The Role of Bright Pixels in Illumination Estimation

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Abstract

The White-Patch method, one of the very first colour constancy methods, estimates the illuminant colour from the maximum response of three colour channels. However, this simple method has been superseded by advanced physical, statistical and learning based colour constancy methods. Recently, a few research works have suggested that the simple idea of using maximum pixel values is not as limited an idea as it seems on first glance. These works show that in several situations some manipulations can indeed made it perform very well. Here, we extend the White-Patch assumption to include any of: white patch, highlights or light source; let us refer to these pixels in an image as the "bright" pixels areas. We propose that bright pixels are surprisingly helpful in the illumination estimation process.

In this paper, we investigate the effects of bright pixels on several current colour constancy algorithms. Moreover, we describe a simple framework for an illumination estimation method based on bright pixels and compare its accuracy to well-known colour constancy algorithms applied to four standard datasets. We also investigate failure and success cases, using bright pixels, and propose desiderata on input images with regard to the proposed method.

Introduction

Illumination estimation, which is the main step in colour constancy processing, is an important prerequisite for many computer vision applications. One of the first colour constancy methods, the so-called White-Patch or Max-RGB method estimates the illuminant colour from the maximum response of three colour channels [24]. With the advent of newer and more precise colour constancy methods such as Grey-World [3], Gamut Mapping [12], Grey-Edge [31] and many other complex methods (refer to [21] for an overview), few researchers or commercial cameras use the White-Patch method. On the other hand, recent research such as that on perceptual color contrast enhancement by Choudhury and Medioni [4] or on the "rehabilitation" of MaxRGB by Funt and Shi [15] propose that a local mean calculation such as local blurring as a preprocessing step can significantly improve the performance of this simple method, consisting of simply finding the maximum in each colour channel. Simply put, these works propose it is advantageous to calculate the max of a local mean image.

Recently, Drew et al. [6] found analytically that the geometric mean of bright (generally, specular) pixels is the optimal estimate for the illuminant, based on a standard dichromatic model for image formation (which accounts for the matte and highlight appearance of objects). This work proposes that in the presence of specular highlights the "mean of the max" is the best illuminant estimate, in contradistinction to previous works [15, 4] which say it is the "max of the mean." The analytical approach [6] claims performance comparable with very complex colour constancy methods despite its simplicity.

The bright areas of images can be white surfaces or light sources as well as highlights and specularity, and all are helpful in the illumination estimation process. Highlights and white surfaces both tend to have the colour of light in ideal conditions for dielectric materials such as plastic.

In this paper, we investigate the effects of bright pixels on different colour constancy algorithms. We describe a simple framework for an illumination estimation method based on bright pixels and compare its accuracy to well-known colour constancy algorithms applied to four standard datasets. We also investigate failure and success cases, using bright pixels, and draw conclusions on input images with regard to the proposed method.

Illumination Estimation by Specular reflection

In specular reflection, light from a single incoming direction is reflected into a small cone of outgoing directions. This contrasts with diffuse reflection, where light is partially absorbed and partially scattered within the surface material. Areas of images that are specular tend to be bright. Moreover, the spectral power distribution (SPD) of specular reflections is the same as the illumination's SPD, within a Neutral Interface Reflection (NIR) [25] condition, which mostly obtains for the surfaces of optically inhomogeneous objects (such as ceramics, plastics, paints, etc.); however it does not always hold for the surfaces of optically homogeneous objects (such as gold, bronze, copper, etc.) [20]. These properties make specular reflection, which is usually in bright areas of image, an appropriate tool for estimating illumination. Many illumination estimation methods derive from the dichromatic model for specular reflection proposed by Shafer [28].

Klinker et al. [23] showed that when the diffuse colour is constant over a surface, the colour histogram of its image forms a skewed-T shaped distribution, with the diffuse and specular pixels forming linear clusters. They used this information to estimate a single diffuse colour. Therefore in order to use this principle, their approach needed to segment an image into several regions of homogeneous diffuse colour.

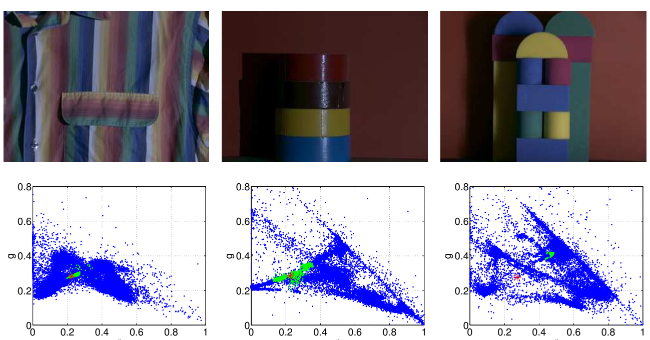
Lee [26] proposed a method which uses specularity to compute illumination by using the fact that in the CIE chromaticity diagram [33] the coordinates of the colours from different points from the same surface will fall on a straight line connected to the specular point. This is the case when the light reflected from a uniform surface is an additive mixture of the specular component and the diffuse component. This seminal work initiated a substantial body of work on identifying specular pixels and using these to attempt to discover the illuminant [27, 30]. Another approach extending these algorithms is to define a constraint on the possible colours of illumination, making estimation more robust [8, 9].

Extending the White Patch Hypothesis

The White-Patch hypothesis is essentially that there is always a white surface in the image. Let us extend this assumption to include any of: white patch, specularities, or light source (or an effective white, e.g. a bright yellow and red pixel which combined have the same max R, G and B as a white patch). We also use the term *gamut* of bright pixels, in contradistinction to maximum channel response of the White-Patch method, which typically deals only with the brightest pixel in the image. Obviously, using a single pixel or very small area is noisy and not robust.

Since are we dealing with bright pixels we need to be very careful about clipped pixels, i.e. pixels where the light reflection exceeds the dynamic range of the camera. Here for each colour channel we remove pixels which exceed 90% of the dynamic range. Then we simply define bright pixels as the top $T\%$ of luminance given by $R+G+B$.

To investigate the utility of this assumption, we carry out a simple experiment. We check whether or not the actual illuminant colour falls inside the 2D gamut of bright pixels. We find that the actual illuminant colour falls in the 2D gamut of the top 5% brightness pixels of each image for the SFU Laboratory Dataset [2] for 88.16% of images, in 74.47% of images for the ColorChecker dataset [29], and in 66.02% of images for the GreyBall Dataset [5]. Fig. 1 shows the 2D gamut in chromaticity space $\{r,g\} = \{R,G\}/(R+G+B)$, with the top-5% brightness pixels in green. The actual measured illuminant is shown as a red star. Clearly, as Fig. 1(c) shows, with no supporting evidence it may happen that the illuminant does not fall within the bright region.



(a) (b) (c)

Figure 1. Examples of image evidence: top-5% brightness pixels in green, other pixels in blue, and red star showing the correct illuminant point in r,g chromaticity space. (a) Image with white patch; (b) Image with specularity; (c) Image without white patch or specularity.

When there are no strong highlights, source of light, or white surfaces in the image, the bright pixels are not helpful; in that case there can be areas of an image belonging to the brightest surface which tend towards that surface's surface colour. Alternatively this situation may simply arise from a set of single pixels from all over the image.

The fundamental question here is what is the probability of having an image without strong highlights, source of light, or white surface, in the real world? Knowing the answer to this question is vital when we investigate the effect of bright pixels in colour constancy.

The Effect of Bright Pixels in Well-known Colour Constancy Algorithms

The foundational colour constancy method, the White-Patch or Max-RGB method, estimates the illuminant colour from the maximum response of the three colour channels [24]. It is based on the assumption that the maximum response in the channels is caused by a white patch. The White-Patch method usually deals with the brightest pixel in the image, so it is noisy and non-robust. Funt and Shi [15, 14] suggested that carrying out a local mean calculation preprocessing step can significantly improve its performance.

Another well-known colour constancy method is based on the Grey-World hypothesis [3], which assumes that the average reflectance in the scene is achromatic. Finlayson and Trezzi [11] formalize grey-based methods by subsuming them into a single formula using the Minkowski p-norm.

$$\left(\frac{\int I_k^p(x)dx}{\int dx} \right)^{\frac{1}{p}} = e_k \tag{1}$$

where e is estimated illuminant color and k denotes R, G or B. For $p=1$ the equation is equal to the grey-world assumption and for $p \to \infty$ it is equal to color constancy by White-Patch; and it is Shades of Grey for p more than 1 and less than infinity. At first glance we see no distinction for bright pixels in the Grey-World assumption; however since it is an averaging, the higher values, which are brighter pixels, contribute a good deal more compared to dark pixels, especially for higher p.

Grey-Edge is a recent version of the Grey-World hypothesis that states: the average of the reflectance differences in a scene is achromatic [31]. Using the same formulation as for grey-based methods, Grey World, Shades of Grey, and Grey Edge can be combined in a single framework for illuminant estimation methods:

$$\left(\int \left\| \frac{\partial^n I_k(x)}{\partial x^n} \right\|^p dx \right)^{\frac{1}{p}} = e_k \tag{2}$$

Where n is grey-edge the "order".

The Gamut Mapping algorithm, a more complex and more accurate algorithm, was introduced by Forsyth [12]. It is based on the assumption that in real-world images, for a given illuminant one observes only a limited number of colours. Several extensions to gamut mapping algorithms have been proposed [1, 7, 10, 19]. The bright pixels are the upper boundaries the of colour gamut for a single image. Vaezi Joze and Drew [22] introduce a White-Patch Gamut algorithm, which includes the top-brightness pixels in a 3D gamut; they show that adding new constraints based on the white patch gamut to standard Gamut Mapping constraints outperforms the Gamut Mapping method and its extensions.

As a simple experiment in order to investigate the effect of bright pixels, we run White-Patch, Grey-World, Grey-Edge and Shades of Grey methods for the top 20% brightness pixels in each image, and compare to using all image pixels.

Table 1: Angular errors for several colour constancy algorithms for linear ColorChecker dataset [29] using all pixels and and using the top 20% brightness pixels.

Dataset / Methods	All Pixels Median	All Pixels Mean	20% brightness Median	20% brightness Mean
White Patch	6.31°	7.82°	6.31°	7.81°
Grey World	6.33°	6.40°	3.46°	4.23°
Grey Edge ($p=1, \sigma=6$)	4.73°	5.56°	4.65°	5.46°
Shades of Grey ($p=4$)	3.51°	4.45°	3.08°	4.17°

We use the standard well-known colour constancy methods: White-Patch, Grey-World, Grey-Edge, and Shades-of-Grey implemented by [31], testing on the re-processed version of the ColorChecker dataset [29], using the dataset's suggested clipping threshold. For those methods which need tunable parameters, we utilize optimal parameters for this dataset.

Table 1 shows the accuracy of using top 20% brightness pixels for reprocessed version of the ColorChecker dataset [29], in terms of the mean and median of angular errors, for several colour constancy algorithms applied to this dataset. The results indicate that although we only use one fifth of the pixels, performance is better than or equal to using all pixels. This is especially true for Grey-World and Shades-of-Grey (both follow eq. (2)), where using top-brightness pixels significantly outperforms using all pixels.

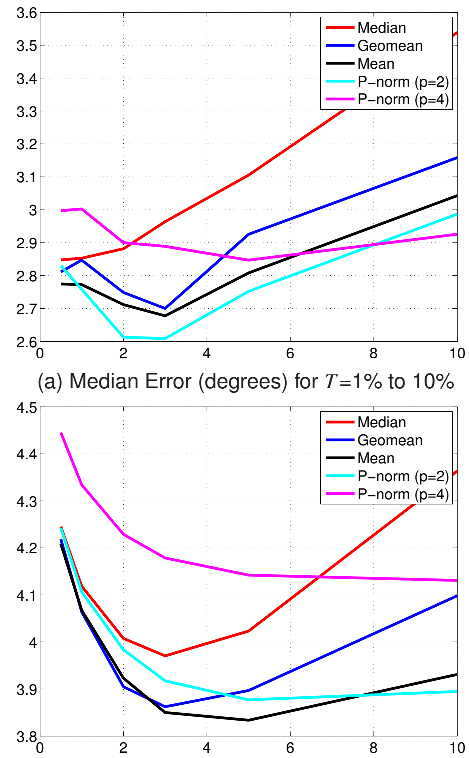
The Bright-Pixels Framework

Here we propose a simple framework in order to investigate the effect of bright pixels for illumination estimation. First of all, since we dealing with bright pixels we need to be careful about clipped pixels. Therefore we remove pixels exceeding 90% of the dynamic range of the camera for each colour channel. We simply define bright pixels as T percentile of the luminance, taken to be the sum of channels, $R+G+B$.

If these bright pixels represent highlights, a white surface, or a light source, they approximate the colour of the illuminant. Any statistical estimator can be brought to bear for estimating the illuminant, e.g. the median, mean, geometric-mean or the Minkowski p-norm.

Figure 2 plots angular errors in terms of mean and median for recovering the illuminant, using T percentile (from 1% to 10%) of brightness pixels, using different statistical estimators: median, geometric-mean, mean and the Minkowski p-norm for $p=2$ and $p=4$, for the linear-image ColorChecker dataset [29]. Considering that the best median and mean angular errors in this dataset have been reported as respectively 2.5° using Gamut Mapping in [18] and 3.5° by the complex High Level Visual Information algorithm [32], the achievement is surprisingly good whilst being very simple (refer to Table 3 for results for other color constancy methods). We see that optimal performance in terms of the median is for the p-norm estimator, with $p=2$ for the top-3% brightness pixels; in terms of using the mean, is for the Mean algorithm for top-5% brightness pixels.

Figure 3 shows examples of images from the ColorChecker Dataset having angular error more than 13°, using the top-3% brightness pixels and p-norm estimator with $p=2$. Figure 3 indicates that a common failure for a bright pixel framework is when there are multiple illuminants in the scene (we can see the same failures in the GreyBall dataset). Examples are skylight from windows plus indoor light, in-shadow plus non-shadow lights, or two different light sources in an indoor room. Although most color constancy methods assume a single light source, nevertheless in these datasets there are some images with more than one illuminant. Obviously, in the case of more than one illuminant the bright-pixel method finds the brightest illuminant while other methods such as Gamut Mapping find the dominant illuminant or combination of illuminants.



(a) Median Error (degrees) for T=1% to 10%

(b) Mean Error (degrees) for T=1% to 10%

***Figure 2.** The plots of angular errors in terms of (a) median error and (b) mean error for recovering the illuminant, using T percentile of brightness pixels using different 3-vector statistical estimators: median, geometric-mean, mean and the Minkowski p-norm for $p=2$ and $p=4$, for the linear-image ColorChecker dataset [29].*

Another failure case happens if bright pixels are not good estimators of the illuminant; or equally there are no highlights, white surfaces, or light sources in the image. Although at first glance this seems to be a common situation, our experiments on current standard color constancy datasets have shown that this happens even less than the multiple-illuminants situation (Figure 3 shows a few examples). In this case bright pixels either capture the colour of the brightest surface in the image or a distribution of bright pixels from all over the image. In the former case we can simply check if these pixels are in the possible chromaticity gamut of illuminants; and the latter case can be distinguished based on the distribution of these pixels in chromaticity space.

As we mentioned, a local mean calculation such as local

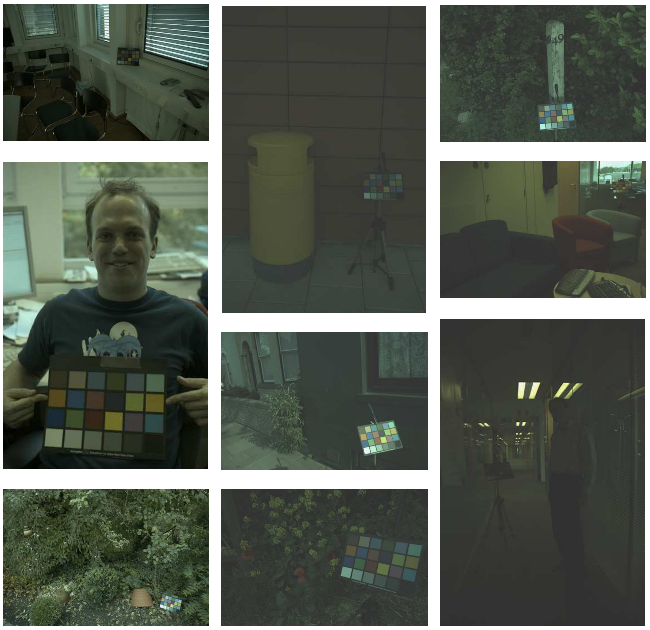


Figure 3. *Examples of images from ColorChecker Dataset with maximum angular error, using top 3% brightness pixels and p-norm estimator with* $p = 2$

Table 2: The median angular errors for the linear-image ColorChecker dataset [29] using top brightness pixels for three variations of eq. 2 when different local mean operations are applied as preprocessing. The first value in parentheses for each element is the optimum value of T and the second is the value of p in the p-norm for that experiment.

	Shades of Grey	n=1 grey-edge	n=2 grey-edge
no local mean	$2.61°$ $(2\%,2)$	$4.61°$ $(5\%,2)$	$4.46°$ $(5\%,2)$
64×64 bicubic	$2.88°$ $(3\%,1)$	$4.86°$ $(5\%,1)$	$4.76°$ $(5\%,2)$
Median filter	$2.69°$ $(3\%,2)$	$4.32°$ $(5\%,1)$	$4.29°$ $(5\%,1)$
Gaussian filter	$2.72°$ $(3\%,2)$	$4.37°$ $(5\%,1)$	$4.13°$ $(5\%,1)$

blurring has been shown to improve the performance of simple methods such as White-Patch [15]. Therefore, here we examined applying three different local mean calculations as preprocessing, as follows: (1) resizing to 64×64 pixels by bicubic interpolation; (2) median filtering (inspired by [15]); and (3) a Gaussian blurring filter.

Figure 3 shows that the p-norm (and we can consider the mean as p-norm with $p = 1$) is a better estimator than median or geomean. Table 2 gives median angular error, with *optimal* parameters (T and p), for the reprocessed ColorChecker dataset using our three local mean preprocessing, for shades of gray and the 1st-order and 2nd-order grey-edge method for top-brightness pixels. For the meaning of "n" the reader is referred to eq. (2).

Further Experiments

We applied the proposed framework to four standard color constancy datasets. The first is Barnard's dataset [2], denoted the SFU Laboratory dataset; this contains 321 measured images under 11 different measured illuminants. The second dataset, which contains out-of-laboratory images, is the re-processed version of the Gehler colour constancy dataset [16], denoted as the ColorChecker dataset, which was provided by Shi and Funt [29]. This dataset consists of 568 images, both indoor and outdoor. The illuminant ground truth for these images is known because each image has a Macbeth ColorChecker placed in the scene (which must masked off in tests). The third dataset, which contains low quality real-world video frames, is the GreyBall dataset of Ciurea and Funt [5]; this contains 11346 images extracted from video recorded under a wide variety of imaging conditions. The ground truth was acquired by attaching a grey sphere to the camera, displayed in the bottom-right corner of the image – and this must be masked off during experiments. The last color constancy dataset is the HDR dataset [13] provided by Funt, which contain 105 images constructed in the standard way from multiple exposures of the same scene. The colour of the scene illumination was determined by photographing an extra HDR image of the scene with 4 Gretag Macbeth. Although HDR is a small dataset, it has two advantages compare to other datasets: it has high quality images and no clipped pixels that might have arisen from exceeding the dynamic range.

We search using brute force for optimal parameters: i.e., the value of p in the p-norm, the gradient order n in edge-based p-norm, which local mean method to apply, and finally the top-brightness threshold. Table 3 shows the overall optimal performance of a bright-pixels framework for our four standard datasets, compared to the standard methods. The Bright Pixels row represents the optimal value reachable by a bright-pixel framework over all methods White-Patch, Grey-World, and Grey-Edge. For the bright-pixels framework, if the estimated illuminant is not in the possible illuminant gamut for that dataset, meaning that there is no white surface, specularity, or light source in the image, we fall back on the Grey-Edge method instead – this is the row labelled Bright Pixels + grey-edge in Table 3. This situation occurs relatively seldom: for 178 out of 11136 images for the GreyBall set, 3 out of 568 for the ColorChecker set, 89 out of 321 for the SFU Laboratory dataset, and 9 out of 105 for the HDR dataset.

Using eq. (2) to test the bright-pixels hypothesis, the optimal parameters for the SFU laboratory dataset are: Gaussian filter as preprocessing plus using the Shades of Grey method with $p = 2$ for the top .5% brightness pixels. Here we test order n in $\{0,1,2\}$, p-norm parameter p in $\{1,2,4,8,16\}$, brightness threshold T in $\{.5\%,1\%,2\%,3\%,5\%\}$. The optimal parameters for the ColorChecker dataset are: no preprocessing, and using the Shades of Grey method with $p = 2$ for the top 2% brightness pixels. The optimal parameters for the GreyBall dataset are: no preprocessing, and using the Shades of Grey method with $p = 2$ for the top 1% brightness pixels. The optimal parameters for HDR dataset are: a Gaussian filter as preprocessing, and then the 2nd-order grey-edge method with $p = 8$ for the top 1% brightness pixels.

Conclusion

In this paper, we investigate the effects of bright pixels in a variety of standard colour constancy algorithms. Moreover, we describe a simple framework for illumination estimation method based on bright pixels. We have demonstrated that this simple method does very well compared to well-known colour constancy algorithms as well as compared to more complex supervised color constancy methods, over four large standard datasets.

Table 3: Comparison of the bright-pixels framework with well-known colour constancy methods.

Dataset	SFU Laboratory		Color Checker		Grey Ball		HDR	
Methods	Median	Mean	Median	Mean	Median	Mean	Median	Mean
White Patch	6.5°	9.1°	5.7°	7.4°	5.3°	6.8°	4.3°	6.3°
Grey World	7.0°	9.8°	6.3°	6.4°	7.0°	7.9°	7.3°	7.9°
Grey Edge	3.2°	5.6°	4.5°	5.3°	4.7°	5.9°	3.9°	6.0°
Gamut Mapping	2.3°	3.7°	**2.5°**	4.1°	5.8°	7.1°	-	-
1st-jet Gamut Mapping [19]	2.1°	3.6°	**2.5°**	4.1°	5.8°	6.9°	-	-
Bayesian [16]	-	-	3.5°	4.8°	-	-	-	-
High Level Visual Information [32]	-	-	**2.5°**	**3.5°**	-	-	-	-
Natural Image Statistics [17]	-	-	3.1°	4.2°	**3.9°**	**5.2°**	-	-
The Rehabilitation of MaxRGB	3.1°	5.6°	-	-	-	-	3.9°	6.3°
Bright Pixels	1.90°	5.84°	2.61°	3.98°	4.71°	5.72°	**3.49°**	**5.77°**
Bright Pixels + grey-edge	**1.62°**	**2.72°**	2.61°	3.96°	4.64°	5.57°	**3.49°**	5.92°

The fundamental question which arises in this paper is what is the probability of having an image without strong highlights, source of light, or white surface in the real world? Based on current standard datasets in the field of color constancy we saw that the simple idea of using the p-norm of bright pixels, after a local mean preprocessing step, can perform surprisingly competitively compared to complex methods. Therefore, we conclude that either the probability of having an image without strong highlights, source of light, or white surface in the real world is not overwhelmingly great or the current color constancy datasets are conceivably not good indicators of performance with regard to possible real world images.

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