Supplementary of DualBLN

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1 Real-time Performance on HR-Photo

1.1 Retouching efficiency

With the popularization of high-resolution(HR) imaging devices, image retouching tasks need to deal with retouching objects that are often HR photographs with more pixels. Therefore, the efficiency of the model when processing large-size images is crucial for practical applications. Larger image resolution also means slower read speeds. Although our method takes less time during the retouching process, there is inevitably some time loss before the images are loaded into the model. These time losses are not related to the DualBLN model and do not affect the evaluation of its performance. To validate the retouching speed of DualBLN for HR-photo, we measured the time required to retouch a single image on a PPR10K-HR dataset. The resolution of these images ranges from 4K to 8K, and these results lie between 130 ms and 200 ms, with an average of only 163 ms required to obtain a HR photo comparable to an expert retouch. The fast retouching allows the model to be used in a wider range of applications with less user wait time in practice.

1.2 Training Model

In practice, the use of HR photographs leads to an increase in training time and the need for hardware equipment, making the cost of training a model unacceptable. Therefore, in order to obtain models that can be applied to HR photographs more efficiently, the resolution of the input images can be reduced during training to obtain the corresponding low-resolution(LR) images, which is more friendly for the training of the models. Training with low-resolution images does not compromise the retouching effect of DualBLN for high-resolution images.

As shown in Fig. 3, the parameters in the DualBLN model were trained using LR images (360p) for both LR-photo and HR-photo, and the two different resolution images were used separately in the final test section to produce a comparison of the effects. The retouched photos, either by observing the difference

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through the error map or by comparing the values of the evaluation metrics, prove that there is no obvious performance difference caused by the training setting. Thus, the DualBLN model trained by LR images is also applicable to the retouching of HR images without any loss in retouching effect.

2 Limitation

Our method is based on 3D LUT, a pixel-level mapping method, so that its capacity to handle cases such as severe noise or extensive overexposure to the image is limited. In addition, since our method mainly changes the color style of the image, there is no deformation or rotation of the photo itself, to get a good photo still requires a certain ability to compose when shooting and find the right angle to take a photo with the right distribution of internal elements. Generally speaking, DualBLN can make photos with better visual effects, but this is based on the fact that the photos themselves do not have too serious imaging quality problems.

In addition, introducing contextual information into the model is a possible solution with better retouching results, which is a research direction for our future work, but still needs to be carefully considered to prevent the significant increase of memory resources and computational cost caused by introducing contextual information.

3 Visualization

3.1 Error map

Experience has shown that for image retouching tasks, the direct comparison of the results between different methods does not reveal the differences between them intuitively and clearly, and we need to further visualize the differences. A possible and common way to handle this is to visualize the errors before and after retouching and transform them into images that can be clearly observed, which we call error maps.

In the image, the difference between the maximum and minimum values of a single channel is 256, and we can map the data to [0,255]. For a conventional RGB three-channel color image, our mapping range becomes three [0,255], corresponding to the three channels R (Red) G (Green) B (BLue) in the image. The pure blue [0,0,255] is defined as two pixels exactly the same or basically without error, and is used as the beginning of the mapping area up to the positive red [255,0,0], which is graded to get the two ends of the color interval of the error mapping. To ensure that the color is continuous, we add another three endpoints to it for the overdose, which are cyan [0,255,255], green [0,255,0], and yellow [255,255,0]. A final uninterrupted mapping region from blue to red is formed.

After the program loads the input image and the target image, it converts them into tensor type data and stores them, and then subtracts the two images

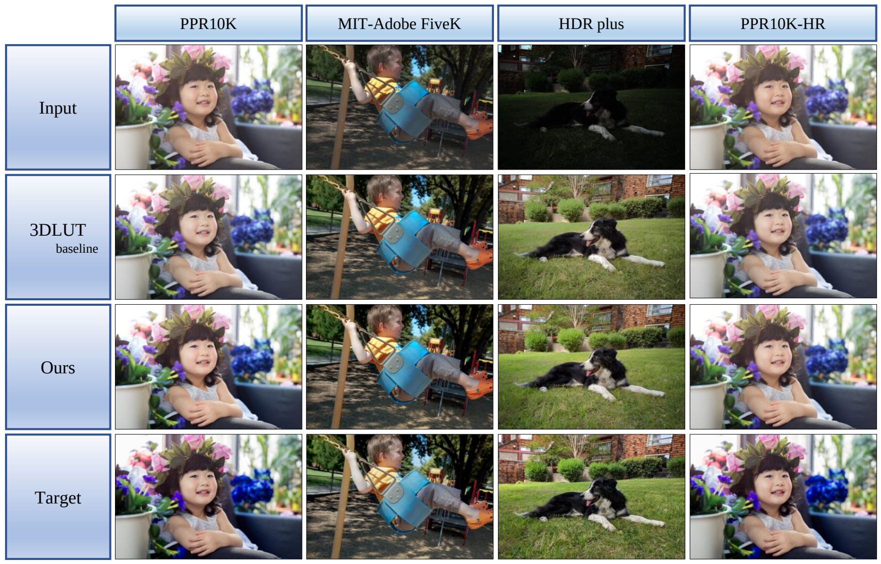

Fig. 1. Qualitative effects of the DualBLN module. The visualization results on different datasets and their corresponding test metric values. Our model has the best visualization with the output image closest to the target images. The baseline we set also has good learning results, but we improve on it.

pixel by pixel to get the data representing their differences. The initial data is then filtered according to the set maximum and minimum values, and the initial data is framed within a preset range, and then converted according to the previously set color area to obtain a good visual effect of the error map.

3.2 More Visualization of DualBLN

To better investigate the behavior of DualBLN, We show the retouching results for different datasets by Fig. 1. The good retouching effect of several different datasets is the guarantee of the generalizability of the model. As can be seen from the images, for the image retouching related dataset, The processing results of DualBLN have a visual effect closer to groundtruth, and it also achieves good results for low-exposure enhancement related tasks, which proves that DualBLN has a certain degree of generalizability. To show that our work is not limited to low-resolution(LR) images, the retouching results for high-resolution(HR) images are shown at the end, which also have very good results. We provide an additional set of visualizations in Fig. 2.

HR images have more pixels, and the mapping process inevitably results in differences from the retouched results of low-definition images, which needs to be avoided to get the greatest result. Therefore, we also compare the retouching results of two different resolution images of the same photo, and compare them with groundtruth and generate error maps. As shown in Fig. 3, there is no

Fig. 2. More visualization on MIT-Adobe FiveK dataset about our DualBLN model.

obvious difference between DualBLN in retouching different resolution images, and the retouching results of the two are basically the same, or have mutual advantages and disadvantages. This shows that the performance of the DualBLN model does not fluctuate depending on the resolution of the input images, and the only effect of the resolution on the model is the change in the time spent in the retouching process.

3.3 Comparison of computing resource consumption

For reasons of rigor, we test the comparison between the baseline model (HRP [CVPR2021] model) used in our paper and our model in terms of model parameters and FLOPs, and the results are shown in Table 1. We can see that we consume more computational resources since the two-branch model we use has almost a whole network more than the previous models.

Table 1. Comparison results of our model with the baseline model

Method	Dataset	$PSNR\uparrow$	$\Delta E_{ab}\downarrow$	$PSNR^{HC}\uparrow$	$Params$	$FLOPs$
HRP(baseline)	PPR-a	25.99	6.76	28.29	**11.179**	**1.825**
Ours	PPR-a	**26.51**	**6.45**	**29.74**	13.187	2.121

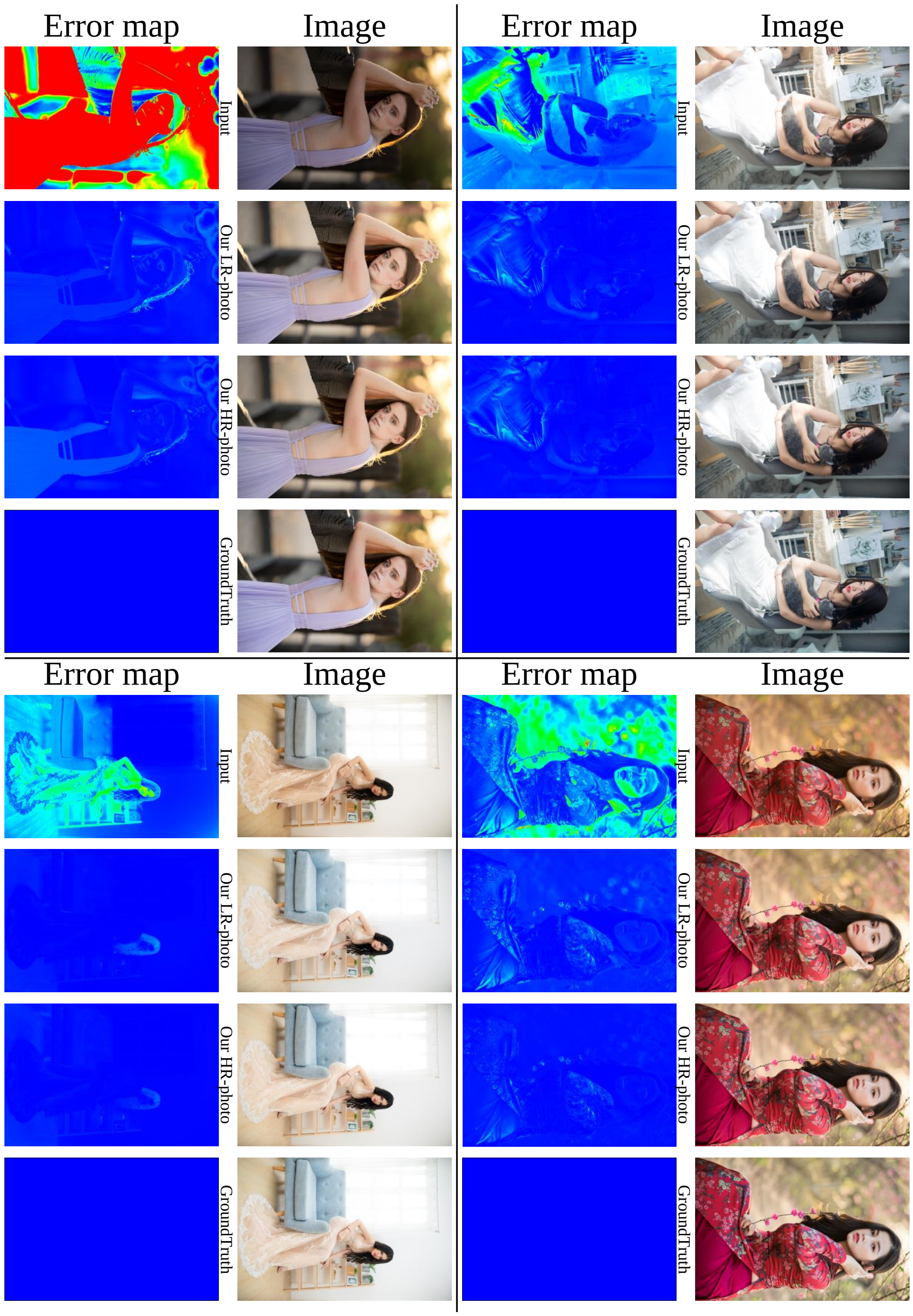

Fig. 3. The visualization results on the PPR10K dataset. Comparing the error maps of LR images (360p) and HR images (4k to 8k), it can be seen that DualBLN can still perform the retouching task of HR images excellently.