Colour Constancy using K-means Clustering Algorithm

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Abstract— **Colour cast is the ambient presence of unwanted colour in digital images due to the source illuminant while colour constancy is the ability to perceive colors of object, invariant to the colour of the source illuminant. Existing statistic based colour constancy methods use whole image pixel values for illuminant estimation. However, not every region of an image contains reliable colour information. Therefore, the presence of large uniform colour patches within the image considerably deteriorates the performance of colour constancy algorithms. This paper presents an algorithm to alleviate the biasing effect of the uniform colour patches of the colour constancy compensation techniques. It employs the k-means clustering algorithm to segment image areas according to their colour information. The Average Absolute Difference (AAD) of each colour component of the segment is calculated and used to identify and exclude segments with uniform colour information from being used for colour constancy adjustments. Experimental results were generated using three benchmark datasets and compared with the state of the art techniques. Results show the proposed technique outperforms existing techniques in the presence of the uniform colour patches and similar to Grey World method in the absent o uniform colour patches.**

Keywords- colour constancy; colour balancing; k-means clustering; average absolute difference

I. INTRODUCTION

Digital imaging devices do not have the capability to capture true colour of the scene being illuminated by non-canonical light sources. Therefore, an image taken under a low colour temperature light source appears yellowish and bluish if it illuminated by a high temperature light source [1]. Human eyes have capability to see the true colour of an object regardless the colour of the light source [2]. The ultimate goal of a colour constancy algorithm is to balance the image colour taken from a scene illuminated by a non-canonical light source, as if, the scene was illuminated by a canonical light [3][4]. Most of the colour constancy algorithms use image-colour components' information to estimate and adjust the image colour temperature [5][6]. Researchers have proposed various colour constancy algorithms such as: Grey World [7], Max-RGB [8], Modified White Patch [9], Shades of Grey [10], 1st and 2nd Order Grey Edge [11], Weighted Grey Edge [12] and Histogram Stretch [13] algorithms, over the past years. The Grey World [7] algorithm is based on the fact that the average reflectance of colour components of a scene illuminated by a natural light source is a representative of the grey level. The white patch algorithm, known as the Max-RGB [8] method considers the highest value of each colour channel represents the brightest point of an image and adjusts the image accordingly. Lam [9] proposed a Modified White Patch algorithm by applying the concept of Max-RGB algorithm to adjust red and blue components of the image. The Shades of Grey [10] technique assumes that the generalized mean or power mean known as Minkowski Norm p of a scene is achromatic. Experimental results given in [10] show the merit of this technique to the Grey World, Max RGB and Modified White Patch algorithm. The Grey Edge [11] estimates the illuminant colour by taking the average absolute derivative of image colour components. Weighted Grey Edge [12] assumes that edges in an image contain significant colour constancy information and uses them for adjusting image colour temperature. Much research has been conducted and various techniques have been developed to adjust the colour constancy of the images taken under non-canonical illumination sources. These techniques perform well in some extent. However, their performance are deteriorates when there are some dominant colour patches within the images and results a biased image toward the colour of the uniform areas.

This paper presents a colour constancy algorithm to mitigate the effect of uniform colour patches of the image on the performance of the existing colour constancy adjustment algorithms. Hence, it applies a k-mean segmentation algorithm to divide the image into a number of segments according to their colour variation information. It then identifies and remove uniform colour segment from being used for colour constancy adjustments. Experimental results show the proposed method outperforms the state of art techniques in the presence of uniform colour areas on the image. The rest of the paper is organised as follows: Section II describes the proposed algorithm, experimental results are given in Section III and section IV concludes the paper.

II. COLOUR CONSTANCY USING K-MEANS CLUSTERING METHOD

A block diagram of the proposed colour constancy method is shown in Fig. 1.a-b. The proposed method is divided into two sections: K-means image segmentation section and colour variation assessment and image colour constancy parameters calculation and compensation section, which will be discussed in the following.

A. K-means clustering algorithm for image segmentation

K-means clustering is an unsupervised learning algorithm to solve well known clustering problems [14]. In this paper, it is used to divide the input image pixels to a number of clusters according to their colour properties. The resulting clusters are then assessed to exclude the clusters representing the image uniform colour patches of being used for image colour constancy compensation. Figure 1.a shows the block diagram of the proposed k-means clustering algorithm for image segmentation. As it can be seen from the block diagram, a RGB image is input to the algorithm. The algorithm converts the input RGB image into $L^*a^*b^*$ colour space ($L^*a^*b^*$ colour space gives exact colour specification of the image. It enables clustering the image pixels according to their colour differences.), where L* carries the lightness and a* and b* components contain the colour information of the image. Hence, k-means algorithm takes a*, b* components of the image, number of clusters, *n*, to classify the image pixels into, and number of iterations, *noi*, and splits the input image pixels into *n* clusters. The centroid selection and segmentation steps of the K-means algorithm are as follows:

i. Randomly select the initial *n* centroids of the clusters from a* and b* components of the input image, which are named as $(c_1 \ldots c_n)_{i=0}$ in the block diagram and initialise *i* variable, which represents current iteration number, with a zero.

ii. Compute point to cluster centroid's Euclidian distances of all a* and b* coefficients to each centroid.

iii. Classify a* and b* coefficients into *n* clusters according to their minimum Euclidian distances to the current *n* centroids, generating *n* clusters named: $(cl_1 \ldots cl_n)_i$.

iv. Calculate the average of the coefficients in each resulting cluster to create *n* new centroid locations, named: $(c_1 \ldots c_n)_i$ and increase *i* variable by one.

v. Check if *i* is greater than *noi*, the previously determined clusters, $(cl_1 \ldots cl_n)_i$, are the final clusters. Re-name them as: $cl_1 \ldots cl_n$, as shown in the block diagram and the clustering process is completed; otherwise go back to step ii.

B. Image clusters selection and performing colour constancy

In this stage, resulting clusters are assessed to identify the clusters represent uniform colour areas of the image. These areas of the image are then excluded from being used for image colour adjustment. This exclusion significantly improves the performance of the colour constancy algorithms. As the uniform colour areas of the image, bias the whole image colour toward the colour of the uniform areas. The larger these areas are, the higher this bias will be. Fig. 1.b shows a block diagram of the proposed colour variation assessment for each image cluster, image colour constancy scaling factor calculation and compensation algorithm. From Fig. 1.b, it can be seen that each resulting cluster area of the RGB image is assessed as it follows:

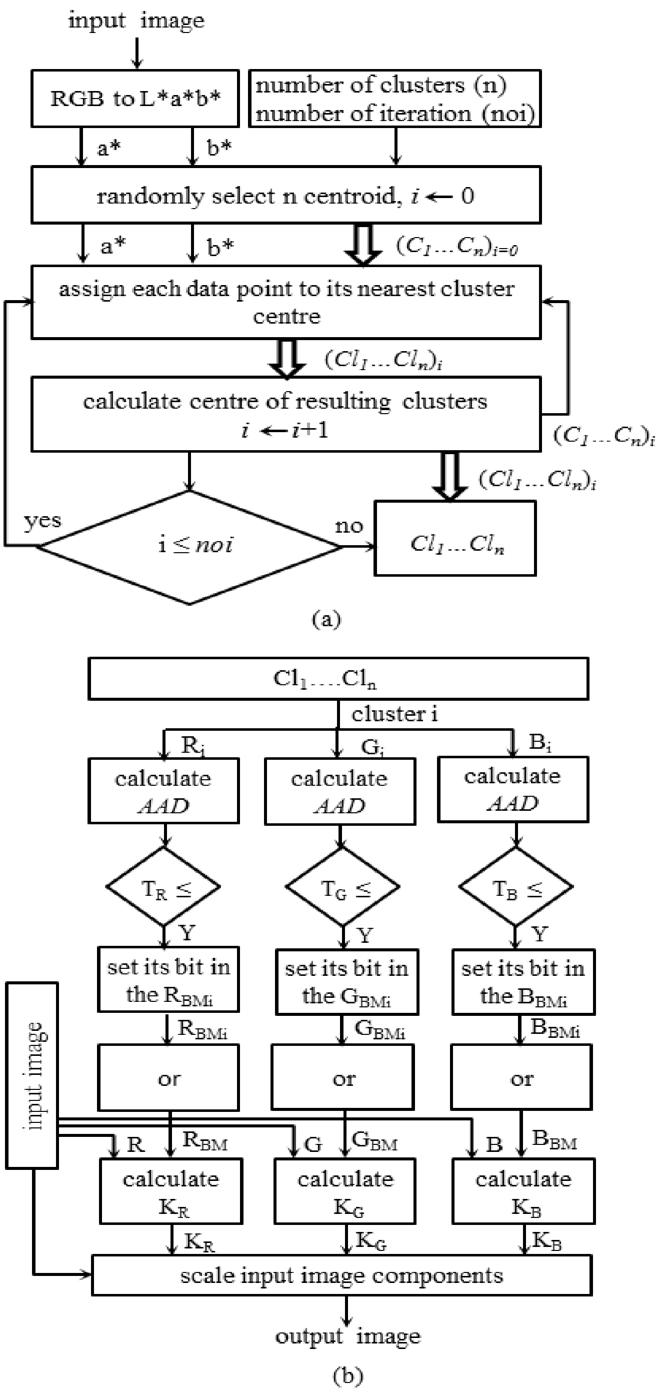

Fig.1. Block diagram of the proposed colour constancy method: (a) block diagram of the K-means clustering algorithm for image segmentation and (b) block diagram of colour variation assessment of each image segment for colour balancing and image colour constancy parameters calculation and compensation.

i. It calculate the Average Absolute Difference (AAD) values of the R, G and B components of the cluster using equation 1:

$$C_{AAD} = \frac{\sum\sum|C(i,j)-\bar{C}|}{N\times N} \qquad (1)$$

where C represents R, G or B component of the cluster; C_{AAD} is the Average Absolute Difference of the C component's coefficients; $C(i, j)$ shows the component C 's coefficients at location of i and j; $\bar{C}$ is the average value of the C component's coefficients of the cluster and N is number of coefficients in component C of the cluster.

ii. The resulting R_{AAD}, G_{AAD} and B_{AAD} values are compared with the empirical threshold values for R, G and B components, called: T_R , T_G and T_B in the block diagram, respectively. If the AAD of the cluster component is greater than its threshold, this cluster's component does not have a uniform colour. Hence, it's coefficients are selected to be used for colour constancy scaling factor calculation and bits representing the locations of these coefficients in the relevant binary matrix are set to one. The binary matrixes are named: R_{BM}, G_{BM} and B_{BM} for R, G and B components, respectively (a zero binary matrix for each cluster's colour component is created at the beginning).

iii. It performs OR logic operation amongst each colour components' binary matrixes, creating one binary matrix for each image colour component. They are called R_{BM}, G_{BM} and B_{BM} in the block diagram. Each of these binary matrixes representing the selected coefficients of the image colour component to be used for colour constancy scaling factor calculation and compensation.

Based on the principal that the average colour components values of a scene are achromatic [7], the scaling factors for the three colour components of the image, which are named: K_R, K_G, and K_B, for R, G and B image components, respectively, are calculated using the selected coefficients, as shown in equation 2-3:

$$\bar{S} = \frac{\sum R_S + \sum G_S + \sum B_S}{N_{R_S} + N_{G_S} + N_{B_S}} \quad (2)$$

$$K_C = \bar{S} \Big/ \frac{\sum C_S}{N_{C_S}} \quad (3)$$

where $\bar{S}$ is the average value of all the selected coefficients in the image; $\sum R_S$, $\sum G_S$ and $\sum B_S$ are the total values of the selected R, G and B's coefficients, respectively; N_{R_S}, N_{G_S} and $N_{B_S}$are the total number of the selected coefficients in the R, G and B image components, respectively. $\sum C_S$ shows the total value of the component C's selected coefficients, where C can be R, G or B component; N_{C_S} is the number of coefficients in the selected C component and K_C represents the calculated scaling factor for colour component C of the image. Experiments over three image datasets showed when uniform areas of the image is also dominant, the calculated scaling factors with the values greater than 1.3, could deteriorate the colour constancy adjustment of the image. Therefore, the resulting scaling factors are limited to 1.2.

Finally the input image colour constancy adjustment will be performed by scaling the R, G, and B components of the image using the resulting K_R, K_G and K_B scaling factors, respectively, generating the colour balanced output image.

The performance of the illuminant estimation of the proposed colour constancy adjustment method as a function of its thresholds values, T_R, T_G and T_B, were investigated using some outdoor images from the Ciurea and Funt [15], Photos Futta.NET [16] and ETHZ[17] datasets. It was empirically found that the best results are obtained by using $T_R = 20$, $T_G = 20$ and $T_B = 20$ threshold values.

III. EXPERIMENTAL RESULT AND EVALUATION

To evaluate the performance of the proposed Colour Constancy Adjustment using K-means Clustering (CAKC) method, it was tested with three benchmark datasets: the Grey Ball dataset [15], Futta.NET [16] and ETHZ dataset [17] and compared against Grey World [7], Max-RGB [8], Modified White Patch [9], 1st Order Grey Edge [11], 2nd Order Grey Edge [11], Shades of Grey [10], Weighted Grey Edge [12] and Histogram Stretch [13]. The datasets are introduced in sub-section A, performance measurement criteria are given in sub-section B and experimental results are presented in sub-section C.

A. Datasets

The Grey Ball dataset were captured by Ciuera and Funt [15], contains 11,340 images of size 240×360, mounting a grey ball in front of the imaging device. The surface area of the grey ball then used to evaluate the scene illuminant. The second dataset known as Futta.NET [16] contains 3000 images of various scenarios taken under different natural lighting condition. The ETHZ dataset contains 255 images collected by Vittorio Ferrari [17] having wide variety of objects in the scene.

To give an insight into the algorithm, an image from Grey Ball data set [15] is taken and the proposed K-means algorithm was applied on the image to divide the image into four clusters. The resulting image clusters are shown in Fig.3. From this image it can be seen that the uniform areas of the image are fallen into cluster 1 and the other clusters represent the remaining areas of the image.

The Average Absolute Difference (AAD) values of the coefficients within each cluster for components R, G, and B are calculated and tabulated in Table 1, where cluster 1 represents the AADs of the uniform areas of the image. From Table 1, it can be seen that the AADs of the uniform area of the image have smaller values than the AADs of the other area of the image. This implies that AAD of the cluster is a good measure for identifying the uniform area of the image and hence excluding them of participating in calculation of the scaling factors for colour balancing of the image. The original image and the selected areas of the image for performing colour constancy adjustment using the proposed K-means based algorithm are shown in Fig. 4. From Fig.4b, it can be seen the proposed method successfully identified and excluded the uniform area of the image. The selected areas of the image are then used for doing the colour constancy adjustment.

B. Performance measure

Image colour constancy quality assessment methods are divided into two categories called objective and subjective methods. Angular error and Euclidean distance are the main two commonly used methods to quantify chromaticity error of the colour balance images. These methods measure the distance between estimated and ground truth illumination. However, Finlayson and Zakizadeh's investigations on the objective methods showed the angular error is not a reliable method for assessing the colour constancy of an image. Different angular errors are resulted for the same scene viewed under different illuminations and adjusted with the same colour constancy adjustment methods [18]. Further, Hordley and Finleyson's investigation on objective methods showed inconsistency of different objective methods, e.g. application of the mean angular error and median angular error for assessing the quality of an image may lead to different conclusions [19]. Due to the significant flaws of the objective colour-constancy-assessment, methods and the fact that the human eyes are the ultimate judge of image quality, researchers mainly use subjective assessment methods to evaluate the quality of the images. Hence, in this paper, subjective evaluation method is used to compare the quality of the colour-balanced images using the proposed method and the state of the art techniques.

C. Experimental Result

The proposed Colour Constancy Adjustment using K-means Clustering (CAKC), Grey World [7], Max-RGB [8], Modified White Patch [9], 1st Order Grey Edge [11], 2nd Order Grey Edge [11], Shades of Grey [10], Weighted Grey Edge [12] and Histogram Stretch [13] colour constancy methods were applied to the images of the Grey Ball [15], Futta.NET [16] and ETHZ datasets [17]. Experimental results show the proposed CAKC method generates highest visual quality to other techniques in the presence of uniform colour patches in the image. To give a sense of achieved visual quality using the proposed CAKC algorithm and enable the reader to compare the performance or the CAKC technique with other state of art methods, two sample images, one from Grey Ball dataset and another from Futta.NET dataset were selected and colour constancy adjusted using the proposed CAKC and the state of art colour-constancy-techniques. Resulting images are shown in Fig. 5 and Fig. 7. Fig. 5a is the original sample image from Grey Ball dataset with colourful tree branches in the lower-left of the image; a grey ball mounted as the foreground object and there is big patch of the blue sky in the background of the image. In this image, the colour cast is yellowish, especially, on the tree branches and grey ball. Fig. 5b is the Grey World [7] image, which appears too bluish. There is distinct blue tint on the grey ball. Fig. 5c shows the Max-RGB image [8]. It exhibits higher colour constancy to that of Grey World. However, with respect to the original image, shown in Fig. 5c, the yellow colour cast of the grey ball is still visible. Fig. 5d shows the Modified White Patch [9]. From this figure, it can be seen that the tree branches and the grey ball have yellow colour casting. With respect to original image, there is not noticeable colour improvement within the image. Fig. 5e shows the 1st Order Grey Edge [11]. In this image the grey ball looks whiter, more natural, in compared to the original image but the three

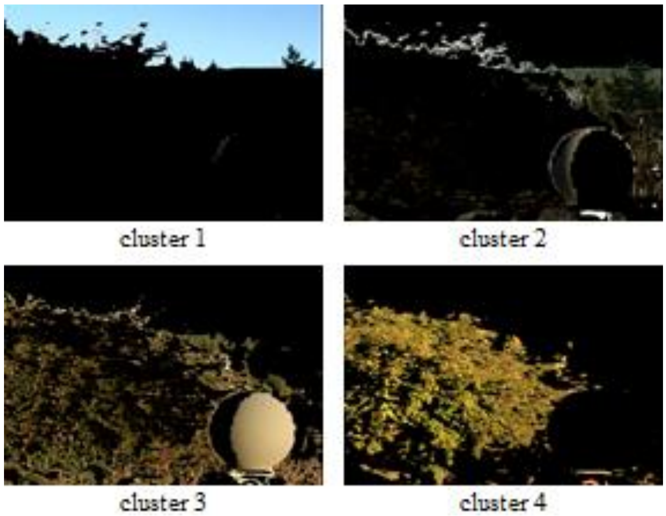

Fig.3. Application of K-means clustering algorithm to an image from Grey Ball data set [15], where it splits the image into four clusters and cluster 1 shows the large uniform colour area of the image.

TABLE 1

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
R_{ADD}	13.58	31.88	40.70	44.16
G_{ADD}	15.41	30.06	41.71	41.11
B_{ADD}	14.26	25.03	41.51	37.50

Table 1. Average Absolute Difference (AAD) values of the coefficients within each image cluster for component R, G, and B, where cluster 1 represent the uniform colour area of the image.

Fig. 4. a) Original image, b) The selected area of the image for calculating the colour constancy adjustment scaling factors using the proposed clustering algorithm (the uniform areas of the image are shown in black in the image).

branches still suffer from yellow colour casting. The 2nd Order Grey Edge [11] is shown in Fig. 5f. This image exhibits little improvement compared to the input image and the image still suffers from yellow colour casting. Fig. 5g shows the image of the Shades of Grey method [10]. In this image, the tree branches illustrate higher colour constancy. However, the grey ball within this image appears greenish. Fig. 5h shows the Weighted Grey Edge image. From Fig. 5h, the over saturation on the grey ball area is highly visible. In addition, the orange-yellowish shades on the tree branches show a shift towards warmer illuminant. Fig. 5i illustrates the Histogram Stretch method image. From this figure, it can be seen that the colour cast of the image particularly the grey ball has not completely be removed. Fig. 5j shows the image of the proposed CAKC method. From this image, it is clear that the yellow cast of the image has almost been fully removed from the image, particularly from the grey ball area, as the ball is appeared pure grey. In summary, the proposed CAKC image exhibits the highest colour constancy to the image of other mentioned state of arts images.

To enable the reader to compare the performance of various colour constancy methods with the proposed CAKC method, a sample part of the grey ball area within the image from colour balanced images using various techniques are shown in Fig. 6. These areas of the images are selected to enable the viewer ease of comparison. From Fig. 6b-i, the presence of different illuminant within the images is evidently visible while the proposed CAKC image, shown in Fig. 6j, demonstrates a pure grey colour and the presence of any colour casts within this image is very hardly visible.

Fig. 7a shows an image from Futta.NET dataset [16]. As it can be seen from the image, the image has a yellow colour cast with a large blue sky in the background. Grey World theory [7] colour balanced image using is illustrated in Fig. 7b. The image looks a little warmer than the original image. It can also be seen that the grey polished wall area of the image in the right side exhibiting higher yellowish colour cast than the area in the original image. Moreover, the white appearance of the sky just above the wall turns out with a modest orange tone. The Max-RGB method [8] image is shown in Fig. 7c. In this figure, the image looks cooler than the original image but the yellow colour cast of the image particularly on ground and the right wall is still evident. Fig. 7d shows the Modified White Patch method [9] image. This image looks much more natural than the original image but still the yellowish colour cast on the ground area of the image is obvious. The 1^{st} Order Grey Edge [11] image is illustrated in Fig. 7e. From Fig. 7e, it is clear that the colour constancy of this image is higher than those are shown in Fig. 7b-d. However, the ground surface and both sidewalls within the image seem to have noticeable colour cast. The 2^{nd} Order Grey Edge [11] image is shown in Fig. 7f. This image has superior colour constancy than that of the 1^{st} Order Grey Edge image. However, this image has a moderate turned down on the colour temperature of the scene. Although the image looks having high level of colour constancy, the grey wall within the image is exhibit some level of colour casting. The Shades of Grey [10] image is shown in Fig.7g. This image suffers from higher yellow colour cast than its original image. Fig. 7h shows the Weighted Grey Edge [12] image. From this image, it can be seen that the grey wall area of the image exhibit infinitesimal colour casting while the ground surface area of the image still exhibit yellow colour cast. Fig. 7i shows the Histogram Stretch [13] method image. This image shows higher intensity than its original image. This can be explained by the fact that histogram method exhibit higher data dependency. However, due to image illumination changes the colour cast of the ground surface and nearby walls has turned toward orange ambience. Fig. 7j show the proposed CAKC image. By comparing this image with its original image and other state of the arts images shown in Fig. 7b-I, it is clear that

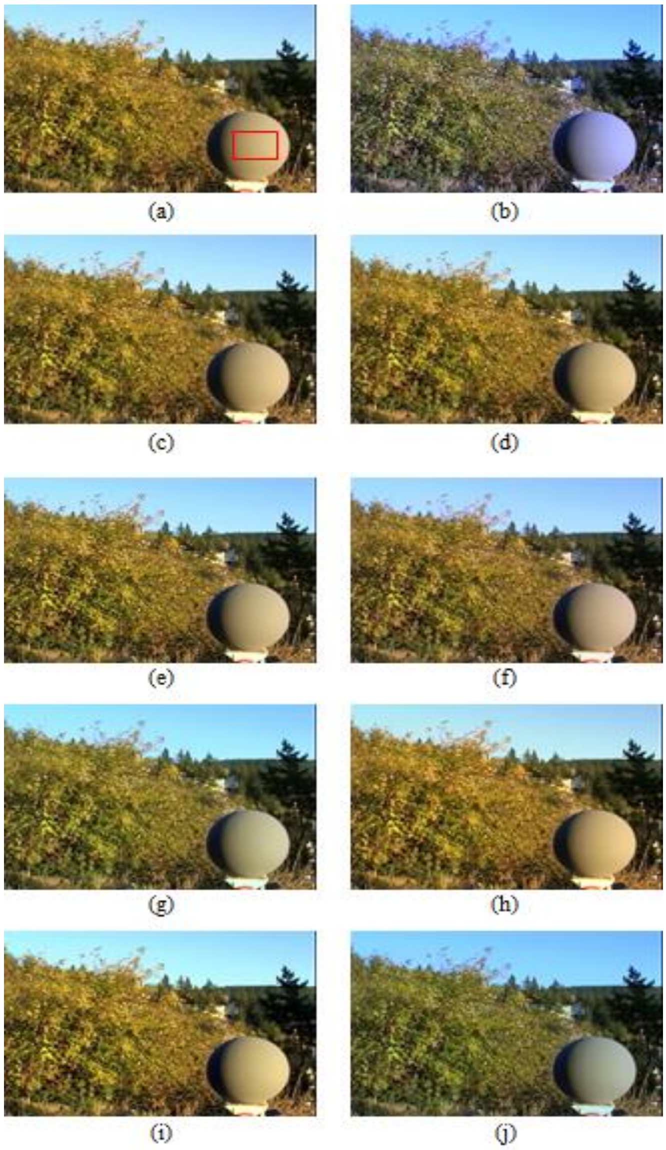

Fig. 5. Original and colour balanced images: a) Original image from Grey Ball dataset [15], b) Grey World [7], c) Max-RGB [8], d) Modified White Patch [9], e) 1st Order Grey Edge [11], f) 2nd Order Grey Edge [11], g) Shades of Grey [10], h) Weighted Grey Edge [12], i) Histogram Stretch [13] and j) Proposed CAKC methods.

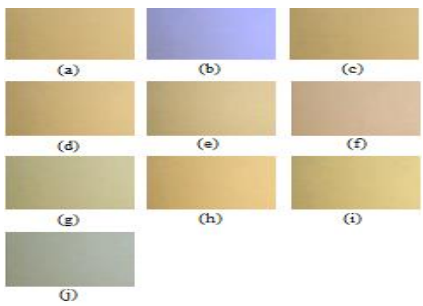

Fig. 6. Sample part of the grey ball area within the image: a) Original image from Grey Ball dataset [15], b) Grey World [7], c) Max-RGB [8], d) Modified White Patch [9], e) 1st Order Grey Edge [11], f) 2nd Order Grey Edge [11], g) Shades of Grey [10], h) Weighted Grey Edge [12], i) Histogram Stretch [13] and j) Proposed CAKC method.

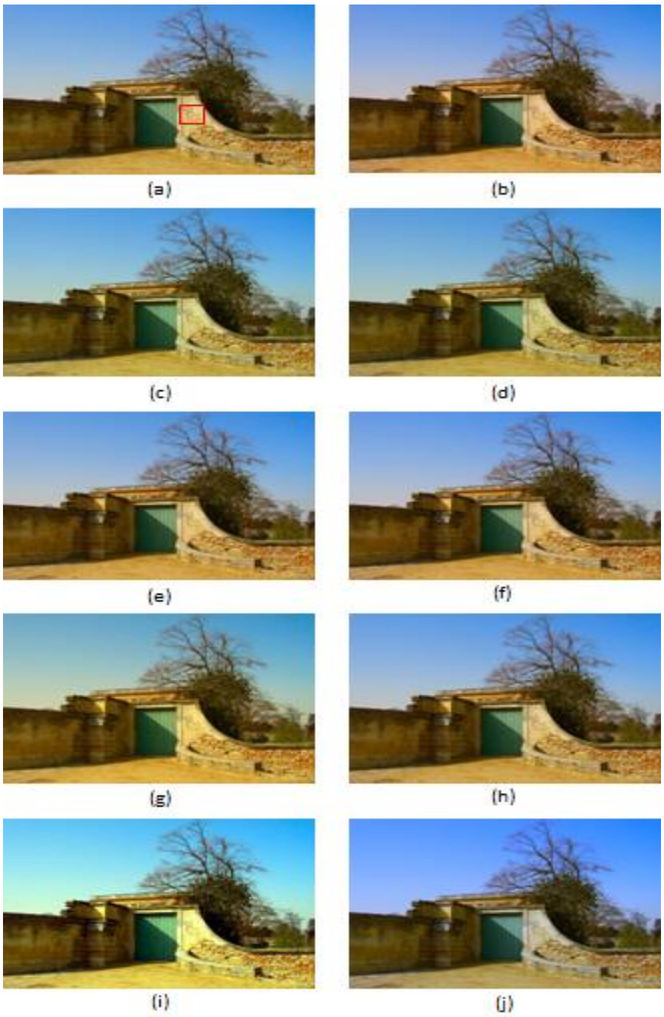

Figure 7. Original and colour balanced images: a) Original image from Futta.NET dataset [16], b) Grey World [7], c) Max-RGB [8], d) Modified White Patch [9], e) 1st Order Grey Edge [11], f) 2nd Order Grey Edge [11], g) Shades of Grey [10], h) Weighted Grey Edge [12], i) Histogram Stretch [13] and j) Proposed CAKC method.

the CAKC image exhibits the highest colour constancy to all of them.

IV. CONCLUSION

This paper presented a color constancy algorithm using the K-means clustering algorithm. The K-means clustering method was used to divide the input image into a number of areas according to their colour variation. The resulting cluster areas were assessed to identify and exclude the uniform colour areas of the image from being used for image colour constancy compensations. Results on images of three image datasets show the merit of the proposed CAKC method.

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