Chromatic Correction Applied to Outdoor Images

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Abstract. The color of an image may be affected by many factors such as illumination, complex and multi-spectral reflections, and even the acquisition device. Especially in outdoor scenes, these conditions cannot be controlled. In order to use the information of an image, the latter must present the information as closer as possible to the original scene. Sometimes images are affected by a dominant color (cast) that changes its chromatic information. In order to avoid this effect, a color correction must be done. In this work, a novel method for correcting the color of outdoor images is proposed. This method consists in a complete improvement process of three steps: cast detection, color correction, and color improvement.

Keywords. Cast detection, color correction, chromatic adaptation, natural outdoor images, color enhancement.

Corrección cromática aplicada a imágenes de exteriores

Resumen. El color de una imagen puede ser alterado por muchos factores como iluminación, reflexiones complejas y multi-espectrales e incluso por el dispositivo de adquisición, especialmente en escenas en exteriores estas condiciones no pueden ser controladas. Con el fin de utilizar la información de una imagen, esta debe presentarse lo más cercano posible a la escena original. Algunas veces, las imágenes se ven afectadas por un color dominante (cast) que altera su información cromática. Para eliminar este efecto, se debe realizar una corrección de color. En este trabajo se presenta un novedoso método para corregir imágenes de exteriores. Este método consiste en un proceso de mejora completo de tres pasos: detección de matiz, corrección de color y mejora de color.

Palabras clave. Detección de matiz, corrección de color, adaptación cromática, imágenes naturales de exteriores, realce de color.

1 Introduction

Information analysis through images is widely used nowadays. Sometimes images are acquired under light controlled conditions, but it is not always possible. When images are taken in outdoor environments, acquisition conditions such as illumination, light scattering, surrounding reflections, etc. cannot be controlled. All these factors, including characteristics of capturing devices, may affect the quality of images [2, 19, 29]. Taking these factors into account, one of the most affected properties of an image is color, which is a useful characteristic as it provides additional information related to an object and permits to distinguish among objects with the same physical characteristics (size, shape, etc.). In image processing, color is used as a discrimination parameter on some low level tasks such as segmentation [3, 12], object tracking and robotics navigation [33], etc. Some processes are designed to associate a particular color with some kind of information (e.g., a green region associated with vegetation), However, if an image is taken under an illuminant which generates a reddish appearance, it may provoke a wrong association or conduct to an inaccurate decision (e.g., move on or stop in robot navigation).

The human visual system has an ability to maintain the chromatic features of an object relatively constant despite illumination changes. It means that even when there is a slight difference in the observed color in the scene, the chromatic concept is maintained [25]. This visual mechanism is called *chromatic adaptation* and permits to recognize the same object or scene when lighting condition changes. Some acquisition devices emulate this mechanism through sensor calibration, yet it is necessary to adapt the sensor to each lighting change. Another solution consists in correcting an image after its acquisition, i.e., by image processing (color balance). Color correction improves not only the appearance of the image but it may also be used as a pre-processing step in order to get a balanced color image for further processing. Color balance is the global adjustment of the intensities of the primary colors (red, green, and blue). An important goal of this adjustment is to correctly render specific colors, particularly neutral colors (gray to white nuances).

This paper is focused on improvement of images which have been affected by an illuminant color. The proposed correction involves three steps: detection of the dominant color, chromatic correction, and color enhancement. These processes take into account the information provided by the image itself; thus, the correction is made to an accurate extent according to the original image characteristics.

Section 2 describes related work available in the literature. The basic concepts and comparative methods used in this work are discussed in Section 3. Section 4 presents the proposed methodology and describes each step individually. Some experimental results are given in Section 5. Finally, Section 6 presents our conclusions.

2 State of the Art

Modern chromatic adaptation methods are usually based, conceptually and mathematically, on the Von Kries assumption. It asserts that color constancy can be achieved if the three cone signals are regulated through their respective gain coefficients [16]. Then any change in adaptation conditions is translated into a simple recalculation of the sensibility spectral curves of the fundamental mechanism expressed as

$$\begin{pmatrix} L' \\ M' \\ S' \end{pmatrix} = \begin{pmatrix} k_L & 0 & 0 \\ 0 & k_M & 0 \\ 0 & 0 & k_S \end{pmatrix} \begin{pmatrix} L \\ M \\ S \end{pmatrix} \tag{1}$$

where L, M, and S represent the initial cone response; k_L, k_M, and k_S are the coefficients used to recalculate the initial responses; L', M', and S' are the resulting responses after adaptation [16]. With this hypothesis, it is possible to obtain a controlled gain since each coefficient has an individual gain for its respective cone; each cone response is considered independent from the others. In order to make a chromatic correction, it is necessary to discount the effects of the illuminant [26, 38[. Then, the coefficients are calculated to be the cone inverse responses and they are estimated as the ratio between the maximum response under the reference illuminant and the response to the current one. The reference illuminant is usually the D65 CIE (*Comission Internationale de l'Eclairage*) standard illuminant due to its similarity to the noon daylight conditions in open-air. For practical purposes, the R, G, and B values are used hereinafter instead of the L', M', and S' values.

Several strategies have been proposed in the literature for color correction. One of the most known algorithms is the gray-world algorithm which assumes that the spatial average of the surface reflectance is achromatic [19, 22]. It means that, when there is a dominant color in the light and this impinges on an achromatic surface, the surface uniformly changes the intensity of its component [8]. A luminance value, relatively uniform and closer to the daylight, is obtained when the intensities of each chromatic component are averaged [28]. Thus, this algorithm recovers an estimate of the original spectral distribution of the illuminant and the surface reflectance [17]. In order to make a color correction, the gray-world algorithm works together with the Von Kries method. First, the average of each RGB channel

a)

(b)

(c)

Fig. 1. Images affected by (a) a self-cast, (b) a cast, and (c) a low luminance

is obtained (μ_R, μ_G, μ_B) in order to determine the intensity with which these were affected and the minimum of them ($\mu_{\min}$) which represents the less dominant channel and is the reference to attenuate the other channels. The coefficients are calculated with these parameters μ_R, μ_G, μ_B, and μ_{min} as shown in (2). Color correction is reached by using these coefficients in (1).

Retinex was the first attempt to develop a computational model in order to emulate the color constancy process of human vision [30]. This theory is considered as an improvement to the Von Kries hypothesis. Retinex improves the visual representation of images when light conditions are not good [34, 36] and is based on the biological mechanism of the human eye for chromatic adaptation. This method combines color constancy with contrast and local luminance of each pixel in order to approach the real appearance of a scene; it also gives a better appreciation of dark regions [7]. The algorithm calculates the luminance of a point x_p (Lx_p) influenced by N points (x_i) chosen randomly (4). There are many Retinex versions like the Brightness-based Retinex or the Change-based Retinex [10, 11]; in this work the Retinex version of Frankle-McCann [20] is used.

$$\begin{aligned} k_R &= \mu_{\min} / \mu_R \\ k_G &= \mu_{\min} / \mu_G \\ k_B &= \mu_{\min} / \mu_B \end{aligned} \tag{2}$$

$$\begin{aligned} k_R &= 1 / R_W \\ k_G &= 1 / G_W \\ k_B &= 1 / B_W \end{aligned} \tag{3}$$

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Finlayson *et al*. [19] proposed a use of histogram equalization for color constancy. This method consists in histogram transformation which distributes the values all the range long in a more uniform way and is applied to each color channel. Other proposals associate one or more correction methods to an image according to its characteristics in order to achieve the best result [4, 13, 23, 27].

There is a big difference between a cast and a wide homogenous area. A cast affects the image in a global uniform manner and it is more evident in lighter regions. For example, Fig. 1(b) shows an image where one can observe that there is a bluish layer over the entire image, which is affecting the other colors. That layer is the cast and it is better reflected on the lighter regions such as the principal building. The observer understands that the building is white; however, it has a bluish appearance that must be corrected.

The difference between these two conditions - cast and self-cast - must be taken into account in image analysis in order to arrive to the conviction that color correction is necessary. In this work, cast detection based on the image information analysis is proposed

3.1 Step 1: Cast Detection by Mean RGB Distances

The first step in color correction is to detect whether color correction can be made and whether a cast is present. As it was previously mentioned, the light regions of an image reflect the cast existence better and also provide information to determine if correction is possible. In order to make a correction, an image must have certain quantity of pixels with enough luminance. In a study concerning cast detection, Gasparini and Schettini [21] suggested to evaluate the luminance values (L*) in the range 30>L*<95; if at least 20% of pixels are within this interval then color correction is possible. For example, Fig. 1(c) shows a blue dominant color, evident on a lighter region; nevertheless, the majority of its pixels have a low luminance level that does not give enough information about the illuminant for an optimal correction. With the aim to analyze the luminance, the L*a*b* color space was used. To transform RGB values to L*a*b* values, a middle step is necessary. First, RGB values must be translated to XYZ tristimulus values by using the transformation matrix in (5). Later, L*a*b* values are obtained as in (6), where X_n=95.047, Y_n=100.0, and Z_n=108.883 according to the illuminant CIE D65, L* is the luminance channel, and a*, b* are the chromatic channels [16, 24].

$$L_{x_p} = \frac{1}{N}\sum_{i=1}^{N}(\log(I(x_p)) - \log(I(x_i))) \tag{4}$$

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{5}$$

$$\begin{aligned} L^* &= 116\, f(Y/Y_n - 16) \\ a^* &= 500[\, f(X/X_n) - f(Y/Y_n)] \\ b^* &= 200[\, f(Y/Y_n) - f(Z/Z_n)] \\ f(w) &= \begin{cases} w^{1/3}, & w > (6/29)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)2w + \frac{4}{29}, & otherwise \end{cases} \end{aligned} \tag{6}$$

If the Gasparini criterion is fulfilled, then the image is analyzed by the proposed cast detector with the aim to determine if color correction is necessary. Since the luminance values change from one image to another, the proposed cast detector is based dynamically on the individual information of an image.

This detector consists in evaluating a cast factor (*factor*) which indicates whether a cast is present. The factor is calculated by using the RGB values from the suspicious cast color and consists basically in determining if this cast color is homogeneously distributed on the image. Thus, the cast color is surely determined if this color is uniformly distributed on the image which is mathematically computed by the expected values of this color on the image. The expected values (μX and μY) are interpreted as the centroid coordinates of the cast color. If these coordinates are close to the center of the image, the cast color is detected (the suspicious color was present entirely in the image); on the contrary, if the coordinates are in another position, it means that

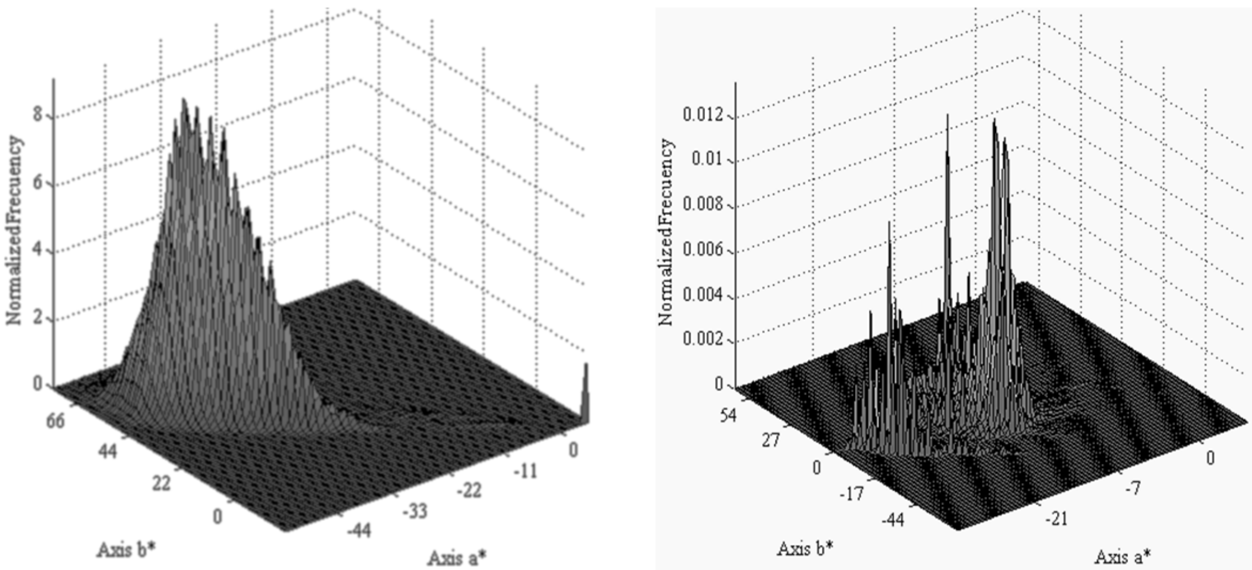


Fig. 2. AB histograms of Fig. 1(a) and Fig. 1(b), respectively

the object contains enough representative color (self-cast) to alter the basic cast detector. The factor parameter is computed by the following equation:

$$factor = \frac{\sqrt{\left(\overline{\mu}_X - \frac{W}{2}\right)^2 + \left(\overline{\mu}_Y - \frac{H}{2}\right)^2}}{\sqrt{\left(\frac{W}{2}\right)^2 + \left(\frac{H}{2}\right)^2}} \qquad (7)$$

where *X*, *Y* are the image axis, and *W*, *H* are the image width and height, respectively. According to several experimental results derived from outdoor images, if the *factor* ≥ 0.07, the image has a cast color, and a self-cast color otherwise. Besides the analysis of luminance, the color distribution of an image (channels a*b*) gives information about the cast if they are represented on a bidimentional histogram, hereinafter referred to as AB histogram. Consider the case of Fig. 1(a) and its AB histogram in Fig. 2(a). It can be observed that there is a wide and distributed peak and that the values are far from the neutral axis (0, 0) which indicates that the colors are intense. Texture and close-up images have these characteristics. When there is a cast, the histogram presents two characteristics: narrow peaks and a far distribution of the neutral axis; it means that the farther the distribution is, the more intense the cast is. Figure 1(b) and its AB histogram (Fig. 2(b)) show an example of the cast condition. Thus, by analyzing the AB histogram of an image, it is possible to detect a cast and its presence can be confirmed by calculating the factor value.

3.2 Step 2: Chromatic Correction by Neutral Values

The lightest values of an image not only give information about the cast but sometimes are used for color correction (as in the white patch algorithm). However, lighter regions do not always represent information of the original scene because some processes can change their values. It is common that acquisition devices make an automatic correction of the image when it is taken; this correction is called white balance and it forces the darkest points to become black and the lightest points to become white. If a process affects the information of the lightest regions, color correction based only on them may result inaccurate.

A chromatic correction method using the highest and lowest values of luminance is proposed in this work. This method is based on the assumption that if the highest and lowest values of luminance are considered in order to find the accurate value (neutral value) for color correction, which works in a similar way as the white of reference for the white patch hypothesis and the RGB average values for the gray-world hypothesis, then it is possible to reach balanced color in an image. This process works over the luminance of an image by combining a percentage of the lightest and darkest values with the aim to find the most accurate percentages. We used a database of 40 outdoor images of texture, close-up, and with a cast for testing different percentages.

$$neutral = [R_n, G_n, B_n] = \frac{1}{N+M}\left(\sum_{i=1}^{N} L^- + \sum_{j=1}^{M} L^+\right) \qquad (8)$$

$$\begin{aligned} k_R &= \max{}_{neutral} / R_n \\ k_G &= \max{}_{neutral} / G_n \\ k_B &= \max{}_{neutral} / B_n \end{aligned} \qquad (9)$$

More satisfactory results were obtained by taking those pixels within the lighter 20% (L^+) and those within the darkest 12% (L^-) of the luminance range of the image. For example, if the luminance range of an image is [0 -255], then L^+ contains all indexes of the pixels that $204 \le L \le 255$ and L^- contains all the indexes of the pixels that $0 \le L \le 31$. Finally, to obtain the neutral value, we calculate the average of RGB values of the indexes contained in both sets L^- and L^+ as shown in (8), where N and M are the number of indexes in L^+ and L^-, respectively, and the neutral contains the RGB values used for color correction. Based on the RGB values of the neutral, the coefficients of correction are calculated as it is shown in (9), where $max_{neutral}$ is the maximum value of R_n, G_n and B_n.

3.3 Step 3: Color Enhancement by Luminance

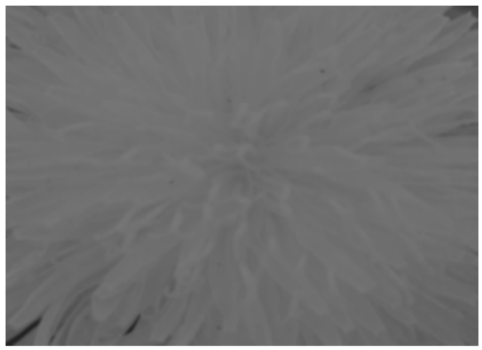
Sometimes after a chromatic correction is made, the image presents grayish colors induced by this procedure. For example, in color segmentation processes, it is more difficult to distinguish one region from another if there are grayish tones, and since this application is focused on image improvement, color enhancement is an important stage.

Nevertheless, color enhancement is not an easy task because false colors may be created thus changing the natural appearance of an image. Color is a delicate feature and a uniform distribution is not always enough for its enhancement. Color enhancement by luminance, which takes into account the individual luminance of each pixel, is proposed as a complement step for chromatic correction. This method consists in increasing color saturation without changing the hue. In a first iteration, color quotients are defined, dividing each RGB channel by its respective luminance, see equation (10).

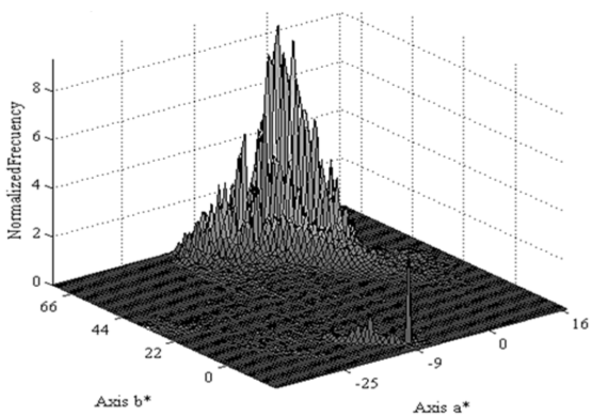
$$\alpha(i) = \frac{1}{k}\frac{C(i)^n}{L(i)} \qquad (10)$$

where $C \in \{R,G,B\}$, L is the luminance, and k is a scale factor defined by $k=max\{C(i)^n/L(i)\}$ to avoid data overflow. These quotients modulate the original RGB values and n can be adjusted to obtain different levels of color saturation, in our experiments n=2 is used. In a second iteration, more saturated and enhanced colors $C_{enh}(i)$ are obtained by (11). This set of equations works in a similar way as gamma color correction.

$$C_{enh}(i) = \alpha(i)C(i) \qquad (11)$$



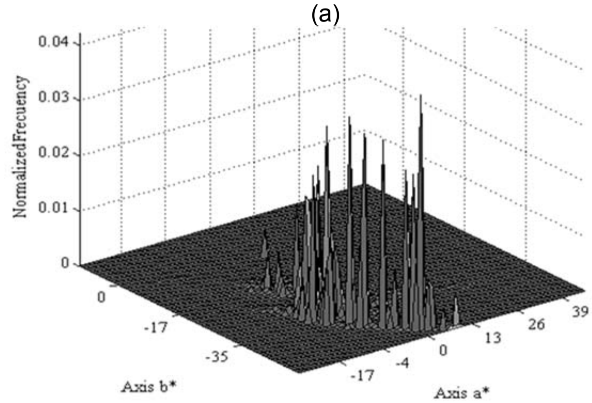
(a)



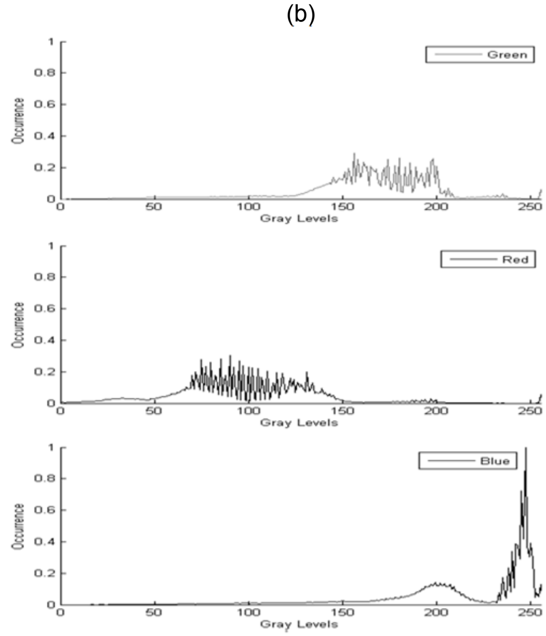
(b)

Fig. 3. (a) A self-cast image and (b) its AB histogram

(a)



(b)



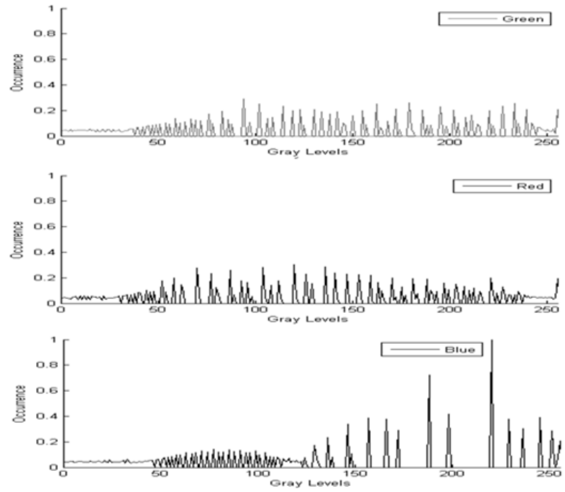
(c)

Fig. 4. (a) Image affected by a blue cast, (b) its AB histogram, and (c) its RGB histogram

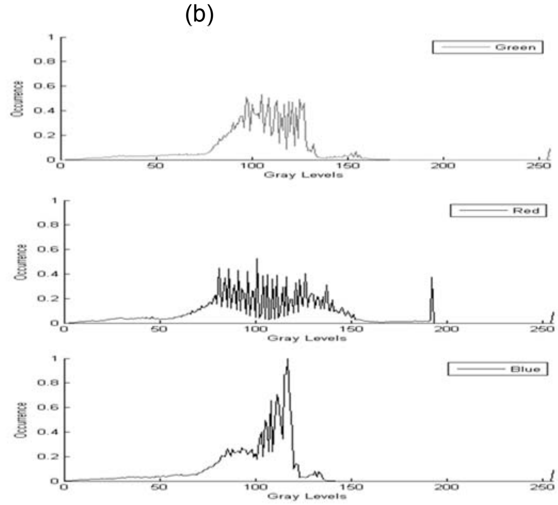
4 Experimental Results

Figure 3(a) shows a wide homogenous area (flower), and although it has an intense color because its AB histogram (Fig. 3(b)) is far from the center, the analysis determines a factor=0.01, which indicates that the image is not affected by any cast but it could be a texture or a close up image, therefore, no chromatic correction method is applied. The Gasparini analysis is used as a comparison method and in this case it also determines the presence of a self-cast.

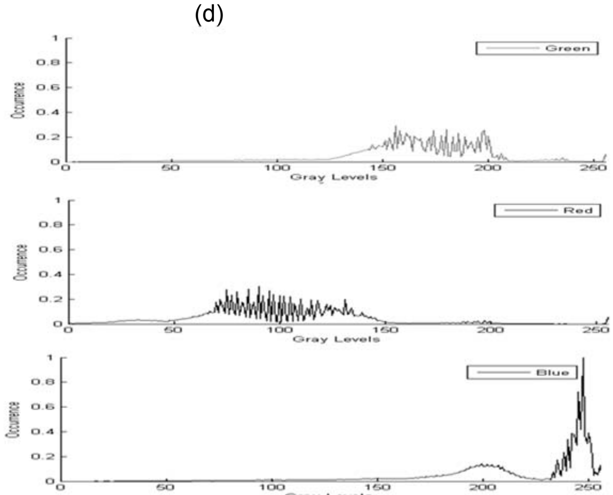
Figure 4(a) demonstrates a global blue cast, its AB histogram shows the values located far from the neutral axis (Fig. 4(b)), and it has a *factor*=0.08.


Green
Occurence
Gray Levels
Red
Occurence
Gray Levels
Blue
Occurence
Gray Levels

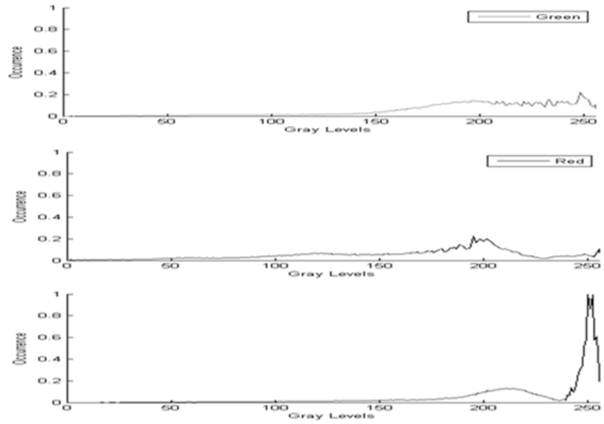
(a) (b)


Green
Occurence
Gray Levels
Red
Occurence
Gray Levels
Blue
Occurence
Gray Levels

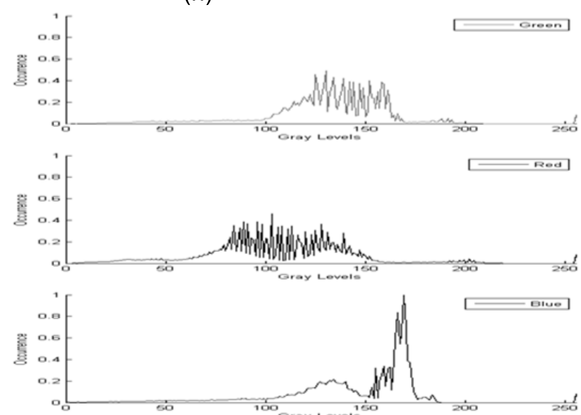
(c) (d)


Green
Occurence
Gray Levels
Red
Occurence
Gray Levels
Blue
Occurence
Gray Levels

(e) (f)



(g) (h)

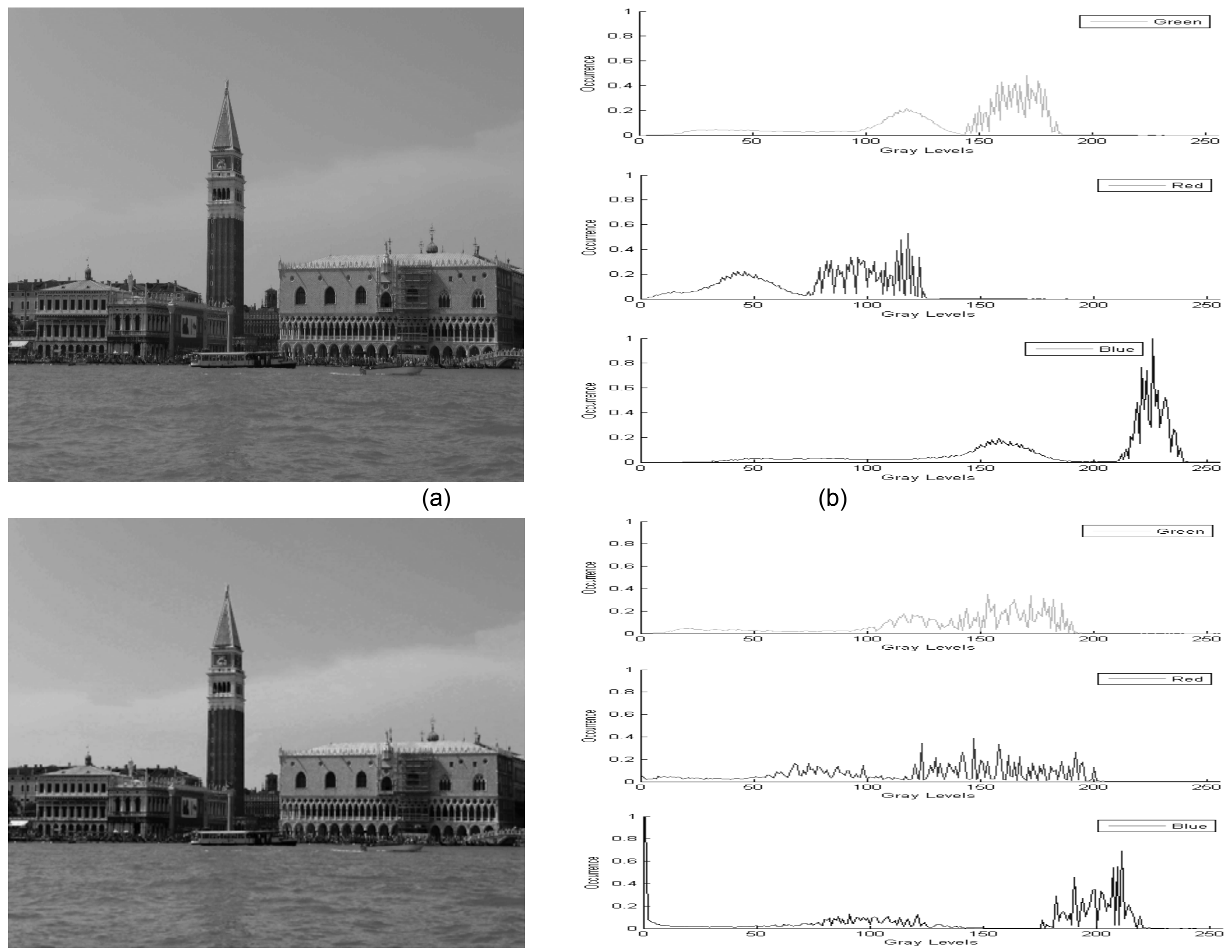


(i) (j)

Fig. 5. Chromatic correction of Fig. 3(a) by using (a) histogram equalization, (c) gray world, (e) white patch, (g) Retinex and (i) neutral values (b, d, f, h, j) with their respective RGB histogram

(a) (b)

Fig. 6. (a) Second correction by neutral values and (b) its color enhancement by luminance



(a) (b)

(c) (d)

Fig. 7. (a) Original image, (b) its chromatic correction by neutral values with color enhancement by luminance, and (c, d) their respective RGB histograms

Statistics show that the distance to the neutral axis is big enough and the cast is intense; both detectors agree to apply a correction. Bluish appearance is explained by the fact that the B channel is affecting the lightest pixels and its peak must be attenuated in order to balance the color (Fig. 4(c)).

Figure 5(a) shows a correction by histogram equalization where the blue cast was eliminated; however, the result presents new colors, which could be observed in its RGB histogram (Fig. 5(b)), and this is not accurate because it implies a change to the original chromatic information. The GW correction has attenuated the blue cast (Fig. 5(c)) and its result looks more natural. This correction often presents grayish colors and low saturation which is also observed in (Fig. 5(d)). When an image has a good level of brightness, the WP method may not present strong changes because the correction is made based on the lightest region information. In this case, WP increases the cast intensity instead of attenuating it (Fig. 5(e)(f)). Retinex has a good correction by attenuating the cast and improving the brightness (Fig. 5(g)). Note that, unlike the previous method, Retinex increases the R and G channels on lightest region instead of attenuating the B channel (Fig. 5(h)), and although the improvement is notorious, some regions have been vanished. This method also causes a halo effect evident on the tower and the white building. The neutral values method provides an adequate result since the blue peak on the lighter region was attenuated (Fig. 5(i)). The R and G channels were increased but their distribution was maintained.

Sometimes, even when the cast is attenuated, the resulting image may still have a weak cast. For this reason, the resulting image is analyzed again and if necessary, a new correction is applied. Again, the coefficients are computed for a new correction according to several tests; significant changes are reached only after the third correction. Figure 4(a) was computed two times by the neutral values method because the image presents a deep and very intense cast. The first correction (Fig. 5(i)) still conserves a little blue cast which is removed in the second correction (Fig. 6(a)). After the chromatic correction, color enhancement by luminance is applied owing to the grayish appearance resulting from the cast attenuation. Observe that the color is better balanced and has a good saturation level, and although there is a wide blue region, it belongs to the natural appearance of the sky and the river but not to the cast (Fig. 6(b)). Another result is demonstrated in Fig. 7 which also combines chromatic correction and color improvement with the methods proposed in this work.

5 Conclusions

The elimination of dominant colors in images not only permits visual improvement, but also provides better results for further processing. Outdoor images are more complicated because illumination conditions cannot be controlled. In this work, a chromatic correction method posterior to image capture was proposed. Before processing the image, an analysis with the objective to detect a cast is made in order to determine if chromatic correction is necessary and possible. Additionally, the proposed cast detector was compared with the detector suggested by Gasparini and both match in the cast detection 94% of the times. Once the cast is detected, a chromatic correction is made based on the image information and its neutral value which permits to have a result more similar to the individual condition of each image. The proposed method is based on simple operations which permit a short processing time. Results were compared, in a qualitative way, with some of the most popular methods for chromatic correction making a best comprehension of its operation, results, and efficiency possible. With the aim of complementing the improvement process, a color enhancement method using luminance as a modulator element was also proposed. Color enhancement is important because processes, as well as color correction, may generate low saturation on the resulting image. Finally, it was demonstrated that all three steps together - cast detection, color correction, and color enhancement - can improve the quality of an image in a complete way.

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