Test-Time Fast Adaptation for Dynamic Scene Deblurring via Meta-Auxiliary Learning Supplementary document

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In this supplementary document, we provide cross validation on different training datasets and additional visual comparisons from the GoPro [1] and HIDE[2] datasets.

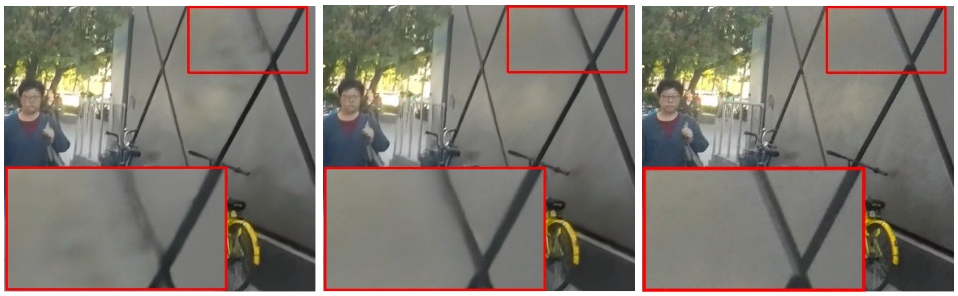
1 Cross validation on different training datasets

To show the impact of different training datasets, we cross validate our method by training on HIDE[2] dataset. Table. 1 shows the results of our method trained on HIDE and GoPro, respectively. As we can see, the final performance of the proposed method depends on both external and internal dataset. However, regardless of the performance of pre-training, the test-time adaptation consistently improves the performance among all testing datasets.

Method	Training data	GoPro		HIDE		Adobe240		REDS	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Pre-trained	HIDE	32.23	0.955	31.03	0.946	32.34	0.939	29.76	0.86
Ours		32.45	0.957	31.24	0.948	32.53	0.942	29.88	0.87
Pre-trained	GoPro	32.30	0.955	30.35	0.932	32.70	0.944	29.76	0.87
Ours		32.50	0.958	30.55	0.935	32.87	0.946	29.96	0.89

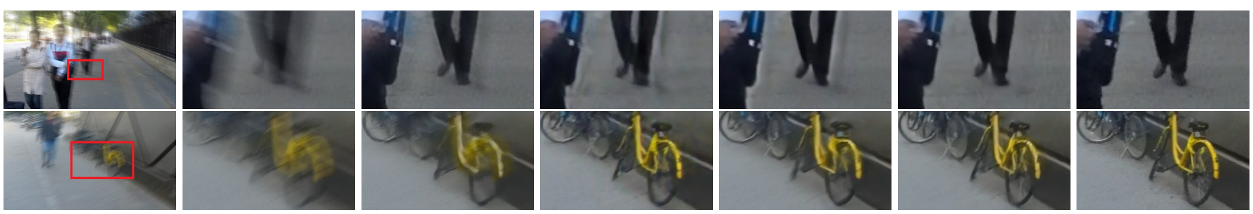
Table 1: Cross validation of our meta-auxiliary training method on different training datasets.

(a) Input blurry image (b) SelfDeblur [3] (2,500 updates)



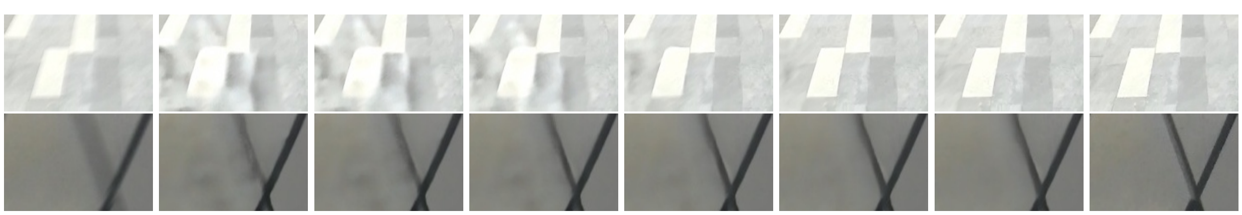
(c) Ours, no updates (d) Ours, *five* updates (e) GT

Figure 1: Sample deblurring results correspond to Fig.1 in the main paper. We add the ground truth for better comparison. It is evident that the results generated by SelfDeblur [3] contain severe artifacts. In contrast, the proposed method generates better results, especially when it is adapted to this particular case, as shown in (d).



Blurry image Blurry patch DeblurGAN-V2 SRN DMPHN Ours GT

Figure 3: Qualitative comparison with state-of-the-art approaches. Addition to Fig.5 in paper.



Input No update 1 update 2 updates 3 updates 4 updates 5 updates GT

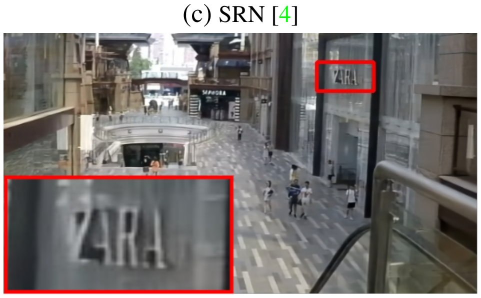
Figure 2: Visual illustration of the unfolded adaptation process for model with K=5 on the HIDE dataset [2]. Addition to Fig. 8 in paper.

(a) Input

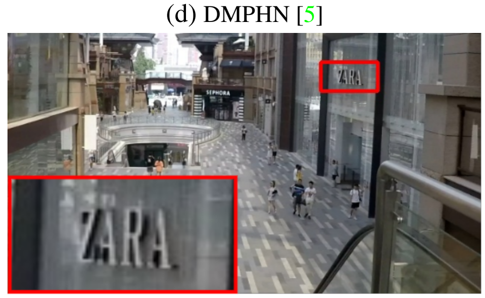
(b) DeblurGAN-V2 [6]

(c) SRN [4]

(d) DMPHN [5]



(e) Ours



(f) GT

Figure 4: Qualitative comparison on HIDE dataset [2].

(a) Input

(b) DeblurGAN-V2 [6]

(c) SRN [4]

(d) DMPHN [5]

(e) Ours

(f) GT

Figure 5: Qualitative comparison on HIDE dataset [2].

(a) Input (b) DeblurGAN-V2 [6]

(c) SRN [4] (d) DMPHN [5]

(e) Ours (f) GT

Figure 6: Qualitative comparison on HIDE dataset [2].

(a) Input

(b) DeblurGAN-V2 [6]

(c) SRN [4]

(d) DMPHN [5]

(e) Ours

(f) GT

Figure 7: Qualitative comparison on GoPro dataset [1].

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