BIL 717

Image Processing

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Image Deblurring

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Introduction

Blind Deconvolution

Non-blind Deconvolution
blur [bl3:(r)]

- Long exposure
- Moving objects
- Camera motion
  - panning shot
blur [b3:(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, ...)

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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

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

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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, ...)

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HONG KONG
Introduction

Blind Deconvolution

Non-blind Deconvolution
Introduction

Blind Deconvolution

Non-blind Deconvolution

• Introduction
  • Recent popular approaches
  • Non-uniform blur
Blind Deconvolution (Uniform Blur)

Blurred image

= ?

* ?

Latent sharp image

Blur kernel or Point Spread Function (PSF)

Convolution operator
Key challenge: Ill-posedness!

Possible solutions.

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

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

* 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

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
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], ...

**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?
Maximize a joint posterior probability with respect to $k$ and $l$

Posterior distribution

$p(k, l \mid b)$

Blur kernel $k$

Latent image $l$

Blurred image $b$
MAP based Approaches

Bayes rule:

\[ p(k, l | b) \propto p(b | l, k) p(l) p(k) \]

- Posterior distribution
- Likelihood
- Prior on \( l \)
- Prior on \( k \)

Blur kernel \( k \)

Latent image \( l \)

Blurred image \( b \)
MAP based Approaches

**Negative log-posterior:**

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

\[\Rightarrow \|k * l - b\|^2 + \rho_l(l) + \rho_k(k)\]

- 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 $l$ estimation
- maximizes posterior w.r.t. $l$

Blur kernel $k$ estimation
- 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
  - \textit{L0 norm based prior on latent images}
• 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

![Success Rate Diagram](Error ratio = 2)

Shan et al. SIGGRAPH 2008

Fergus et al. SIGGRAPH 2006
(variational Bayesian based)
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**

- **Maximum a-Posteriori (MAP)**
- **Variational Bayes**

**Score**

**Pixel intensity**
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

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

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

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**

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

**Variational Bayesian based**

- Explicitly try to recover sharp edges using heuristic image filters
- Fast

**Edge Prediction based**

- 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
• Key idea: blur can be estimated from a few edges
→ No need to restore every detail for kernel estimation
Input
Simple deconvolution
Prediction
Fast Kernel Estimation
Output

Quickly restore important edges using simple image filters
Quickly restore important edges using simple image filters. 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++
Xu & Jia, ECCV 2010

- Extended edge prediction to handle blur larger than image structures

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

- 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

![Bar chart showing PSNR (dB) for different methods: MAP, Variational Bayesian, and Edge prediction.]
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 $\rightarrow$ 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)

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:

  - **Input blurred image** $b$
  - **Latent image** $l$
  - **Blur kernel** $k$
  - **Output** $l$

  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:

  - Loss of high-freq info & noise \(\approx\) 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
Levin et al. SIGGRAPH 2007

- Propose a parametric model for natural image priors based on image gradients

Proposed prior

\[ \log p(x) = - \sum |\nabla x_i|^{\alpha} \]

where:
- \( x \): image
- \( \alpha \): model parameter, \( \alpha < 1 \)

Derivative histogram from a natural image

Parametric models

Gaussian: \(-x^2\)

Laplacian: \(-|x|\)

- \(|x|^{0.5}\)

- \(|x|^{0.25}\)
Natural Image Statistics

Levin et al. SIGGRAPH 2007

\[ l = \arg \min_l \left\{ \| k * l - b \|^2 + \lambda \sum_i |\nabla l_i|^\alpha \right\} \quad (\alpha < 1) \]
• 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, …
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:

$$\arg \min_l \left\{ \|k \ast l - b\|^2 - \lambda \sum_i \log p(l_i) \right\}$$

Log-likelihood of a patch $l_i$ at $i$-th pixel based on GMM
• 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
• Natural image statistics
• High-order natural image statistics
• 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
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]

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

  Severe ringing

  Less ringing

Residual deconvolution

Residual blur

Guide image

Detail layer = deblurred residual

Guide image + detail layer
Progressive Inter-scale & Intra-scale Deconvolution [Yuan et al. SIGGRAPH 2008]

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

  ![Progressive inter-scale deconvolution](image)

  ![Progressive intra-scale deconvolution](image)

  - scale 0
  - scale 2
  - scale 4
  - scale 6

  - guide image
  - detail layer (1)
  - detail layer (2)
  - detail layer (3)
<table>
<thead>
<tr>
<th>Blurred image</th>
<th>Richardson-Lucy</th>
<th>TV regularization</th>
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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]
• 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:

\[ b = k \ast l + n \]

Equivalent to a small amount of Gaussian noise.
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

- $L^1$-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
More accurate blur model reflecting outliers

\[ \text{Latent image} \rightarrow \text{Motion blur} \rightarrow \text{Clipping} \rightarrow \text{Noise and outliers} \rightarrow \text{Blurred image} \]

\[ c(u) = \begin{cases} 
    u & \text{if } u \in \text{DynamicRange} \\
    \text{LowerBound} & \text{if } u < \text{LowerBound} \\
    \text{UpperBound} & \text{if } u > \text{UpperBound} 
\end{cases} \]
• **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 \(m\)
• MAP estimation

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

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

$= \arg \max_l \sum_{m \in M} p(b|m, k, l)p(m|k, l)p(l)$
Cho et al. ICCV 2011

- **EM based optimization**

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

M-step updates $l$ (Deconvolution using inliers)
L1-norm based deconv. [Harmeling et al. 2010] [Cho et al. ICCV 2011]
L1-norm based deconv.

[Harmeling et al. 2010]

[Cho et al. ICCV 2011]
Summary & Remaining Challenges

- **Ill-posed problem - Noise & blur**
  - Noise
    - High-freq & unstructured
    - Natural image priors
  - Ringing
    - Mid-freq & structured
    - More difficult to handle
- **Outliers**
  - Cause severe ringing artifacts
  - More accurate blur model
- **Speed**
  - More complex model → Slower
- **Many source codes are available on the authors' website**