THE DICHROMATIC REFLECTION MODEL: FUTURE RESEARCH DIRECTIONS AND APPLICATIONS

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Abstract: The dichromatic reflection model (DRM) predicts that color distributions form a parallelogram in color space, whose shape is defined by the body reflectance and the illuminant color. In this paper we resume the assumptions which led to the DRM and shortly recall two of its main applications domains: color image segmentation and photometric invariant feature computation. After having introduced the model we discuss several limitations of the theory, especially those which are raised once working on real-world uncalibrated images. In addition, we summerize recent extensions of the model which allow to handle more complicated light interactions. Finally, we suggest some future research directions which would further extend its applicability.

1 INTRODUCTION

Understanding the color content of images is a very challenging problem. The colors we observe are a mix of the illuminant color and the object color. Furthermore, the color depends on a number of other factors such as viewpoint, illuminant angle with respect to surface normal, shadow and shading effects, specularities, and the sensitivity curves of the acquisition devise. Physics laws of light reflectance provide a means to disentangle the variety of causes which resulted in the color measurement (Kubelka and Munk, 1931).

One of the most popular reflection models is the *dichromatic reflection model* (DRM) proposed by Shafer (Shafer, 1985). The model focusses on the color aspects of light reflection and has only limited usage for geometry recovery of scenes. It separates reflectance into surface body reflectance and interface reflectance. Both terms can be further separated into a geometric term, dependent on scene geometry, and a spectral term which is depended on the wavelength but independent of geometry. The model is valid for the class of inhomogeneous materials, which covers a wide range of materials such as wood, paints, papers and plastics (but excludes homogeneous materials such as metals). It predicts that values of a single colored object lie on a parallelogram in color space, defined by the body reflectance and the illuminant color.

The original application to which the DRM was applied, was the separation of shading from specularities (Shafer, 1985). The specularities, being dependent on scene incidental events such as viewpoint and surface normal, could be removed to simplify color image understanding. The removal of specularities allowed for improved segmentation algorithms (Klinker and Shafer, 1990; Maxwell and Shafer, 1997). Furthermore, the estimation of the specularities also provides an illuminant estimation, thereby allowing for color constancy. A second application field which has benefited from the DRM is photometric invariant feature computation (Gevers and Smeulders, 1999; van de Weijer et al., 2006).

In this paper, we focus on the dichromatic reflection model and its applications in computer vision. In Section 2 the DRM model is explained. Next, in Section 3 we discuss two of its main application domains: image segmentation and photometric invariance. In Section 4 we look at some limitations of the model once applied to real-world images. In addition, several extensions of the model are suggested.

2 THE DICHROMATIC REFLECTION MODEL

In this section we rehearse the DRM model proposed by Shafer(Shafer, 1985). The light source is modeled as a single light source, $e(\lambda)$, where λ is the wavelength. For multiple light sources we assume that the combination can be approximated as a single light source for the local feature. In this case, the measured observation values, $\mathbf{f} = \{R, G, B\}$, of the camera with spectral sensitivities f^C, are modeled by integrating over the visible spectrum ω,

$$\begin{aligned} \mathbf{f}(\mathbf{x}) = m^b(\mathbf{x}) \int_\omega b(\lambda, \mathbf{x})\, e(\lambda) f^C(\lambda)\, d\lambda + \\ m^i(\mathbf{x}) \int_\omega i(\lambda)\, e(\lambda) f^C(\lambda)\, d\lambda. \end{aligned} \tag{1}$$

where b is the surface albedo. We assume neutral interface reflection, meaning that the Fresnel reflectance i is independent of λ. Accordingly, we will omit i in further equations. The geometric dependence of the reflectance is described by the terms m^b and m^i which depend on the viewing angle, light source direction and surface orientation. $\mathbf{x}$ denotes the spatial coordinates, and bold face is used to indicate vectors. In vector notation we can now write:

$$\mathbf{f}(\mathbf{x}) = m^b(\mathbf{x})\, \mathbf{c^b}(\mathbf{x}) + m^i(\mathbf{x})\, \mathbf{c^i}(\mathbf{x}) \tag{2}$$

The reflection of the light consist of two parts: 1. a body reflection part $m^b(\mathbf{x})\, \mathbf{c}^b$, which describes the light which is reflected after interaction with the surface albedo, and 2. the interface reflection $m^i(\mathbf{x})\, \mathbf{c}^i$ which describes the part of the light that is immediately reflected at the surface, causing specularities. Both parts consist of a geometrical part dependent on the location in the scene, and a spectral part dependent on the spectral wavelength.

3 APPLICATIONS OF THE DICHROMATIC REFLECTION MODEL

To illustrate the applicability of the DRM model we shortly touch upon two computer vision fields which have benefited from the model: color image segmentation and photometric invariant feature derivation.

3.1 Color Image Segmentation

One of the main challenges in object segmentation is caused by scene incidental events such as shading and specularities. The DRM provides a model which predicts the behavior of color distributions in the case of such events. The body reflectance of the object forms a line from the origin of the color space which angle is dependent on both the object color and the illuminant color. Specularities will form a second line in the direction of the illuminant color. This led to the well-known work of (Klinker and Shafer, 1990) in which an algorithm is proposed to infer the object and illuminant color by fitting lines through the L and T-shapes which are formed in color space (see Fig. 1).

The main problem is that to correctly segment the image, information on the body reflectances and illuminant color is required, and visa versa, to correctly estimate the body reflectances and illuminant color a good segmentation is needed (Klinker and Shafer, 1990; Maxwell and Shafer, 1997). This chicken and egg problem can be tackled in a iterative procedure in which based on an initial segmentation, hypotheses for illuminant color and body reflectances are generated. A solution which does not require segmentation was proposed by Tan and Ikeuchi (Tan and Ikeuchi, 2005). Based on the observation that specularities lower the saturation of pixels, they propose an algorithm that iteratively converges to the specular free image. Recently the theory has been extended to multi-spectral images (Huynh and Robles-Kelly, 2010).

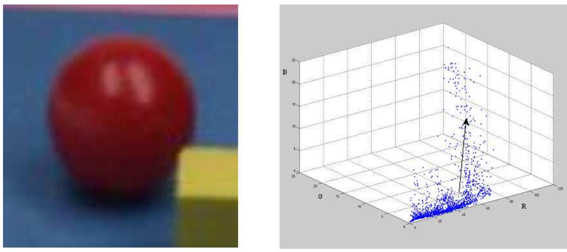


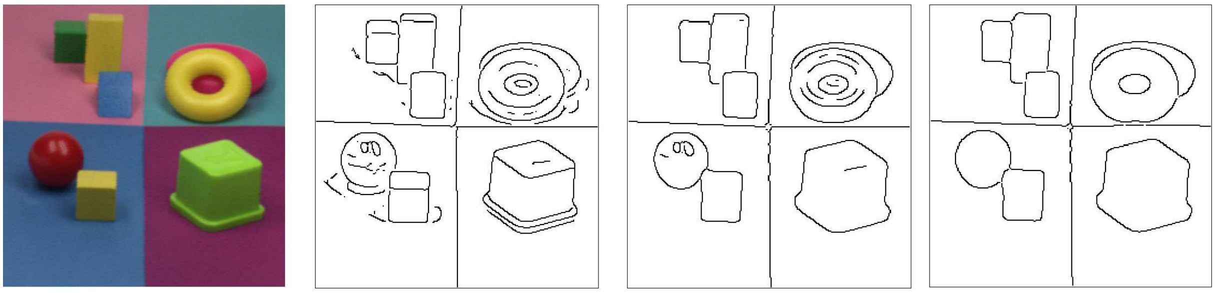
Figure 1: Color distributions for a red ball. The superimposed arrow indicate the illuminant color. The color distribution can be easily separated in a body reflectance part and a part in the specular reflection part in the illuminant direction.

3.2 Photometric Invariant Features

Here we shortly show how the DRM can be applied to derive photometrically invariant features. For more details see (Gevers and Smeulders, 1999), (van de Weijer et al., 2005).

Zero-order invariants. Let us first consider the case of a matte surface ($m^i = 0$). For this case normalized rgb can be considered invariant with respect to lighting geometry and viewpoint, m^b. Since,

$$r = \frac{R}{R+G+B} = \frac{m^b b^R e^R}{m^b\left(b^R e^R + b^G e^G + b^B e^B\right)}. \tag{3}$$



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

Figure 2: Photometric invariant image derivatives: a) input image. b) RGB color edges. c) shadow-shading quasi-invariant c) the specular quasi-invariant. d) the specular-shadow-shading quasi-invariant.

Similar equations hold for normalized g and b.

Furthermore, in the case of a white illuminant ($e^R = e^G = e^B = e$) and specular reflectance ($m^i \neq 0$), opponent colors (Gevers and Smeulders, 1999) can be proven to be invariant with respect to specularities, m^i. Since,

$$\begin{array}{l} O1 = \frac{1}{\sqrt{2}}(R-G) = \frac{1}{\sqrt{2}}\left(m^b e\left(b^R - b^G\right) + m^i e - m^i e\right) \\ O2 = \frac{1}{\sqrt{6}}(R+G-2B) \\ \quad = \frac{1}{\sqrt{6}}\left(m^b e\left(b^R + b^G - 2b^G\right) + 2m^i e - 2m^i e\right) \end{array}, \tag{4}$$

are invariant for m^i. The opponent colors are still variant for lighting geometry variations. Invariance with respect to both the lighting geometry and specularities is obtained by hue,

$$hue = \arctan\left(\frac{O1}{O2}\right) = \arctan\left(\frac{\sqrt{3}\left(b^R - b^G\right)}{\left(b^R + b^G - 2b^G\right)}\right) \tag{5}$$

First-order invariants. Extending this theory to the first-order structure of images (i.e. to edge-detection) seems straight-forward. By taking the derivatives of the zero-invariants derived above, photometrically invariant edge detection is achieved. However, the non-linearities of normalized *RGB* and *hue* result in unstable image derivatives. A way around this problem is given in (van de Weijer et al., 2005), where a class of quasi-invariant image derivatives is proposed. First the standard image derivative is computed $\mathbf{f_x} = \{R_\mathbf{x}, G_\mathbf{x}, B_\mathbf{x}\}$. This derivative is projected onto a photometrically relevant coordinate system. Since the derivative operation and coordinate projection are both linear, the photometric invariants which are thus computed are more robust too noise and have greater discriminative power. The solution is similar to work on color subspaces (Zickler et al., 2008).

As an example we look at shadow-shading invariant image derivatives. Projecting on spherical coordinates results in:

$$\mathbf{f}_x = \begin{pmatrix} r_x \\ r\varphi_x \\ r\sin\varphi\,\theta_x \end{pmatrix} = \begin{pmatrix} r_x \\ 0 \\ 0 \end{pmatrix} + r\begin{pmatrix} 0 \\ \varphi_x \\ \sin\varphi\,\theta_x \end{pmatrix} \tag{6}$$

The second part of this equation is independent of shadow-shading variations, and can be used to construct photometric invariant edge, corner detection, optical flow, etc. In Fig. 2 an example of photometric invariant edge detection is given.

4 FUTURE RESEARCH DIRECTIONS ON DRM

After having briefly looked at application areas of DRM we will discuss some recent developments. The extension of the DRM with more complicated light object interaction models, and the applications of the DRM to uncalibrated real-world images.

4.1 EXTENSIONS TO THE DRM

In cases that the assumptions made by the original DRM are not met, more complex reflectance models are required. One such case is ambient light, i.e. light coming from all directions. Ambient light occurs in outdoor scenes where next to the dominant illuminant, i.e. the sun, there is diffuse light coming from the sky. Similarly, it occurs in indoor situations where diffuse light is caused by reflectances from walls and ceilings. Shafer (Shafer, 1985) models the diffuse light, a, by a third term

$$C(\mathbf{x}) = m^b(\mathbf{x})C^b(\mathbf{x}) + m^i(\mathbf{x})C^i(\mathbf{x}) + a^C. \tag{7}$$

Later work improved the modeling (Maxwell et al., 2008; Riess et al., 2009) and showed that the ambient term results in an object color dependent offset which could perform crucial in handling the case of colored shadows. Furthermore, in (Maxwell et al., 2008) a photometric invariant with respect to ambient light is proposed.

Another case is the presents of multiple illuminants in the scene (a more generalized case of ambient light). A typical example of a ”multi-illuminant” is the interreflections occurring between objects in the complex scenes.

4.2 UNCALIBRATED REAL-WORLD IMAGES

Most of the early work on DRM (Klinker and Shafer, 1990; Maxwell and Shafer, 1997; van de Weijer et al., 2005) focussed on high-quality images of relatively simple objects taken in controlled laboratory settings. These works have clearly proven the validity of the theory, but extending the proposed theory thereafter to real-world images is not straight-forward.

Application of the DRM model to uncalibrated real-world images led to multiple problems. Unknown gamma compression leads to non-linearities in the DRM. The color distribution will still form a plane in the RGB space. However, specularities will now trail curves instead of lines in the RGB cube. Further complications are caused by unknown compression algorithm settings such as JPEG or MPEG. Based on the observation that the human visual system is less sensitive to chromatic changes, compression algorithms compress color information significantly more than luminance, thereby considerably reducing the available color information. In a recent work Vazquez et al. (Vazquez et al., 2011) track ridges in the color spaces, and robustly segment objects in the presence of shadows and specularities for uncalibrated images.

A second observation which complicates applying earlier algorithms developed on relatively easy objects is shown in Fig. 3. For more complex objects the L and T-shapes (recall Fig. 1) do no longer occur. The L and T shape theory was based on the assumption of located specularities for which m_b remains constant as m_s changes. For more complex objects this is not true and new algorithms are needed to infer the illuminant in these cases.

In conclusion, the DRM model has proven to be a very useful model for color image understanding. Its main challenges lie in finding algorithms which can be applied to uncalibrated real-world images, and which can solve for more complex reflectance models which include multiple illuminants and ambient light.

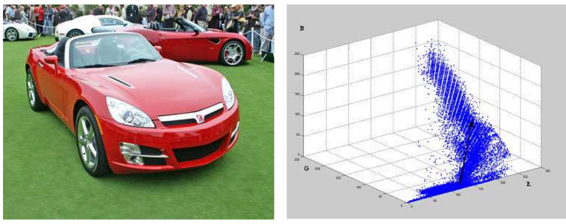


Figure 3: Color distributions for red car. The superimposed arrow indicate the illuminant color. For the more complex distribution on the right, deriving the illuminant color from the shape of the color distribution is unfeasible.

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