Blind Image Deblurring Based on Sparse Representation and Structural Self-Similarity

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Motion Blur

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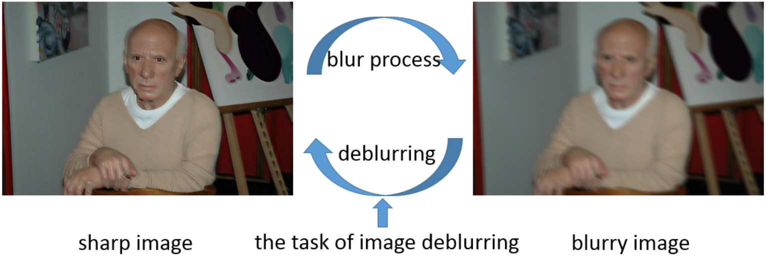
More recently, deblurring has received renewed attention due to the emerging need for removing motion blur in images captured by mobile phones.

Deblurring

Deblurring attempts to reconstruct or recover a blurry image by modeling the degradation and applying the inverse process.



Blur Model

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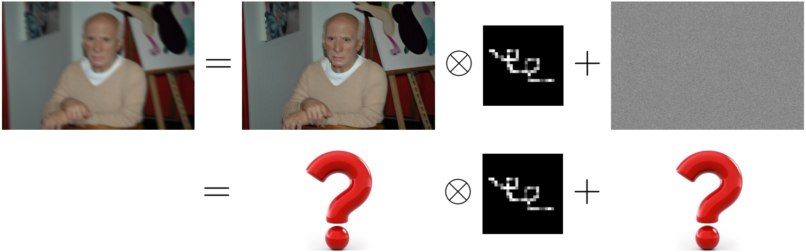

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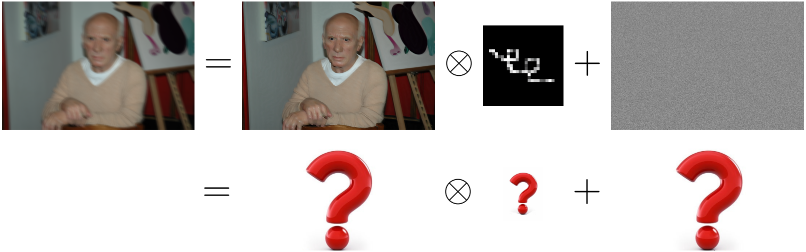
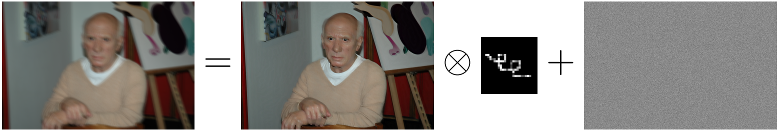


- the blur kernel is known: **non blind deconvolution**, only need to estimate the sharp image
- the blur kernel is unknown: **blind deconvolution**, need to estimate both the sharp image and blur kernel

Challenge:ill-posed

In blind deconvolution, the number of unknowns is larger than the number of constraints and the problem is ill posed.



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Additional priors about the sharp image or the blur kernel are needed.

Structural Self-Similarity Prior

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- $\mathbf{Q}\boldsymbol{X}$: patch extracted from sharp image$\boldsymbol{X}$

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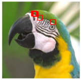

down-sampled image($\boldsymbol{X}^{\alpha}$)

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similar patches($\mathbf{R}_i\boldsymbol{X}^{\alpha}$)

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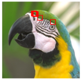

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The linear combination of the L most similar patches of $\mathbf{Q}\boldsymbol{X}$ (put into the set $\mathcal{S}$) can be used to predict $\mathbf{Q}\boldsymbol{X}$:

$$\mathbf{Q}\boldsymbol{X} \approx \sum_{i\in\mathcal{S}} w_i \mathbf{R}_i \boldsymbol{X}^{\alpha}$$

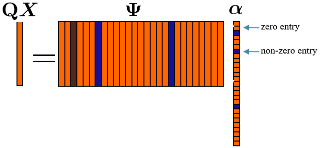
$$w_i = \frac{\exp(-\|\mathbf{Q}\boldsymbol{X} - \mathbf{R}_i\boldsymbol{X}^{\alpha}\|_2^2/h)}{\sum_{l\in\mathcal{S}} \exp(-\|\mathbf{Q}\boldsymbol{X} - \mathbf{R}_l\boldsymbol{X}^{\alpha}\|_2^2/h)}$$

Sparse Representation Prior

Image patches can always be represented well as a sparse linear combination of atoms in an appropriate dictionary.

$$\mathbf{Q}\boldsymbol{X} = \Psi\boldsymbol{\alpha} \quad ||\boldsymbol{\alpha}||_0 \ll n$$

- $\mathbf{Q}\boldsymbol{X} \in \mathbb{R}^n$:the vector form of patch extracted from image $\boldsymbol{X}$
- $\boldsymbol{\Psi} = [\boldsymbol{\psi_1}, \cdots, \boldsymbol{\psi_t}] \in \mathbb{R}^{n \times t}$:dictionary.$\psi_i$ is called the atom of the dictionary
- $\boldsymbol{\alpha} = [\alpha_1, \cdots, \alpha_t]^T \in \mathbb{R}^t$:the representation coefficient of $\mathbf{Q}\boldsymbol{X}$



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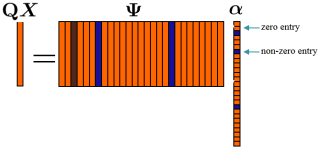

The choice of the dictionary:

- prespecified transform matrix(e.g.wavelets,curvelets):simple,poor adaptability
- learn the dictionary from training data(e.g.K-SVD):good adaptability,widely used;need to choose good training data

Proposed dictionary learning method

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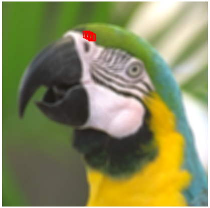
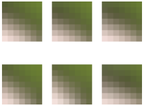
sharp image



blurry image

sharp patch



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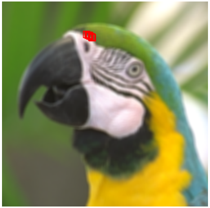
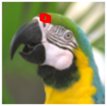
We use an over-complete dictionary trained on down-sampled blurry patches to help exploit the sparse prior of sharp patches.

sharp image

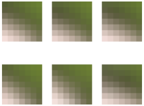


blurry image



down-sampled blurry image

sharp patch



similar patches in blurry image

similar patches in down-sampled blurry image

Objective function

By taking the down-sampled blurry image as dictionary training data and incorporating both sparse representation and structural self-similarity as regularization constraints, we get the following joint minimization problem of both image and blur kernel

$$\min_{\boldsymbol{x},\boldsymbol{h}} \Big\{ \overbrace{\|\nabla \boldsymbol{y} - \nabla \boldsymbol{x} \otimes \boldsymbol{h}\|_2^2}^{\text{observation model}} + \overbrace{\lambda_c \sum_j \|\mathbf{Q}_j \boldsymbol{X} - \Psi \boldsymbol{\alpha}_j\|_2^2}^{\text{sparsity}} + \overbrace{\lambda_s \sum_j \|\mathbf{Q}_j \boldsymbol{X} - \sum_{i \in S_j} w_i^j \mathbf{R}_i \boldsymbol{X}^{\alpha}\|_2^2}^{\text{structural self-similarity}}$$

$$+ \underbrace{\lambda_g \|\nabla \boldsymbol{x}\|_2^2}_{\text{smoothness}} + \underbrace{\lambda_h \|\boldsymbol{h}\|_2^2}_{\text{blur kernel}} \Big\} \quad \text{s.t. } \forall j \ \|\boldsymbol{\alpha}_j\|_0 \leq T$$

- $\boldsymbol{y}$:blurry image
- $\boldsymbol{x}$:sharp image
- $\boldsymbol{h}$:blur kernel
- $\nabla = \{\partial_x, \partial_y\}$:the spatial derivative operator in two directions
- λ_c,λ_s,λ_g,λ_h:regularization weights

Optimization

$$\min_{\boldsymbol{x},\boldsymbol{h}} \Big\{ ||\nabla \boldsymbol{y} - \nabla \boldsymbol{x} \otimes \boldsymbol{h}||_2^2 + \lambda_c \sum_j ||\mathbf{Q}_j \boldsymbol{X} - \Psi \boldsymbol{\alpha}_j||_2^2 + \lambda_s \sum_j ||\mathbf{Q}_j \boldsymbol{X} - \sum_{i \in S_j} w_i^j \mathbf{R}_i \boldsymbol{X}^{\alpha}||_2^2 + \lambda_g ||\nabla \boldsymbol{x}||_2^2 + \lambda_h ||\boldsymbol{h}||_2^2 \Big\} \quad \text{s.t. } \forall j \ ||\boldsymbol{\alpha}_j||_0 \le T$$

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The above objective function is non-convex.We take an iterative process to solve this problem that alternately optimizes the motion blur kernel and the latent image.

- fix $\hat{\boldsymbol{x}}_k$,update $\hat{\boldsymbol{h}}_k$
- fix $\hat{\boldsymbol{h}}_k$,update $\hat{\boldsymbol{x}}_{k+1}$

Initialization:$k = 0$,$\hat{\boldsymbol{x}}_0 = \boldsymbol{y}$

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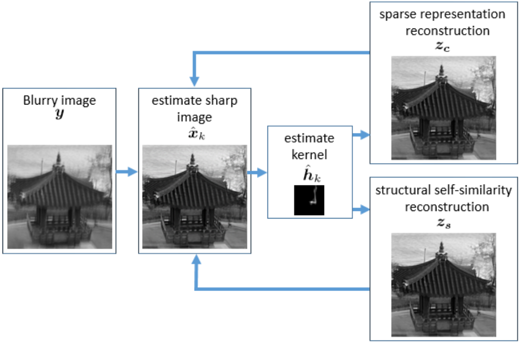

Quantitative Evaluation on Synthetic Dataset

We measure the quality of an estimated blur kernel using the error ratio measure r proposed by Levin et.al.

$$\mathrm{ER} = \frac{||\boldsymbol{x} - \hat{\boldsymbol{x}}_{\hat{\boldsymbol{h}}}||_2^2}{||\boldsymbol{x} - \hat{\boldsymbol{x}}_{\boldsymbol{h}}||_2^2}$$

- $\boldsymbol{h}$: real kernel
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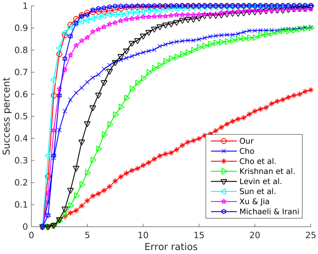

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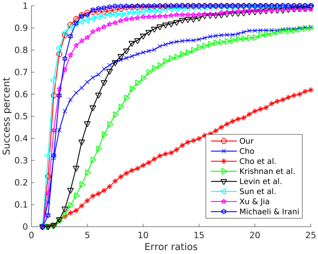

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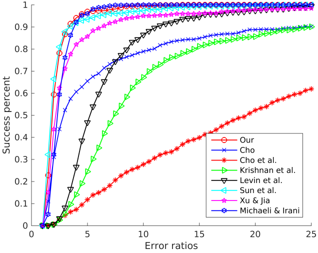

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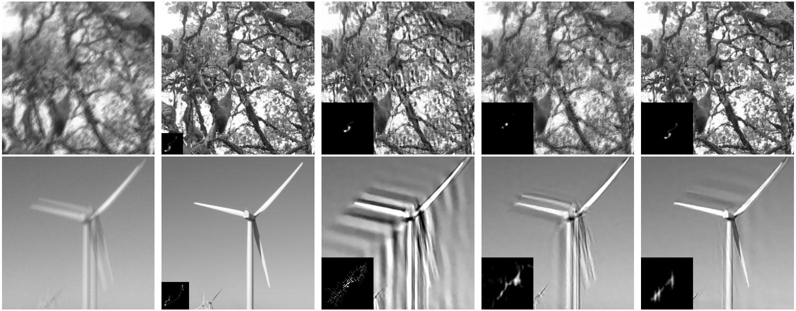
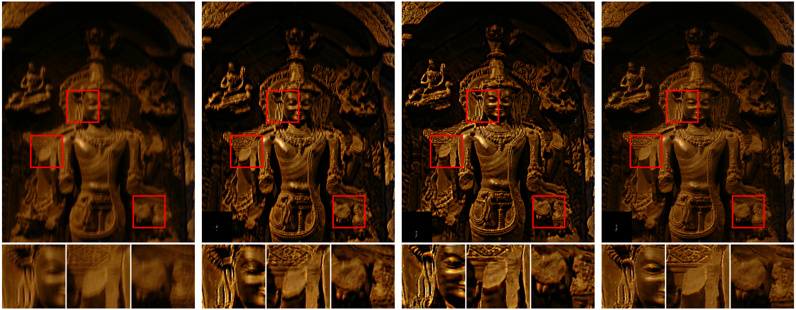
	success rate%	mean error ratio
Ours	96.88	2.2181
Michaeli & Irani[2014]	95.94	2.5662
Sun et al.[2013]	93.44	2.3764
Xu & Jia[2010]	85.63	3.6293
Levin et al.[2011]	46.72	6.5577
Cho & Lee[2009]	65.47	8.6901
Krishnan et al.[2011]	24.49	11.5212
Cho et al.[2011]	11.74	24.7020

Visual Comparison(Synthetic image)



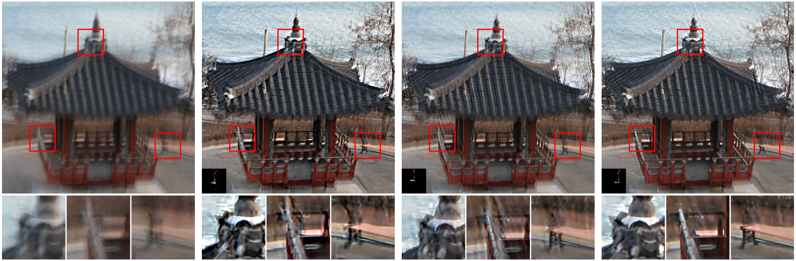
Blurry image	Real sharp image	Sun et al.[2013]	Michaeli & Irani[2014]	Ours

Visual Comparison(Real Image)



Blurry image — Krishnan et al.[2011] — Levin et al.[2011] — Ours

Visual Comparison(Real Image)



Blurry image | Perrone & Favaro [2014] | Michaeli & Irani[2014] | Ours

Thanks!