IMPROVING COLOR CONSTANCY BY SATURATION WEIGHTING

Hyunchan Ahn[*], Soobin Lee[†], and Hwang Soo Lee[*]

[*] Department of Electrical Engineering, KAIST, Daejeon, Korea
[†] KAIST Institute for Information Technology Convergence, Daejeon, Korea

ABSTRACT

A variety of methods for color constancy have been proposed in order to come up with the ability of the human visual system which recognizes the inherent colors of objects under different illuminants. The methods based on the low-level statistics are widely used due to their low computational complexity and satisfactory results with adequate parameters. However, none of these methods utilize color channel correlation explicitly to improve the color constancy. In this paper, we propose a novel color constancy method using the color correlation. From a lot of observations, we find tendencies according to saturation values and finally incorporate a saturation weighting function into the existing methods. Experiments are performed on two widely used datasets and the results demonstrate that the proposed method improves the color constancy with a simple and effective manner.

Index Terms— Color constancy, auto white balance, illuminant estimation, saturation weighting.

1. INTRODUCTION

The human visual system can perceive the original colors of objects to some degree in spite of illuminant changes. This innate nature of the human visual system is called color constancy [1-2]. The ability of the color constancy is important for computer vision applications because they exploit the color feature for an important cue [2]. However, since an image is composed of the product of the illuminant, surface reflectance, and camera sensitivity function, the color property of each pixel in the image varies according to the illuminant changes, which causes the performance degradation of the computer vision applications. Therefore, the color constancy is an essential step for exploiting the robust color feature of the applications.

The purpose of the color constancy in an image is to obtain an illuminant invariant image. The color constancy is achieved by estimating a light source from the image and then canceling the influence of the light source, i.e., representing the image under the canonical (white) illuminant. Thus, accurate light source estimation is the key point of the color constancy.

The existing color constancy methods can be divided into two categories: One is a learning-based group and the other is a low-level statistics-based group. The learning-based methods need prior knowledge about scenes. Well known methods include the gamut based methods [3-4], the color by correlation [5], the Bayesian approach [6], and the combination method [7]. These methods perform well when trained correctly. However, they require a lot of data for the training phase and high computational complexity [2].

The low-level statistics-based methods are widely used because these methods are simple and give satisfactory results when their parameters are adequately tuned [2]. The methods have simple assumptions from a scene to estimate the light source. The max-RGB method [8], the gray world method [9], the shades of gray method [10], and the gray edge method [11] are the representatives of this type of methods.

In this paper, we propose a novel algorithm for the color constancy based on the low-level statistics. By exploiting color channel correlation explicitly, we extend the existing low-level statistics-based methods to a more general framework and thereby improve the color constancy.

The paper is organized as follows. First, in Section 2, we describe the problem of the color constancy and related work. Section 3 demonstrates how the color channel correlation affects the performance of the color constancy. Then, we propose a novel algorithm for the color constancy in Section 4. In Section 5, we compare our method with the state-of-the-art methods on two widely used datasets and finally Section 6 concludes our work.

2. RELATED WORK

Based on the Lambertian assumption, an image f is formed as:

$$f_i(x) = \int_{\omega} L(\lambda) r(x,\lambda) \rho_i(\lambda) d\lambda, \tag{1}$$

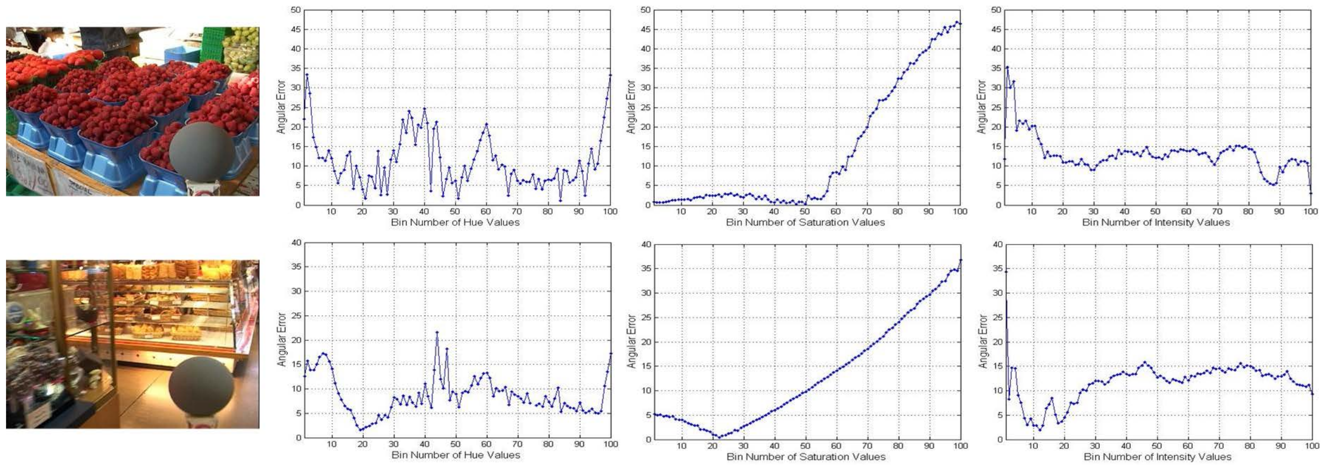
where $i \in \{R, G, B\}$, x is the pixel coordinate in the image, ω denotes the visible spectrum, $L(\lambda)$ is the spectral distribution of the light source, $r(x, \lambda)$ is the surface reflectance, and $\rho_i(\lambda)$ denotes the camera sensitivity function of i-th color channel.

So as to achieve the color constancy in the image, the light source should be known. Assuming that the image is illuminated by one light source, the light source e can be obtained by

$$e_i = \int_{\omega} L(\lambda) \rho_i(\lambda) d\lambda. \tag{2}$$

Once the light source is obtained, the image can be represented under the canonical light source using the simple diagonal model [12]. However, because it is difficult to divide the image into each component L, r, and ρ separately, the color constancy is an under-constrained problem and the light source cannot be estimated without prior assumptions.

The max-RGB method proposed by Land [8] assumes that



(a) (b) (c) (d)

Fig. 1. The examples of our observation on each HSI channel. (a) The input images. (b) The performance for each bin according to hue values. (c) The performance for each bin according to saturation values. (d) The performance for each bin according to intensity values. The gray ball presented on the right-bottom of each image is excluded since it disturbs the objective observations of the performance.

the maximum response of each RGB value in an image reflects the light source. The method fails to estimate the light source when the image is clipped or the pixels which have the maximum response of each RGB value do not reflect the light source. The Buchsbaum [9] proposed the gray world method assuming that the average reflectance in an image is achromatic. In case that the image is covered with large color surfaces, the method fails to estimate the light source. Later, Finlayson and Trezzi [10] generalized these two methods, which is called the shades of gray method. According to each RGB value, the significance of each pixel is adjusted by the Minkowski norm and thereby the method improved the max-RGB and the gray world method. Recently, Weijer *et al.* [11] presented the gray edge method. The method assumes that the average of the reflectance differences in an image is achromatic. They also presented the general gray world method that incorporates smoothing operation into the shades of gray method. The gray edge method is presented as

$$\left(\int\left|\frac{\partial^n f_{i,\sigma}(x)}{\partial x^n}\right|^p dx\right)^{1/p} = k\begin{pmatrix}e_R\\ e_G\\ e_B\end{pmatrix} = ke_i, \qquad (3)$$

where n denotes the order of derivative, p is the Minkowski norm, σ denotes the scale of smoothing operation, and k is the normalization factor which makes the light source e unit length. Using the higher order structure of the image, they presented a general framework including the previous methods.

However, all the methods described above exploit the values of each RGB channel independently, i.e., estimating the each RGB value of the light source separately, which does not consider the color channel correlation for the color constancy. On the contrary to these methods, our method considers the color correlation based on the observations of the relationship between the color correlation and the performance of the color constancy. By exploiting the color correlation explicitly, we aim to improve the color constancy.

3. RELATIONSHIP BETWEEN COLOR CONSTANCY AND COLOR CORRELATION

In this section, we describe the motivation of our method. In order to observe how the color correlation affects the performance of the color constancy, we make use of the gray ball dataset [13] because it contains a lot of images taken from various indoor and outdoor locations with the ground truth light source of each image. Our observation procedures are described as follows:

1) Convert the image of the dataset from RGB to HSI (hue, saturation, and intensity) to divide the image into the chrominance and luminance values.
2) Divide each HSI channel into 100 bins uniformly, e.g., the value of the first bin ranges from zero to one hundredth of the maximum value. Then, map each pixel in the image into each bin of HSI channels according to its HSI values.
3) Estimate the light sources by simply averaging the RGB values of the pixels that are mapped into the same bin for each HSI channel.
4) Measure the performance from the estimated light sources and observe the tendency of the performance changes for each HSI channel. For the performance measurement, the angular error [2], [4], [11] between the ground truth light source and the estimated light source is used.

Some examples of the observation are shown in Fig. 1. The different characteristics on each HSI channel are observed. According to the varying hue values, no distinct tendency is observed. However, there exist tendencies for the intensity and saturation values. Dark pixels, i.e., the pixels with low intensity values, generally tend to reflect the less information of the light source than bright pixels. Interestingly, the clearest tendency is observed according to varying saturation values.

After observing over 100 images, we conclude that the pixels which contain a lot of information of the light source are mostly distributed from a certain saturation value and the pixels with high saturation values generally tend to contain the less information of the light source. Consequently, these observations lead us to propose a novel method to improve the color constancy by introducing a saturation weighting scheme.

4. SATURATION WEIGHTING SCHEME

From the observations in the previous section, we found the tendencies according to the saturation and intensity values. Though the tendency in accordance with the intensity values was observed, there was a similar method using this type of characteristic. The shades of gray method [10] gives high weights to the high values of each RGB channel according to the Minkowski norm p. Even if the method does not use the intensity channel but uses each RGB channel, since the values of each RGB channel can be thought as the independent intensity values of each channel, similar effects are expected. Therefore, the shades of gray method performs generally better than the gray world method.

Our method is based on the strong tendency of the performance changes according to the saturation values. We convince that differently weighted pixels based on their saturation values will improve the performance of the color constancy. First, we incorporate a saturation weighting function into the gray world method, which is called the gray world with saturation weighting (GWSW) given by

$$\int w^{s}(f(x))f_{i}(x)dx = ke_{i}, \tag{4}$$

where s denotes the saturation strength factor and $w(\cdot)$ is the saturation weighting function,

$$w(f(x)) = (1 - S(f(x))), \tag{5}$$

where $S(\cdot)$ is the saturation value of the pixel.

The saturation weighting function is designed for reflecting our observations. Since the pixels which have low saturation values tend to contain more information related to the light source than the pixels which have high saturation values, we make the value of the saturation weighting function decrease as the saturation value of a pixel increases. In addition, we assign the saturation strength factor to the weighting function so as to adjust the strength of the weights according to each testing environment.

Our method can be thought as a generalization between the gray world method and the "do nothing" approach. For $s = 0$, our method becomes the gray world method because all values of the saturation weighting function have equal weights. On the contrary, for $s = \infty$, our method becomes the "do nothing" approach. Only when the saturation value is equal to zero, the weight becomes one but otherwise the weight converges to zero. Since the pixels whose saturation values are equal to zero are achromatic, they do not have color information, which results in estimating the light source as the canonical light source, i.e., the "do nothing" approach.

A more advanced extension is achieved by unifying our idea with the general gray world method [11] called the general gray world with saturation weighting (GGWSW) presented as

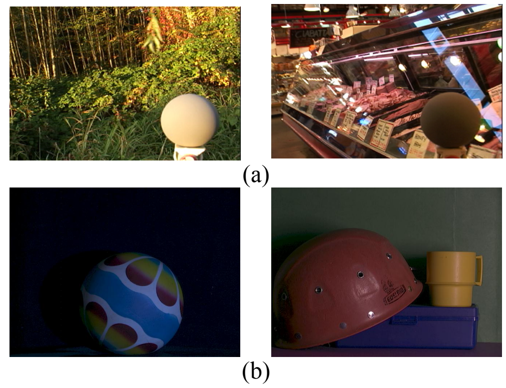


Fig. 2. The examples of the datasets. (a) The images of the gray ball dataset. (b) The images of the controlled indoor dataset.

$$\left(\int w^{s}(f(x))\left(f_{i,\sigma}(x)\right)^{p}dx\right)^{1/p} = ke_{i}. \tag{6}$$

The scale of smoothing operation σ handles local correlation between pixels. The smoothing operation reduces the influence of noise in an image and it was proven to be beneficial for improving the color constancy [14], [11]. By incorporating p and σ into GWSW, we can achieve the better performance than the general gray world method.

5. EXPERIMENTAL RESULTS

In this section, we evaluate and compare the proposed method with state-of-the-art methods including the low-level statistics-based methods [8-11] and the generalized gamut mapping [4] which is a representative of the learning-based methods. Two widely used datasets in Fig. 2 are chosen for the performance evaluation, i.e., the gray ball dataset [13] and the controlled indoor dataset [15].

The performance of each method is evaluated by measuring how similar the estimated light source to the ground truth light source provided by each dataset. The angular error ϵ is used for the similarity measurement:

$$\epsilon = \cos^{-1}\left(\hat{e}_g \cdot \hat{e}_e\right), \tag{7}$$

where $\hat{e}_g$ is the ground truth light source with normalization and $\hat{e}_e$ denotes the estimated light source with normalization. In order to take the statistics of the angular errors on each dataset, the median is chosen since it is the most suitable parameter for reflecting the performance of the color constancy, which is reported in [16], [11]. For reliable comparison, the low-level statistics-based methods implemented by Weijer *et al.* [11] and the results of the generalized gamut mapping provided by Gijsenij *et al.* [4] are exploited (refer to [4] for the detailed information about the parameters and the experimental methodology of the generalized gamut mapping).

5.1. Gray ball dataset

The gray ball dataset [13] has a large amount of images consisting of 11,346 extracted from a digital video camera. Since the gray ball is mounted on the camera, the ground truth light source can be measured and the light source is provided

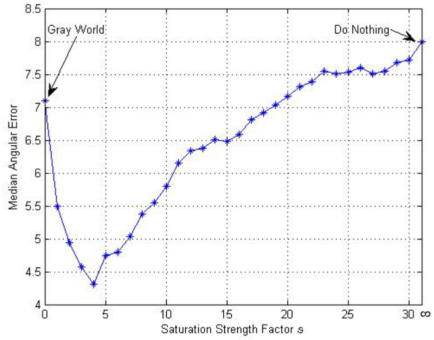


Fig. 3. The performance of GWSW with the varying saturation strength factor s.

TABLE I
Median Angular Errors on the Gray Ball Dataset.

Methods	Parameters	Median
Do Nothing	-	8.0
Gray World	$p = 1, \sigma = 0$	7.1
Max-RGB	$p = \infty, \sigma = 0$	6.3
General Gray World	$p = 16, \sigma = 0$	4.9
1-order Gray Edge	$p = 1, \sigma = 1$	4.7
2-order Gray Edge	$p = 2, \sigma = 2$	4.7
Gen. Gamut Mapping	1-order gradient, $\sigma = 1$	5.2
Proposed (GWSW)	$p = 1, \sigma = 0, s = 4$	4.3

with the dataset. From each location, the dataset is classified into 15 subsets. However, within each subset, high correlations exist among consecutive images because the dataset was taken from the video. Furthermore, since a different number of images are included within each subset, it also disrupts the proper evaluation of the color constancy algorithms. Thus, the evaluation is performed on 225 images which consist of uncorrelated 15 images from each subset. During the color constancy process, the gray ball presented in each image is excluded because it affects the color constancy result.

First, the influence of the saturation strength factor s is investigated. For fixed $p = 1$ and $\sigma = 0$, we observe the performances by changing s, i.e., GWSW. The tendency of the performance changes can be observed in Fig. 3. For $s = 4$, the best performance is achieved. It is shown that the proper selection of s ensures the significant improvement than both the gray world method and the “do nothing” approach.

The comparison with the existing methods is presented in Table I. The parameters of the existing methods are optimally tuned for our experimental environment. Our method outperforms the existing methods including the generalized gamut mapping. By just incorporating the saturation weighting to the gray world method, we achieve the significant improvement of the gray world method from 7.1 to 4.3, i.e., the improvement rate is 39.4%.

5.2. Controlled indoor dataset

The second dataset for our experiment is the controlled indoor dataset [15]. By changing 11 light sources, different 30 sets of objects are taken under a laboratory environment. Except for some images which have deficiencies in the calibration data, 321 images are composed on this dataset and the evaluation is performed on all the 321 images for the low-level statistics-based methods and 290 images for the generalized gamut mapping because 31 images are used for the training phase.

TABLE II
Median Angular Errors on the Controlled Indoor Dataset.

Methods	Parameters	Median
Do Nothing	-	15.6
Gray World	$p = 1, \sigma = 0$	7.1
Max-RGB	$p = \infty, \sigma = 0$	6.5
General Gray World	$p = 11, \sigma = 1$	3.2
1-order Gray Edge	$p = 7, \sigma = 4$	3.2
2-order Gray Edge	$p = 7, \sigma = 5$	2.8
Gen. Gamut Mapping	2-jet, $\sigma = 4$	2.1
Proposed (GGWSW)	$p = 36, \sigma = 3, s = 3$	2.6

The performance of each method is shown in Table II. We set the optimal parameters for the low-level statistics-based methods reported in [11]. Without using the image derivatives, GGWSW shows the superior result to the existing low-level statistics-based methods. By adding one more parameter to the general gray world method, the performance is considerably improved from 3.2 to 2.6, i.e., the improvement rate is 18.8%. Although our result is worse than the generalized gamut mapping, it is more complex than the low-level statistics-based methods and requires the training phase. Since it is clear that our method improve the existing low-level statistics-based methods, this experiment also supports the validity of our idea.

6. CONCLUSIONS

The low-level statistics-based methods [8-11] are widely used because of their simplicities, low computational complexity, and satisfactory performances with adequate parameters [2]. However, none of these methods exploit the explicit model for the dependency of RGB channels so far. From a lot of observations, we aim to improve the color constancy performance by assigning the different weights to the pixels based on each saturation value.

The experiments on the two widely used datasets show that the proposed method significantly improves the existing methods and clearly demonstrates that the color correlation is the important feature for the color constancy. Consequently, the proposed method is simple, fast, and effectively improving the color constancy.

In most case, our method shows satisfactory performances. However, in some cases that a lot of pixels with low saturation values have different color characteristics from the light source, our method shows less accurate performances. In the future, we will improve our method by combining it with other low-level statistics-based methods, as the combination method in [7], and achieve the better performance of the color constancy.

7. ACKNOWLEDGEMENTS

This research is currently funded by the Korea Communication Commission under grant number 12912-03001 (Development of Context-Aware Tele-Screen System Technology) and the Ministry of Education, Science and Technology (Basic Science Research Program) under grant number 2012R1A1A2004947.

8. REFERENCES

[1] S. Hordley, "Scene illuminant estimation: Past, present, and future," *Color Res. Appl.*, vol. 31, no. 4, pp. 303–314, Aug. 2006.

[2] A. Gijsenij, T. Gevers, and J. van de Weijer, "Computational color constancy: Survey and experiments," *IEEE Trans. Image Process.*, vol. 20, no. 9, pp. 2475–2489, Sep. 2011.

[3] D. Forsyth, "A novel algorithm for color constancy," *Int. J. Comput. Vis.*, vol. 5, no. 1, pp. 5–36, Aug. 1990.

[4] A. Gijsenij, T. Gevers, and J. van de Weijer, "Generalized Gamut Mapping Using Image Derivative Structures for Color Constancy," *Int. J. Comput. Vis.*, vol. 86, no. 2, pp. 127-139, 2010.

[5] G. Finlayson, S. Hordley, and P. Hubel, "Color by correlation: A simple, unifying framework for color constancy," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 11, pp. 1209–1221, Nov. 2001.

[6] P. Gehler, C. Rother, A. Blake, T. Minka, and T. Sharp, "Bayesian Color Constancy Revisited," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* pp. 1–8, 2008.

[7] A. Gijsenij and T. Gevers. "Color Constancy Using Natural Image Statistics and Scene Semantics," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 4, pp. 687–698, Apr. 2011.

[8] E. Land, "The retinex theory of color vision," *Sci. Amer.*, vol. 237, no. 6, pp. 108–128, Dec. 1977.

[9] G. Buchsbaum, "A spatial processor model for object colour perception," *J. Franklin Inst.*, vol. 310, no. 1, pp. 1–26, Jul. 1980.

[10] G. Finlayson and E. Trezzi, "Shades of gray and colour constancy," in *Proc. IS&T/SID's Color Imag. Conf.*, pp. 37–41, 2004.

[11] J. van de Weijer, T. Gevers, and A. Gijsenij, "Edge-based color constancy," *IEEE Trans. Image Process.,* vol. 16, no. 9, pp. 2207–2214, Sep. 2007.

[12] J. von Kries, "Influence of adaptation on the effects produced by luminous stimuli," in *Sources of Color Vision*, D. MacAdam, Ed. Cambridge, MA: MIT Press, pp. 109–119, 1970.

[13] F. Ciurea and B. Funt, "A large image database for color constancy research," in *Proc. IS&T/SID's Color Imag. Conf.*, pp. 160–164, Nov. 2003.

[14] K. Barnard, L. Martin, A. Coath, and B. Funt, "A comparison of computational color constancy algorithms-part ii: Experiments with image data," *IEEE Trans. Image Process.*, vol. 11, no. 9, pp. 985–996, Sep. 2002.

[15] K. Barnard, L. Martin, B. Funt, and A. Coath, "A data set for colour research," *Color Res. Appl.*, vol. 27, no. 3, pp. 147–151, 2002.

[16] S. Hordley and G. Finlayson, "Reevaluation of color constancy algorithm performance," *J. Opt. Soc. Amer. A*, vol. 23, no. 5, pp. 1008–1020, 2006.