High Dynamic Range Imaging of Dynamic Scenes with Saturation Compensation but without Explicit Motion Compensation
Supplementary Material

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1. Network Architecture

We illustrate the detailed architecture of the proposed brightness adjustment network (BAN) in Fig. 1. Here, the residual dense blocks (RDBs) [7] have two 3×3 convolutional layers with leakyReLU and a 1×1 convolution layer without activation. The convolutional layer before kernel generation has 144 channels to produce 3×3 kernels for features with 16 channels, and the convolutional layer before offset generation has 18 channels to produce two-dimensional offsets for 3×3 grid.

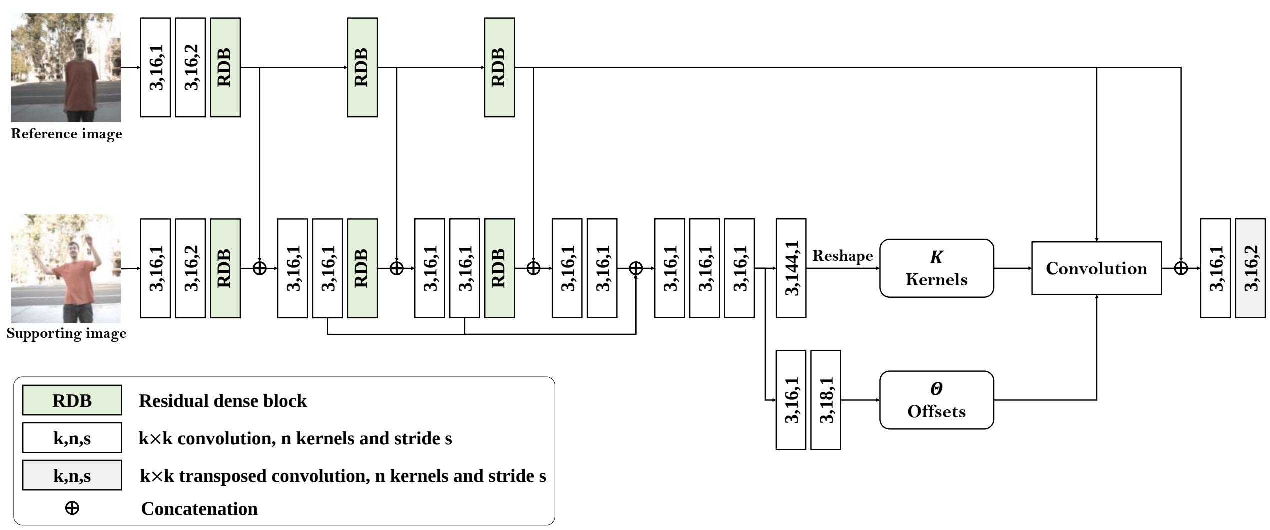

Figure 1: The detailed architecture of the proposed brightness adjustment network (BAN).

2. Additional Qualitative Results

This section provides more qualitative results to demonstrate the effectiveness of our method. We compare our visual results on Kalantari *et al*.'s dataset [2] with other state-of-the-art methods [4, 1, 2, 5, 6, 3]. Figs. 2, 3, and 4 demonstrate the ability of our approach to generate detailed texture and suppress color distortions even in the saturated regions with occlusions and motions. Specifically, Fig. 3 shows that our method successfully handles undesirable glow light effects which are commonly observed in real images and produces artifact-free HDR results. The patch-based approaches [4, 1] fail to reconstruct content in the regions where large motions exist. The methods using flow-based alignment [2, 3] introduce distortions which result from flow estimation error. Wu *et al*. [5] and Yan *et al*. [6] struggle to generate details in the severely saturated areas. The overall results show that the proposed method generates high-quality HDR results even in the presence of saturation and dynamic motions. The artifact regions are pointed by red arrows, which can be better observed by magnification.

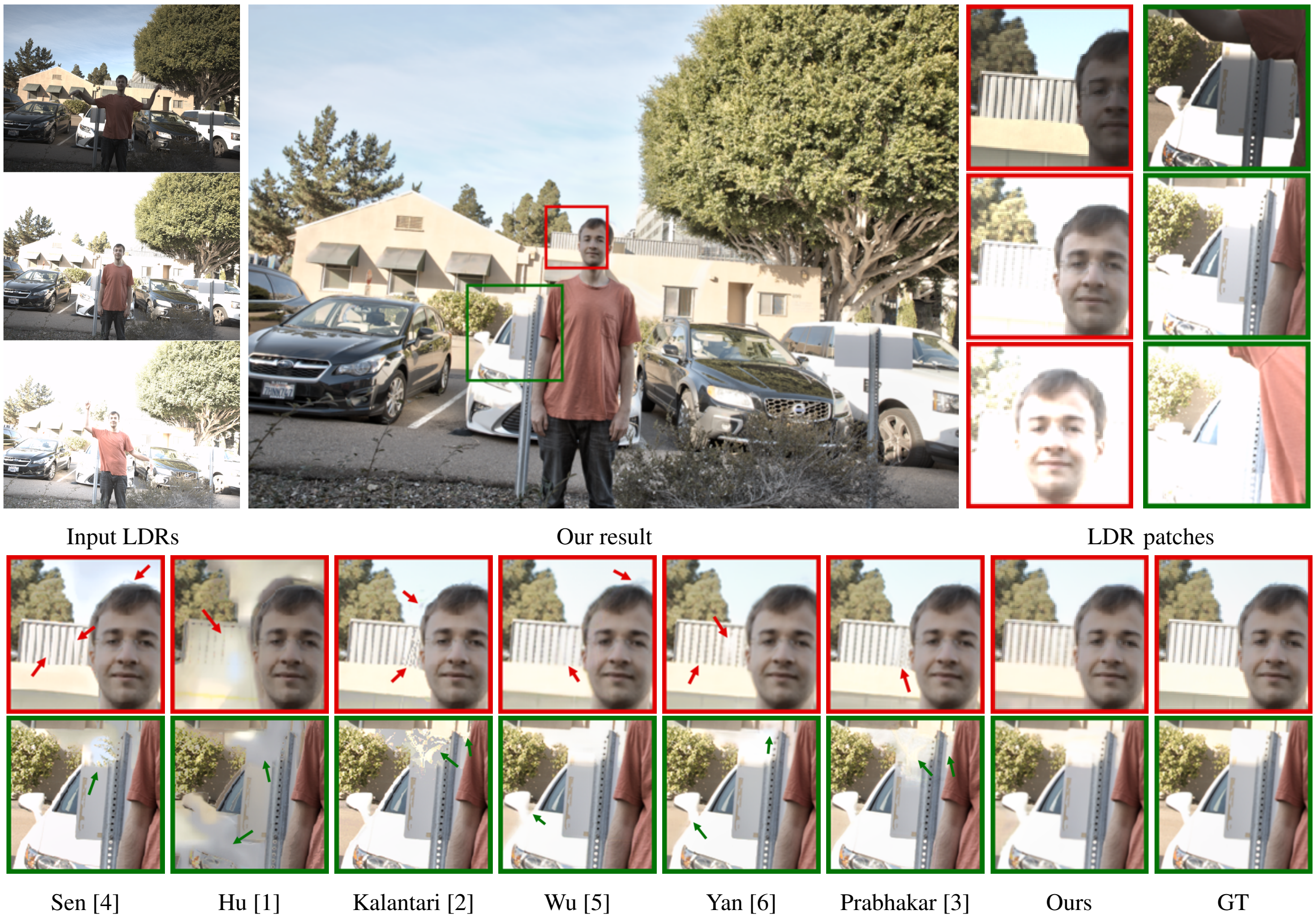

Figure 2: Qualitative comparisons of our method with state-of-the-art methods.

Figure 3: Qualitative comparisons of our method with state-of-the-art methods.

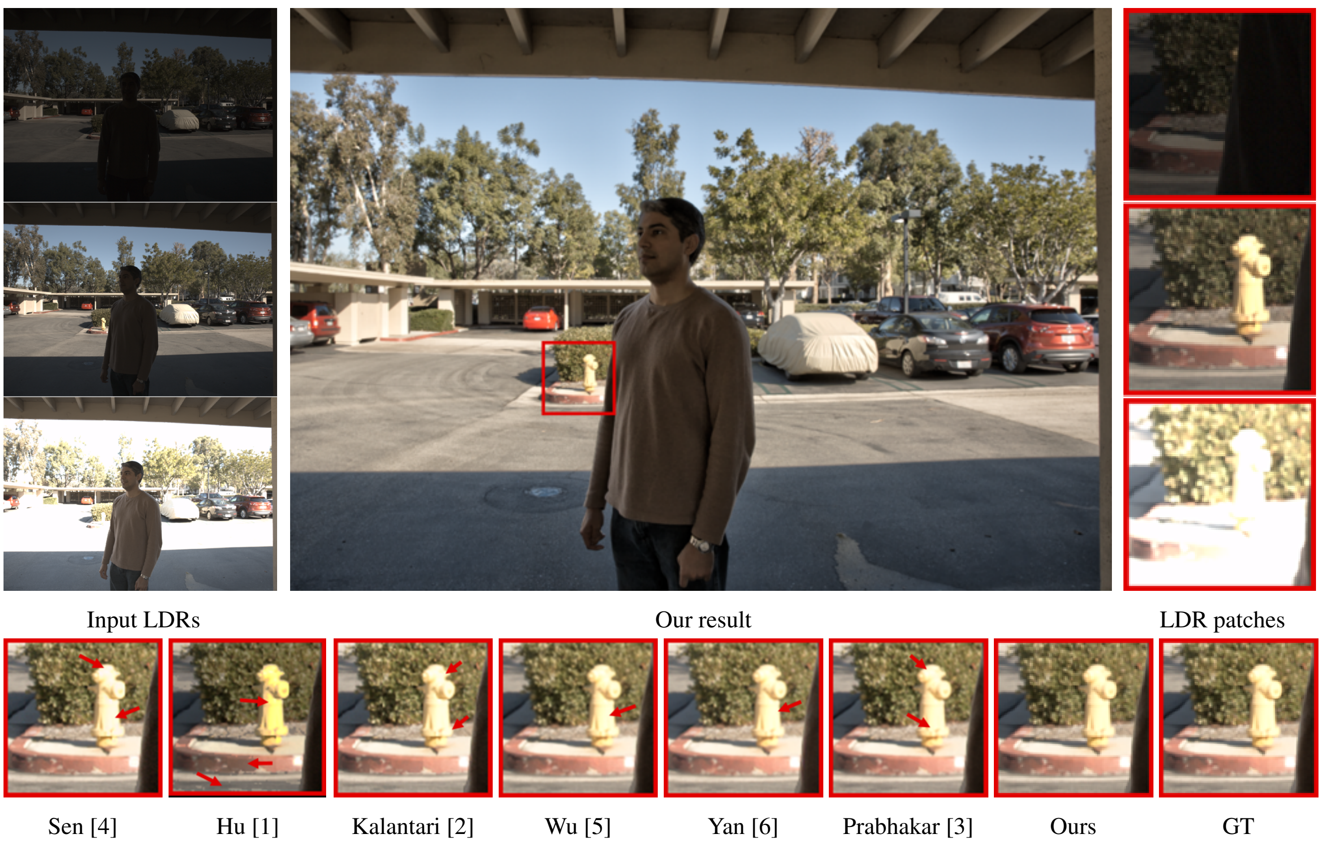

Figure 4: Qualitative comparisons of our method with state-of-the-art methods.

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