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Color constancy from physical principles ☆

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Abstract

A well known property of human vision, known as color constancy, is the ability to correct for color deviations caused by a difference in illumination. A common approach to investigate color constant behavior is by psychophysical experiments, regarding the human visual system as a black box responding to a well defined change in an laboratory setup.

A fundamental problem in psychophysical experiments is that significant conclusions are hard to draw due to the complex experimental environment necessary to examine color constancy. An alternative approach to reveal the mechanisms involved in color constancy is by modeling the physical process of spectral image formation. In this paper, we aim at a physical basis for color constancy rather than a psychophysical one.

By considering spatial and spectral derivatives of the Lambertian image formation model, object reflectance properties are derived independent of the spectral energy distribution of the illuminant. Gaussian spectral and spatial probes are used to estimate the proposed differential invariant. Knowledge about the spectral power distribution of the illuminant is not required for the proposed invariant.

The physical approach to color constancy offered in the paper confirms relational color constancy as a first step in color constant vision systems. Hence, low-level mechanisms such as color constant edge detection may play an important role in front-end vision. The research presented raises the question of whether the illuminant is estimated at all in pre-attentive vision.

Keywords: Color constancy; Photometric invariance; Scale-space; Differential invariants; Gaussian color model

1. Introduction

Color seems to be an unalienable property of objects. It is the orange that has that color. However, the heart of the matter is quite different. Human perception actively assigns colors to an observed scene. There is a discrepancy between the physics of light, and color as signified by the brain. It is evolution that has shaped the actual mechanism of color vision. Evolution, such that a species adapts to its (physical) environment, has driven the use of color by perception. Although the effect known as color constancy (see Fig. 1) is a long standing research topic (Land, 1977; Maloney and

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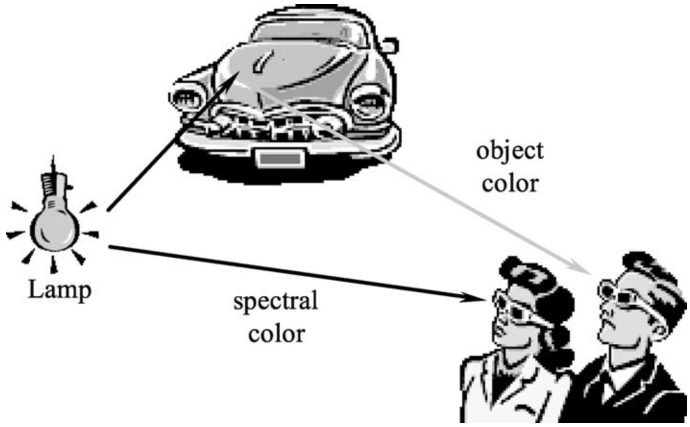

Fig. 1. The problem of color constancy. The light emitted by the lamp is reflected by the (yellow) car, causing a color sensation in the brain of the observers. The physical composition of the reflected light depends on the color of the light source. However, this effect is compensated for by the visual system. Hence, regardless the color of the light source, we will see a yellow car. This light source compensation is not trivial to obtain with a color camera in an unconstrained scene.

Wandell, 1986; von Kries, 1878), the mechanism involved is only partly resolved.

A common approach to investigate color constant behavior is by psychophysical experiments (Brainard, 1998; Land, 1977; Lucassen and Walraven, 1996). Despite the exact nature of such experiments, there are intrinsic difficulties to explain the experimental results. For relatively simple experiments, the results may not explain in enough detail the mechanism underlying color constancy.

For example, in (Lucassen and Walraven, 1996) the same stimulus patch, either illuminated by the test illuminant, or by the reference illuminant, was presented to the left and right eye. The subject was asked to match the appearance of the color under the reference illuminant to the color under the test illuminant. As discussed by the authors, the experiment is synthetical in that the visual scene lacks a third dimension. Although the results correspond to their predictions, they are unable to prove their theory on natural scenes, the scenes where shadow plays an important role. On the other hand, for complex experiments, with inherently a large amount of variables involved, the results do not describe color constancy isolated from other perceptual mechanisms (Brainard, 1998). Hence, a fundamental problem in experimental colorimetry is that the complex experimental environment necessary to examine color constancy makes it hard to draw conclusions.

An alternative approach to reveal the mechanisms involved in color constancy is by considering the spectral image formation (Geusebroek et al., 2002b). Modeling the physical process of spectral image formation provides insight into the effect of different parameters on object reflectance (Finlayson, 1996; Foster and Nascimento, 1994; Funt and Finlayson, 1995; Geusebroek et al., 2002a; Gevers and Smeulders, 1999; Sapiro, 1999; D'Zmura and Lennie, 1986). In terms of physics, daylight is reflected by an object and reaches the eye. It is the reflectance ratio over the wavelengths of radiant energy that is an object property, hence the reflection function for an orange indeed is a physical characteristic of the fruit. However, the amount of radiant energy falling onto the retina depends on both the object reflectance function, the geometry of the object, and the light source illuminating the object. Still, we observe an orange to be orange in sunlight, by candlelight, independent of shadow, frontal illumination, or oblique illumination. All these variables influence the energy distribution as it enters the eye, the variability being imposed by the physical laws of light reflection. Human color vision has adapted to include these physical laws, due to which we neglect the scene induced variations. In this paper, we aim at a physical basis for color constancy rather than a psychophysical one.

From a computer vision perspective, a fundamental question is *how to integrate the physical laws of light reflection into color measurement?* The question boils down to deriving the invariant properties of color vision. With *invariance* we mean a property f of object t which receives value $f(t)$ regardless unwanted conditions W in the appearance of t. For human color vision, the group of disturbing conditions W' are categorized by *shadow*, *highlights*, *light source*, and *scene geometry*. Scene geometry is determined by the number of light sources, light source directions, viewing direction, and object shape. The invariant class W' is referred to as *photometric invariance*. For observation of images, *geometric invariance* is of importance (Florack, 1997; Gool et al., 1995; Koenderink, 1984; Lindeberg, 1994; ter Haar Romeny, 1994). The group of spatial disturbing conditions is given by *translation*, *rotation*, and *observation scale*. Since the human eye projects the three-dimensional world onto a two-dimensional image, the group may be extended with *projection* invariance. Both photometric and geometric invariance are required for a color vision system to reduce the complexity intrinsic to color images (Geusebroek et al., 2001).

In this paper, we focus on local measurements which are robust to a change in illumination color, as proposed in (Geusebroek et al., 2001). We experimentally show the robustness of these local invariants to a change in illumination color, and compare the performance with color constancy algorithms derived from psychophysical experiments. The organization of the paper is as follows. Section 2 derives illumination invariant differential expressions. Measurement of spatio-spectral differential quotients is described in Section 3. Finally, a confrontation between physics based and perception based color constancy is given in Section 5.

2. Illumination invariant properties of object reflectance

Any method for finding invariant color properties relies on a photometric model and on assumptions about the physical variables involved. For example, hue is known to be insensitive to surface orientation, illumination direction, intensity and highlights, under a white illumination (Gevers and Smeulders, 1999). Normalized *rgb* is an object property for matte, dull surfaces illuminated by white light. 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, robust to a change in illumination color over time.

Consider the Lambertian photometric reflection model and an illumination with locally constant color,

$$E(\lambda,\vec{x}) = e(\lambda)i(\vec{x})m(\lambda,\vec{x}) \tag{1}$$

where $e(\lambda)$ represents the illumination spectrum, $i(\vec{x})$ the effect of shadow and shading, and $m(\lambda,\vec{x})$ the reflectance function of the object. The assumption of locally constant color allows for the extraction of expressions describing material changes independent of the illumination. In general, any mixed $x\lambda$ partial derivatives of $\log(E)$ are independent of $e(\lambda)$ and $i(\vec{x})$, see (Geusebroek et al., 2001). Hence,

$$\frac{\partial}{\partial x}\left\{\frac{1}{E(\lambda,x)}\frac{\partial E}{\partial \lambda}\right\} = \frac{\partial}{\partial x}\left\{\frac{1}{m(\lambda,x)}\frac{\partial m}{\partial \lambda}\right\} \tag{2}$$

which results in the invariant

$$N_{\lambda x} = \frac{E_{\lambda x}}{E} - \frac{E_\lambda E_x}{E^2} \tag{3}$$

which determines material changes independent of the viewpoint, surface orientation, illumination direction, illumination intensity, and illumination color. Here, indices denote differentiation. Application of the chain rule for differentiation yields the higher order expressions in terms of the spatio-spectral energy distribution. For instance, the spectral derivative of $N_{\lambda x}$ is given by

$$N_{\lambda\lambda x} = \frac{E_{\lambda\lambda x}E^2 - E_{\lambda\lambda}E_xE - 2E_{\lambda x}E_\lambda E + 2E_\lambda^2 E_x}{E^3} \tag{4}$$

where $E(\lambda,x)$ is written as E for simplicity and indices denote differentiation. Without loss of generality, we have restricted ourselves to the one-dimensional case; two-dimensional expressions may be derived according to Geusebroek et al. (2000a). These expressions are invariant for a change of illumination over time. The major assumption underlying the proposed invariants is a single colored illumination, effectuating a spatially constant illumination spectrum. For an illumination color varying slowly over the scene with respect to the spatial variation of the object reflectance, simultaneous color constancy is achieved by the proposed invariant.

3. Measurement of spatio-spectral energy

Up to this point we did establish invariant expressions describing material changes robust to a change in illumination color. These are formal expressions, exploring the infinite dimensional Hilbert space of spectra at an infinitesimal spatial neighborhood. The spatio-spectral energy distribution is only measurable at a certain spatial resolution and spectral bandwidth, yielding a limited amount of measurements. Hence, physical realizable measurements inherently imply integration over the spectral and spatial dimensions. General aperture functions, or Gaussians and its derivatives, may be used to probe the spatio-spectral energy distribution.

In order to measure the invariant properties, the partial derivative operator is replaced by Gaussian derivative convolutions. Hence, the incoming spatio-spectral energy density function is probed with Gaussian and Gaussian derivative functions. These measurements approximate the differential expressions derived above. For the spatial derivatives, convolution with a Gaussian derivative function yields the correct approximation. The spectral derivatives may be approximated by linear combinations of the eye receptor sensitivities, such that the combination of these sensitivities approximate the shape of the Gaussian (derivative) function. For human vision, spectral derivatives up to second order are measured (Hering, 1964). Hence, higher order derivatives do not affect color as observed by the human visual system. The spectrum is correlated with the Gaussian and its derivatives, producing three color values per pixel. The Gaussian color model approximates the Hering basis for human color vision when taking the parameters $\lambda_0 \simeq 520$ nm and $\sigma_\lambda \simeq 55$ nm (Geusebroek et al., 2000b). The measured differential quotients are denoted by $\widehat{E}$, $\widehat{E}_\lambda$ and $\widehat{E}_{\lambda\lambda}$. The spectral measurements may be interpreted as measuring intensity, yellow-bluish, and red-greenish, respectively. The spectral intensity and its first and second order derivatives only, combined in the spatial derivatives up to a given order, together form a framework of color scale-space.

4. Experiments

In order to demonstrate the performance of the proposed color invariant, experiments are conducted. In these experiments we test the extent of invariance of the proposed model to a change in illumination, and try to relate the results to the imperfect color constancy of human vision. The interaction of light and material is simulated on spectral transmission data of colored patches. The image formation of spectral transmission is identical to the multiplicative Lambertian image formation for reflection of light, hence the results may be regarded as indicative for reflective samples too. The experiments aim in demonstrating the quality of the proposed color constant measurement under changing illuminations. The human visual system is known to be not perfectly color constant. As our framework applies both spectral and spatial integration, we expect the proposed color invariant not to be perfectly constant either. Further, as parameters of the proposed color scale-space framework are tuned to the human color vision, the experiments aim in demonstrating how well the performance of the proposed method agrees with the performance of the human visual system as derived from colorimetric experiments.

The transmission of 168 patches from a calibration grid (IT8.7/1, Agfa, Mortsel, Belgium) were measured (Spectrascan PR-713PC, Photo Research, Chatsworth, CA) from 390 to 730 nm, resampled at 5 nm intervals. The patches include achromatic colors, skin like tints and full colors (Fig. 2). Each patch i will be represented by its spectral transmission $\hat{m}_i$.

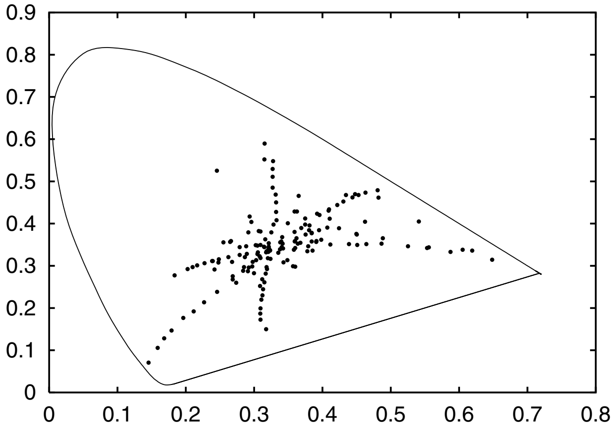

Fig. 2. The CIE 1964 chromaticity diagram of the colors in the calibration grid used for the experiments, illuminated by average daylight D65.

For the case of daylight, incandescent and halogen light, the emission spectra are known to be a one parameter function of color temperature. For these important classes of illuminants, the spectral energy distribution $e_k(\lambda)$ were calculated according to the CIE method as described in (Wyszecki and Stiles, 1982). Daylight illuminants were calculated in the range of 4000 K up to 10,000 K color temperature in steps of 500 K. The 4000 and 10,000 K illuminants represent extremes of daylight, whereas 6500 K represents average daylight. Emission spectra of halogen and incandescent lamps are equivalent to blackbody radiators, generated from 2000 K up to 5000 K according to Wyszecki and Stiles (1982, Section 1.2.2).

For the case of fluorescent light, illuminants F1–F12 are used, as given by Hunt (1995). These are 12 representative spectral power distributions for fluorescent lamps.

Assuming Lambert–Beer absorption, the spectrum $s_i^k(\lambda)$ transmitted by a planar patch i under illuminant k is given by

$$s_i^k(\lambda) = e_k(\lambda)m_i(\lambda) \tag{5}$$

where $m_i(\lambda)$ is the spectral transmittance and $e_k(\lambda)$ the illumination spectrum. Note that Lambert–Beer absorption can be treated similar to Lambertian reflection, as their image formation equations are identical.

Color values are calculated by the weighted summation over the transmitted spectrum s_i^k at 5 nm intervals. For the CIE 1964 XYZ sensitivities, the XYZ value is obtained by Wyszecki and Stiles (1982, Section 3.3.8).

$$\begin{aligned} X &= \frac{1}{k_{10}} \sum_{\lambda} \bar{x}_{10}(\lambda)e_k(\lambda)m_i(\lambda) \\ Y &= \frac{1}{k_{10}} \sum_{\lambda} \bar{y}_{10}(\lambda)e_k(\lambda)m_i(\lambda) \\ Z &= \frac{1}{k_{10}} \sum_{\lambda} \bar{z}_{10}(\lambda)e_k(\lambda)m_i(\lambda) \end{aligned} \tag{6}$$

where k_{10} is a constant to normalize $Y_w = 100$, Y_w being the normalized luminance of the light source. Similarly, for the Gaussian color model we have

$$\begin{aligned} E &= \Delta\lambda \sum_{\lambda} G(\lambda; \lambda_0, \sigma_\lambda)e_k(\lambda)m_i(\lambda) \\ E_\lambda &= \Delta\lambda \sum_{\lambda} G_\lambda(\lambda; \lambda_0, \sigma_\lambda)e_k(\lambda)m_i(\lambda) \\ E_{\lambda\lambda} &= \Delta\lambda \sum_{\lambda} G_{\lambda\lambda}(\lambda; \lambda_0, \sigma_\lambda)e_k(\lambda)m_i(\lambda) \end{aligned} \tag{7}$$

where $\Delta\lambda = 5$ nm. Further, $\sigma_\lambda = 55$ nm and $\lambda_0 = 520$ nm to be colorimetric with human vision (Geusebroek et al., 2000b).

Color constancy is examined by evaluating edge strength under different simulated illumination conditions. Borders are formed by combining all patches with one another, yielding 14,028 different color combinations. A ground truth is obtained by taking a perfect white light illuminant. The reference boils down to an equal energy spectrum. The ground truth represents the patch transmission function up to multiplication by a constant a,

$$s_i^{\mathrm{ref}}(\lambda) = a m_i(\lambda) \tag{8}$$

The difference in edge strength for two patches illuminated by the test illuminant and the reference illuminant indicates the error in color constancy. We define the color constancy ratio as

$$\epsilon^k = 1 - \left| \frac{d^k(i,j) - d^{\mathrm{ref}}(i,j)}{d^{\mathrm{ref}}(i,j)} \right| \tag{9}$$

where d^k is the color difference between two patches i, j under the test illuminant k, and d^{ref} is the difference between the same two patches under the reference illuminant, that is equal energy illumination. The color constancy ratio ϵ^k measures the relative deviation in edge strength between two patches i, j due to illuminant k relative to the edge strength under the reference illuminant. The ratio is essentially a chromatic Brunswik ratio (Brunswik, 1928), taken at the center of the border between the patches.

The proposed invariant is evaluated against the performance for color constancy of von Kries (1970) and uv color space (Wyszecki and Stiles, 1982). For the colorimetric experiment, Gaussian weighted samples are taken at $\lambda_0 = 520$ nm and $\sigma_\lambda = 55$ nm. Color difference is defined by

$$d_N = \sqrt{N_{\lambda x}(i,j)^2 + N_{\lambda\lambda x}(i,j)^2} \tag{10}$$

where $N_{\lambda x}(i,j)$ (Eq. (3)) and $N_{\lambda\lambda x}(i,j)$ (Eq. (4)) measure total chromatic edge strength between patch i and j, as derived from the Gaussian weighted samples. Again, the measurements are taken at the center of the border between the patches. Color constancy is determined by Eq. (9), using d_N as measure for color difference.

For comparison, the experiment is repeated with the CIE XYZ 1964 sensitivities for observation. Color difference is defined by the Euclidian distance in the CIE 1976 $u'v'$ color space (Wyszecki and Stiles, 1982, Section 3.3.9),

$$d_{uv} = \sqrt{(u_i' - u_j')^2 + (v_i' - v_j')^2} \tag{11}$$

where i, j represent the different patches. Color constancy is determined by Eq. (9), using d_{uv} as measure for color difference. Note that for the $u'v'$ color space no information about the light source is included. Further, $u'v'$ space is similar to uv space up to a transformation of the achromatic point. The additive transformation of the white point makes uv space a color constant space. Differences in $u'v'$ are equal to differences in uv space. Hence, d_{uv} is an illumination invariant measure of color difference.

As a well known reference, the von Kries transform for chromatic adaptation (von Kries, 1970) is evaluated in a similar experiment. Von Kries method is based on Lambertian reflection, assuming that the (known) sensor responses to the illuminant may be used to eliminate the illuminant from the measurement. For the experiment, von Kries adaptation is applied on the measured color values, and the result is transformed to the equal energy illuminant (Hunt, 1995). Thereafter, color difference between patches i and j taken under the test illuminant is calculated according to Eq. (11). Comparison to the color difference between the same two patches under the reference illuminant is obtained by Eq. (9), using the von Kries transformed $u'v'$ distance as measure for color distance.

Results for the color constancy measurements are given for daylight illumination (Table 1), blackbody radiators (Table 2), and fluorescent light (Table 3).

Average constancy over the different phases of daylight is for the proposed invariant $91.8 \pm 6.1\%$. Difference in $u'v'$ color space performs similar with an average of $91.9 \pm 6.3\%$. The von Kries transform is 5% more color constant, $96.0 \pm 3.3\%$. As expected, the von Kries transform has a better performance given that the color of the illuminant is taken into account.

For blackbody radiators, the proposed invariant is on average $88.9 \pm 12.5\%$ color constant. The proposed invariant is more color constant than $u'v'$ differences, average $82.4 \pm 15.1\%$. Again, von Kries transform is even better with an average of $93.4 \pm 6.8\%$. For these types of illuminants, often

Table 1
Results for the different colorimetric experiments with daylight illumination, ranging from 4000 to 10,000 K color temperature

T (K)	N		von Kries		$u'v'$	
	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.
4000	92.2	5.6	96.1	3.2	86.9	10.0
4500	94.5	4.2	97.9	1.8	91.1	7.1
5000	94.9	2.8	99.2	0.7	94.5	4.6
5500	94.1	1.8	98.9	1.0	96.6	2.0
6000	93.2	2.7	97.9	1.7	97.6	1.8
6500	92.5	4.0	96.9	2.4	96.1	2.7
7000	91.8	5.2	96.1	2.9	94.3	3.8
7500	91.2	6.2	95.4	3.4	92.7	4.9
8000	90.6	7.0	94.8	3.8	91.2	6.0
8500	90.1	7.6	94.3	4.2	89.9	6.9
9000	89.6	8.2	93.8	4.5	88.8	7.7
9500	89.2	8.7	93.4	4.8	87.8	8.4
10,000	88.8	9.1	93.0	5.1	86.9	9.1

Average percentage constancy $\bar{\epsilon}$ and standard deviation for the proposed invariant N, the von Kries transform, and $u'v'$ difference.

Table 2
Results for the different colorimetric experiments with blackbody radiators from 2000 to 5000 K color temperature

T (K)	N		von Kries		$u'v'$	
	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.
2000	75.6	24.5	85.6	12.4	65.8	24.9
2500	82.5	16.5	89.0	9.4	72.3	20.6
3000	87.1	11.2	91.9	6.8	78.3	16.3
3500	90.8	7.5	94.3	4.7	83.7	12.4
4000	93.7	4.9	96.3	3.0	88.4	8.9
4500	96.0	3.0	97.9	1.7	92.5	6.0
5000	96.9	1.7	99.1	0.7	95.9	3.4

Average percentage constancy $\bar{\epsilon}$ and standard deviation for the proposed invariant N, the von Kries transform, and $u'v'$ difference.

Table 3
Results for the colorimetric experiments with representative fluorescent illuminants

T (K)	N		von Kries		$u'v'$	
	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.	$\bar{\epsilon}$ (%)	S.D.
F1	82.4	14.4	89.4	7.9	88.6	7.9
F2	82.7	12.4	87.8	7.9	82.9	7.5
F3	79.9	13.5	85.5	9.8	76.4	11.4
F4	77.2	15.4	83.6	11.6	71.4	14.9
F5	81.1	15.4	88.1	8.6	87.4	8.9
F6	80.6	13.7	85.9	8.9	79.7	8.8
F7	90.2	7.8	95.2	3.7	93.7	3.9
F8	93.6	3.1	97.8	1.6	94.6	4.4
F9	93.3	4.4	95.3	3.6	90.1	7.8
F10	87.2	9.1	91.1	8.8	91.7	9.2
F11	87.1	10.1	88.3	11.2	85.5	12.6
F12	84.9	13.6	85.0	13.8	74.9	18.7

Average percentage constancy $\bar{\epsilon}$ and standard deviation for the proposed invariant N, the von Kries transform, and $u'v'$ difference.

running at a low color temperature, variation due to illumination color is drastically reduced by the proposed method.

The proposed method is less color constant than von Kries adaptation, which requires knowledge on the color of the light source. In comparison to $u'v'$ color differences, the proposed invariant offers better performance for low color temperature illuminants.

Color constancy for fluorescent illuminants is on average $85.0 \pm 11.8\%$ for the proposed invariant, $84.7 \pm 10.5\%$ for $u'v'$ difference, and $89.4 \pm 8.8\%$ for the von Kries transform. As expected, the large integration filters are not capable in offering color constancy for the class of fluorescent illuminants. The use of broad-band filters limits the applicability to smooth spectra, for which the Gaussian weighted differential quotients are accurate estimations. For outdoor scenes, halogen illumination and incandescent light, the illumination spectra may be considered smooth.

5. Discussion

Color constancy was considered in (Lucassen and Walraven, 1996; Brainard, 1998) from an experimental colorimetric background, where subjects are asked to match the reference and test illumination condition. As a consequence their experiments do not include shadow and shading. The result of their approach shows approximate color constancy under natural illuminants. However, their approach is unable to cope with color constancy of three-dimensional scenes, where shadow plays an important role. The advantage of our physical approach over an empirical colorimetric approach, is that invariant properties are deduced from the image formation model. Our proposed equation (3) is designed to be insensitive to intensity changes due to the scene geometry.

The proposed invariant equation (3) is evaluated by experiments on spectral data of 168 transparent patches, illuminated by daylight, blackbody, and fluorescent illuminants. Average constancy is $90 \pm 5\%$ for daylight, $90 \pm 10\%$ for blackbody radiators, and $85 \pm 10\%$ for fluorescent illuminants. The performance of the proposed method is slightly less than that of the von Kries transform. Average constancy for von Kries on the 168 patches is $95 \pm 3\%$ for daylight, $95 \pm 5\%$ for blackbody radiators, and $90 \pm 10\%$ for fluorescent illuminants. This is explained from the fact that the von Kries transform requires explicit knowledge of material and illuminant, and even than the difference is small. There are many circumstances where such a knowledge of material and illuminant is missing, especially in image retrieval from large databases, or when calibration is not practically feasible as is frequently the case in light microscopy. The proposed method requires knowledge about the material only, hence is applicable under a larger set of imaging circumstances.

As an alternative for color constancy under an unknown illuminant, one could use *Luv* color space differences (Wyszecki and Stiles, 1982) instead of the proposed method. We have evaluated color constancy for both methods. Ignoring the fact that the proposed color scale-space framework allows spatial integration, the proposed invariant offers similar performance to $u'v'$ color differences. This is remarkable, given the different background against which the methods are derived. Whereas $u'v'$ is derived from colorimetric experiments, hence from human perception, the proposed invariant N is derived from measurement theory—the physics of observation—and physical reflection models. Apparently, it is the physical cause of color, and the environmental variation in physical parameters, to which the human visual system adapts.

As pointed out in (Lucassen and Walraven, 1996), mechanisms responding to cone-specific contrast offer a better correspondence with human vision than by a system that estimates illuminant and reflectance spectra. The research presented here raises the question whether the illuminant is estimated at all in pre-attentive vision. The physical model presented demands spatial comparison in order to achieve color constancy, thereby confirming relational color constancy as a first step in color constant vision (Foster and Nascimento, 1994; Nascimento and Foster, 2000). Hence, low-level mechanisms as color constant edge detection reported here may play a role in front-end vision.

6. Conclusion

This paper presents a physics-based background for color constancy, valid for Lambertian light reflectance. By considering spatial and spectral derivatives of the image formation model, object reflectance properties are derived independent of the spectral energy distribution of the illuminant. Knowledge about the spectral power distribution of the illuminant is not required for the proposed invariant, as opposed to the well known von Kries transform for color constancy (von Kries, 1970).

The derivation of object properties from color images yields the extraction of geometric and photometric invariants from color images. Modeling the physical process of color image formation gives insight into the disturbing conditions during image acquisition. The robustness of our invariant Eq. (3) is assured by using color scale-space, as introduced in (Geusebroek et al., 2001). The Gaussian color model is considered an adequate approximation of the human tri-stimulus sensitivities. The Gaussian color model measures the intensity, first, and second order derivative of the spectral energy distribution, combined in a well-established spatial observation theory. Application of color scale-space techniques in color constancy ensures compatibility with colorimetry, while inherently physically sound and robust measurements are derived. Hence, color scale-space as proposed in (Geusebroek et al., 2001) provides a framework for the calculation of photometric invariance, while maintaining compatibility with human perception.

We have proven that spatial differentiation is necessary to achieve color constancy when preknowledge about the illuminant is not available. Hence, any color constant system should perform both spectral and spatial comparison in order to be invariant against illumination changes, which confirms the theory of relational color constancy as proposed in (Foster and Nascimento, 1994). We plan to undertake similar experiments as Nascimento and Foster (2000) in order to compare performance of the proposed invariants with the imperfect color constancy of human vision.

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