Two Illuminant Estimation and User Correction Preference

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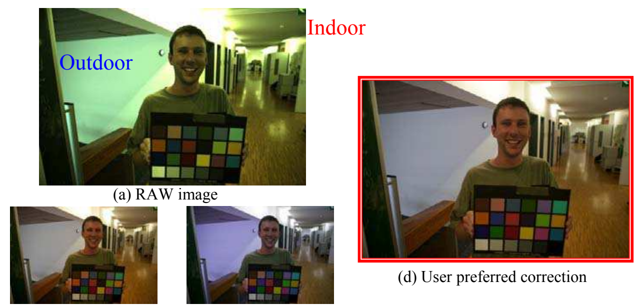
Abstract

This paper examines the problem of white-balance correction when a scene contains two illuminations. This is a two step process: 1) estimate the two illuminants; and 2) correct the image. Existing methods attempt to estimate a spatially varying illumination map, however, results are error prone and the resulting illumination maps are too low-resolution to be used for proper spatially varying white-balance correction. In addition, the spatially varying nature of these methods make them computationally intensive. We show that this problem can be effectively addressed by not attempting to obtain a spatially varying illumination map, but instead by performing illumination estimation on large sub-regions of the image. Our approach is able to detect when distinct illuminations are present in the image and accurately measure these illuminants. Since our proposed strategy is not suitable for spatially varying image correction, a user study is performed to see if there is a preference for how the image should be corrected when two illuminants are present, but only a global correction can be applied. The user study shows that when the illuminations are distinct, there is a preference for the outdoor illumination to be corrected resulting in warmer final result. We use these collective findings to demonstrate an effective two illuminant estimation scheme that produces corrected images that users prefer.

1. Introduction

Scene illumination affects the overall color of a captured image. Estimating the illumination and subsequent correction, i.e. white-balance, to remove the color cast caused by the illumination is a fundamental processing step applied to virtually all images. Most white-balance methods assume the imaged scene is uniformly illuminated with a single light source, however, it is not uncommon for a scene to be illuminated by more than one light as shown in Figure 1-(a). Most existing approaches that attempt to estimate multiple illuminations use a sliding window strategy or image segmentation to perform local illumination estimation. This results in a spatially varying illumination map over the image. Such illumination maps are typically low-resolution (e.g. 15×20) and their effectiveness in subsequent white-balance correction is often not demonstrated. Moreover, these methods tend to be slow and require prior knowledge that the imaged scene contains two illuminations.



(a) RAW image

(b) Image corrected by the outdoor illuminant

(c) Image corrected by the indoor illuminant

(d) User preferred correction

Figure 1: An example scene with two different illuminations (indoor and outdoor). The color of the original RAW image is biased by two illuminations. (b) and (c) show the images corrected by each of the illuminants respectively. (d) shows the corrected image preferred by users.

In this paper, we advocate a different strategy for addressing the two illuminant estimation problem. Specifically, we find it more effective not to attempt to estimate a spatially varying illumination map. Instead, we show that applying a single-illuminant estimation method on a relatively small number of large sub-images in the input image can not only detect if two distinct illuminants are present, but provide accurate estimations for these illuminations. Since our strategy does not provide spatial information about the two illuminations, the image must be corrected in a global manner. To this end, we perform a user study to determine if users have a preference for which illumination they would prefer to be corrected (see Figure 1). Our study found that users have a clear preference for a result that is a mixture of the two illuminations, with more weight on the outdoor illumination.

*Both authors contributed equally to this work.

Contributions This paper makes several contributions towards the estimation and correction of images containing two illuminations. First, an efficient method for accurately estimating one or two illuminations from a single image is proposed. Second, a user study is performed that reveals that users do have a strong preference for a particular correction when two distinct illuminations are present in the image. Third, we demonstrate how to combine findings from 1 and 2 into a framework for correcting images containing scenes with two illuminations. Finally, most prior works use synthetically generated two-illumination images as test cases. As part of our work, we provide a new image data set extracted from existing illumination and image-processing data sets in which the ground truth for the two illuminations has been manually identified.

We believe the findings in this paper will be beneficial in helping to develop further approaches for multi-illuminant estimation and subsequent image correction.

2. Related Work

Most computational color constancy methods focus on single illumination estimation. We assume readers are familiar with well-known single illuminant estimation methods such as Grey-world [6] and weighted Grey-edge [14]. For a good survey on single illumination estimation, see [13]. In this section, estimation methods addressing more than one illuminant are discussed. Single illumination estimation methods are only discussed in the context of their application to multiple illumination.

One of the first methods to consider non-uniform illumination is the Retinex method [19] that assumed illumination smoothly varies across a scene and abrupt changes in an image's content are caused by changes in scene reflectance properties. Ebner [9] used this assumption and proposed a method that computes the local average color as the local scene illumination by convolving the image with a Gaussian or Exponential kernel. This method can be interpreted as applying Grey-world [6] locally at every pixel. While simple, this approach [9] established a common framework adopted by many later methods: namely, divide an image into local patches/regions, apply single illuminant estimation methods locally, and post process the local results to obtain an illumination map.

Bleier et al. [4] proposed a method that segmented an image into super-pixels and then applied multiple single-illuminant estimation methods for each super-pixel. These per super-pixel estimations were fused to obtain the final local estimates. In a similar approach, Riess et al. [20] applied an improved version of the physics-based illuminant estimation method by [22] on images segmented into homogeneous regions. Gijsenij et al. [15] proposed a general method that uses local image patches that were selected by three sampling methods (grid-based, keypoint-based and segmentation-based sampling). After sampling each of the patches, single illuminant estimation techniques were applied to obtain local illuminant estimates. These initial estimates are clustered into two groups and spatial filters are applied to smooth the illuminant distributions. Beigpour et al. [2] formulated a multi-illuminant estimation within a conditional random field framework over a set of local illuminant estimates from single illuminant estimation methods.

Although many works adapt this overall framework, the results are often not satisfactory as they are bounded by the quality of the single illuminant estimation methods used. Such single illumination methods tend to perform poorly on local regions. Another drawback is that these local methods are computationally intense. As a result, the spatial resolution used by these methods are lowered to reduce the computational time. However, many are too coarse to be practical, e.g. approximately 30 super-pixels in [4] and an illumination map of size 15×20 in [2]. In addition, most of these methods do not demonstrate how to use the estimated illumination map for image correction. The ability to perform good spatially varying illumination correction is unclear.

There have been a number of bottom-up single illuminant estimation methods that have been adopted to handle multi-illumination images. Bianco and Schettini [3] and Joze and Drew [18] respectively extended the face-based and exemplar-based color constancy algorithms to deal with a known number of multiple illuminants. Yang et al. [23] proposed to identify grey pixels to estimate single and multiple illuminants. For these methods, the type of image (single or multiple illuminant) must be given explicitly.

There are works that focus only on correcting scenes with multiple illumination with user assistance. Hsu et al. [17] proposed treating two-illumination image correction as a mixture estimation problem using background-foreground matting where examples of illumination in the scene were provided by user markup. Boyadzhiev et al. [5] extended this matting approach to handle more illuminants with the addition of more user markup used to indicate neutral color, correct color and homogenous scene regions.

As discussed in Section 1, the method in this paper takes a departure from the strategy of attempting to perform local illumination estimation. This decision is made for a number of reasons. First, the nature of many of the aforementioned local approaches makes the algorithm too slow for practical purposes. More importantly, the resulting illumination estimations have not been shown to be sufficiently dense to support high-quality spatially varying illumination correction. As a result, it is felt that focusing on a computationally efficient method that can reveal the two illuminations in the scene, even without useful spatial information, is desirable as users likely have a preference of which illuminant they would prefer to be corrected.

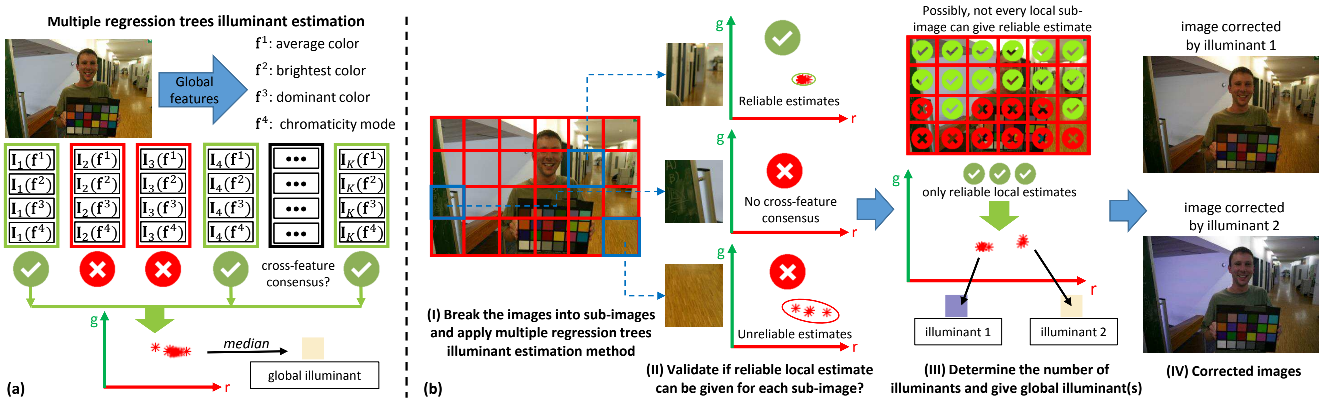


Figure 2: (a) This image provides an illustration of the regression trees method proposed by Cheng et al. [7]. This method produces a set of candidate estimates in the 2D rg-chromaticity space. The median of the candidates is used as the final estimate. (b) This image is an overview of our two-illumination method. The image is divided into sub-images. The method in (a) is applied on each sub-image. If the illumination estimate candidates obtained by (a) per sub-image are similar, the estimate result is kept (denoted with a ✓, otherwise they are rejected denoted with an $\times$). The final set of reliable estimations (i.e. those kept) are examined to see if they form one or two clusters, which are used as the illuminant estimations.

3. Proposed Two Illuminant Estimation

This section overviews the design of the proposed two illuminant estimation method. The main idea is to use a single illumination estimation method on a number of large sub-images to obtain several candidate illumination estimations. If these candidate estimations show little variation, it is assumed the image contains a single illumination. Conversely, if the candidates estimations show large variation, it is likely there are two illuminants among the candidates that can be extracted.

The accuracy of this strategy depends highly on which single illumination method is used. When determining the most suitable method, it was desirable to have a method that was not only fast and accurate, but also provided the ability to determine if a candidate estimation for a sub-image was reliable or not. To this end, we decided to use the recent work by Cheng et al. [7]. As will be discussed, not only is this method fast, but its design based on multiple classifiers provides a suitable mechanism to determine if a candidate estimation is reliable or not. We first provide a brief overview of the method in [7] in Section 3.1 and then describe the whole procedure in Section 3.2.

3.1. Single Illumination Estimation Review

Figure 2-(a) illustrates the method proposed in [7]. Illumination estimate (and correction) is perform on the RAW camera image. Given a RAW image, four features from the camera-specific RGB color distribution are extracted: $\mathbf{f^1}$: average chromaticity; $\mathbf{f^2}$: brightest chromaticity; $\mathbf{f^3}$: dominant chromaticity and $\mathbf{f^4}$: chromaticity mode of the color palette. These four features are supplied to a bank of 30 regression trees to get illuminant estimate candidates, $I_i(\mathbf{f^j})$, where $i \in [1-30]$ indicates the index of the tree and $j \in [1-4]$ indicates the feature.

These trees are trained using labeled images with known illuminations from a single camera. Given a new input image, the four features are computed on the input and the features are evaluated on the 30 regression trees to produce illumination estimation candidates in the 2D r-g chromaticity space. Note that each tree produces four candidate estimations, one for each feature. A cross-feature consensus is used to identify potential candidates per tree. In particular, when any three out of four results for a particular tree are sufficiently similar, these results are kept, otherwise they are rejected. The final estimate for the entire method is the median of all kept estimates from the 30 trees.

As noted in [7], there are cases when all of the estimates are rejected. There are also cases when the results that were kept have a great deal of discrepancy. In these cases, [7] uses the median of all the 30 trees as the final output. However, in our case, we can use these scenarios to reject this result as not being reliable for the current sub-image.

3.2. Two-Illuminant Estimation Procedure

The overall framework of our method is illustrated in Figure 2-(b). The image is divided into 4×8 sub-images (the effect of different sized sub-windows is discussed in Section 3.3). For each sub-image, the multiple regression tree [7] method just described is applied. Cross-feature consensus is examined on these initial candidates and only candidates in agreement are kept. If the regression tree approach does not obtain a consensus or the collective candidates from the trees have too high variance (set to 0.0001 in chromaticity space in our approach), the results for this sub-image are ignored, otherwise the median of the results is kept as the estimate for that sub-image. Figure 2 (b) shows an example, where rejected sub-images are marked with an $\times$ and those that have passed are marked with a $\checkmark$.

After the sub-images have been processed, we are left with a set of 2D illumination estimates in the r-g chromaticity space of the input image. We then compute the pair-wise distance of all candidates. If the average pair-wise distance is less than 0.025, it is assumed there is only a single illumination in the scene and the median of all the candidates is reported as the illumination estimation. Otherwise, the image is classified as having two illuminations, and k-means ($k = 2$) clustering is applied and the centroids of the two clusters are taken as the estimates of the two illuminations.

3.3. Evaluation and Data Set

In this section, we evaluate the performance of the proposed illumination estimation method. We also compare this with alternative designs using different single illumination estimation methods, namely: Grey-world [6] and the learning-based Corrected-Moment method [10]. We also modify an existing multi-illumination method by Gijsenij et al. [15] to fit our framework for comparison. Our evaluation is performed on images containing both two illuminations and those with single illuminations.

Before we begin, we describe how we obtained the images with two illuminations. Interestingly, we found a large number of such images in the Gehler-Shi data set [12, 21], which is a data set intended and often used for single illumination estimation. It has been noted by others (e.g. [18]) that many of the images in fact contain two illuminations. We identified 66 of the 568 images from the Gehler-Shi data set as having two illuminants. Almost all of these images contain distinct illuminations of indoor and outdoor light. The original ground truth was measured by the neutral patches on the color checker chart, and it is typically positioned such that it measures the indoor illuminant. For the ground truth of the other illuminant, we manually marked it from the image by finding neutral objects in the scene. While our manual marking is arguably not as accurate as having a color checker chart, we believe it provides a sufficiently accurate ground truth for studying this problem.

We note that Cheng et al. [7] and the Corrected-Moment method [10] require training. Since our proposed framework uses sub-images, we train these methods on sub-images. For each method, we train using images from the Gehler-Shi images that only contain a single illumination. This gives us the ground truth illuminant for every sub-image. For each training image, we randomly sample 40 sub-images from the original image for training. To evaluate the whole data set, we follow the standard three-fold cross validation procedure.

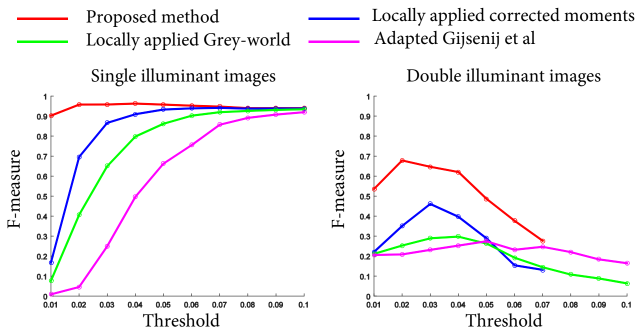


Figure 3: F-Measure curves for single and double illuminant images for the four different methods evaluated with the same set of threshold parameter values.

Table 1 shows the results. The first two methods report results of our proposed method by breaking the image into different numbers of sub-images: 4×6 and 8×12. The third and fourth methods are the same framework as described in Section 3.2, but replace the Cheng et al. method with the Grey-world [6] method and Corrected-Moment method [10] respectively using the 4×6 sub-image grid. To get the best performance of these methods, different values of the average pair-wise distance were used to determine the numbers of illuminations. We select the parameter for each method that achieves the highest F-Measure[1] for the double illumination images as shown in Figure 3. Note that [6] and [10] have no mechanism to reject outliers, so the result from all sub-images are used to compute the final result. Finally, the method by [15] is shown in the last rows. This method estimates the results on small local windows. We use all of these local window results and apply the pair-wise test as described in Section 3.2 to determine the final results.

The results are reported as follows. There are four possible outcomes. If the input image is a single illumination and is detected correctly as a single illuminant image, only one estimate is given and there is only one angular error. For an image containing two illuminations, if it is correctly detected as having two illuminants, we sort the two illuminant estimates according to their temperature and compare with the ground truth respectively: illuminant 1 represents the outdoor and illuminant 2 represents the indoor illuminant. For images detected incorrectly, we test to see if the method computed one illuminant estimate correctly, thus we report the minimal angular error and maximal angular error.

As shown in the Table 1 the proposed method achieves the highest F-Measure for both single and double illumination images. When we apply our proposed method in a finer scale (method 2), however, it does not improve the performance. The chance of correctly detecting the two-illumination image may increase, but it drops quickly for

[1] See supplemental material for more details.

Table 1: Performance Comparison.

Method	Type	Total #	Detected	F-Measure	Error for Correct Detections		Error for Incorrect Detections	
					Illuminant 1	Illuminant 2	Min Error	Max Error
Proposed (4×6)	Single	502	477	**0.9578**	**1.34**	-	**1.79**	**11.28**
	Double	66	49	**0.7000**	**1.87**	**2.05**	**2.33**	15.48
Proposed (8×12)	Single	502	464	0.9450	1.53	-	2.35	14.77
	Double	66	50	0.6494	2.32	2.33	2.51	16.48
Locally applied Grey-world [6]	Single	502	352	0.8000	4.60	-	4.31	14.27
	Double	66	40	0.3125	8.89	6.04	4.22	13.29
Locally applied Corrected-Moment [10]	Single	502	393	0.8656	1.88	-	2.76	14.16
	Double	66	53	0.4649	3.83	7.64	2.87	**10.32**
Adapted Gijsenij et al. [15]	Single	502	256	0.6615	4.92	-	4.57	18.03
	Double	66	50	0.2762	9.23	7.44	4.94	13.56

single illumination images; thus the F-measure gets slightly worse. Angular error of the illuminant estimates is also worse for smaller sub-images. Compared with our proposed method using multiple regression illuminant estimation [7], it is not surprising that the local Grey-world and Corrected moment methods tend to mis-classify the number of illuminants, especially the single illumination images. However, we can see that the learning-based method (Corrected-Moment) gives better illuminant estimates than the statistical method (Grey-world). In contrast to our proposed method of estimating the illumination on big sub-images, the traditional spatially varying illuminant map in [15] obtains the worst result on almost every metric.

4. User Preference for Image Correction

As demonstrated in Section 3, the proposed approach is able to estimate two illuminants that are sufficiently distinct; however, there does not exist a corresponding illumination map and thus spatially varying white-balance correction is not possible. As such, we seek to determine, given an image with two illuminants, which illuminant do users prefer to be corrected. To answer this, we carried out two user studies to elicit users' preferences. For the user studies we used images from two publicly available data sets, Gehler-Shi data set [12, 21] and RAISE data set [8]. The RAISE data set contains a large number of RAW images from various cameras that are used for image forensics. We examined these data sets and found 35 images suitable for our user studies. The following sections detail our experiments and findings.

4.1. User Study 1 (Two Choices)

For this study we used 33 images that contain two distinct illuminations (namely indoor and outdoor). The number of participants in the study was 39. We carried out the experiments in an indoor room with standard fluorescent light and calibrated monitors.

Procedure For each image, the two illuminants L_1 and L_5 were estimated by manually selecting a small patch from each image that contains neutral material under the different illuminations (the second illuminant is termed L_5 in this study as it will be used slightly differently in the next study). Each image was corrected (white-balanced) using the two estimated illumination, generating a pair of differently white-balanced images. In Figure 4, the second and last columns show sample images corrected using the two illuminants. Each user was shown the 33 pairs of differently white-balanced images in random order. They were asked to choose the image they prefer. The images were viewed on the same screen and in the same place to avoid the effects of different lighting conditions on the visual appearance of the images.

Outcomes The choices of the users were averaged. The results showed a higher user preference (almost 80%) of images corrected using illuminant L_5, which was the outdoor illumination. This is shown in Figure 5 (a). This means that users preferred the outdoor color casts to be corrected, which results in the indoor color casts in the image being kept. This has the effect of producing a "warm" (reddish) output image. We also performed statistical testing over the user choices to make sure they are statistically significant, which resulted in the 95% confidence interval shown as error bars in Figure 5 (a).

4.2. User Study 2 (Five Choices)

The first user study only gave the users two choices. In that test, the results correcting one of the illuminants was strongly preferred. For the next user study, we wanted to see if the users would prefer some mixture of the results. We used the same images as user study 1, but also added some extra images that contain similar illuminants. We added these to see if we observed a similar preference trend when the images did not have distinct illuminations. This means we have two categories of images: *Cat. I*, two distinct illuminants (indoor and outdoor), and *Cat. II*, two similar illuminants, such as sun and shade illuminants.

Procedure Images were sought to have sufficient neutral

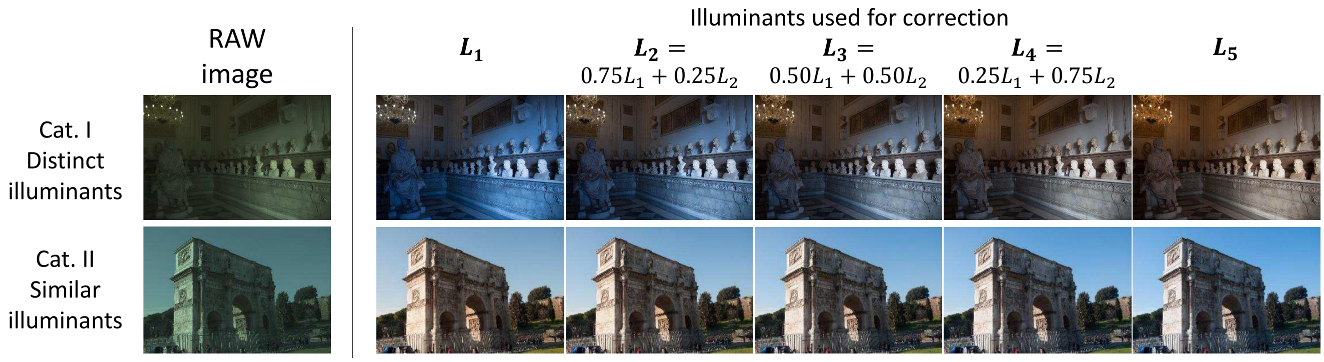


Figure 4: An example of image categories with 5 different illuminant corrections. The two rows represent images with two distinct indoor and outdoor illuminants (*Cat. I*) and images having two similar illuminants (*Cat. II*), such as sun and shade illuminants. The first column shows the raw image with the following showing the image corrected using 100%–0%, 75%–25%, 50%–50%, 25%–75%, and 0%–100% weights of the identified two illuminants, respectively.

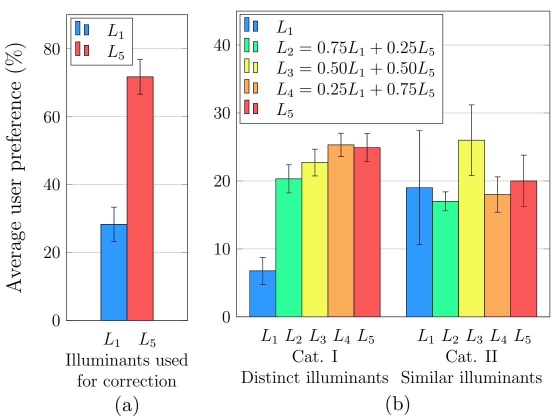


Figure 5: (a) User preferences for the indoor (L_1) and outdoor illuminant (L_5) corrections. (b) User preferences for each of the 5 illuminants, over the two categories (distinct and similar illuminants). Error bars represents the 95% confidence intervals.

materials in the scene that we could accurately identify the two illuminations. In the end, we obtained 24 images from *Cat. I*, and 5 images from *Cat. II*. Since our main concern was two distinct illumination images (*Cat. I*), we selected more images from this category. We enlisted 34 users for the study - their average age was 22 years, with 26 males and 8 females.

For each image, two illuminants were estimated by manually selecting a small patch that contains neutral material to provide an estimation of the illumination. We label these two illuminants L_1 and L_5. We then generated mixtures of these two illuminations. Specifically, illuminant values for labels L_1-L_5 are computed using:

$$L_i = \alpha_i L_1 + (1 - \alpha_i) L_5, \tag{1}$$

where α_i is set to 1.0, 0.75, 0.50, 0.25, and 0.0 for L_1, L_2, L_3, L_4, and L_5 respectively. Each image I_k was corrected (white-balanced) using the 5 different illuminants. This results in 5 white-balanced images $\{I_k^{(L_1)}, ..., I_k^{(L_5)}\}$, for each image k, where $I_k^{(L_i)}$ means the correction of image I_k using illuminant L_i. Figure 4 shows some sample images.

We used a two-alternative forced choice approach within a game-based strategy as recommended by [16]. A two-player game is used where both players are shown 50 randomly-selected pairs of images $\{I_k^{(L_i)}, I_k^{(L_j)}\}$ at the same time, where $i, j \in \{1, ..., 5\}$ and $i \neq j$. In other words, each pair are the same image corrected using two different illuminants picked randomly from the 5 illuminants for this image. Each pair is viewed in random order. Instead of asking each player to choose the image they prefer, each player is asked to select the image they think their partner (the other player) would prefer. This game-based strategy has been shown to be more effective in eliciting user preferences from such studies [16]. The same pair of images appear at least 4 times through the whole user study. The total number of image pair comparisons was 1700, where each of the 5 images appears for comparison at least 16 times.

As there are 5 different illuminant corrections for each image, and these corrections are shown to the users in pairs, the total number of comparisons needed to cover all 5 images in a pair-wise manner is $\binom{5}{2} = 10$ comparisons. To combine the relative user choices into an overall score that represents the user preference for each of the 5 corrected images, we count the number of times each corrected image $I_k^{(L_i)}$ is preferred over any other corrected image $I_k^{(L_j)}$, then normalize it by the total number of pair-wise comparisons for this image. The user study used color calibrated monitors [1] under the same lighting conditions to avoid environmental biases.

Outcomes The average user choices of each of the 5 illu-

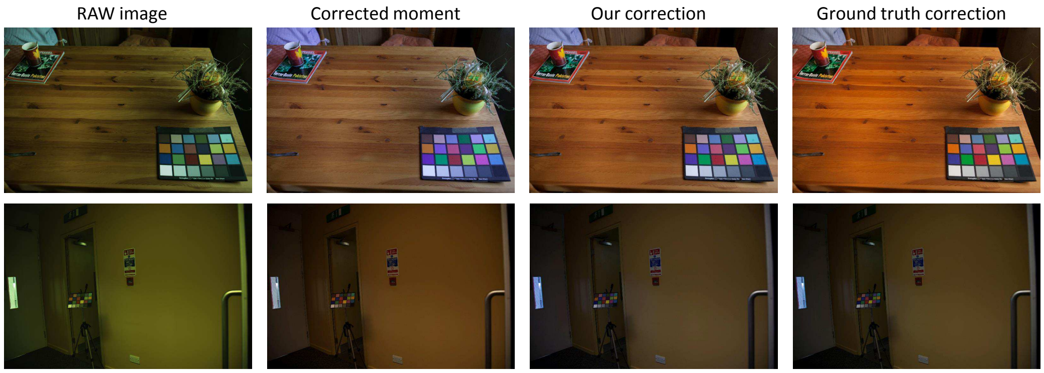


Figure 6: Example images that our method fails to correctly determine the number of illuminant(s). The first row shows example images that have a single illuminant, but our method estimated two illuminations. The second row shows images having two illuminants, but our proposed method can only detect one.

minant corrections for each category of images are shown in Figure 5 (b) along with their 95% confidence intervals represented by error bars. From this result, we see that *Cat. I* (two distinct illuminations) have a clear preference leaning towards the correction using a higher weight of the outdoor illuminant (i.e. the $L_4 = 0.25L_1 + 0.75L_5$ illuminant). For *Cat. II* (two similar illuminations) the preference is less pronounced and slightly favors an average result. This is consistent with the finding in [11] that visual difference illuminant corrections within 3° is not noticeable.

5. Two-Illumination Estimation Application

Our combined findings in Section 3 and Section 4 point to an approach for handling images that potentially contain two illuminations. Naming, run the algorithm in Section 3.2 to determine if two distinct illuminations exist. If so, correct the image with a 75%-25% mixture weighting the outdoor correction more. Figure 7 shows some examples for two-illumination images. To have a comparison, the Corrected Moments [10] and weighted Grey-edge [14] methods were used to represent single illuminant estimation methods. We can see that for these images, the Corrected Moment method and the weighted Grey-edge method tend to give the indoor illuminant estimation or the mixture of indoor/outdoor. These illuminant estimates make the corrected images bluish in nature. In contrast, our correction results are close to the user preferred correction.

Figure 6 shows some failure cases for our method. There are two types of failure cases: single illumination image detected as multiple illumination image (first row) and the multiple illumination image detected as single illumination (second row). For the first case, this is usually because the image contains a large homogeneous region, making it hard to estimate the illuminant. For these images, the state-of-art single illuminant estimation methods also tend to fail. Although the illuminant classification is wrong, our method can still detect one of the illuminants correctly. Thus the image correction is still biased towards this illuminant. The second type of failure occurs when the image contains two illuminants, but where one illuminant is significantly more prominent. For these images, our method often estimates the dominant illumination.

6. Conclusion and Discussion

We proposed a simple and fast algorithm to determine if there are one or two illuminants for a scene and to estimate these illuminants. The key to our method is to use a high quality single illumination algorithm on large sub-images for robust estimation instead of small patches as in previous methods. We only use the spatially varying estimates to decide if there are one or two illuminants and to globally estimate the illuminants present. Given the difficulty of local correction, we performed the first user studies to see whether users have a preference for correcting one illuminant or the other. Indeed, our studies showed that users have a clear preference for correcting the outdoor illuminant to produce warmer images. For two illuminant detections, we perform a global correction based on this user preference.

Our two illuminant framework is general and works with any single estimation method, ideally one that provides a confidence so that erroneous estimates can be discarded. The results of our two illuminant detection and correction will potentially improve in the future by using improved single illuminant estimation methods. This work focused on images where there are reasonably large areas that are illuminated mainly by each illuminant. Our method will fail when the illuminants are significantly mixed almost everywhere in an image. It will be interesting to see if our method can be improved to handle such cases and to see if the user preference to correct towards warmer images remains.

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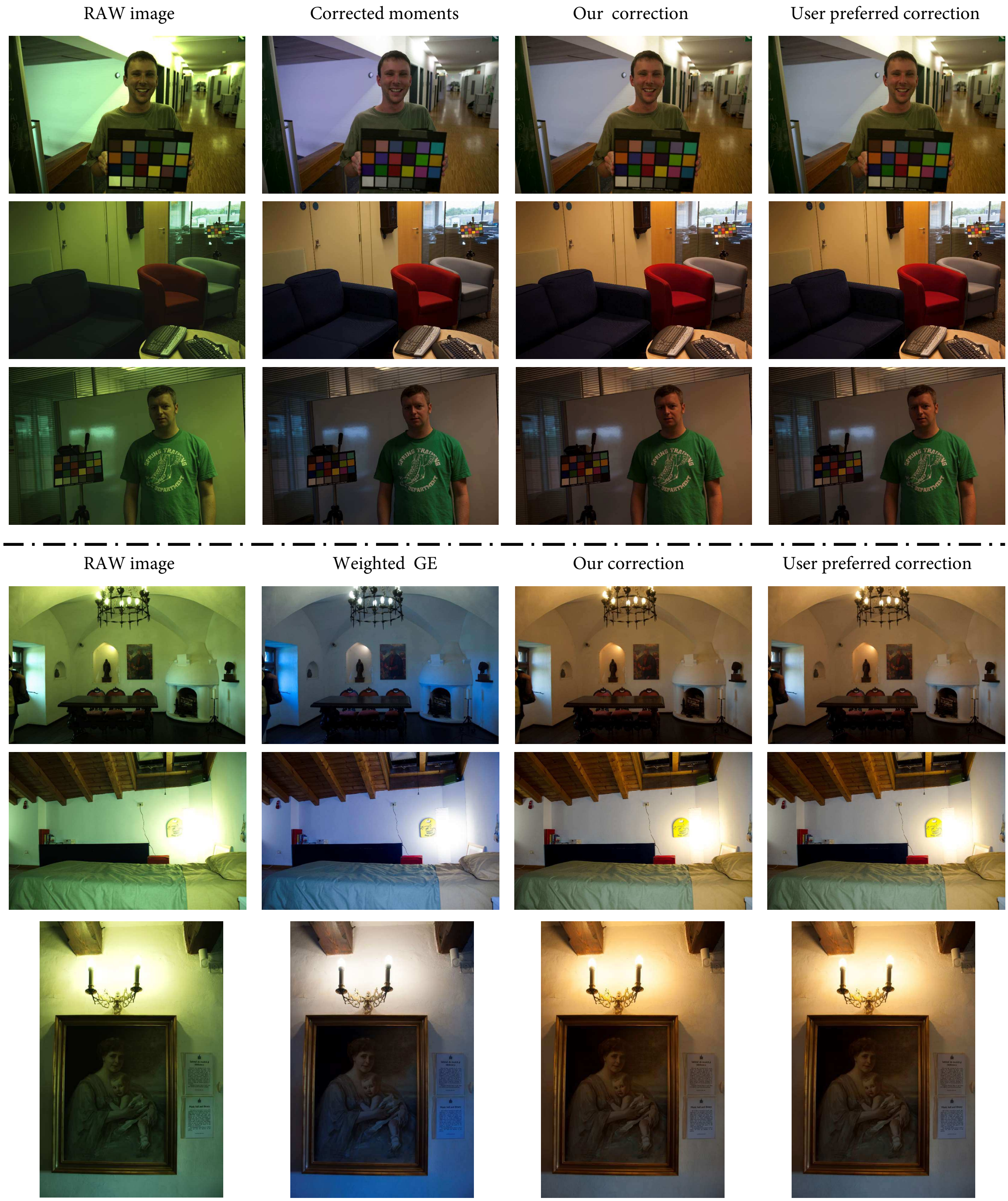

Figure 7: Visual comparison of image global correction. Top three images are from the Gehler-Shi data set [12, 21] while the bottom three are from the RAISE data set [8]. For the images from the Gehler-Shi data set, the Corrected moment [10] result is compared and for the images from the RAISE data set, the weighted Grey-edge [14] result is compared.

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