Temporal-color space analysis of reflection

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We propose a novel method to analyze a sequence of color images. A series of color images is examined in a four-dimensional space, which we call the temporal-color space, whose axes are the three color axes red, green, and blue and one temporal axis. The significance of the temporal-color space lies in its ability to represent the change of image color with time. A conventional color space analysis yields a histogram of the colors in an image, only for an instant of time. Conceptually, the two reflection components from the dichromatic-reflection model, the specular-reflection component and the body-reflection component, form two subspaces in temporal-color space. These two components can be extracted at each pixel in the image locally. Using this fact, we analyzed real color images and separated the two reflection components successfully. We did not make any assumptions about surface properties or the global distribution of surface normals. Finally, object shape was recovered.

1. INTRODUCTION

Color spaces, especially the red–green–blue (RGB) color space, have been widely used by the computer vision community to analyze color images. The first application of color space analysis was image segmentation by partitioning a color histogram into Gaussian clusters.1 Shafer proposed that, illuminated by a single light source, a cluster of uniformly colored dielectric objects in the color space forms a parallelogram defined by two color vectors, namely, the specular-reflection vector and the body-reflection vector.2 This is also known as the dichromatic-reflectance model.3 Subsequently, Klinker et al.4,5 demonstrated that the cluster actually forms a T shape instead of a parallelogram in the color space, and they separated the body-reflection component and the specular-reflection component by geometrically clustering a scatterplot of the image in the RGB color space. They used the separated body-reflection component for segmentation of a color image without its suffering from disturbances of highlights in the image. This method is based on the assumption that the directions of the surface normals in an image are widely distributed in all directions. This assumption guarantees that both the body-reflection vector and the specular-reflection vector will be visible. Therefore their algorithm cannot handle cases in which only a few planar surface patches exist in the image. Recently Novak6 examined the features of clusters caused by surface roughness and interreflection.

Techniques to separate the two reflection components by using a polarization filter have also been studied. Wolff7 has shown that the specular-reflection component can be successfully separated from the body-reflection component in a black-and-white image by use of a polarization filter. Recently Nayar et al.8 introduced the technique to separate the two reflection components by using polarization in the case of a color image and produced impressive experimental results. Recently, Funt and Drew introduced an algorithm to separate two different body-reflection components, no-bounce body reflection and one-bounce body reflection, from reflection on convex surfaces of uniform color and diffuse reflectance.9 We found that the algorithm that we introduce in this paper is equivalent to their algorithm in the sense that one can separate two reflection components by using their different colors.

Two other techniques that have been used to analyze images are shape-from-shading and photometric stereo. The shape-from-shading technique introduced by Horn10 recovers object shapes from a single intensity image. In this method one can calculate surface orientations, starting from a chosen point whose orientation is known a priori, by using the characteristic strip expansion method. Ikeuchi and Horn11 developed a shape-from-shading technique that uses occluding boundaries of an object to calculate surface orientation iteratively. Woodham12 proposed a new technique for shape recovery that uses multiple images with different light source locations. His technique does not rely on assumptions such as the surface smoothness constraint. Nayar et al.13 developed a technique for recovering object shape and reflectance without any knowledge of surface reflectance. The techniques used by Woodham and Nayar are collectively called photometric stereo; the object shape is recovered based on intensity change that is due to different light source directions.

In this paper we propose a new technique to analyze object shape and surface properties from color images. We observe how the color of the image changes with a moving light source in a four-dimensional RGB-plus-light-direction space, which we call the temporal-color space. (The temporal-color space is defined in Subsection 2.C.) The proposed technique does not require any knowledge
of surface reflectance. Only local information is needed in our analysis. In other words we can recover the surface orientation and reflectance based on color change at each pixel individually. This method has been successfully applied to real color images, resulting in the decomposition of pixel intensities into the specular- and body-reflection components, which are subsequently used to recover surface orientation and reflectance.

In Section 2 the temporal-color space is introduced and compared with the spaces currently used in color and photometric analysis. Our proposed algorithm to decompose reflection into the two reflection components in the temporal-color space is described in Section 3. The results of experiments conducted using objects of different types of material are presented in Section 4. Finally, we conclude this paper in Section 5.

2. TEMPORAL-COLOR SPACE

The spaces most commonly used in color space analysis and in photometric stereo are the RGB color space and the $I-\theta_s$ (image intensity–light source direction) space, respectively. In this paper we propose a new space called the temporal-color space in order to analyze color change with time, which cannot be analyzed in either the RGB color space or the $I-\theta_s$ space. In this section we describe these three spaces and their relationships with one another. Note that, in this paper, the term pixel value refers to pixel intensity.

A. RGB Color Space

An image intensity $I$ is determined by the spectral distribution of incident light to the camera $h(\lambda)$ and the camera response to the various wavelengths $s(\lambda)$, i.e.,

$$I = \int s(\lambda)h(\lambda)d\lambda. \quad (1)$$

A color camera has color filters attached in front of its sensor device. Each color filter has a transmittance function $\tau(\lambda)$ that determines the fraction of light transmitted at each wavelength $\lambda$. Then, pixel intensities $I_R$, $I_G$, and $I_B$ from red, green, and blue channels of the color camera are given by the following integrations:

$$I_R = \int \tau_R(\lambda)s(\lambda)h(\lambda)d\lambda,$$

$$I_G = \int \tau_G(\lambda)s(\lambda)h(\lambda)d\lambda,$$

$$I_B = \int \tau_B(\lambda)s(\lambda)h(\lambda)d\lambda, \quad (2)$$

where $\tau_R(\lambda)$, $\tau_G(\lambda)$, and $\tau_B(\lambda)$ are the transmittance functions of the red, green, and blue filters, respectively. The three intensities $I_R$, $I_G$, and $I_B$ form a $3 \times 1$ color vector $C$ that represents the color of a pixel in the RGB color space:

$$C = \begin{bmatrix} I_R \\ I_G \\ I_B \end{bmatrix} = \begin{bmatrix} \int \tau_R(\lambda)s(\lambda)h(\lambda)d\lambda \\ \int \tau_G(\lambda)s(\lambda)h(\lambda)d\lambda \\ \int \tau_B(\lambda)s(\lambda)h(\lambda)d\lambda \end{bmatrix}. \quad (3)$$

Klinker et al.\textsuperscript{4,5} demonstrated that the histogram of dielectric object color in the RGB color space forms a T shape (Fig. 1). They clustered the two components of the T shape in order to separate the specular-reflection component and the body-reflection component.

A significant limitation of the method is that it works only when surface normals in the image are well distributed in all directions. Suppose that the image has only one planar object illuminated by a light source that is located far away from the object. Then, all the pixels on the object are mapped to a single point in the color space because observed color is constant over the object surface. The T shape converges to a single point in the RGB color space that represents the color of the object, because the plane has uniform color. As a result, we cannot separate the reflection components. This indicates the dependence of the method on global information, and thus it cannot be applied locally.

B. $I-\theta_s$ (Intensity–Light Source Direction) Space

Nayar et al.\textsuperscript{13} analyzed an image sequence given by a moving light source in the $I-\theta_s$ space. They consider how the pixel intensity changes as the light source direction $\theta_s$ varies in the viewer-centered coordinate system (Fig. 2).

The pixel intensity from a monochrome camera is written as a function of $\theta_s$:

$$I(\theta_s) = g(\theta_s)\int s(\lambda)h(\lambda)d\lambda, \quad (4)$$

where $g(\theta_s)$ represents intensity change with respect to

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\textsuperscript{1} Klinker et al.

\textsuperscript{4} Y. Sato and K. Ikeuchi

\textsuperscript{5} Nayar et al.
Each point in the space is represented by the light source omitted, the temporal-color space becomes equivalent to the RGB color space, and when two color axes are axis omitted, the temporal-color space becomes equivalent to the RGB color space and the temporal-color space implies an augmentation of the RGB color space with an additional dimension that varies with time. This dimension represents the geometric relationship among the viewing direction, the illumination direction, and the surface normal orientation. Here we keep the viewing direction and the illumination direction fixed and varied the viewing direction or if we kept the illumination direction fixed and varied the viewing direction. However, as an approximation, we assume that the function $h(\lambda)$ is independent of these factors. The vector $p(\theta_s, I(\theta_s))$ shows how pixel intensity changes with respect to light-source direction in $I-\theta_s$ space (Fig. 3).

As opposed to analysis in the RGB color space, the $I-\theta_s$ space analysis is applied locally. All the necessary information is extracted from the intensity change at each individual pixel. Nayyar et al. used the $I-\theta_s$ space to separate the surface-reflection component and the body-reflection component, using a priori knowledge of the geometry of the photometric sampler.\(^{13}\)

C. Temporal-Color Space
Neither the RGB color space nor the $I-\theta_s$ space can be used to separate the two reflection components by using local pixel information without resorting to relatively strong assumptions. To address this weakness we propose a new four-dimensional space, which we call the temporal-color space. The four-dimensional space is spanned by the B, G, R, and $\theta_s$ axes. The term temporal-color space implies an augmentation of the RGB color space with an additional dimension that varies with time. This dimension represents the geometric relationship among the viewing direction, the illumination direction, and the surface normal. Here we keep the viewing direction and the surface normal orientation fixed. We vary the illumination direction with time, taking a new image at each new illumination direction. (The same information could be obtained if we kept the illumination direction and the surface normal’s orientation fixed and varied the viewing direction or if we kept the viewing direction and the illumination direction fixed and varied the surface normal orientation.)

The temporal-color space can be thought of as a union of the RGB color space and the $I-\theta_s$ space. When the $\theta_s$ axis is omitted, the temporal-color space becomes equivalent to the RGB color space, and when two color axes are omitted, the temporal-color space becomes the $I-\theta_s$ space. Each point in the space is represented by the light source direction $\theta_s$ and the color vector $C(\theta_s)$, which is a function of $\theta_s$:

$$p(\theta_s, C(\theta_s)) = \left[ \begin{array}{c} I_g(\theta_s) \\ I_r(\theta_s) \\ I_b(\theta_s) \end{array} \right] \left[ \begin{array}{c} g(\theta_s) \\ \int \tau_R(\lambda)s(\lambda)h(\lambda)d\lambda \\ \int \tau_G(\lambda)s(\lambda)h(\lambda)d\lambda \end{array} \right].$$

The temporal-color space represents how the observed color of a pixel $C(\theta_s)$ changes with time while the direction of the light source $\theta_s$ changes (Fig. 4). Note that, in Fig. 4, the dimensions of the temporal-color space are reduced from four to three for clarity. In this diagram one axis of the RGB color space is ignored.

3. DECOMPOSITION OF REFLECTION

A. Reflectance Model
The hybrid reflectance model (Appendix A) proposed by Nayar et al.\(^{13}\) is used as the reflectance model for dielectric materials in our experiments. From Eqs. (A8) and (A9) of Appendix A, the pixel value $I(\theta_s)$ in the viewer-centered coordinate system (Fig. 2) is given by

$$I(\theta_s) = I_{body}(\theta_s) + I_{specular}(\theta_s)$$
$$= K_L I_{L}(\theta_s - \theta_n) \cos(\theta_s - \theta_n)$$
$$+ K_S I_{S}(\theta_s - \theta_n) \delta(2\theta_n - \theta_s),$$

(7)

$$K_L = \int \lambda s(\lambda)c(\lambda) c_L(\lambda) d\lambda,$$

(8)

$$K_S = c_s \int \lambda s(\lambda)c(\lambda) d\lambda,$$

where $c(\lambda)$ is the spectral distribution of incident light, $L(\theta_s - \theta_n)$ is the geometrical term of the incident light [Eq. (A6)], $s(\lambda)$ is the spectral response of the camera, and $c_L(\lambda)$ and $c_s$ are the spectral reflectance distributions of the body-reflection component and the specular-reflection component, respectively [Eq. (A3)]. In Eqs. (7) and (8), $L(\theta_s - \theta_n) \cos(\theta_s - \theta_n)$ and $L(\theta_s - \theta_n) \delta(2\theta_n - \theta_s)$ correspond to $g(\theta_s)$ in Eq. (4); $c(\lambda)c_L(\lambda)$ and $c_s c(\lambda)$ correspond to $h(\lambda)$ in Eq. (4).

$I(\theta_s)$ for an extended light source obeys the following formula (Appendix B):

$$I(\theta_s) = K_L \cos(\theta_s - \theta_n) + K_S L(\theta_s - 2\theta_n).$$

(9)

The hybrid reflectance model is valid when there is no interreflection and there is only one light source. Therefore our algorithm cannot be applied when there is interreflection or when there are multiple light sources with different spectral distributions. Our algorithm can be applied only to images taken under the illumination of a single spectral distribution in the absence of interreflection.

![Fig. 4. Temporal-color space (synthesized data).](image-url)
B. Decomposition of Reflection in the Temporal-Color Space

In this subsection the algorithm used to separate the two reflection components in the temporal-color space is described. Red, green, and blue filters are used; the coefficients $K_L$ and $K_S$, in Eq. (8) become two linearly independent vectors, $K_L$ and $K_S$, unless the colors of the two reflection components are accidentally the same:

$$K_L = \begin{bmatrix} k_{LR} \\ k_{LG} \\ k_{LB} \end{bmatrix} = \begin{bmatrix} \int \tau_R(\lambda)s(\lambda)c(\lambda)\gamma_L(\lambda)d\lambda \\ \int \tau_G(\lambda)s(\lambda)c(\lambda)\gamma_L(\lambda)d\lambda \\ \int \tau_B(\lambda)s(\lambda)c(\lambda)\gamma_L(\lambda)d\lambda \end{bmatrix}, \quad (10)$$

$$K_S = \begin{bmatrix} k_{SR} \\ k_{SG} \\ k_{SB} \end{bmatrix} = \begin{bmatrix} c_s\int \tau_R(\lambda)s(\lambda)c(\lambda)d\lambda \\ c_s\int \tau_G(\lambda)s(\lambda)c(\lambda)d\lambda \\ c_s\int \tau_B(\lambda)s(\lambda)c(\lambda)d\lambda \end{bmatrix} \cdot \quad (11)$$

These two vectors represent the colors of the body- and specular-reflection components in the dichromatic reflectance model.\(^3\)

First, the pixel intensities in the R, G, and B channels with $m$ different light-source directions are measured at one pixel. It is important to note that all the intensities are measured at the same pixel. The intensity values are shown in Fig. 5.

The three sequences of intensity values are stored in the columns of an $m \times 3$ matrix $I$. The matrix is called the temporal-color matrix. Considering the hybrid reflectance model and two color vectors in Eqs. (9)–(11), the intensity values in the R, G, and B channels can be represented as

$$I = [I_R\ I_G\ I_B]$$

where the two vectors $D_L$ and $D_S$ represent the intensity values of the body- and specular-reflection components with respect to the light source direction $\theta_a$. Vector $K_L$ represents the body-reflection color vector; vector $K_S$ represents the specular-reflection color vector. We call the two matrices $D$ and $K$ the geometry matrix and the color matrix, respectively. The color vectors and the $\theta_a$ axis span the space in the temporal-color space. We call the space spanned by the color vector $K_S^T$ and the $\theta_a$ axis the body-reflection plane, and the space spanned by the color vector $K_S^T$ and the $\theta_a$ axis the specular-reflection plane.

In the case of a conductive material, such as metal, Eq. (12) becomes

$$I = [I_R\ I_G\ I_B]$$

because only the secular-reflection component exists.

Suppose we have an estimation of the color matrix $K$. Then we can obtain the two reflection components represented by the geometry matrix $D$ by projecting the observed reflection stored in $I$ onto the two color vectors $K_L$ and $K_S$:

$$D = IK^+, \quad (14)$$

where $K^+$ is a $3 \times 2$ pseudoinverse matrix of the color matrix $K$.

This derivation is based on the assumption that the color matrix $K$ is known. It can be seen from Eq. (11) that the specular-reflection color vector is the same as a light source color vector. Several algorithms have been proposed to estimate illuminant color.\(^{14,15}\)

1. Estimation of Illuminant Color

(1) According to the dichromatic reflection model,\(^3\) the color of reflection from a dielectric object is a linear combination of the body-reflection component and the specular-reflection component. The color of the specular-reflection component is equal to the illuminant color. In the $x$–$y$ chromaticity diagram, the observed color of the dielectric object lies on a segment whose end points represent the colors of the body- and specular-reflection components. By representing the color of each object as a segment in the chromaticity diagram, one can determine the illuminant color from the intersection of the two segments attributed to the two objects of interest (Fig. 6).\(^{14,15}\)

(2) Tominaga and Wandell\(^{15}\) indicated that the spectral power distributions of all possible observed color of a dielectric object with a highlight exist on the plane spanned by the spectral power distributions of the body-reflection component and the specular-reflection component. They called this plane the color signal plane. Each object color forms its own color plane. The spectral power distribution of the specular-reflection component, which is the
same as the spectral power distribution of the illuminant, can be obtained by taking the intersection of the color planes. The singular-value decomposition technique was used to determine the intersection of color planes.

In our experiment we estimate the row $K_S^T$ of the color matrix $K$, which represents illumination color, using a method that is similar to the first method described above. First, several pixels of different colors in the image are manually selected (Fig. 7). The observed reflection color from those selected pixels is a linear combination of the body-reflection component and the specular-reflection component. By plotting the observed reflection color of each pixel in the $x$-$y$ chromaticity diagram over the image sequence, we obtain several line segments in the $x$-$y$ chromaticity diagram. The illuminant color can then be determined by the intersection of those line segments in the diagram. This is shown in Fig. 6 for the case of the real image shown in Fig. 7.

This technique is limited to the case for which there are objects of different colors in the image. In other words, if the image contains objects of only one color the light-source color cannot be estimated. In these cases one can obtain the illumination color by measuring the color vector of the light source directly.

However, the other row $K_L^T$ of the color matrix cannot be obtained in the same manner because it depends on the material of the object. Fortunately, to solve this problem we can use the fact that the distribution of the specular-reflection component for the extended light source is limited to a fixed angle $2\alpha$, determined by the geometric relation between the diffuser and the point light source [Eqs. (B1) and (B2) of Appendix B]. This fact results in the following important lemma.

2. Estimation of the Color Vector of the Body-Reflection Component

If two vectors, $w_i = [I_1 I_2 I_3]^T (i = 1, 2)$, are sampled on the $\theta_e$ axis at an interval greater than $2\alpha$, at least one of these vectors is equal to the color vector of the body-reflection component $K_L^T$. This vector has no specular-reflection component. It is guaranteed that both vectors $w_i$ exist in the row space of the color matrix $K$ spanned by the base $K_L^T$ and $K_S^T$. Therefore the desired color vector of the body-reflection component $K_L^T$ is the vector $w_i$ that subtends the largest angle with respect to the vector $K_S^T$ (Fig. 8). The angle between the two color vectors can be calculated as

$$\beta = \cos^{-1} \frac{K_S^T \cdot w_i}{|K_S^T||w_i|}.$$  

Once we get the color matrix $K$, the geometry matrix $D$ can be calculated from Eq. (14) (Fig. 9). Once matrix $D$ has been obtained, the loci of the body-reflection component and the specular-reflection component in the temporal-color space can be extracted as shown in Eqs. (16) and (17):
\[ I_{\text{body}} = D_L K_L^T, \quad I_{\text{specular}} = D_S K_S^T. \]

The loci on the body-reflection plane and the specular-reflection plane are shown in Fig. 10. Note that the dimensions of the temporal-color space are reduced from four to three for clarity. In this diagram the blue channel is omitted.

4. EXPERIMENTAL RESULTS

A. Experimental Setup

The algorithm outlined in this paper was applied to color images of several kinds of object, a shiny dielectric object, a matte dielectric object, and a metal object, in order to demonstrate the feasibility of the proposed algorithm. The surface normal and the albedo of the objects were obtained by use of the algorithm. The algorithm was applied to the metal object to demonstrate that it also works in the case in which only the specular-reflection component exists. The algorithm was subsequently applied to each pixel of the entire image to extract the needle map of the object in the image. The object shape was recovered from the needle map. Finally, the decomposed two-reflection components are used to create image sequences of each of the two reflection components.

In our experiment a lampshade with a diameter of 20 in. (51 cm) was used as the light diffuser. The object was placed inside the spherical diffuser. It is important to note that the use of the light diffuser for generating an extended light source is not essential for the algorithm to separate two reflection components. It is used only to avoid camera saturation when input images are taken. With the light diffuser, highlights observed on objects become less bright and are distributed to larger area of the objects’ surfaces. The algorithm introduced in this paper can be applied to images taken without a light diffuser when the objects are not very shiny. A Sony CCD video camera module Model XC-57 to which three color filters (#25, #58, #47) are attached is placed at the top of the diffuser. A point light source attached to a Puma 560 manipulator is moved around the diffuser on its equatorial plane. The whole system is controlled by a Sun Sparc workstation through a LISP program. A geometry of the experimental setup is shown in Fig. 11. The maximum dispersion angle \( \alpha \) [Eq. (B2)] of the extended light source is determined by the fixed diameter \( R \) and the distance from the point light source to the surface of diffuser \( H \), which is controlled from a workstation (Fig. 12).

B. Fitting Algorithm

After the geometry matrix \( \mathcal{D} \) has been recovered, the two curves [Eqs. (18) and (19)] are fitted to the body- and specular-reflection components, respectively. A Gaussian curve is used as the approximation of \( L(2\theta_s - \theta_a) \) [Eqs. (B1), (B2), and (B4)] of the specular-reflection component:

\[ A_1 \cos(\theta_s - A_2) + A_3, \quad (18) \]
\[ B_1 \exp \left[ \frac{-\left(\theta_s - B_2\right)^2}{B_3^2} \right]. \quad (19) \]

\( B_2/2 \) and \( A_2 \) are the directions of the surface normal. \( B_1 \) and \( A_1 \) are the albedos of the specular- and body-reflection components, respectively.
the temporal-color space (Fig. 14) has been successfully decomposed into the body- and specular-reflection components by use of our algorithm described in Subsection 3.B.

The body-reflection plane and the specular-reflection plane are shown in Fig. 17. This diagram is the result of viewing Fig. 16 along the \( \theta_r \) axis. Note that the slope of the specular-reflection plane is 45° in the diagram. This is because the specular-reflection vector [Eq. (11)] has been normalized to

\[
K_S = \left( \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \right). \tag{20}
\]

The body-reflection plane is shifted toward the green axis because the color of the observed object is green in this experiment.

The result of the fitting procedure described in Subsection 4.B is shown in Fig. 18. From the result we obtain the direction of the surface normal and the albedos as follows: the surface normal \( (B_2/2) = 52.09° \), the albedo of the specular-reflection component \( (B_1) = 230.37 \), and the albedo of the body-reflection component \( (A_1) = 75.00 \). Notations \( A_1, B_1, \) and \( B_2 \) follow Eqs. (18) and (19).

D. Matte Dielectric Object

A green plastic cylinder with a relatively rough surface was used in this experiment (Fig. 19). The measured intensities are plotted in the temporal-color space (Fig. 20).
colors of the two plastic objects despite their different surface roughnesses.

Figure 22 depicts the result of curve fitting to the two decomposed reflection components. The surface normal and the albedos of the two reflection components obtained are the surface normal \( B_2/2 = 49.61^\circ \), the albedo of the specular-reflection component \( B_1 \) 219.83, and the albedo of the body-reflection component \( A_1 \) 308.1.

Note that the standard deviation of the Gaussian curve that represents the specular-reflection component \( B_3 \) in Eq. (19) is 26.68. This value is greater than that of the shiny plastic object (13.56). The difference is consistent with the fact that the matte object's surface roughness is larger than the shiny object's surface roughness. Further study is necessary to make any quantitative statement about the relationship between the standard deviation and the surface roughness.

E. Metal Object

The dichromatic-reflection model\(^9\) cannot be applied to nondielectric objects such as a metallic specular object. As an example of these objects, an aluminum triangular prism was used in this experiment (Fig. 23). This type of material does not have the body-reflection component but only the specular-reflection component. This results in the fact that the matrix \( J \) has a rank of 1 when the object is metallic.

The measured intensities shown in Fig. 24 indicate that the reflection from the aluminum triangular prism possesses only the specular-reflection component. This observation is justified by the result of the decomposition in the same manner as explained in Subsection 3.B. Note that the width of the specular-reflection component is larger than that in the previous experiment. This is attributed mainly to different surface roughnesses of two plastic cylinders. It seems that the width can be an important and revealing indication of surface roughness from observed images. The interpretation of the width is a subject of further study.

The intensity is decomposed into the two reflection components according to the algorithm shown in Subsection 3.B. The result of the decomposition is shown in Fig. 21. Note that the directions of the specular-reflection plane and the body-reflection plane are the same as those for the shiny green plastic cylinder (see Subsection 4.C). The specular-reflection plane does not change its direction because the color of the specular-reflection component \( K_S \) is that of the light source (Fig. 10). In other words, the specular-reflection component has the same spectrum as the light source. Also, the correspondence of the direction of the body-reflection component is due to the similarity of surface
The resulting needle map is shown in Fig. 27. We obtained the depth map of the purple plastic cylinder by a simple integration method. Figure 28 depicts the resulting depth map.

G. Generating Body-Reflection Image and Specular-Reflection Image

By using the pixel-based separation algorithm, we can easily generate images of the two reflection components. The algorithm was applied to all the pixels of the input images locally, and each separated reflection component was used to generate the body-reflection image and of the two reflection components (Fig. 25). The body-reflection component is negligibly small compared with the specular-reflection component.

F. Shape Recovery

In the previous subsections the decomposition algorithm was applied to real color images in order to separate the two reflection components using intensity change at a single pixel. In other words, the reflection components were separated locally. After this separation the surface normal and the albedo at each pixel were obtained by nonlinear curve fitting of the two reflection component models [Eqs. (18) and (19)] to the decomposed reflection components. The surface normals of the pixel are $B_2/2$ and $A_2$, and the albedos are $B_1$ and $A_1$ in Eqs. (18) and (19). We repeated the same operation over all pixels in the image to obtain surface normals over the entire image. Then the needle map and the depth map of the object in the image were obtained from these recovered surface normals.

We used a purple plastic cylinder as the observed object in this experiment. The image is shown in Fig. 26. Results of the curve fitting of the body-reflection component were used to obtain surface normal directions.
that the input image is successfully decomposed into the images of the two reflection components, even though the input image has a complex object with many color regions on the surface. This is because the proposed algorithm is pixel based and does not require global information. In this kind of situation the traditional separation algorithm based on the RGB color histogram would easily fail because clusters in the RGB color space become crowded and obscure, so that clustering in the RGB space becomes impossible. On the other hand, since our algorithm is pixel based and applied to each pixel separately, the two reflection components can be successfully separated even in the face of inconspicuous specular reflection.

5. CONCLUSIONS

We have proposed temporal-color space analysis as a new concept for color image analysis in which the body-reflection component and the specular-reflection component from the dichromatic-reflection model span subspaces. We have presented an algorithm to separate the two reflection components at each pixel from a sequence of color images and to obtain the surface normal and the albedo without prior knowledge of the reflectance properties. The significance of our method lies in its use
of local (i.e., pixel-based) and not global information of intensity values in the images. This characteristic separates our algorithm from previously proposed algorithms for segmenting the body-reflection component and the specular-reflection component in the RGB color space.

Our algorithm has been applied to objects of different materials to demonstrate the algorithm's effectiveness. We have successfully separated the two reflection components in the temporal-color space and have obtained surface normals and albedos of the two reflection components. In addition, we are able to reconstruct the shapes of the objects.

APPENDIX A: HYBRID REFLECTANCE MODEL

A mechanism of reflection is described in terms of three reflection components, namely, the specular spike, the specular lobe, and the diffuse lobe. These reflection components are represented by the Beckmann–Spizzichino model, the Torrance–Sparrow model (or the Beckmann–Spizzichino model), and the Lambertian model, respectively. The model of reflection mechanism that accounts for all three components is usually too complicated to be used for actual applications: it is useful to simplify this reflection model into a simpler form. On a rough surface, distributions of the specular spike and the specular lobe with respect to a light source direction θ have a large overlap around a specular angle. As a result it is not easy to separate these two components. On the other hand, the two distributions converge into a narrow angle around the specular angle when the wavelength is comparable with the surface roughness, i.e., when the surface is reasonably smooth. Therefore the specular spike and the specular lobe can be combined as the specular-reflection component as a reasonable approximation. A unit impulse function is used to approximate the specular component. The Lambertian model is also used to represent the diffuse lobe component, which is also called the body-reflection component.

The reflectance model that has the specular- and body-reflection components is called the hybrid reflectance model by Nayar et al. Nayar et al. used the hybrid reflectance model for analyzing reflection, which includes both the surface- and body-reflection components. In the hybrid reflectance model the intensity of an image in each pixel is expressed as

$$I = I_L + I_S,$$  \hspace{1cm} (A1)

where $I_L$ is the body-reflection component and $I_S$ is the specular-reflection component.

The dichromatic-reflection model in the two-dimensional planar case can be represented in terms of the bidirectional spectral-reflectance distribution function proposed by Nicodemus et al. as

$$f_r(\theta_1, \theta_r, \lambda) = c_L(\lambda)g_L(\theta_1, \theta_r) + c_S g_S(\theta_1, \theta_r),$$  \hspace{1cm} (A2)

where $f_r$ is the bidirectional spectral-reflectance distribution function, $c_L(\lambda)$ and $c_S(\lambda)$ are the spectral-reflectance distributions, and $g_L(\theta_1, \theta_r)$ and $g_S(\theta_1, \theta_r)$ are the geometrical terms. The subscripts $L$ and $S$ refer to the body-reflection component and the specular-reflection component, respectively. $\theta_1$ and $\theta_r$ are the incident angle and the reflecting angle, respectively, as shown in Fig. 31.

In most reflection models it is assumed that the body-reflection component has a spectral distribution that is different from that of incident light, whereas the surface-reflection component has a similar spectral distribution. Lee et al. called this model the neutral-interface-reflection model. Considering the neutral-interface-reflection model, Eq. (A2) can be rewritten as

$$f_r(\theta_1, \theta_r, \lambda) = c_L(\lambda)g_L(\theta_1, \theta_r) + c_S g_S(\theta_1, \theta_r).$$  \hspace{1cm} (A3)

Since we assume that the body-reflection component is modeled by the Lambertian model and the surface-reflection component is modeled by a unit impulse function, geometrical terms $g_L(\theta_1, \theta_r)$ and $g_S(\theta_1, \theta_r)$ in Eq. (A3) become

$$g_L(\theta_1, \theta_r) = \max(0, \cos \theta_1),$$
$$g_S(\theta_1, \theta_r) = \delta(\theta_1 - \theta_r).$$  \hspace{1cm} (A4)

Substituting Eq. (A4) into Eq. (A3), we get

$$f_r(\theta_1, \theta_r, \lambda) = c_L(\lambda)\cos \theta_1 + c_S \delta(\theta_1 - \theta_r).$$  \hspace{1cm} (A5)

On the other hand, the intensity of incident light onto the object surface (and not into the camera) is represented as

$$L_i(\theta_1, \lambda) = c(\lambda)L(\theta_1),$$  \hspace{1cm} (A6)

where $c(\lambda)$ is the spectral distribution and $L(\theta_1)$ is a geometrical term of incident light onto the object surface. The intensity of light reflected on the object surface and coming into the camera can be expressed as the product of $L_i(\theta_1, \lambda)$ and the bidirectional spectral-reflectance distribution function $f_r(\theta_1, \theta_r, \lambda)$. Finally, the pixel value $I$ is given by

$$I(\theta_1, \theta_r) = \int \lambda s(\lambda)L_i(\theta_1, \lambda)f_r(\theta_1, \theta_r, \lambda)d\lambda$$
$$= \int \lambda s(\lambda)c(\lambda)L(\theta_1)[c_L(\lambda)\cos \theta_1 + c_S \delta(\theta_1 - \theta_r)]d\lambda$$
$$= L(\theta_1)\cos \theta_1 \int \lambda s(\lambda)c(\lambda)c_L(\lambda)d\lambda$$
$$+ L(\theta_1)\delta(\theta_1 - \theta_r)c_S \int \lambda s(\lambda)c(\lambda)d\lambda,$$  \hspace{1cm} (A7)
where $s(\lambda)$ is the spectral response of a camera.

The hybrid reflectance model is expressed by Eq. (A7). When the coordinate system is changed into the viewer-centered coordinate system shown in Fig. 2, Eq. (A7) becomes

$$I(\theta_s) = K_LL(\theta_s - \theta_n) \cos(\theta_s - \theta_n) + K_SL(\theta_s - \theta_n) \delta(2\theta_n - \theta_s), \quad (A8)$$

where

$$K_L = \int_{\lambda} s(\lambda)c(\lambda)c_L(\lambda)d\lambda,$$

$$K_S = c_s \int_{\lambda} s(\lambda)c(\lambda)d\lambda. \quad (A9)$$

**APPENDIX B: EXTENDED LIGHT SOURCE**

An extended light source instead of a point light source is used in our experiments. The extended light source is generated by a spherical diffuser that is composed of white light-diffusing material. The geometry of the diffuser is shown in Fig. 12. The distribution of the extended light source is given by

$$L(\theta) = L(\theta - \theta_s) = \frac{CJ[R + H] \cos(\theta - \theta_s) - R}{([R + H - R \cos(\theta - \theta_s)]^2 + [R \sin(\theta - \theta_s)]^2)^{3/2}}. \quad (B1)$$

This distribution is limited to the interval $\theta_s - \alpha < \theta < \theta_s + \alpha$, where

$$\alpha = \cos^{-1} \frac{R}{R + H}. \quad (B2)$$

A derivation of this formula is shown in the appendix of Ref. 13.

The hybrid reflectance model [Eq. (7)] can be rewritten by using the extended light source as follows:

$$I(\theta_s) = \int_{(\theta_s - \alpha)}^{(\theta_s + \alpha)} L(\theta_s, \theta_s) \cos(\theta - \theta_n) \times \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)c_L(\lambda)d\lambda \times \lambda \delta(\theta - \theta_n) + \int_{(\theta_s - \alpha)}^{(\theta_s + \alpha)} L(\theta_s, \theta_s) \delta(\theta - 2\theta_n) \times \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)d\lambda \times \lambda \delta(\theta - \theta_n)$$

$$= \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)c_L(\lambda)d\lambda \cos(\theta_s - \theta_n) + c_s \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)d\lambda \cos(\beta_s - \beta_n). \quad (B3)$$

Therefore

$$I(\theta_s) = K_L \cos(\theta_s - \theta_n) + K_S L(\theta_s - 2\theta_n), \quad (B4)$$

where

$$K_L = \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)c_L(\lambda)d\lambda,$$

$$K_S = c_s \int_{\lambda} \tau(\lambda)s(\lambda)c(\lambda)d\lambda. \quad (B5)$$

Equation (B4) shows that the intensity curve with respect to a direction of the extended light source is a linear combination of a cosine curve that represents the body-reflection component and the $L(\theta_s - 2\theta_n)$ curve that represents the specular-reflection component (Fig. 32).

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**REFERENCES**


