Recent Advances in Image Deblurring

Seungyong Lee @ POSTECH
Sunghyun Cho @ Adobe Research

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...

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)

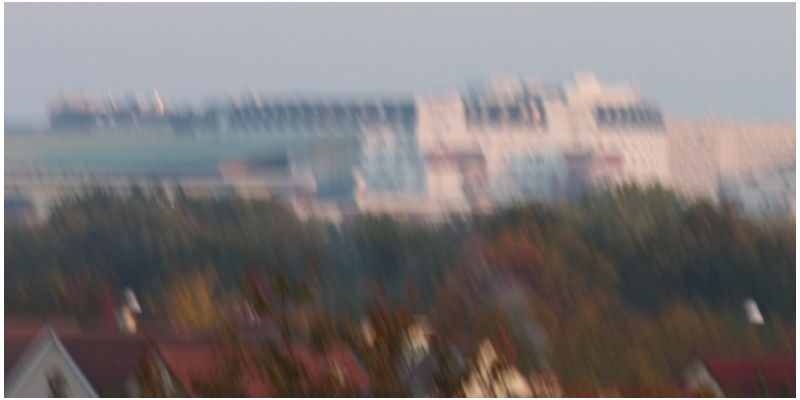
Object movement (Object motion blur)

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

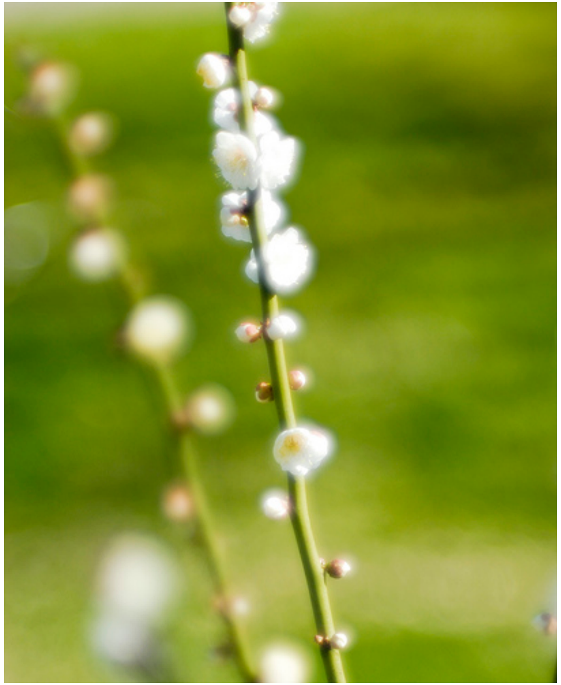


Object Motion Blur

- Caused by object motions during exposure time

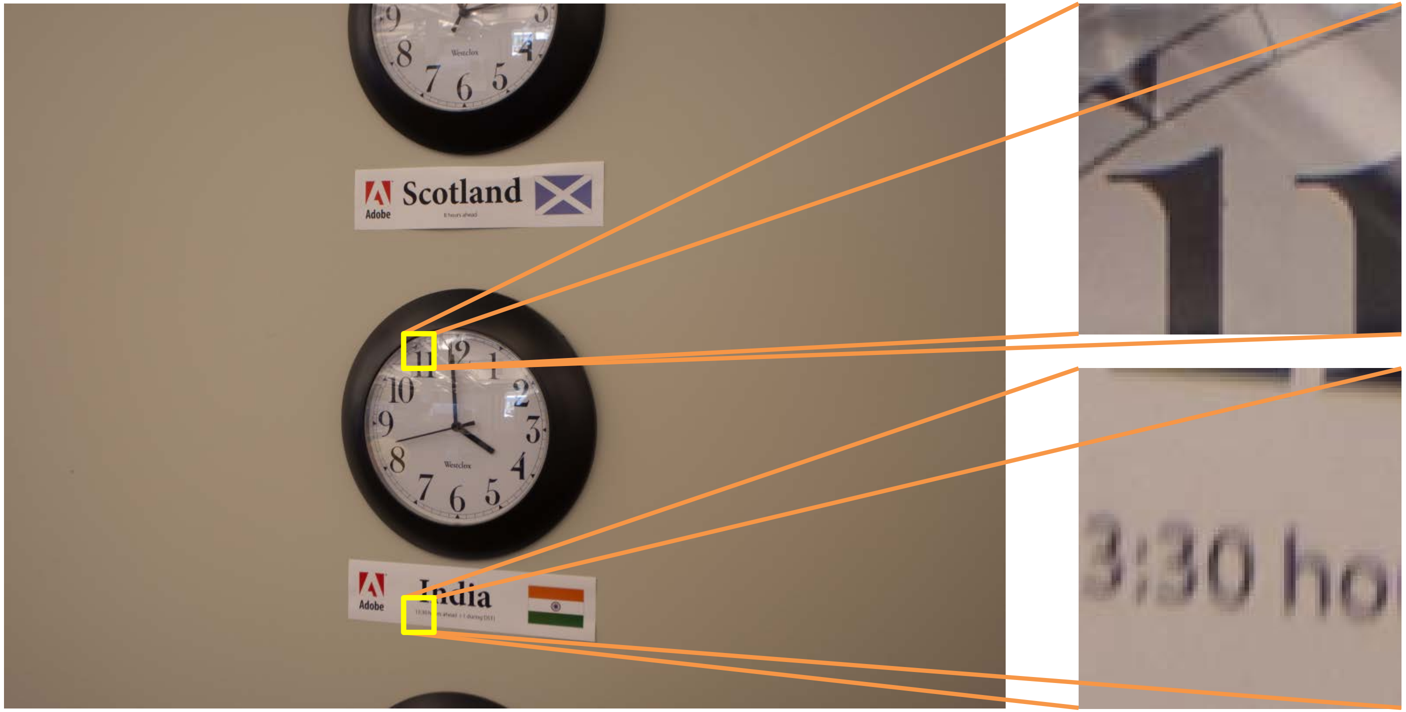
Defocus Blur

- Caused by the limited depth of field of a camera



Optical Lens Blur

- Caused by lens aberration



Deblurring?

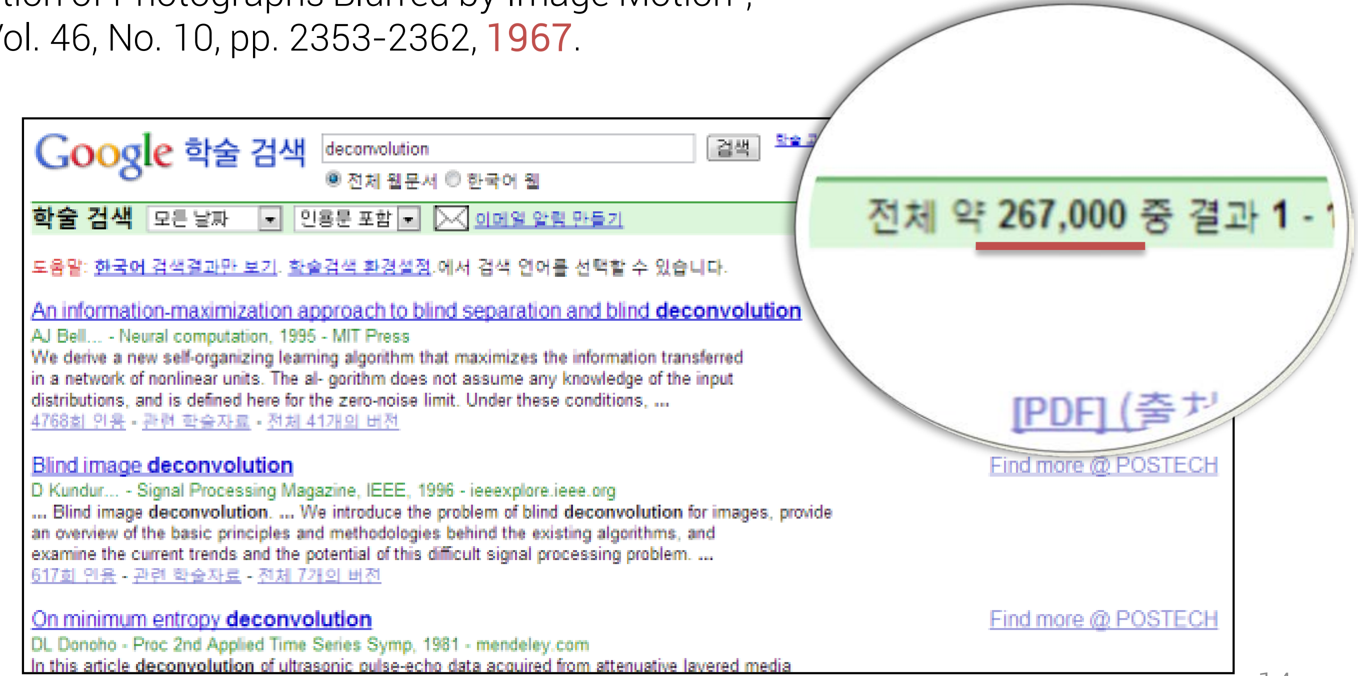
- Remove blur and restore a latent sharp image

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*?

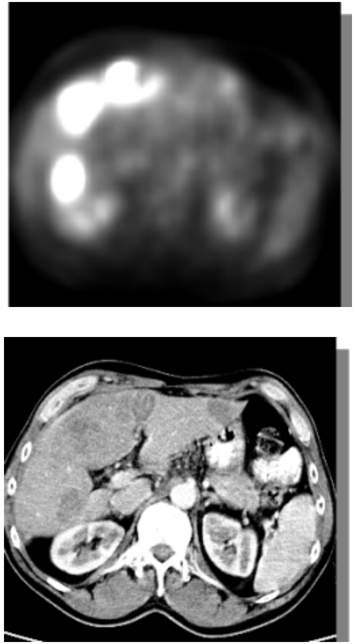
- Image/video in our daily lives
  - Sometimes a retake is difficult!



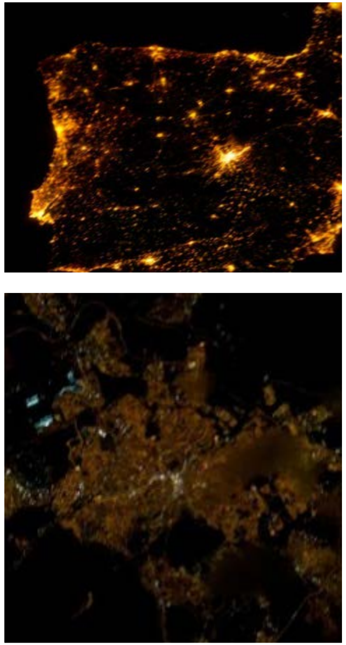
Why is it *important*?

- Strong demand for high quality deblurring

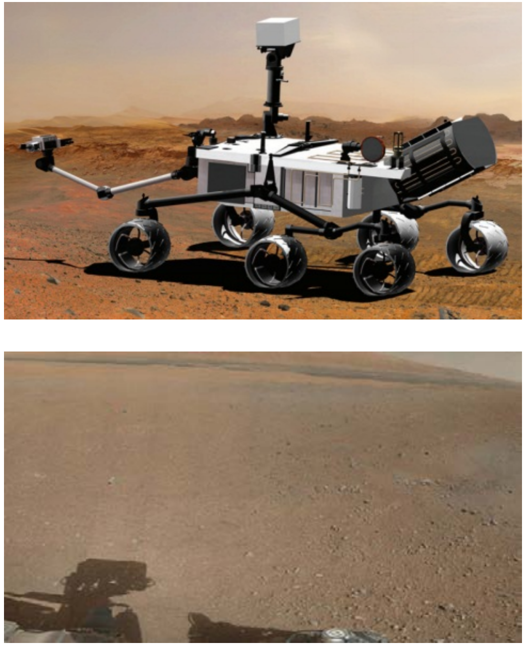
CCTV, car black box



Medical imaging



Aerial/satellite photography



Robot vision

Deblurring

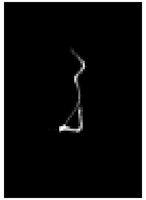
from a given blurred image

find its latent sharp image

Commonly Used Blur Model

Blurred image

=



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Latent sharp image

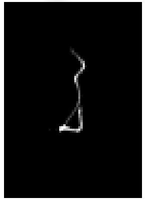
Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

Blind Deconvolution

Blurred image

=



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Latent sharp image

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Non-blind Deconvolution

Blurred image

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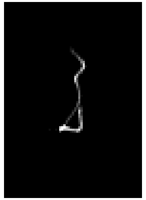

Blur kernel
or Point Spread
Function (PSF)

*

Convolution
operator

Latent sharp image

Uniform vs. Non-uniform Blur

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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

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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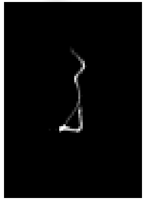

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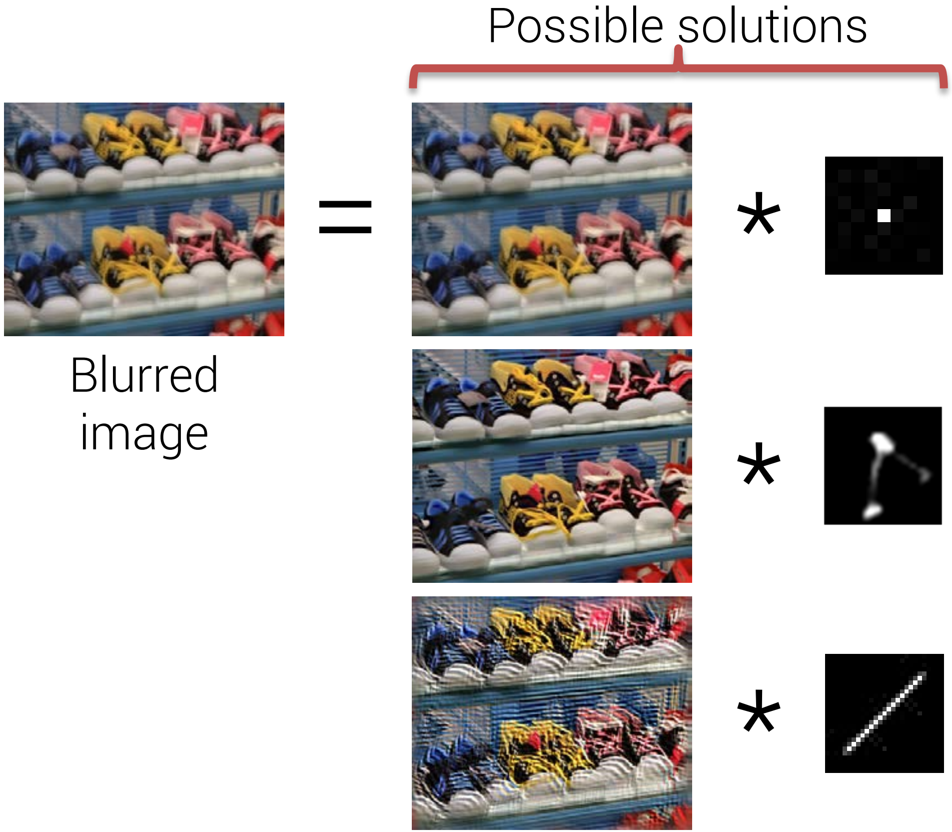
Latent sharp image

Blur kernel
or Point Spread
Function (PSF)

Convolution
operator

Key challenge: Ill-posedness!

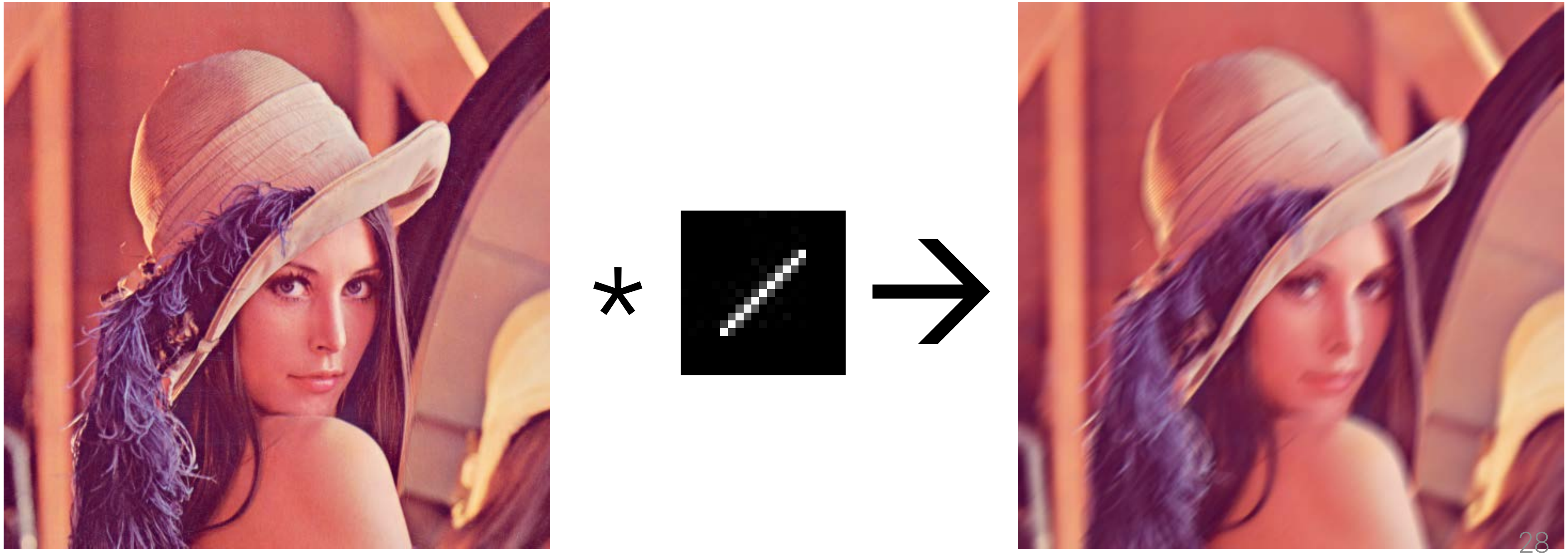


- Infinite number of solutions satisfy the blur model
- Analogous to

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

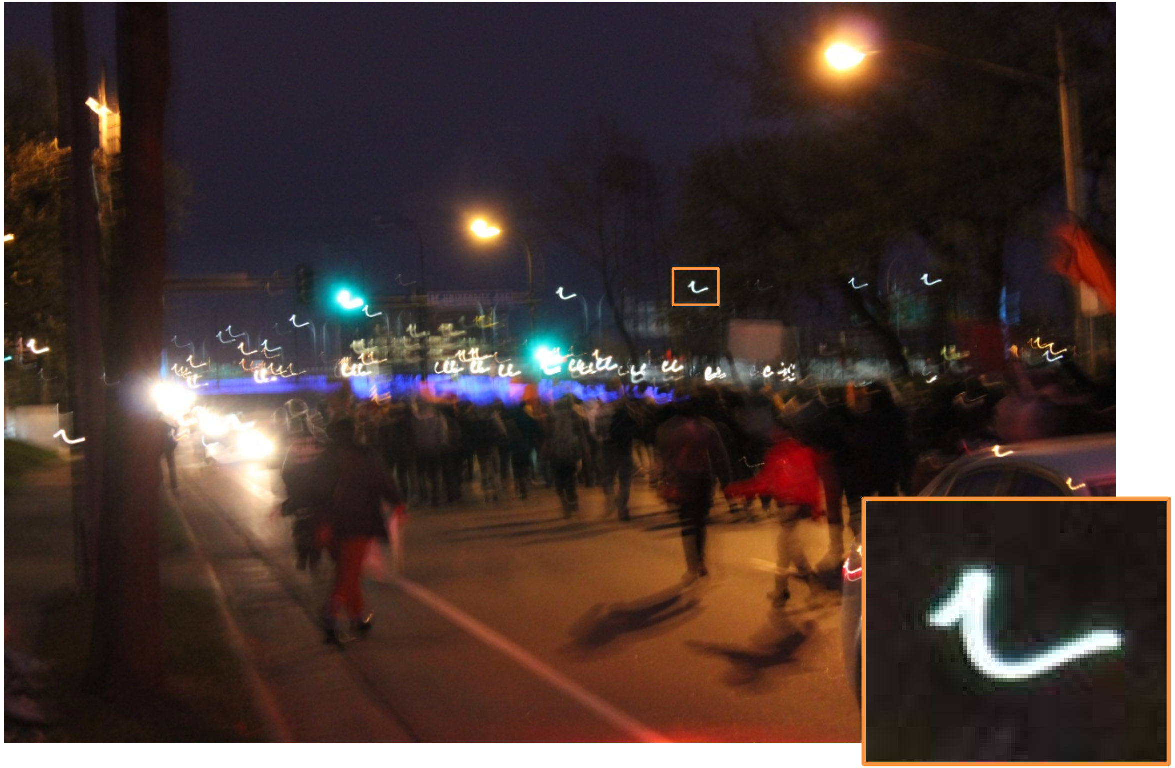
In The Past…

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



In The Past…

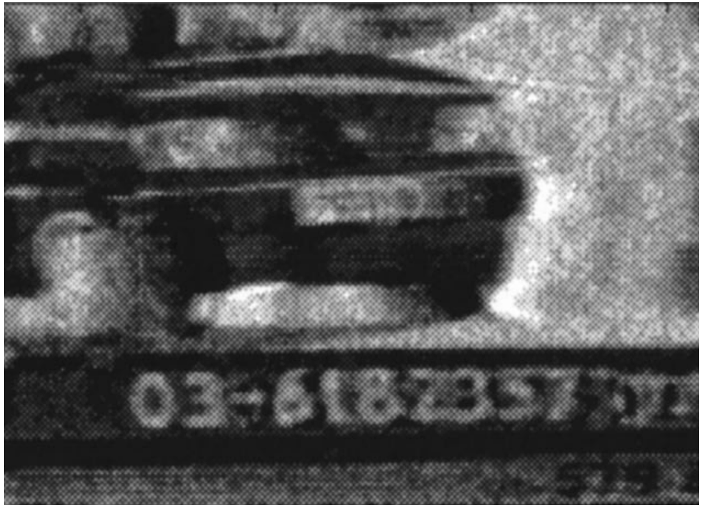
- But real camera shakes are much more complex



In The Past…

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

Blurred image



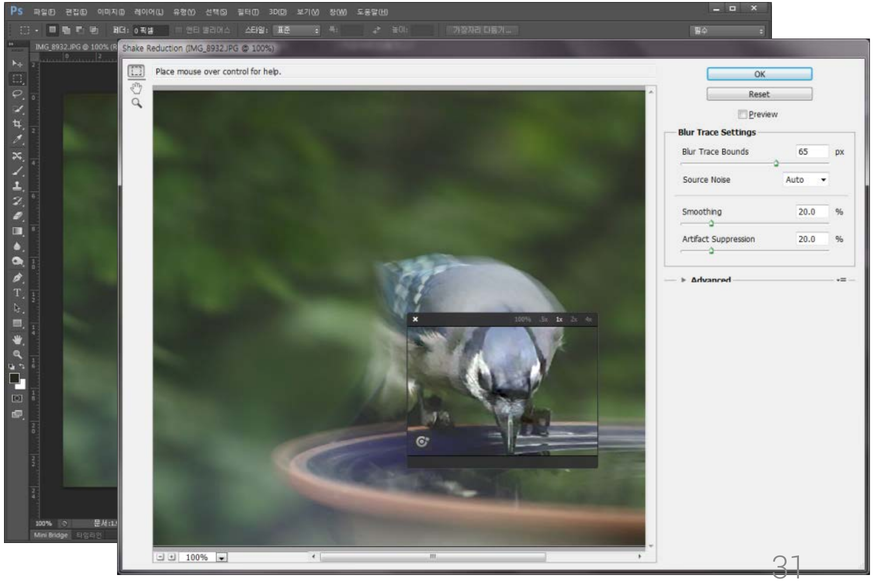
Latent sharp image

* Images from [Yitzhaky et al. 1998]

Nowadays…

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

- Commercial software
  - Photoshop CC Shake reduction



Introduction

Blind Deconvolution

Non-blind Deconvolution

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

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?

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Variational Bayesian based

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Which one is better?

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

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

Recent Popular Approaches

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Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

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- Easy to understand
- Convergence problem

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

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

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

Negative $\log$-posterior:

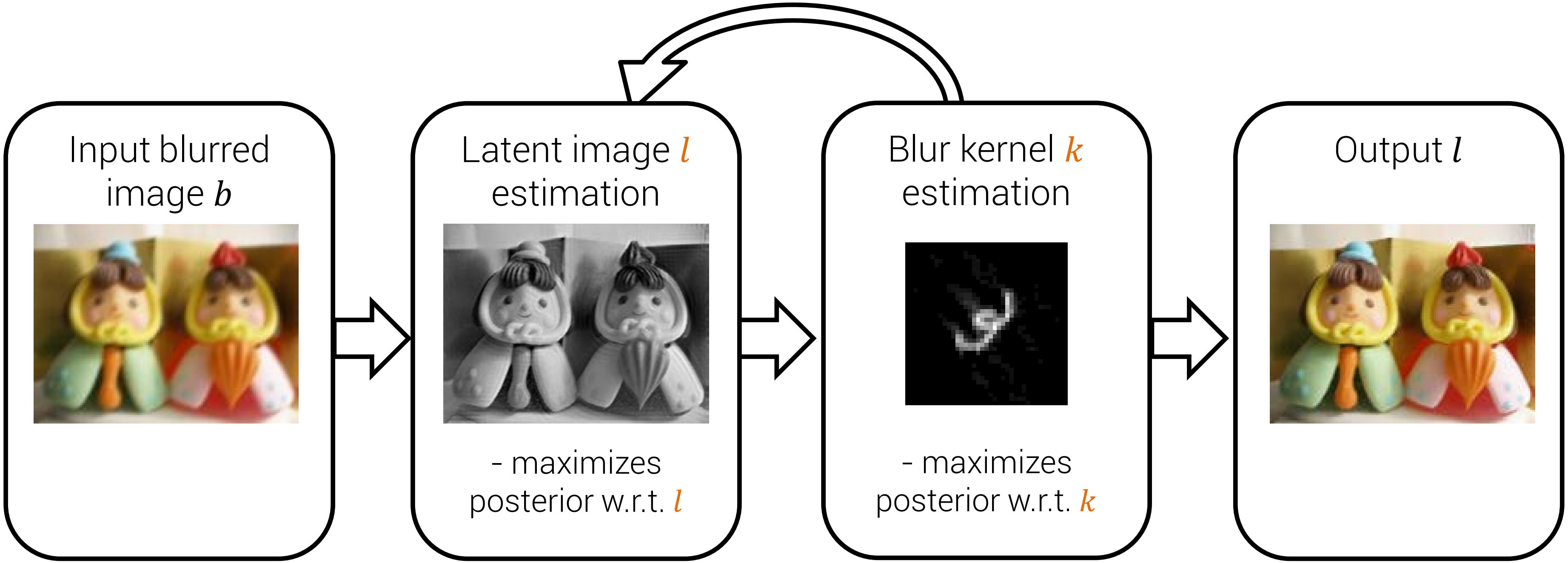
$$-\log p(k,l|b) \Rightarrow -\log p(b|k,l) - \log p(l) - \log p(k)$$
$$\Rightarrow \underbrace{\|k * l - b\|^2}_{\text{Data fitting term}} + \underbrace{\rho_l(l)}_{\text{Regularization on latent image } l} + \underbrace{\rho_k(k)}_{\text{Regularization on blur kernel } k}$$

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

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

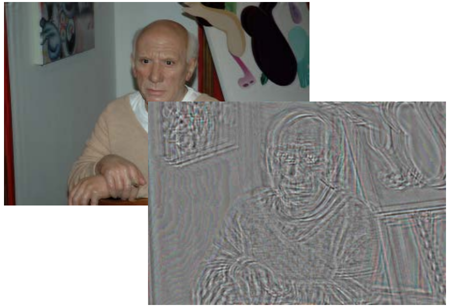
- Chan and Wong, TIP 1998
  - Total variation based priors for estimating a parametric blur kernel
- Shan et al. SIGGRAPH 2008
  - First MAP based method to estimate a nonparametric blur kernel
- Krishnan et al. CVPR 2011
  - Normalized sparsity measure, a novel prior on latent images
- Xu et al. CVPR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

Shan et al. SIGGRAPH 2008

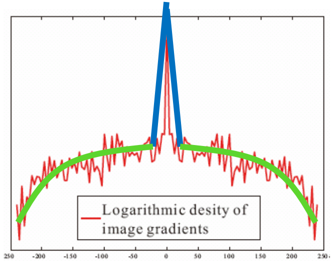
- Carefully designed likelihood & priors

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

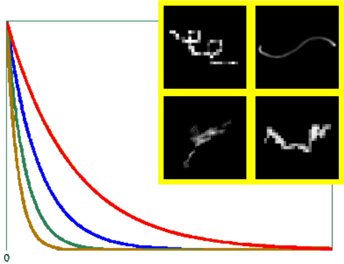
Likelihood based on intensities & derivatives



Natural image statistics based prior on l



Kernel statistics based prior on k



Shan et al. SIGGRAPH 2008

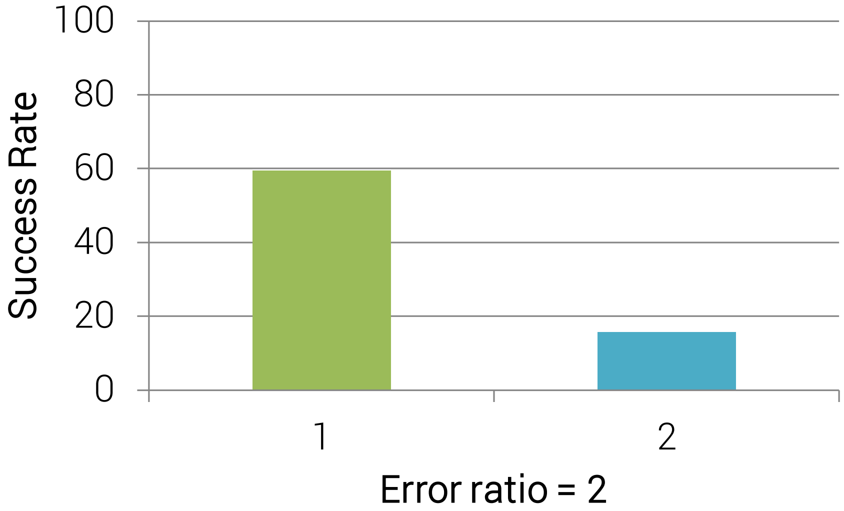
- A few minutes for a small image
- High-quality results

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

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

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

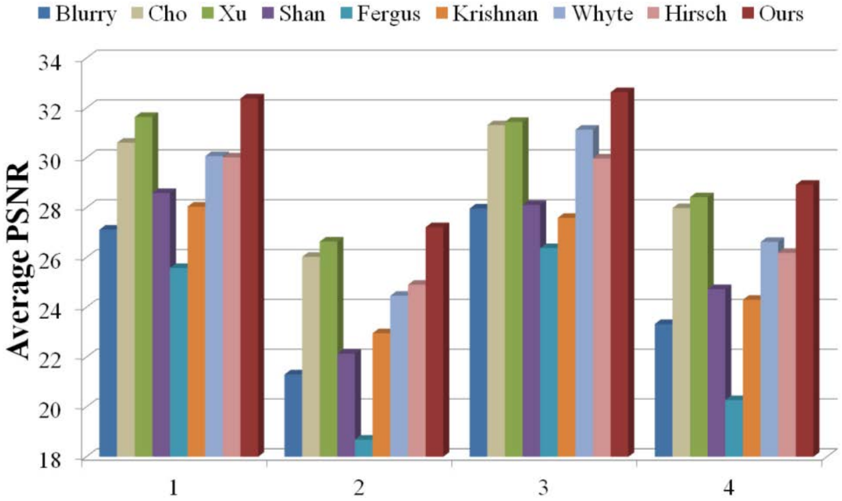
Natural image

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], …

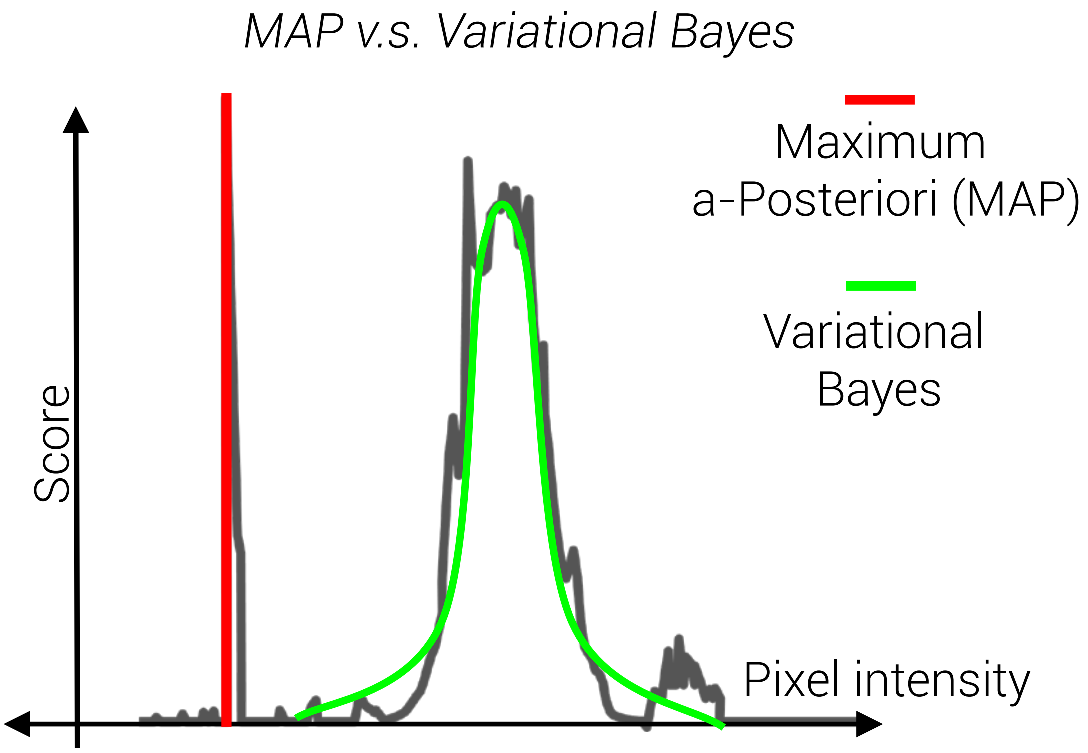
Variational Bayesian based

- 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



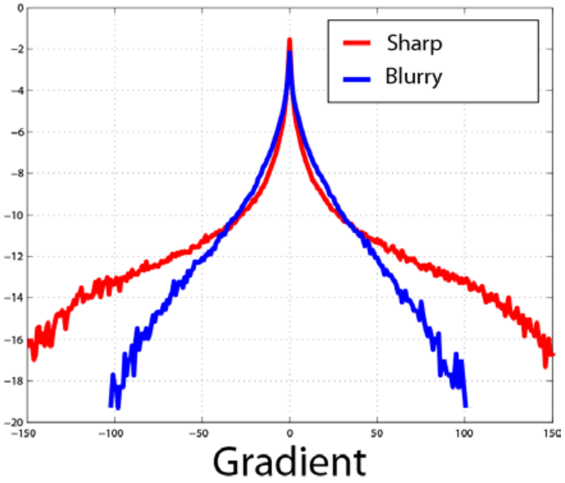
- MAP
  - Find the most probable solution
  - May converge to a wrong solution
- Variational Bayesian
  - Approximate the underlying distribution and find the mean
  - More stable
  - Slower

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

- Posterior distribution

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



Fergus et al. SIGGRAPH 2006

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

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

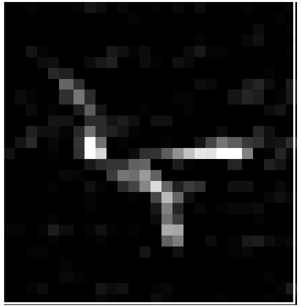
- cf) MAP based approach:

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

Fergus et al. SIGGRAPH 2006

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





Levin et al. CVPR 2010

- Efficient optimization based on EM

$$\begin{aligned} p(k|b) &\propto p(b|k)p(k) \\ &= \int_l p(b,l|k)p(k)dl \\ &= \int_l p(b|l,k)p(l)p(k)dl \end{aligned}$$

Marginalizing over l

- cf) MAP based approach:

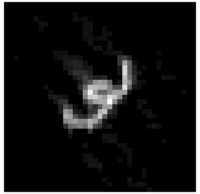
$$p(k,l|b) \propto p(b|l,k)p(l)p(k)$$

Levin et al. CVPR 2010

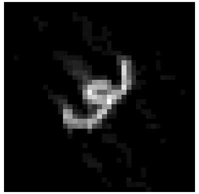
Input
blurred image b

E-step
mean &
covariance of l

M-step
update k using
mean &
covariance of l



Output
mean of k



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

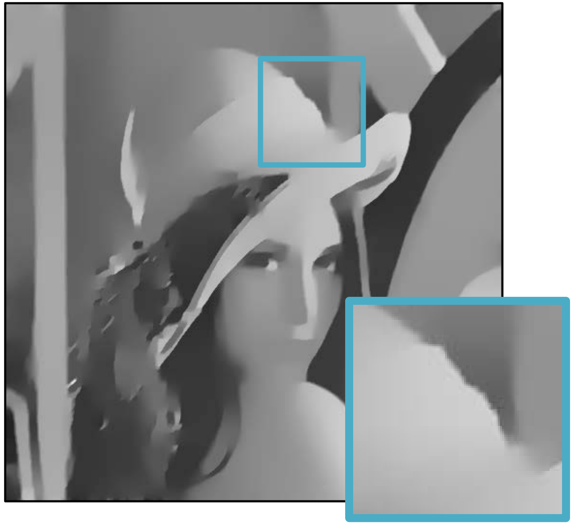
- Joshi et al. CVPR 2008
  - Proposed sharp edge prediction to estimate blur kernels
  - No iterative estimation
  - Limited to small scale blur kernels
- Cho & Lee, SIGGRAPH Asia 2009
  - Proposed sharp edge prediction to estimate large blur kernels
  - Iterative framework
  - State-of-the-art results & 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

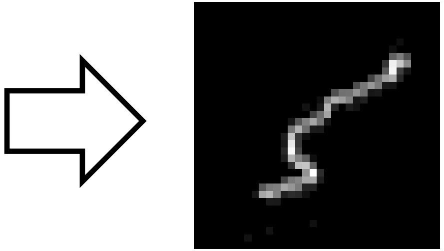
- Key idea: blur can be estimated from a few **edges**

➔ No need to restore every detail for kernel estimation

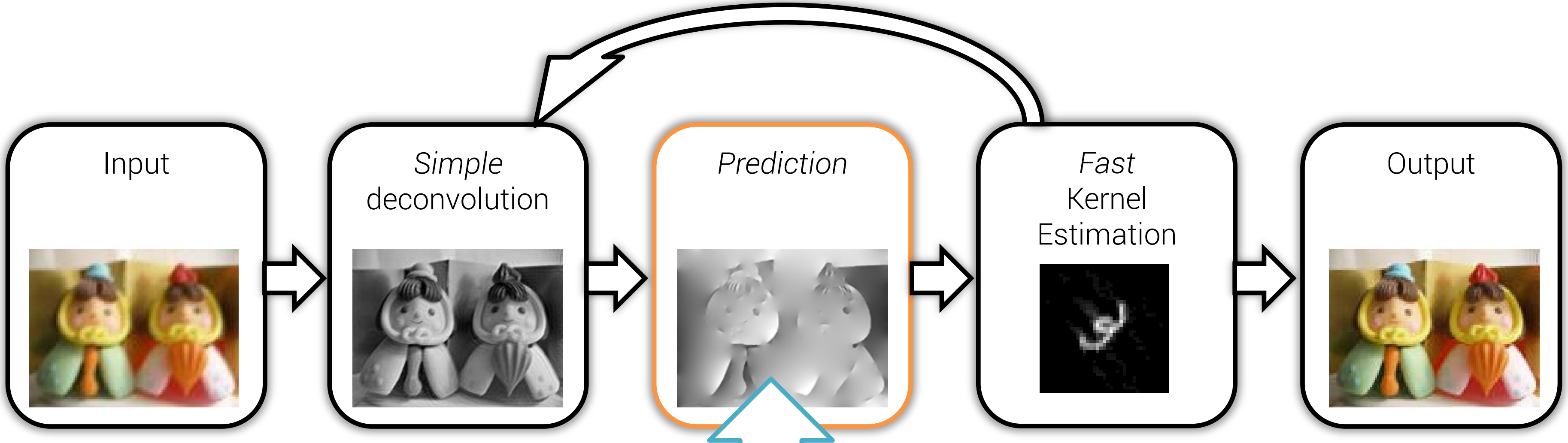
Blurred image



Latent image with only a few edges and no texture

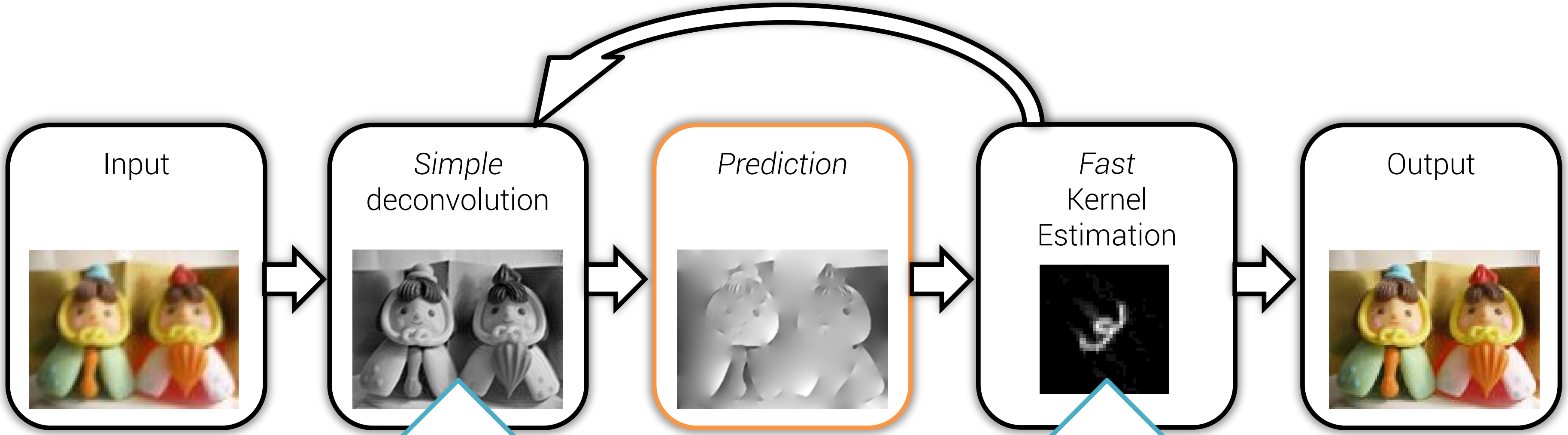


Cho & Lee, SIGGRAPH Asia 2009



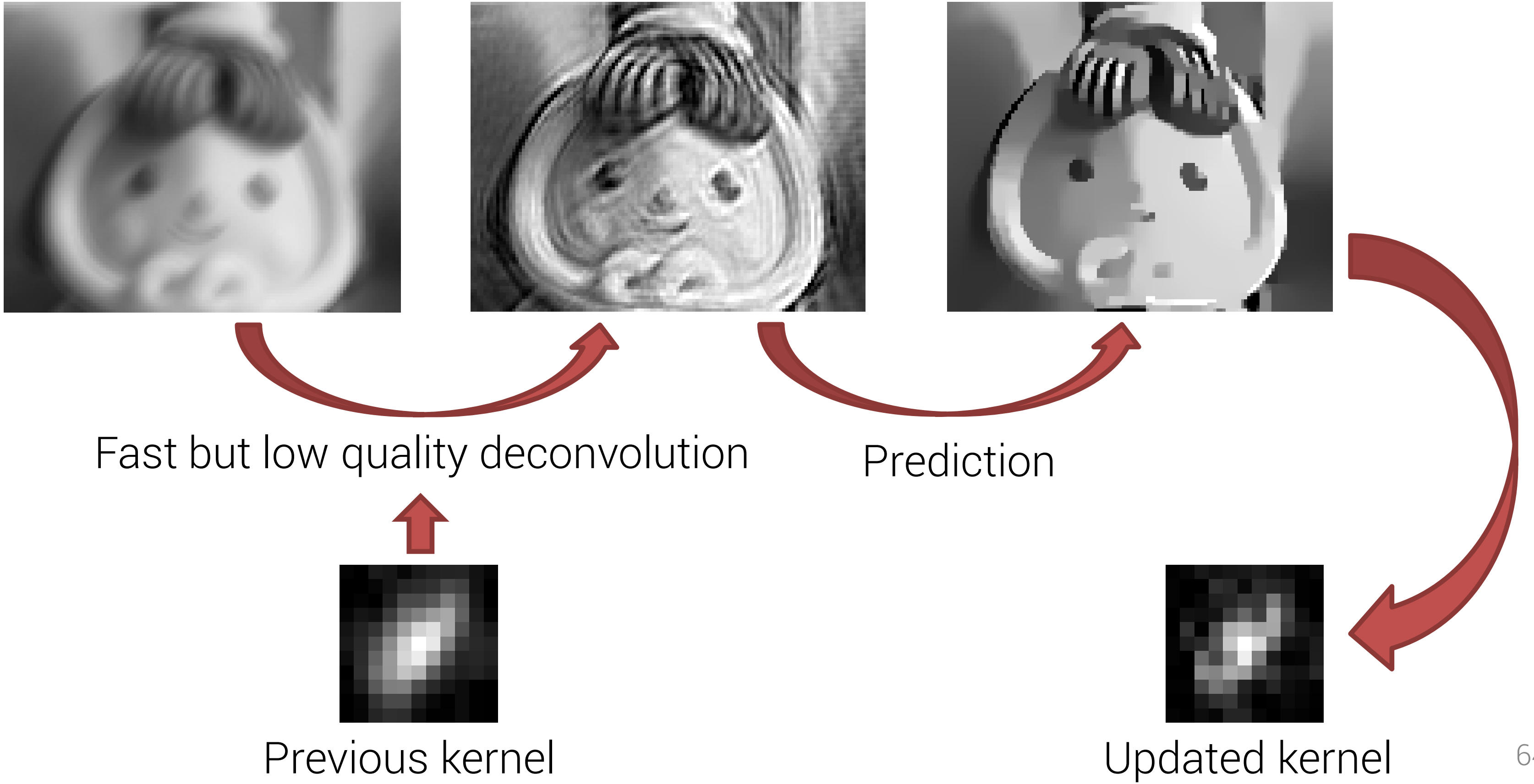
Quickly restore important edges
using simple image filters

Cho & Lee, SIGGRAPH Asia 2009

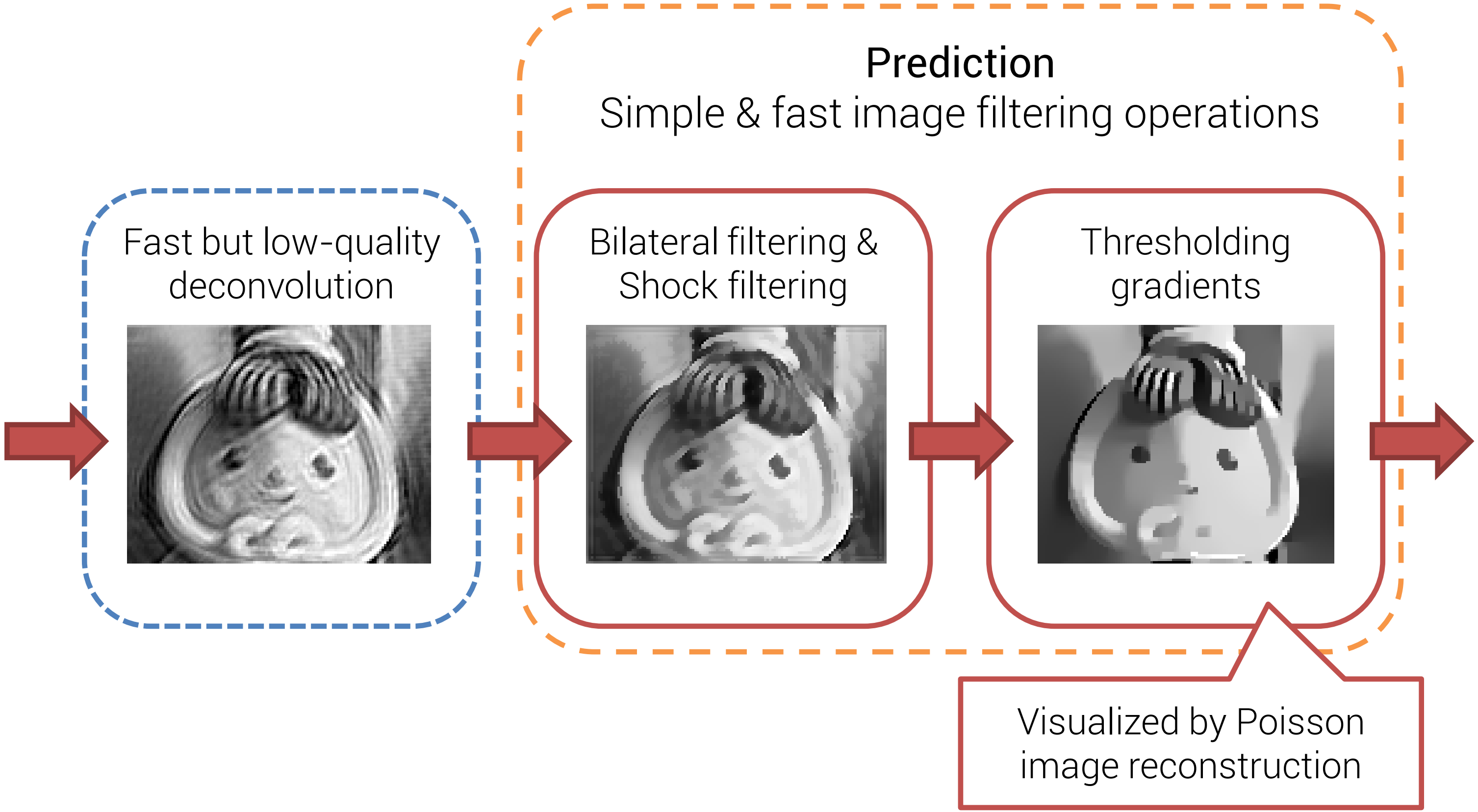


Do not need complex priors for the latent image and the blur kernel
➔ Significantly reduce the computation time

Cho & Lee, SIGGRAPH Asia 2009



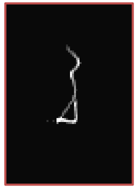
Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009


Blurry input


Deblurring result


Blur kernel

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

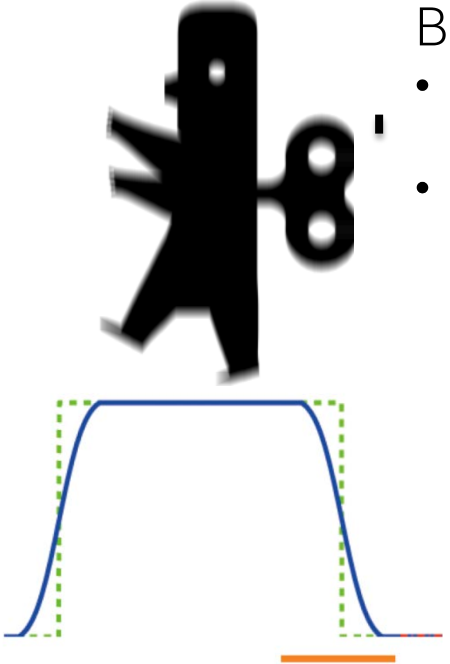
Xu & Jia, ECCV 2010

- Extended edge prediction to handle blur larger than image structures

Blurred image | Fergus et al. SIGGRAPH 2006 | Shan et al. SIGGRAPH 2008

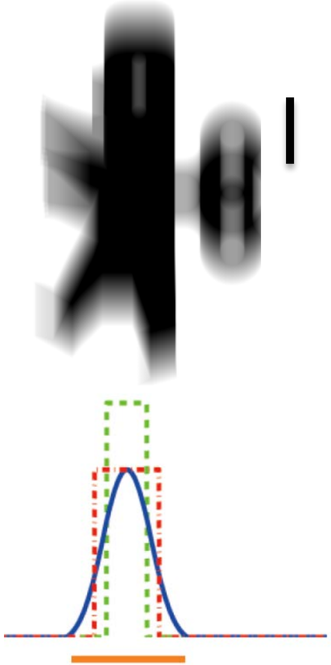
For this complex scene, most methods fail to estimate a correct blur kernel. Why?

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

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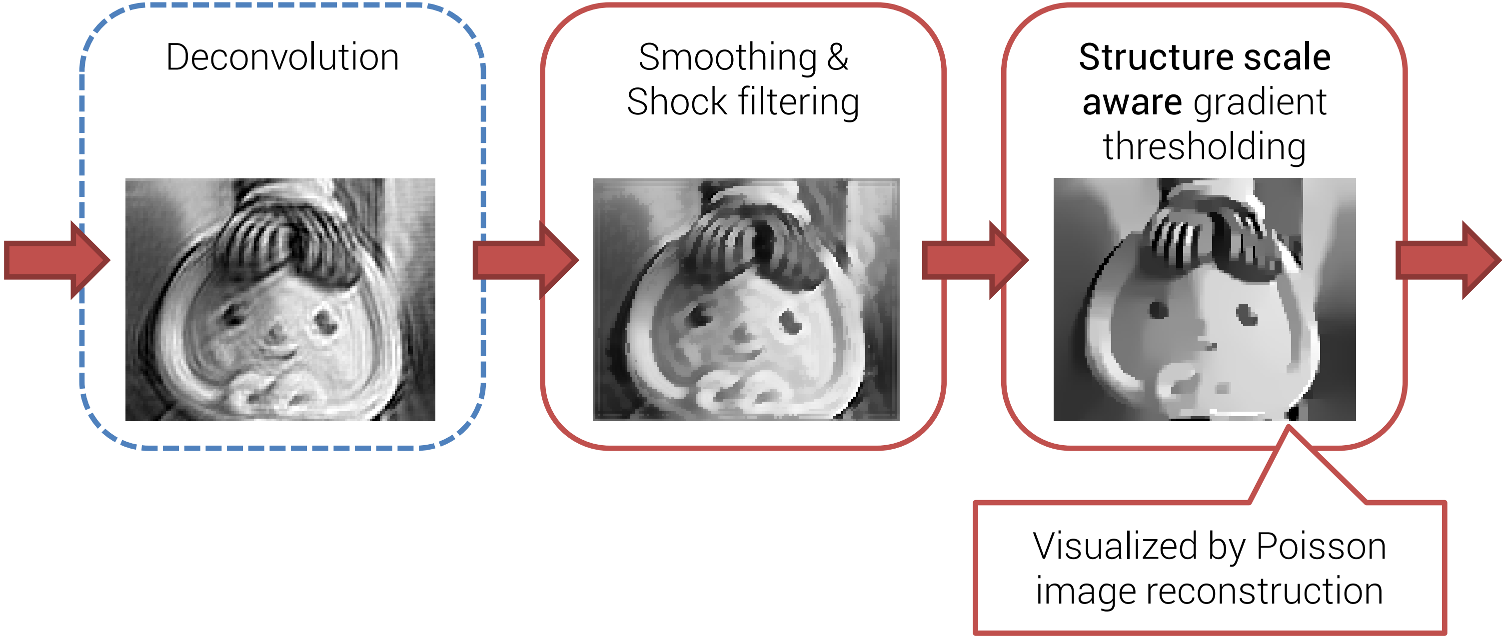
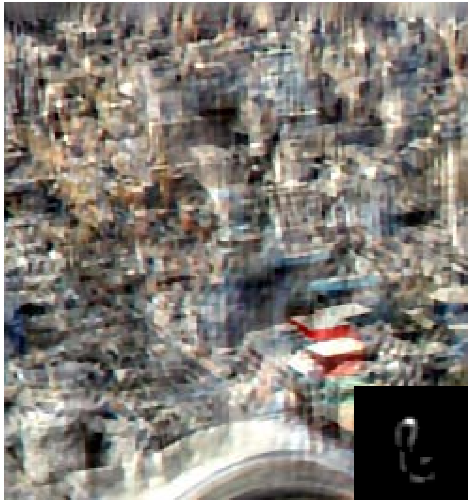


Xu & Jia, ECCV 2010

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

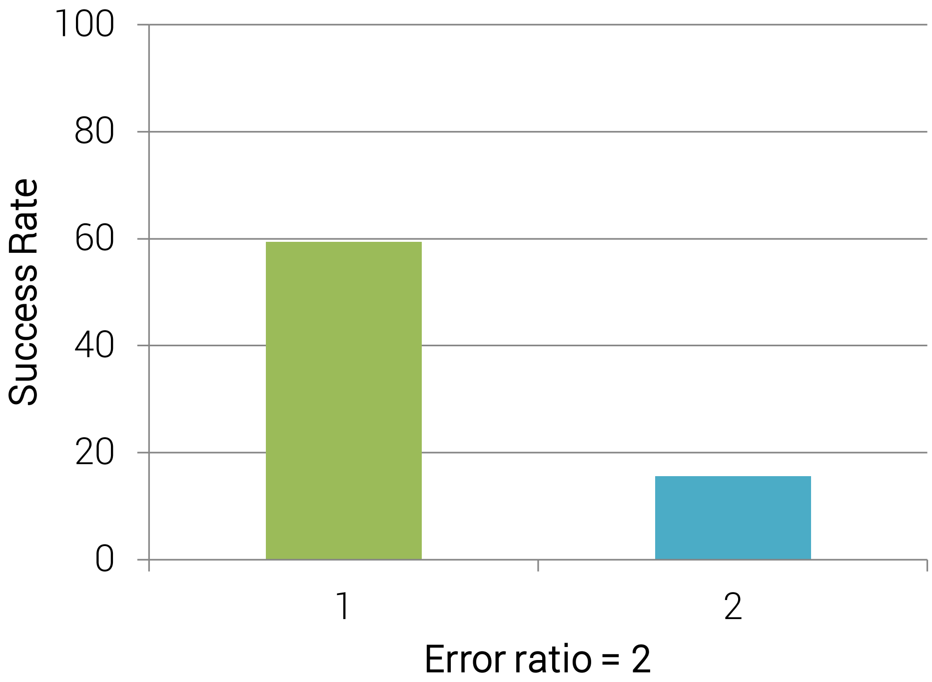
- Many different methods…
- Which one is the best?
  - Quality
  - Speed
- Different works report different benchmark results
  - Depending on test data
  - Levin et al. CVPR 2009, 2010
  - Köhler et al. ECCV 2012

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

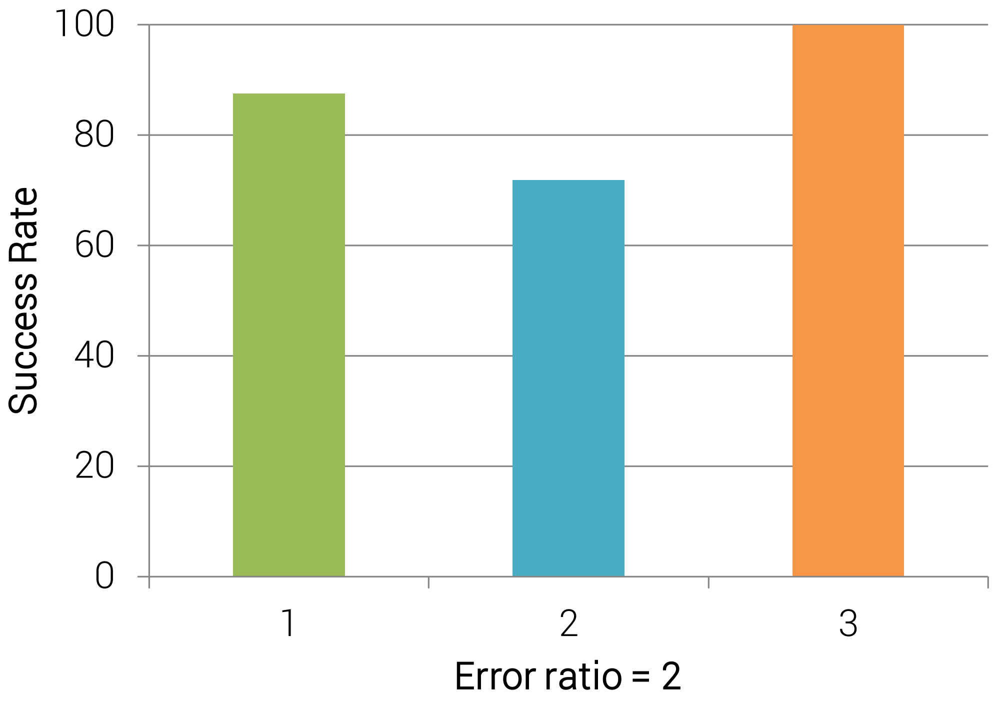
Benchmarks

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



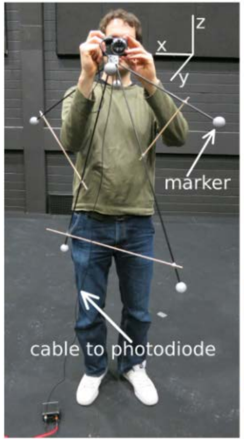
Benchmarks

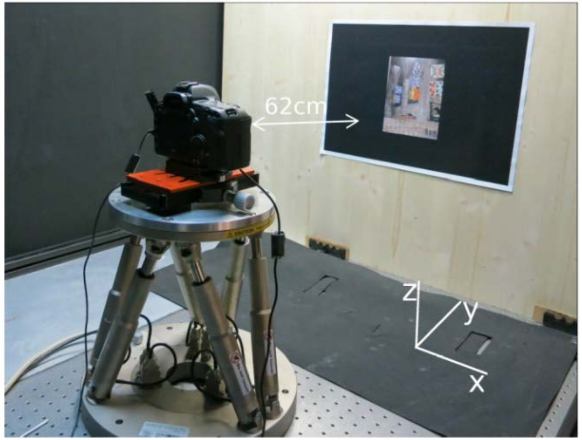
- Cho & Lee, SIGGRAPH Asia 2009
  - Comparison based on Levin et al.'s dataset
  - Slightly different parameter settings



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



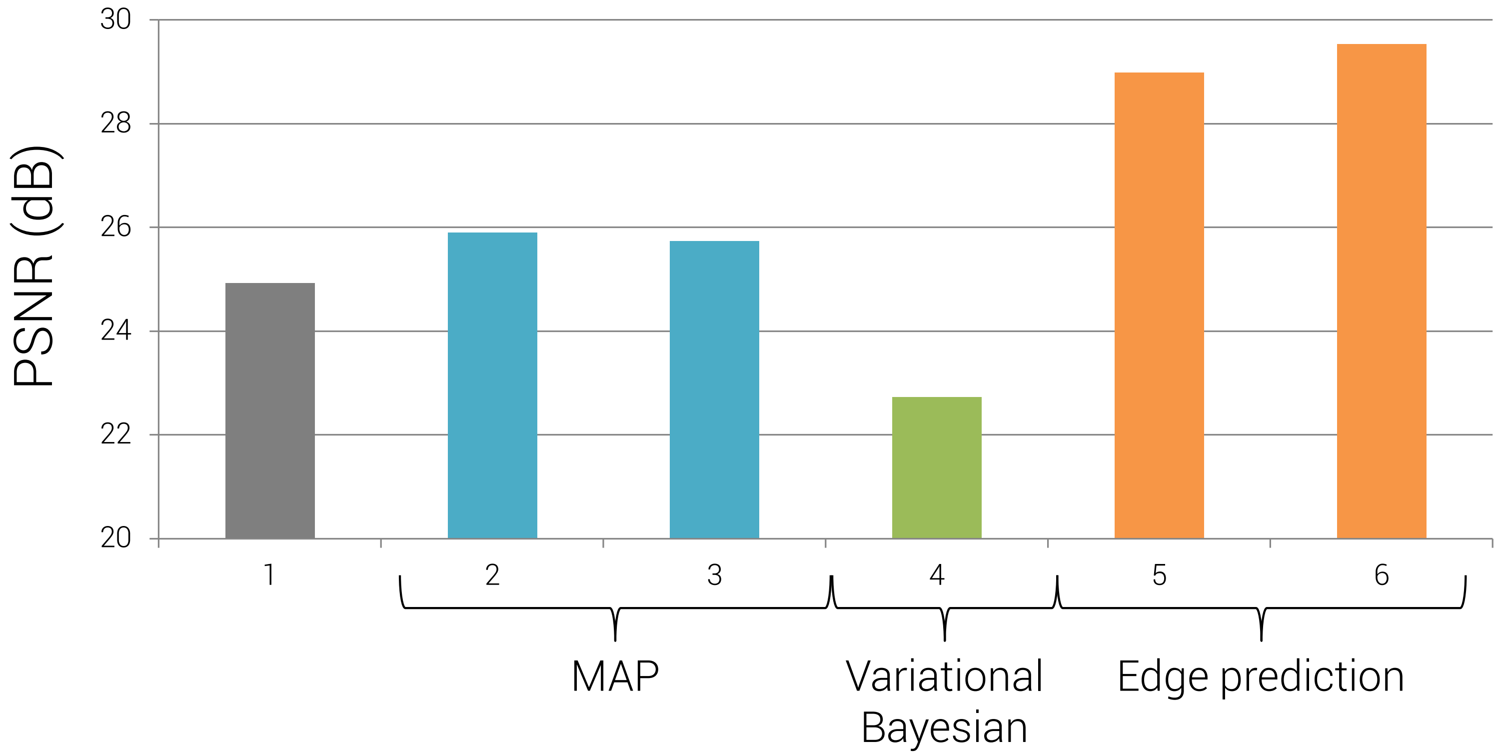


Benchmarks

- 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

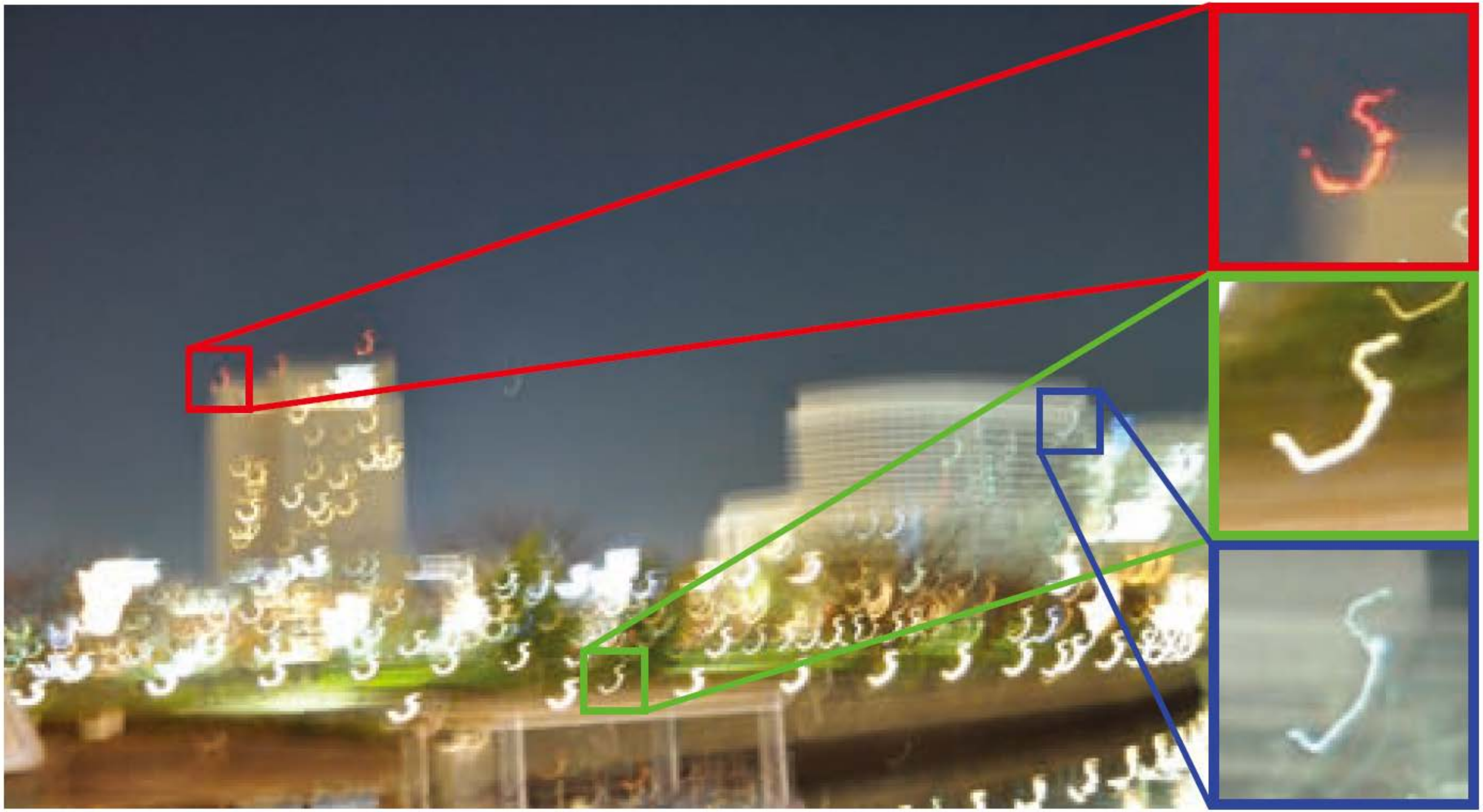
Advanced Issues

- 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

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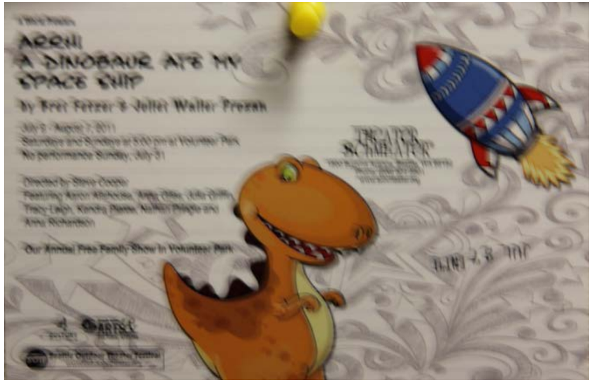
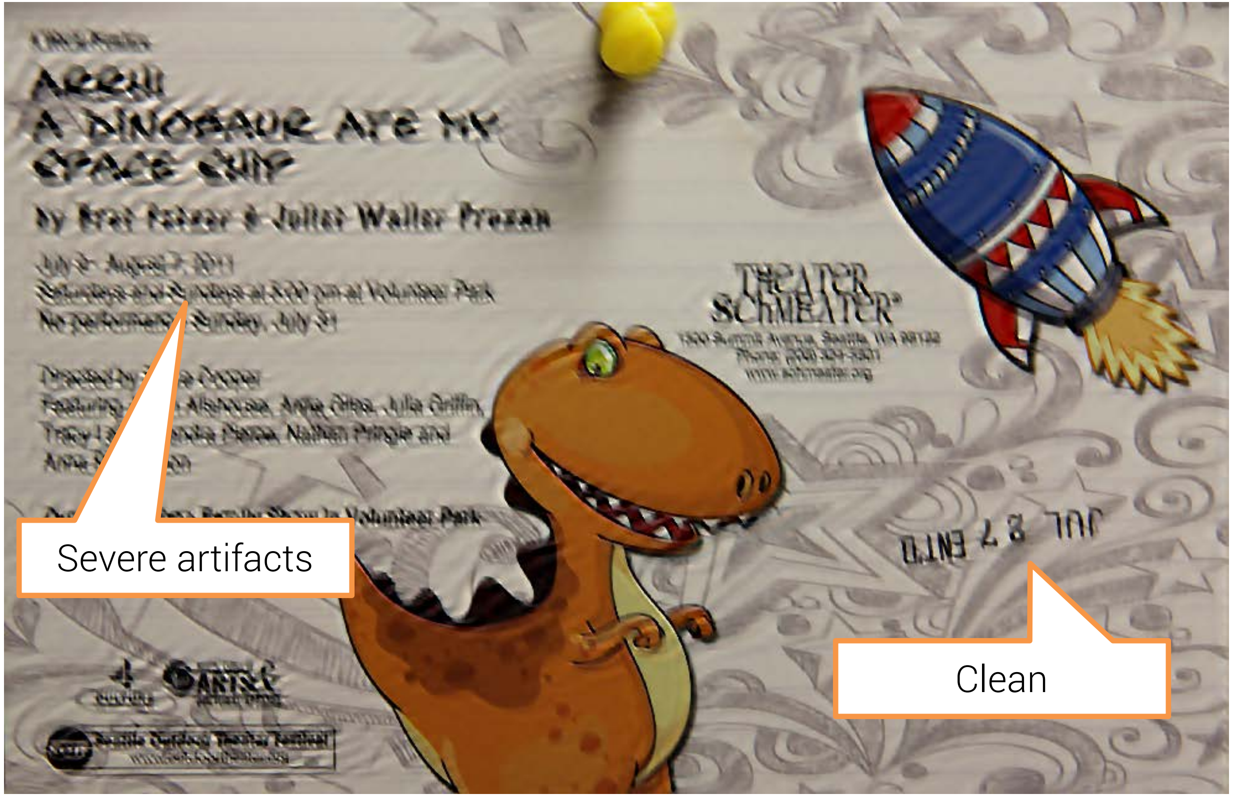


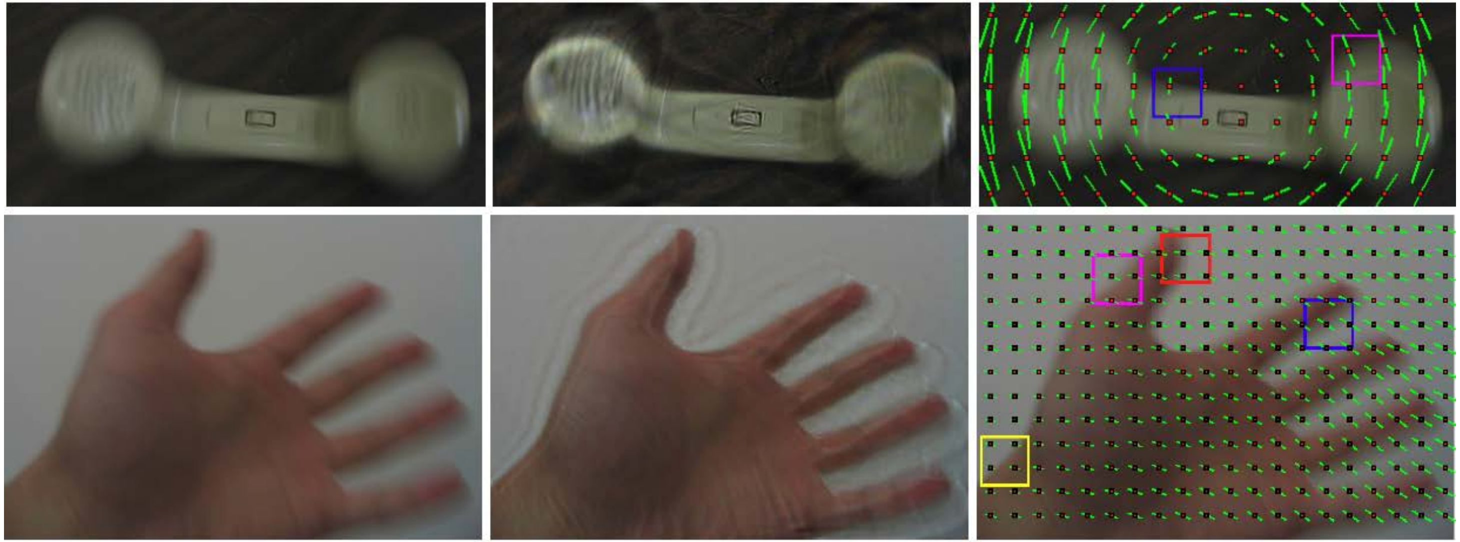
Non-uniformly blurred image



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

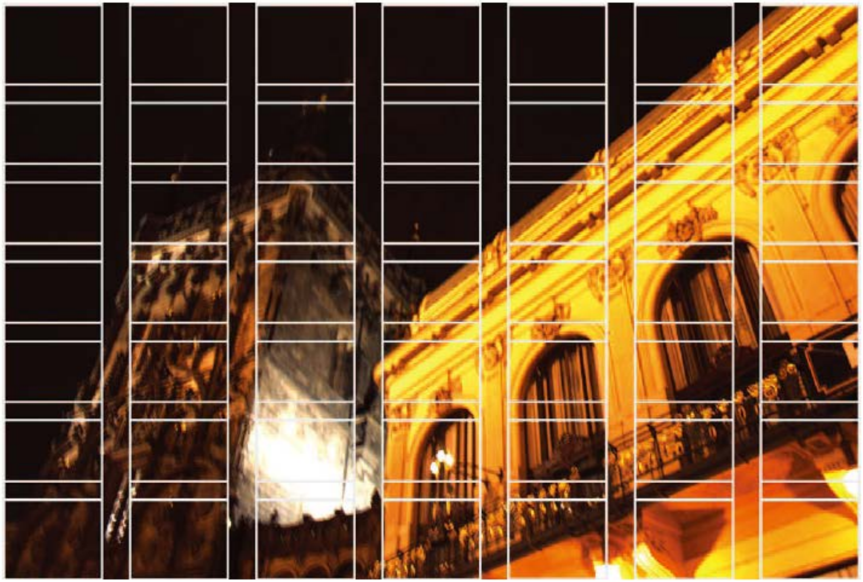


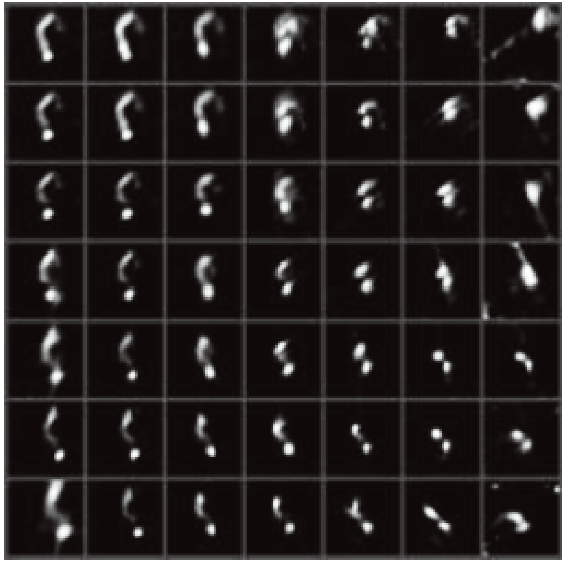
Pixel-wise Blur Model

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

Patch-wise Blur Model

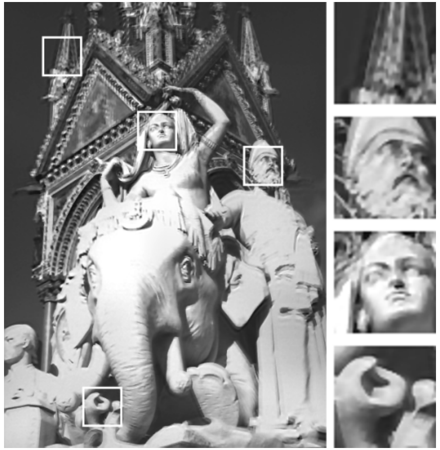
- Sorel and Sroubek, ICIP 2009
  - Estimate per-patch blur kernels from a blurred image and an underexposed noisy image





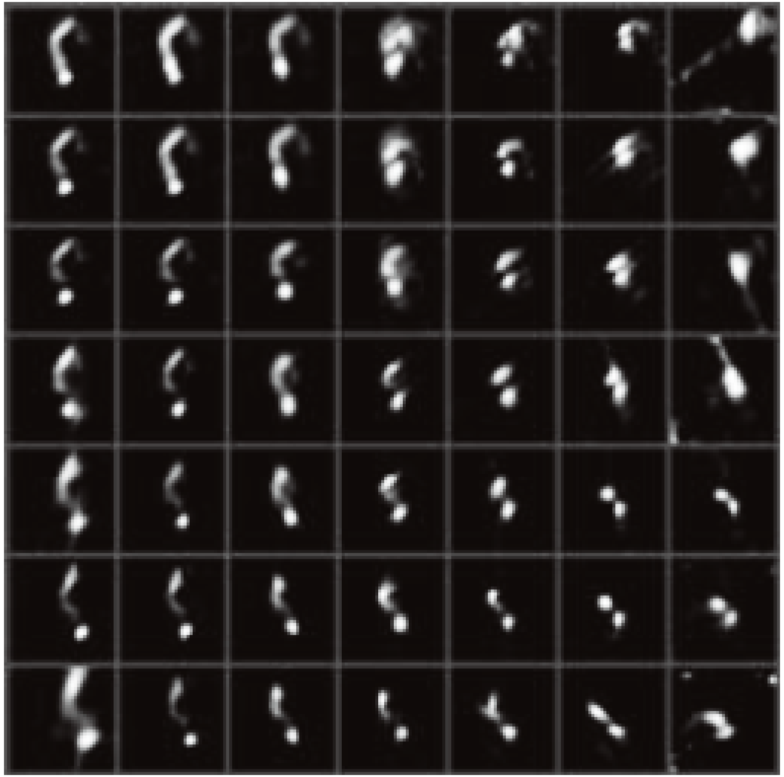
Patch-wise Blur Model

- 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

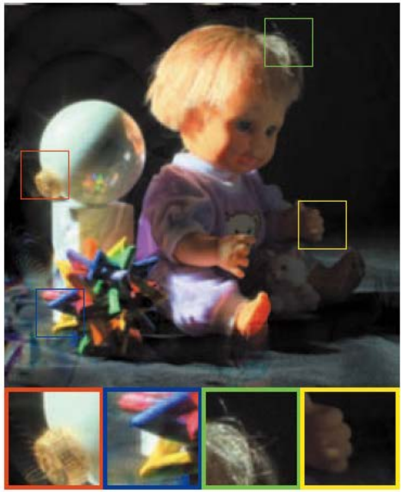
- Tai et al. TPAMI 2011
  - Homography based blur model
  - Non-blind deconvolution method


Blurred image

$$= \sum_{i=1}^{N} \underbrace{w_i}_{\text{Weight}} \underbrace{P_i}_{\text{Homography}} \left(\text{Latent image} \right)$$


Latent image


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

weight Homography

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

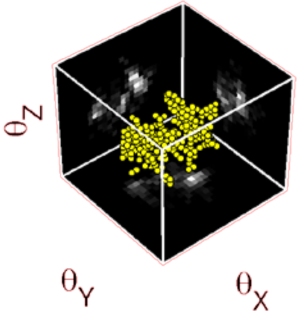
Blurred image

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

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



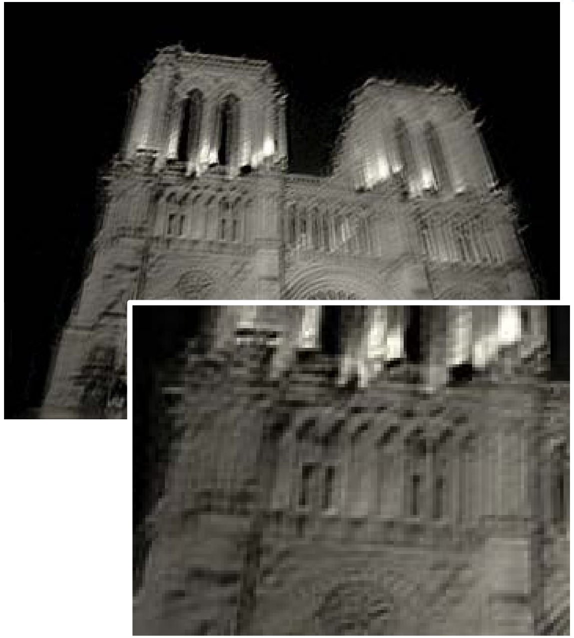
- Much easier to use with existing blind deconvolution frameworks

Projective Motion Path

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

Blurry

Whyte et al. – non-uniform



Fergus et al. – uniform

Projective Motion Path

- Gupta et al. ECCV 2010

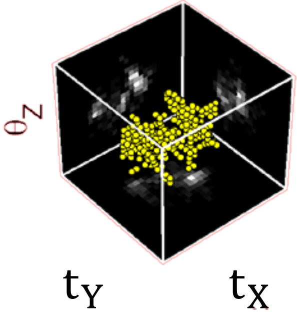
Blurred image

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

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

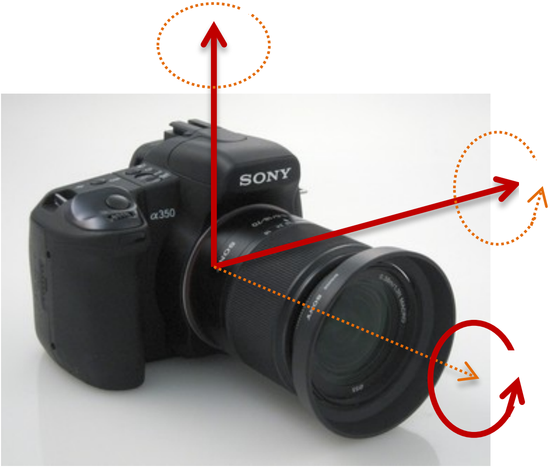
Blurred image

Gupta et al. ECCV 2010

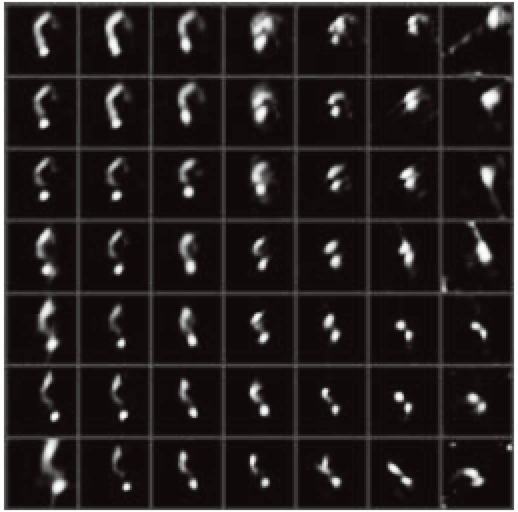
Shan et al. SIGGRAPH 2008

More Efficient Blur Model

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



Projective Motion Path:
Globally consistent &
physically plausible

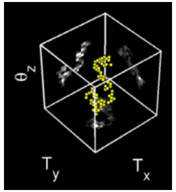


Patch-wise Blur Model:
Computationally efficient

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

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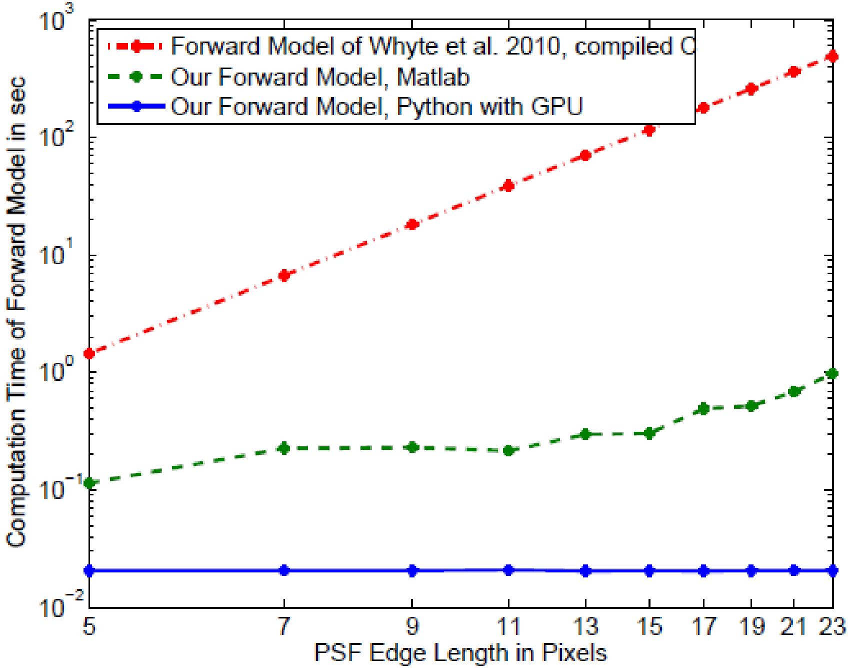
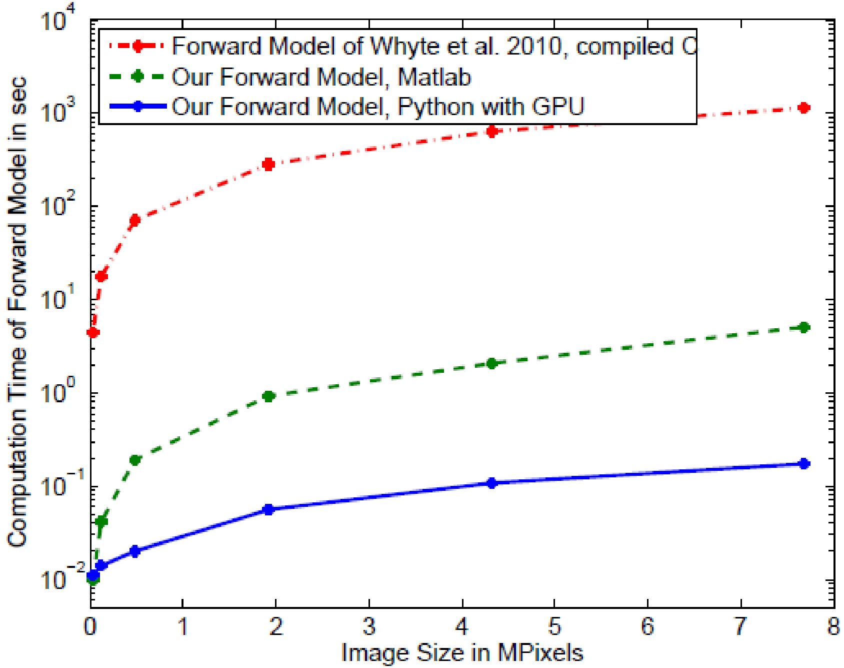
- Hirsch et al. ICCV 2011

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

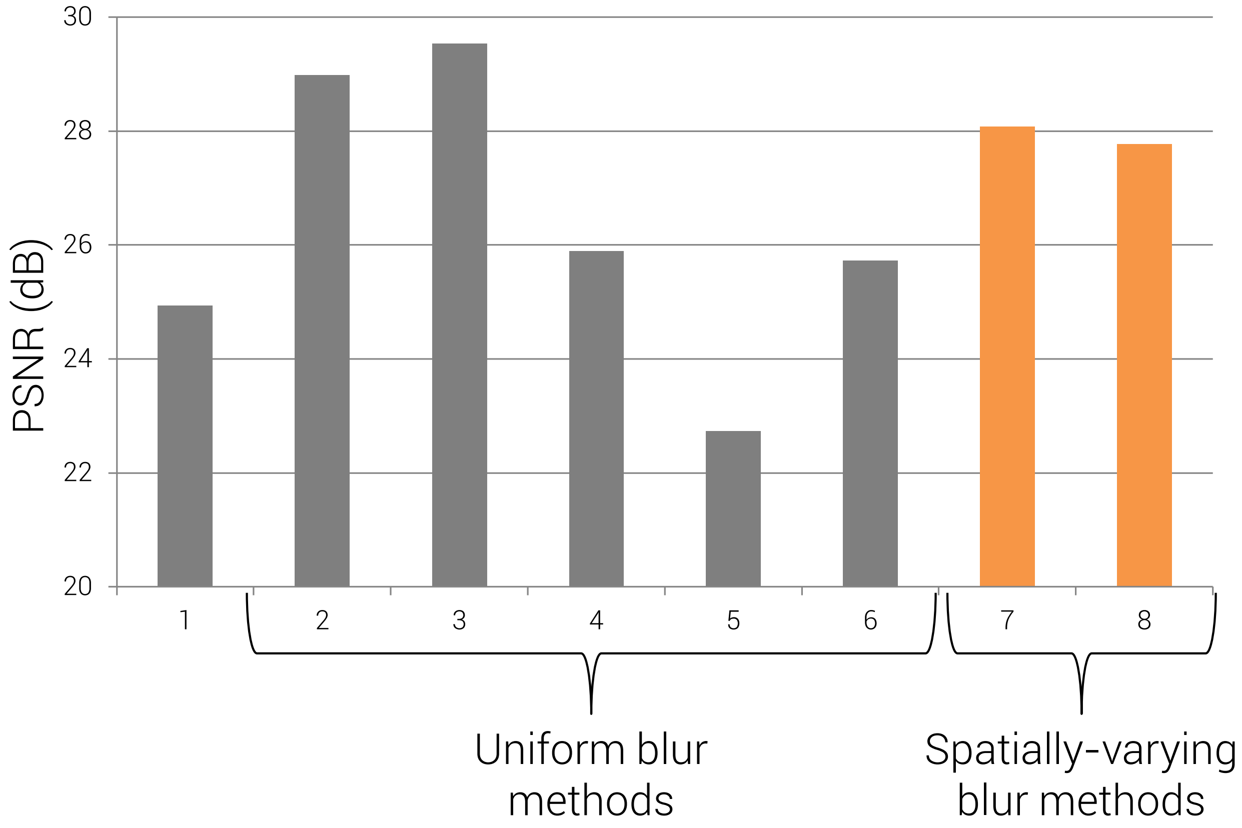


Dependence of PSF size



Dependence of image size

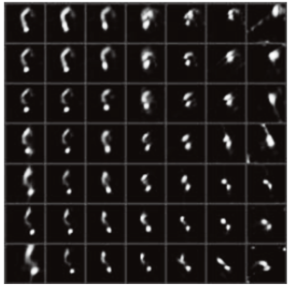
Benchmark [Köhler et al. ECCV 2012]



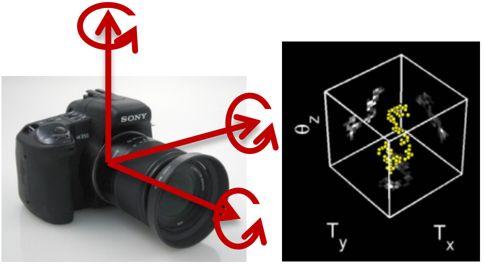
Due to high dimensionality, spatially-varying blur methods are less stable.

Summary

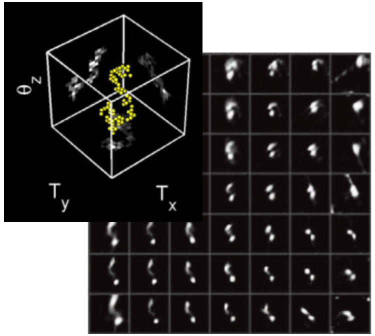
- Different blur models



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

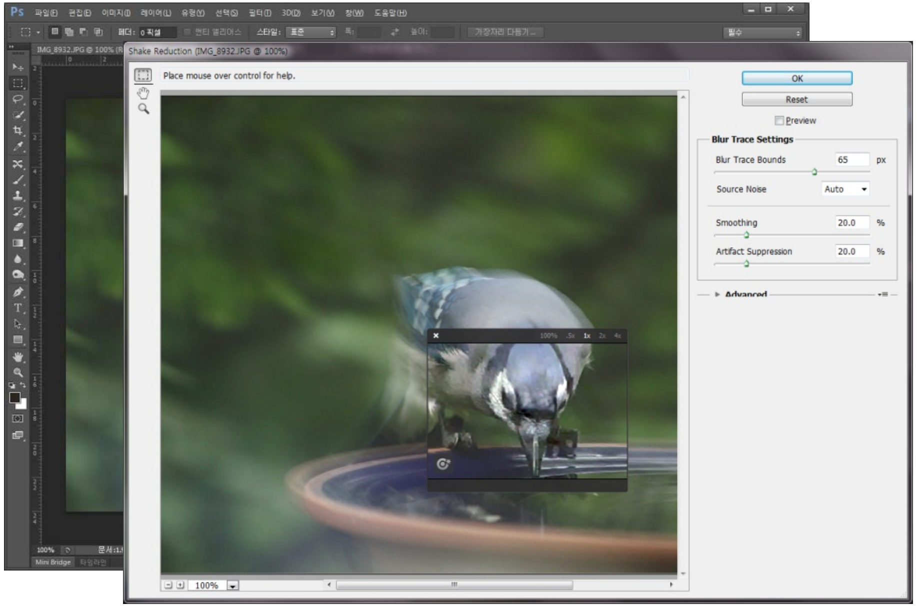
Failure example of Photoshop Shake Reduction

- 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

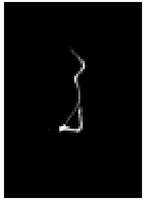
Blind Deconvolution

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

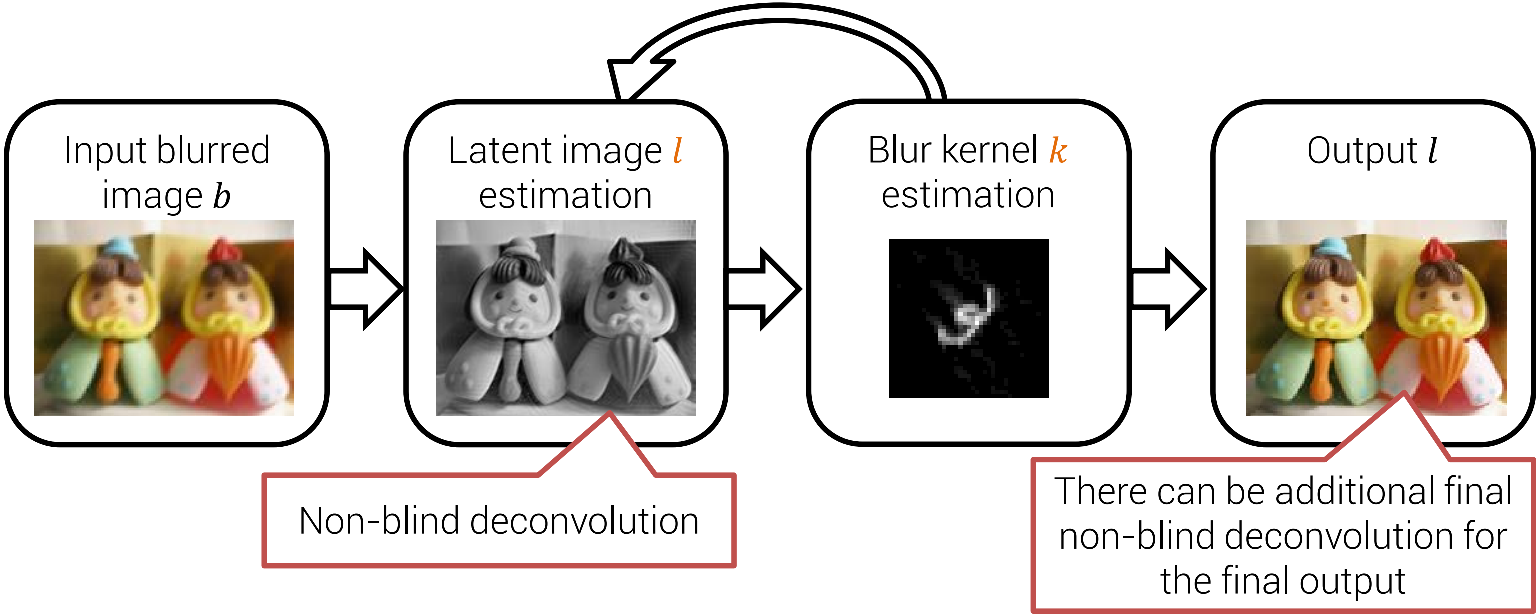
Blur kernel

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…

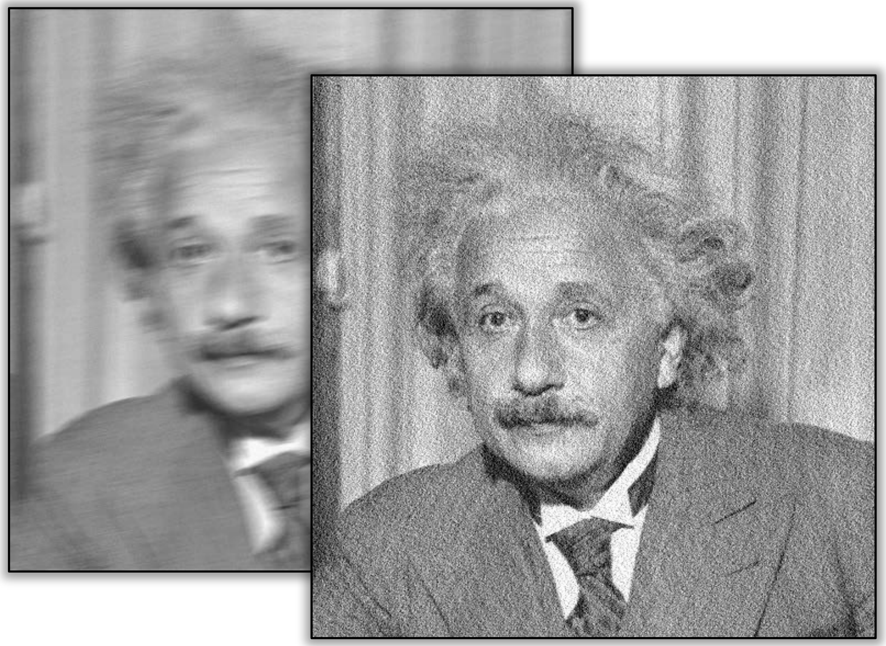
Ill-Posed Problem

- 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

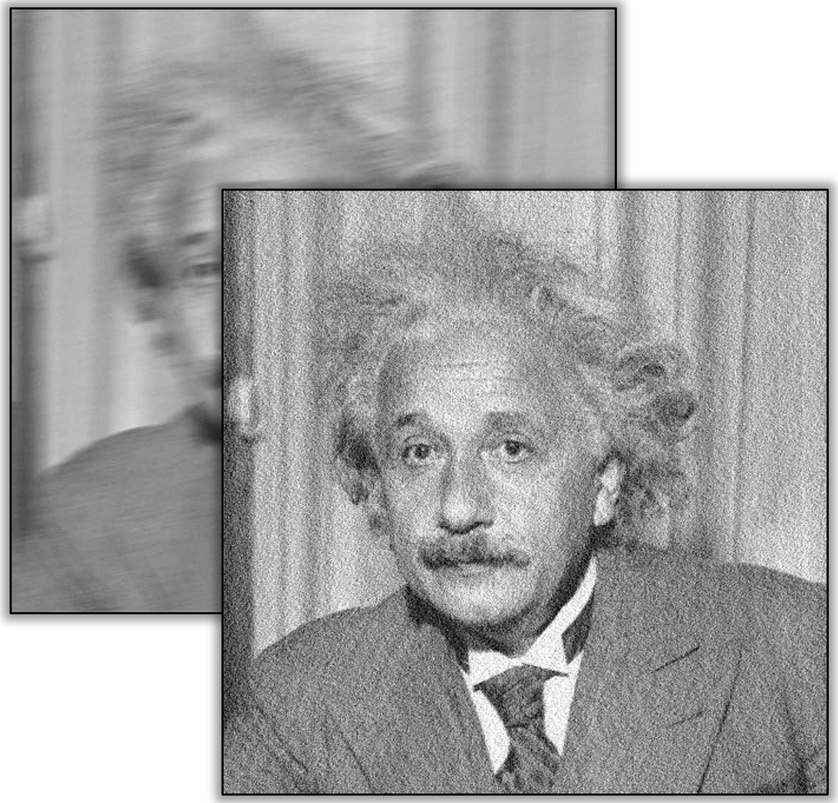
- Deconvolution amplifies noise as well as sharpens edges



- Ringing artifacts
  - Inaccurate blur kernels, outliers cause ringing 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
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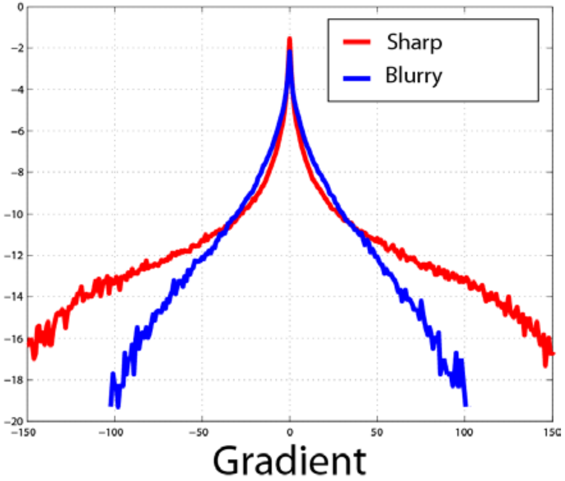
Natural Image Statistics

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

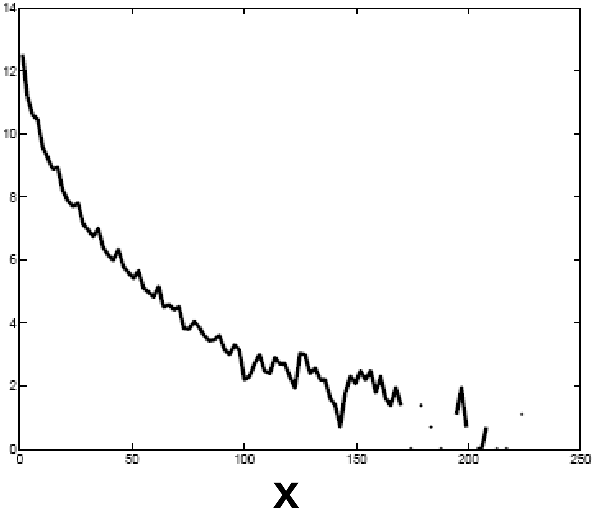
Natural Image Statistics

- 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

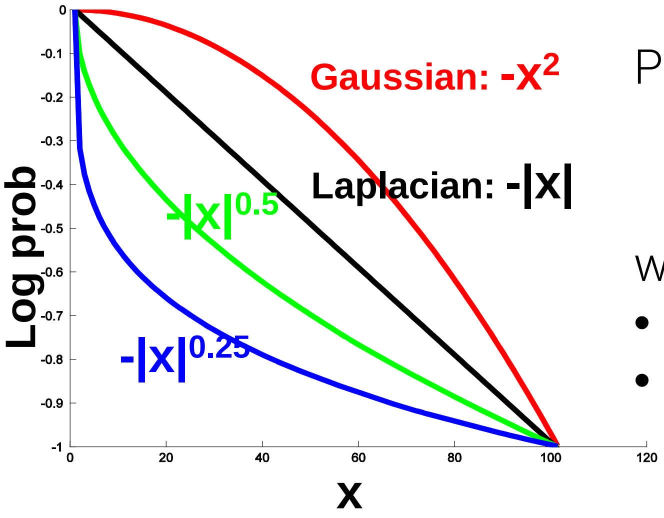



Natural Image Statistics

- 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

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

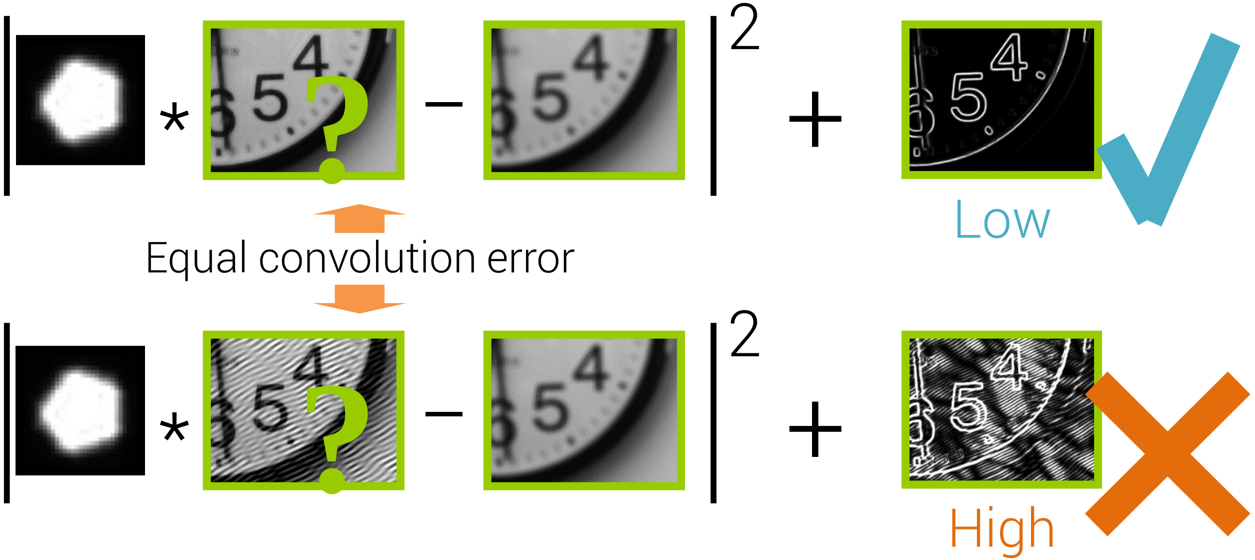
where:

- 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:

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

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

Natural Image Statistics

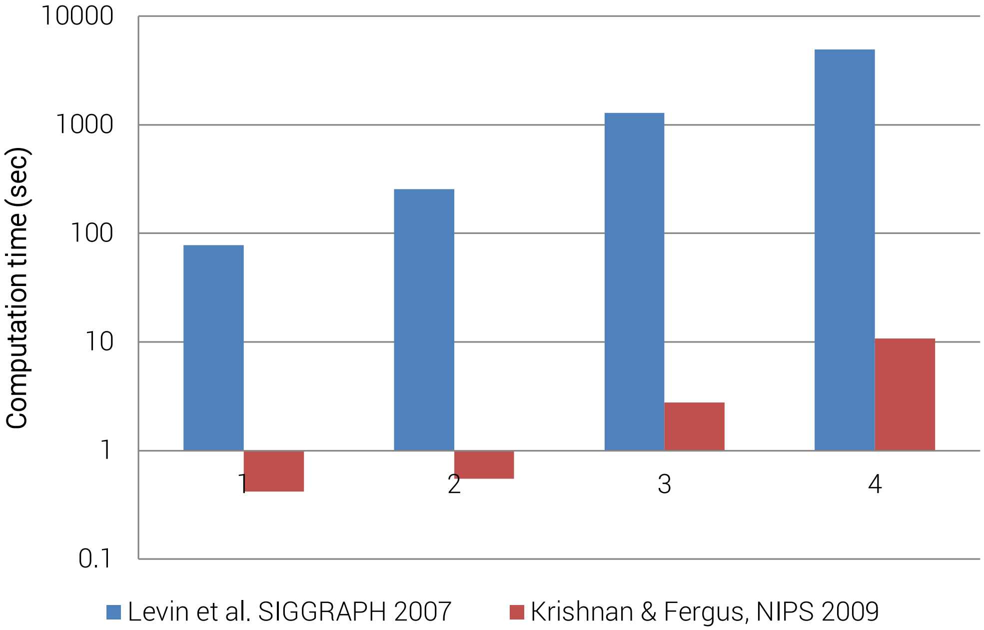
- Krishnan & Fergus, NIPS 2009

Original

Blurred

Krishnan & Fergus

Levin et al.



Similar quality, but more than 100x faster

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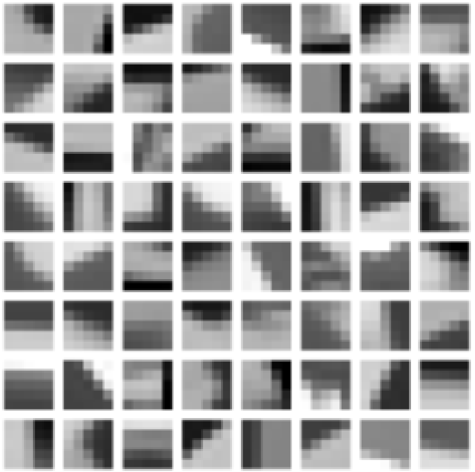
High-order Natural Image Priors

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



High-order Natural Image Priors

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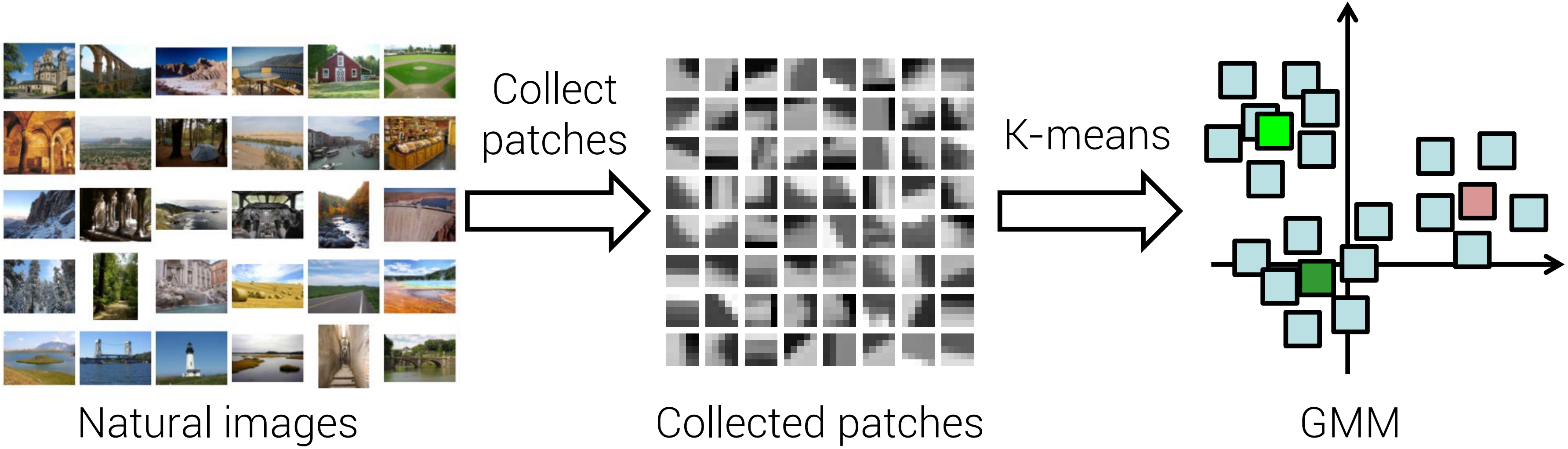
- Schmidt et al. CVPR 2011
  - Fields of Experts
- Zoran & Weiss, ICCV 2011
  - Trained Gaussian mixture model for natural image patches
- Schuler et al. CVPR 2013
  - Trained Multi-layer perceptron to remove artifacts and to restore sharp patches
- Schmidt et al. CVPR 2013
  - Trained regression tree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

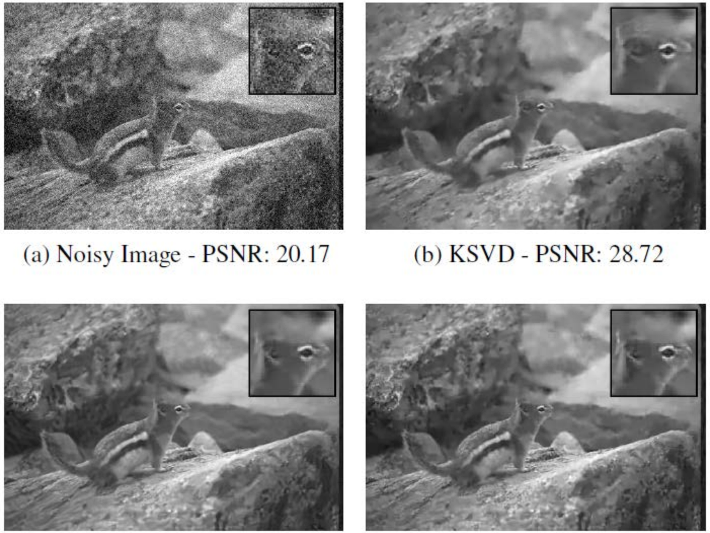
- Zoran & Weiss, ICCV 2011
  - Given a patch, we can compute its likelihood based on the GMM.
  - Deconvolution can be done by solving:

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

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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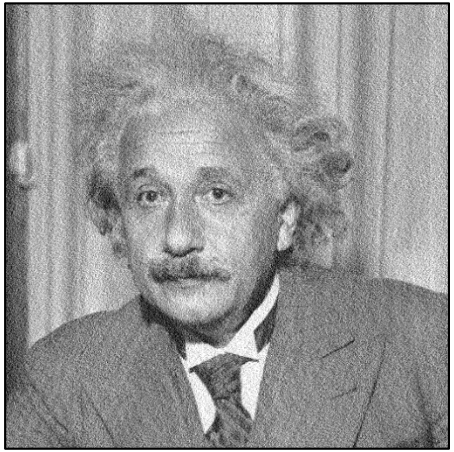
Ringing Artifacts

- 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]

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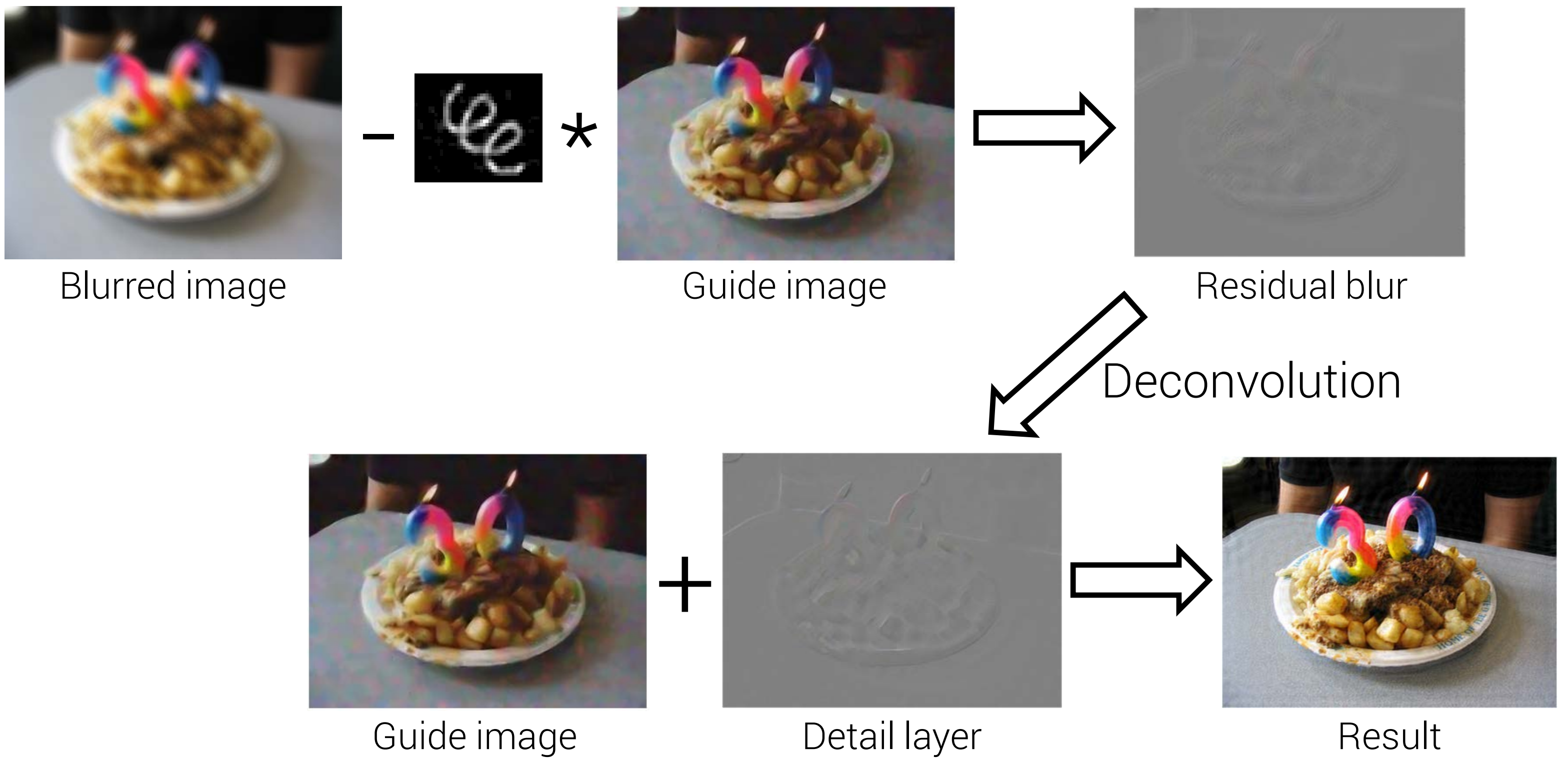
Blurred image

Guide image

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

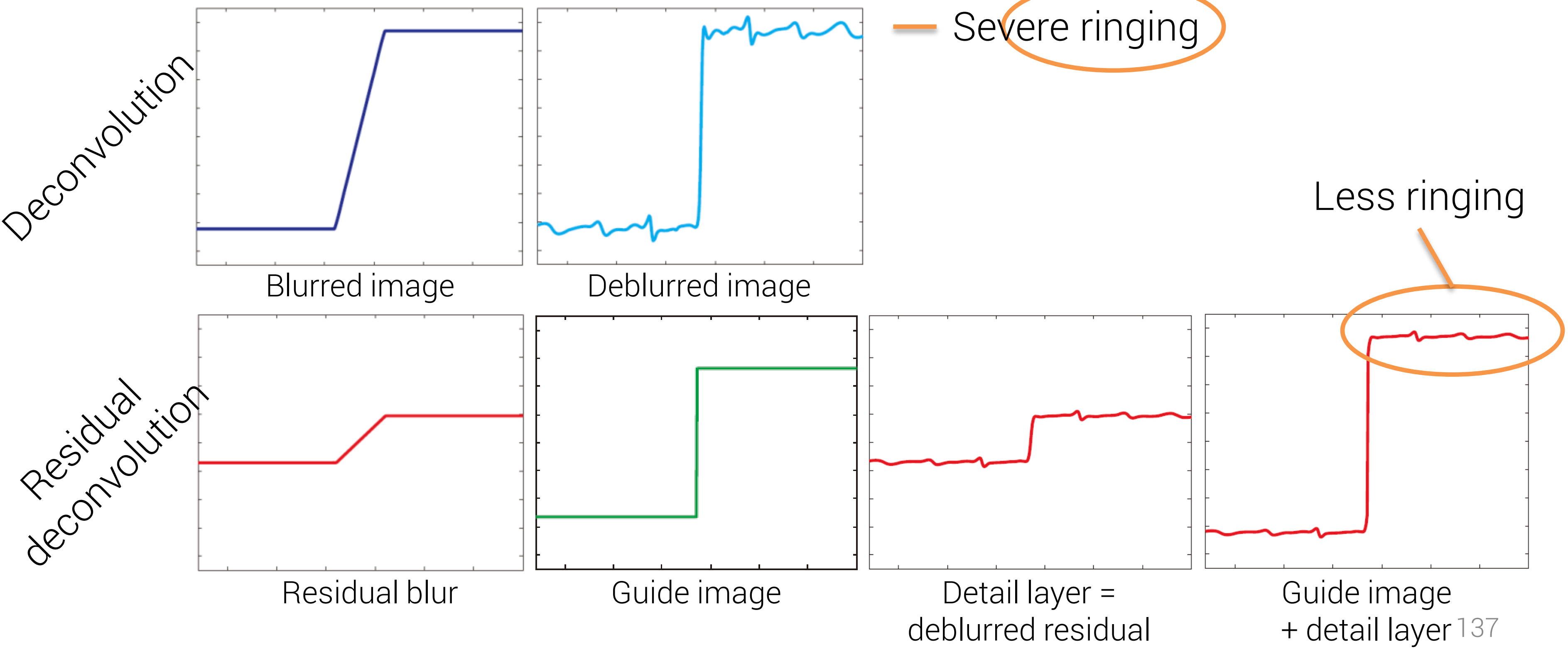
- Relatively accurate edges, but less details
- Obtained from a deconvolution result from a smaller scale

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



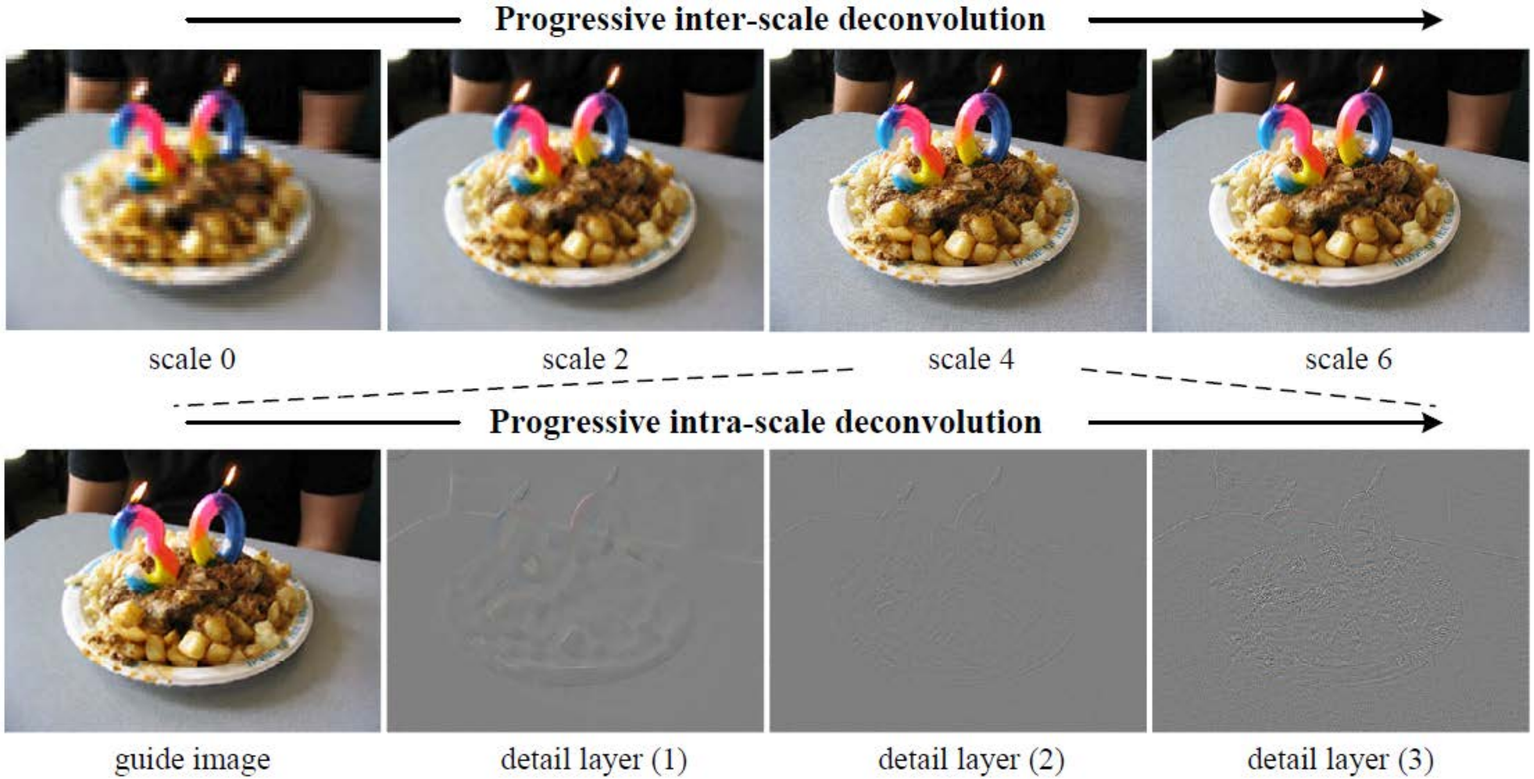
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

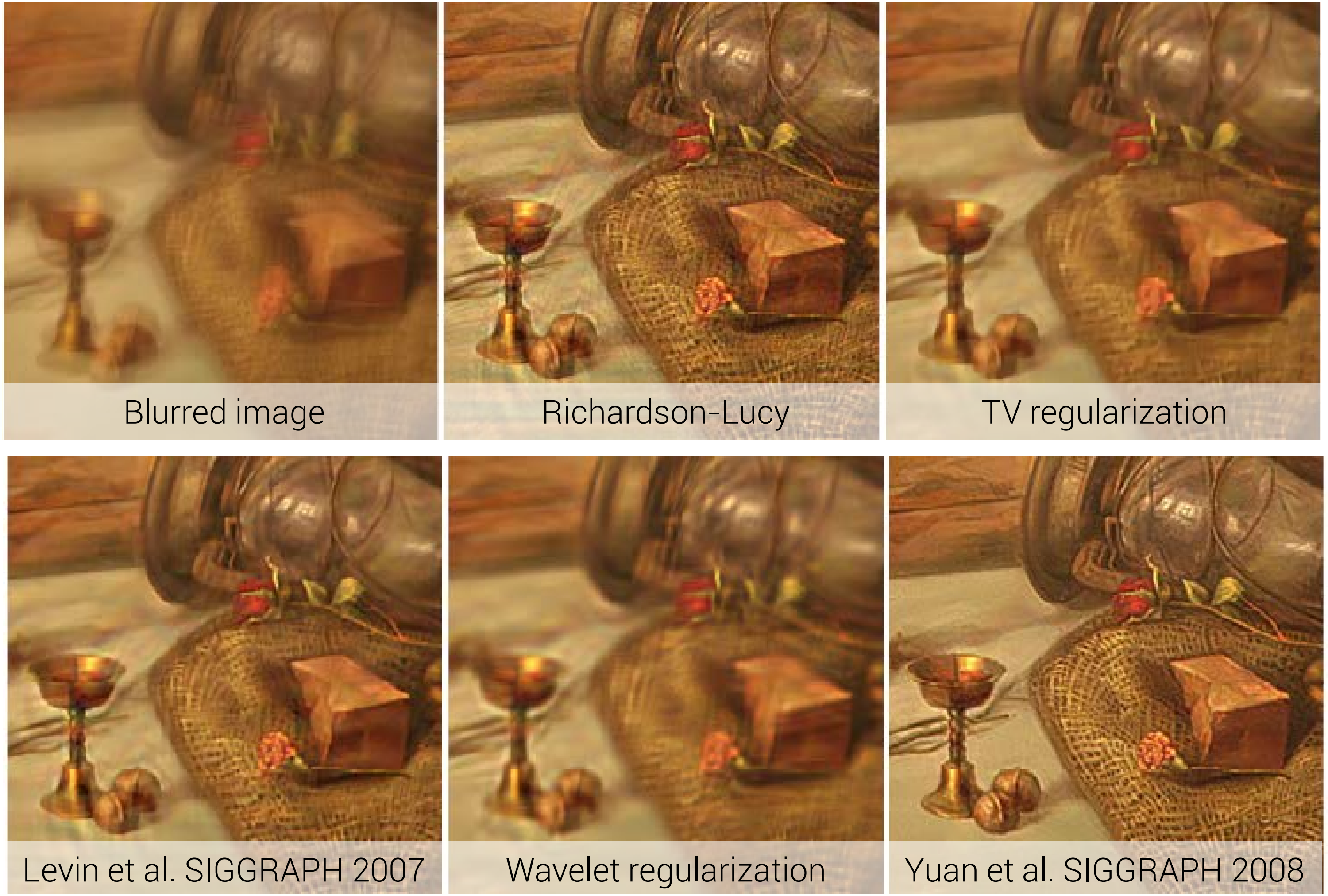
- Residual deconvolution



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

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

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

Outliers

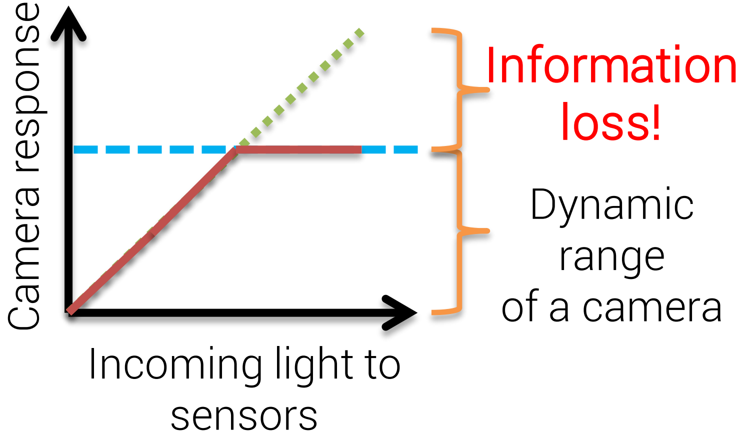
- A main source of severe ringing artifacts

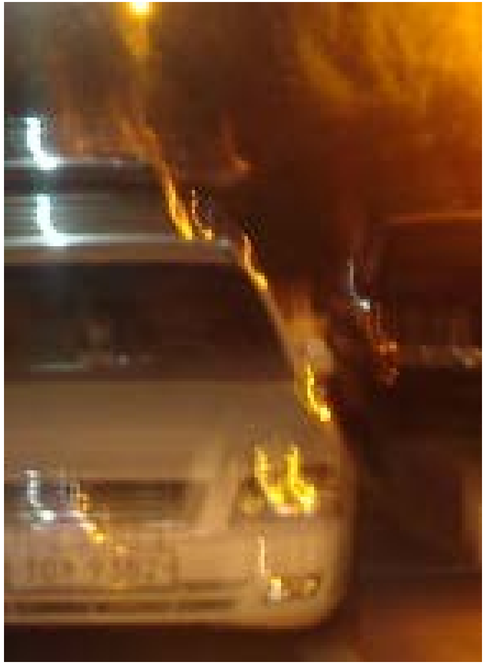
Blurred image with outliers

Deblurring result
[Levin et al. SIGGRAPH 2007]

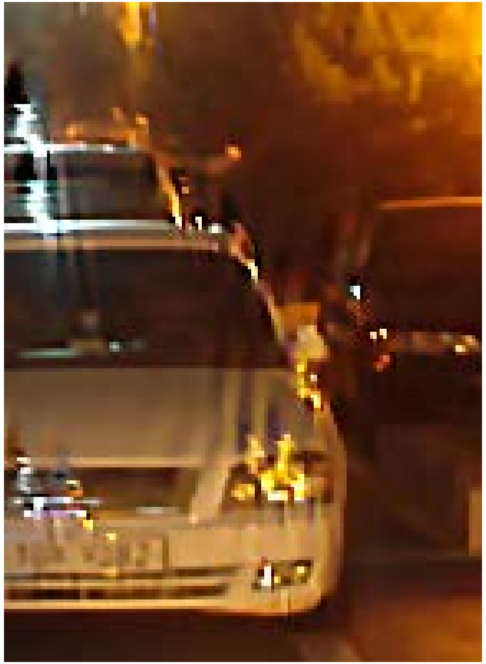
Outliers

- Saturated pixels caused by limited dynamic range of sensors





Blurred image



[Levin et al. 2007]

Outliers

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

Hot pixel

Blurred image with outliers [Levin et al. 2007]

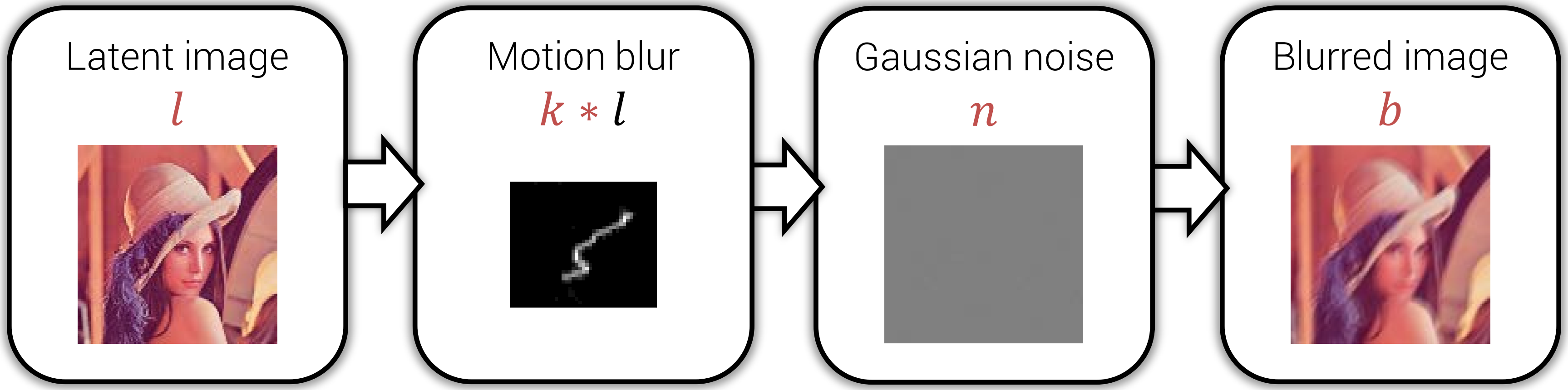
Outlier Handling

- 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

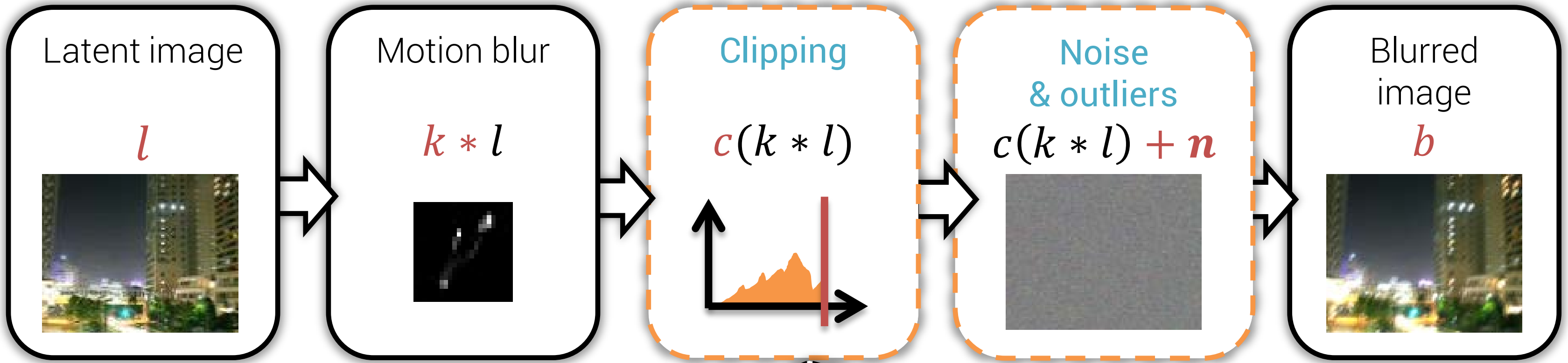
- L^1-norm based data term
  - Simple & efficient
  - Effective on salt & pepper noise
  - Not effective on saturated pixels

L^2-norm based data term

L^1-norm based data term

Cho et al. ICCV 2011

- More accurate blur model reflecting outliers



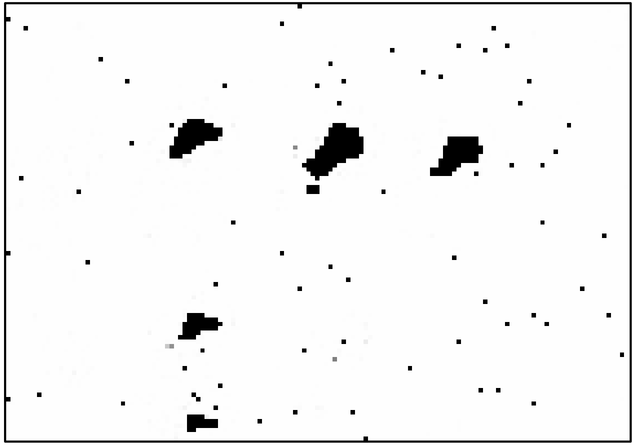
$$c(u) = \begin{cases} u & \text{if } u \in \text{DynamicRange} \\ \text{LowerBound} & \text{if } u < \text{LowerBound} \\ \text{UpperBound} & \text{if } u > \text{UpperBound} \end{cases}$$

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

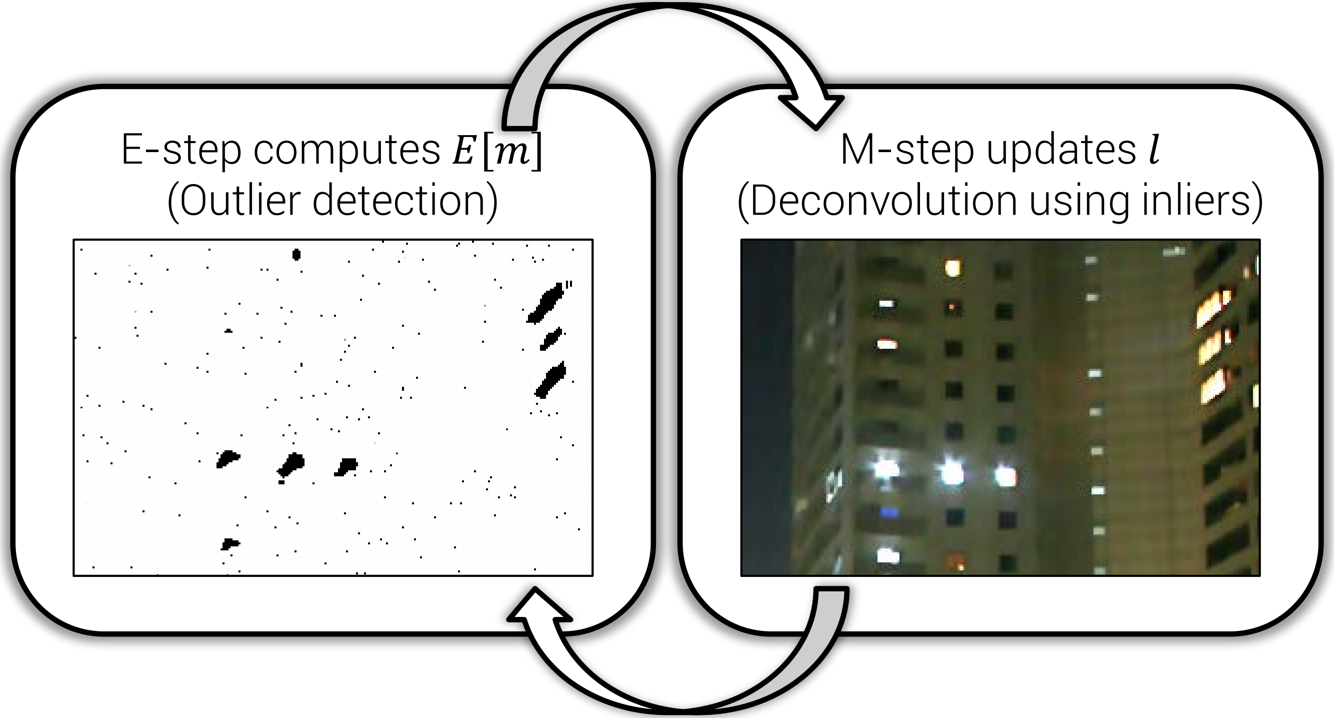
Given b & k, find the most probable l

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

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

Cho et al. ICCV 2011

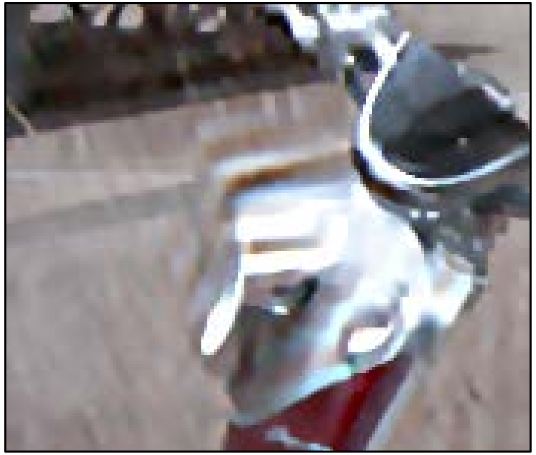
- EM based optimization



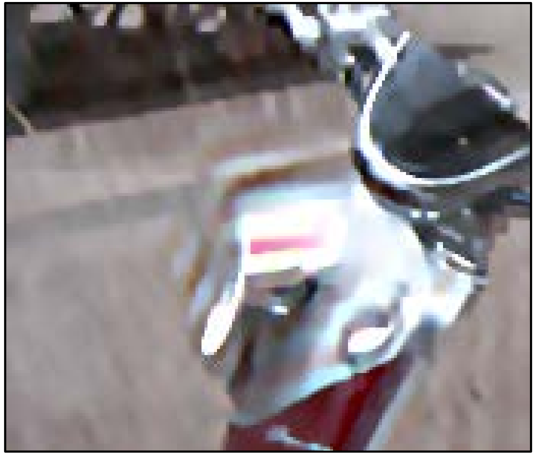
Blurred image

Blurred image

[Levin et al. 2007]



L1-norm based deconv.



[Harmeling et al. 2010]

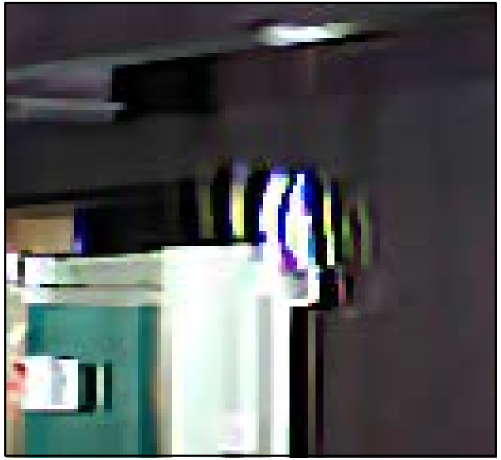
[Cho et al. ICCV 2011]

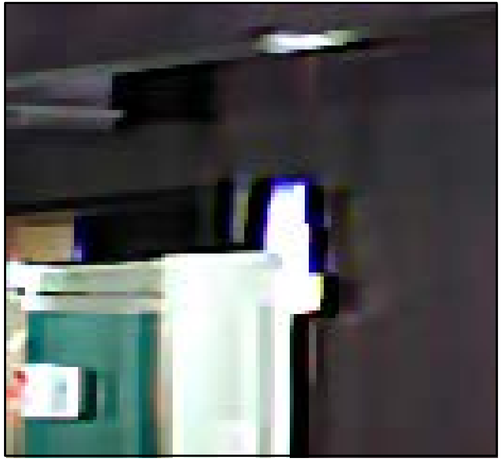

Blurred image


Blurred image


[Levin et al. 2007]


L1-norm based deconv.


[Harmeling et al. 2010]


[Cho et al. ICCV 2011]

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

- Introduction
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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

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

Introduction

Blind Deconvolution

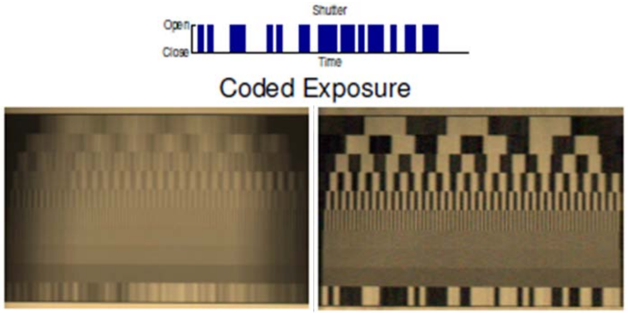
Non-blind Deconvolution

Advanced Issues

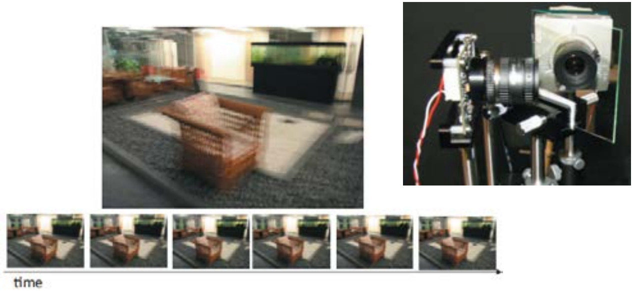
- Hardware based approaches
- Defocus / optical lens / object motion / video blur…
- Other issues

Hardware based Approaches

- To estimate blur kernels
- To restore sharp images better



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

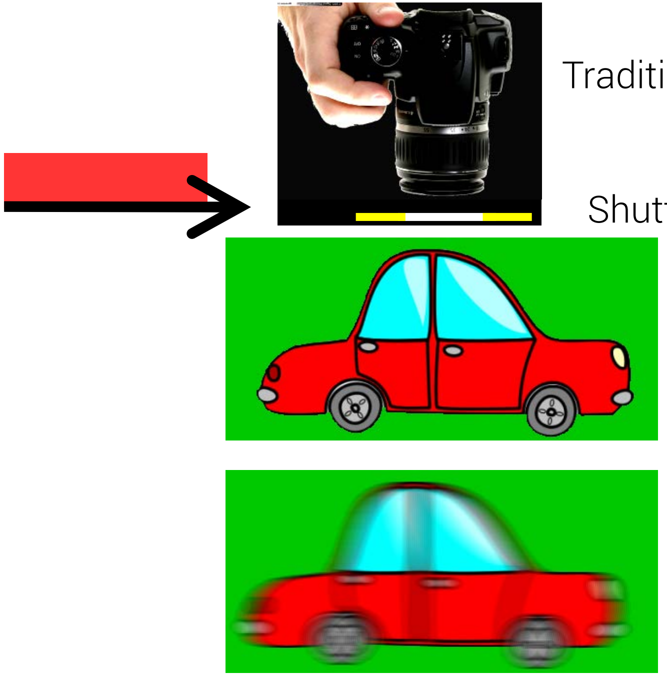


[Tai et al., CVPR 2008]
High-speed low-resolution camera &
low-speed high-resolution camera

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

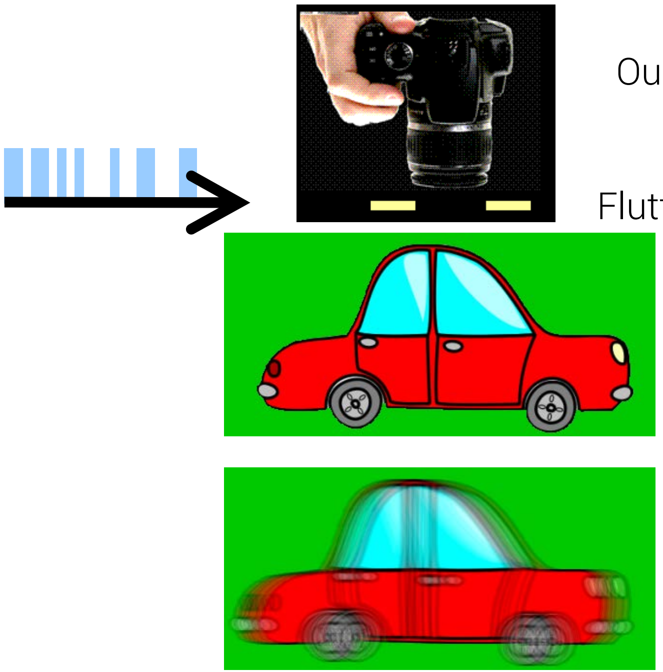
Coded Exposure

- Raskar et al. SIGGRAPH 2006



Traditional Camera

Shutter is OPEN

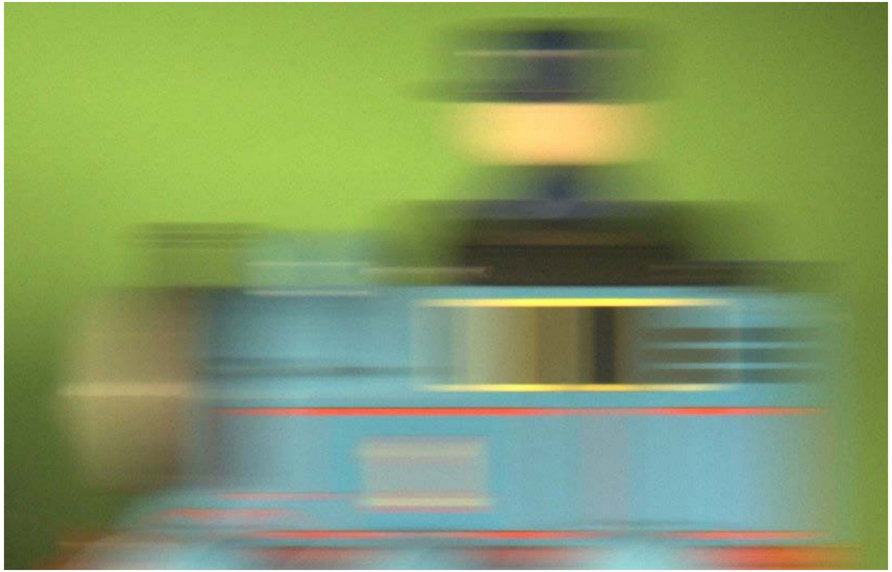


Our Camera

Flutter Shutter

Coded Exposure

- Raskar et al. SIGGRAPH 2006

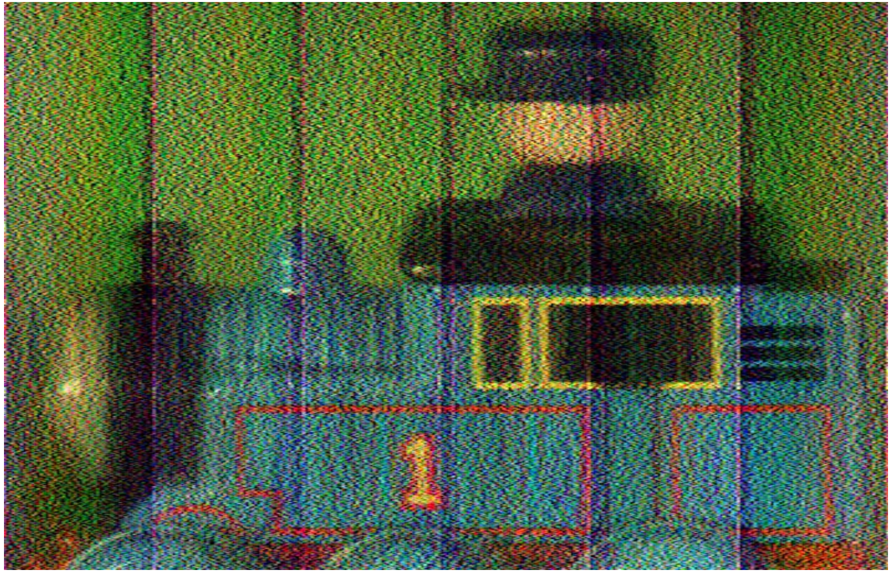


Traditional camera
Completely destroys high-freq info

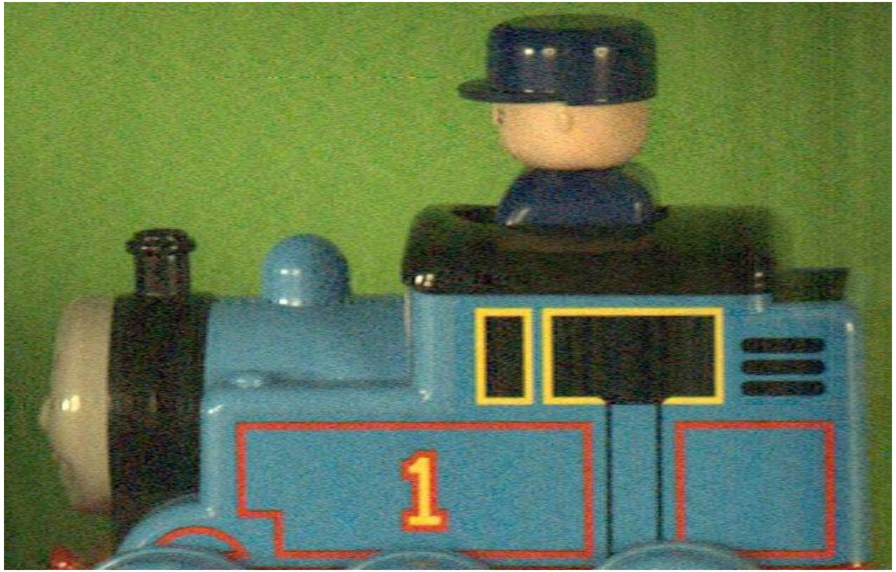
Fluttered shutter
High-freq info is preserved

Coded Exposure

- Raskar et al. SIGGRAPH 2006



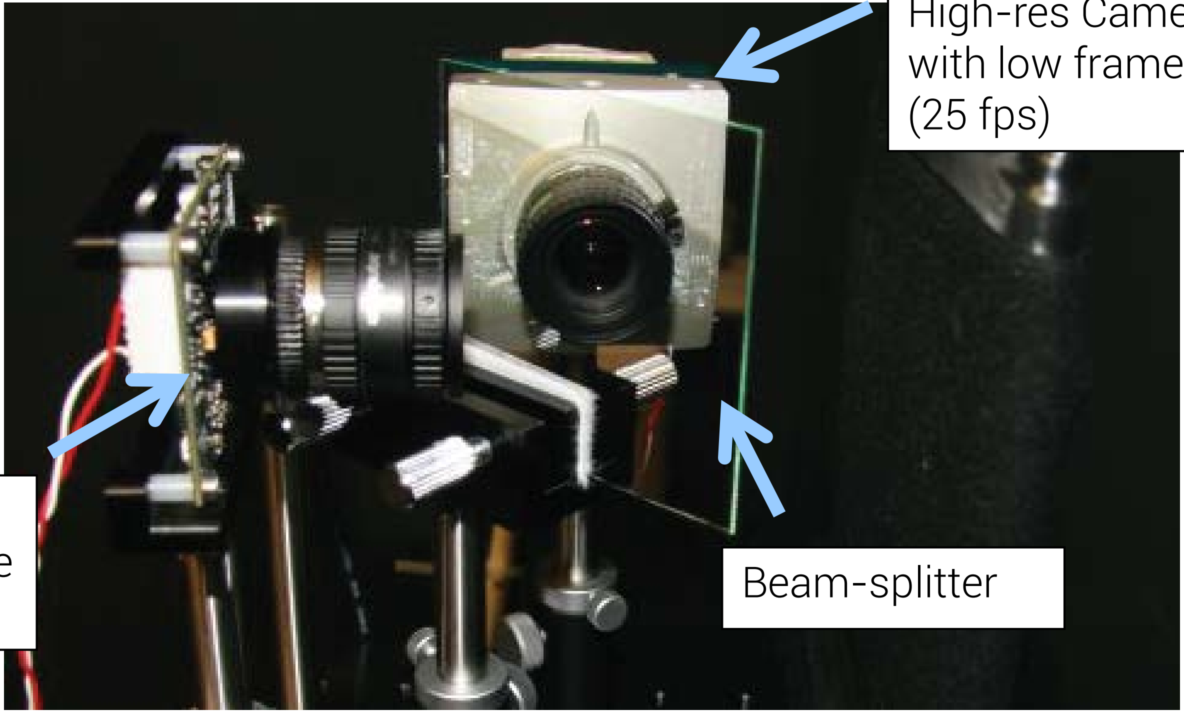
Traditional camera
High-freq details couldn't be restored accurately



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

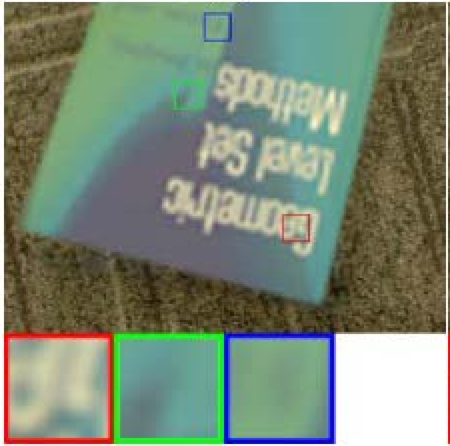
Low-res. video

time


Input


[Shan et. al. ICCV’07]


[Ben-Ezra et. al. CVPR’03]

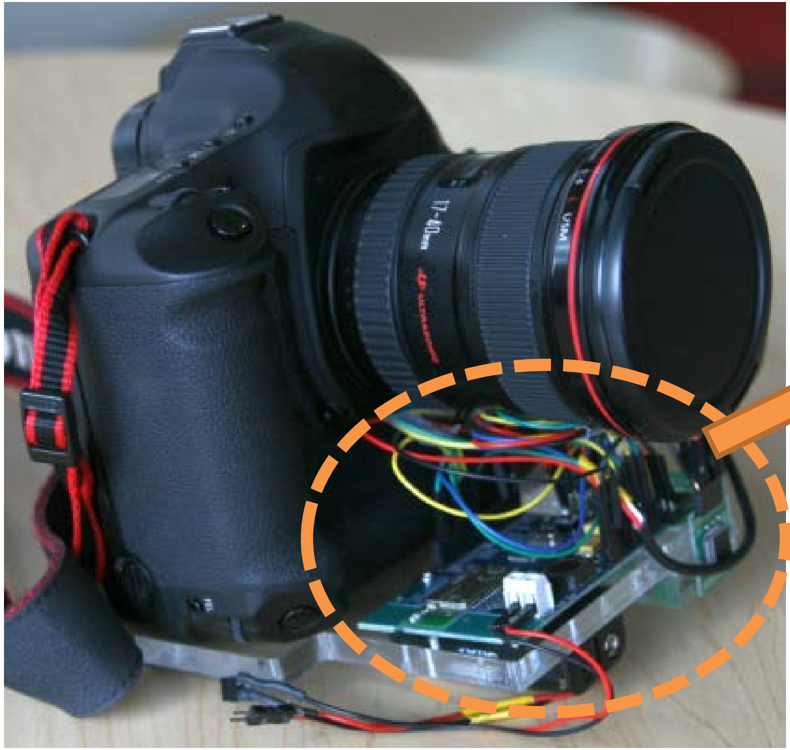

Back Projection


Our Result


Ground Truth

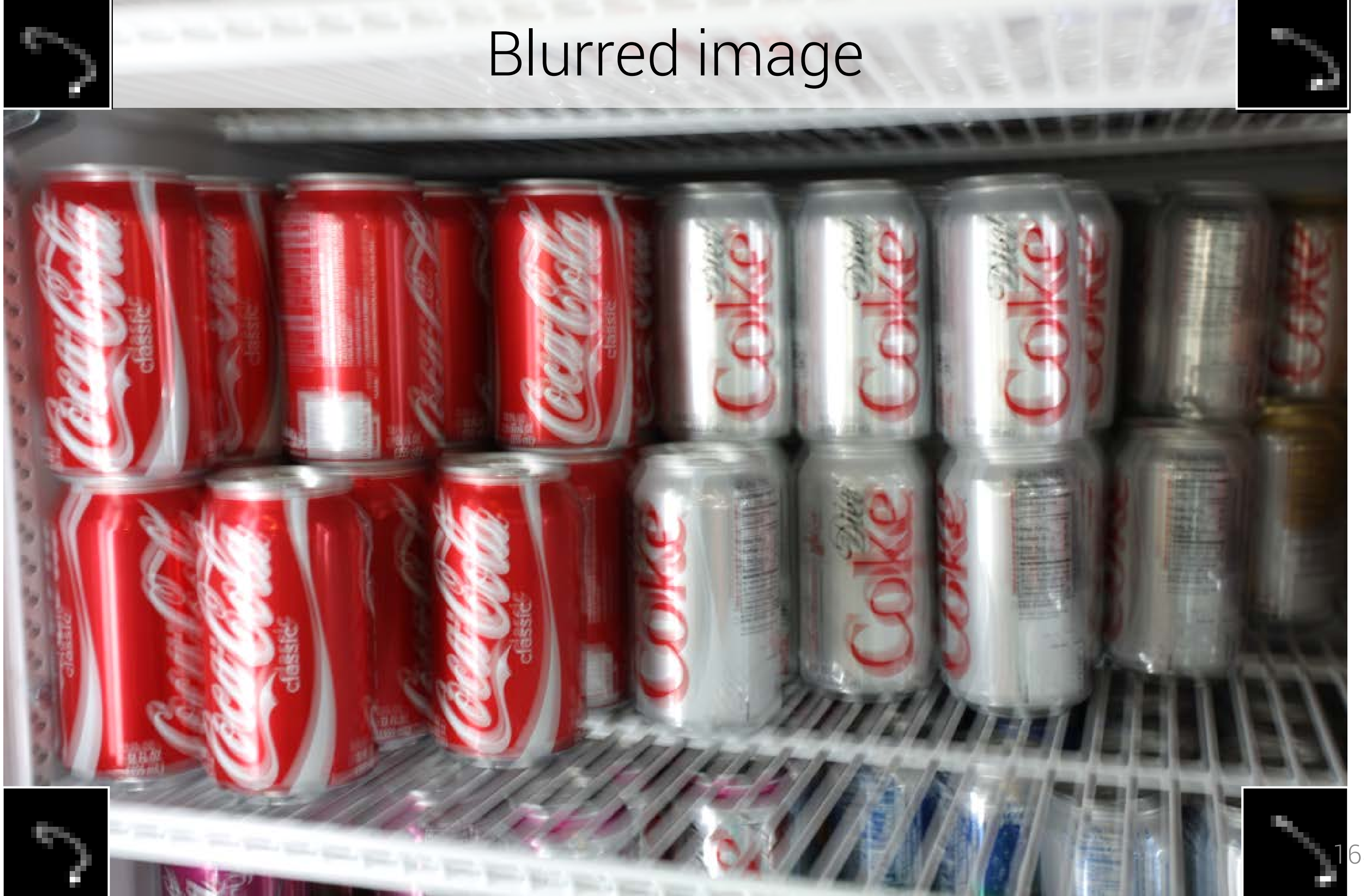
Gyro Sensors + Accelerometers

- Joshi et al. SIGGRAPH 2010



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

Blurred image



Deblurred image

Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

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

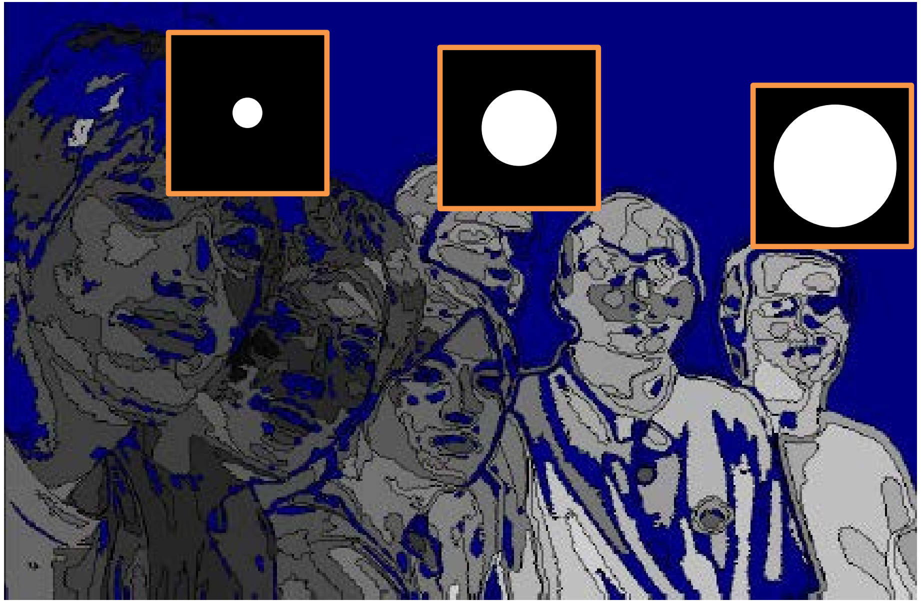
Defocus blur

- 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]

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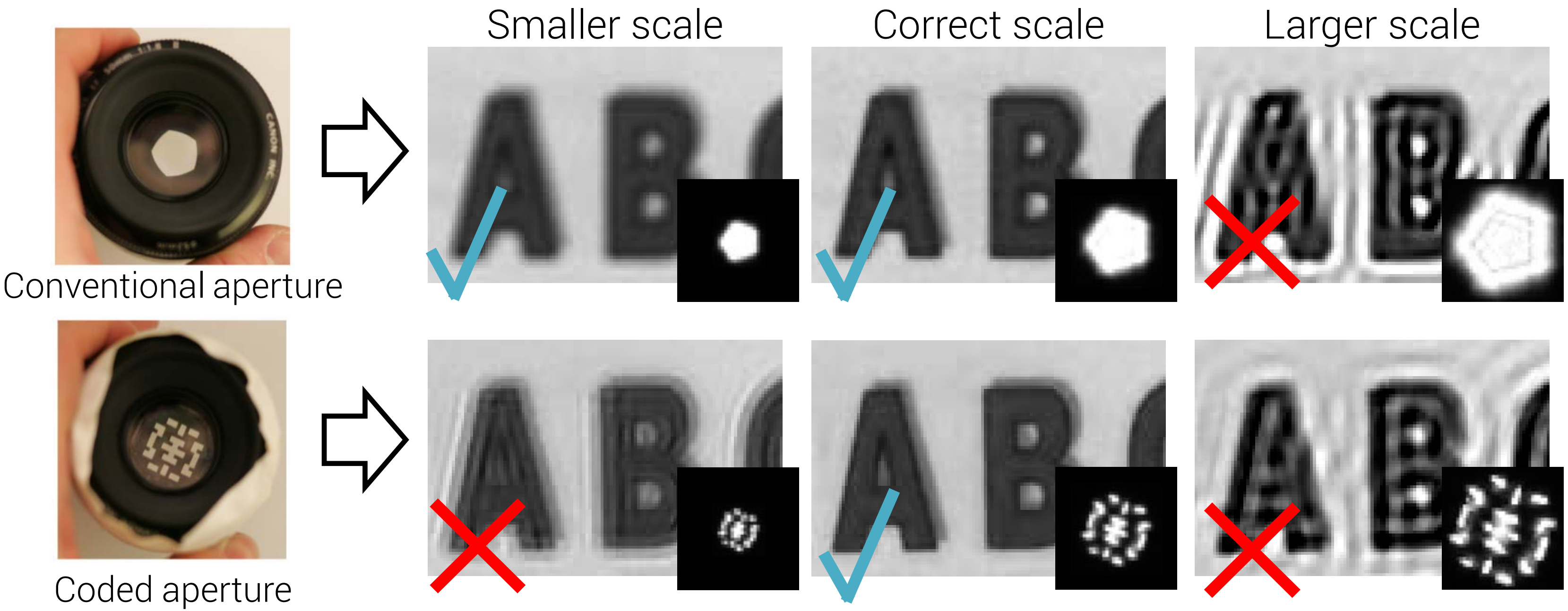
- Coded aperture to more accurately estimate local blur kernels



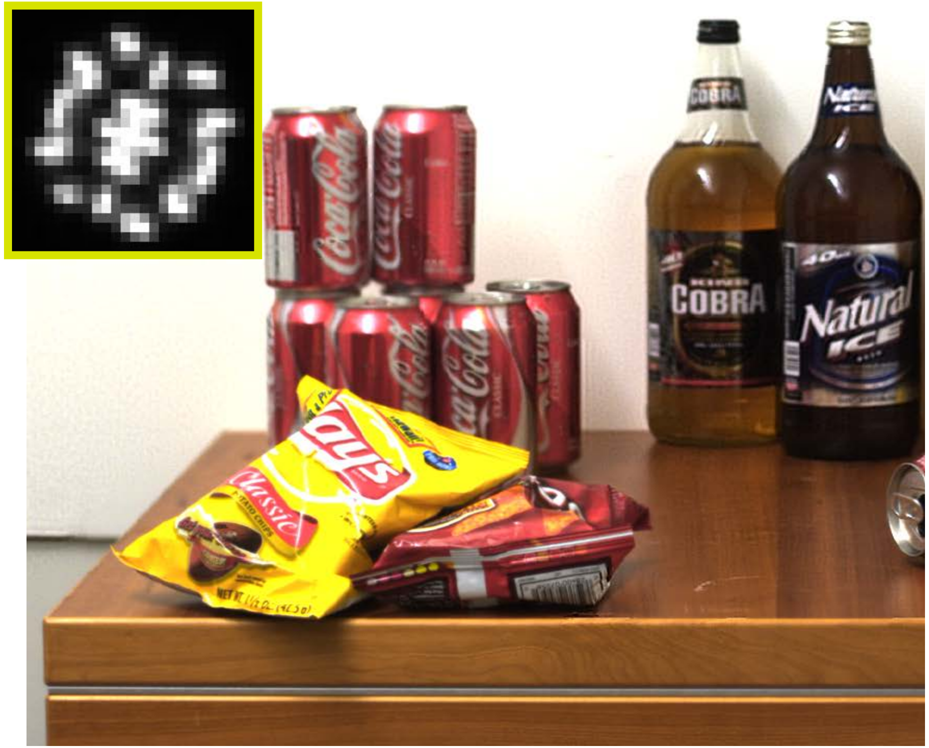
Coded Aperture [Levin et al. SIGGRAPH 2007]

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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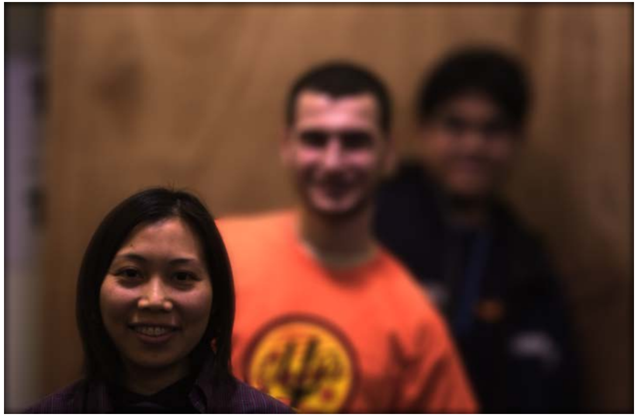
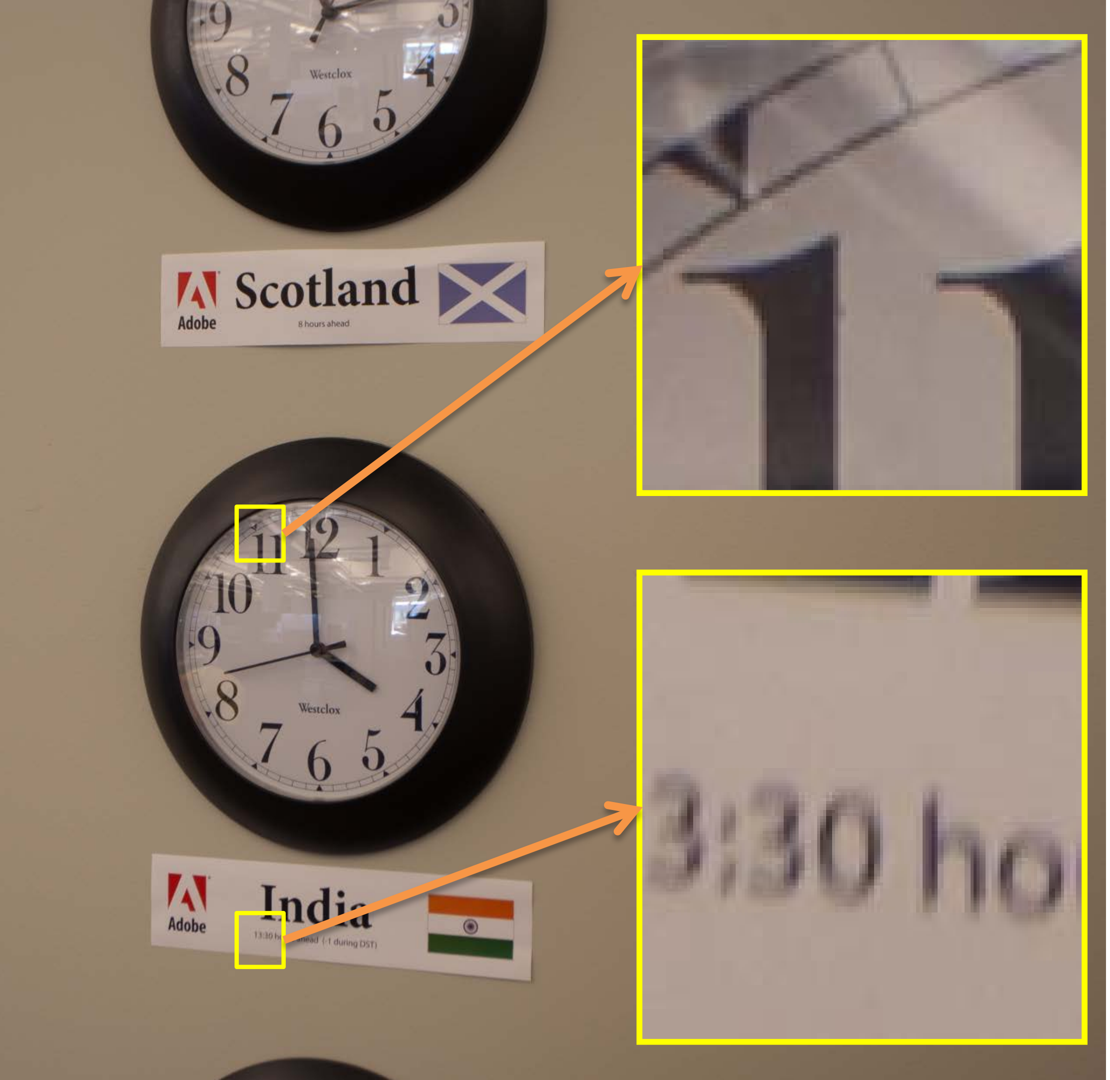
Refocusing



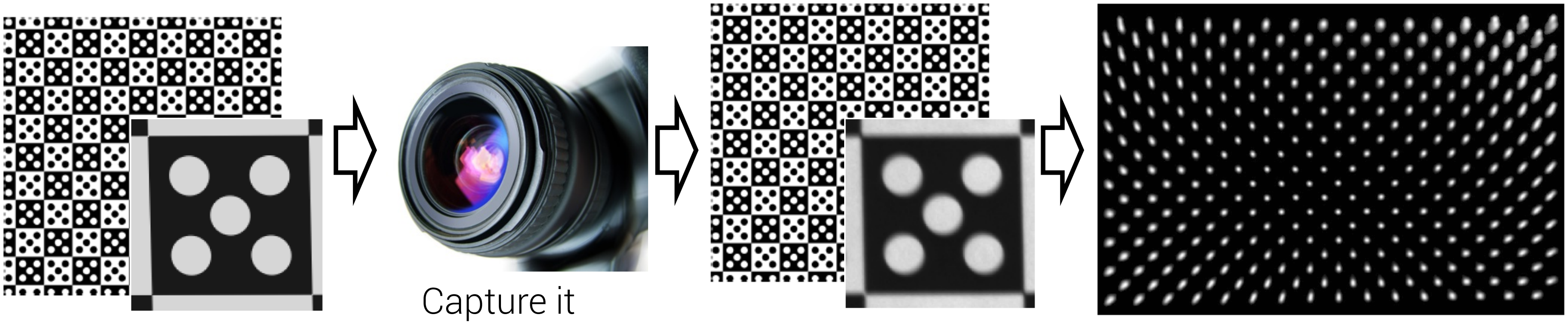


Optical Lens Blur

- 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



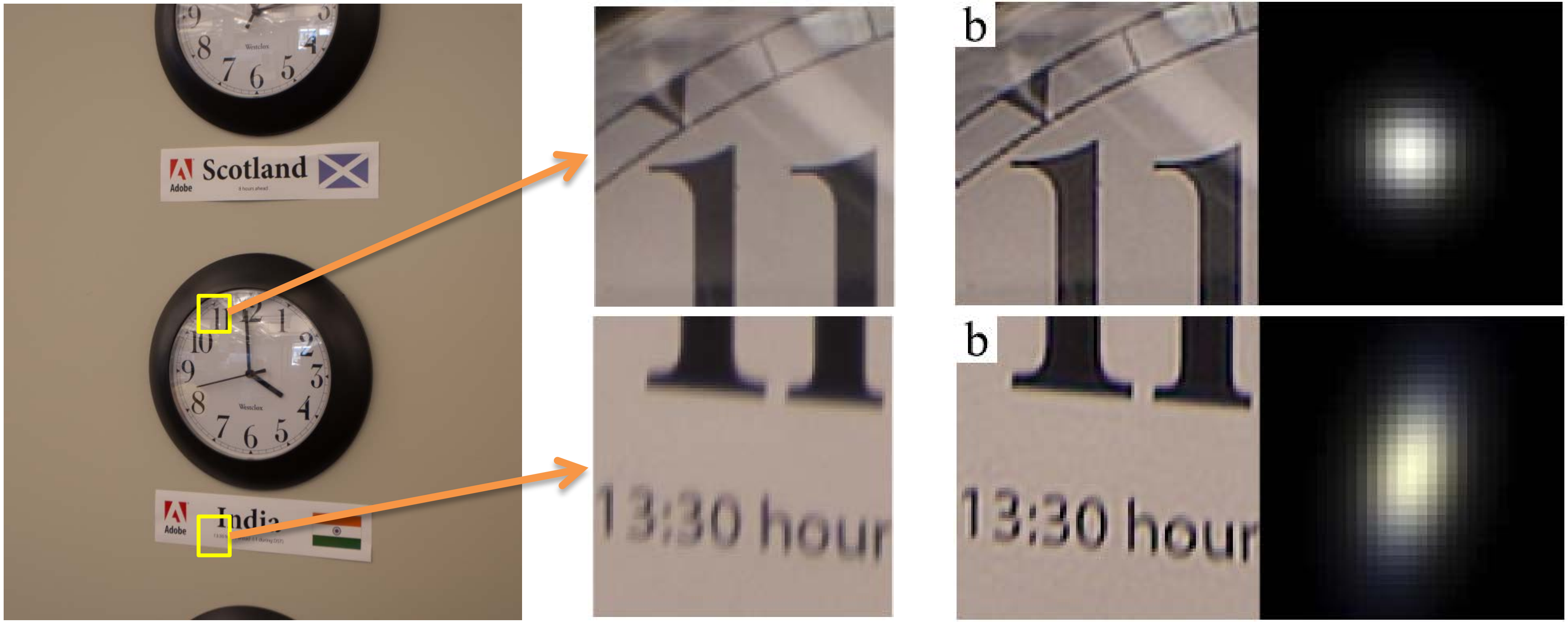
Test chart

Capture it

Captured chart

Estimated blur kernels

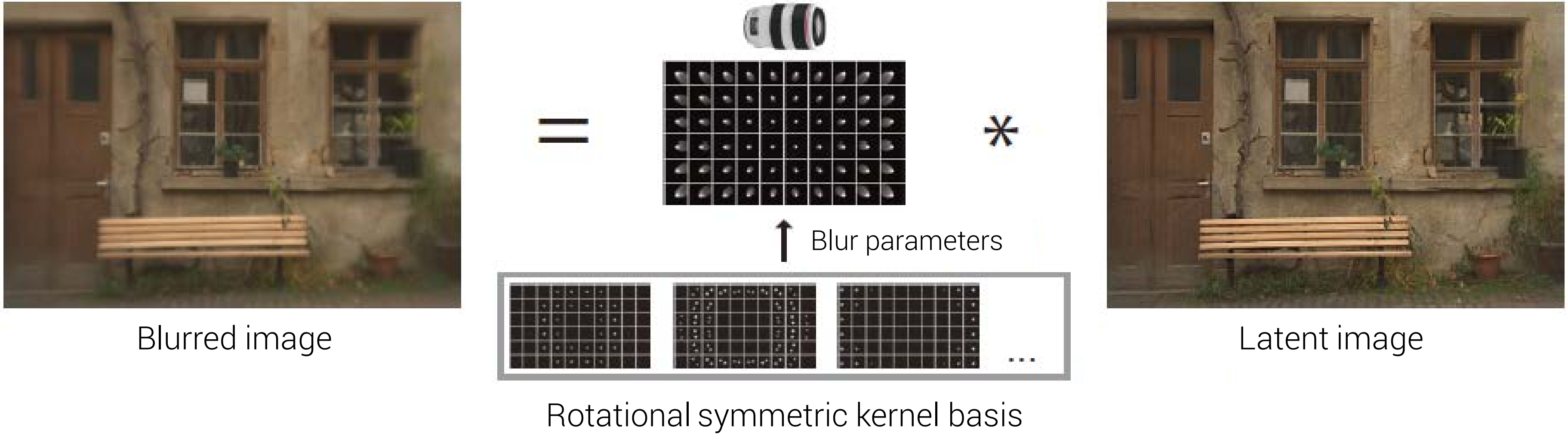
Calibration based Approach [Kee et al. ICCP 2011]



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)

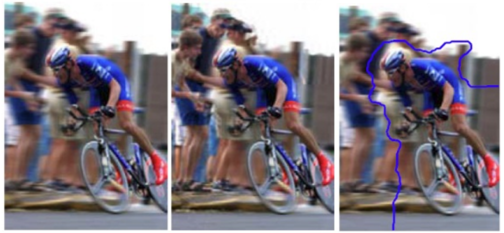
Schuler et al. ECCV 2012

Object Motion Blur

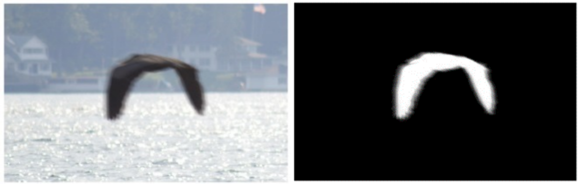
- Due to object motions
- Most challenging
- Spatially-varying blur
  - Much more arbitrary than spatially-varying camera shakes
- Limited information
  - Small portions of an image are blurred

Software based Approaches

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

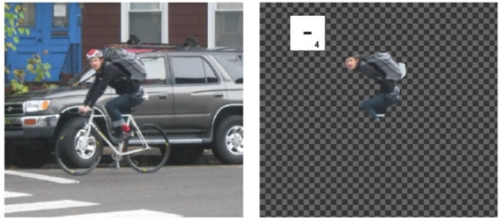


[Levin, NIPS 2006]
Blur estimation and segmentation based on natural image prior



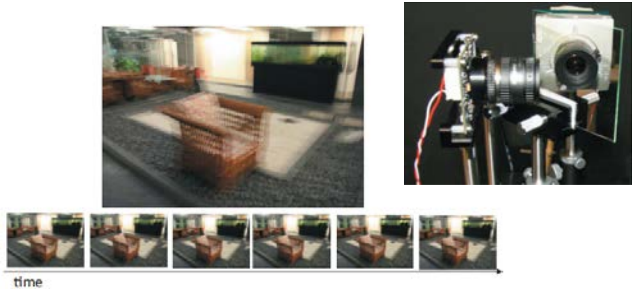
[Jia, CVPR 2007]
Blur estimation based on alpha matting

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



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

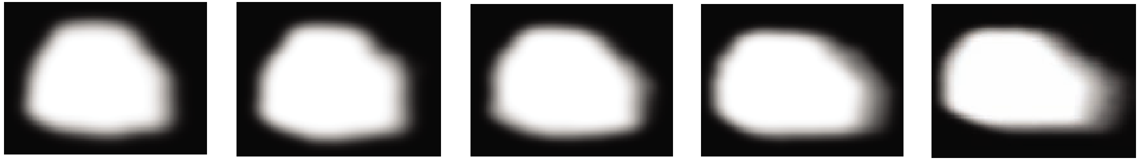
Hardware based Approaches



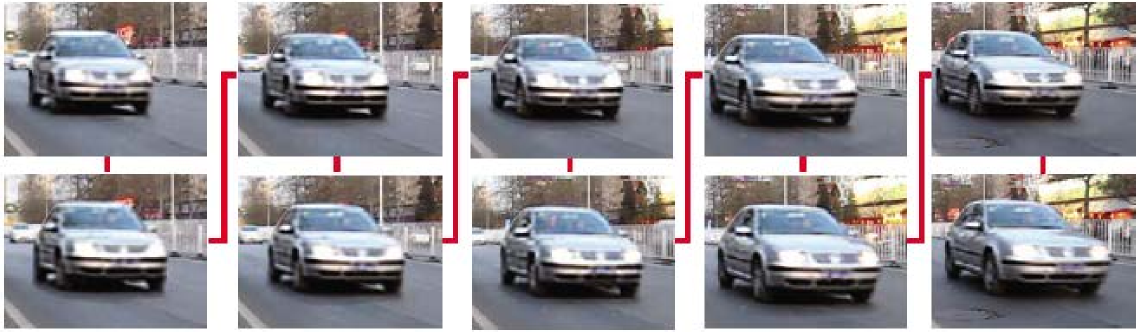
[Tai et al., CVPR 2008]

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…

Motion Blur in Video Frames

Shaky video

Motion Blur in Video Frames

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]

Restored frame | Neighboring frame

- 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

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Non-blind Deconvolution

Advanced Issues

- Hardware based approaches
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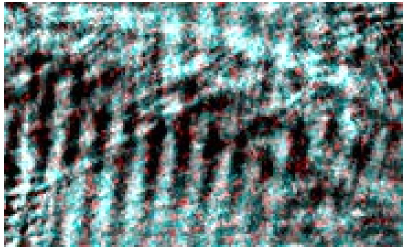
- Other issues

Outliers & Noise

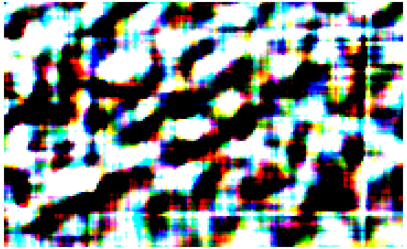
- Blurred images often have significant amount of noise & outliers
  - Low-lighting environment
  - But, relatively less explored

- 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

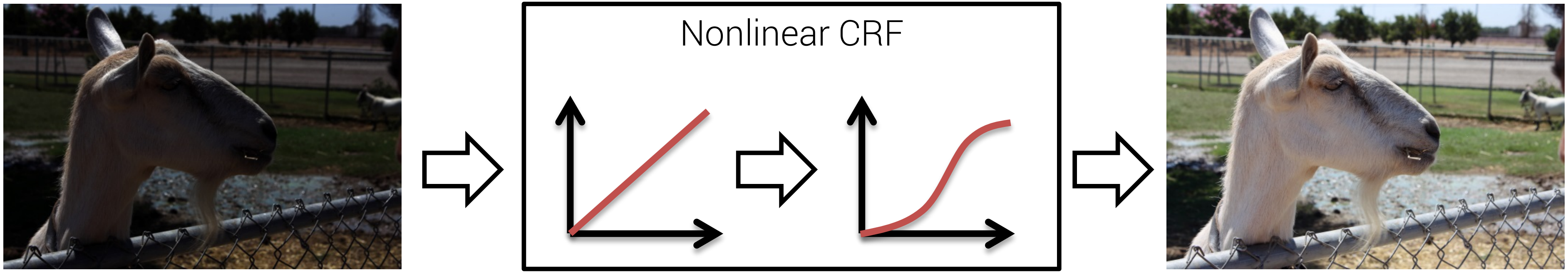


Levin et al.
CVPR 2011

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

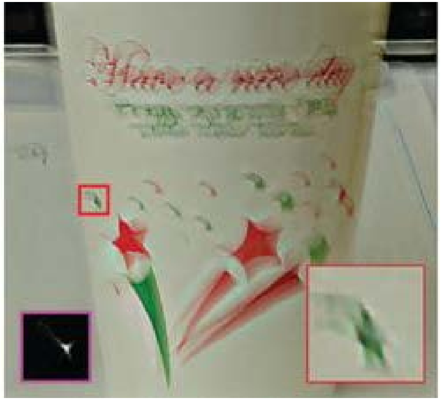
- Common blur model:

$$b \neq k * l$$

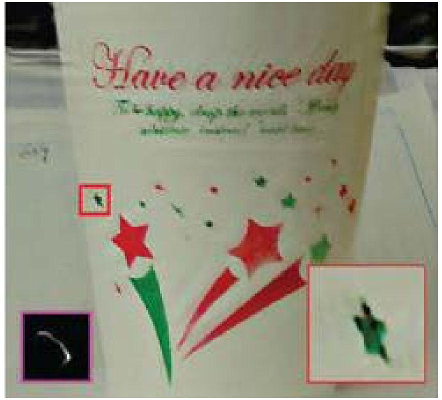
Due to CRF

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

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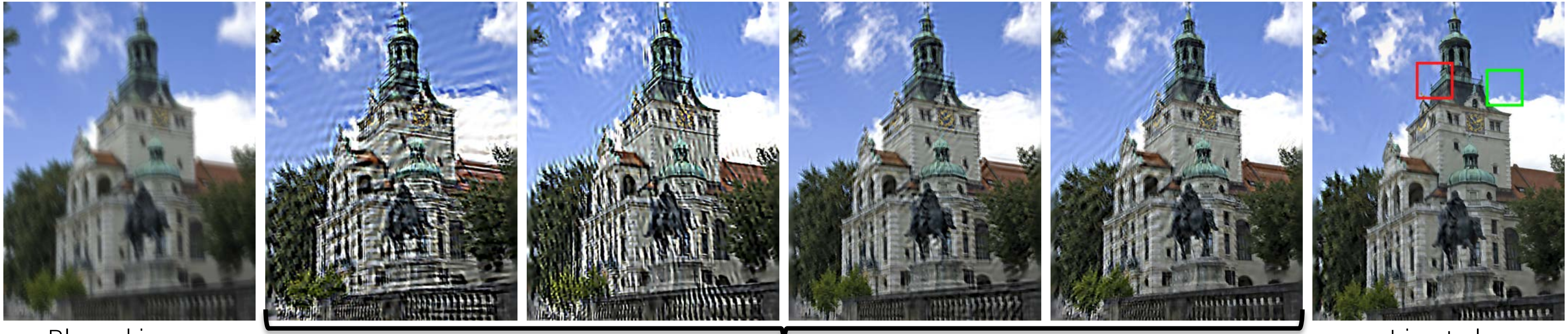
- Light streaks?
  - Light streaks show the shape of the blur kernel
    - Can be a very useful information about blur kernels
  - But, most methods don't use them, and fail when they present

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



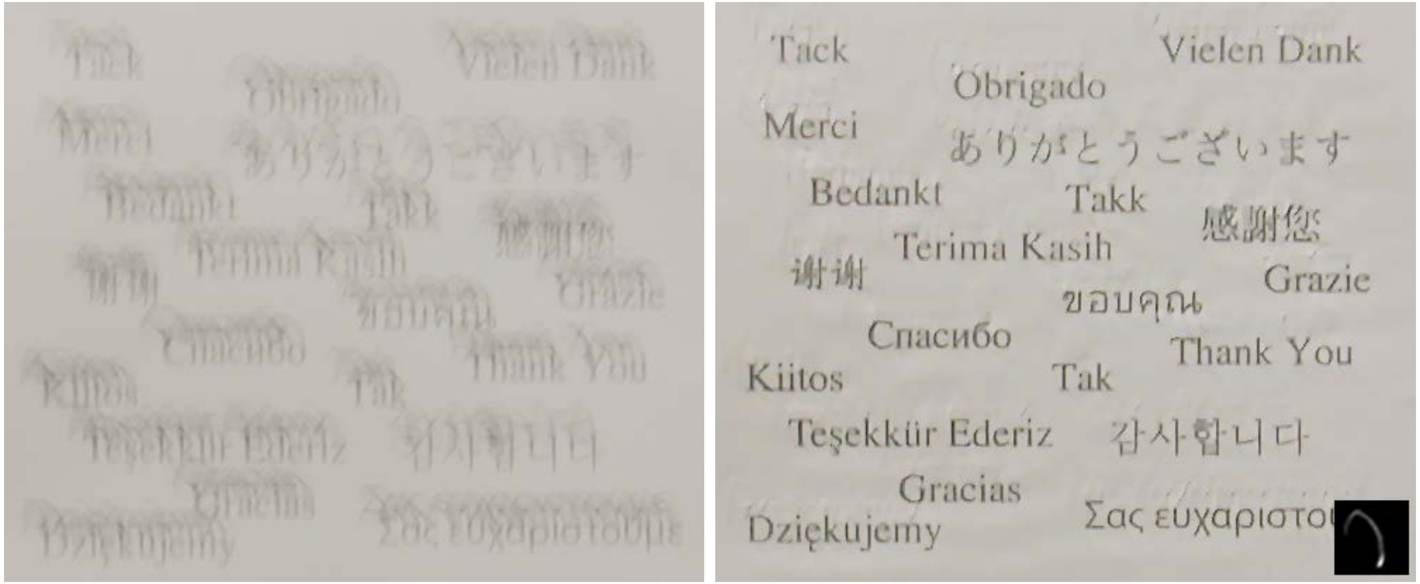
Blurred image

Different deblurring results

Liu et al.
Fusion using the quality metric

Domain Specific Deblurring

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

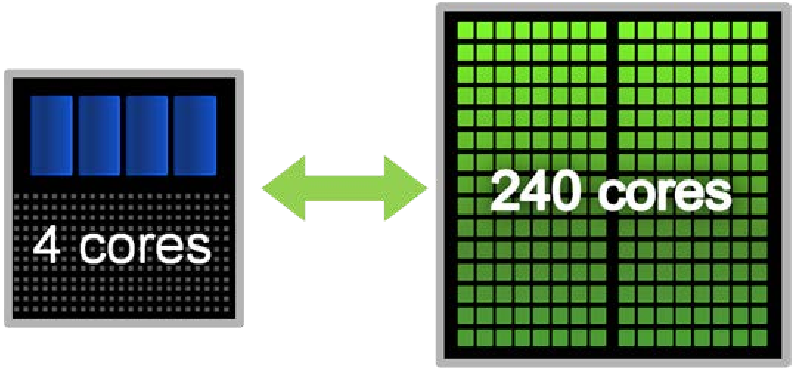


[Cho et al. ECCV 2012] Text image deblurring using text-specific properties

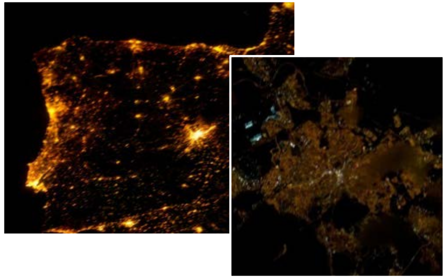
Computational Time

- 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

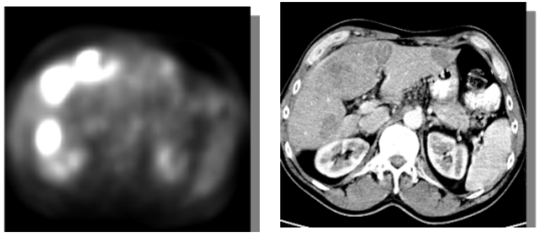


Applications

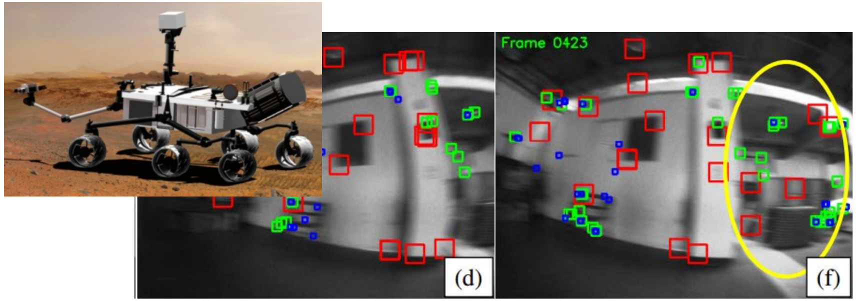


Satellite & aerial photographs

CCTV & Car black box



Medical imaging



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

Historical images

Smart phones

Q & A

Seungyong Lee @ POSTECH
Sunghyun Cho @ Adobe Research