Chapter 46
Color Invariant Representation and Applications

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ABSTRACT

Illumination factors such as shading, shadow, and highlight observed from object surfaces affect the appearance and analysis of natural color images. Invariant representations to these factors were presented in several ways. Most of these methods used the standard dichromatic reflection model that assumed inhomogeneous dielectric material. The standard model cannot describe metallic objects. This chapter introduces an illumination-invariant representation that is derived from the standard dichromatic reflection model for inhomogeneous dielectric and the extended dichromatic reflection model for homogeneous metal. The illumination color is estimated from two inhomogeneous surfaces to recover the surface reflectance of object without using a reference white standard. The overall performance of the invariant representation is examined in experiments using real-world objects including metals and dielectrics in detail. The feasibility of the representation for effective edge detection is introduced and compared with the state-of-the-art illumination-invariant methods.

INTRODUCTION

Color observed from object surfaces provides crucial information in computer vision and image analysis which include the essential problems of feature detection, image segmentation, object recognition, and image retrieval. However, in real-world applications there are various illumination factors that can affect color images observed from object surfaces. The observed images do not only depend on surface-spectral reflectances and illuminant spectrum, but also include reflection effects such as shading, gloss, and highlight, which mainly depend on illumination geometries and surface materials. Therefore, image representation invariant to shading, shadow, lighting, and highlight was proposed for color image (Slater et al., 1996; Finlayson, 1996; Gevers, 1999; Gevers et al., 2000, 2003; Geusebroek et al., 2000; Smeulders

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et al., 2001; Geusebroek et al., 2001; Narasimhan et al., 2003; Tan et al., 2005; Park, 2003; Mallick et al., 2005; Van De Weijer et al., 2005, 2006) so far in several ways. These invariant representations play an important role in many applications such as image segmentation (Narasimhan et al., 2003; Park, 2003; Gevers, 2002; Ibrahim et al., 2009a, 2009b, 2010, 2011, 2016; Ali et al., 2015), feature detection, such as edge and corner detection (Geusebroek et al., 2001; Gevers et al., 2000, 2003, 2005; Van De Weijer et al., 2005, 2006; Stokman et al., 2007), object recognition (Gevers et al., 1999, 2004; Van de Sande et al., 2010; Tharwat et al., 2015b), image retrieval (Gevers et al., 2000), cast shadow segmentation (Salvador et al., 2004), optical flow calculation (Mallick et al., 2005: Zickler et al., 2008; Van de Weijer et al., 2004), biometrics (Tharwat et al., 2012a, 2012b, 2015a; Ibrahim et al., 2014, 2015; Gaber et al., 2015, 2016), and robots (Maier et al., 2009, 2010).

Most of the illumination-invariant methods used the standard dichromatic reflection model by Shafer (Shafer, 1985). The model assumes inhomogeneous dielectric material for object surfaces and separates the reflected light into body reflection and interface reflection. This separation results in the classification of physics events, such as shadows and highlights. This model is valid for such limited materials as plastics and paints (Lee et al., 1990; Tominaga, 1994, 1996a). It should be noted that there are metallic objects in real-world scenes, which cannot be described by the standard dichromatic reflection model.

The present chapter introduces an effective illumination-invariant representation for natural color images (Ibrahim et al., 2012; Horiuchi et al., 2012). The invariant representation is derived from the standard dichromatic reflection model for inhomogeneous dielectric (Shafer, 1985) and the extended dichromatic reflection model for homogeneous metal (Tominaga, 1994, 1996a). The invariant formulas for natural color images are invariant to highlight, shadow, surface geometry, and illumination intensity. The overall performance of the invariant representation is examined in experiments using real-world objects including metals and dielectrics in detail. The illumination color is estimated from two inhomogeneous surfaces to recover the surface reflectance of objects without using a reference white standard.

Edge detection plays an important role as a basic tool of feature detection in a variety of fields including image analysis and computer vision (Koschan et al., 2005; Trémeau et al., 2008). Images captured in a real scene contain various physical phenomena such as shadow, shading, specular reflection, and reflectance changes, thus it is important to differentiate between the various physical causes of features. In this chapter, the transformed color image with the invariant properties is used as an invariant operator in the edge detection application. The feasibility of the invariant representation for effective edge detection is compared with the state-of-the-art illumination-invariant methods.

The reminder of this chapter is organized as follow: Section 2 presents the related color invariant representation methods. In Section 3, the standard and the extended dichromatic reflection models are presented. Section 4 describes the color invariant representation in detail. Experimental results are discussed in Sections 5. This chapter ends with conclusions in Section 6.

BACKGROUND

Illumination-invariant for color image has received extensive theoretical and experimental treatment, due to color information in comparison to grey-value information. Slater et al. (1996), Finlayson (1996), and Gevers et al. (1999, 2000) have all stressed the importance of achieving invariant color measurements to varying lighting conditions. Gevers et al. (1999) discount the effects of shadow, shading, and highlights on their image by deriving several sets of invariants. These sets are invariant under the standard dichromatic

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