Hybrid Color Space Transformation to Visualize Color Constancy

Ramón Moreno, José Manuel López-Guede, Alicia d'Anjou

Computational Intelligence Group
Universidad del País Vasco, UPV/EHU
http://www.ehu.es/cwintco

Abstract. Color constancy and chromatic edge detection are fundamental problems in artificial vision. In this paper[1] we present a way to provide a visualization of color constancy that works well even in dark scenes where such humans and computer vision algorithms have hard problems due to the noise. The method is an hybrid and non linear transform of the RGB image based on the assignment of the chromatic angle as the luminosity value in the HSV space. This chromatic angle is defined on the basis of the dichromatic reflection model, having thus a physical model supporting it.

KeyWords:

Color Constancy, Chromatic Edge, Color Segmentation, Illumination Transform

1 Introduction

Color constancy (CC) is fundamental problem in artificial vision [4,9,14], and it has been the subject of neuropsicological research [1], it can be very influential in Color Clustering processes [2,10,6,3]. It is the ability of the human observer to identify the same surface color in spite of changes of environmental light, shadows and diverse degrees of noise. A related problem is that of Chromatic Edge detection (CE), meaning the ability to detect the location of surface and scene color transitions, corresponding to object boundaries. In the artificial vision framework, works ensuring CC or trying to perform CR, must assume some color space, often they must perform the estimation of the illumination source chromaticity [5,13] and proceed by the separation of diffuse and specular image components [8,11,15]. Usually, CC is associated with the diffuse component of the image.

Measurements on human subjects lead to the conclusion that retinal processing is not enough to extract chromatic features and chromatic based structural image information. Some works demonstrate that CC analysis is done in the visual cortex, in the areas V4 and V4A [1]. Assuming the analogy with the human

[1] This work been supported by Ministerio de Ciencia e Innovación of Spain TIN2009-05736-E/TIN

vision biology, artificial vision systems need no trivial processing to ensure CC results on the processing real images. Dark scenes are critical for CC, because dark image regions are usually very noisy, that is, the signal to noise ratio is very high due to the low magnitude of the visual signal. In these regions, the ubiquitous thermodynamical noise has an amplified effect that distorts region and edge detection ensuring CC conditions. Our approach obtains remarkable good results in these critical regions.

In this paper we present a hybrid and non linear transformation of the RGB image based on the assignment of the chromatic angle of the pixel (computed in the RGB space) as the luminosity value in the HSV space. The image is preprocessed to remove the specular component [12]. The chromatic angle was defined on the basis of the Dichromatic Reflection Model (DRM), having thus a physical interpretation supporting it. In the HSV color space the intensity is represented in the V value, changing it does not change the pixel chromatic information. Thus, to visualize CC we assign constant intensity to the pixels having common chromatic features, by assigning the chromatic angle as the V value in HSV space.

The paper has the following structure: section 2 is a brief overview of the dichromatic reflection model (DRM). Section 3 presents our approach. Section 4 shows and explains the experimental results. Section 5 gives the conclusions and directions for further works.

2 Dichromatic Reflection Model (DRM) in the RGB Space

The Dichromatic Reflection Model (DRM) was introduced by Shafer [7]. It explains the perceived color intensity $\mathbf{I} \in \mathbb{R}^3$ of each pixel in the image as addition of two components, one diffuse component $\mathbf{D} \in \mathbb{R}^3$ and a specular component $\mathbf{S} \in \mathbb{R}^3$. The diffuse component refers to the chromatic properties of the observed surface, while the specular component refers to the illumination color. Surface reflections are pixels with a high specular component. The mathematical expression of the model, when we have only one surface color in the scene, is as follows:

$$\mathbf{I}(x) = m_d(x)\mathbf{D} + m_s(x)\mathbf{S}, \tag{1}$$

where m_d and m_s are weighting values for the diffuse and specular components, taking values in $[0,1]$. In figure1 the stripped region represents a convex region of the plane Π_{dc} in RGB that contains all the possible colors expressed by the DRM equation 1. For an scene with several surface colors, the DRM equation must assume that the diffuse component may vary spatially, while the specular component is constant across the image domain:

$$\mathbf{I}(x) = m_d(x)\mathbf{D}(x) + m_s(x)\mathbf{S}.$$

That the specular component is space invariant in both cases, means that the illumination is constant for all the scene. Finally, assuming several illumination colors we have the most general DRM

$$\mathbf{I}(x) = m_d(x)\mathbf{D}(x) + m_s(x)\mathbf{S}(x),$$

where the surface and illumination chromaticity are spatially variant.

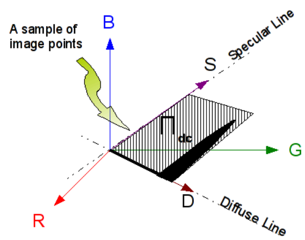


Fig. 1. Typical distribution of pixels in the RGB space according to the Dichromatic Reflection Model

In the HSV color space, chromaticity is identified with the pair (H, S), and the V variable represents the luminosity or light intensity. Plotting on the RGB space a collection of color points that have constant (H, S) components and variable intensity I component, we have observed that chromaticity in the RGB space is geometrically characterized by a straight line crossing the RGB space's origin, determined by the ϕ and θ angles of the polar coordinates of the points over this chromaticity line. The plot of the pixels in a chromatically uniform image region appear as straight line in the RGB space. We denote L_d this *diffuse line*. If the image has surface reflection bright spots, the plot of the pixels in these highly specular regions appear as another line L_s intersecting L_d.

For diffuse pixels (those with a small specular weight $m_s(x)$) the zenith ϕ and azimuthal θ angles are almost constant, while they are changing for specular pixels, and dramatically changing among diffuse pixels belonging to different color regions. Therefore, the angle between the vectors representing two neighboring pixels $\mathbf{I}(x_p)$ and $\mathbf{I}(x_q)$, denoted $\angle(I_p, I_q)$, reflects the chromatic variation among them. For two pixels in the same chromatic regions, this angle must be $\angle(I_p, I_q) = 0$ because they will be collinear in RGB space.

The angle between I_p, I_q is calculated with the equation:

$$\angle(I_p, I_q) = \arccos\left(\frac{\mathbf{I}(x_p)^T \mathbf{I}(x_q)}{\sqrt{\|\mathbf{I}(x_p)\|^2 + \|\mathbf{I}(x_q)\|^2}}\right). \tag{2}$$

3 An Approach for Regular Region Intensity

The basic idea of our approach is to assign a constant luminosity to the pixels inside an homogeneous chromatic region. To do that we must combine manipulations over the two color space representations of the pixels, the HSV and RGB. The process is highly non linear and it is composed of the following steps:

1. Isolate the diffuse component removing specular components ($m_s = 0$): we are interested only in the diffuse component because it is the representation of the true surface color. We use the method presented in [11] to perform the diffuse and specular component separation.
2. Transform the diffuse RGB image into the HSV color space.
3. Compute for each pixel in the image the chromaticity angle as the angle between the gray diagonal line in the RGB space, going from the black space origin to the pure white corner, and the chromaticity line of the pixel.
4. Assume the normalized chromaticity angle as the new luminosity value in the HSV space pixel representation.

In an homogeneous chromatic region, all pixels fall on the same diffuse line $L_d : (r, g, b) = \mathbf{O} + s\boldsymbol{\sigma}; \forall s \in \mathbb{R}^+$ where $\mathbf{O} = [0, 0, 0]$ and $\boldsymbol{\sigma} = [\sigma_r, \sigma_g, \sigma_b]$ is the region chromaticity. The chromatic reference is the pure white line L_{pw} which is defined as $L_{pw} : (r, g, b) = c + s\mathbf{u}; \forall s \in \mathbb{R}^+$ where $\mathbf{O} = [0, 0, 0]$ and $\mathbf{u} = [1, 1, 1]$. Therefore, if all pixels is a region belong to the same chromatic line, the angle between each pixel and the line L_{pw} must be the same, and the result of this angular measurement is a constant for whole region. Our strategy is to normalize this measure in his domain of definition (the RGB cube) and assume it as the constant luminosity value V. This method is expressed with the equation:

$$V^{new}(x) = \frac{\angle(\mathbf{I}(x), \mathbf{u})}{\arccos(\vartheta)} \tag{3}$$

where the denominator $\arccos(\vartheta)$ is the normalization constant corresponding to the maximum angle between the extreme chromatic lines of the RGB space (red, green or blue axes) and the pure white line. Algorithm 1, shows a Matlab/Scilab implementation of the method, where ϑ takes the value $\frac{1}{3}$ and $\arccos(\vartheta) = 0.9553166$.

Algorithm 1 Regular Region Intensity

```
function IR = SF3(I)
  Idiff = imDiffuse(I); // look for the diffuse component
  new_intensity = angle(Idiff, [1 1 1]); // return a matrix of chromatic angles
  Ihsv = rgb2hsv(Idiff);
  Ihsv(:,:,3) = new_intensity; // assign the normalized angles as image intensity
  IR = hsv2rgb(Ihsv);
endfunction
```

4 Experimental Results

We present the results from three computational experiments. The first one using a synthetic image and the remaining using natural images. The figure 2 displays the first experimental results. The figure 2a is the original image. The figure 2b is the diffuse image obtained applying the method in [12]. The image 2c is the result applying our proposed method in the image 2a. The figure 2d display the result applying the method in the image 2b. It can be appreciated that our method is able to identify the main chromatic regions even without component separation (figure 2c), with some artifact due to the bright reflections. After removal of these reflections, the method has a very clean identification of the chromatic regions.

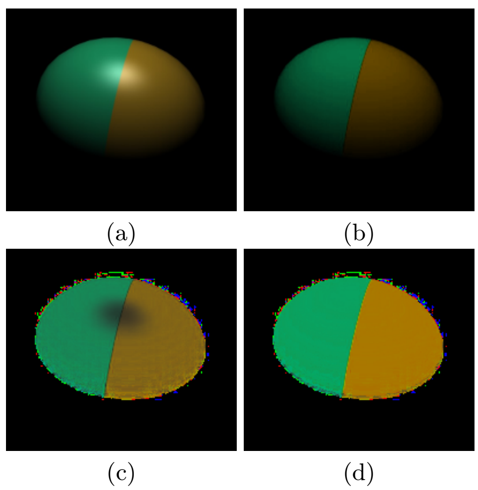
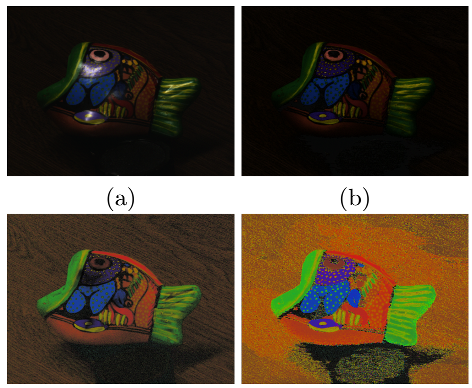


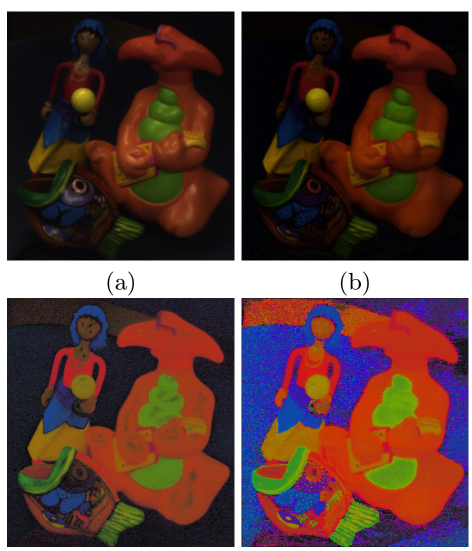
Fig. 2. Synthetic image results (a) original image, (b) diffuse component of the image, (c) our method on image (a), our method on image (b).

For the next experiments we use natural images that have been used by other researchers previously. The figures 3 and 4 show the experimental results. In both cases the subfigure (a) has the original image, subfigure (b) shows the diffuse image, subfigure (c) displays the results applying our proposed method to the original image (a), subfigure (d) show the results applying our method in the diffuse image (b). In both experiments we can see a similar effect of applying specular correction. The images (c) obtained without component separation, show a better chromatic preservation, although with some degradation in the regions corresponding to the specular brights. The images obtained after diffuse component identification [12] are less sensitive to specular effects, however they show some chromatic region oversegmentation. It is important to note that no clustering process has been performed to obtain these images.



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

Fig. 3. Natural image results, (a) original image, (b) diffuse component of the image, (c) our method on image (a), our method on image (b).



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

Fig. 4. Natural images, (a) original image, (b) diffuse component of the image, (c) our method on image (a), our method on image (b).

5 Conclusions and Further works

In this work we present a color transformation that enables good visualization of Color Constancies in the image, changing only the image luminosity and preserving its chromaticity. The result is a new image with strong contrast between chromatic homogeneous regions, and good visualization of these regions as uniform regions in the image. This method performs very well in dark regions, which are critical for most CC methods and image segmentation based on color clustering processes. The method could be the basis for such a process, applying the clustering process to the chromaticity angle.

We have found that specular correction of the image improves the results on highly specular regions of the image, however our approach performs well also on images that have not been preprocessed. Future works will be addressed to the computation of color edge detection and color image segmentation based on this approach.

References

1. John L Barbur and Karoline Spang. Colour constancy and conscious perception of changes of illuminant. *Neuropsychologia*, 46:853–63, February 2008. PMID: 18206187.
2. H.D. Cheng, X.H. Jiang, Y. Sun, and Jingli Wang. Color image segmentation: advances and prospects. *Pattern Recognition*, 34(12):2259–2281, December 2001.
3. Maite Garcia-Sebastian, Ana Isabel Gonzalez, and Manuel Grana. An adaptive field rule for non-parametric mri intensity inhomogeneity estimation algorithm. *Neurocomputing*, 72(16-18):3556 – 3569, 2009. Financial Engineering; Computational and Ambient Intelligence (IWANN 2007).
4. Arjan Gijsenij, Theo Gevers, and Joost van de Weijer. Generalized gamut mapping using image derivative structures for color constancy. *International Journal of Computer Vision*, 86(2):127–139, 2010.
5. Yoo-Jin Choi Kuk-Jin Yoon and In So Kweon. Illuminant chromaticity estimation using dichromatic slope and dichromatic line space. In *Korea-Japan Joint Workshop on Frontiers of Computer Vision*, pages 219–224. FCV, 2005.
6. O. Lezoray and C. Charrier. Color image segmentation using morphological clustering and fusion with automatic scale selection. *Pattern Recognition Letters*, 30(4):397–406, March 2009.
7. Steven A. Shafer. Using color to separate reflection components. *Color Research and Aplications*, 10:43–51, april 1984.
8. Hui-Liang Shen, Hong-Gang Zhang, Si-Jie Shao, and John H. Xin. Chromaticity-based separation of reflection components in a single image. *Pattern Recognition*, 41:2461–2469, August 2008.
9. Sandra Skaff, Tal Arbel, and James J. Clark. A sequential bayesian approach to color constancy using non-uniform filters. *Computer Vision and Image Understanding*, 113(9):993–1004, September 2009.

10. Robby T Tan, Ko Nishino, and Katsushi Ikeuchi. Color constancy through inverse-intensity chromaticity space. *J Opt Soc Am A Opt Image Sci Vis*, 21(3):321–334, Mar 2004.
11. Robby T Tan, Ko Nishino, and Katsushi Ikeuchi. Separating reflection components based on chromaticity and noise analysis. *IEEE Trans Pattern Anal Mach Intell*, 26(10):1373–1379, Oct 2004.
12. R.T. Tan and K. Ikeuchi. Reflection components decomposition of textured surfaces using linear basis functions. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 125–131vol.1, 20-25 June 2005.
13. T.T. Tan, K. Nishino, and K. Ikeuchi. Illumination chromaticity estimation using inverse-intensity chromaticity space. In *Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on*, volume 1, pages I–673–I–680vol.1, 18-20 June 2003.
14. Kuk-Jin Yoon, Yoo Jin Chofi, and In-So Kweon. Dichromatic-based color constancy using dichromatic slope and dichromatic line space. In *Image Processing, 2005. ICIP 2005. IEEE International Conference on*, volume 3, pages III–960–3, 11-14 Sept. 2005.
15. Kuk-Jin Yoon, Yoojin Choi, and In So Kweon. Fast separation of reflection components using a specularity-invariant image representation. In *Image Processing, 2006 IEEE International Conference on*, pages 973–976, 8-11 Oct. 2006.