Toward Non-stationary Blind Image Deblurring: Models and Techniques

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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)

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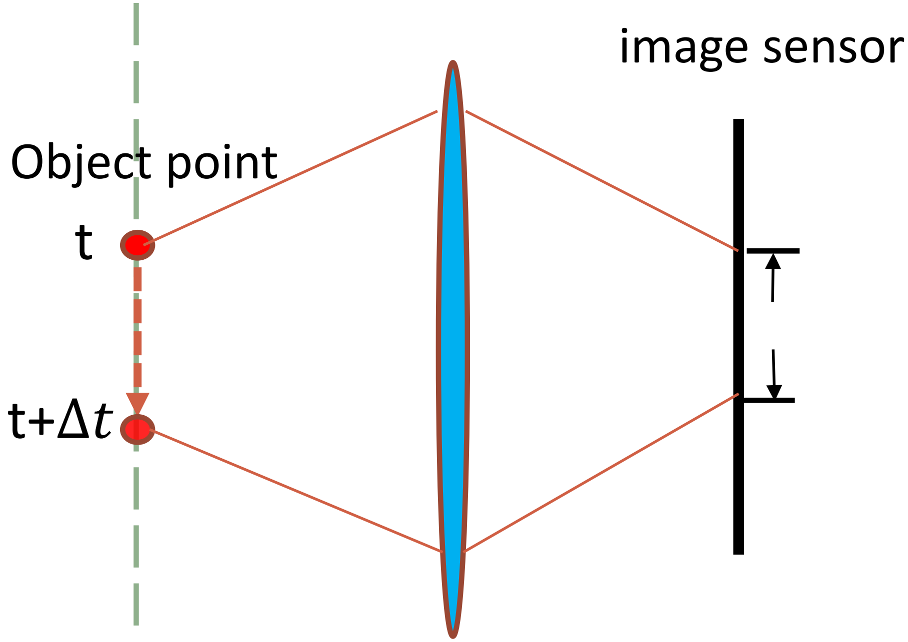
Motion blurring

Out-of-focus blurring

Motion blurring

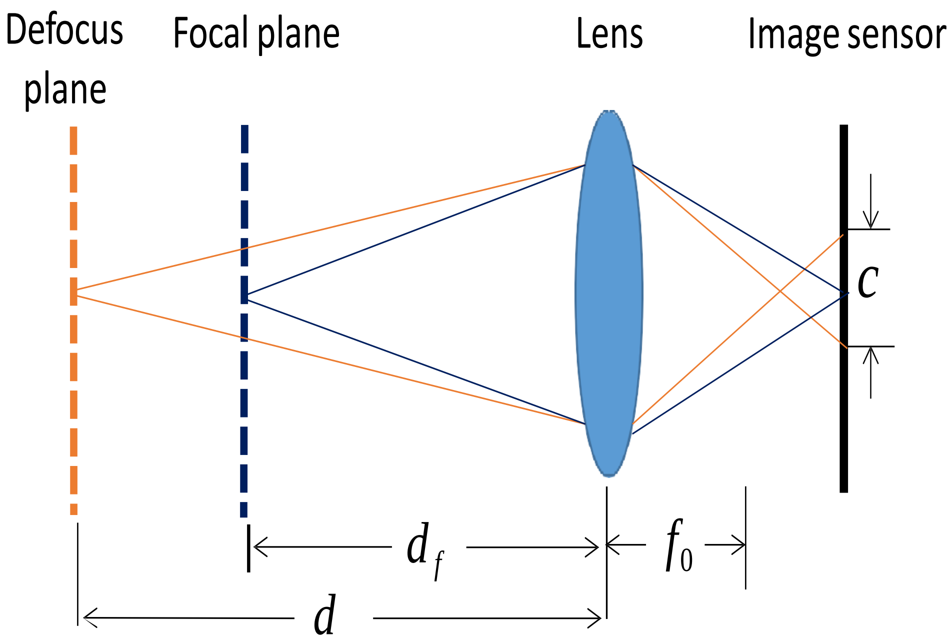
- Blurring caused by the relative motion between camera or object during shutter time
  - Larger motion; more blurring



Motion 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

$$\dot{r}(t) = \begin{pmatrix} \dot{x}(t) \\ \dot{y}(t) \end{pmatrix} = \frac{f}{\mathbf{Z}} \begin{pmatrix} -t_x + t_z x \\ -t_y + t_z y \end{pmatrix} + \begin{pmatrix} xy\varpi_x - (x^2+1)\varpi_y + y\varpi_z \\ (y^2+1)\varpi_x - xy\varpi_y - x\varpi_z \end{pmatrix}$$

  – 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

Slanted scene depth
In-plane camera translation

Rotational camera motion

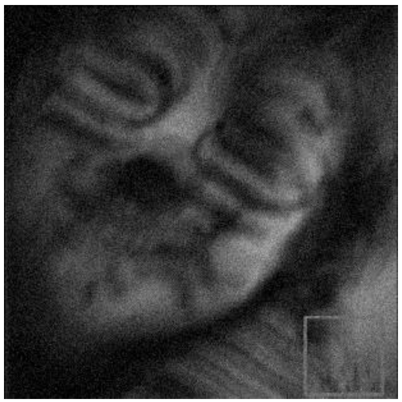
Dynamic scene with moving object

De-focus blurring: usually nonstationary

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

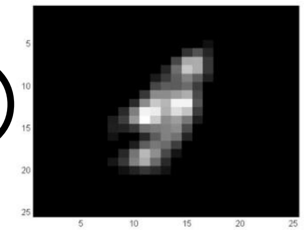
De-focus blurring amount ≈ Ordinal scene depth

Convolution model for stationary image blurring



$=$

$\otimes$



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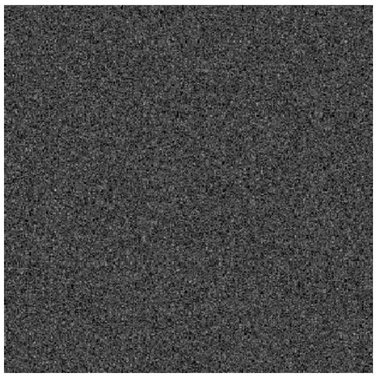

$\otimes$: Convolution
(non-invertible)

$$g \otimes p = \sum_{m,n} g[k_1, k_2]\, p[m-k_1, n-k_2]$$

Blind deblurring:

$$f = g \otimes p + \eta$$

Blurred image	Sharp image	Kernel (PSF)	Noise
known	unknown	unknown	unknown

Regularization for blind image deconvolution

$$f = g \otimes p + \eta$$

- Infinite number of solutions: how to avoid the trivial solution: $f = f \otimes \delta$
- ℓ_1-norm relating regularization (either TV or wavelet)

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

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

[1] J. Cai, H. Ji, C. Liu and Z. Shen, Blind motion deblurring from a single image using sparse approximation, CVPR'09

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Remark: $||h||_2^2$ is for avoiding convergence to δ, as

$$n^{-1}[1, \ldots, 1] = \arg\min \| h \|_2^2 \text{ s.t. } h \in \Phi$$

[1] J. Cai, H. Ji, C. Liu and Z. Shen, Blind motion deblurring from a single image using sparse approximation, CVPR'09

Demonstration

Real blurred image

Our result

Demonstration

Real blurred image

Our result

Non-stationary image blurring

Motion blurring

Out-of-focus blurring

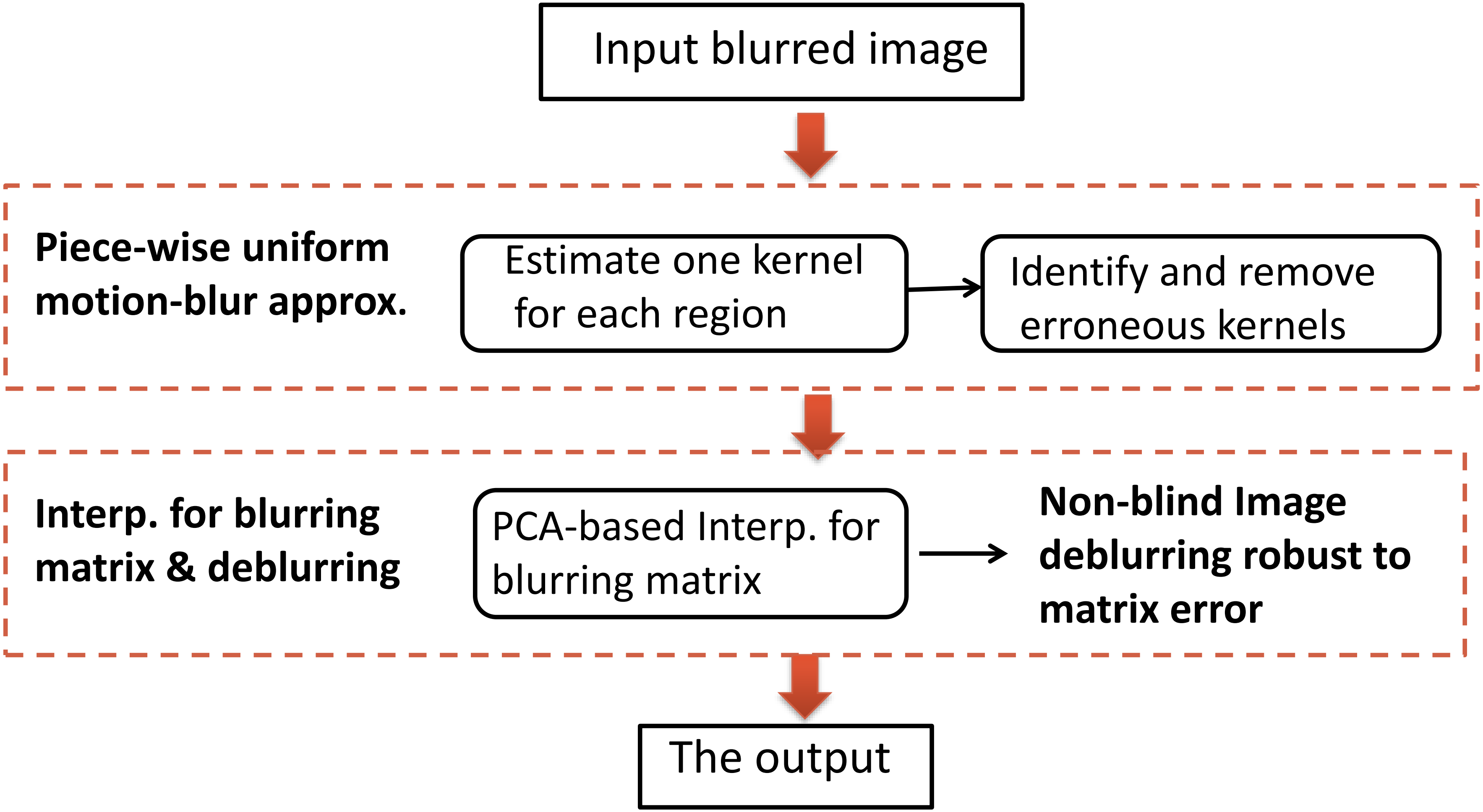
Stationary VS Non-stationary (in 1D case)

- 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 ℓ_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

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

δ_p : kernel error; n: image noise

- Problem : given f and $\tilde{p}$, estimate g

[3] H. Ji and K. Wang, Robust image de-convolution with an inaccurate blur kernel. *IEEE Trans. Image Proc.*. 2012

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- Problem : given f and $\tilde{p}$, estimate g
- Reformulation:

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

Two unknowns: $\begin{cases} g: \text{ clear image} \\ q = \delta p \otimes g: \text{ image distortion by kernel error} \end{cases}$

[3] H. Ji and K. Wang, Robust image de-convolution with an inaccurate blur kernel. *IEEE Trans. Image Proc.*. 2012

Two sparsity-relating regularization

- Sparsity of $q = dp * g$ in pixel space

g $\quad$ $p * g$ $\quad$ $\tilde{p} * g$ $\quad$ $dp * g$

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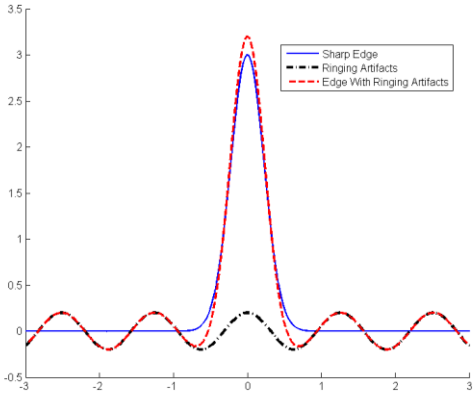
- Second: Artifacts in solution caused by kernel error is sparse in DCT domain

Result using Erroneous kernel



The resulting error along edges

Convex minimization model

- Model for robust image deconvolution

$$\begin{cases} g^* = W^\top c^*, \\ [c^*, h^*, u^*] = \operatorname{argmin}_{c,h,u} \Phi(c,h,u) + \lambda_1 \| c \|_1 + \lambda_2 \| h \|_1 + \lambda_3 \| u \|_1 \end{cases}$$

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

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)

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Demo.

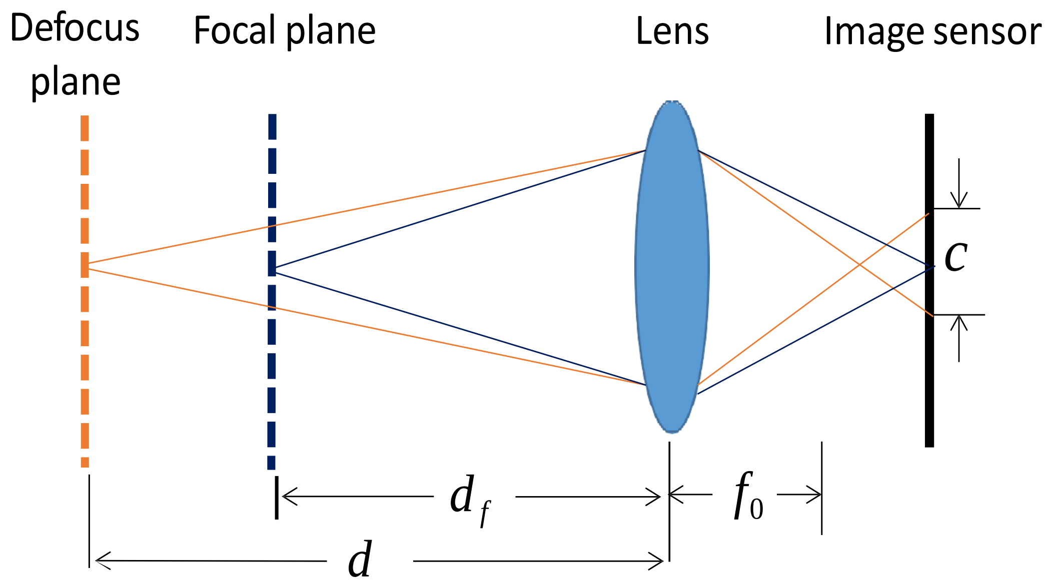
Blurry image

Stationary blind deconvolution

Whyte et al. CVPR'10 (non-stationary)

Our nonstationary method

Out-of-focus (defocus) blurring



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

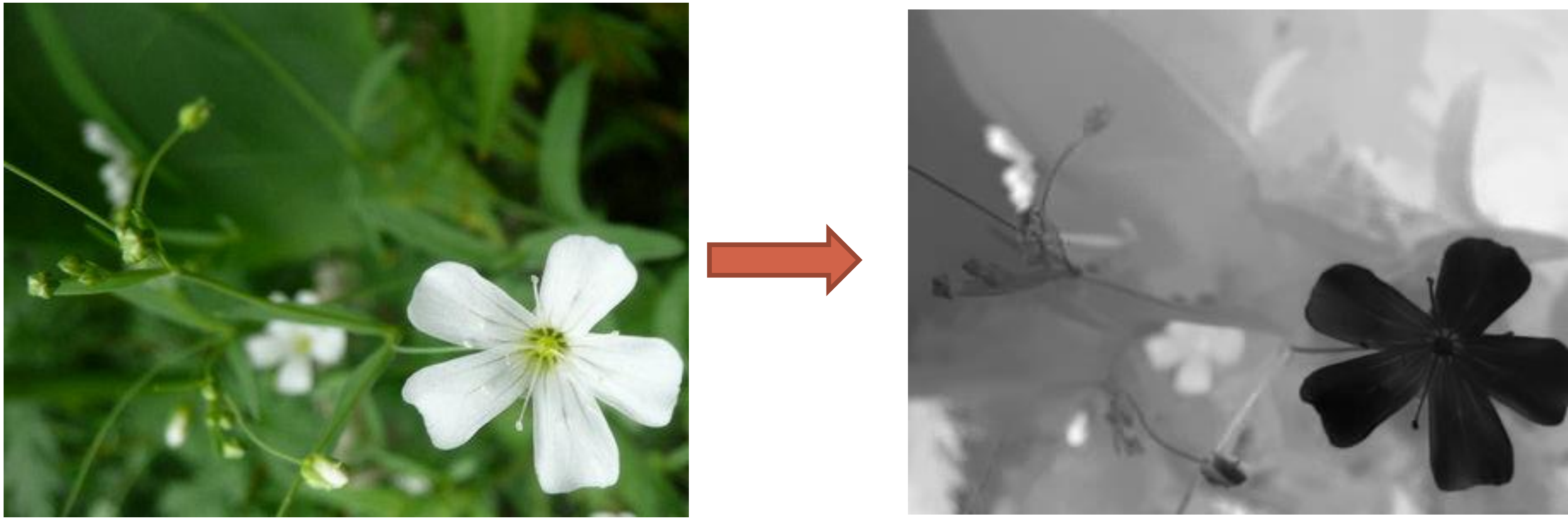
Circle of Confusion

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

$$p(\vec{r}_0) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{\|\vec{r} - \vec{r}_0\|_2^2}{\sigma^2(\vec{r}_0)}\right)$$

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

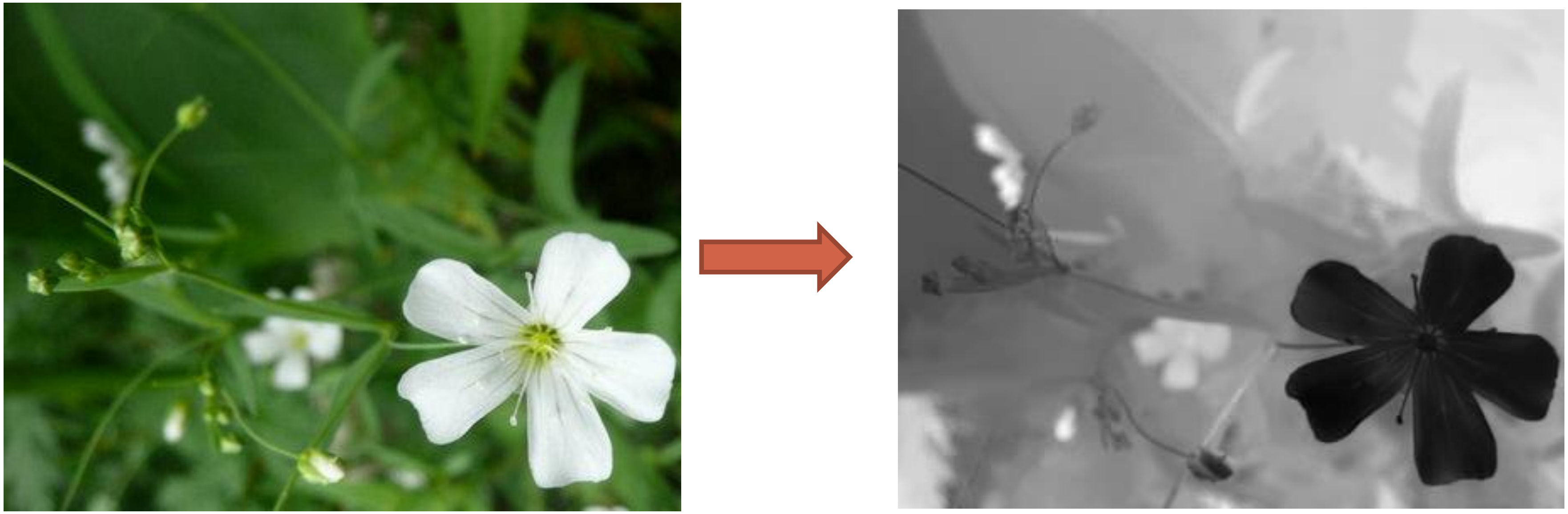
Defocus amount estimation from a single image [4]



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

[4] G. Xu, Y. Quan and H. Ji, Defocus amount estimation via maximum rank of patches, 2017

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

[4] G. Xu, Y. Quan and H. Ji, Defocus amount estimation via maximum rank of patches, 2017

Rank of patches and Separable blur kernel

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, 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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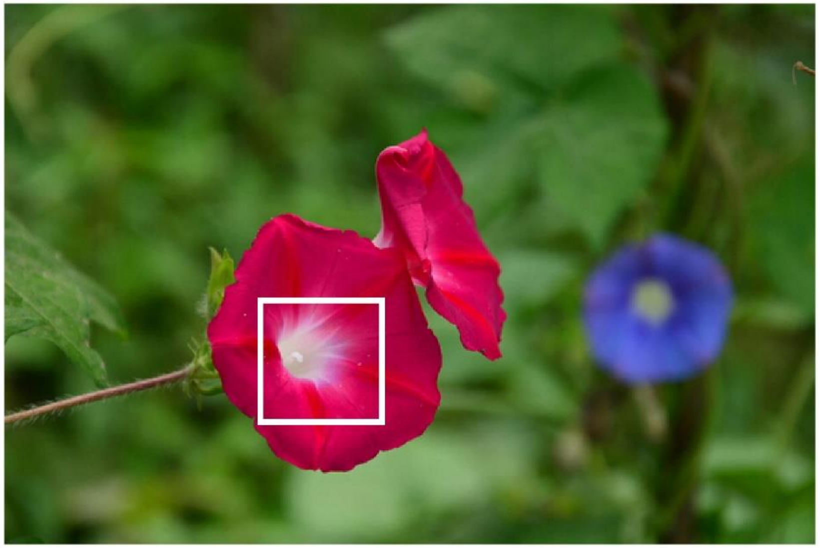
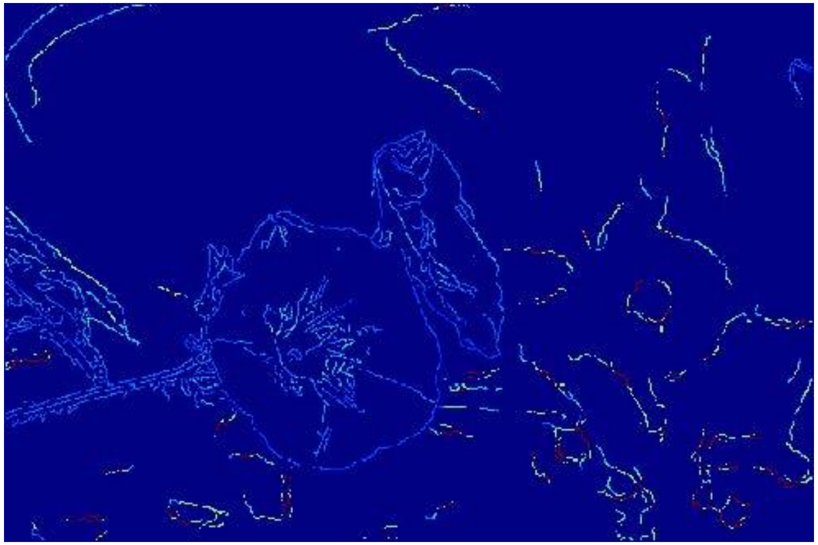
  - One of these different oriented patches is positive definite.
- Defocus amount and maximum rank of oriented patches

$$\frac{1}{c}\left(\text{or } \frac{1}{\sigma}\right) \sim -\ln\left(1 - \frac{\max_{0 \le k \le K} \mathrm{Rank}(\mathrm{P}_k)}{n}\right)$$

Completion of defocus map

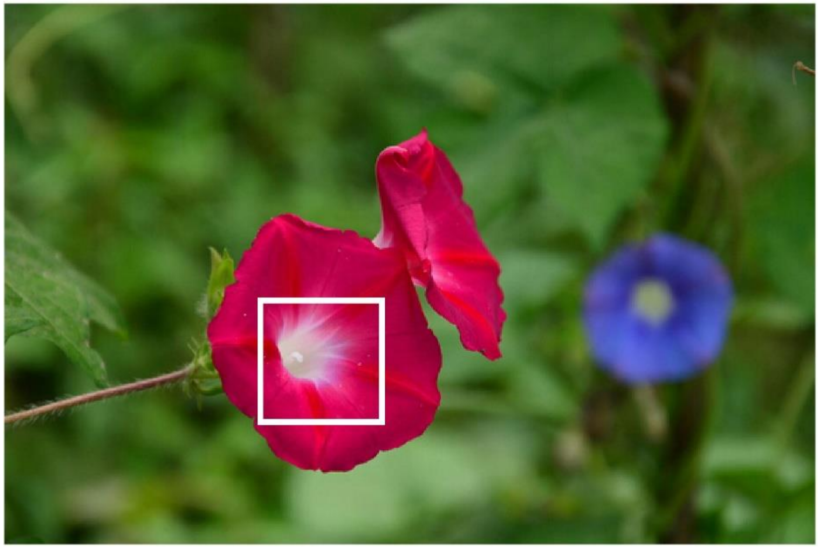


Input image



Defocus estimation at edge points

Completion of defocus map



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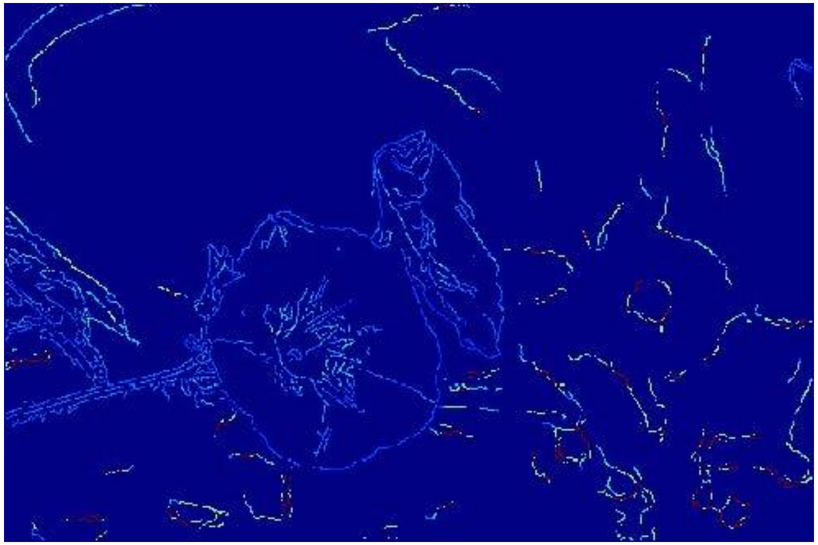
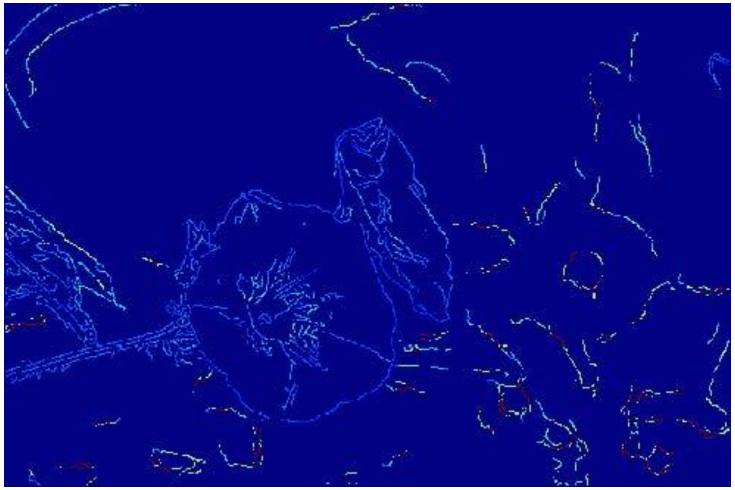


Defocus estimation at edge points

- 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

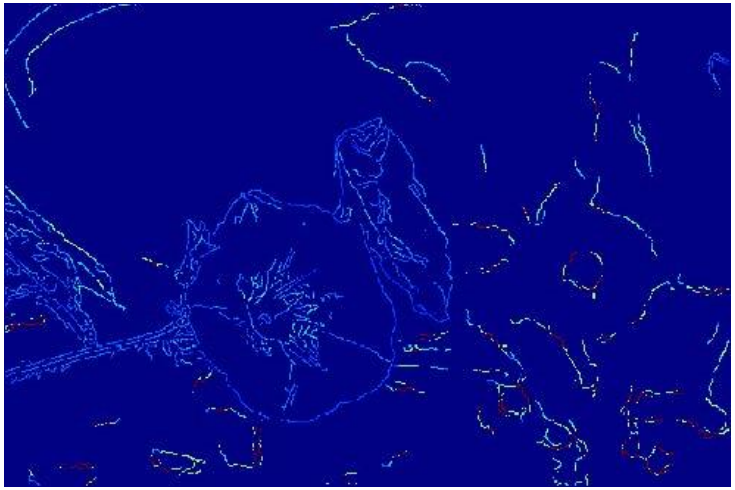
Input image



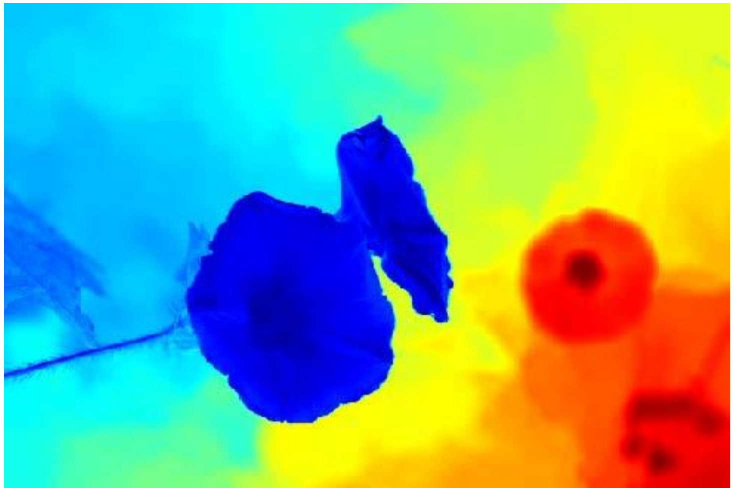
defocus map at edges

Demonstration

Input image



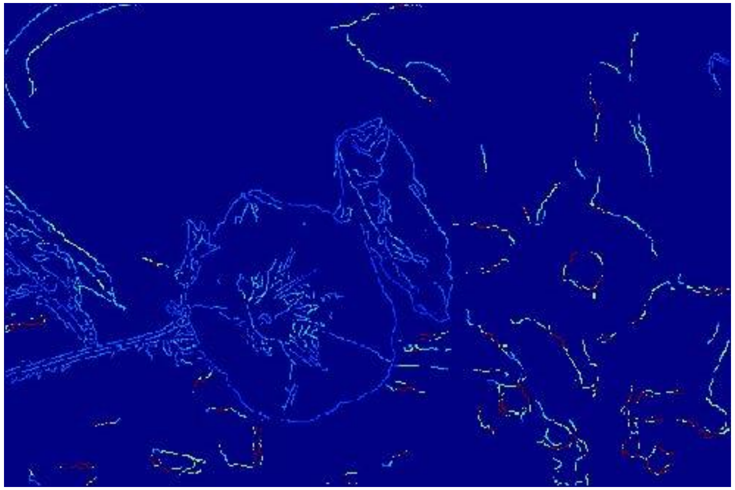
defocus map at edges



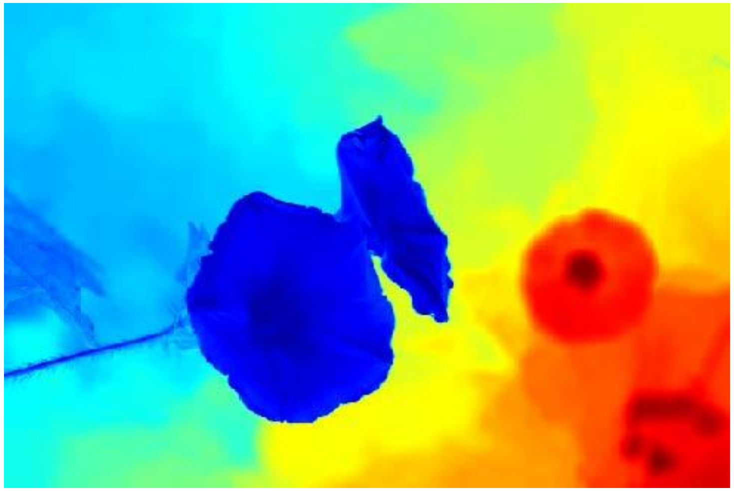
Complete defocus map

Demonstration

Input image



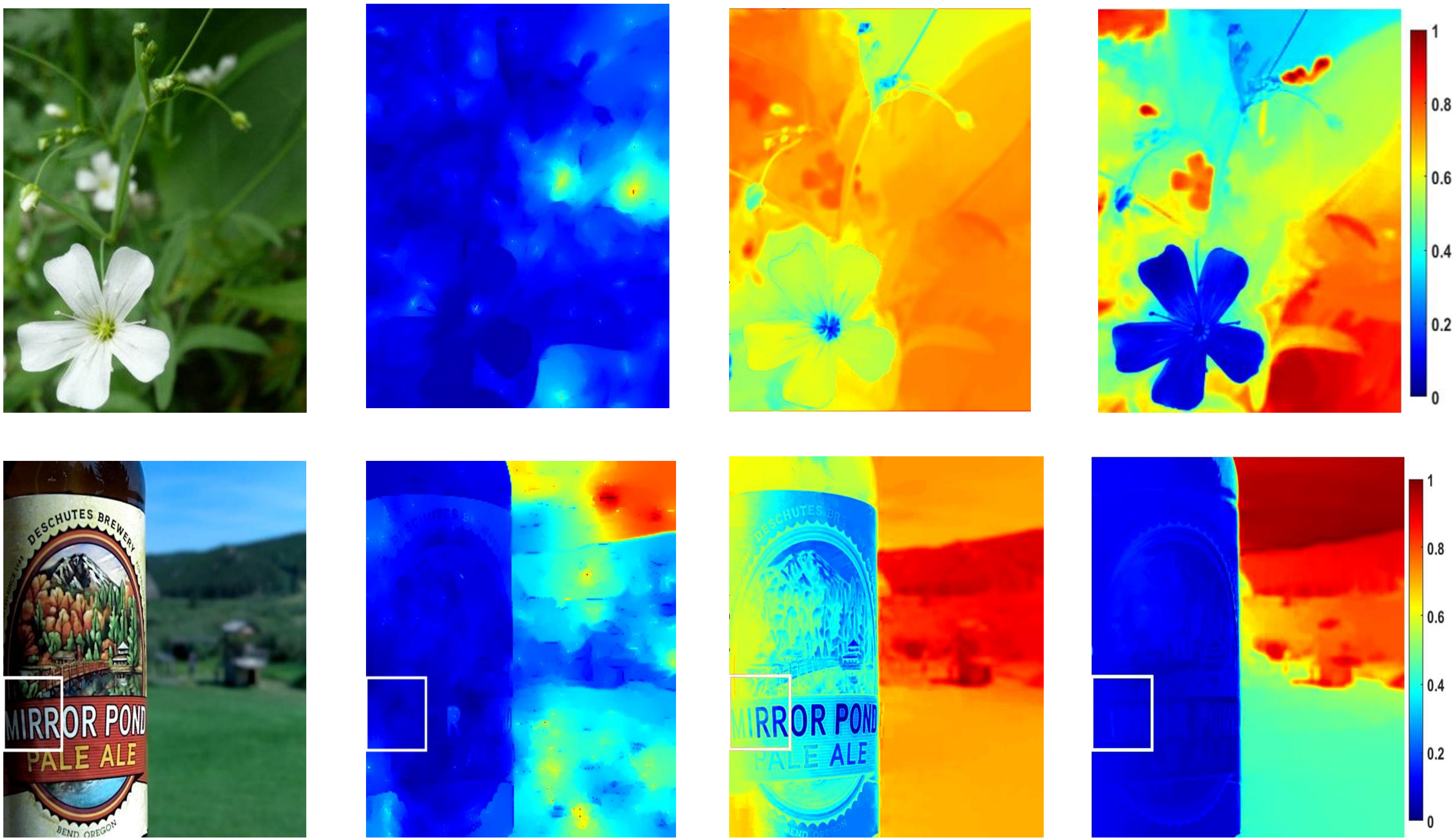
defocus map at edges



Complete defocus map

Foreground segmentation

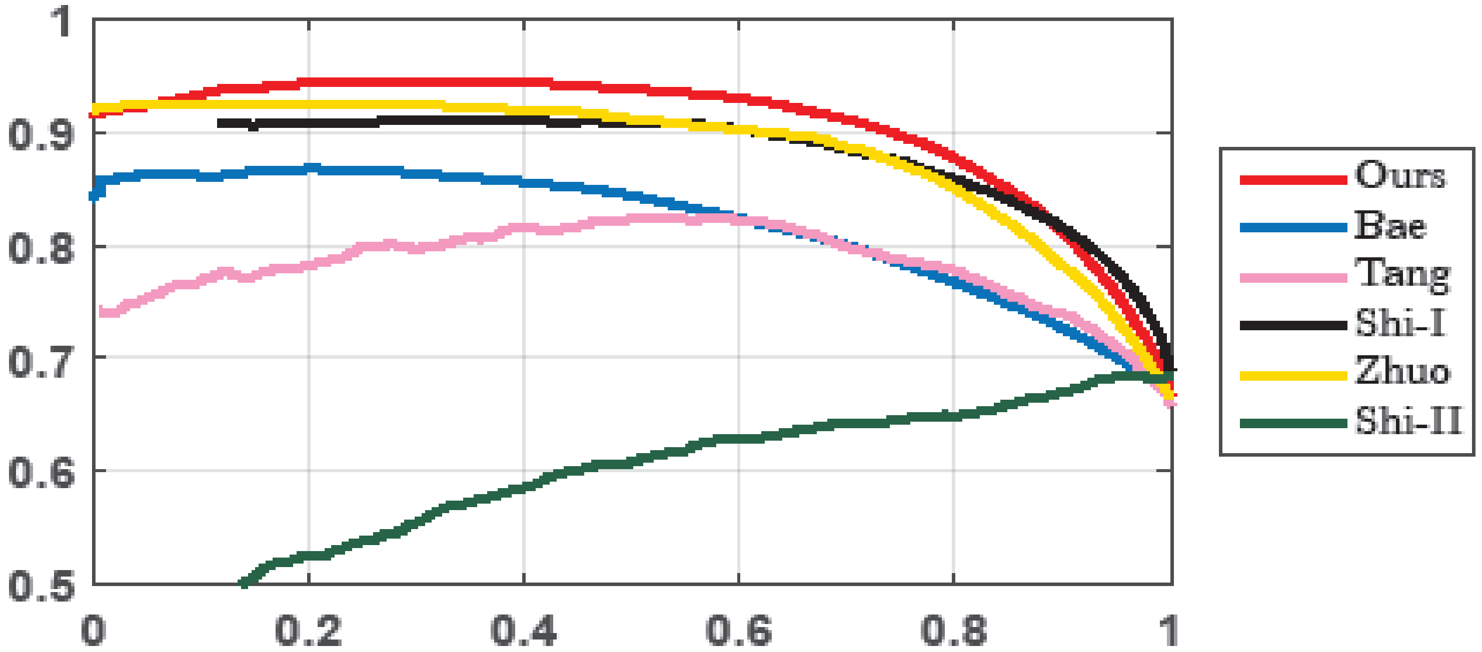
More



Input image Bae et al. Tang et al. ours

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

Image composition 1

Target

Occlusion-aware image composition

Source image

Image composition 1

Target

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