Recent Advances in Image Deblurring

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Presenters

Seungyong Lee

- Professor @ POSTECH

- 1995 Ph.D. KAIST
- 1990 M.S. KAIST
- 1998 B.S. Seoul National University

- 1996 ~ now Professor @ POSTECH
- 2010 ~ 2011 Visiting Professor @ Adobe Research
- 2003 ~ 2004 Visiting Senior Researcher @ MPI Informatik
- 1995 ~1996 Research Associate @ City College of New York/CUNY

Sunghyun Cho

- Post-doctoral Research Scientist @ Adobe Research

- 2012: Ph.D. in CS, POSTECH
- 2005: B.S. in CS & Math, POSTECH

- 2012.3 ~ now: Post-doctoral Research scientist @ Adobe Research
- 2010.7 ~ 2010.11: Intern @ Adobe Research
- 2006.8 ~ 2007.2: Intern @ MSRA

Disclaimer

- Many images and figures in this course note have been copied from the papers and presentation materials of previous deblurring and deconvolution methods.
- In those cases, the original papers are cited in the slides.

In This Course...

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15 min	**Introduction** (Seungyong Lee) - Basic concepts
90 min	**Blind deconvolution** (Sunghyun Cho) - Recent popular approaches & benchmarks - Uniform & non-uniform blur
15 min	Break
60 min	**Non-blind deconvolution** (Seungyong Lee) - Noise, ringing, outliers
45 min	**Advanced Issues** (Sunghyun Cho) - Hardware based deblurring - Defocus / optical lens / object motion / video blurs - Other issues

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

blur [blɜː(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

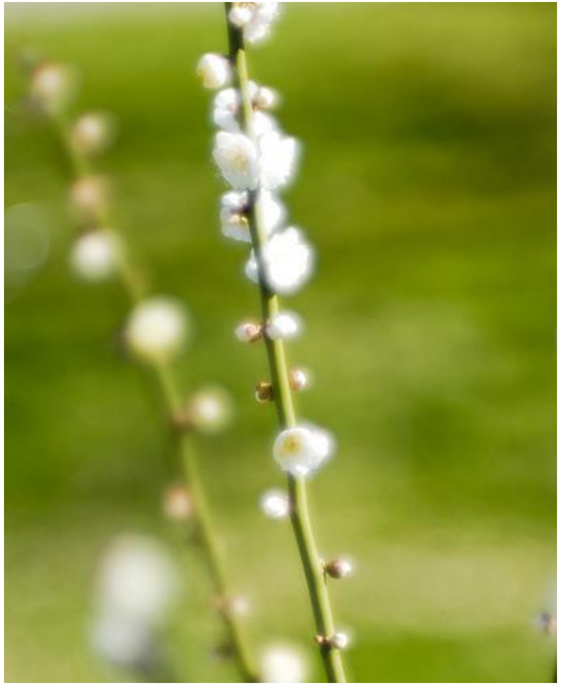
- Caused by camera shakes during exposure time
  - Motion can be represented as a camera trajectory

Object Motion Blur

- Caused by object motions during exposure time

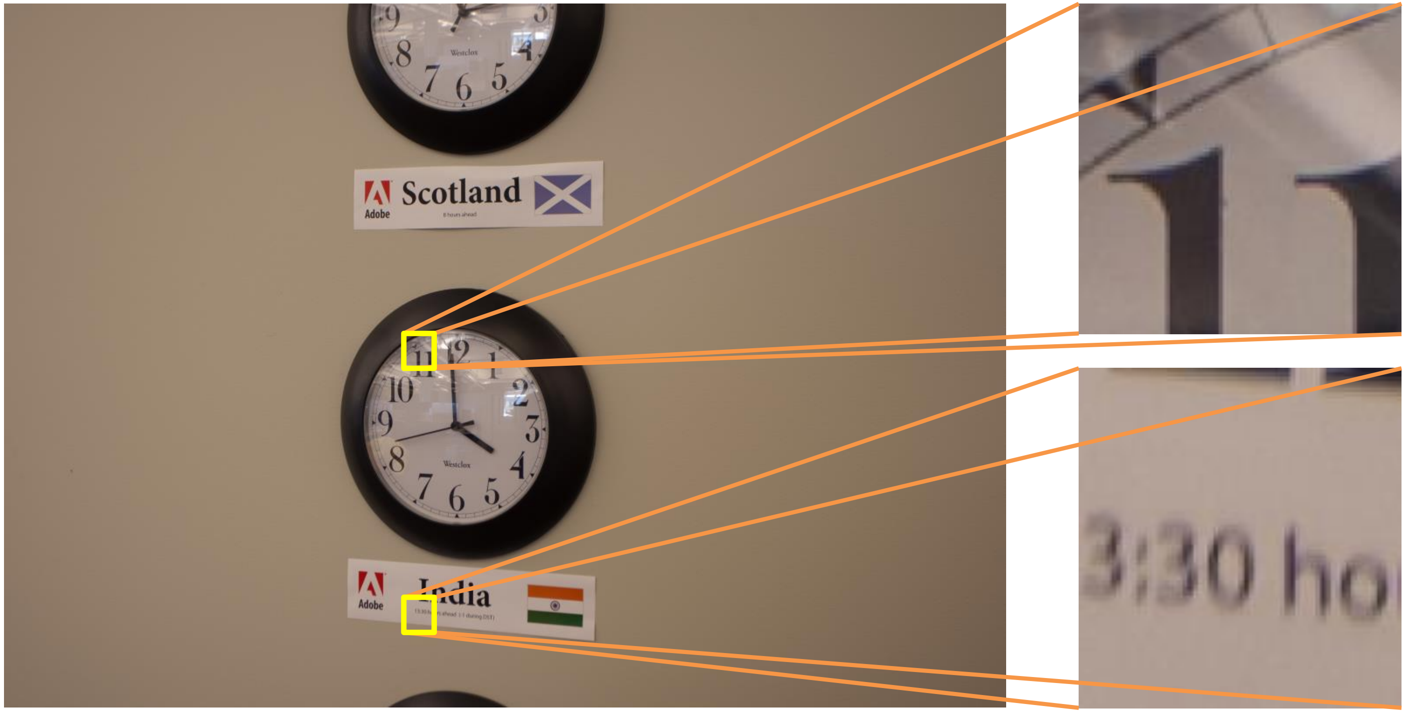
Defocus Blur

- 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*?

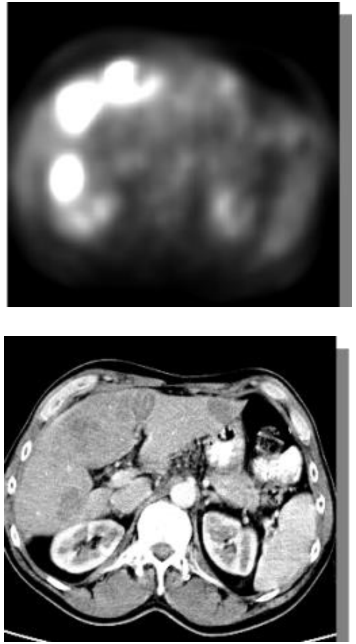
- Image/video in our daily lives
  - Sometimes a retake is difficult!



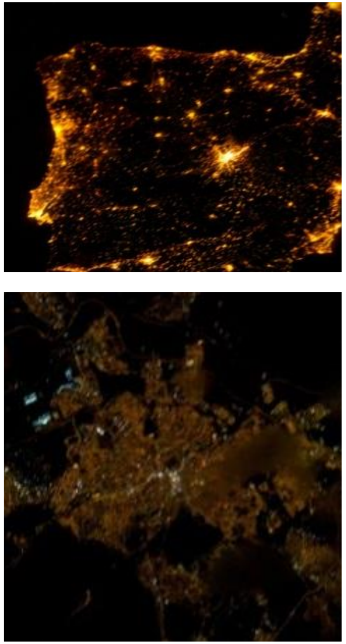
Why is it *important*?

- Strong demand for high quality deblurring

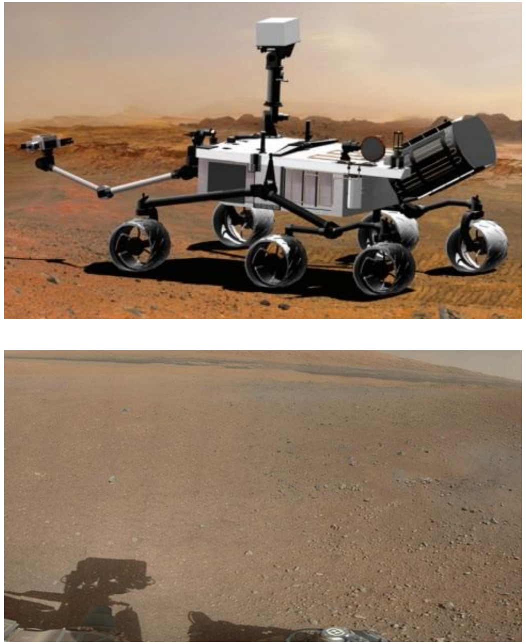
CCTV, car black box



Medical imaging



Aerial/satellite photography



Robot vision

Deblurring

from a given blurred image

find its latent sharp image

Commonly Used Blur Model

Blurred image

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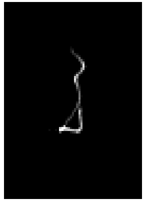

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Latent sharp image

Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

Blind Deconvolution

Blurred image

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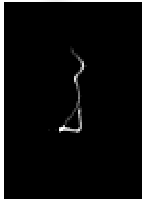

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Latent sharp image

Blur kernel
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Convolution
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Non-blind Deconvolution

Blurred image

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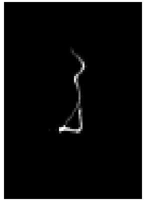

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Latent sharp image

Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

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

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Camera shake (Camera motion blur)

Object movement (Object motion blur)

Out of focus (Defocus blur)

Combinations (vibration & motion, …)

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

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

Blind Deconvolution (Uniform Blur)

Blurred image

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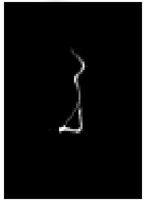


Blur kernel or Point Spread Function (PSF)

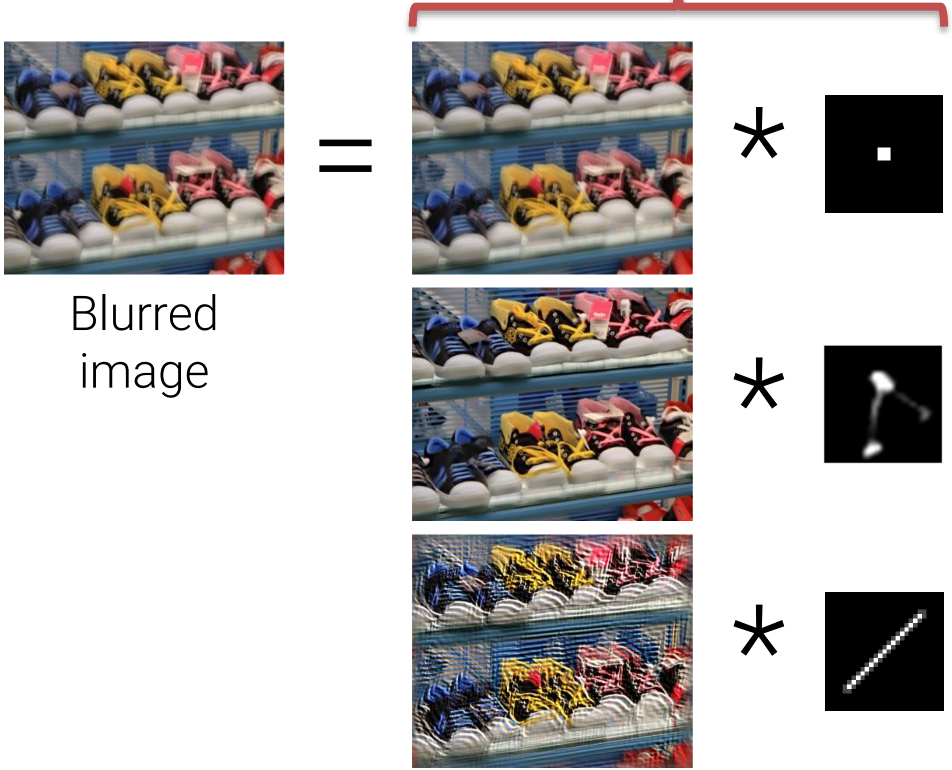
*

Convolution operator

Latent sharp image

Key challenge: Ill-posedness!

Possible solutions



Blurred image

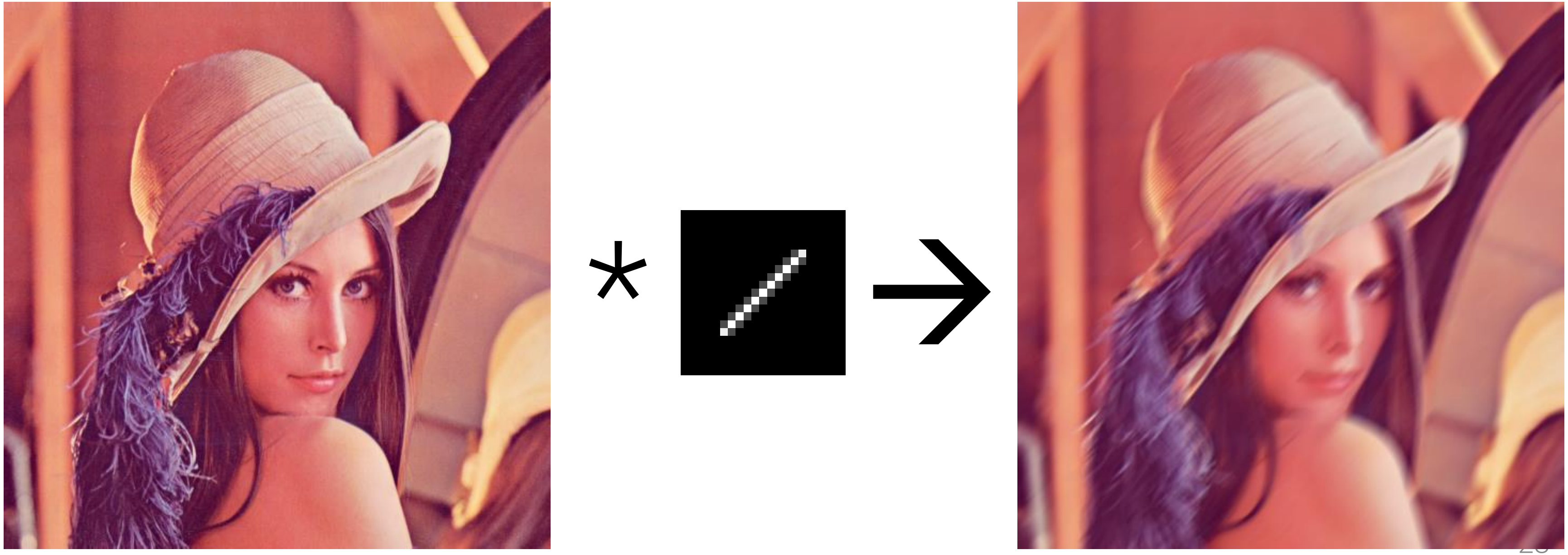
- Infinite number of solutions satisfy the blur model

- Analogous to

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

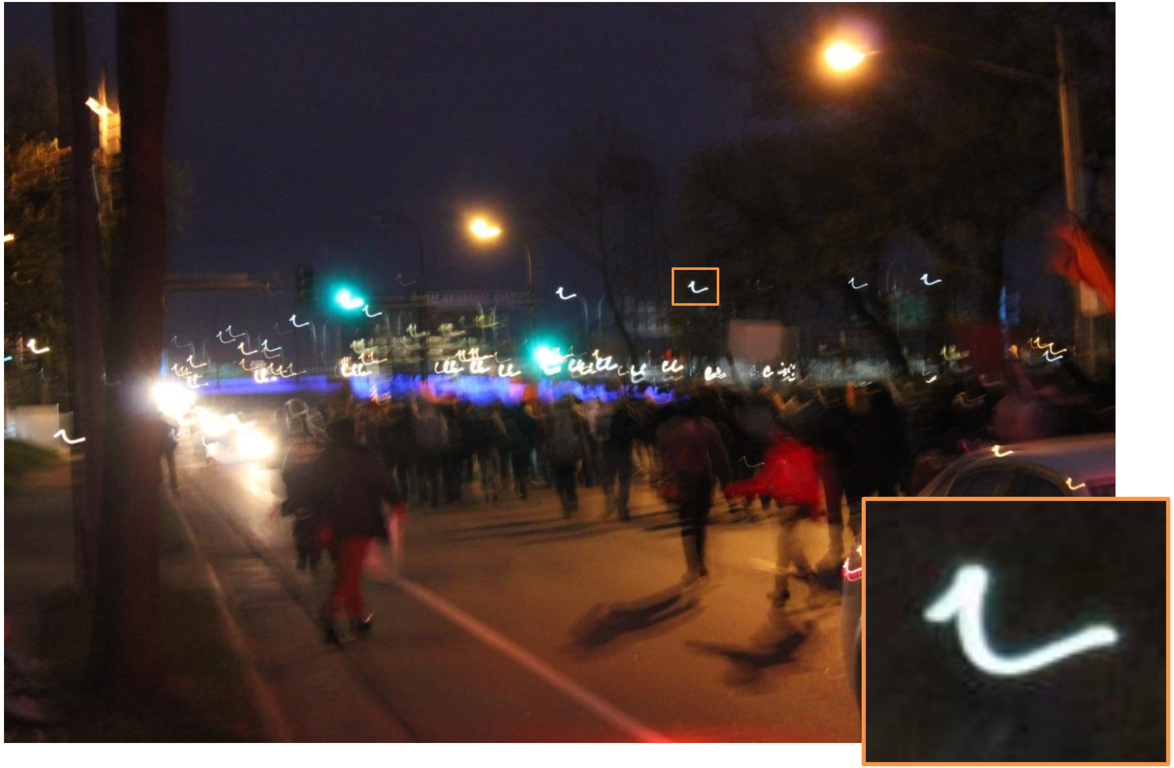
In The Past…

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



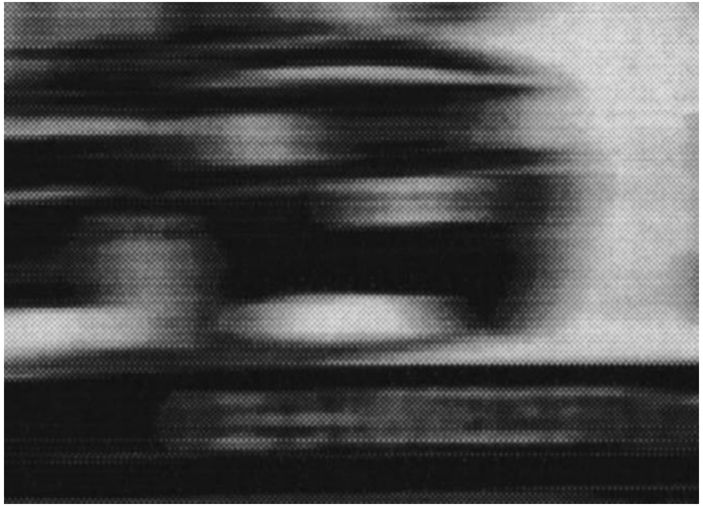
In The Past…

- But real camera shakes are much more complex

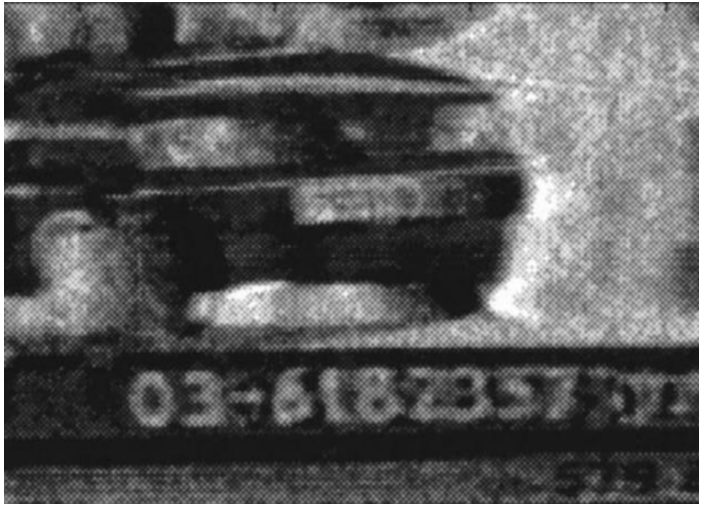


In The Past…

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



Blurred image



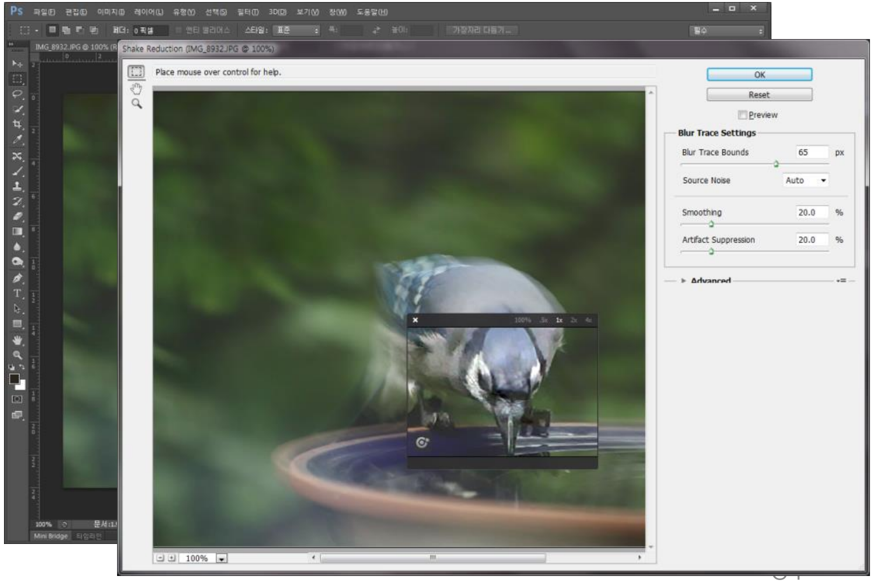
Latent sharp image

* 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

Advanced Issues

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

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

Recent Popular Approaches

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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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- [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

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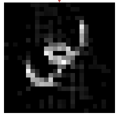
MAP based Approaches

Maximize a joint posterior probability with respect to k and l

Posterior distribution

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



Blur kernel k

Latent image l

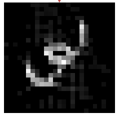
Blurred image b

MAP based Approaches

Bayes rule:

Posterior distribution — Likelihood — Prior on l — Prior on k

$$\underbrace{p(k,l|b)}_{\text{Posterior distribution}} \propto \underbrace{p(b|l,k)}_{\text{Likelihood}}\underbrace{p(l)}_{\text{Prior on } l}\underbrace{p(k)}_{\text{Prior on } k}$$



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:

$$-\log p(k,l|b) \Rightarrow -\log p(b|k,l) - \log p(l) - \log p(k)$$
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Alternatingly minimize the energy function w.r.t. k and l

MAP based Approaches

Negative $\log$-posterior:

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

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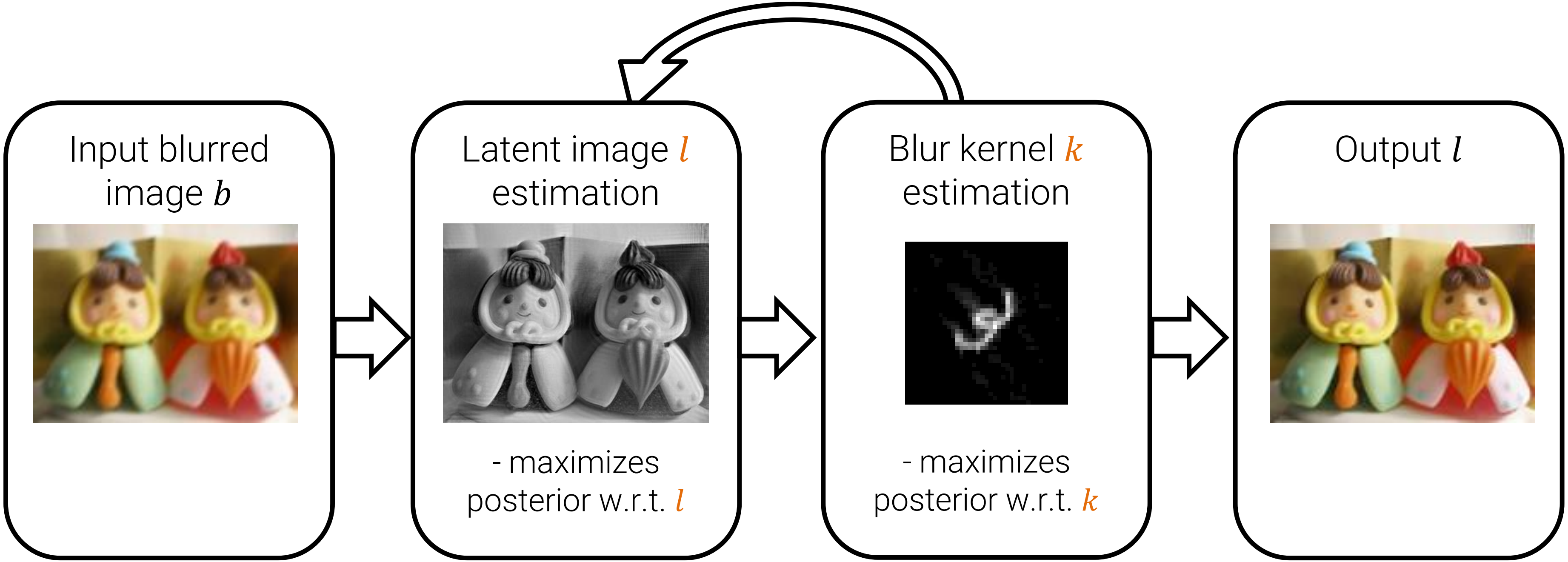
Alternatingly minimize the energy function w.r.t. k and l

Ill-posedness:

- Data fitting term has several solutions
- Thus, $\rho_l(l)$ and $\rho_k(k)$ are very important for resolving the ill-posedness!

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

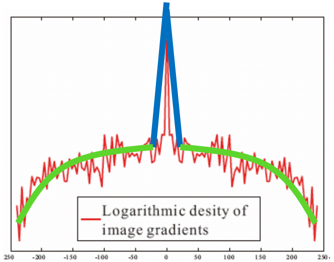
Shan et al. SIGGRAPH 2008

- Carefully designed likelihood & priors

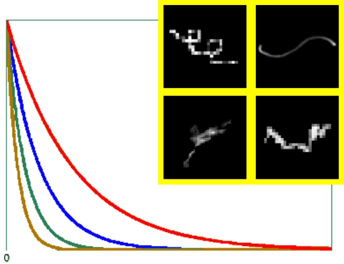
$$p(k, l|b) \propto p(b|l,k)p(l)p(k)$$

Likelihood based on intensities & derivatives

Natural image statistics based prior on l



Kernel statistics based prior on k

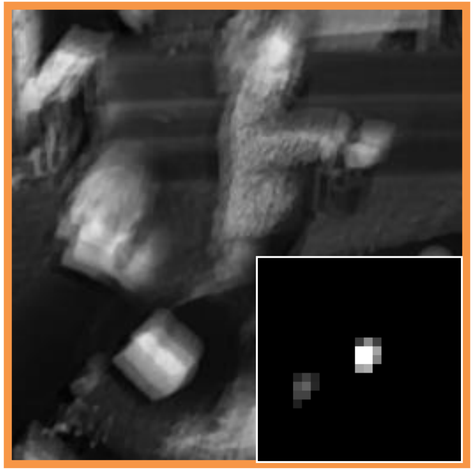


Shan et al. SIGGRAPH 2008

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

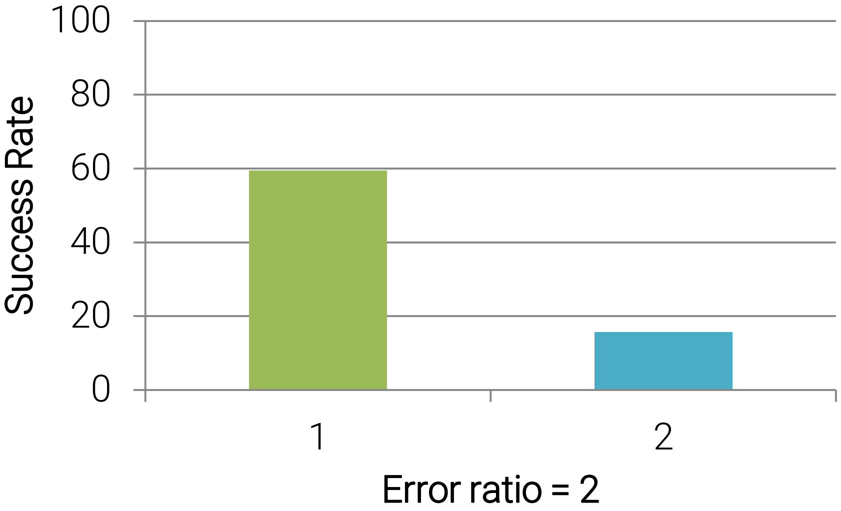
Shan et al. SIGGRAPH 2008

- 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)



Xu et al. CVPR 2013

- L_0 norm based prior for latent image l

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

L_0 norm based prior on l $(\|\nabla l\|_0)$

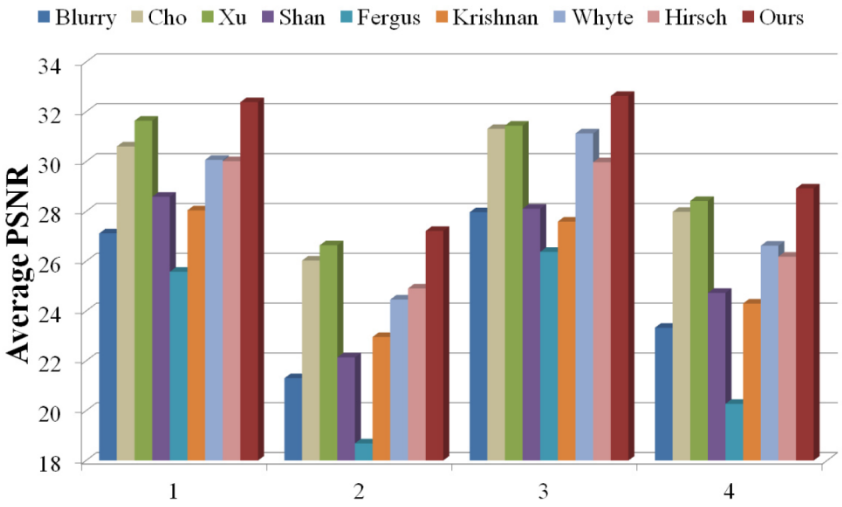
Natural image

L_0 minimized

- No natural prior, i.e., does not seek for naturally-looking latent images
- But, unnatural images with a few sharp edges
- Better for resolving the ill-posedness

Xu et al. CVPR 2013

- Better prior & sophisticated optimization methods
  ➔ better convergence & better quality



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

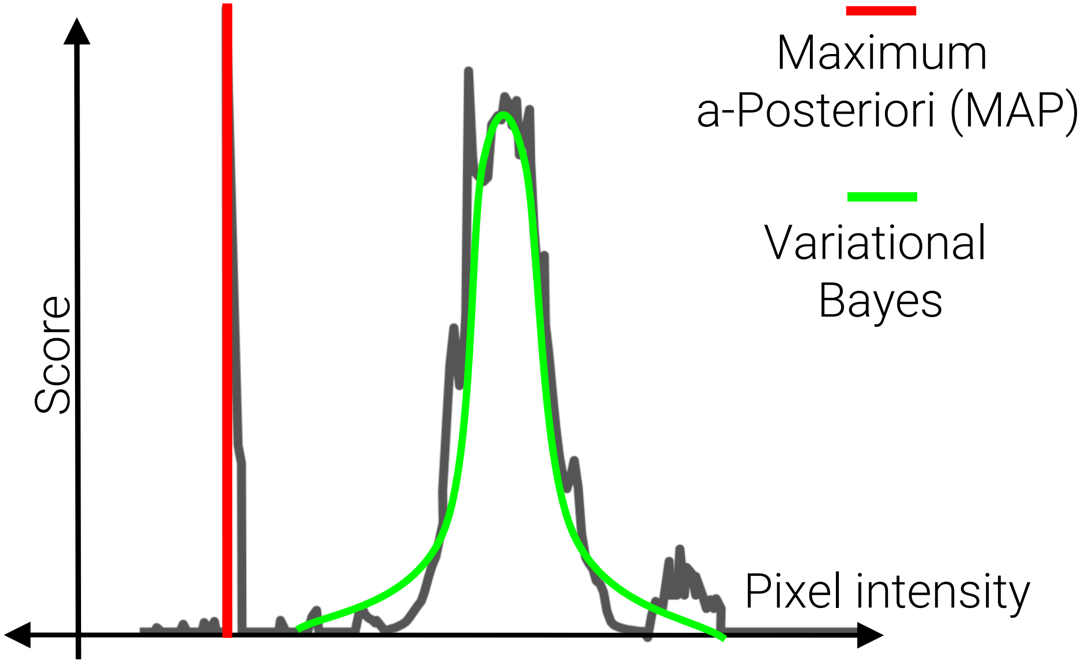
- Not seek for one most probable solution, but consider all possible solutions
- Theoretically more robust
- Slow

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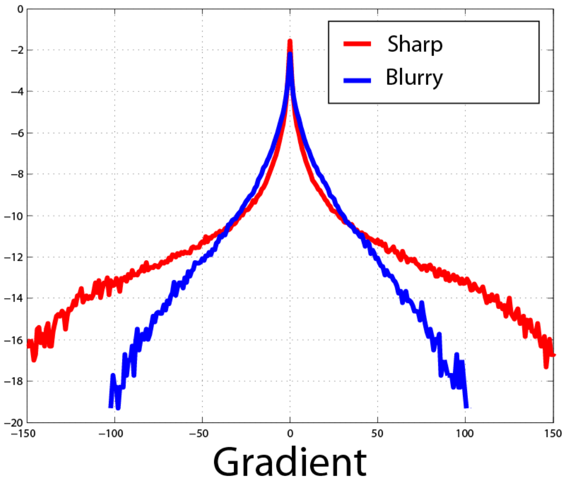
- Fergus et al. SIGGRAPH 2006
  - First approach to handle non-parametric blur kernels
- Levin et al. CVPR 2009
  - Show that variational Bayesian approaches can perform more robustly than MAP based approaches
- Levin et al. CVPR 2010
  - EM based efficient approximation to variational Bayesian approach

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

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

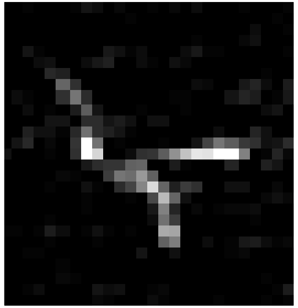
- cf) MAP based approach:

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

Fergus et al. SIGGRAPH 2006

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





Levin et al. CVPR 2010

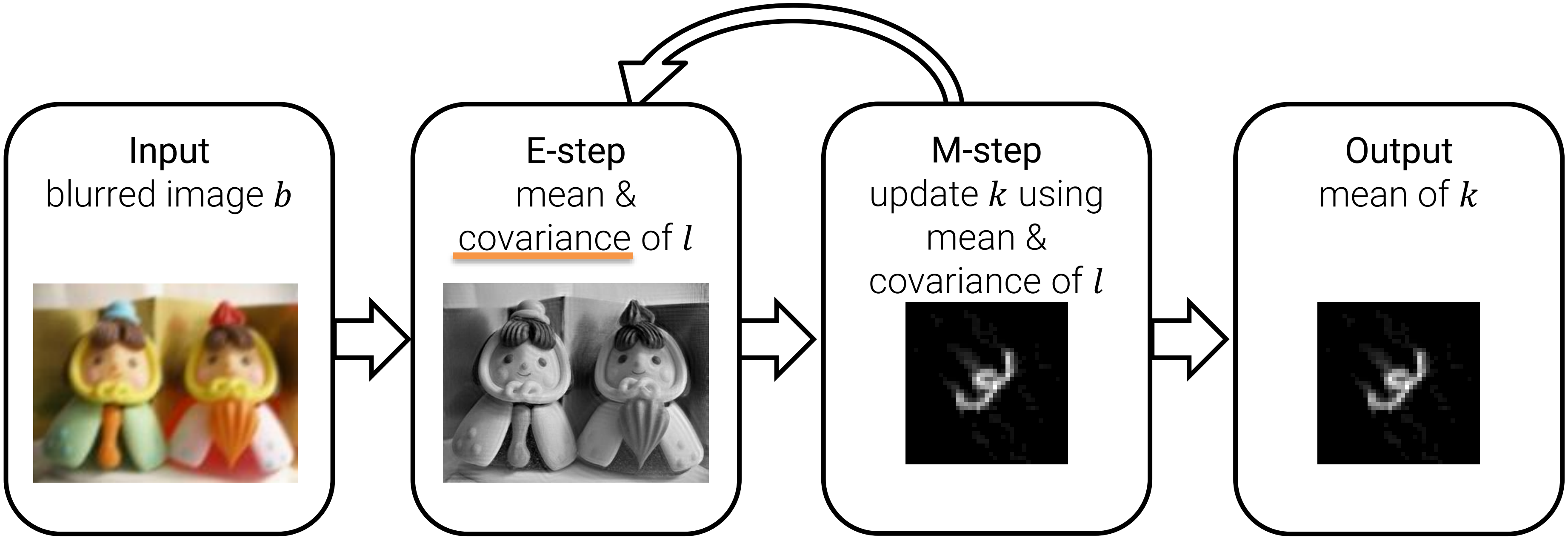
- Efficient optimization based on EM

$$\left.\begin{aligned} p(k|b) &\propto p(b|k)p(k) \\ &= \int_l p(b,l|k)p(k)dl \\ &= \int_l p(b|l,k)p(l)p(k)dl \end{aligned}\right\} \text{Marginalizing over } l$$

- cf) MAP based approach:

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

Levin et al. CVPR 2010



Similar to MAP, but also considers covariance of l

Levin et al. CVPR 2010

Input blurred image

Levin et al. CVPR 2010

State-of-the-art results

Speed:

- 255x255
- 2-4 minutes
- MATLAB

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

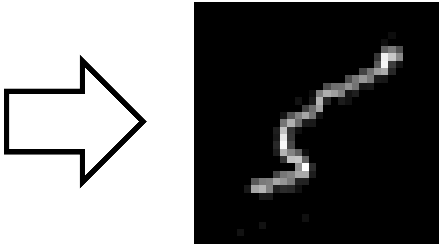
Cho & Lee, SIGGRAPH Asia 2009

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

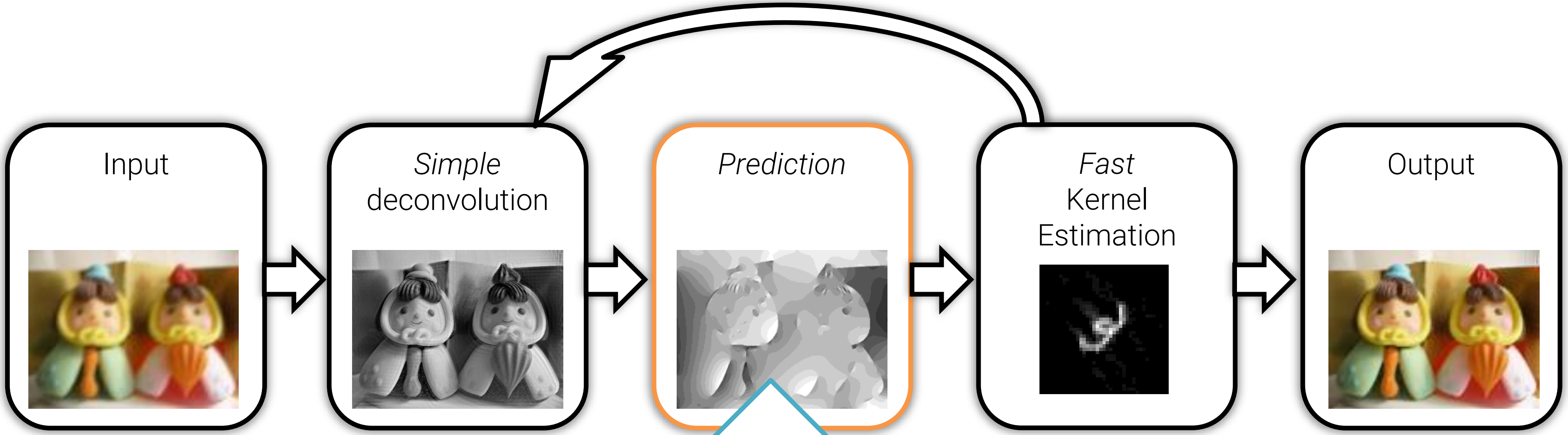
→ No need to restore every detail for kernel estimation

Blurred image

Latent image with only a few edges and no texture

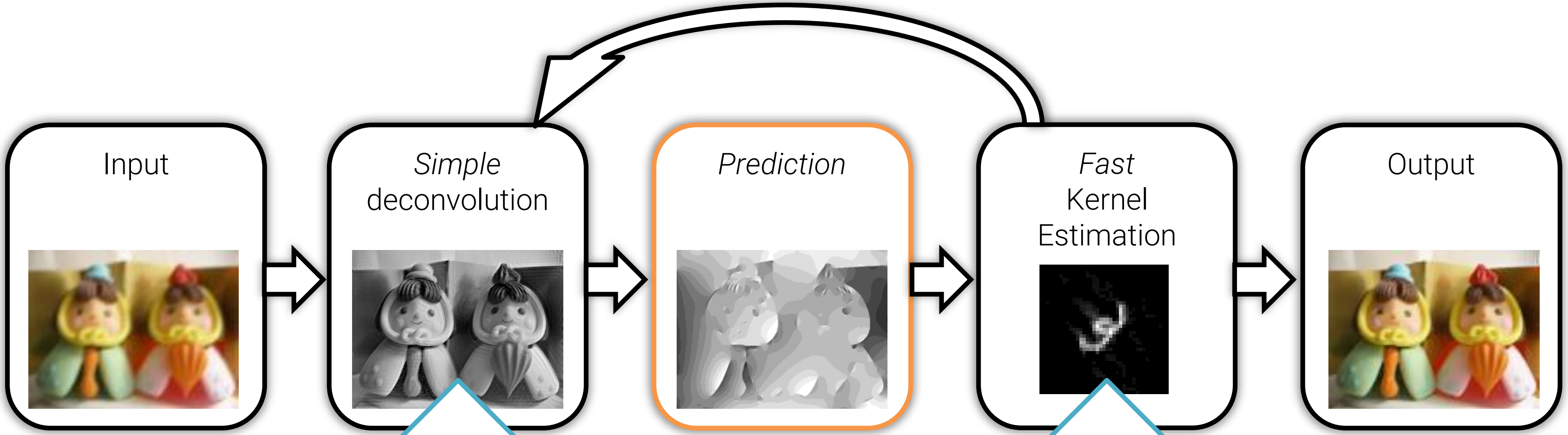


Cho & Lee, SIGGRAPH Asia 2009



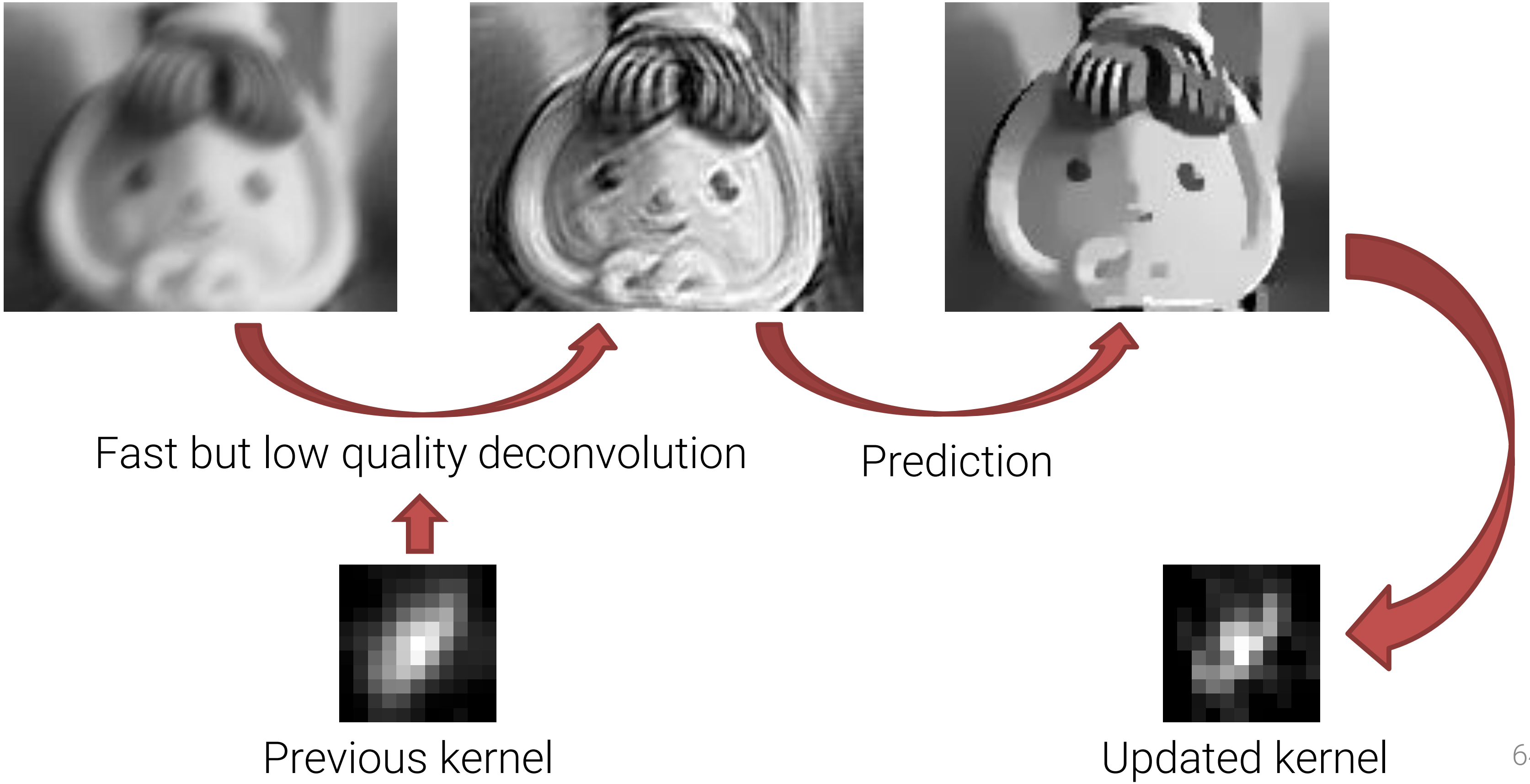
Quickly restore important edges using simple image filters

Cho & Lee, SIGGRAPH Asia 2009



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

Prediction

Simple & fast image filtering operations

Fast but low-quality deconvolution

Bilateral filtering & Shock filtering

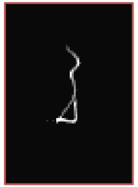
Thresholding gradients

Visualized by Poisson image reconstruction

Cho & Lee, SIGGRAPH Asia 2009


Blurry input


Deblurring result


Blur kernel

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

Xu & Jia, ECCV 2010

- Extended edge prediction to handle blur larger than image structures

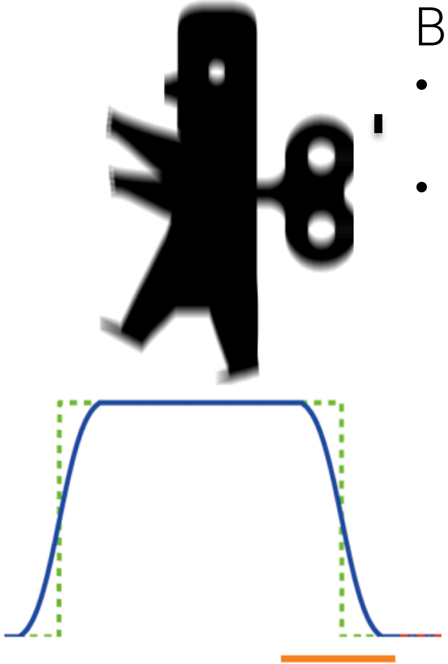
Blurred image

Fergus et al.
SIGGRAPH 2006

Shan et al.
SIGGRAPH 2008

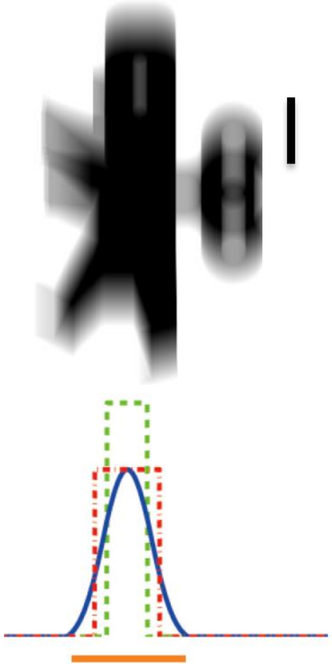
For this complex scene, most methods fail to estimate a correct blur kernel. Why?

Xu & Jia, ECCV 2010



Blur < structures

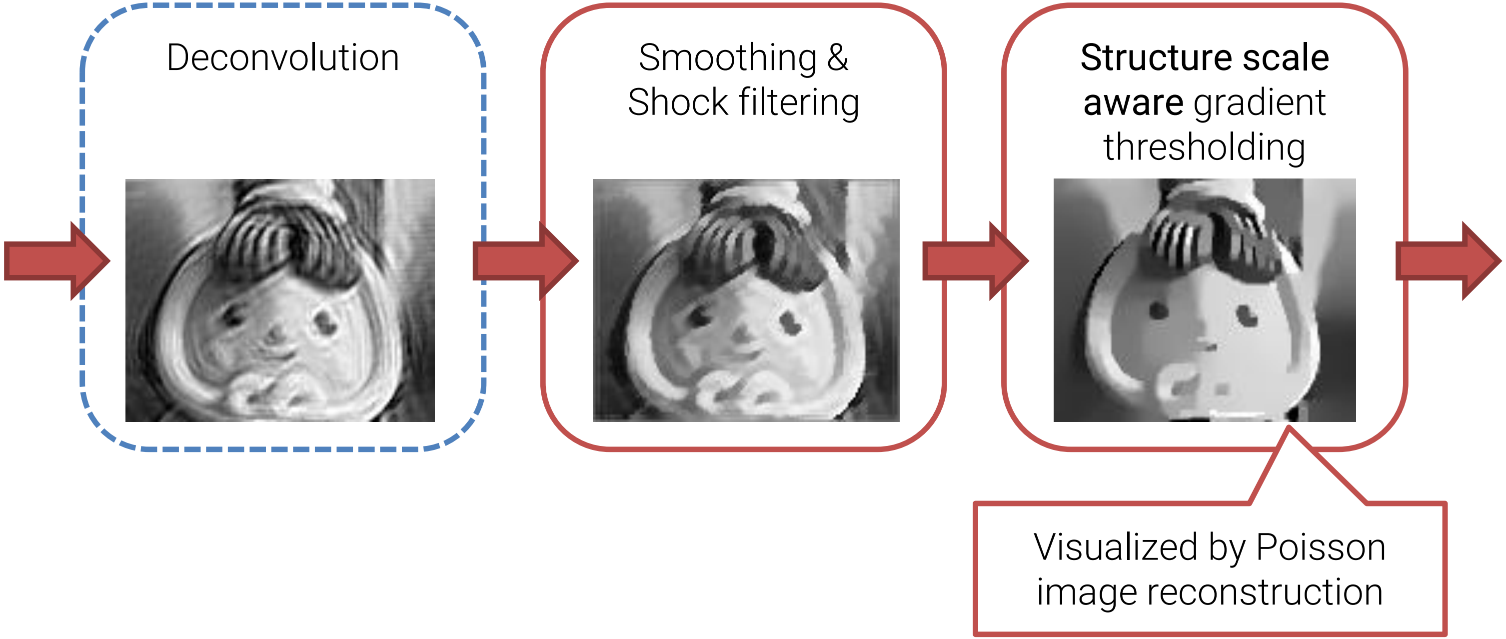
- Each blurry pixel is caused by one edge
- Easy to figure out the original sharp structure



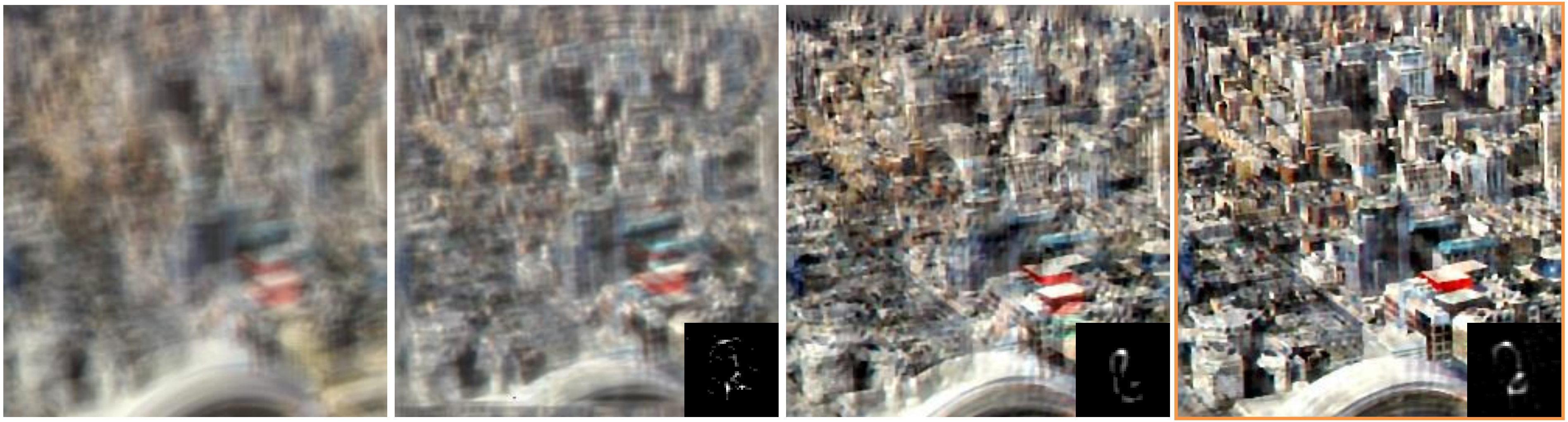
Blur > structures

- 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

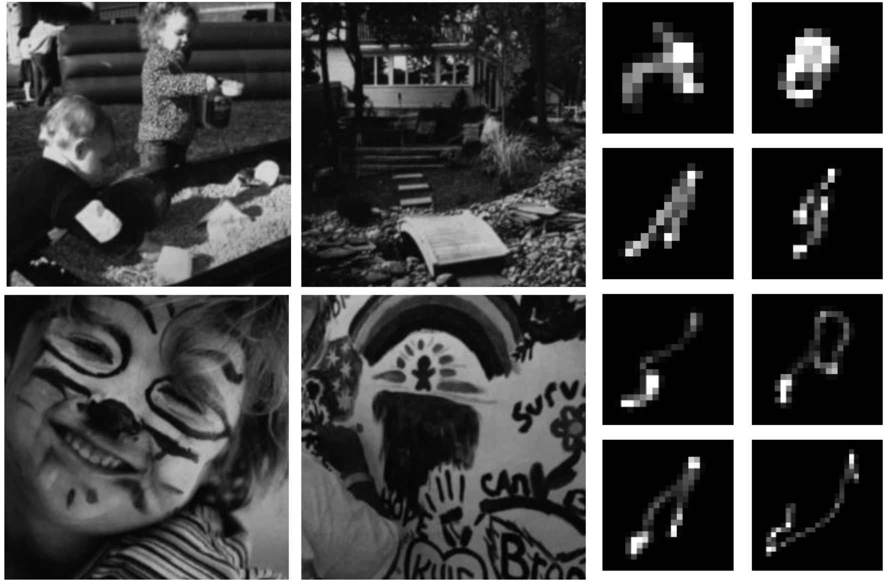
Which one is better?

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

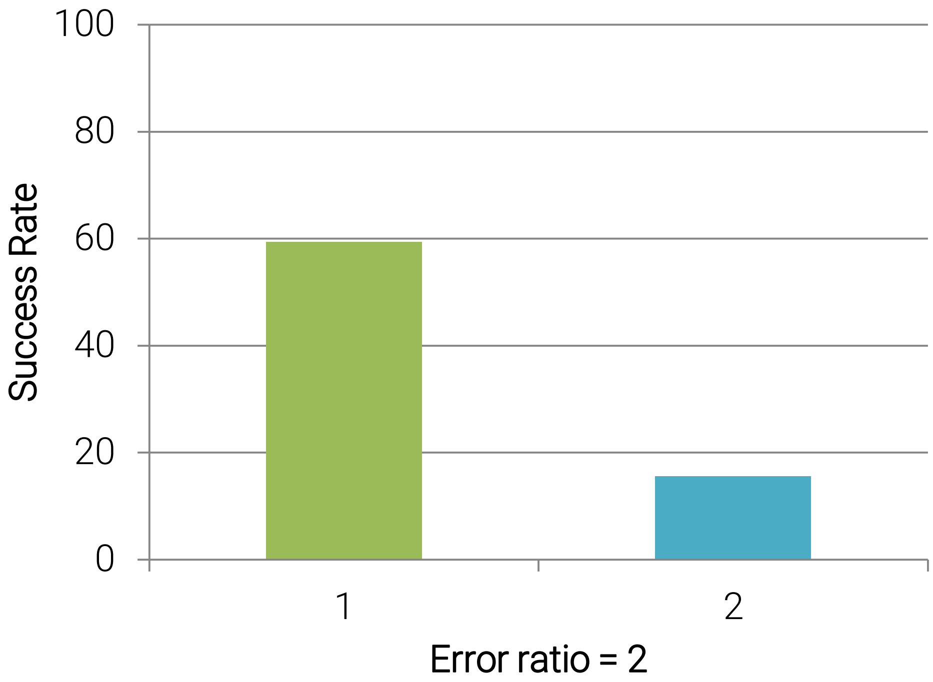
Benchmarks

- 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



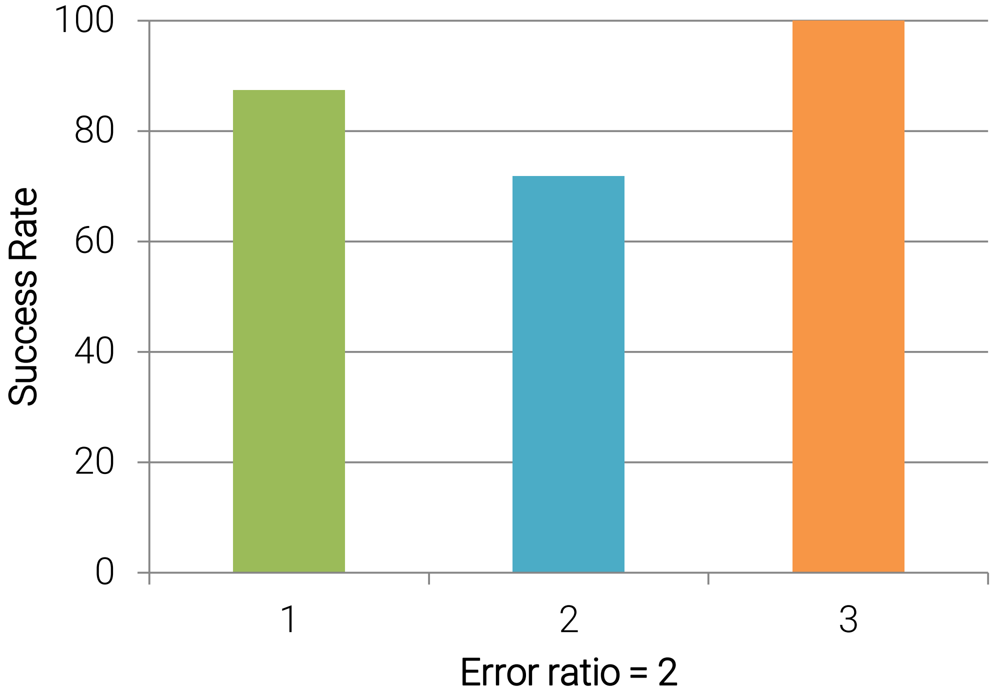
Benchmarks

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



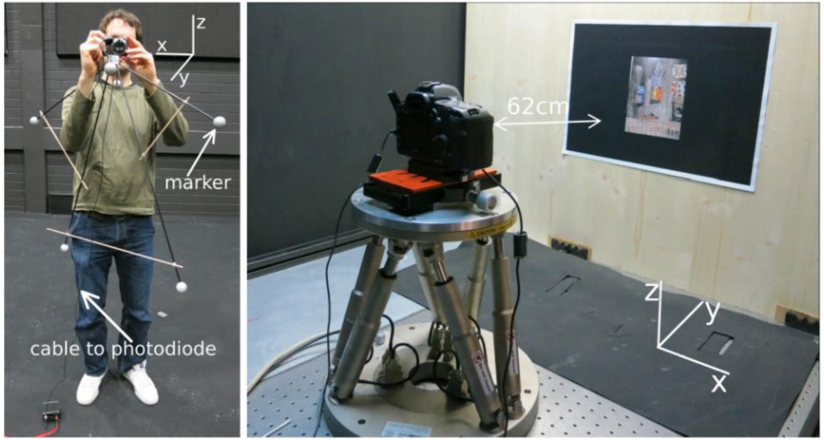
Benchmarks

- 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

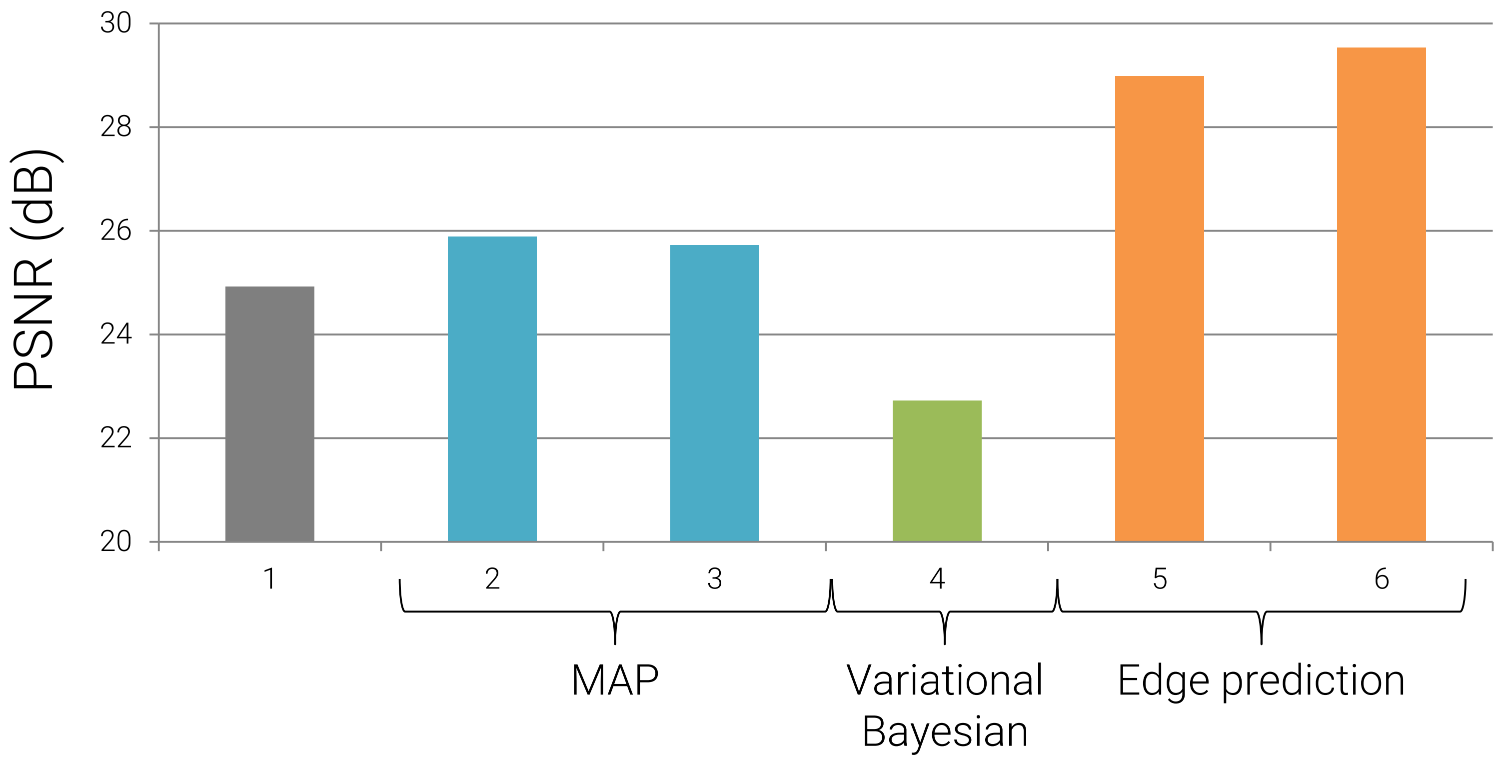


Benchmarks

- 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

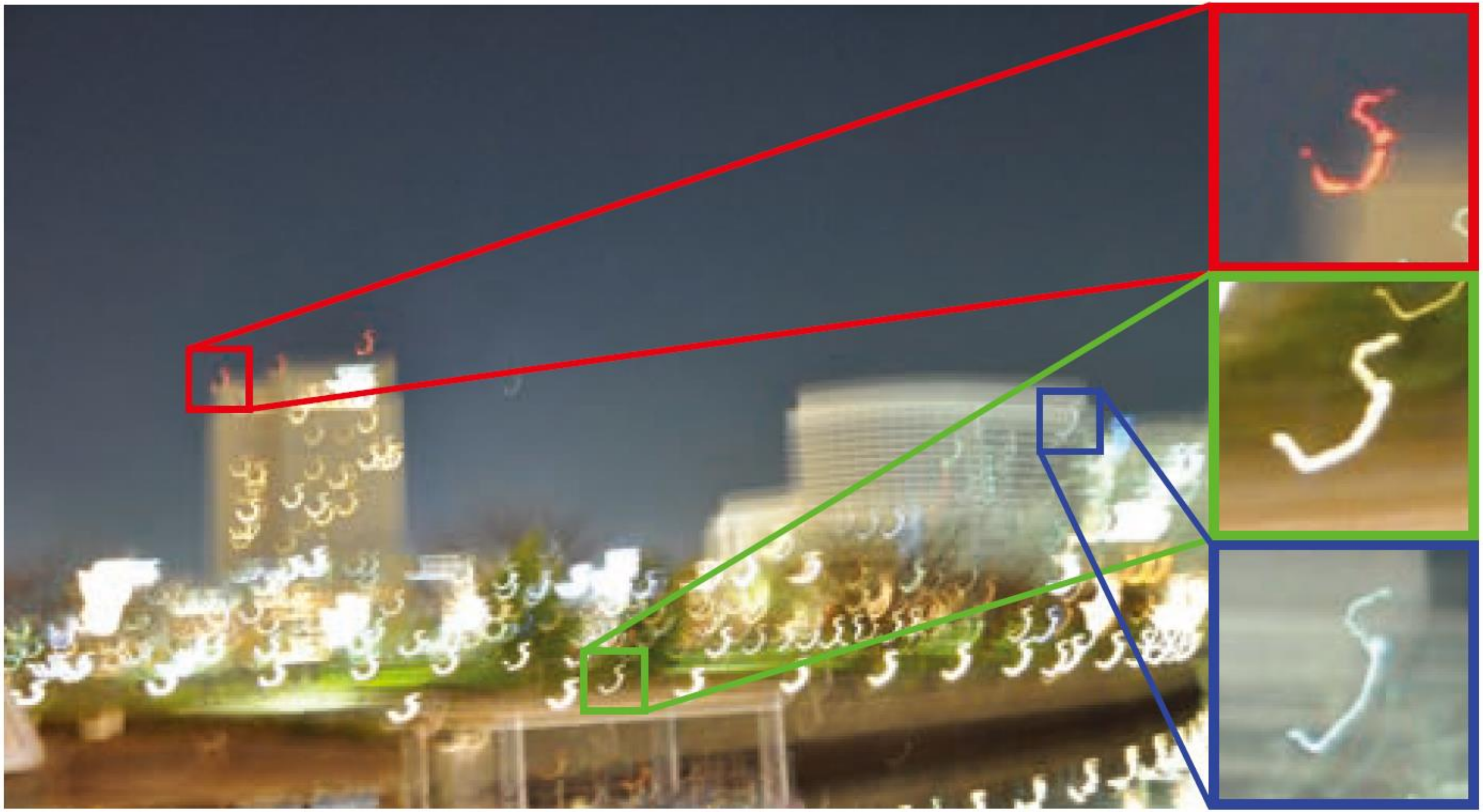
Advanced Issues

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

Convolution based Blur Model

- Uniform and spatially invariant blur

Real Camera Shakes: Spatially Variant!



Uniform Blur Model Assumes

x & y translational
camera shakes

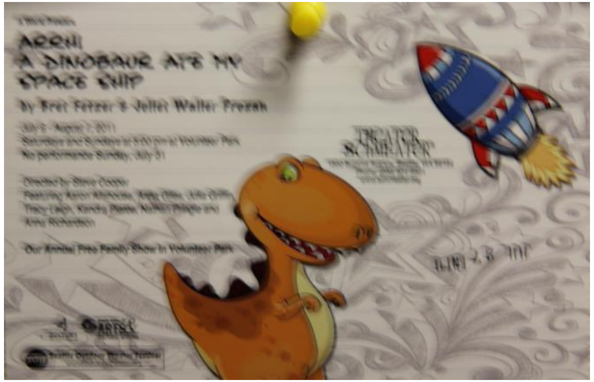
Planar scene

Real Camera Shakes

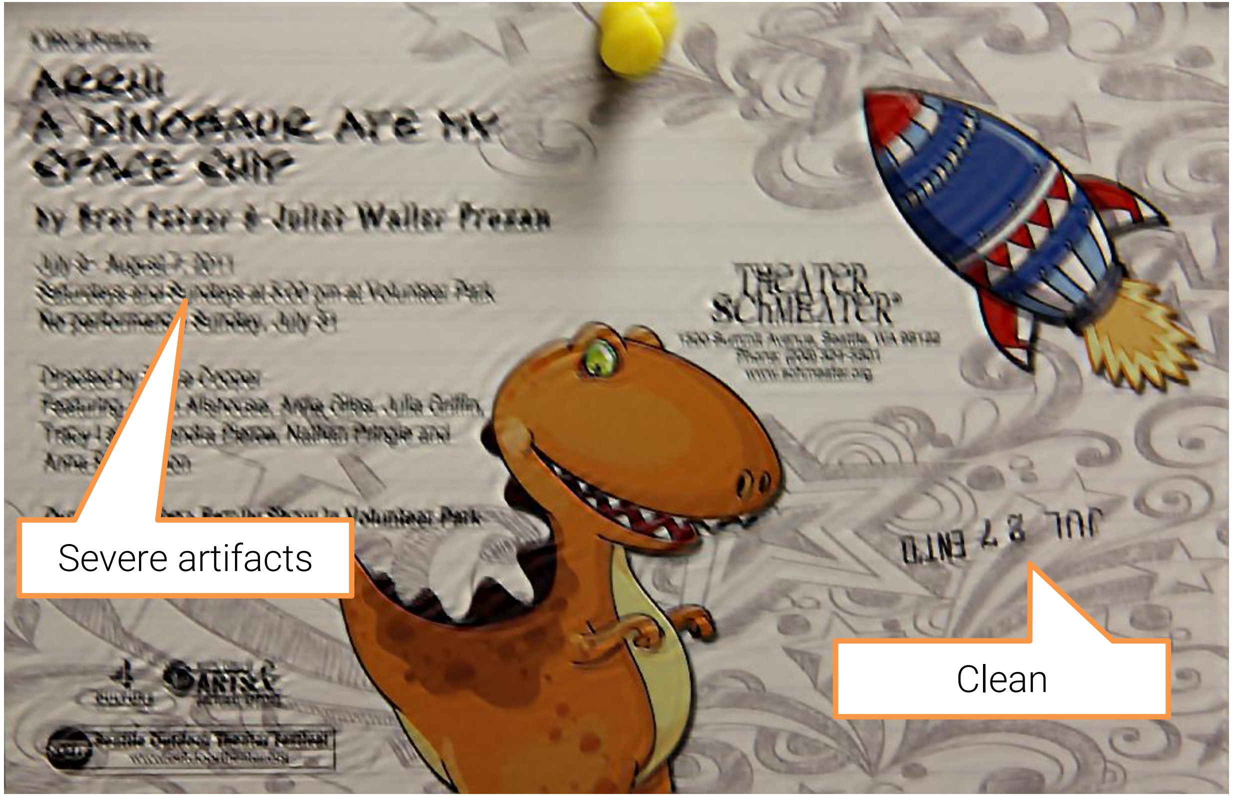
6D real camera motion

Different depths

Real Blurred Image



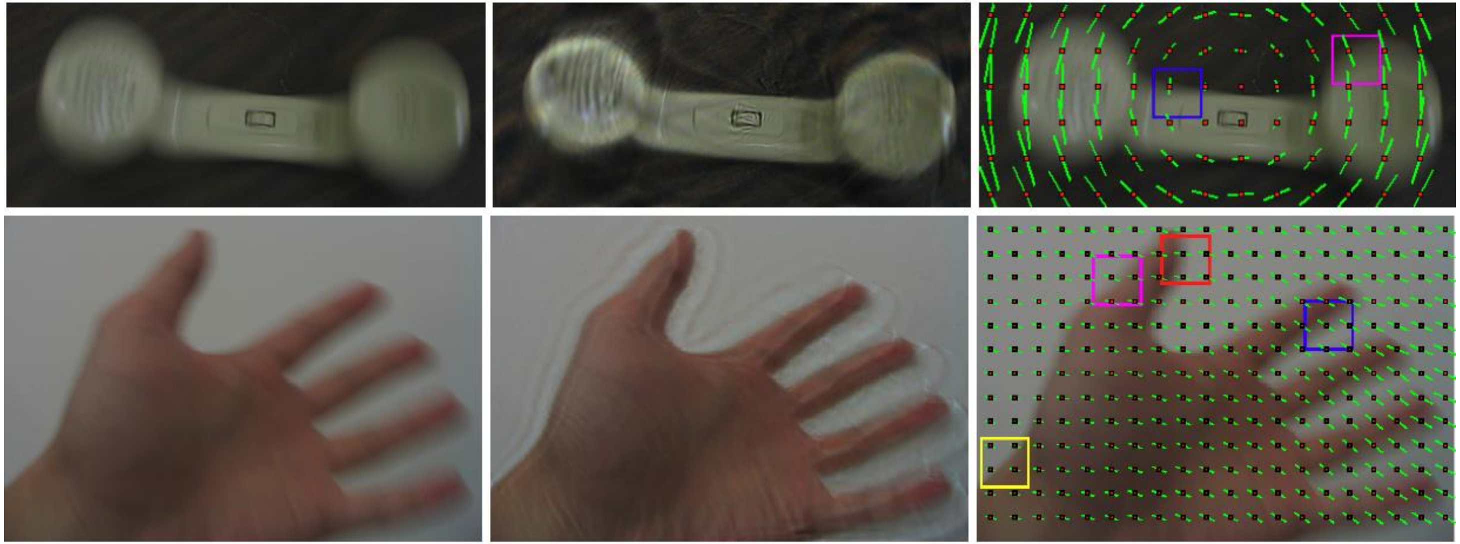
Non-uniformly blurred image



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

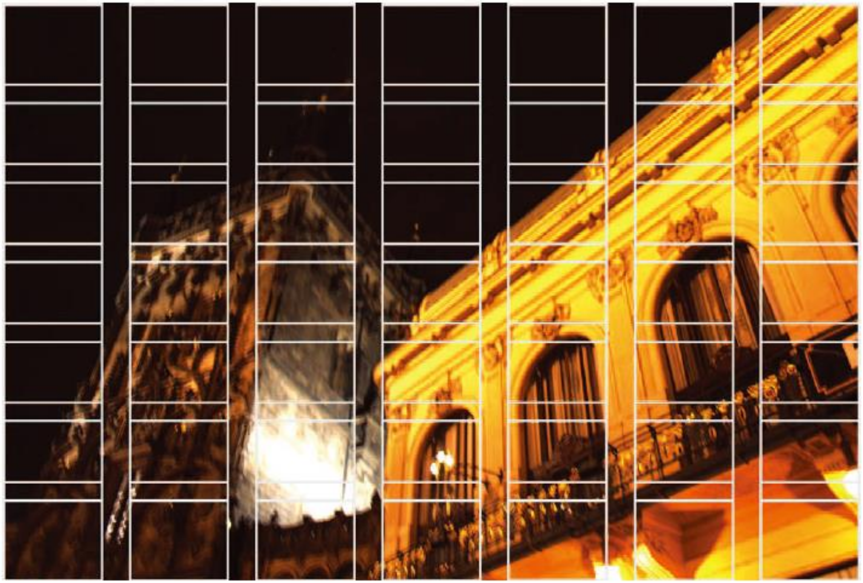
Hi-res.
image

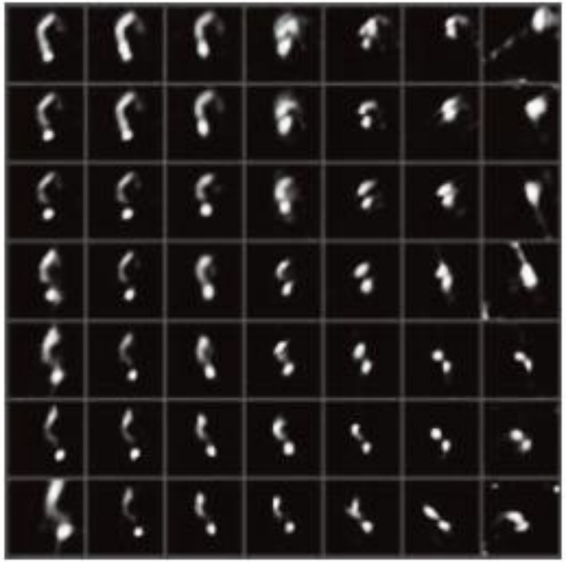
Low-res.
video

time

Patch-wise Blur Model

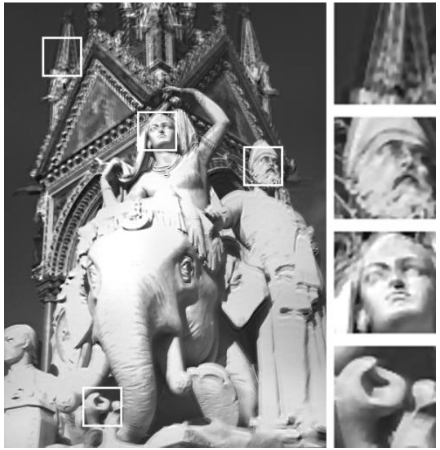
- Sorel and Sroubek, ICIP 2009
  - Estimate per-patch blur kernels from a blurred image and an underexposed noisy image





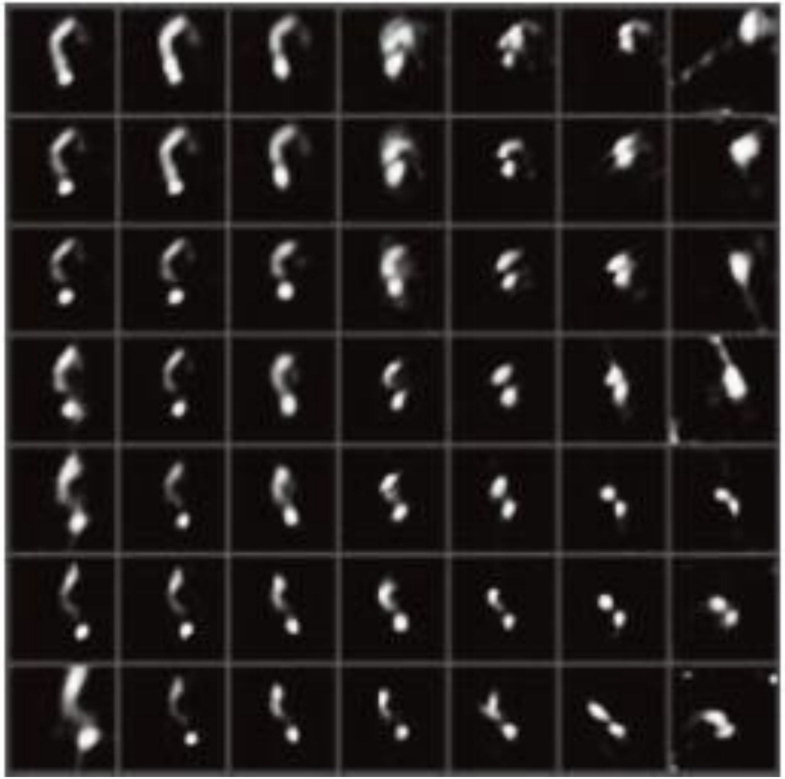
Patch-wise Blur Model

- 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

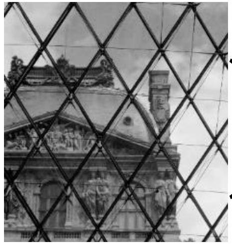


Projective Motion Path

- Tai et al. TPAMI 2011
  - Homography based blur model
  - Non-blind deconvolution method

Blurred image

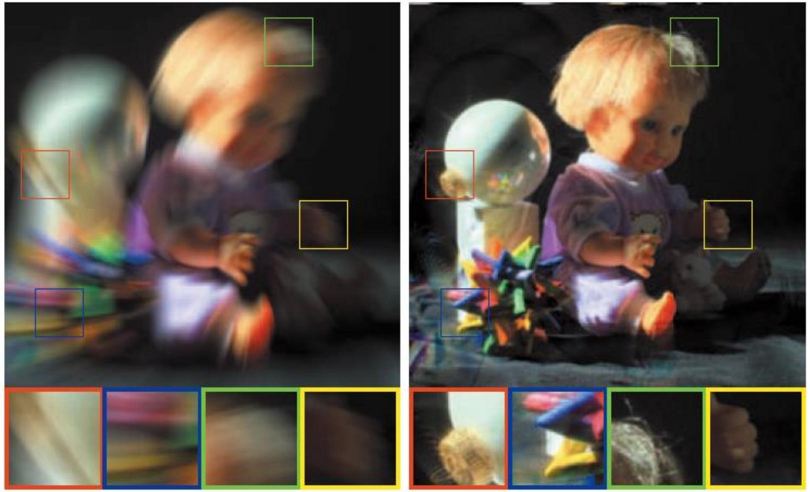
$$= \sum_{i=1}^{N} w_i P_i \left(\quad \right)$$



Latent image

Weight

Homography



Blurred image

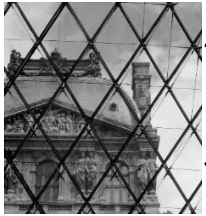
Tai et al. TPAMI 2011

Projective Motion Path

- Tai et al. TPAMI 2011

Blurred image

$$= \sum_{i=1}^{N} \underbrace{w_i}_{\text{weight}} \underbrace{P_i}_{\text{Homography}} \Big(\quad \Big)$$



Latent image

6D real camera motion

Planar scene

Pros

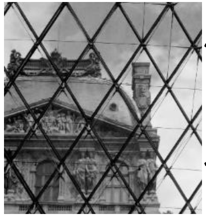
- 6 DoF camera motions
- Globally consistent & physically plausible

Projective Motion Path

- Tai et al. TPAMI 2011

Blurred image

$$= \sum_{i=1}^{N} w_i P_i \left(\quad \right)$$



Latent image

weight Homography

6D real camera motion

Planar scene

Cons
- Slow computation
    - Can't use FFTs
- Didn't provide blur kernel estimation

Pros
- 6 DoF camera motions
- Globally consistent & physically plausible

Projective Motion Path

- Cho et al. PG2012
  - Blind deconvolution from multiple blurred images
  - 6 DoF camera motions
  - Try to estimate homographies one by one

Input blurred images Deblurred image

Projective Motion Path

- Cho et al. PG2012
  - Sensitive to noise
  - Convergence problem due to highly non-linear optimization process


Input blurred images

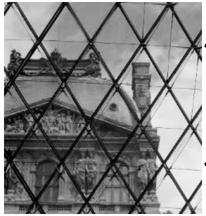
Deblurred image

Projective Motion Path

- Whyte et al. CVPR 2010

Blurred image

$$= \sum_{i=1}^{N} w_i \color{blue}{P_i} \left(\right.$$

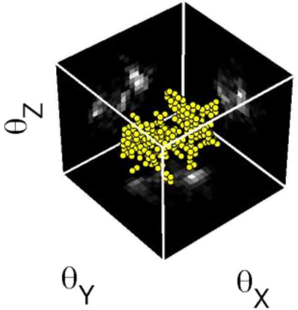


$$\left. \right)$$

Latent image

Homography with only
x, y, z rotations

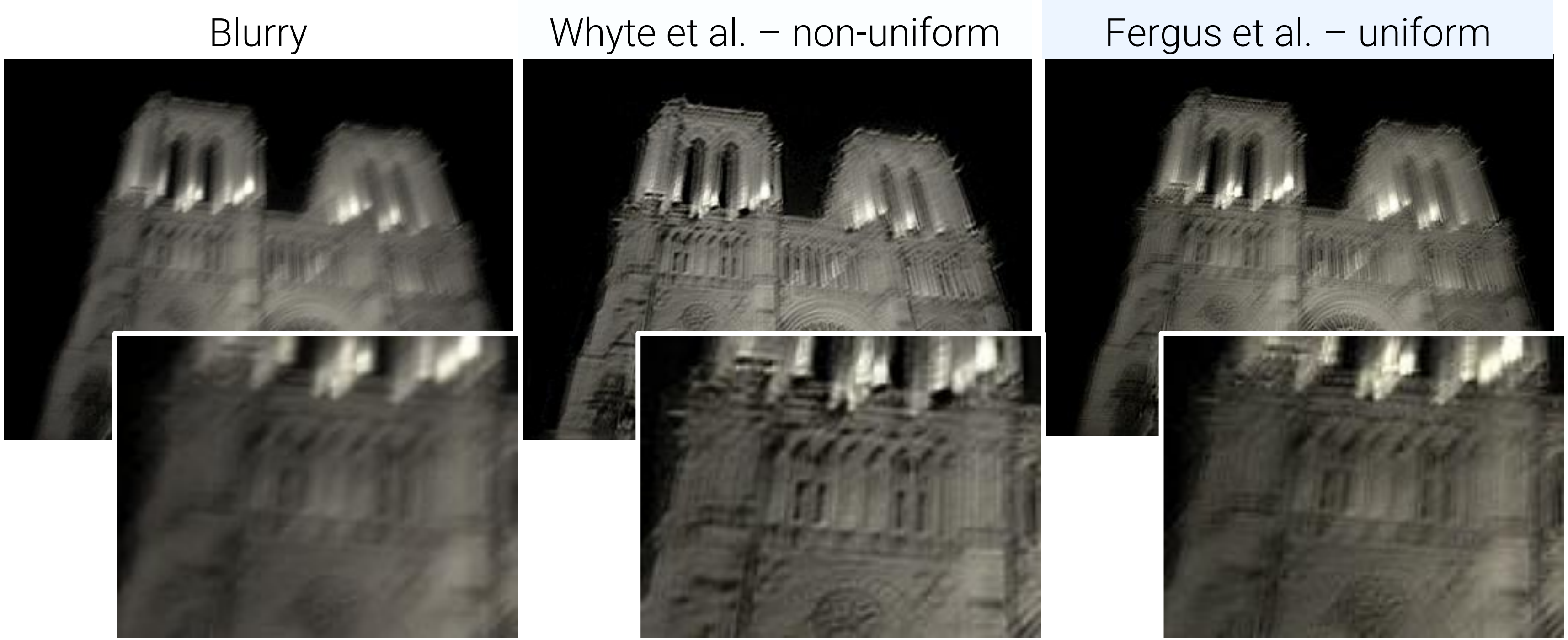
- 3 DoF camera motions
- Roll, yaw, pitch $(\theta_X, \theta_Y, \theta_Z)$
- Discretize 3D motion parameter space
  ➔ 3D blur kernel



- Much easier to use with existing blind deconvolution frameworks

Projective Motion Path

- Whyte et al. CVPR 2010
  - Blind deconvolution from a single image

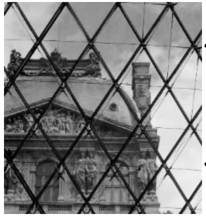


Projective Motion Path

- Gupta et al. ECCV 2010

Blurred image

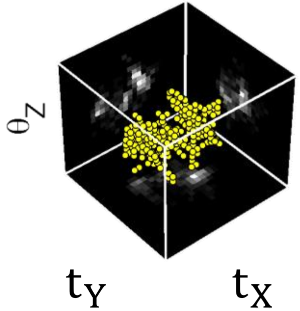
$$= \sum_{i=1}^{N} w_i P_i \Big(\quad \Big)$$



Latent image

Homography with only
in-plane rotation and x,y translations

- 3 DoF camera motions
- x, y translations & in-plane rotation
- Discretize 3D motion parameter space
  ➔ 3D blur kernel



- Much easier to use with existing blind deconvolution frameworks

Projective Motion Path

- Gupta et al. ECCV 2010

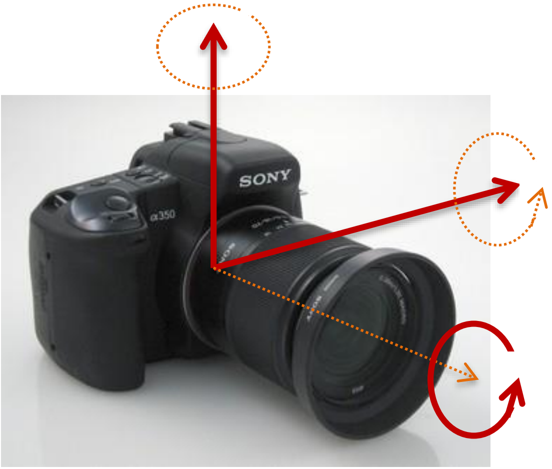
Blurred image

Gupta et al. ECCV 2010

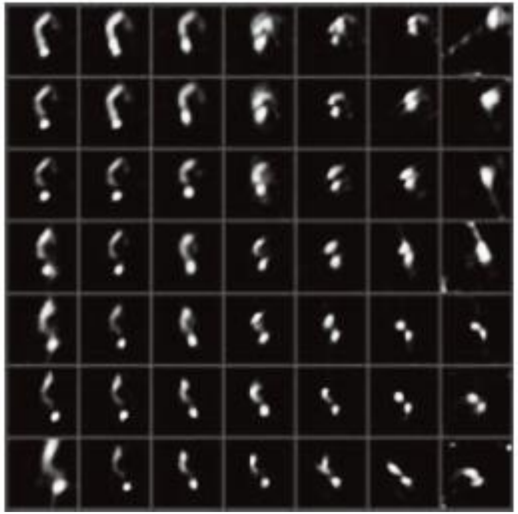
Shan et al. SIGGRAPH 2008

More Efficient Blur Model

- Hirsch et al. ICCV 2011
  - Propose a hybrid model



Projective Motion Path:
Globally consistent &
physically plausible

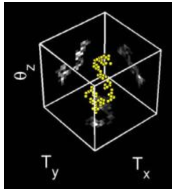


Patch-wise Blur Model:
Computationally efficient

More Efficient Blur Model

- Hirsch et al. ICCV 2011

Globally consistent & physically plausible



3D blur kernel based on projective motion chain

2D local blur kernels

Computationally efficient

Sharp image

Patch-wise blur using Fourier transforms

Blurred image

More Efficient Blur Model

- Hirsch et al. ICCV 2011

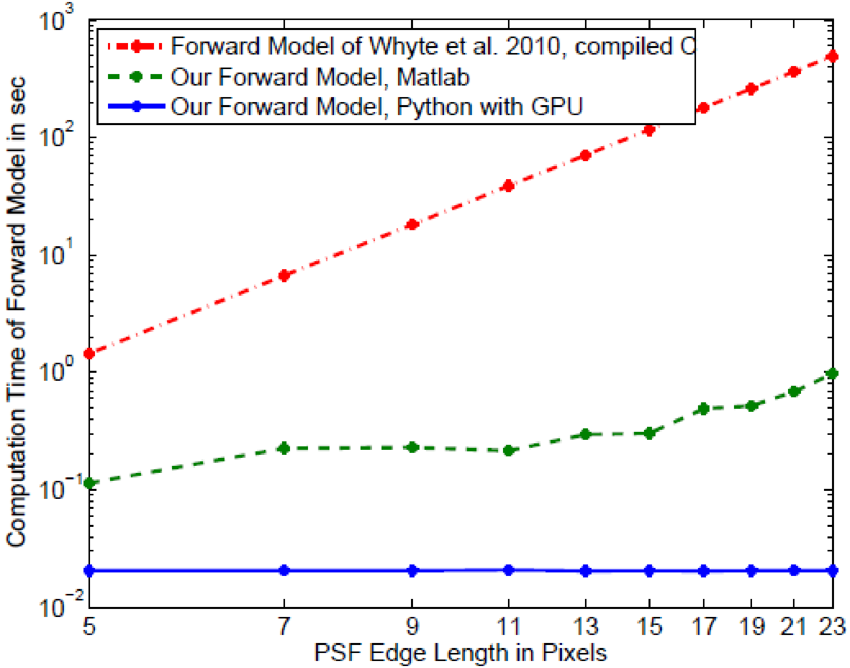
Blurred image

Xu & Jia, ECCV 2010
(uniform blur)

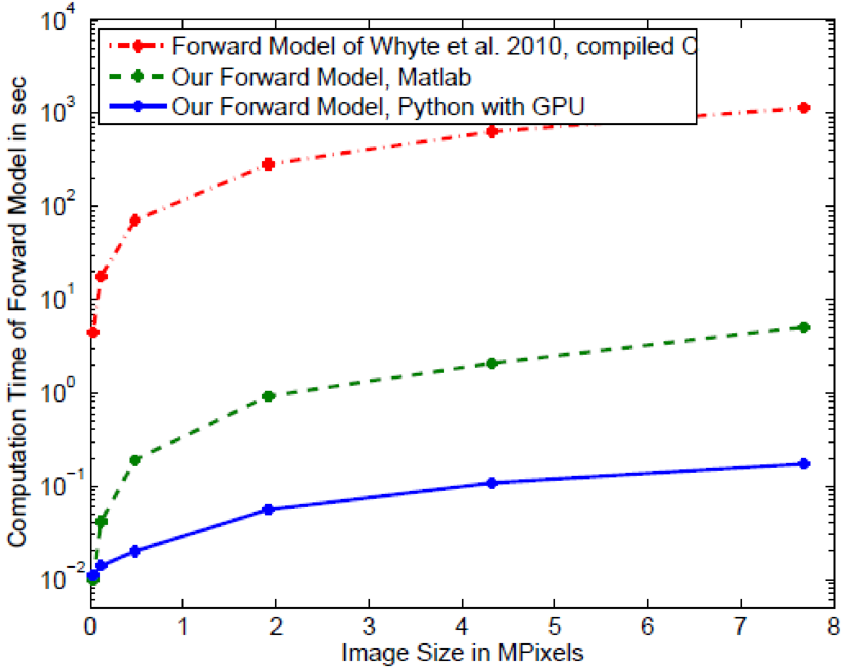
Gupta et al. ECCV 2010
(non-uniform)

Hirsch et al. ICCV 2011
(non-uniform)

More Efficient Blur Model

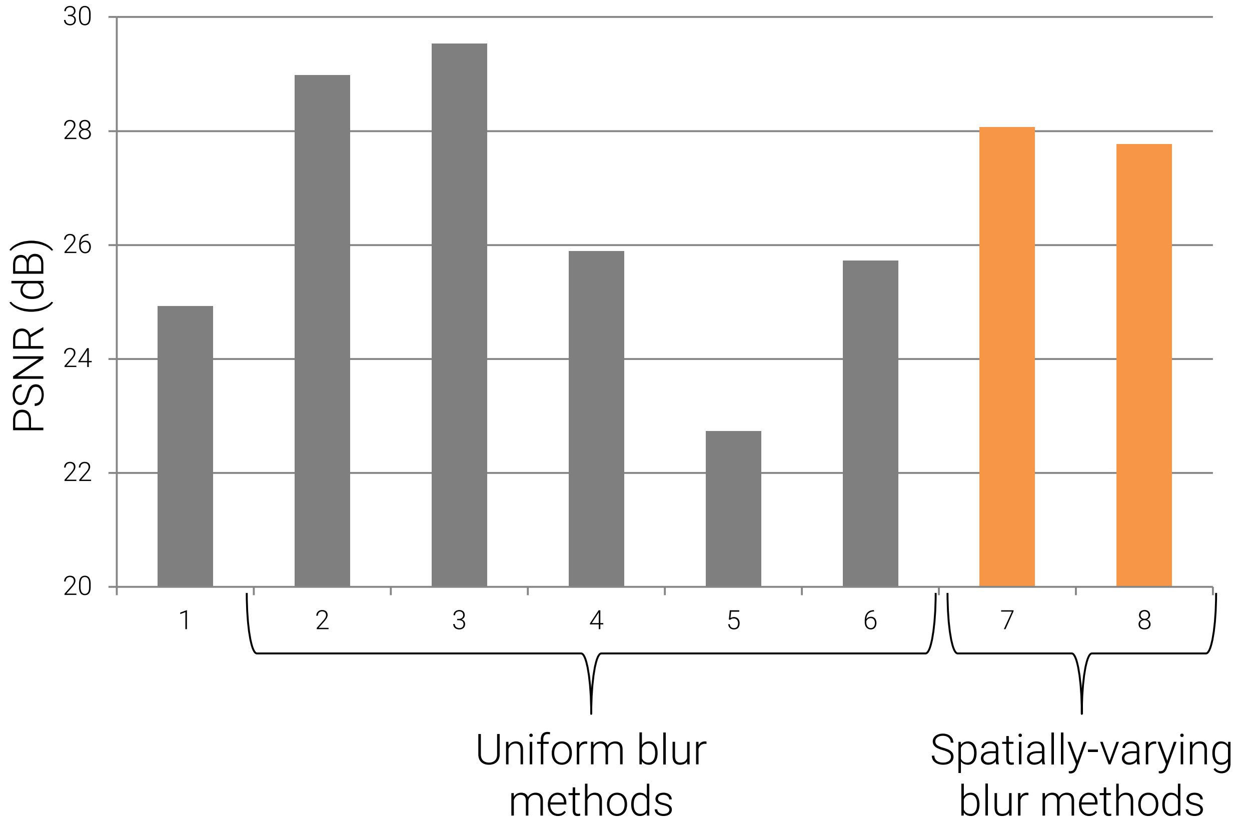


Dependence of PSF size



Dependence of image size

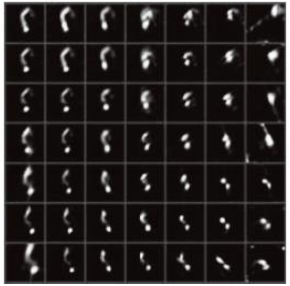
Benchmark [Köhler et al. ECCV 2012]



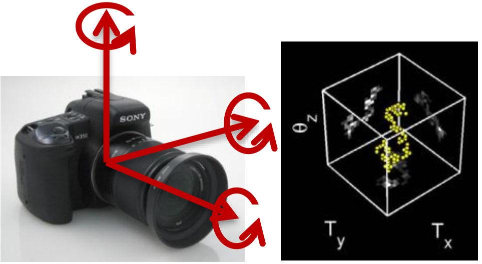
Due to high dimensionality, spatially-varying blur methods are less stable.

Summary

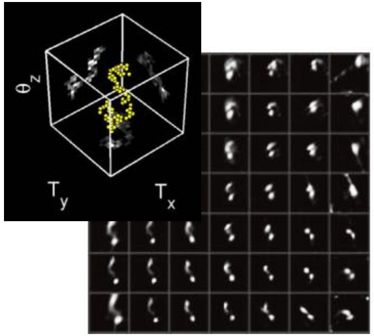
- Different blur models



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

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

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

Remaining Challenges

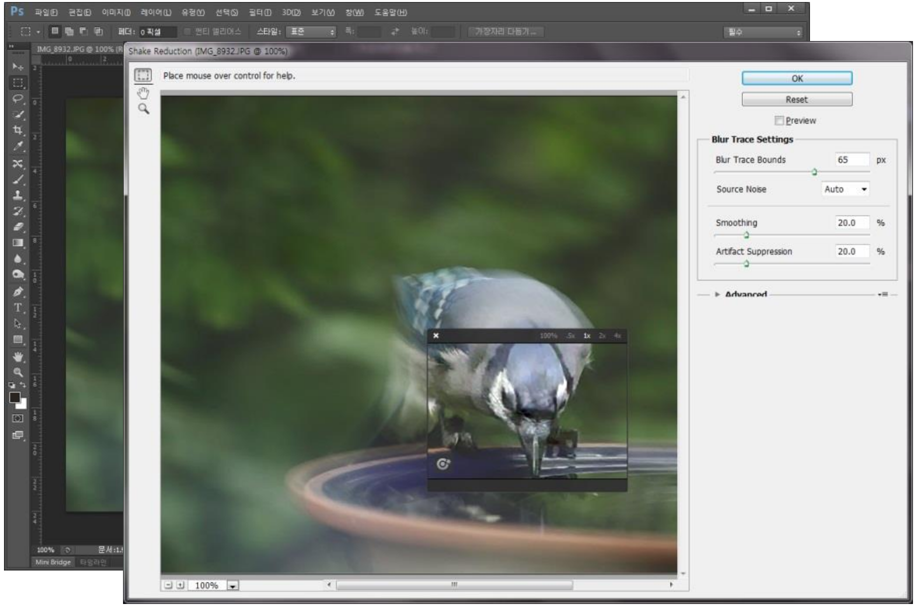
Failure example of Photoshop Shake Reduction

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

Photoshop Shake Reduction

- Based on [Cho and Lee, SIGGRAPH ASIA 2009]
- Improved noise handling
- Automatic kernel size estimation
- Automatic region suggestion for blur kernel estimation

- DEMO



Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

Introduction

Blind Deconvolution

Non-blind Deconvolution

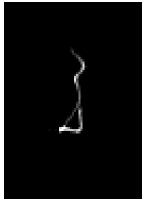
Advanced Issues

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

Non-blind Deconvolution (Uniform Blur)

Blurred image

=



*

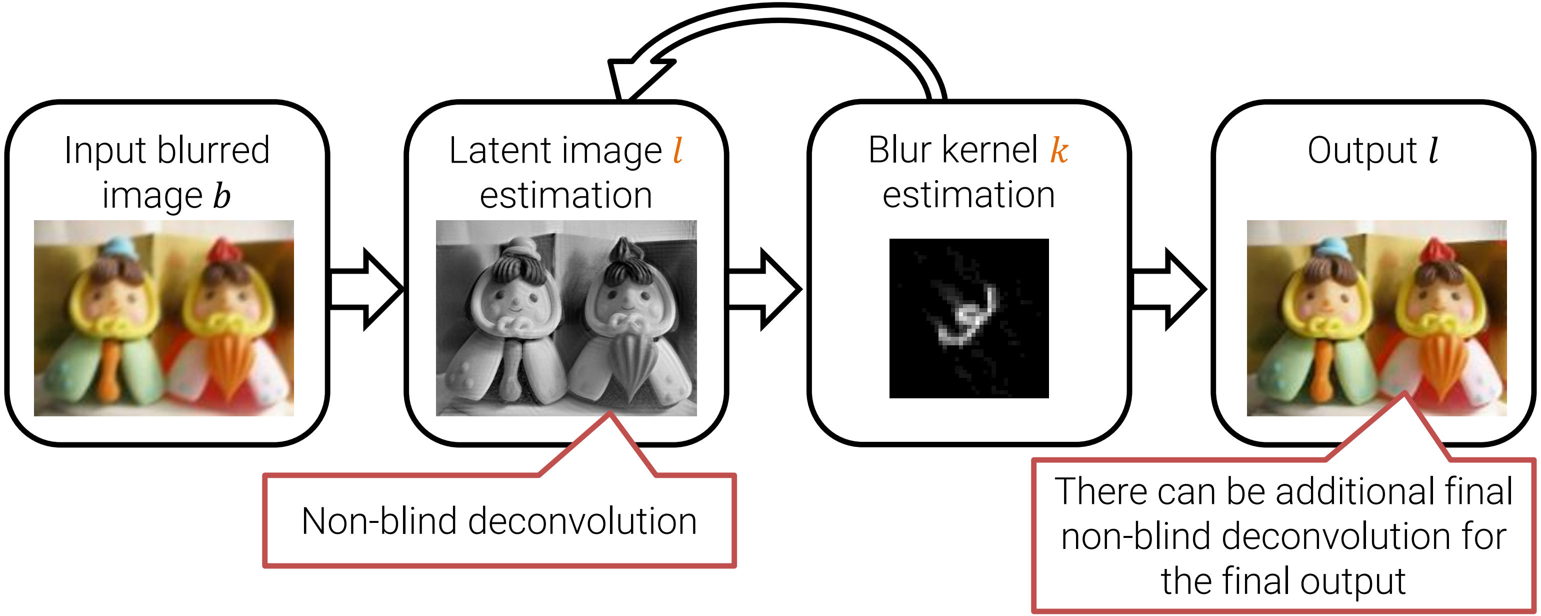
Latent sharp image

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…

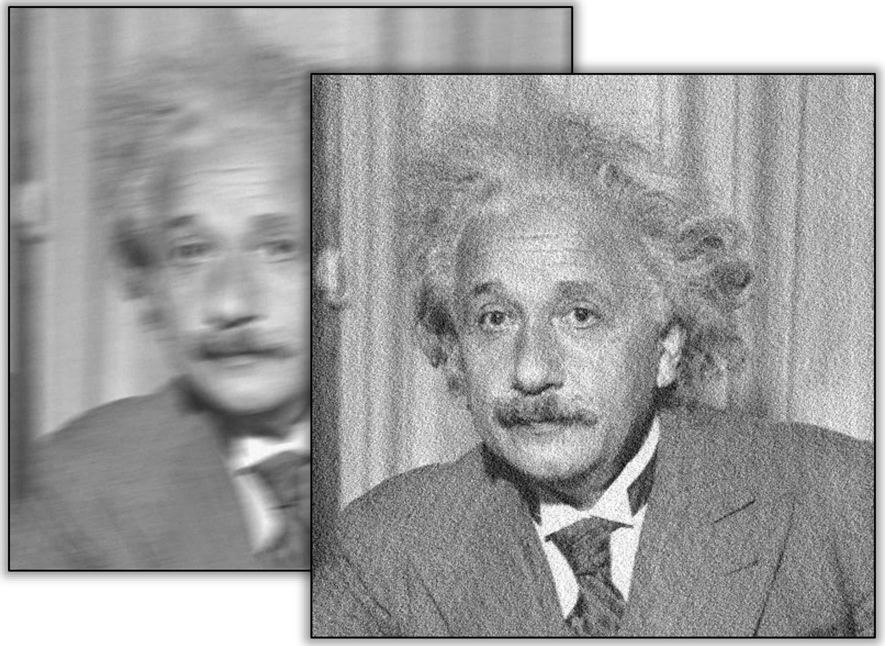
Ill-Posed Problem

- 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

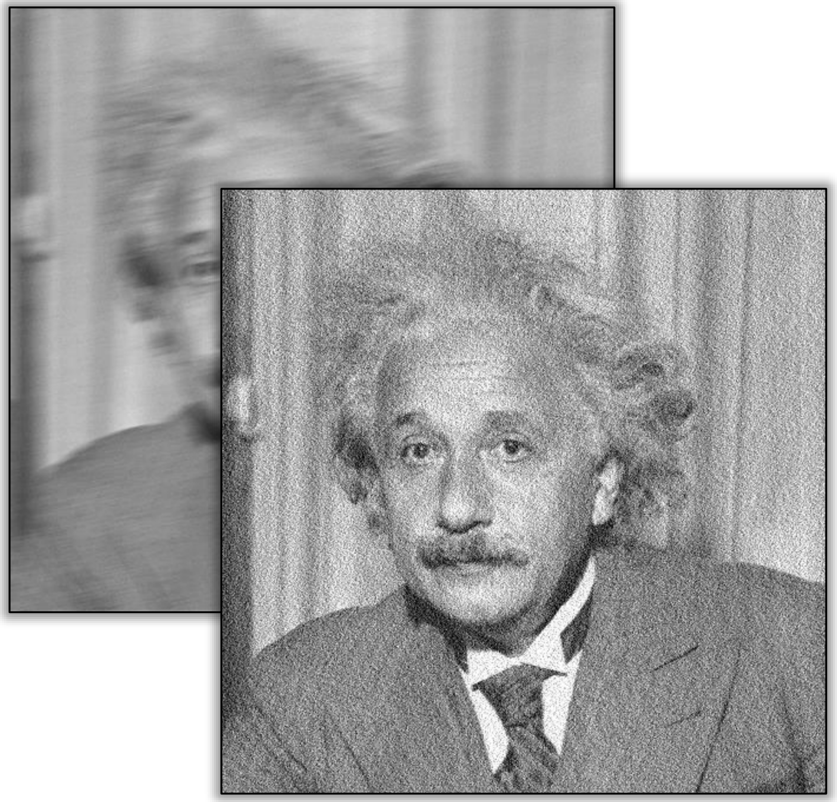
- Deconvolution amplifies noise as well as sharpens edges



- 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

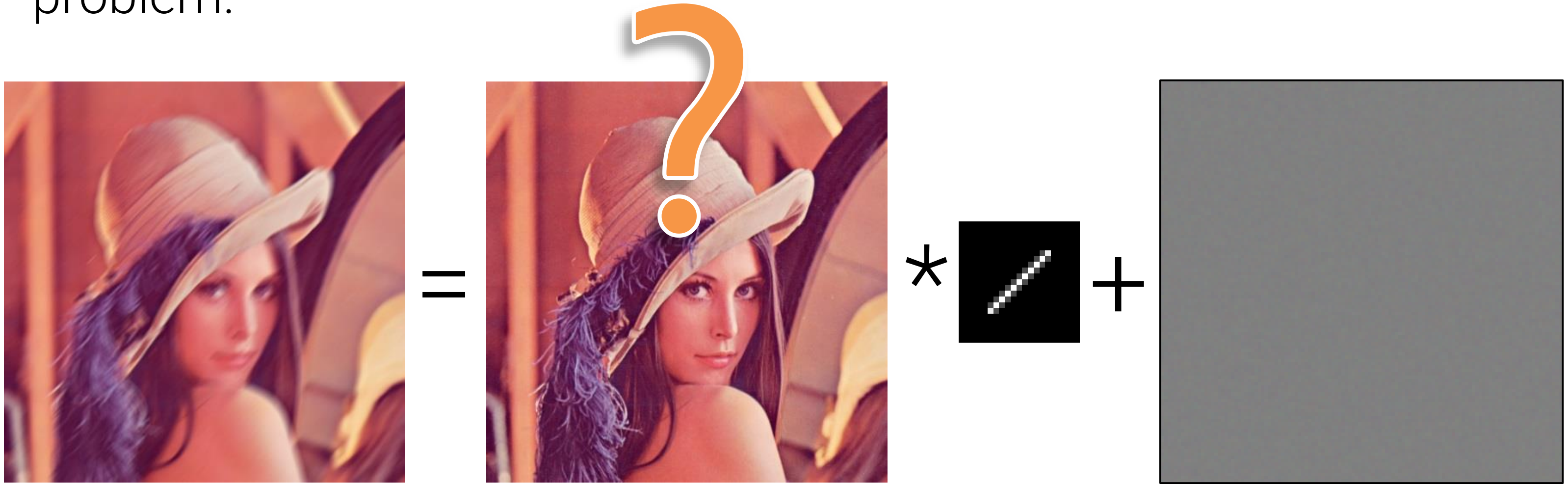
Non-blind Deconvolution

Advanced Issues

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

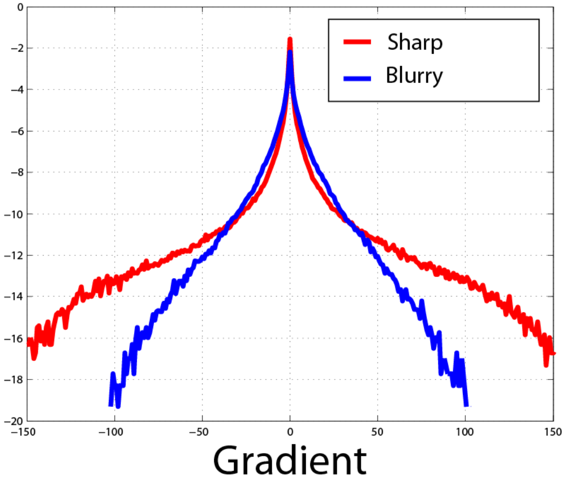
Natural Image Statistics

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



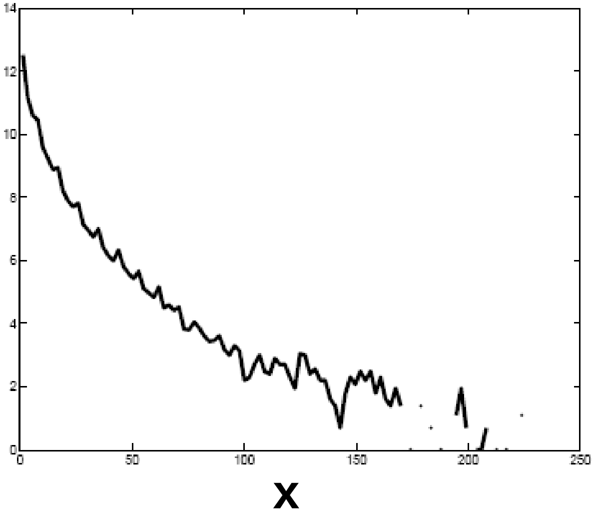
Natural Image Statistics

- 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

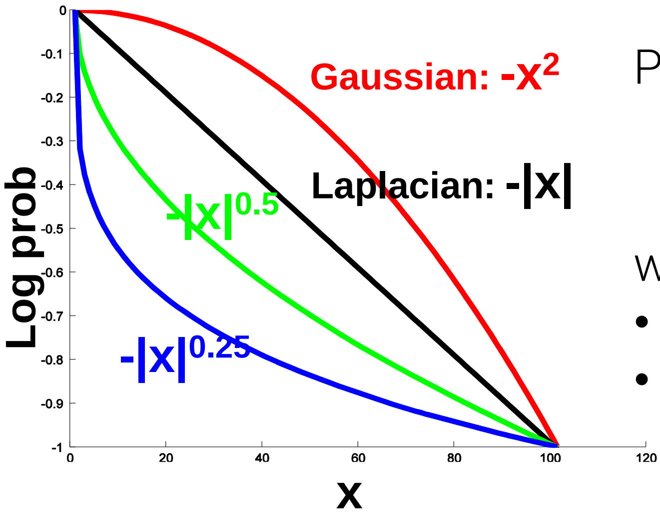


Natural Image Statistics

- 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

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

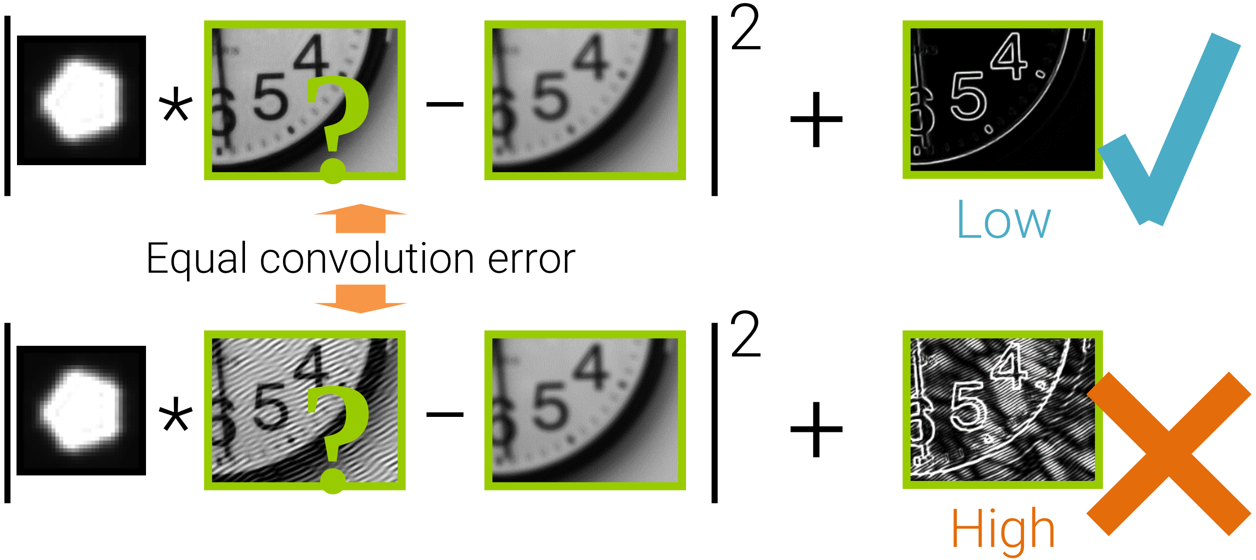
where:

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

Natural Image Statistics

- Levin et al. SIGGRAPH 2007

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



Natural Image Statistics

- Levin et al. SIGGRAPH 2007

Input

Richardson-Lucy

"spread" gradients

Gaussian prior

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

"localizes" gradients

Sparse prior

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

Natural Image Statistics

- Krishnan & Fergus, NIPS 2009
  - Minimizes the same energy function:

$$l = \arg\min_{l} \{ \|k * l - b\|^2 + \lambda \sum_i |\nabla l_i|^\alpha \} \quad (\alpha < 1)$$

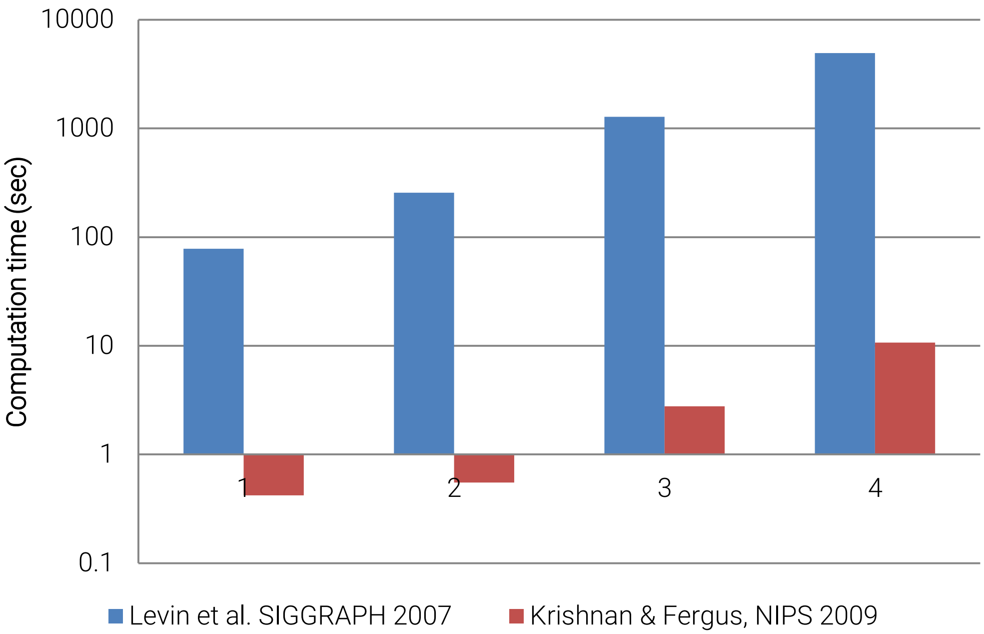
  - But much faster
  - Efficient optimization based on half-quadratic scheme

Natural Image Statistics

- Krishnan & Fergus, NIPS 2009

Original | Blurred

Krishnan & Fergus | Levin et al.



Similar quality, but more than 100x faster

Introduction

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- **High-order natural image statistics**
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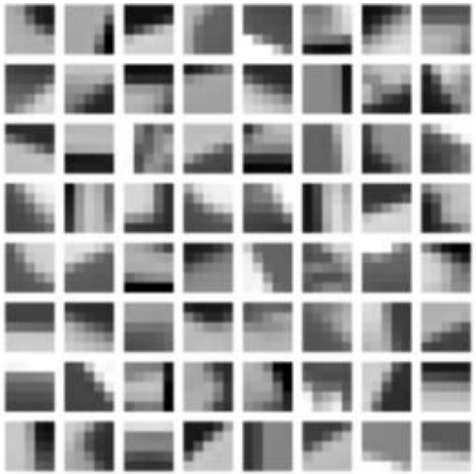
High-order Natural Image Priors

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

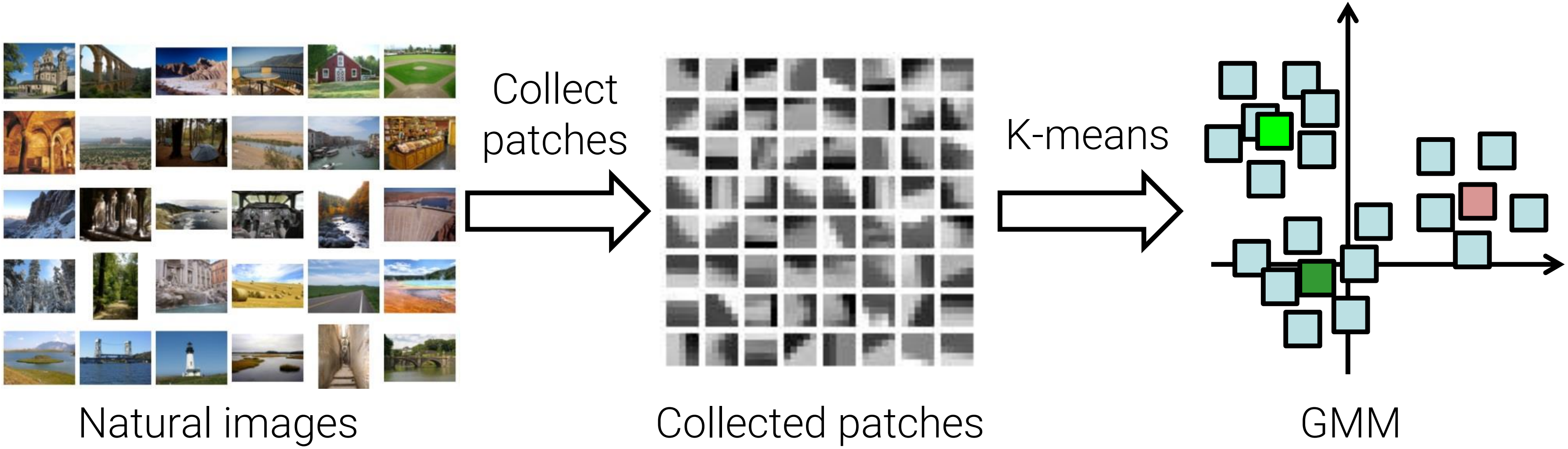


High-order Natural Image Priors

- 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

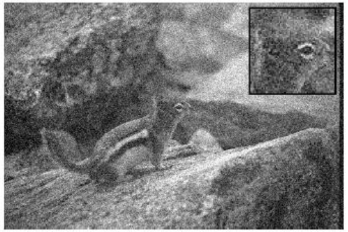
- Zoran & Weiss, ICCV 2011
  - Given a patch, we can compute its likelihood based on the GMM.
  - Deconvolution can be done by solving:

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

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

Advanced Issues

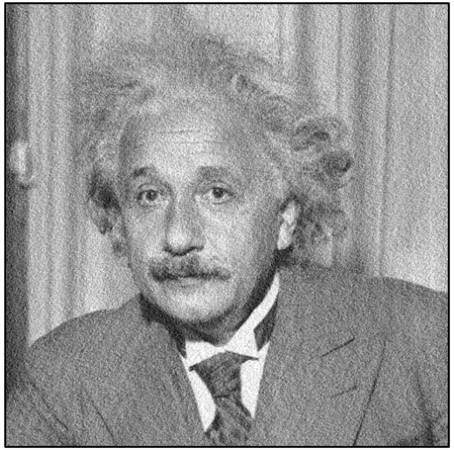
- Introduction
- Natural image statistics
- High-order natural image statistics
- **Ringing artifacts**
- Outliers
- Summary

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]

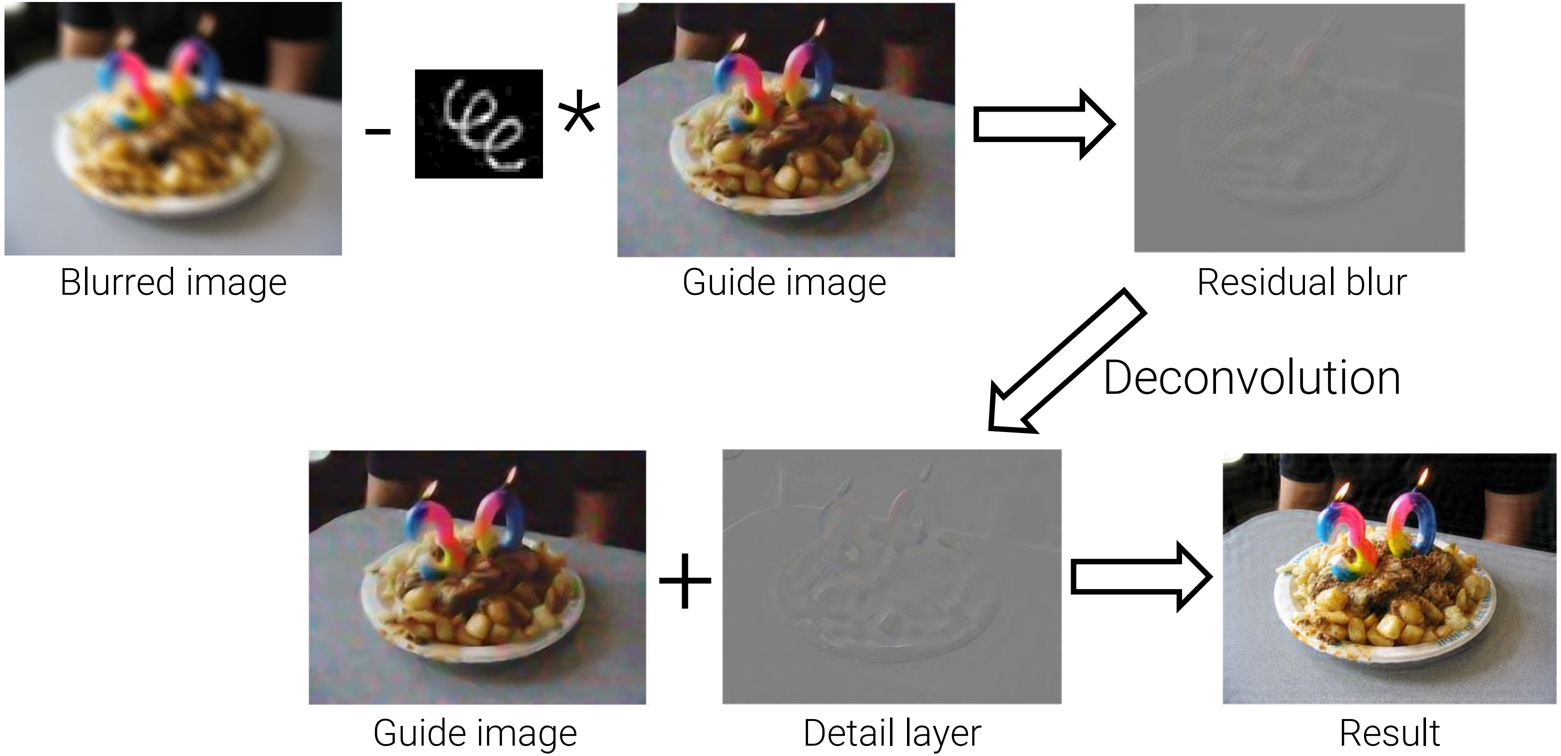
Blurred image

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]

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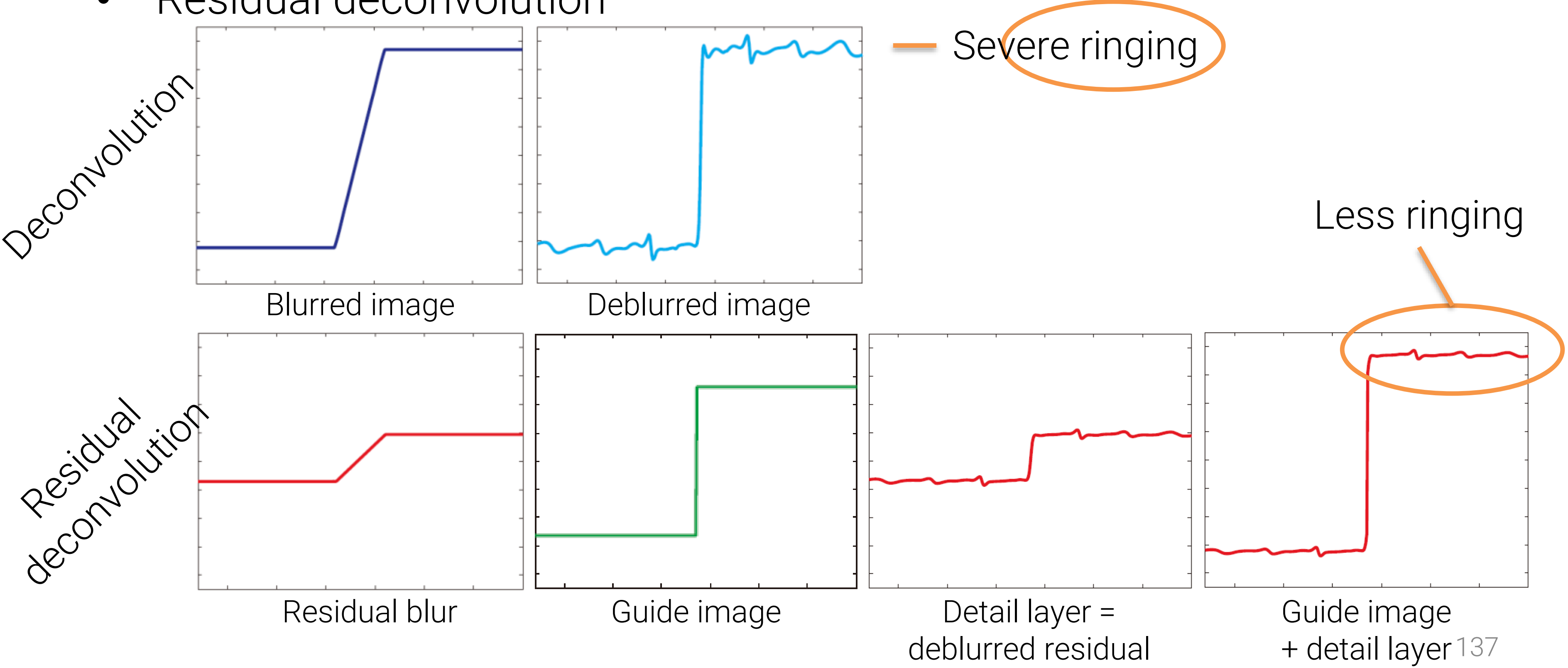
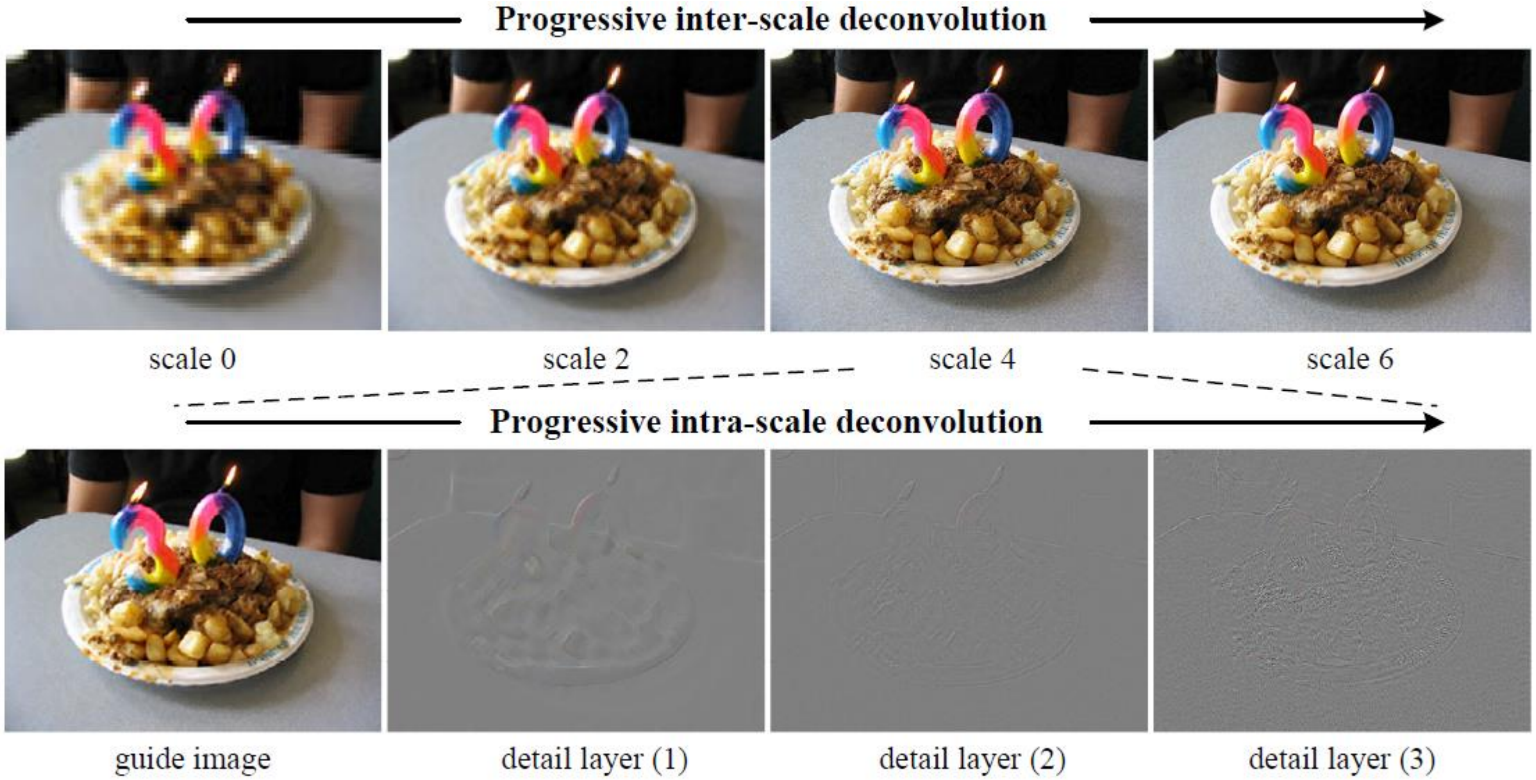
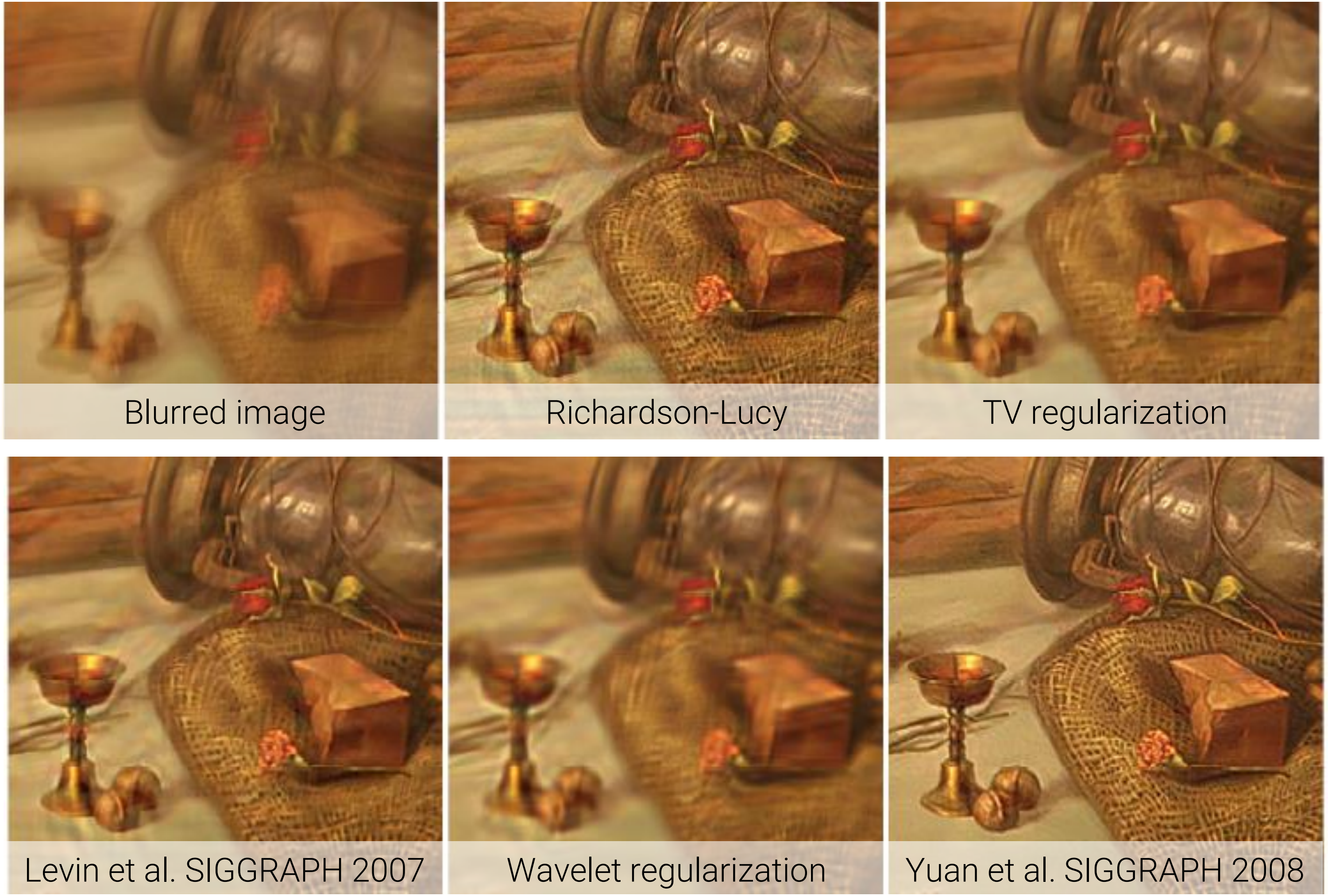
- Residual deconvolution



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

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- Introduction
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- Summary

Outliers

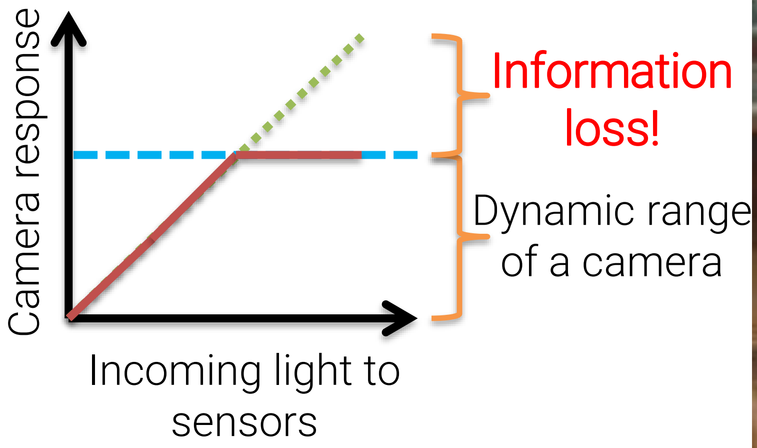
- A main source of severe ringing artifacts

Blurred image with outliers

Deblurring result
[Levin et al. SIGGRAPH 2007]

Outliers

- Saturated pixels caused by limited dynamic range of sensors



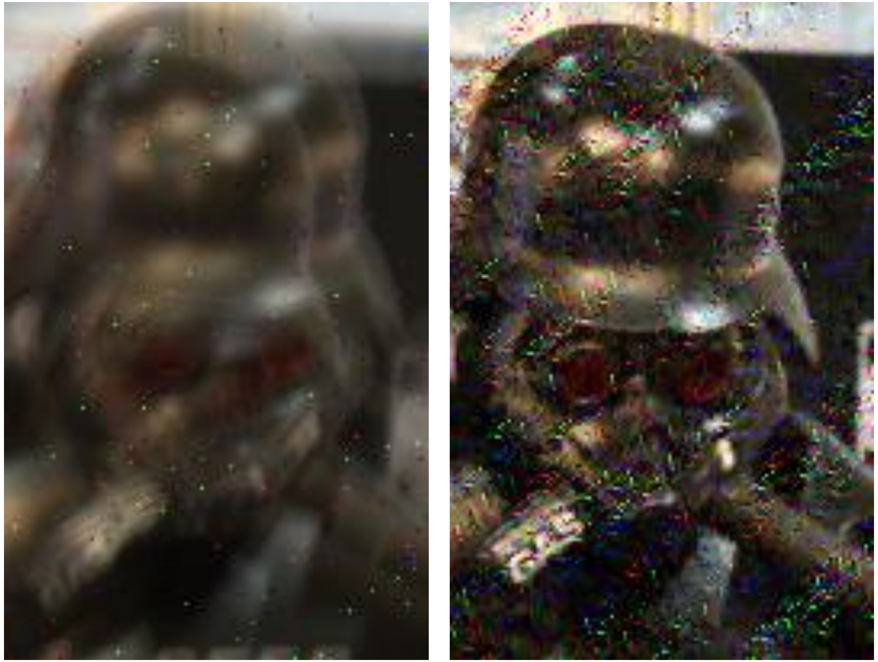
Blurred image

[Levin et al. 2007]

Outliers

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

Hot pixel



Blurred image with outliers [Levin et al. 2007]

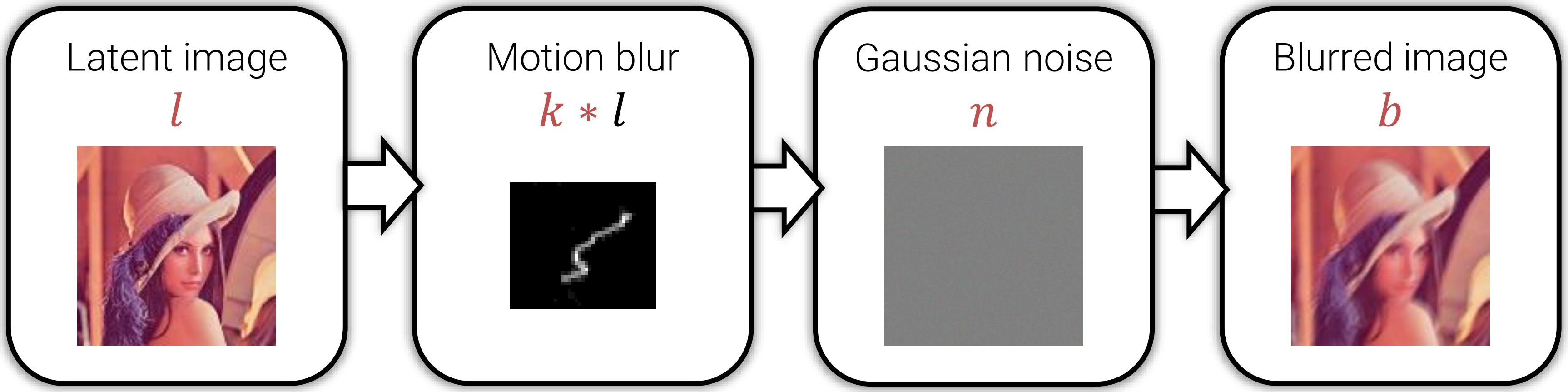
Outlier Handling

- Most common blur model:

$$b = k * l + n$$

small amount of Gaussian noise

Equivalent to



Outlier Handling

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- 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

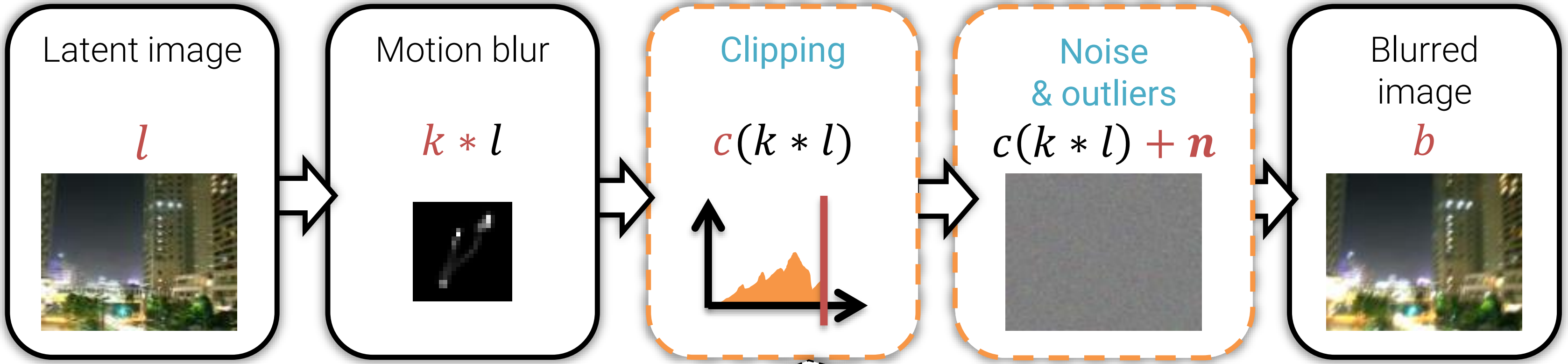
- L^1-norm based data term
  - Simple & efficient
  - Effective on salt & pepper noise
  - Not effective on saturated pixels

L^2-norm based data term

L^1-norm based data term

Cho et al. ICCV 2011

- More accurate blur model reflecting outliers



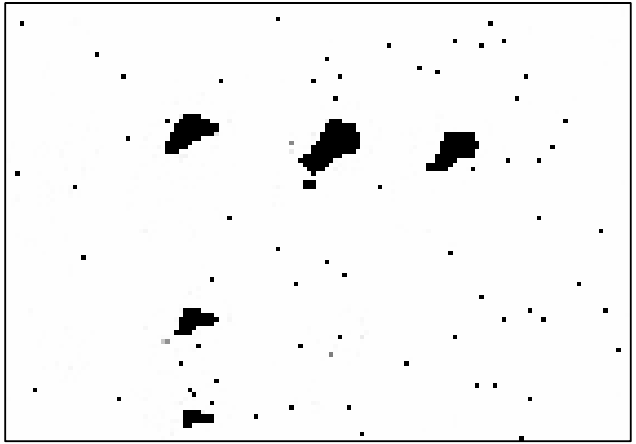
$$c(u) = \begin{cases} u & \text{if } u \in \text{DynamicRange} \\ \text{LowerBound} & \text{if } u < \text{LowerBound} \\ \text{UpperBound} & \text{if } u > \text{UpperBound} \end{cases}$$

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

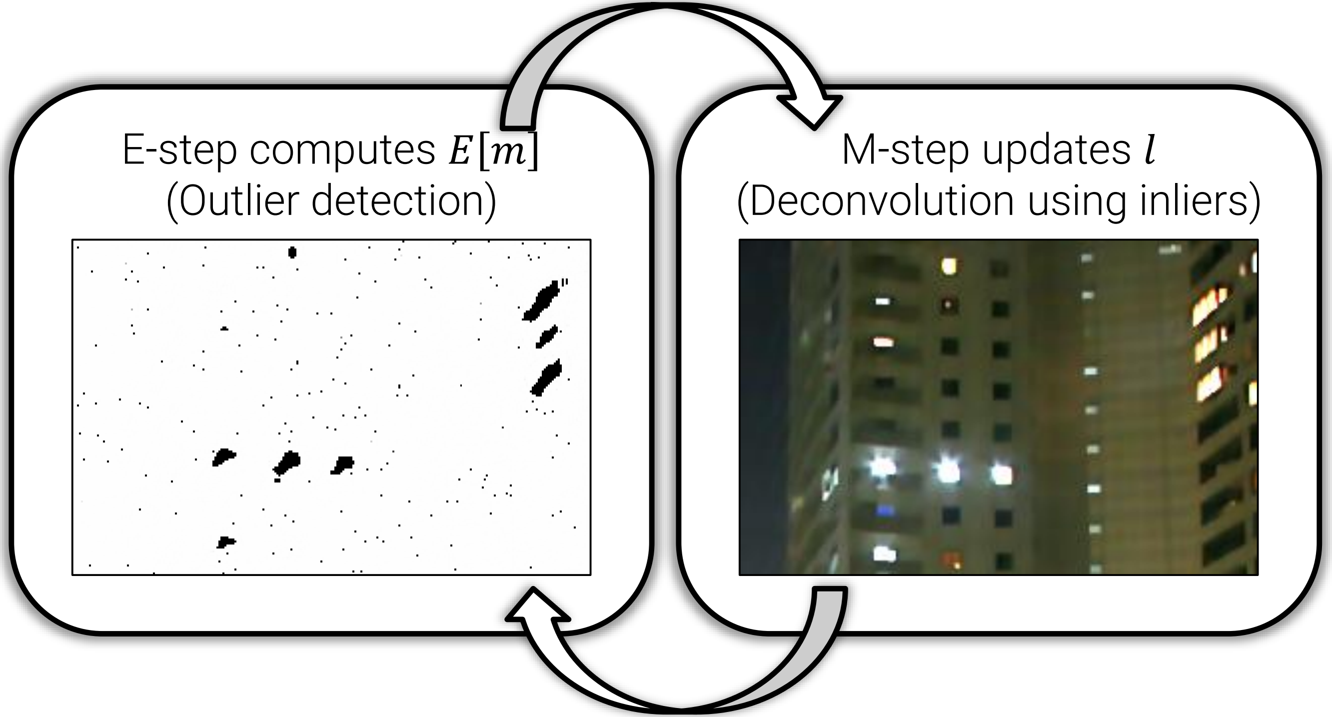
Given b & k, find the most probable l

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

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

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]

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

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

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

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Advanced Issues

Introduction

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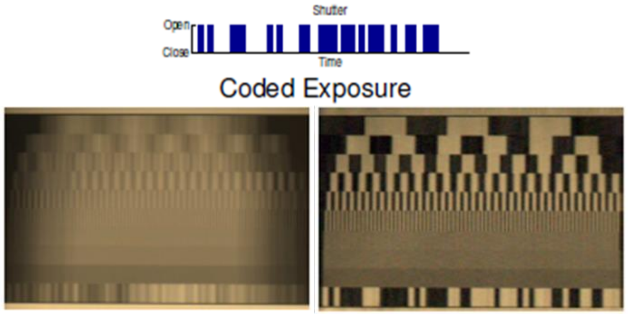
Advanced Issues

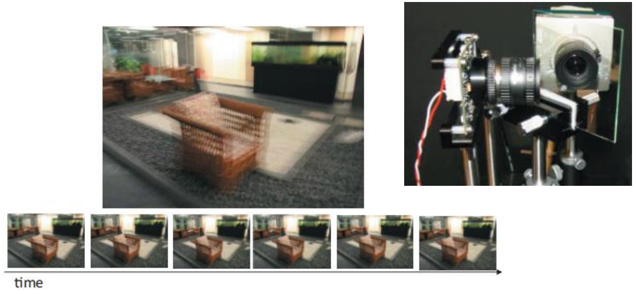
- Hardware based approaches
- Defocus / optical lens / object motion / video blur…
- Other issues

Hardware based Approaches

- To estimate blur kernels
- To restore sharp images better



[Raskar et al., SIGGRAPH 2006]
Coded exposure using fluttered shutter

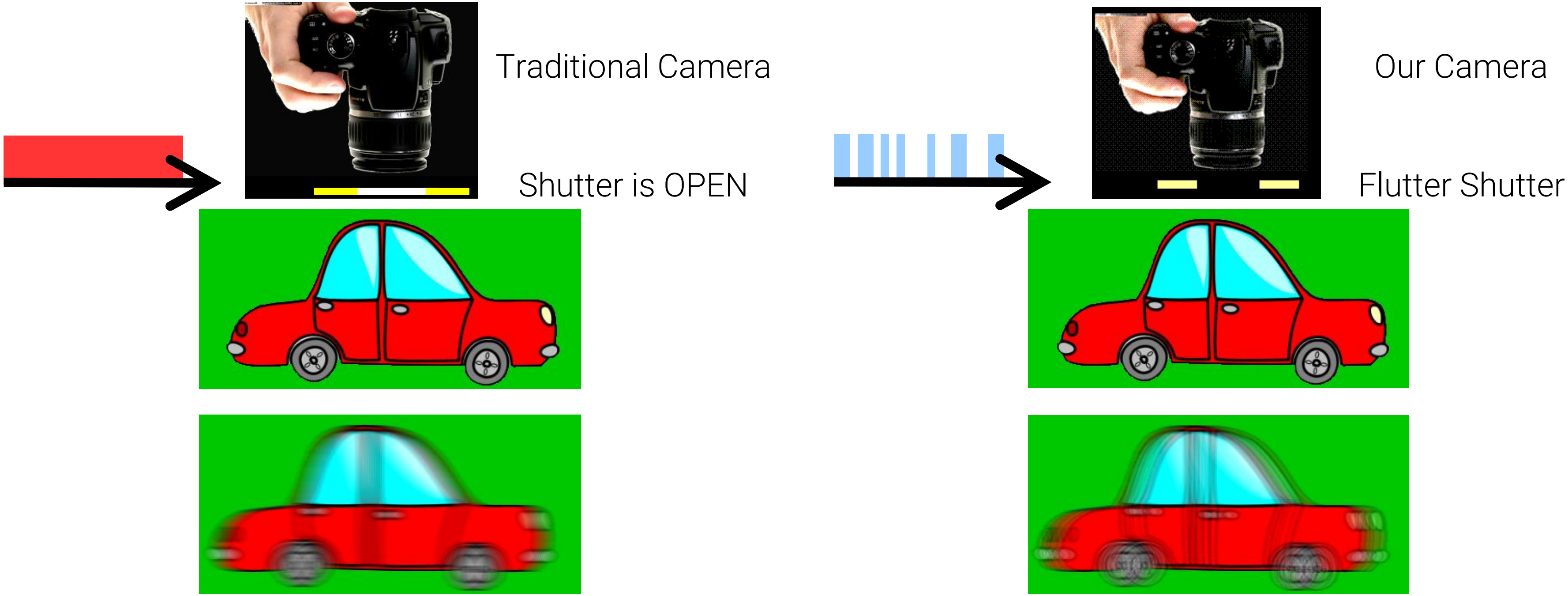


[Tai et al., CVPR 2008]
High-speed low-resolution camera &
low-speed high-resolution camera

[Joshi et al., SIGGRAPH 2010]
Gyro sensor + accelerometer

Coded Exposure

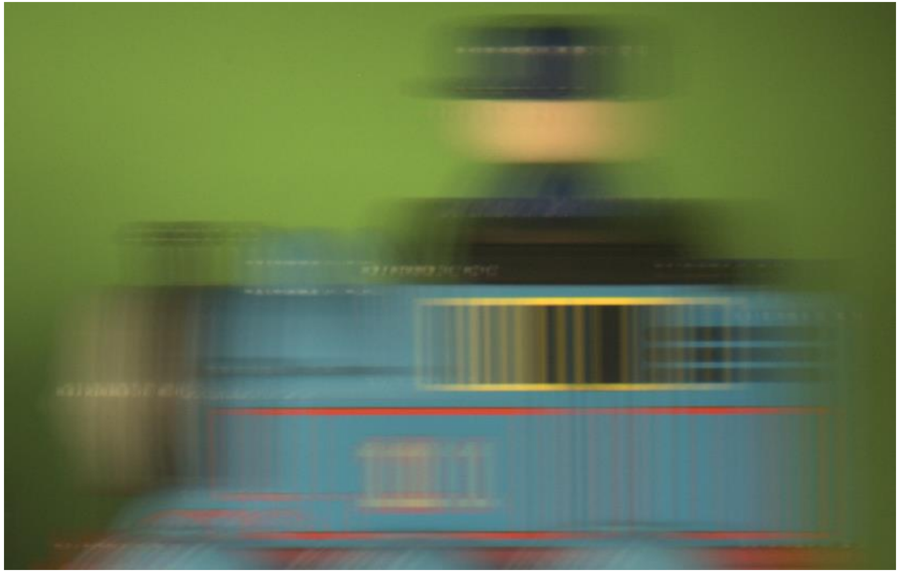
- Raskar et al. SIGGRAPH 2006



Coded Exposure

- Raskar et al. SIGGRAPH 2006

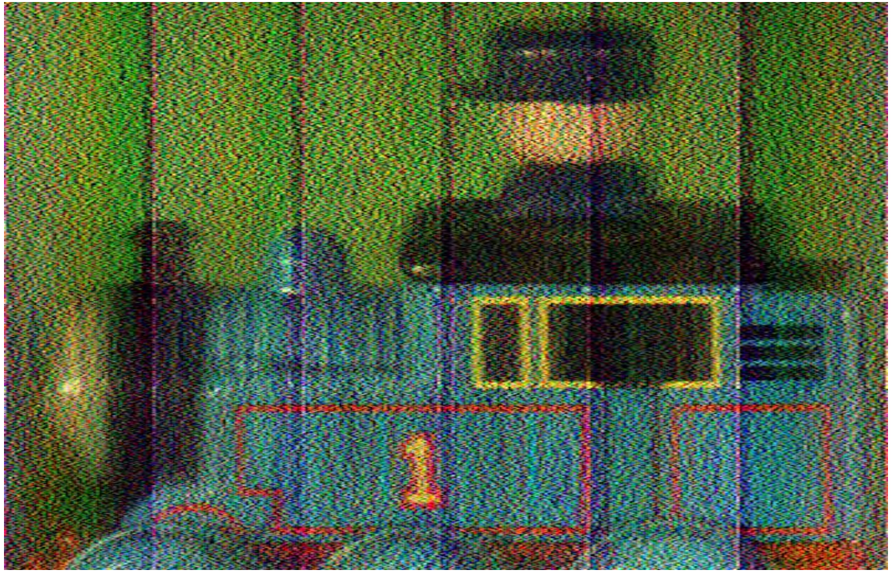
Traditional camera
Completely destroys high-freq info



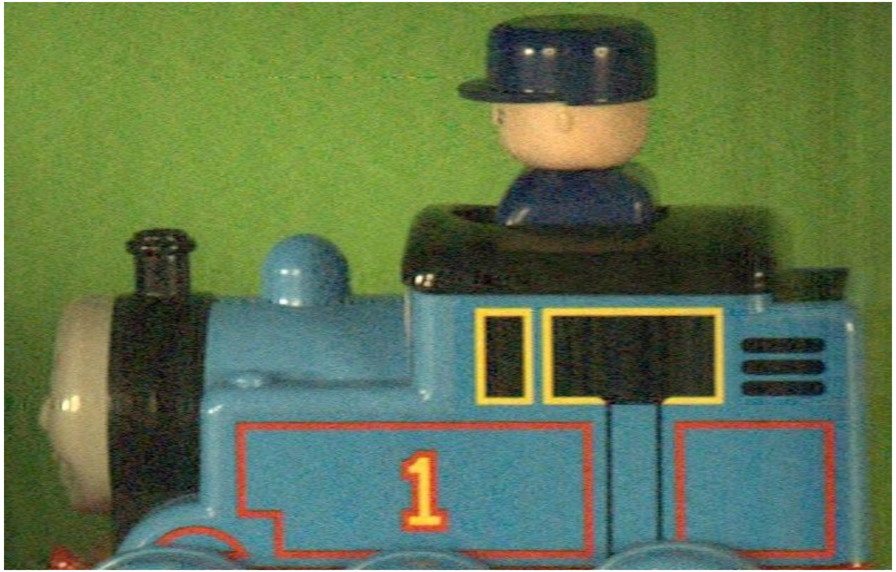
Fluttered shutter
High-freq info is preserved

Coded Exposure

- Raskar et al. SIGGRAPH 2006



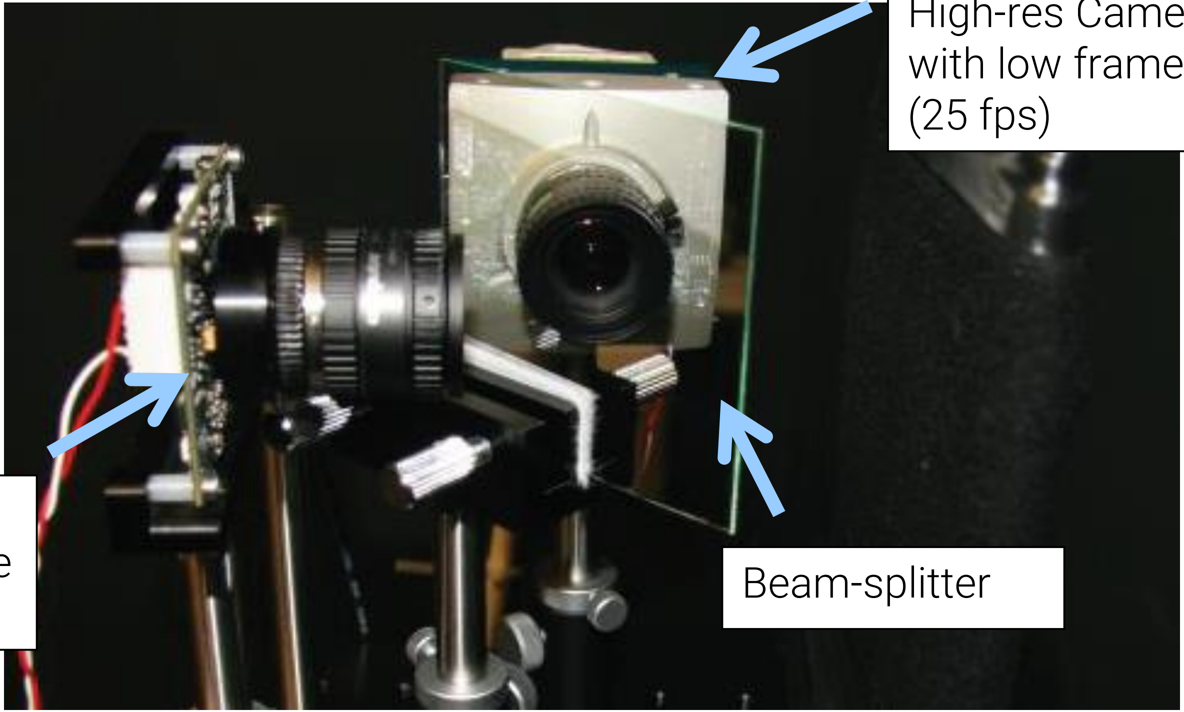
Traditional camera
High-freq details couldn't be restored accurately



Fluttered shutter
High-freq details are restored accurately

Hybrid Camera

- Tai et al. CVPR 2008



Hybrid Camera

- Tai et al. CVPR 2008
  - Deblur hi-res image using low-res & high frame rate video

Hi-res.
image

Low-res.
video

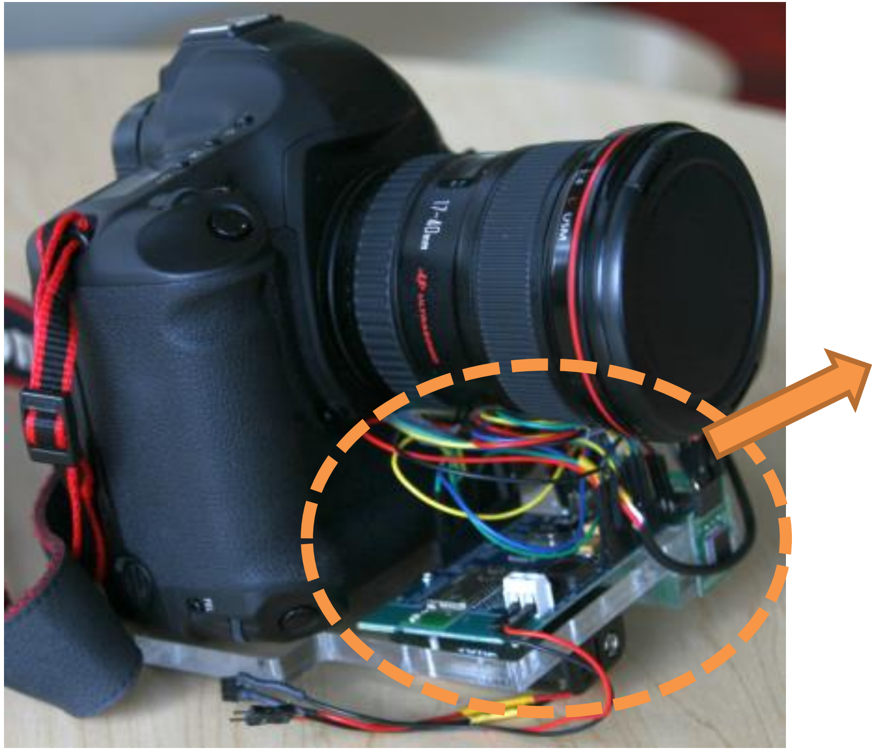
time

Input | [Shan et. al. ICCV'07] | [Ben-Ezra et. al. CVPR'03]

Back Projection | Our Result | Ground Truth

Gyro Sensors + Accelerometers

- Joshi et al. SIGGRAPH 2010



- 3 gyro sensors
- 3 accelerometers
- 6 DoF camera motion

Blurred image

Deblurred image

Introduction

Blind Deconvolution

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Advanced Issues

- Hardware based approaches
- Defocus / optical lens / object motion / video blur…
- Other issues

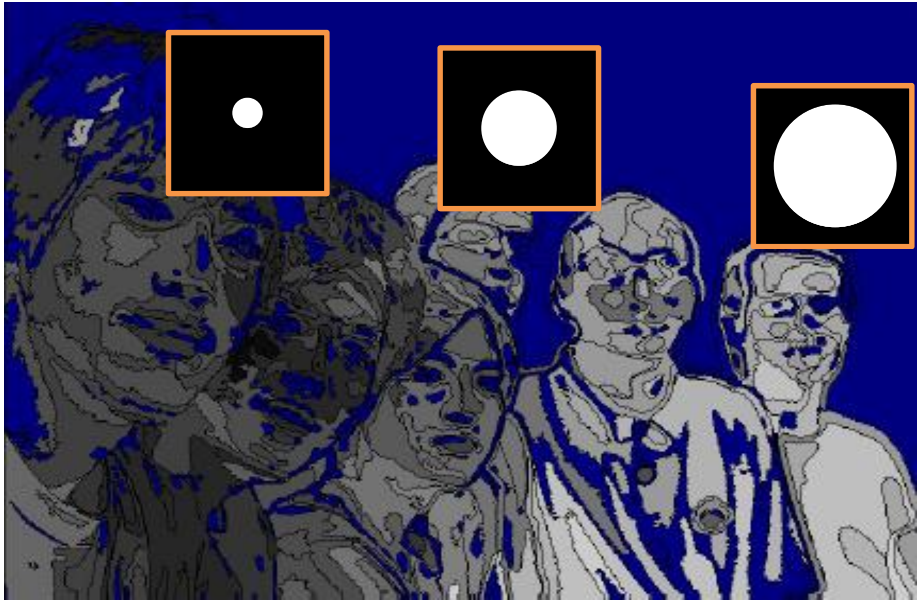
Defocus blur

- Shallow depth of field
- Often intentionally used for visually aesthetic pictures
- However, a user may focus a wrong spot by mistake
- Spatially variant
  - Dependent on depths

Bando & Nishita PG 2007

- Segmentation + local blur estimation

Blurry input



Segmentation + local blur estimation result

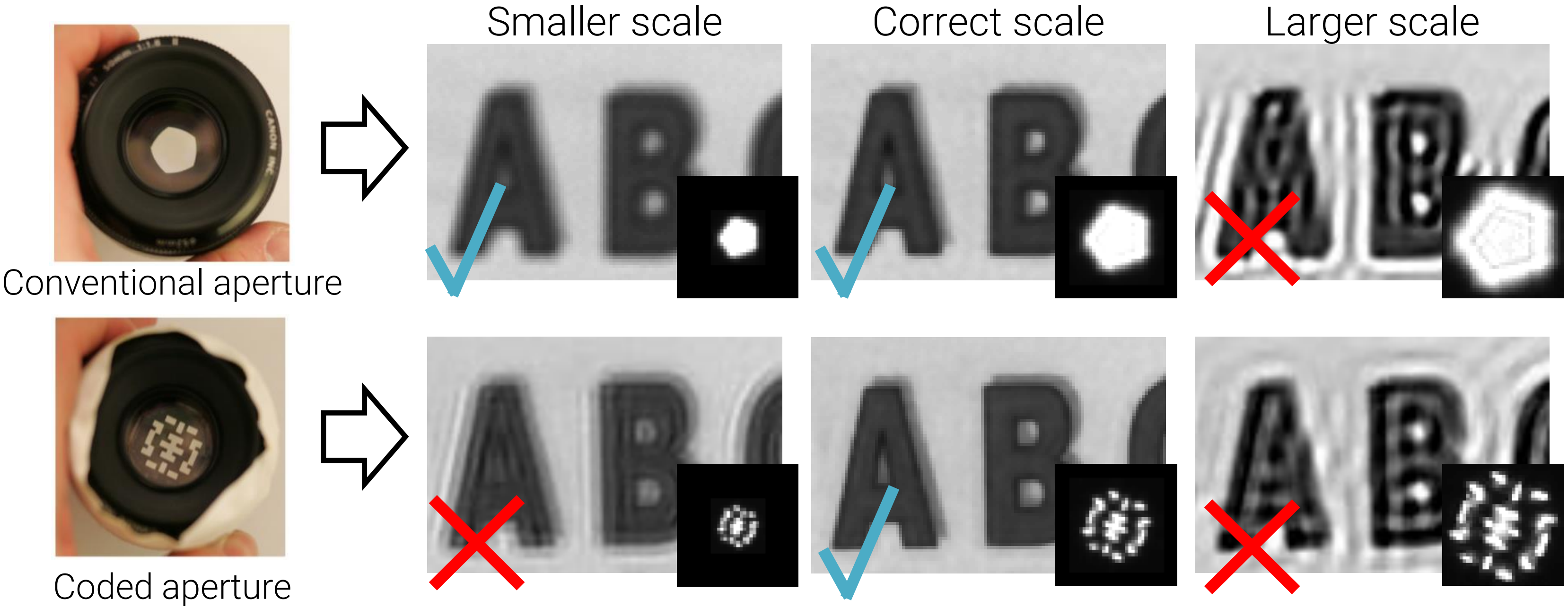
Bando & Nishita PG 2007

Digital Refocusing

Input image | Shallower depth-of-field | Refocused on the orange crayon

Coded Aperture [Levin et al. SIGGRAPH 2007]

- Coded aperture to more accurately estimate local blur kernels



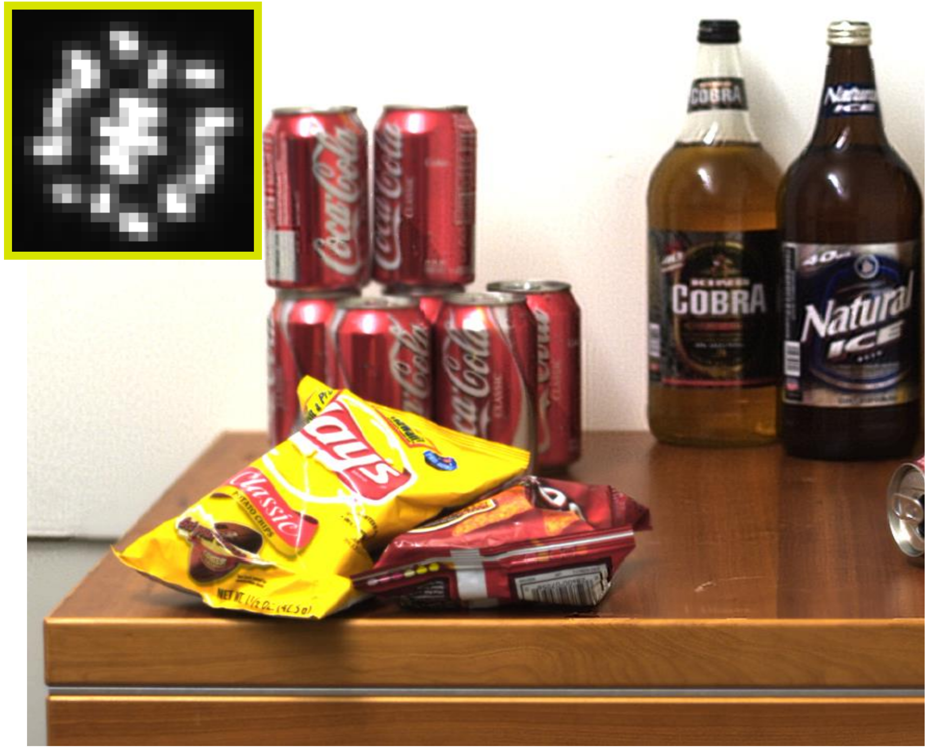
Coded Aperture [Levin et al. SIGGRAPH 2007]

Input blurred image

All focused result

Coded Aperture [Levin et al. SIGGRAPH 2007]

Conventional aperture:
ringing due to incorrect blur estimation



Coded aperture

Coded Aperture [Levin et al. SIGGRAPH 2007]

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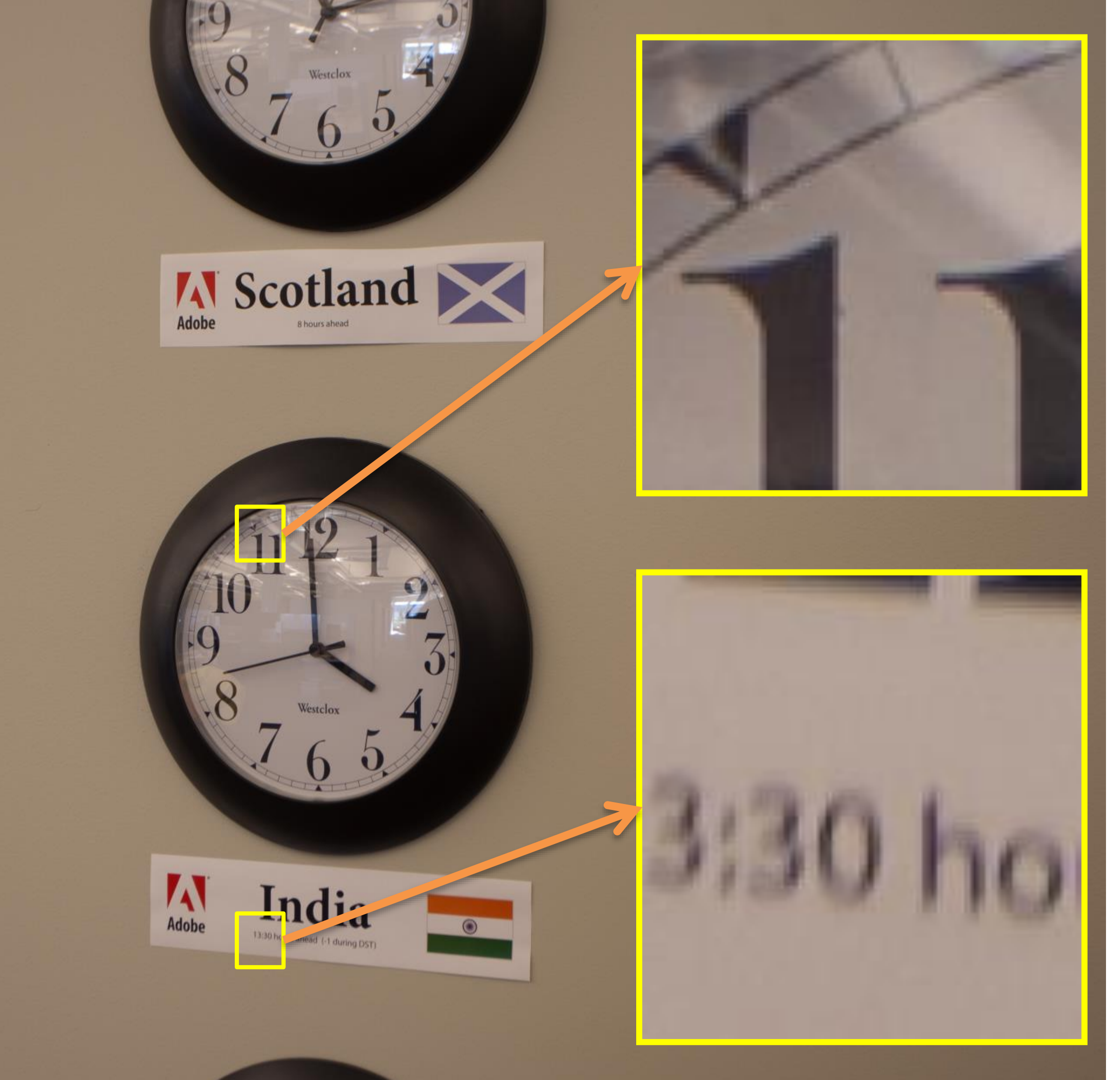
Refocusing

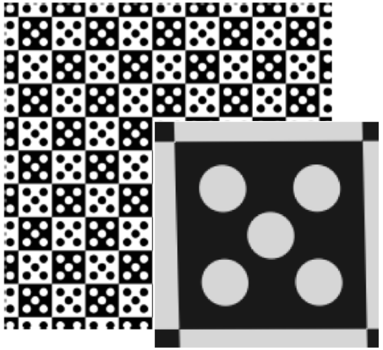


Optical Lens Blur

- Lens imperfection
- Spatially-varying blur
- Image boundaries get blurrier

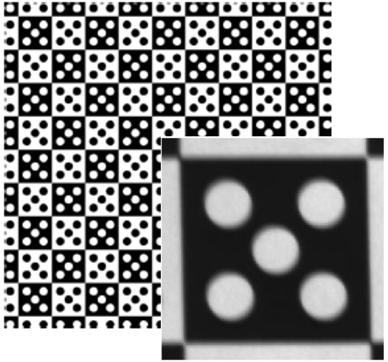
Calibration based Approach [Kee et al. ICCP 2011]

- Calibration step estimates spatially-varying blur using a test chart

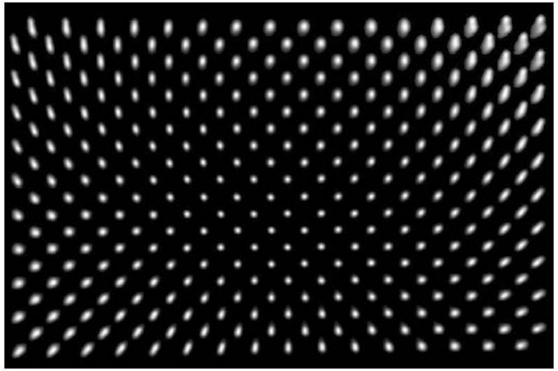


Test chart

Capture it

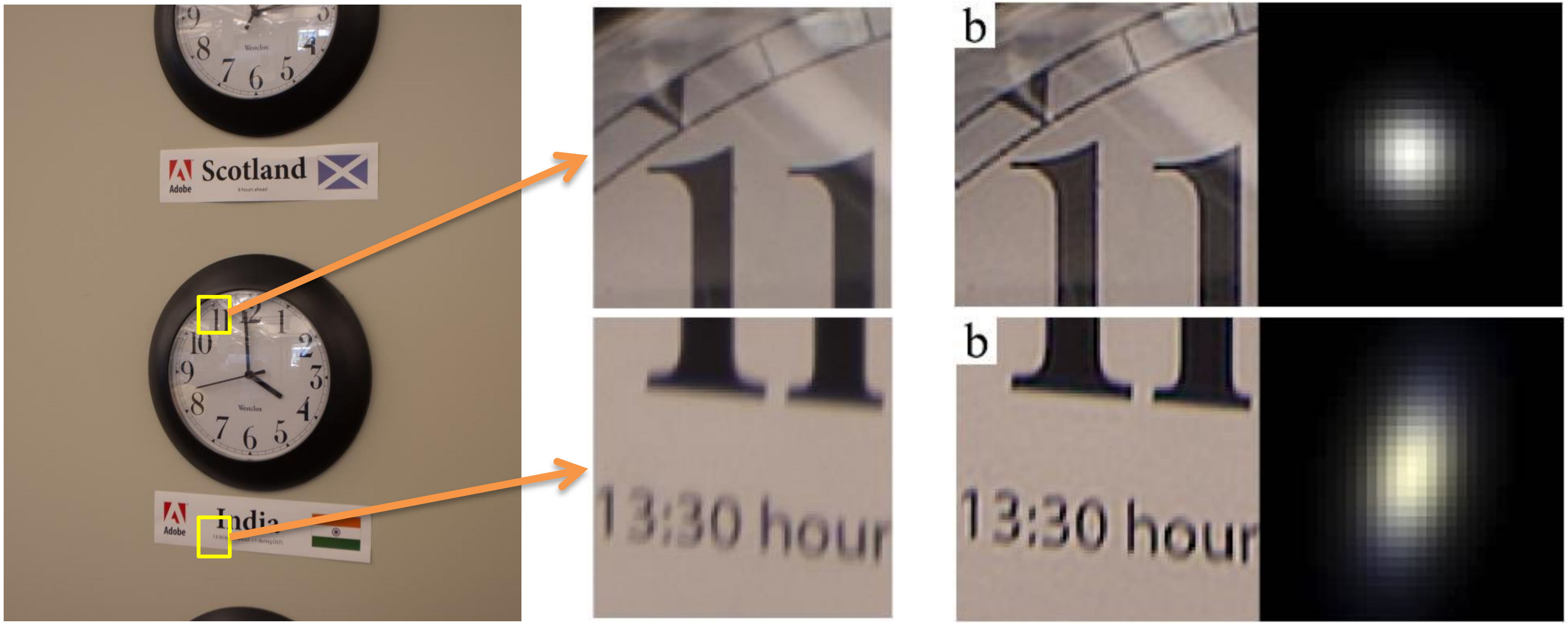


Captured chart



Estimated blur kernels

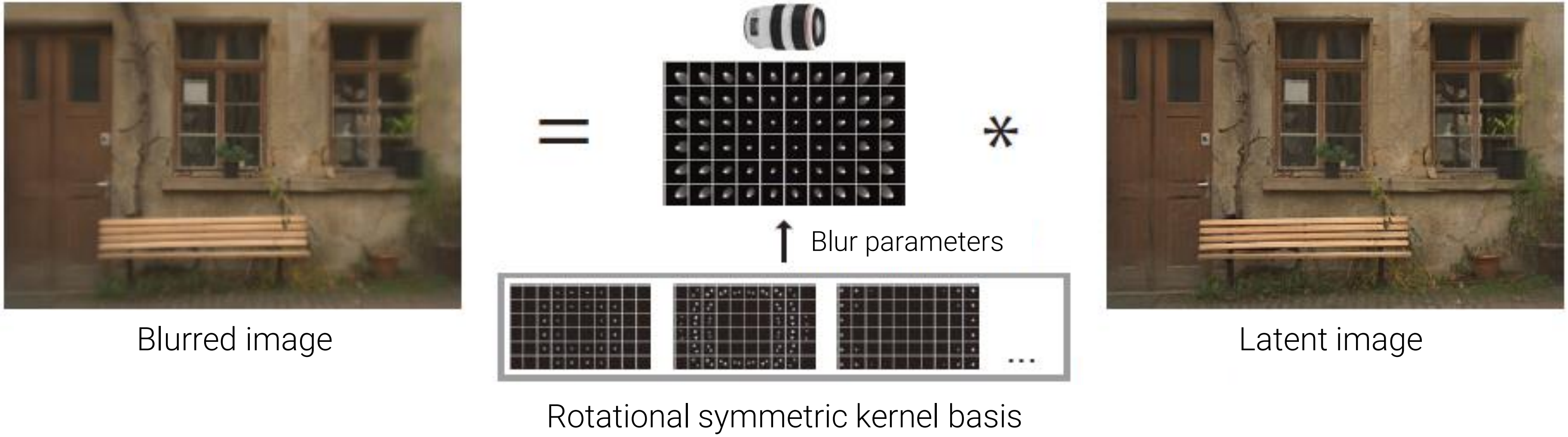
Calibration based Approach [Kee et al. ICCP 2011]



Blurry input | Restored | Blur kernels

No Calibration [Schuler et al. ECCV 2012]

- Assume blur kernels rotationally symmetric to the image center
- Use an edge prediction framework for estimating blur kernels



No Calibration [Schuler et al. ECCV 2012]

Blurred image (captured in 1940)

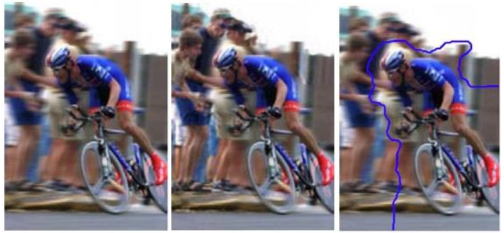
Schuler et al. ECCV 2012

Object Motion Blur

- Due to object motions
- Most challenging
- Spatially-varying blur
  - Much more arbitrary than spatially-varying camera shakes
- Limited information
  - Small portions of an image are blurred

Software based Approaches

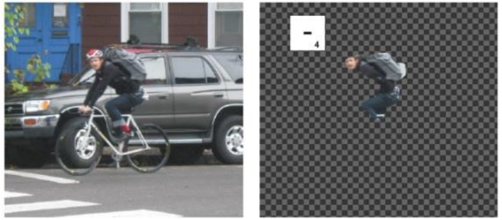
- Severely ill-posed problem
- Segmentation & blur kernel estimation
- Often impose very limited assumptions
  - Parametric linear blur kernels
  - Only one moving object



[Levin, NIPS 2006]
Blur estimation and segmentation based on natural image prior

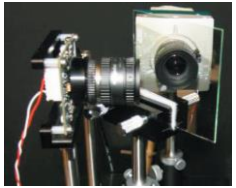
[Jia, CVPR 2007]
Blur estimation based on alpha matting

[Cho et al. ICCV 2007]
Blur estimation & segmentation using multiple blurred images



[Charkrabarti et al., CVPR 2010]
Blur estimation & segmentation from a single image

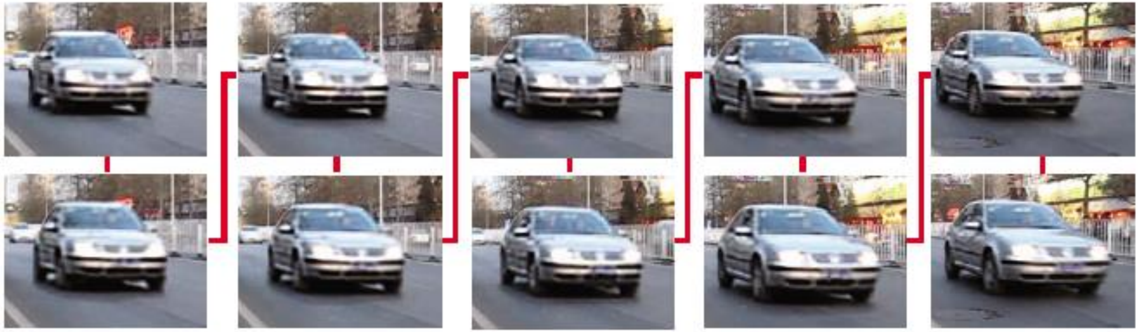
Hardware based Approaches



[Tai et al., CVPR 2008]
High-speed low-resolution camera &
low-speed high-resolution camera

Input video sequence

Alpha matte of the moving object



Deblurred video frames

Video Deblurring

- Camera shakes
- Moving objects
- Temporal coherence

Video Deblurring

[Li et al. CVPR 2010]
Generate a sharp panorama image from blurred video frames

[Cho et al. SIGGRAPH 2012]
Generate a sharp video using patch-based synthesis

Video Deblurring

[Li et al. CVPR 2010]
Generate a sharp panorama image from blurred video frames

[Cho et al. SIGGRAPH 2012]
Generate a sharp video using patch-based synthesis

Shaky Video

After Stabilizing the Video...

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Motion Blur in Video Frames

Shaky video

Motion Blur in Video Frames

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After video stabilization

Video Deblurring [Cho et al. SIGGRAPH 2012]

Comparison

Blurred frame

Single image deblurring

Multiple image deblurring

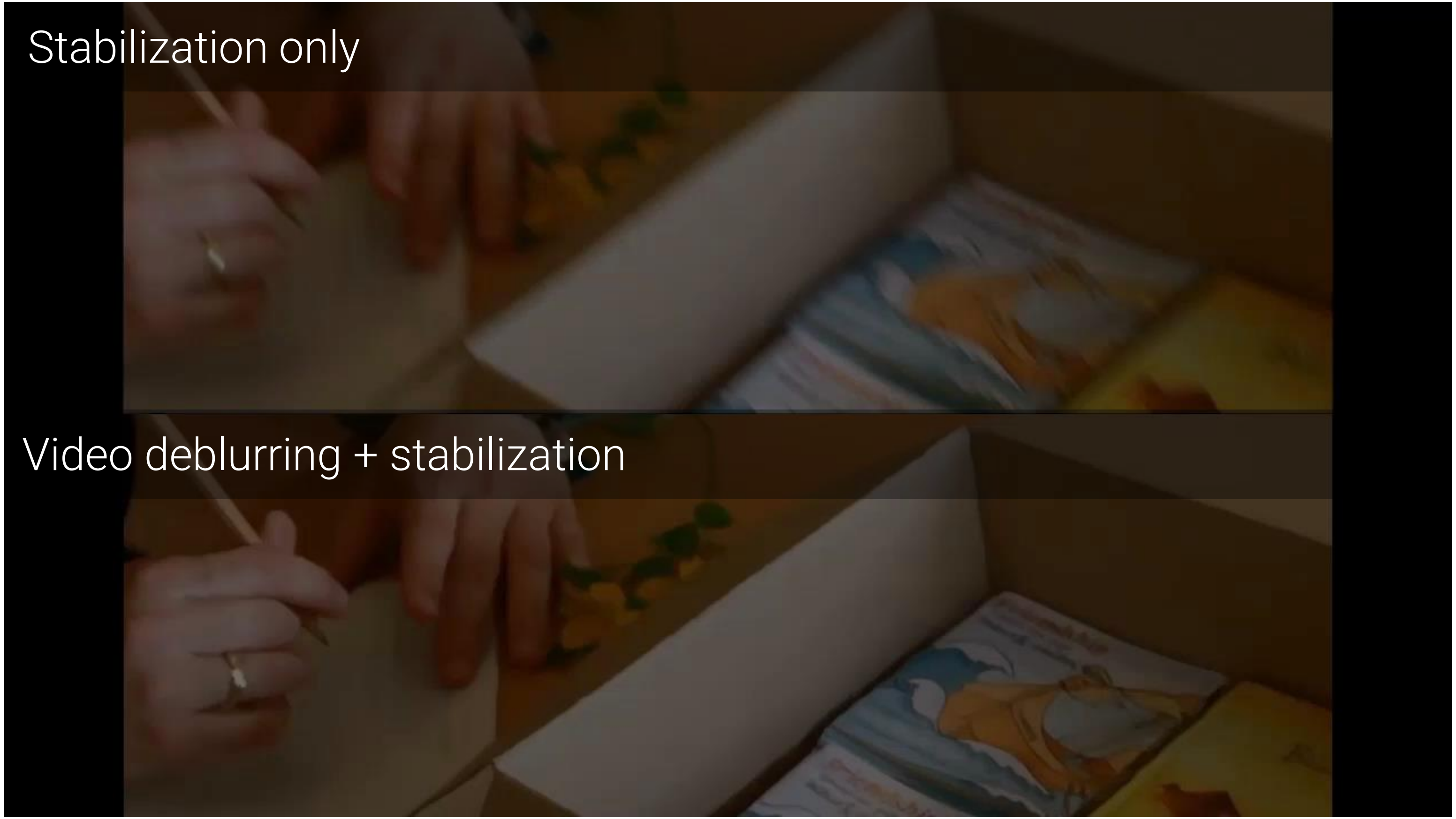
Cho et al. SIGGRAPH 2012

Video Deblurring [Cho et al. SIGGRAPH 2012]

- Find sharp patches from neighboring frames → blend them together
  - Patch search taking account of **spatially varying blur**
  - **No deconvolution** → no deconvolution artifacts
  - **Local window based patch search** → depth difference & moving objects
  - **Patches from nearby frames** → Temporal coherence

➔ Reliable & robust

Video Deblurring [Cho et al. SIGGRAPH 2012]



Video Deblurring [Cho et al. SIGGRAPH 2012]

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

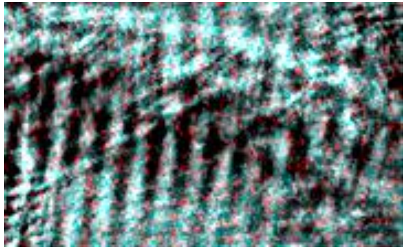
- Hardware based approaches
- Defocus / optical lens / object motion / video blur…
- Other issues

Outliers & Noise

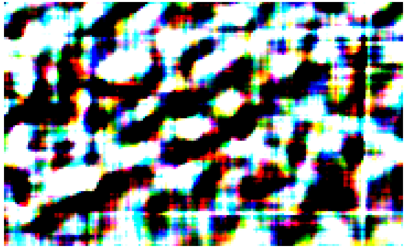
- Blurred images often have significant amount of noise & outliers
  - Low-lighting environment
  - But, relatively less explored

- Non-blind deconvolution
  - Cho et al. ICCV 2012 – Outlier handling
- Blind deconvolution
  - Tai & Lin, CVPR 2012
    Nonlocal denoising & deblurring
  - Zhong et al. CVPR 2013
    Noise handling using directional filters

Cho & Lee
SIGGRAPH Asia 2009



Cho et al.
CVPR 2011

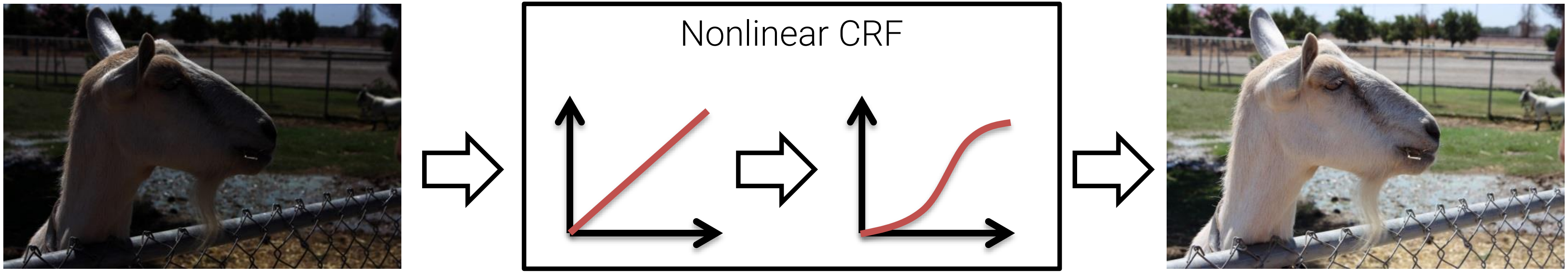


Levin et al.
CVPR 2011

Zhong et al.
CVPR 2013

Nonlinear Camera Response Functions

- Nonlinear Camera Response Functions (CRF)
  - Cameras apply CRFs to captured scene irradiance to produce an image
  - To mimic human visual perception
  - To improve the visual aesthetics



Scene irradiance

In-camera processing

Image intensity

Nonlinear Camera Response Functions

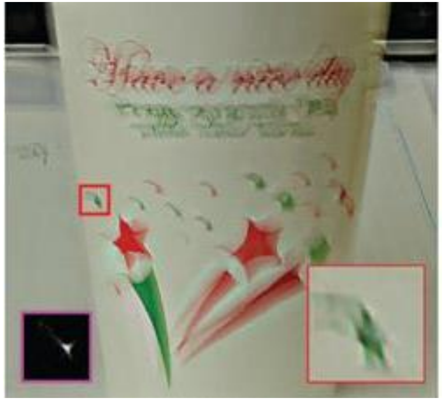
- Common blur model:

$$b \neq k * l$$

Due to CRF

Blurred image

- Previous methods often fail to estimate a blur kernel & produce severe ringing
- Kim et al. CVPR 2012
  - Estimate a CRF from a blurred image

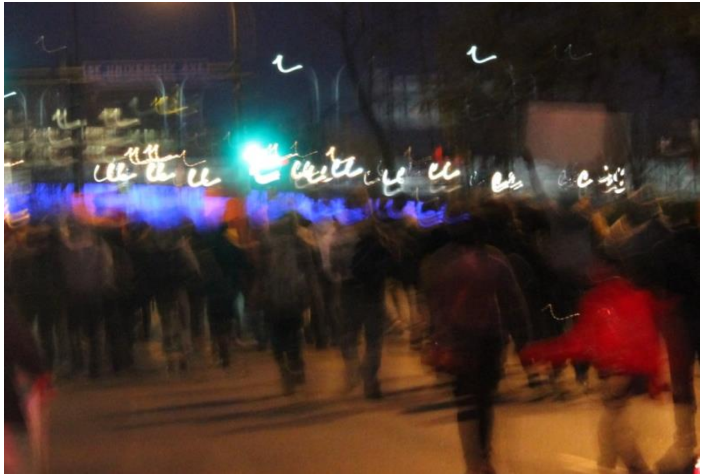


Without CRF handling

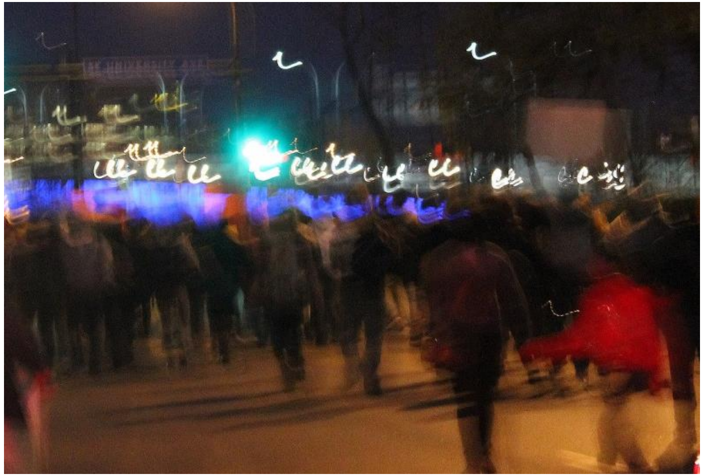
Kim et al. CVPR 2012

Other Information

- Light streaks?
  - Light streaks show the shape of the blur kernel
    - Can be a very useful information about blur kernels
  - But, most methods don't use them, and fail when they present



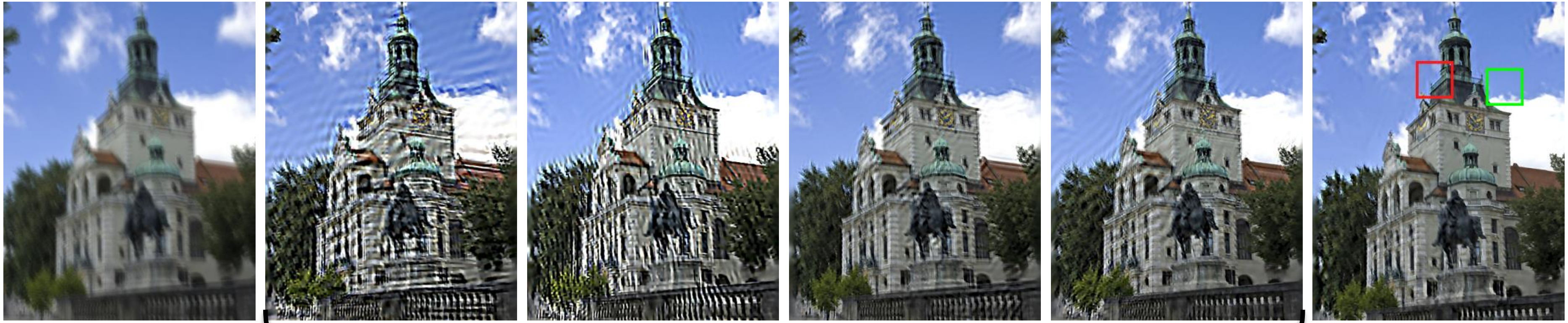
Blurry image with light streaks



Photoshop Shake Reduction

Quality Metric

- Different methods may produce different results with different artifacts
- Which one is better?
- Liu et al. SIGGRAPH Asia 2013
  - No-reference metric for evaluating the quality of motion deblurring



Blurred image

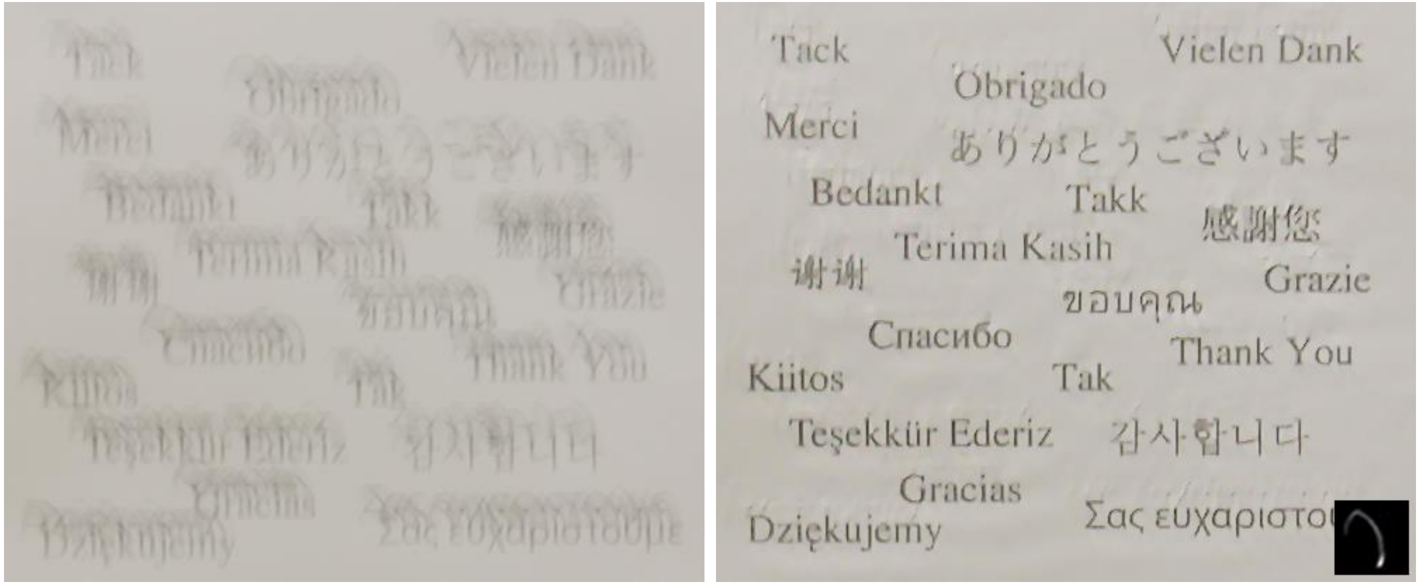
Different deblurring results

Liu et al.
Fusion using the quality metric

Domain Specific Deblurring

SIGGRAPH ASIA 2013 HONG KONG

- Exploit domain specific properties
  - Text images, medical images, etc

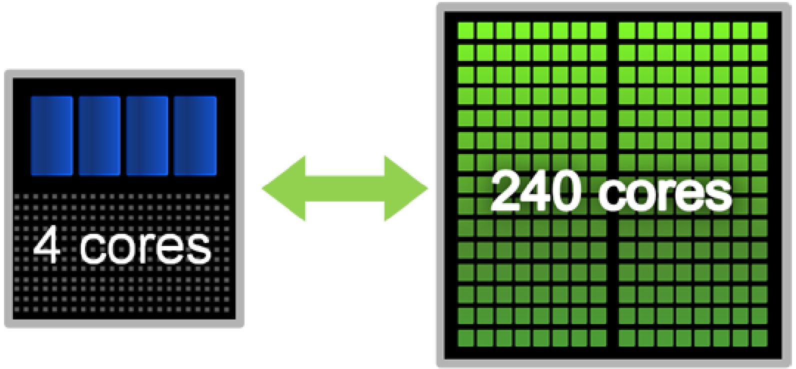


[Cho et al. ECCV 2012] Text image deblurring using text-specific properties

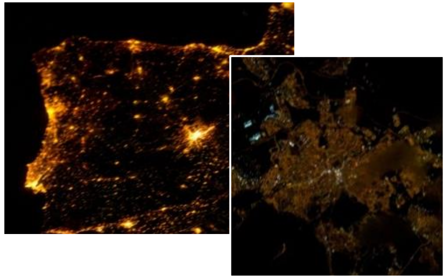
Computational Time

- Cameras these days
  - iPhone 5: 8 Mega pixels
  - Canon EOS 60D: 18 Mega pixels
- Many blind/non-blind deblurring methods
  - more than several minutes for an 1 Mega pixel image

- Parallelizing operations on pixels
- Cloud computing

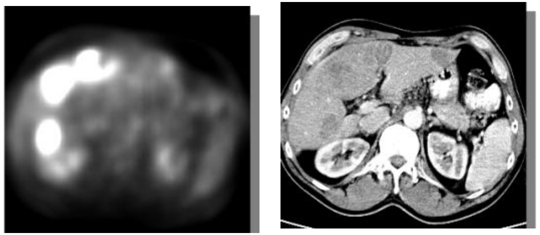


Applications

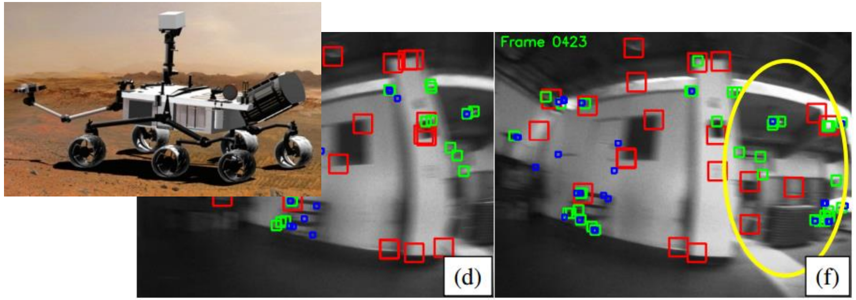


Satellite & aerial photographs

CCTV & Car black box



Medical imaging



Robotics - [Lee et al. ICCV 2011] SLAM & Deblurring

Historical images

Smart phones

Q & A

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