CHROMATIC ADAPTATION AND WHITE-BALANCE PROBLEM

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ABSTRACT

The problem of adjusting the color such that the output image from a digital camera, viewed under a standard condition, matches the scene observed by the photographer's eye is called white-balance. While most white-balance algorithms approach the problem using the coefficient law (von Kries), the coefficient law has been shown inaccurate. In this paper, we instead formulate the white-balance problem using Jameson and Hurvich's induced opponent response chromatic adaptation theory. The solution to this white-balance problem reduces to a single matrix multiplication. The experimental results using existing illuminant estimation methods verify that the induced opponent response approach to solving the white-balance problem yields more neutral colors in the *white* panels of the Macbeth color chart than the traditional methods. The computational cost of the proposed method is virtually zero.

1. INTRODUCTION

Chromatic adaptation is a study of change in the photoreceptive sensitivity of the human visual system (HVS) under various viewing conditions, such as illumination. Generally, the chromatic adaptation mechanism has the effect of discounting the illuminant, and thus metameric colors under one illuminant often appear metameric under another illuminant. In particular, a piece of white paper is believed to appear white regardless of the illuminant. A human vision is said to have a *color constancy* property if a color of an object appears invariant to the illuminant.

The von Kries *coefficient law* is a theory that describes the relationship between the illuminant and the HVS sensitivity [7] and it accounts for the approximate color constancy in the HVS [15] [11]. However, Hess, Pretori, and Wallach demonstrate that the coefficient law is false under the context of chromatic adaptation [5] [8] [9]. Instead, Hurvich and Jameson suggest that the surround activity induces an opposite physiological response through incremental processes [9].

The chromatic adaptation phenomenon poses a particularly challenging problem in digital photography. Because the measured light intensity strongly depends on the illuminant, the captured image often appears different from the scene the photographer sees. The process of adjusting the image appearance to a different viewing condition is commonly known as the *white-balance* problem. If the end user of the output image is a human eye, it is critical to be sensitive to the HVS chromatic adaptation mechanism. Although a series of recent studies verifies the weaknesses in the the coefficient law, most existing white-balance algorithms are a combination of the von Kries coefficient law and an illuminant estimation technique. Perhaps this is a testimony to the disconnectedness between the engineering field and cognitive science.

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In this paper, we propose to formulate the white-balance problem using Jameson and Hurvich's induced opponent response theory (section 3.3). The solution to this problem also requires the knowledge of the illuminant. In section 4, we will compare our technique to the coefficient law-based white-balance solution using the *same* illuminant estimation method. We show that the images generated with the white-balance algorithm based on induced opponent response appear more natural.

2. COLOR SCIENCE

2.1. Colorimetry

Colorimetry is the science of measuring color. More complete details of colorimetry are found in [22]. Here, we cover only the basics necessary to understand the white-balance algorithm.

There are four types of photoreceptors, one *rod* and three *cones*. Under well-lit viewing conditions (photopic vision), cones, denoted L, M, S, are are highly active and rods are inactive. In this paper, we strictly assume photopic vision. Let $\lambda \in \mathbb{R}$ be spectral frequency and $l(\lambda) \in \mathbb{R}_+$ be the spectrum distribution of a color at frequency $\lambda \in \mathbb{R}$. Let $\phi_j(\lambda) \in \mathbb{R}_+, j \in \{1,2,3\}$ be the cone sensitivity function of L, M, S photoreceptors, respectively. Then the following inner product models the response vector $\Phi(l) = [\Phi_1(l), \Phi_2(l), \Phi_3(l)]^T \in \mathbb{R}^3$ of the cone photoreceptors to the spectrum distribution $l(\cdot)$:

$$\Phi_j(l) = \langle \phi_j, l \rangle = \int_{-\infty}^{\infty} \phi_j(\lambda) l(\lambda) d\lambda. \quad (1)$$

When $\Phi(l_1) = \Phi(l_2)$ for given spectrum distributions $l_1(\cdot)$ and $l_2(\cdot)$, $l_1(\cdot)$ and $l_2(\cdot)$ appear identical and are said to be *metameric*.

Let $\{p_1(\lambda), p_2(\lambda), p_3(\lambda)\}$ be three spectrum distributions of colors, where $\Phi(p_j)$ are linearly independent of each other. Then it is easy to verify that $\Phi(w_1p_1 + w_2p_2 + w_3p_3) = \Phi(l)$ if and only if $\vec{w} = [\Phi(p_1), \Phi(p_2), \Phi(p_3)]^{-1}\Phi(l)$ where $\vec{w} = [w_1, w_2, w_3]^T$. The weights $\vec{w}$ is often referred to as the *tristimulus values* of $l(\cdot)$ in *color space* defined by the *primary colors* $\{p_1, p_2, p_3\}$.

2.2. Opponent Color

Hering proposed that there are two levels of interpreting a color in the HVS: at the receptor level, and in the opponent color space [3]. Since his proposal, there have been numerous experiments confirming that low-level image processing (spatial [12] [14] [13], temporal [21], chromatic adaptation [8] [9]) is being performed in this opponent color space. The colors red, green, yellow, and blue are called the *unique* hues; the opponent color theory asserts that red neutralizes green, and yellow neutralizes blue. Hurvich and Jameson's experiment is credited with giving conclusive evidence that the opponent color system exists in the HVS, and this theory continues to have many proponents [4] [12] [20] [19] [18].

Let $l(\lambda)$ be the spectral distribution of a light at the frequency λ, as before. At the basic level, opponent color representation is assumed to be formed by taking a linear combination of the cone response $\Phi(l) \in \mathbb{R}^3$ (though recent work reveals that the transformation is slightly more complicated than that [13]). That is, let $M \in \mathbb{R}^{3\times 3}$ be a non-singular color conversion matrix from L, M, S cone responses to the opponent color space. Then $\vec{v} = M\Phi(l)$ where $\vec{v} = [v_1, v_2, v_3]^T$, consisting of a achromatic channel v_1 and chromatic channels v_2 (red-green) and v_3 (yellow-blue). Large positive v_2 (v_3) values have large red (yellow) values; large negative v_2 (v_3) values have large green (blue) values. The opponent color system is difficult to derive precisely. Typically, the $M \in \mathbb{R}^{3\times 3}$ matrix is computed from measurements made in visual experiments [10] [8] [12].

2.3. Chromatic Adaptation

There is a considerable amount of literature reported on how the HVS sensitivity to color changes when the human eye adjusts to the chromaticity of the background. This property is called chromatic adaptation, and some have sought to characterize it [7] [9].

The von Kries *coefficient law* has been popularized by many [7] [17] [2]. It asserts that the sensitivity of each cone type adapts to changes in viewing conditions by controlling the amplitude of ϕ_j [7]. Suppose $l_{\mathtt{S}}(\cdot)$ is the spectral distribution of the surrounding field color that a human eye has adopted to, and let $l_{\mathtt{F}}(\cdot)$ be the spectral distribution of the focal field color that are observing. According to the von Kries coefficient law, the HVS response to the focal field color is

$$\Psi_{\mathtt{K},j}(l_{\mathtt{F}}, l_{\mathtt{S}}) = \int_{-\infty}^{\infty} d_j \phi_j(\lambda) l_{\mathtt{F}}(\lambda) d\lambda = d_j \Phi_j(l_{\mathtt{F}}), \quad (2)$$

where $\phi_j(\cdot), \Phi(\cdot)$ is defined as before, and d_j the proportionality constant. Furthermore, (2) is attributed to chromatic adaptation mechanism by assuming that the magnitudes of d_1, d_2, d_3 are inversely proportional to $\Phi_1(l_{\mathtt{S}}), \Phi_2(l_{\mathtt{S}}), \Phi_3(l_{\mathtt{S}})$, respectively [7].

It has been shown, however, that (2) is an inaccurate model for chromatic adaptation [9]. Instead, a series of psycho-visual experiments yielded a different chromatic adaptation model called *induced opponent response* [8] [9]. As before, let $l_{\mathtt{F}}(\cdot)$ be the spectral distribution of the focal field color and $l_{\mathtt{S}}(\cdot)$ be the spectral distribution of the surrounding field color. The HVS response to the focal ($\Psi_{\mathtt{F}}$) and the surrounding ($\Psi_{\mathtt{S}}$) are

$$\begin{aligned} \Psi_{\mathtt{F}}(l_{\mathtt{F}}, l_{\mathtt{S}}) &= M^{-1}(c(M\Phi(l_{\mathtt{F}}))^n - \vec{i}_{\mathtt{F}}) \\ \Psi_{\mathtt{S}}(l_{\mathtt{S}}, l_{\mathtt{F}}) &= M^{-1}(c(M\Phi(l_{\mathtt{S}}))^n - \vec{i}_{\mathtt{S}}), \end{aligned} \quad (3)$$

where $\vec{u}^n$ means $[u_1^n, u_2^n, u_3^n]^T$. Here, c is a constant, n is the transducing constant, and $\vec{i}_{\mathtt{F}}$ and $\vec{i}_{\mathtt{S}}$ are the induced activities in the focal and surrounding, respectively. The matrix $M \in \mathbb{R}^{3\times 3}$ represents a color space transformation from L, M, S to opponent color space. The induced responses are proportional to the response to the inducing fields:

$$\vec{i}_{\mathtt{F}} = kM\Psi_{\mathtt{S}}(l_{\mathtt{S}}, l_{\mathtt{F}}) \qquad \vec{i}_{\mathtt{S}} = kM\Psi_{\mathtt{F}}(l_{\mathtt{F}}, l_{\mathtt{S}}), \quad (4)$$

where k is some constant which usually depends on the size of the inducing field. It was found that when $l_{\mathtt{F}}$ and $l_{\mathtt{S}}$ are isoluminant then $n = 1$ [5]. When the stimuli are neutral, instead, $n = 1/3$ [6] [9]. Interactions between the several inducing elements is approximated as a weighted average [5].

2.4. Image Acquisition Models

In this paper, we make several assumptions about the image sensor. Let $l(\lambda)$ be the spectral distribution of a light at frequency λ. The

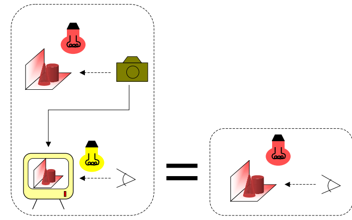

Fig. 1. Two different viewing conditions. The goal of the white-balance algorithm is to make the two scenes appear identical.

sensor response $\Theta(l) \in \mathbb{R}^3$ to light l is modeled as

$$\Theta_j(l) = \langle \theta_j, l \rangle = \int_{-\infty}^{\infty} \theta_j(\lambda) l(\lambda) d\lambda, \quad (5)$$

where $\theta_j(\lambda) \in \mathbb{R}_+$, $j \in \{1, 2, 3\}$ are the sensor sensitivity functions for red, green, and blue pixel components, respectively. $\theta_j(\cdot)$ is usually characterized by the color filter array. Furthermore, the sensor is called *colorimetric* if for all l, there exists a matrix $M_{\theta,\phi} \in \mathbb{R}^{3\times 3}$ such that $\Phi(l) = M_{\theta,\phi}\Theta(l)$. In this paper, we assume that the sensor response is colorimetric.

3. WHITE-BALANCE ALGORITHM

3.1. White-Balance Problem

The problem of color constancy poses a difficult challenge to digital photography. The output color from a camera often differs from how it appeared to the eyes of the photographer that took the picture. Problem of *correcting* the output color from a camera is called *white-balance*. But what is the criteria for this *correction*? The authors believes that this is an often misunderstood issue. With the *a priori* knowledge that the observer of the output image is a human eye, the task of white-balance algorithm is to adjust the color such that the output image viewed under a standard condition matches *the scene observed by the photographer's eye*.

To make this point clear, we refer to the example in fig. 1. Let $\Psi(l_{\mathtt{F}}, l_{\mathtt{S}})$ be a HVS response to the focal field light $l_{\mathtt{F}}$ when the eye has adapted to the surrounding light $l_{\mathtt{S}}$. The right system in fig. 1 shows a scene lit by a red illuminant observed by the photographer's human eye. Assuming that the eye has adapted to the red illuminant, the system's HVS response to the color $l(\lambda)$ is $\Psi(l, \textit{red light})$. The left system shows a human eye observing display device viewed under a yellow illuminant. Assuming that the eye has adopted to the yellow illuminant, its HVS response is $\Psi(w_1p_1 + w_2p_2 + w_3p_3, \textit{yellow light})$, where $p_1(\lambda), p_2(\lambda), p_3(\lambda)$ are the spectrum distribution of the primary colors of the phosphors used in the CRT monitor, and $\vec{w} = [w_1, w_2, w_3]^T$ is the tristimulus value controlling the intensity of $p_i(\cdot)$, respectively. Note that $\vec{w}$ is the output from the camera. The purpose of the white-balance algorithm is to process sensor data inside the digital camera such that the two systems in fig. 1 are equivalent. That is, we would like to find $\vec{w}$ such that

$$\Psi(l, \textit{red light}) = \Psi(w_1p_1 + w_2p_2 + w_3p_3, \textit{yellow light}) \quad (6)$$

3.2. Common Approaches to White-Balance

Following the example in fig. 1, let $l_{\mathtt{R}}$ and $l_{\mathtt{Y}}$ be the spectral density of the *red* and *yellow* illuminants in (6), respectively. In this section, we assume that $l_{\mathtt{Y}}$ and $l_{\mathtt{R}}$ are known.

Nearly all commercial digital cameras sold today assume a variation of the von Kries coefficient law, even though the model is inaccurate and inadequate [5] [9]. Nevertheless, let us solve (6) assuming the von Kries coefficient law $\Psi_{\mathtt{K}}(\cdot,\cdot)$. Suppose

$$\Psi(l_{\mathtt{F}}, l_{\mathtt{S}}) = \Psi_{\mathtt{K}}(l_{\mathtt{F}}, l_{\mathtt{S}}) = \mathtt{diag}(d_1, d_2, d_3)\Phi(l_{\mathtt{F}}).$$

Substituting this into (6), the solution $\vec{w}$ to (6) is given by

$$\begin{aligned}\vec{w} &= [\Psi_{\mathtt{K}}(p_1, l_{\mathtt{Y}}), \Psi_{\mathtt{K}}(p_2, l_{\mathtt{Y}}), \Psi_{\mathtt{K}}(p_3, l_{\mathtt{Y}})]^{-1}\Psi_{\mathtt{K}}(l, l_{\mathtt{R}}) \quad (7)\\ &= [\Phi(p_1), \Phi(p_2), \Phi(p_3)]^{-1}\mathtt{diag}\left(\frac{e_1}{d_1}, \frac{e_2}{d_2}, \frac{e_3}{d_3}\right)M_{\theta,\phi}\Theta(l),\end{aligned}$$

where d_j and e_j are inversely proportional to $\Phi_j(l_{\mathtt{Y}})$ and $\Phi_j(l_{\mathtt{R}})$, respectively.

3.3. Jameson-Hurvich Model

We continue to assume that $l_{\mathtt{R}}$ and $l_{\mathtt{Y}}$ are made available. In this section, we propose an alternative to the existing white-balance algorithms by solving (6) assuming a chromatic adaptation model $\Psi_{\mathtt{F}}(\cdot,\cdot)$ instead of the von Kries coefficient law [4] [5] [8] [9] [6]. We begin by combining (3) and (4). After simplifying,

$$\Psi_{\mathtt{F}}(l_{\mathtt{F}}, l_{\mathtt{S}}) = M^{-1}((M\Phi(l_{\mathtt{F}}))^n - k(M\Phi(l_{\mathtt{S}}))^n),$$

where, without loss of generality, $c = 1 - k^2$. Experiments indicate that $n = 1$ when $l_{\mathtt{F}}$ and $l_{\mathtt{S}}$ are isoluminant [9]. The method for choosing an appropriate value for n in the general case, however, is not very well understood. We, therefore, approximate the formula by operating as if stimuli are isoluminant (with $n = 1$):

$$\Psi_{\mathtt{F}}(l_{\mathtt{F}}, l_{\mathtt{S}}) = M^{-1}\left(M\Phi(l_{\mathtt{F}}) - k\left(\frac{m_1\Phi(l_{\mathtt{F}})}{m_1\Phi(l_{\mathtt{S}})}\right)BM\Phi(l_{\mathtt{S}})\right)$$

where $B = \mathtt{diag}(0, 1, 1)$ and $m_1 \in \mathbb{R}^{1\times 3}$ is the first row of M (hence $m_1\Phi(l)$ is the achromatic channel value of l in opponent color space). Above, $\frac{m_1\Phi(l_{\mathtt{F}})}{m_1\Phi(l_{\mathtt{S}})}$ normalizes the induction response $M\Phi(l_{\mathtt{S}})$ using the ratio between the luminance values of the focal and surrounding stimuli, and $\frac{m_1\Phi(l_{\mathtt{F}})}{m_1\Phi(l_{\mathtt{S}})} = 1$ when $l_{\mathtt{F}}$ and $l_{\mathtt{S}}$ are isoluminant. Matrix $B = \mathtt{diag}(0, 1, 1)$ is used because the techniques for estimating the illuminants $l_{\mathtt{Y}}$ and $l_{\mathtt{R}}$ are inherently limited to evaluating the chromatic content of the illuminant only. Because $m_1\Phi(l_{\mathtt{F}})$ is scalar, the above formula simplifies significantly:

$$\Psi_{\mathtt{F}}(l_{\mathtt{F}}, l_{\mathtt{S}}) = \left(I - \frac{k}{m_1\Phi(l_{\mathtt{S}})}M^{-1}BM\Phi(l_{\mathtt{S}})m_1\right)\Phi(l_{\mathtt{F}})$$

where $I \in \mathbb{R}^{3\times 3}$ is an identity matrix. Define $L(\cdot,\cdot) \in \mathbb{R}^{3\times 3}$ as

$$L(\vec{v}, k) = I - \frac{k}{m_1\vec{v}}M^{-1}BM\vec{v}m_1.$$

Now we are ready to solve the white-balance equation. Substituting $\Psi(\cdot,\cdot) = L(\Phi(l_{\mathtt{S}}), k)\Phi(l_{\mathtt{F}})$ to (6),

$$\begin{aligned}\vec{w} = [\Phi(p_1), \Phi(p_2), \Phi(p_3)]^{-1}L(\Phi(l_{\mathtt{Y}}), k_2)^{-1}\\ L(\Phi(l_{\mathtt{R}}), k_1)M_{\theta,\phi}\Theta(l). \quad (8)\end{aligned}$$

The equation above is significant for computational costs. $\Phi(p_j)$ can be pre-computed. The digital camera output $\vec{w}$ can be computed from image sensor data $\Theta(l)$ with a single matrix multiplication. This implies that the white-balance step and the color space conversion, which is also a matrix multiplication, can be combined into a single matrix multiplication procedure, making the computational cost of the white-balance algorithm virtually zero.

Finally, because the sizes of the focal and surrounding fields are unavailable, the parameter values k_1 and k_2 are adaptively chosen. Let $\Omega_{\mathtt{MAX}}$ be a set of K brightest pixels in the image. Following the examples of MacAdam's reflectance efficiency theory [1], we are interested in choosing k_1 and k_2 such that pixels in $\Omega_{\mathtt{MAX}}$ are neutral (i.e. close to $l_{\mathtt{Y}}$). Mathematically, we solve the following:

$$\min_{k_1 k_2} \sum_{i\in\Omega_{\mathtt{MAX}}} \|N[\Phi(p_1), \Phi(p_2), \Phi(p_3)]\vec{w}_i\|^2, \quad (9)$$

where $\vec{w}_i$ is the ith pixel value according to (8). If we set $N = BML(\Phi(l_{\mathtt{L}}), 1)$, then the multiplication by N measures the chromaticity difference between $[\Phi(p_1), \Phi(p_2), \Phi(p_3)]\vec{w}_i$ and $l_{\mathtt{Y}}$, normalized by $m_1\Phi(l_{\mathtt{Y}})$. Let $M_1 = L(\Phi(l_{\mathtt{R}}), 1) - I$, $M_2 = L(\Phi(l_{\mathtt{Y}}), 1) - I$, and $\bar{w} = \sum_{i\in\Omega_{\mathtt{MAX}}}\vec{w}_i$. The solution to (9) has a closed form:

$$\begin{bmatrix} k_1 \\ k_2 \end{bmatrix} = \begin{bmatrix} \bar{w}^T M_1^T N^T N M_1 \bar{w} & -\bar{w}^T M_1^T N^T N M_2 \bar{w} \\ -\bar{w}^T M_1^T N^T N M_2 \bar{w} & \bar{w}^T M_2^T N^T N M_2 \bar{w} \end{bmatrix}^{-1} \begin{bmatrix} \bar{w}^T N^T N M_1 \bar{w} \\ -\bar{w}^T N^T N M_2 \bar{w} \end{bmatrix}.$$

Fig. 2. Macbeth Color Chart used to calibrate the camera.

Fig. 3. Images taken with no white-balance algorithms. The solid colors represent illuminants detected by (left) gray-world [11] and (right) method in [16].

4. EXPERIMENTAL RESULTS

The images used in our experiments are taken from Texas Instruments camera evaluation board DM270 DDS, equipped with a Sony 3 mega-pixel CCD sensor and Ricoh lens module. *Unprocessed* raw sensor data is acquired from these cameras, and the experimental results shown below are processed using Matlab codes simulating the image pipeline in a digital camera. The color conversion matrix is calibrated using Macbeth color chart shown in fig. 2, taken on a typical cloudy day in Ithaca, New York (approximates a $D55$ illuminant). A *reader* of this paper should also calibrate her display using fig. 2 in order to see the results properly. We assume that CRT monitor with $\gamma = 2.2$ is viewed with eye adapted to monitor white.

Fig. 3 shows indoor images processed *without* a white-balance algorithm applied. The adjacent solid colors show illuminant estimation using (left) *gray-world* method and (right) the method in [16]. Fig. 4 shows the same sensor data processed with a variety of white-balance methods. In each respective scene, the images in the first row assumed the illuminant estimated from the gray-world method, while the images in the second row assumed the illuminant color estimated from the method in [16]. The images in the left columns were generated using (7), while the images in the right

Table 1. CIELAB Δ_{ab} distance between the *white* panel and a neutral white. *Left, middle, right* correspond to images in fig. 4.

illuminant estimation	chromatic adaptation	Δ_{ab} left	middle	right
gray-world	von Kries	1.2353	1.2526	3.5937
method in [16]	von Kries	3.0351	0.8294	5.2194
gray-world	proposed	0.8454	0.7062	0.8456
method in [16]	proposed	0.8143	0.7062	0.8456

Fig. 4. TI CCD camera sensor data, processed with various white-balance methods. See text.

columns use the proposed formula, (8). The images generated using (7) often suffer from a hazy appearance, while the colors processed using (8) are slightly desaturated. Overall, the images generated by (8) appear more natural than those using (7) (though not perfect). The colors observed in the *white* panels in the Macbeth chart give a rough indication of how well the algorithms work—we would like an object, whose reflectance spectral distribution is constant, to appear neutral in the output image. The solid-color squares in the center of each figure show the colors taken from the *white* panels. Table 1 shows the CIELAB Δ_{ab} distance between the processed white panel color and a neutral white. Compared to the images generated by (7), the images generated by the proposed white-balance formula yield more neutral colors in the *white* panels, regardless of the method of illuminant estimation assumed.

5. CONCLUSION

In this paper, we formulated the white-balance problem using Jameson and Hurvich's induced opponent response chromatic adaptation theory. This is in a sharp contrast to the von Kries approach to the white-balance problem. Approximation with a scaling constant was introduced to operate as if the focal and surrounding fields were isoluminant. The solution to the white-balance problem reduces to a single matrix multiplication. The experimental results, using the basic and the state-of-the-art illuminant estimation methods, verify that the induced opponent response approach to solving the white-balance problem yields more neutral colors in the *white* panels of the Macbeth color chart than the traditional methods. The algorithm is computationally efficient, because it can be combined with the color conversion step in the image pipeline.

6. REFERENCES

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