Learning Continuous Exposure Value Representations for Single-Image HDR Reconstruction Supplementary Material

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1. Supplementary

We present additional results in the supplementary material to supplement our primary study. First, we create a demo video to further demonstrate our CEVR model's flexibility in generating LDR images with continuous exposure values (EV), which is critical for our two major contributions, *continuous stack* and *cycle training*. Second, we provide additional qualitative comparisons of LDR stacks and HDR images to demonstrate the effectiveness of our approach. Finally, we demonstrate the effectiveness of continuous stack by analyzing the estimated inverse camera response function (CRF) from Debevec's method [1].

1.1. Demo Video

Existing methods [2, 3] mainly generate discrete EV LDR stacks and then fuse them to reconstruct HDR images. By contrast, our approach integrates the implicit neural representation into our model and makes it able to generate continuous EV LDR stacks. Based on this flexibility, we propose two main strategies, continuous stack and cycle training, to improve the quality of LDR stacks and HDR images. We also design the intensity transformation to further enhance the quality of estimated LDR images. Our demo video (included in the supplementary files) shows the flexibility of our CEVR model in generating LDR images with continuous EVs and visualizes the effectiveness of our three main contributions (i.e., intensity transformation, cycle training, and continuous stack).

1.2. More Qualitative Comparisons

Results presented in this section are generated with the model designs mentioned in the main manuscript (intensity transformation, continuous stack, and cycle training). Our model is trained on the training data in the VDS dataset [2] and predicts the LDR images with different EVs from the testing data in the VDS and HDREye datasets [5].

Estimated LDR stack. We provide additional visual comparisons of the estimated LDR stack on the VDS dataset to verify the effectiveness of our approach compared to the existing approach, Deep recursive HDRI [3]. As shown in Fig. 1, our approach can predict LDR images with more accurate color tones while reducing artifacts.

Reconstructed HDR images. We showcase extra visual comparisons of reconstructed HDR images compared to the recent single-image HDR reconstruction methods, Deep recursive HDRI [3] and Liu et al. [4], on both the VDS and HDREye datasets. As shown in Figs. 2 and 3, our approach can generate tone-mapped images with better color tones and fewer artifacts.

1.3. Analysis of estimated inverse CRF

Existing LDR stack-based methods, e.g., [2, 3], build the deep learning-generated LDR stack with predefined exposure values first, and Debevec's method [1] then generates the estimated inverse camera response function from the LDR stack and reconstructs the final HDR result. The inverse CRF, which should be *monotonic* and *smooth*, is used to transform the intensity value of LDR images into the relative radiance values of HDR images.

Based on the observation in Fig. 2 in the main paper, we propose the CEVR model to generate an enriched and denser LDR stack. As shown in Fig. 4, the estimated camera response function generated from the continuous stack setting is smoother than the one generated from the predefined stack setting. Due to the lack of ground truth camera response curves in both the VDS [2] and HDREye [5] datasets, we analyze the smoothness and monotonicity of the estimated CRF generated from two stack settings to evaluate the quality of estimated camera response curves.

References

[1] Paul E. Debevec and Jitendra Malik. Recovering high dynamic range radiance maps from photographs. *ACM Transactions on Graphics*, 1997. 1, 5

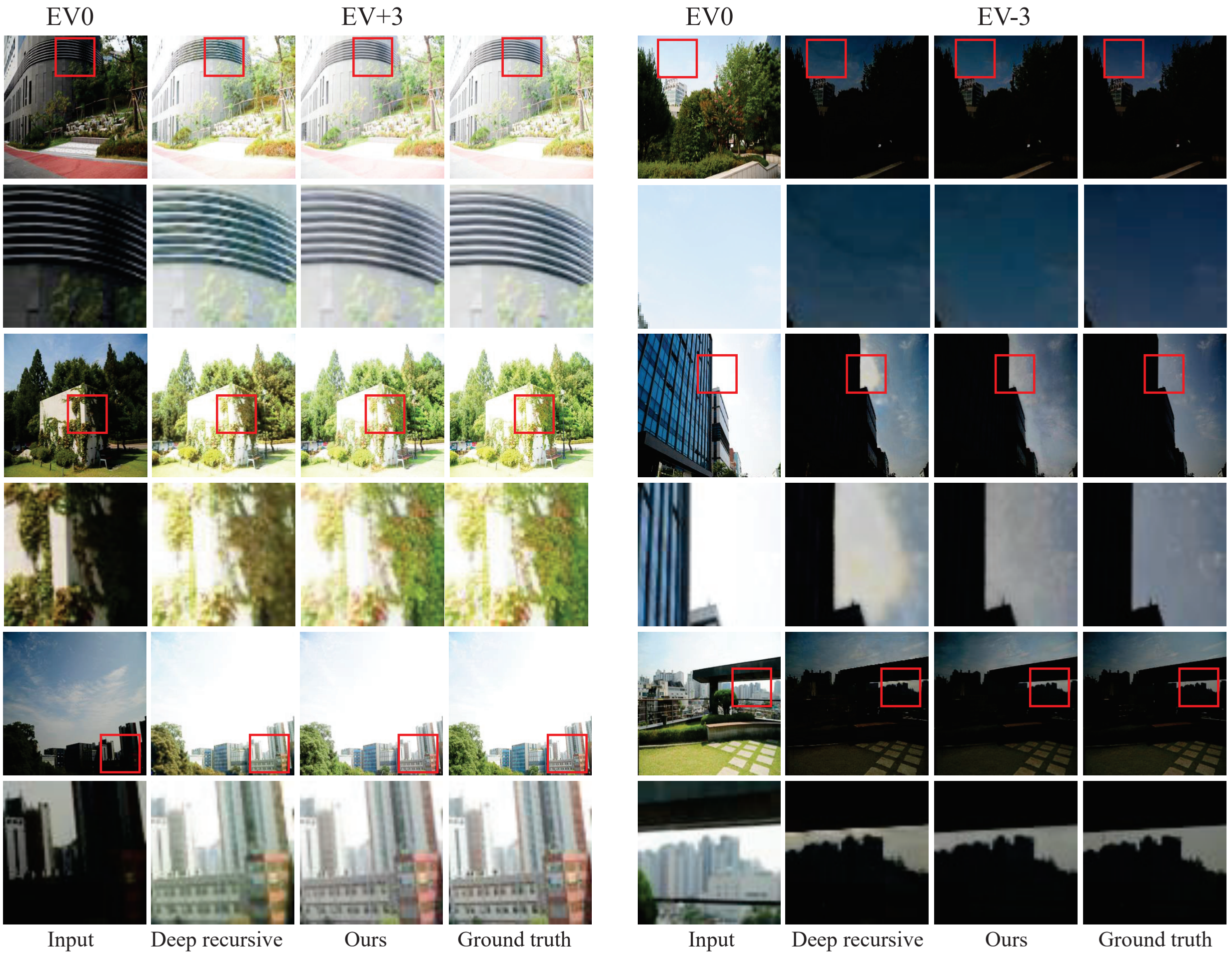

Figure 1: **Extra qualitative comparisons of the LDR stack on the VDS dataset.** With the proposed intensity transformation and cycle training, our approach can generate high-quality estimated LDR images.

[2] Siyeong Lee, Gwon Hwan An, and Suk-Ju Kang. Deep chain HDRI: Reconstructing a high dynamic range image from a single low dynamic range image. *IEEE Access*, 2018. 1

[3] Siyeong Lee, Gwon Hwan An, and Suk-Ju Kang. Deep Recursive HDRI: Inverse tone mapping using generative adversarial networks. In *ECCV*, 2018. 1

[4] Yu-Lun Liu, Wei-Sheng Lai, Yu-Sheng Chen, Yi-Lung Kao, Ming-Hsuan Yang, Yung-Yu Chuang, and Jia-Bin Huang. Single-image hdr reconstruction by learning to reverse the camera pipeline. In *CVPR*, 2020. 1

[5] Hiromi Nemoto, Pavel Korshunov, Philippe Hanhart, and Touradj Ebrahimi. Visual attention in ldr and hdr images. In *9th International Workshop on Video Processing and Quality Metrics for Consumer Electronics (VPQM)*, 2015. 1

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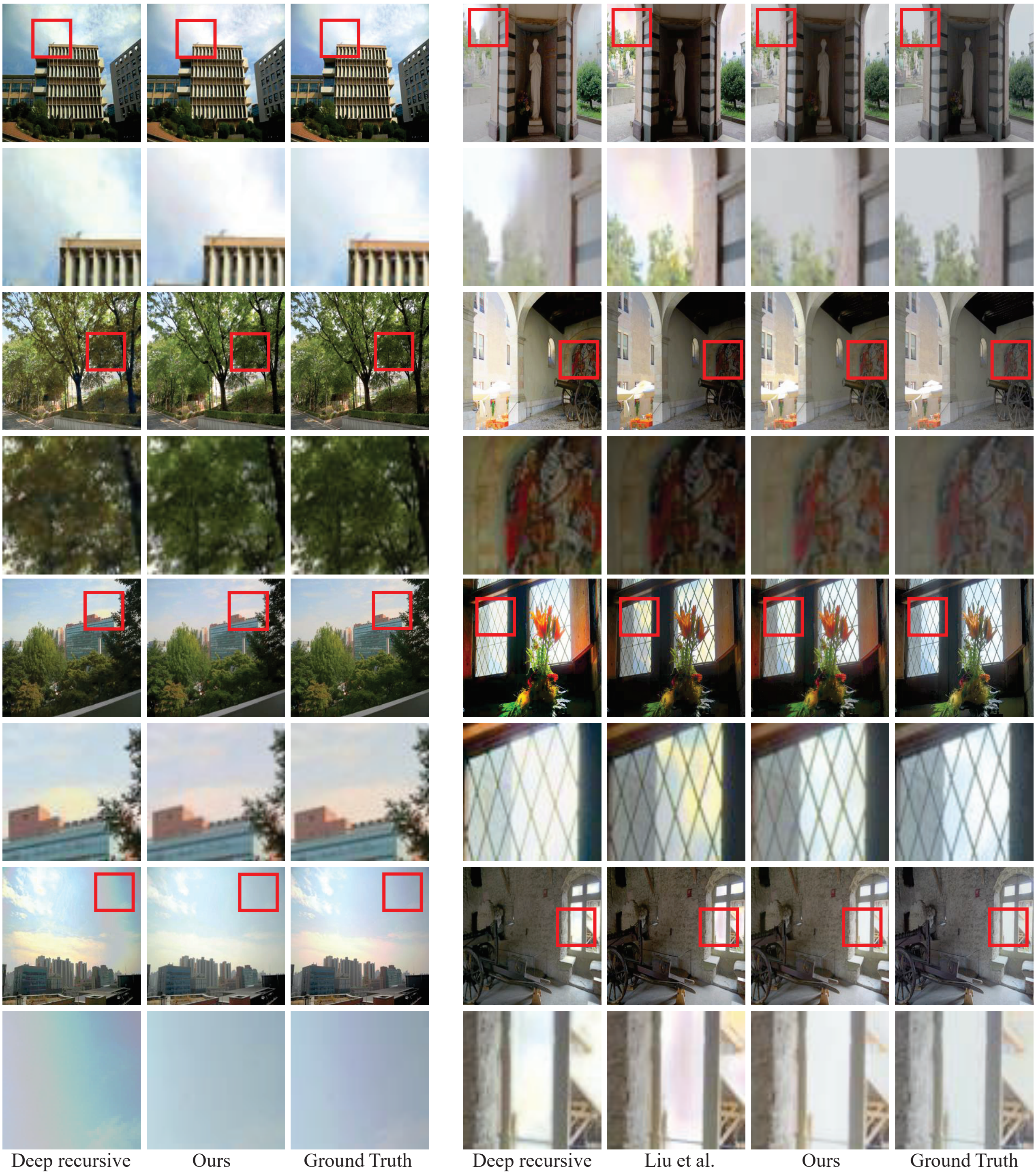
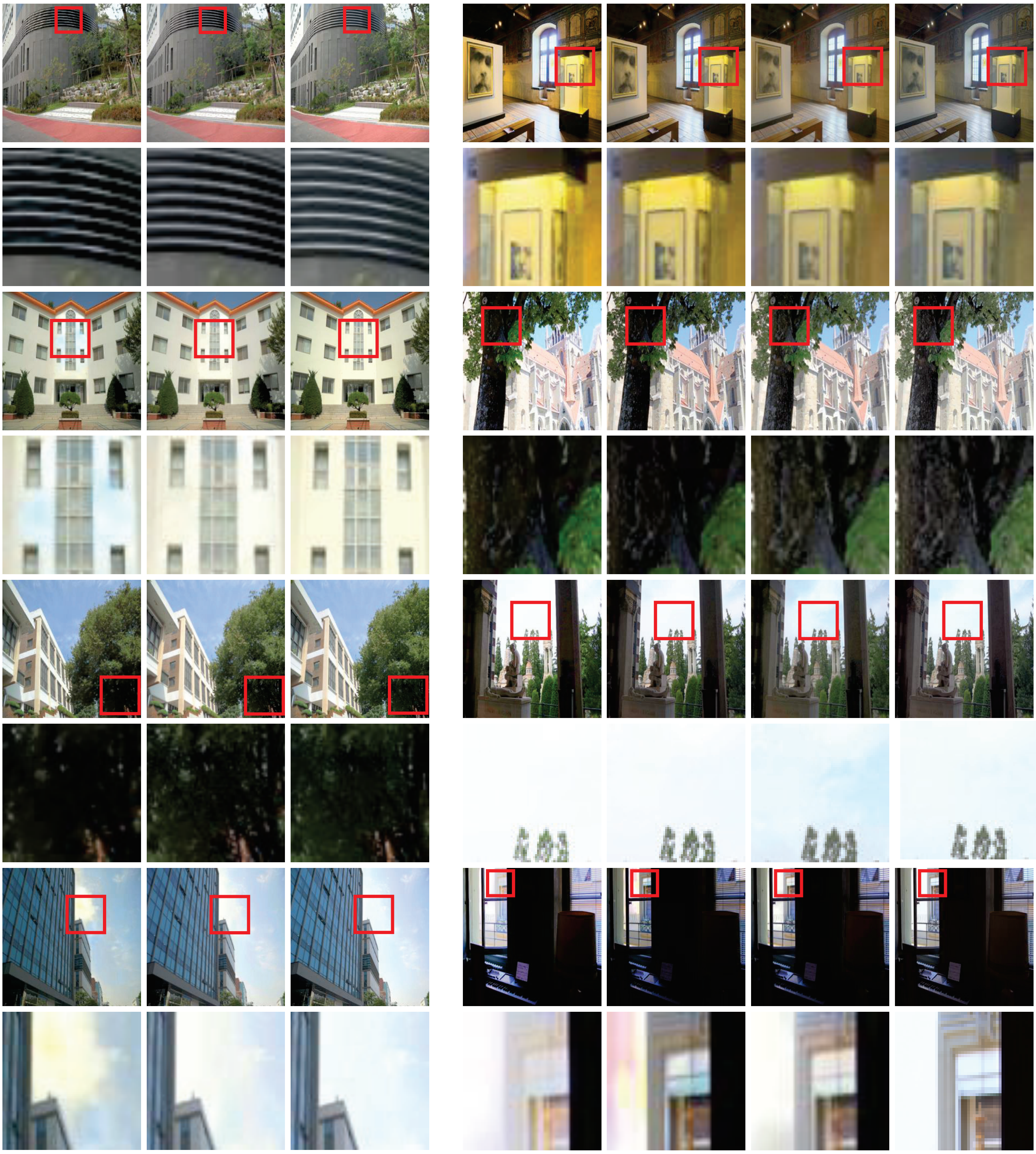


(a) VDS dataset

(b) HDREye dataset

Figure 2: **Extra qualitative comparisons of HDR images.** With the continuous stack, our approach can generate more visually pleasing HDR images.



Deep recursive | Ours | Ground Truth

(a) VDS dataset

Deep recursive | Liu et al. | Ours | Ground Truth

(b) HDREye dataset

Figure 3: **Extra qualitative comparisons of HDR images.** With the continuous stack, our approach can generate more visually pleasing HDR images. In this figure, we conduct the same comparison as in Fig. 2 but in different scenes.

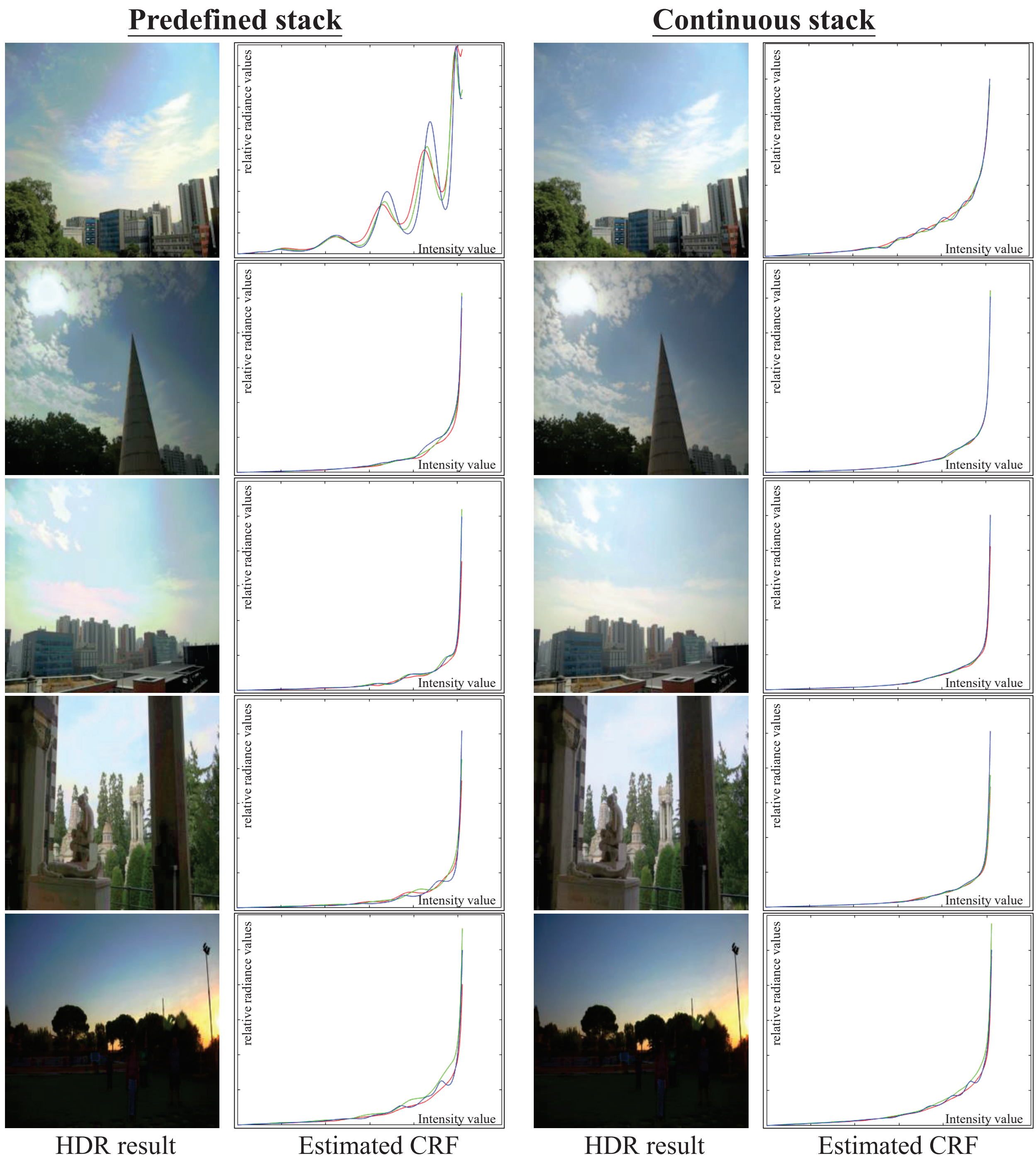


Figure 4: **Analysis of the estimated inverse CRF.** Continuous stack, adding additional LDR images with dense and continuous EVs, can help Debevec's method [1] generate more accurate inverse CRF and generate HDR images with better quality.