Real-World Blur Dataset for Learning and Benchmarking Deblurring Algorithms

Jaesung Rim[1], Haeyun Lee[1], Jucheol Won[2], and Sunghyun Cho[2]

[1] DGIST, Daegu, Korea
{jsrim,haeyun}@dgist.ac.kr
[2] POSTECH, Pohang, Korea
{jcwon,s.cho}@postech.ac.kr

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Presenter: Hao Wang

Advisor: Prof. Chia-Wen Lin

Introduction

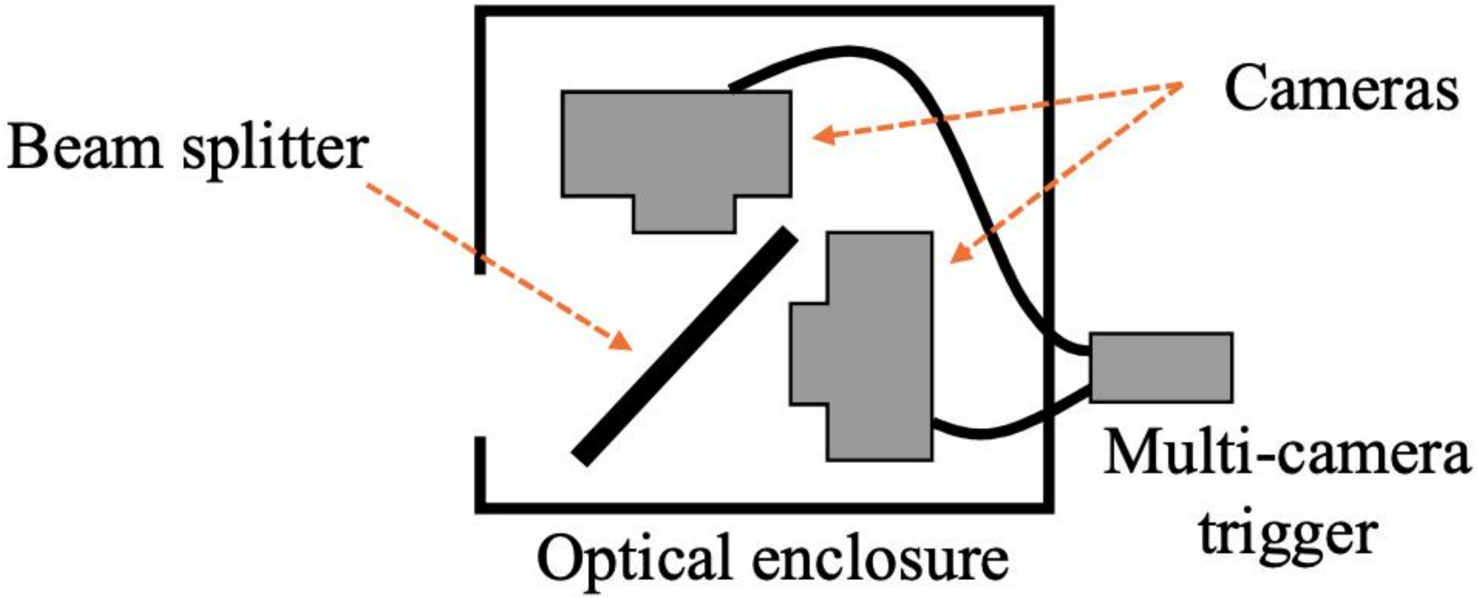
(a) GoPro dataset (b) Magnified view of (a) (c) GoPro dataset (d) Magnified view of (c) (e) Real-world low-light blurred image

- **Synthetic**
  - well-lit environments
- **Real world**
  - **saturated light streaks** due to the limited dynamic range

Outline

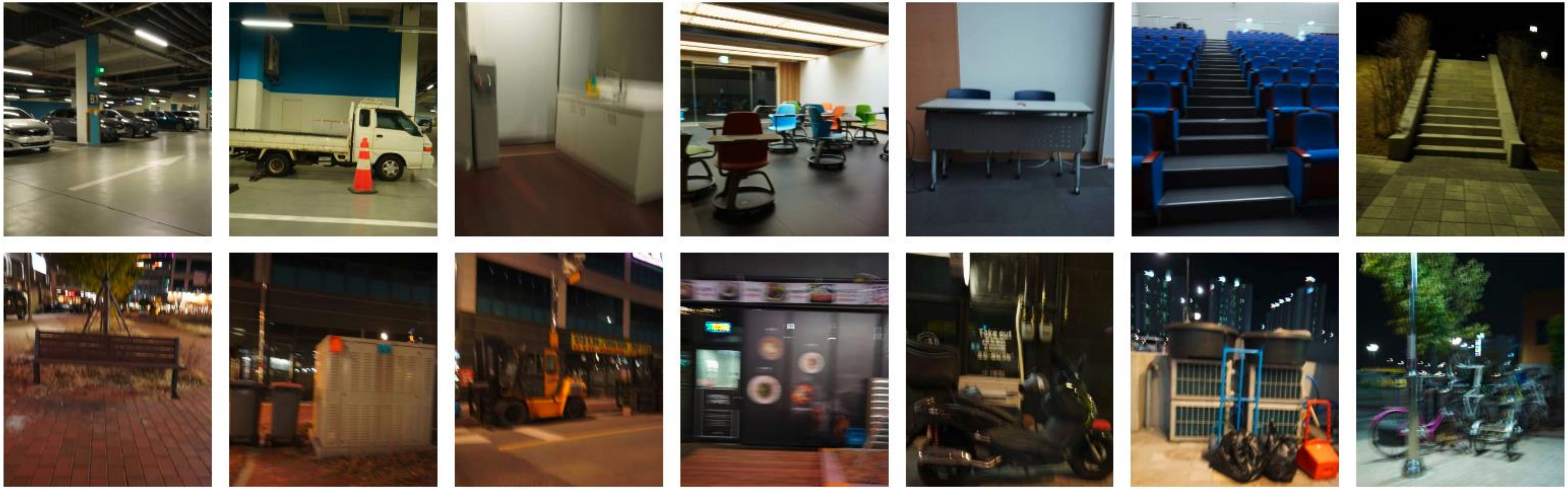
- Introduction
- Method
- Experiment
- Conclusion

Image Acquisition Process



- **Sharp**
  - Shutter speed to 1/80 sec
- **Blur**
  - **Blur**: Shutter speed to 1/2 sec
  - **Same brightness**: ISO value 40 times lower to capture blurred images
  - **Diverse shake**: held system still or randomly moved the system

Image Acquisition Process

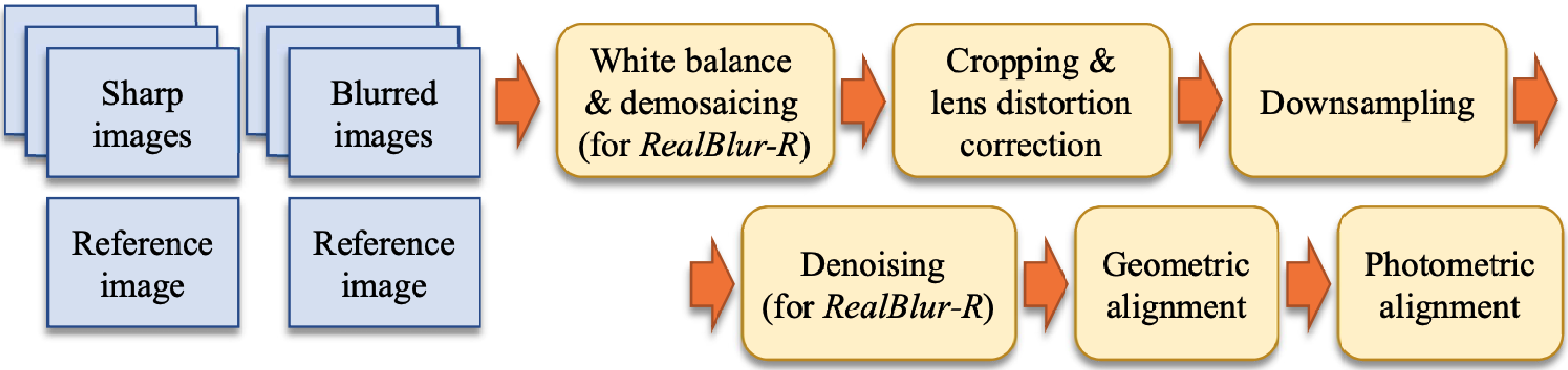


- consists of two subsets **raw images**, and **JPEG images** processed by the camera ISP
- including **4,556 pairs** of blurred and ground truth sharp images of **232 low-light static scenes**, blurred by **camera shakes**, such as **streets at night**, and **indoor**.

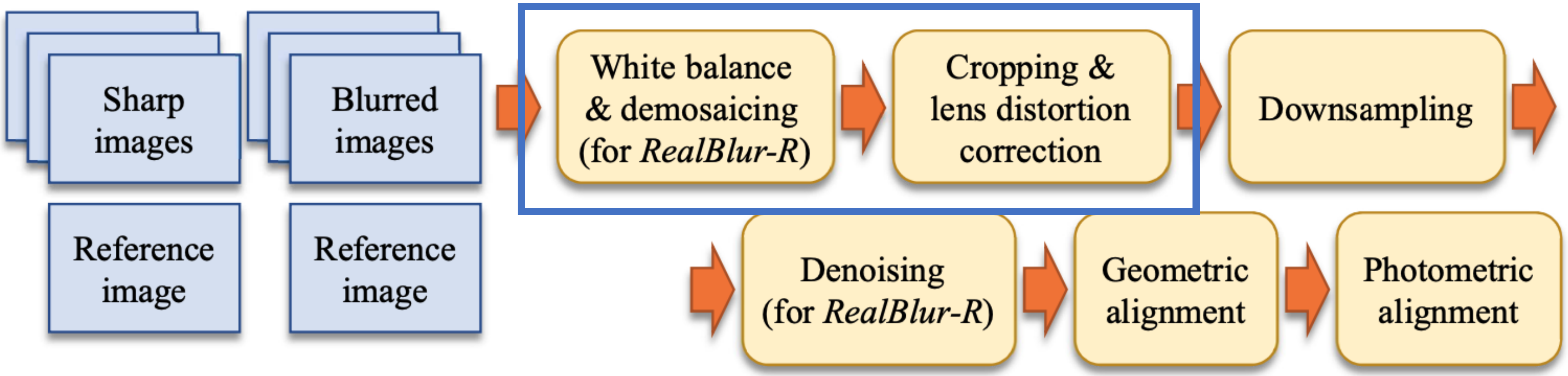
Image Acquisition System

- **Sony A7RM3, Samyang 14mm F2.8 MF**
  - **high-end mirrorless cameras**
    - reflect the **in-camera processing** of conventional cameras into dataset (processed by camera ISPs are more common than raw)
  - **full-frame sensors**
    - gather a **larger amount of light** than small sensors and narrow-angle lenses so they can more effectively **suppress noise**
  - **wide-angle lenses**
    - also help **avoid defocus blur** that may adversely affect learning of **motion deblurring**
  - **physically aligned** as much as possible
    - To evaluate, conducted **stereo calibration** and **estimated the baseline** between the cameras.

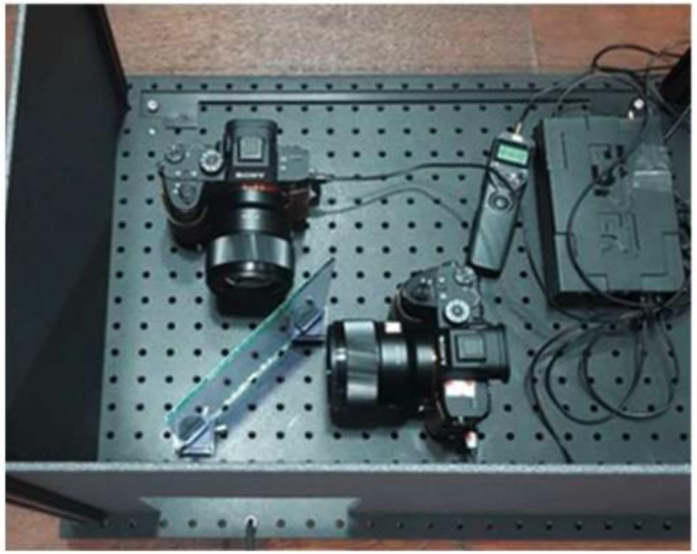
Postprocessing



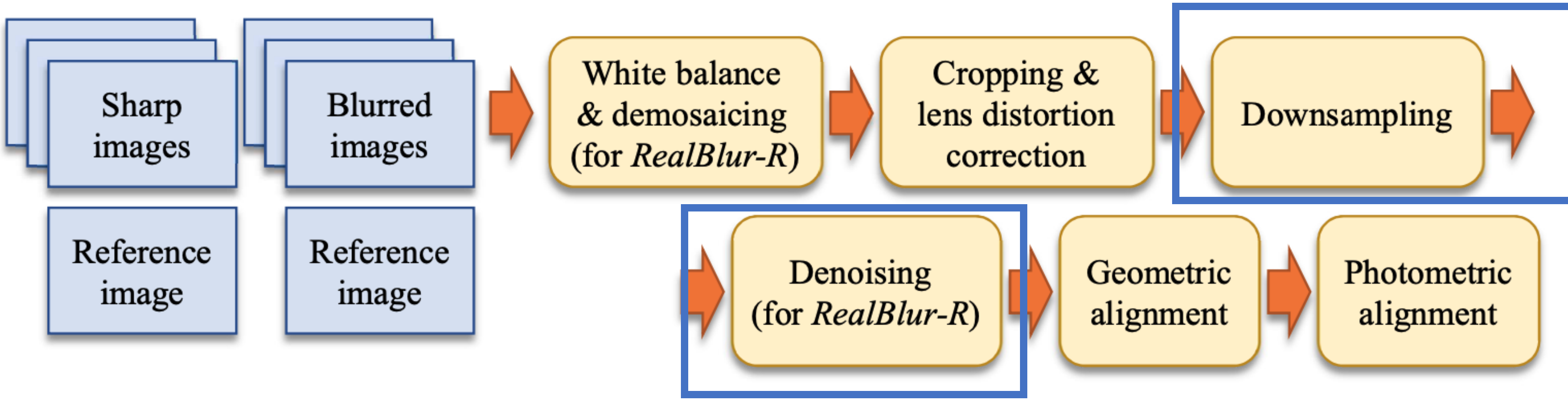
Postprocessing



- **White balance & demosaicing**
  - parameters obtained from the cameras
  - use the **adaptive homogeneity-directed demosaicing** [16]
  - RealBlur-J are already performed by camera ISPs
- **Cropping & lens distortion correction**
  - outside the beam splitter or inside the optical enclosure
  - distortion parameters estimated in a **separate calibration step** [15]



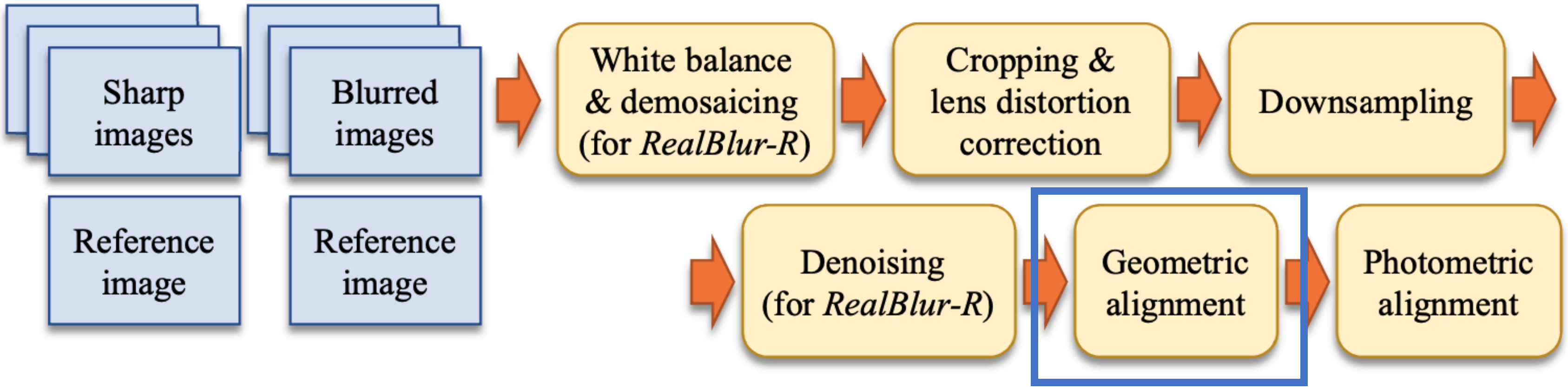
Postprocessing



- **Downsampling**
  - by 1/4 for each axis
  - ➢ latest deep learning-based deblurring methods **cannot handle such high-resolution** images
  - ➢ **high ISO** values to capture sharp images, they have **amplified noise**
  - ➢ **alignment** of the cameras in our image acquisition system is **not perfect**
- **Denoising**
  - then apply the **BM3D** denoising method [10] on sharp image

Postprocessing

- **Geometric Alignment**



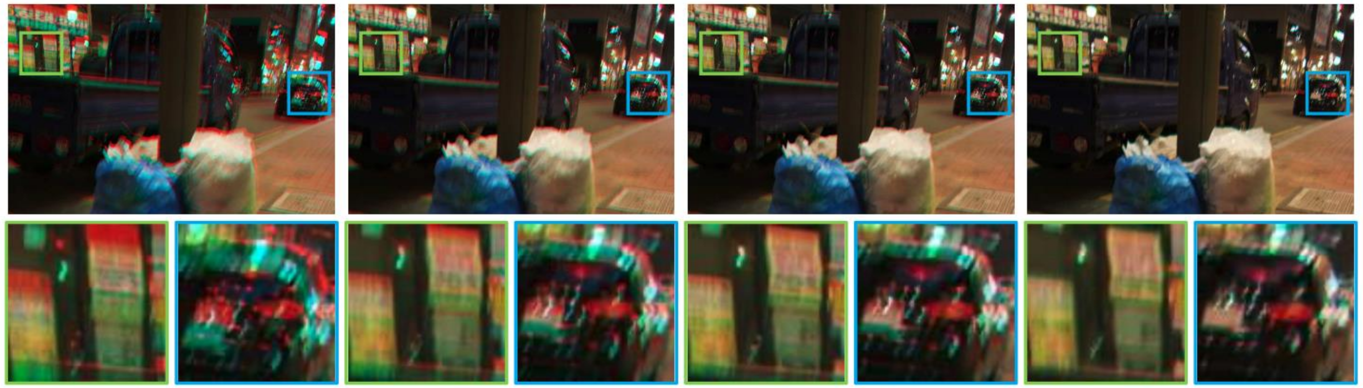
(a) Before geometric alignment

(b) After alignment using a reference homography

(c) After phase-correlation based alignment

(d) After blur kernel-based alignment

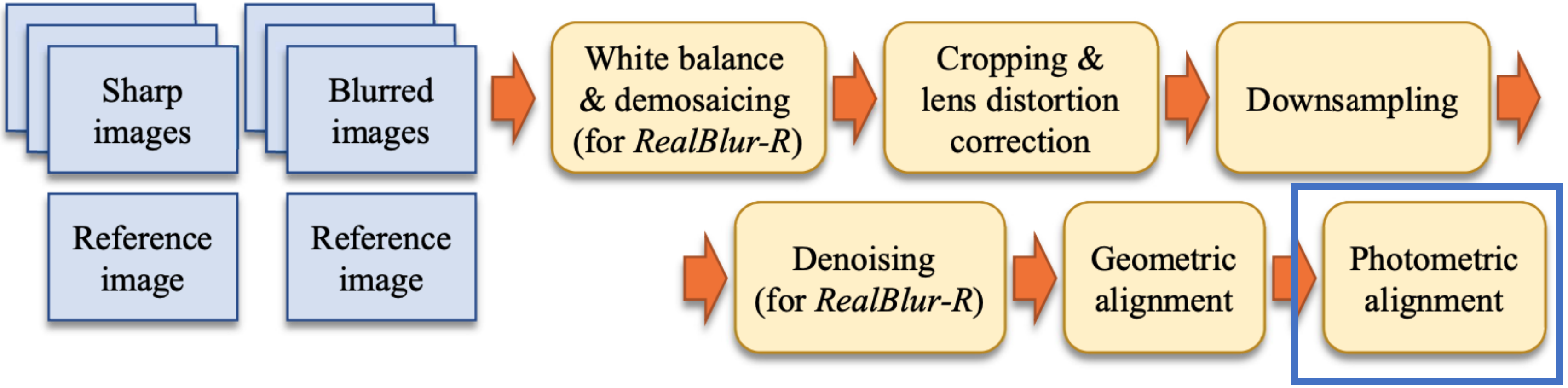
Postprocessing


(a) Before geometric alignment
(b) After alignment using a reference homography
(c) After phase-correlation based alignment
(d) After blur kernel-based alignment

- **Geometric Alignment**
  1. **homography**
     - align each blurred and sharp image pair using a homography
     - homography **estimated from the reference pair** corresponding to the target blurred and sharp image pair
  2. **phase correlation**
     - due to their **different shutter speeds**, captures **incoming lights while moving**, causing misalignment
     - use a **phase correlation-based approach** [35], that can robustly estimate a similarity transform under the presence of blur
  3. **center matching**
     - model-based approaches[37, 4, 9] to match the **center of an object** first
     - estimate a **blur kernel** by minimizing the following energy function, then, **compute the centroid of** the estimated blur kernel **k**, and shift

$$E(k) = \|k * \nabla s - \nabla b\|^2 + \lambda \|\nabla k\|^2$$

Postprocessing



- **Photometric alignment**
  - although use cameras and lenses of the same models, their images may have slight **intensity difference**
  - photometrically **align s to b** by applying a **linear transform** $\alpha s + \beta \approx b$,estimate them from the reference pair $\alpha = \sigma_1/\sigma_2$ and $\beta = \mu_1 - \alpha\mu_2$, sigma is standard deviations of the reference images, and $\mu 1$ and $\mu 2$ are their means.
  - each color **channel independently**

Outline

Result

Training sets				Test sets (PSNR/SSIM)		
RealBlur-R	GoPro	BSD-B	Pre-trained	*RealBlur-R*	Köhler	GoPro
	✓			35.66/0.9472	26.79/0.7963	30.72/0.9074
		✓		34.96/0.9132	28.07/0.8259	29.01/0.8768
✓				36.47/0.9515	24.72/0.7422	23.99/0.7675
✓	✓			38.47/0.9632	26.96/0.7991	30.02/0.8946
✓		✓		38.62/0.9649	27.99/0.8249	29.02/0.8774
✓	✓	✓		38.58/0.9646	28.00/0.8241	29.93/0.8931
✓			✓	38.73/0.9646	26.38/0.7942	26.56/0.8422
✓	✓		✓	38.65/0.9646	27.04/0.8017	30.53/0.9045
✓		✓	✓	38.71/0.9657	28.18/0.8294	29.22/0.8824
✓	✓	✓	✓	38.65/0.9652	28.14/0.8311	30.30/0.9006

Training sets				Test sets (PSNR/SSIM)		
RealBlur-J	GoPro	BSD-B	Pre-trained	*RealBlur-J*	Köhler	GoPro
	✓			28.56/0.8674	26.79/0.7963	30.72/0.9074
		✓		28.68/0.8675	28.07/0.8259	29.01/0.8768
✓				31.02/0.8987	26.57/0.7986	26.68/0.8403
✓	✓			31.21/0.9018	26.94/0.8044	29.91/0.8923
✓		✓		31.30/0.9058	27.88/0.8249	28.97/0.8785
✓	✓	✓		31.37/0.9063	27.74/0.8229	29.90/0.8926
✓			✓	31.32/0.9070	26.77/0.8044	27.18/0.8603
✓	✓		✓	31.40/0.9078	27.13/0.8113	30.46/0.9034
✓		✓	✓	31.44/0.9105	28.06/0.8319	29.21/0.8842
✓	✓	✓	✓	31.38/0.9091	27.82/0.8260	30.30/0.9004

Result

RealBlur-J		*RealBlur-R*	
Methods	PSNR/SSIM	Methods	PSNR/SSIM
SRN-DeblurNet* [42]	31.38/0.9091	SRN-DeblurNet* [42]	38.65/0.9652
DeblurGAN-v2* [22]	29.69/0.8703	DeblurGAN-v2* [22]	36.44/0.9347
DeblurGAN-v2 [22]	28.70/0.8662	Zhang *et al.* [49]	35.70/0.9481
SRN-DeblurNet [42]	28.56/0.8674	SRN-DeblurNet [42]	35.66/0.9472
Zhang *et al.* [49]	28.42/0.8596	Zhang *et al.* [48]	35.48/0.9466
DeblurGAN [21]	27.97/0.8343	DeblurGAN-v2 [22]	35.26/0.9440
Nah *et al.* [31]	27.87/0.8274	Xu *et al.* [46]	34.46/0.9368
Zhang *et al.* [48]	27.80/0.8472	Pan *et al.* [33]	34.01/0.9162
Pan *et al.* [33]	27.22/0.7901	DeblurGAN [21]	33.79/0.9034
Xu *et al.* [46]	27.14/0.8303	Hu *et al.* [18]	33.67/0.9158
Hu *et al.* [18]	26.41/0.8028	Nah *et al.* [31]	32.51/0.8406

Result

(a) Blurred image PSNR/SSIM | (b) Nah et al. [31] 24.61/0.7824 | (c) Zhang et al. [49] 24.90/0.8448 | (d) Zhang et al. [48] 24.76/0.8447 | (e) DeblurGAN [21] 24.33/0.8000

(f) DeblurGAN-v2 [22] 24.76/0.8381 | (g) DeblurGAN-v2* [22] 28.53/0.8707 | (h) SRN-DeblurNet [42] 24.79/0.8478 | (i) SRN-DeblurNet* [42] 31.12/0.9089 | (j) Ground truth

Result

(k) Blurred image PSNR/SSIM | (l) Nah et al. [31] 23.37/0.8136 | (m) Zhang et al. [49] 23.46/0.8354 | (n) Zhang et al. [48] 23.36/0.8155 | (o) DeblurGAN [21] 23.18/0.7997

(p) DeblurGAN-v2 [22] 23.47/0.8453 | (q) DeblurGAN-v2* [22] 26.68/0.8988 | (r) SRN-DeblurNet [42] 23.56/0.8507 | (s) SRN-DeblurNet* [42] 29.42/0.9321 | (t) Ground truth

Result

- Handle **dynamic scenes** with moving objects?
- collected a set of real blurred images with moving objects without ground truth sharp images, used a camera of a **different model** (Sony A7M2) and **different lenses** (SEL85F18, SEL1635Z)

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Conclusion

- Presented the **RealBlur** dataset, which is the **first large-scale real-world blur dataset** building an image acquisition.

- Developed a **postprocessing method** to produce high-quality ground truth images.

- Experiments showed that the dataset can **greatly improve the performance** of deep learning-based deblurring approaches on real-world blurred images by camera shakes and moving objects.