A Color Constancy Model for Advanced Television Cameras

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ABSTRACT

In high-fidelity color sensing, one may attempt to use recorded video image data from an electronic camcorder to generate a rendering that appears the same as the original image did at the time of acquisition. To achieve the goal, a color constancy mechanism is proposed to perceive the image color from the strengths of three RGB responses of a color camera or the like, independent of the color of the light illuminating the object. Being able to extract the color descriptors that are independent of the illumination is desirable because of the variety of the situation in which color is important, but illumination conditions cannot be controlled. The first step of our method is to use a finite dimensional linear model to estimate the color signals. We have shown that any color signal can be characterized as a linear combination of four principal component basis functions. Once the color signals have been estimated, the unknown illuminant can be determined by solving a constrained least square problem with a normalization equality constraint. Consequently, the surface reflectance is determined automatically. Hence, the color fidelity in video camera has been achieved under the standard light $D_65$.

In this paper, we consider a finite-dimensional approximation to the color signal and not approximations to surface spectral reflectance. It has been shown that any color signal can be expressed in terms of only four principal component functions. Therefore the weighting coefficients of the color signal representation can be determined by solving a set of equations based on the receptor values. In other words, the sensor measurements are transformed into an approximate linear model to the spectral power distribution of the light entering the camera. To achieve the recovery of perceived surface color descriptors which are independent of illuminant, the knowledge of surface spectral reflectance permits us to compute this canonical color constancy descriptors. Once the color signals have been identified, a procedure used to separate the color signal into the desired materials is that of interline transfer. The Toshiba CCD chip of 25mm image size with $1920 \times 1036$ pixels claims to have an amorphous silicon photoconductive surface layer to improve sensitivity. Beside the functions of lightness constancy [15] for improving the quality and dynamic range of image acquisition, one would likely to provide a high-fidelity color reproduction that appears the same as the object color appearance despite variation in the spectral power distribution of the ambient light. The color constancy mechanism is defined as the maintenance of color appearance that is independent of the color of the light illuminating the object.

In their early and important works on color constancy, Land and McCann [3] introduced an algorithm to perform color constancy, which they named the Retinex algorithm. This algorithm was based on the assumption that color information could be processed in three separate wavebands. More recent algorithms [4][5][6][7][8][9] have been investigated based on finite-dimensional linear models of surface reflectance or illuminant functions. These have either required that some form of spatial average of surface color be constant, or have required complex interaction between these functions. Wandell [4] and Maloney [8] started with the idea of describing color spectra with finite-dimensional linear models. The model condenses all spectral information into a few numbers by supposing that illumination and reflectance can each be approximated by weighted sums of basis functions. Making use of the relationship between receptor values and basis function weights, Wandell and Maloney showed how to recover both weights representing surface reflectance and those representing illumination. Another approach to render the correct colors of any color acquisition system under a variety of illuminant conditions is based on the color correction techniques [18][17]. They used eight correction matrices to compensate the actual scene illuminant and reduce the color error in the uniform CIE LUV color space.

In this paper, we consider a finite-dimensional approximation to the color signal and not approximations to surface spectral reflectance. It has been shown that any color signal can be represented by a finite set of basis functions. Therefore the weighting coefficients of the color signal representation can be determined by solving a set of equations based on the receptor values. In other words, the sensor measurements are transformed into an approximate linear model to the spectral power distribution of the light entering the camera. To achieve the recovery of perceived surface color descriptors which are independent of illuminant, the knowledge of surface spectral reflectance permits us to compute this canonical color constancy descriptors. Once the color signals have been identified, a procedure used to separate the color signal into the desired materials is that of interline transfer. The Toshiba CCD chip of 25mm image size with $1920 \times 1036$ pixels claims to have an amorphous silicon photoconductive surface layer to improve sensitivity. Beside the functions of lightness constancy [15] for improving the quality and dynamic range of image acquisition, one would likely to provide a high-fidelity color reproduction that appears the same as the object color appearance despite variation in the spectral power distribution of the ambient light. The color constancy mechanism is defined as the maintenance of color appearance that is independent of the color of the light illuminating the object.

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last section, a number of typical test images are conducted to verify the proposed color constancy mechanism. It is found that the proposed method can recover the correct color descriptors under several lighting conditions.

II. Color Constancy Model

A color sensing device consists of a lens that focuses light reflected from an object onto a planar sensor array. The location of any object is identified with the location on the sensor array to which its image projects. The light arriving at array location \( p = (x, y) \) is called the color signal and denoted by \( I(x, y, \lambda) \), where \( \lambda \) is visible wavelength and \( x \) and \( y \) are the spatial coordinates on the array, and \( T \) is the matrix transpose. The function \( I(x, y, \lambda) \) specifies the quanta/second arriving at \( p \) at each wavelength \( \lambda \) across the electromagnetic spectrum. It is assumed to be a product of the ambient light \( E(\lambda) \) and the surface spectral reflectance at \( p, S(x, y, \lambda) \). At any location in the object, the ambient light is specified by its spectral power distribution which describes the energy per second at each wavelength \( \lambda \), or in units of quanta/sec. In this paper, the spectral power distribution of the light is assumed to be constant over a restricted region of the scene. The ambient light is reflected from surfaces and focused onto the sensor array. The proportion of light of wavelength \( \lambda \) reflected from object toward location \( p \) on the sensor array is determined by the surface spectral reflectance, \( S(x, y, \lambda) \).

At each image location, we assume that there are \( L \) distinct classes of sensors corresponding to their associated sensor sensitivities. In video camera, there are three sensor classes, termed R, G, and B. This comes from color images obtained by taking pictures of the scene, through a red, a green, and a blue color filter. Each sensor quantum catch \( Q_j(x, y, j = 1, 2, ..., L) \) is of the form

\[
Q_j(x, y) = \int I(x, y, \lambda) q_j(\lambda) d\lambda = \int E(\lambda) S(x, y, \lambda) q_j(\lambda) d\lambda
\]

where \( q_j(\lambda) \) is the \( j \)-th sensor sensitivity and takes on only values between \( 0 \) and \( 1 \) inclusive. The information about the scene available to the visual system is contained in the \( L \) sensor quantum catches at each position \( p \). The spectral reflectance at each location \( S(x, y, \lambda) \) is assumed to be unknown.

The color constancy problem usually means that the recovery of perceived surface color descriptor from the strengths of the three \( (L = 3) \) sensors quantum catches representing the RGB responses of a color camera is independent of the light illuminating the object. In other words, color constancy attempts to provide color descriptors that are unaffected by changes in the illuminant and also predict the color appearance of the object under a canonical illuminant. Maloney [4] defines a canonical color descriptor which is a functional of \( S(x, y, \lambda) \) and denoted by \( \psi(S(x, y, \lambda)) \). The functional \( \psi \) takes a function as argument and returns a single real number. An example of a canonical color descriptor \( \psi_j(S(x, y, \lambda)) \) is

\[
\psi_j(S(x, y, \lambda)) = \int D_0(\lambda) S(x, y, \lambda, q_j(\lambda)) d\lambda = \int B_0(\lambda) S(x, y, \lambda, q_j(\lambda)) d\lambda
\]

where \( D_0(\lambda) \) is a CIE standard source corresponding to normal daylight and has color temperature 6500°K.

From (2), it is known that the knowledge of \( S(x, y, \lambda) \) permits us to compute the canonical color descriptors that are independent of the ambient light \( E(\lambda) \). Hence, the purpose of color constancy involves performing the inversion of equation (1), the recovery of the estimates of \( S(x, y, \lambda) \) and the computation of the desired canonical color descriptors. The difficulty inherent in this approach is the mismatch between the amount of information available at the sensor array and the infinitely large number of parameters needed to fully specify each light and reflectance. To tackle this problem, [5] showed that equation (1) becomes invertible when both light and surface reflectance can be represented by a particular class of finite-dimensional linear models. Hence, the color constancy problem becomes solvable.

A. A Finite-Dimensional Representation for Color Signal

Over the visible spectrum \([400\text{nm}-700\text{nm}]\), the surface spectral reflectance curves of natural objects are usually reasonably smooth and continuous. Many experiments on empirical surface spectral reflectances show that most of them can be modeled using only a few basis functions. For example, Cohen [5] found that over 99 percent of the variance of the spectral reflectance functions of the Munsell chips can be expressed using only three principal components. This analysis has been confirmed and extended by Maloney [6]. Higher dimensions result in better approximation, yet three functions still suffice when the filtering effect of the cone response functions is taken into account. The estimate of the surface spectral reflectance corresponding to position \((x, y)\) in the sensor array is expressed as

\[
S(x, y, \lambda) = \sum_{i=1}^{3} a_{ij}(x, y) s_i(\lambda)
\]

where \( s_i(\lambda) \) is the \( i \)-th basis function and \( a_{ij}(x, y) \) is its associated position-dependent coefficient.

Consider approximating the spectral power distribution of light. Judd et al. [6] reported that nearly all of the variations in the spectral power distribution of natural daylight can be described using a linear model consisting of three terms. This was confirmed in the later studies by Satri and Das as well as Maloney [8]. In addition, Maloney [8] has shown that the principal components that describe the observed variations in daylight and also describe the variations across another class of light sources: the blackbody radiators. From these results, the spectral power distributions of lights can be characterized as

\[
E(\lambda) = \sum_{j=1}^{3} \beta_j c_j(\lambda)
\]

where \( c_j(\lambda) \) is the \( j \)-th basis function and \( \beta_j \) is its associated coefficient.

Hence, the color signal \( I(x, y, \lambda) \) at a position in a sensory array can be expressed as a linear combination of nine functionals.

\[
I(x, y, \lambda) = \sum_{j=1}^{3} \sum_{i=1}^{3} \phi_{ij}(x, y) q_j(\lambda) = \sum_{i=1}^{3} \sum_{j=1}^{3} \phi_{ij}(x, y) a_{ij}(x, y)
\]

\[
\phi_{ij}(x, y) = a_{ij}(x, y) \beta_j
\]

In fact, the product terms \( \phi_{ij}(x, y) \) are not guaranteed to constitute a basis for \( I(x, y, \lambda) \) even though \( \{s_i(\lambda)\} \) and \( \{c_j(\lambda)\} \) are bases for \( S(x, y, \lambda) \) and \( E(\lambda) \) respectively. Meanwhile \( \{\phi_{ij}(x, y)\} \) forms a spanning set for the Hilbert space of \( I(x, y, \lambda) \). It is likely to reduce \( \{\phi_{ij}(x, y)\} \) to a linearly independent spanning set by using singular value decomposition (SVD) technique. The SVD is a useful tool for orthogonal decomposition of general rectangular matrices. The application to data analysis is similar to the idea of the well-known principal-component analysis. Let \( \phi_{ij} \) represent an \( nx1 \) column vector consisting \( n \) samples \( \phi_{ij}(x_k, \lambda_k), k = 1, 2, ..., n \) over the visible spectrum \([400\text{nm}-700\text{nm}]\), that is, \( \phi_{ij} = [\phi_{ij}(x_1, \lambda_1), \phi_{ij}(x_2, \lambda_2), ..., \phi_{ij}(x_n, \lambda_n)]^T \) where \( n \) is chosen to be larger than thirty practically. Hence one may use an \( nx9 \) sampling matrix \( \Phi = [\phi_{11}, \phi_{21}, ..., \phi_{91}] \) to describe the whole feature of \( \{\phi_{ij}(x, \lambda)\} \). By performing the singular value decomposition on \( \Phi \), we have

\[
\Phi = U \Sigma V^T
\]

or equivalently

\[
\Phi = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + ... + \sigma_9 u_9 v_9^T
\]
where \( U = [u_1, u_2, \ldots, u_9] \) and \( V = [v_1, v_2, \ldots, v_9] \) are the 9x9 left-hand singular matrix and the 9x9 right-hand singular matrix, respectively, and \( \Sigma \) is the 9x9 diagonal matrix with elements of the singular values \( \sigma_1, \sigma_2, \ldots, \sigma_9 \). The \( n \)-dimensional left-hand singular vectors \( u_1, u_2, \ldots, u_n \) and \( 9 \)-dimensional right-hand singular vectors \( v_1, v_2, \ldots, v_9 \) are both orthonormal eigenvectors of \( \Phi \Phi^T \) and \( \Phi^T \Phi \) respectively. The singular values \( \sigma_i \) are the square roots of the eigenvalues of \( \Phi \Phi^T \) and \( \Phi^T \Phi \) and in descending order. [10] showed that a fairly reliable way to estimate the rank is to compare the singular values by using the following performance index:

\[
R(k) = \sum_{i=k+1}^{9} \sigma_i^2 / \left( \sum_{i=1}^{9} \sigma_i^2 \right)
\]

The approximate rank of \( \Phi \) is defined as the least integer of \( k \)'s such that \( R(k) \) is almost identical to one, i.e., \( |R(k) - 1| \leq \epsilon \), where \( \epsilon \) is a small positive number. The SVD of \( \Phi \) gave the singular values of \( \sigma_1 = 2304.815, \sigma_2 = 722.428, \sigma_3 = 378.058, \sigma_4 = 131.211, \sigma_5 = 33.848, \sigma_6 = 13.614, \sigma_7 = 9.390, \sigma_8 = 2.271, \) and \( \sigma_9 = 1.340 \), when \( n = 31 \). The performance index was \( R(1) = 0.8860, R(2) = 0.9730, R(3) = 0.9969, \) and \( R(4) = 0.9997 \). The contributions of the remaining five components were negligibly small.

For this result, it can be found that the approximate rank of \( \Phi \) is almost identical to four. This implies that the spanning set \( \{ \phi_i(\lambda) \} \) can be replaced by the first four principal component basis vectors which are the left-hand singular vectors \( u_1, u_2, u_3, u_4 \) and shown in Fig.1. It follows that the color signal \( I(x, y, \lambda) \) can be expressed as

\[
I(x, y, \lambda) = \sum_{i=1}^{4} Q_i(x, y) u_i(\lambda)
\]

where \( u_i(\lambda) \) is the \( i \)-th principal component basis function corresponding to \( u_i \) of \( \Phi \) and \( \eta_i(x, y) \) is its associated coefficient. Substituting (8) into (1), it gets

\[
Q_i(x, y) = \sum_{i=1}^{4} \eta_i(x, y) w_{ij}
\]

where \( w_{ij} = \int \phi_i(\lambda) \eta_j(\lambda) d\lambda, 1 \leq i, j \leq 4 \) or equivalently

\[
\bar{Q}_{xy} = W \eta_{xy}
\]

where \( \bar{Q}_{xy} = [Q_1(x, y), Q_2(x, y), Q_3(x, y), Q_4(x, y)]^T \) and \( \eta_{xy} = [\eta_1(x, y), \eta_2(x, y), \eta_3(x, y), \eta_4(x, y)]^T \) are 3x1 and 4x1 column vectors respectively. \( W = [w_{ij}] \) is a 3x4 matrix. Since each sensor quantum catch \( Q_i(x, y) \) at position \((x, y)^T\) is measurable and \( \phi_i \) are then computed, the unknown representation for \( I(x, y, \lambda) \) can be determined by inverting equation (9) or (10). Then we have

\[
\bar{\eta}_{xy} = W^+ \bar{Q}_{xy}
\]

where \( W^+ \) is the Moore-Penrose generalized inverse [12].

### III. General Color Reflection Model

The reflectance is divided into two parts: interface (specular) reflectance and body (diffuse or subsurface) reflectance [11]. The interface reflectance characterizes light reflection at the interface between the object's surface and the air. Reflection from optically inhomogeneous materials like metals and glasses is based mostly on this interface reflectance. Healey [11] showed that a unichromatic reflection model is a reasonable approximation for the homogenous materials. For optically inhomogeneous materials like plastics and paints, the body reflectance becomes significantly. The body reflectance occurs for light that crosses the object's surface, and causes significant scattering among the pigment colorant layer. [11] used the Reimsen body-scattering model to show that the dichromatic reflection model is a reasonable approximation for a large class of optically inhomogeneous materials. Although the surface spectral reflectance varies with the illumination geometries of an object. The model suggests that the spectral reflectance is described as a weighted sum of two functions of the interface and body reflectances under all illumination geometries. Thus an approximate color reflectance model (ACRM) is proposed to combine the dichromatic reflection model for inhomogeneous dielectrics with a unichromatic reflectance model for homogeneous materials. The ACRM model is expressed in the form

\[
I(x, y, \lambda) = \begin{cases} 
C_I(g) I_{s}(\lambda) & \text{for homo.} \\
C_I(g) I_{s}(\lambda) + C_B(g) I_B(\lambda) & \text{for in-homo.} 
\end{cases}
\]

where \( g \) is a scene geometry function indicates dependence on the direction angle \( \theta \), the viewing angle \( \theta \), and the phase angle \( \theta \) of the illumination geometry. By assuming a fixed mapping geometry, it can be shown that the scene geometry \( g \) is a function of image location \((x, y)^T\) at the sensor array [11]. \( I_{s}(\lambda) \) and \( I_B(\lambda) \) are the spectral power distributions of the interface and body reflection components, respectively. These components are unchanged as the geometric angles vary. The weights \( C_I(g) \) and \( C_B(g) \) are the geometric scale factors.

To express the ACRM model in terms of the surface reflectance functions, let \( S_I(\lambda) \) and \( S_B(\lambda) \) be the surface spectral reflectance for the two components of interface and body reflections, and let \( I_E(\lambda) \) be the spectral power distribution of the incident light. Then the color signal at location \((x, y)^T\) in a sensor array is

\[
I(x, y, \lambda) = \begin{cases} 
C_I(g) S_I(\lambda) E(\lambda) & \text{for homo.} \\
C_I(g) S_I(\lambda) E(\lambda) + C_B(g) S_B(\lambda) E(\lambda) & \text{for in-homo.} 
\end{cases}
\]

and equivalently the total reflectance is described as

\[
S_I(x, y, \lambda) = \begin{cases} 
C_I(g) S_I(\lambda) & \text{for homo.} \\
C_I(g) S_I(\lambda) + C_B(g) S_B(\lambda) & \text{for in-homo.} 
\end{cases}
\]

The interface reflectance component \( S_I(\lambda) \) is determined by Fresnel's law [11]. It is reported that many types of materials serving as vehicles in the surface layer are oil based and have constant refractive index. For these surfaces, the interface reflectance component becomes a constant over the visible wavelength.
A. Classification of Materials

From equation (12), it is known that the color signal \( I(x,y,\lambda) \) can be expressed as a linear combination of the two component vectors \( L_r(\lambda) \) and \( L_I(\lambda) \) for the inhomogeneous materials or only a vector \( L_r(\lambda) \) for homogeneous materials. For example, the two vectors \( L_r(\lambda) \) and \( L_I(\lambda) \) span a two-dimensional plane or subspace for the dichromatic model of the inhomogeneous materials. The spanned subspace containing all the possible color signals observed from an inhomogeneous surface is called the color-signal plane \( P \). Similarly, there exists a spanned one-dimensional color-signal plane for the achromatic model of the homogeneous materials. Based on the above discussion, the classification of materials is dependent on the determination of the dimensionalities of their corresponding color-signal planes.

It is assumed that there are \( m \) color signals reflected from a region of the same material and arriving at \( m \) different image locations. Each color signal is sampled at \( n \) points over the visible wavelength. The \( m \) sampled color signals are represented by \( n \)-dimensional column vectors denoted by \( f_i = (I(x, y, \lambda_1), I(x, y, \lambda_2), ..., I(x, y, \lambda_n))^T \), where \( (x, y) \) is the image location for the \( i \)-th color signal where \( 1 \leq i \leq m \). Consequently, the \( m \) color signal vectors span a color signal plane \( P \), and are summarized in an \( n \times m \) observation matrix \( M \) defined by

\[
M = [f_1, f_2, ..., f_m] \tag{15}
\]

The dimensionality of the space spanned by the measured color signals can be identified by the rank of the matrix \( M \). Similarly, one may use the singular performance index \( R(k) = \sigma_1^2 (\sum_{i=1}^n \sigma_i^2)^{-1} \) defined in equation (7) to determine the rank of \( M \), where \( \sigma_i \) is the \( i \)-th singular value of the SVD of the matrix \( M \). If \( R(k) \geq 1.0 \), then the measured data from one dimensional color signal plane. In this case the observation conditions reveal only the interface reflections from the region. It can be concluded that the region contains the inhomogeneous material. For the case of data having a higher dimensionality than two, it can be concluded that the ACRM model is in error for this material.

B. Estimation of Illuminant and Surface Reflectances

More recently, Ho, Funt, and Drew [9] proposed a separation algorithm to extract the illuminant from a color signal. Unfortunately, it is found that their method is not very efficient. Another cost-effective approach to estimate the illuminant is proposed in appendix 1. It is noted that the illuminant vector is contained in both planes. Consequently, the process of extracting an illuminant spectrum can be reduced to a computational problem of finding an intersection of two color signal planes. The intersection formulation can be extended to the case of three or more materials. All the planes must intersect at only a common line corresponding to the illuminant spectrum.

For the case of two inhomogeneous materials, The SVDs of the observation matrices for both \( P(1) \) and \( P(2) \) become

\[
M_1 = U_1 \Sigma_1 V_1^T = \sigma_1 u_1^T \vec{v}_1 \quad \text{and} \quad M_2 = U_2 \Sigma_2 V_2^T = \sigma_2 u_2^T \vec{v}_2 \tag{17}
\]

The color signal planes \( P(i) \) \( (i = 1, 2) \) are constructed by a set of two vectors \( L_r(\lambda) \) and \( S_B(\lambda)E(\lambda) \). It is noted that illuminant vector is contained in both planes. Consequently, the process of extracting an illuminant spectrum can be reduced to a computational problem of finding an intersection of two color signal planes. The intersection formulation can be extended to the case of three or more materials. All the planes must intersect at only a common line corresponding to the illuminant spectrum.

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\[ \hat{E} = r_1^{\text{mm}} u_1^i + r_2^{\text{mm}} u_2^j \]  
(22.a)

or

\[ \hat{E} = -r_1^{\text{mm}} u_1^i - r_2^{\text{mm}} u_2^j \]  
(22.b)

where \( r_{imm} \) is the \( ith \) component of \( r_{mm} \).

It should be noted that the method of estimating the illuminant is also true when the scene contains more than two inhomogeneous materials. Once the spectral power distribution of illumination is identified, the remainder of the problem is straightforward. The estimate of total surface reflectance at \((x,y)\) can then be computed using

\[ \hat{S}(x,y,\lambda) = \hat{R}(x,y,\lambda)/\hat{E}(\lambda) \]

(23)

where \( f(x,y,\lambda) \) is the estimated color signal and \( \hat{g}(x,y) \) is the \( ith \) weighting coefficient.

IV. Experimental Results

A laboratory setup has been used to test the above algorithm. Color images are digitized using a Sony XC-711 CCD camera and gelatin filter. The camera is equipped with a primary color vertical stripe filter which gives color separation. Fig.2 illustrates the spectral sensitivity characteristics of the sensors. These curves have been taken from manufacturer's specifications.

To demonstrate the effectiveness of the proposed color constancy method, a test pattern made of two different inhomogeneous materials, that is, yellow and brown NPL ceramic tiles with shadows, is particularly considered in our simulation. Assume that this test pattern is illuminated under two different typical light sources illuminant \( A \) and illuminant \( C \) which are defined in Wyszecki and Stiles [14]. Illuminant \( A \) and illuminant \( C \) are termed as the incandescent lamp and the correlated average daylight which have color temperatures 2854°K and 6770°K respectively. The images of test pattern taken under illuminant \( A \) and illuminant \( C \) are shown in Fig.6 and Fig.7 respectively. It is observed that the color appearances of both images seem quite different. To predict what an image would have looked like under a canonical illuminant \( D_65 \), the color signals at sensor array should be identified by performing equation (11) based on the sensor measurements. The estimated color signals at three typical sensor locations under illuminant \( A \) and illuminant \( C \) are shown in Fig.3.a and Fig.3.b respectively. For comparison, the dashed curves for the estimated color signals are approximately the same as the solid curves for the actual color signals. Next, one may use equation (22) to estimate the spectral power distributions of illuminant \( A \) and illuminant \( C \). Both the estimated illuminants are shown in Fig.4.a and Fig.4.b. Finally, the resultant surface reflectances at three typical sensor locations derived from images under illuminant \( A \) and illuminant \( C \) are shown in Fig.5.a and Fig.5.b. As expected, the estimation method yields satisfactory approximations to the actual surface reflectances. Fig.8 and Fig.9 are the images of the color descriptors under the canonical illuminant \( D_65 \) which are derived from the estimated surface reflectances of Fig.4.a and Fig.4.b respectively. For comparison, it turns out that the color appearances of both Fig.8 and Fig.9 are quite similar to that of the actual canonical color descriptor shown in Fig.10.

V. Conclusion

We have shown that any color signal can be characterized as a linear combination of four principal component basis functions. Hence the weighting coefficients of the color signal representation are identified by solving a system of equations based on the ICB responses of a color camera. Furthermore, it has indicated that the Tommenga and Wandell's illuminant estimation problem can be reformulated as solving a constrained least square error problem. Once both color signals and illuminant have been estimated, the surface reflectance is then computed automatically.
Fig. 4.a The Estimated SPD of Light Source

Fig. 4.b The Estimated SPD of Light Source

Fig. 5.a The estimated Reflectances of 3 typical sensor locations

Fig. 5.b The estimated Reflectances of 3 typical sensor locations

Fig. 6 Image of test pattern under illuminant A

Fig. 7 Image of test pattern under illuminant C

Fig. 8 Image derived from Fig. 5.a and under canonical D65
It is shown that \( \mathbf{r} \) and \( \lambda = (-\gamma) \) are an eigenvector and an eigenvalue of \( \mathbf{A}^T \mathbf{A} \) respectively. Substituting (A.4) and (A.5) into (A.2), we have

\[
L(\mathbf{r}, \lambda) = \lambda
\]

(A.6)

If \( \mathbf{r} \) is chosen to have minimum eigenvalue \( \lambda_{\text{min}} \), such that 

\[
L(\mathbf{r}_{\text{min}}, \lambda_{\text{min}}) \leq L(\mathbf{r}, \lambda) \quad \text{for all } \mathbf{r}
\]

VII. REFERENCE

Po-Rong Chang (M'87) received the B.S. degree in electrical engineering from the National Tsing Hua University, Taiwan, in 1980, the M.S. degree in telecommunication engineering from National Chiao-Tung University, Hsinchu, Taiwan, in 1982, and the Ph.D. degree in electrical engineering from Purdue University, West Lafayette, IN, 1988.

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