Single Image Deblurring with Adaptive Dictionary Learning

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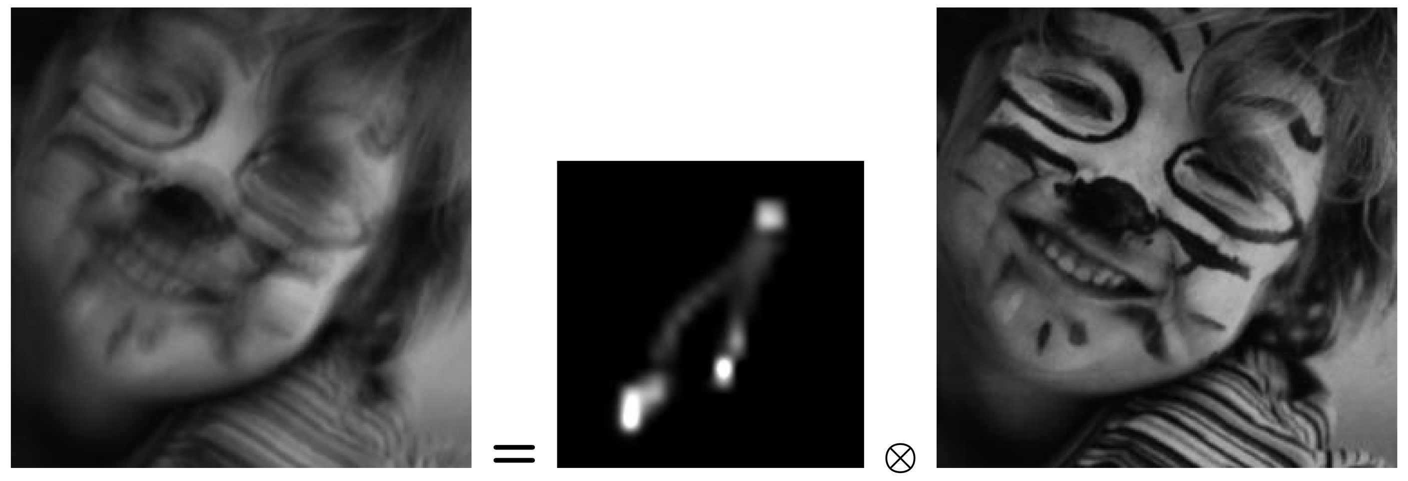
Introduction

- The image blur problem can be modeled by latent image $\boldsymbol{I}$ convolving with a spatial-invariant kernel $\boldsymbol{K}$:



$\boldsymbol{B} = \boldsymbol{K} \otimes \boldsymbol{I}$

- Non-blind deconvolution problem: Given $\boldsymbol{B}$ and $\boldsymbol{K}$, find $\boldsymbol{I}$
- Blind deconvolution problem: Given $\boldsymbol{B}$, find $\boldsymbol{K}$ and $\boldsymbol{I}$ (ill-posed, multiple solutions, priors needed)

Motivation

- Impose image sparsity prior

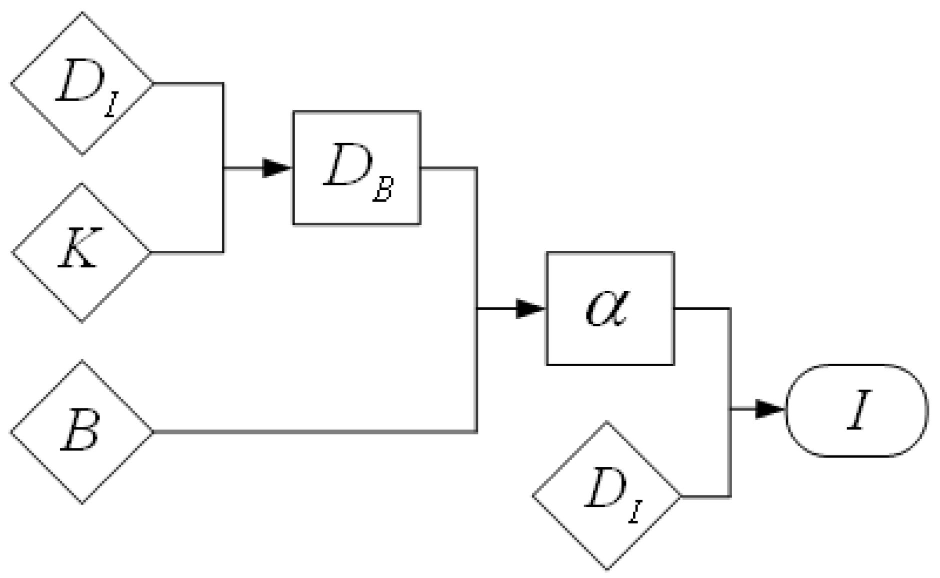
$$\min \|\alpha\|_0, \quad \text{s.t.} \quad \|\boldsymbol{I} - \boldsymbol{D}\alpha\|_2 \leq \epsilon \tag{1}$$

- Adaptive dictionary
  - fixed $\boldsymbol{D} \rightarrow$ ignoring the information on input image
  - adaptive $\boldsymbol{D} \rightarrow$ exploiting structure/details on input image
- Avoid computing deconvolution by enforcing consistent α

$$\begin{array}{ccc} \boldsymbol{B} \approx \boldsymbol{D_B} \cdot \alpha \\ \updownarrow \text{same coefficients } \alpha \\ \boldsymbol{I} \approx \boldsymbol{D_I} \cdot \alpha \end{array} \tag{2}$$

where $\boldsymbol{D_B}$ and $\boldsymbol{D_I}$ denote the dictionaries for blurred and latent images, and $\boldsymbol{D_B} = \boldsymbol{K} \otimes \boldsymbol{D_I}$.

- Given $\boldsymbol{B}$, $\boldsymbol{K}$ and $\boldsymbol{D_I}$,



Algorithm

- **Formulation**

Joint optimization problem of $\boldsymbol{K}$ and α with l_1 regularization:

$$\begin{aligned} &\min_{\boldsymbol{K},\alpha} \|\boldsymbol{B} - \boldsymbol{K} \otimes \boldsymbol{D_I}\alpha\|_2^2 + \lambda\|\alpha\|_0 \\ \Leftrightarrow &\min_{\boldsymbol{K},\alpha} \|\boldsymbol{B} - \boldsymbol{K} \otimes \boldsymbol{D_I}\alpha\|_2^2 + \lambda\|\alpha\|_1 \end{aligned} \tag{3}$$

- **Iterative Optimization**

Figure: Algorithm flowchart

- Estimating α with fixed $\boldsymbol{D}$ and $\boldsymbol{K}$ using sparse representation

$$\begin{aligned} \alpha^{(n+1)} &= \min_{\alpha} \|\boldsymbol{b} - (\boldsymbol{K}^{(n)} \otimes \boldsymbol{D}_I^{(n)})\alpha\|_2^2 + \lambda\|\alpha\|_1 \\ &= \min_{\alpha} \|\boldsymbol{B} - \boldsymbol{D}_{\boldsymbol{B}}^{(n)}\alpha\|_2^2 + \lambda\|\alpha\|_1 \end{aligned} \tag{4}$$

- Updating $\boldsymbol{D}$ with fixed $\boldsymbol{K}$ and α using K-SVD algorithm

$$\begin{aligned} \boldsymbol{d}_i^{(n+1)} &= \min \|\boldsymbol{I}^{(n)} - \boldsymbol{D}^{(n)}\alpha^{(n+1)}\|_2^2 \\ &= \min_{d_i} \|\boldsymbol{I}^{(n)} - (\boldsymbol{d}_i\alpha_i^{n+1}) + \sum_{j\neq i} \boldsymbol{d}_j^{(n)}\alpha_j^{(n+1)})\|_2^2 \\ &= \min_{d_i} \|\boldsymbol{E}_i^{(n+1)} - \boldsymbol{d}_i\alpha_i^{(n+1)}\|_2^2 \end{aligned} \tag{5}$$

- Recovering $\boldsymbol{K}$ with reconstructed $\boldsymbol{I}$

First reconstruct latent image $\boldsymbol{I}$ with coefficients α from (4) and dictionary $\boldsymbol{D}$ from (5),

$$\boldsymbol{I}^{(n+1)} = \boldsymbol{D}^{(n+1)}\alpha^{(n+1)} \tag{6}$$

After that, use Tikhonov regularization to solve kernel estimation problem:

$$\boldsymbol{K}^{(n+1)} = \arg\min_{\boldsymbol{K}} \|\boldsymbol{B} - \boldsymbol{K} \otimes \boldsymbol{I}^{(n+1)}\|_2^2 \tag{7}$$

Quantitive Experimental Results

- RMSE on testing images

Methods	Koala	Babara	Castle1	Castle2
Fergus	5.41	5.53	7.87	6.58
Shan	6.57	7.02	7.46	7.21
Ours	5.10	4.61	6.73	6.94

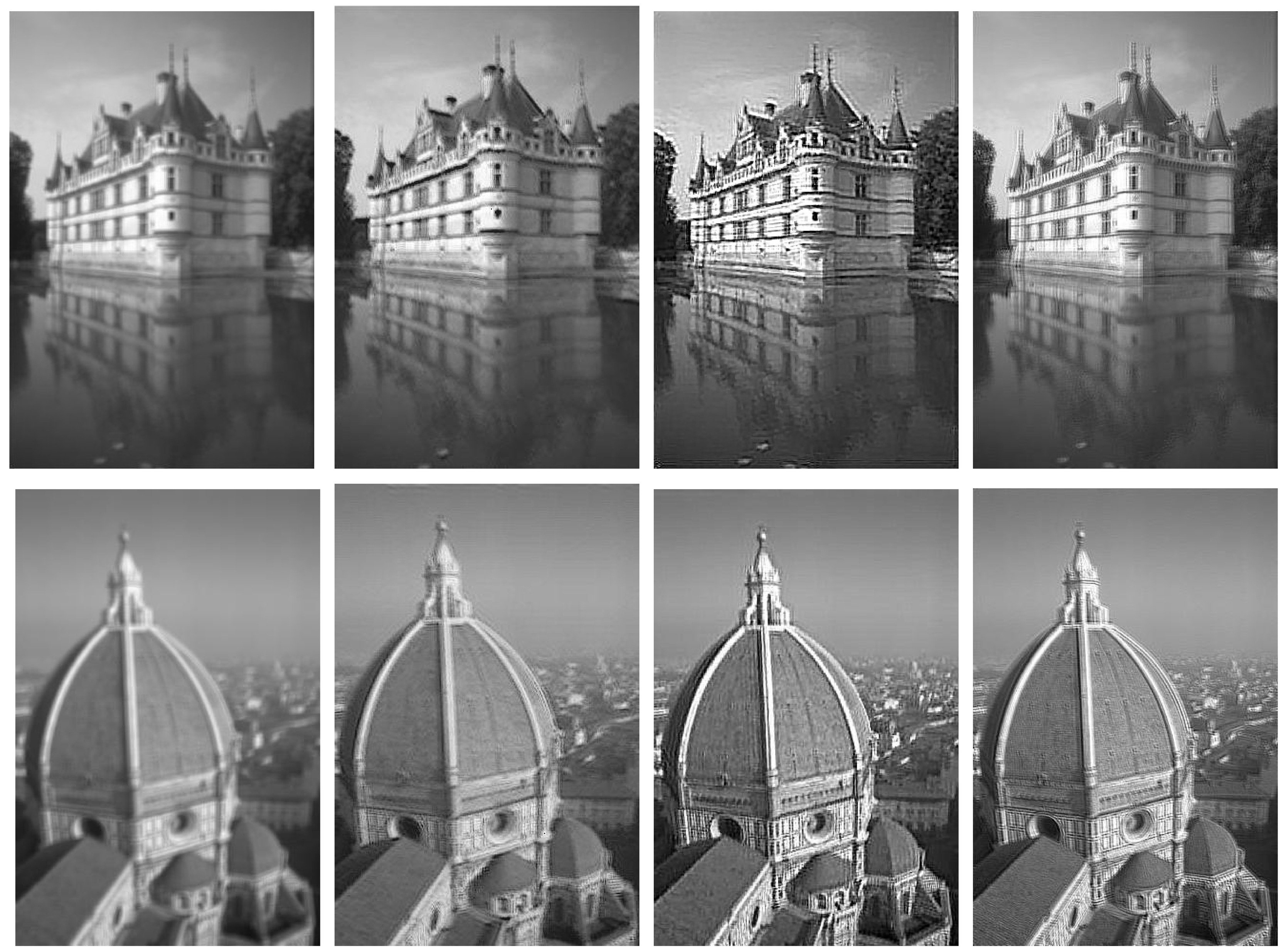
- More information can be found at
`http://eng.ucmerced.edu/people/zhu`

Qualitative Experimental Results

- **Motion Blur Kernel**

(a) Blurred (b) Fergus (c) Shan (d) Ours

- **Randomly Generated Kernel**



(a) Blurred (b) Fergus (c) Shan (d) Ours