Unconstrained Motion Deblurring for Dual-lens Cameras

Mahesh Mohan M. R., Sharath Girish, and A. N. Rajagopalan

Image Processing and Computer Vision Lab
Department of Electrical Engineering
Indian Institute of Technology Madras

Why Dual-lens Cameras?

A DL camera captures depth information, hence supporting many applications.

Left-view

Right-view

Depth

Segmentation [1]

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Scene Understanding

Binocular or 3D Vision

Bokeh Rendering

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Constrained Dual-lens Cameras?

Two cameras share the **same** configuration.

Examples of constrained DL cameras

1. Same focal lengths (or field-of-views).
2. Fully overlapping exposure times.
3. Same image resolutions.

Unconstrained Dual-lens Cameras?

Two cameras **need not** share the **same** configuration.

Examples of unconstrained DL cameras

1. Focal lengths
   - Same: Binocular or 3D vision.
   - Different: Capture narrow, wide, or wider field-of-views.
2. Exposure times
   - Full-overlap: Super-resolution and visual odometry [2, 3, 4].
   - Differently exposed: HDR imaging, low-light photography, and stereoscopics [5, 6, 7, 8].
3. Can have different image resolutions.

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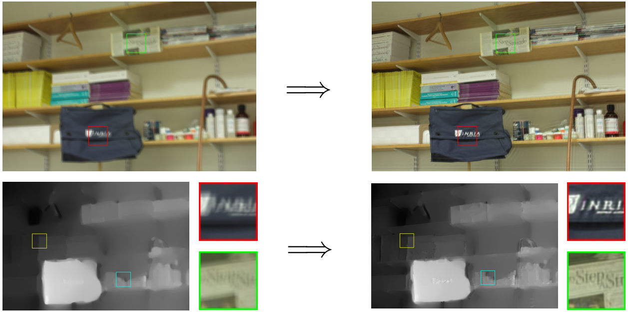
Motion Blur in Unconstrained DL Cameras

1. Motion blur due to camera motion is a ubiquitous phenomenon.
2. But it is *unexplored* in unconstrained DL set-ups.

Our objective: Motion deblurring with scene-consistent disparities.



Input

Output

Motion Deblurring in Unconstrained DL Cameras

Has additional challenges (over single-lens cameras).

1. Popular narrow-FOV: Amplifies blur and center-of-rotation effect.
   - We introduce a generalized dual-lens blur model, including COR.
2. Ensure scene-consistent disparities.
   - We reveal an inherent ill-posedness present in dual (or multi) lens cameras.
   - To this end, we devise a prior that is convex and admits efficient optimization.
3. Handle more than one image: Higher dimensional optimization.
   - We introduce a practical deblurring method (suitable for all multi-lens set-ups).

iPhone's "unconstrained triple-lens" launch, 2019 September.

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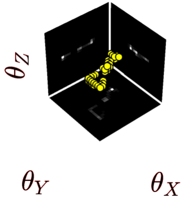
Generalized Dual-lens Motion Blur model

Motion blurred image is a combination of multiple warped images.

Latent image



Camera motion (MDF)

Motion blurred image

$$\mathbf{I}_B^n = \sum_{p \in \mathbb{P}^3} w^n(p) \cdot P^n\Big(R_p(\mathbf{X} - \mathbf{l_c}) + \mathbf{l_c} + \mathbf{l_b}\Big)\, dp, \quad (1)$$

$\mathbf{I}_B^n \rightarrow$ blurred image $\quad \mathbf{l_c} \rightarrow$ COR $\quad \mathbf{l_b} \rightarrow$ base-line $\quad \mathbb{P}^3 \rightarrow$ Camera pose-space (rotations)

$w^n(p) \rightarrow$ proportion of time camera stayed in pose p $\quad P^n(\cdot) \rightarrow$ World-to-sensor projection

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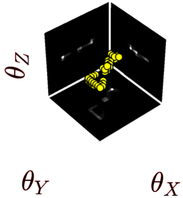

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$\mathbf{I}_B^n \rightarrow$ blurred image $\mathbf{l_c} \rightarrow$ COR $\mathbf{l_b} \rightarrow$ base-line $\mathbb{P}^3 \rightarrow$ Camera pose-space (rotations)

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Ill-posedness in Unconstrained DL Motion Deblurring

Claim 1: There exist multiple valid solutions of deblurred image-pairs.

$$
\begin{aligned}
\mathbf{I}_B^n &= \sum_p w^n(p) P^n \Big(R_p(\underbrace{\mathbf{X}}_{true} - \mathbf{I_c}) + \mathbf{I_c} + \mathbf{I_b} \Big), \\
&= \sum_p w^n(p) P^n \Big(R_p R_n^{-1} (\underbrace{R_n(\mathbf{X} - \mathbf{I_c}) + \mathbf{I_c}}_{apparent} - \mathbf{I_c}) + \mathbf{I_c} + \mathbf{I_b} \Big), \quad \forall R_n.
\end{aligned} \tag{3}
$$

(a) True solution (b) An apparent solution (inplane rotation)

- True: Scene-features A, B, and C are at the same depth.
- Apparent: Erroneously, A, B, and C have different depths.

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\end{aligned} \tag{4}
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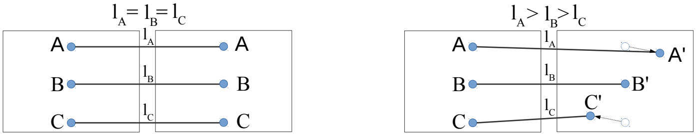

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A new prior for Unconstrained DL Motion Deblurring

Ill-posedness is due to relative shifts among individual MDFs.

$$\text{DL Cost} = \underbrace{\text{Image-pair cost}}_{\text{Convex}} + \underbrace{\text{MDF-pair cost}}_{\text{Convex, Not interdependent}} \tag{5}$$

1. Properties of our DL deblurring Cost:
   - It is biconvex with respect to image-pair and MDF-pair (which aid convergence).
   - But, as MDFs are not interdependent, it admits relative MDF shifts.

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$$\text{DL Cost} = \underbrace{\text{Image-pair cost}}_{\text{Convex}} + \underbrace{\text{MDF-pair cost}}_{\text{Convex, Not interdependent}} + \underbrace{\text{Prior } (\|\mathbf{w}_n - \mathbf{w}_w\|_2)}_{\text{Convex, Interdependent}}. \quad (6)$$

1. Properties of our DL deblurring Cost:
   - It is biconvex with respect to image-pair and MDF-pair (which aid convergence).
   - But, as MDFs are not interdependent, it admits relative MDF shifts.

---

2. The prior increases the DL Cost with relative MDF shifts.
3. Properties of our Prior:
   - Convex, and thus retains the biconvexity (for convergence).
   - Allows for efficient LASSO optimization.
   - Reinforces camera motion estimation.

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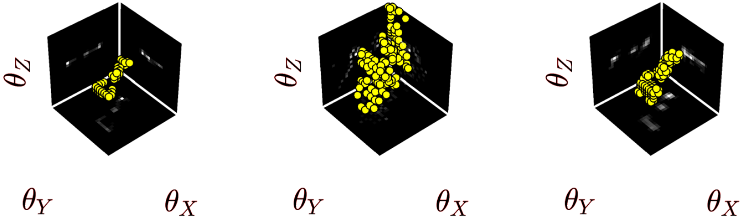
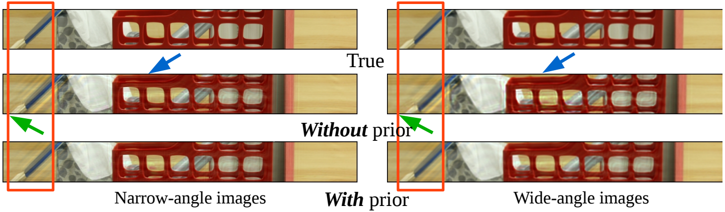
A new prior for Unconstrained DL Motion Deblurring

The prior curbs the relative shifts among individual MDFs.



(a) True MDF (b) *Without* prior (c) With prior



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A practical algorithm for Unconstrained DL Deblurring

We show that a multi-lens deblurring problem can be:

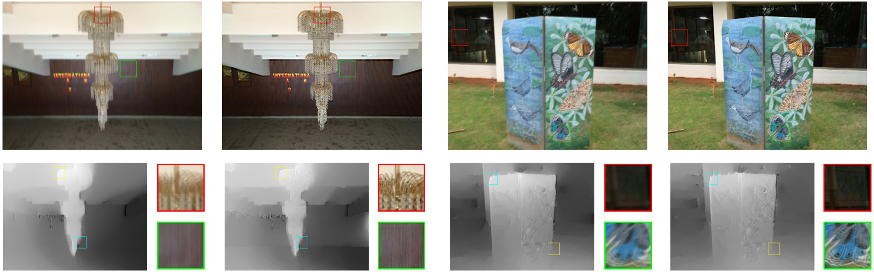
1. divided into subproblems (with optimization dimension as that of single-lens);
2. instilled with the proposed prior and biconvexity property;
3. solved using alternating minimization for COR, depth, MDFs, and images.

Representative Results

Our method outperforms SotA deep learning methods [9, 10] by **3.50 dB & 2.72 dB** for image and **4.39 dB & 4.36 dB** for depth.

PSNR (dB)	Blur	W/o Prior W/o COR	W/o Prior W/ COR	W/ Prior W/o COR	W/ prior W/ COR
Image	22.39	25.69	26.59	27.28	28.88
Depth	28.33	23.35	**23.59**	29.12	**30.52**

Ablation study: The DL prior reduces the ill-posedness by a good margin (i.e., by 7 dB, as indicated in bold).



Conclusions

1. Introduced a motion blur model for unconstrained DL cameras.
2. Introduced an efficient prior to address the inherent ill-posedness in DL deblurring that corrupts depth cues.
3. Introduced a practical algorithm for unconstrained DL deblurring.

Please find us at poster # 25. All are Welcome!

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