Learning Discriminative Data Fitting Functions for Blind Image Deblurring

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Contents

Introduction

- Image deblurring is the process of recovering an un-blurred image from a blurred image.

Non-uniform blur

Uniform blur

Introduction

- Photos are taken everyday.
  (mobile phone, digital camera, GoPros)
- Blur images are undesirable.
- Hard to reproduce the capture moment.

a moving object in a static scene

Introduction

- The general objective is to recover a sharp latent image (non-blind deblurring) from a blurred input.

- Or to recover a latent image and blur kernel (blind deblurring).

- Blind deblurring is the problem of recovering a sharp version of a blurred input image when the blur parameters are unknown.

- Blind image deblurring is an ill-posed problem. Why ?

Introduction

- The goal of blind image deblurring is to recover a blur kernel and a sharp latent image from a blurred input.

- Blind deblurring is the problem of recovering a sharp version of a blurred input image when the blur parameters are unknown.

- There are infinite pairs of I and k that satisfy $\longrightarrow$ $B = I * k + n,$

Introduction

- In this paper, the effect of data fitting functions for kernel estimation is studied.
- Proposes a data-driven approach to learn effective data fitting functions.
- A two-stage approach for blind image deblurring is proposed.
- Proposed algorithm can be applied to other domain-specific deblurring tasks.

Related Works

- Exploit image priors
  - Normalized sparsity prior
    - D. Krishnan, T. Tay, and R. Fergus. Blind deconvolution using a normalized sparsity measure. In *CVPR*, 2011.
  - Current internal patch recurrence
    - T. Michaeli and M. Irani. Blind deblurring using internal patch recurrence. In *ECCV,* 2014.
  - Text image prior
    - J. Pan, Z. Hu, Z. Su, and M.-H. Yang. Deblurring text images via L0-regularized intensity and gradient prior. In *CVPR,* 2014.
  - Dark channel prior
    - J. Pan, D. Sun, H. Pfister, and M.-H. Yang. Blind image deblurring using dark channel prior. In *CVPR, 2016.*

Related Works

- Sharp edge predictions
  - Noise suppression in smooth regions
  - Blur can be estimated reliably at edges
    - S. Cho and S. Lee. Fast motion deblurring. In *SIGGRAPH Asia*, 2009.
    - L. Xu and J. Jia. Two-phase kernel estimation for robust motion deblurring. In *ECCV*, 2010.
- Intensity in latent image restoration and gradient in the kernel estimation
  - Minimizing reconstruction errors
    - Deblurring text images via L0-regularized intensity and gradient prior. In *CVPR*, 2014.
    - L. Xu, S. Zheng, and J. Jia. Unnatural L0 sparse representation for natural image deblurring. In *CVPR*, 2013.

Related Works

- Discriminative methods
  - Use trainable models for image restoration
  - Learn the parameters from training dataset.
    - L. Xiao, J. Wang, W. Heidrich, and M. Hirsch. Learning high-order filters for efficient blind deconvolution of document photographs. In *ECCV*, 2016.
    - W. Zuo, D. Ren, S. Gu, L. Lin, and L. Zhang. Discriminative learning of iteration-wise priors for blind deconvolution. In *CVPR,* 2015.

Related Works

- Sparsity of image gradients
  - The most favorable solution under a sparse prior is usually a blurry image and not a sharp one.
  - The contribution of this term is usually small.
    - T. Chan and C. Wong. Total variation blind deconvolution. *IEEE TIP*, 1998.
    - R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman. Removing camera shake from a single photograph. *ACM SIGGRAPH*, 2006.
    - A. Levin, Y. Weiss, F. Durand, and W. T. Freeman. Understanding and evaluating blind deconvolution algorithms. In *CVPR,* 2009.
    - A. Levin, Y. Weiss, F. Durand, and W. T. Freeman. Efficient marginal likelihood optimization in blind deconvolution. In *CVPR*, 2011.

Proposed Method

- Two-stage approach for blind image deblurring
  - Learn an effective data fitting function
  - Optimize the function for latent image restoration

$$E(I,k) = \sum_i \omega_i \| f_i * I * k - f_i * B \|_2^2 + \varphi(I) + \phi(k),$$

ω_i : i-th weight

f_i : linear filter operator

$\varphi(I)$: latent image prior

$\phi(k)$: blur kernel prior

The goal is to estimate weights effectively.

Proposed Method

- From collected set of ground truth blur kernels and set of clear images :

$$\min_{\omega_i} \frac{1}{2} \sum_j \|k_j(\omega) - k_j^{gt}\|_2^2$$

$$\text{s.t.} \quad \omega_i \geq 0, \sum_i \omega_i = 1,$$

$k_j(\omega)$: j-th estimated blur kernel

k_j^{gt} : j-th ground truth blur kernel

- To derive the relationship between blur kernels and weights :

$$\arg\min_{k_j, I_j} \sum_j \sum_i \omega_i \| f_i * I_j * k_j - f_i * B_j \|_2^2 + \varphi(I_j) + \phi(k_j).$$

Proposed Method

- Proposes an efficient algorithm to solve (4) :

$$\min_{k_j, I_j, g_j} \sum_j \sum_i \omega_i \| f_i * I_j * k_j - f_i * B_j \|_2^2 + \beta \| g_j - \nabla I_j \|_2^2 + \lambda \| g_j \|_0 + \gamma \| k_j \|_2^2. \quad (5)$$

$\varphi(I_j) = \lambda \|\nabla I_j\|_0$: latent image regularizer

$\phi(k_j) = \gamma \|k_j\|_2^2$: blur kernel regularizer

- Introduce an auxiliary variable using the half-quadratic splitting L_0 minimization method

$g_j = (g_j^v, g_j^h)$: auxiliary variable

which can globally control how many non-zero gradients are resulted in to approximate prominent structure in a sparsity-control manner.

Proposed Method

- Estimation of intermediate blur kernel

$$\min_{k_j} \sum_j \sum_i \omega_i \| f_i * I_j * k_j - f_i * B_j \|_2^2 + \gamma \| k_j \|_2^2. \quad (6)$$

$$\min_{\mathbf{k}_j} \sum_j \sum_i \omega_i \| \mathbf{A}_{ij} \mathbf{k}_j - \mathbf{b}_{ij} \|_2^2 + \gamma \| \mathbf{k}_j \|_2^2, \quad (7)$$

- Based on (7) the solution is : $$\mathbf{k}_j = \left(\sum_i \omega_i \mathbf{A}_{ij}^\top \mathbf{A}_{ij} + \gamma \right)^{-1} \left(\sum_i \omega_i \mathbf{A}_{ij}^\top \mathbf{b}_{ij} \right). \quad (8)$$

Proposed Method

- Estimation of intermediate latent image

$$\min_{I_j, g_j} \sum_j \sum_i \omega_i \| f_i * I_j * k_j - f_i * B_j \|_2^2 + \beta \| g_j - \nabla I_j \|_2^2 + \lambda \| g_j \|_0. \tag{9}$$

  - For each iteration :

$$g_j = \begin{cases} \nabla I_j, & |\nabla I_j|^2 \geqslant \frac{\lambda}{\beta}, \\ 0, & \text{otherwise}. \end{cases} \tag{10}$$

  - Latent image can be obtained :

$$\min_{I_j} \sum_j \sum_i \omega_i \| f_i * I_j * k_j - f_i * B_j \|_2^2 + \beta \| g_j - \nabla I_j \|_2^2, \tag{11}$$

Proposed Method

- Estimation of intermediate latent image
  - The closed-form solution for the problem :

$$I_j = \mathcal{F}^{-1}\left(\frac{\sum_i \omega_i \overline{\mathcal{F}(f_i)\mathcal{F}(k_j)}\mathcal{F}(f_i * B_j) + \beta F_g}{F_k + \beta(\sum_{i\in\{h,v\}} \overline{\mathcal{F}(\nabla_i)}\mathcal{F}(\nabla_i))}\right), \quad (12)$$

$$F_k = \sum_i \omega_i \overline{\mathcal{F}(f_i)\mathcal{F}(k_j)}\mathcal{F}(k_j)\mathcal{F}(f_i)$$

$$F_g = \overline{\mathcal{F}(\nabla_h)}\mathcal{F}(g_j^h) + \overline{\mathcal{F}(\nabla_v)}\mathcal{F}(g_j^v)$$

  - If all the values of ω_i are zero set $\omega_0 = (\omega_0 + 1)$

Proposed Method

Algorithm 1 Solving (9)

Input: Blurred image B_j and blur kernel k_j.
$I_j \leftarrow B_j$, $\beta \leftarrow 2\lambda$.
repeat
  solve g_j using (10).
  solve I_j using (12).
  $\beta \leftarrow 2\beta$.
until $\beta > \beta_{\max}$
Output: Intermediate latent image I_j.

$$g_j = \begin{cases} \nabla I_j, & |\nabla I_j|^2 \geqslant \frac{\lambda}{\beta}, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

$$I_j = \mathcal{F}^{-1}\left(\frac{\sum_i \omega_i \overline{\mathcal{F}(f_i)\mathcal{F}(k_j)}\mathcal{F}(f_i * B_j) + \beta F_g}{F_k + \beta(\sum_{i\in\{h,v\}} \overline{\mathcal{F}(\nabla_i)}\mathcal{F}(\nabla_i))}\right), \tag{12}$$

Solve the optimization problem with respect to intermediate latent image :

$$\min_{I_j, g_j} \sum_j \sum_i \omega_i \|f_i * I_j * k_j - f_i * B_j\|_2^2 + \beta\|g_j - \nabla I_j\|_2^2 + \lambda\|g_j\|_0. \tag{9}$$

Proposed Method

- After estimated blur kernels are obtained:
  - Weights can be estimated by :

$$\min_{\omega_i} \frac{1}{2} \sum_j \|k_j(\omega) - k_j^{gt}\|_2^2$$

  - Solve the equation using gradient descent :

$$\frac{\partial \mathcal{L}_j}{\partial \omega_i} = \frac{\partial \mathcal{L}_j}{\partial \mathbf{k}_j} \frac{\partial \mathbf{k}_j}{\partial \omega_i}$$

where $\mathcal{L}_j = \frac{1}{2} ||\mathbf{k}_j(\omega) - \mathbf{k}_j^{gt}||_2^2$

Proposed Method

Algorithm 1 Solving (9)

Input: Blurred image B_j and blur kernel k_j.
$I_j \leftarrow B_j$, $\beta \leftarrow 2\lambda$.
repeat
  solve g_j using (10).
  solve I_j using (12).
  $\beta \leftarrow 2\beta$.
until $\beta > \beta_{\max}$
Output: Intermediate latent image I_j.

Algorithm 2 Learning discriminative features

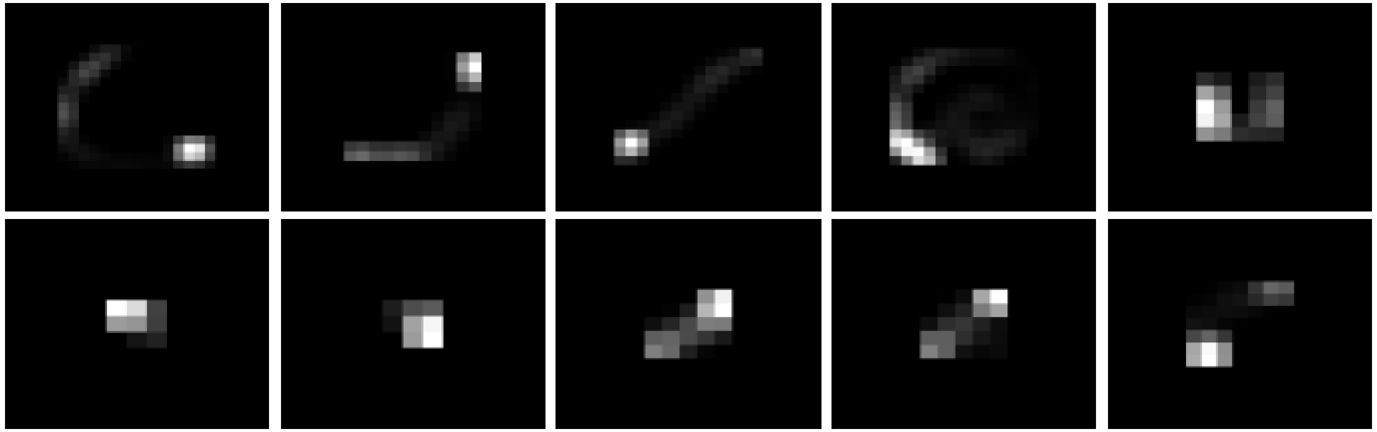
Input: Blurred images $\{B_j\}$, ground truth blur kernels $\{k_j^{gt}\}$.
$\omega_i \leftarrow 0$.
initialize k_j with results from the coarser level.
while $l \leq$ max_iter1 **do**
  while $t \leq$ max_iter2 **do**
    solve I_j using Algorithm 1.
    solve k_j using (8).
  end while
  $\omega_i = \omega_i - \alpha \sum_j \frac{\partial \mathcal{L}_j}{\partial \omega_i}$.
end while
Output: The weight ω_i.

$$\mathbf{k}_j = \left(\sum_i \omega_i \mathbf{A}_{ij}^\top \mathbf{A}_{ij} + \gamma\right)^{-1} \left(\sum_i \omega_i \mathbf{A}_{ij}^\top \mathbf{b}_{ij}\right). \quad (8)$$

- Learn discriminative data fitting functions using estimated blur kernels.
- Learning rate is set to 0.01.

Proposed Method

- Training Data
  - A training dataset to learn the weights.
  - 200 images from the BSDS dataset.
  - Synthesize realistic blur kernels by sampling random 3D trajectories.
  - Random square kernel sizes in the range from 11 × 11 up to 27 × 27 pixels.



Proposed Method

- After learning weights using generated dataset solve :

$$E(I,k) = \sum_i \omega_i \| f_i * I * k - f_i * B \|_2^2 + \varphi(I) + \phi(k),$$

- Alternatively solve intermediate latent image and intermadite blur kernel.

Table 1. Concrete forms of the linear filters used in the learning process.

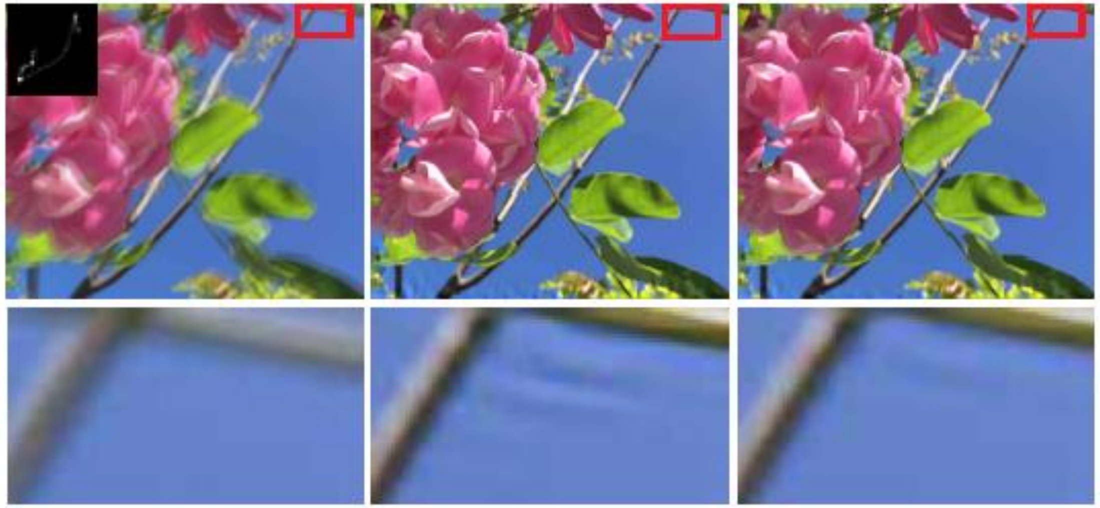
Filters	f_1	f_2	f_3	f_4	f_5	f_6
Type	zero-order	first order	first order	second order	second order	second order
Forms	$I * k - B$	$\nabla_h I * k - \nabla_h B$	$\nabla_v I * k - \nabla_v B$	$\nabla_h \nabla_h I * k - \nabla_h \nabla_h B$	$\nabla_v \nabla_v I * k - \nabla_v \nabla_v B$	$\nabla_h \nabla_v I * k - \nabla_h \nabla_v B$

Discriminative Non-Blind Deconvolution

- Kernel estimation processes can be applied to non-blind deconvolution.

$$\min_I \sum_i \omega_i \|f_i * I * k - f_i * B\|_2^2 + \phi(I), \qquad (14)$$

$\phi(I) = \mu\|\nabla I\|_1 \longrightarrow$ total variation regularization



(a) (b) (c)

Obtain the weights by solving :

$$\min_{\omega_i} \frac{1}{2} \sum_j \|I_j(\omega) - I_j^{gt}\|_2^2$$

Same minimization method to obtain the solution :

$$\omega_i = \omega_i - \alpha_I \sum_j (\mathbf{I}_j - \mathbf{I}_j^{gt})^\top \mathbf{W}_i,$$

Extension to Non-Uniform Deblurring

- Method can be directly extended to handle non-uniform deblurring.
- The non-uniform blur process can be formulated as :

$$\mathbf{B} = \mathbf{K}\mathbf{I} + \mathbf{n} = \mathbf{A}\mathbf{k} + \mathbf{n},$$

- The problem can be solved by minimizing :

$$\min_{\mathbf{I}} \sum_i \omega_i \|\mathbf{K}\mathbf{F}_i\mathbf{I} - \mathbf{F}_i\mathbf{B}\|_2^2 + \lambda\|\nabla\mathbf{I}\|_0,$$

$$\min_{\mathbf{k}} \sum_i \omega_i \|\mathbf{A}_i\mathbf{k} - \mathbf{B}_i\|_2^2 + \gamma\|\mathbf{k}\|_2^2,$$

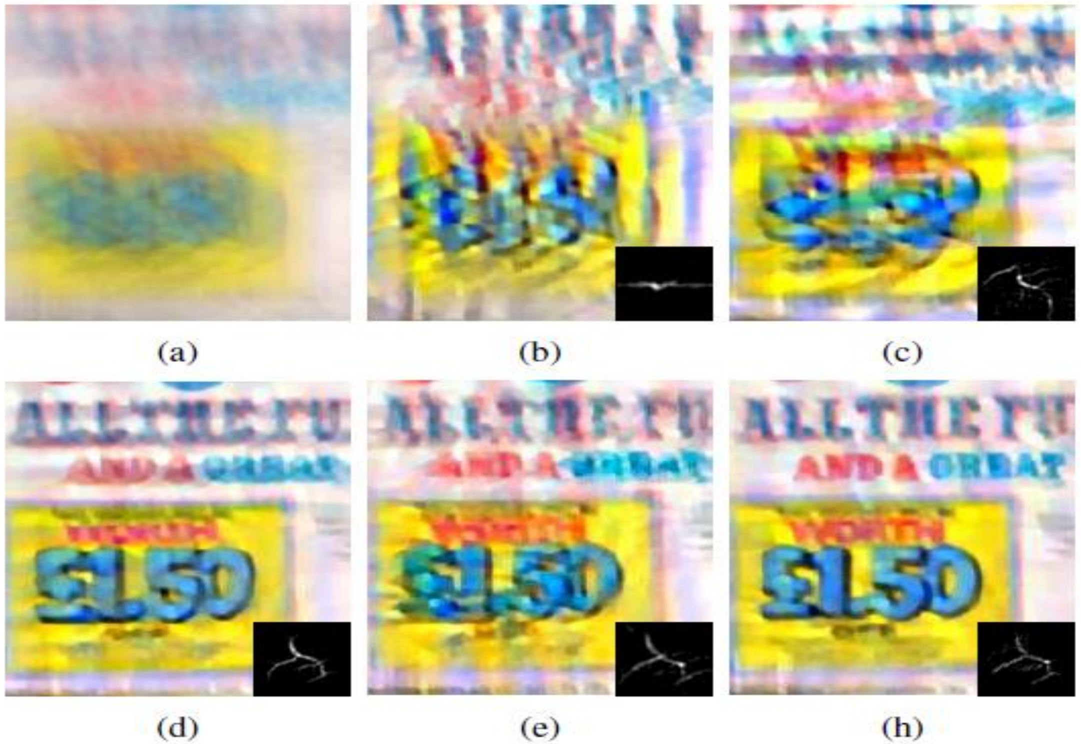
Analysis of Proposed Algorithm

- Method automatically learns the most relevant data fitting function.

- Effect on Blur Kernel Estimation
  - Methods lean on intensity or gradient contains ringing artifacts.

  - Intensity for intermadiate latent image, gradient for kernel estimation is better.

  - Learned data fitting functions facilitate blur kernel estimation in proposed method.



Analysis of Proposed Algorithm

- Learned Weights for Data Fitting Terms

Table 3. Learned weights for blur kernel estimation.

ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
0	0.1954	0.1850	0.2463	0.2625	0.1108

  - Intensity does not help the blur kernel estimation.
  - Similar results to the experimental analysis of the state-of-the-art methods.
  - Higher order information plays more important roles for blur kernel estimation.

Analysis of Proposed Algorithm

- Effect on Non-Blind Deconvolution

Table 4. Learned weights for latent image estimation.

ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
0.2095	0.1581	0.1581	0.1581	0.1581	0.1581

  - Zero-order filter plays more important role in non-blind deconvolution.
  - Different data fitting terms should be used.

Analysis of Proposed Algorithm

- Fast Convergence Property
  - Additional data fitting terms does not increase computation time.

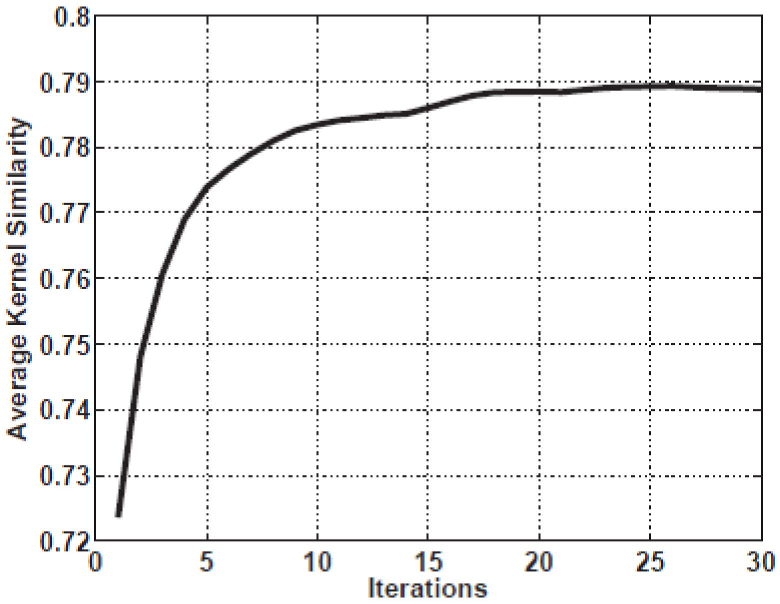


Figure 5. Fast convergence property of the proposed algorithm.

Table 5. Run time (seconds) on the same computer with an Intel Core i7-4800MQ processor and 16 GB RAM. The run time of Xu et al. [35] is based on our implementation.

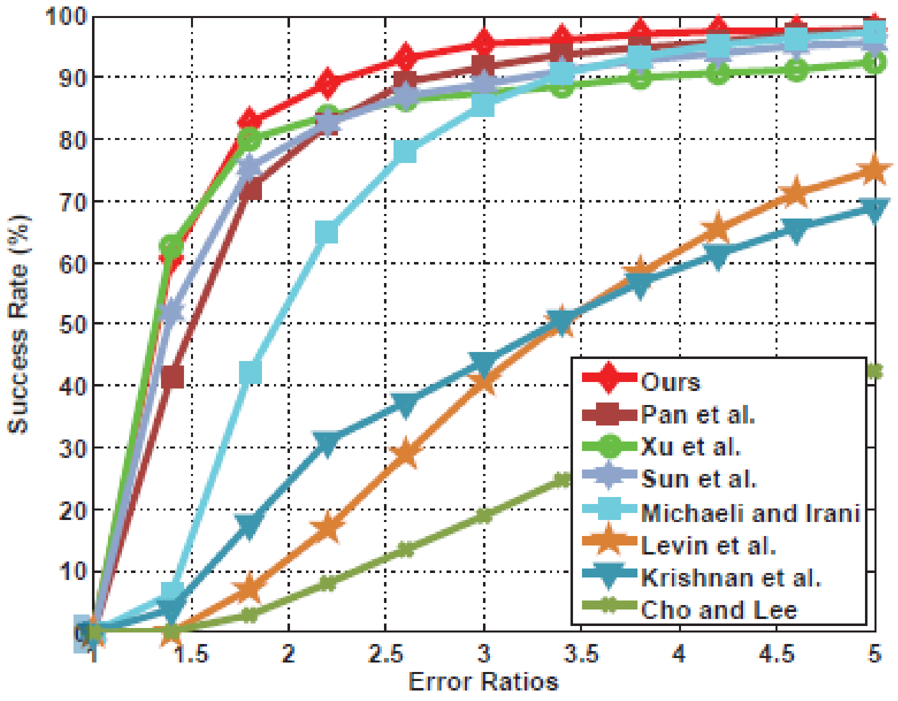
Method	255×255	600×600	800×800
Xu et al. [35]	3.10	19.10	36.53
Krishnan et al. [13]	34.01	196.09	315.41
Levin et al. [16]	144.61	501.67	862.81
Pan et al. [23]	17.07	115.86	195.80
Ours	4.93	23.11	41.52

Experiments

- All the experiments are carried out on a machine with an Intel Core i7-4800MQ processor and 16 GB RAM.
- The run time for a 255 × 255 image is 5 seconds on MATLAB.
- They set $\lambda = 0.002$, $\gamma = 2$ and $\beta max = 10^5$.
- Deblurring datasets by Sun et al. and Levin et al. used as the main test datasets.
- For fair comparison, they tune the parameters of other methods to generate best possible results.

Quantitative Evaluation

- The proposed method is evaluated on the synthetic dataset by Sun et al.
- Non-blind deblurring method is used.
- Higher success rates indicates the effectiveness of the learned data fitting functions.



Real Images

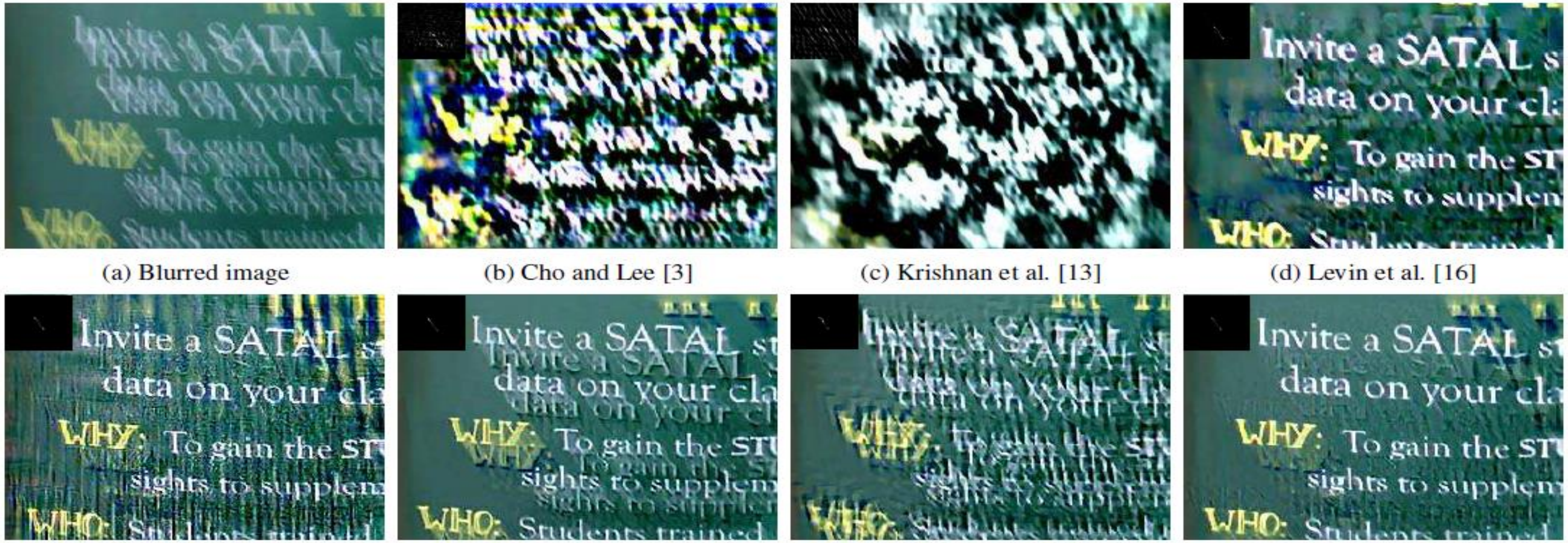
(a) Blurred image (b) Cho and Lee [3] (c) Krishnan et al. [13] (d) Levin et al. [16]

(e) Xu et al. [35] (f) Pan et al. [20] (g) Pan et al. [23] (h) Ours

- Learned function with different weighted combination of data fitting terms is effective for kernel estimation.

Real Images

- Methods focuses on text image deblurring and methods based on sparsity of dark channel priors does not perform well.



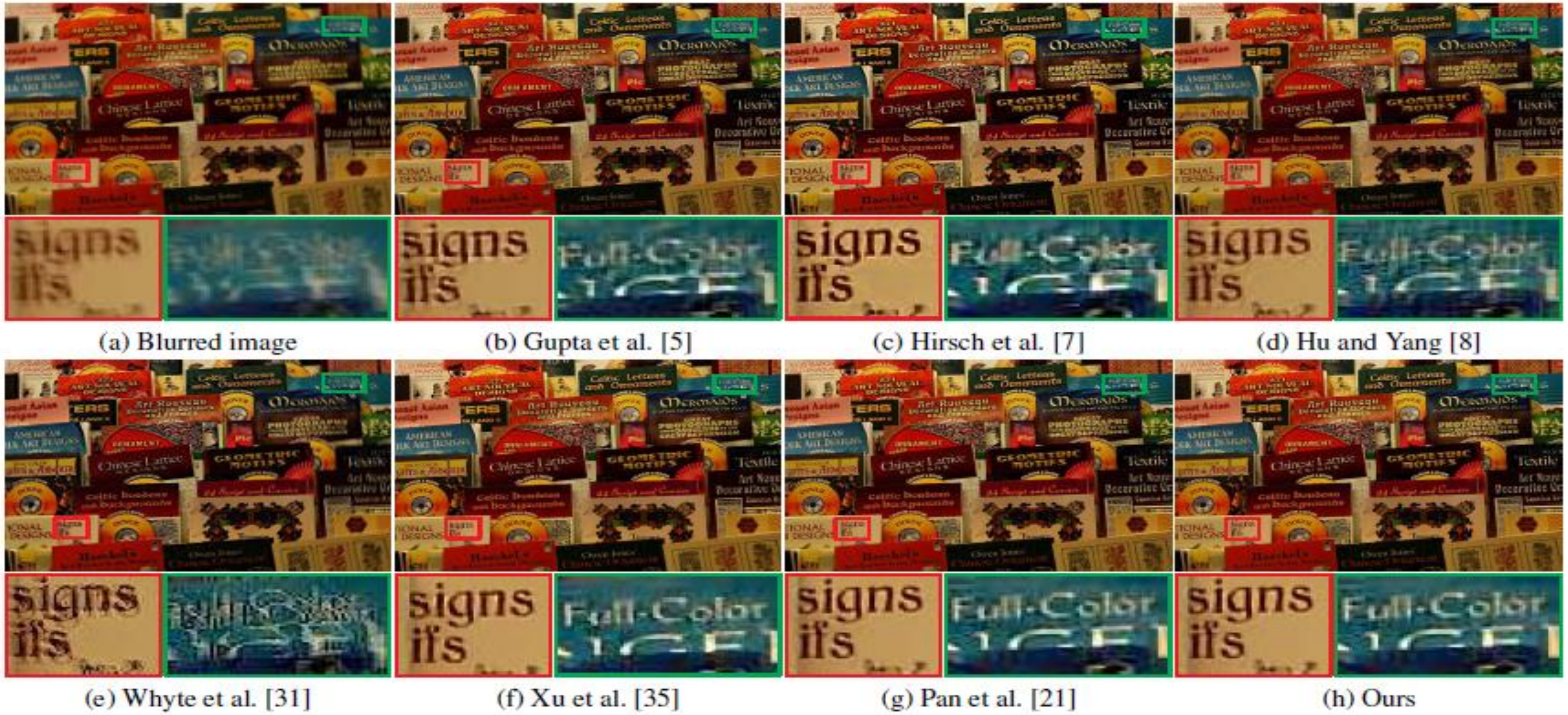
(a) Blurred image (b) Cho and Lee [3] (c) Krishnan et al. [13] (d) Levin et al. [16]

(e) Xu et al. [35] (f) Pan et al. [20] (g) Pan et al. [23] (h) Ours

- Comparison of (e) and (h) shows the importance of learned data fitting function.

Non-uniform Deblurring

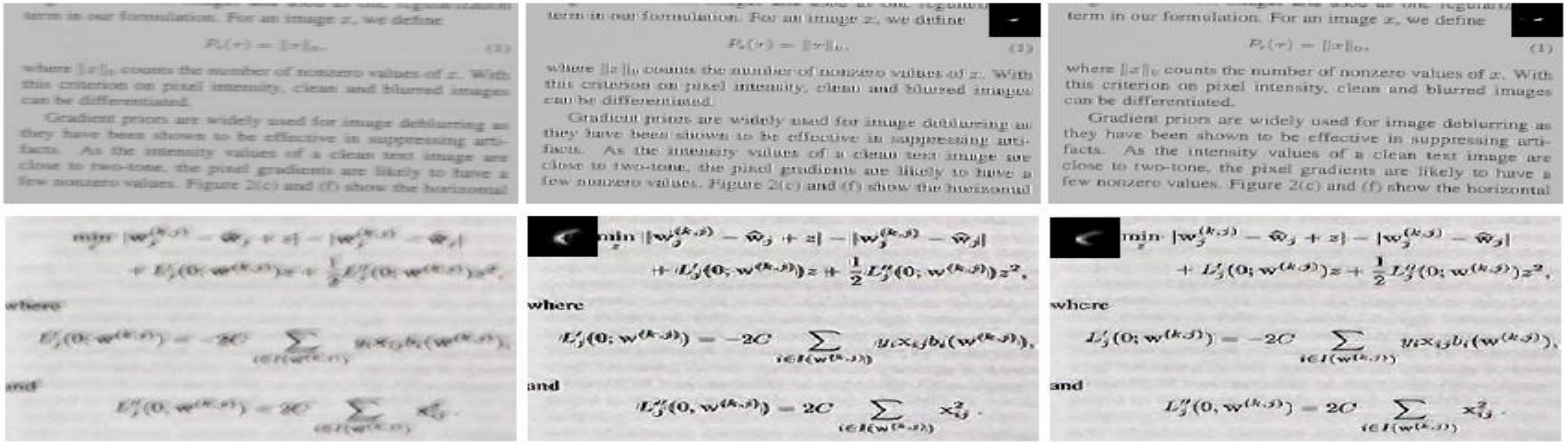
- They present results on an image degraded by spatially variant motion blur.



The restored image by the proposed algorithm contains sharper contents

Extensions of Proposed Method

- Method can be applied to other deblurring tasks with specific image priors such as normalized sparsity prior and dark channel prior.



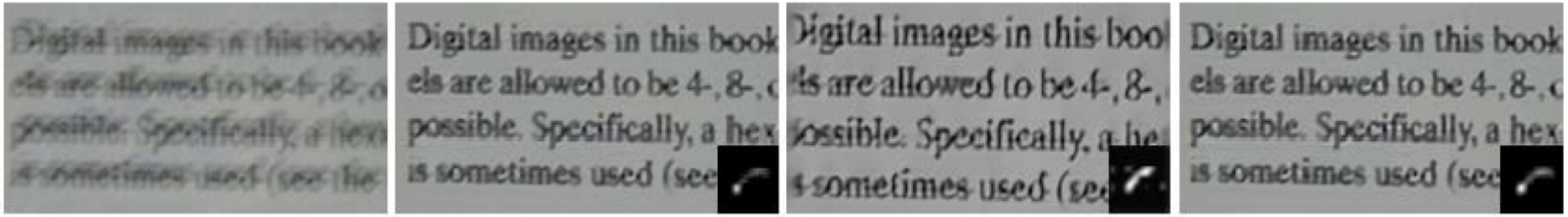
(a) Blurred images (b) Pan et al. [20] (c) Ours

L_0-regularized intensity and gradient prior

- Proposed method generates deblurred images with clearer characters.

Extensions of Proposed Method

- Image prior based on the learned high-order filters is especially effective for text images.



(a)Blurred image (b) Pan et al. [20] (c) Xiao et al. [32] (d) Ours

- The proposed method with the L_0-regularized intensity and gradient prior performs competitively against the state-of-the-art methods.

Conclusion

- An effective algorithm is proposed which learns effective data fitting functions for both blur kernel estimation and latent image restoration.
- Usage of the learned data fitting functions can significantly improve the performance of deblurring.
- The proposed method can be extended to other specific deblurring tasks.
- The proposed algorithm performs favorably for uniform as well as non-uniform deblurring.

Conclusion

- Proposed method focuses on learning data fitting function, the choice of linear filters is fixed.
- Optimization method and the choice of linear filters are important.
- Learning effective linear filters and optimization methods may improve the results of image deblurring.

Thank You !