Photometric approach to surface reconstruction of artist paintings

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Abstract. We propose a method for surface reconstruction of artist paintings. In order to reproduce the appearance of a painting, including color, surface texture, and glossiness, it is essential to acquire the pixel-wise light reflection property and orientation of the surface and render an image under an arbitrary lighting condition. A photometric approach is used to estimate bidirectional reflectance distribution functions (BRDFs) and surface normals from a set of images photographed by a fixed camera with sparsely distributed point light sources. A robust and computationally less expensive nonlinear optimization algorithm is proposed that optimizes the small number of parameters to simultaneously determine all of the specular BRDF, diffuse albedo, and surface normal. The proposed method can be applied to moderately glossy surfaces without separating captured images into diffuse and specular reflections beforehand. Experiments were conducted using oil paintings with different surface glossiness. The effectiveness of the proposed method is validated by comparing captured and rendered images. © 2011 SPIE and IS&T. [DOI: 10.1117/1.3533329]

1 Introduction

Digital imaging of cultural artifacts and its research have been attracting increasing interest.^{1–9} The purposes of dig-

itization include recording of the current condition of the artifacts for restoration in the future, scientific study of valuable artifacts that are difficult to access, exhibition via publication or the Internet, duplication, and many other applications.

Regarding fine arts, especially artist paintings, much research focuses on estimating the accurate color of target objects from digitized images. In most cases, objects are photographed under a fixed lighting condition that is carefully controlled so that gloss on the object surface is not observed by the camera. This approach is plausible since the surface gloss conceals the color of the object body.

However, glossiness plays an important role for the observers to know the material of the object. To make the stored digital data more informative and useful for a wide variety of applications, it is necessary to record the gloss property as well as color. It is also necessary to recover the fine geometry or orientation of the object surface, not only because it is an essential factor to know the surface asperity but also the light reflection behavior is a function of incident and viewing angles.

The light reflection behavior is described as a bidirectional reflectance distribution function (BRDF),^{10–12} while the surface orientation is usually expressed as a normal vector. Together with the three-dimensional (3-D) shape of the object, recording the BRDFs and surface normals makes

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it possible to reproduce accurate appearance of the target object under arbitrary lighting conditions with image rendering techniques.

The present paper focuses on the estimation of BRDFs and surface normals of flat oil paintings. Oil paintings often have large asperity on the surface due to the canvas textures and brush strokes. In museums, they are commonly varnished and have specularity.

In order to estimate BRDFs and surface normals at each point on the object, a set of images needs to be captured with different lighting or viewing directions. In this research, a photometric approach is employed where images are photographed with a camera fixed perpendicular to the painting surface by changing light source locations. Regarding the image-capture apparatus, a simple prototype was built that requires minimal user operations and ensures the safety of target paintings in consideration of the applicability in museums. A nonlinear optimization algorithm is proposed that is computationally less expensive and robust to estimate pixel-wise BRDFs and surface normals without separating the captured images into diffuse and specular reflections beforehand.

Section 2 addresses previous work on acquisition of geometry and reflection property and relation to this research. Section 3 describes the BRDF model used in this research. The nonlinear optimization algorithm is proposed in Sec. 4. In Sec. 5, BRDF parameters and surface normals are estimated using oil paintings with different glossiness and the results are evaluated. Section 5 also describes the parameter correction method for varnished and strongly glossy surfaces. Limitations of the proposed method and future work are mentioned in Sec. 6 with a summary of this article.

2 Related Work

Research on digital imaging of fine arts has traditionally focused on object color estimation where the purpose is to derive accurate colorimetric values of the object from sensor responses of a camera. Multispectral imaging techniques have been actively studied since the 1990s to improve the colorimetric accuracy, including research targeting artist paintings.^{1,13–15} In most of this research, images photographed under fixed viewing and lighting conditions were used for color estimation, and angle dependency of the object appearance was not managed.

In the field of computer graphics, much research has been carried out regarding angle dependency of light reflection and a lot of BRDF models have been proposed.¹⁶⁻²⁰ Inverse rendering techniques are also actively researched where shape, surface normals, and BRDFs are estimated from images of the target object.²¹ Boivin and Gagalowicz²² proposed a method to recover an approximation of the BRDF from a single photograph and a 3-D geometric model of the scene. Lensch et al.²³ presented a high-quality image-based measuring method that fits BRDFs to different materials of a 3-D object surface. Tarini et al.²⁴ introduced a shape-fromdistortion technique for inverse rendering of objects with mirroring optical characteristics. Goldman et al.25 addressed a surface reconstruction method for recovering spatially varying BRDFs based on the observation that most objects are composed of a small number of fundamental materials. Zickler et al.²⁶ presented a reflectance-sharing technique to

capture spatially varying BRDFs from a small number of images without a parametric reflectance model. Atkinson and Hancock²⁷ presented a shape-recovery technique that uses polarization information and the Fresnel theory. Francken et al.²⁸ proposed a technique for surface normal acquisition by using an LCD screen as a polarized light source. Chen et al.²⁹ proposed an active 3-D scanning method using a modulated phase-shifting technique. Lamond et al.³⁰ presented an image-based method for separating diffuse and specular reflections by illuminating a scene with high-frequency illumination patterns. Once 3-D geometries, surface normals, and reflectance properties are estimated, it is possible to render an image of the scene for arbitrary view points and lighting conditions. Research on inverse rendering mainly aims at digitizing 3-D objects for applications such as motion pictures, computer games, and virtual reality. In the present research, a simple data acquisition apparatus is used by restricting the target object to be dielectric flat paintings with fine asperities.

For surface recovery of flat objects, Gardner et al.³¹ developed an imaging system with a fixed camera and moving light sources. In this system, light sources, a neon tube, and a linear laser emitter, are translated above the object. This method however cannot usually be applied to valuable heritages in museums from the viewpoint of safety of the target objects due to the system design that the device must be set above the object. In the present research, in order to guarantee the safety of the target object, images are photographed with a camera and multiple light sources located horizontally away from the object.

Chen et al.⁷ present a framework for surface reconstruction of oil paintings. In their experiment, a light source is moved along an arc locus around the target painting at dense sampling intervals while a trichromatic camera is fixed perpendicular to the painting surface. They assume that the index of refraction of the varnished painting is constant over the surface, and estimate BRDFs and normals by nonlinear optimization. They examined two BRDF models, the Phong model¹⁷ and the Torrance–Sparrow model,¹⁶ and showed that the latter has better agreement with actual observations. In the present research, the Torrance–Sparrow model is selected to express BRDFs based on their evaluation results.

A limitation of the framework by Chen et al. is that it only guarantees images rendered under light sources located on the 2-D light source locus used for image capturing. In the present research, images are photographed with light sources sparsely distributed in the 3-D space so that synthetic images can be created for arbitrary lighting conditions. Furthermore, the present paper proposes a nonlinear optimization algorithm which is computationally less expensive to estimate BRDFs and surface normals.

Tominaga and Tanaka⁹ employed a photometric technique with a multispectral camera for estimating spectral BRDFs and surface normals of oil paintings. In their method, surface normals and diffuse BRDFs were first estimated based on the photometric stereo method.^{32, 33} Specular BRDFs were next estimated by nonlinear optimization assuming that they are constant across the entire surface. In order to estimate surface normals in the first step, they needed to filter out image intensities (sensor responses of the camera) that seem to contain specular reflection. However, it is difficult to completely distinguish whether an image intensity contains specular reflection or not, if the target surface demonstrates broad specular reflection and several light-source locations give some specularity to the image intensities. In that case, empirical filtering may decline the accuracy of normal estimation. That also results in the low estimation accuracy of specular BRDFs because their method uses the estimated normals for estimation of specular BRDFs. In the present research, surface normals and both specular and diffuse BRDFs are simultaneously estimated by nonlinear optimization. Therefore, it is not necessary to completely extract image intensities not containing specular reflection (although rough estimation helps the nonlinear optimization procedure quickly converge).

Since Chen et al.⁷ and Tominaga and Tanaka⁹ used BRDF models that are not energy conservation compliant, rendered images under novel lighting conditions may deviate from physical consistency. The BRDF model used in the present research approximately incorporates the law of energy conservation.

Ma et al.³⁴ proposed a method to independently derive surface normals from diffuse and specular reflections, later modified by Chen et al.³⁵ based on a data-driven reflectance model. They created gradational illumination patterns by many light sources densely distributed on a hemisphere and captured images by using polarization filters. This approach reduces the number of images required to estimate both specular-based and diffuse-based surface normals. Their method however, cannot estimate a surface roughness parameter of the specular BRDF. Furthermore, a particular lighting device is required that is not applicable to practical image capturing situations in museums. In the present research, a photometric approach is employed from the practical point of view, as well as to assure safety as mentioned above. The proposed method determines single normal vector at each point on the surface by using both specular and diffuse reflections.

3 Modeling the Light Reflection on Oil Painting Surfaces

3.1 BRDF Model Based on the Microfacet Theory

The light reflection behavior on inhomogeneous dielectric object surfaces can be represented as the dichromatic light-reflection model.³⁶ A fraction of the incident light does not penetrate into the object body but is reflected at the inter-face according to Fresnel's law of reflection and observed as specular reflection. The remaining incident light that penetrates into the object body is emitted out after being scattered and is absorbed inside the body and is observed as diffuse reflection.

In order to mathematically represent this kind of light reflection behavior, a lot of BRDF models have been proposed.^{16–20} In the present paper, the Torrance–Sparrow model¹⁶ is employed because of its simplicity and the validity for oil paintings presented by Chen et al.⁷

3.1.1 Specular reflection model

The Torrance–Sparrow model assumes that the object surface is composed of a large number of microfacets, each of which reflects light only to the specular direction according to Fresnel's law. The specular BRDF ρ_s is modeled as Eq. (1)

$$\rho_{\rm s} = \frac{D \cdot F \cdot G}{4(\mathbf{n}^{\rm T} \mathbf{l})(\mathbf{n}^{\rm T} \mathbf{v})},\tag{1}$$

where **n** is the normal vector of the object surface, **l** is the light vector pointing to the light source from the object surface, and **v** is the view vector pointing to the observer (or the camera) from the object surface. All vectors have the length of unity.

In Eq. (1), D represents the probability distribution function of the normal vector **a** of microfacets for which a number of mathematical models have been proposed.^{16,37–40} In this research, the normal distribution function of Eq. (2) is used to model the isotropic reflection on the surface of oil paintings

$$D(\mathbf{a}, \mathbf{n}; \sigma) = \frac{1}{\pi \sigma^2} e^{-(\alpha/\sigma)^2},$$
(2)

where α is the angle between the microfacet normal **a** and the surface normal **n**, and σ is a constant that represents the surface roughness (or a spatial broadness of the specular reflection). Only the microfacets with the normal vector **a** = **h** reflect the incident light to the direction of **v** in the proportion of $D(\mathbf{h}, \mathbf{n}; \sigma)$, where $\mathbf{h} = (\mathbf{v} + \mathbf{l})/|\mathbf{v} + \mathbf{l}|$ is the halfway vector of the light vector **l** and the view vector **v**.

In Eq. (1), G is the geometrical attenuation factor. The Fresnel reflectance F of the microfacets is determined by the microfacet normal **a**, light vector **l**, and the refractive index n of the material.

3.1.2 Diffuse reflection model

As the diffuse component of BRDF, the Lambert model⁴¹ is used in this research because of its simplicity. The Lambert model represents the diffuse BRDF ρ_d as

$$\rho_{\rm d} = \frac{1}{\pi} A(\lambda),\tag{3}$$

where A is the spectral diffuse reflectance and λ denotes the wavelength of light. In the Lambert model, the BRDF is independent of the incident and reflection directions but is dependent only on the spectral characteristics of the object body.

3.1.3 Dichromatic reflection model

In the dichromatic reflection model, the BRDF of the object surface is represented by a linear combination of ρ_s and ρ_d . Suppose the specular reflection on the object surface is caused only by the Fresnel reflection on the microfacets; then the specular component of BRDF is represented as ρ_s in Eq. (1). Also suppose the intensity of the diffuse reflection is proportional to the amount of light that proceeds into the object body without specular reflection at the interface. The BRDF in total can be written as

$$\rho = k_{\rm d}\rho_{\rm d} + \rho_{\rm s},\tag{4}$$

where k_d is a constant representing the ratio of light flux that proceeds into the object body to the entire incident light flux. Since the light flux ratio of each microfacet is $1 - F(\mathbf{a}, \mathbf{l}; \nu)$, the constant k_d is calculated as

$$k_{\rm d} = \int_{\Omega_{\rm a}} \left[1 - F\left(\mathbf{a}, \mathbf{l}; \nu\right) \right] \cdot D\left(\mathbf{a}, \mathbf{n}; \sigma\right) \, d\omega_{\rm a},\tag{5}$$

where $d\omega_{\mathbf{a}}$ is the infinitesimal solid angle along a microfacet normal, and the domain of integration $\Omega_{\mathbf{a}}$ is the hemisphere that covers the object surface (the surface normal **n** corresponds to the zenithal angle of 0 deg). The geometrical attenuation factor *G* is assumed to be constant (*G* = 1) here for simplification because the Torrance–Sparrow model does not incorporate the effect of inter-reflection among microfacets into *G* (as the Oren–Nayar model does¹⁹).

3.2 Model Simplification

Although the Fresnel reflectance F depends on the incident angle to the microfacet, it does not significantly change when the incident angle is less than about $\pi/3$ and can be approximated as a constant.^{42–44} This assumption holds for a surface normal illuminated with a small incident angle because microfacet normals are assumed to be normally distributed around the surface normal with relatively small variance. It can also be applied to the entire 2-D object surface when photographed perpendicular to the object because the surface cannot be lit from behind and any surface point with large incident angle reflects only negligible specular reflection to the camera direction. In this research, a constant $F_0 = F(\mathbf{n}, \mathbf{n}; \nu)$ is therefore substituted to the Fresnel reflectance F in Eq. (1) for all incident angles.

The geometrical attenuation factor is also approximated to G = 1 since there is little effect on the reflection to the camera direction when the incident angle to the object surface is small.^{43,45}

The approximation of the Fresnel reflectance is also applied to k_d in Eq. (5) for small incident angles as Eq. (6)

$$k_{d} \approx \int_{\Omega_{a}} (1 - F_{0}) \cdot D(\mathbf{a}, \mathbf{n}; \sigma) \, d\omega_{\mathbf{a}}$$
$$= (1 - F_{0}) \int_{\Omega_{a}} D(\mathbf{a}, \mathbf{n}; \sigma) \, d\omega_{\mathbf{a}}$$
$$= 1 - F_{0}. \tag{6}$$

This approximation can be considered a simplified version of the BRDF model by Kelemen and Szimary-Kalos.⁴⁶

The final simplified BRDF model used in this research is then given by

$$\rho = \frac{1}{\pi} (1 - F_0) A(\lambda) + \frac{1}{\pi} F_0 \frac{e^{-(\alpha/\sigma)^2}}{4\sigma^2 (\mathbf{n}^{\mathrm{T}} \mathbf{l}) (\mathbf{n}^{\mathrm{T}} \mathbf{v})}.$$
(7)

4 Surface Reconstruction Method

In order to express the light reflection behavior at each image pixel, the BRDF and surface normal at the corresponding point on the target object are required. This section addresses an algorithm that estimates the pixel-wise BRDF and surface normal from a set of images based on the BRDF model described in Sec. 3.

4.1 Sensor Responses of a Camera

The spectral radiance of the light reflected on the object surface with BRDF ρ is given as $R(\lambda)$ by

$$R(\lambda) = \int_{\Omega_{\mathbf{l}}} \rho L(\lambda)(\mathbf{n}^{\mathrm{T}}\mathbf{l}) d\omega_{\mathbf{l}}, \qquad (8)$$

where $L(\lambda)$ is the spectral radiance of the incident light, $d\omega_{\rm I}$ is an infinitesimal solid angle along the incident direction, and $\Omega_{\rm I}$ is its integration domain. When using a point light source and assuming $d\omega_{\rm I}$ is small enough, Eq. (6) can be represented as Eq. (9) with a constant $\Delta\omega_{\rm I}$

$$R(\lambda) = \rho L(\lambda)(\mathbf{n}^{\mathrm{T}}\mathbf{l})\Delta\omega_{\mathbf{l}}.$$
(9)

The sensor response of a camera for channel c is given as $q_{c,n}$ by

$$q_{c,n} = \beta_c \int_{\lambda} \rho L(\lambda)(\mathbf{n}^{\mathrm{T}} \mathbf{l}_n) \Delta \omega_{\mathbf{l},n} S_c(\lambda) \, d\lambda$$

where *n* denotes the light source location, $S_c(\lambda)$ is the spectral sensitivity of the camera for channel *c*, and β is a quantization coefficient. From Eq. (7),

$$q_{c,n} = \frac{\beta_c \Delta \omega_{\mathbf{l},n}}{\pi} (1 - F_0) (\mathbf{n}^{\mathrm{T}} \mathbf{l}_n) q_{\mathrm{d};c} + \frac{\beta_c \Delta \omega_{\mathbf{l},n}}{\pi} F_0 \frac{e^{-(\alpha/\sigma)^2}}{4\sigma^2 (\mathbf{n}^{\mathrm{T}} \mathbf{v})} q_{\mathrm{s};c},$$

where

$$q_{\mathrm{d};c} = \int_{\lambda} L(\lambda)A(\lambda)S_{c}(\lambda)\,d\lambda$$
$$q_{\mathrm{s};c} = \int_{\lambda} L(\lambda)S_{c}(\lambda)\,d\lambda.$$

For convenience, let the normalized sensor response $p_{c,n} = [\pi/(\beta_c \cdot q_{s;c} \cdot \Delta \omega_{l,n})] \cdot q_{c,n}$, which can be obtained through camera calibration. Then,

$$p_{c,n} = p_{d;c,n} + p_{s;n},$$
 (10)

where

$$p_{\mathbf{d};c,n} = (1 - F_0)(\mathbf{n}^{\mathrm{T}} \mathbf{l}_n) t_{\mathbf{d};c}, \qquad (11)$$

$$p_{\mathrm{s};n} = F_0 \frac{e^{-(\alpha/\sigma)^2}}{4\sigma^2 \mathbf{n}^{\mathrm{T}} \mathbf{v}},\tag{12}$$

and $t_{d;c} = q_{d;c}/q_{s;c}$, which is referred to as diffuse albedo, hereafter. Equation (10) represents the dichromatic reflection model in terms of sensor responses where $q_{d;c}$ is the diffuse component, while $q_{s;c}$ is the specular component and not affected by the color of the object body.

4.2 Parameter Estimation by Nonlinear Optimization

The photometric approach in this research uses the normalized sensor responses $p_{c,n}$ given as Eq. (10) for multiple light source locations $n = 1, 2, \dots, N$ to estimate the pixel-wise surface normal and BRDF. Since the light vector \mathbf{I}_n and view vector \mathbf{v} are obtained via geometric calibration of the devices, unknown parameters are \mathbf{n} , $t_{d,c}$, F_0 , and σ . The normal vector has two degrees of freedom because its length is unity. When using an RGB camera (c = R, G, B), the degrees of freedom of the diffuse albedo $t_{d,c}$ is 3. Therefore, the total number of unknown parameters is seven. To find an optimal value for each of these seven parameters, a nonlinear optimization method needs to be used. The problem is that it becomes computationally expensive and easily trapped at local minima independently when optimizing all parameters. In this research, these seven parameters are determined

by using a nonlinear optimization algorithm shown in

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Fig. 1 Proposed nonlinear optimization algorithm to estimate the BRDF parameters and the surface normal. See text for details of each step (1 to 6).

Fig. 1, which is robust, and requires computationally less expensive operations. Details are as follows:

Step 1. Set initial values to **n**, F_0 , and σ . These parameters determine the specular reflection. Section 4.3 describes how to determine the initial values in detail.

Step 2. From Eq. (12), calculate the specular component of the normalized sensor response. Let the result be $\hat{p}_{s;n}$.

Step 3. Subtract $\hat{p}_{s;n}$ from the observed normalized sensor responses $p_{c,n}$ and calculate the residual diffuse component $\tilde{p}_{d;c,n}$ as

$$\tilde{p}_{d;c,n} = p_{c,n} - \hat{p}_{s;n}.$$
 (13)

The closer the parameters **n**, F_0 , and σ are to the optimal values, the closer $\tilde{p}_{d;c,n}$ is to the observed diffuse component $p_{d;c,n}$.

Step 4. Calculate the diffuse albedo $t_{d;c}$ in Eq. (11) by means of the least squares method. By substituting $\tilde{p}_{d;c,n}$ to $p_{d;c,n}$ in Eq. (11), Eq. (14) is obtained

$$\tilde{\mathbf{p}}_{\mathrm{d};c}^{\mathrm{T}} \approx (1 - F_0) \mathbf{m}^{\mathrm{T}} t_{\mathrm{d};c},\tag{14}$$

where

$$\tilde{\mathbf{p}}_{\mathrm{d};c}^{\mathrm{T}} = [\tilde{p}_{\mathrm{d};c,1} \quad \tilde{p}_{\mathrm{d};c,2} \quad \cdots \quad \tilde{p}_{\mathrm{d};c,N}]$$

$$\mathbf{m}^{\mathrm{T}} = \mathbf{n}^{\mathrm{T}} [\mathbf{l}_{1} \quad \mathbf{l}_{2} \quad \cdots \quad \mathbf{l}_{N}].$$

In Eq. (14), $t_{d;c}$ is the diffuse albedo that minimizes the approximation error and is calculated by means of the least squares method as

$$t_{\mathrm{d};c} = \frac{1}{1 - F_0} \cdot \frac{\tilde{\mathbf{p}}_{\mathrm{d};c}^{\mathrm{T}} \mathbf{m}}{\mathbf{m}^{\mathrm{T}} \mathbf{m}}.$$
(15)

Step 5. Using F_0 , **n**, and the diffuse albedo $t_{d;c}$ given by Eq. (15), calculate the diffuse component of the normalized sensor responses $p_{d;c,n}$ of Eq. (11) for all *c*'s and *n*'s. Let the results be $\hat{p}_{d;c,n}$.

Step 6. Calculate the difference between $\tilde{p}_{d;c,n}$ derived in Step 3 and $\hat{p}_{d;c,n}$ derived in Step 5, and determine the cost function \mathcal{O} of the nonlinear optimization as

$$\mathcal{O}(\mathbf{n}; F_0, \sigma) = \sum_n \sum_c (\tilde{p}_{d;c,n} - \hat{p}_{d;c,n})^2 + \sum_c \max(|t_{d;c} - 0.5| - 0.5, 0)^2.$$
(16)

The second term of the right side of the equation is a penalty that restricts the range of the diffuse albedo $t_{d:c}$ to [0, 1].

By using a nonlinear optimization method, the optimal value for each of **n**, F_0 , and σ is determined following the algorithm mentioned above. Any nonlinear optimization method can be applied to this algorithm. In this research, the Nelder–Mead downhill simplex method⁴⁷ is employed that does not need to derive the gradient of the cost function.

The procedure described above decreases the number of parameters to be optimized from seven to four, because $t_{d;c,n}$, the parameter with 3 degrees of freedom, is computed uniquely dependent on **n**, F_0 , and σ . This leads to the less computational cost and robustness of nonlinear optimization compared with the case where all seven parameters are simultaneously optimized.

4.3 Initial Values

The algorithm mentioned in Sec. 4.2 requires appropriate initial values for **n**, F_0 , and σ . This section describes how to determine those initial values.

Regarding the surface normal **n**, the initial value is calculated based on the principle of the photometric stereo method.^{32,33} Although the photometric stereo method can be applied to each of red, green, and blue channel of the camera, one channel that gives the largest $p_{c;n}$ among those three channels is used here by taking into account the robustness against noise.

This method assumes that sensor responses from the camera include no specular component. Since actual normalized sensor responses $p_{c,n}$ may include specular component depending on the light source location and the surface normal, it is required to exclude those observations. However, it cannot be strictly judged before parameter estimation whether a normalized sensor response includes specular reflection, especially when the object has a reflection property that broadly reflects specular. A tentative judgment is hence made so that normalized sensor responses larger than a threshold are omitted. In this research, the threshold is empirically determined as $m_c + 2s_c$, where m_c and s_c denote the mean and standard deviation of normalized sensor responses for all light source locations. Sensor responses smaller than $m_c - 2s_c$ are also omitted because they may indicate that the incident angle is large and Eq. (6) does not hold. The photometric stereo method is applied only for the set of remaining light source locations.



Fig. 2 An oil painting used for the experiment. (a) entire image, (b), (c) analyzed region in the white rectangle of (a), and (d) manually created mask image to discriminate the surface conditions (gray: glossy, black: matte or semi-glossy).

Regarding F_0 and σ , the parameters for the specular component of BRDF, fixed values are used for all pixels. Hara et al.⁴⁴ estimated specular BRDF parameters from logarithms of sensor responses. However, when using this method, it is required that sensor responses including specular components have been obtained for many light source locations and the surface normal has been obtained with high accuracy. This method cannot be used in this research because the light sources are sparsely distributed. Alternatively, $F_0 = 0.05$ and $\sigma = 0.4$ are used as empirically determined initial values. These values do not deviate far from the actual properties of dielectric objects. It was confirmed through experiments that using these values does not largely affect the results of the nonlinear optimization by the downhill simplex method and the number of iterations for convergence.

5 Experiments

Experiments were carried out where oil paintings were photographed and pixel-wise BRDFs and surface normals were estimated.

Figure 2(a) shows one of the target oil paintings used in this experiment. Pixel-wise estimation was executed for the region enclosed by the white rectangle $(1121 \times 1130 \text{ pixels})$. This painting was selected because its surface had both glossy and semi-glossy (or matte) regions so that the proposed method can be evaluated for different finishing conditions. Figure 2(d) illustrates a mask image that was manually created based on the visual observation to distinguish those two regions. The painting in the gray mask region was thickly painted and varnished. The surface was smooth and high specularity was observed as appearing in the captured image shown in Figs. 2(b) and 2(c). On the other hand, the painting in the black mask region was thinly painted, not varnished, and rough. Specular reflection was moderately weak.

5.1 *Image Capture*

An image-capture system was designed in consideration of the applicability in museums. Figure 3 shows the prototype used in the experiments, which was simply composed of a



Fig. 3 Prototype of image-capture apparatus with a digital camera and 16 LED lamps.

computer-controlled RGB camera and 16 light sources (white LED lamps). In order to minimize users' task and the time to acquire whole necessary data, structured-light-based geometry reconstruction and polarization-based diffuse/specular separation strategies were not employed. No movable parts were used to ensure the safety of target paintings.

The light sources were small enough to be treated as point light sources. They were carefully selected from 25 LED lamps within the same lot so that the variance of their spectral characteristics was negligibly small. Camera parameters (pose, focal length, etc.) were obtained beforehand by the geometric calibration procedure.⁴⁸ For each light source, pixelwise incident radiance on the painting surface was calibrated by photographing a diffuse white board with known BRDF placed on the same plane as the painting.

Target paintings were photographed at multiple exposures for each light source to create high dynamic range images.^{49,50} All images were automatically captured.

5.2 Parameter Estimation Results

Figure 4 shows estimated parameters visualized as map images. Figure 4(a) is a map of diffuse albedo $t_{d;c}$. Compared with the captured image in Fig. 2, it can be seen that specularity and asperity of the surface have disappeared and only the pigment color is extracted. Figure 4(b) is a map of surface normal **n**, where red, green, and blue channels are assigned to the vector coordinates *X*, *Y*, and *Z*, respectively. Patterns of the paint thickness and canvas texture can be observed. Figures 4(c) and 4(d) show maps of Fresnel reflectance F_0 and surface roughness σ , respectively, where brightness of the image was assigned to the value of estimated parameters.

Figure 5 shows examples of image rendering results. Figure 5(a) is one of the captured images used for the parameter estimation. A synthetic image rendered under the same lighting condition is shown as in Fig. 5(b), accompanied with the difference image as Fig. 5(c). For comparison, Fig. 5(d) shows a rendered image with surface normals and diffuse albedos estimated by the conventional photometric stereo method^{32,33} and specular BRDF parameters by nonlinear optimization by fixing the surface normals and diffuse albedos. The difference between Figs. 5(a) and 5(d) is shown



Fig. 4 Visualized maps of estimated parameters. (a) Diffuse albedo, (b) surface normal, (c) Fresnel reflectance, and (d) surface roughness. In (c) and (d), range [0.0, 1.0] was mapped to grayscale [0, 255].

in Fig. 5(e). Similar results were obtained for other light sources.

The conventional photometric stereo method resulted in a larger difference even if the pixel-wise nonlinear optimization was applied to estimate specular BRDF parameters. This is considered mainly due to the estimation error on surface normals because other parameters are dependently estimated on the surface normals.

Figure 6 shows the estimation accuracy at two pixels in the semi-glossy surface region. Normalized sensor responses derived from the BRDF model agree well with the observation by the camera. Figure 6(a) indicates that relatively



Fig. 5 Image rendering results: (a) captured image, (b) rendered image by the proposed method, (c) absolute difference between (a) and (b), (d) rendered image by the conventional photometric stereo method (specular parameters were estimated by nonlinear optimization), and (e) absolute difference between (a) and (d).



Fig. 6 Normalized sensor responses observed by a camera and calculated from the BRDF model with estimated parameters. (a) Surface with broad specular property. (b) Surface with relatively narrow specular property.

large specular may have been observed by the camera for several light source locations. In this case, the surface normal cannot be calculated based on the conventional photometric stereo method because the diffuse reflection components cannot be completely separated from the observed sensor responses before estimation. The proposed method, however, can accurately estimate the normal of this kind of surfaces by using both specular and diffuse reflections in the nonlinear optimization procedure. Surface reconstruction results of another semi-glossy oil painting are shown in Fig. 7.

In Fig. 5, although the image rendering result by the proposed method (b) looks quite similar to the captured image (a), estimated parameters have latent errors. As described above, the surface of the painting in the gray mask region is highly glossy. According to the visual observation, specular reflection property is spatially uniform in this region and it was expected that the estimated parameters F_0 and σ should be uniform across this region.

The results illustrated in Figs. 4(c) and 4(d), however, clearly show significant nonuniformity, which implies the low estimation accuracy. When using sparsely distributed light sources as in this experiment, object surfaces that have narrow specular properties may not reflect specular to the camera direction for any light source locations, depending on the surface normal. In that case, the estimation accuracy of the specular reflection parameter significantly declines.

Section 5.3 describes the way to correct the parameters for objects with narrow specular reflection.



Fig. 7 Image rendering results for a semi-glossy oil painting (non-varnished): (a) captured image, (b) rendered image, (c) surface normal map, and (d) specular component (upper right) and diffuse component (lower left) of (b).

5.3 Parameter Correction

Many oil paintings in museums are varnished for surface protection. Those paintings usually have narrow specular reflection properties as the painting used in this experiment with gray mask in Fig. 2(d). As described in Sec. 5.2, when using a sparse set of light sources, large errors may occur for



Fig. 8 Visualized maps of estimated parameters after correction: (a) diffuse albedo, (b) surface normal, (c) Fresnel reflectance, and (d) surface roughness.



Fig. 9 Difference maps of diffuse albedo and surface normal between before and after correction: (a) diffuse albedo (absolute difference [0.0, 0.1]) and (b) surface normal (difference in degree [0.0, 10.0]) were mapped to grayscale [0, 255].

highly glossy paintings. Although densely distributed light sources could improve the estimation accuracy, it increases the time for image capturing and the amount of image data.

In order to compensate for the estimation error for glossy surfaces, parameters were corrected from the first estimation based on the assumption as exploited by Tominaga and Tanaka⁹ that the specular BRDF is spatially uniform a cross the painting surface. The correction method first determined the spatially uniform Fresnel reflectance \bar{F}_0 and surface roughness $\bar{\sigma}$ from the estimation results obtained in Sec. 5.2. The surface normal **n** and diffuse albedo $t_{d;c}$ were next updated by using these values.

The specular BRDF parameters \bar{F}_0 and $\bar{\sigma}$ estimated in Sec. 4 have optimal values at pixels where the reflection observed by the camera includes a large specular component. By extracting pixels where the sensor responses calculated by the BRDF model include relatively large specular component, F_0 's and σ 's are averaged and used as \bar{F}_0 and $\bar{\sigma}$. By considering miscalculation of HDR images and dead pixels of the camera sensor, data with extremely large specular component were omitted. In this research, the strategy for



Fig. 10 Image rendering results after parameter correction: (a) captured image used for parameter estimation, (b) rendered image under the same lighting condition as (a), (c) absolute difference between (a) and (b), (d) captured image under a novel lighting condition, (e) rendered image under the same lighting condition as (c), and (f) absolute difference between (d) and (e).

 Table 1
 Statistics of the specular BRDF parameters estimated by the leave-one-out evaluation for all cases, accompanied with the estimation results by using all 16 light sources.

	Fresnel reflectance	Surface roughness
Mean	0.05394	0.03621
Min.	0.05376	0.03613
Max.	0.05402	0.03629
Std. Dev.	0.00007	0.00005
All lights	0.05398	0.03620

selecting proper pixels was between 0.5 and 5.0 % in specular magnitude across the entire pixels.

The surface normal **n** and diffuse albedo $t_{d;c}$ were next updated using \overline{F}_0 and $\overline{\sigma}$ determined above. In the algorithm mentioned in Sec. 4.2, F_0 and σ were fixed at \overline{F}_0 and $\overline{\sigma}$, respectively; only **n** was optimized ($t_{d;c}$ was dependently determined from **n**, \overline{F}_0 , and $\overline{\sigma}$).

Parameter correction was applied to the gray mask regionshown in Fig. 2(d). Figure 8 shows the corrected parameters as visualized maps. Although the albedo map and surface normal map look almost the same as in Figs. 4(a) and 4(b) (before correction), some modification has been made as shown in Fig. 9 in order to better fit the model to the observed sensor responses with new specular BRDF parameters.

Figure 10 shows examples of image rendering results using the corrected parameters. Figure 10(a) is the captured image with one of the 16 light sources that was used for parameter estimation. Figure 10(b) is the rendered image; in



Fig. 11 Image rendering results for a glossy oil painting (varnished): (a) captured image, (b) rendered image, (c) surface normal map, and (d) specular component (upper right) and diffuse component (lower left) of (b).

this case, the corrected parameters were $\bar{F}_0 = 0.05398$ and $\bar{\sigma} = 0.03620$. The rendered image represents the very similar appearance to the captured image in terms of both color and specularity.

In order to evaluate image rendering under novel lighting conditions, one of the 16 light sources was omitted from parameter estimation and an image was rendered under the omitted one. Four light sources that had caused strong specular for many pixels were not omitted because the estimation accuracy of specular BRDF significantly decreases if they are omitted.

Figures 10(d) and 10(e) show an example of a captured image and a rendered image, respectively. Although some differences can be observed, the location and intensity of gloss in the rendered images well correspond to the captured image. The same was true for other light sources.

Table 1 shows statistics of the specular BRDF parameters estimated by the leave-one-out evaluation described above for all cases. Estimated parameters are fairly stable, revealing that the proposed optimization method robustly estimated those parameters.

Figure 11 shows another example of the surface reconstruction results for a varnished, glossy oil painting. Specular parameters correction resulted in $\bar{F}_0 = 0.05309$ and $\bar{\sigma} = 0.04843$.

6 Conclusions and Future Work

A method to estimate BRDFs and normals on oil painting surfaces that uses a set of images photographed with multiple light sources was proposed. The method utilizes a robust and computationally less expensive nonlinear optimization algorithm that derives diffuse albedos dependently and uniquely from other estimation parameters. In contrast to the conventional photometric stereo method, the proposed method can estimate normals of surfaces with moderate glossiness. For highly glossy surfaces, parameters are corrected by assuming that the specular BRDF is spatially constant across the surface. Experiments were carried out using oil paintings with different glossiness. The proposed method was validated by creating synthetic images with estimated parameters and comparing them with captured images.

For image reproduction of an oil painting, it is required that not only the paint color but also the asperity by brush strokes be accurately represented because both of them are what an artist had intended to express in a work. Glossiness of the painting surface is also important since many oil paintings in museums are varnished for surface protection. Recording surface normals and BRDFs on the painting surfaces makes it possible to reproduce accurate appearance of the target paintings.

Future work includes inter-reflection removal, reproduction of cast shadows, and optimization on lighting conditions for image capture.

The proposed method does not take into account the effect of inter-reflection on the object surface. For oil paintings with strong brush strokes, the parameter estimation accuracy may decline due to inter-reflection. It is required to eliminate biases caused by inter-reflections from sensor responses of a camera.

In actual lighting situations, cast shadows may occur on the surface for large incident angles. Although the normals on the painting surface can be acquired by the proposed method, cast shadows cannot be reproduced in rendered images because the 3-D geometry of the painting is unknown. It is required to estimate not only surface normals but the fine 3-D geometry in order to reproduce the accurate appearance in rendered images.

The proposed method assumes that the specular BRDF is constant across the highly glossy surface even for pixels where sensor responses do not include a large specular component for any light source locations. To improve the estimation accuracy, it is desired that sensor responses include moderately large specular components at every pixel at least for one light source location. A possible solution is to increase the number of light source locations. In that case, the number of light source locations and the arrangement should be carefully optimized to reduce the time and the total image data size.

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