BIL 717
Image Processing
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Image Deblurring

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

Introduction
Blind Deconvolution
Non-blind Deconvolution

blur [bl3:(r)]
- *Long exposure*
- *Moving objects*
- *Camera motion*
  - *panning shot*

blur [bl3:(r)]
- *Often degrades image/video quality severely*
- *Unavoidable under dim light circumstances*

Various Kinds of Blurs

Camera shake (Camera motion blur)

Object movement (Object motion blur)

Out of focus (Defocus blur)

Combinations (vibration & motion, …)

Camera Motion Blur

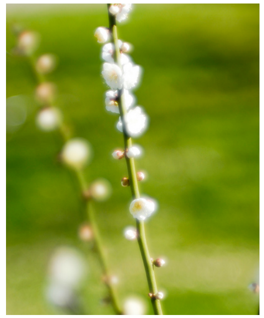
- *Caused by camera shakes during exposure time*
  - *Motion can be represented as a camera trajectory*

Object Motion Blur

- *Caused by object motions during exposure time*

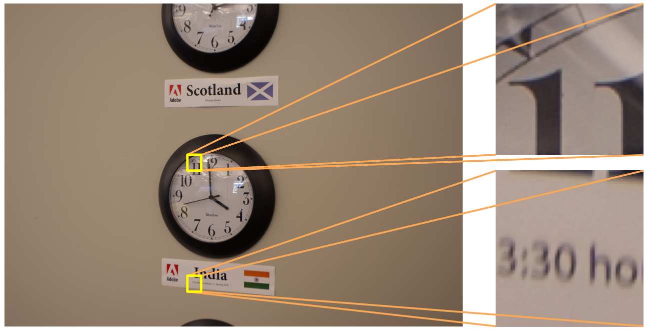
Defocus Blur

- *Caused by the limited depth of field of a camera*



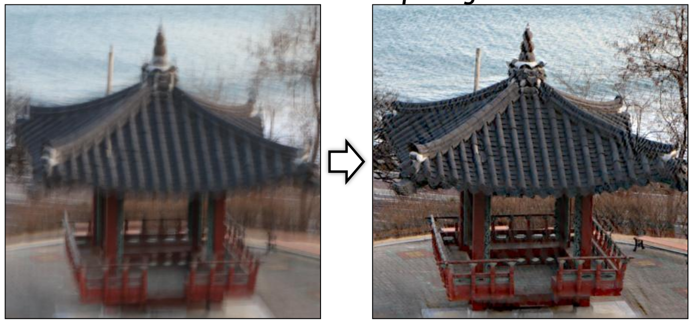
Optical Lens Blur

- ***Caused by lens aberration***



Deblurring?

- ***Remove blur and restore a latent sharp image***



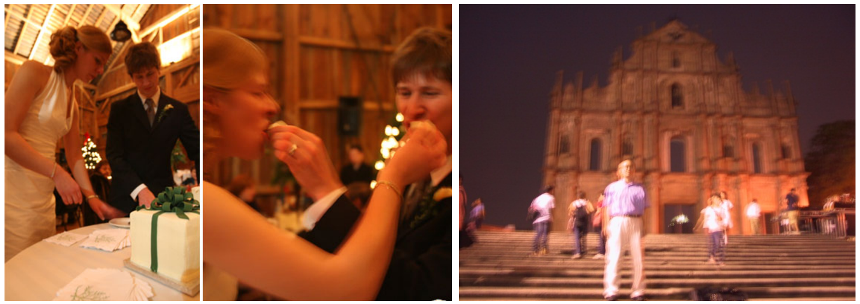
from a given blurred image *find its latent sharp image*

Deblurring: Old Problem!

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

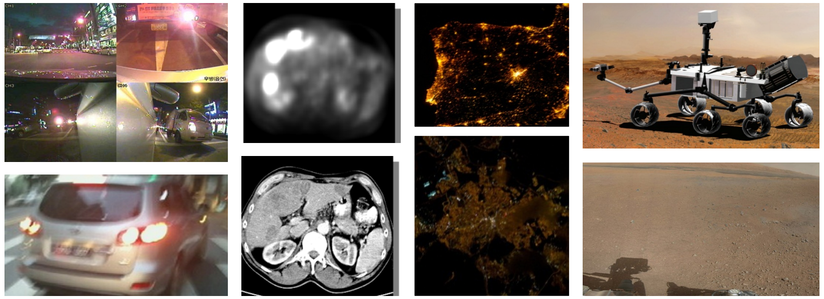
Why is it *important*?

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



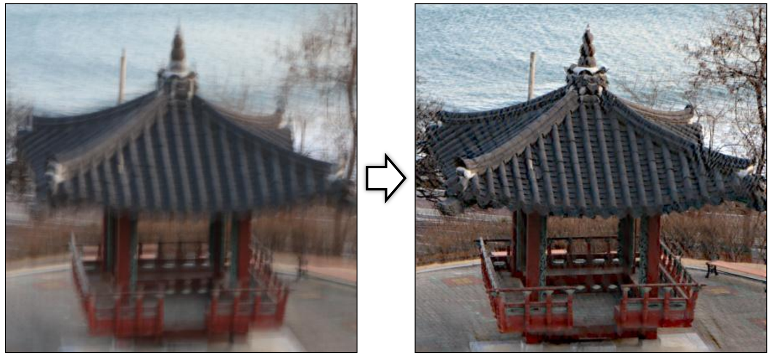
Why is it *important*?

- *Strong demand for high quality deblurring*



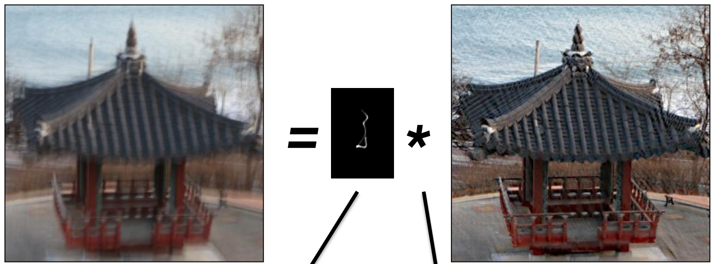
CCTV, car black box | *Medical imaging* | *Aerial/satellite photography* | *Robot vision*

Deblurring



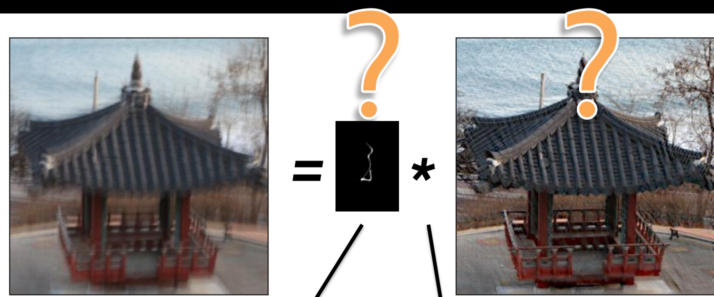
from a given blurred image → *find its latent sharp image*

Commonly Used Blur Model



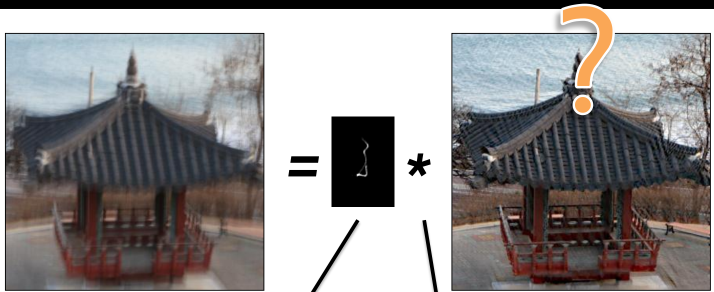
Blurred image = *Blur kernel or Point Spread Function (PSF)* * (*Convolution operator*) *Latent sharp image*

Blind Deconvolution



Blurred image = *Blur kernel or Point Spread Function (PSF)* * (*Convolution operator*) *Latent sharp image*

Non-blind Deconvolution



Blurred image

Blur kernel or Point Spread Function (PSF)

Convolution operator

Latent sharp image

Uniform vs. Non-uniform Blur

Uniform blur

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

Uniform vs. Non-uniform Blur

Non-uniform blur

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

Most Blurs Are Non-Uniform

Camera shake (Camera motion blur)

Object movement (Object motion blur)

Out of focus (Defocus blur)

Combinations (vibration & motion, …)

Introduction

Blind Deconvolution

Non-blind Deconvolution

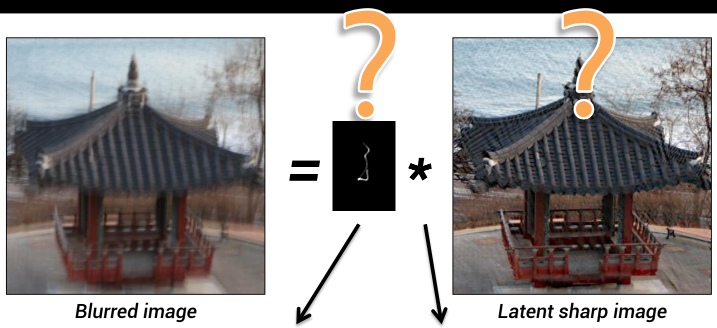
Introduction

Blind Deconvolution

Non-blind Deconvolution

- Introduction
- Recent popular approaches
- Non-uniform blur

Blind Deconvolution (Uniform Blur)



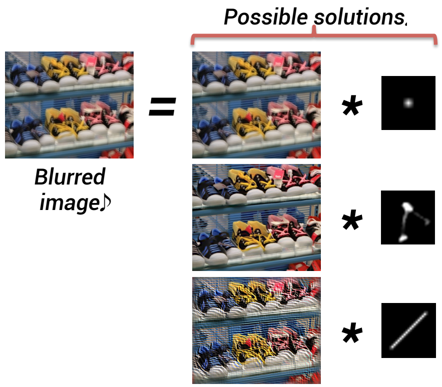
Blurred image

Blur kernel or Point Spread Function (PSF)

Convolution operator

Latent sharp image

Key challenge: Ill-posedness!



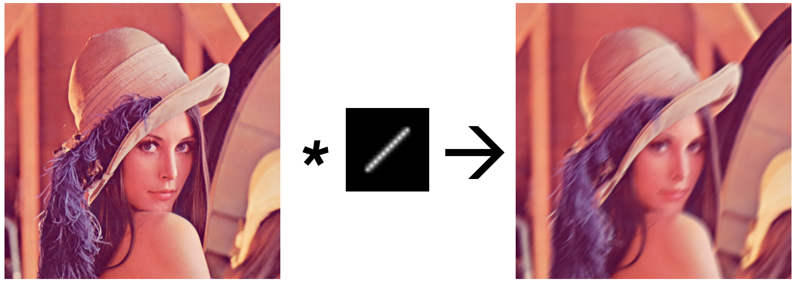
Blurred image

- ***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)*



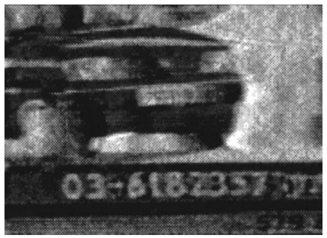
In The Past…

- *But real camera shakes are much more complex*

In The Past…

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

Blurred image

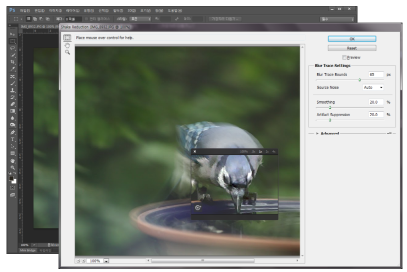


Latent sharp image

** 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

- Introduction
- Recent popular approaches
- Non-uniform blur

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

Recent Popular Approaches

Maximum Posterior (MAP) based

- *[Shan et al. SIGGRAPH 2008], [Krishnan et al. CVPR 2011], [Xu et al. CVPR 2013], …*
- *Seek the most probable solution, which maximizes a posterior distribution*
- *Easy to understand*
- *Convergence problem*

Variational Bayesian based

Edge Prediction based

Which one is better?

Recent Popular Approaches

Maximum Posterior (MAP) based

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

Variational Bayesian based

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

Edge Prediction based

Which one is better?

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

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

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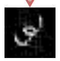
- Easy to understand
- Convergence problem

MAP based Approaches

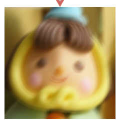
Maximize a joint posterior probability with respect to k and l

Posterior distribution

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


Blur kernel k


Latent image l

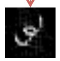

Blurred image b

MAP based Approaches

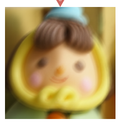
Bayes rule:

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

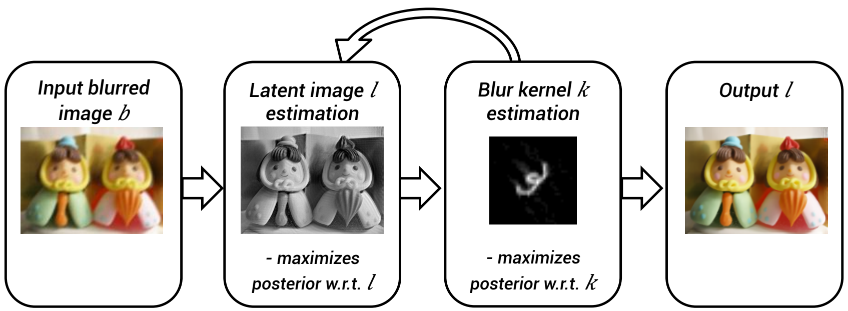
Negative* log*-posterior:

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

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

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

MAP based Approaches



MAP based Approaches

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

Shan et al. SIGGRAPH 2008

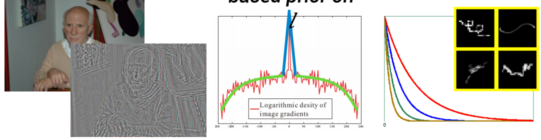
- *Carefully designed likelihood & priors*

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

Likelihood based on intensities & derivatives

Natural image statistics based prior on l

Kernel statistics based prior on k

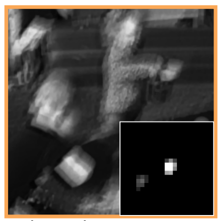


Shan et al. SIGGRAPH 2008

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

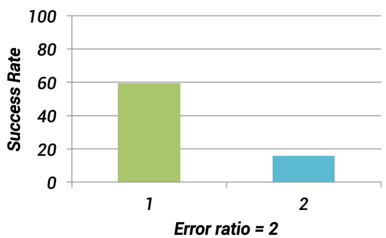
Shan et al. SIGGRAPH 2008

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



Shan et al. SIGGRAPH 2008

Fergus et al. SIGGRAPH 2006 (variational Bayesian based)



Recent Popular Approaches

Maximum Posterior (MAP) based

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

Variational Bayesian based

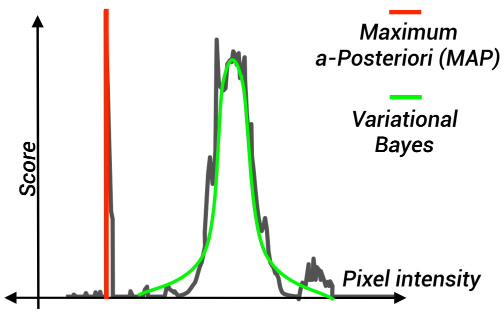
- *Not seek for one most probable solution, but consider all possible solutions*
- *Theoretically more robust*
- *Slow*

Edge Prediction based

Which one is better?

Variational Bayesian

MAP 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*

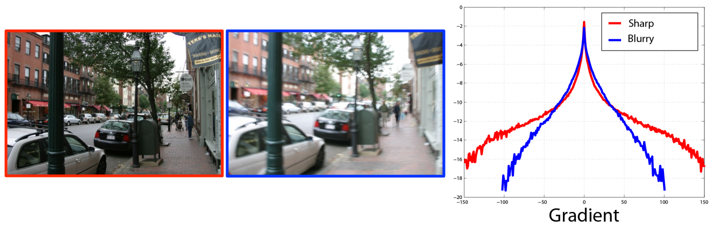
Variational Bayesian

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

Fergus et al. SIGGRAPH 2006

- *Posterior distribution*

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



Fergus et al. SIGGRAPH 2006

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

$$\arg\min_{q(k),q(l),q(\sigma^{-2})} KL\big(\underbrace{q(k)q(l)q(\sigma^{-2})}\big\|p(k,l|b)\big)$$

approximate distributions for blur kernel k,
latent image l, and noise variance σ^2

- *cf) MAP based approach:*

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

Fergus et al. SIGGRAPH 2006

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

Recent Popular Approaches

Maximum Posterior (MAP) based

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

Variational Bayesian based

Edge Prediction based

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

Which one is better?

Edge Prediction based Approaches

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

Cho & Lee, SIGGRAPH Asia 2009

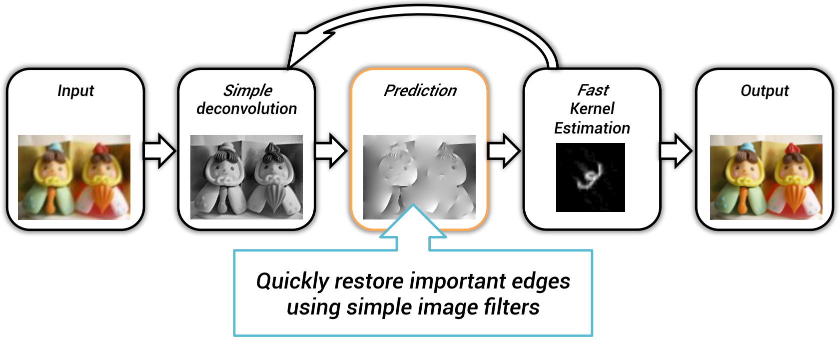
- *Key idea: blur can be estimated from a few* edges

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

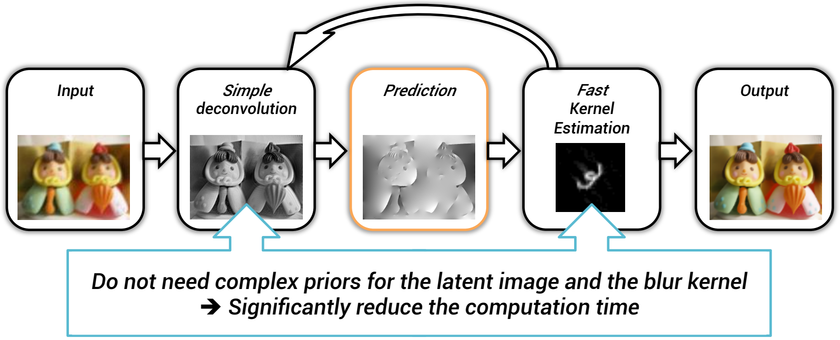
Blurred image

Latent image with only a few edges and no texture

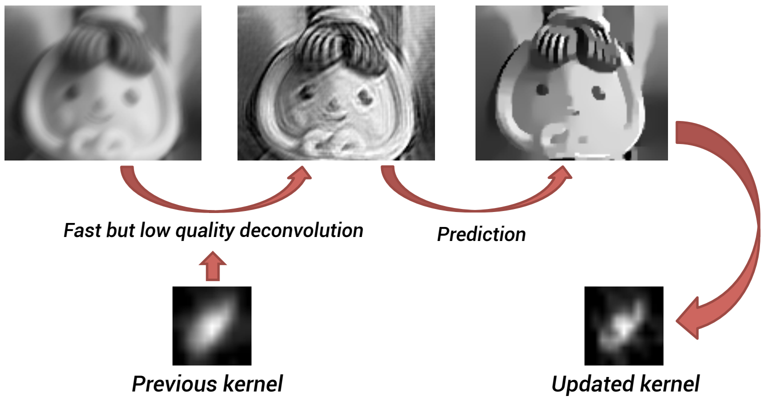
Cho & Lee, SIGGRAPH Asia 2009



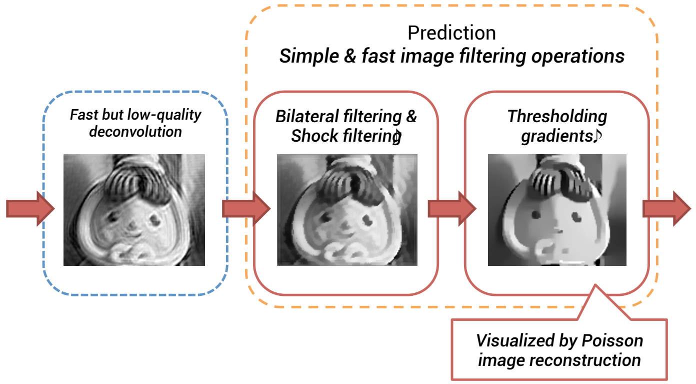
Cho & Lee, SIGGRAPH Asia 2009



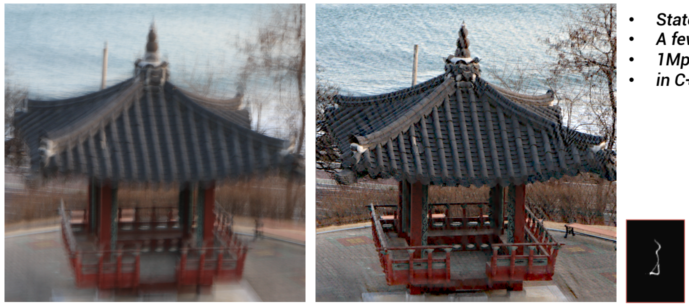
Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009



Cho & Lee, SIGGRAPH Asia 2009

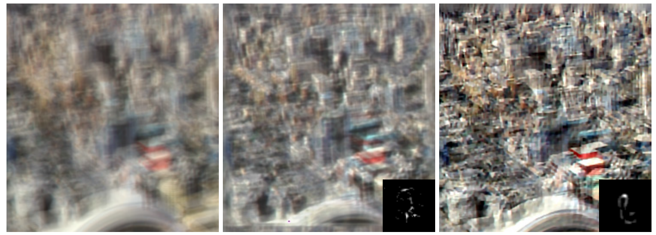


Blurry input   Deblurring result   Blur kernel

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

Xu & Jia, ECCV 2010

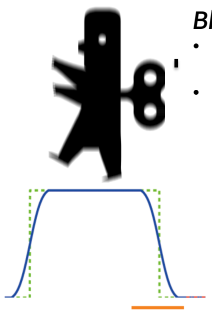
- ***Extended edge prediction to handle blur larger than image structures***



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

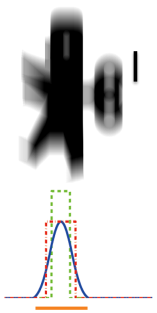
For this complex scene, most methods fail to estimate a correct blur kernel. Why?

Xu & Jia, ECCV 2010



Blur < structures

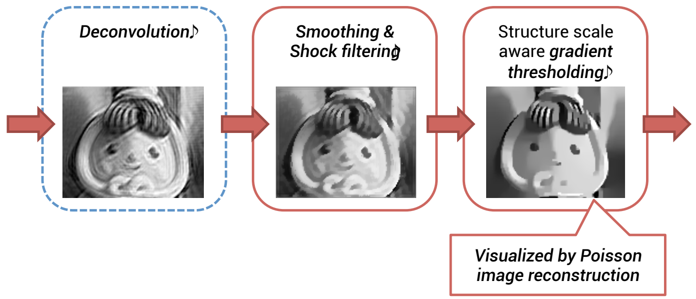
- *Each blurry pixel is caused by one edge*
- *Easy to figure out the original sharp structure*



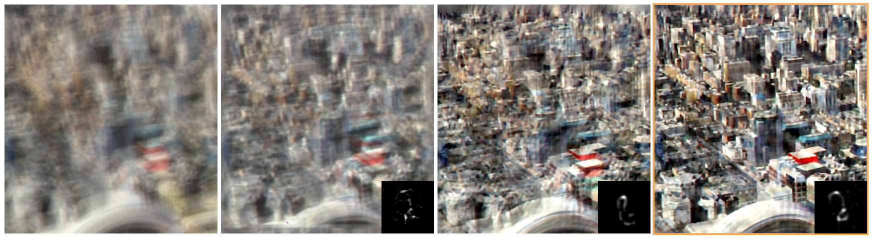
Blur > structures

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

Xu & Jia, ECCV 2010



Xu & Jia, ECCV 2010



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

Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

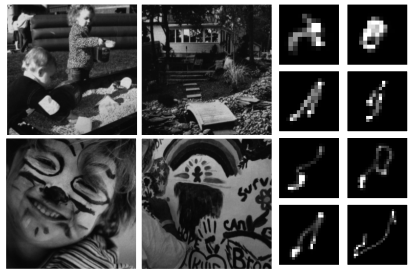
Which one is better?

Benchmarks

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

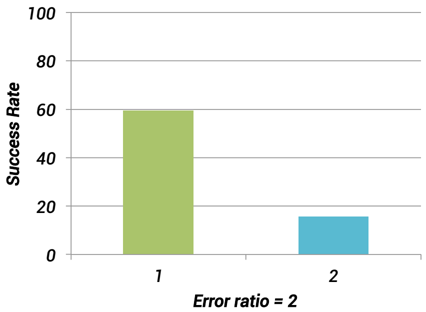
Benchmarks

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



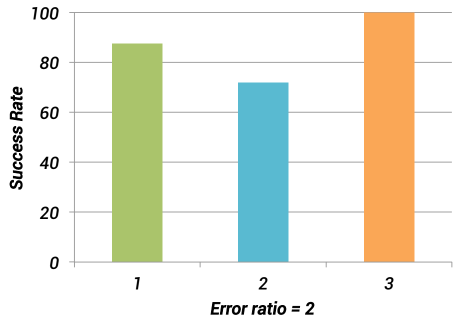
Benchmarks

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



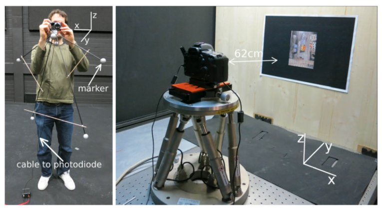
Benchmarks

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



Benchmarks

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

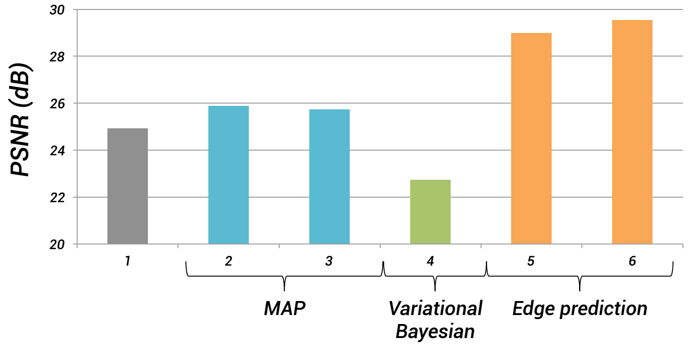


Benchmarks

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

Benchmarks

- *Köhler et al. ECCV 2012*



Benchmarks

- *Benchmark results depend on*
  - *Implementation details & tricks*
  - *Benchmark datasets*
  - *Parameters used in benchmarks*
- *But, in general, more recent one shows better quality*
- *Speed?*
  - *Edge prediction > MAP >> Variational Bayesian*

Introduction

Blind Deconvolution

Non-blind Deconvolution

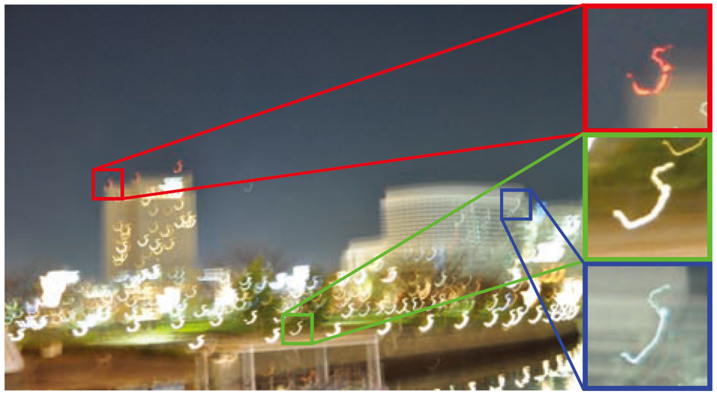
Advanced Issues

- Introduction
- Recent popular approaches
- Non-uniform blur

Convolution based Blur Model

- *Uniform and spatially invariant blur*

Real Camera Shakes: Spatially Variant!

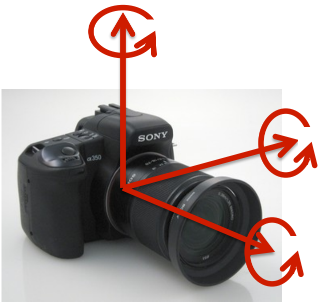


Uniform Blur Model Assumes

x & y translational camera shakes

Planar scene

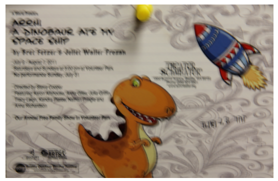
Real Camera Shakes



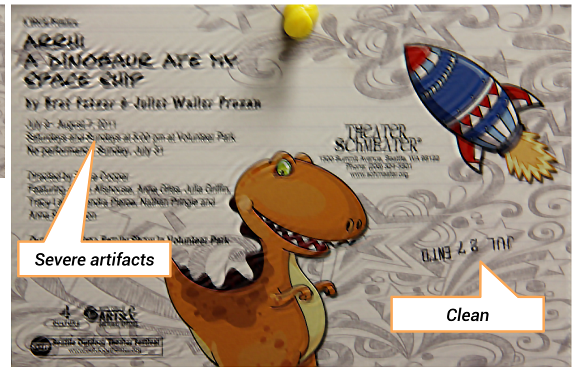
6D real camera motion

Different depths

Real Blurred Image



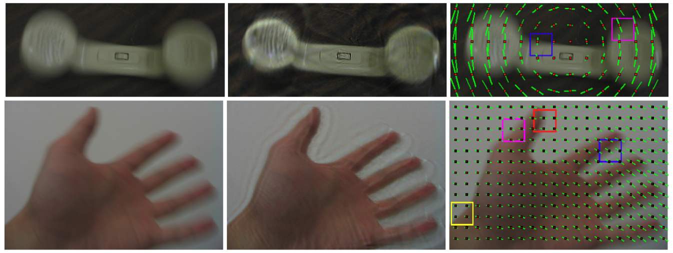
Non-uniformly blurred image



Uniform deblurring result

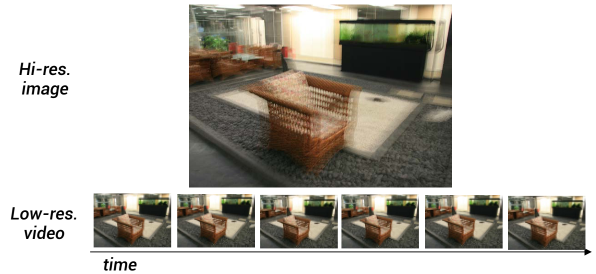
Pixel-wise Blur Model

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



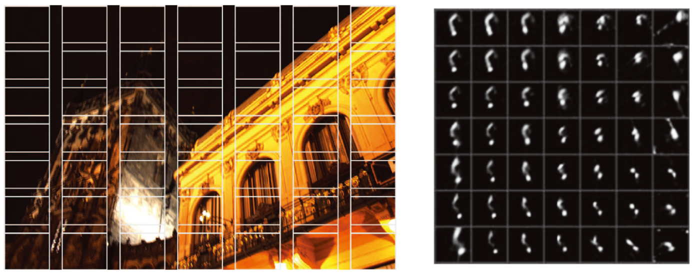
Pixel-wise Blur Model

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



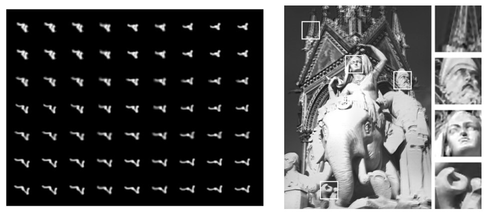
Patch-wise Blur Model

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



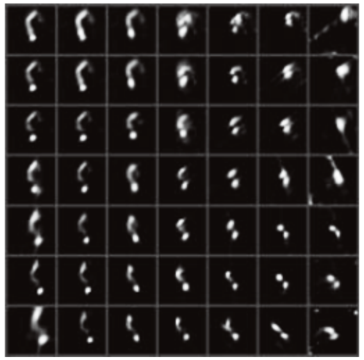
Patch-wise Blur Model

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

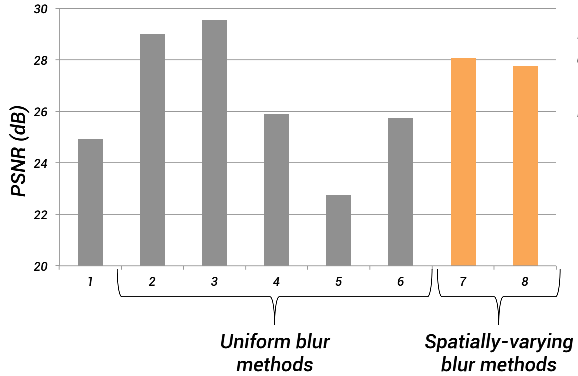


Patch-wise Blur Model

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



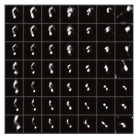
Benchmark [Köhler et al. ECCV 2012]



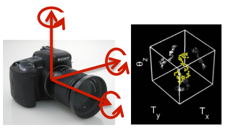
Due to high dimensionality, spatially-varying blur methods are less stable.

Summary

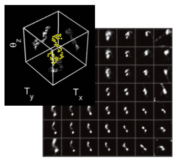
- Different blur models



Patch based
Efficient but no global constraint



Projective Motion Path
Globally consistent but inefficient



Hybrid
Efficient & globally consistent

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

Remaining Challenges

Failure example of Photoshop Shake Reduction

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

Introduction

Blind Deconvolution

Non-blind Deconvolution

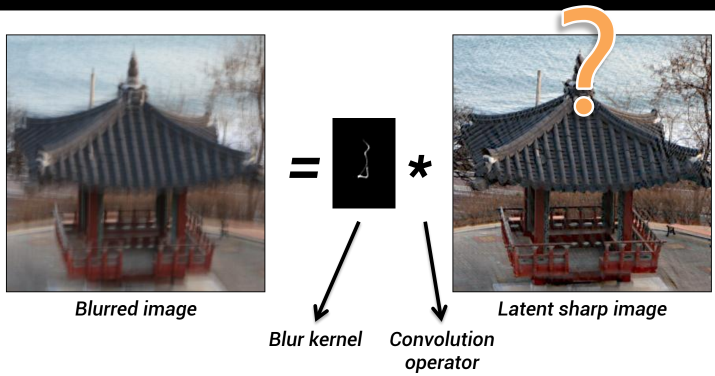
Introduction

Blind Deconvolution

Non-blind Deconvolution

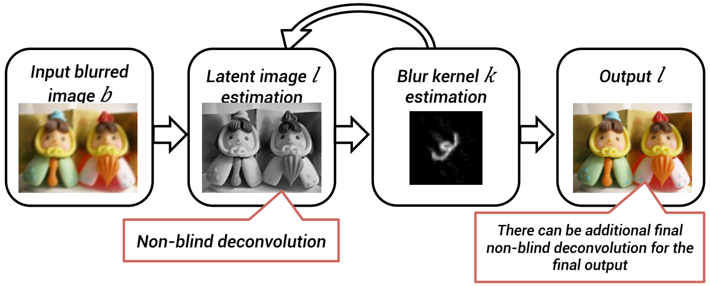
- Introduction
- Natural image statistics
- High-order natural image statistics
- Ringing artifacts
- Outliers

Non-blind Deconvolution (Uniform Blur)



Non-blind Deconvolution

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



Non-blind Deconvolution

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

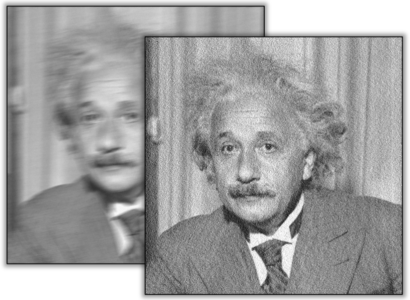
Ill-Posed Problem

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

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

Ill-Posed Problem

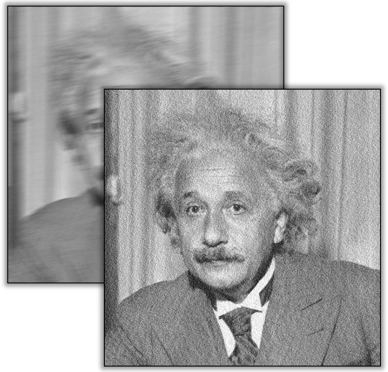
- *Deconvolution amplifies noise as well as sharpens edges*



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

Classical Methods

- *Popular methods*
  - *Wiener filtering*
  - *Richardson-Lucy deconvolution*
  - *Constrained least squares*
- *Matlab Image Processing Toolbox*
  - *deconvwnr, deconvlucy, deconvreg*
- *Simple assumption on noise and latent images*
  - *Simple & fast*
  - *Prone to noise & artifacts*



Introduction

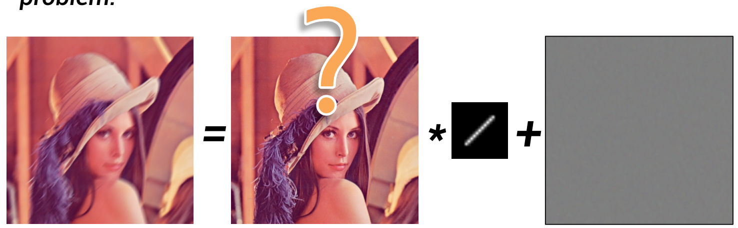
Blind Deconvolution

Non-blind Deconvolution

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

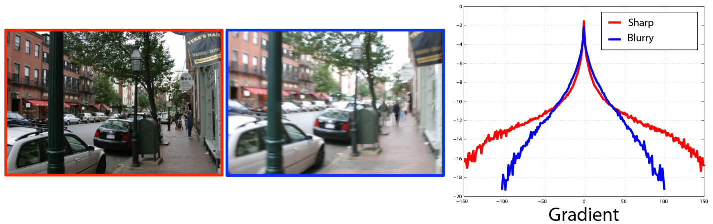
Natural Image Statistics

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



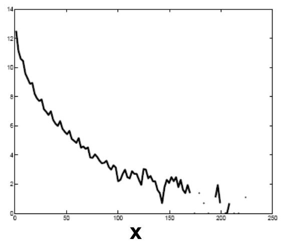
Natural Image Statistics

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

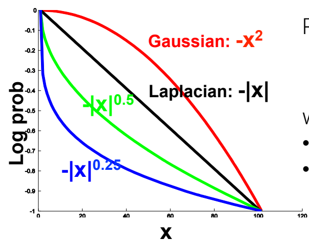


Natural Image Statistics

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



Derivative histogram from a natural image



Parametric models

Proposed prior

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

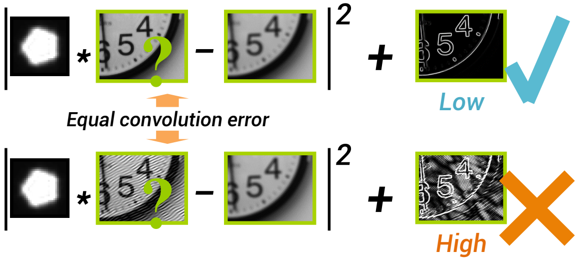
where:

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

Natural Image Statistics

- *Levin et al. SIGGRAPH 2007*

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



Natural Image Statistics

- *Levin et al. SIGGRAPH 2007*

"spread" gradients | "localizes" gradients

Input | Richardson-Lucy | Gaussian prior $\sum_i |\nabla l_i|^2$ | Sparse prior $\sum_i |\nabla l_i|^{0.8}$

Introduction

Blind Deconvolution

Non-blind Deconvolution

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

High-order Natural Image Priors

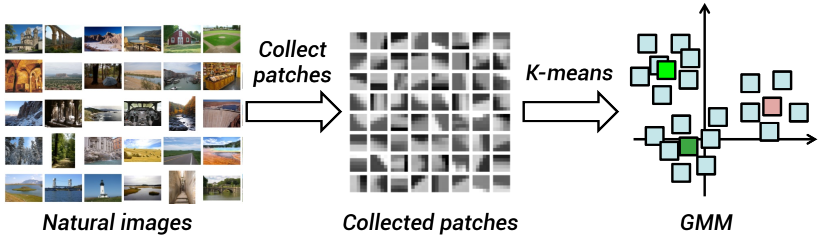
- *Patches, large neighborhoods, …*
- *Effective for various kinds of image restoration problems*
  - *Denoising, inpainting, super-resolution, deblurring, …*

High-order Natural Image Priors

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

High-order Natural Image Priors

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



High-order Natural Image Priors

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

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

High-order Natural Image Priors

- *Zoran & Weiss, ICCV 2011*

Denoising *Deblurring*

(a) Noisy Image - PSNR: 20.17
(b) KSVD - PSNR: 28.72
(c) LLSC - PSNR: 29.30
(d) EPLL GMM - PSNR: 29.39

Blurred image
Krishnan & Fergus PSNR: 26.38
Zoran & Weiss PSNR: 27.70

Introduction

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- Introduction
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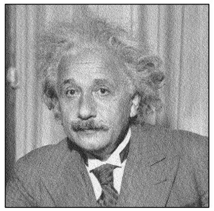
Ringing Artifacts

- *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

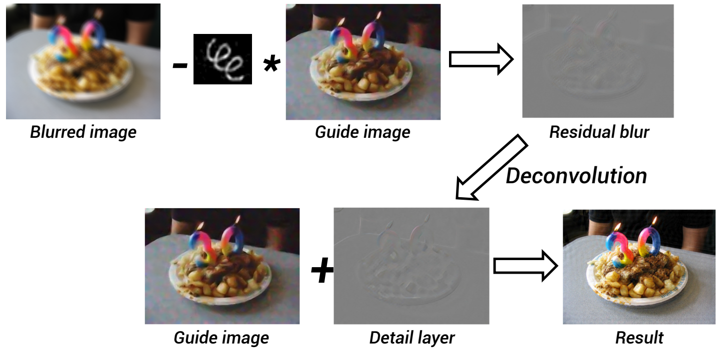
Richardson-Lucy

Yuan et al. SIGGRAPH 2008

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

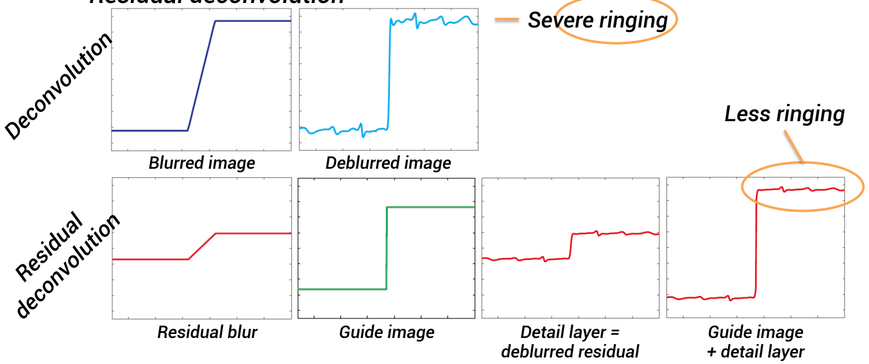
- Relatively accurate edges, but less details
- Obtained from a deconvolution result from a smaller scale

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



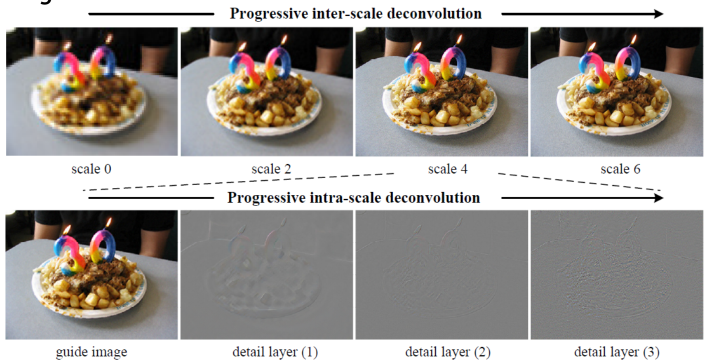
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

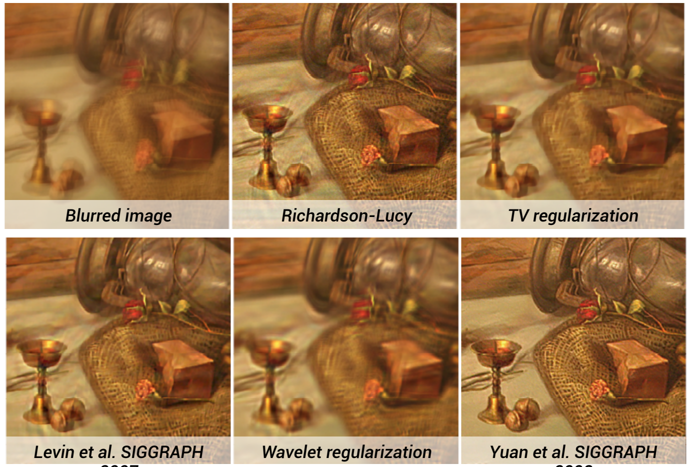
- *Residual deconvolution*



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

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





Introduction

Blind Deconvolution

Non-blind Deconvolution

- Introduction
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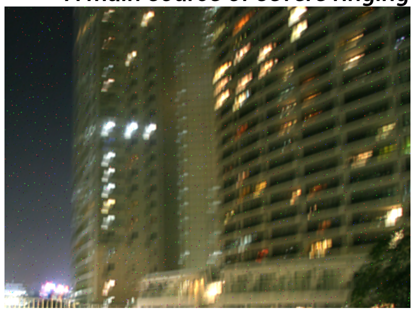
Outliers

- *A main source of severe ringing artifacts*

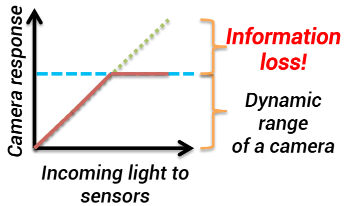


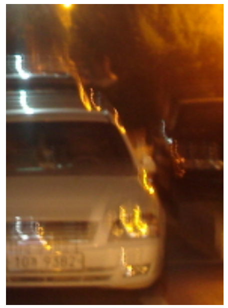
Blurred image with outliers

Deblurring result
[Levin et al. SIGGRAPH 2007]

Outliers

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



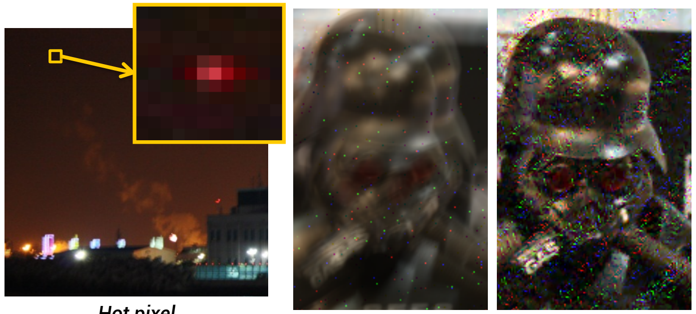


Blurred image

[Levin et al. 2007]

Outliers

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



Hot pixel

Blurred image with outliers [Levin et al. 2007]

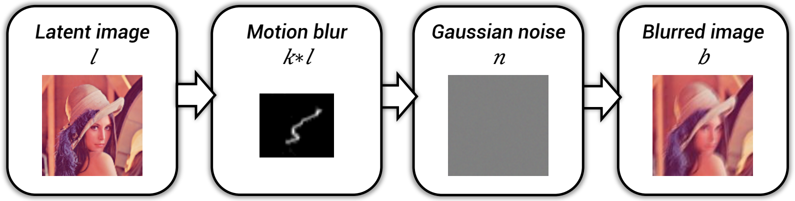
Outlier Handling

- Most common blur model:

$$b = k * l + n$$

small amount of Gaussian noise

Equivalent to



Outlier Handling

- An energy function derived from this model:

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

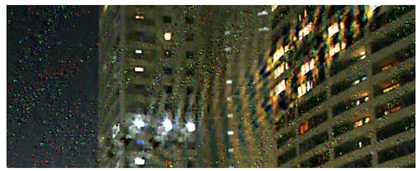
- More robust norms to outliers
  - L^1-norm, other robust statistics…

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

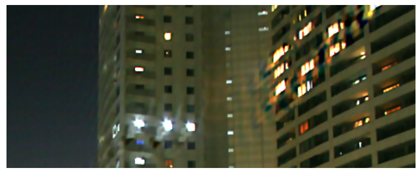
  - Bar et al. IJCV 2006, Xu et al. ECCV 2010, …

Outlier Handling

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



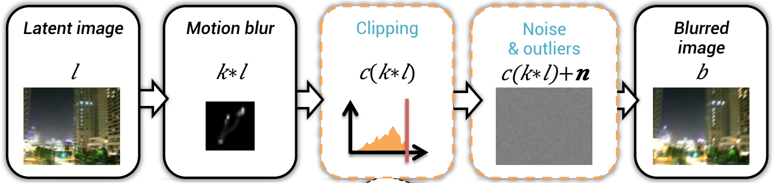
L^2-norm based data term



L^1-norm based data term

Cho et al. ICCV 2011

- *More accurate blur model reflecting outliers*

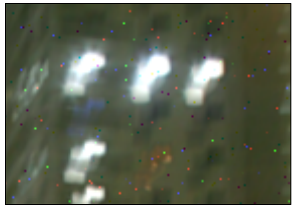


$$c(u) = \begin{cases} u & \text{if } u \in \text{DynamicRange} \\ \text{LowerBound} & \text{if } u < \text{LowerBound} \\ \text{UpperBound} & \text{if } u > \text{UpperBound} \end{cases}$$

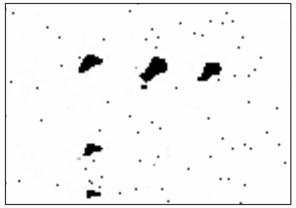
Cho et al. ICCV 2011

- *Classification mask*

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



Blurred image b



Classification mask m

Cho et al. ICCV 2011

- *MAP estimation*

Classification mask m

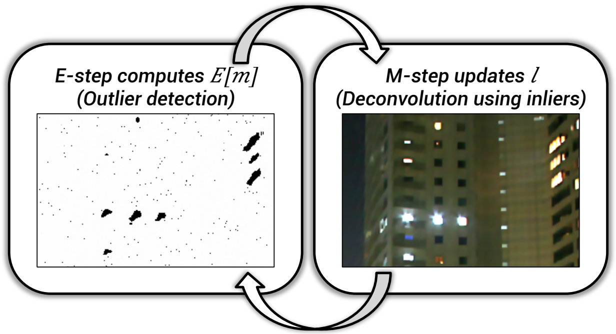
Given b & k, find the most probable l

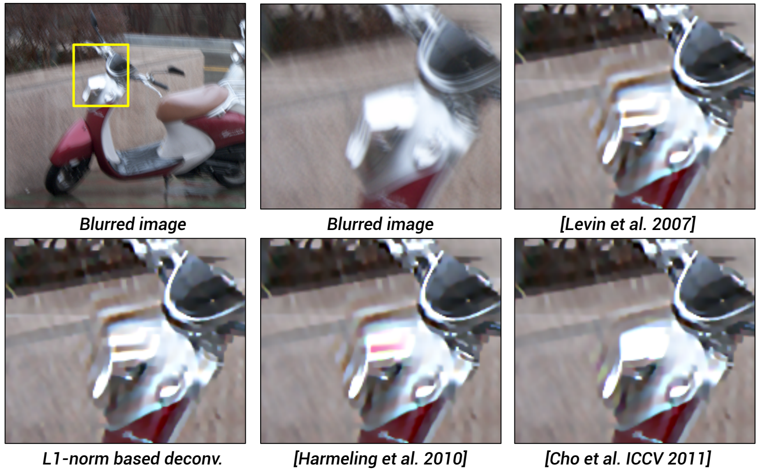
$$l_{MAP} = \arg\max_{l} p(l|b,k)$$

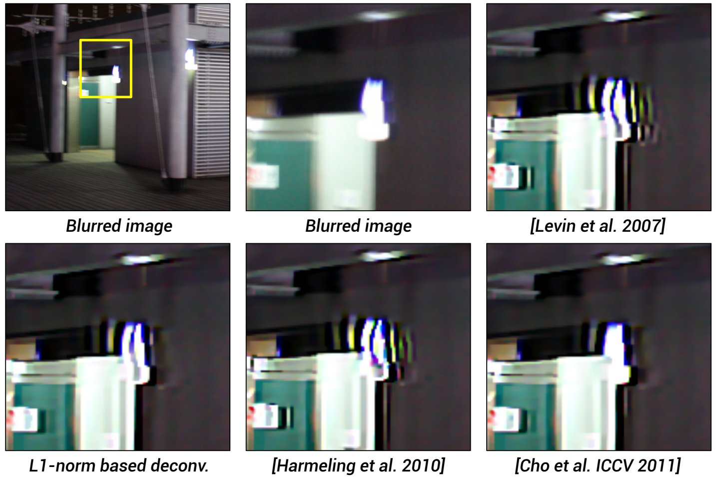
$$= \arg\max_{l} \sum_{m \in M} p(b|m,k,l)p(m|k,l)p(l)$$

Cho et al. ICCV 2011

- *EM based optimization*







Summary & Remaining Challenges

SIGGRAPH ASIA 2013 HONG KONG

- *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*