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K-means and Particle Swarm Optimization based Color Constancy of Images

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Abstract*: Color constancy is a fundamental requirement for many image processing and computer vision applications. Since color constancy is an under constrained problem, the existing methods are based on some assumptions and hence no method exists that works for all types of images. The proposed approach uses Particle Swarm Optimization (PSO) algorithm to combine different existing algorithms in an optimal way so that a single method works for almost all types of images. The combination of existing algorithms is done in weighted proportion, where each existing algorithm has an associated weight, which varies with the type of image. These weights are learned during the training phase. In the training phase, similar types of image are clustered using K-Mean clustering algorithm. The clustering is performed over Weibull parameters and for each cluster the optimal weights are obtained using PSO. Once the system is trained, given any input image the system can correct the image by grouping the image into one of the clusters based on similarity measure, and then applying the optimal weights corresponding to that group/cluster (obtained during training). The median angular error criterion is used to compare the results of the proposed approach with some of the existing color constancy methods. Obtained results show the effectiveness of the proposed approach compared with other considered approaches.

Index Terms*: Color Constancy, Illuminant Estimation, k-means Clustering, Particle Swarm Optimization, Weibull Parameters

I. INTRODUCTION

Ability to perceive different color by human depends on the brain and photoreceptors *viz.* rods and cones cells in retina. In Human Visual System, perceived color of different objects plays major role in identification of these objects. On the similar verge, colors of different objects play major role in identification of objects in various image processing/ computer vision based applications, *viz.* human computer/robot interaction [1][2], color feature extraction [3][4], and color appearance models [5], *etc.*

Color of an object depends on (a) the reflectance of the surface and (b) the incident illumination of the light source. However, captured color of an object majorly affected by the incident light source. Figure 1 depicts an example of the perceived color of the same flower captured or rendered under different light sources [6].

Variations in perceived color of the objects due to different illumination are insignificant in such image processing/computer vision applications where objects are recognized using shapes/contents of the objects [7]. However, these variations in perceived color of the objects due to different illumination reduce the performance of various image processing/computer vision applications where objects are recognized using colors of the objects [3].

Fig. 1 An example of the perceived color of the same flower captured under different light sources [http://colorconstancy.com/?page_id=9]

Color constancy [8][9] is a phenomenon which allows transforming an image taken in unknown light source to a corresponding image without the effect of that light source (*i.e.* under white light). To develop a robust system for image processing/computer vision based applications, color constancy is a fundamental requirement, and therefore the effect of the light source should be filtered out giving a color constant image.

Many solutions to color constancy problem have been proposed in the past. These approaches can be divided into following three main categories: approaches based on the low-level image features, approaches based on the constraint over set of colors which can be observed, and fusion of existing algorithms. As detailed in subsequent section, existing methods of color constancy are based on various assumptions and considering the requirement of color constancy in various image processing/computer vision applications, an efficient and effective scheme for color constancy is highly needed.

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Hence, in this paper, we propose an effective scheme for color constancy. The proposed approach uses clustering to group the data based on Weibull parameters and performs learning using the Particle Swarm Optimization (PSO) algorithm. The proposed approach calculates image features using Weibull parameterization as introduced by Gijsenij [10]. After computing features, images are clustered using k-means clustering algorithm. Finally for each cluster, optimal weights are obtained by learning the system using PSO. Effectiveness of the proposed scheme is observed on the dataset introduced by Ciurea and Funt [11] which consists of more than 11,000 images and its performance has been compared with some of the contemporary schemes detailed in subsequent section.

Rest of the paper is organized as follows: Section II discusses some of the previous work for color constancy; Section III briefs the required preliminaries *viz.* color constancy based on low-level image features and fundamentals of PSO; the proposed approach is discussed in Section IV; results and comparisons with some of the existing methods are presented in Section V; finally the paper is concluded in Section VI.

II. RELATED WORKS

As discussed in previous section, contemporary approaches explored for color constancy can be categorized into three categories. Subsequently, we discuss these categories and the approaches proposed by the researchers under these categories.

The approaches considered under first category include such contributions where low-level image features had been used for color constancy. Some of the previous contributions in this category of the solutions approach are as follows: Land and McCann [12]; max-RGB algorithm [13]; the gray-world algorithm [14]; the shades-of-grey algorithm [15]; and the grey-edge algorithm [16].

In [12], Land and McCann conducted numerous subjective experiments and developed the Retinex theory (*i.e.* the combination of retinal and cortical mechanisms), for color constancy. This theory explicitly treats the spatial distribution of colors in a scene, finds the ratio of the signal in the scene, and normalizes it throughout the scene. In [13], Land extended the work done in [12]. His work was based on the principles of the Retinex theory where he concluded that the color appearance is independent of the spectral distribution of the reflected light. Further, he demonstrated that the surface reflectance controls the color appearance. Time to time, many researchers [17][18] explored the feasibility of the color constancy using Retinex theory and highlighted the flaws, specifically in its sensitiveness to changes in the color of nearby objects and the physiological implementation of the Retinex model.

Buchsbaum in [14] formulated comprehensive mathematical model (Gray world) for color constancy. His approach was one of the simplest color constancy algorithms. However, the proposed model was constrained over various assumptions and gray-world hypothesis, like, “the visual system must implicitly estimate and illuminant” and “the estimate of the illuminant is made on the basis of spatial information from the entire visual field”. To overcome some of the limitations (in terms of various assumptions and hypothesis) of previous approaches, Finlayson and Trezzi [15] proposed Shade of grey algorithm for color constancy. Besides some assumptions, their approach required significant computational cost.

Further contribution under this category was made by Weijer, Gevers, and Gijsenij. In this paper, an Edge-based method for color constancy was proposed where the higher order structure of images was used [16]. The basis of their method was gray-edge hypothesis, *i.e.* the average edge difference in a scene is achromatic.

In general, the Retinex theory based approaches suffers with various assumptions and hypothesis, poor color fidelity and requires optimal selection of various parameters, whereas the gray world approach lacks in reliability and are not much adaptive.

Approaches used in the second category are based on the fact that under a given illuminant only a limited set of colors can be observed. All possible color values that can be observed form a canonical gamut. Forsyth [19] have proposed a first such kind of method called gamut mapping algorithm with the aim to find a mapping between canonical and observed gamut. However, this approach was constrained with the knowledge of the canonical illuminants and the range of occurrence of the illuminant.

Approaches used in the third category aims at the fusion of existing algorithms. A weighted average approach for illuminant estimation was proposed by Cardie *et al* [20]. Schaefer *et al* [21] used a weighted average to combine statistics and physics based methods and optimized weights using genetic algorithms. Besides these contributions, Gijsenij *et al*. [10] used natural image statistics (Weibull parameters) to achieve the selection and combination of existing color constancy algorithms.

III. PRELIMINARIES

In this section we first discuss the introductory concepts of color constancy using low level image features, followed by the fundamentals of PSO.

A. Color Constancy

Color constancy is referred as to make corrections in the images so that the perceived color is robust to the changes in the illumination spectrum. Irrespective of the illumination spectrum, the perceived color of the corrected images gives an indication that the image would have been clicked under white light source. The correction process usually involves following steps: (a) estimation of the color of the light source and (b) transformation of the original image. Subsequently we present the reflection model where we briefly discuss the image formation model, color estimation models, *i.e.* illumination estimation, and diagonal model for transformation of the image from one light source to another.

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1) *Reflection Model:* A surface that reflects light in such a way that the brightness of the surface appears same irrespective of the observer's angle of view is called Lambertian surface. For such surface, image intensity value,$I = (I_R, I_G, I_B)^T$ is a function of (a) light source$L(\lambda)$, (b) the camera sensitivity $\rho(\lambda)$ where., $\rho(\lambda) = (\rho_R(\lambda), \rho_G(\lambda), \rho_B(\lambda))^T$ and (c) surface reflectance $S(x, \lambda)$, where, x, λdenotes the spatial coordinate and wavelength of the light respectively. As described in [10], the image intensity value along all the color channels can be obtained using Equation 1 as follows:

$$I_c(x) = m(x) \int_\omega L(\lambda)\rho_c(\lambda)S(x,\lambda)d\lambda \quad (1)$$

where, $m(x)$ denotes the Lambertian shading, ω is the visible light spectrum,λ's are the sample points, $d\lambda$ is the width between them and $c = \{R, G, B\}$ is the three color channels.

The Equation (1) is based on an assumption that only one light source illuminates the scene and observed color of light source$F$ is a function of the camera sensitivity function $\rho(\lambda)$ and the color of the light source $L(\lambda)$. The observed color of the light source is given as:

$$F = \begin{pmatrix} f_R \\ f_G \\ f_B \end{pmatrix} = \int_\omega L(\lambda)\rho_c(\lambda)d\lambda \quad (2)$$

2) Illumination Estimation: The illumination estimation methods are used to estimate the light source, leaving the intensity of the image unaltered. This is one of the important steps required to obtain the color constancy for the given image. Prior to this step, the color of the light source L is required to be estimated for the given image with known image values. For the given image, estimation of the perceived color of the light source F is an under constrained problem, as both $L(\lambda)$and $\rho(\lambda)$ are unknown. Thus, number of assumptions is required to solve for estimating the observed/perceived color F.

Based on the Retinex model, Land and McCann [12] proposed the first color constancy method in early 70's. Later, several other methods (max-RGB, gray-world, grey-edge, and shades-of-grey) were derived from this model. The estimation of an observed color requires various assumptions, as stated previously. In max-RGB, it is assumed that the max response in RGB-channel is caused by a white patch [13]. In gray-world algorithm, the average reflectance for a scene under a natural light source is assumed to be achromatic [16]. According to [10], many color constancy methods can be derived from Equation 3.

$$\left(\left|\frac{\partial I_{c,\sigma}(x)}{\partial x^n}\right| dx\right)^{1/p} = kW_c^{n,p,\sigma} \quad (3)$$

where n is the order of the derivative; c is the color channel, *i.e.* R, G, B; p is the Minkowski norm; and σ is the smoothness parameter.

Algorithms like gray-world, max-RGB, shades-of-grey and grey-edge can be generated by substituting appropriate values for n, p and σ as follows: (a) n, p and σ as 0, 1, and 0 respectively, *i.e.* $W_c^{0,1,0}$ is equivalent to the gray-world algorithm, (b) n, p and σ as 0, ∞, and 0 respectively, *i.e.* $W_c^{0,\infty,0}$ is equivalent to the max-RGB or white-patch algorithm, (C)n, p and σ as 0, p, and σ respectively, *i.e.* $W_c^{0,P,\sigma}$ is called the general shades-of-grey algorithm, and (d) n, p and σ as 1, p, and σ respectively, *i.e.* $W_c^{1,P,\sigma}$ is the first-order grey-edge algorithm, *etc*.

3) Diagonal Model: After the illuminant estimate, the transformation of the original image is obtained using the diagonal transform or*von-kries* Model [22]. The diagonal model used in this paper is given in Equation 4 as follows:

$$I_f = D_{u,f} I_u \quad (4)$$

where, I_u denotes the image intensity under an unknown light source,$I_f$is the final corrected image, and $D_{u,f}$ is the diagonal matrix which maps I_u to I_f as follows (Equation 5):

$$\begin{pmatrix} R_f \\ G_f \\ B_f \end{pmatrix} = \begin{pmatrix} d_1 & 0 & 0 \\ 0 & d_2 & 0 \\ 0 & 0 & d_3 \end{pmatrix} \begin{pmatrix} R_u \\ G_u \\ B_u \end{pmatrix} \quad (5)$$

This diagonal mapping is used for transformation to create the output images after illumination estimate and produce a color constant image. In this diagonal mapping, the canonical illuminant is taken as the perfect white light.

B. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is one of the optimization techniques developed by Eberhart and Kennedy. This optimization technique is inspired by the social behaviour of the particles like birds and fishes [23]. The PSO algorithm consists of a number of particles wandering in the search space with the aim to reach a global minimum value of the fitness function. Each particle in the search space represents a candidate solution and has some associated velocity. According to the associated velocity, these particles wanders in the given search space. During the wandering process, previously visited spaces are memorised. Movement of each particle in the search space depends on following factors: local best solution (*i.e.* self best solution) and the global best solution (*i.e.* best solution among all particles). If a better solution is found during iterations of the algorithm, local and global best positions of the particles are updated accordingly. The process is repeated until the desired result is achieved or specified number of iterations have completed.

In N-dimensional space, the position of the ith particle, S_i and the velocity of the ith particle, V_i are denoted as $S_i = (s_{i1}, s_{i2}, \dots s_{in})$, and $V_i = (v_{i1}, v_{i2}, \dots v_{in})$ respectively. Further, particle's local best position (Pb_i) and global best position (Gb) of all the particles in the solution space are denoted as $Pbest_i = (p_{i1}, p_{i2}, \dots p_{in})$ and $gbest = (p_{g1}, p_{g2}, \dots p_{gn})$ respectively. Velocity (V_i) and position (S_i) of the particle at i^{th} iteration is computed [23] using Equation 6 and Equation 7 respectively.

$$V_i^{k+1} = \omega \times V_i^k + \alpha(Pb_i - S_i^k)r_1 + \beta(Gb - S_i^k)r_2 \quad (6)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (7)$$

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where, $i = 1, 2, \ldots n$; n is the number of particles; α is the cognitive parameter; β is the social parameter; r_1 and r_2 are random numbers between the range 0 and 1; ω is inertia weight; and $k = 1, 2, 3, \ldots$ are iteration steps.

IV. Proposed Approach

The key idea of the proposed approach is to group images of similar characteristics together to form a cluster. With every cluster, a set of optimized weights (obtained using PSO) for illuminant estimation methods (gray-world, max-RGB, shades-of-grey and grey-edge) are assigned, *i.e.* with every cluster a set of weights exists. Therefore any image similar to that cluster is assigned the weights corresponding to that cluster. Using those weights, calculation of weighted average of gray-world, max-RGB, shades-of-grey and grey-edge gives the illuminant estimate of that image.

Following steps are involved in our proposed method: (a) calculation of image features, (b) fusion using weighted average, (c) modified PSO, and (d) training module. Performance of the proposed approach is evaluated in testing module. Subsequently we discuss the involved steps.

A. Image Feature Calculation

Calculation of the image features is the first step of our proposed approach. In this paper, important features of the given image are calculated using Weibull parameters. Gijsenij et al [10] have shown that the Weibull parameters correspond to those image features on which color constancy algorithms depend. Weibull distribution [24] is given as follows (Equation 8):

$$W(e) = N\, exp\left(-\frac{1}{\gamma}\left|\frac{e}{\beta}\right|^{\gamma}\right) \tag{8}$$

where, e is the edge responses to the Gaussian filter, N is normalization constant, β is the contrast of the image and γ is the granularity of the image.

For each color channel, Weibull-parameters are computed separately. These color channels however are highly correlated [25]. Therefore, the image is first transformed to opponent color space [10] using Equation 9, Equation 10, and Equation 11.

$$O_1 = (R - G)/\sqrt{2} \tag{9}$$

$$O_2 = (R + G - 2B)/\sqrt{6} \tag{10}$$

$$O_3 = (R + G + B)/\sqrt{3} \tag{11}$$

Thus for each image a feature vector is obtained using Weibull parameters.

B. Fusion using Weighted Average

Weighted average approach in color constancy was first introduced by Cardie *et al* [20]. The approach proposed in this paper performs fusion of four methods, max-RGB [13], gray-world [14], shades-of-grey [15] and the grey-edge [16] using weighted average to estimate the illuminant. If e_i is the illuminant estimated by i^{th} method, then the weighted average (e') is defined as follows (Equation 12):

$$e' = \sum_{i=1}^{4} W_i e_i \tag{12}$$

where, sum of W_i's is 1.

Further, weights for different image categories are optimized using the modified PSO explained subsequently.

C. Modified PSO

As discussed earlier, the proposed approach uses a modification in the Particle Swarm Optimization algorithm introduced by Kennedy *et al* [23]. In modified PSO, each particle is represented by a point in four dimensional search spaces. Each dimension corresponds to one of the four weights of four methods used in the fusion. Hence position of the ith particle is represented as follows (Equation 13):

$$S_i = [W_{i1}, W_{i2}, W_{i3}, W_{i4}] \tag{13}$$

where, $\sum_{j=1}^{4} W_{ij} = 1$

To satisfy the constraint specified in Equation 13, modified PSO normalizes weights every time they are updated. Normalized weights are computed as follows (Equation 14):

$$W_i = \frac{w_i}{\sum_{j=1}^{4} w_j} \tag{14}$$

Swarm size of K particles (in our implementation, we considered it as 20) is taken and the position of each particle is initialized randomly. The velocity of each particle is initialized to zero. The median angular error (defined in Equation 15) between the estimated illuminant, e_e and the known illuminant, e_l is minimized to optimize the weights.

$$E = cos^{-1}\left(\frac{e_l . e_e}{\|e_l\|\|e_e\|}\right) \tag{15}$$

where, $e_l . e_e$ is the dot product of the two vectors representing the true color of the light source, e_l and the estimated color of the light source, e_e and $\|\cdot\|$ indicates the Euclidean norm.

The fitness value of each particle is calculated using Equation 15. Based on the fitness value obtained, local best position ($pbest$) of each particle and global best positions ($gbest$) are updated using Equation 6 and Equation 7 respectively.

D. Training Module

Training is one of the important modules/steps of our proposed approach. Using earlier discussed steps (Feature calculation, Fusion, and modified PSO), this module makes a trained system capable enough for color constancy. Subsequently we discuss the training module.

Total 65 images from the color constancy data set of Ciurea and Funt [11] have been used for training module, *i.e.* our training database contained the 65 images with respective illuminant values.

A flow chart of the training module of the proposed approach is shown in Fig 2. As presented in the flowchart (Fig. 2), feature vector for each image in the training database is calculated using Weibull parameters. Based on their feature vectors, we divided the training images into 6 clusters using k-Mean clustering algorithm. Each cluster contains images with similar characteristics and hence the same set of weights can be applied for the images belonging to one or same cluster.

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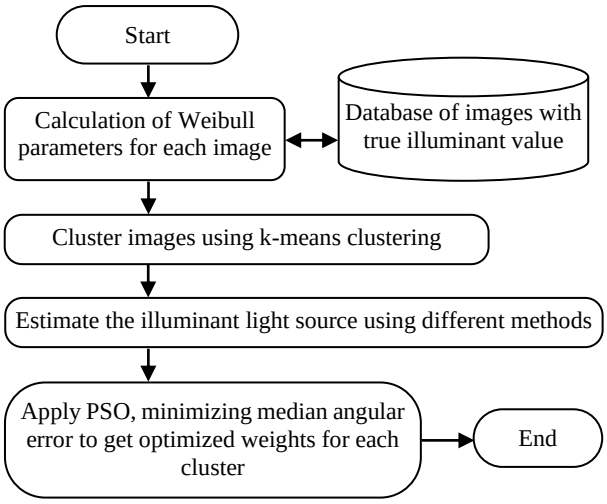

Fig. 2 Flowchart depicting the steps involved in training module

For all images in the training phase, the correct color of the light source e_l is known a priori. The median angular error between the estimated and the known illuminant is minimized using modified PSO to optimize the weights for each cluster. After training the system we optimized the weights to be used for each cluster.

E. Testing Module

This module is used to evaluate the performance of the proposed approach for color constancy. Various images (excluding the images used in training module) from the dataset [11] have been used for testing the color constancy.

Fig. 3 shows the flow chart explaining the testing phase of the proposed approach. We first calculate the Weibull parameters for the images to be tested. The cluster to which the test image belongs is found using minimum Euclidean distance criterion. Once the cluster is known, the weights corresponding to that cluster are applied to the image to calculate the estimated illuminant. Diagonal model is then used to obtain the color constant image.

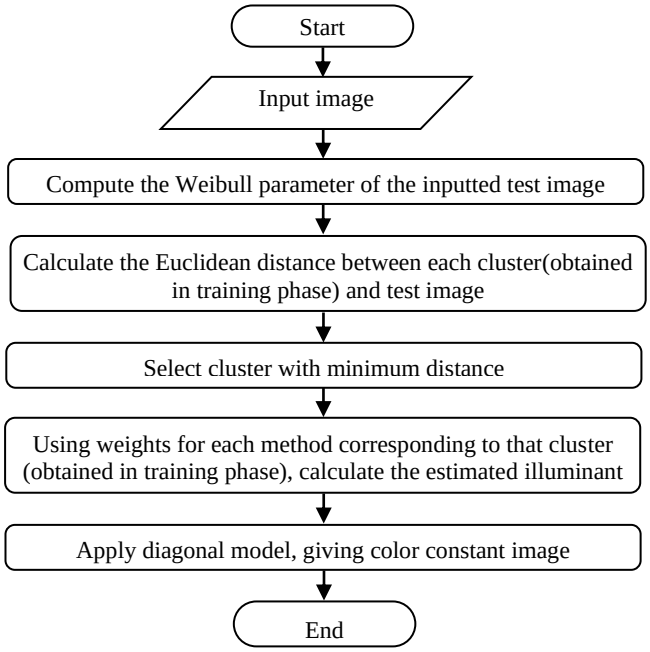

Fig. 3 Flowchart depicting the steps involved in testing module

V. Results and Discussions

In this section, we present the dataset, evaluation metric, and performance of the proposed approach in comparison with following color constancy algorithms: gray-world, max-rgb, shades-of-grey, grey-edge. A well known dataset discussed in next section has been used for the comparative performance analysis. The size, the nature, their benchmark status (*i.e.*, the gray ball) has been the reason for the selection of this dataset.

A. Dataset

We have used the dataset introduced by Ciurea and Funt [11] for evaluation of the performance of the proposed approach. The dataset introduced by Ciurea and Funt consists of more than 11,000 images of indoor and outdoor scenes. These images are basically still frames extracted from a video clip performing progressive scanning. During scanning, it created 15 frames per second, out of which 3 frames were included in the database. A grey ball is mounted in front of camera to obtain the true illuminant estimate of the scene. The RGB value on the sphere is used to determine the scene illuminant. This dataset also consists of the true illuminant value corresponding to each image.

We randomly selected 65 images from this dataset (of 11,000 images) for the training module of our proposed approach. Besides these 65 images, we randomly picked 15 other images for the testing module and analyzed the performance of the proposed approach using the evaluation metric discussed subsequently.

B. Evaluation Metric

The Median Angular Error [16] has been used as an evaluation criterion to compare the performance of the proposed approach with other methods. This measure is independent of brightness and depends only on color of the illuminant [26].

As discussed in Section IV, the median angular error (Equation 15) is expressed as the angle between known illuminant value, e_l and estimated illuminant value, e_e.

C. Experiments Details and Results

Proposed approach had been implemented, where we trained the system using PSO to obtain optimized weights corresponding to each type of image. For each training image features were obtained using Weibull parameters. The Weibull distribution vector acted as the feature vector. The k-mean clustering algorithm was applied using k=6, such that based on the feature values, the images of same types are clustered together.

For each cluster the weights were then optimized using PSO. The illumination estimation for a test image was then obtained by measuring the Euclidean distance between each cluster and the test image Weibull parameters. Weights of the cluster to which image belongs were then used to estimate the illuminant.

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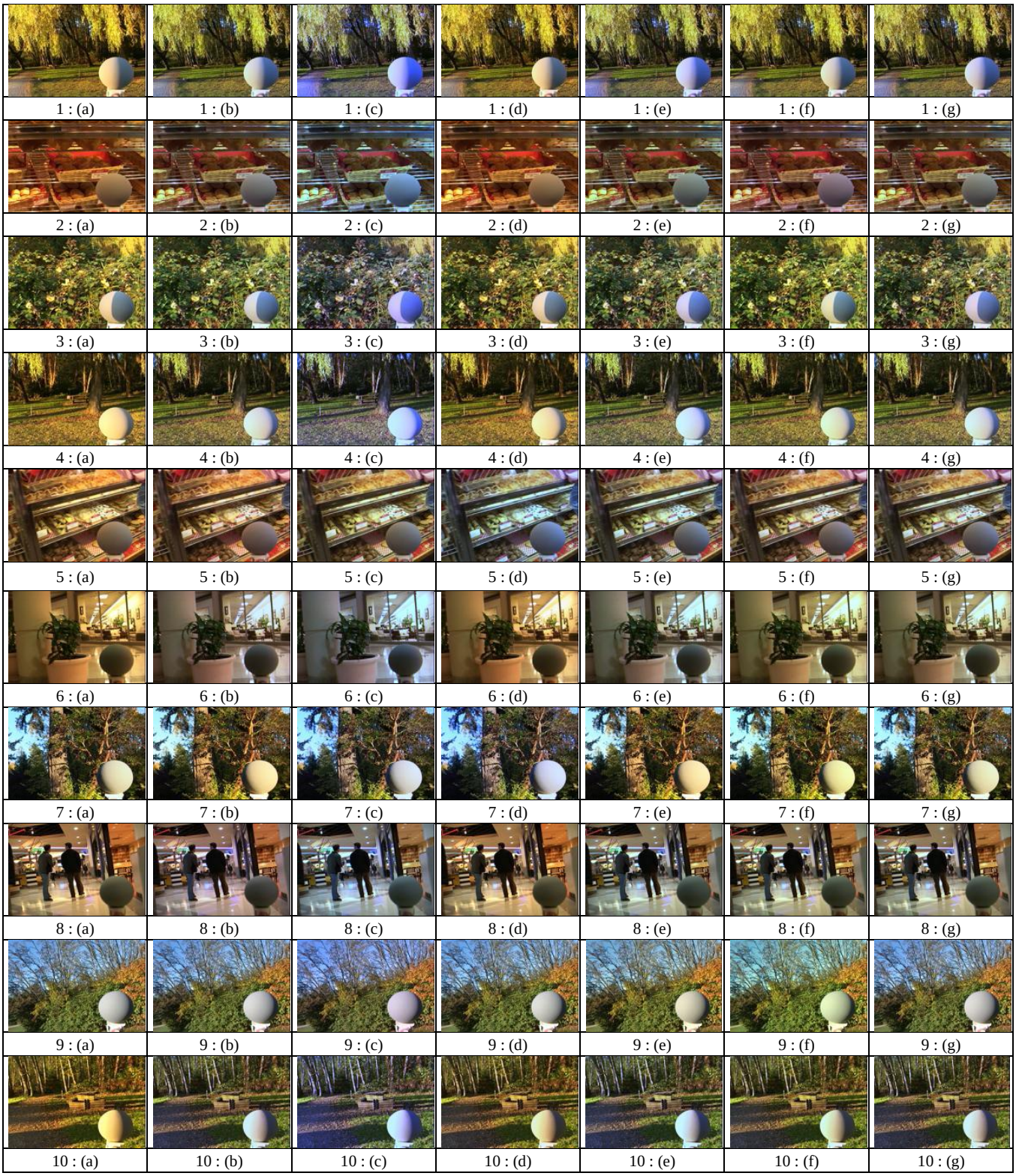
Fig. 4 shows corrected images obtained by the proposed algorithm and other existing algorithms (gray-world, max-rgb, shades-of-grey, and grey-edge). It can be observed that images obtained using proposed approach is closer to the ideal corrected images. The original image and ideal correction are also shown for qualitative result comparison. For each of the images in Fig 4, the median angular error is obtained using gray-world, max-rgb, shades-of-grey, grey-edge and proposed approach. The obtained median angular errors are summarized in Table I, in the same order.



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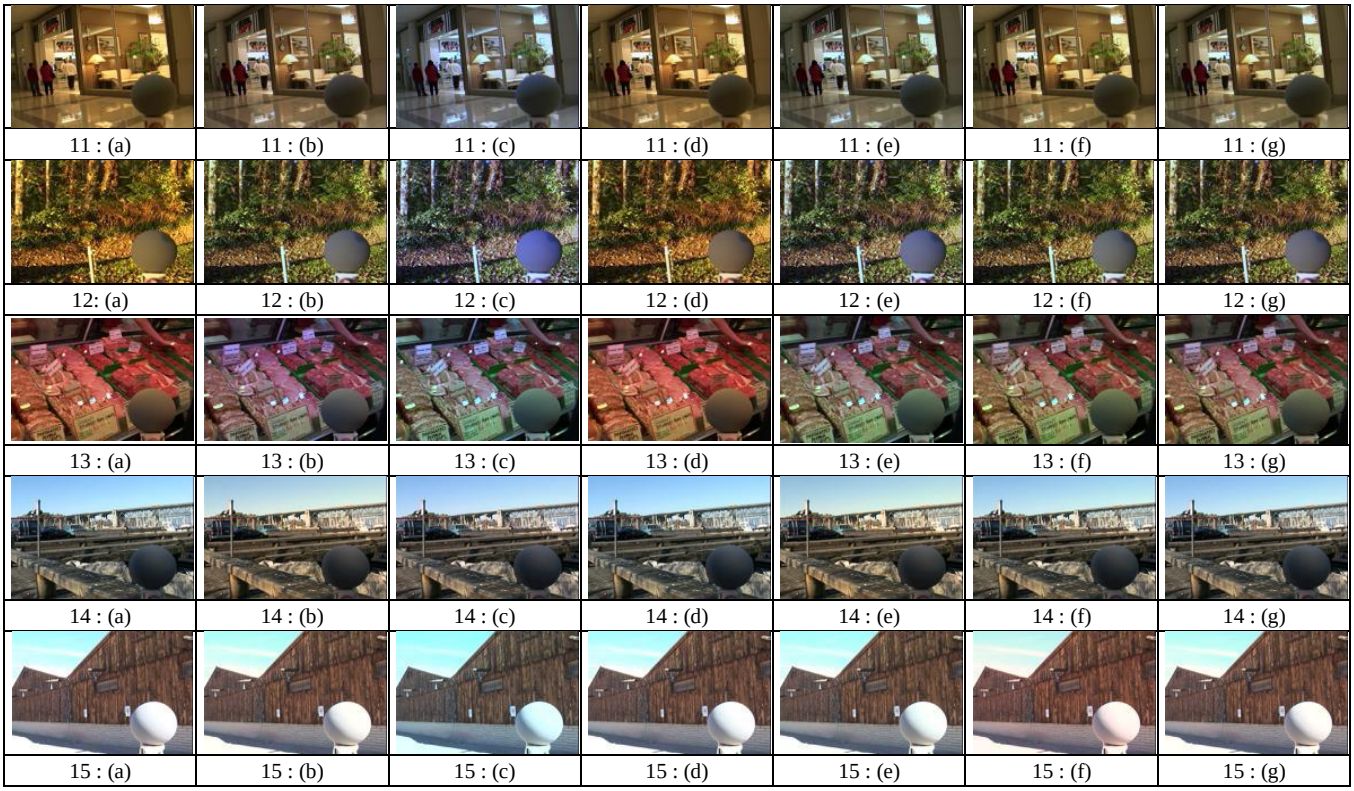

Fig. 4 Results of the Color Constancy for test images (1-15) where (a) is the original test image; (b) is the iamge representing the ideal correction; (c) is the color constancy image obtained using gray-world algorithm; (d) is the color constancy image obtained using max-rgb algorithm; (e) is the color constancy image obtained using shades-of-grey method; (f) is the color constancy image obtained using grey-edge method; and (g) is the color constancy image obtained using proposed approach

TABLE I
MEDIAN ANGULAR ERROR USING DIFFERENT METHODS FOR DIFFERENT TEST IMAGES

Test Image #	Median Angular Error				
	Gray-world[6]	Max-RGB [5]	Shades of grey[7]	Grey-edge [8]	Proposed Approach
1	11.5920812	7.3592250	5.4165079	2.1866030	2.5482130
2	10.9125397	10.6154755	4.1840857	2.6416471	0.9964887
3	6.9928073	9.5442235	2.5789884	3.3860648	1.0280696
4	10.1214379	9.8477516	5.5969658	0.2571637	1.0879800
5	10.0334314	6.1495032	3.3496631	4.2640666	2.3225982
6	10.6882145	13.9568708	2.2600716	4.0123758	1.2243222
7	9.8318480	5.1164938	4.4665987	1.6097487	2.7319540
8	7.3792891	14.5128955	5.4695561	7.6127578	5.4846579
9	2.3378504	10.0410038	5.7270355	10.2435174	6.3499808
10	6.7801411	12.0244442	3.4657376	6.6846073	3.4087869
11	9.6410134	5.2680353	1.6577004	2.7450985	2.2277468
12	8.8533934	7.1378986	1.8731815	5.4621556	0.4794637
13	7.5283845	6.3593423	3.8600612	4.2672040	1.6367101
14	2.4824813	0.6954202	3.9435104	5.7774425	0.5603728
15	10.5687484	8.3454336	5.7403958	4.6333819	1.7774513

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As seen from Table I, in general, performance (based on median angular error) of the Gray world algorithm [14] and max RGB method [13] to obtain the color constancy images are worst. Performance of the shades-of-grey [15] algorithm is much better than the Gray world and max RGB methods. Among considered approaches, performances of grey-edge [16] and our proposed approach are best and comparable to each other. In some cases (test images), performance of grey-edge approach for color constancy is better than our proposed approach, but in most of the cases, our proposed approach performed best. Hence, from the results, it can be stated that our proposed approach for color constancy outperforms the considered previous approaches. The values of median angular can be seen to be the lowest for the proposed approach in majority of cases. Overall it can be concluded that the proposed method, has improved performance over other illuminant estimation methods.

VI. CONCLUSION

In this paper, an algorithm for color constancy based on PSO and k-means clustering is proposed and its performance is investigated. In the proposed approach, the k-mean algorithm clusters the dataset based on feature vector obtained from Weibull distribution. Next, the PSO algorithm optimizes weights for each cluster by minimizing the median angular error between known values of the illuminant and estimated illuminants using weighed fusion, during the training phase. For a given test image, the cluster to which it belongs is calculated using Euclidean distance and optimized weights corresponding to that cluster are applied to obtain a color constant image. The performance of the proposed approach is compared with other existing methods and results show that PSO based weighted fusion approach outperforms other existing approaches, gray-world, max-rgb, shades-of-grey, and grey-edge.

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