Development and Calibration of a Gonio-Spectral Imaging System for Measuring Surface Reflection

Akira KIMACHI, Norihiro TANAKA, and Shoji TOMINAGA, Members

SUMMARY This paper proposes a gonio-spectral imaging system for measuring light reflection on an object surface by using two robot arms, a multi-band lighting system, and a monochrome digital camera. It allows four degrees of freedom in incident and viewing angles necessary for full parametrization of a reflection model function. Spectral images captured for various incident and viewing angles are warped as if they were all captured from the same viewing direction. The intensity of reflected light is thus recorded in a normalized image form for any incident and viewing directions. The normalized images are used to estimate reflection model parameters at each surface point. To ensure point-wise reflection modeling, a calibration method is also proposed based on a geometrical model of the robot arms and camera. The proposed system can deal with objects with surface texture. Experiments are done on system calibration, reflection model, and spectral estimation. The results using colored objects show the feasibility of the proposed imaging system.

key words: goniphotometry, spectral imaging system, surface-spectral reflection, light reflection model, robot arm

1. Introduction

Behavior of light reflection on an object surface plays an important role both in computer vision and in computer graphics. It is therefore an important task to establish a reflection model that well describes the actual behavior of light reflection on an object surface.

A reflection model for most surface materials of natural objects and artificial ones is formulated as a function consisting of a diffuse reflection component and a specular reflection component [1]–[3]. The simplest system for estimating the reflection parameters is to use only a single RGB image captured for fixed illumination and camera geometry [4].

Precise reflection modeling requires reflection measurement at a variety of directional angles of light incidence and viewing. Toward this measurement, several imaging systems were developed with only one degree of freedom (1DOF) available in mechanical movement of the light source. To increase sample points in incident and viewing directions, these systems used either a hemispherical mirror and a fish-eye camera [5], or a spherical object [6], [7], and exploited camera pixels to sample incident and viewing angles. However, because of the 1DOF limitation, these systems cannot arbitrarily change incident and viewing directions at any surface point, and so cannot be applied to point-wise reflectance measurement for textured surfaces. In contrast, the systems accepting surface texture are based on simultaneous multi-point measurements [8]–[12], which use image pixels only to sample different points of an object surface, not to sample incident and viewing angles. Thus, these systems are goniometric systems with arbitrary angles of light incidence and viewing.

The precise optical analysis of object surface reflection should be based on surface-spectral information of the object surfaces. However, the above goniometric imaging systems [8]–[12] did not take surface-spectral reflectance into consideration. From the standpoint of spectral acquisition, the authors developed a measuring system consisting of a collimated white light source, a turntable for rotating the object, and a six-channel spectral camera that can be rotated coaxially to the turntable [13]. This system had only 2DOF in incident and viewing directions with a limited working range of the camera arm. It enabled us to estimate such an optical parameter as refractive index for inhomogeneous dielectric objects [14]. Recently, a gonio-spectral imaging system was developed by Haneishi et al. [15]. This system can change only the incident direction of the illumination. Tsuchida et al. [16] proposed a system that can change both the viewing and incident directions. Unfortunately, this system limited the object to a uniform colored surface and did not give any results of pixel-wise spectral reflectance measurement.

The present paper proposes a gonio-spectral imaging system for measuring spectral reflection properties of an object surface. The prototype system is a goniophotometric system using two commercial robot arms, a collimated white light source and a digital camera [17]. It realizes 4DOF in incident and viewing angles necessary for full parameterization of a reflection model. The digital camera captures images of the object for various directions of the light source and the camera. The collected images are then warped as if they were all captured from the same viewing direction (see [11], [12]). In this way, the intensity of reflected light is recorded individually at each surface point for any incident and viewing directions.

We extend the prototype system to a reliable spectral imaging system. First, a multi-band lighting system is constructed with narrow wavelength bands of seven channels.
and one broad band. Second, a calibration method of the entire system, including camera calibration and geometry calibration, is developed for precise image warping and reliable estimation of surface reflection parameters. Therefore, once multi-band images are observed, we can estimate the parameters at each surface point for a three-dimensional (3D) reflection model, such as diffuse spectral reflectance, specular intensity, and surface roughness.

Compared to other goniometric imaging systems, our system has a similarity to the widely-known system proposed by Dana et al. [9]. Both systems realize 3DOF in incident and viewing directions by rotating the object surface by a multi-joint robot arm while the last 1DOF is assigned to camera position. The biggest difference, however, is that our system has the spectral imaging capability while that of Dana et al. does not. As another significant difference, our system can position the camera precisely by another robot arm, whereas in the system of Dana et al. the camera had to be positioned manually, which affects the accuracy of imaging geometry and prevents fine sampling in the viewing direction.

In the following part, Sect. 2 describes the system construction for gonio-spectral reflection measurement. We assume that the target object has a flat surface. Section 3 discusses the geometry of light reflection in the system. Section 4 describes the algorithm of image warping. Section 5 describes a calibration method for the camera and system geometry. Section 6 shows experimental results for the system calibration, image warping, and surface-spectral reflectance. Section 7 concludes this paper.

2. System Construction

Figure 1 (a) shows a photograph of the proposed gonio-spectral measurement system consisting of two robot arms with six joints each, a multi-band lighting system, and a monochrome digital camera. One of the robot arms (Mitsubishi Electric RV-4A), called RA1 hereafter, holds an object on its end and rotates it around a fixed point on the surface of the object to change only its pose with 3DOF. The other robot arm (Mitsubishi Electric RV-2A), called RA2, hangs down a 10-bit monochrome digital CCD camera (Tokyo Electronic Industry CS3920, 1636 × 1236 pixels) from its end via a cantilever and rotates it horizontally to give 1DOF.

Figure 1 (b) shows the multi-band lighting system, which consists of a source unit (Asahi Spectra MAX301), seven narrow-band interference filters, an optical guide with a lens, and a filter wheel with eight filter pockets. The light source is a 500-W xenon lamp. The seven filters are interference type with 20-nm bandwidth. The filters are set to the seven of the eight filter wheel pockets, leaving one pocket empty. Rotating the filter wheel to one of the eight pocket positions, the lighting system projects either a narrow-band light through one of the seven filters or one broad-band light through the empty filter pocket from the xenon lamp. The output light is collimated by a lens and illuminates the object horizontally.

Figure 2 shows the spectral characteristics of the lighting and imaging systems. Figure 2 (a) depicts the measurements of spectral power distributions for the eight-band spectral light sources. The peak wavelengths of the seven narrow bands are 420, 450, 500, 550, 600, 650, and 680 nm with approximately 20-nm bandwidth for all bands. Figure 2 (b) shows the spectral sensitivity function of the monochrome camera. Combining the camera and the light source provides a stable imaging system with eight-spectral bands in the visible wavelength range of 400–700 nm.

3. Light Reflection Geometry at a Surface Point

3.1 Definition of Coordinate Systems

Figure 3 (a) illustrates the geometry of the gonio-spectral imaging system. We arbitrarily choose a point of the object surface as the center of rotation given by RA1. This point serves as the origin of the world coordinate system (WCS) XYZ and also as that of the object-centered coordinate system (OCS) xyz. The WCS is defined such that the XY plane lies parallel to the horizontal ground plane, with the X axis pointing toward the light source. In the OCS, the xy plane is defined by the object surface itself, which is flat overall by
our assumption, and thus the $z$ axis points toward the surface normal direction.

We also define the camera-centered coordinate system (CCS) $\xi\eta\zeta$ and the pixel coordinates $(u, v)$ in the image plane of perspective projection by the camera. The origin of the CCS is taken at the optical center of perspective projection. This origin is displaced from that of the WCS by a translation vector $t_2$. The $\xi$ and $\eta$ axes in the CCS are taken in parallel to the $u$ and $v$ axes in the image plane. Figure 3 (b) shows the correspondence of the defined coordinate systems to the developed imaging system.

A point $\xi = [\xi, \eta, \zeta]^T$ in the CCS is projected to a pixel $p = [u, v]^T$ in the image plane by the relation

$$ p_1 = A \xi, \quad (1) $$

which follows the notation introduced for camera calibration by Zhang [18]. In Eq. (1), $A$ denotes a $3 \times 3$ perspective projection matrix from the CCS to the image plane with the form

$$ A = \begin{bmatrix} f_u & f_{uv} & u_0 \\ 0 & f_v & v_0 \\ 0 & 0 & 1 \end{bmatrix}, \quad (2) $$

where $f_u$ and $f_v$ denote the focal lengths divided by the pixel spacings in the $u$ and $v$ directions, $f_{uv}$ the skewness factor of the image plane, and $(u_0, v_0)$ the pixel coordinates at which the optical axis of the camera penetrates the image plane. $s$ is a parameter, actually implying $s = \zeta$ in this formulation. From Eq. (1) the pixel coordinates $p$ are obtained as

$$ p = \zeta^{-1} \left[ \begin{array}{c} f_u \xi + f_{uv} \eta \\ f_v \eta \end{array} \right] + \left[ \begin{array}{c} u_0 \\ v_0 \end{array} \right]. \quad (3) $$

The poses of the OCS and CCS relative to the WCS are represented by three-dimensional rotation matrices $R_1$ and $R_2$, respectively. Suppose a point $X = [X, Y, Z]^T$ in the WCS is alternately represented by $x = [x, y, z]^T$ in the OCS and by $\xi = [\xi, \eta, \zeta]^T$ in the CCS. Then $R_1$ and $R_2$ are defined in terms of coordinate transform relationship among $X$, $x$ and $\xi$ as

$$ X = R_1 x = R_2 \xi + t_2. \quad (4) $$

3.2 Relating a Pixel to a Surface Point

We relate a pixel $p$ to a surface point $x_0 = [x, y, 0]^T$ in the OCS. Figure 4 illustrates the geometrical relationship between $p$ and $x_0$. From Eq. (4) the CCS representation of $x_0$ is given by

$$ \xi = R_2^{-1}(R_1 x_0 - t_2). \quad (5) $$

Substituting Eq. (5) into Eq. (1) reveals that the surface point $x_0$ is projected to a pixel $p$ as

$$ s \begin{bmatrix} p_1 \\ 1 \end{bmatrix} = A R_2^{-1}(R_1 x_0 - t_2). \quad (6) $$

Conversely, $x_0$ is obtained from the pixel coordinates $p$ as

$$ x_0 = R_1^{-1} \left( s R_2 A^{-1} \begin{bmatrix} p_1 \\ 1 \end{bmatrix} + t_2 \right). \quad (7) $$
3.3 Pixel-Wise Computation of Incident and Viewing Directions

For precise modeling of surface reflection, it is necessary, at any point of the object surface, to specify the incident direction of illumination and the viewing direction toward the corresponding pixel of the camera. At a surface point \( x_0 = [x, y, 0]^T \), we denote the unit vectors pointing toward the light source and the camera optical center by \( n_i(x_0) \) and \( n_e(x_0) \), respectively, both represented in the OCS, as depicted in Fig. 4. The vectors \( n_i(x_0) \) and \( n_e(x_0) \) are expressed with the polar and azimuth angles of the incident and viewing directions, \((\theta_i(x_0), \phi_i(x_0))\) and \((\theta_e(x_0), \phi_e(x_0))\), as

\[
\begin{bmatrix} n_i \end{bmatrix} = \begin{bmatrix} \sin \theta_i \cos \phi_i, \sin \theta_i \sin \phi_i, \cos \theta_i \end{bmatrix}^T
\]

and

\[
\begin{bmatrix} n_e \end{bmatrix} = \begin{bmatrix} \sin \theta_e \cos \phi_e, \sin \theta_e \sin \phi_e, \cos \theta_e \end{bmatrix}^T.
\]

Since the incident direction of illumination is assumed to be parallel to the negative \( x \) axis, we obtain \( n_i(x_0) \) by transforming the unit vector \([1, 0, 0]^T\) in the WCS to the OCS with \( R_1^{-1} \) as

\[
\begin{bmatrix} n_i \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix}.
\]  

(8)

Note that \( n_i(x_0) \) is independent of \( x_0 \) or pixel location \( p \), i.e. \( n_i(x_0(p)) \equiv n_i \) due to the assumption of collimated illumination and flat surface.

On the other hand, \( n_e(x_0) \) depends on \( x_0 \) due to perspective projection. In Eq. (6), \( R_1 x_0 - t_2 \) stands for the location of the surface point \( x_0 \) relative to the camera optical center in the WCS. It follows that the location of the camera optical center relative to the WCS is given as \(-R_1 x_0 + t_2\) by flipping its sign. Since \( n_e(x_0) \) points from \( x_0 \) toward the camera optical center, it is obtained by transforming \(-R_1 x_0 + t_2\) to the OCS and then normalizing it as

\[
\begin{bmatrix} n_e \end{bmatrix} = N^{-1} R_1^{-1} (-R_1 x_0 + t_2) = -N^{-1} (x_0 - R_1^{-1} t_2),
\]  

(9)

where \( N \) denotes a normalization factor. Substituting Eq. (7) into Eq. (9) also gives an expression in terms of pixel location \( p \) as

\[
\begin{bmatrix} n_e \end{bmatrix} = N^{-1} s R_1^{-1} R_2 A^{-1} \begin{bmatrix} p \end{bmatrix}.
\]  

(10)

We use the robot arms to change the incident and viewing directional vectors \( n_i, n_e \) with 4DOF. 3DOF are assigned to RA1 by rotating the object about a fixed surface point, which determines \( R_1 \). The last one DOF is realized by rotating only one joint of RA2 to scan the camera along a horizontal circle, which jointly determines \( R_2 \) and \( t_2 \).

In practice, we often want to determine \( R_1, R_2 \) and \( t_2 \) from the incident and viewing directions \( n_i \) and \( n_e \) for a given surface point \( x_0 \). From Eq. (8) we can obtain \( R_1 \) by specifying a unit vector \( n_j \) orthogonal to \( n_i \) in the OCS and parallel to the \( y \) axis in the WCS, as

\[
R_1 = [n_i, n_j, n_i \times n_i]^T.
\]  

(11)

Substituting \( R_1, x_0 \) and \( n_i(x_0) \) into Eq. (9) then yields \( t_2 \) for an arbitrarily chosen parameter \( N \) as

\[
t_2 = R_1 [x_0 + N n_e(x_0)].
\]  

(12)

Note, however, that Eqs. (11) and (12) do not uniquely determine \( R_1, R_2 \) and \( t_2 \) because there is still 1DOF in choosing \( n_j \) and \( N \) each, and \( R_2 \) is independent of \( n_i \) and \( n_e \). A unique determination of these matrices and vector requires the horizontal rotation angle of RA2, denoted by \( \psi_{RR} \). As described above, the pose matrix \( R_2 \) and translation vector \( t_2 \) of the CCS relative to the WCS are jointly determined by horizontal rotation of RA2. This means that \( R_2 \) and \( t_2 \) have only 1DOF with the lone parameter \( \psi_{RR} \), as will later be formulated by Eqs. (23) and (26) in Sect. 5.2. Using this constraint, we can uniquely determine \( R_1, R_2 \) and \( t_2 \) by the following procedure:

1. Construct a set of three equations from Eq. (12) for three unknown parameters \( \psi_{RR}, n_j \) and \( N \).
2. Solve this set of equations for \( \psi_{RR}, n_j \) and \( N \).
3. Compute \( R_2 \) and \( t_2 \) using \( \psi_{RR} \) in Eqs. (23) and (26).
4. Compute \( R_1 \) using \( n_j \) in Eq. (11).

4. Image Warping for Pixel-Wise Reflection Measurement

Light reflection is determined individually at each point of the object surface from a set of spectral images captured for a variety of incident and viewing angles. It is desirable to always establish the same correspondence between pixel and surface point for any viewing direction of the camera. To realize this, we introduce image warping to normalize all the images to the same frontal view of the object.

Figure 5 illustrates the geometry for the image warping. We warp all the images so that the \( \xi \) and \( \eta \) axes of the CCS lie parallel to the \( x \) and \( y \) axes of the OCS, respectively, with the positive direction of the \( y \) and \( \eta \) axes being the same.
First, we find the surface point \( \mathbf{x}_0 = [x, y, 0]^T \) that corresponds to a pixel \( \mathbf{p} = [u, v]^T \) in the warped image. Denoting by \( z_0 \) the distance from the \( xy \) plane to the \( \xi \eta \) plane, we transform OCS coordinates \( \mathbf{x} = [x, y, z]^T \) to CCS coordinates \( \xi = [\xi, \eta, \zeta]^T \) as

\[
\xi = \begin{bmatrix}
-x \\
y \\
z_0 - z
\end{bmatrix} = \mathbf{P}_0 \mathbf{x} + \mathbf{w}_0,
\] (13)

where

\[
\mathbf{P}_0 = \begin{bmatrix}
-1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & -1
\end{bmatrix}, \quad \mathbf{w}_0 = \begin{bmatrix}
0 \\
0 \\
z_0
\end{bmatrix}.
\] (14)

Using the fact that \( \zeta = z_0 \) for any surface point and substituting Eq. (13) into Eq. (1) with \( s = \zeta = z_0 \), we find that a surface point \( \mathbf{x}_0 \) is projected onto a pixel \( \mathbf{p} \) as

\[
\begin{bmatrix}
\mathbf{p} \\
p \end{bmatrix} = \mathbf{A} (\mathbf{P}_0 \mathbf{x}_0 + \mathbf{w}_0).
\] (15)

Inverting Eq. (15) then gives the surface point \( \mathbf{x}_0 \) as

\[
\mathbf{x}_0 = \mathbf{P}_0^{-1} \left( z_0 \mathbf{A}^{-1} \begin{bmatrix}
p \\
p \end{bmatrix} - \mathbf{w}_0 \right).
\] (16)

Next, we look for the pixel \( \mathbf{p'} = [u', v']^T \) in the originally captured image onto which \( \mathbf{x}_0 \) is projected. The CCS coordinates are denoted as \( (\xi', \eta', \zeta') \). Replacing \( \mathbf{p} \) with \( \mathbf{p'} \) and using \( s = \zeta' \) in Eq. (6), and substituting Eq. (16) into it, we find

\[
\zeta' \begin{bmatrix}
p' \\
p' \end{bmatrix} = \mathbf{A} \mathbf{R}_2^{-1} \left( \mathbf{R}_1 \mathbf{P}_0^{-1} \left( z_0 \mathbf{A}^{-1} \begin{bmatrix}
p \\
p \end{bmatrix} - \mathbf{w}_0 \right) - \mathbf{t}_2 \right).
\] (17)

The distance \( \zeta' \) of the point \( \mathbf{x}_0 \) from the \( \xi' \eta' \) plane can be computed from \( \mathbf{R}_1, \mathbf{R}_2 \) and \( \mathbf{t}_2 \) by Eq. (6). Dividing the first and second elements by the third of the left-hand side vector in Eq. (17) yields the pixel coordinates \( \mathbf{p'} \) in the original image that corresponds to the pixel location \( \mathbf{p} \) in the warped image.

Denoting the images before and after warping by \( I(\mathbf{p}) \) and \( \hat{I}(\mathbf{p}) \), respectively, we can obtain the pixel value of \( \hat{I}(\mathbf{p}) \) from that of \( I(\mathbf{p}) \) as

\[
\hat{I}(\mathbf{p}) = I(\mathbf{p'}).
\] (18)

Since \( \mathbf{p'} \) generally does not coincide with an image grid point, an interpolation technique such as bilinear interpolation is employed in this study to compute \( \mathbf{p'} \) from neighboring pixels.

5. System Calibration

5.1 Camera Calibration

To compute the pixel coordinates \( \mathbf{p'} \) in Eq. (17), we have to know the perspective projection matrix \( \mathbf{A} \). We determine \( \mathbf{A} \) using the calibration method by Zhang [18]. Using a flat calibration target as an object, this method can estimate only the matrix \( \mathbf{A} \) but also the pose and position of the object in the CCS. Note as seen in Eq. (5) that this pose and position are represented by the matrix \( \mathbf{R}_2^{-1} \mathbf{R}_1 \) and the translation vector \( -\mathbf{R}_2^{-1} \mathbf{t}_2 \), respectively.

Figure 6 shows the geometry for camera calibration, where the camera is horizontally rotated by RA2 while the calibration target is held at a pose by RA1. The calibration procedure takes the following steps:

1. Hold a calibration target object at some pose by RA1.
2. Capture a number of images of the target object from different viewing directions while rotating the camera horizontally by RA2 (Fig. 6).
3. Extract the pixel coordinates of feature points on the target object in each image.
4. Obtain \( \mathbf{A} \) as well as \( \mathbf{R}_2^{-1} \mathbf{R}_1 \) and \( -\mathbf{R}_2^{-1} \mathbf{t}_2 \), for each viewing condition of the camera by applying Zhang’s algorithm to the extracted pixel coordinates and the actual coordinates of the feature points represented in the OCS.

5.2 System Geometry Calibration

For precise modeling of surface reflection, we have to know the actual viewing direction \( \mathbf{n} \) at each pixel for any pose and position of the robot arms. As pointed out in the previous section, the pose and position of the object surface relative to the camera are represented by the matrix \( \mathbf{R}_2^{-1} \mathbf{R}_1 \) and the translation vector \( -\mathbf{R}_2^{-1} \mathbf{t}_2 \), respectively. Once they are available, we can immediately obtain the viewing direction vector \( \mathbf{n}_0 \) via Eq. (9) using the identity \( \mathbf{R}_1^{-1} \mathbf{t}_2 = (\mathbf{R}_2^{-1} \mathbf{R}_1)^{-1} \mathbf{R}_2^{-1} \mathbf{t}_2 \) for any surface point.

The main purpose of system geometry calibration is to derive a formula for computing \( \mathbf{R}_2^{-1} \mathbf{R}_1 \) and \( -\mathbf{R}_2^{-1} \mathbf{t}_2 \) for any pose and position of the robot arms. However, \( \mathbf{R}_2^{-1} \mathbf{R}_1 \) and \( -\mathbf{R}_2^{-1} \mathbf{t}_2 \) cannot be obtained correctly without the geometry calibration of the whole system, because the relative geometry of the two robot arms and the camera, which are all separate apparatuses, is unknown at first.
There are two approaches for this kind of calibration. One is to use calibration control points during each image capture [6], [11], [12], which we call control point method. The other is to use a geometrical model of the measuring system, which we call model-based method. The control point method does not need relative geometry of the robot arms and the camera. However, it requires control points to be attached to the object, and also has to deal with image processing problems, such as correspondence among multiple control points, distortion by oblique view, and occlusion caused by three-dimensional shape. To avoid these problems, we adopt the model-based calibration method.

We make use of the matrices \( R_{2}^{-1} R_{1} \) and vectors \(-R_{2}^{-1} t_{2}\) obtained in the camera calibration. By introducing homogeneous coordinate representation [18], we can combine these quantities into a single \( 4 \times 4 \) matrix \( M_{CO} \), which implies coordinate transformation from OCS to CCS, as

\[
M_{CO} = \begin{bmatrix} R_{2}^{-1} R_{1} & -R_{2}^{-1} t_{2} \\ 0^T & 1 \end{bmatrix} .
\]  

(19)

We can decompose Eq. (19) into two matrices, \( M_{WO} \) and \( M_{CW} \), accounting for transformations from OCS to WCS and from WCS to CCS, respectively, as

\[
M_{CO} = M_{CW} M_{WO} \tag{20}
\]

where

\[
M_{WO} = \begin{bmatrix} R_{1} & 0 \\ 0^T & 1 \end{bmatrix} ,
\]

(21)

\[
M_{CW} = \begin{bmatrix} R_{2}^{-1} & -R_{2}^{-1} t_{2} \\ 0^T & 1 \end{bmatrix} = \begin{bmatrix} R_{2} & t_{2} \\ 0^T & 1 \end{bmatrix}^{-1} .
\]

(22)

In Eq. (22), \( M_{CW} \) is changed with horizontal rotation of the camera by RA2. We consider how \( M_{CW} \) depends on the horizontal camera rotation angle, which we denote by \( \psi_{RR} \), via \( R_{2} \) and \( t_{2} \) in Eq. (22). Figure 7 shows the coordinate systems for the calibration. The horizontal rotation causes the position of the camera optical center, represented by \( t_{2} \), to move along a circle, and the pose of the camera, represented by \( R_{2} \), to rotate about an axis perpendicular to the plane including the circle. We denote the rotation axis and plane and the circle by \( \Lambda \), \( \Pi \) and \( C \), respectively. We then define a coordinate system \( X'Y'Z' \), as shown in Fig. 7, which we call the RA2-centered coordinate system or RCS. We define the \( X'Y' \) plane and \( Z' \) axis by \( \Pi \) and \( \Lambda \), respectively, and take the origin of the RCS at the point where \( \Lambda \) crosses \( \Pi \).

We can now decompose \( M_{CW} \), a function of \( \psi_{RR} \), into three components as

\[
M_{CW}(\psi_{RR}) = M_{CR} M_{RR}(\psi_{RR}) M_{RW} ,
\]

(23)

where the \( 4 \times 4 \) matrices \( M_{RW} \), \( M_{RR}(\psi_{RR}) \), and \( M_{CR} \) account for three coordinate transformations: 1) from WCS \( (X, Y, Z) \) to RCS \( (X', Y', Z') \), 2) rotating the RCS about the \( Z' \) axis by \( \psi_{RR} \), and 3) from RCS to CCS, respectively. Figure 8 illustrates this decomposition. \( M_{RW} \) and \( M_{CR} \) are constant matrices invariant to the movement of the robot arms. \( \psi_{RR} \) can be constructed based on the mathematical expressions for the rotation axis \( \Lambda \) and plane \( \Pi \), since they define the RCS relative to the WCS. \( M_{RR}(\psi_{RR}) \) is explicitly given by

\[
M_{RR}(\psi_{RR}) = \begin{bmatrix} \cos \psi_{RR} & \sin \psi_{RR} & 0 & 0 \\ -\sin \psi_{RR} & \cos \psi_{RR} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} .
\]

(24)

Substituting Eq. (23) into Eq. (20) yields

\[
M_{CO} = M_{CR} M_{RR}(\psi_{RR}) M_{RW} M_{WO} .
\]

(25)

In Eq. (25), \( M_{RW} \) and \( M_{CR} \) are unknown whereas \( M_{CO} \) is obtained from Eq. (19) by the camera calibration, and \( M_{WO} \) and \( M_{RR}(\psi_{RR}) \) are determined by the joint angles of RA1 and RA2, respectively. From Eqs. (20) and (22) the known matrices \( M_{CO} \) and \( M_{WO} \) are combined into a single matrix as

\[
M_{CW}^{-1}(\psi_{RR}) = M_{WO} M_{CO}^{-1} = \begin{bmatrix} R_{2} & t_{2} \\ 0^T & 1 \end{bmatrix} .
\]

(26)

From Eqs. (23), (24) and (26), our problem is now reduced to the estimation of \( M_{RW} \) and \( M_{CR} \) from \( M_{CW}^{-1}(\psi_{RR}) \) and \( M_{RR}(\psi_{RR}) \). We take the following steps to solve it:

1. Estimate the circle \( C \) in Fig. 7, which is drawn by the tip of the vector \( t_{2} \) for different \( \psi_{RR} \), with a nonlinear estimation algorithm such as the Levenberg-Marquardt method.
2. Extract the rotation axis \( \Lambda \) and plane \( \Pi \) in the WCS, which directly give \( M_{RW}^{-1} \).
3. Estimate \( M_{CR} \) by solving Eq. (23) with \( M_{RW}^{-1} \) and \( M_{RW}^{-1}(\psi_{RR}) \) and averaging over different \( \psi_{RR} \).
With the estimated matrices $M_{RW}$ and $M_{CR}$, we can now compute $M_{CO}$ via Eqs. (21), (24) and (25) for any given pose of the object surface $R_1$ and any rotation angle of the camera $\psi_{RR}$. From $M_{CO}$ we easily obtain the actual viewing direction $n_e$.

6. Experimental Results

6.1 System Calibration

Figure 9 (a) shows a calibration target used for testing the proposed algorithms of system calibration and image warping. We fixed the target by RA1 and captured eleven images of it while rotating the camera horizontally by RA2 to $0^\circ$, $\pm 30^\circ$, $\pm 40^\circ$, $\pm 50^\circ$, $\pm 60^\circ$ and $\pm 70^\circ$ away from the surface normal direction of the target, in the manner as depicted in Fig. 6. At $0^\circ$ the camera faces the target right in front. Figure 9 (a) shows the captured images for camera angles of $\pm 40^\circ$ and $\pm 70^\circ$. Extracting the center of each feature point and then applying Zhang’s method, we estimated the intrinsic parameter matrix $A$ and the unknown $4 \times 4$ matrices $M_{RW}$ and $M_{CR}$.

To verify the estimated matrices, we applied the warping algorithm to the captured eleven images. Figure 9 (b) shows the resultant images warped from Fig. 9 (a), where the distance of the camera center from the object surface, $z_0$ in Eq. (17), was chosen to $z_0 = 3.48 \times 10^2$ mm. All the images in Fig. 9 (b) are normalized to the frontal view images of the calibration target. The deviation of the feature points in the warped images were mostly kept within two pixels, which correspond to less than 0.1 mm on the object surface at the distance of 348 mm from the camera.

The images for rotation angles of $\pm 70^\circ$ in Fig. 9 (b) appear to have some blur around the leftmost or rightmost points within the calibration target. This can be explained by the following two effects:

- These areas of the object stick out of the depth of focus of the camera.
- Spatial averaging caused by each pixel of the camera becomes severer as the rotation angle of the camera increases, especially in the region lying farther from the camera due to perspective projection.

The first effect can be suppressed by increasing the distance between the object surface and the camera or by changing the camera lens. The second, on the other hand, is a physical effect inherent in this kind of goniometric imaging systems and therefore cannot be avoided. Thus, spatial resolution of reflection measurement tends to become lower with the increase of viewing angles in the peripheral area of the object.

Except for this point, these results confirm that the proposed calibration algorithms work successfully enough to allow point-wise surface reflection measurement.

6.2 Modeling Surface Reflection

The top-left photograph in Fig. 10 shows a test object for surface reflectance measurement, which consists of four patches of colored plastic sheets. This object was illuminated by the broad-band light of the multi-band lighting system. Figure 10 shows the measurement results, which plots the pixel value of the warped images, averaged over $20 \times 20$ pixels within each color patch.

In Fig. 10, the incident angle $\theta_i$ of the illumination was varied from $30^\circ$ to $65^\circ$ in $5^\circ$ steps, while $\phi_i$ was fixed to $180^\circ$. The camera captured the object from the opposite to the illuminating direction with respect to the surface normal. For each $\theta_i$, the viewing angle $\theta_e$ of the camera was changed from $0^\circ$ to $80^\circ$ in $5^\circ$ steps except in the vicinity of the specular reflection angle $\theta_e = \theta_i$, where the scanning step was set.
Fig. 11 Fitting results of the measurements to the Torrance-Sparrow model for color patches A and C. Solid—measured light intensities. Dashed—estimated Torrance-Sparrow model.

Fig. 12 Estimation results of surface-spectral reflectance for the Macbeth Color Checker.

to 0.5° over ±15° on both sides of it. The other angle $\phi_e$ was fixed to 0°. The actual value of $(\theta_e, \phi_e)$ was computed for each 20 × 20-pixel region by the formula in Eq. (10). Figure 11 depicts the fitting results of the measurements to the Torrance-Sparrow model for color patches A and C. The curves are in good agreement especially for small incident angles $\theta_i$.

6.3 Estimation of Surface-Spectral Reflectance

The Macbeth Color Checker was used for testing reliability of the surface-spectral reflectance estimation. This object consists of 24 color patches. Spectral images of it were captured for each spectral band of the lighting system. We then applied a Wiener filter [19] to the eight-dimensional vector of the spectral image intensities at individual pixels based on a spectral imaging model with the spectra in Fig. 2. Figure 12 plots the surface-spectral reflectances of the twelve patches in the left half of the chart, estimated from the averaged pixel value over 20 × 20 pixels. The results show good agreement of the estimated spectra to the spectra measured by a spectroradiometer.

6.4 Estimation for an Object with Complex Color Texture

We conducted an experiment of pixel-wise estimation of surface reflectance for an object surface with complex color texture. Figure 13 (a) shows a coaster used in this experiment, the surface of which was a color-printed paper coated with thin wax. We measured the reflected light at the three locations A, B and C in Fig. 13 (a) and estimated the spectral reflectance for each pixel point.

Figure 13 (b) plots the measured intensities of reflected light against the viewing angle $\theta_e$ at each single pixel corresponding to either A, B or C in the image plane. The incident and viewing angles ($\theta_i, \phi_i$), ($\theta_e, \phi_e$) were the same as in
the experiment in Sect. 6.2 except that $\theta_i$ was changed up to 60°.

Figure 13(c) plots the surface-spectral reflectances estimated from eight-band spectral images. Note that the estimated curves agree well with the spectral reflectances measured by a spectroradiometer.

7. Conclusions

We have developed a gonio-spectral imaging system for measuring surface reflection on an object using two commercial robot arms, a multi-band lighting system and a monochrome digital camera. To ensure point-wise reflectance measurement and modeling, we have also proposed a system calibration algorithm. The experimental results on system calibration, modeling of 3D surface reflection and estimation of surface-spectral reflectance have confirmed the feasibility of the proposed system for colored objects with complex surface texture.

The proposed system has several advantages as follows:

1. It performs spectral measurement of surface reflectance for colored objects.
2. It can determine the incident and viewing angles precisely in all of the 4DOF by use of two robot arms, which was difficult in the approach of using only one robot arm [9].
3. It realizes point-wise reflectance measurement for complex textured surfaces, which is an improvement over other gonio-spectral imaging systems [15], [16].
4. The proposed calibration method, based on the geometrical model of the camera and robot arms, does not require additional image processing for calibration control points during each image capture as employed in other goniometric imaging systems [6], [11], [12].

References


Akira Kimachi is an Associate Professor with the Department of Engineering Informatics, Osaka Electro-Communication University, Neyagawa, Osaka, Japan. His research interests include image sensing, photo-optical measurement, computer vision, image processing and imaging devices. He received the B.E., M.E. and Ph.D. degrees in mathematical engineering and information physics from The University of Tokyo, Bunkyo-ku, Tokyo, Japan, in 1993, 1995, and 1999, respectively. He is a member of IEEE.
Norihiro Tanaka is an Associate Professor at Nagano University, Ueda, Nagano, Japan. He received the B.E., M.E. and Ph.D. degrees in computer science from Osaka Electro-Communication University in 1995, 1997 and 2001, respectively. From 2001 to 2004 he served as a post-doctoral fellow at Osaka Electro-Communication University. His research interests include reflection modeling and its application to computer graphics and computer vision.

Shoji Tominaga is a Professor with the Department of Engineering Informatics, Osaka Electro-Communication University, Neyagawa, Osaka, Japan. His research interests include color image analysis, reflection modeling, color image rendering, and computational color vision. He received the B.E., M.S. and Ph.D. degrees in electrical engineering from Osaka University, Toyonaka, Osaka, Japan, in 1970, 1972 and 1975, respectively. He is a Fellow of IEEE and a member of Optical Society of America, IS&T, SID and ACM.