Neural Color Operators for Sequential Image Retouching

Supplementary Material

Yili Wang[1], Xin Li[2], Kun Xu[1], Dongliang He[2], Qi Zhang[2], Fu Li[2], and Errui Ding[2]

[1] BNRist, Department of CS&T, Tsinghua University
[2] Department of Computer Vision Technology (VIS), Baidu Inc.

A Visual Comparison

In this section, we provide more visual comparison with state-of-the-art methods on five dataset variants. Figures 1 and 2 show the retouching results of MIT-Adobe-5K-lite dataset. For each pair, we show the input and ground truth (GT) image alongside the retouched images under which suggest the corresponding approaches being applied. We can observe that the input of MIT-Adobe-5K-Lite tends to have dim tones and low contrast, while all approaches have successfully increase the contrast, our results are more consistent with the GT and greatly surpass other methods in terms of color tone correction, which is clearly shown in Figure 1 fifth row and Figure 2 first row. Moreover, our results appear more vibrant in saturation (see last two rows of Figure 2).

Figures 3, 4, 5, and 6 show the visual comparison on MIT-Adobe-5K-Dark. The input of MIT-Adobe-5K-Dark is rather challenging since it has very low pixel intensity, which makes finding appropriate color transform extremely difficult. However, all methods have done a great job in 'shedding the light' on these challenging examples. Nevertheless, we can observe similar retouching patterns for some specific methods. For example, while Pix2Pix [20] performs comparable with NeurOp in correcting the tones, it sometimes creates artifacts which are apparently undesirable (see Figure 3-2, Figure 5-3); Distort-and-Recover [38] tends to have less colorful results compared with other approaches; White-Box [16], DUPE [42], MIRNet [48] perform poorly when image need white balance adjustment (see Figure 3-3, Figure 4-1). Generally, NeurOp, CSRNet [14,33], 3D-LUT [49] and HDRNet [11] perform better in most cases compared to the above methods. However, 3D-LUT [49] sometimes generates color banding artifacts due to the use of color space interpolation (see Figure 5-3); noticeable color shifts sometimes appear in the results generated by HDRNet [11] (greenish in Figure 5-4, Figure 6-1) and CSRNet [14,33] (purplish in Figure 3-2, Figure 4-1).

Figures 7, 8, and 9 show the visual comparison results on PPR10K-a, PPR10K-b, and PPR10K-c, respectively. The input of all these three variants are the same, and the results exhibit specific style and preference of a particular artist. Therefore, we believe that the consistency of tonal style and similarity compared with GT are crucial for evaluating the retouching results. We can see that NeurOp and NeurOp+HRP are more consistent and visually more similar to GT for all variants of PPR10K.

B Strength Control

In this section, we present more results of our proposed strength control for each neurOp, we also provide a baseline for comparison which was originally mentioned by CSRNet [14,33], *i.e.*, they achieve a certain amount of controllability by performing linear interpolation of the retouched image and the input image. As we can see in Figures 10, 11, and 12, the first three rows are the results generated by adjusting the predicted scalar value of an individual neurOp. The fourth row shows the generated results by performing a simple interpolation formula $(1-\alpha)\cdot I+\alpha\cdot I^R$. It's clear to see that our strength control could generate more diverse and realistic results compared to the vanilla linear interpolation.

C Intermediate Image and Feature Map Visualization

In this section, we show two examples of intermediate images with high dimensional feature maps generated by each neurOp. We are interested to find that the intermediate images do not follow the *monotonous* pattern, *i.e.*, rather than gradually looking better, the neurOp learns nontrivial composite color mappings which we suspect can better model the complex transform.

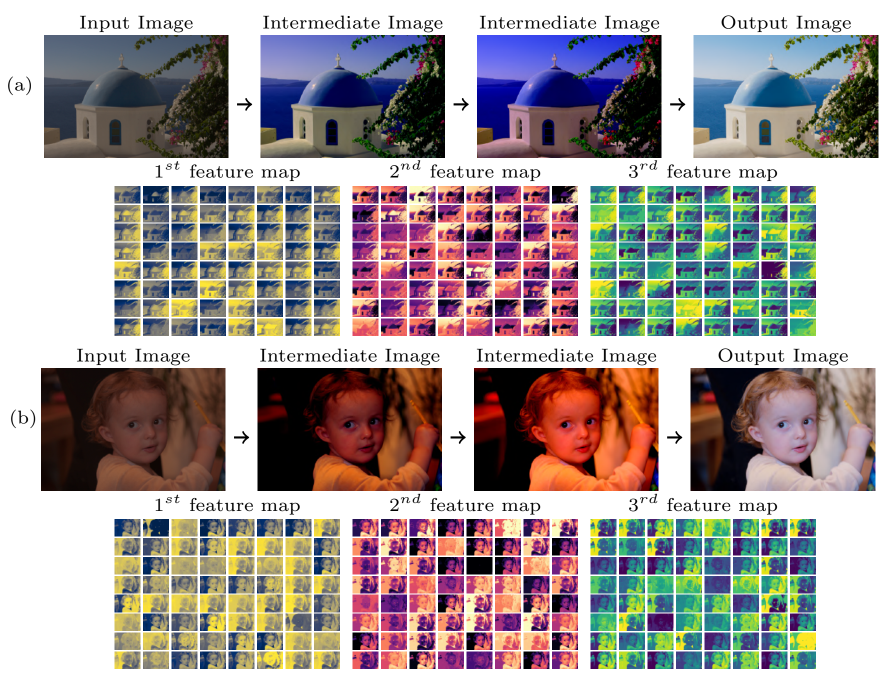


Fig. 1: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Lite.

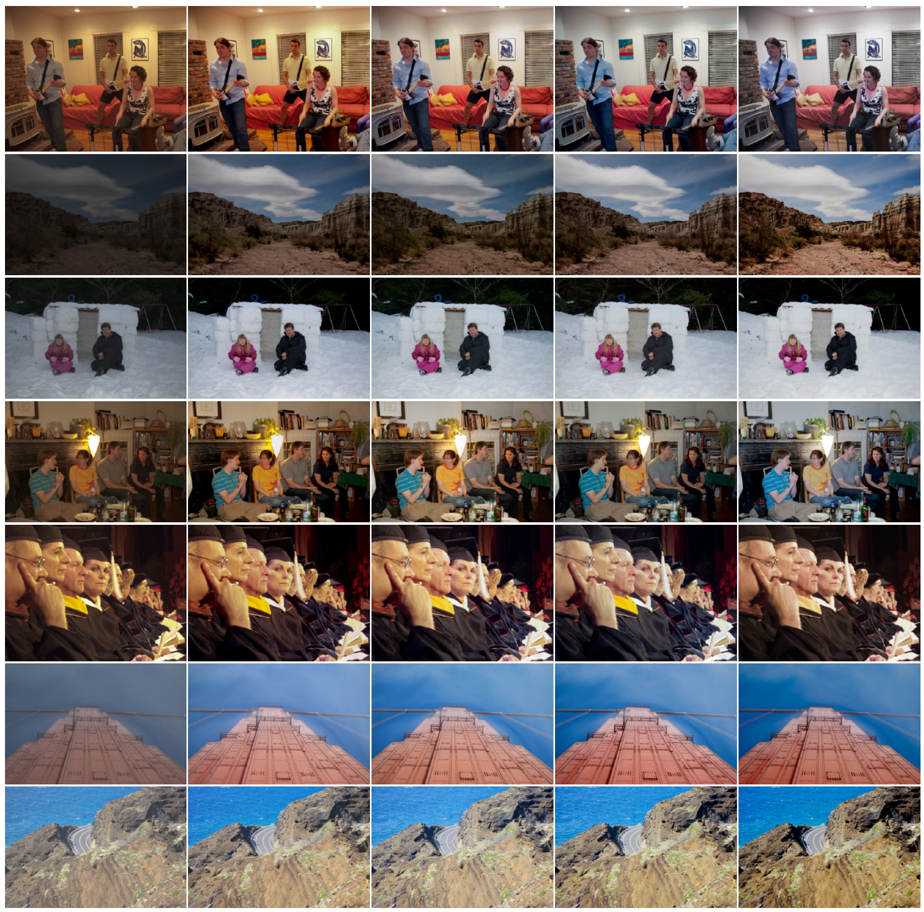


Fig. 2: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Lite.

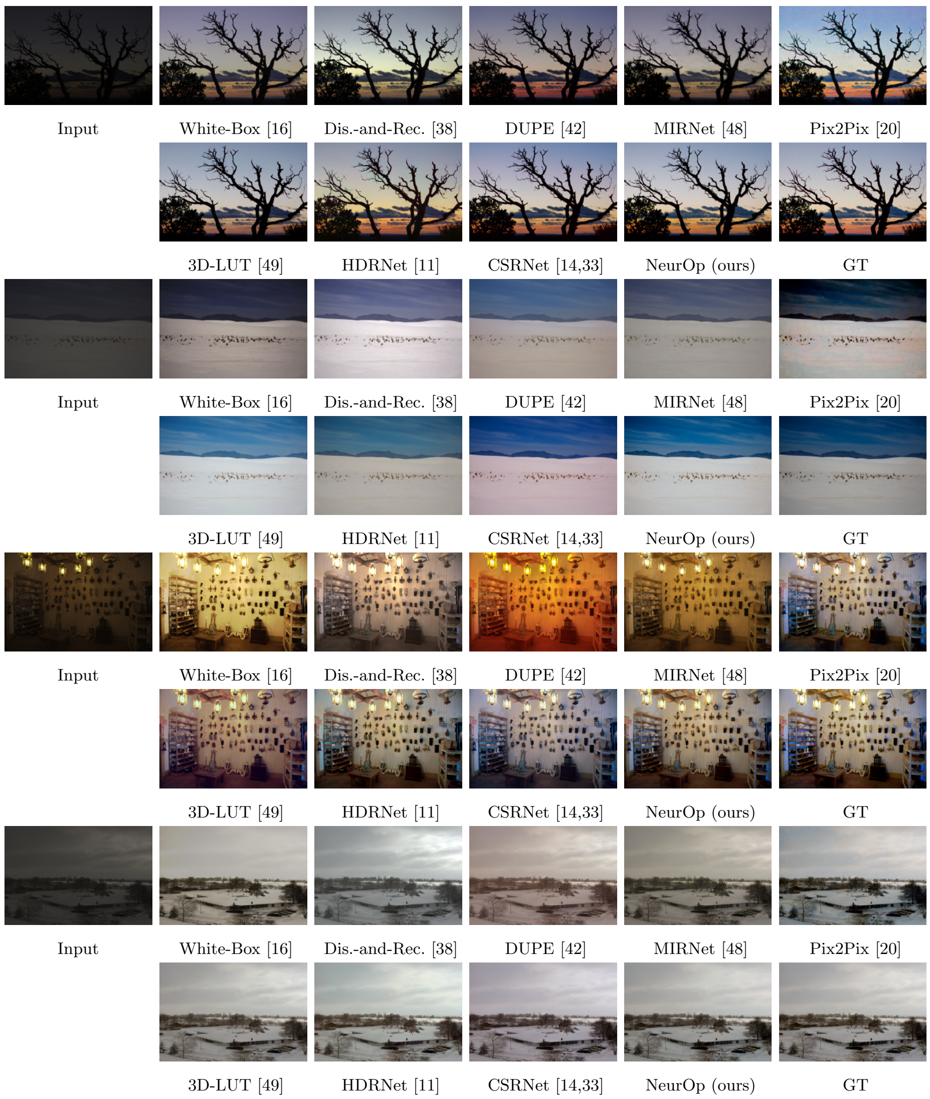


Fig. 3: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Dark.

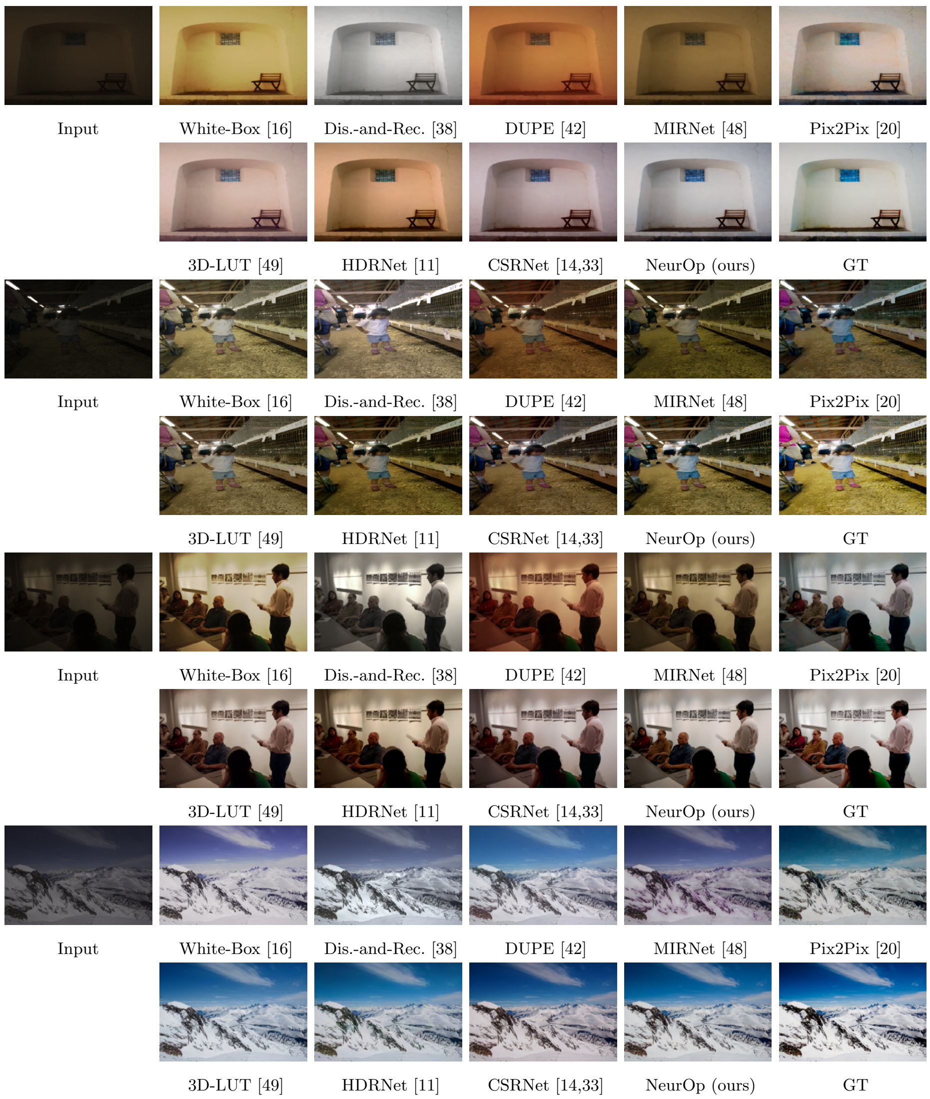


Fig. 4: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Dark.

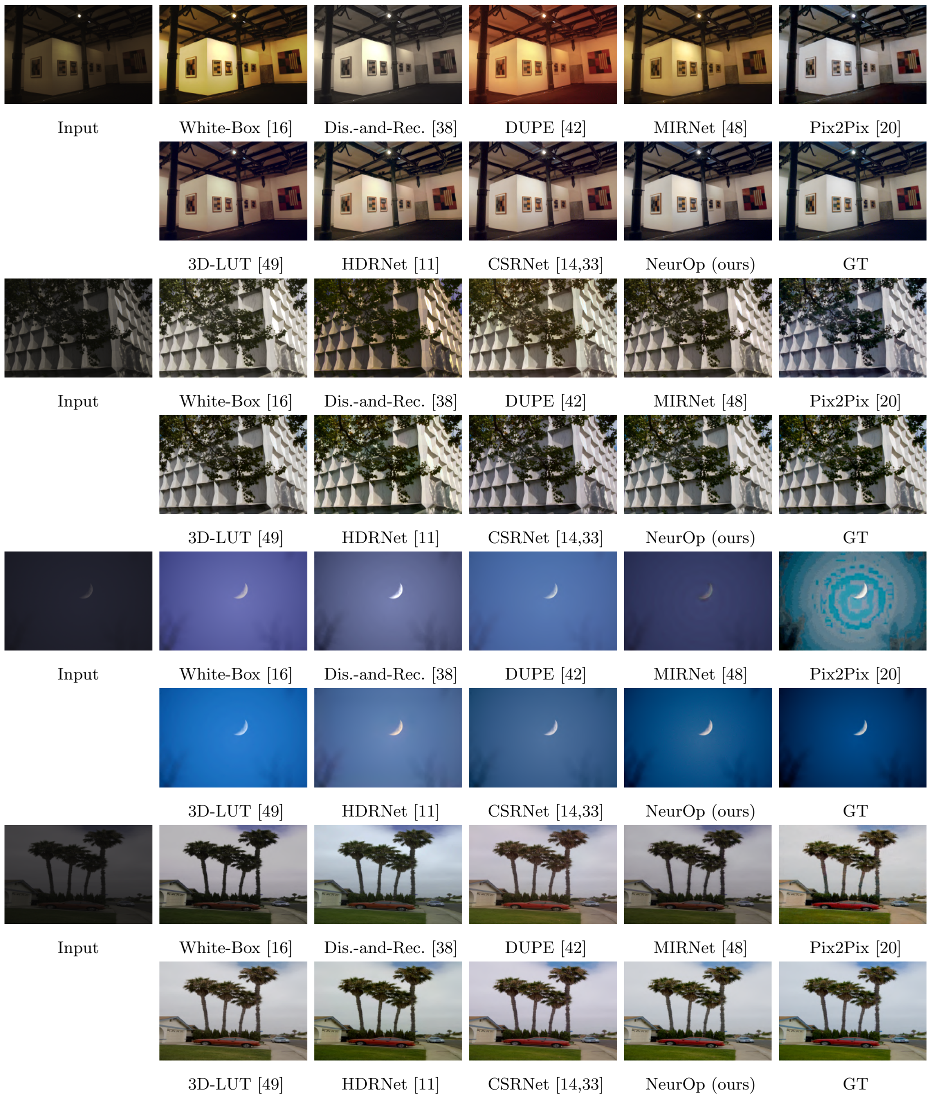


Fig. 5: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Dark.

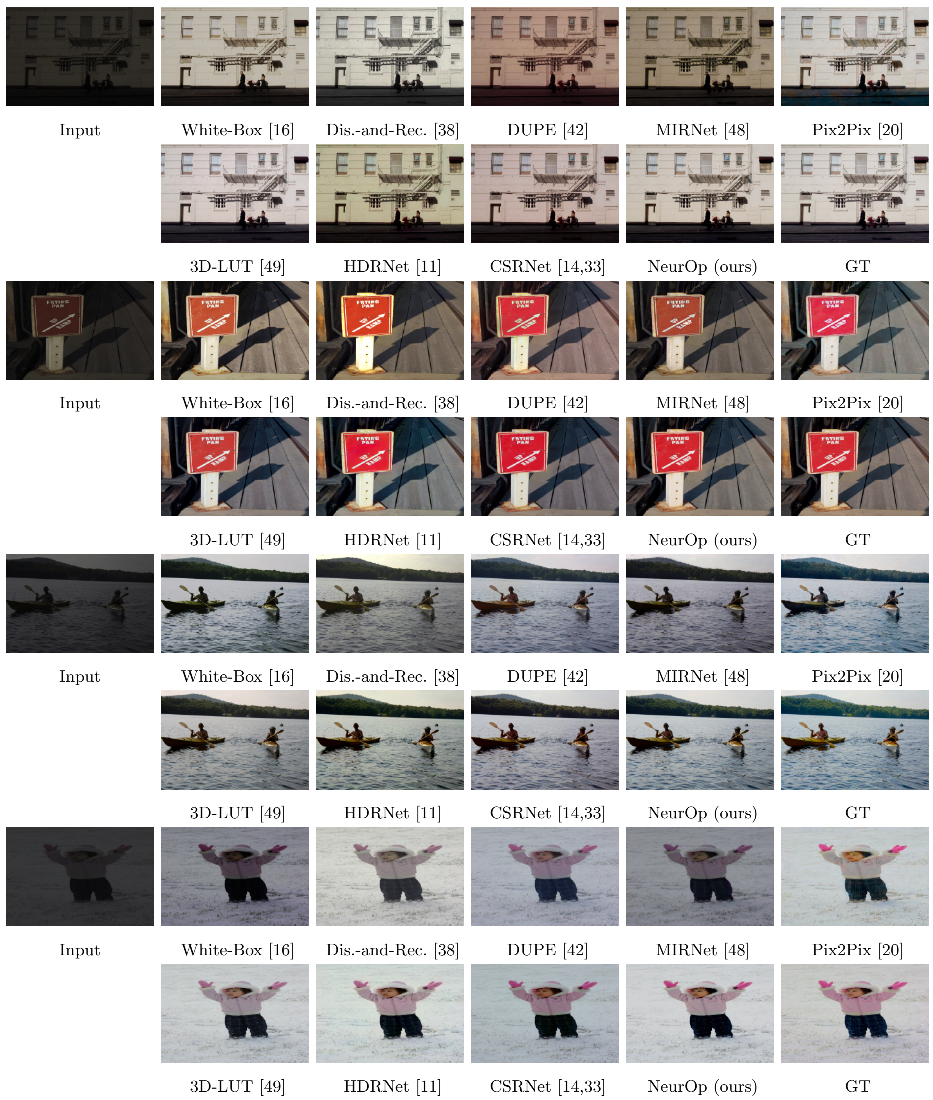
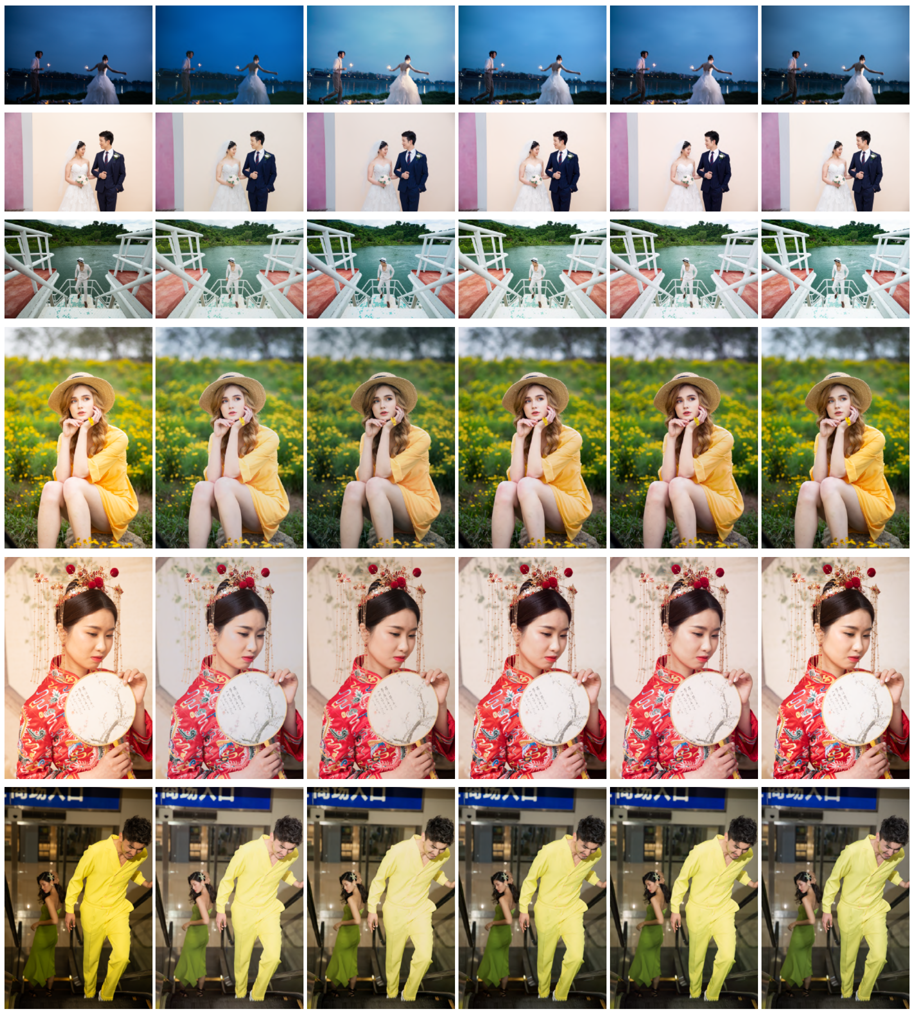


Fig. 6: Visual comparison with state-of-the-art methods on MIT-Adobe-5K-Dark.



Input CSRNet 3D-LUT+HRP NeurOp NeurOp+HRP GT

Fig. 7: Visual comparison with state-of-the-art methods on PPR10K-a.

Fig. 8: Visual comparison with state-of-the-art methods on PPR10K-b.

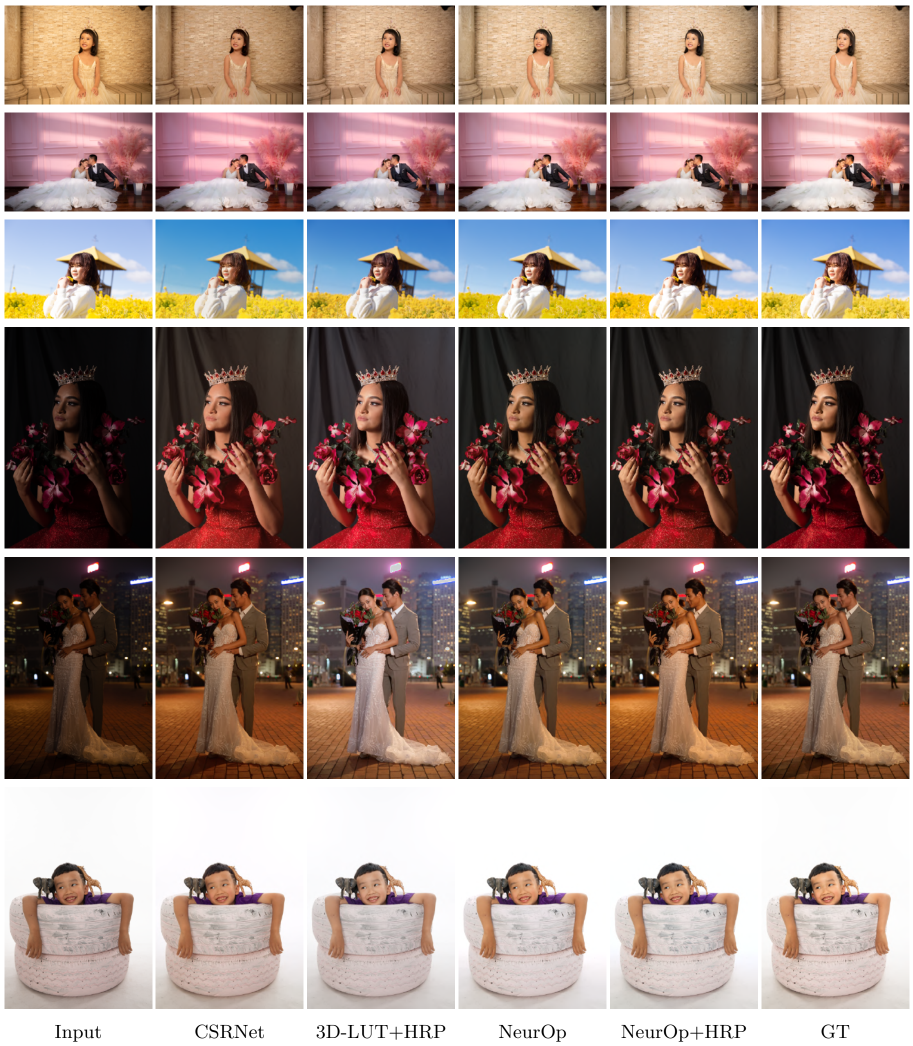


Fig. 9: Visual comparison with state-of-the-art methods on PPR10K-c.

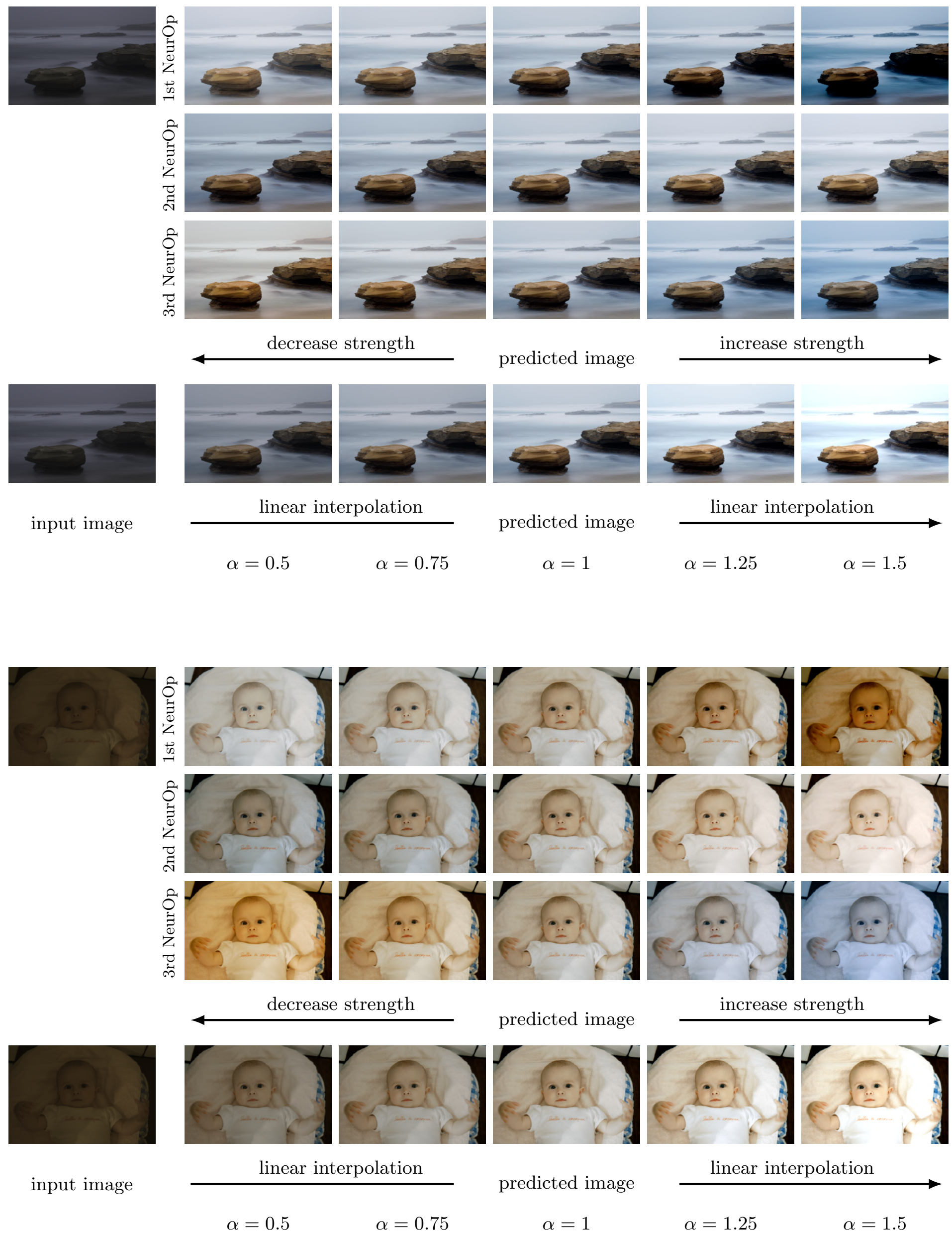


Fig. 10: Visual comparison of the proposed strength control and image interpolation.

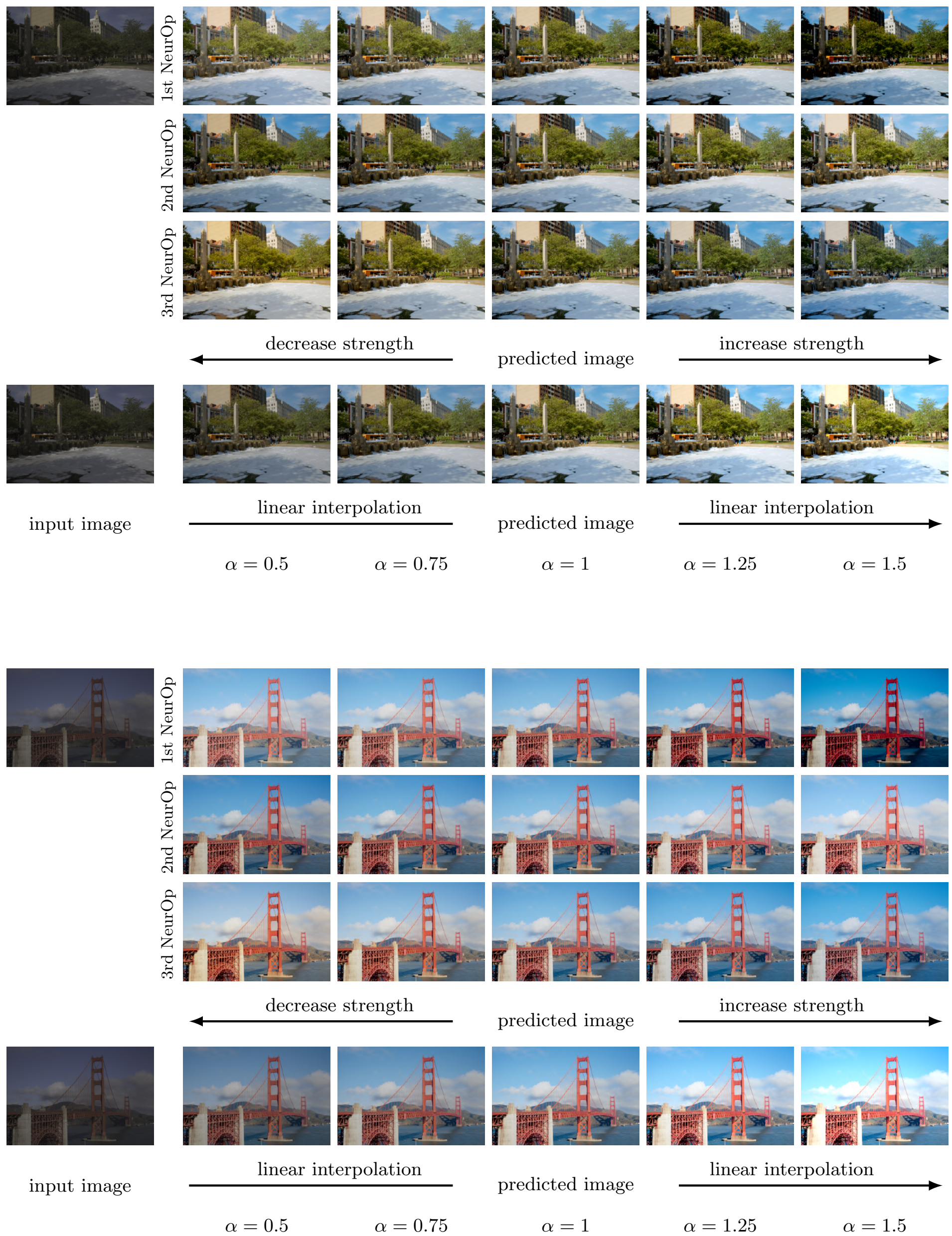


Fig. 11: Visual comparison of the proposed strength control and image interpolation.

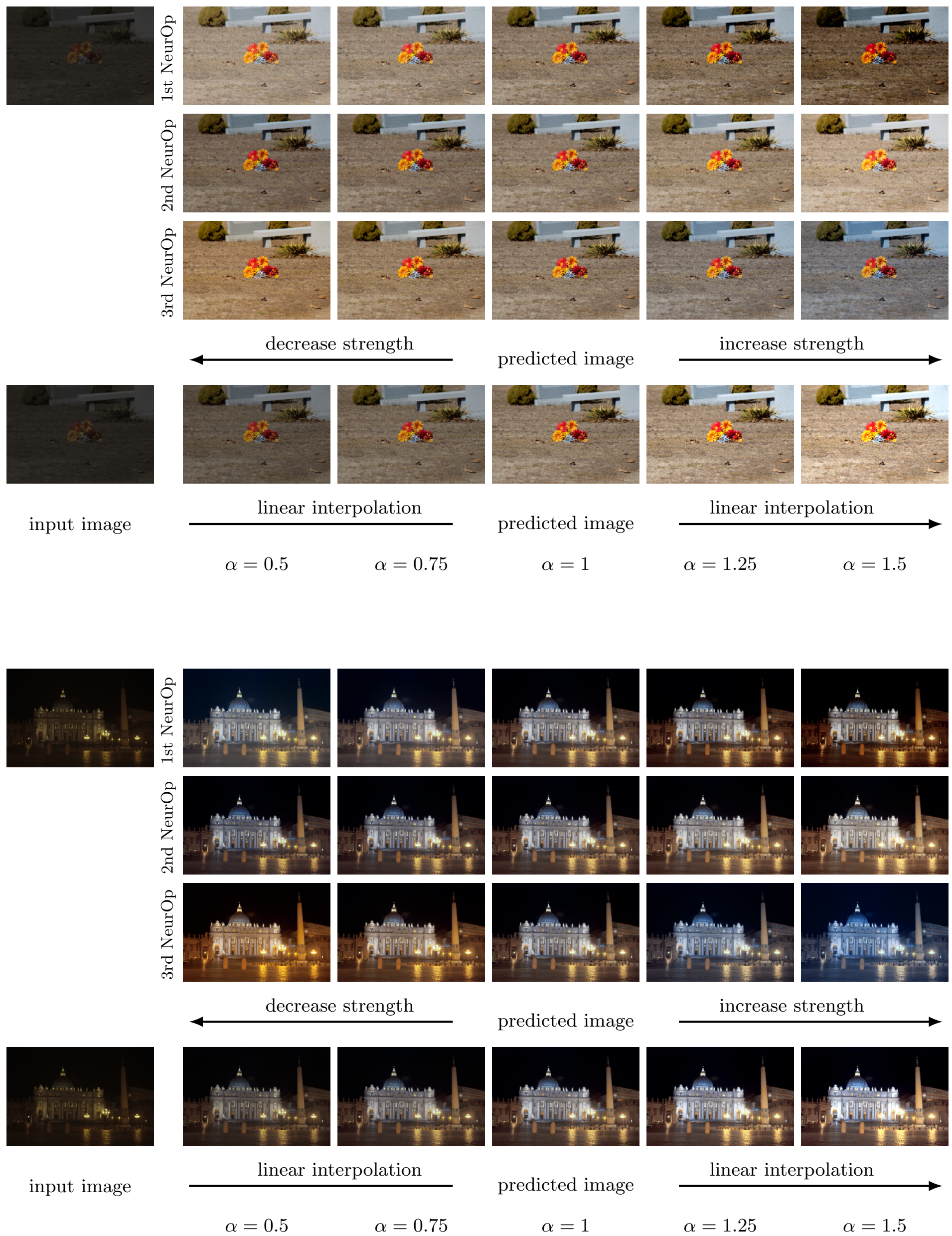


Fig. 12: Visual comparison of the proposed strength control and image interpolation.