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Abstract. Segmentation based on color, instead of intensity only, provides an easier distinction between materials, on the condition that robustness against irrelevant parameters is achieved, such as illumination source, shadows, geometry and camera sensitivities. Modeling the physical process of the image formation provides insight into the effect of different parameters on object color.
In this paper, a color differential geometry approach is used to detect material edges, invariant with respect to illumination color and imaging conditions. The performance of the color invariants is demonstrated by some real-world examples, showing the invariants to be successful in discounting shadow edges and illumination color.

1 Introduction

Color is a powerful clue in the distinction between objects. Segmentation based on color, instead of intensity only, provides an easier discrimination between colored regions. It is well known that values obtained by a color camera are affected by the specific imaging conditions, such as illumination color, shadow and geometry, and sensor sensitivity. Therefore, object properties independent of the imaging conditions should be derived from the measured color values. Modeling the physical process of the image formation provides insight into the effect of different parameters on object color [4, 5, 10, 12]. We consider the determination of material changes, independent of the illumination color and intensity, camera sensitivities, and geometric parameters as shadow, orientation and scale.

When considering the estimation of material properties on the basis of local measurements, differential equations constitute a natural framework to describe the physical process of image formation. A well known technique from scale-space theory is the convolution of a signal with a derivative of the Gaussian kernel to obtain the derivative of the signal [8]. The introduction of wavelength in the scale-space paradigm leads to a spatio-spectral family of Gaussian aperture functions, introduced in [2] as the Gaussian color model. As a result, measurements from color images of analytically derived differential expressions may be obtained by applying the Gaussian color model. Thus, the model defines how to measure material properties as derived from the photometric model.

In this paper, the problem of determining material changes independent of the illumination color and intensity is addressed. Additionally, robustness against changes in the imaging conditions is considered, such as camera viewpoint, illumination direction and sensor sensitivities and gains. The problem is approached by considering a Lambertian reflectance model, leading to differential expressions which are robust to a change in imaging conditions. The performance of these color invariants is demonstrated on a real-world scene of colored objects, and on transmission microscopic preparations.

2 Determination of Object Borders

Any method for finding invariant color properties relies on a photometric model *and* on assumptions about the physical variables involved. For example, hue and saturation are well known object properties for matte, dull surfaces, illuminated by white light [5]. Normalized rgb is known to be insensitive to surface orientation, illumination direction and intensity, under a white illumination. When the illumination color varies or is not white, other object properties which are related to constant physical parameters should be measured. In this section, expressions for determining material changes in images will be derived, under the assumption that the scene is uniformly illuminated by a colored source, and taking into account the Lambertian photometric model.

Consider a homogeneously colored material patch illuminated by incident light with spectral distribution $e(\lambda)$. When assuming Lambertian reflectance, the reflected spectrum by the material in the viewing direction $\boldsymbol{v}$, ignoring secondary scattering after internal boundary reflection, is given by [7, 13]

$$E(\lambda) = e(\lambda) \left(1 - \rho_{\mathrm{f}}(\boldsymbol{n}, \boldsymbol{s}, \boldsymbol{v})\right)^2 R_\infty(\lambda) \tag{1}$$

where $\boldsymbol{n}$ is the surface patch normal and $\boldsymbol{s}$ the direction of the illumination source, and ρ_{f} the Fresnel front surface reflectance coefficient in the viewing direction, and R_∞ denotes the body reflectance.

Because of projection of the energy distribution on the image plane vectors $\boldsymbol{n}$, $\boldsymbol{s}$ and $\boldsymbol{v}$ will depend on the position at the imaging plane. The energy of the incoming spectrum at a point $\boldsymbol{x}$ on the image plane is then related to

$$E(\lambda, \boldsymbol{x}) = e(\lambda, \boldsymbol{x}) \left(1 - \rho_{\mathrm{f}}(\boldsymbol{x})\right)^2 R_\infty(\lambda, \boldsymbol{x}) \tag{2}$$

where the spectral distribution at each point x is generated off a specific material patch.

Consider the photometric reflection model (2) and an illumination with locally constant color. Hence, the illumination may be decomposed into a spectral component $e(\lambda)$ representing the illumination color, and a spatial component $i(\boldsymbol{x})$ denoting the illumination intensity, resulting in

$$E(\lambda, \boldsymbol{x}) = e(\lambda) i(\boldsymbol{x}) \left(1 - \rho_{\mathrm{f}}(\boldsymbol{x})\right)^2 R_\infty(\lambda, \boldsymbol{x}) \ . \tag{3}$$

The aim is to derive expressions describing material changes independent of the illumination. Without loss of generality, we restrict ourselves to the one dimensional case; two dimensional expressions will be derived later. The procedure of deriving material properties can be formulated as finding expressions depending on the material parameters in the given physical model only.

Differentiation of (3) with respect to λ results in

$$\frac{\partial E}{\partial \lambda} = i(x)(1 - \rho_{\mathrm{f}}(x))^2 R_\infty(\lambda, x) \frac{\partial e}{\partial \lambda} + e(\lambda) i(x)(1 - \rho_{\mathrm{f}}(x))^2 \frac{\partial R_\infty}{\partial \lambda} \ . \tag{4}$$

Dividing (4) by (3) gives the relative differential,

$$\frac{1}{E}\frac{\partial E}{\partial \lambda} = \frac{1}{e(\lambda)}\frac{\partial e}{\partial \lambda} + \frac{1}{R_\infty(\lambda, x)}\frac{\partial R_\infty}{\partial \lambda} \ . \tag{5}$$

The result consists of two terms, the former depending on the illumination color only and the latter depending on the body reflectance. Since the illumination depends on λ only, differentiation to x yields a reflectance property.

Lemma 1. *Assuming matte, dull surfaces and an illumination with locally constant color,*

$$\frac{\partial}{\partial x}\left\{\frac{1}{E}\frac{\partial E}{\partial \lambda}\right\} \tag{6}$$

determines material changes independent of the viewpoint, surface orientation, illumination direction, illumination intensity and illumination color.

Proof. See (4)—(5). Further, the reflectivity R_∞ and its derivative with respect to λ depend on the material characteristics only, that is on the material absorption- and scattering coefficient. Hence, the spatial derivative of their product is determined by material transitions. □

Note that Lemma 1 holds whenever Fresnel (mirror) reflectance is neglectable, thus in the absence of interreflections and specularities. The expression given by (6) is the fundamental lowest order illumination invariant. Any spatio-spectral derivative of (6) inherently depends on the body reflectance only. According to [11], a complete and irreducible set of differential invariants is obtained by taking all higher order derivatives of the fundamental invariant.

Proposition 2. *Assuming matte, dull surfaces and an illumination with locally constant color, N is a complete set of irreducible invariants, independent of the viewpoint, surface orientation, illumination direction, illumination intensity and illumination color,*

$$N = \frac{\partial^{n+m}}{\partial \lambda^n \partial x^m}\left\{\frac{1}{E}\frac{\partial E}{\partial \lambda}\right\} \tag{7}$$

for $m \geq 1$, $n \geq 0$.

These invariants may be interpreted as the spatial derivatives of the normalized slope (N_λ) and curvature ($N_{\lambda\lambda}$) of the reflectance function R_∞.

3 Measurement of Spatio-Spectral Energy

So far, we have established invariant expressions describing material changes under different illuminations. These are formal expressions, assumed to be measurable at an infinitesimal small spatial resolution and spectral bandwidth. The physical measurement of electro-magnetic energy inherently implies integration over a certain spatial extent and spectral bandwidth. In this section, physically realizable measurement of spatio-spectral energy distributions is described. We emphasize that no essentially new color model is proposed here, but rather a theory of color *measurement*. The specific choice of color representation, often referred to as color coordinates or color model, is irrelevant for our purpose.

Let $E(\lambda)$ be the energy distribution of the incident light, and let $G(\lambda_0; \sigma_\lambda)$ be the Gaussian at spectral scale σ_λ positioned at λ_0. Measurement of the spectral energy distribution with a Gaussian aperture yields a weighted integration over the spectrum. The observed energy in the Gaussian color model, at infinitely small spatial resolution, approaches in second order to [2, 9]

$$\hat{E}^{\sigma_\lambda}(\lambda) = \hat{E}^{\lambda_0,\sigma_\lambda} + \lambda \hat{E}_\lambda^{\lambda_0,\sigma_\lambda} + \frac{1}{2}\lambda^2 \hat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda} + \ldots \tag{8}$$

$$\hat{E}^{\lambda_0,\sigma_\lambda} = \int E(\lambda) G(\lambda; \lambda_0, \sigma_\lambda) d\lambda \tag{9}$$

$$\hat{E}_\lambda^{\lambda_0,\sigma_\lambda} = \int E(\lambda) G_\lambda(\lambda; \lambda_0, \sigma_\lambda) d\lambda \tag{10}$$

$$\hat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda} = \int E(\lambda) G_{\lambda\lambda}(\lambda; \lambda_0, \sigma_\lambda) d\lambda \tag{11}$$

were $G_\lambda(.)$ and $G_{\lambda\lambda}(.)$ denote derivatives of the Gaussian with respect to λ.

Definition 3. *The Gaussian color model measures, up to the 2^{nd} order, the coefficients $\hat{E}^{\lambda_0,\sigma_\lambda}$, $\hat{E}_\lambda^{\lambda_0,\sigma_\lambda}$ and $\hat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda}$ of the Taylor expansion of the Gaussian weighted spectral energy distribution at λ_0 [9].*

Introduction of spatial extent in the Gaussian color model yields a local Taylor expansion at wavelength λ_0 and position $\boldsymbol{x_0}$ [2]. Each measurement of a spatio-spectral energy distribution has a spatial as well as spectral resolution. The measurement is obtained by probing an energy density volume in a three-dimensional spatio-spectral space, where the size of the probe is determined by the observation scale σ_λ and σ_x,

$$\hat{E}(\lambda, \boldsymbol{x}) = \hat{E} + \begin{pmatrix} \boldsymbol{x} \\ \lambda \end{pmatrix}^T \begin{bmatrix} \hat{E}_{\boldsymbol{x}} \\ \hat{E}_\lambda \end{bmatrix} + \frac{1}{2} \begin{pmatrix} \boldsymbol{x} \\ \lambda \end{pmatrix}^T \begin{bmatrix} \hat{E}_{\boldsymbol{xx}} & \hat{E}_{\boldsymbol{x}\lambda} \\ \hat{E}_{\lambda\boldsymbol{x}} & \hat{E}_{\lambda\lambda} \end{bmatrix} \begin{pmatrix} \boldsymbol{x} \\ \lambda \end{pmatrix} + \ldots \tag{12}$$

where

$$\hat{E}_{\boldsymbol{x}^i\lambda^j}(\lambda, \boldsymbol{x}) = E(\lambda, \boldsymbol{x}) * G_{\boldsymbol{x}^i\lambda^j}(\lambda, \boldsymbol{x}; \sigma_x) \ . \tag{13}$$

Here, $G_{\boldsymbol{x}^i\lambda^j}(\lambda, \boldsymbol{x}; \sigma_x)$ are the spatio-spectral probes, or color receptive fields. The coefficients of the Taylor expansion of $\hat{E}(\lambda, \boldsymbol{x})$ represents the local image structure completely. Truncation of the Taylor expansions results in an approximate representation, which is best possible in the least squares sense [8].

For human vision, the Taylor expansion is spectrally truncated at second order [6]. Hence, higher order derivatives do not affect color as observed by the human visual system. The Gaussian color model approximates the Hering basis for human color vision when taking the parameters $\lambda_0 \simeq 515$ nm and $\sigma_\lambda \simeq 55$ nm [2]. Again, this approximation is optimal in least square sense.

For an *RGB* camera, principle component analysis of all triplets results in a decomposition of the image independent of camera gains and dark-current. The principle components may be interpreted as the intensity of the underlying spectral distribution, and the first- and second-order derivative, describing the largest and one but largest variation in the distribution. Hence, the principal components of the *RGB* values denote the spectral derivatives as approximated by the camera sensor sensitivities.

Concluding, measurement of spatio-spectral energy implies probing the energy distribution with Gaussian apertures at a given observation scale. The human visual system measures the intensity, slope and curvature of the spectral energy distribution, at fixed λ_0 and fixed σ_λ. Hence, the spectral intensity and its first and second order derivatives, combined in the spatial derivatives up to a given order, describe the local structure of a color image.

4 Results

Geometrical invariants are obtained by combining the color invariants N_λ and $N_{\lambda\lambda}$ in the polynomial expressions proposed by Florack et al. [3]. For example, the first order spatial derivatives yields the edge detectors

$$N_{\lambda_x}{}^2 + N_{\lambda_y}{}^2 \quad \text{and} \quad N_{\lambda\lambda_x}{}^2 + N_{\lambda\lambda_y}{}^2 \ . \tag{14}$$

Figure 1a–c shows the result of applying the edge detector $\sqrt{N_{\lambda_x}{}^2 + N_{\lambda_y}{}^2}$ under different illuminants.

Color edges can be detected by examination of the directional derivatives in the color gradient direction [1], by solving for

$$\begin{aligned} N_{\lambda ww} &= \frac{N_{\lambda_y}{}^2 N_{\lambda yy} + 2N_{\lambda_y} N_{\lambda x} N_{\lambda xy} + N_{\lambda_x}{}^2 N_{\lambda xx}}{N_{\lambda_x}{}^2 + N_{\lambda_y}{}^2} = 0 \\ N_{\lambda w} &= \sqrt{N_{\lambda_x}{}^2 + N_{\lambda_y}{}^2} \geq \alpha \end{aligned}$$

and similar for $N_{\lambda\lambda}$. Salient edges are determined by the value of α. An example is shown in Fig. 1d.

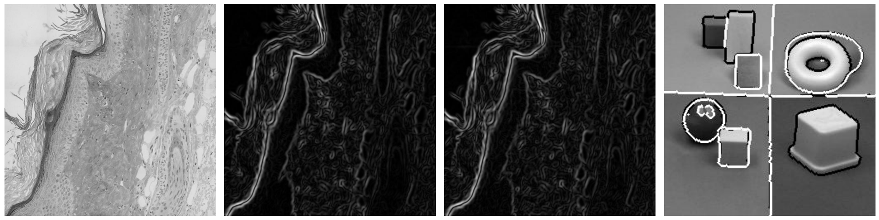

Fig. 1. Illumination invariant edges for epithelial tissue (**a**) visualized by transmission light microscopy. Edges $N_{\lambda w} = \sqrt{{N_{\lambda x}}^2 + {N_{\lambda y}}^2}$ are shown for (**b**) a white illumination (halogen 3400K), and (**c**) a reddish illumination (halogen 2450K). Despite the different illuminants, edge strength is comparable. Figure **d** shows zero crossing detection in an image of colored objects. In white the $N_{\lambda ww}$ crossings (bluish-yellow edges), in black the $N_{\lambda\lambda ww}$ crossings (reddish-green edges).

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