Multidomain Pixel Analysis for Illuminant Estimation and Compensation

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ABSTRACT

The illuminant estimation has an important role in many domain applications such as digital still cameras and mobile phones, where the final image quality could be heavily affected by a poor compensation of the ambient illumination effects. In this paper we present an algorithm, not dependent on the acquiring device, for illuminant estimation and compensation directly in the color filter array (CFA) domain of digital still cameras. The proposed algorithm takes into account both chromaticity and intensity information of the image data, and performs the illuminant compensation by a diagonal transform. It works by combining a spatial segmentation process with empirical designed weighting functions aimed to select the scene objects containing more information for the light chromaticity estimation. This algorithm has been designed exploiting an experimental framework developed by the authors and it has been evaluated on a database of real scene images acquired in different, carefully controlled, illuminant conditions. The results show that a combined multi domain pixel analysis leads to an improvement of the performance when compared to single domain pixel analysis.

Keywords: Illuminant Estimation, illuminant compensation, Automatic White Balancing.

1. INTRODUCTION

A huge number of images acquired by non professional users under uncontrolled illuminant conditions are nowadays produced by digital still and video cameras. These devices do not have the ability of the human visual system[1,2] to discount the illuminant, rendering the perceived colors of objects almost independent of illumination. Illuminant estimation and compensation should be obtained through an automatic white balancing algorithm, operating directly in the image acquiring device. Different approaches have been investigated in the literature: Finlayson at al.[3] have proposed an algorithm to estimate the illuminant color temperature starting from the correlation between the observed gamut and the sensor responses to real world reflectances under different illuminant situations. Tominaga et al.[4,5] have developed a similar approach taking also into account the intensity response of the sensors, showing that brighter reflectances on real scenes play the most important role in the illuminant estimation process. Ciurea and Funt[6] have collected an image database useful to test algorithms developed to solve the problem of color constancy, also including a framework for the quantitative analysis of their performance. Cooper et al.[7,8] have shown the role of spatial segmentation and color saturation to improve illuminant estimation and compensation. Gasparini et al.[9] have demonstrated that a color cast presents in unbalanced images, coming from unknown sources, can be compensated by analyzing different pixel features, taking also into account some semantic aspects related to common chromatic classes. These classes are often present on natural scene images and produce the most visual impact on the human visual system, thus their chromatic and spatial features should be considered in the illuminant estimation process. Some approaches mentioned above need a calibration step in order to model the chromatic correlation between standard reflectances of real scenes under different illuminants and the sensor responses. In this paper we present an algorithm, not dependent on the acquiring device, for illuminant compensation directly in the color filter array (CFA) domain of digital still cameras. The algorithm proposed uses both the chromaticity and the intensity of the image to estimate the illuminant, and performs the compensation by a diagonal transforms. In particular it combines a spatial segmentation process with empirical designed weighting functions aimed to select the scene objects containing more information for the light chromaticity estimation. This algorithm has been designed exploiting an experimental framework developed by the authors and it has been evaluated on a database of carefully controlled real scene images, containing uniform reflectance patches, acquired under direct daylight, incandescent lamps, fluorescent lamps, cloudy and shaded daylights. The performance of the proposed algorithm is illustrated and compared with that of the classical gray world approach. The results show that a combined multi domain pixel analysis leads to an improvement in the performance. Section two describes the methodology and the

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framework used for the analysis, Section three describes the algorithm proposed, Section four illustrates the experimental results, whereas in the last section the conclusions are summarized and possible future developments are presented.

2. METHODOLOGY

The power spectrum $E(\lambda)$ of the light that illuminates a scene is reflected by the objects according to their reflectance $R(\lambda)$. The sensors of an image acquisition device are usually equipped with a mosaic color array composed of micro lenses. This color filter array (CFA) filters the light reflected by the scene with different sensitivities $S_i(\lambda)$, producing three analogical levels $\rho_{i.,}$ as shown in Figure 1, where the image acquisition scheme of a digital color sensor device is summarized.

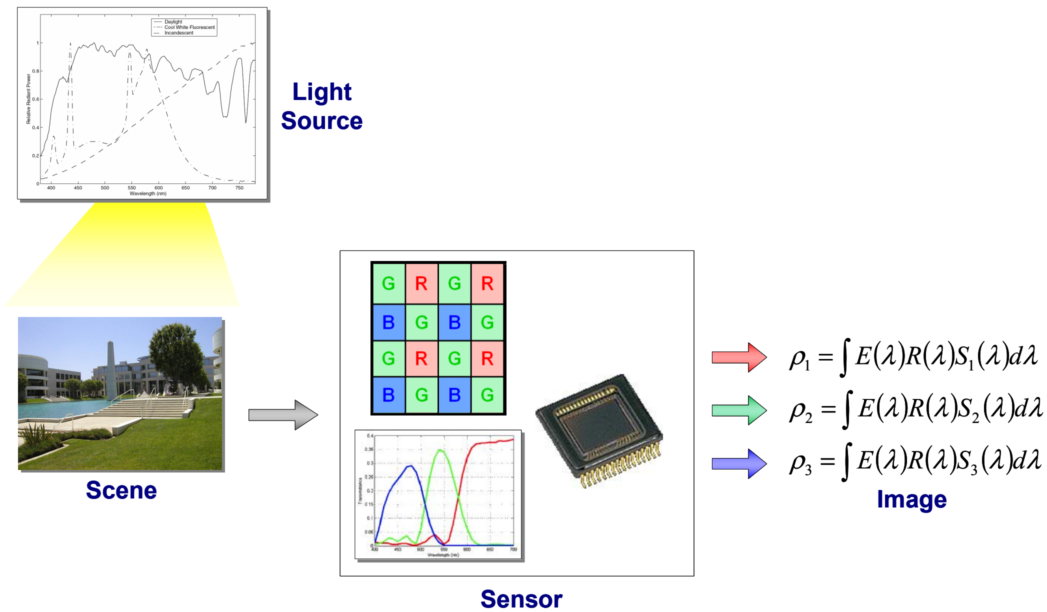


Figure 1. Image acquisition scheme of a digital color sensor device.

The spectral distribution of the illuminant is usually estimated and compensated, through an automatic white balancing algorithm, considering the R, G, B obtained from the ρ_i levels after an analog to digital conversion process. This problem formulation is under constrained, since two objects of the scene with different reflectance spectra could produce the same color triplet under a fixed illuminant.
In this paper we propose an algorithm to estimate and compensate the illuminant in the CFA domain, based on the wide accepted consideration[4,6,7,8,] that not all the pixels of the scene have the same significance in terms of illuminant information.

2.1. The Framework

To perform quantitative evaluation of the proposed solution, we have developed a HW and SW framework. Using it, a database of 150 raw format images in the CFA domain has been collected. These images were grabbed under common illuminant situations: daylight, incandescent lamps, fluorescent lamps, cloudy, shaded daylights. In order to measure the light chromaticity and to calibrate the images, a neutral patch with uniform reflectance was properly positioned in the scenes.

Working in the *r*,*g* normalized color space:

$$r = \frac{R}{R+G+B}; \qquad g = \frac{G}{R+G+B} \tag{1}$$

the Euclidean distance from neutral axis, (r_N=g_N=$1/3$) of the neutral reference patch after the automatic white balancing (r_w,g_w) provides an error measure of the color correction:

$$Err = \sqrt{(r_w - r_N)^2 + (g_w - g_N)^2} \tag{2}$$

The framework used to perform the quantitative analysis of the proposed algorithm is shown in Figure 2.

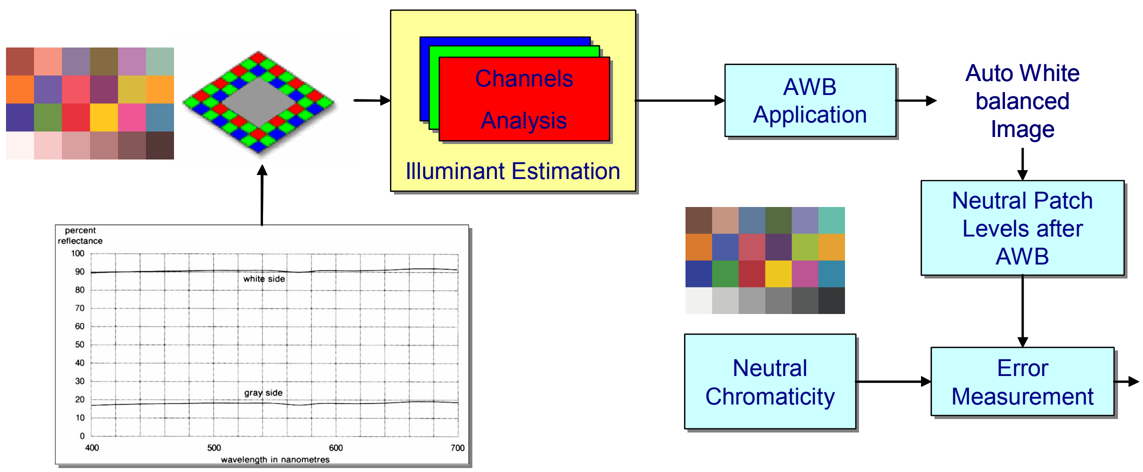


Figure 2. The framework used to perform the quantitative analysis of the proposed algorithm.

3. ALGORITHM

Unlike human vision, imaging devices (such as digital cameras) can not adapt their spectral responses to cope with different lighting conditions. To recover the original appearance of the scene under different lighting, the measured tristimulus values must be transformed. Such transformations are called *chromatic adaptation models,* and are the basis of several color balancing methods available in the literature[10,11].

A chromatic adaptation model[12], does not include correlates of appearance attributes, such as lightness, chroma and hue, but simply provides a transformation from tristimulus values in one viewing condition to matching tristimulus values in a second set of viewing conditions. Most of these models are based on the Von Kries hypothesis, which states that chromatic adaptation is an independent gain regulation of the three cone signals *L*, *M*, *S*, through three different gain coefficients. Adaptation models vary in how the particular values of the coefficients are obtained. In these models the RGB channels are usually considered an approximation of the *L*, *M*, *S* retinal wavebands[13], so that the post-adaptation values, R_a, G_a, B_a can be obtained with the following Von Kries diagonal transform:

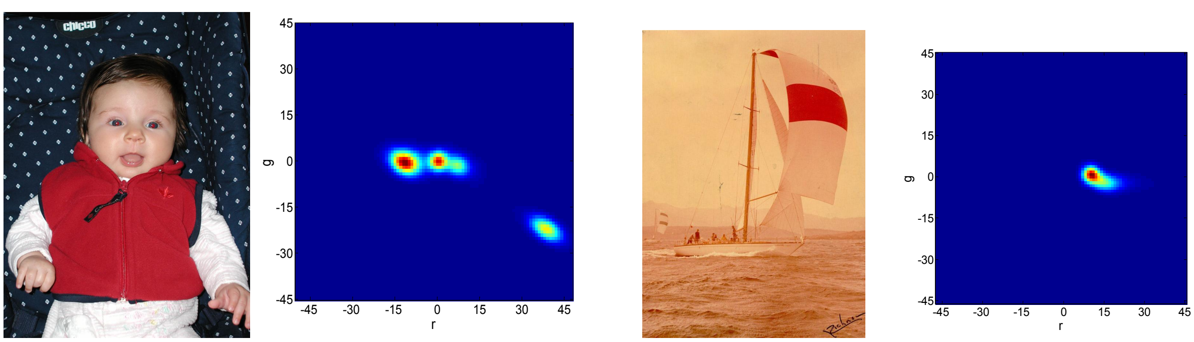
$$\begin{bmatrix} R_a \\ G_a \\ B_a \end{bmatrix} = \begin{bmatrix} k_R & 0 & 0 \\ 0 & k_G & 0 \\ 0 & 0 & k_B \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3}$$

Many algorithms have been developed for color balancing based on the Von Kries assumption that each sensor channel is transformed independently. The gray world algorithm assumes that, given an image of sufficiently varied colors, the average surface color in a scene is gray[14]. This means that the shift from gray of the measured averages on the three

channels corresponds to the color of the illuminant. The three scaling coefficients in Eq. 3 are therefore set to compensate this shift.
Assuming that there is always a white in the scene, the white point and white patch algorithms look for this white in the image, the chromaticity of which will then be the chromaticity of the illuminant[15,16]. The white point algorithm determines this white as the maximum R, maximum G and maximum B found in the image, while the white patch takes as white the average of a region that appears reasonably white in the real scene. The scaling coefficients are now obtained setting this point or region at the white of the reference illuminant.
However, when one of these color balance adjustments is performed automatically, the mood of the original scene can be altered in the output image. For example, an automatic color balancing adjustment applied to a sunset image may drastically modify the nature of the scene, removing the characteristic reddish cast, while methods based on the gray world assumption will generate a wholly grayish scene in the case of scenes not enough colorful. In fact, most color balancing algorithms work well only when prior assumptions are satisfied, (gray world assumption), or the illuminant varies only slightly. When these prerequisites are not met, the results may be distorted, or the colors grayed out. The algorithm here proposed is a modified version of the traditional white patch algorithm. It is developed to be applied directly in the color filter array (CFA) domain of digital still cameras. The main peculiarity of this color balancing lies in how it determines the region to be set at white, here called white balancing region (WB region). Accordingly to wide accepted results that not all the pixels have the same significance in terms of information content of scene illuminant, it takes into account both chromaticity, intensity and spatial information of the image data. In particular it works by combining a spatial segmentation process and proper weighting profiles aimed to select the scene objects containing more information for the light chromaticity estimation. The RGB channels of the raw format images in the CFA domain are first mapped in the normalized *r*,*g* color space, shifted to be centered with respect to the neutral axis R=G=B:

$$r = \frac{R}{R+G+B}100 - 33 \; ; \qquad\qquad g = \frac{R}{R+G+B}100 - 33 \tag{4}$$

The 2-dimensional histogram, $F(r,g)$, of the image colors in the *rg*-plane is computed. For a multicolor image without color shift, this histogram will present several peaks distributed over the whole *rg*-plane (Figure 3ab), while for an image with a dominant color, there will be a single peak, or a few peaks in a limited region (Figure 3cd). The more concentrated the histogram and the farther from the neutral axis, the more intense the color shift.



(a) (b) (c) (d)

Figure 3. Examples of images with different chromatic properties. The histogram (b) of a multicolor image (a) shows several peaks distributed over the whole rg-plane, whereas an image with evident cast (c) presents a color histogram with few peaks in a limited region of the *rg*-plane (d).

To study the histogram distribution, we use the mean values and the variances of the histogram projections along the two axes *r,g*, ($k = r,g$):

$$\mu_k = \int_k kF(r,g)dk \; . \tag{5}$$

$$\sigma_k^2 = \int_k (\mu_k - k)^2 F(r,g)dk \; . \tag{6}$$

Defining $D = \mu - \sigma$, ($\mu = \sqrt{\left(\mu_r^2 + \mu_g^2\right)}, \sigma = \sqrt{\sigma_r^2 + \sigma_g^2}$), a measure of how far the whole histogram lies from the neutral axis ($r = 0,\ g = 0$), we introduce the ratio $D_\sigma = D/\sigma$, as a useful parameter for measuring the intensity of the color shift: the greater the D_σ, the stronger the color shift. If the histogram is concentrated (small σ value) and far from the neutral axis (high value of μ and D_σ), the colors of the image are confined to a small region that could correspond to what we have called an intrinsic dominant color (to be preserved), as in the presence of widespread areas of vegetation, skin, sky, or sea, (Figure 4). For this kind of images no processing is considered, to avoid color distortion in the output image.

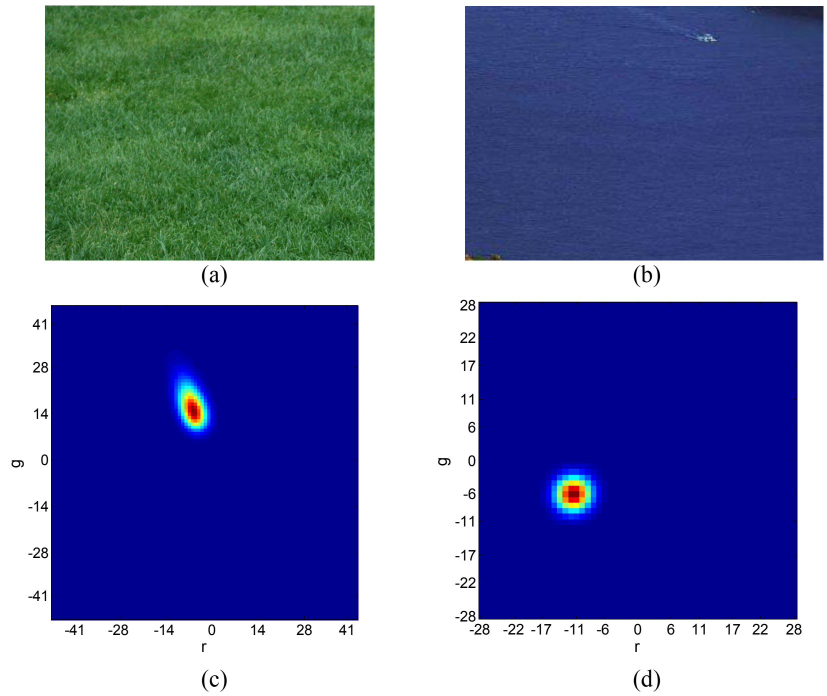


Figure 4. Examples of images with an intrinsic dominant color (a)(b), and relative histograms (c)(d). Typically an intrinsic cast is found in the presence of a widespread region of sky, sea, or vegetation, or in portraits.

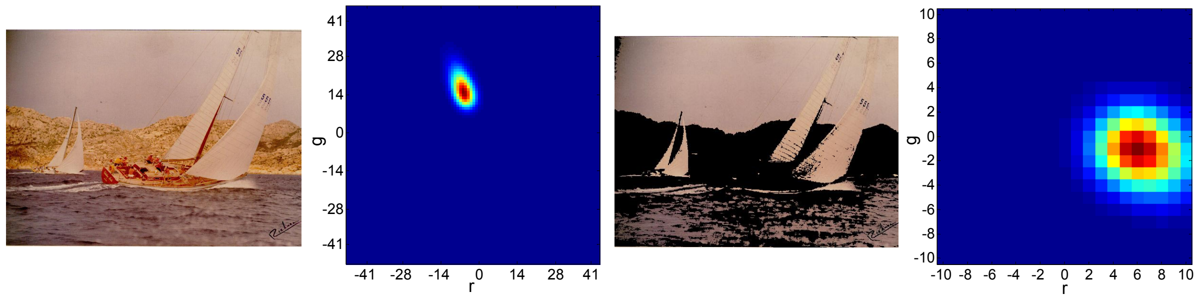
Images where an intrinsic dominant color is not identified are analyzed with a following procedure based on the criterion that a color shift has a greater influence on a neutral region than on objects with colors of high chroma (chroma=$(r^2+g^2)^{1/2}$). The color distribution of Near Neutral Objects (NNO)[8] is studied.

A pixel of the image belongs to the NNO region if its chroma is less than an initial fixed value and if it is not isolated, but has some neighbors that present similar chromatic characteristics. If the percentage of pixels that satisfies these requisites is less than a predefined percentage of the whole image, the minimum radius of the neutral region is extended, and the region recursively evaluated, till the desired percentage or either a maximum radius are reached. The minimum and maximum radii are previously estimated from the analysis of the histogram distribution of the whole image. Once this recursive iteration ends, the segmentation of the NNO region is completed including all the pixels corresponding to the peaks identified in its color histogram. In Figure 5 an example of cast image (a) with its corresponding color histogram (b), NNO region (c) and NNO histogram (d) are shown.

The white balancing region to be used in the Von Kries diagonal transform of Eq. 3 is finally obtained by applying to the NNO region, both an intensity weighting profile empirically designed (shown in Figure 6a) and a saturation weighting function[17] obtained as:

$$S_w = 1 - S \;; \qquad S = 1 - 3\frac{\min(R,G,B)}{R+G+B} \tag{7}$$

Figure 6b reports the image of Figure 5a after applying the saturation weighting function of Eq. 7, whereas the white balancing region and the output image are reported in Figure 6c and d.



(a) (b) (c) (d)

Figure 5. An example of cast image (a) with its corresponding color histogram (b), NNO region (c) and NNO histogram (d)

(a) (b) (c) (d)

Figure 6. The intensity weighting profile (a), the mask of Figure 5a related to the saturation function *S* of equation 7 (b), the white balancing region(c), the color balanced image (d).

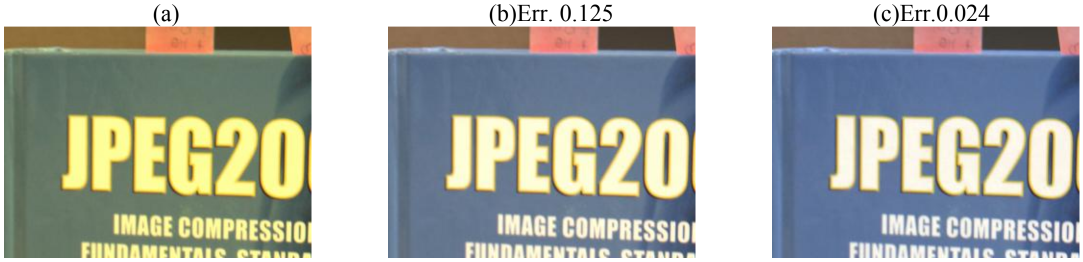
4. EXPERIMENTAL RESULTS

The proposed solution has been compared with a classical gray world approach in order to verify the significance of the multi domain pixel selection methods. The gray world algorithm assumes that, given an image of sufficiently varied colors, the average surface color in a scene is gray. This means that the shift from gray of the measured averages on the three channels corresponds to the color of the illuminant. We used a gray world approach without any weighting function for the energy channel estimation, leading to a uniform use of the pixel chromatic information.
Eq. 8 reports the formulation of this approach as it has been implemented, where E_c is the energy of the *c* color channel, I_{ci} is the intensity of the the *ith* pixel of the *c* channel, *N* is the number of the pixels in the whole image, and K_c is the multiplicative gain applied to the *c* channel according to the gray world assumption.

$$E_c = \sum_{i=1}^{N} I_{c_i} \qquad ; \qquad K_c = \frac{\underset{c}{avg}\{E_c\}}{E_c} \qquad ; \qquad c=R,G,B \tag{8}$$

This channel energy estimation and color correction allowed us to put in evidence the benefits of the multiple domain approach of the proposed solution, which assigns different weights to the pixels according to empirical and theoretical results.
The two algorithms have been tested over the entire calibrated image collection, and have been compared in terms of mean square error, related to the error measure of Eq. 2. The proposed solution, based on the multiple domain pixel selection, shows significant improvement when compared to uniform pixel weighting approach, showing an MSE equal to $1.63\cdot10^{-3}$, whereas the gray world solution produces an MSE equal to $2.34\cdot10^{-3}$. Figure 7a and d reports two examples of calibrated images, where the weak matching with the gray world assumption, due to the limited number of objects present on the scene, could lead to a poor estimation when all the pixels are taken into account in the same way, as in the case of the gray world (Figure 7b and e). Instead, the proposed solution, which adopts multi-domain weighting profiles, shows better performance (Figure 7c and f).

(a) (b)Err. 0.125 (c)Err.0.024



(d) (e)Err. 0.050 (f)Err. 0.026

Figure 7. Two input images (a)(d), images processed with gray world algorithm and corresponding error measures(b)(e), images processed with multi-domain analysis and corresponding error measures(c)(f).

5. CONCLUSIONS

In this paper we have shown a solution for auto white balancing on digital still camera sensors. The proposed algorithm does not depend on the acquiring device and takes into account both chromaticity and intensity information in order to carefully estimate the scene illuminant. It has been quantitatively evaluated and outperforms the classical gray world algorithm. As a future research we plan to improve the multi domain analysis that drives the automatic white balancing, considering more features, related to objects whose reflactances have the most perceptual impact on the human visual system, such as skin, vegetation or sky. We also intend to introduce the influence of the device in the illuminant estimation, investigating the role of the sensor profiling.
Finally, we plan to perform both qualitative and quantitative analyses and comparisons adopting error metrics more related to human visual perception.

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