Performing Defocus Deblurring by Modeling its Formation Process

Supplementary Material

1. Supplementary material

1.1. More experimental details

More details on the training. In the training datasets, we are provided with pairs of defocused images I_d and their ground truth deblurred images I_{gt}. We train our initializer in an end-to-end manner by minimizing the loss L (see Sec. 3.4 in the main paper) between the input images (both defocused and ground truth sharp images) and the rendered images from the predicted Gaussian representations. Our blob deblurrer is also trained end-to-end with the same loss L, computed between our predicted images I_p and the ground truth sharp images I_{gt}. When the variant of our method excludes the depth-based regularization loss, we set L_{reg} to zero during the training of the initializer, the blob deblurrer, and the optimization process. Furthermore, in this variant, the depth map is omitted as input to the initializer, and the depth information d_2 associated with the Gaussian blob representation is excluded. Similarly, the optimized image-level parameters (d_1, K) are not provided to the blob deblurrer.

More details on the testing. Besides, for the variant (w/o depth), we maintain consistency with the training setup by omitting the depth map as input to the initializer and excluding both the Gaussian blob's depth information and the image-level parameters from the blob deblurrer.

1.2. More visualization results

More visualizations of the predicted depth map. As can be seen in Fig. 1, we provide additional visualizations of depth maps corresponding to defocused images from the DPDD and CUHK datasets. These depth maps are estimated using DPT [1], and it can be observed that the quality of the estimated depth maps is high.

1.3. More ablation study

Ablation study on adjusting covariance matrix and opacity. We conduct ablation experiments on the adjustment of covariance matrix ($\theta_i, s_{1,i}, s_{2,i}$) and opacity ($o_i$) in our blob deblurrer, as shown in Tab. 1. The results demonstrate that variants "Ours w/o opacity adjustment" and "Ours w/o covariance matrix adjustment" of our method lead to performance degradation compared to our full method ("Ours w/o depth"). It is worth noting that when our method does not adjust the covariance parameters or opacity, introducing the depth-based regularization loss is meaningless. Therefore, in the ablation experiments in Tab. 1, we do not incorporate the depth-based regularization loss for any of the variants.

Table 1. Quantitative comparison on DPDD dataset.

Method	DPDD		
	PSNR ↑	SSIM ↑	LPIPS ↓
Ours w/o covariance matrix adjustment	14.257	0.378	0.612
Ours w/o opacity adjustment	24.112	0.751	0.297
Ours w/o depth	26.431	0.827	0.171

References

[1] René Ranftl, Alexey Bochkovskiy, and Vladlen Koltun. Vision transformers for dense prediction. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 12179–12188, 2021. 1, 2

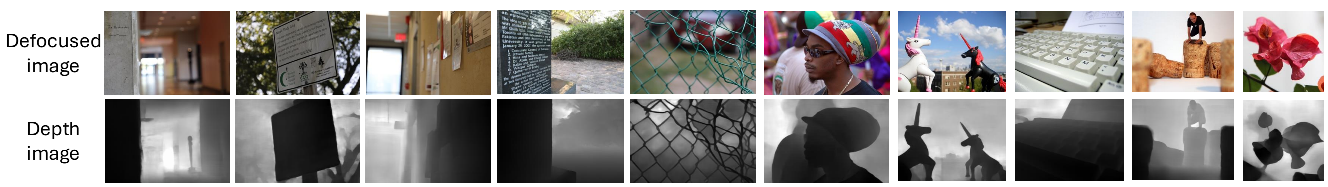

Figure 1. Additional defocused images from the DPDD and CUHK datasets, along with their corresponding depth maps estimated using the pretrained depth estimation model, DPT [1].