On Finding Gray Pixels - Supplement

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1. Detailed settings of learning-based methods

To evaluate the performance of learning-based method in camera-agnostic scenario, we re-run the Bayesian method [4], Chakrabarti *et al.* 2015 [2], FFCC [1], and the method by Cheng *et al.* 2015 [3], using the codes provided by the authors. FFCC shows the best overall performance in the camera-known setting. Our experimental settings for re-running the aforementioned algorithms are summarized below:

Bayesian method [4]	Among all variations of Bayesian methods stated in [4], we use Bayes (GT) but without indoor/outdoor split, to which Bayes (tanh) is sensible. The ground truth of training illuminations (*e.g.* Gehler-Shi) is used as point-set prior for testing on the other dataset (*e.g.* NUS 8-camera)
Chakrabarti *et al.* 2015 [2]	We use both variations given by the author: the empirical and the end-to-end trained method. We keeps all training hyperparameters same, *e.g.* epoch number, momentum and learning-rate for SGD.
FFCC [1]	For fair comparison, we use Model (J) (FFCC full,4 channels) in [1], which is free of camera metadata and semantic information but still state-of-the-art.
Cheng *et al.* 2015 [3]	Same as [3], we use four 2D features with an ensemble of regression trees (K=30).

2. Uniform black level and saturation correction

Since the original learning-based methods mentioned previously in Section 1 do not share the same process to correct black-level offset and pixel saturation, we implemented a unique pre-processing pipeline for all the methods. Although this implementation detail is often neglected in the literature, we realized that this can change slightly the linear relationship between the scene illumination and the captured image values. Table 1 summarizes black level B and saturation level S for each camera of the Gehler-Shi and NUS 8-camera datasets. In this work, we pre-process all images as:

$$I_i^{(x,y)} = \max\left\{0, I_i^{(x,y)} - B\right\}, \tag{1}$$

$$I_i^{(x,y)} = \min\left\{1, \frac{I_i^{(x,y)}}{0.95S - B}\right\}, \tag{2}$$

In addition, we include a boolean mask $M^{(x,y)}$ aimed at discarding very dark pixels for subsequent analysis:

$$M^{(x,y)} = \begin{cases} 1, & |I|^{(x,y)} \le 0.0315 \times \max(I) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

3. More Visual Results

- See Fig. 1 for More visual results on spatial-illumination MIMO benchmark.
- See Fig. 2 for More visual results on single-illumination Gehler-Shi benchmark.
- See Fig. 3 for More visual results on single-illumination NUS 8-camera benchmark.

Table 1: Black level and Saturation level for each camera of two benchmarks.

	Gehler-Shi		NUS 8-camera							
	Canon 1D	Canon 5D	Canon 1DS Mark3	Canon 600D	Fujifilm X-M1	Nikon D5200	Olympus E-PL6	Panasonic DMC-GX1	Samsung NX2000	Sony SLT-A57
B	0	129	1024	2048	256	0	255	143	0	128
S	4095	4095	15279	15303	4079	15892	4043	4095	4095	4093

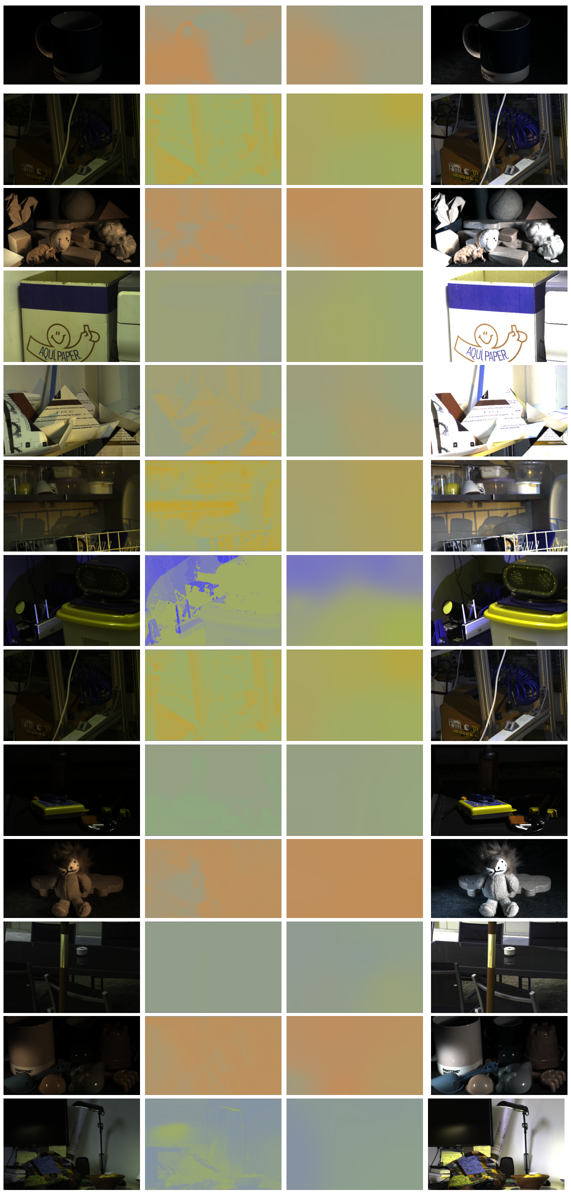

Figure 1: Qualitative results on (multi-illumination) MIMO dataset. From left to right, color-biased input, groundtruth spatial illumination, our spatial estimation using GI, our corrected image.

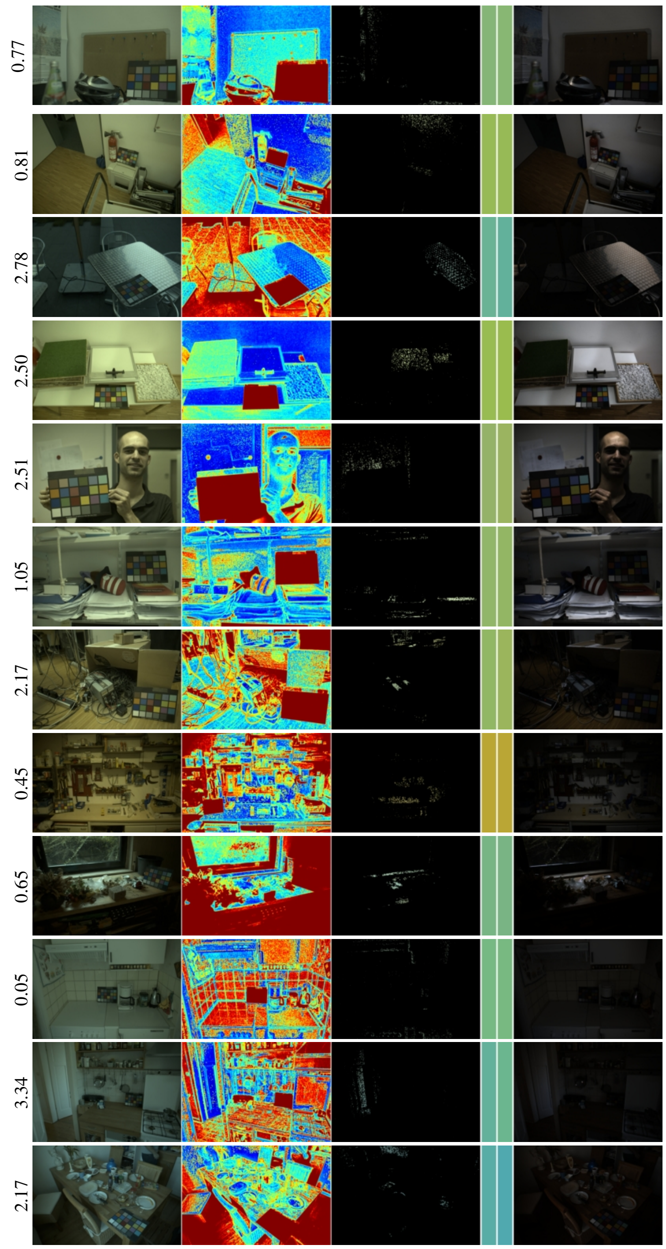

Figure 2: Qualitative results on the single-illumination Gehler-Shi. From left to right: angular error, input image, GI, top 1% pixels chosen as gray pixel, estimated illumination color, the ground truth color and corrected image using the predicted illumination. Macbeth Color Checker is always masked as GI finds perfect gray patch as gray pixels.

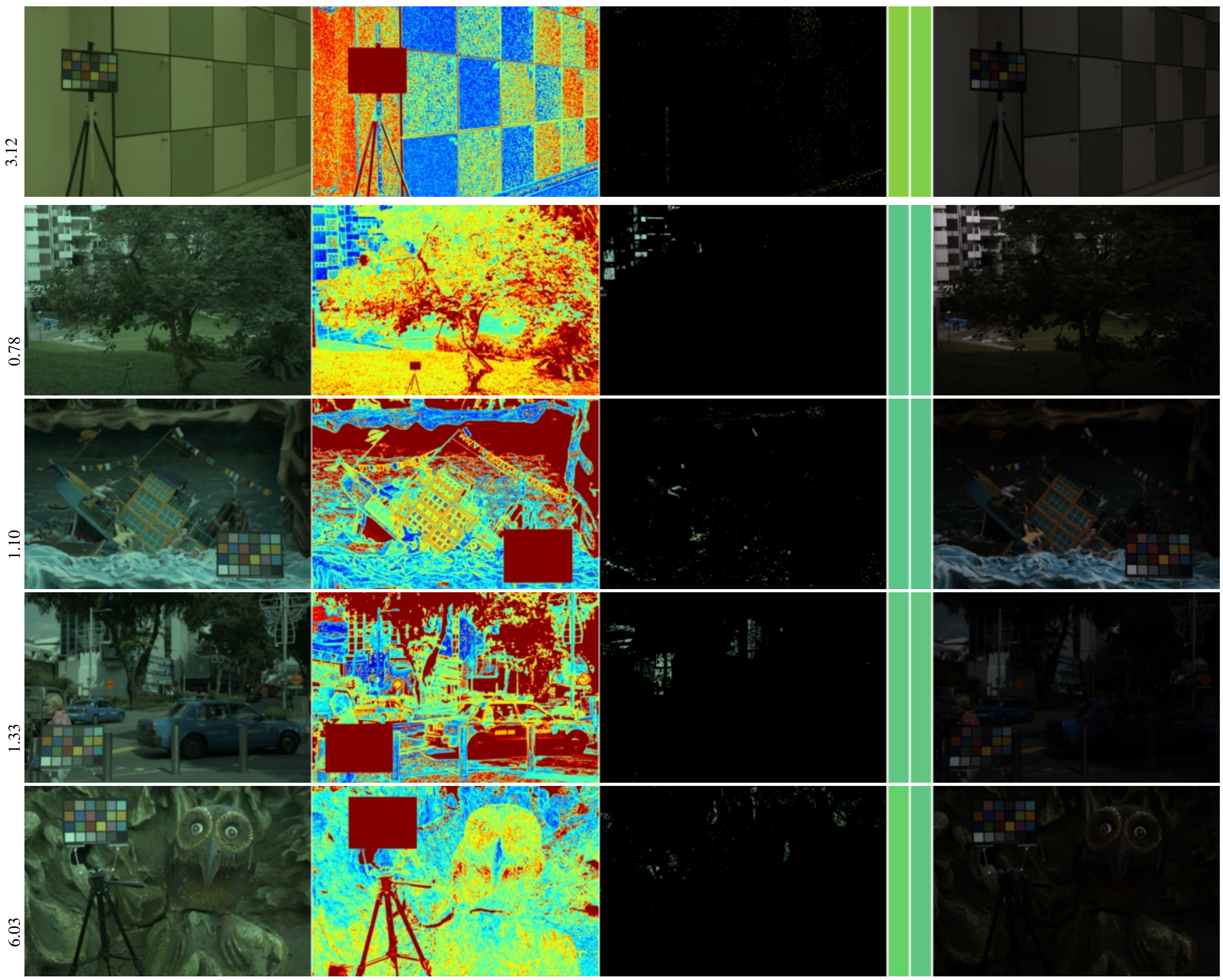

Figure 3: Qualitative results on the single-illumination NUS 8-camera benchmark. From left to right: angular error, input image, GI, top 1% pixels chosen as gray pixel, estimated illumination color, the ground truth color and corrected image using the predicted illumination.Macbeth Color Checker is always masked as GI finds perfect gray patch as gray pixels.

References

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[4] P. V. Gehler, C. Rother, A. Blake, T. Minka, and T. Sharp. Bayesian color constancy revisited. In *CVPR*, 2008. 1