

Effective Learning-Based Illuminant Estimation Using Simple Features

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1. Supplementary Material Description

This supplementary material provides additional metrics to evaluate the performance of our method with regards to prior work. In the main paper, we provide the following statistics: mean, median, tri-mean, best-25% and worst-25%. Here we examine three additional performance indicators. The first two follow the recommendation by Hordley and Finlayson [13] by using hypothesis testing to determine if there is a statistical significant difference in the results between two methods. The metric used for this testing was the *sign test* [12] and the *Kolmogorov-Smirnov (K-S) test* [12]. The sign test computes the median result on a data set for two methods, A and B . In Hordley and Finlayson [13] approach, if the difference is statistically significant a “+1” or “-1” is used to indicate that the A ’s result was better or worse than B ’s result respectively. If the difference is not statistically significant a “0” is assigned. The K-S test examines if the errors in A tend to be larger or smaller than those in B based on the cumulative distribution function (more technically the empirical distribution function) of the errors over the data sets. Again, the “+1”, “-1” or “0” is used to denote if the K-S test is better, worse, or the difference was not statistically significant. Table 1 and Table 2 report the sign test and K-S test of every pair of algorithms (20 different algorithms including ours) on the Gehler-Shi [9, 15] data set with confidence level of 98%. It can be seen that both hypothesis testings for the mean test and K-S test indicate the proposed approach outperform the others. Here we only evaluate on the Gehler-Shi data set because this is the only data set we have the complete results for all the methods.

We provide an additional test that computes the percentage of images in the data set that a particular algorithm outperforms another. Table 3 reports this metric for every pair of 20 different algorithms including ours, again on the Gehler-Shi [9, 15] data set. Table 4 provides an average summary statistic of Table 3. It can be seen that learning-based methods usually outperform statistical methods over more than 50% of the images. The proposed method outperforms all other methods.

Finally, Figure 1 and Figure 2 provides additional subjective comparisons on a number of images and methods to give a better idea of the visual impact of the results.

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	Grey-world [2]	White-patch [14]	Shades-of-grey [6]	General Grey-world [17]	1st-order Grey-edge [17]	2nd-order Grey-edge [17]	Bright-and-dark Colors PCA [4]	Local Surface Reflectance [8]	Pixel-based Gamut [11]	Edge-based Gamut [11]	Intersection-based Gamut [11]	SVR Regression [7]	Bayesian [9]	Spatio-spectral [3]	Natural Image Statistics [10]	CART-based Combination [1]	Bottom-up+Top-down [18]	Exemplar-based [16]	19-Edge Corrected-moment [5]	Our Proposed
1	0	0	-1	-1	-1	-1	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
2	0	0	-1	-1	0	0	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
3	+1	+1	0	-1	+1	+1	-1	-1	0	+1	0	+1	0	-1	-1	-1	-1	-1	-1	-1
4	+1	+1	+1	0	+1	+1	-1	-1	0	+1	0	+1	+1	-1	-1	-1	-1	-1	-1	-1
5	+1	0	-1	-1	0	-1	-1	-1	-1	+1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
6	+1	0	-1	-1	+1	0	-1	-1	-1	+1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
7	+1	+1	+1	+1	+1	+1	0	+1	+1	+1	+1	+1	+1	0	+1	+1	+1	0	0	-1
8	+1	+1	+1	+1	+1	+1	-1	0	0	+1	0	+1	+1	0	+1	+1	-1	-1	-1	-1
9	+1	+1	0	0	+1	+1	-1	0	0	+1	0	+1	+1	-1	0	-1	0	-1	-1	-1
10	0	0	-1	-1	-1	-1	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
11	+1	+1	0	0	+1	+1	-1	0	0	+1	0	+1	+1	-1	0	-1	0	-1	-1	-1
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1
13	+1	+1	0	-1	+1	+1	-1	-1	-1	+1	-1	+1	0	-1	-1	-1	-1	-1	-1	-1
14	+1	+1	+1	+1	+1	+1	0	0	+1	+1	+1	+1	+1	0	+1	0	0	-1	-1	-1
15	+1	+1	+1	+1	+1	+1	-1	-1	0	+1	0	+1	+1	-1	0	0	-1	-1	-1	-1
16	+1	+1	+1	+1	+1	+1	-1	-1	+1	+1	+1	+1	+1	0	0	0	-1	-1	-1	-1
17	+1	+1	+1	+1	+1	+1	-1	+1	0	+1	0	+1	+1	0	+1	+1	0	-1	-1	-1
18	+1	+1	+1	+1	+1	+1	0	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	0	0	-1
19	+1	+1	+1	+1	+1	+1	0	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	0	0	-1
20	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	0

Table 1: Sign test results on the Gehler-Shi data set [9, 15] with 98% confidence level. A positive value (+1, indicated by green cells) at table location ($row = i, column = j$) means algorithm i has statistically significant lower errors. A negative value (-1, indicated by red cells) means the opposite. Zero (indicated by yellow cells) means the different in the methods errors is not statically significant. The proposed method is in the last row and column. The “+1”s in the last row show that the proposed method produces statically significant better results on the sign test than all other methods.

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	Grey-world [2]	White-patch [14]	Shades-of-grey [6]	General Grey-world [17]	1st-order Grey-edge [17]	2nd-order Grey-edge [17]	Bright-and-dark Colors PCA [4]	Local Surface Reflectance [8]	Pixel-based Gamut [11]	Edge-based Gamut [11]	Intersection-based Gamut [11]	SVR Regression [7]	Bayesian [9]	Spatio-spectral [3]	Natural Image Statistics [10]	CART-based Combination [1]	Bottom-up+Top-down [18]	Exemplar-based [16]	19-Edge Corrected-moment [5]	Our Proposed
1	0	0	-1	-1	-1	-1	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
2	0	0	-1	-1	-1	0	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
3	+1	+1	0	0	+1	+1	-1	-1	-1	+1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
4	+1	+1	0	0	+1	+1	-1	-1	-1	+1	-1	+1	0	-1	0	-1	-1	-1	-1	-1
5	+1	+1	-1	-1	0	0	-1	-1	-1	+1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
6	+1	0	-1	-1	0	0	-1	-1	-1	+1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
7	+1	+1	+1	+1	+1	+1	0	0	0	+1	0	+1	+1	+1	+1	+1	+1	0	0	-1
8	+1	+1	+1	+1	+1	+1	0	0	0	+1	0	+1	+1	+1	+1	+1	-1	-1	-1	-1
9	+1	+1	+1	+1	+1	+1	0	0	0	+1	0	+1	+1	0	+1	+1	0	0	-1	-1
10	0	0	-1	-1	-1	-1	-1	-1	-1	0	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
11	+1	+1	+1	+1	+1	+1	0	0	0	+1	0	+1	+1	0	+1	+1	0	0	-1	-1
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1
13	+1	+1	+1	0	+1	+1	-1	-1	-1	+1	-1	+1	0	-1	-1	-1	-1	-1	-1	-1
14	+1	+1	+1	+1	+1	+1	-1	-1	0	+1	0	+1	+1	0	0	0	-1	-1	-1	-1
15	+1	+1	+1	0	+1	+1	-1	-1	-1	+1	-1	+1	+1	0	0	0	-1	-1	-1	-1
16	+1	+1	+1	+1	+1	+1	-1	-1	-1	+1	-1	+1	+1	0	0	0	-1	-1	-1	-1
17	+1	+1	+1	+1	+1	+1	-1	+1	0	+1	0	+1	+1	+1	+1	+1	0	0	-1	-1
18	+1	+1	+1	+1	+1	+1	0	+1	0	+1	0	+1	+1	+1	+1	+1	0	0	0	-1
19	+1	+1	+1	+1	+1	+1	0	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	0	0	-1
20	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	0

Table 2: K-S test results on the Gehler-Shi data set [9, 15] with 98% confidence level. A positive value (+1, indicated by green cells) at table location ($row = i, column = j$) means algorithm i has statistically significant lower errors. A negative value (-1, indicated by red cells) means the opposite. Zero (indicated by yellow cells) means the different in the methods errors is not statically significant. The proposed method is in the last row and column. The “+1”s in the last row show that the proposed method produces statically significant better results on the K-S test than all other methods.

	Grey-world [2]	White-patch [14]	Shades-of-grey [6]	General Grey-world [17]	1st-order Grey-edge [17]	2nd-order Grey-edge [17]	Bright-and-dark Colors PCA [4]	Local Surface Reflectance [8]	Pixel-based Gamut [11]	Edge-based Gamut [11]	Intersection-based Gamut [11]	SVR Regression [7]	Bayesian [9]	Spatio-spectral [3]	Natural Image Statistics [10]	CART-based Combination [1]	Bottom-up+Top-down [18]	Exemplar-based [16]	19-Edge Corrected-moment [5]	Our Proposed
1	-	53.2	26.1	25.0	34.7	35.0	21.0	17.4	31.7	46.7	32.0	57.9	33.5	16.0	25.2	23.8	20.4	15.1	17.4	14.4
2	46.8	-	29.4	29.0	47.9	46.5	24.3	24.5	16.9	53.9	17.3	57.0	35.9	27.5	24.3	23.2	23.6	19.9	20.2	17.6
3	73.9	70.6	-	45.2	59.3	56.5	31.9	32.0	48.9	71.3	49.1	73.1	52.6	29.8	41.5	35.2	33.6	27.1	26.6	22.5
4	75.0	71.0	54.8	-	63.7	62.0	35.2	35.7	48.8	73.2	48.9	75.7	54.6	35.0	44.7	37.3	37.1	31.3	32.7	24.8
5	65.3	52.1	40.7	36.3	-	41.7	26.1	24.8	30.3	65.1	30.1	67.6	33.1	22.9	30.3	31.5	27.5	17.4	21.0	18.1
6	65.0	53.5	43.5	38.0	58.3	-	25.7	22.4	30.5	63.4	30.6	69.4	37.3	22.0	30.1	31.7	28.0	17.4	21.3	19.0
7	79.0	75.7	68.1	64.8	73.9	74.3	-	57.7	57.2	77.8	57.4	81.3	66.4	53.7	60.9	59.7	55.3	48.9	47.2	37.9
8	82.6	75.5	68.0	64.3	75.2	77.6	42.3	-	52.1	78.7	52.5	87.1	63.6	52.5	60.2	56.3	44.2	37.9	37.7	28.3
9	68.3	83.1	51.1	51.2	69.7	69.5	42.8	47.9	-	82.7	50.4	78.5	62.3	44.0	51.8	44.7	48.8	41.9	43.1	36.8
10	53.3	46.1	28.7	26.8	34.9	36.6	22.2	21.3	17.3	-	17.1	61.4	24.1	21.8	22.0	21.3	21.8	16.9	14.3	13.9
11	68.0	82.7	50.9	51.1	69.9	69.4	42.6	47.5	46.5	82.9	-	77.8	62.3	43.8	51.8	44.5	48.4	41.7	42.8	36.6
12	42.1	43.0	26.9	24.3	32.4	30.6	18.7	12.9	21.5	38.6	22.2	-	23.8	14.4	21.5	20.2	13.6	10.9	11.4	9.3
13	66.5	64.1	47.4	45.4	66.9	62.7	33.6	36.4	37.7	75.9	37.7	76.2	-	35.2	43.0	37.7	35.4	27.6	26.1	21.3
14	84.0	72.5	70.2	65.0	77.1	78.0	46.3	47.5	56.0	78.2	56.2	85.6	64.8	-	58.6	53.9	45.8	37.9	35.4	30.3
15	74.8	70.2	58.5	55.3	69.7	57.0	39.1	39.8	48.2	78.0	48.2	78.5	57.0	41.4	-	45.6	43.0	32.2	34.5	27.5
16	76.2	76.6	64.8	62.7	68.5	68.3	40.3	43.7	55.3	78.7	55.5	79.8	62.3	46.1	54.2	-	42.3	34.3	34.3	28.2
17	79.6	76.4	66.4	62.9	72.5	72.0	44.7	55.8	51.2	78.2	51.6	86.4	64.6	54.2	57.0	57.7	-	45.4	40.7	31.0
18	84.9	80.1	72.9	68.7	82.6	82.6	51.1	62.1	58.1	83.1	58.3	89.1	72.4	62.1	67.8	65.7	54.6	-	46.8	37.5
19	82.6	79.8	73.4	67.3	79.0	78.7	52.8	62.3	56.9	85.7	57.2	88.6	73.9	64.6	65.5	65.7	59.3	53.2	-	39.4
20	85.6	82.4	77.5	75.2	81.9	81.0	62.1	71.7	63.2	86.1	63.4	90.7	78.7	69.7	72.5	71.8	69.0	62.5	60.6	-

Table 3: Outperforming percentage on the Gehler-Shi data set [9, 15]. Number at location ($row = i, column = j$) means the percentage of images on which algorithm i outperforms algorithm j .

1	Grey-world [2]
2	White-patch [14]
3	Shades-of-grey [6]
4	General Grey-world [17]
5	1st-order Grey-edge [17]
6	2nd-order Grey-edge [17]
7	Bright-and-dark Colors PCA [4]
8	Local Surface Reflectance [8]
9	Pixel-based Gamut [11]
10	Edge-based Gamut [11]
11	Intersection-based Gamut [11]
12	SVR Regression [7]
13	Bayesian [9]
14	Spatio-spectral [3]
15	Natural Image Statistics [10]
16	CART-based Combination [1]
17	Bottom-up+Top-down [18]
18	Exemplar-based [16]
19	19-Edge Corrected-moment [5]
20	Our Proposed

28.8	30.8	46.4	49.6	35.9	37.2	63.0	59.8	56.2	27.5	55.9	23.1	46.1	60.2	52.6	56.4	60.4	67.4	67.7	74.0
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Table 4: Average outperforming percentage on the Gehler-Shi data set [9, 15] for each method against all other 19 methods. Number for each method is actually the average for each row in Figure 3 (without the diagonal entries). This provides a summary statistic of Table 3 which is easier to interpret. It can be seen our proposed method has the largest average outperforming percentage against other methods.

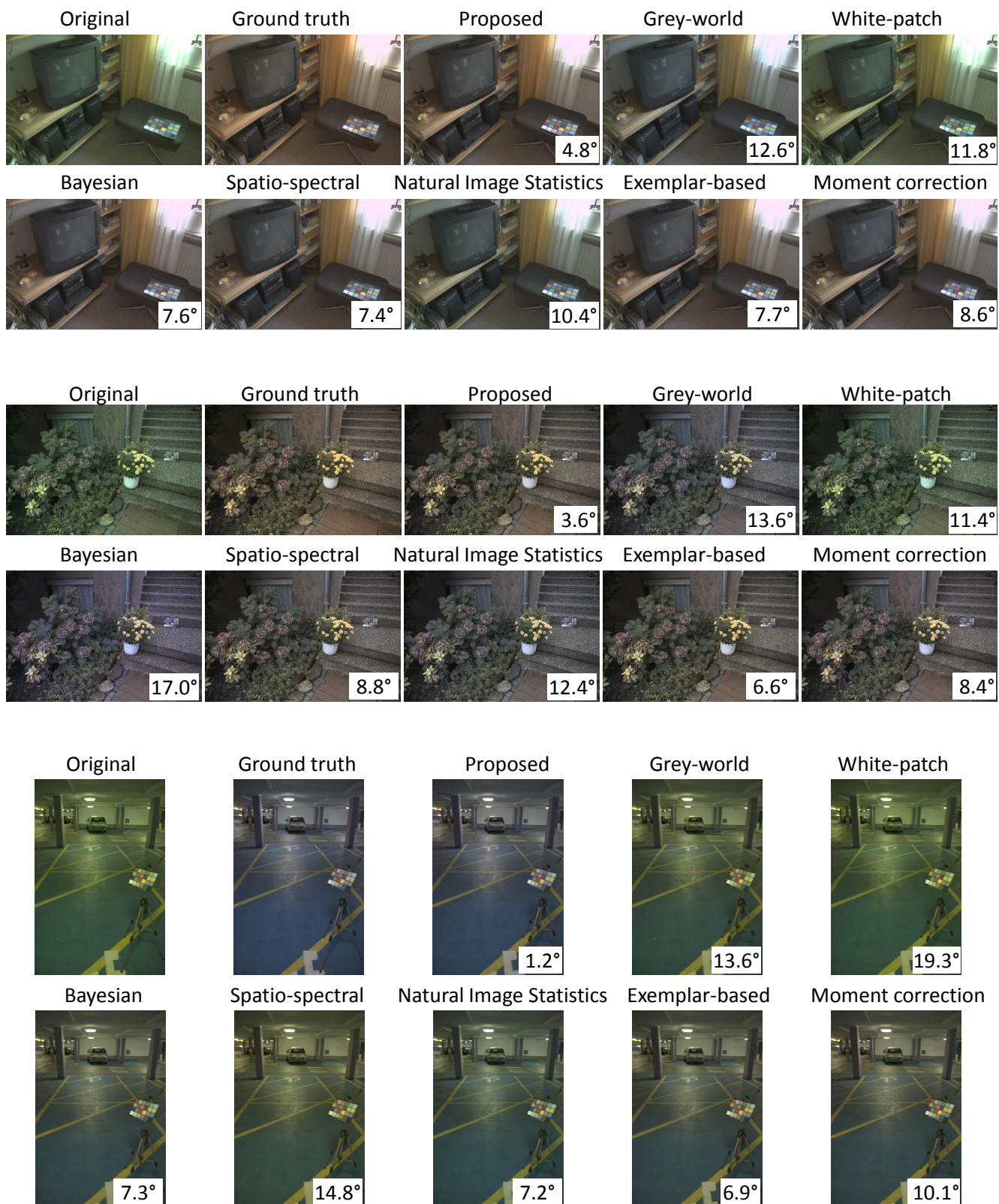


Figure 1: Corrected images using the estimated illuminant from two statistical methods and sox learning-based methods (including our proposed one). The angular error is given at the lower right corner of the image. The RAW images have been applied gamma function to boost the contrast for a better visualization. It is best viewed online.



Figure 2: Corrected images using the estimated illuminant from two statistical methods and sox learning-based methods (including our proposed one). The angular error is given at the lower right corner of the image. The RAW images have been applied gamma function to boost the contrast for a better visualization. It is best viewed online.