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 [bł3:(r)]

- Often degrades image/video quality severely
- Unavoidable under dim light circumstances
Various Kinds of Blurs

- Camera shake (Camera motion blur)
- Out of focus (Defocus blur)
- Object movement (Object motion 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!

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

\[ \text{Blurred image} = (\text{Latent sharp image}) \ast (\text{Blur kernel or Point Spread Function (PSF)}) \]

Convolution operator
Blind Deconvolution

Blurred image

= *

Latent sharp image

Blur kernel or Point Spread Function (PSF)

Convolution operator
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)
- Out of focus (Defocus blur)
- Object movement (Object motion 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  \[=\]  Convolution operator  \[\ast\]  Latent sharp image

- Blur kernel or Point Spread Function (PSF)

Latent sharp image
Key challenge: Ill-posedness!

Possible solutions

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

\[ 100 = \left\{ \begin{array}{l}
2 \times 50 \\
4 \times 25 \\
3 \times 33.333 \ldots
\end{array} \right. \]

Blurred image
• 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

* Images from Yitzhaky et al. 1998

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], ...

**Variational Bayesian based**

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

**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
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?
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 $b$
Bayes rule:

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

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

- Blur kernel $k$
- Latent image $l$
- Blurred image $b$
MAP based Approaches

Negative log-posterior:

\[-\log p(k, l|b) \Rightarrow -\log p(b|k, l) - \log p(l) - \log p(k)\]
\[\Rightarrow \|k \ast l - b\|^2 + \rho_l(l) + \rho_k(k)\]

- Data fitting term
- Regularization on latent image \(l\)
- Regularization on blur kernel \(k\)
MAP based Approaches

Negative log-posterior:

\[- \log p(k, l|b) \Rightarrow - \log p(b|k, l) - \log p(l) - \log p(k) \]
\[\Rightarrow \|k \ast l - b\|^2 + \rho_l(l) + \rho_k(k)\]

Alternatingly minimize the energy function w.r.t. $k$ and $l$
MAP based Approaches

Input blurred image $b$

Latent image $l$
- maximizes posterior w.r.t. $l$

Blur kernel $k$
- maximizes posterior w.r.t. $k$

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

Success Rate

Error ratio = 2
Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

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

• Not seek for one most probable solution, but consider all possible solutions

• Theoretically more robust

• Slow
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

*MAP v.s. Variational Bayes*
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

\[ p(k, l|b) \propto p(b|k, l)p(l)p(k) \]
Find an approximate distribution by minimizing Kullback-Leibler (KL) divergence

\[
\arg\min_{q(k), q(l), q(\sigma^{-2})} KL(q(k)q(l)q(\sigma^{-2}) \| p(k, l|b))
\]

approximate distributions for blur kernel \( k \), latent image \( l \), and noise variance \( \sigma^2 \)

- cf) MAP based approach:

\[
\arg\min_{k,l} p(k, l|b)
\]
Fergus et al. SIGGRAPH 2006

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

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

- 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

[Cho et al. SIGGRAPH Asia 2009], [Xu et al. ECCV 2010], [Hirsch et al. ICCV 2011], ...
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
• Key idea: blur can be estimated from a few edges
  ➔ No need to restore every detail for kernel estimation
Quickly restore important edges using simple image filters
Cho & Lee, SIGGRAPH Asia 2009

Input

Simple deconvolution

Prediction

Fast Kernel Estimation

Output

Do not need complex priors for the latent image and the blur kernel

⇒ Significantly reduce the computation time
Cho & Lee, SIGGRAPH Asia 2009

Fast but low quality deconvolution

Prediction

Previous kernel

Updated kernel
Prediction
Simple & fast image filtering operations

Fast but low-quality deconvolution
Bilateral filtering & Shock filtering
Thresholding gradients

Visualized by Poisson image reconstruction
Cho & Lee, SIGGRAPH Asia 2009

- State of the art results
- A few seconds
- 1Mpix image
- in C++
Extended edge prediction to handle blur larger than image structures

For this complex scene, most methods fail to estimate a correct blur kernel. Why?
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
Deconvolution → Smoothing & Shock filtering → Structure scale aware gradient thresholding

Visualized by Poisson image reconstruction
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

\[ x & y \text{ translational camera shakes} \]

Planar scene
Real Camera Shakes

6D real camera motion

Different depths
Real Blurred Image

Non-uniformly blurred image

Severe artifacts

Clean

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
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

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

Failure example of Photoshop Shake Reduction
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)

Equation: $\text{Blurred image} = \text{Blur kernel} \ast \text{Convolution operator} \ast \text{Latent sharp image}$
Non-blind Deconvolution

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

  \[ \text{Input blurred image } b \rightarrow \text{Latent image } l \text{ estimation} \rightarrow \text{Blur kernel } k \text{ estimation} \rightarrow \text{Output } l \]

  Non-blind deconvolution

  There can be additional final non-blind deconvolution for the final output
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:

  - Blur destroys high-freq info
  - Noise

• Loss of high-freq info & noise ≈ denoising & super-resolution
Ill-Posed Problem

- Deconvolution amplifies noise as well as sharpens edges
- Ringing artifacts
  - Inaccurate blur kernels, outliers cause ringing artifacts
Classical Methods

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

- Matlab Image Processing Toolbox
  - deconvwnr, deconvlucy, deconvreg

- Simple assumption on noise and latent images
  - Simple & fast
  - Prone to noise & artifacts
Introduction
Blind Deconvolution
Non-blind Deconvolution

• Introduction
• Natural image statistics
• High-order natural image statistics
• Ringing artifacts
• Outliers
Natural Image Statistics

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

\[ ? = \star \]
Natural Image Statistics

- Natural images have a heavy-tailed distribution on gradient magnitudes
  - Mostly zero & a few edges
Levin et al. SIGGRAPH 2007
- Propose a parametric model for natural image priors based on image gradients

Proposed prior
\[
\log p(x) = - \sum_i |\nabla x_i|^\alpha
\]
where:
- \( x \): image
- \( \alpha \): model parameter, \( \alpha < 1 \)
Natural Image Statistics

- Levin et al. SIGGRAPH 2007

\[ l = \arg\min_{l} \left\{ \| k \ast l - b \|^2 + \lambda \sum_{i} |\nabla l_i|^\alpha \right\} \quad (\alpha < 1) \]
Natural Image Statistics

- Levin et al. SIGGRAPH 2007

Input
Richardson-Lucy
Gaussian prior
Sparse prior

“spread” gradients
“localizes” gradients

\[ \sum_i |\nabla l_i|^2 \]

\[ \sum_i |\nabla l_i|^{0.8} \]
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, ...

![Image of high-order natural image priors](image.png)
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

Natural images → Collect patches → Collected patches → K-means → GMM
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:

\[
\arg \min_{l} \left\{ \| k * l - b \|^2 - \lambda \sum_{i} \log p(x_i) \right\}
\]

Log-likelihood of a patch \( l_i \) at \( i \)-th pixel based on GMM
High-order Natural Image Priors

- Zoran & Weiss, ICCV 2011

**Denoising**

(a) Noisy Image - PSNR: 20.17

(b) KSVD - PSNR: 28.72

(c) LLSC - PSNR: 29.30

(d) EPLL GMM - PSNR: 29.39

**Deblurring**

Blurred image

Krishnan & Fergus
PSNR: 26.38

Zoran & Weiss
PSNR: 27.70
Introduction
Blind Deconvolution
Non-blind Deconvolution

• Introduction
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• Ringing artifacts
• Outliers
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

Blurred image  Guide image  Residual deconvolution result with less ringing artifacts
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

- Blurred image
- Guide image
- Residual blur
- Deconvolution
- Guide image
- Detail layer
- Result
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

- Residual deconvolution

Deconvolution:
- Blurred image
- Deblurred image

Residual deconvolution:
- Residual blur
- Guide image
  - Detail layer = deblurred residual
  - Guide image + detail layer

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

- Progressive inter-scale & intra-scale deconvolution
<table>
<thead>
<tr>
<th>Blurred image</th>
<th>Richardson-Lucy</th>
<th>TV regularization</th>
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<td>Wavelet regularization</td>
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Introduction
Blind Deconvolution
Non-blind Deconvolution

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

[Levin et al. 2007]
Outliers

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

Blurred image with outliers [Levin et al. 2007]
Outlier Handling

- Most common blur model:
  \[ b = k \ast l + n \]
  
  Equivalent to
  
  small amount of Gaussian noise

Latent image

Motion blur

Gaussian noise

Blurred image
Outlier Handling

• An energy function derived from this model:
  \[ E(l) = \| k \ast l - b \|^2 + \rho(l) \]
  - \( L^2 \)-norm based data term: known to be vulnerable to outliers
  - Regularization term on a latent image \( l \)

• More robust norms to outliers
  - \( L^1 \)-norm, other robust statistics...
    \[ E(l) = \| k \ast l - b \|_1 + \rho(l) \]
  - Bar et al. IJCV 2006, Xu et al. ECCV 2010, ...
Outlier Handling

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

- $L^2$-norm based data term

$L^1$-norm based data term

$L^2$-norm based data term
• More accurate blur model reflecting outliers

\[
\text{Latent image: } l \\
\text{Motion blur: } k \ast l \\
\text{Clipping: } c(k \ast l) \\
\text{Noise \& outliers: } c(k \ast l) + n \\
\text{Blurred image: } b
\]

\[
c(u) = \begin{cases} 
u & \text{if } u \in \text{DynamicRange} \\ 
\text{LowerBound} & \text{if } u < \text{LowerBound} \\ 
\text{UpperBound} & \text{if } u > \text{UpperBound} 
\end{cases}
\]
Cho et al. ICCV 2011

- Classification mask

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

Given $b$ & $k$, find the most probable $l$

\[ l_{MAP} = \arg\max_l p(l|b, k) \]
\[ = \arg\max_l \sum_{m \in M} p(b|m, k, l)p(m|k, l)p(l) \]
• EM based optimization

E-step computes $E[m]$ (Outlier detection)

M-step updates $l$ (Deconvolution using inliers)
L1-norm based deconv.  [Levin et al. 2007]

[Cho et al. ICCV 2011]
Blurred image

L1-norm based deconv.

[Levin et al. 2007]

[Cho et al. ICCV 2011]

[Harmeling et al. 2010]
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 $\rightarrow$ Slower
• Many source codes are available on the authors’ website