Pixel distribution shifting color correction for digital color images

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A R T I C L E   I N F O

Article history:
Received 1 July 2011
Received in revised form 7 March 2012
Accepted 19 April 2012
Available online 17 May 2012

Keywords:
Color image
Color correction
Grey world
White point
Pixel distribution

A B S T R A C T

This paper is concerned with a proposed color correction method called the Pixel Distribution Shifting Color Correction (PDSCC). This method employs a shifting process on the pixel distribution of a color image to correct its white reference point and ensure the white reference point is achromatic. The proposed method has been tested on numerous types of images which include indoor, outdoor, and underwater images. The qualitative and quantitative analyses have shown ample evidence that the proposed method outperforms some state-of-the-art methods, such as the Grey World, the White Patch and the General Grey World methods. The resultant images are viewed to be more natural and suggest more pleasant visualization without the intervention of the saturation problems.

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1. Introduction

The human visual system perceives the combined object’s spectral reflectance with the illuminant’s spectrum rather than perceiving solely an object’s color. This can be observed when a white patch with a blue illuminant and a blue patch with a white illuminant can reflect the same spectral distribution. Human visual system (HVS) has the ability called color consistency or color correction which steadily perceives a scene regardless of change in lighting condition [1,2]. This makes white patches look white regardless of the illumination applied to the image.

Digital imaging devices (i.e., digital camera) nowadays are becoming common consumer electronic devices. This has led to a huge variety of subjects generally acquired by non-professional photographers under unknown lighting conditions. However, digital imaging devices do not have the ability of color consistency as the HVS. Due to this problem, the images acquired often look unnatural as compared to how human eyes perceive them. Even though there are software packages that can correct the color and contrast of the images, those packages are performed manually. Users are required to obtain the surrounding illumination color and correct the color by trial and error. Furthermore, these procedures are difficult and tedious for inexperienced users.

There are two definitions of color consistency. The first definition states that color consistency is the ability to isolate the object reflectance from the surrounding illumination [3–5], whereas the second definition refers to the recovery of the object’s chromatic appearance regardless the surrounding light source [6]. Even though both definitions seem similar, the first definition tries to mimic the HVS’s ability whereas the second definition tries to obtain the real color of an object regardless the surrounding light source.

Automatic or unsupervised color correction is a challenging issue and in recent years numerous studies have been conducted in this area. According to [7], the quality of a RGB image recorded by a digital imaging device depends on several factors such as the response of camera’s sensor to each color channel as a function of intensity, the device’s white balancing used, the relative spectral sensitivity of capturing devices as a function of wavelength, the surface properties of the objects present in the scene, and the lighting condition (i.e., surrounding illuminant). Some of these factors serve are important and even indispensable information when performing color correction. Unfortunately, they are not known a priori in real photography applications. This unknown information could post a huge challenge for designing a color-correction method and therefore, it is the sole obstacle that the presents color correction purpose from being implemented.

According to [8], color consistency or color correction is still an ongoing research due to the fact that no general method can be used to correct all images in most general cases. This statement is also supported by [7,9–13]. There are several methods proposed in the literature where most of them require prior information about the digital imaging device used and the statistical properties of the image to estimate the luminance of the image. According to [9].
the earliest works on digital color correction has been published in 1989 by [10], in which the bleaching model of various types of films was put under focus.

Other than that, many color correction methods in the literature are based on the diagonal model of illuminant change from the Von Kries hypothesis [4,7,8,11–13]. Von Kries hypothesis in [14], the research states that color consistency can be achieved by regulating the three independent gain coefficients for the three cone signals. Thus, color consistency is generally divided into two steps. The first step is to estimate the gain coefficient for the three cone signals, while the second stage is the color correction procedure using the gain coefficient signals.

Based on the Von Kries hypothesis, the color image \( f = (R,G,B)^T \) can be modeled as the lambertian reflectance model as follows [3,4]:

\[
f(x) = \int_\omega \varepsilon(\lambda) s(\lambda, \lambda) c(\lambda) d\lambda,
\]

where \( x, \lambda, \) and \( \omega \) are the spatial coordinates, wavelength, and visible spectrum respectively. Here, the color of the light source or illuminant is denoted as \( \varepsilon(\lambda), s(\lambda, \lambda) \) and \( c(\lambda) \) are the object surface reflectance and the camera sensitivity function respectively. The goal of color consistency is to obtain \( s(\lambda, \lambda) \) by estimating and removing the spectral error \( S_{err} \) using:

\[
S_{err} = \int_\omega \varepsilon(\lambda) c(\lambda) d\lambda.
\]

As the values of \( \varepsilon(\lambda), s(\lambda, \lambda), \) and \( c(\lambda) \) are unknown, some approximations have been made in the literature to solve the issue of color consistency. A well-known color consistency method, called the Grey World (GW) [15], assumes that the surface color in a scene is grey due to the fact that the scene has sufficiently varied colors. The GW method assumes the average intensities for red, green, and blue channels are equal (i.e., achromatic). Thus, by measuring the shift (i.e., inequality) of these average intensities, the illumination of a scene can be estimated. To correct the image, the scaling coefficient gained from the Von Kries hypothesis is set to a certain value to compensate this shift.

Another popular and well-known color-correction method is the White Patch (WP). The WP method assumes that the maximum responses in each color channel are achromatic [2,3,16]. Thus, the scaling gain coefficients are obtained by comparing the maxima of each color channel.

The advantages of the GW and WP methods are that they can be used without any training and the implementation is simple. Furthermore, the computational costs are low and can be applied to any types of images. Despite these advantages, each method has its own drawbacks. The GW method for example will fail when a predominant color (i.e., single color) image exists in the image such as colors of the cloud and sea. On the other hand, the performance of the WP method will suffer if the images do not have a sufficient intensity.

Shades of Grey or General Grey World (gGW) method is proposed to overcome the weaknesses of the aforementioned methods [17]. The method links both the GW and WP methods using the Minkowski-norm in order to estimate the color of the light source as follows:

\[
\left( \int \frac{f^p(x) dx}{dx} \right)^{1/p} = k S_{err},
\]

where \( p \) is the Minkowski-norm. Based on (3), the method performs as the conventional GW method when \( p = 1 \), whereby (3) will compute the average of \( f(x) \), and the method performs as the WP when \( p = \infty \), whereby (3) will compute the maximum of \( f(x) \). In general, for every data set, this parameters need to be tuned to achieve the best results. According to [7,11,13,18], they have proven that the best value of \( p \) is 6. An extension of (3) has been proposed in [13], which results in the Grey-Edge (GE) assumption. The study in [13] assumes that the reflectance difference in the image which is obtained by taking the image’s derivative, is achromatic and can be modeled as follows:

\[
\left( \int \frac{|f^p(x) dx|}{dx} \right)^{1/p} = k S_{err}^{p,p,o}.
\]

Here, \( n \) is the order of the derivative, \( p \) is the Minkowski-norm and \( f^p(x) = f \circ G^o \) is the convolution of the image with the Gaussian filter with scaling parameter \( o \). Although the GE method is proposed to improve the performance of the gGW, [12,13,18,19] have provided some evidences that both techniques have produced a similar color-correction performance.

There are other techniques proposed in the literature such as the Gamut Mapping [20], which uses more advanced statistical information about the image and it involves a learning stage. Color-by-Correlation [21–23] and the Gamut-Constrained Illuminant Estimation [24] adopt the idea from [20] to develop a more suitable method that is able to improve the accuracy of the corrected image. Recently, [25] has proposed feature-based color correction approach where the algorithm is designed based on five independent color-correction techniques namely the GW, WP, gGW, First Order Grey Edge (GE1), and Second Order Grey Edge (GE2). The low level features of the image are first obtained and the most significant method to correct the images color based on the obtained features is chosen. Another feature-based method has been proposed by [26] where the selection of the most suitable color-correction methods is done based on the image power spectrum. Despite the good illumination color estimation, the feature-based methods needs training and consume time due to complex calculation.

Despite the advancement of these recent color-correction techniques, according to [18], the implementation of these methods is difficult and time-consuming as compared to the simpler GW-based method. Apart from various techniques proposed in the literature, those techniques only concentrate on the illumination color estimation, which is used to obtain the three independent gain coefficients while they correct the color image based on the same Von Kries hypothesis.

From extensive experimentation using numerous images, the Von Kries algorithm is fast and has simple implementation. Nevertheless, we notice that, by obeying the Von Kries hypothesis, the color correction is performed linearly and independently on each color channel. This could result in a saturation phenomenon that leads to the unnatural look of the resultant image as compared to the original image. This saturation phenomenon can be clearly seen when the conventional color correction algorithm is used to correct images under non-homogenous illumination such as underwater images.

Thus, this paper introduces a new color correction algorithm to substitute and enhance the performance of the conventional color correction stage which obeys the Von Kries hypothesis. The introduced method, which is called Pixel Distribution Shifting Color Correction (PDSCC), uses some statistical analyses on the image to gather relevant information and if necessary, it will perform color correction. The proposed method can possibly be implemented as software-based restoration and enhancement for digital images which is completely device-independent and applicable to numerous fields such as:

- Consumer electronic: Designing economical digital camera, scanners, and image-based instruments while producing good quality images.
Scientific imaging: Enhancing images captured from microscopes (medical), telescopes (astronomy), surveillance system (law enforcement), and spectroscopy (remote sensing).

The rest of the paper is organized as follows: Section 2 describes the automatic color correction procedure of our proposed method. The procedure of our proposed method is divided into two sections, where Section 2.1 discusses the information-gathering needed for the color correction, and Section 2.2 discusses the method of correcting the image using the information gathered from Section 2.1. The proposed method is analyzed qualitatively and quantitatively using a large data set and the results obtained are presented in Section 3. For qualitative assessment, real world images are used where the images are downloaded from the public database available in internet as well as captured by our team members. The images are categorized into three categories which are the indoor, outdoor and underwater images. Lastly, the conclusion of this paper is drawn in Section 4.

2. Methodology

Generally, an ideal color image that provides a natural and pleasant view of a scene should be captured in a white illumination surrounding, i.e., to preserve the object reflectance as shown in Fig. 1(a) for the “Clock” image. For this type of color image with white surrounding illumination color, its pixel distribution is located around the diagonal axis of its 3D RGB color model as shown in Fig. 1(b). For a non-white surrounding illumination color image as shown in Fig. 2(a) (“Clock” image with yellowish surrounding illumination), its pixel distribution is located in a specific area away from its diagonal axis as shown in Fig. 2(b). This image seems less natural and pleasant for one’s viewing. The proposed method employs this aforementioned concept for the color correction process where the original non-ideal pixel distribution of an image is re-located to be distributed as near as possible to the diagonal axis of its 3D RGB color model.

In this paper, two 3D rotational methods for color correction are proposed. The methods are specifically designed to shift the pixel distribution of an image such that the surrounding insignificant illumination will be suppressed from the processed image. This is done by moving the pixel distribution of the image to the diagonal plane of the 3D RGB color model. Such procedure could ensure the surrounding illumination pixel distribution to be rendered achromatic. The first 3D rotational method used is the 3D rotational matrix (3DMAT). 3DMAT is chosen due to its simplicity of usage and fast execution [27,28]. In image processing, 3DMAT employs the 3D pixel distribution rotational by rotating the pixel three times (yaw, pitch, and roll) using three different rotational angles. For image in RGB color space, the 3DMAT rotational is defined as follows:

\[
3DMAT = \begin{bmatrix}
1.00 & 0.00 & 0.00 \\
0.00 & \cos \sigma & -\sin \sigma \\
0.00 & \sin \sigma & \cos \sigma \\
\end{bmatrix} \cdot \begin{bmatrix}
\cos \epsilon & 0.00 & \sin \epsilon \\
0.00 & 1.00 & 0.00 \\
-\sin \epsilon & 0.00 & \cos \epsilon \\
\end{bmatrix}
\]

\[
\begin{bmatrix}
\cos \phi & -\sin \phi & 0.00 \\
\sin \phi & \cos \phi & 0.00 \\
0.00 & 0.00 & 1.00 \\
\end{bmatrix}
\]

where \(\sigma, \epsilon, \) and \(\phi\) are the three rotational angles.

The image pixel distribution is then rotated based on:

\[
\begin{bmatrix}
R' \\
G' \\
B' \\
\end{bmatrix} = 3DMAT \cdot \begin{bmatrix}
R \\
G \\
B \\
\end{bmatrix}
\]

where \(R, G, \) and \(B\) are the input of red, green, and blue color channels, while \(R', G', \) and \(B'\) are the resultant of red, green, and blue color channels respectively.

Although the 3DMAT methods are proven to be fast and simple to be executed, a thorough analysis on 210 images taken from public database available from internet as well as captured by our team members reveal one problem. From the analysis carried out, the 3DMAT method is often unable to rotate and suppress the surrounding illumination color to the 3D RGB color model diagonal axis. As a result, the method fails to suppress the surrounding illumination, and the color of the resultant images appears “unnaturally blended” compared to the original image. One of the examples is shown in Fig. 3.

Fig. 3 shows the original image, called “Smile”, and the resultant image corrected using the 3DMAT method with their respected 3D RGB color models. From the original “Smile” image in Fig. 3(a), it can be observed that the image has been influenced by a yellowish illumination color. This can also be observed from its 3D RGB color model in Fig. 3(b) where its pixel distribution concentrates on the yellow side of the model. Due to the effect of yellowish illumination, the image looks yellowish and unnatural to the HVS.

Having seen the surrounding illumination effects on images, the purpose of color correction method is to suppress or remove the effect of insignificant surrounding illumination from the image. As for the case of “Smile” image, the color correction method should remove the yellowish color from the image in order to make the resultant image looks more natural as compared to the original image. However, when the “Smile” image is corrected using the 3DMAT method, it is clear that the 3DMAT method is unable to suppress the illumination color from the original image. To make...
thing worse, the resultant image of the 3DMAT method looks more unnatural as compared to the original image. From its 3D RGB color model as shown in Fig. 3(d), it can be observed that the method is unable to rotate the pixel distribution, which should lie on the diagonal axis of the 3D RGB color model. This problem could be further observed in Appendix A, where another four examples are included. Due to the issue, this paper proposes a modified version of 3D distribution rotation based on the 3DMAT method which
is implemented on 2D two-color channel plane (i.e., red-green plane ($H_{RG}(r,g)$), red-blue plane ($H_{RB}(r,b)$), and green-blue plane ($H_{GB}(g,b)$)) instead of on 3D RGB color model. The 2D two-color channel planes as proposed in this paper are constructed from the 3D RGB color model as shown in Fig. 4.

Based on Fig. 4, from the 3D RGB color model, this study creates three 2D two-color channel planes for combinations of red-green (i.e., $H_{RG}(r,g)$ plane), green-blue (i.e., $H_{GB}(g,b)$ plane), and red-blue (i.e., $H_{RB}(r,b)$ plane). Note that the variable $r$, $g$, and $b$ represent the intensity value (i.e., 0–255 for 24-bit color image) of each color channel respectively. The $H_{RG}(r,g)$ plane consists of the coordinates of all intensities in red and green axes of the image looking from the top or bottom of the 3D RGB color model. The $H_{GB}(g,b)$ plane consists of all intensities’ coordinates in green and blue axes of the images looking from the left or right of the 3D RGB color model, while the $H_{RB}(r,b)$ plane consists of all intensities’ coordinates in red and blue axes of the image looking from the front (or back) of the 3D RGB color model.

Based on this explanation, the 2D two-color channel planes for different “Clock” images shown in Figs. 1(a) and 2(a) are constructed from its 3D RGB color model. The constructed 2D two-color channel planes for these images are illustrated in Figs. 5 and 6, respectively. As the “Clock” image in Fig. 1(a) is captured under white-surrounding illumination color, the pixel distribution for each 2D two-color channel plane is distributed around its diagonal axis as shown in Fig. 5. However, as the “Clock” image in Fig. 2(a) is captured in a yellowish (a secondary color with the combination of primary color red and green) surrounding illumination, the pixels are distributed more to the red and green axes on each 2D two-color channel plane as shown in Fig. 6.

Thus, this paper suggests a hypothesis that by correcting the pixel distribution in 2D two-color channels planes, the process could significantly correct the color of colored images. This hypothesis is employed by the proposed Pixel Distribution Shifting Color Correction (PDSCC) method which will be explained in detail in the next sections. As mentioned in Section 1, the proposed PDSCC method is divided into two sections. Section 2.1 focuses on obtaining fundamental information regarding an image such as the white point of the image, 3D RGB color model, 2D two-color channel planes, etc. Then, the proposed method will apply a color correction process as will be explain in Section 2.2.

2.1. Acquiring of image fundamental information

Consider a color digital image $F_{RGB}(x,y)$ of dimension $M \times N$, where $M$ and $N$ are the respective height and width of the image, that is spatially defined by $x$ and $y$, in which $0 \leq x \leq (M-1)$ and $0 \leq y \leq (N-1)$, respectively. The $F_{RGB}(x,y)$ image can be divided into $f_r(x,y), f_g(x,y)$, and $f_b(x,y)$ which represent the red, green, and blue color channels respectively. The first information sought in this study is to obtain the estimated white reference point for the image. A white reference point in an image is a crucial point in the color correction method. Based on this point, we can determine whether the color of the image is balanced or has been influenced by a color cast. If an image has been influenced by a non-white illuminant, this white reference point will vary to the color of the illumination. Thus, to correct the image, a color correction method should shift the color distribution of the image in order for the estimated white reference point to be achromatic. From the literature, several assumptions of this white or achromatic reference point have been introduced. According to [7,11,13,18], the $gGW$ method with the value of 6 offers the best estimation of the white reference point with a simple computational process. In our study, we will adapt this method to estimate the white reference point. From (3), the white reference point of the RGB values in the spatial coordinate denoted as $k_R$, $k_G$, and $k_B$ are calculated as follow:

$$kc = \left(\frac{1}{M \times N} \sum_{x=0}^{M} \sum_{y=0}^{N} f_c(x,y)\right)^{1/6} \quad c \in \{R, G, B\}$$

The second information acquired in this study involves obtaining 2D two-color channel plane from its 3D RGB color model cube.

![Fig. 4](https://example.com/f4.png)

**Fig. 4.** Separation diagram of the 3D RGB color model, $H_{RGB}(r,g,b)$ into the 2D $H_{RG}(r,g)$, the 2D $H_{GB}(g,b)$, and the 2D $H_{RB}(r,b)$ planes.

![Fig. 5](https://example.com/f5.png)

**Fig. 5.** 2D two-color channel planes for the “Clock” image captured in a white surrounding illumination. (a) $H_{RG}(r,g)$ plane, (b) $H_{GB}(g,b)$ plane, and (c) $H_{RB}(r,b)$ plane.
which has been presented in the early part of this section. After the information has been gathered, the color-correction method will now be applied to the image.

2.2. Color correction process

Based on aforementioned details in Section 2.1, consider a general 2D two-channel plane, \( H(i,j) \) as shown in Fig. 7 that could represent the \( H_{RC}(r,g) \), \( H_{GB}(g,b) \), or \( H_{RG}(r,b) \). Previously, all steps taken by the proposed algorithm to correct the color of an image by shifting its pixel distribution have been listed. In this section, a brief explanation regarding the steps taken is summarized.

The color-correction process can be implemented in an outline below:

1. Find the white reference point on each plane \( Q(i,j) \) (i.e., \( i \) and \( j \) are the combination of \( k_l \) and \( k_g \), \( k_b \), or \( k_r \) and \( k_b \), if the considered 2D plane is \( H_{RC}(r,g) \), \( H_{GB}(g,b) \), or \( H_{RG}(r,b) \), planes, respectively).
2. Construct a line \( l_0 \) from the origin \((0,0)\) to the point \( Q(i,j) \).
3. Calculate the angle \( \theta \) between the line \( l_0 \) and the \( i \)-axis.
4. Obtain the correction angle \( \gamma \) using:
   \[
   \gamma = 45^\circ - \theta. \tag{8}
   \]
5. Choose the first pixel to be corrected, \( P(i,j) \) of the plane.
6. Construct a line \( l_P \) from origin \((0,0)\) to \( P(i,j) \).
7. Construct a line \( l_{P_{\max}} \) from origin \((0,0)\) through point \( P(i,j) \) to the border of the 2D plane.
8. Calculate the angle \( \alpha \) between \( l_P \) and the \( i \)-axis.
9. Calculate the corrected angle, \( \alpha_{\text{new}} \) of the pixel \( P(i,j) \) using:
   \[
   \alpha_{\text{new}} = \alpha + \gamma. \tag{9}
   \]
10. Perform the first correction on the \( P(i,j) \) by finding a new value of \( i \) and \( j \) based on Eqs. (10) and (11) respectively,
   \[
   i = \begin{cases} \frac{|P(i,j)|}{\sqrt{1 + \tan^2 \alpha_{\text{new}}}} & \text{if } \alpha_{\text{new}} < 0^\circ \\ \frac{|P(i,j)|}{\sqrt{1 + \tan^2 \alpha_{\text{new}}}} & \text{if } 0^\circ < \alpha_{\text{new}} < 90^\circ \\ 0 & \text{if } \alpha_{\text{new}} > 90^\circ \\ \end{cases} \tag{10}
   \]
   \[
   j = \begin{cases} \frac{|P(i,j)|}{\tan(180^\circ - \alpha_{\text{new}})} & \text{if } \alpha_{\text{new}} < 0^\circ \\ \frac{|P(i,j)|}{\tan(180^\circ - \alpha_{\text{new}})} & \text{if } \alpha_{\text{new}} > 90^\circ \\ 0 & \text{if } 0^\circ < \alpha_{\text{new}} < 90^\circ \\ \end{cases}. \tag{11}
   \]

Note that the new corrected point from the first correction is denoted as \( P'(i,j) \).
11. Construct a line \( l_{P'} \) from origin \((0,0)\) to \( P'(i,j) \).
12. Construct a line \( l_{P'_{\max}} \) from origin \((0,0)\) through point \( P(i,j) \) to the border of 2D plane.
13. Perform the second correction process (i.e., the pixel is now denoted as \( P''(i,j) \)) by moving the pixel \( P'(i,j) \) on the \( l_{P'} \) until it fulfills the following condition:
   \[
   \frac{|l_{P'}|}{|l_{P'_{\max}}|} = \frac{|l_{P}|}{|l_{P_{\max}}|}. \tag{12}
   \]
14. For each pixel of \( f_{RC}(i,j) \), apply Steps 1–12, to each \( H_{RC}(r,g) \), \( H_{GB}(g,b) \), or \( H_{RG}(r,b) \) plane. Note that after all pixels have been considered, the corrected planes are denoted as \( H'_{RC}(r,g) \), \( H'_{GB}(g,b) \), or \( H'_{RG}(r,b) \) planes, respectively.
15. Determine the corrected \( f_k(x,y) \), \( f_c(x,y) \), and \( f_b(x,y) \) (i.e., denoted as \( f'_k(x,y) \), \( f'_c(x,y) \), and \( f'_b(x,y) \) respectively), from the three corrected planes using:
   \[
   f'_k(x,y) = \frac{R_1 + R_2}{2}. \tag{13}
   \]
\[ f_c(x, y) = \frac{G_1 + G_2}{2}, \quad (14) \]
\[ f_b(x, y) = \frac{B_1 + B_2}{2}, \quad (15) \]

where \( R_1 \) is the red coordinate of \( P'(i, j) \) in \( H_{RG}(r, g) \); \( R_2 \) is the red coordinate of \( P'(i, j) \) in \( H_{GB}(r, b) \); \( G_1 \) is the green coordinate of \( P'(i, j) \) in \( H_{RG}(r, g) \); \( G_2 \) is the green coordinate of \( P'(i, j) \) in \( H_{GB}(r, b) \); \( B_1 \) is the blue coordinate of \( P'(i, j) \) in \( H_{GB}(g, b) \); \( B_3 \) is the blue coordinate of \( P'(i, j) \) in \( H_{GB}(r, b) \).

16. Construct the corrected color image using all corrected pixels.

As mentioned previously in this subsection, the hypothesis of the color correction is to shift the pixels' distribution of an image in its 3D RGB color model to be re-distributed around its diagonal axis. This is done by first separating the 3D RGB color model into three 2D two-color channel planes (i.e., \( H_{RG}(r, g) \), \( H_{GB}(g, b) \), and \( H_{GB}(r, b) \)). The color correction will then be applied to each 2D two-color channel plane by shifting the pixels distribution to be located around its diagonal axis. The degree of shifting for each pixel is based on the white reference points (i.e., \( k_r \), \( k_g \), and \( k_b \)) obtained in Section 2.1.

After the white reference points (i.e., \( k_r \), \( k_g \), and \( k_b \)) have been estimated, the points are mapped onto each plane which is denoted as \( Q(i,j) \) as described in Step 1. This point is used to determine the correction angle \( \gamma \), which is the angle needed to shift the pixels' distribution on each plane in such a way so that the estimated white reference point will be achromatic, or lie on the diagonal axis of each plane as described in Steps 2–4. After the correction angle \( \gamma \) has been determined, all pixels are shifted to their new locations according to \( \gamma \). The shifting process is described in Steps 5–10.

After the considered pixel \( P(i,j) \) is re-distributed to \( P'(i, j) \), the length of the line \( l_P \) has become different from the line \( l_P \) as well as between \( l_P_{\text{max}} \) and \( l_P_{\text{max}} \). Thus, the ratio between \( l_P \) and \( l_P_{\text{max}} \) is not equal to the ratio between \( l_P \) and \( l_P_{\text{max}} \). This will affect the contrast of the image. In order to preserve the image contrast, the pixel \( P'(i, j) \) is re-located to be on the line \( l_P \) until (12) is fulfilled.

By implementing the color correction process on 2D two-color channel, after Step 14, each corrected pixel will have two values for each color channel (i.e., two values for red channel obtained from the \( H_{RG}(r, g) \) and \( H_{GB}(r, b) \) planes, two values for green channel obtained from the \( H_{RG}(r, g) \) and \( H_{GB}(g, b) \) planes, and two values for blue channel obtained from the \( H_{GB}(g, b) \) and \( H_{GB}(r, b) \) planes).

Thus, the final value for each color channel is set by taking an average value of those two values as specified by (13)–(15) for the red, green, and blue components respectively. Finally, the corrected color image is constructed in Step 16 using all the corrected pixel values.

3. Experimental results and discussion

In the previous section, it has been mentioned that the visualization of the concept of our proposed method will precede the qualitative and quantitative analyses. Generally, based on the observation of numerous images, for an image subjected to certain illuminant, its 3D RGB color model distribution tends to concentrate on a specific region for example, as shown in Fig. 3(a) and (b), that is for the “Smile” image. From Fig. 3(a), it can be observed that the image of “Smile” looks unnatural which can clearly be seen via the skin color of the man. For this image, the nature of the exposed illuminant is unknown and it is hard to correct the image automatically without the knowledge of the illuminant’s background. Previously, numerous studies were done to correct the image by estimating the color of the illuminant, in which several assumptions have been made. In this paper, we adapt the assumption from a well-known color consistency method which is the gGW method and come up with several modifications. Instead of obeying the Von Kries hypothesis, the proposed PDSCC method applies the color correction process by shifting the distribution of the image in the 3D RGB color model. Thus, the white reference point estimated as discussed in Section 2.1 will be achromatic and lie on the diagonal axis of the color model. The resultant image of “Smile” after the application of our proposed method is shown in Fig. 8(a) and the corrected 3D RGB color model is illustrated in Fig. 8(b).

To visualize the concept of the proposed method, consider several unbalanced color images called “Veteran”, “Swan Towel”, and “Children” as shown in Fig. 9. Based on the proposed method, the first information to be acquired is the estimated white reference point (surrounding illumination) of the image. This information can be acquired by adopting the gGW method as calculated using (3) with the value of 6 for the Minkowski-norm. The 3D RGB color model is separated into three 2D two-channel histogram planes as shown in Fig. 9 for the respective images. The first, second, and third rows of the second column show the 3D RGB color models of “Veteran”, “Swan Towel”, and “Children” images respectively. For each image, the third to fifth columns show the 2D two-channel planes of the \( H_{RG}(r, g) \), \( H_{GB}(g, b) \), and \( H_{GB}(r, b) \) respectively. The intersection of the two yellow lines on each plane indicate the estimated white reference point, \( Q(i,j) \). This point should be shifted so that it will lie on the diagonal axis of each plane.

Then, the correction angles \( \lambda_{RG}, \lambda_{GB} \) and \( \lambda_{GB} \) will be calculated for the \( H_{RG}(r, g) \), \( H_{GB}(g, b) \), and \( H_{GB}(r, b) \) planes respectively. The correction angle \( \gamma \) shows how much the pixel distribution of an image in the 3D RGB color model should be shifted in order for the \( Q(i,j) \) point to lie on the diagonal axis. Fig. 10 shows the corrected images, the corrected 3D RGB model, and the three corrected 2D two-channel histogram planes using our proposed method. After the images have been corrected, the distribution of the image will concentrate along the diagonal axis as viewed from the corrected 3D RGB color model and the three corrected 2D two-channel distribution planes.

To prove the color correction's capability, the proposed PDSCC method has been tested on numerous images for the qualitative analysis. The chosen images are mostly images that contain a color cast and therefore, need to be corrected. The images used are divided into three categories which are the indoor, outdoor, and underwater images. According to [7], the GW and the WP are the two color correction methods that are widely used in imaging devices. Furthermore, both methods are also used for performance comparisons in other previous works [7,9,11–13,17,18]. Thus, in this paper, we compare the performance of our proposed method to those of the GW and WP, methods both qualitatively and quantitatively. Furthermore, the performance of the proposed PDSCC method is also compared to the gGW, the method modified from the combination of the GW and WP methods. The qualitative analysis is conducted based on the feedback given by a panel of imaging experts from Universiti Sains Malaysia.

The panel of experts consists of nine researchers and scientists who specialize in the image-processing field. Each member of the panel is given a set of images which includes the original images (i.e., no color correction algorithm applied) and the resultant images corrected using various techniques, namely GW, WP, General gGW, and the proposed PDSCC methods. The judgment of resultant images is confined to their perception and visualization on the capabilities of those techniques to correct the images' colors and those that tend to produce more natural images for pleasant viewing. The best technique is determined based on the majority of votes decided by this panel of experts.

The first qualitative analysis of our proposed method involves the indoor images as shown in Fig. 11. The first row is the original images while the second to fifth rows illustrate the images corrected by the GW, WP, gGW and the proposed PDSCC methods respectively. Overall, the proposed method outperforms
GW, the WP and the gGW methods in terms of the quality of the images based on the feedback supplied by the panel of experts. The corrected images by the proposed PDSCC method are more natural with a more pleasant visualization. The GW and the gGW methods seem to over-correct the images where most of the corrected images look bluish and unnatural. On the other hand, the images corrected using the WP method look similar to the original images with less correction applied to the images. In terms of

<table>
<thead>
<tr>
<th>Image</th>
<th>3D RGB Color Model</th>
<th>$H_{RG}(r, g)$</th>
<th>$H_{GB}(g, b)$</th>
<th>$H_{RB}(r, b)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="histogram1.png" alt="Histogram1" /></td>
<td><img src="histogram2.png" alt="Histogram2" /></td>
<td><img src="histogram3.png" alt="Histogram3" /></td>
</tr>
<tr>
<td>(b)</td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="histogram1.png" alt="Histogram1" /></td>
<td><img src="histogram2.png" alt="Histogram2" /></td>
<td><img src="histogram3.png" alt="Histogram3" /></td>
</tr>
<tr>
<td>(c)</td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="histogram1.png" alt="Histogram1" /></td>
<td><img src="histogram2.png" alt="Histogram2" /></td>
<td><img src="histogram3.png" alt="Histogram3" /></td>
</tr>
</tbody>
</table>

Fig. 8. Image of Smile: (a) the corrected image using the proposed PDSCC method with its 3D RGB color model in (b).

Fig. 9. The uncorrected image and their 3D RGB color model, and 2D two-channel histogram planes before applying the color correction for the images (a) “Veteran”, (b) “Swan Towel” and (c) “Children”.

Table 1: The corrected 3D RGB color model and 2D two-channel histogram planes after applying the proposed PDSCC method for the images (a) “Veteran”, (b) “Swan Towel” and (c) “Children”.

<table>
<thead>
<tr>
<th>Image</th>
<th>The corrected 3D RGB color model</th>
<th>$H'_{RG}(r,g)$</th>
<th>$H'_{GB}(g,b)$</th>
<th>$H'_{RB}(r,b)$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Veteran Image" /></td>
<td><img src="image2.png" alt="Veteran Histogram" /></td>
<td><img src="image3.png" alt="Veteran Histogram" /></td>
<td><img src="image4.png" alt="Veteran Histogram" /></td>
<td><img src="image5.png" alt="Veteran Histogram" /></td>
</tr>
<tr>
<td><img src="image6.png" alt="Swan Towel Image" /></td>
<td><img src="image7.png" alt="Swan Towel Histogram" /></td>
<td><img src="image8.png" alt="Swan Towel Histogram" /></td>
<td><img src="image9.png" alt="Swan Towel Histogram" /></td>
<td><img src="image10.png" alt="Swan Towel Histogram" /></td>
</tr>
<tr>
<td><img src="image11.png" alt="Children Image" /></td>
<td><img src="image12.png" alt="Children Histogram" /></td>
<td><img src="image13.png" alt="Children Histogram" /></td>
<td><img src="image14.png" alt="Children Histogram" /></td>
<td><img src="image15.png" alt="Children Histogram" /></td>
</tr>
</tbody>
</table>

The second qualitative analysis is applied to the outdoor images as shown in Fig. 12. The first row of Fig. 12 is the original image while the second, third, fourth and fifth rows illustrate the images corrected using the GW, WP, gGW, and the proposed PDSCC methods respectively. As shown in Fig. 12, the proposed method outperforms others by producing more natural and more pleasant visualization as well as coming up with better quality images. This follows by the results obtained using the GW, which produces quite similar quality of images but with less natural and pleasant visualization and in some cases, the resultant images’ quality is worse when compared to the original images. The WP method once again fails to produce a good performance as less color correction is produced. The performance of the proposed method and the gGW are quite similar in terms of the color distribution. Despite these similarities, the brightness and contrast of the proposed method are significantly better as compared to those of the gGW method.

The visualization’s capability of the proposed method is further proven using several underwater images as shown in Fig. 13. For all the tested underwater images, the proposed method clearly outperforms others. According to the panel of experts, the resultant images are clearer, which automatically suggests better image quality. From Fig. 13, the drawback of the images corrected using the GW method has been vividly illustrated. The saturation problem (i.e., a state whereby the images turn reddish) occurs after the application of the GW method. For the images corrected using the WP method, less color correction can be observed where the resultant images look similar to the original images. On the other hand, the resultant images from the gGW and the proposed methods are capable in overcoming these problems. However, according to the panel of experts, the proposed method produces better resultant images in terms of brightness and contrast as compared to the gGW method. Overall, from the qualitative perspective, the proposed method has exhibited a better performance as compared to the GW, WP and gGW methods.

Based on the literature conducted on the past and recent research on color-correction method, there is no standard quantitative measurement to analyze the performance of the color correction methods. Most of these researches have only been able to analyze the performance of their method qualitatively (i.e., through visual comparison) rather than quantitatively. There are some quantitative analyses used in the literature such as the mean angular error [11–13,18,19] and mean error matrix [4,9]. The mean angular error analysis nevertheless, is not suitable to be used as a performance measurement of our proposed method. This is reasoned by the fact that our method emphasizes on the color correction of the image rather than estimating the color of the illuminant. Thus, in this paper, in order to perform the quantitative analysis, only the mean error matrix will be employed.

In [29], one quantitative analysis, called the mean error matrix $\Delta_E_{\text{mean}}$, is proposed to determine the superiority of a given color...
correction method. The mean error matrix $\Delta E_{\text{mean}}$ is defined as follows:

$$\Delta E_{\text{mean}} = \frac{\sum_{p \in \text{image}} \Delta E[I_1(p), I_2(p)]}{M \times N},$$

(16)

where $I_1$ and $I_2$ are the two images to be compared, and $P$ is the coordinate of the image in the spatial domain. For example, we shall consider a scene illuminated by two or more different illumination colors. According to [4,9], for an ideal color correction algorithm, it should be able to fully discard the effects of those different illumination colors from the image, and produce only resultant images due to the object reflectance. By having this capability, the color correction algorithm will produce similar resultant images for all illuminants regardless of the illumination color supplied to the images' scenes. Thus, by employing the mean error matrix $\Delta E_{\text{mean}}$, the similarity between two resultant images could be determined. Similar resultant images will produce very small $\Delta E_{\text{mean}}$ value while the exactly same resultant images will produce zero value of $\Delta E_{\text{mean}}$. As a conclusion, an ideal color correction algorithm will have a null $\Delta E_{\text{mean}}$ value for its resultant images under various surrounding illumination colors.

As far as the literature review highlighted in this study is concerned, no color correction algorithm has yet been proven to completely discard the illumination color from an image (i.e., producing null $\Delta E_{\text{mean}}$ value). Thus, for performance comparison between various algorithms in this paper, lower value of $\Delta E_{\text{mean}}$ obtained by an algorithm indicates that the algorithm produces a better color correction compared to others.

For quantitative analysis, 210 images from 35 scenes taken from [30] are used as test images. Each chosen scene comprises of a complete set of images exposed to the illumination of Sylvania cool white fluorescent light (cwf), Solux 3500 K temperature (3500 K), Solux 3500 K temperature + Roscolux 3202 filter (3500 K + 3202), Solux 4100 K temperature (4100 K), Solux 4100 K temperature + Roscolux 3202 filter (4100 K + 3202), and Solux 4700 K temperature (4700 K).

The results obtained are tabulated in Tables 1–5 for the original images and images corrected using the GW, WP, gGW, and the proposed PDSCC methods respectively. The tabulated values are the average mean error matrix $\Delta E_{\text{mean}}$, for all tested images. The best results tabulated in Tables 1–5 are presented in bold font. From the results tabulated in Tables 1–5, the GW, WP, gGW, and the proposed PDSCC methods produce lower $\Delta E_{\text{mean}}$ values for each type of images as compared to the original image. The GW method outperforms others for 8 combinations of image types, namely (4100 + 3202) vs (3500 + 3202), (4700) vs (4100), (4700) vs (4100 + 3202), (cwf) vs (3500), (cwf) vs (3500 + 3202), (cwf) vs (4100), (cwf) vs (4100 + 3202), and (cwf) vs (4700). This is followed by the proposed PDSCC method where it outperforms other methods by producing lower $\Delta E_{\text{mean}}$ value for six combinations of image types, which are (3500 + 3202) vs (3500), (4100) vs (3500), (4100) vs (3500 + 3202), (4100 + 3202) vs (3500), (4100 + 3202) vs (4100), and (4700) vs (3500). Meanwhile, the
Fig. 12. Various outdoor images after applying with the GW, WP, gGW, and the proposed PDSCC methods.

Table 1
Average $\Delta E_{\text{mean}}$ on original images.

<table>
<thead>
<tr>
<th>Original</th>
<th>3500</th>
<th>3500 + 3202</th>
<th>4100</th>
<th>4100 + 3202</th>
<th>4700</th>
<th>cwf</th>
</tr>
</thead>
<tbody>
<tr>
<td>3500</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3500 + 3202</td>
<td>27.81606</td>
<td>14.982521</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4100</td>
<td>14.745569</td>
<td>14.982521</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4100 + 3202</td>
<td>33.261637</td>
<td>7.252515</td>
<td>19.838633</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4700</td>
<td>22.501546</td>
<td>10.567831</td>
<td>9.53303</td>
<td>14.40978</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>cwf</td>
<td>22.630288</td>
<td>18.710293</td>
<td>15.825374</td>
<td>22.694321</td>
<td>16.040397</td>
<td>0</td>
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</table>

Table 2
Average $\Delta E_{\text{mean}}$ on images corrected using the GW.

<table>
<thead>
<tr>
<th>GW</th>
<th>3500</th>
<th>3500 + 3202</th>
<th>4100</th>
<th>4100 + 3202</th>
<th>4700</th>
<th>cwf</th>
</tr>
</thead>
<tbody>
<tr>
<td>3500</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3500 + 3202</td>
<td>22.823677</td>
<td>12.851489</td>
<td>11.673318</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4100</td>
<td>12.851489</td>
<td>11.673318</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4100 + 3202</td>
<td>32.68976</td>
<td>6.363068</td>
<td>16.0732</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4700</td>
<td>19.981467</td>
<td>8.082866</td>
<td>8.572699</td>
<td>10.610891</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>cwf</td>
<td>21.707149</td>
<td>12.84071</td>
<td>14.78891</td>
<td>15.989644</td>
<td>13.660117</td>
<td>0</td>
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</table>

Table 3
Average $\Delta E_{\text{mean}}$ on images corrected using the WP.

<table>
<thead>
<tr>
<th>WP</th>
<th>3500</th>
<th>3500 + 3202</th>
<th>4100</th>
<th>4100 + 3202</th>
<th>4700</th>
<th>cwf</th>
</tr>
</thead>
<tbody>
<tr>
<td>3500</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>3500 + 3202</td>
<td>25.743096</td>
<td>13.922138</td>
<td>13.47213</td>
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<td>0</td>
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</tr>
<tr>
<td>4100</td>
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<td>13.47213</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4100 + 3202</td>
<td>31.288521</td>
<td>7.484315</td>
<td>18.74821</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4700</td>
<td>21.504934</td>
<td>9.221247</td>
<td>9.219491</td>
<td>12.677986</td>
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<td>0</td>
</tr>
<tr>
<td>cwf</td>
<td>22.61883</td>
<td>14.491776</td>
<td>15.029815</td>
<td>18.196544</td>
<td>14.356198</td>
<td>0</td>
</tr>
</tbody>
</table>
gGW method outperforms other methods for only one combination namely (cwf) vs (4100). The WP method produces the lowest qualitative performance by obtaining the highest $\Delta E_{\text{mean}}$ values.

According to [4,9], to measure the performance of a color correction method, the qualitative analysis is more preferable as compared to the quantitative analysis. The quantitative analysis is applied in order to support the findings of the qualitative analysis. If we correlate the quantitative analysis with the qualitative analysis, there are some uncertainties in the results obtained. From qualitative analysis, the GW has the lowest rank and this justify its production of the worst resultant images. However, from the quantitative analysis standpoint, the GW method obtained the lowest $\Delta E_{\text{mean}}$ values. Thus, based on suggestion from [4,9], the GW method can be considered to be the least preferred color correction method although it has the best value for the quantitative analysis among the tested methods. This can be proven by the saturation problem which has occurred in the corrected images especially for underwater images. The measurement performance analysis as suggested by [4,9], in overall favors the proposed PDSCC method as the best color correction method because it produces the best qualitative analysis as well as a significantly credible quantitative analysis (i.e., ranked second for the quantitative analysis).

![Fig. 13](image_url)

Various underwater images after applying with the GW, WP, gGW, and the proposed PDSCC methods.

### Table 4
Average $\Delta E_{\text{mean}}$ on images corrected using the gGW.

<table>
<thead>
<tr>
<th>Original</th>
<th>3500</th>
<th>3500 + 3202</th>
<th>4100</th>
<th>4100 + 3202</th>
<th>4700</th>
<th>cwf</th>
</tr>
</thead>
<tbody>
<tr>
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<td>23.568805</td>
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<td>28.79347</td>
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<td>21.752677</td>
</tr>
<tr>
<td>4100</td>
<td>0</td>
<td>3202</td>
<td>4100</td>
<td>4100</td>
<td>4700</td>
<td>cwf</td>
</tr>
<tr>
<td>4700</td>
<td>0</td>
<td>3202</td>
<td>4100</td>
<td>4100</td>
<td>4700</td>
<td>cwf</td>
</tr>
<tr>
<td>cwf</td>
<td>0</td>
<td>3202</td>
<td>4100</td>
<td>4100</td>
<td>4700</td>
<td>cwf</td>
</tr>
</tbody>
</table>

### Table 5
Average $\Delta E_{\text{mean}}$ on images corrected using the proposed PDSCC method.

<table>
<thead>
<tr>
<th>Original</th>
<th>3500</th>
<th>3500 + 3202</th>
<th>4100</th>
<th>4100 + 3202</th>
<th>4700</th>
<th>cwf</th>
</tr>
</thead>
<tbody>
<tr>
<td>3500</td>
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<td>19.815542</td>
<td>11.512321</td>
<td>23.701946</td>
<td>18.163354</td>
<td>22.052601</td>
</tr>
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<td>4100</td>
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<td>15.875499</td>
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<tr>
<td>4700</td>
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<td>11.496557</td>
<td>8.995742</td>
<td>11.496557</td>
<td>15.875499</td>
</tr>
<tr>
<td>cwf</td>
<td>0</td>
<td>16.962924</td>
<td>18.189619</td>
<td>18.189619</td>
<td>15.875499</td>
<td>0</td>
</tr>
</tbody>
</table>
4. Conclusion

This paper presents an alternative color-correction method called the Pixel Distribution Shifting Color Correction (PDSCC). The proposed method has been analyzed and tested qualitative and quantitatively using numerous outdoor, indoor, and underwater images. The proposed method is then compared with three well-known color correction methods, namely the GW, WP and gGW. From the qualitative analysis, it has been shown that the proposed method outperforms the GW and WP methods. However, when comparing the proposed method with the gGW method, the results are quite similar but overall, according to the panel of experts, the proposed method is better in terms of quality and contrast as compared to the gGW method. Although the proposed PSDCC method shows good result as compared to other conventional methods, the proposed PSDCC method depends solely on the conventional illumination color estimation process (i.e., GW, WP, SG, gGW). This poses one main drawback. As the limitation of the employed conventional illumination color estimation process sometimes inaccurately estimates the surrounding illumination color, the resultant image produced will look worse as compared to the original image. Thus, as a future work for this research, new illumination color estimation processes have to be investigated. This will possibly improve the illumination estimation process thus increasing the resultant image quality.

Acknowledgements

The authors would like to express their sincere gratitude to all that have contributed ideas, guidance and assistance toward the accomplishment of this paper. This work was partially supported by the Ministry of Higher Education under the Fundamental Research Grant Scheme, titled “Investigation of New Color Image Illumination Estimation Concept for Development of New Color Correction Techniques”, and the Postgraduate Fellowship Scheme.
Appendix A.

Images corrected using 3DMAT method.

<table>
<thead>
<tr>
<th>Images</th>
<th>Original</th>
<th>Corrected Using 3DMAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow</td>
<td>![Original Snow Image]</td>
<td>![Corrected Snow Image]</td>
</tr>
<tr>
<td>Bar</td>
<td>![Original Bar Image]</td>
<td>![Corrected Bar Image]</td>
</tr>
<tr>
<td>Tiger</td>
<td>![Original Tiger Image]</td>
<td>![Corrected Tiger Image]</td>
</tr>
<tr>
<td>Underwater</td>
<td>![Original Underwater Image]</td>
<td>![Corrected Underwater Image]</td>
</tr>
</tbody>
</table>

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