Inverse Global Illumination Rendering for Dense Estimation of Surface Reflectance Properties

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Abstract. This paper investigates the problem of object surface reflectance modeling, which is sometimes referred to as *inverse reflectometry*, for photorealistic rendering and effective multimedia applications. A number of methods have been developed for estimating object surface reflectance properties in order to render real objects under arbitrary illumination conditions. However, it is still difficult to densely estimate surface reflectance properties faithfully for complex objects with interreflections. This paper describes a new method for densely estimating the non-uniform surface reflectance properties of real objects constructed of convex and concave surfaces. Specifically, we use registered range and surface color texture images obtained by a laser rangefinder. Then, we determine the positions of light sources in order to capture color images to be used in discriminating diffuse and specular reflection components of surface reflection. The proposed method can densely estimate the reflectance parameters of objects with diffuse and specular interreflections based on an inverse global illumination rendering. Experiments are conducted in order to demonstrate the usefulness and the advantage of the proposed methods through comparative study.

1 Introduction

Inverse rendering is an effective technique to produce a photorealistic image, object geometry, reflectance properties and lighting effect in a scene. In the fields of computer vision and graphics, a number of methods have been developed to estimate reflectance properties from images [1, 2, 3, 4, 5, 6, 7, 8, 9]. These approaches, which are sometimes referred to as *inverse reflectometry*, reproduce the object shape and surface reflectance properties. If the object surface reflectance properties are estimated at once, the virtualized object can be rendered appropriately under arbitrary illumination conditions. In this paper, estimation of object surface reflection in *inverse rendering* framework is focused.

Especially, it is necessary to estimate the incident radiances of surfaces in the scene because the light that any particular surface receives may arrive not only from the light sources but also from the rest of the environment through indirect illumination. The estimation of incident radiances allow to estimate the reflectance properties of the surfaces

in the scene via an iterative optimization procedure, which allows to re-estimate the incident radiances. That is called *Inverse Global Rendering*. Loscos et al. [7] and Dretakis et al. [4] have attempted to estimate object surface reflectance properties based on radiosity equations. Yu et al. [9] have estimated surface reflectance properties of a room from color and geometry data considering both diffuse and specular inter-reflections based on the inverse global illumination rendering. Boivin et al. [3] have also attempted to estimate surface reflectance properties with considering diffuse inter-reflections. These methods assume that the surface of interest has uniform reflectance properties. Therefore their algorithms cannot be applied to a non-uniform surface reflectance object.

We have also conducted the study on reflectance estimation based on the radiosity rendering for considering interreflections, which is called *inverse radiosity rendering* [2]. The radiosity algorithm is quite efficient in computing the lighting distribution for a simple model with diffuse materials. However, because the radiosity rendering method considers only diffuse interreflections, when object reflectance properties are estimated it is impossible to eliminate the influence of specular interreflections. In addition, it becomes very costly for complex models and non-diffuse materials. The high computational cost for complex models is due to the fact that the radiosity algorithm computes values for all the patches in the model. Furthermore, there is a problem that the finite mesh representation can be very inaccurate if the mesh is not carefully constructed. Therefore, in the case of using the radiosity for estimating surface reflectance properties, we must have accurate object geometry and efficiently tessellate it.

In this paper, we take notice of the photon mapping [10] that is a global illumination rendering method. The photon mapping can represent diffuse and specular interreflections based on computing emission of photons from a light. Using the photon mapping, we propose a new method for estimating non-uniform reflectance properties of objects with both diffuse and specular interreflections. Additionally, the proposed method can densely estimate reflectance parameters by densely observing both reflection components.

2 Reflectance Modeling from Range and Color Images

Figure 1 shows a flow diagram of estimating surface reflectance properties. Our process consists of five parts: measurement of an object (A, C), selection of light source (B), initial estimation of reflectance parameters using our previous method [2] (D), and reflectance estimation using photon mapping (E).

2.1 Measurement and Selection of Positions of Light Source

We use a laser rangefinder (Cyberware 3030RGB) with known positions of point light sources and a camera for acquiring surface color images, as shown in Figure 2(a). This system can obtain registered range and surface color texture images at the same time by rotating the rangefinder and the camera around an object.

In the present experimental setup, multiple positions of a light are determined among 60 possible positions prepared around the laser rangefinder and these are two-

Fig. 1. Flow diagram of estimating surface reflectance properties

(a) Appearance of 3D-Digitizer and acquired data (b) Multiple possible light source positions

Fig. 2. Experimental setup

dimensionally arranged at the interval of 5 cm as shown in Figure 2(b). The positions of a camera and a light source are calibrated in advance. After optimum light positions are selected, a single light is attached at the selected positions in turn so that the calibration of brightness among multiple lights is not needed. We can also ignore the influence of environmental light by measuring the object in a dark room.

Here, we employ the Torrance-Sparrow model [11] to represent object reflectance properties physically. The Torrance-Sparrow model is given as:

$$i_x = \frac{Y}{D^2} \left\{ P_{dx} \cos \theta_{dx} + \frac{P_{sx}}{\cos \theta_{vx}} \exp\left(-\frac{\theta_{rx}^2}{2\sigma_x^2}\right) \right\}, \quad (1)$$

where i_x represents an observed intensity corresponding to the surface point x , i_{dx} and i_{sx} denote the diffuse and specular reflection components, respectively, C is an attenuation coefficient related to the distance between a point light source and an object surface point, and Y represents the strength of a light source. P_{dx} , P_{sx} and σ_x are the diffuse reflectance parameter, specular reflectance parameter, and surface roughness parameter, respectively. θ_{dx} is the angle between light source vector and surface normal vector, θ_{vx} is the angle between viewing vector and surface normal vector, and θ_{rx} is the

angle between surface normal vector and half vector. Note that half vector is the vector located halfway between light vector and viewing vector. All vectors are unit vectors.

Dense and independent estimation for non-uniform surface reflectance parameters requires observation of each surface point x under at least three different lighting conditions: one lighting condition for determining the unknown parameter P_{dx} , and the other two lighting conditions for acquiring the remaining two unknown parameters P_{sx} and σ_x . The selection of the optimum positions of the light source in Figure 1(B) is repeated until almost all of the pixels satisfy the three different lighting conditions [1]. As a result of this process, a certain number of light positions, say m , are selected in order to densely observe both diffuse and specular reflection components.

A texture image is obtained with a selected light position p ($p = 1, \dots, m$) and consists of γ pixels $(i_{p1}, \dots, i_{p\gamma})$, where i_{px} means a color intensity of a surface point x . Each pixel is classified into three types T_{diff} , T_{spec} and T_{none} . T_{diff} means a pixel containing only the diffuse reflection component and T_{spec} means a pixel containing strong specular reflection component. T_{none} means a pixel which is classified into neither T_{diff} nor T_{spec} .

2.2 Inverse Photon Mapping for Estimation of Reflectance Parameters

In this paper, we employ the *photon mapping* rendering method for resolving the problem with the inverse radiosity rendering method [2]. By using the inverse photon mapping method, both diffuse and specular interreflections on the object surface can be taken into account. The photon mapping rendering method also does not require tessellated patches due to its pixel base calculations, and thus even if the object has a complicated shape, the photon mapping can render efficiently compared with the radiosity rendering method.

Photon Mapping. In the photon mapping rendering method [10], an outgoing radiance L from a surface point x is calculated in order to decide the surface color. The following equations form the rendering equations in the photon mapping method.

$$L(x, \vec{\omega}) = L^e(x, \vec{\omega}) + L^r(x, \vec{\omega}), \quad (2)$$

$$L^r(x, \vec{\omega}) = \int_{\Omega} f(x, \vec{\omega}', \vec{\omega}) L^o(x, \vec{\omega}') (\vec{\omega}' \cdot \vec{n}) d\vec{\omega}', \quad (3)$$

x : Surface point

$\vec{n}$: Unit vector of surface normal at x

$\vec{\omega}$: Direction from outgoing radiance

$\vec{\omega}'$: Direction of incoming radiance

$d\vec{\omega}$: Differential solid angle

Ω : Hemisphere of directions

where L^e , L^r , L^o and f are the emitted radiance, the reflected radiance, the incoming radiance, and a BRDF (i.e. the Torrance-Sparrow model), respectively.

Here, the outgoing radiance L in Equation (2) is equivalent to the reflected radiance L^r due to the assumption that the underlying objects have no emissions. Equations (2) and (3) are theoretical models. Using Equation (1), the color $\hat{i}_x$ at surface point x

Fig. 3. Flow diagram of estimating surface reflectance properties based on inverse photon mapping

is represented by the following equation, which is referred to as the Ward reflectance model [12]:

$$\begin{aligned} \hat{i}_x &= I_x \left\{ \frac{P_{dx}}{\pi} + P_{sx} \frac{\exp(-\tan^2 \theta_{rx} / \sigma_x^2)}{4\pi\sigma_x^2} \right\} \\ &= I_x \left\{ \frac{P_{dx}}{\pi} + P_{sx} K(\theta_{vx}, \theta_{rx}, \sigma_x) \right\}, \end{aligned} \quad (4)$$

where I_x is the incoming radiance. $K(\theta_{vx}, \theta_{rx}, \sigma_x)$ denotes the specular term in Equation (1) and is a non-linear equation, and the other parameters are the same as in Equation (1). In practice, the Ward model described above has five parameters for representing anisotropic object surface reflectance properties. Because the object is assumed to have isotropic reflectance properties in this study, there are three unknown parameters: the diffuse reflectance, the specular reflectance and the surface roughness parameters. I_x is decided by counting the number of photons that arrive at the point x . The photon is specifically traced using a Monte Carlo ray tracing method [13]. In this case, the photon is reflected or absorbed according to the reflectance properties, and only the photons that are reflected are traced iteratively.

Iterative Estimation of Reflectance Parameters. Figure 3 shows the flow diagram of the present method. As an initial estimation, the reflectance parameters are obtained by our previous method based on *inverse radiosity rendering* [2] in the process (D) in Figure 1. In the initial preprocessing, the diffuse reflectance parameter is estimated based on the inverse radiosity to consider diffuse interreflections. The specular reflectance and the surface roughness parameters are estimated based on the inverse local rendering (i.e. Torrance-Sparrow model) with no consideration of specular interreflections. Here, let P_{dx}^{init} , P_{sx}^{init} and σ_x^{init} be the reflectance parameters obtained in this process. These parameters are used as initial parameters in the next process (E) in Figure 1. In this process, our approach uses the photon mapping method and it is called *inverse photon mapping*. In the following, the detail of reflectance parameter estimation is described.

The reflectance parameter estimation method based on inverse photon mapping is separated into two processes, (a) and (b), as shown in Figure 3. The first process is for the diffuse reflectance parameter estimation ((a) in Figure 3), and the second process is for the estimation of the specular reflectance and surface roughness parameters ((b) in Figure 3). These processes are performed iteratively. In each process, the following equation, which is derived from Equation (4), is minimized at each pixel in the texture image:

$$\begin{aligned} E(P_{dx}, P_{sx}, \sigma_k) &= \sum_{p=1}^q (i_{px} - \widehat{i_{px}})^2 \\ &= \sum_{p=1}^q \left(L_x - \frac{P_{dx}}{\pi} I_x - P_{sx} K(\theta_{vx}, \theta_{rx}, \sigma_x) I_x \right)^2, \end{aligned} \quad (5)$$

where i_{px} is the measured radiance (color intensity) at surface point x with light source position p , $\widehat{i_{px}}$ is the irradiance that is computed from Equation (4) at surface point x with light source position p , and q denotes the number of selected light positions at surface point x in categories T_{diff} , T_{spec} and T_{none} among the selected light positions m .

In process (a), the diffuse reflectance parameter P_{dx} is estimated using a pixel that is categorized as T_{diff} . P_{dx}^{init} , P_{sx}^{init} and σ_x^{init} are used to compute $\widehat{i_{px}}$ only at the first iteration. Here, the specular reflection term in Equation (4), $I_x P_{sx} K(\theta_{vx}, \theta_{rx}, \sigma_x)$, is set to be 0 because the specular reflection cannot be observed.

In process (b), the specular reflectance P_{sx} and the surface roughness σ_x parameters are estimated using only pixels that are categorized as T_{spec} or T_{none} . P_{sx}^{init} and σ_x^{init} are again used to compute $\widehat{i_{px}}$ only at the first iteration. The P_{dx} estimated above is used in Equation (4). When P_{sx} and σ_x are estimated, the value of each reflectance parameter is updated, and processes (a) and (b) are iterated th times. The reflectance parameter is selected when differences between the real and synthetic images is the minimum value among th samples. Because this is a non-linear equation with unknown parameters, the photon mapping rendering and estimation of surface reflectance parameters is performed iteratively, and the difference between the real image and the synthesized image is minimized (Equation (5)). A number of methods can be used to minimize this equation, and the downhill simplex method is selected for this problem [3].

After the estimation process is complete, the specular reflectance and the surface roughness parameters may not be correct, if the specular reflection component is exceedingly small. Such parameters are interpolated linearly by scanning the texture image horizontally.

3 Experimental Results

In experiments, we compare the proposed method with our previous two methods [1, 2] (hereinafter referred to as Method I and Method II). It should be noted that Method I does not consider interreflections at all and Method II considers only diffuse interreflections. See Figure 4 for the test objects used in the experiments. In the following, we first show the result of comparing reflectance parameters estimated by the proposed method (hereafter referred to as Method III) with Methods I and II using Object A. We

Fig. 4. Three objects used in experiment and measurability of both reflection components

then examine the effect of considering interreflections in surface reflectance parameter estimation using Objects B and C with uniform and non-uniform surface properties. Finally, we show rendered images based on reflectance parameters estimated by using Method III. Figure 4(d) shows the number of selected light positions and the measurability of both diffuse and specular reflection components for Objects B and C by using our previous method [1]. The parentheses means the number of selected light positions to observe diffuse reflection component of the whole object.

A standard PC (Pentium 4, 3.06 GHz, memory: 2 GB) is used in the following experiments. The number of photons is 2 million, and the proposed algorithm requires approximately four hours to estimate the reflectance parameters of each object. The threshold is fixed at $th = 50$.

3.1 Removal of an Influence of Both Diffuse and Specular Interreflections

The performance of the proposed method was demonstrated in preliminary experiments using a simple object (Object A). In particular, the present method (Method III) was compared with Methods I and II. Object A consists of two plates (Regions I and II) situated at a 90-degree angle with respect to each other. We have conducted two setups. One is that the same white paper with a uniform diffuse reflectance surface is pasted up on both regions (Setup 1). The other is that the same glossy paper with a uniform reflectance surface is pasted up on both regions (Setup 2). In both setups, the Object A is put on the table obliquely, so that the influence of interreflections can be observed. It is expected that, if interreflections occur, reflectance parameters estimated by the inverse local rendering method must exhibit incorrect values in that part. The results are shown in Figure 5 for Setup 1 and in Figure 6 for Setup 2. Each graph represents the RGB channels of the diffuse reflectance parameter estimated by the three methods. The horizontal axis represents the position of the pixel along the vertical direction of the object, and the vertical axis represents the average diffuse reflectance parameter along the horizontal direction of the object. In Methods I and II, the value of the diffuse reflectance parameter is large around the boundary between Regions I and II due to the influence of interreflections. However, in Method III, the estimated parameter is more stable, indicating that Method III can eliminate the influence of both diffuse and specular interreflections.

(a) R channel

(a) R channel

(b) G channel

(b) G channel

(c) B channel

(c) B channel

Fig. 5. A comparison among three methods for Object A in Setup 1

Fig. 6. A comparison among three methods for Object A in Setup 2

3.2 Comparison of Rendering Results with Conventional Methods

In the next experiment, we use Objects B and C shown in Figures 4. These objects have non-uniform or uniform diffuse and specular reflectance properties. Figure 7 shows the cylindrical images of real objects and difference images between real and synthetic images (rendered by photon mapping) in Method II and Method III for each test object (Object B and C), respectively. The light position locates at the above on the rangefinder. Synthetic images are rendered using estimated reflectance parameters under the same illumination condition as in the real images. Note that linear interpolation is conducted when the specular reflectance and the surface roughness parameters can not be estimated due to small value of the specular reflection. In Method II, the error due to the influence of specular interreflections is confirmed. Especially, Objects B and C exhibit large errors at the part of inequalities (i.e. duck's legs and pigs' nose). The present method (Method III) does not have such an influence. Additionally, Table 1 shows the average and the variance of differences between real and synthetic images, and the computational time. Method III has much smaller variances than Method II for all the objects. These results show Method III can accurately estimate each reflectance parameter even if diffuse and specular interreflections occur. It is also clear that the *inverse photon mapping rendering* takes more time to estimate the surface reflectance

Fig. 7. A comparison of differences between real and synthetic images for Object B and C

Table 1. Comparison of the differences between real and synthetic images and computational costs of three methods

Object	Method	Average of differences between real and synthetic images	Variance of differences between real and synthetic images	Computational time [h:m]
B	Method I	28.6	894.7	0:23
	Method II	17.7	501.9	3:51
	Method III	1.11	6.8	4:39
C	Method I	14.2	671.0	0:23
	Method II	8.7	493.3	3:11
	Method III	0.51	3.2	4:43

properties than the previous two methods. This is because it takes too much time to render the object image based on estimated reflectance parameters.

3.3 Rendering Results with the Photon Mapping Method

Figure 8 shows rendered images of Objects B and C based on reflectance parameters estimated by the *inverse photon mapping rendering*. It is clear that these images are

(a) Rendering results of Object B

(b) Rendering results of Object C

Fig. 8. Rendering of Objects B and C under varying illumination conditions **Fig. 9.** Residuals in minimization with respect to the number of iterations for Objects B and C

photorealistically rendered. However, there are some errors with respect to the geometry. For example, some parts of duck's legs are not rendered and there are spike noises at pig's nose. These errors are due to noise in range images. To solve this problem, it is necessary to interpolate the range data using the data around these parts.

3.4 Discussion

Figure 9 shows the relationship between the iterated process and the differences between real and synthetic images by Method III. The vertical axis indicates the sum of differences between the real and synthetic images, while the horizontal axis indicates the number of iterations. Each graph shows that the iterated estimation process decreases the difference between real and synthetic images. However, the minimum difference may not be the global minimum because the proposed iteration method ends when the number of iterations reaches 50. Each graph exhibits the pulsation of residuals and implies that if the number of iterations is more than 50, the residuals may become lower. In this experiment, the reflectance parameters of each object is determined when the number of iterations are 34 and 35, respectively.

Inverse photon mapping rendering has estimated the object surface reflectance properties with both diffuse and specular interreflections. However, the method has a prob-

lem with respect to computational time. This problem is due to the time consumed by the photon mapping rendering. Simply implementing and calculating the photon mapping rendering algorithm on fast graphics hardware (GPU) [14] can solve this problem.

4 Conclusions

In this paper, we have proposed a new method for densely estimating non-uniform reflectance properties of real objects. In our approach, we employ the photon mapping method which can represent all of the lighting effects in the real world. This method is independent of complexity of the object geometry unlike the radiosity rendering method. Therefore, the inverse photon mapping method can be applied to objects with various reflectance properties. Experiments have shown that the proposed method exhibits the best performance compared with conventional methods. The advantage of the inverse photon mapping method is that not only diffuse interreflections but also specular interreflections are considered in reflectometry estimation. As a result, estimated parameters can be available without the influence of both interreflections. In future work, we will synthesize a virtualized object into a real world to construct a mixed environment. We will also be concerned with rapid estimation by implementing the algorithm on GPU. Real time estimation has grateful usefulness in computer vision and graphics.

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