







# Supplementary for “Luminance Attentive Networks for HDR Image and Panorama Reconstruction”

Hanning Yu<sup>1\*</sup>, Wentao Liu<sup>1\*</sup>, Chengjiang Long<sup>2†</sup>, Bo Dong<sup>3</sup>, Qin Zou<sup>1</sup>, Chunxia Xiao<sup>1†‡</sup>

<sup>1</sup> School of Computer Science, Wuhan University, Wuhan, Hubei, China 430072

<sup>2</sup> JD Finance America Corporation, Mountain View, CA, USA 94043

<sup>3</sup> SRI international, Princeton, NJ, USA 08540

fishaning@whu.edu.cn, liu136583410@gmail.com, cjfykx@gmail.com, dongshuhao12@gmail.com, qzou@whu.edu.cn, cxxiao@whu.edu.cn

## Abstract

*In this supplementary, we provide the method of image visualization, detail information about the used datasets, network architectures, as well as more visual comparison results. Note that we do not put all these materials in the main paper due to the page limits.*

## 1. Image Visualization

### 1.1. Visualizing HDR Images in LDR Format

As HDR images can't be displayed on common devices, we use linear mapping with a limited dynamic range at a certain exposure to compare HDR images in LDR format. Specifically, we use the preview window of the LuminanceHDR software (<http://qtpfsgui.sourceforge.net>) as the tool for visualizing HDR images. As shown in Fig. 1, we can use different exposures to present the overall information of HDR images as much as possible.

### 1.2. Visualizing LDR Images at the Adjusted Exposure

In order to highlight the difference between LDR images and HDR images more clearly, we also reduce or increase the exposure of LDR images for visualizing some figures in our paper. We complete the exposure reduction by scaling the LDR image in linear RGB space. Specifically, we first normalize the LDR image from the range  $[0, 255]$  to  $[0, 1]$ , and then convert it from sRGB color space to linear RGB color space using the following formula:

$$I_{linear} = \begin{cases} \frac{I_s}{12.92}, & \text{if } 0 \leq I_s \leq 0.04045 \\ \left(\frac{I_s + 0.055}{1.055}\right)^{2.4}, & \text{if } 0.04045 < I_s \leq 1 \end{cases} \quad (1)$$

Then we can adjust the exposure of LDR image in the same way as HDR image. For example, in Figure 1 of our paper, the left "Input LDR" shown on paper is the reduced version of the actual input

image, and the right "Our result" is the output HDR image at the same dynamic range and reduced exposure.

## 2. Datasets

For the readers' convenience, we summarize the used datasets according to the data type in Table 1. We also provide the data source of each dataset.

## 3. Network Architecture Details of LANet

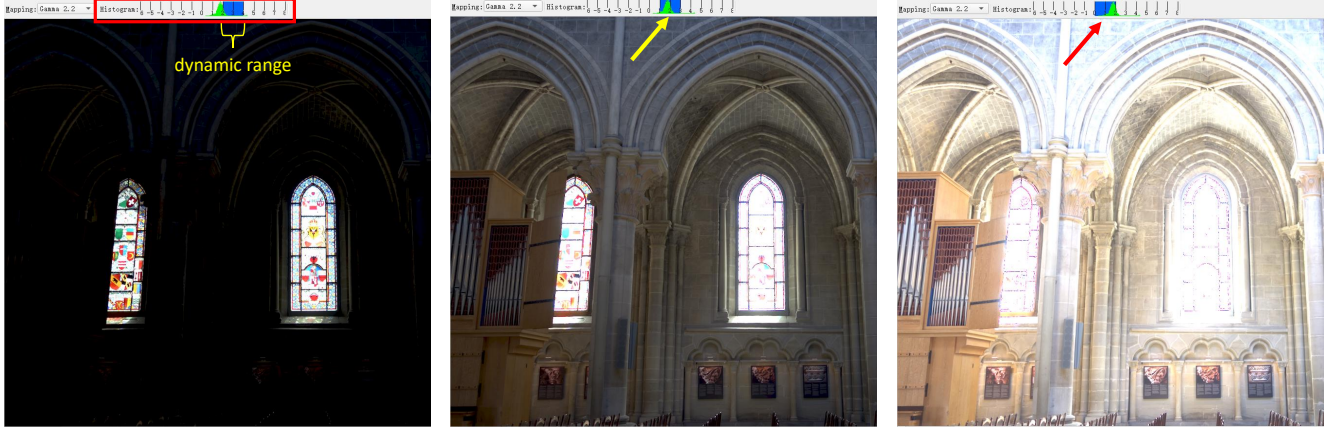
We implement our network architecture in Tensorflow and Tensorlayer. The resolution of the input images is any size greater than  $256 \times 256$ , and the output images are the same size as the input. During the training stage, the size of images is set to  $256 \times 256$ . Before inputting the images to the network, we first converted them from sRGB color space to linear RGB space using the above method, then normalized them to  $[-1, 1]$  as the final inputs for our network. The output HDR images from the network are in the logarithmic domain and need an exponential operation to get the final result. Here we describe our network architecture in detail. We first define some operations as follows:

- $R_x$ : Denoting the residual block in our network. We use the first five convolutional layers of ResNet50 [HZRS16] with the version of "Relu before addition" [HZR16] as the structure of five residual blocks in our network and define them in turn as  $R_1$  to  $R_5$ .
- $C(s, k)$ : Denoting Relu-Convolution-InstanceNorm layer with filters size  $s \times s$  and output channels  $k$ .
- $DC(s, k)$ : Denoting Relu-Convolution-InstanceNorm layer with convolution stride 2, filters size  $s \times s$  and output channels  $k$ .
- $UC(s, k)$ : Denoting Upsample-Relu-Convolution-InstanceNorm

† This work was co-supervised by Chengjiang Long and Chunxia Xiao.

\* Hanning Yu and Wentao Liu are joint first authors.

‡ Chunxia Xiao is the corresponding author.



**Figure 1:** An HDR image shown in LDR format at different exposures. The histogram bar represents the distribution of the HDR image on the log scale. The range marked in blue indicates the dynamic mapping range and the position indicates the exposure. Note that here "Mapping: gamma 2.2" means mapping the linear result of LDR image on a display which gamma is 2.2.

**Table 1:** The list of HDR datasets we use in our experiments.

Type	Dataset Name	Source	Number
Pano	Laval Indoor HDR Dataset	<a href="http://indoor.hdrdb.com">http://indoor.hdrdb.com</a>	2233
	Laval Outdoor HDR Dataset	<a href="http://outdoor.hdrdb.com">http://outdoor.hdrdb.com</a>	205
	HDRi Haven	<a href="https://hdrihaven.com/hdriis">https://hdrihaven.com/hdriis</a>	322
	sIBL	<a href="http://www.hdrlabs.com/sibl/archive.html">http://www.hdrlabs.com/sibl/archive.html</a>	79
Img	HDR Photographic Survey	<a href="http://rit-mcsl.org/fairchild/HDR.html">http://rit-mcsl.org/fairchild/HDR.html</a>	105
	Funt et al. HDR Dataset	<a href="https://www2.cs.sfu.ca/~colour/data/funt_hdr/#DATA">https://www2.cs.sfu.ca/~colour/data/funt_hdr/#DATA</a>	105
	Stanford HDR Data	<a href="http://scarlet.stanford.edu/~brian/hdr/hdr.html">http://scarlet.stanford.edu/~brian/hdr/hdr.html</a>	88
	Ward	<a href="http://www.anywhere.com/gward/hdrenc/pages/originals.html">http://www.anywhere.com/gward/hdrenc/pages/originals.html</a>	33
	HDR-Eye	<a href="https://www.epfl.ch/labs/mmspg/downloads/hdr-eye/">https://www.epfl.ch/labs/mmspg/downloads/hdr-eye/</a>	42
Video	LiU HDRv	<a href="http://hdrv.org/Resources.php">http://hdrv.org/Resources.php</a>	10

layer with a nearest-neighbor upsample which stride equals to 2, filters size  $s \times s$  and output channels  $k$ .

- $SC_x(k)$ : Denoting the skip connection layer with output channels set to  $k$ . For  $SC_1$  to  $SC_5$ , the skip connections are used from  $R_1$  to  $R_5$  respectively. They first apply a  $C(3, k)$  for each skip connection, then concatenate them with the output from last layer and apply a  $C(1, k)$  to get the final outputs. For  $SC_0$ , it directly concatenates the network inputs with the LAM outputs, then applies a  $C(3, k)$  to get the final network outputs.

Then the whole network with the HDR reconstruction stream is defined as:

$$\begin{aligned}
 & (\text{Inputs}) - R_1 - R_2 - R_3 - R_4 - R_5 - \\
 & DC(3, 1024) - DC(3, 1024) - UC(3, 1024) - \\
 & UC(3, 512) - C(3, 512) - SC_5(512) - \\
 & UC(3, 256) - C(3, 256) - SC_4(256) - \\
 & UC(3, 128) - C(3, 128) - SC_3(128) - \\
 & UC(3, 64) - C(3, 64) - SC_2(64) - \\
 & UC(3, 64) - C(3, 64) - SC_1(64) -
 \end{aligned}$$

LAM -  $SC_0(3)$  - (Outputs)

And the luminance segmentation stream is defined as:

$$\begin{aligned}
 & (SC_3(128)) - UC(3, 64) - C(3, 64) - UC(3, 64) - \\
 & UC(3, 3) - (\text{Seg. Outputs})
 \end{aligned}$$

#### 4. More Visual Comparison Results

We show more qualitative comparison detail results of predicted HDR images in Figure 2 to 5 and results of predicted HDR panoramas in Figure 6 to 8, which represent the performance of our method under different exposure conditions.

#### References

- [HZR16] HE K., ZHANG X., REN S.: Identity mappings in deep residual networks. In *ECCV* (2016), pp. 630–645. 1
- [HZRS16] HE K., ZHANG X., REN S., SUN J.: Deep residual learning for image recognition. In *CVPR* (2016), pp. 770–778. 1



Figure 2: Comparison on indoor scene at different visualization exposures.

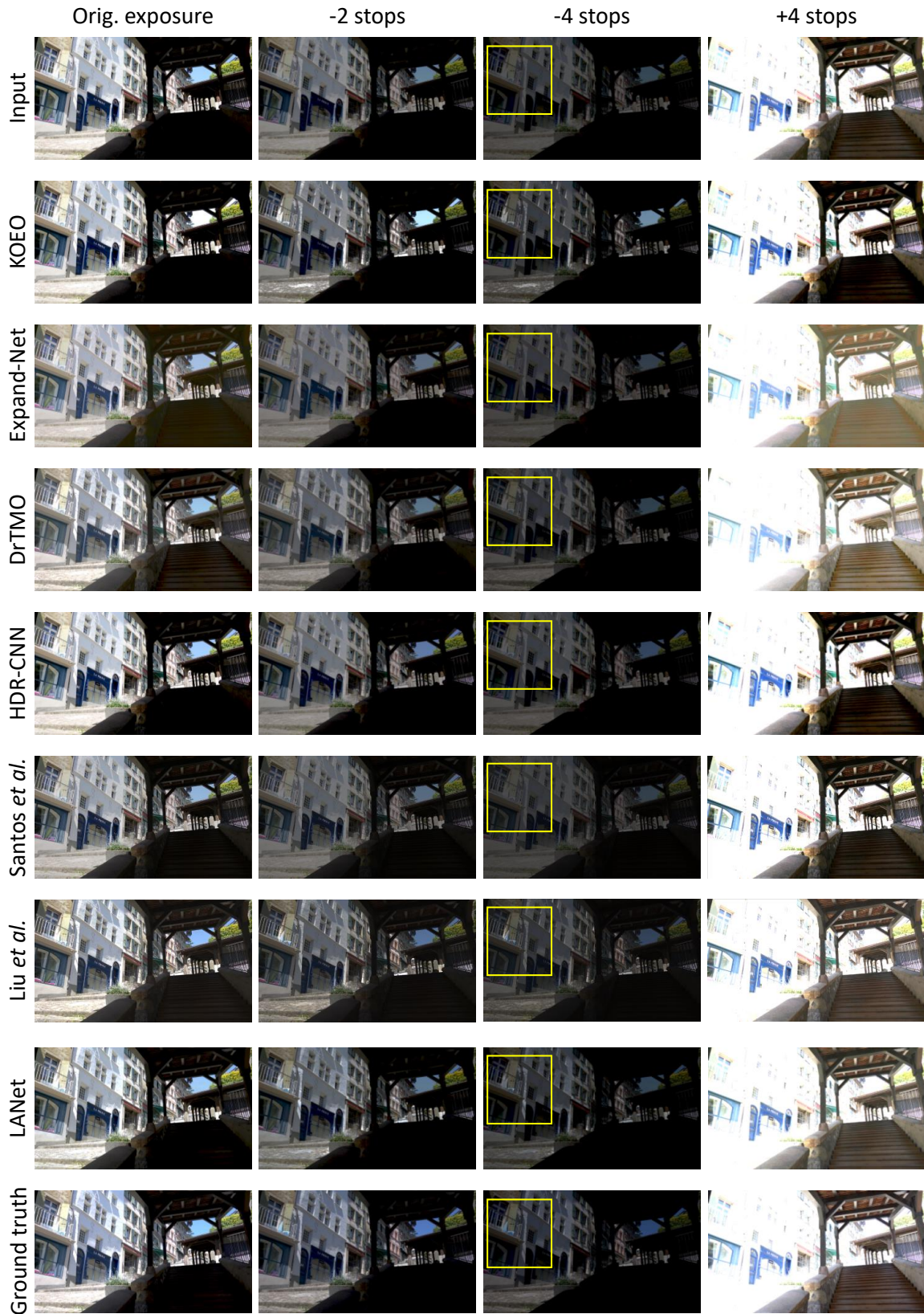


Figure 3: Comparison on outdoor scene at different visualization exposures.

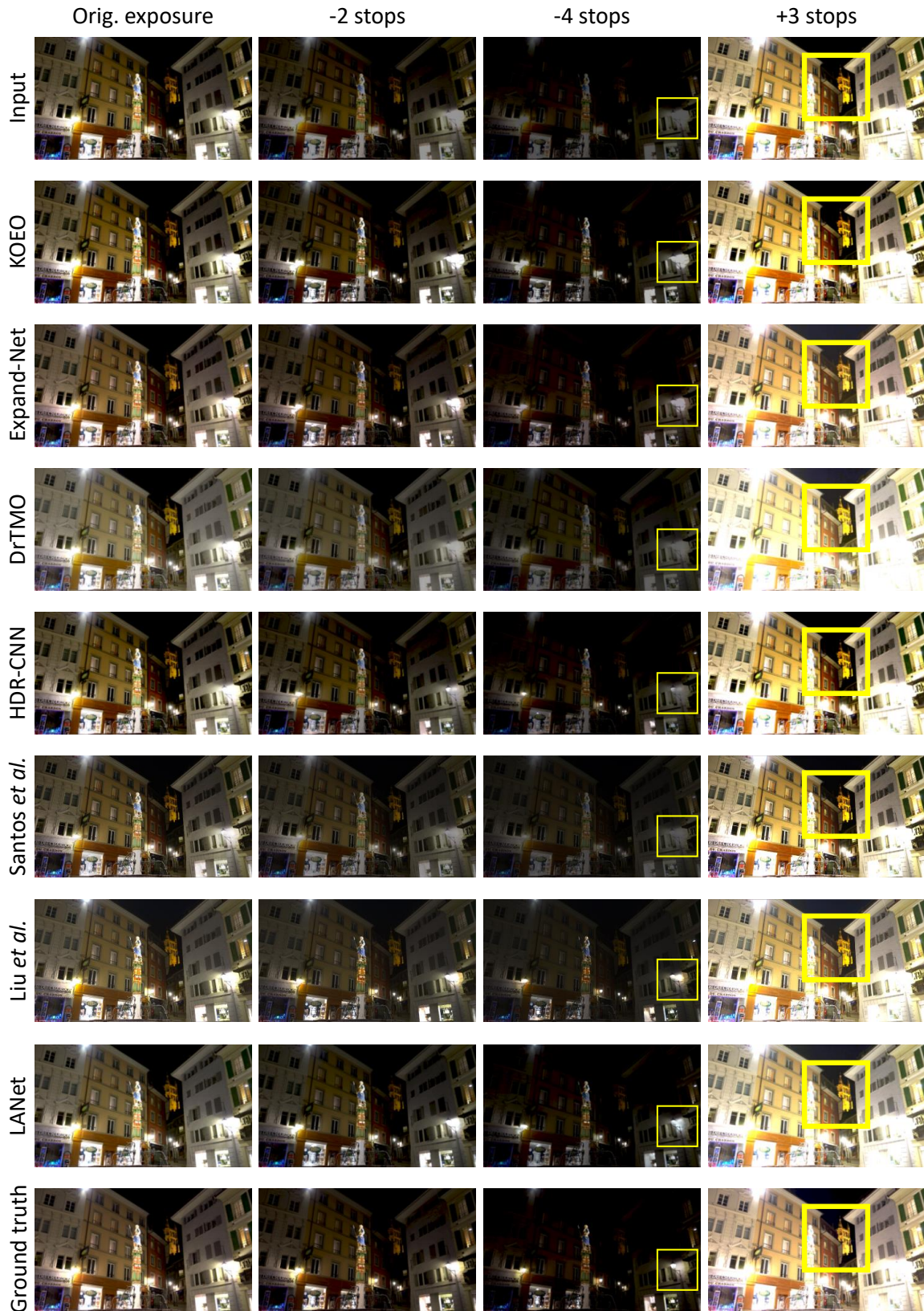


Figure 4: Comparison on night scene at different visualization exposures.



Figure 5: Comparison on extreme highlight scene at different visualization exposures.

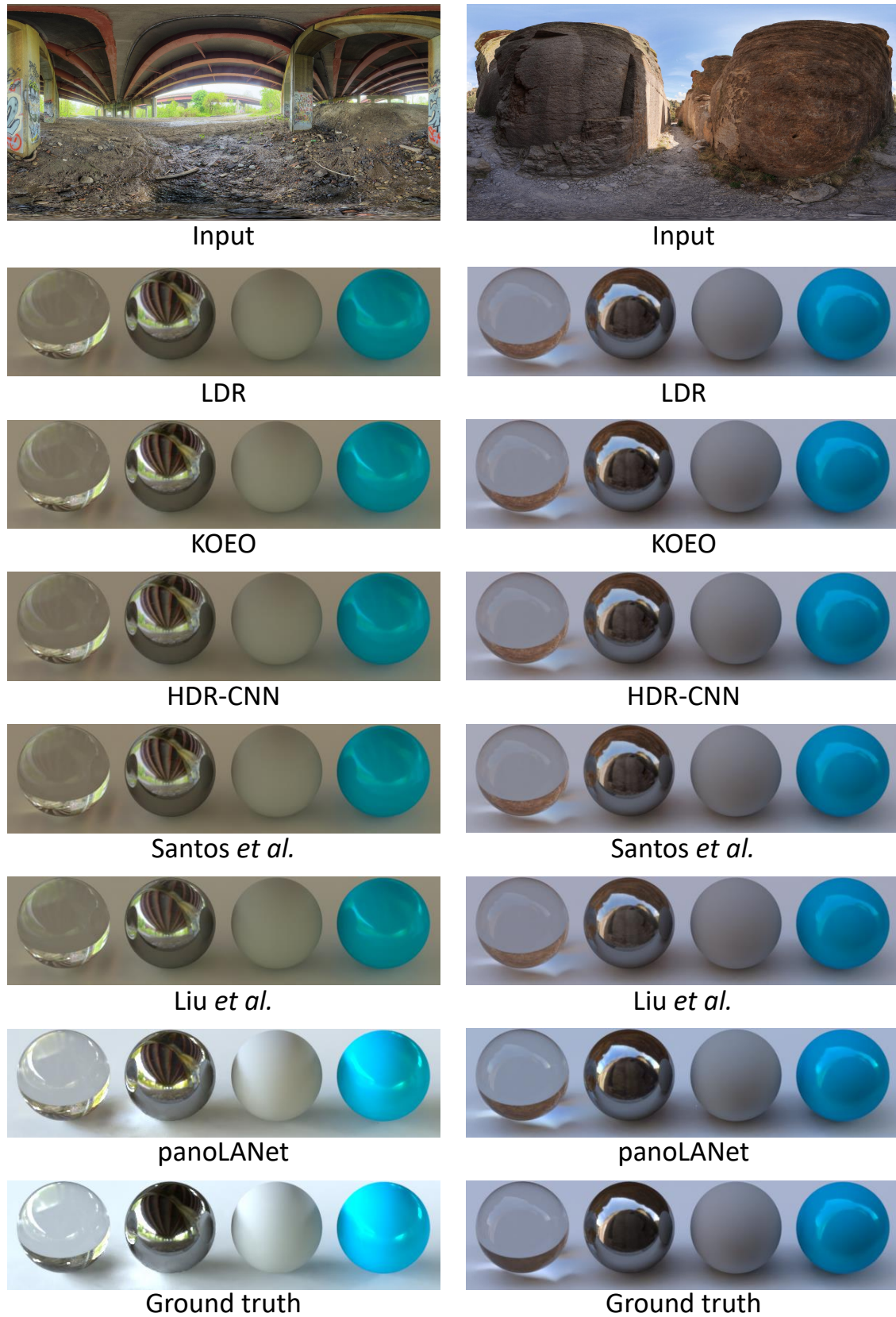


Figure 6: Comparison on rendering result of predicted panoramas.

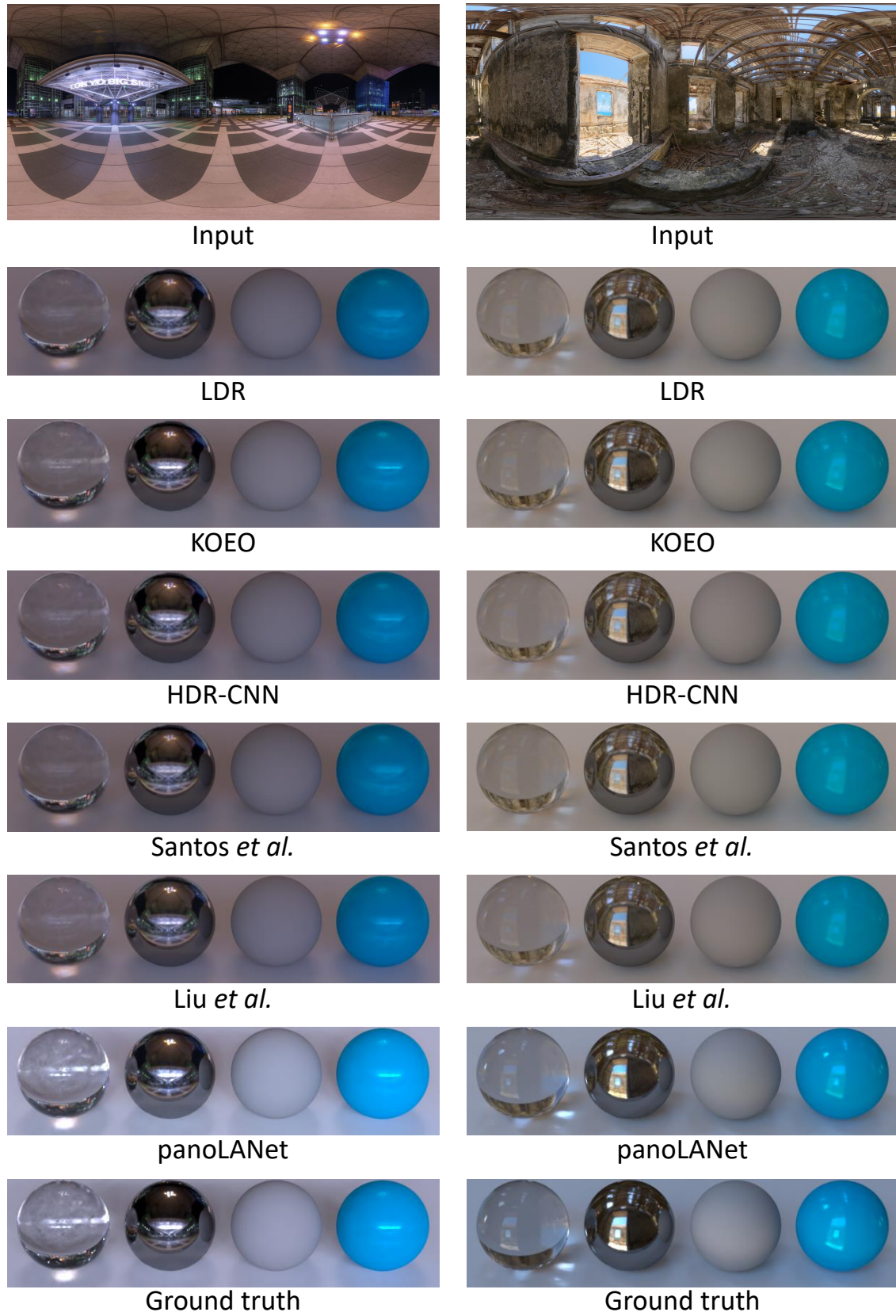


Figure 7: Comparison on rendering result of predicted panoramas.



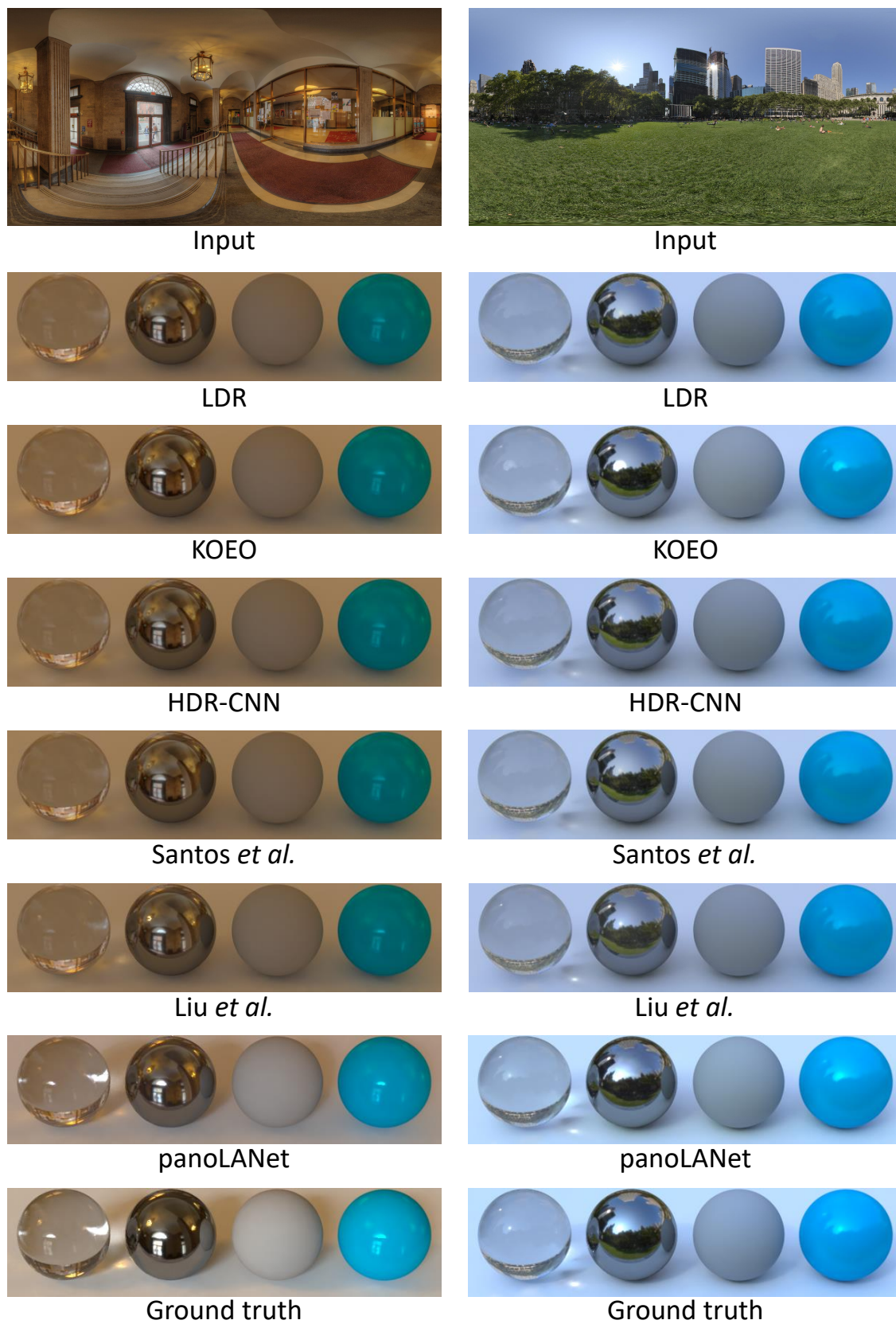


Figure 8: Comparison on rendering result of predicted panoramas.