An Image Color Gradient preserving Color Constancy

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***Abstract*—We present a color gradient with good color constancy preservation properties. The approach does not need a priori information or changes in color space. It is based on the angular distance between pixel color representations in the RGB space. It is naturally invariant to intensity magnitude, implying high robustness against bright spots produced be specular reflections and dark regions of low intensity.**

I. 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], [11], [6]. In the artificial vision framework, CC assumes some color space, the illumination chromaticity estimation [5], [13] and the separation of diffuse and specular image components [8], [12], [15].

In the present work, we assume a physical interpretation of the image reflectance and its behavior in the RGB space. We use polar coordinates to specify points in the RGB space, because we will be interested in the zenithal ϕ and azimuthal angles θ, because the characterize the chromatic component of the RGB point. We are looking for color image edge detection under a CC constraint and founded on the Dichromatic Reflection Model (DRM).

The paper has the following structure: section II gives a short overview of the DRM. Section III explains the relative meaning of Color Constancy (CC) and Color Edges (CE) in the RGB space. Section IV explain the concept of image gradient and the naive approach to computed them in color images. Section V gives details of our method for color gradient detection. Section VI shows some experimental results on well known test images. Finally, section VII gives some conclusions and lines for future works.

II. Dichromatic Reflection Model (DRM)

The Dichromatic Reflection Model (DRM) was introduced by Shafer [7]. It explains the perceived color intensity of each pixel in the image as addition of two components, one diffuse component D and a specular component S. 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 is as follows:

$$I(x) = m_d(x)D + m_s(x)S, \qquad (1)$$

where m_d and m_s are weighting values for the diffuse and specular components, taking values in $[0, 1]$.

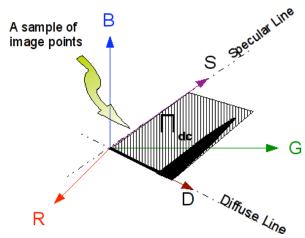
From the DRM we can deduce some interesnting features of the distribution of the pixels in the RGB cube. In figure 1 we illustrate the main expected effects for a single color image (disregarding the black background) with a bright spot due to the illumination source. According to DRM we need to know only two colors: D corresponding to the observed surface and S corresponding to the illumination source. Drawing a line in the RGB cube passing over these colors and the RGB origin (black), we obtain two chromatic lines L_d and L_s, respectively. These two lines define a chromatic plane in RGB illustrated as the stripped region in figure 1a. All the image pixels must fall in this plane, discounting additive Gaussian noise perturbations, accordgin to DRM equation 1 for image colors D and S. Looking to the image pixel distribution inside the chromatic plane, we obtain the plot in figure 1b, whose axes are the chromatic lines L_d and L_s. We have that non-specular pixels fall close to the diffuse line L_d, while specular pixels go away from the origin and the diffuse line parallel to the specular line L_s. There is an intensity threshold for the pixels having a significative specular component ($m_s(x) >> 0$). This threshold is the albedo of the material in the scene. For intensities greater than the albedo, pixels fall away from the L_d diffuse line along the direcction of L_s.

Figure2 shows the pixel distribution for a synthetic image. The RGB cube plot in 2b shows the pixel RGB color distribution of the image 2a. These images confirm our previous discussion, for a case of a single color object in the image. When there are more than one color in the image, we can expect several diffuse lines, so that the we can base our image segmentation on this observation. All these lines cross the RGB origin, therefore the pixel polar coordinates of diffuse pixels contain much information relative to underlying reflectance regions.

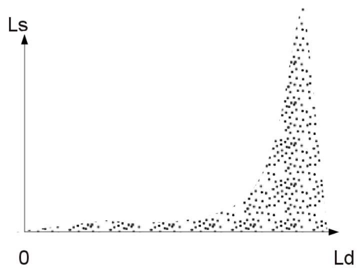
For an scene with several surface colors, the DRM equation assumes that the diffuse component may vary spatially: $I(x) = m_d(x)D(x) + m_s(x)S$. However, the specular component is space invariant in both cases, because the illumination is constant for all the scene. Finally, assuming several illumination colors we have the most general DRM $I(x) = m_d(x)D(x) + m_s(x)S(x)$ where the surface and illumination chromaticity are space variant.

III. Color Constancy (CC) in the RGB Space

The CC is the mental ability to identify chromatically homogeneous surfaces under illumination changes. This mental

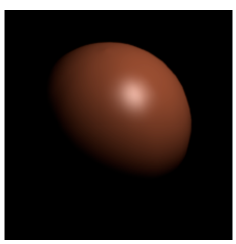


(a)

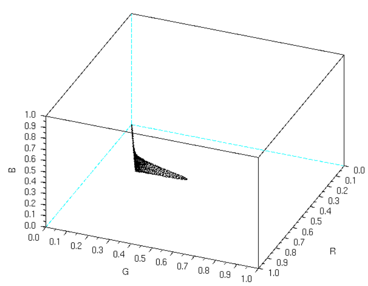


(b)

Figure 1. Expected distribution of the pixels in the RGB cube according to DRM for a single color image.



(a)



(b)

Figure 2. Distribution of pixels in the RGB space

ability is still an open neupsicological research topic [10]. The CC property is inversely proportional to the color discontinuity represented by the color edges (CE). In essence, given a chromatic image gradient, low intensity gradient magnitude corresponds to CC and high magnitude to CE. In the HSI and HSV color spaces, chromaticity is identified with the pair (H, S) and the I or V variable represents the intensity. We have observed that chromaticity in the RGB space is 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 the line, by plotting on the RGB space a collection of color points that have constant HS components and variable intensity I component. 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 regios appear as another line L_s intersecting L_d.

For diffuse pixels (those with a small specular weight $m_s(x)$) the zenithal 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 I_p and I_q, denoted $\angle(I_p, I_q)$, reflects the chromatic variation. For two pixels in the same chromatic regions, this angle is $\angle(I_p, I_q) = 0$ because they will be colinear in RGB space.

IV. Gradient Operators

The notion of CC is closely related to the response to the gradient operators [3]. Regions of constant color must have low gradient respose, while color edges must have a strong gradient response. To set the stage for our chromatic gradient proposition, we must recall the definition of the image gradient

$$G[I(i,j)] = \begin{bmatrix} G_i \\ G_j \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial i} I(i,j) \\ \frac{\partial}{\partial j} I(i,j) \end{bmatrix}, \quad (2)$$

where $f(i,j)$ is the image function at pixel (i,j). For edge detection, the usual convention is to examine the gradient magnitude:

$$G(I) = |G_i| + |G_j|. \quad (3)$$

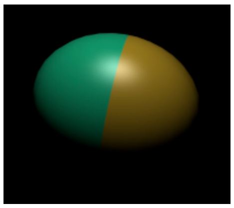
For color images, the basic approach to perform edge detection is to drop all color information, computing the intensity $Intensity = (Red + Green + Blue)/3$ (sometimes computed as $Intensity = .2989 * Red + .587 * Green + .114 * Blue$), and then convolve the intensity image with a pair of high-pass convolution kernels to obtain the gradient components and gradient magnitude. The most popular edge detectors are the Sobel and the Prewitt detectors, illustrated in figure 3 because we will build our own operators following a similar pattern structure. To take into account color information, the easiest approach is to apply the gradient operators to each color band image and to combine the results afterwards: $G(I) = [G(I_r) + G(I_g) + G(I_b)]/3$. Figure 4 illustrates these ideas. It can be appreciate how the gradient magnitude amplifies noise on one hand when we combine the color band gradient magnitudes, and how the color edge is not detected by the edge operator applied to the intensity image, because the two color regions have quite near intensity values. The edge magnitude computed by the straighforward approaches is also misled by the specular suface reflections, which highlighted as can be appreciated in figure 4(d).

V. Proposed Method

We first discuss how do we build a distance between color pixel values which preserves chromatic coherence and, thus, color consistency. Then we formulate the gradient operators which are consistent with this color distance.

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$
(a)
$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$
(b)

Figure 3. Convolution kernels for the (a) Sobel and (b) Prewitt edge detection operators.



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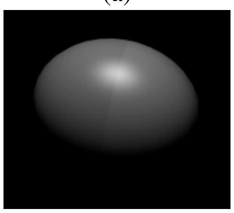

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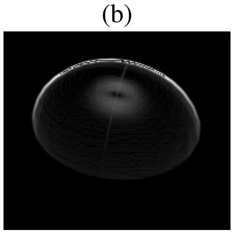

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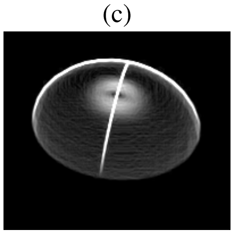


(d)

Figure 4. (a) Original synthetic RGB image, (b) Intensity image, (c) Gradient magnitude computed on the intensity image, (d) gradient magnitude combining the gradient magnitudes of each color band

A. A chromatic coherent RGB pixels distance

First, we convert the RGB cartesian coordinates of each pixel to polar coordinates, withe the black color as the RGB space origin. Let us denote the cartesian coordinate image as $I = \left\{(r,g,b)_p ; p \in \mathbb{N}^2\right\}$ and the polar coordinate as $P = \left\{(\phi,\theta,l)_p ; p \in \mathbb{N}^2\right\}$, where p denotes the pixel position. In this second expression, we discard the l because it does not contain chromatic information. For a pair of image pixels p and q, the color distance between them is defined as:

$$\angle(P_p, P_q) = \sqrt{(\theta_q - \theta_p)^2 + (\phi_q - \phi_p)^2}, \tag{4}$$

that is, the color distance corresponds to the euclidean distance of the Azimuth and Zenith angles of the pixel's RGB color polar representation. This distance is not influenced by the intensity and, thus, will be robust against specular surface reflections.

B. Chromatic coherent gradient operators

We will formulate a pair of Prewitt-like gradient convolution operations on the basis of the above distante. Note that the $\angle(P_p, P_q)$ distance is always positive. Note also that the process is non linear, so we can not express it by convolution kernels. The row convolution is defined as

$$CG_R\left(P\left(i,j\right)\right) = \sum_{r=-1}^{1} \angle\left(P\left(i-r, j+1\right), P\left(i-r, j-1\right)\right),$$

and the column convolution is defined as

$$CG_C\left(P\left(i,j\right)\right) = \sum_{c=-1}^{1} \angle\left(P\left(i+1, j-c\right), P\left(i-1, j-c\right)\right),$$

so that the color distance between pixels substitutes the intensity substraction of the Prewitt linear operator. The color gradient image is computed as:

$$CG(P) = CG_R\left(P\right) + CG_C\left(P\right) \tag{5}$$

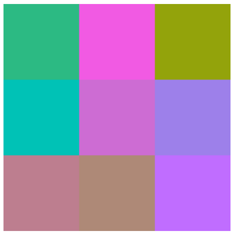
VI. Experimental Results

To demonstrate the efficiency of our proposed approach, we will show three experimental results. Two of the experiments are done on synthetic images whose ground truth is know.

Figure 5 contains two synthetic images 5(a) and 5(b) which are chromatically identical. The image in figure 5(a) hs constant intensity inside each color region, while the image in figure 5(b) contains a central square with lower intensity (0.8), preserving the chromatic content of figure 5(a). Applying the Prewitt operator to each color band of figure 5(b) we obtain the detection swhon in figure 5(c), while applying our color edge detection of equation (5) we obtain the detection in figure 5(d). It is clear that our approach has superior Color Constancy properties and an improved intensity invariant detection of color edges.

The second computational experiment was performed on the image shown in figure 4(a). This image has a strong specular reflection region, and two color regions with a black background. We have tested a Sobel like and a Prewitt like variation of the basic schema of equation (5). The figure 6 gives the results of the RGB band combined detection and our approach. It can be appreciated that our approach discovers the edge even in very dark areas, it is also robust against specular reflections, which the linear operators do confound with color edges. The color edge between the two regions is better detected in both cases by our approach.

Final results are given on a natural image, shown in figure 7. This image contains many color regions, with specular reflections, shadows and light effects. Figure 8 shows the results of the linear operators based on the Sobel and Prewitt masks. Besides the lower response of the Prewitt operator, it can be appreciated the high sensitivity to specular reflections



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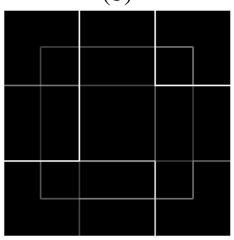
(b)



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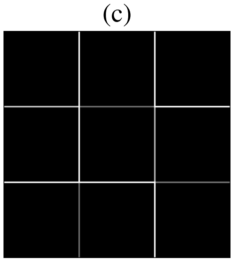
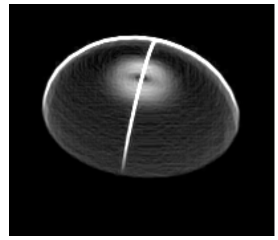
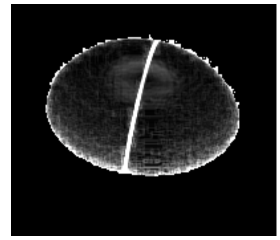


(d)

Figure 5. Results of the color edge detection on a synthetic image with nine uniform chromatic regions and a variation of intensity. (a) Original color distribution, (b) lower intensity central square, (c) Prewitt detection on RGB bands, (c) our approach in equation (5).

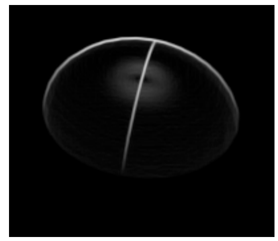


(a)

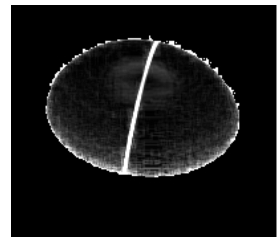


(b)

Sobel



(c)



(d)

Prewitt

Figure 6. Color edge on the synthetic image of fig. 4(a) with two color regions. (a) The Sobel operator over the RGB bands with specular component, (b) our approach in a Sobel-like structure, (c) the Prewitt linear operator, (d) our approach in a Prewitt like structure.

Figure 7. Natural image

and low color constancy. All bright spots are interpreted as color edges. In the figure 9 we show the results of our approach under two variations of the neighborhood considered. The 4 neighborhood follows the same pattern of equation 5 but over a reduced set of neighboring pixels. Again our approach is very robust against specular reflectance. Bright spots do not appear to be detected. Dark regions of the image are equalized in their results relative to brighter regions. A very significative result is the detection of color edges even in the almost black background. A drawback that appears in our approach is the high spurious detection in the black background. This is due to the high angular variations induced by noise. It could be avoided by a simple intensity thresholding.

VII. Conclusions and Further Work

We have presented an innovative chromatic gradient computation, which is chromatically coherent, preserves the Color Constancy and gives good detection of Color Edges. The method is grounded in the DRM which is a widely accepted image model for reflectance analysis. Our method is intensity invariant, and, thus, is robust against the bright spots of specular reflections. It does not imply or need color segmentation, on the contrary can provide good color region separation with little assumptions. It works on the RGB space, which the most common color processing space.

In the future we will try to apply this approach to robust reflectance analysis, helping to provide good separation of color regions as the starting point for diffuse and specular component separation. It can provide the basis to build good a priori mappings for Bayesian methods using Random Markov Field modeling tools.

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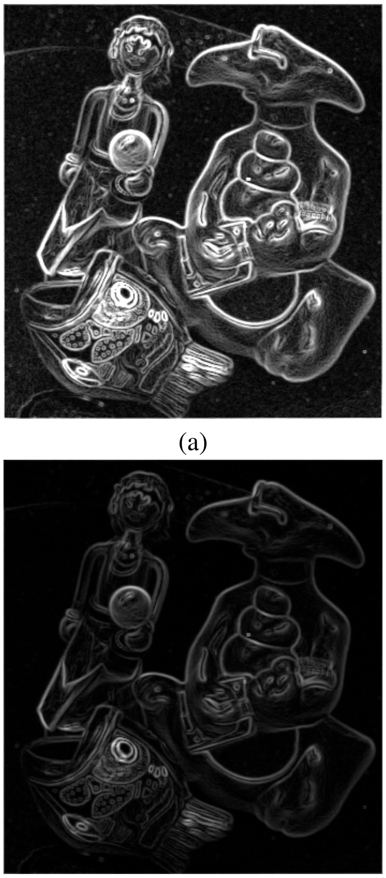
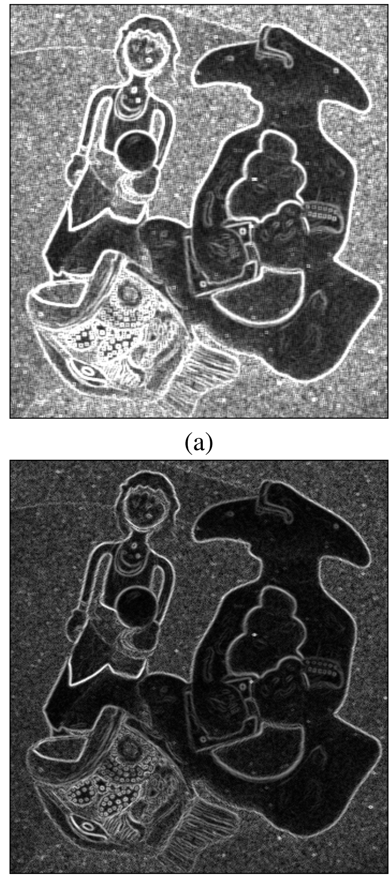


(a)

(b)

Figure 8. Results of the linear operators on the natural image (a) Sobel detector, (b) Prewitt detector



(a)

(b)

Figure 9. Resuls of our approach on the natural image (a) taking 8 neighbors, (b) taking 4 neighbors

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