Rehabilitating the ColorChecker Dataset for Illuminant Estimation

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Abstract

In a previous work, it was shown that there is a curious problem with the benchmark ColorChecker dataset for illuminant estimation. To wit, this dataset has at least 3 different sets of ground-truths. Typically, for a single algorithm a single ground-truth is used. But then different algorithms, whose performance is measured with respect to different ground-truths, are compared against each other and then ranked. This makes no sense. We show in this paper that there are also errors in how each ground-truth set was calculated. As a result, all performance rankings based on the ColorChecker dataset – and there are scores of these – are inaccurate.

In this paper, we re-generate a new ‘recommended’ ground-truth set based on the calculation methodology described by Shi and Funt. We then review the performance evaluation of a range of illuminant estimation algorithms. Compared with the legacy ground-truths, we find that the difference in how algorithms perform can be large, with many local rankings of algorithms being reversed.

Finally, we draw the readers attention to our new ‘open’ data repository which, we hope, will allow the ColorChecker set to be rehabilitated and once again become a useful benchmark for illuminant estimation algorithms.

1. Introduction

The ColorChecker dataset was introduced by Gehler et al. in 2008 [1]. It has 568 images of various daily and ordinary tourist scenes (see Figure 1) mainly taken in Cambridge with two popular cameras, the Canon 1D and the Canon 5D. The ColorChecker dataset is probably the most widely used dataset in evaluating the performance of algorithms for illuminant estimation.

The goal of most illuminant estimation algorithms is to infer the chromaticity of the light. The reader will notice that each image in Figure 1 has a Macbeth ColorChecker placed in the scene. The RGB from the brightest non-saturated achromatic patch (see last row of color chart) is the correct answer – or ground-truth – for illuminant estimation, according to the calculation methodology described by Shi and Funt [2]. In fact, most of the recent work in illuminant estimation uses a linear version of the dataset, with linear images reprocessed by Shi and Funt [2] from Gehler’s original raw images [1].

Naturally, the performance of illuminant estimation algorithms – which adopt a range of strategies to infer the RGB of the illuminant – is determined by how well they predict the ground-truth illuminant color. Because we cannot distinguish between a bright scene dimly lit and the converse (because the intensity of the illuminant is not recovered), the measure which is used to quantify the accuracy of the estimation is the angular error. Given a set of angular errors, various statistical summaries are used to summarise performance. These include the mean, median or 95% quantile angular error. Given a set of algorithms and their summary performance statistics, it is natural to rank all the algorithms (according to the statistic), and then to conclude that algorithm A is better than B which is better than C (e.g. if their respective means are in an ascending order).

While there are many image sets (with respect to which, algorithms might be evaluated in performance and ranked), the ColorChecker dataset is the most widely used. Indeed, perhaps the most comprehensive survey of algorithms performance was carried out by Gijsenij et al. [3]. The results reported there are often quoted in more recent papers with the paper now cited ~400 times (April 13, 2018). The algorithms considered in this survey also form the basis of the color constancy evaluation site (color-constancy.com).

Figure 1: Images from the Macbeth ColorChecker dataset; here the images are the camera pipeline outputs.
Of course, this evaluation process makes perfect sense, in principle. In practice, we observed in [4] a surprising flaw in the methodology. Namely, we discovered that there are 3 different sets of ground-truths, one ground-truth – SFU – on www.cs.sfu.ca/~colour/data/shi_gehler/ [2] and two ground-truths – Gt1 and Gt2 – on colorconstancy.com. Unfortunately, these 3 ground-truths are used in a haphazard way. Specifically, an author will adopt one of the three ground-truths, then will evaluate the algorithm and, say, calculate the median angular error. In the next step, this median is compared against other algorithms’ median errors. But, the medians for these competitor algorithms have been calculated with respect to all 3 ground-truth correct answers. This makes no sense, especially since [4] demonstrated that using different sets of ground-truths would drastically affect the ranking of algorithms. At the time of writing this paper, there is no definitive ranking of illuminant estimation algorithms (for the ColorChecker dataset).

Here, we seek to explain why we find ourselves in this multiple ground-truth world. We then go on to make a new ‘recommended’ ground-truth (REC) for the community. Then, we present the results evaluating algorithms using this recommended ground-truth and compare our results to the benchmark evaluation and rankings. The rankings relative to the new recommended ground-truth reveal for the first time the actual pecking order in illuminant estimation for the ColorChecker dataset.

In Section 2, we discuss how we compute the new REC ground-truth and explain why this ground-truth differs from the other 3 in the literature. In section 3, we present some analysis of the relative performance of different algorithms using REC compared to the legacy data. The paper ends with a short conclusion.

2. Derivation of the RECommended Ground-truth

We adopt directly the methodology introduced by Shi and Funt [2] to re-process the raw images and re-calculate the ground-truth set of illuminants of the ColorChecker dataset. However, we have used our own code and in the interests of transparency, we will make our code accessible online [5].

![Figure 2: REC ground-truth chromaticities are plotted as black crosses. The green circles and red dots respectively denote the SFU and Gt1 ground-truths.](image)

Readers who ‘click through’ to this code and the data will find some additional information. Specifically, we explain that our data repository is ‘open’. We set forth a mechanism for the community to provide further suggested modifications to this ground-truth dataset (if necessary). In the short term, we will monitor any suggestions that the community makes and incorporate these suggestions – if they are significant – into the data. This would lead to a new recommended ground-truth. This said, we have been quite careful in our calculations so it is our hope that our new REC ground-truth will stand the test of time. If a modification is suggested, then both the current REC and the updated version will be retained and labelled with clear time stamps.

Let us outline the REC ground-truth calculation. We re-processed Gehler’s raw images to obtain linear demosaiced images using dcraw [6]. Every image has a ColorChecker in the scene. This color chart provides a reference for measuring the ground-truth illuminant. In each image, the ColorChecker chart is selected and the median RGB from the brightest achromatic patch (ranked by average of the selected squares with no digital count > 3300 [each image is in 12 bits]) defines a ground-truth illuminant. The main steps of the color chart processing are presented in Figure 3.

One point to highlight is the importance of using the same patch or patches when defining the R, G and B of the light color. We found that this property was not properly enforced in the calculation of the SFU ground-truth. In fact, we found 3 images where saturated color channels/patches were not correctly identified which resulted in having the ground-truth R, G and B values not taken from the same patch, in these three cases.

![Figure 3: The 4 main steps of the color chart processing. A) we select roughly the chart area in the image. B) we select the 4 corners of the chart. C) the chart image is geometrically transformed to be in front of the camera, then we select more precisely its contour. D) we select the centers of the 4 corners patches as well as one square of interest in one patch, this square selection is then automatically replicated over all patches. The medians per channel of the achromatic red-square regions are calculated.](image)
the ground-truth. The offsets were estimated from the minimum pixels across the whole dataset [2].

Let us discuss the ground-truths. The ground-truth set we call SFU has the 568 estimates of the RGB lights colors and it appears currently on the SFU site. On colorconstancy.com, there are two additional ground-truths, GI1 and GI2. GI1 was calculated and put online by Gijsemij in 2011. It refers to the same data as SFU but without the black level being subtracted. GI1 was calculated based on the color chart patches RGB data which is available on the SFU site [2] but without subtracting the offset. A little investigation on our part led us to the following explanation: on the current site [2], it is stated that the black level needs to be subtracted before using the data: “Note that for most applications... the black level offset will still need to be subtracted from the original images”. When looking at the same web-page using the waybackmachine.org site – that allows recovering web-pages from many years ago – the previous statement is not present and instead we can read "[the processing] also takes into account that the Canon 5D has a black level of 129, which we subtract.” We spoke to a number of researchers in the field and asked them to read the current and past web-pages. Everyone agreed that on reading the past instructions they could easily have made the same “mistake” (and not subtracted the black level). Gijsemij believes the web-page instructions are a plausible explanation of why he did not subtract the black point.

Researchers who have been in the field a long time have been using GI1 but more recent workers are using SFU. Potentially, all of these researchers think that they are using the same ground-truth. But in fact, the data are very different.

The third legacy ground-truth dataset we call GI2. It is very similar to GI1 (and so, also, different from SFU). The reason for Table 1: Ranking of 23 algorithms in terms of median recovery error for REC vs SFU vs GI1; the Minkowski norm p and the smoothing value σ are the optimal parameters.

| Algorithm | REC | SFU | GI1 |
|-----------|-----|-----|-----|
| Fast Fourier Color Constancy (model Q) [7] | 1.43° | 4.37° | 4.89° |
| 1st order Grey-Edge (p=1, r=0) [8] | 3.06° | 2.66° | 2.68° |
| Edge-based Gamut (r=4) [9] | 3.27° | 3.22° | 3.60° |
| 2nd order Grey-Edge (p=1, r=1) [8] | 3.75° | 3.59° | 4.44° |
| Bayesian1 (p=1) [10] | 3.85° | 3.78° | 3.46° |
| Deep Color Constancy using CNNs [11] | 3.94° | 3.93° | 3.99° |
| Exemplar-based Colour Constancy [12] | 4.30° | 4.31° | 4.34° |
| Pixel-based Gamut (r=4k) [9] | 4.41° | 4.43° | 4.56° |
| Intersection-based Gamut (r=4k) [9] | 4.44° | 4.43° | 4.54° |
| Bottom-up + Top-down [13] | 4.50° | 4.55° | 4.67° |
| Top-Down [13] | 4.60° | 4.62° | 4.73° |
| Using Natural Image Statistics [14] | 4.70° | 4.72° | 4.83° |
| Heavy Tailed-based Spatial Correlations [15] | 4.86° | 4.80° | 5.06° |
| Bottom-Up [13] | 4.90° | 4.90° | 5.06° |
| CART-based Selection [16] | 5.09° | 5.09° | 5.35° |
| AlexNet + SVR using CNNs [11] | 5.30° | 5.31° | 5.31° |
| CART-based Combination [19] | 5.32° | 5.32° | 5.31° |
| Natural Grey-World (p=3, r=9) [8] | 5.39° | 5.39° | 5.48° |
| White-Patch [17] | 6.00° | 6.46° | 7.35° |
| Shades-of-Grey (p=4) [18] | 6.80° | 6.85° | 7.98° |
| Regression (SVR) [19] | 9.60° | 9.62° | 10.73° |
| Grey-World [20] | 9.90° | 9.99° | 11.98° |
| Inverse-Intensity Chromaticity Space [21] | 11.68° | 11.58° | 11.32° |

3. Evaluating the Performance of Illuminant Estimation Algorithms

In what follows, we provide performance evaluation and ranking of 23 illuminant estimations for the RECOMMended and the legacy SFU and GI1 ground-truths. In Table 2 the 23 algorithms are ranked according to the median recovery angular error (i.e. the conventional error measure, which gives the angle between the estimated illuminant RGB vector and the ground-truth illuminant RGB). The ranking is the same for REC and SFU, although the median errors are slightly different. This is expected as (recall Figure 2) the number of differences between REC and
SFU is small (due to errors in the calculation). However, the ranking of algorithms according to the Gt1 dataset is markedly different (due as opposed to a different methodology of calculation).

The five best algorithms with Gt1 are not in the top 5 according to REC. Vice versa, the 5 best algorithms according to REC are among the worst-performing algorithms with Gt1. The algorithms Edge-based Gamut Mapping [9], 2nd order Grey-Edge [8] and Bayesian [1][10] are, for example, in reverse order. Fast Fourier Color Constancy [2] – which is in significant part built on top of a machine learning algorithm – is best according to the RECommended ground-truth but is the 15th best on Gt1. This may not be surprising as this algorithm was trained on SFU. Deep Color Constancy using CNNs [11] is 6th based on REC and top ranked based on Gt1. Again, this is not surprising since this algorithm was trained on Gt2 (which, we recall, is very similar to Gt1 but very different from SFU and REC).

In Table 2 we consider the ranking of the 23 illuminant estimation algorithms in terms of median reproduction angular error [23]. Reproduction error is an angle-type error that evaluates how well a white surface is reproduced. Since image reproduction is the goal of most illuminant estimation algorithms, reproduction error provides a more useful measure of algorithm performance. This time, results with REC and SFU locally differ. Once again, the results with Gt1 are significantly different. Finally notice that the ranks for the same ground-truth but recovery vs reproduction angular error results in different rankings.

In Tables 7 and 8 we do not include the results for Gt2 because they are very comparable to Gt1, however we invite the reader to consult our previous work on this topic [4]. A more complete survey is accessible on colorconstancy.com.

Conclusion

Illuminant estimation algorithms have been evaluated and compared on the benchmark ColorChecker dataset with at least three different ground-truths, with one of the three being very different to the other two. In addition, we found that all three of these sets of ground-truths were inaccurately or incorrectly calculated in the sense that small errors were made. The problem of multiple ground-truths and calculation errors has led to misleading results in the performance evaluation of illuminant estimation algorithms.

In this paper we have introduced a new RECommended ground-truth for this dataset which we hope rehabilitates the ColorChecker dataset. Broadly, we followed the methodology set forth by Shi and Funt but using our own code and we corrected a few errors made (e.g. those reported in [22]). We re-evaluated all the algorithms on the widely used comparison site for illuminant estimation algorithms, colorconstancy.com. We invite the community to refer to what we hope is a more definitive comparison in future research.

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