Supplementary Material for Sensor-Independent Illumination Estimation for DNN Models

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The supplemental material provides examples of our RGB-*uv* histograms in the original sensor raw-RGB space and our learned space. We also provide additional results, including failure cases.

Examples of Generated RGB-*uv* Histograms As discussed in the main paper, our framework learns an image-specific transformation to map input images to our *working space*. Fig. 1 shows examples of the generated histograms of input images in original raw-RGB space and our learned space.

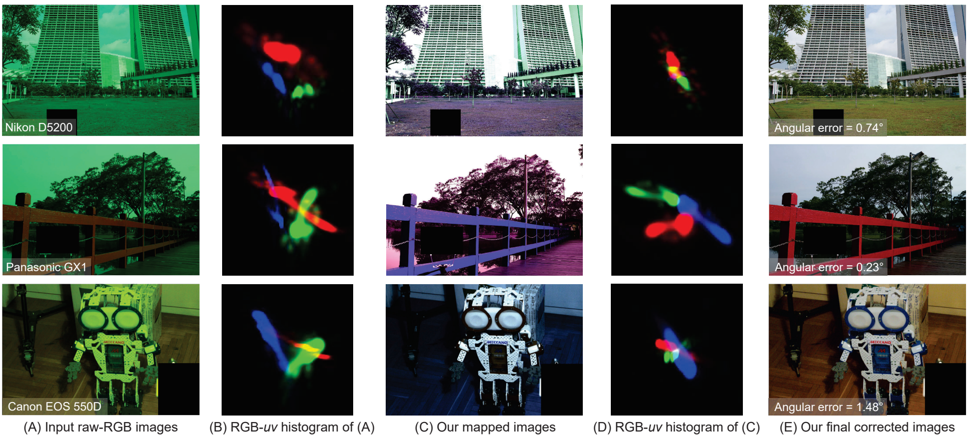


Figure 1: Example of our generated RGB-*uv* histograms. (A) Input raw-RGB images. (B) Generated histograms of images in (A). (C) After mapping images in (A) to the learned space. (D) Generated histograms of images in (C). (E) After correcting images in (A) based on our estimated illuminants. Shown images are rendered in the sRGB color space by the camera imaging pipeline in [6] to aid visualization.

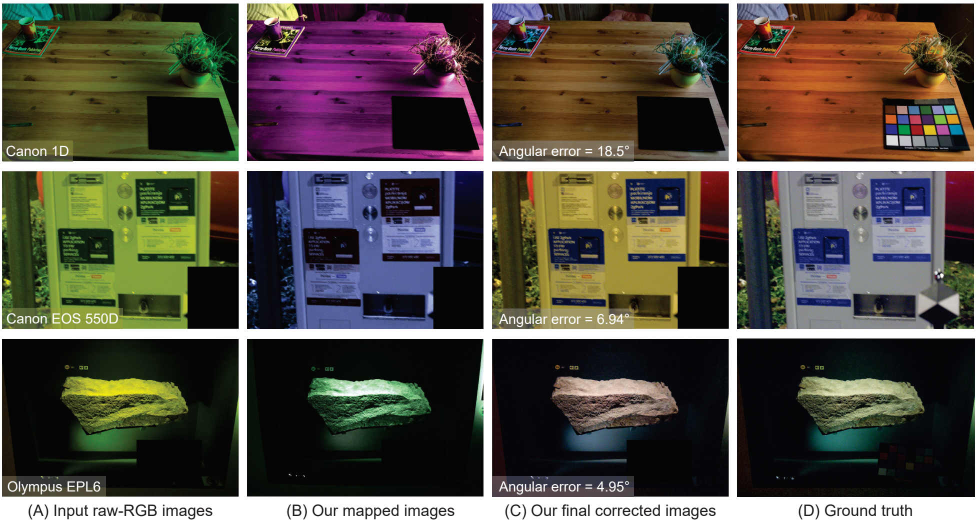


Figure 2: Failure cases of our method. (A) Input raw-RGB images. (B) After mapping images in (A) to the learned space. (C) After correcting images in (A) based on our estimated illuminants. (D) Corrected by ground truth illuminants. Shown images are rendered in the sRGB color space by the camera imaging pipeline in [6] to aid visualization.

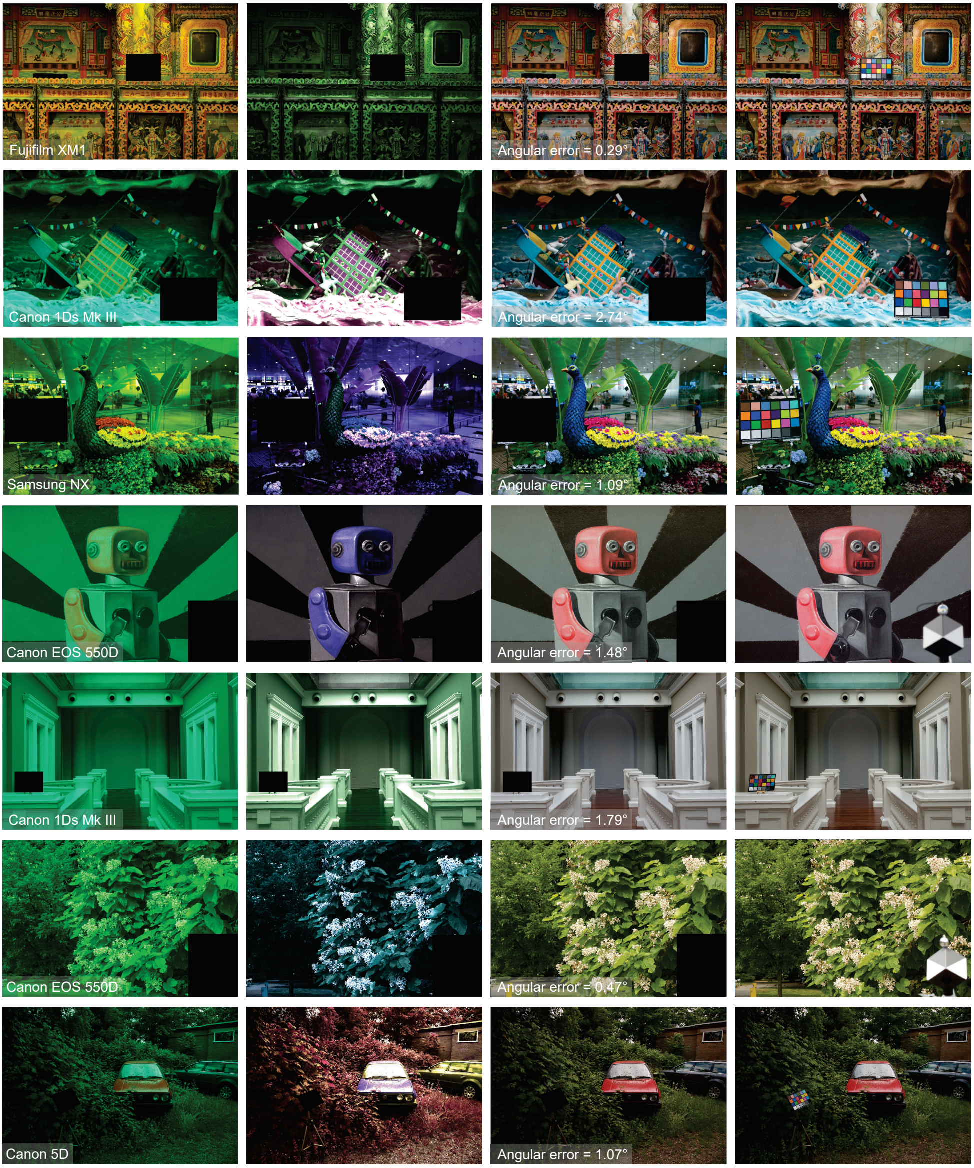
Additional Results In Table 1, we show our results on each camera of the NUS 8-Camera dataset. We report the mean, median, best 25%, and the worst 25% of the angular error between our estimated illuminants and ground truth.

Table 2 provides our results obtained on the Cube+ challenge [1] using different trained models. The models were originally trained for evaluation on NUS 8-Camera [3], Gehler-Shi [5], and Cube+ [2] datasets using the leave-one-out cross-validation scheme, as discussed in the main paper. We did not use any example from the Cube+ challenge testing set in the training/validation phases.

We note that our method does fail in some cases. Fig. 2 shows failure examples. Fig. 3 shows additional qualitative results from NUS 8-Camera [3], Gehler-Shi [5], and Cube+ [2] datasets. The shown results were obtained by models trained without any example from the testing camera sensor.

Table 1: Our results (angular errors) on each camera of the NUS 8-Camera [3].

	NUS 8-Cameras Dataset							
Camera	**Canon EOS 1Ds MrkIII**	**Canon EOS 600D**	**Fujifilm XM1**	**Nikon D5200**	**Olympus EPL6**	**Panasonic GX1**	**Samsung NX2000**	**Sony SLT-A57**
Mean	2.07	1.99	2.08	2.06	2.26	1.82	1.71	2.29
Median	1.59	1.43	1.46	1.51	1.73	1.41	1.32	1.78
Best 25%	0.48	0.56	0.56	0.55	0.63	0.49	0.41	0.54
Worst 25%	4.51	4.43	4.63	4.44	4.70	3.83	3.71	5.16



(A) Input raw-RGB images (B) Our mapped images (C) Our final corrected images (D) Ground truth

Figure 3: Additional qualitative results of our method. (A) Input raw-RGB images. (B) After mapping images in (A) to the learned space. (C) After correcting images in (A) based on our estimated illuminants. (D) Corrected by ground truth illuminants. Shown images are rendered in the sRGB color space by the camera imaging pipeline in [6] to aid visualization.

Table 2: This table shows the angular and reproduction angular errors [4] obtained on the Cube+ challenge [1] using our trained models. The shown results were obtained by the same models used for evaluation on the other datasets (i.e., NUS, Gehler-Shi, and Cube+). The models were trained using the leave-one-out cross-validation scheme, as mentioned in the main paper. We did not use any example from the Cube+ challenge testing set in the training/validation sets. The reported results in the main paper are highlighted in green.

Cube+ challenge Method	**Mean**	**Med.**	**Best 25%**	**Worst 25%**
Trained wo/ Canon EOS 550 D (Cube+)	2.89	1.72	0.71	7.06
Trained wo/ Canon 1Ds MkIII (NUS)	1.98	1.22	0.43	4.89
Trained wo/ Canon 600D (NUS)	1.96	1.31	0.44	4.72
Trained wo/ Fujifilm XM1 (NUS)	2.31	1.61	0.52	5.36
Trained wo/ Nikon D5200 (NUS)	1.97	1.22	0.47	4.75
Trained wo/ Olympus EPL6 (NUS)	2.4	1.92	0.58	5.21
Trained wo/ Panasonic GX1 (NUS)	2.21	1.44	0.65	5.14
Trained wo/ Samsung NX2000 (NUS)	2.02	1.38	0.38	4.92
Trained wo/ Sony SLT-A57 (NUS)	2.1	1.23	0.47	5.38
Trained wo/ Sony Canon 5D (Gehler-Shi)	2.02	1.27	0.432	4.927

Cube+ challenge Method	**Mean**	**Med.**	**Best 25%**	**Worst 25%**
Trained wo/ Canon EOS 550 D (Cube+)	3.97	2.31	0.86	10.07
Trained wo/ Canon 1Ds MkIII (NUS)	2.65	1.59	0.54	6.54
Trained wo/ Canon 600D (NUS)	2.59	1.69	0.53	6.248
Trained wo/ Fujifilm XM1 (NUS)	3.08	2.19	0.67	7.1
Trained wo/ Nikon D5200 (NUS)	2.62	1.73	0.57	6.29
Trained wo/ Olympus EPL6 (NUS)	3.23	2.59	0.76	6.97
Trained wo/ Panasonic GX1 (NUS)	2.89	1.86	0.74	6.86
Trained wo/ Samsung NX2000 (NUS)	2.7	1.89	0.48	6.51
Trained wo/ Sony SLT-A57 (NUS)	2.8	1.54	0.58	7.27
Trained wo/ Sony Canon 5D (Gehler-Shi)	2.69	1.68	0.54	6.59

References

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