Recent Advances in Image Deblurring

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Presenters

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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.
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Introduction
Blind Deconvolution
Non-blind Deconvolution
Advanced Issues
blur  [bʌr]

- Long exposure
- Moving objects
- Camera motion
  - panning shot
**blur** [bɜː(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, ...)

[Images of examples for each type of blur]
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)  *  Latent sharp image

Convolution operator
Blind Deconvolution

Blurred image

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

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

- Every pixel is blurred in the same way
- Convolution based blur model
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, ...)

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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 $\ast$ blur kernel or Point Spread Function (PSF) = Latent sharp image

Convolution operator
Key challenge: Ill-posedness!

Possible solutions

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

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

Maximum Posterior (MAP) based

• [Cho & Lee. 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
• Proven to be effective in practice, but hard to analyze because of heuristic steps

Edge Prediction based

Which one is better?
Recent Popular Approaches

Maximum Posterior (MAP) based

Variational Bayesian based

Edge Prediction based

Which one is better?

- [Shan et al. SIGGRAPH 2008], [Krishnan et al. CVPR 2011], [Xu et al. CVPR 2013], ...

- Seek the most probable solution, which maximizes a posterior distribution
- Easy to understand
- Convergence problem
Maximize a joint posterior probability with respect to $k$ and $l$

$P(k, l|b)$

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**: \( p(k, l | b) \)
- **Likelihood**: \( p(b | l, k)p(l) \)
- **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 $l$
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 \(l\)

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

- 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
  – 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
Xu et al. CVPR 2013

- $L_0$ norm based prior for latent image $l$

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

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

- 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
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
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

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

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
• Efficient optimization based on EM

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

\[ = \int_l p(b, l|k)p(k)dl \]

\[ = \int_l p(b|l, k)p(l)p(k)dl \]

\[ \text{Marginalizing over } l \]

• cf) MAP based approach:

\[ p(k, l|b) \propto p(b|l, k)p(l)p(k) \]
Levin et al. CVPR 2010

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 $l$
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
• 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
Quickly restore important edges using simple image filters
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
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?
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
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

\[\text{Error ratio} = 2\]
Benchmarks

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

![Success Rate Chart]

Success Rate

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<th>1</th>
<th>2</th>
<th>3</th>
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<td>90</td>
<td>80</td>
<td>100</td>
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Error ratio = 2
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. The PSNR values are 24, 26, and 30, respectively.]
Benchmarks

• Benchmark results depend on
  – Implementation details & tricks
  – Benchmark datasets
  – Parameters used in benchmarks

• But, in general, more recent one shows better quality

• Speed?
  – Edge prediction > MAP >> Variational Bayesian
Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

• Introduction
• Recent popular approaches
• Non-uniform blur
• Summary
Convolution based Blur Model

- Uniform and spatially invariant blur
Real Camera Shakes: Spatially Variant!
Uniform Blur Model Assumes

x & y translational camera shakes

Planar scene
Real Camera Shakes

6D real camera motion

Different depths
Real Blurred Image

Non-uniformly blurred image

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
Projective Motion Path

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

\[ \sum_{i=1}^{N} w_i P_i \]
Projective Motion Path

- Tai et al. TPAMI 2011

\[ \sum_{i=1}^{N} w_i P_i \]

Blurred image \[ \xrightarrow{\text{weight}} \] Latent image \[ \xrightarrow{\text{Homography}} \] 6D real camera motion

Pros
- 6 DoF camera motions
- Globally consistent & physically plausible
Projective Motion Path

- Tai et al. TPAMI 2011

\[
\sum_{i=1}^{N} w_i P_i \]

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
Projective Motion Path

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

- Whyte et al. CVPR 2010

\[
\sum_{i=1}^{N} w_i P_i \begin{pmatrix} \theta_x \\ \theta_y \\ \theta_z \end{pmatrix}
\]

- 3 DoF camera motions
  - Roll, yaw, pitch ($\theta_x, \theta_y, \theta_z$)
  - Discretize 3D motion parameter space
    $\Rightarrow$ 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

\[ \sum_{i=1}^{N} w_i P_i \]

- Blurred image
- 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 \( \Rightarrow \) 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

3D blur kernel based on projective motion chain

Globally consistent & physically plausible

2D local blur kernels

Computationally efficient

Patch-wise blur using Fourier transforms

Sharp image

Blurred image
More Efficient Blur Model

- Hirsch et al. ICCV 2011

Blurred image

Xu & Jia, ECCV 2010 (uniform blur)

Gupta et al. ECCV 2010 (non-uniform)

Hirsch et al. ICCV 2011 (non-uniform)
More Efficient Blur Model

- Dependence of PSF size
- Dependence of image size
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

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Non-blind Deconvolution

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• Summary
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
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
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Advanced Issues

• Introduction
• Natural image statistics
• High-order natural image statistics
• Ringing artifacts
• Outliers
• Summary
Non-blind Deconvolution (Uniform Blur)

\[ \text{Blurred image} = \text{Blur kernel} \ast \text{Convolution operator} \]

\[ \ast \]

\[ \text{Latent sharp image} \]
Non-blind Deconvolution

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

  - Input blurred image $b$
  - Latent image $l$ estimation
  - Blur kernel $k$ estimation
  - 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:
  - 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

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

\[ ? = \ast \]
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

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

Data term

Prior

Equal convolution error
Natural Image Statistics

- Levin et al. SIGGRAPH 2007

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

“spread” gradients

“localizes” gradients
Krishnan & Fergus, NIPS 2009
- Minimizes the same energy function:
  \[ l = \arg \min_l \{\|k \times l - b\|^2 + \lambda \sum_i |\nabla l_i|^\alpha \} \quad (\alpha < 1) \]
  - But much faster
  - Efficient optimization based on half-quadratic scheme
• Krishnan & Fergus, NIPS 2009

Similar quality, but more than 100x faster
Introduction
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- Introduction
- Natural image statistics
- High-order natural image statistics
- Ringing artifacts
- Outliers
- Summary
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
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

Blurred image

Krishnan & Fergus
PSNR: 26.38

Zoran & Weiss
PSNR: 27.70

Deblurring
Introduction
Blind Deconvolution
Non-blind Deconvolution
Advanced Issues

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

• Wave-like artifacts around strong edges
• Caused by
  – Inaccurate blur kernels
  – Nonlinear response curve
  – Etc...
Ringing Artifacts

- **Noise**
  - High-freq
  - Independent and identical distribution
  - Priors on image gradients work well

- **Ringing**
  - Mid-freq
  - Spatial correlation
  - Priors on image gradients are not very effective
Ringing Artifacts

- Yuan et al. SIGGRAPH 2007
  - Residual deconvolution & de-ringing
- Yuan et al. SIGGRAPH 2008
  - Multi-scale deconvolution framework based on residual deconvolution
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

Blurred image  Guide image  Residual deconvolution result with less ringing artifacts

• Relatively accurate edges, but less details
• Obtained from a deconvolution result from a smaller scale
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]
Residual Deconvolution [Yuan et al. SIGGRAPH 2007, 2008]

- Residual deconvolution

![Graphs showing deblurring process]

- Severe ringing
- Less ringing

Blurred image → Deblurred image → Residual blur

Guide image

Detail layer = deblurred residual + detail layer
Progressive Inter-scale & Intra-scale Deconvolution [Yuan et al. SIGGRAPH 2008]

- Progressive inter-scale & intra-scale deconvolution

---

Progressive inter-scale deconvolution

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

Progressive intra-scale deconvolution

- guide image
- detail layer (1)
- detail layer (2)
- detail layer (3)
Blurred image
Richardson-Lucy
TV regularization

Levin et al. SIGGRAPH 2007
Wavelet regularization
Yuan et al. SIGGRAPH 2008
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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

[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 a small amount of Gaussian noise

Latent image \( l \)

Motion blur \( k \ast l \)

Gaussian noise \( n \)

Blurred image \( b \)
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
Cho et al. ICCV 2011

- More accurate blur model reflecting outliers

\[
l \xrightarrow{k \ast l} c(k \ast l) \xrightarrow{c(k \ast l) + n} b
\]

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

- Classification mask

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

Blurred image \( b \)

Classification mask \( m \)
Given $b$ & $k$, find the most probable $l$

\[ l_{\text{MAP}} = \arg \max_l p(l|b, k) \]

\[ = \arg \max_l \sum_{m \in M} p(b|m, k, l)p(m|k, l)p(l) \]
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]
Blurred image

Blurred image

[Levin et al. 2007]

L1-norm based deconv.

[Harmeling et al. 2010]

[Cho et al. ICCV 2011]
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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
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Advanced Issues

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

- To estimate blur kernels
- To restore sharp images better

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

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

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

• Raskar et al. SIGGRAPH 2006

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

- Low-res Camera with high frame rate (100 fps)
- High-res Camera with low frame rate (25 fps)
- Beam-splitter
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
Gyro Sensors + Accelerometers

- Joshi et al. SIGGRAPH 2010

- 3 gyro sensors
- 3 accelerometers
- 6 DoF camera motion
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
• Segmentation + local blur estimation
Digital Refocusing

Input image

Shallower depth-of-field

Refocused on the orange crayon
Coded Aperture [Levin et al. SIGGRAPH 2007]

- Coded aperture to more accurately estimate local blur kernels

![Diagram showing conventional and coded aperture comparisons](image-url)
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]

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
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

Blurred image

Rotational symmetric kernel basis

Latent image
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

Generate a sharp panorama image from blurred video frames

[Li et al. CVPR 2010]

Generate a sharp video using patch-based synthesis

[Cho et al. SIGGRAPH 2012]
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]

- 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]

Stabilization only

Video deblurring + stabilization
Video Deblurring [Cho et al. SIGGRAPH 2012]

Stabilization only

Video deblurring + stabilization
Introduction

Blind Deconvolution

Non-blind Deconvolution

Advanced Issues

• Hardware based approaches
• Defocus / optical lens / object motion / video blur...
• Other issues
Outliers & Noise

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

• Non-blind deconvolution
  – Cho et al. ICCV 2012 – Outlier handling

• Blind deconvolution
  – Tai & Lin, CVPR 2012
    Nonlocal denoising & deblurring
  – Zhong et al. CVPR 2013
    Noise handling using directional filters
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
Nonlinear Camera Response Functions

- Common blur model: \( b \neq k \ast l \)

  *Due to CRF*

- Previous methods often fail to estimate a blur kernel & produce severe ringing

- Kim et al. CVPR 2012
  - Estimate a CRF from a blurred image

**Blurred image**

**Without CRF handling**  
**Kim et al. CVPR 2012**
Other Information

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

Blurry image with light streaks  Photoshop Shake Reduction
Quality Metric

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

Blurred image

Different deblurring results

Liu et al. Fusion using the quality metric
Domain Specific Deblurring

• 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