Supplemental Materials: Toward Fast, Flexible, and Robust Low-Light Image Enhancement

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In this document, we supply some details and experiments of our proposed SCI. We first provide an elaborated exploration for the architecture $\mathcal{K}_\vartheta$. And then, we make the analysis of the weighting parameters in the loss function. Besides, more visual results for different tasks are also provided to further indicate our superiority.

1. Exploring Architecture of Self-Calibrated Module

Fig. 1 showed the visual results of different settings for self-calibrated module $\mathcal{K}_\vartheta$. We can easily see that our method always generated stable outputs no matter how the number of convolutions. Thus we can actually use the lightweight enough architecture to instantiate it. More importantly, the self-calibrated module is just adopted in the training phase. This is to say, the architecture for $\mathcal{K}_\vartheta$ will be not appeared during the inference.

2. Analyzing Parameters in Loss

Here we considered some cases of different settings for weighting parameters in the loss function. As demonstrated in Fig. 2, we can observe that the exposure level became higher along with the increase of α. But when $\alpha = 2$, the color appears the deviation that tends to present white. When increasing the β, the exposure level became low. By comparison, we set $\alpha = 1, \beta = 1$ as our default setting in our all experiments.

3. More Visual Results

3.1. Low-Light Image Enhancement

As shown in Fig. 3-4, we demonstrated visual results of different learning-based methods including DRBN [9], KinD [12], EnGAN [4], SSIENet [11], ZeroDCE [2], and RUAS [5]. We can easily see that our method consistently performed superiority over other state-of-the-art methods in different scenes.

3.2. Dark Face Detection

Fig 5 showed the visual comparison among different methods on the DARK FACE dataset [10]. We can easily see that our method can detect more targets, but other methods cannot do it.

3.3. Nighttime Semantic Segmentation

In Fig. 6, we provided more visual comparison of nighttime semantic segmentation among different methods. Obviously, it can be observed that the results of our methods can accurately segment more areas than others.

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Figure 1. Visual results of different settings for $\mathcal{K}_\vartheta$.

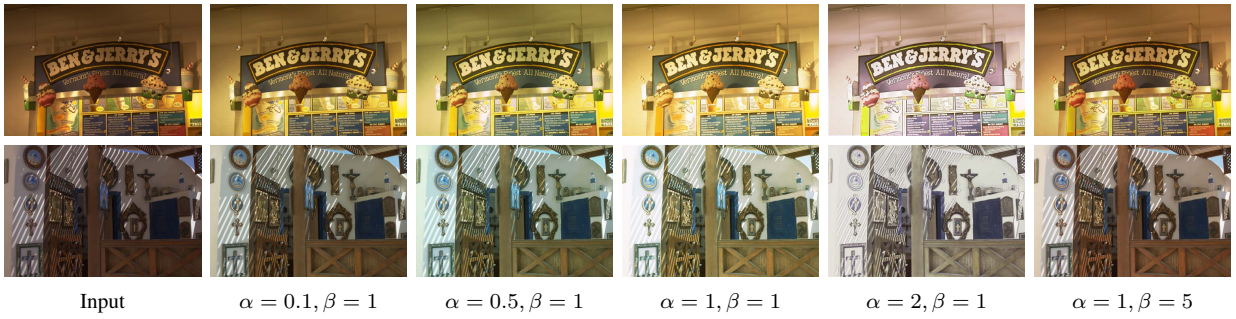

Figure 2. Visual results of different settings for weighting parameters in loss functions.

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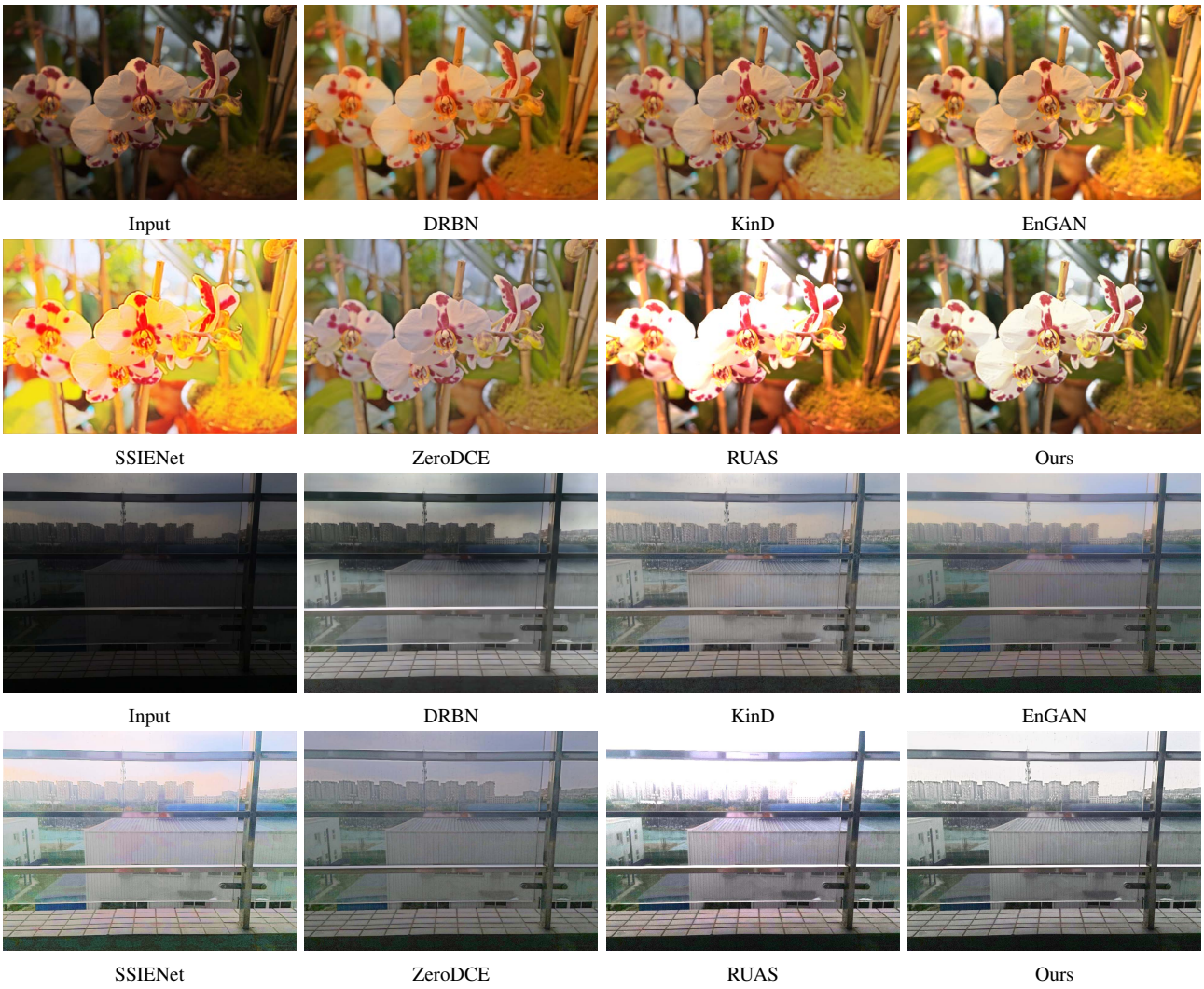

Figure 3. Visual results of state-of-the-art methods and our method on benchmarks. Top and bottom rows are results on the MIT-Adobe 5K [1] and LSRW [3] datasets, respectively.

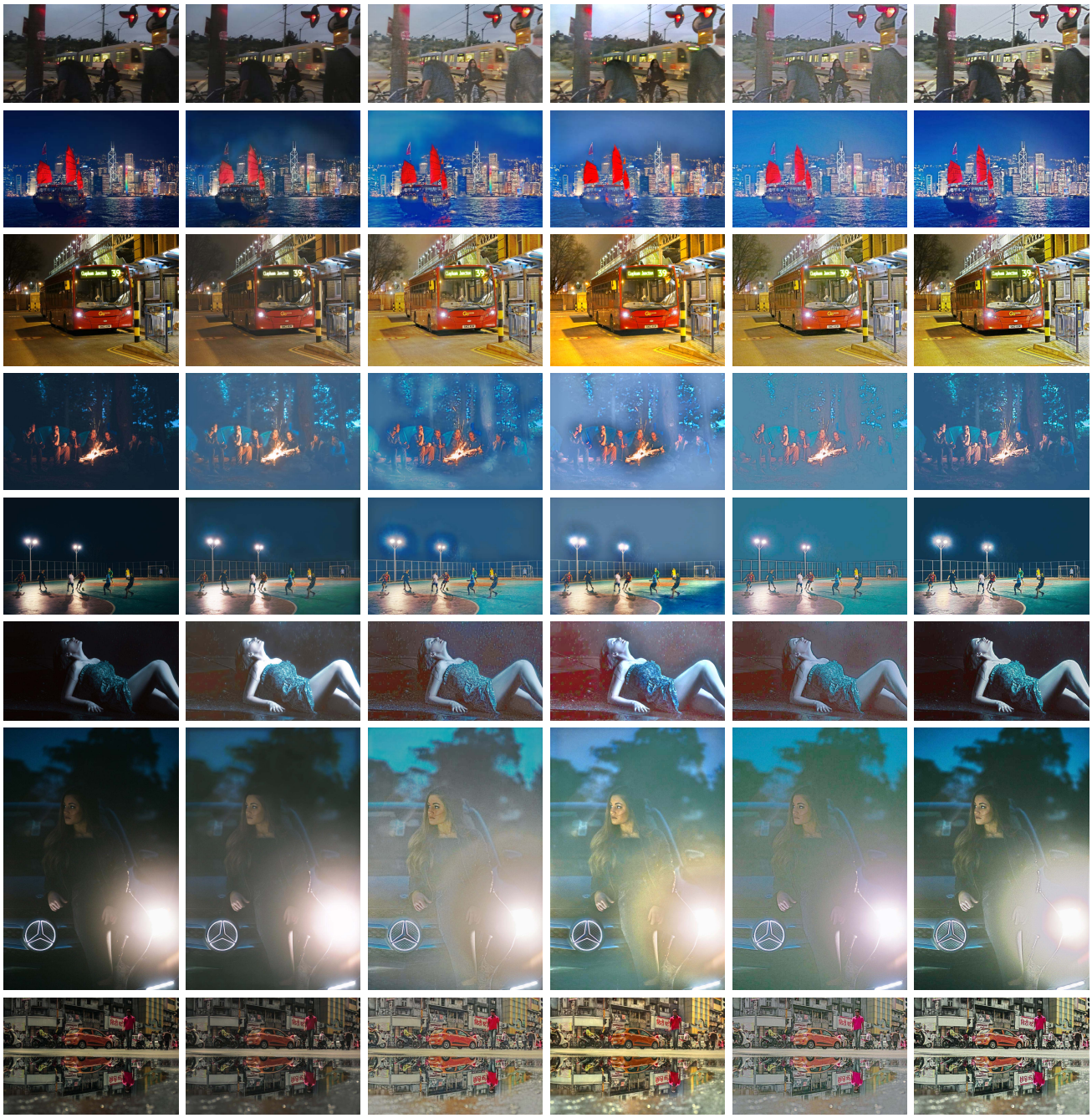

Figure 4. Visual results of state-of-the-art methods and our method on real-world scenarios. Top three and bottom five rows are results on the ExDark [6] and UFDD [7] datasets, respectively.

Figure 5. Visual results of dark face detection on the DARK FACE dataset [10]. Red box indicates the obvious differences.

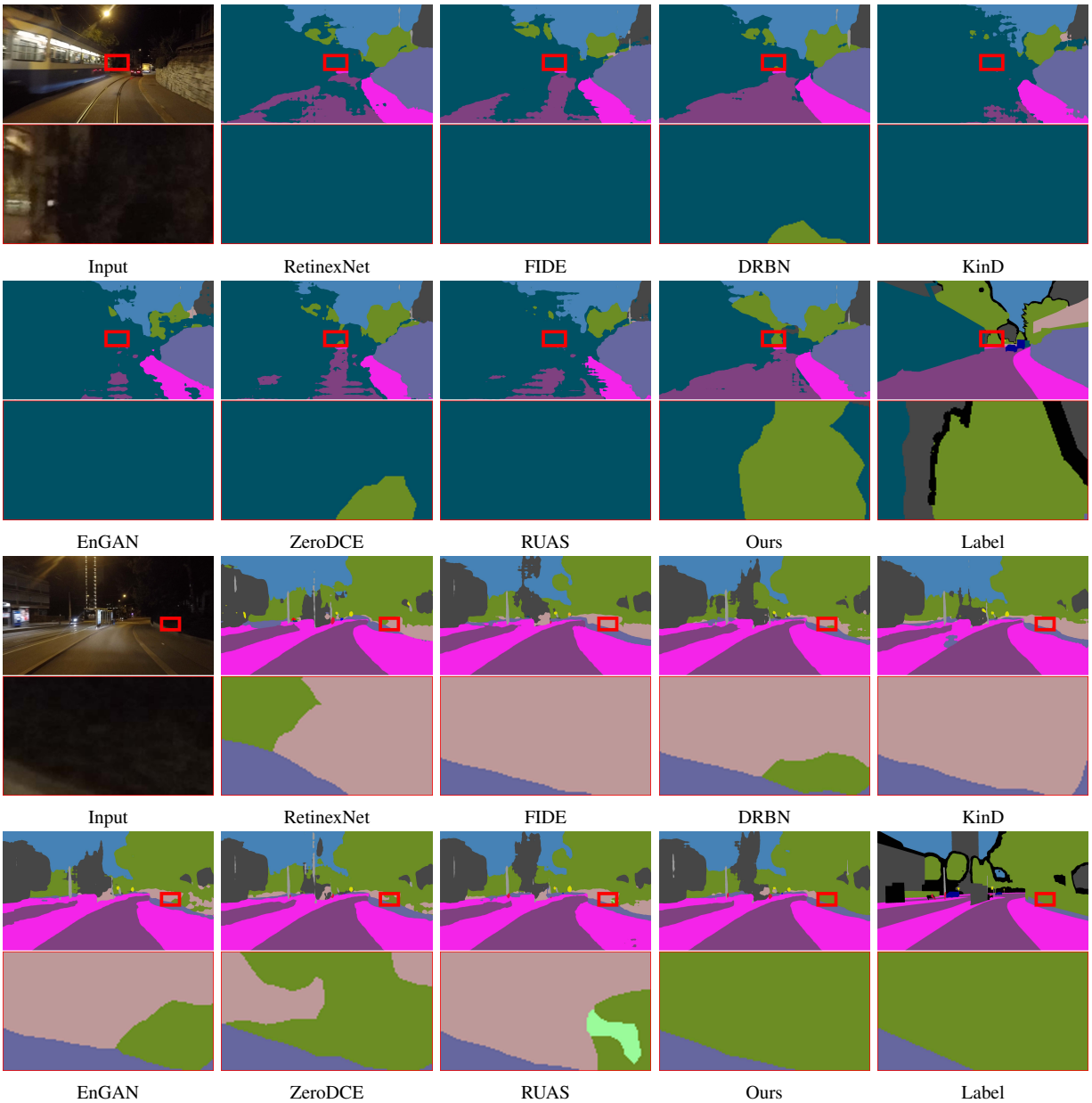

Figure 6. Visual results of semantic segmentation on the ACDC dataset [8]. Red box indicates the obvious differences.