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Experiments on the White Patch Retinex in RGB and CIELAB color spaces

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ABSTRACT

Color constancy is an important process in a number of vision tasks. Most devices for capturing images operate on the RGB color space and, usually, the processing of the images is in this space, although some processes have shown a better performance when a perceptual color space is used instead. In this paper, experiments on the White Patch Retinex, a color constancy algorithm commonly used, are performed in two color spaces, RGB and CIELAB, for comparison purposes. Experimental results using an imagery set are analyzed using a no-reference quality metric and outcomes are discussed. It has been found that the White Patch Retinex algorithm shows a better performance in RGB than in CIELAB, but when color adjustments are implemented in sequence, firstly in CIELAB and then in RGB, much better results are obtained.

RESUMEN

La constancia de color es un proceso importante en una variedad de tareas de visión. La mayoría de los dispositivos para la captura de imágenes operan en el espacio de color RGB y, por lo general, el procesamiento de las imágenes es en este espacio, aunque algunos procesos han mostrado un rendimiento mejor cuando un espacio de color perceptual se utiliza en su lugar. En este trabajo, experimentos con un algoritmo de constancia del color de uso común, el llamado Parche Blanco Retinex, se llevan a cabo en dos espacios de color, RGB y CIELAB, con fines de comparación. Los resultados experimentales utilizando un conjunto de imágenes se analizan con una métrica de calidad sin referencia y los resultados se discuten. Se ha encontrado que el algoritmo de Parche Blanco Retinex muestra un mejor rendimiento en RGB que en CIELAB, pero cuando los ajustes de color se aplican en secuencia, en primer lugar en CIELAB y luego en RGB, se obtienen resultados mucho mejores.

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INTRODUCTION

Color is an important cue for computer vision and image processing related topics, like feature extraction [1], human-computer interaction [2], and color appearance models [3].

Colors observed in images are determined by the intrinsic properties of objects and surfaces, as well as the color of the light source. For a robust color-based system, the effects of the light source should be filtered out [4]. Color Constancy is the ability of distinguishing the correct color, independently of the light source present in the scene[5].

Palabras clave:

Constancia de color; retinex; CIELAB; métrica de espectro de potencia.

Keywords:

Color constancy; retinex; CIELAB; power spectrum metric

Over decades, researchers have tried to solve the problem of color constancy by proposing a number of algorithmic and instrumentation approaches. Although, due to the wide range of computer vision applications that require color constancy, it is not possible to have a unique solution for all cases [6]. Color is a human visual property [3]. In other words, the color depends on the individual perception. For this reason, it is considered pertinent to analyze a basic algorithm in a perceptual color space. Unfortunately, the majority of researchers have not addressed directly the color

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correction in perceptual color spaces. Two main components are considered in this study. In one hand, *White Patch Retinex* (WPR from now on), is an algorithm based on statistical methods [7] [8].

This algorithm considers the maximum intensity value in each color channel. On the other hand, the CIE 1976 (L^* , a^* , b^*), or CIELAB, is a perceptual color space. Also, it can be considered a color appearance model [3]. This work tests the performance of the WPR in the CIELAB color space. In addition, the non-perceptual color space RGB is included for reference purposes.

According to our results, we suggest the application of the WPR in new and practical approach for addressing the color correction.

The paper is organized as follows: Section Methodology presents the color constancy methodology used, the White Patch Retinex theory, and the manner this algorithm is applied in CIELAB. The experimental results for test series are given in Section Experimental Results. Here, the observations on the data obtained are also included. Finally, some concluding remarks are given in Section Conclusions.

METHODOLOGY

Most color constancy algorithms have been proposed and implemented in the RGB color space [9]. In this paper, a basic algorithm, the WPR, is compared in RGB and CIELAB color spaces using three particular approaches, as depicted in figure 1.

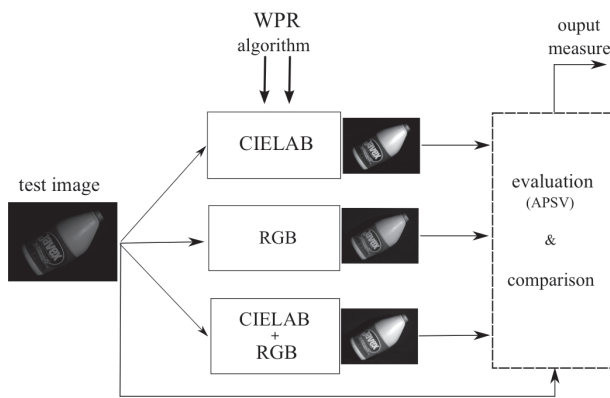


Figure 1. Three approaches for experimental evaluation of the WPR

Basically, the methodology consists in the next modules:

- Applying the WPR algorithm for all images in the CIELAB space.

- Applying the WPR algorithm for all images in the RGB space.
- Applying the WPR algorithm first in the CIELAB space and then in the RGB space.
- Get a quality measure for each test image and its corresponding outputs.
- The comparison of the four quality measures obtained.

The White Patch Retinex algorithm

Based on the retinex algorithm proposed by Land and McCann [7]. The algorithm considers the highest value in each color channel as the white representation for the image.

It is assumed that $f(x, y)$ is the intensity of a pixel in an image or a frame, $G(x, y)$ is a geometry term, $R_i(x, y)$ the reflectance, I_i is the intensity of the current illumination, and i is one of the color channels in the image. Eq. 1 gives the relationship for the color intensity

$$f_i(x, y) = G(x, y)R_i(x, y)I_i. \quad (1)$$

Assuming $G(x, y) = 1$ and $R_i(x, y) = 1$, the relation in Eq. 2 applies.

$$f_i(x, y) = I_i, \quad (2)$$

Computationally, this white patch is found searching for the maximum intensity in each channel, as indicated in Eq. 3.

$$I_{i_{max}} = \max\{f_i(x, y)\}. \quad (3)$$

Later, all pixel intensities are scaled according to these values using Eq. 4.

$$o_i(x, y) = \frac{f_i(x, y)}{I_{i_{max}}}. \quad (4)$$

The WPR algorithm can be made more robust by computing a histogram H_i for each color channel i . The histogram tells us how many image pixels have a particular intensity for a given color channel. Let n_b be the number of bins of the histogram and $H_i(j)$ is the channel histogram, j is the index of the corresponding intensity bin in the histogram. Instead of choosing the pixel with the maximum intensity for each color channel, one can choose the intensity such that all pixels with intensity higher than the one chosen account for some percentage of the total number of pixels. This method is used in [8] for shadow removal. Let $f_i(j)$ be the intensity of color channel i represented by bin j of the histogram H_i . Then the estimate of the illuminant is given by the Eq. 5

$$I_i = f_i(j_i). \quad (5)$$

For the selection of the j_i some conditions must be fulfilled:

$$pn \leq \sum_{k=j_i}^{n_b} H_i(k) \quad (6)$$

$$pn \geq \sum_{k=j_i+1}^{n_b} H_i(k), \quad (7)$$

where pn is a percentage (usually about 1%) of the total of pixels in the image [9].

Color spaces transformations

In order to transform an image from RGB to CIEXYZ, the RGB working space needs to be determined. Here, the standard sRGB is assumed because it is based on a calibrated colorimetric RGB color space [10].

All the perceptual space transformations used in this study are applied to the CIEXYZ color space [11]. Therefore, all images need to be converted from sRGB into CIEXYZ, so that the transformation equations can be applied. For this purpose, Eq. 8 is used, where $r, g, b \in [0, 1]$, obtained by dividing each pixel ($R_{sRGB}, G_{sRGB}, B_{sRGB}$) component by 255,

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} r \\ g \\ b \end{bmatrix}. \quad (8)$$

Once the image is transformed into the CIEXYZ color space, the transformation equations for the CIELAB color space can be applied. The CIELAB [11] color space is calculated from CIEXYZ using the Eq. 9 and, then, Eq. 10-12 are used, to obtain the components in the space.

$$f(x) = \begin{cases} x^{1/3} & x > \sigma^3 \\ x/(3\sigma^2) + 16/116 & x \leq \sigma^3, \end{cases} \quad (9)$$

$$L^* = 116(Y/Y_N)^{1/3}, \quad (10)$$

$$a^* = 500 [f(X/X_N) - f(Y/Y_N)], \quad (11)$$

$$b^* = 200 [f(Y/Y_N) - f(Z/Z_N)], \quad (12)$$

where X_N, Y_N and Z_N are the white stimuli reference for the scene in CIEXYZ and $\sigma = 6/29$. L^* describes the lightness and ranges from 0 (black) to 100 (white). The a^* coordinate represents the redness-greenness of the sample and has a range of $[-86.1367, 98.2964]$. The b^* coordinate represents the yellowness-blueness, and has a range of $[-107.8650, 94.4756]$. The limits of the range channels were calculated by transforming all possible values in RGB into CIELAB, allowing the application of the described equation.

For the inverse transformation from CIELAB to CIEXYZ, it is required the calculation of three intermediate variables, f_Y, f_X and f_Z , obtained using Eqs. 13-15.

$$f_Y = (L^* + 16)/166, \quad (13)$$

$$f_X = f_Y + (a^*/500), \quad (14)$$

$$f_Z = f_Y - (b^*/200), \quad (15)$$

Equations 16-18 are used to transform an image from the CIELAB back into the CIEXYZ color space,

$$Y = \begin{cases} Y_n f_Y^3 & f_Y > \sigma \\ f_Y - 16/116 & f_Y \leq \sigma, \end{cases} \quad (16)$$

$$X = \begin{cases} X_n f_X^3 & f_X > \sigma \\ f_X - 16/116 & f_X \leq \sigma, \end{cases} \quad (17)$$

$$Z = \begin{cases} Z_n f_Z^3 & f_Z > \sigma \\ f_Z - 16/116 & f_Z \leq \sigma, \end{cases} \quad (18)$$

whereas the transform to CIE XYZ to sRGB coordinates is given by Eq. 19,

$$\begin{bmatrix} r \\ g \\ b \end{bmatrix} = \begin{bmatrix} 3.2410 & -1.5374 & -0.4986 \\ -0.9692 & 1.8760 & 0.0416 \\ 0.0556 & -0.2040 & 1.0570 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}. \quad (19)$$

where $r, g, b \in [0, 1]$. Finally, $R_{sRGB}, G_{sRGB}, B_{sRGB}$ are obtained by multiplying each component by 255.

White Patch Retinex in CIELAB

In the theory of the WPR algorithm only the maximum intensity values are considered. This assumption is made because it is common to process dark images and its minimum value is (0,0,0) in RGB. However, it is possible to find cases where there exists a minimum different to this value. Eq. 20 describes the WPR without this assumption

$$o_i(x, y) = \frac{f_i(x, y) - I_{i_{min}}}{I_{i_{max}} - I_{i_{min}}}, \quad (20)$$

where $I_{i_{min}}$ is

$$I_{i_{min}} = \min\{f_i(x, y)\}. \quad (21)$$

If we consider the dynamic range of the color space, the final equation is given in Eq. 22

$$o_i(x, y) = \left(\frac{f_i(x, y) - I_{i_{min}}}{I_{i_{max}} - I_{i_{min}}} \right) (S_{i_{max}} - S_{i_{min}}) + S_{i_{min}}, \quad (22)$$

where $S_{i_{min}}$ and $S_{i_{max}}$ are the minimum and maximum values, respectively, for each component in a color space. In RGB, the Eq. 22 is simplified because $S_{i_{min}}$ is 0. For CIELAB the $S_{i_{min}}$ and $S_{i_{max}}$ are the limits of the components described in last section.

Image quality using Power Spectrum Metric

In this study, the quality of an image is evaluated using the *Power Spectrum Metric* (PSM) [12]. The PSM determines the chromatic information in the image.

Transforming an image into the frequency domain enables the analysis of characteristics of signals from another point of view. The discrete Fourier transform of the image $f(x, y)$ of size $M \times N$ is defined by Eq. 23.

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \exp\left[-2\pi i x \frac{u}{M}\right] \exp\left[-2\pi i y \frac{v}{N}\right] f(x, y), \quad (23)$$

where u, v are the frequency response components, being x and y the spatial components. The power spectrum of image $f(x, y)$ is defined as $|F(u, v)|^2$, is an important feature of the image. This reflects the intensity of each spatial frequency component.

The *Average Power Spectrum Value* (APSV) is the mean value of the power spectrum in the image. This measure, used in this work as a quality index, is given by Eq. 24

$$APSV = \frac{1}{i} \sum_i |F_i|^2, \quad (24)$$

where i stands for the color component in RGB and $|F|^2$ is given in Eq. 25.

$$|F|^2 = \frac{1}{N * M} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} |F(u, v)|^2. \quad (25)$$

It is important to note that the APSV indicates the quality of each image. That is, the higher the APSV is, the better the quality is. Besides, the APSV is a no-reference image quality metric. In other words, is not necessary any image to be compared with or illumination information for the evaluation of an image.

EXPERIMENTAL RESULTS

In this section we show the experimental results and the performance of the three approaches taken.

The image dataset selected consists of 100 images. Most images belong to the Barnard dataset [13] and the others are images taken from a particular collection or popular images from the web. Approximately the 75% are dark images with only one illumination source or uniform illumination. The rest are natural images under daylight conditions.

Three approaches were taken on the experimental series: in the first one, the whole set of images was transformed into CIELAB, and in this space the WPR algorithm was applied for each image. This set of images was transformed back into RGB and the APSV was calculated for each image.

In the second approach, WPR algorithm was also applied to the whole set of images in RGB. For this case, also the APSV was calculated for each image. Finally, the third approach considers the combination of first applying the WPR algorithm in CIELAB and then in RGB, successively.

The image index for all images was rearranged based on the APSV of the original images. The index goes in ascendant order, according to the quality measure. That is, the index 0 corresponds to the image with the lowest APSV, while the index 100 stands for the image with the highest quality.

The experimental results for WPR in RGB, CIELAB, and CIELAB + RGB, are shown in Figure 2. In order to clarify the interpretation of results, the APSVs obtained were approximated by curve fitting. This approximation was computed by a third grade polynomial, such that, the curve fitting shows the tendency of the particular approach, as shown in Figure 3.

A thorough review let us observe that applying the WPR in CIELAB results on a worse quality of images when compared to the results in the RGB space. Nonetheless, the sequential combination of the adjustments consistently outperforms the single approaches.

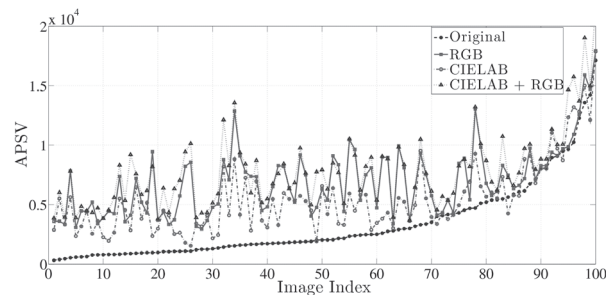


Figure 2 . APSV for each test image and its resultants in the approaches to WPR.

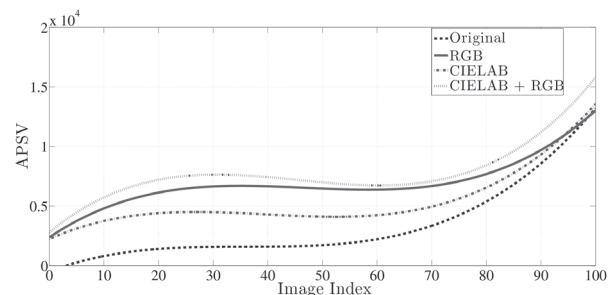


Figure 3 . Tendency of the APSV measures in the dataset image.

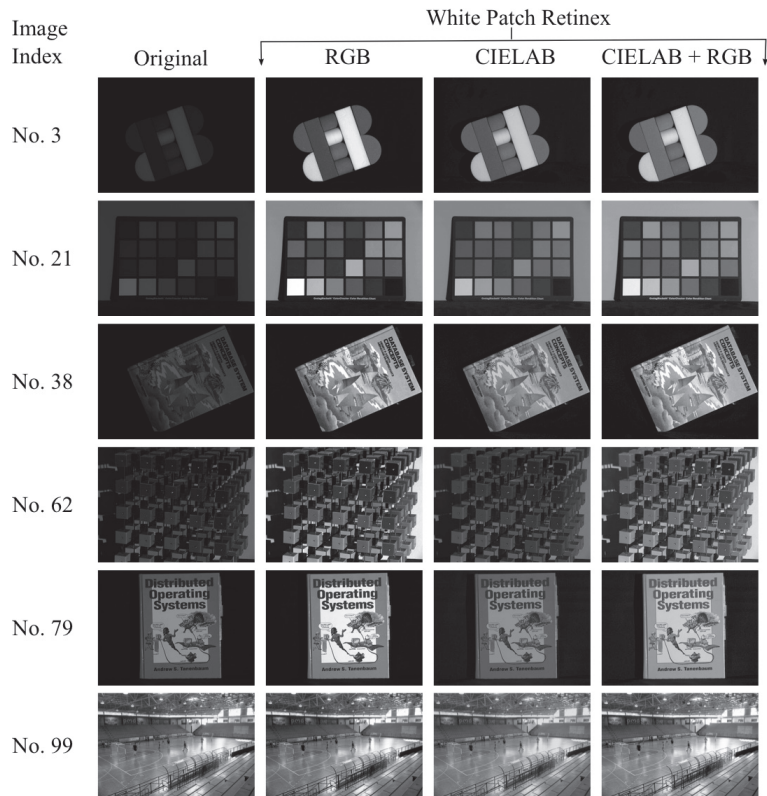


Figure 4 . Six samples out of 100 images under test and their corresponding results.

A qualitative analysis of results

Figure 4 shows six sample images and their corresponding results. These images are samples taken approximately at intervals of twenty images, according to their image index.

Table 1 .

Quality measures (APSV) for images in Fig. 4.

| Image index | Original | White Patch Retinex | | |
|-------------|----------|---------------------|----------|-------------|
| | | RGB | CIELAB | CIELAB +RGB |
| 3 | 441,77 | 3339,39 | 3324,00 | 3926,28 |
| 21 | 1039,38 | 4393,36 | 4499,47 | 6385,03 |
| 38 | 1663,77 | 7343,47 | 6963,36 | 8707,58 |
| 62 | 2743,98 | 8762,07 | 4316,49 | 8841,02 |
| 79 | 5112,61 | 9824,82 | 6528,07 | 10117,70 |
| 99 | 14221,00 | 14698,50 | 12121,30 | 14977,70 |

Table 1 shows the APSVs for each image present in Figure 4. The APSV for the first input image is lower than the one for the last image shown. The majority of the original images are dark. For this reason, the APSV for these images is lower than the value for the corrected images, despite of the approach taken.

The approach employing WPR only in CIELAB is the worst of the three. However, the resultant applying this approach is in fact better than the original image, in the majority of the cases. We can appreciate that using the sequential approach consistently results in better images, in accordance with the quantitative results previously given.

CONCLUSIONS

The WPR is an algorithm depending on the maximum intensity value in each color component. In this work, the WPR has been applied in the CIELAB color space, in the RGB, and in both in a sequential manner. A quality measure has been obtained for each resulting image, in order to compare the outcomes of each approach. Such a metric, the APSV, adequately resembles our qualitative appreciation of image quality. It has been found that the performance of WPR in RGB is better than in CIELAB, but when color adjustments are implemented in sequence, firstly in CIELAB and then in RGB, much better results are obtained.

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