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Illuminant chromaticity estimation via optimization of RGB channel standard deviation

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Abstract

Illuminant estimation is the primary step to solve the color constancy problem. There are various statistical-based, learning-based and combinational-based color constancy algorithms already exist. However, the statistical-based algorithms can only perform well on images that satisfy certain assumptions, learning-based methods are complex methods that require proper preprocessing and training data, and combinational-based methods depend on either pre-determined or dynamically varying weights, which are difficult to determine and prone to error. Therefore, this paper presents a new optimization based illuminant estimation method which is free from complex preprocessing and can estimate the illuminant under different environmental conditions. A strong color cast always has an odd standard deviation value in one of the RGB channels. Based on this observation, a cost function called the degree of color cast(DCC) is formulated to determine the quality of illuminant color-calibrated images. Here, a swarm intelligence based particle swarm optimizer(PSO) is used to find the optimum illuminant using the degree of illuminant tinge. The proposed method is evaluated using real-world datasets and the experimental results validate the effectiveness of the proposed method.

Introduction

Differences in illumination cause the camera captured scene color biased towards the color of the light source. In computational approach, to discount the influence of illuminant color, an implied assumption is that the influence of light source color is static throughout a scene. Therefore, the scene illuminant is estimated first and the scene colors are then corrected using a chromatic adaptation model. The main objective of a color constancy algorithm is to estimate the scene illuminant. However, illuminant estimation is very difficult process and various approximations have been made on physical world scenes to cope up with that. State-of-the-art color constancy approaches can be categorized into three groups: 1) statistics-based methods, 2) learning-based methods, and 3) combinational methods [1]. The first type of algorithm is based on low level statistics or a physics based reflection model, the second type algorithm makes use of information extracted from the training phase to estimate the light source color, and the third type is formulated by combining statistics-based algorithms or choosing a superlative algorithm for a given image.

The Max-RGB or white patch retinex algorithm is a well known statistics-based color constancy method that uses the assumption that the highest luminance in RGB channels corresponds to perfect reflectance [2]. Another well known statistics-based color constancy method is the gray world algorithm, which is based on the assumption that the average reflection in a scene is achromatic [3]. In shades of gray [4], a gray world based method is used as an instantiation of the Minkowski p-norm instead of regular averaging. Gray edge [5] is a latest statistics-based color constancy method with an assumption that the average reflection difference in a scene is achromatic. Yet, since statistics-based methods are based on specific assumption, these methods do not perform well across a wide range of images and only perform well on images that satisfy the different assumptions [6]. The second category of color constancy method consists of machine learning based methods, gamut-based methods and probabilistic methods. Meanwhile, the most recent combination-based color constancy methods include the natural image statistics (NIS) [7] algorithm and classification based algorithm selection (CAS) [8] algorithm. NIS uses the Weibull parameter to predict the best algorithm for the given image, whereas CAS uses a decision tree to predict the best algorithm. Yet, even though the second and third type of algorithm can solve some of the problems with statistics-based methods, learning-based methods are complex and require proper preprocessing and training data, while the third type of color constancy method depends on either a pre-determined weight or dynamically varying weight, and finding the suitable weight is a difficult and error-prone task [9].

Nowadays evolutionary computational techniques like genetic algorithm (GA), genetic programming (GP) [10], particle swarm optimization (PSO) [9] are used for color constancy problems. PSO-based methods are particularly straightforward, as they are free of selection, crossover and mutation operations, which are necessary for GP and GA. In addition, PSO has a higher convergence speed compared to GA and GP [11]. Faghih and Mohaddam recently used PSO to solve color constancy problem [9]. Their method combines different statistics-based algorithms to find the scene illuminant color, does not require a weight factor and performs well compared to conventional statistics-based algorithms. However, the complexity is similar to that of combinational algorithms.

The main contribution of this paper can be summarized as 1) the formulation of a cost function called the degree of color cast (DCC) and 2) the first direct use of swarm intelligence to find the optimal scene illuminant. Experiments are performed on two real-world datasets, and the results reveal the effectiveness of the proposed DCC, which is used with PSO to find the scene illuminant. The remainder of this paper is organized as follows. Section II discusses DCC, PSO, and the proposed method in detail. The experiments and comparisons are presented in section III Finally, Section IV concludes the paper.

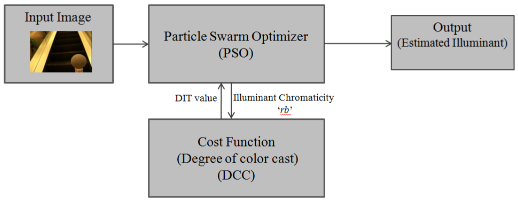

Figure 1. *Block diagram of the proposed method*

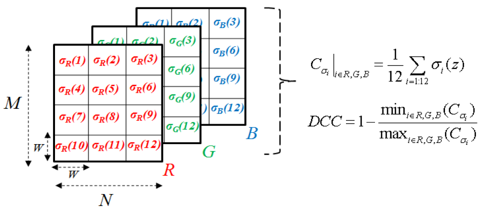

Figure 2. *The computational steps of DCC calculation*

Proposed approach

The proposed method is an optimization-based color constancy method that uses swarm intelligence to find the optimal scene illuminant. The main distinction between the proposed method and existing swarm intelligence-based color constancy algorithms is that previous methods use a selective approach or combination of conventional statistic-based methods to find the scene illuminant, whereas the proposed method directly searches for the optimum scene illuminant. Fig. 1 shows the overall structure of the proposed algorithm. PSO is initially used to generate some random 'rb' chromaticity coordinates for the illuminant and the input images are then corrected using this illuminant. Thereafter, the degree of color cast (DCC) of the corrected images is calculated and this information is then used by PSO to generate a new set of illuminant coordinates. This process is repeated until the maximum number of iterations reaches and the PSO finds the optimum 'rb' illuminant chromaticity coordinate that minimizes the DCC. This optimal coordinates is then used to generate illuminant-corrected output image. The detail explanation on the DCC formulation is given in the following sections.

Degree of color cast (DCC)

The proposed method introduces the degree of color cast (DCC) to differentiate the image with and without color cast, which is used as a cost function to find the optimum illuminant chromaticity. In [12], Anustup et. al. finds that local patches of an image under standard illuminant have a similar standard deviation in all 3 color channels and a color cast can change this equilibrium. Mathematically, This can be illustrated by the ratio of minimum to maximum RGB channel standard deviation as shown below.

$$I_\sigma(x,y) = \frac{\min_{i\in R,G,B,\widehat{z}\in W(x,y)}(\sigma_i(\widehat{z}))}{\max_{i\in R,G,B,\widehat{z}\in W(x,y)}(\sigma_i(\widehat{z}))} \qquad (1)$$

where $\sigma_i(\widehat{z})$ is the standard deviation of i_{th} channel pixel values in a window centered at (x,y). $I_\sigma(x,y)$ will be low for images with colorcast and high for images without color cast.

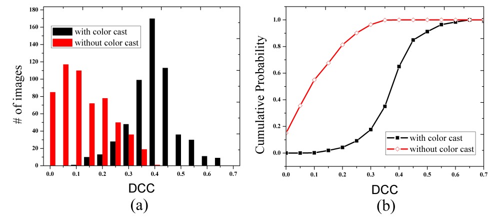

Figure 3. *DCC statistics of color checker dataset images, (a) Histogram of DCC over all color checker dataset images and (b) its cumulative distribution.*

The concept of $I_\sigma(x,y)$ is used to formulate the cost function .i.e., DCC for illuminant estimation. For this, the image is divided into different blocks of size W and for each block $\sigma_i(\widehat{z})$ is calculated. Later, the centroid of $\sigma_i(\widehat{z})$ is calculated as in equation (2). Then the DCC is computed from the ratio of minimum to maximum of average RGB channel standard deviation (C_{σ_i}) as shown in equation (3). Here, DCC is formulated in such a way that the images without color cast has a lower value compared to the images with color cast. Therefore, the proposed algorithm finds the illuminant chromaticity of the input image by minimizing DCC. For more clarity, the overall flow of DCC calculation is shown in Fig. 2.

$$\begin{aligned} C_{\sigma_i} &= \tfrac{1}{CT}\sum_{z=1}^{CT}\sigma i(\widehat{z}) \\ CT &= \left\lfloor \tfrac{M}{W} \right\rfloor \left\lfloor \tfrac{N}{W} \right\rfloor \end{aligned} \qquad (2)$$

$$DCC = 1 - \frac{\min_{i\in R,G,B,\widehat{z}\in W(x,y)}(C_{\sigma_i})}{\max_{i\in R,G,B,\widehat{z}\in W(x,y)}(C_{\sigma_i})} \qquad (3)$$

where CT is the total number of blocks, M and N are the height and width of the image, W is the size of the block and $\lfloor\,\rfloor$represents integer division.

Gehler-Shi color checker dataset [13][14] images were used to verify how good is DCC to distinguish images with and without color cast. Fig. 3 shows the DCC histogram and its cumulative distribution for original dataset images (red) and ground truth images (black) of color checker dataset. The cumulative histogram of DCC shows that 96% of images without color cast have DCC less than 0.3, while only 17% percentage of images with color cast have DCC less than 0.3. This proves that DCC can distinguish the image with and without color cast. To demonstrate the effectiveness of the proposed DCC for illuminant chromaticity estimation, three sample images were selected from the color checker dataset with different contents. Then, the DCC value of color corrected image were calculated by varying its illuminant chromaticity 'r' and 'b' value in between 0.15 and 0.5. Fig. 4 shows the sample images, its DCC heat map and illuminant chormaticity 'rb' value that minimizes DCC. Table 1 shows the angular error comparison of estimated illuminant using grey world (GW) assumption and DCC. In all the three cases DCC has estimated illuminant with lower angular error compared to the illuminant estimated using GW algorithm. This comparison confirms the capability of DCC in illuminant chromaticity estimation.

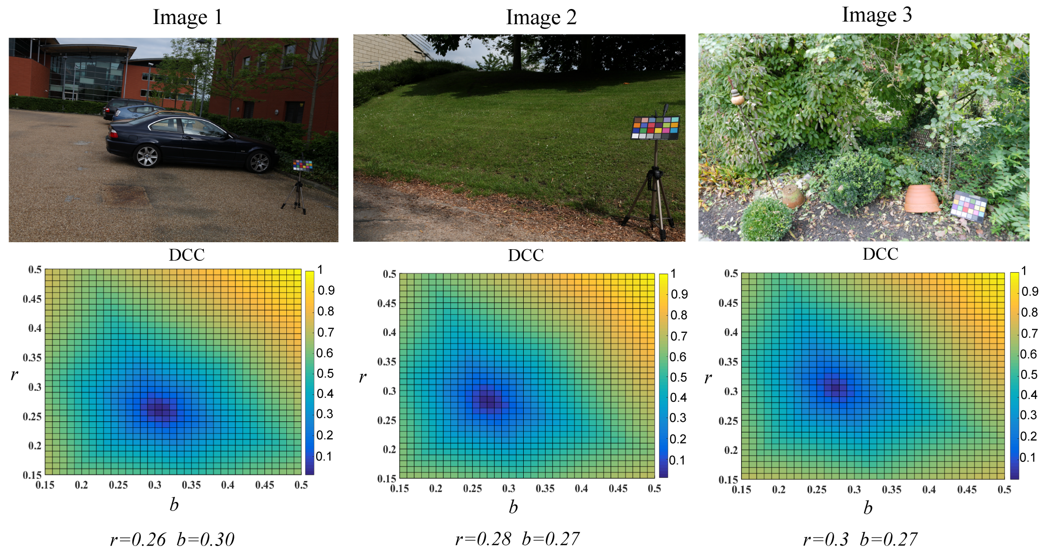

Figure 4. *DCC heat map of three sample images taken from color checker dataset. The value mentioned at the bottom of each heat map represents chromaticity coordinates at which DCC value is minimum.*

Illuminant Estimation

This section mainly focuses on illuminant estimation by DCC optimization. This paper uses evolutionary swarm intelligence based particle swarm optimizer (PSO). Generally, PSO or swarm intelligence based algorithm is used in very high dimensional optimization problems. An alternate solution for DCC optimization is to uniformly sample the 2D search space ('rb' space) with some reasonable density. For example, consider all possible combinations of 'r' and 'b' value between 0.15 to 0.5 with an interval of 0.01. The lower and upper limit of this 'r' and 'b' empirically selected by analyzing dataset images. In this way total 1225 (35x35) samples need to be considered. Therefore, all together 1225 times the cost function (DCC) has to be evaluated to get the optimum 'r' and 'b' value. For this same problem, PSO has found the optimum value within 400 function evaluations (DCC). In most of the cases the algorithm only took less than 200 DCC evaluations to find the optimum value. Therefore, we have used particle swarm optimizer (PSO)for DCC minimization to estimate the illuminant. The following subsection discuss more on PSO and illuminant chromaticity estimation using PSO.

PSO and Proposed methodology

Particle swarm optimization (PSO) is a swarm intelligence-based evolutionary optimization technique developed by Ebherhat and Kennedy [15, 16]and inspired by the swarm behavior

Table 1. Performance comparison (Angular error) of grey world (GW) algorithm and proposed DCC on sample images shown in Fig. 4

	Grey World	Using DCC
Image 1	8	5.3
Image 2	7.5	3.8
Image 3	19.1	13.9

Step. 1 Start

Step. 2 Initialize the PSO particle i.e., 'r' and 'b' with n random position $p_k = \{r_k, b_k\}\big|_{k=1:n}$ between 0.15 and 0.5 and velocity $v_k = \{v_{r_k}, v_{b_k}\}\big|_{k=1:n}$

Step. 3 Calculate DIT for each particle.

Step. 4 Initialize $p_{best_k}\big|_{k=1:n}$ with the DCC corresponds to k^{th} particle.

Step. 5 Assign 'r' and 'b' value of particle with minimum DCC (i.e., less color cast) to g_{best}.

Step. 6 Loop until t reaches the maximum iteration t_{max} (for t = 1 to t_{max})

- **Step. 6.1** Loop until all particle exhaust (k=1 to n)
  - **Step. 6.1.1** Position and velocity of k^{th} particle are updated with the present p_{best_k} and g_{best} using equation (5) and (4) respectively.
  - **Step. 6.1.2** Calculate DCC for the k^{th} particle using equation (3).
  - **Step. 6.1.3** If DCC of the k^{th} particle is less than the DCC of the p_{best_k} then $p_{best_k} = p_k$
  - **Step. 6.1.4** Go to step 6.1
- **Step. 6.2** If any of the $p_{best_k}\big|_{k=1:n}$ has DCC value less than g_{best} then then assign its 'r' and 'b' to g_{best}.
- **Step. 6.3** Go to step 6

Step. 7 Output g_{best} the optimum 'r' and 'b' value.

Step. 8 Stop

Figure 5. *Pseudo code of PSO based illuminant estimation using DCC.*

of bird flocking and fish schooling. The simplicity, high convergence speed, and easy implementation of PSO have made it a successful optimization tool for many real-world applications [17, 18, 19]. The PSO algorithm consists of a swarm of particles, where each particle k is represented by a position vector $\mathrm{p}_k = \{p_{k1}, p_{k2}, ..., p_{kD}\}$in D-dimentional space and a velocity vector $\mathrm{v}_k = \{v_{k1}, v_{k2}, ..., v_{kD}\}$. Each particle represents a potential solution and flies through the multidimensional solution space to find the optimum solution. The position and velocity vector of each particle k is first randomly initialized within the range, and then updated with each iteration as follows:

$$\mathrm{v_k}(t+1) = \omega \mathrm{v_k}(t) + c_1 r_1 [\mathrm{p}_{best_k} - \mathrm{p}_k] + c_2 r_2 [\mathrm{g}_{best} - \mathrm{p}_k] \quad (4)$$

$$\mathrm{p}_k(t+1) = \mathrm{p}_k(t+1) + \mathrm{v_k}(t+1) \quad (5)$$

where p_{best_k} is the best position attained by k^{th} particle, g_{best} is the global best position, t is the iteration number, c_1 and c_2 are the two positive acceleration coefficients that adjust the movement of particles towards local and global best position and r_1 and r_2 are the uniformly distributed random values. The inertial weight ω linearly varies within a range of $[\omega_{min}, \omega_{max}]$ as follow.

$$\omega = \omega_{max} - \left(\frac{(\omega_{max} - \omega_{min})t}{t_{max}} \right) \tag{6}$$

where t is the iteration number and t_{max} is the maximum number of iterations. As shown in equations (4) and (5) particle accelerate towards p_{best_k} and g_{best} location with a random weighed acceleration.

Thus, each particle moves around the solution space in a random manner looking for the best solution. The quality of each particle is then evaluated with the help of a cost or objective function. In the proposed PSO based color constancy method, each particle considered as the potential 'r' and 'b' values and quality of each particle evaluated with *DCC*. PSO find the optimal 'r' and 'b' value that minimizes the *DCC* and estimate the illuminant using equation. The overall flow of the proposed PSO based illuminant estimation method is illustrated in Fig. 5

Experimental Evaluation

To evaluate its performance, the proposed method was applied to two standard color constancy datasets: SFU grey ball dataset [20] and color checker dataset]. The SFU grey ball dataset consists of 11,346 nonlinear images and the color checker dataset contains 568 high dynamic images that include both indoor and outdoor scenes. The color checker board and grey ball in the datasets were masked during the experiments for an unbiased comparison of the proposed method with the existing color constancy methods. The proposed method was compared with various conventional methods, including statistical-based methods, a learning-based method and combinational method. The result of these methods were taken directly from the color constancy algorithm survey papers by Gijsenij et al. [1] and Li et al. [30]. The results of the methods not included in the survey papers were referenced from the respective journal papers.

In this experiment, PSO parameters of the proposed method were configured as same as the conventional PSO[30]. The inertia weight upper limit and lower limit of the PSO set at 0.9 and 0.4, respectively, acceleration parameter c1 and c2 maintained at 2.1. The particle swarm size i.e., the number of illuminant rb' chromaticity coordinates, was set at 20, while the maximum number of iterations tmax was set at 20. The lower and upper limit for the particles was set at 0.15 and 0.5, respectively. Plus, the maximum magnitude of velocity was set at 0.1. The proposed method was then evaluated based on the angular error between the estimated illuminant and the ground truth illuminant [31].

Mathematically, angular error can be represented as

$$er_{ang}\left(e_{gd}, e_{est}\right) = cos^{-1}\left(\frac{e_{gd} . e_{est}}{\left\|e_{gd}\right\| \left\|e_{est}\right\|} \right) \tag{7}$$

where e_{gd} and e_{est} are the ground truth and estimated illuminant.

Fig.6 shows the visual comparison of the color-corrected images using proposed method, grey world, white patch and grey edge algorithm. The angular error of all the methods is indicated at the bottom right corner of each image. For quantitative comparison, the proposed method was applied to two real world color constancy datasets. Table 2 shows the performance statistics of various methods on Gehler-Shi color checker dataset. The proposed method surpassed most of the illuminant estimation methods (Table 2) in terms of mean angular error. Note that the exemplar based, 19-Edge Corrected moment, illuminant estimation using simple features and Bright and dark colors PCA algorithms performed better compared to the proposed approach. However, PCA based method has higher worst 25% mean angular error, and exemplar based and 19-Edge Corrected moment has higher run time compared to the proposed method. Therefore, the proposed method has the supremacy over all the statistical-based method mentioned in Table 2. Also, the proposed method has shown competitive mean angular error compared to the combinational methods.

Nextly, we have compared the performance of the proposed method on the grey ball dataset. The proposed approach has outperformed all the statistical-based and combinational algorithm in terms of mean angular error as shown in the Table 3. More specifically, the proposed approach has improved its mean and median angular error approximately by 10% and 14% respectively, compared to the best statistical-based method, i.e., the grey edge algorithm. Except exemplar based method, the proposed method surpassed all other learning based method. Even though, the proposed methods performance is not up to the exemplar based method, it only requires less computation power. Also, the proposed method is free from pre-determined or dynamically varying weights. The main highlight of the proposed method was the reduction of the mean 'worst 25 %' angular error on color checker and grey ball dataset images.

Timing comparison

Table 4 shows the run time comparison of the proposed method with maxRGB, grey world, grey edge and gamut mapping algorithm on color checker dataset images. Here, the mean time taken by the algorithm to estimate illuminant of 100 images used for comparison. The proposed method using DCC has a slightly higher run time compared to grey world and white patch algorithm. However, the proposed method has outperformed both of this algorithm in illuminant estimation (Tables 2 & 3). Also, the run time of proposed method is 2 times better than grey world algorithm and 5 times better than the gamut mapping algorithm. The only algorithm that surpassed our method in illuminant estimation is the exemplar based method. In [38], the author has mentioned that the run time of exemplar based method is twice that of the gamut mapping method. Therefore, our proposed method is far better than exemplar based method in terms of computational speed.

DCC parameter settings

This section examines the effect of DCC window size W on illuminant estimation. Fig. 7 shows the mean angular error of proposed algorithm using different window size. The red plot represents the grey ball data set's mean angular error and black plot is for a color checker dataset. Both the plot shows that pro-

Table 2. Performance of various color constancy algorithm on color checker dataset

	Method	Median	Mean	Best 25%	Worst 25%
Statistical-based method	Grey World [3]	6.28	6.36	2.33	10.58
	White Patch [2]	5.68	7.55	1.45	16.12
	Shades of grey [4]	4.01	4.93	1.14	10.20
	1st order grey edge [5]	4.52	5.33	1.86	10.03
	2nd order grey edge [5]	4.44	5.13	2.11	9.26
	Bright and Dark color PCA [21]	2.14	3.52	0.50	8.74
Learning Based Method	Pixel based Gamut [22]	2.33	4.20	0.50	10.72
	Edge based Gamut [22]	5.04	6.52	1.90	13.58
	Intersection based Gamut [22]	2.39	4.20	0.51	10.70
	SVR Regression [23]	-	3.23	-	-
	Bayesian [13]	3.46	4.82	1.26	10.49
	Exemplar based [24]	2.27	2.89	0.82	5.97
	19-Edge Corrected-moment [25]	2.04	2.86	0.70	6.84
	CNN based method [26]	2.75	1.99	0.74	6.08
	Deep learning based method [27]	3.10	2.3	-	-
	Illuminant estimation using simple features [28]	1.65	2.42	0.38	5.87
Combinational Method	Natural Image Statistics [7]	3.13	4.19	1.00	9.22
	Support Vector Regression based combination)[29]	-	1.97	-	-
	Multi-objective optimization based color constancy [9]	3	4.3	-	-
	Proposed Method	3.53	4.10	1.5	8.32

posed algorithm has better performance .i.e., minimum angular error while using a 13x13 window.

Conclusion

This paper proposed an optimization based illuminant estimation method which make use of statistical assumptions. The proposed method used the degree of color cast (DCC) as a measure to determine the quality of a color-corrected image, which is used by PSO for estimating optimal illuminant parameters. The proposed method is evaluated using two standard real-world datasets. Experiments showed that the proposed approach outperformed all the statistical-based methods in illuminant chormaticity estimation of the color checker and grey ball dataset images. The computational time of the proposed method is similar to the best performing statistical-based method and better compared to the learning based methods. Therefore, the proposed swarm intelligence-based illuminant estimation method can definitely be used in various computer vision applications to discount or regularize the scene illuminant color. As a future work we plan to investigate more on image feature which can improve the illuminant predictability of the cost function.

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Table 3. Performance of various color constancy algorithm on grey ball dataset

	Method	Median	Mean	Best 25%	Worst 25%
Statistical-based method	Grey World [3]	6.97	7.87	2.16	15.25
	White Patch [2]	5.31	6.81	1.18	14.72
	Shades of grey [4]	5.29	6.11	1.76	11.84
	1st order grey edge [5]	4.89	5.74	1.7	11.31
	2nd order grey edge [5]	5.08	5.96	1.72	11.73
Learning based method	Pixel based Gamut [22]	5.82	7.07	1.67	14.75
	Edge based Gamut [22]	5.82	6.82	1.92	13.49
	Intersection based Gamut [22]	5.88	6.90	1.92	13.65
	SVR Regression [23]	-	1.32	-	-
	Exemplar based [24]	3.42	4.38	1.01	9.36
	Deep learning based method [27]	3.90	3.0	-	-
Combinational method	Natural Image Statistics statistics [7]	3.93	5.19	1.21	11.15
	Multi-objective optimization based color constancy [9]	3.3	5.2	-	-
	Proposed Method	4.2	5.18	1.37	10.61

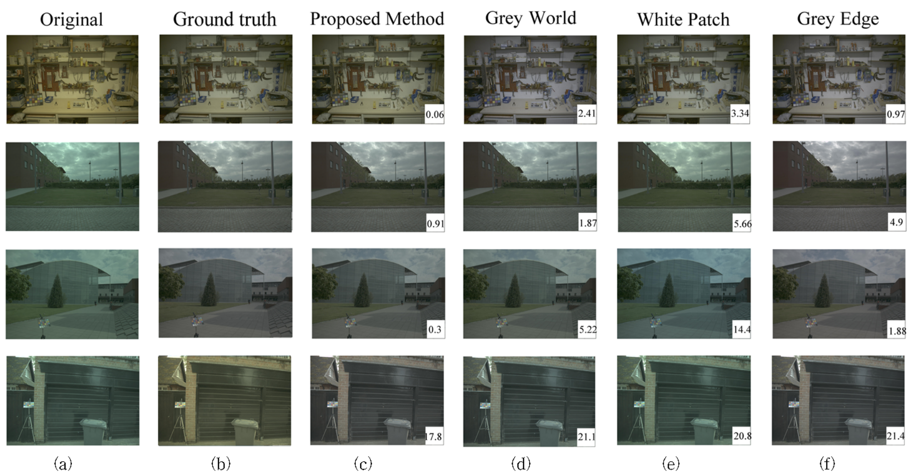

Figure 6. *Color calibrated images using the illuminant estimated from four different methods including the proposed method. (a) Input Image, (b) Ground truth (c) Proposed Method, (d) Grey world, (e) White patch, (f) Grey Edge. The angular error is mentioned at the bottom right corner of each color corrected image.*

Table 4. Computational time comparison of selected statistical-based methods with the proposed method

Algorithm	**Mean Computational time (100 images)**
Grey world	0.15 sec
White patch	0.17 sec
1st Order grey Edge	1.13 sec
2nd Order grey Edge	1.32 sec
Pixel based Gamut	2.71 sec
Edge based Gamut	3.68 sec
Proposed	0.53 sec

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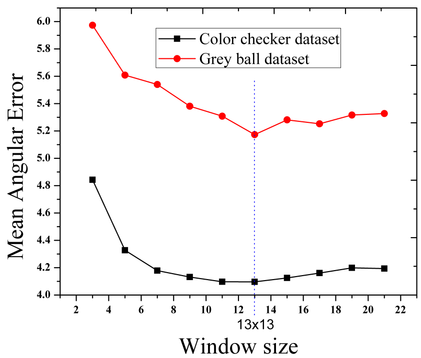

Figure 7. *Effect of the window size in illuminant estimation of color checker and grey ball dataset images using DCC.*

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