

Defocus Deblurring

Restoration of an all-in-focus image from a defocused image



Input DPDNet [1] Ours GT
Qualitative comparison on the proposed RealDOF test set

Motivation

Challenging to deal with **spatially varying and large blur**

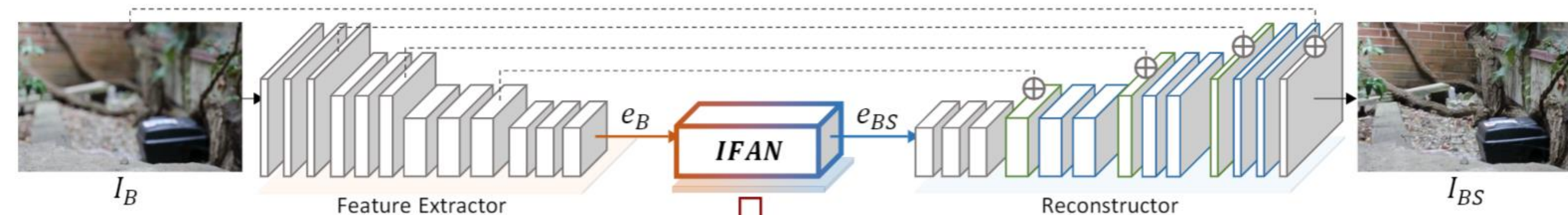
- **Conventional defocus map-based approaches [12, 14]**
→ Fails due to **restrictive blur model** (e.g. Gaussian) that constrains the blur shape
- **Recent end-to-end deep learning-based approach [1]**
→ Produces artifacts and remaining blur due to **naïve U-Net [26] architecture** that is not flexible for handling spatially varying and large defocus blur
→ Requires **dual-pixel images that are not easily obtainable** for ordinary camera users

So, we designed an end-to-end network that effectively handles **spatially varying and large blur** for **a single image** defocus deblurring

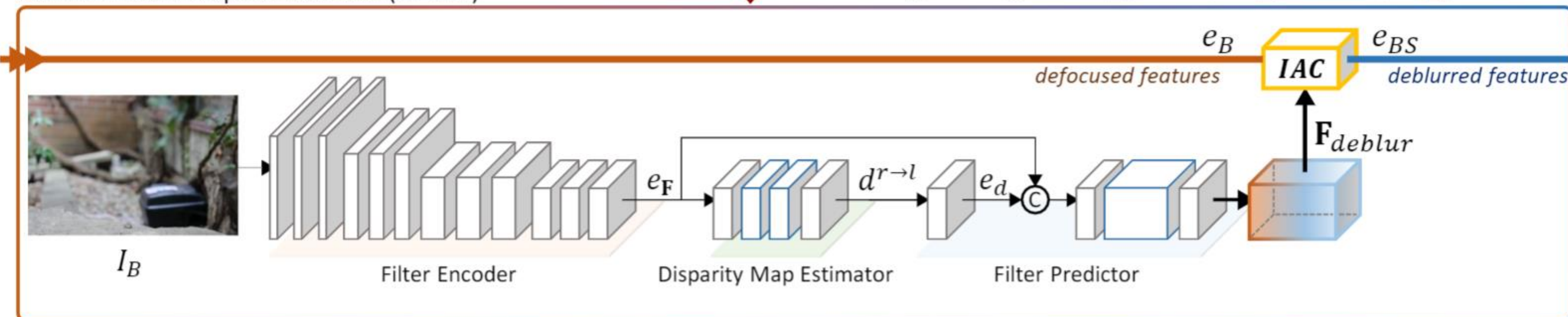
Contributions

- **Iterative Filter Adaptive Network (IFAN)**
→ For effectively handle spatially varying and large blur
- **Disparity map estimation & reblurring**
→ Maximum use of defocus blur cues in a single image
- **The RealDOF test set for quantitative evaluation**
- **State-of-the-art performance of defocus deblurring**

Proposed Deblurring Network with Iterative Filter Adaptive Network (IFAN)

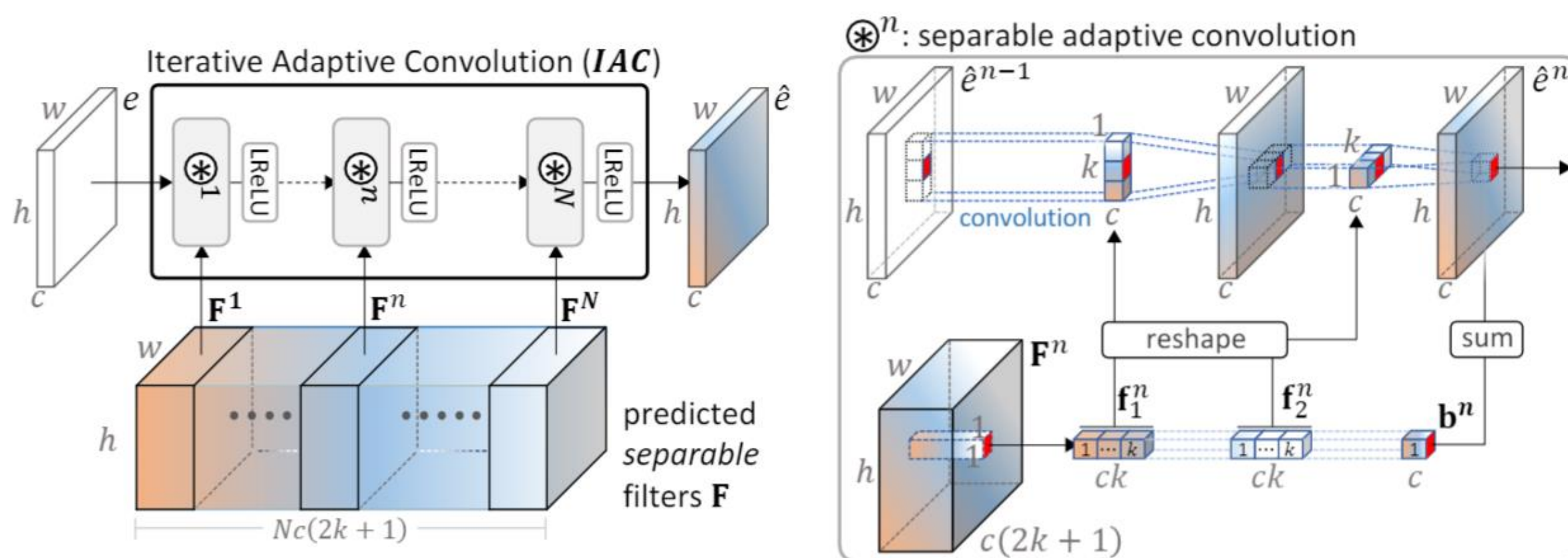


Iterative Filter Adaptive Network (IFAN) ⊕ Sum ⊙ Concat Conv Layer DeConv Layer Residual Block



- Predicts **per-pixel stacked separable filters F**, which is applied to defocused features by **IAC**
→ Per-pixel filters allows flexible handling of spatially varying blur

Iterative Adaptive Convolution (IAC) Layer



- Leveraging separable filters
→ Motivated by [34] that showed **1-dim filters** can approximate **a large inverse filter** for the deconvolution task
- Iterative applying of the separable filters
→ **Compensates possible error** may be caused by utilizing separable filters
→ Establishes a **large receptive field** for dealing with **large blur**

Training

- Trained with DPDD dataset [1]

- Objective functions

→ Deblurring

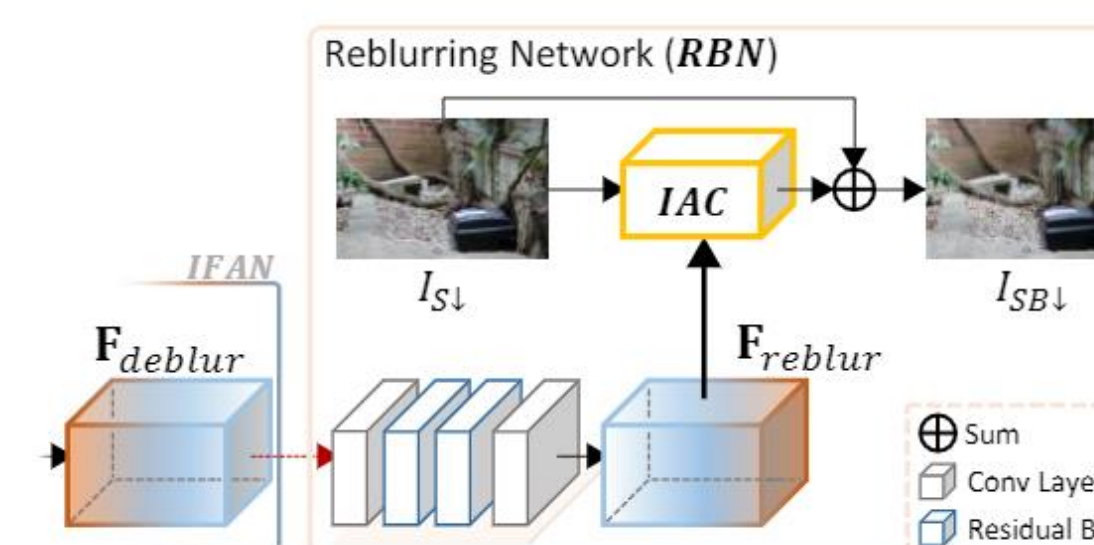
$$L_{deblur} = MSE(I_{BS}, I_S)$$

→ Disparity Map Estimation

$$L_{disp} = MSE(I_{B\downarrow}^{r\rightarrow l}, I_{B\downarrow}^l)$$

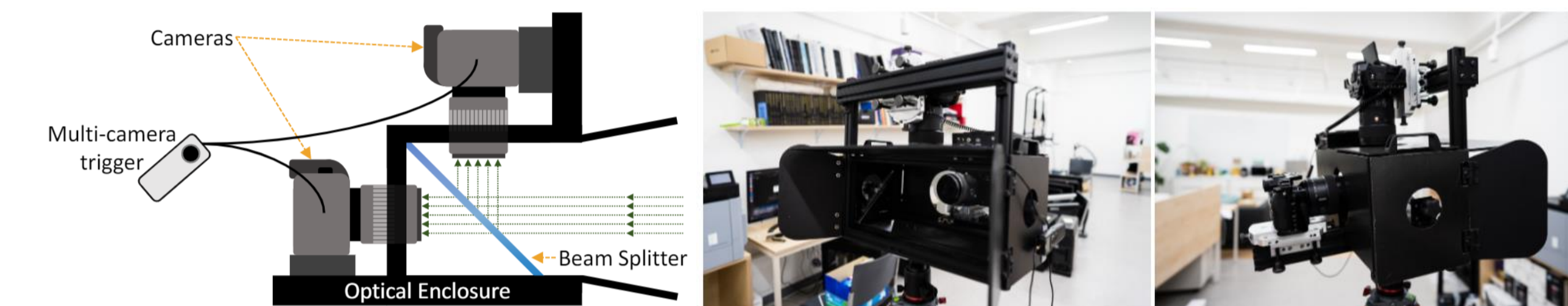
→ Reblurring

$$L_{reblur} = MSE(I_{SB\downarrow}, I_{B\downarrow})$$



Real Depth of Field (RealDOF) Test Set

- Pair images are concurrently captured with the dual-camera system



Our image acquisition system for the RealDOF test set

Experimental Results

1) Ablation Study

\mathcal{F} : filter predictor + IAC layer \mathcal{D} : disparity map estimator \mathcal{R} : reblurring network

IFAN	\mathcal{D}	\mathcal{R}	Evaluations on the DPDD Dataset [1]				Computational Costs	
			PSNR \uparrow	SSIM \uparrow	MAE($\times 10^{-1}$) \downarrow	LPIPS \downarrow	Params (M)	MACs (B)
			24.88	0.753	0.416	0.289		
	✓		24.97	0.761	0.412	0.280	10.58	364.3
✓			25.07	0.765	0.406	0.271		
✓	✓		25.18	0.780	0.403	0.233	10.48	362.9
✓		✓	25.28	0.780	0.400	0.245		
✓	✓	✓	25.37	0.789	0.394	0.217		

Quantitative results of an ablation study on the DPDD dataset [1]

2) Comparisons

Model	Evaluations the DPDD Dataset [1]				Computational Costs		
	PSNR \uparrow	SSIM \uparrow	MAE($\times 10^{-1}$) \downarrow	LPIPS \downarrow	Params (M)	MACs (B)	Time (Sec)
Input	23.89	0.725	0.471	0.349	-	-	-
JNB [28]	23.69	0.707	0.480	0.442	-	-	105.8
EBDB [12]	23.94	0.723	0.468	0.402	-	-	96.58
DMENet [14]	23.90	0.720	0.470	0.410	26.94	1172.5	77.70
DPDNet _S [1]	24.03	0.735	0.461	0.279	35.25	989.8	0.462
DPDNet _D [1]	25.23	0.787	0.401	0.224	35.25	991.4	0.474
Ours	25.37	0.789	0.394	0.217	10.48	362.9	0.014

Quantitative comparison on the DPDD dataset [1]



Input DPDNet_S Ours
Qualitative comparison on the CUHK dataset [27]

Model	PSNR \uparrow	SSIM \uparrow	MAE($\times 10^{-1}$) \downarrow	LPIPS \downarrow
Input	22.33	0.633	0.513	0.524
JNB [28]	22.36	0.635	0.511	0.601
EBDB [12]	22.38	0.638	0.509	0.594
DMENet [14]	22.41	0.639	0.508	0.597
DPDNet _S [1]	22.67	0.666	0.506	0.420
Ours	24.71	0.748	0.407	0.306

Quantitative comparison on the proposed RealDOF test set