Dictionary Replacement for Single Image Restoration of 3D Scenes

Nimisha T M, Arun M and A.N. Rajagopalan
Department of Electrical Engineering, Indian Institute of Technology Madras

Motivation

- Trade-of between aperture size and exposure time for acquiring a well exposed image.
- Results in either defocus or motion blurred images.

Input Our result Depthmap

- Goal: Jointly estimating the depth and the latent image from a single space- variantly blurred image using blur as a cue

Blur-Invariant Sparse Representations

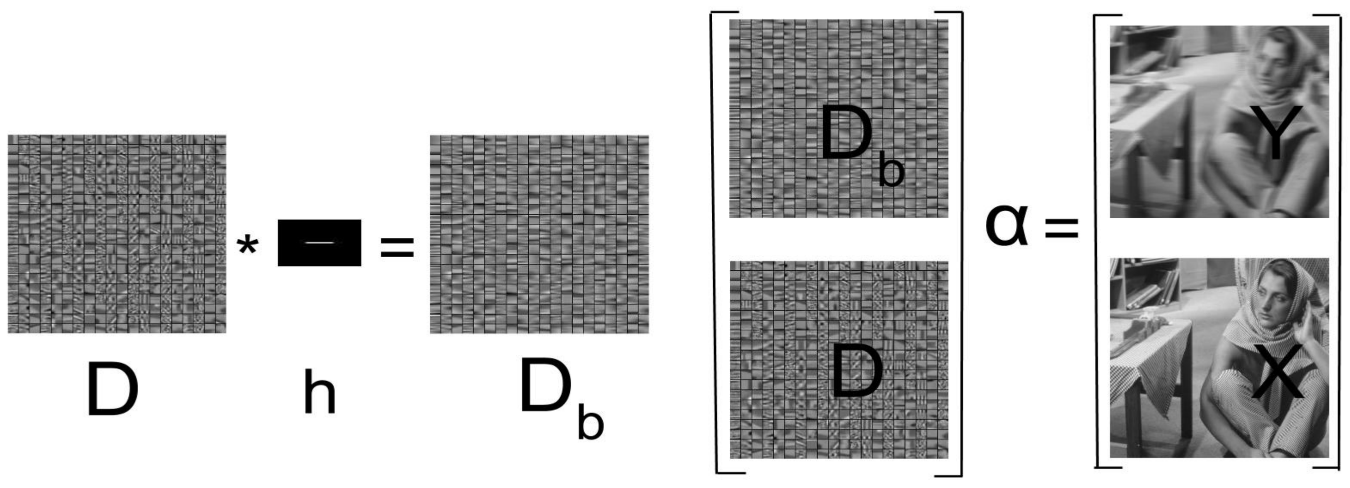


Figure 1: Dictionary replacement and blur-invariant sparse representation.

- A blurred image $\boldsymbol{Y}$ can be represented in terms of latent image $\boldsymbol{X}$ and kernel $\boldsymbol{h}$ as

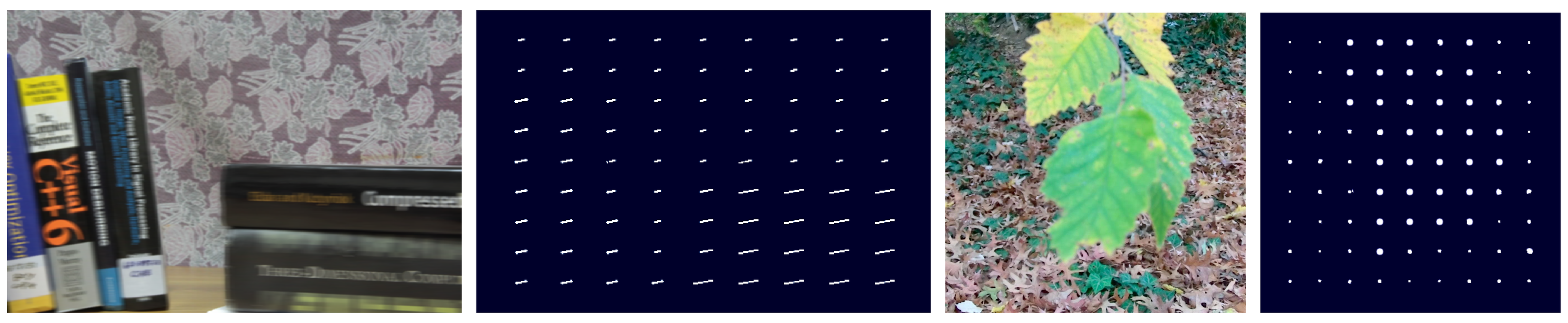
$$\boldsymbol{Y} = \boldsymbol{h} \otimes \boldsymbol{X} = \boldsymbol{h} \otimes \boldsymbol{D} \circ \boldsymbol{\Lambda} = \boldsymbol{D}_b \circ \boldsymbol{\Lambda} \quad (1)$$

$\boldsymbol{h} \otimes \boldsymbol{D}$ is denoted as $\boldsymbol{D}_b$, a blurred version of dictionary $\boldsymbol{D}$.

- If blur kernel is known the latent image can be recovered from the blur-invariant sparse representation $\boldsymbol{\Lambda}$ by **dictionary replacement**

Dictionary based Depth Estimation

- Blur and depth are inter-related



(a) (b) (c) (d)

Figure 2: Scaling of blur kernels with depth. (a-b) Motion blurred image and corresponding kernel grid. (c-d) Defocused image and corresponding kernel grid.

- $\boldsymbol{Y}$: the observed blurred image of a 3D scene and $\boldsymbol{h}_0$: the blur kernel corresponding to the most blurred region in the image.
- Blur at any other position is a scaled down version of $\boldsymbol{h}_0$ by blur depth relation.
- Depth estimation boils down to estimating the scale of the blur kernel at each location.
- Solved by MRF

$$\arg\min_{i} \quad DC_i(k) + \sum_{k' \in \mathcal{N}} SC(\bar{i}_{k'}, i_k) \quad (2)$$

$DC_i(k)$ is the data cost and SC is the edge aware smoothness cost.

- For a particular sparsity, the dictionary $\boldsymbol{D}_{b_i}$ that gives the best representation of $\boldsymbol{Y}$ is used to choose the correct scale at that patch location.
- Data cost for assigning a scale i at pixel location k is

$$DC_i(k) = ||\boldsymbol{Y}(k) - \bar{\boldsymbol{Y}}_i(k)||_2^2 \quad \text{where} \quad \bar{\boldsymbol{Y}}_i = \boldsymbol{D}_{b_i} \circ \boldsymbol{\Lambda}_i \quad (3)$$

where $\bar{\boldsymbol{Y}}_i$ is an approximation of $\boldsymbol{Y}$ obtained from the sparse representation $(\boldsymbol{\Lambda}_i)$ and the blurred dictionary $(\boldsymbol{D}_{b_i})$ corresponding to blur kernel $\boldsymbol{h}_i$.

- The deblurred image is formed by picking pixels from a stack of deblurred results according to the estimated scale.

Experimental Results

Blur Magnification

(a) (b) (c) (d)

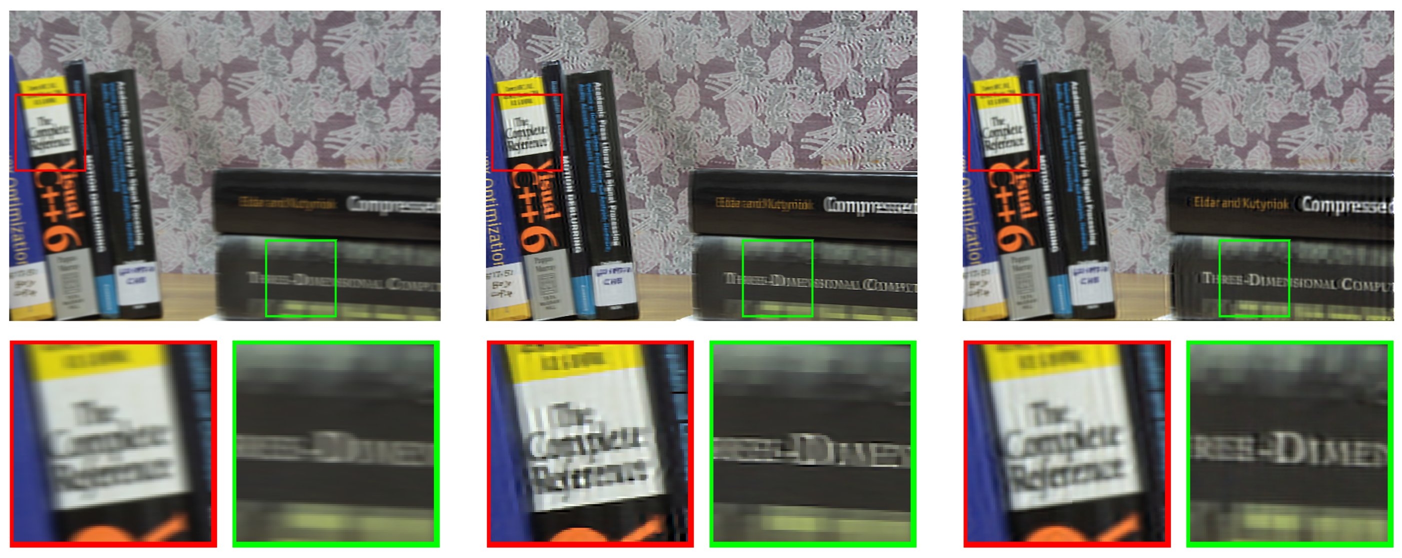
Figure 3: Blur magnification: (a) Input image focused in the front. (b) Deblurred result. (c) Estimated blur map. (d) Background blur magnified.

Refocusing

(a) (b) (c) (d)

Figure 4: Refocusing application: (a) Input image along with zoomed-in patches. (b) Deblurred result. (c) Blur map. (d) Refocused image along with zoomed-in patches.

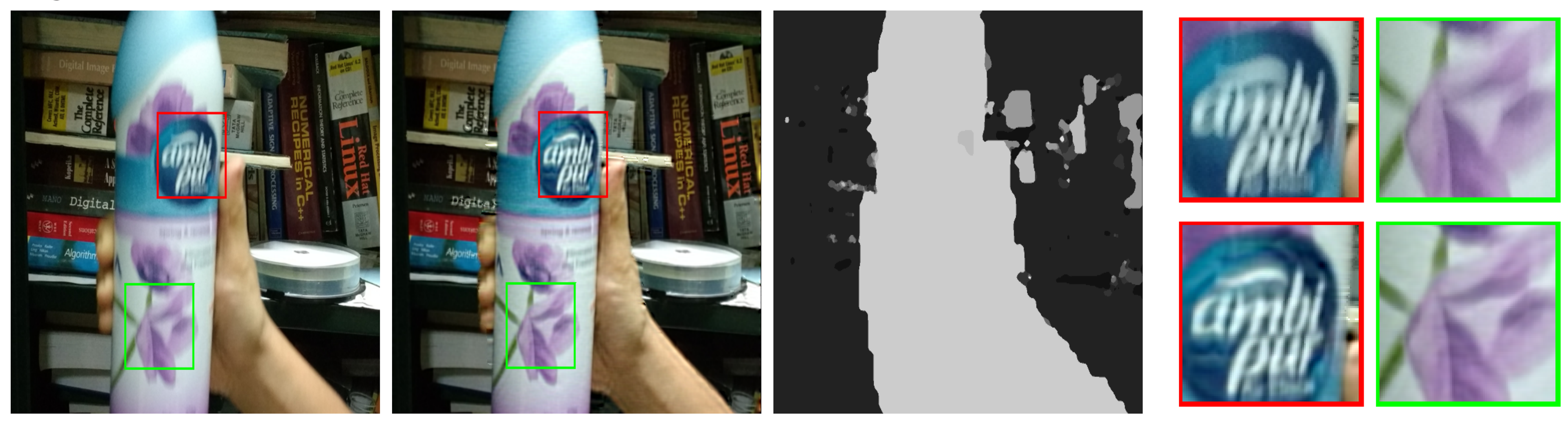
Motion Deblurring



(a) (b) (c)

Figure 5: (a) Blurred input image. Deblurred using (b) [2] and (c) our method.

Object blur



(a) (b) (c) (d)

Figure 6: Object motion: (a) Blurred input image. (b) Our result. (c) Recovered blur map. (d) Zoomed-in patches from (a) and (b), respectively.

Comparison

(a) (b) (c) (d)

Figure 7: Comparison with Hu et. al [1]: (a) Input image. (b) Deblurred result of [1]. (c) Our result. (d) Zoomed-in patches from (a), (b) and (c), respectively.

References

1. Hu, Zhe, Li Xu, and Ming-Hsuan Yang. "Joint depth estimation and camera shake removal from single blurry image." CVPR 2014.
2. Xu, Li, Shicheng Zheng, and Jiaya Jia. "Unnatural l0 sparse representation for natural image deblurring." CVPR 2013.