Realistic Blur Synthesis for Learning Image Deblurring

Jaesung Rim, Geonung Kim, Jungeon Kim, Junyong Lee,
Seungyong Lee, and Sunghyun Cho

POSTECH, Pohang, Korea

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Presenter: Hao Wang

Advisor: Prof. Chia-Wen Lin

Outline

- Introduction
- Framework
- Method
- Experiment
- Conclusion

Introduction

- First present RSBlur, that provides pairs of a **real blurred image** and a **sequence of sharp** images

- Then, using the dataset, we **analyze** the difference between the generation process of real and synthetic blurred images

- Present a **realistic blur synthesis** method based on the analysis

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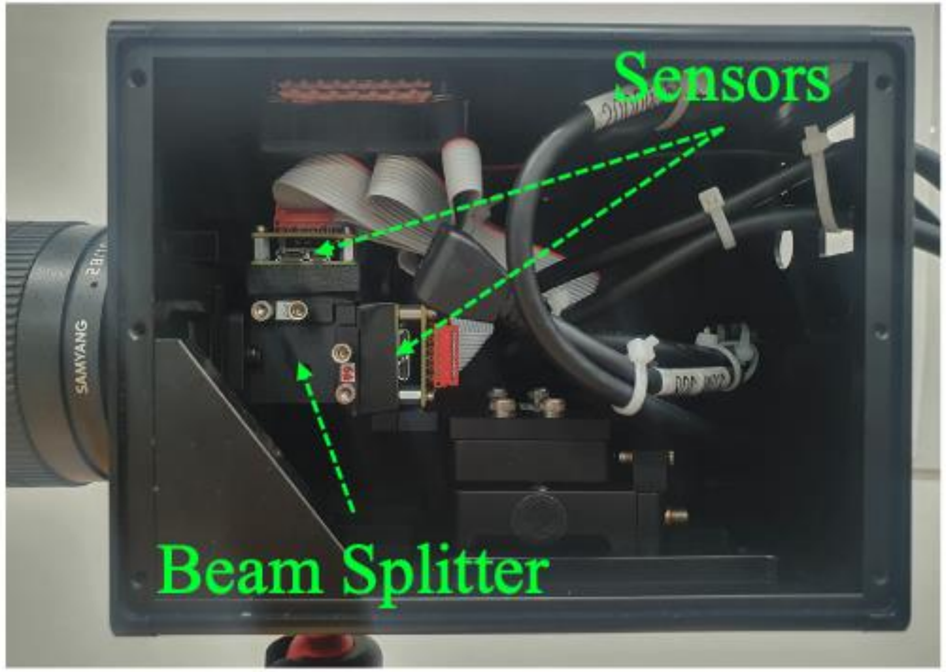
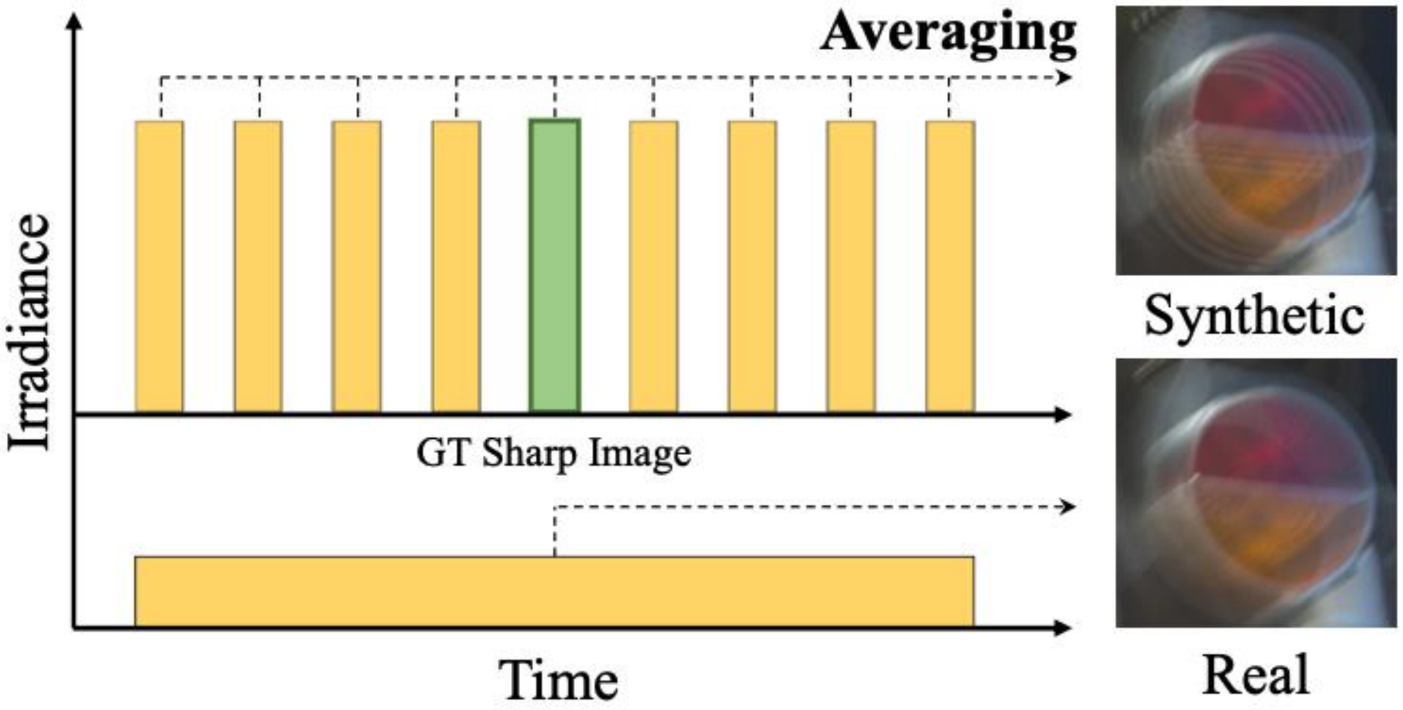
Framework

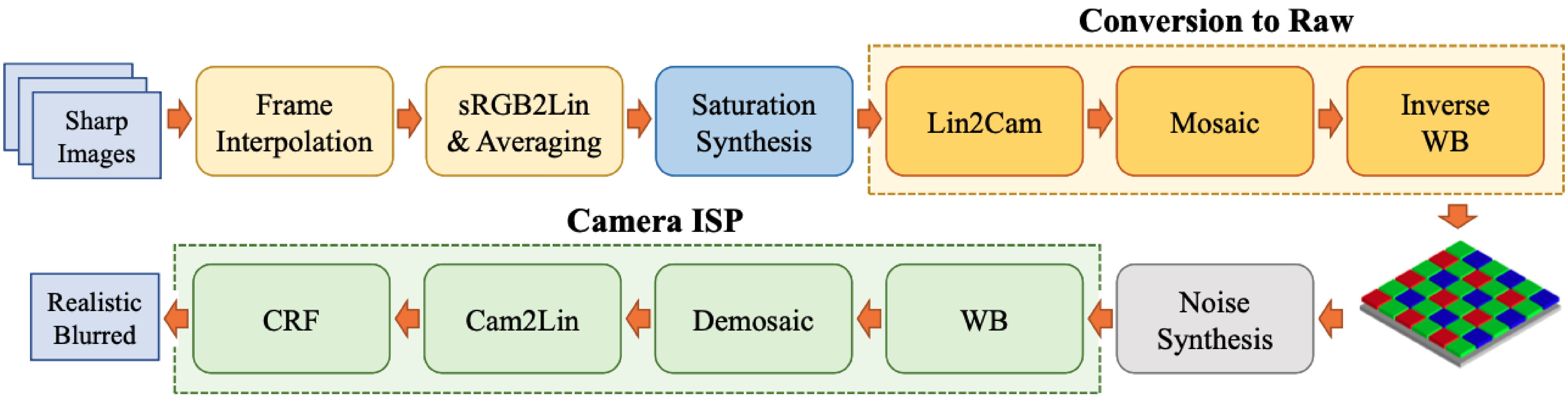


Sensors
Beam Splitter



Averaging
Irradiance
GT Sharp Image
Time
Synthetic
Real

Framework


Conversion to Raw
Sharp Images
Frame Interpolation
sRGB2Lin & Averaging
Saturation Synthesis
Lin2Cam
Mosaic
Inverse WB
Camera ISP
Realistic Blurred
CRF
Cam2Lin
Demosaic
WB
Noise Synthesis

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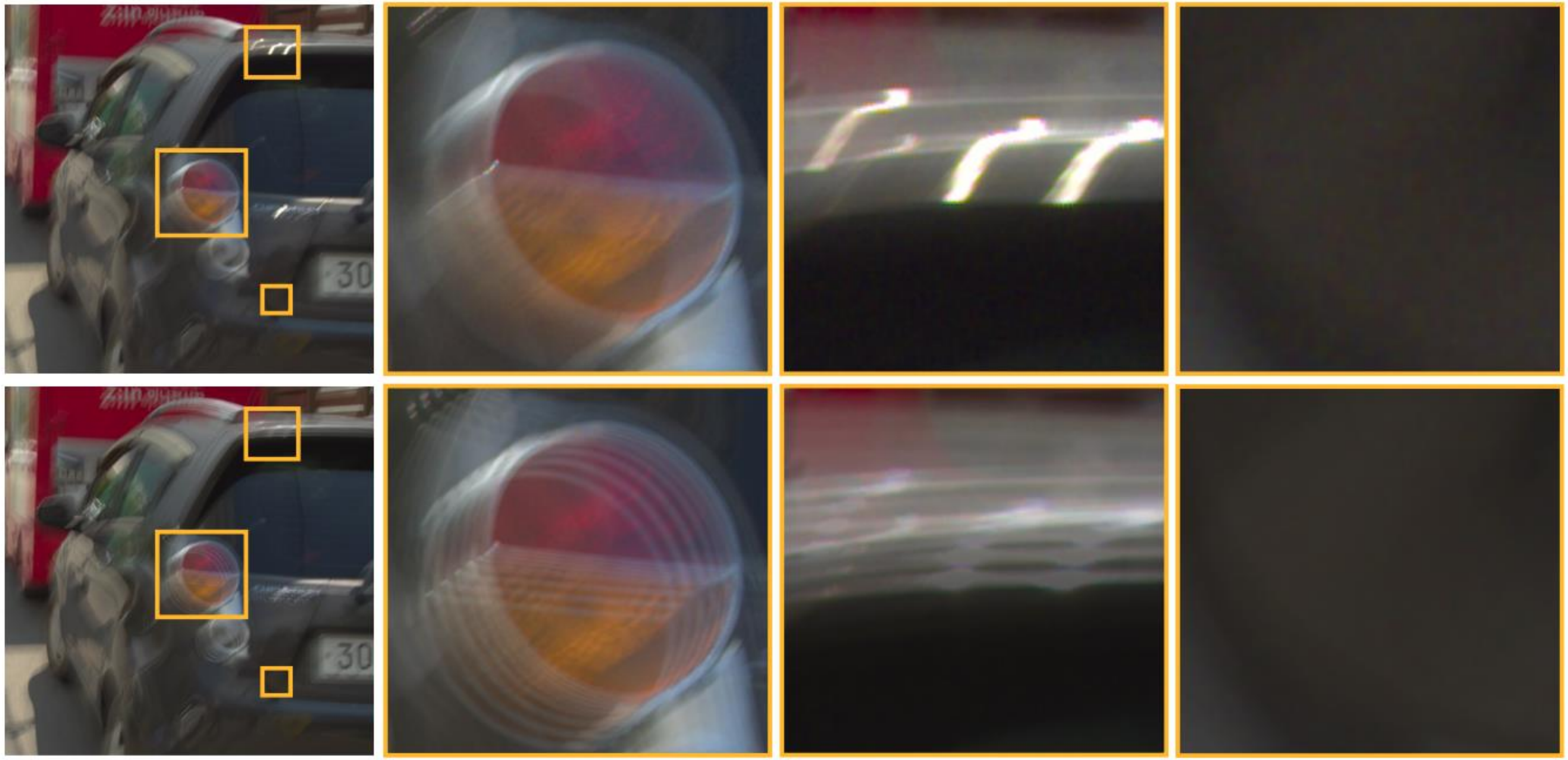
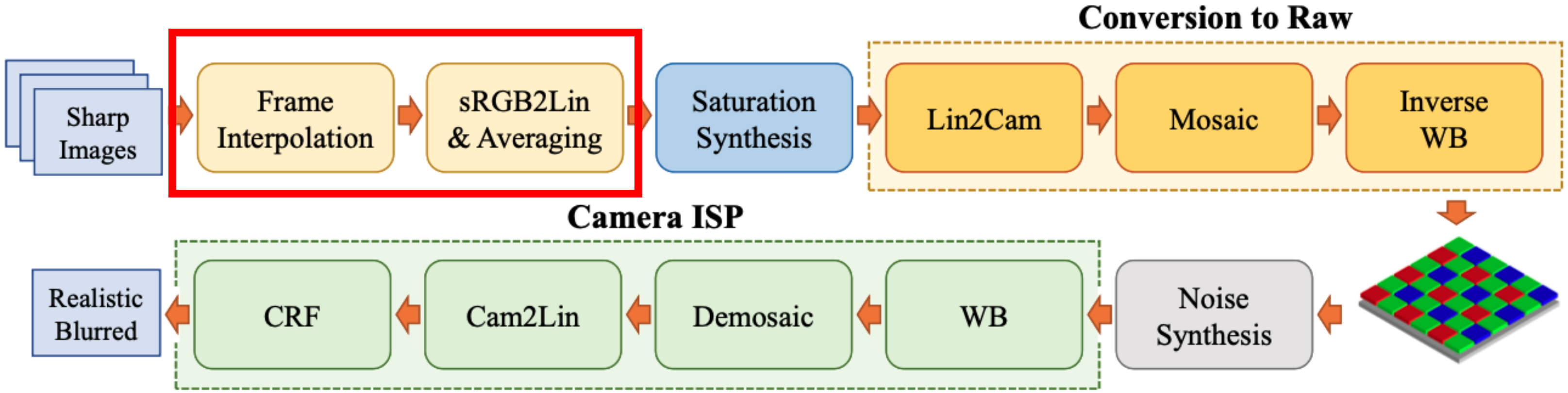
Analysis



(a) Blurred image (b) Discontinuity (c) Saturation (d) Noise

- **simply average** sharp images do not have such saturated pixels
- Even for high-end sensors, noise cannot be avoided due to the statistical **property of photons** and the **circuit readout process**.
- **ISPs** perform various operations, including white balancing, color correction, demosaicing, and nonlinear mapping using CRFs, which affect the noise distribution and introduce distortions



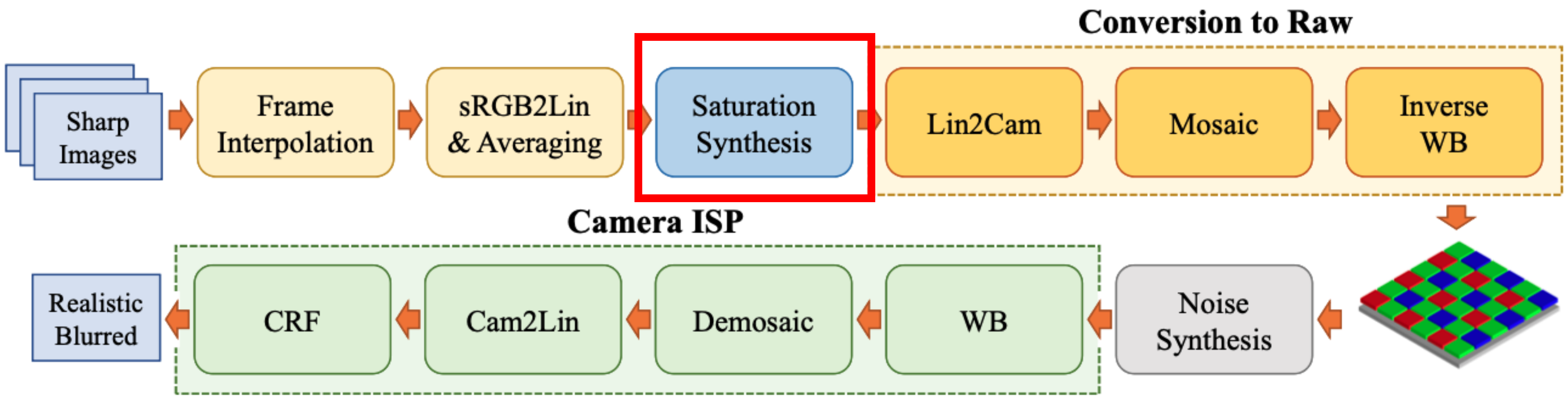
Frame Interpolation

- Increase nine sharp images to 65 images using ABME

sRGB2Lin & Averaging

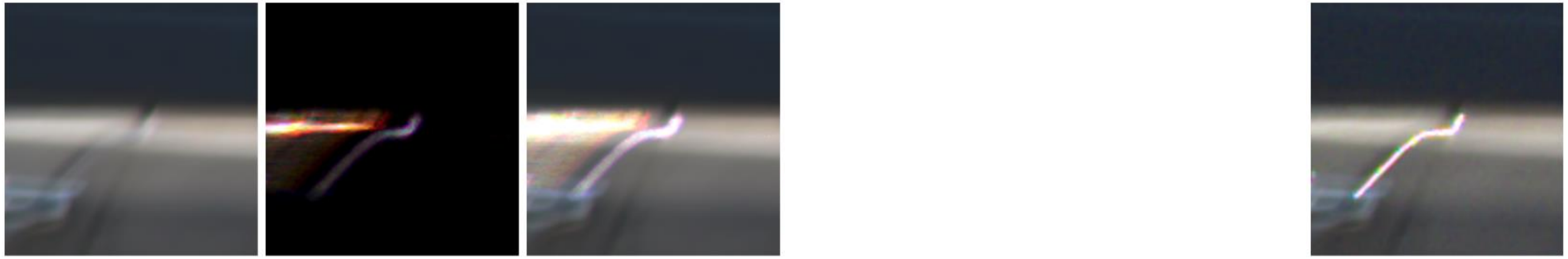
- Convert the images into the linear space, and **average them to precisely mimic the real blur generation process**.
- While the actual accumulation of incoming light happens in the camera RAW space, averaging in the **camera RAW space and in the linear space are equivalent** to each other as the two spaces can be converted using a linear transformation.

Saturation Synthesis



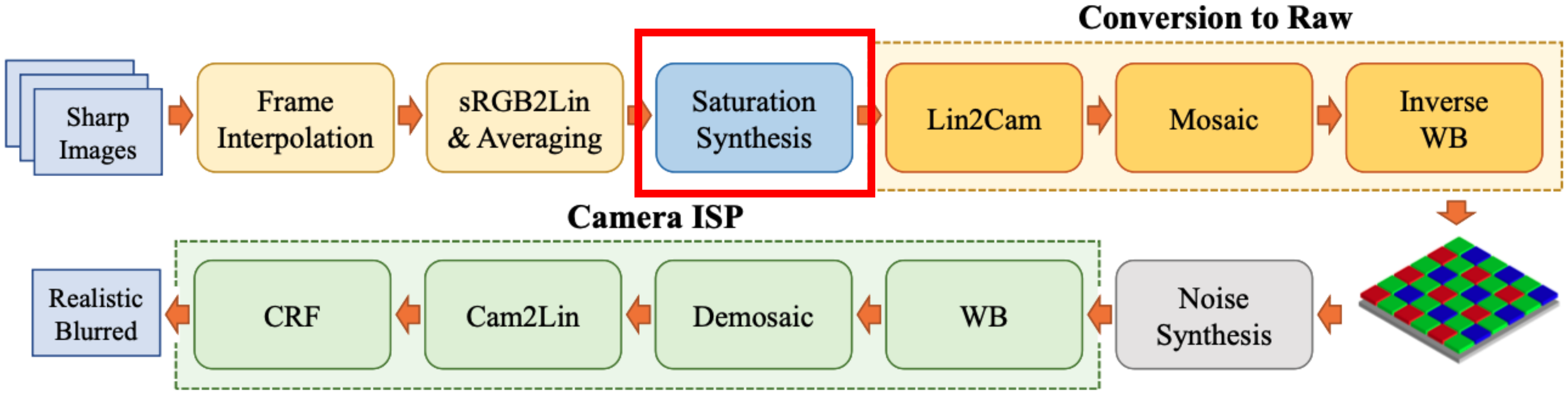
$$M_i(x,y,c) = \begin{cases} 1, & \text{if } S_i(x,y,c) = 1 \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

$$B_{sat} = \text{clip}(B_{syn} + \alpha M_{sat}) \tag{2}$$

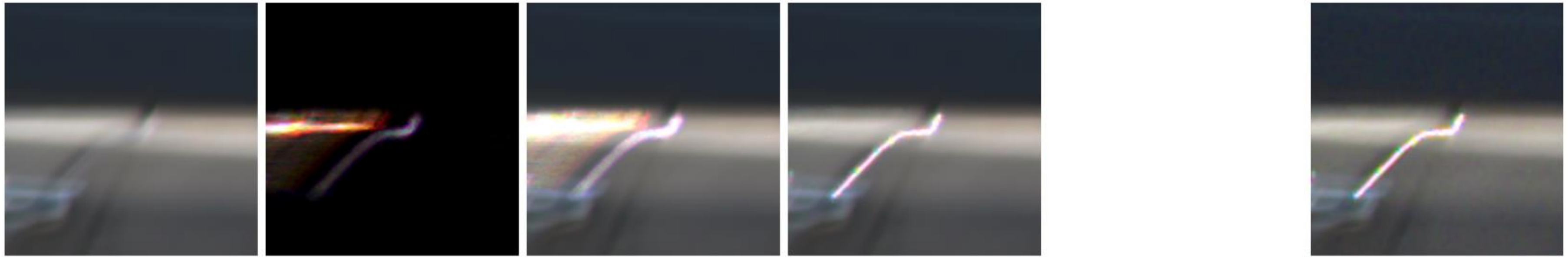


(a) Averaging (b) M_{sat} (×3) (c) B_{sat} (f) Real

Saturation Synthesis

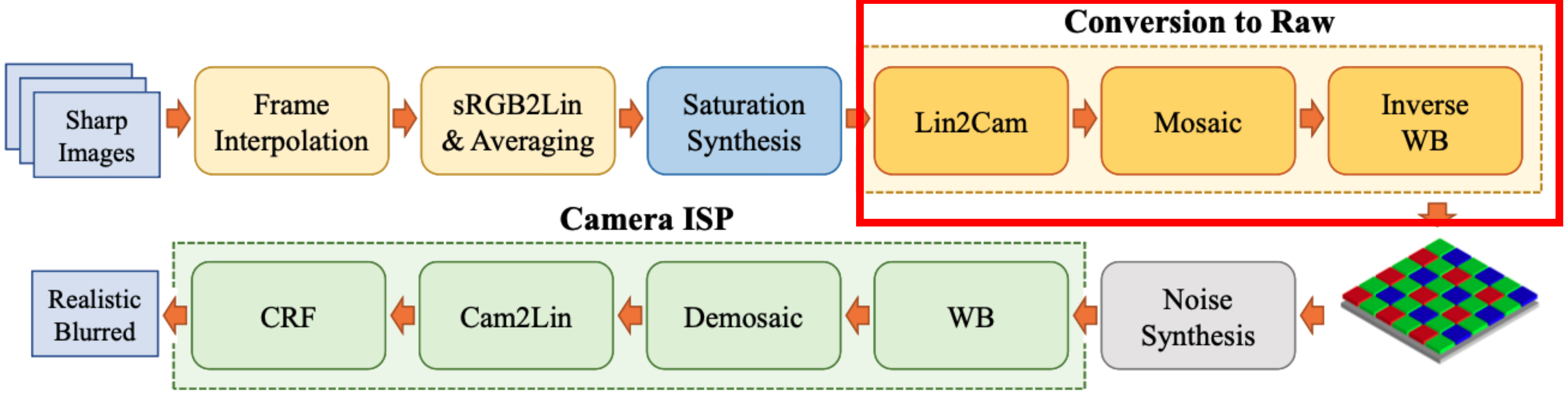


$$B_{oracle}(x,y,c) = \begin{cases} B_{real}(x,y,c), & \text{if } M_{sat}(x,y,c) > 0 \\ B_{syn}(x,y,c), & \text{otherwise.} \end{cases} \quad (3)$$



(a) Averaging (b) M_{sat} (×3) (c) B_{sat} (d) B_{oracle} (f) Real

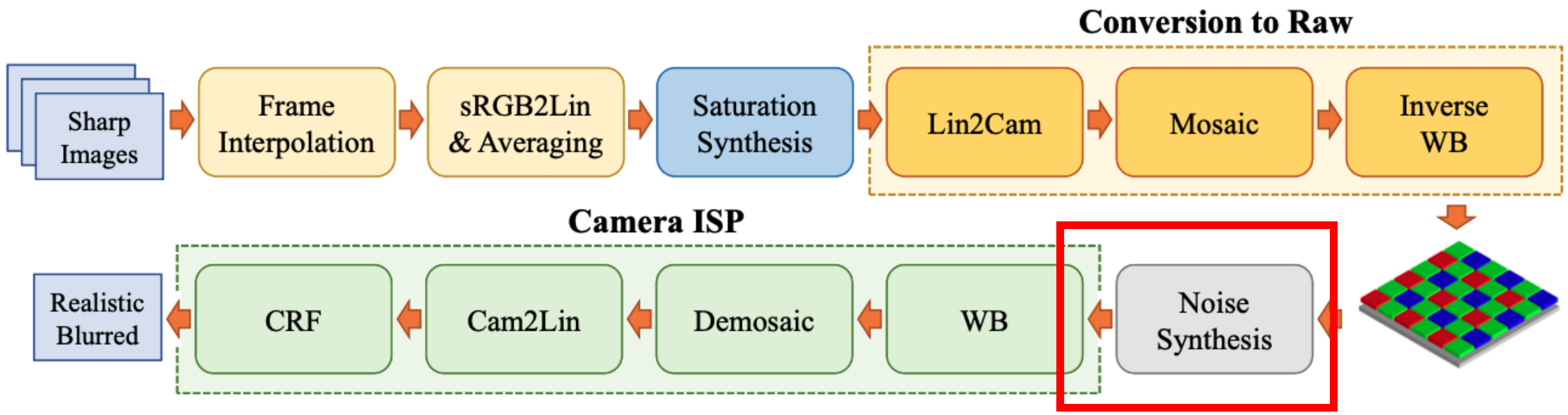
Conversion to RAW



- reflect the distortion introduced by the camera ISP

- Apply the inverse of each step of our ISP, including inverse color correction transformation, mosaicing, and inverse white balance except for the CRF step (non-linear) in the reverse order.

Noise Synthesis



$$B_{noisy} = \beta_1 \underline{(I + N_{shot})} + \underline{N_{read}}$$

- photon shot noise

$$\underline{(I + N_{shot})} \sim \mathcal{P}\left(\frac{B_{raw}}{\beta_1}\right)\beta_1,$$

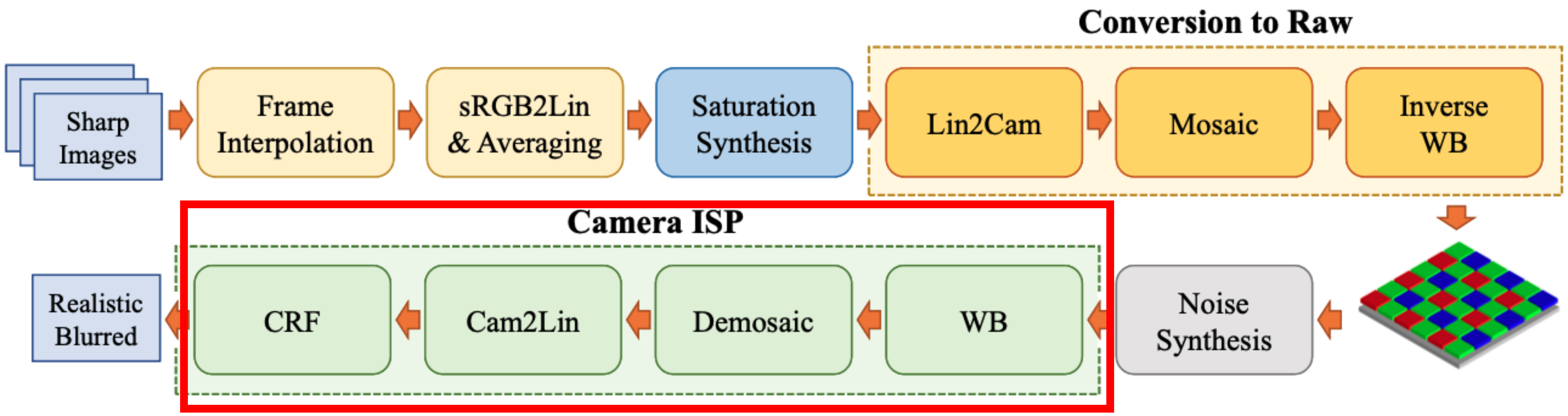
- circuit readout noise

$$\underline{N_{read}} \sim \mathcal{N}(0, \beta_2)$$

- For analysis

$$B_{noisy} = B + N_{gauss}$$

Applying Camera ISP



- apply the camera ISP to the noisy image to obtain a blurred image in the sRGB space
- consists of white balance, demosaicing, color correction, and CRF steps

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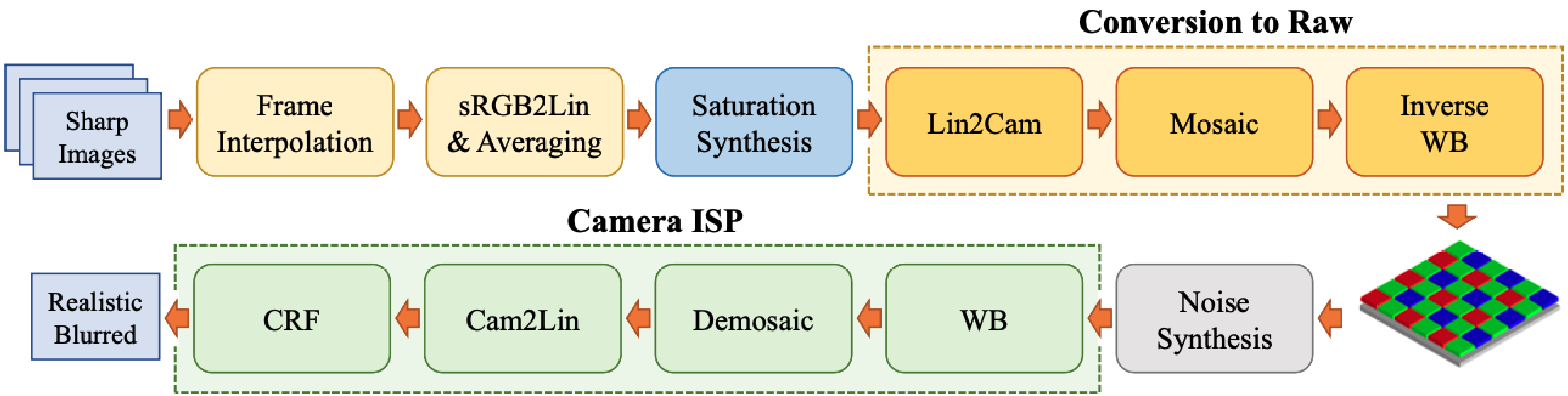

Blur Synthesis Methods							PSNR / SSIM		
No.	Real	CRF	Interp.	Sat.	Noise	ISP	All	Saturated	No Saturated
1	✓						32.53 / 0.8398	31.20 / 0.8313	33.78 / 0.8478
2		Linear					30.12 / 0.7727	28.67 / 0.7657	31.47 / 0.7793
3		sRGB					30.90 / 0.7805	29.60 / 0.7745	32.13 / 0.7861
4		sRGB			G		31.69 / 0.8258	30.18 / 0.8174	33.11 / 0.8336
5		sRGB	✓				30.20 / 0.7468	29.06 / 0.7423	31.27 / 0.7511
6		sRGB	✓		G		31.77 / 0.8275	30.28 / 0.8194	33.17 / 0.8352
7		sRGB	✓	Oracle	G		31.89 / 0.8267	30.58 / 0.8191	33.12 / 0.8338
8		sRGB	✓	Ours	G		31.83 / 0.8265	30.47 / 0.8187	33.12 / 0.8339
9		sRGB	✓	Oracle	G+P	✓	32.06 / 0.8315	30.79 / 0.8243	33.25 / 0.8384
10		sRGB	✓	Ours	G+P	✓	32.06 / 0.8322	30.74 / 0.8248	33.30 / 0.8391

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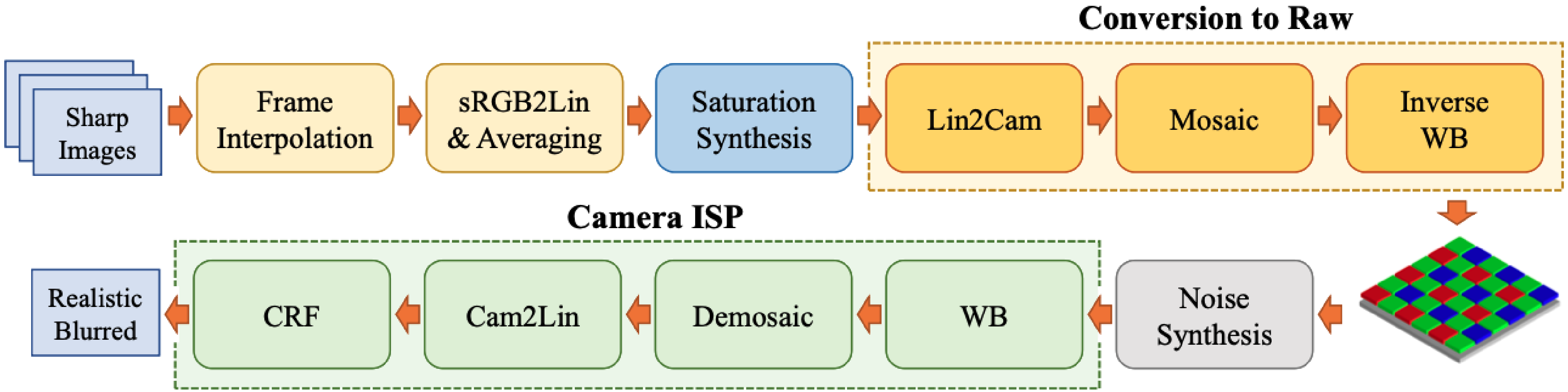
10		sRGB	✓	Ours	G+P	✓	32.06 / 0.8322	30.74 / 0.8248	33.30 / 0.8391

(a) Blurred image PSNR/SSIM (b) Method 1 29.81/0.8066 (c) Method 5 26.87/0.7129 (d) Method 6 27.45/0.7938 (e) Method 10 29.38/0.8027 (f) Ground truth



Blur Synthesis Methods							PSNR / SSIM	
No.	Training set	CRF	Interp.	Sat.	Noise	ISP	RealBlur_J	BSD_All
1	RealBlur_J						30.79 / 0.8985	29.67 / 0.8922
2	BSD_All						28.66 / 0.8589	33.35 / 0.9348
3	GoPro	Linear					28.79 / 0.8741	29.17 / 0.8824
4	GoPro	sRGB					28.93 / 0.8738	29.65 / 0.8862
5	GoPro	sRGB	✓				28.92 / 0.8711	30.09 / 0.8858
6	GoPro	sRGB	✓		G		29.17 / 0.8795	31.19 / 0.9147
7	GoPro	sRGB	✓	Ours	G		29.95 / 0.8865	31.41 / 0.9154
8	GoPro	sRGB, A7R3	✓	Ours	G+P	A7R3	30.32 / 0.8899	30.48 / 0.9060
9	GoPro_U	Linear					29.09 / 0.8810	29.22 / 0.8729
10	GoPro_U	sRGB					29.28 / 0.8766	29.72 / 0.8773
11	GoPro_U	sRGB			G		29.50 / 0.8865	30.22 / 0.8973
12	GoPro_U	sRGB		Ours	G		30.40 / 0.8970	30.31 / 0.8995
13	GoPro_U	sRGB, A7R3		Ours	G+P	A7R3	30.75 / 0.9019	29.72 / 0.8925

Results

(a) Blurred image PSNR/SSIM

(b) Method 1 28.27/0.8562 RealBlur_J

(c) Method 5 26.00/0.8218

(d) Method 6 26.69/0.8430

(e) Method 8 28.16/0.8562 Ours (GoPro)

(f) Ground truth

(g) Method 2 24.68/0.7471 BSD_All

(h) Method 10 26.27/0.8191

(i) Method 11 26.50/0.8534

(j) Method 13 28.67/0.8870 Ours (GoPro_U)

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Conclusion

- RSBlur dataset, the first dataset that provides **pairs of a real-blurred image** and a **sequence of sharp** images.

- **Analyzed several factors** that introduce the difference between them with the dataset and presented a novel blur synthesis pipeline.

- Using our pipeline, we showed that our blur synthesis pipeline could **greatly improve the deblurring performance on real-world blurred images**.