Toward Non-stationary Blind Image Deblurring: Models and Techniques

Ji, Hui

Department of Mathematics
National University of Singapore

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Outline of the talk

• Non-stationary Image blurring
  – Motion blurring
  – Out-of-focus blurring

• Brief Introduction to blind deconvolution (stationary image blurring)

• A two-stage approach for recovering images with non-stationary motion blurring

• A fast method for estimating de-focus map of images with non-stationary out-of-focus blurring
Image blurring

• Degradation of sharpness and contrast of the image, causing loss of image details (high frequency information)
Image blurring

- Degradation of sharpness and contrast of the image, causing loss of image details (high frequency information)

Motion blurring  
Out-of-focus blurring
Motion blurring

- Blurring caused by the relative motion between camera or object during shutter time
  - Larger motion; more blurring
Out-of-focus (defocus) blurring

- Blurring caused by objects away from focal plane
  - More away from focal plane; more blurring
Motion blur: motion path on image plane

- Pinhole camera

\[
\begin{pmatrix}
x \\ y \\ 1 \\
\end{pmatrix} = \frac{f}{Z} \begin{pmatrix}
X \\ Y \\ Z \\
\end{pmatrix}
\]

3D rigid camera motion:

\[
t = \begin{pmatrix}
t_x \\ t_y \\ t_z \\
\end{pmatrix}, \quad \omega = \begin{pmatrix}
\omega_x \\ \omega_y \\ \omega_z \\
\end{pmatrix}
\]

- 2D Motion field in image

\[
\dot{r}(t) = \begin{pmatrix}
\dot{x}(t) \\ \dot{y}(t) \\
\end{pmatrix} = \frac{f}{Z} \begin{pmatrix}
-t_x + t_z x \\ -t_y + t_z y \\
\end{pmatrix} + \begin{pmatrix}
xy\omega_x - (x^2 + 1)\omega_y + y\omega_z \\ (y^2 + 1)\omega_x - xy\omega_y - x\omega_z \\
\end{pmatrix}
\]

- Spatially invariant motion blur == constant motion field
  - Scene depth \( Z \) is close to constant
  - Camera motion: \( t = (t_x, t_y, 0); \omega = 0 \)
Motion blurring: Stationary VS Non-stationary

- Constant scene depth
- In-plane camera translation
- Rotational camera motion

- Slanted scene depth
- In-plane camera translation

- Dynamic scene with moving object
De-focus blurring: usually nonstationary

- Image usually contains several depth layer
- Different layer has different blurring

De-focus blurring amount $\approx$ Ordinal scene depth
Convolution model for stationary image blurring

\[ f = g \otimes p + \eta \]

\( \otimes \): Convolution (non-invertible)

Blurred image known
Sharp image unknown
Kernel (PSF) unknown
Noise unknown
Regularization for blind image deconvolution

\[ f = g \otimes p + \eta \]

- Infinite number of solutions: how to avoid the trivial solution: \( f = f \otimes \delta \)
- \( \ell_1 \)-norm relating regularization (either TV or wavelet)

\[
\min_{g,p} 2^{-1} \| f - g * p \|_2^2 + \lambda_1 \psi_1 (g) + \lambda_2 \psi_2 (p) \quad \text{s.t.} \quad p \in \Phi
\]

\[
\begin{align*}
\psi_1 (g) &= \| Wg \|_1 + \tau \| Ws \|_1 + \tau \| h \|_2^2 \\
\psi_2 (h) &= \| Wh \|_1 + \tau \| h \|_2^2 \\
\Phi &= \{ p : \sum_{j \in J} p[j] = 1, \ p[j] \geq 0 \}
\end{align*}
\]

Regularization for blind image deconvolution

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\[
\begin{align*}
\psi_1 (g) &= \| Wg \|_1; \\
\psi_2 (h) &= \| Wh \|_1 + \tau \| h \|_2^2
\end{align*}
\]

Remark: \( \| h \|_2^2 \) is for avoiding convergence to \( \delta \), as \( n^{-1} [1, \ldots, 1] = \arg \min \| h \|_2^2 \) s.t. \( h \in \Phi \)

Demonstration

Real blurred image

Our result
Demonstration

Real blurred image

Our result
Non-stationary image blurring

Motion blurring

Out-of-focus blurring
Stationary VS Non-stationary (in 1D case)

- Matrix form of Convolution:
  \[ f = Kg + \eta, \quad K \in \mathbb{R}^{n \times n} \]
  - Stationary: all rows of \( K \) are same, up to a shift
  - Nonstationary: each row of \( K \) might be different

- Motion blurring
  - Each row is of free-form, but with compact support

- Out-of-focus blurring
  - Each row is a Gaussian, but with different standard deviation
A piece-wise stationary model based framework [2]

[2] H. Ji and K. Wang, A two-stage approach to remove spatially-varying motion blur from a single photograph, CVPR’12
Sensitivity of deconvolution to blur kernel error

Clear image

Image blurred by horizontal constant kernel of size 10 pixels
Sensitivity of deconvolution to blur kernel error

Clear image

Image blurred by horizontal constant kernel of size 10 pixels

Image de-blurred by $\ell_1$-norm based regularization, and an erroneous kernel (horizontal constant of size 12 pixels)
Robust non-blind image deconvolution [3]

• An EIV (Error-In-Variable) model for de-convolution

\[ f = p \otimes g + n = (\tilde{p} - \delta_p) \otimes g + n \]

\( \delta_p \) : kernel error; \( n \) : image noise

• Problem : given \( f \) and \( \tilde{p} \), estimate \( g \)

Robust non-blind image deconvolution [3]

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• Reformulation:

\[ f = (\tilde{p} - d_p) * g + n = \tilde{p} * g - q + n \]

Two unknowns:

\[ \begin{cases} 
    g : \text{clear image} \\
    q = \delta_p \otimes g : \text{image distortion by kernel error}
\end{cases} \]

Two sparsity-relating regularization

- Sparsity of $q = p^*g$ in pixel space
Two sparsity-relating regularization

- Sparsity of \( q = p^*g \) in pixel space

- Second: Artifacts in solution caused by kernel error is sparse in DCT domain

Result using Erroneous kernel

The resulting error along edges
Convex minimization model

- Model for robust image deconvolution

\[
\begin{align*}
\begin{cases}
g^* = W^\top c^*, \\
[c^*, h^*, u^*] = \arg\min_{c,h,u} \Phi(c,h,u) + \lambda_1 \| c \|_1 + \lambda_2 \| h \|_1 + \lambda_3 \| u \|_1
\end{cases}
\end{align*}
\]

\[
\Phi(c,h,u) = \frac{1}{2} \| f - \tilde{p}^* (W^\top c + D^\top u) + h \|_2^2 + \frac{1}{2} \| (I - W^\top W) c \|_2^2
\]

- Clear image
- Artifacts
- System error

- W: framelet transform, D: DCT transform
Demo.

Blurry image

Stationary blind deconvolution

Gupta et al. ECCV’10 (nonstationary)

Our nonstationary method
Demo.

Blurry image

Stationary blind deconvolution

Gupta et al. ECCV’10 (non-stationary)

Our nonstationary method
Demo.

Blurry image

Stationary blind deconvolution

Whyte et al. CVPR’10 (non-stationary)

Our nonstationary method
Demo.

Blurry image

Whyte et al. CVPR’10 (non-stationary)

Stationary blind deconvolution

Our nonstationary method
Out-of-focus (defocus) blurring

Circle of Confusion

\[
    c = \frac{|d - d_f|}{d} \frac{f_0^2}{n_s(d_f - f_0)}
\]

(defocus amount) \( c(\vec{r}_0) \sim \sigma(\vec{r}_0) \) (Gaussian s.t.d.)

for each pixel \( \vec{r}_0 \), blur kernel

\[
    p(\vec{r}_0) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{||\vec{r} - \vec{r}_0||^2}{\sigma^2(\vec{r}_0)}\right)
\]
Defocus amount estimation from a single image [4]

Darker color = less defocus amount = less blurring = closer distance

Defocus amount estimation from a single image [4]

Darker color = less defocus amount = less blurring = closer distance

- Defocus amount ≈ ordinal scene depth
  - foreground/background segmentation
  - Image matting; image refocusing

**Proposition**  Consider three matrices $U, I, G$ associated by 2D convolution: $I = U \otimes G$. Suppose $U$ is positive (negative) definite and $G = gg^\top$. Then, $\text{Rank}(I) = \|\hat{g}\|_0$, where $\hat{g}$ is DFT of $g$.

- Constructing positive (negative) patches at edges points
  - Sampling $K$ image patches with different orientations.
  - One of these different oriented patches is positive definite.
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**Proposition**  
Consider three matrices $U, I, G$ associated by 2D convolution: $I = U \otimes G$. Suppose $U$ is positive (negative) definite and $G = gg^\top$. Then, $\text{Rank}(I) = ||\hat{g}||_0$, where $\hat{g}$ is DFT of $g$.

- Constructing positive (negative) patches at edges points
  - Sampling $K$ image patches with different orientations.
  - One of these different oriented patches is positive definite.

- Defocus amount and maximum rank of oriented patches
  \[
  \frac{1}{c} \left( \frac{1}{\sigma} \right) \sim -\ln \left( 1 - \frac{\max_{0 \leq k \leq K} \text{Rank}(P_k)}{n} \right)
  \]
Completion of defocus map

Input image

Defocus estimation at edge points
Completion of defocus map

• Defocus map completion by matting Laplacian method
  – Keep the values in complete map are close to the ones given at edge points
  – Keeping the discontinuities of defocus map consistent with image edges.
Demonstration

- Input image
- Defocus map at edges
Demonstration

- Input image
- Defocus map at edges
- Complete defocus map
Demonstration

Input image

Complete defocus map

defocus map at edges

Foreground segmentation
More

Input image | Bae et al. | Tang et al. | ours

The figure shows comparisons between an input image and its processing results by Bae et al., Tang et al., and their proposed method (ours). The color maps illustrate the saliency or attention maps, highlighting areas of interest in the images.
Evaluation on fore/background segmentation

• Test defocus dataset from CUHK: 704 images
  – Manually segmented in-focus foreground and out-of-focus background

Precision and recall curves of foreground/background segmentation using the defocus maps generated by different methods
Occlusion-aware image composition

Source image

Target
Occlusion-aware image composition

Source image

Target

Image composition 1
Occlusion-aware image composition

Source image

Target

Image composition 1

Image composition 2
List of co-authors

• Blind deconvolution for removing motion blur
  – Jianfeng Cai, Chaoqiang Liu and Zuowei Shen

• Non-stationery blind motion deblurring
  – Wang Kang

• Non-stationary out-of-focus blurring estimation and applications
  – Xu Guodong and Yuhui Quan
Thank You