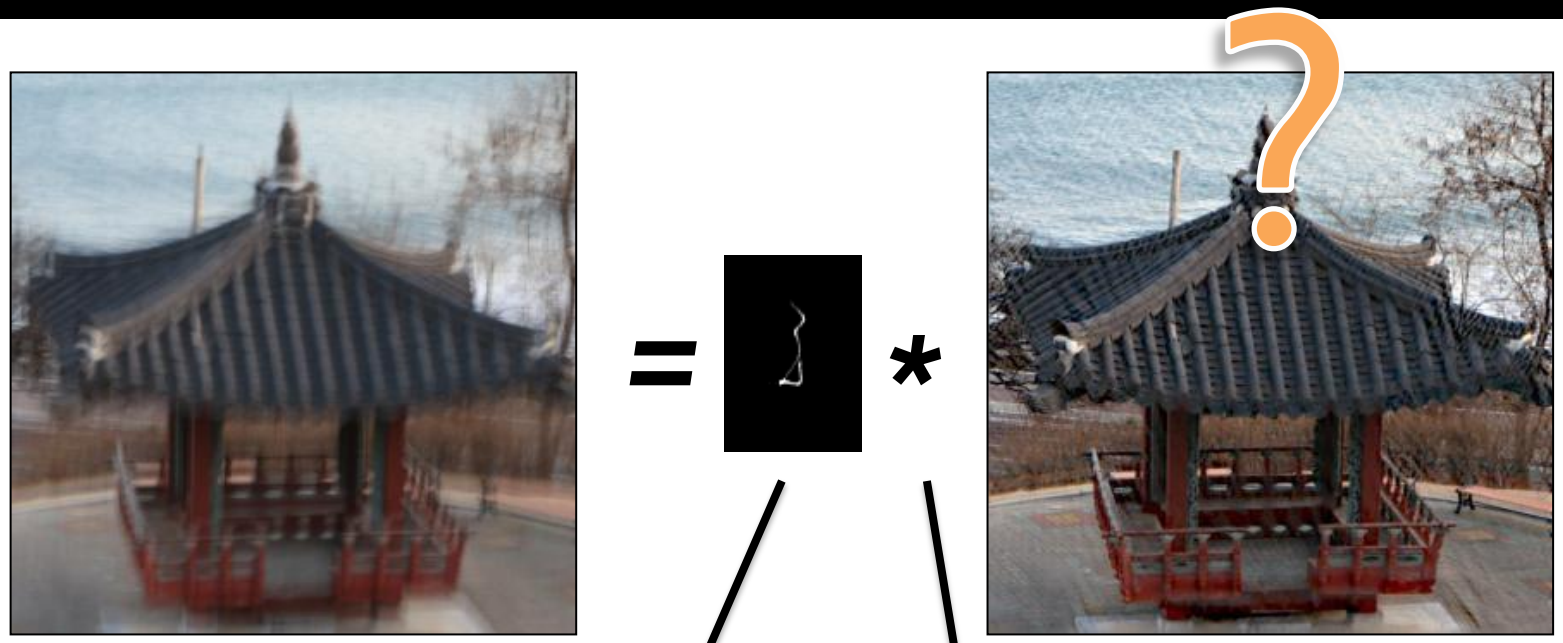
Introduction

Blind Deconvolution

Non-blind Deconvolution

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

Non-blind Deconvolution (Uniform Blur)



Blurred image

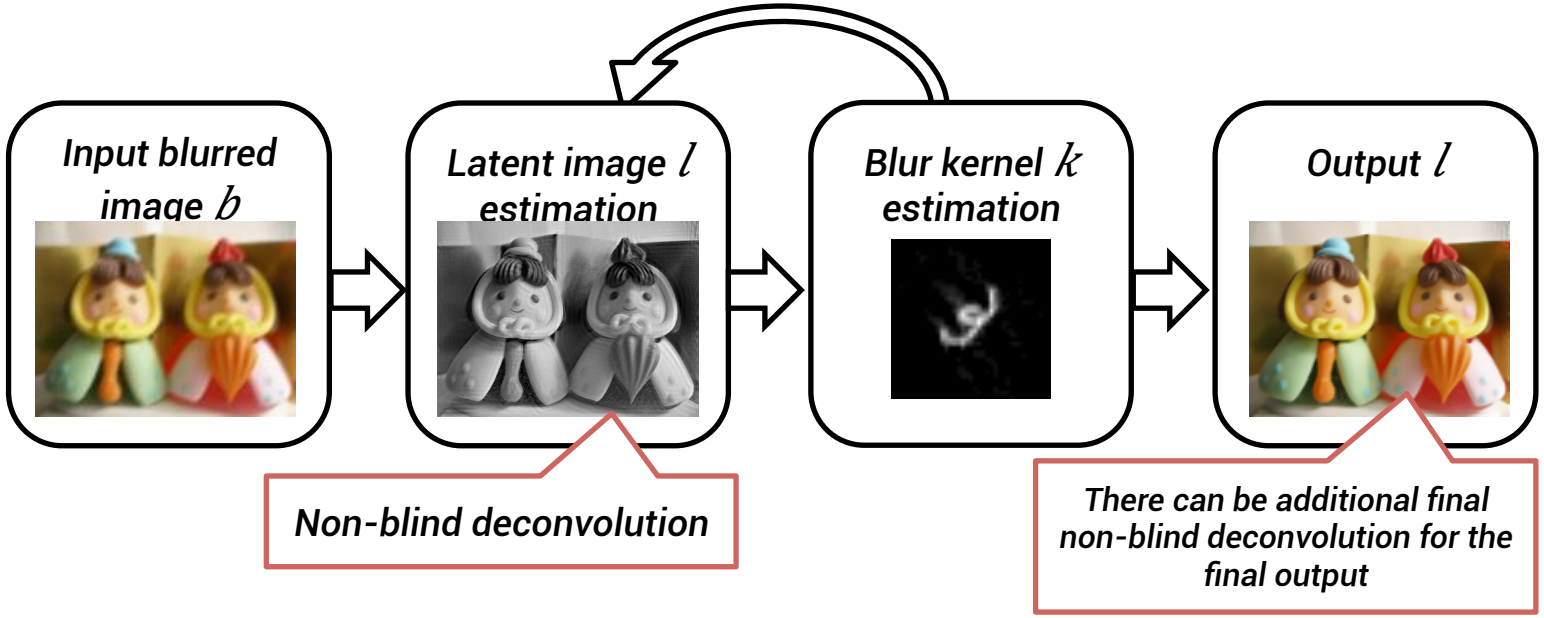
Blur kernel

Convolution operator

Latent sharp image

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…*

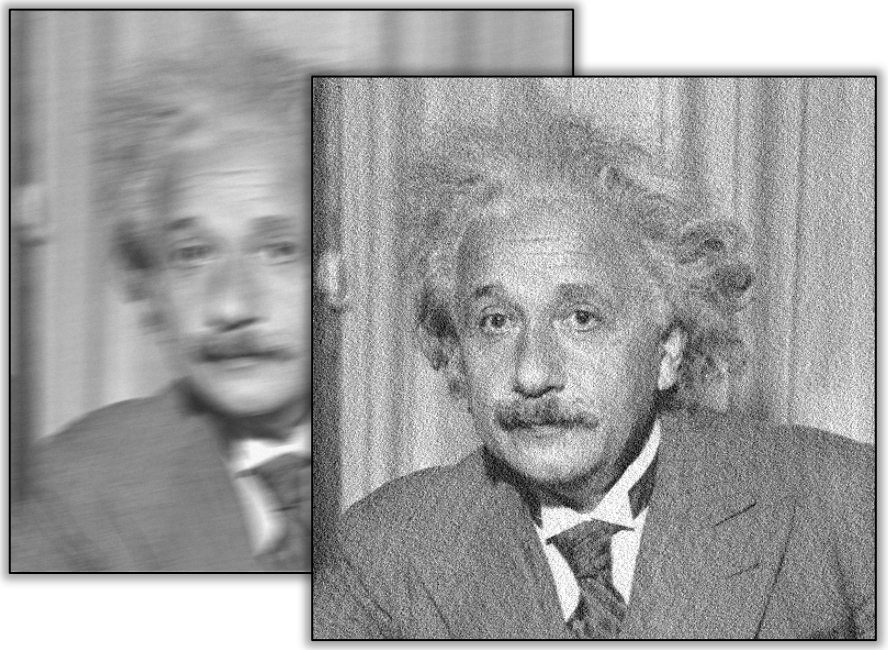
Ill-Posed Problem

- *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

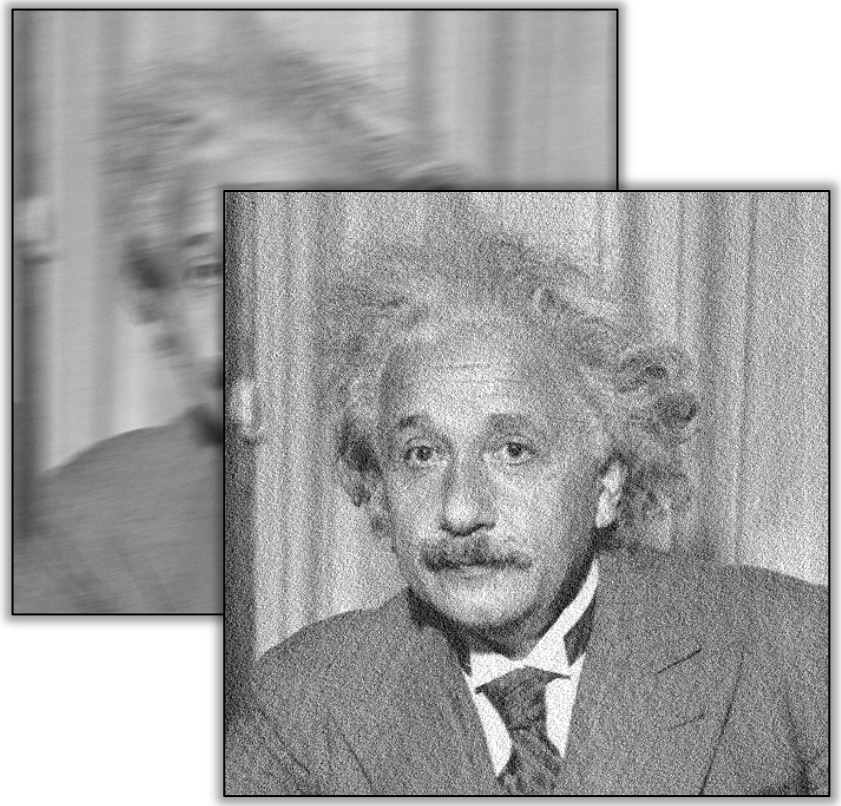
- ***Deconvolution amplifies noise as well as sharpens edges***



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

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

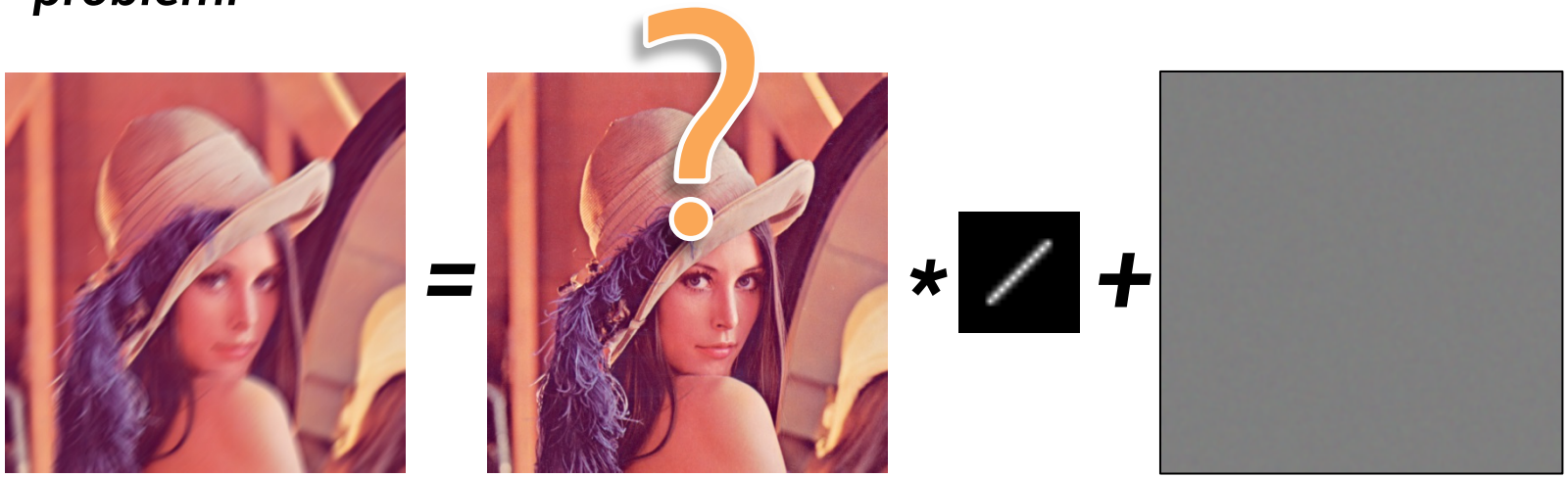
Blind Deconvolution

Non-blind Deconvolution

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

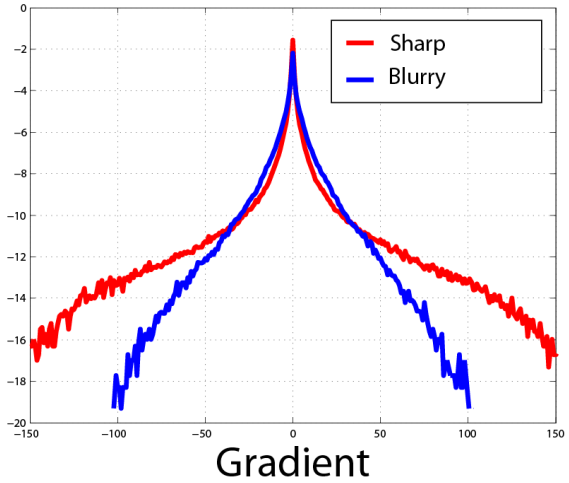
Natural Image Statistics

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



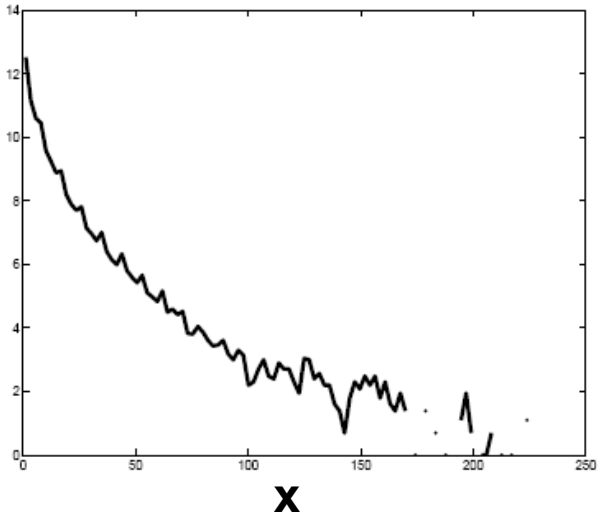
Natural Image Statistics

- ***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***

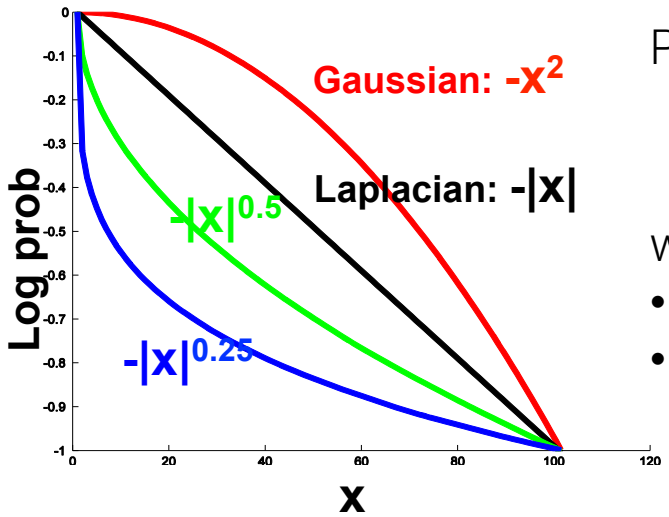


Natural Image Statistics

- ***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

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

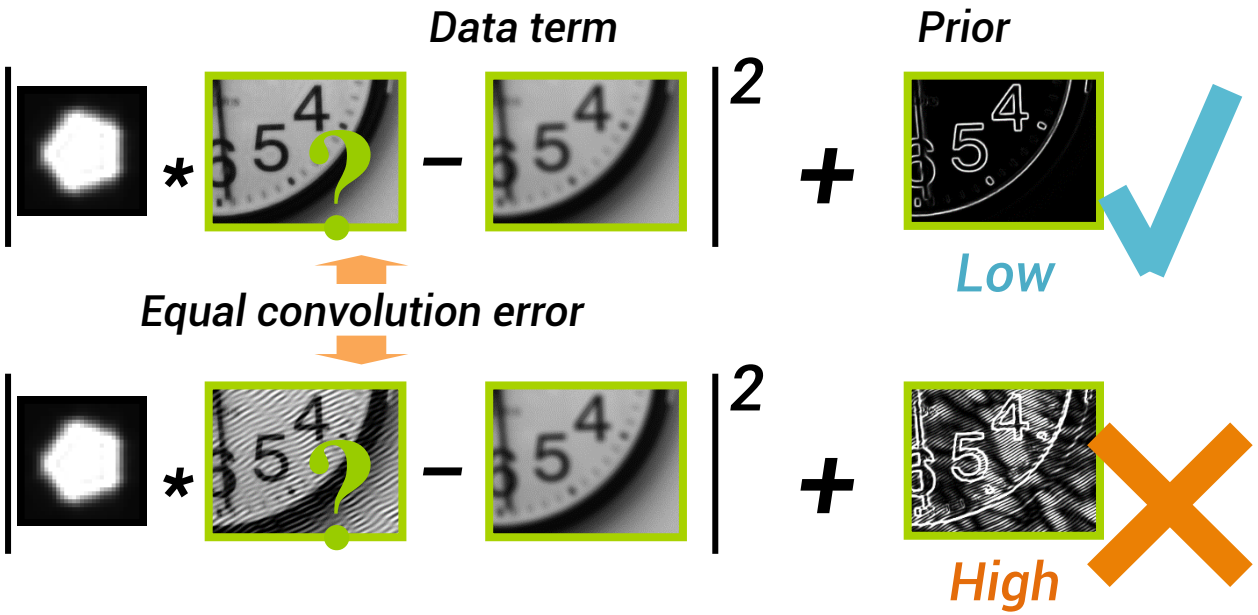
where:

- 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

- ***Levin et al. SIGGRAPH 2007***

"spread" gradients ***"localizes" gradients***

Input

Richardson-Lucy

Gaussian prior

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

Sparse prior

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

Introduction

Blind Deconvolution

Non-blind Deconvolution

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

High-order Natural Image Priors

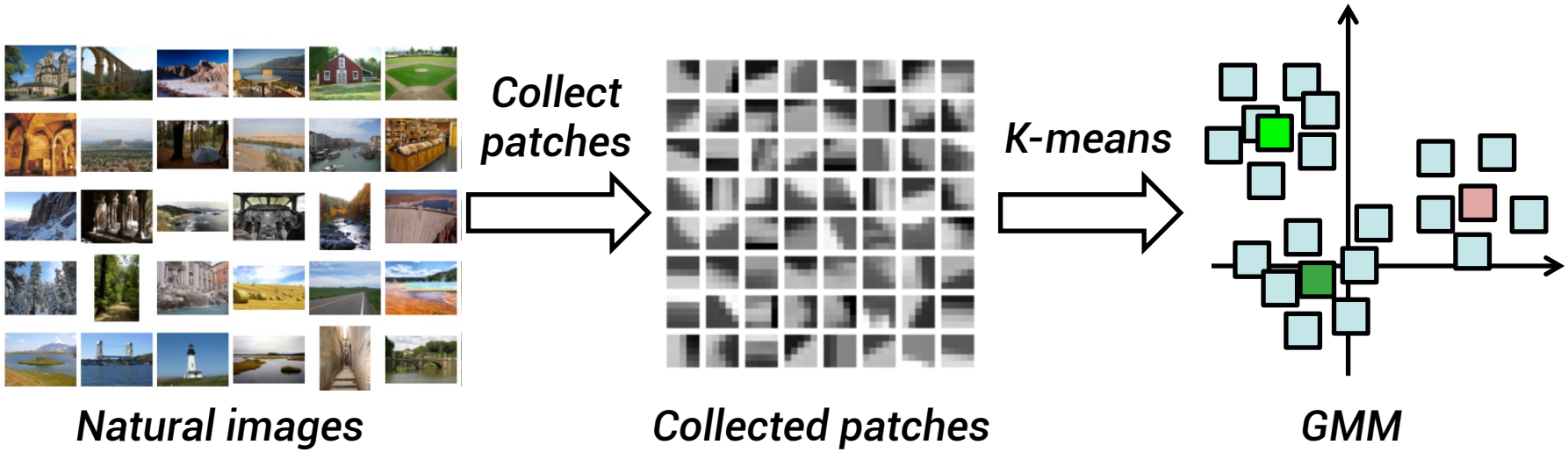
- ***Patches, large neighborhoods, …***
- ***Effective for various kinds of image restoration problems***
  - ***Denoising, inpainting, super-resolution, deblurring, …***

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

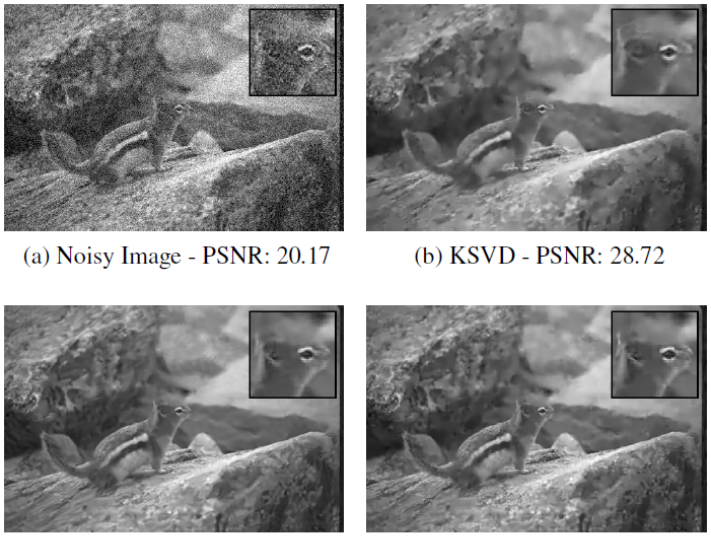
- ***Zoran & Weiss, ICCV 2011***
  - ***Given a patch, we can compute its likelihood based on the GMM.***
  - ***Deconvolution can be done by solving:***

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

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***

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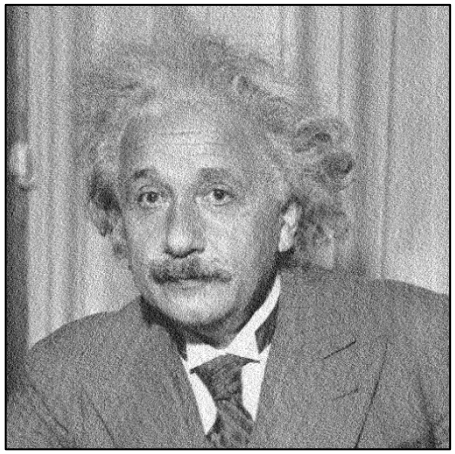
Ringing Artifacts

- ***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]

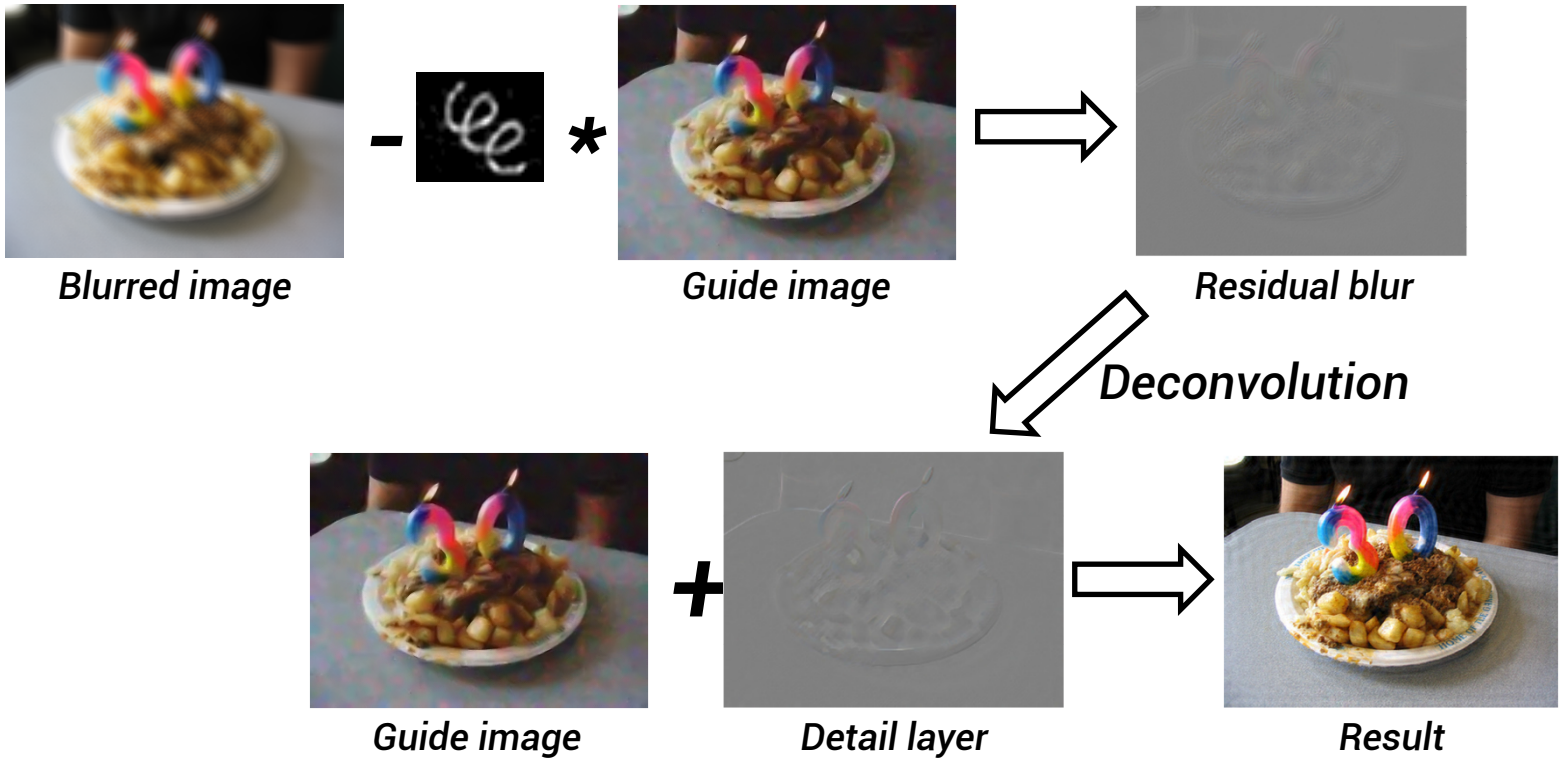
Blurred image

Guide image

***Residual deconvolution result with** less ringing artifacts*

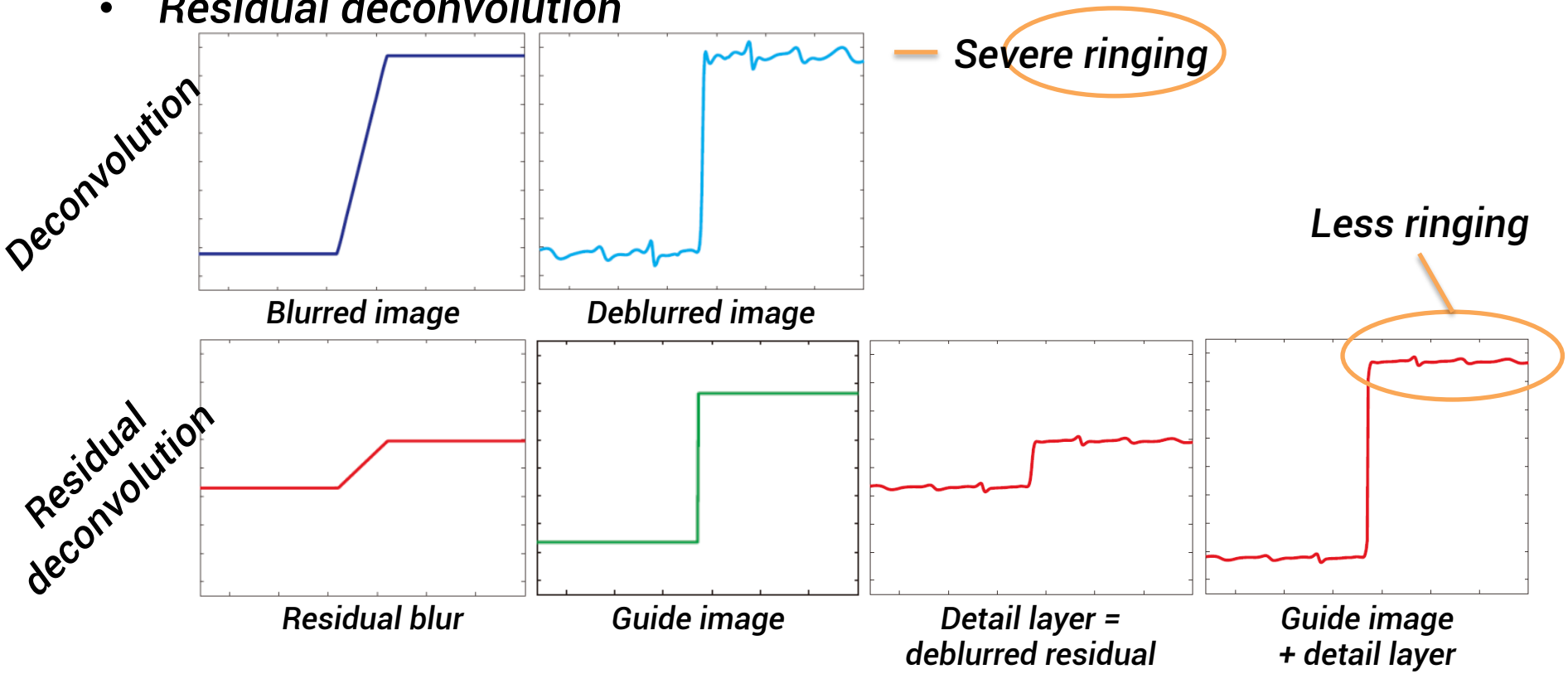
- ***Relatively accurate edges, but less details***
- ***Obtained from a deconvolution result from a smaller scale***

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



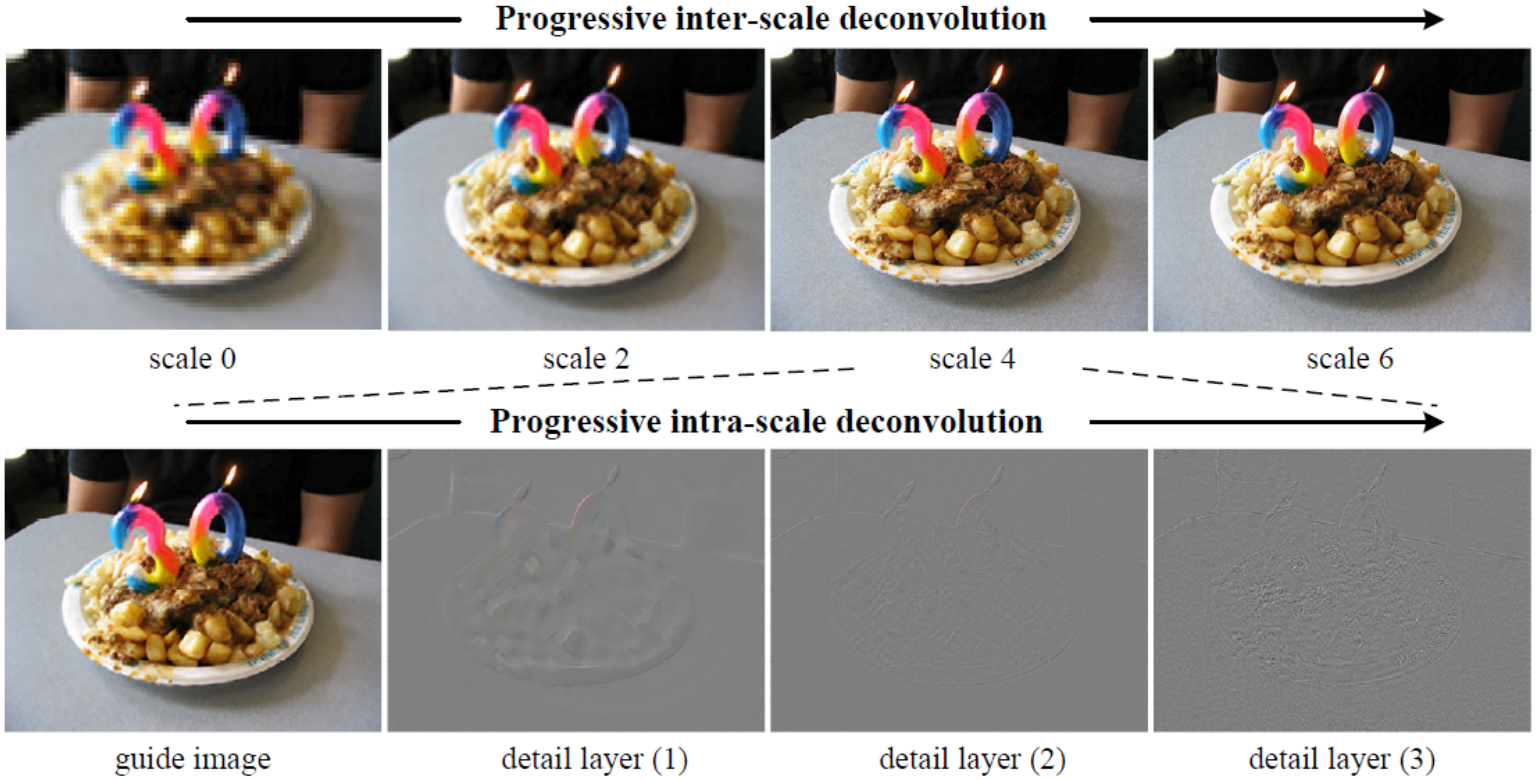
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

- ***Residual deconvolution***



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

- ***Progressive inter-scale & intra-scale deconvolution***

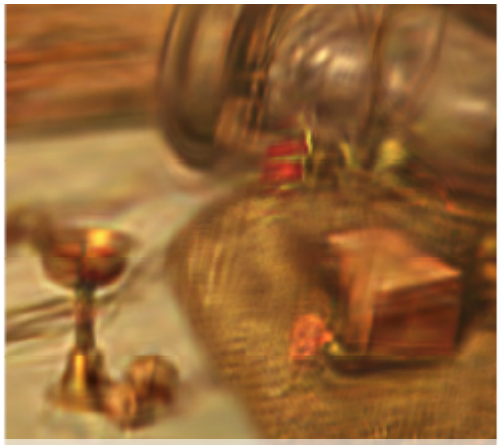


Blurred image

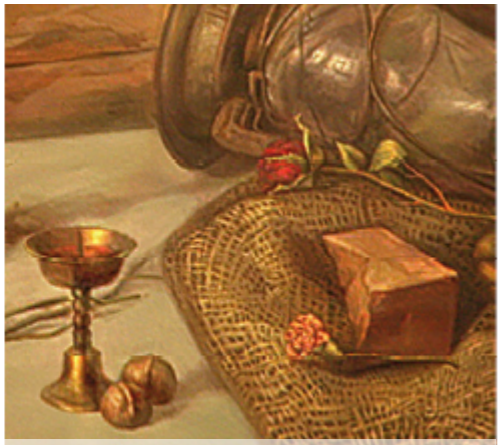
Richardson-Lucy

TV regularization

Levin et al. SIGGRAPH 2007



Wavelet regularization



Yuan et al. SIGGRAPH 2008

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Outliers

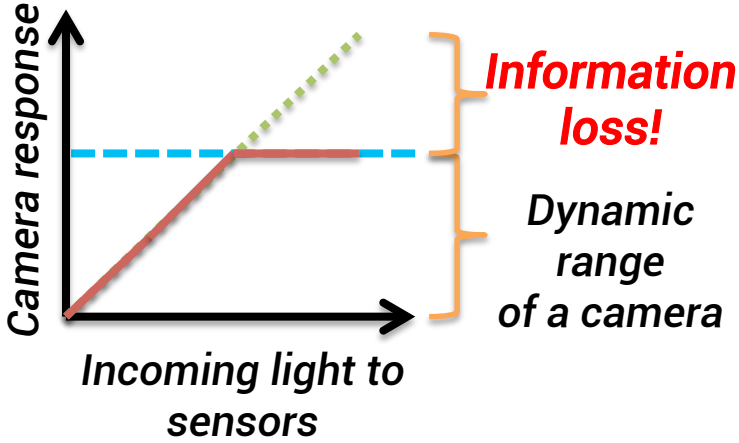
- ***A main source of severe ringing artifacts***

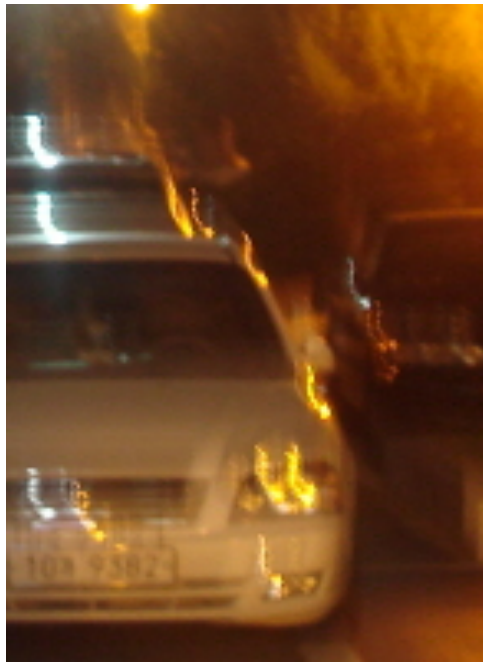
Blurred image with outliers

Deblurring result
[Levin et al. SIGGRAPH 2007]

Outliers

- *Saturated pixels caused by limited dynamic range of sensors*





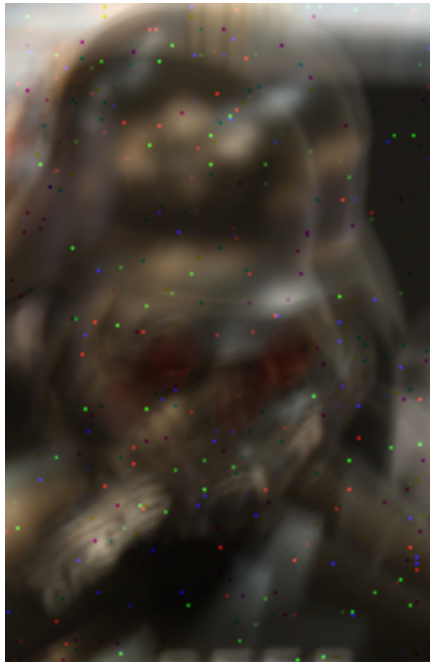
Blurred image

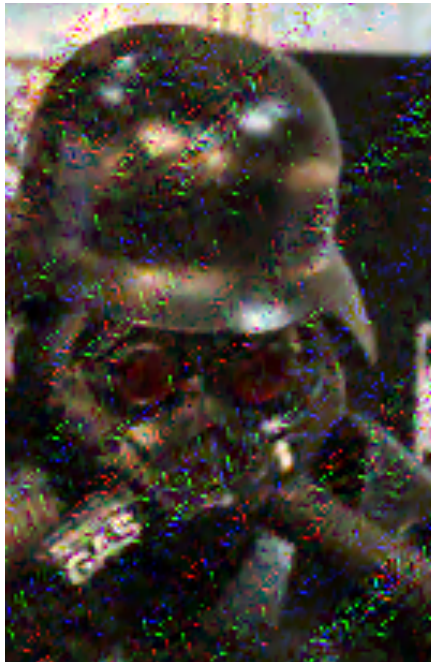
[Levin et al. 2007]

Outliers

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

Hot pixel





Blurred image with outliers [Levin et al. 2007]

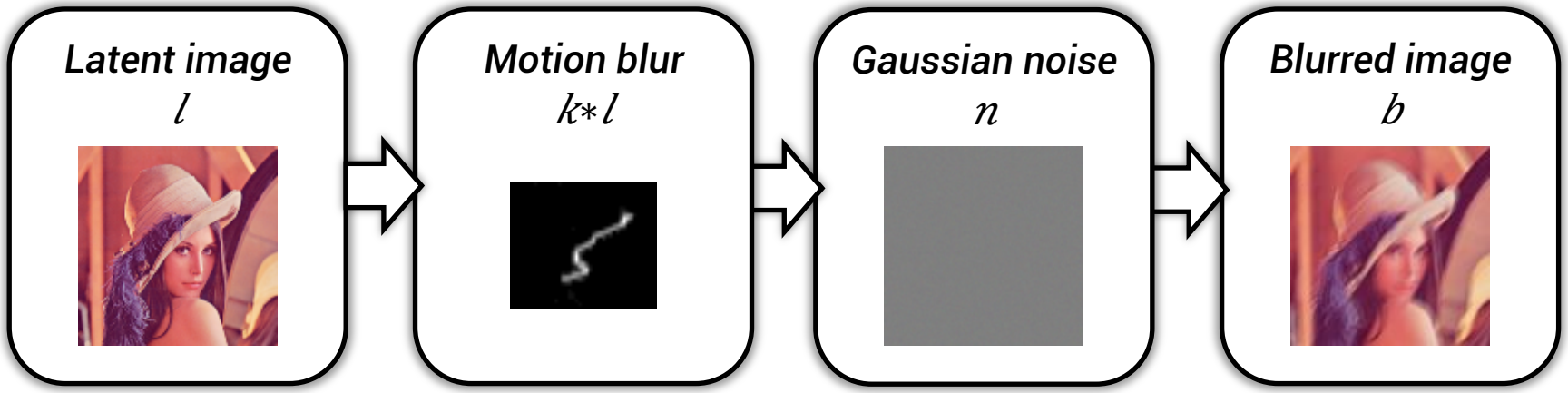
Outlier Handling

- Most common blur model:

$$b = k * l + n$$

small amount of Gaussian noise

Equivalent to



Outlier Handling

- An energy function derived from this model:

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

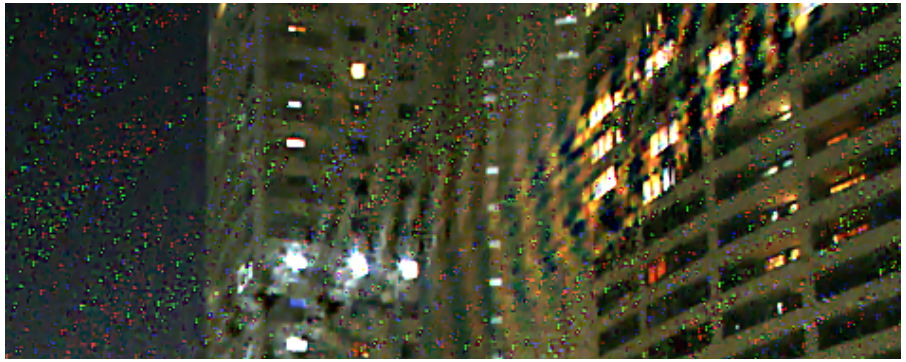
- More robust norms to outliers
  - L^1-norm, other robust statistics…

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

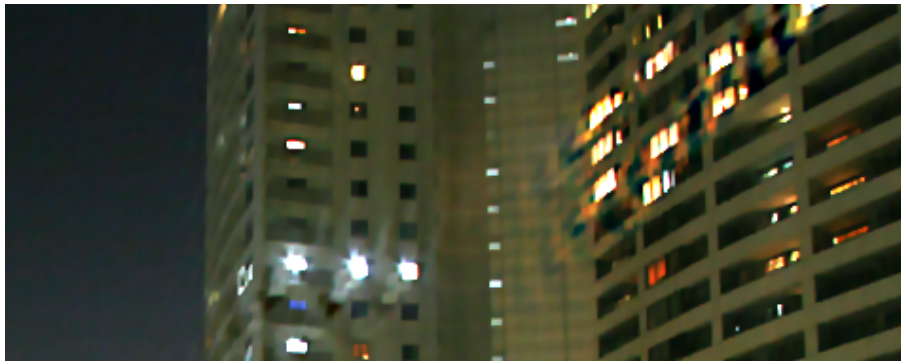
  - Bar et al. IJCV 2006, Xu et al. ECCV 2010, …

Outlier Handling

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



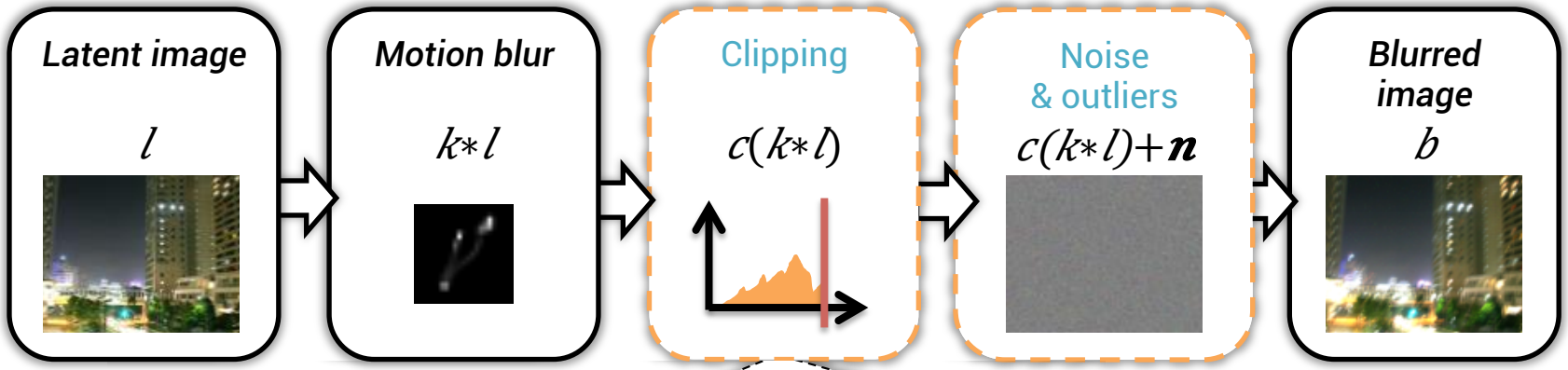
L^2-norm based data term



L^1-norm based data term

Cho et al. ICCV 2011

- ***More accurate blur model reflecting outliers***

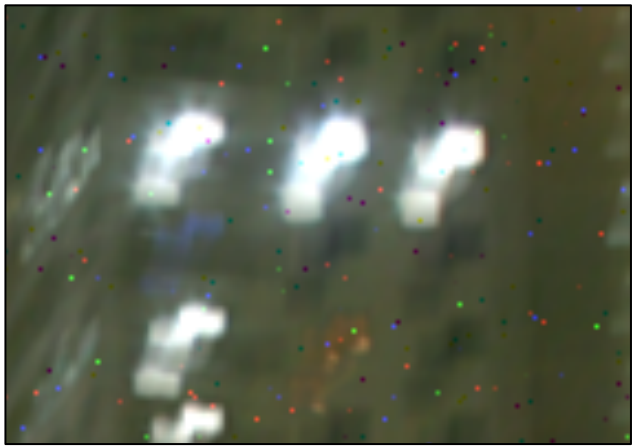


$$c(u) = \begin{cases} u & \text{if } u \in \text{DynamicRange} \\ \text{LowerBound} & \text{if } u < \text{LowerBound} \\ \text{UpperBound} & \text{if } u > \text{UpperBound} \end{cases}$$

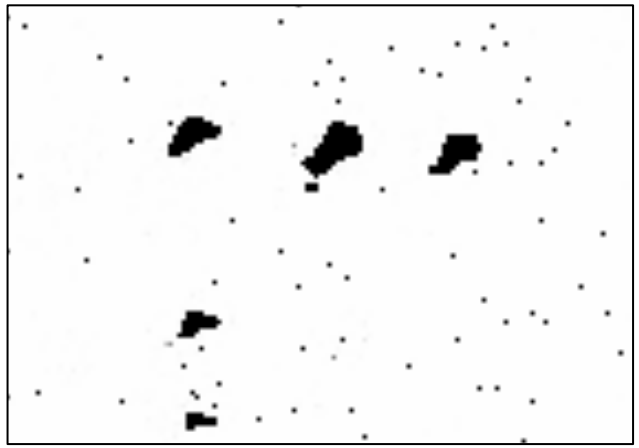
Cho et al. ICCV 2011

- ***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

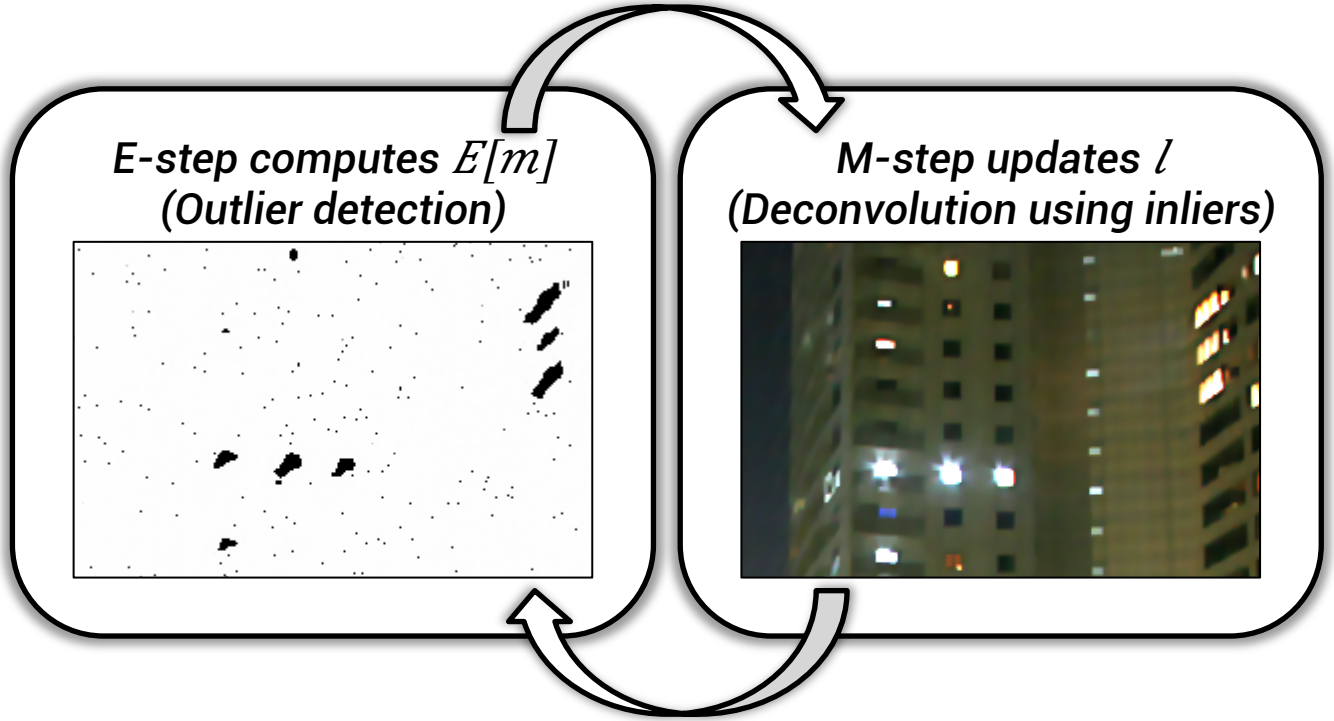
Given b & k, find the most probable l

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

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

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*