From Motion Blur to Motion Flow: a Deep Learning Solution for Removing Heterogeneous Motion Blur

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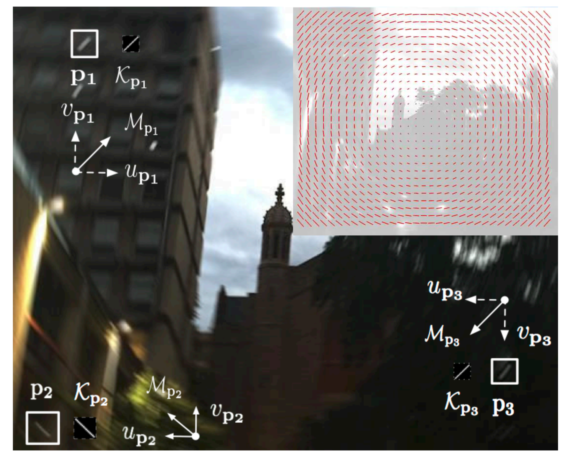
IEEE 2017 Conference on Computer Vision and Pattern Recognition
CVPR July 21-26 Honolulu 2017

Introduction

Heterogeneous motion blur removal:

- Recovering a blur-free latent image from a single observation with heterogeneous motion blur.
- The blur kernels may independently vary from pixel to pixel.



Motion flow based blur model:

- Heterogeneous blur model:

$$\mathbf{Y} = \mathcal{K} * \mathbf{X} + \mathbf{N}$$

$$\mathcal{K} * \mathbf{X} = \sum_{i',j'} \mathcal{K}_{(i,j)}(i',j')\mathbf{X}(i+i',j+j')$$

- Pixel-wise linear motion blur kernel.
- Motion flow $\mathcal{M} = (\mathbf{U}, \mathbf{V})$.

$$\mathcal{M}_\mathbf{p} \longleftrightarrow \mathcal{K}_\mathbf{p}$$

Existing methods: iterative optimization based methods [2], patch-based learning methods [1].

Limitations: limited motion type, manually defined prior, time-consuming.

Contributions

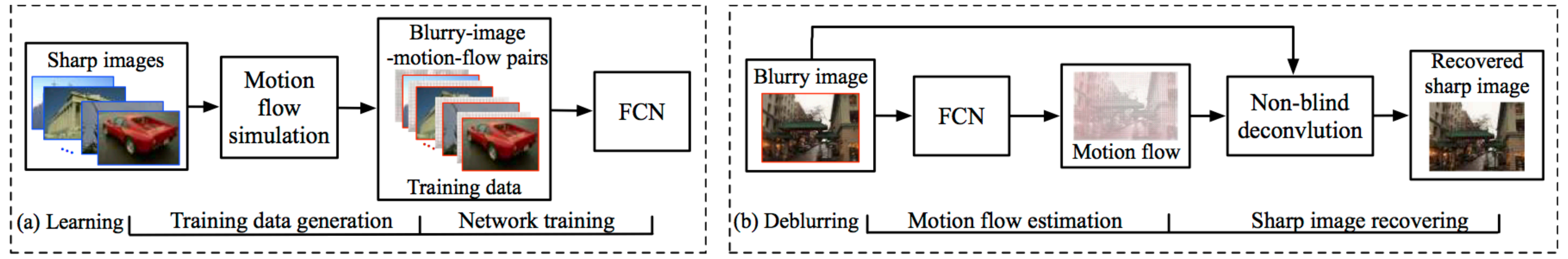
We propose a deep neural network based method able to directly estimate a pixel-wise motion flow map from a single blurred image.

Core contributions:

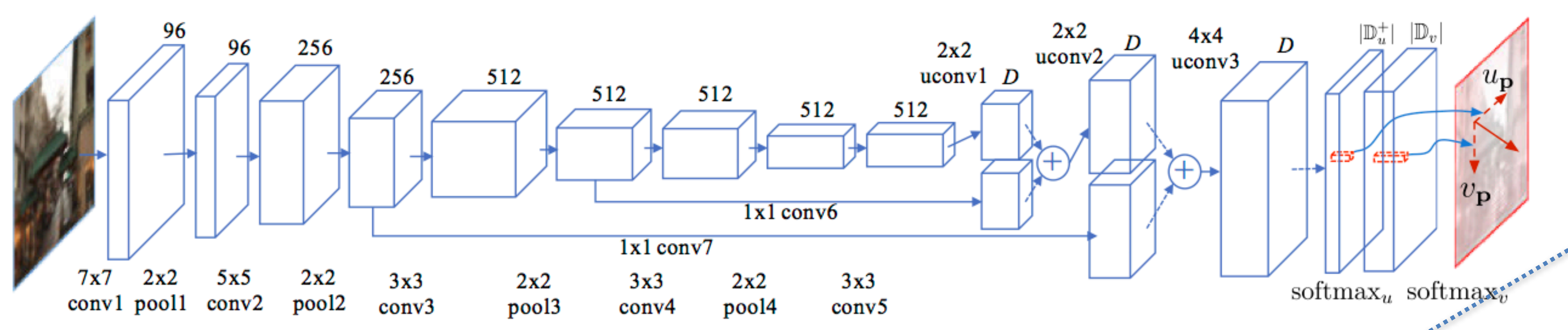
- We estimate and remove pixel-wise motion blur by training on simulated examples. Our method uses a flexible blur model and makes almost no assumptions about the underlying images, resulting in effectiveness on diverse data.
- We introduce a universal FCN for end-to-end estimation of dense heterogeneous motion flow from a single blurry image. The proposed method utilizes the spatial context over a wider area, and does not require any post-processing.

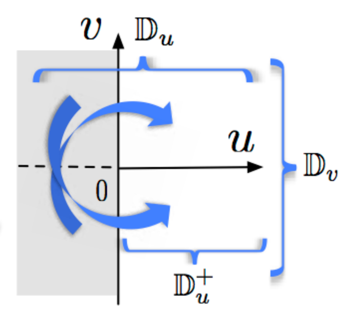
Estimating Motion Flow for Blur Removal

Deblurring: Given a blurred image $\mathbf{Y}$, estimate the motion flow map $\mathcal{M}$ using the learned end-to-end estimation model (FCN) $\mathcal{M} = f(\mathbf{Y})$. Then we recover the unblurred image $\mathbf{X}$ via non-blind deconvolution.



Learning: Learn the FCN from a set of training data $\{(\mathbf{Y}^t, \mathcal{M}^t)\}_{t=1}^T$.





Estimating Motion Flow as Classification:

- Adopt integer domain for both $\mathbf{U}$ and $\mathbf{V}$.
- Restrict motion in the horizontal direction to be nonnegative.
- Treat motion flow estimation as classification.

$$\mathbb{D}_v = \{v | v \in \mathbb{Z}, |v| \leq v_{max}\}$$

$$\mathbb{D}_u^+ = \{u | u \in \mathbb{Z}_0^+, |u| \leq u_{max}\}$$

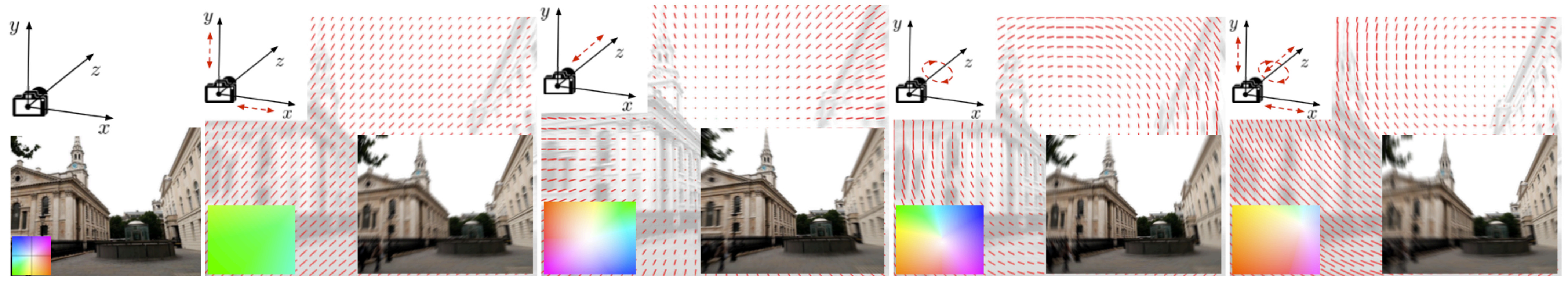
Feasible Domain of U and V

Training Data Generation

Generating Training Data by Simulating Camera Motion: Simulate a motion flow $\mathcal{M}$ by sampling four additive components -- translations along x, y and z axis and rotation around z axis:

$$\mathcal{M} = \mathcal{M}_{T_x} + \mathcal{M}_{T_y} + \mathcal{M}_{T_z} + \mathcal{M}_{R_z}$$

- Sample motion parameters → directly generate 2D motion flow map.
- Generate training data on BSD500 (200 sharp images).
- Training on 10200 samples $\{(\mathbf{Y}^t, \mathcal{M}^t)\}_{t=1}^T$ (T=10,200).



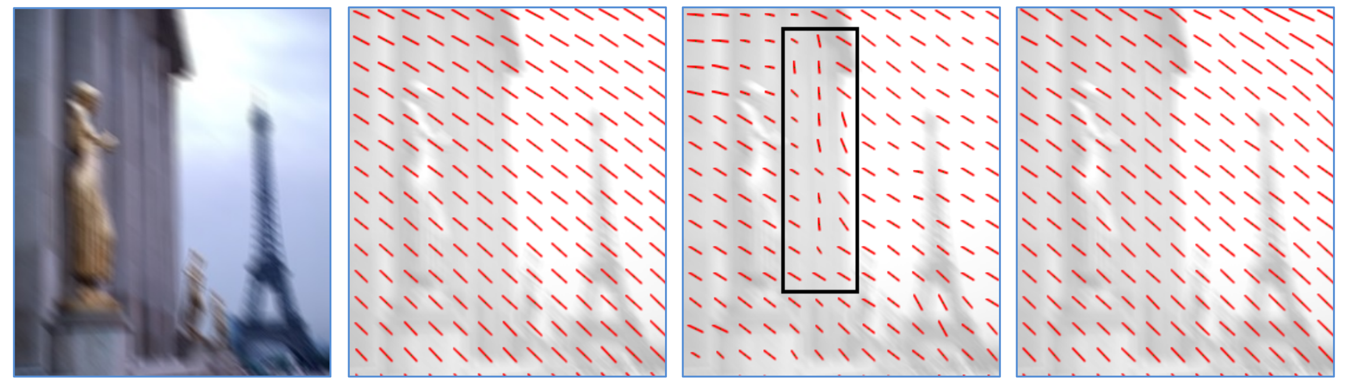
(a) Sharp Image (b) x and y-axis translation (c) z-axis translation (d) z-axis rotation (e) Arbitrary sampled motion

Experiments

Synthetic Data: Test on synthetic datasets generated using BSD500 and Microsoft COCO.

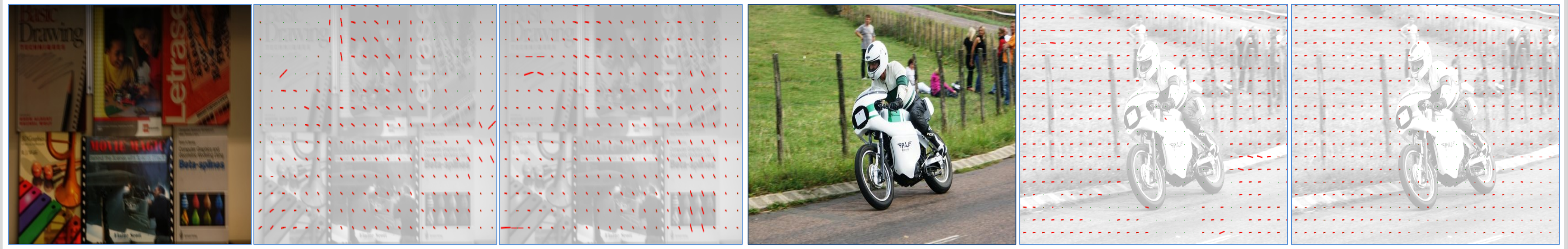
Mean Squared Error (MSE)

Dataset	patchCNN [1]	noMRF[1]	Ours
BSD-S	50.1168	54.4863	**6.6198**
BSD-M	15.6389	20.7761	**5.2051**
MC-S	52.1234	60.9397	**7.8038**
MC-M	22.4383	31.2754	**7.3405**



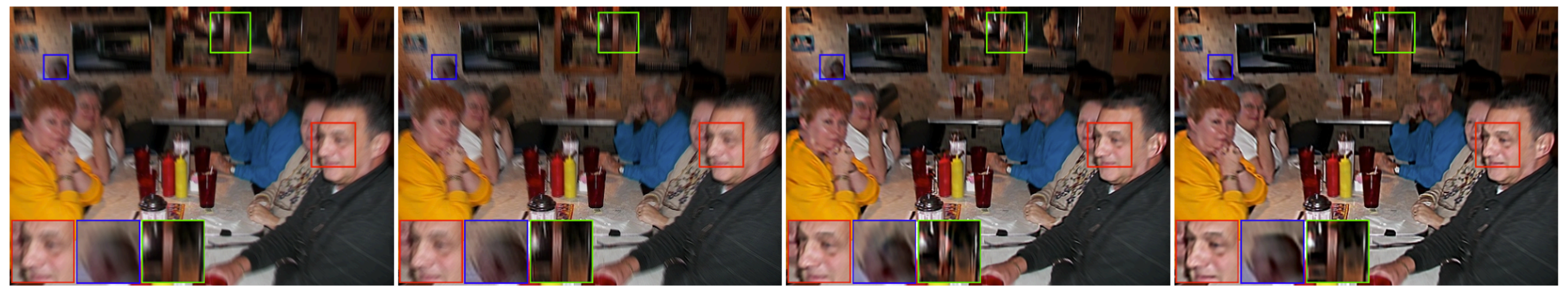
Blurred image Ground truth patchCNN [1] Ours

Real-world images: Evaluation the motion flow estimation and image recovering on real-world images.



Blurry image Sun *et.al* [1] Ours Blurry image Sun *et.al* [1] Ours

(a) Blurry image (b) Xu and Jia [4] (c) Sun *et.al.* [1] (d) Ours



(a) Blurry image (b) Whyte *et.al.* [3] (c) Sun *et.al.* [1] (d) Ours

*More details and results in our paper and the project page:

Reference

[1] J. Sun, W. Cao, Z. Xu, and J. Ponce. Learning a convolutional neural network for non-uniform motion blur removal. In *CVPR*, 2015.
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