A Reflectance Model for Metallic Paints Using a Two-Layer Structure Surface with Microfacet Distributions

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SUMMARY We present a new method that can represent the reflectance of metallic paints accurately using a two-layer reflectance model with sampled microfacet distribution functions. We model the structure of metallic paints simplified by two layers: a binder surface that follows a microfacet distribution and a sub-layer that also follows a facet distribution. In the sub-layer, the diffuse and the specular reflectance represent color pigments and metallic flakes respectively. We use an iterative method based on the principle of Gauss-Seidel relaxation that stably fits the measured data to our highly non-linear model. We optimize the model by handling the microfacet distribution terms as a piecewise linear non-parametric form in order to increase its degree of freedom. The proposed model is validated by applying it to various metallic paints. The results show that our model has better fitting performance compared to the models used in other studies. Our model provides better accuracy due to the non-parametric terms employed in the model, and also gives efficiency in analyzing the characteristics of metallic paints by the analytical form embedded in the model. The non-parametric terms for the microfacet distribution in our model require densely measured data but not for the entire BRDF (bidirectional reflectance distribution function) domain, so that our method can reduce the burden of data acquisition during measurement. Especially, it becomes efficient for a system that uses a curved-sample Based measurement system which allows us to obtain dense data in microfacet domain by a single measurement.

key words: metallic paint, reflectance modeling, multi-layer surface, measure-and-fit, non-parametric basis function

1. Introduction

As the appearance of a product plays a crucial role in its commercial success, the design of appearance material becomes an essential part in the process of a product development. Among various materials, metallic paints have been commonly used for stylish products such as automobiles, home appliances and personal electronic devices due to their luxurious appearance. Under these circumstances, an accurate and efficient reflectance modeling of metallic paints that can allow realistic simulation of product appearance has drawn particular attention in the field of computer aided product design.

For CG applications such as movies and computer games, the physical validity or manufacturability of the appearance material has not been a major concern. But for applications in manufacturing industries, the accuracy of BRDF[1] which represents the reflectance of appearance material has utmost importance. Recently, modeling methods ensuring the accuracy requirement of appearance materials by measuring the reflectance characteristics have been developed. These measurement-based methods can be classified into two types: factorization methods [2]–[4] and measure-and-fit methods [5]–[7].

A factorization method decomposes huge and high-dimensional measured data into sub-dimensional basis functions using a decomposition technique such as PCA (principal component analysis), SVD (singular value decomposition) and NMF (non-negative matrix factorization). Due to the flexibility of the non-parametric form in their models, the factorization method gives good fitting performance and shows robustness in the optimization process. Since its main role is in efficient representation of measured data, it requires densely measured data in the entire BRDF domain, and this limits its use in practice. In addition, a non-parametric model shows low editability due to its discrete basis functions. In this method, it is necessary to measure the material sample again or to perform a complex data processing for every material sample even if it only differs by the color. But, for parametric models, we can represent the same glossy material with a different color by simply changing some parameter values without measurement and data processing.

On the other hand, the measure-and-fit method fits an analytical model to the measured BRDF data using an optimization technique in order to estimate the values of the model parameters corresponding to the given material. Analytical models are usually expressed as parametric forms so that the parameters of a model can be determined using a small number of measured data. It also gives rendering results that are smooth in visual appearance. Since analytical models can express only the phenomena which are considered in the models, it is essential to select a model that properly represents the reflectance characteristics of the target material. As an analytical model for metallic paints, either specialized models for paint coatings like the Ershov model[8] or general models for opaque surfaces like the Cook-Torrance [9] with multiple lobes can be used [7].

Specialized models are generally expressed by using many physical parameters, so that they can allow the testing of paint appearance according to their paint formulations. But these models usually use many assumptions to represent the reflectance of metallic paints with a simple and explicit form while a metallic paint actually has a complex multi-layer structure. They often assume that the layers are parallel to each other, and the surface of the top (or binder) layer...
is as smooth as a mirror. Due to these assumptions, some terms of a model are too simplified to give a good fitting performance to the measured data. In addition, the highly non-linear and restrictive forms of the models often lead to difficulties during optimization.

The general models based on multi lobes, on the other hand, are relatively simple and flexible compared to the specialized model in which basis functions are coupled by physical parameters. But the general models require many lobes to represent complex materials since they are simply lobe-based models. Besides they show limitations in accurately describing complex visual effects of metallic paints like color shifts and glitters due to the lack of considerations of physical characteristics in multi-layer surfaces.

As discussed thus far, the factorization and measure-and-fit methods have a trade-off between the amount of data acquisition and the accuracy of representation, so that each method shows a drawback in one end. To overcome these problems, we propose a hybrid model that is expressed by using both parametric and non-parametric terms. In this model, the reflectance of metallic paints is derived from a two-layer surface; a binder layer that has a specific microfacet distribution and another layer that consists of subsurface particles by which the reflectance characteristics of metallic paints can be generalized. We handle the facet distribution of each layer as a non-parametric form to increase the degree of freedom. In addition, the non-parametric terms require densely measured data but not for the entire BRDF domain, so that the proposed method allows us to reduce the amount of data and acquisition time for measurement. It is because we handle the other terms using a parametric form except the facet distribution functions.

2. Previous Work

In the past few decades, many researchers in optics and computer graphics have developed BRDF models to achieve realistic representation of appearance material with computational efficiency. These models have evolved to describe more complex materials employing physics and the measured BRDF. In this section, we discuss previous research on various BRDF modeling approaches that can be applied to metallic paints.

2.1 Physically Based Reflectance Models

Among various analytical models, physically based models which quantitatively describe BRDF of real-world materials have been derived by using either ‘the microfacet theory’ or ‘the multi-layer theory’. The microfacet theory assumes that a surface is composed of a large number of very small microfacets, of which orientations are randomly distributed. So, the reflectance angles of a surface follow the microfacet distribution. In computer graphics, many models have been proposed to represent opaque materials applying the microfacet theory to the material with a single layer structure [9]–[11]. These models additionally consider diffuse reflectance caused by multiple and internal scattering of the microfacets, and they are represented by linear combination of two independent basis functions: a specular term that is based on microfacet distribution and a diffuse term often represented by a constant. Among them, Cook-Torrance model [9] has often been used due to its computational efficiency and good fitting performance. These single layer surface models based on the microfacet theory are relatively efficient in terms of computation and also provide intuitive user interactions since colors and glossiness of a material can be controlled by using small number of parameters. However, they are limited in representing the reflectance characteristics of multi-layered surfaces like metallic paints since they consider only the scatterings on a single layered surface.

The other type of physically-based reflectance models is based on a multi-layer surface and they derive the reflectance from subsurface scattering in the layers [12]–[14]. Generally, subsurface scattering is expressed by 8D Birefringent Scattering Surface Reflectance Distribution Function or BSSRDF [1], but it can be described by BRDF when the thickness of a layer is very small. This assumption is valid for most paint coated materials used for industrial products because their coating thickness is usually from 10 to 100 μm. Numerous models based on multi-layer surface have been developed, but only a few models deal with metallic paints that contain metallic flakes in the coating layer. We discuss some of them which are most relevant to our model below.

Callet has presented a reflectance model of interference colors for metallic paints based on a dielectric-metal structure [15]. His interference model can only be applied to special cases of paint coatings since the visual effect of interference fringes appear only when the thickness of the coating becomes extremely thin (ex. less than 1 μm). He also assumes that all the flakes imbedded in the binder layer are parallel, but the statistical distribution of orientations of metallic flakes causes the glitter effect, one of main characteristics of metallic paints [16].

Ershov et al. has developed a BRDF model that fully expresses the physical parameters of metallic paints, by applying the adding and doubling method to a two-layer surface [8]. Their model can be quite useful in testing of paint formulations since it contains many actual manufacturing parameters such as albedo of color pigments, refractive index of binder, size and density of metallic flakes. However, they assume that the specific structure of a material in which metallic flakes are in the top layer and color pigments are in the bottom layer. In addition, the R-V coordinate system, consisting of two vectors of the specular direction and the observation direction, employed for describing the specular reflection in their model can limit its use to represent the reflectance of real-world materials since the R-V coordinate system runs counter to the microfacet theory [6].

Germer et al. have proposed a ray model of light scattering by flake pigments or rough surfaces with smooth dielectric coatings considering the distribution of the flake ori-
orientations and the polarization [17]. Their model is somewhat incomplete as a model for metallic paints since it does not consider the reflectance at the binder surface as well as the color pigment. It is also very complex and highly nonlinear due to the consideration of the depolarized light.

Weidlich et al. [18] have attempted to develop a computationally inexpensive model that can simulate both smooth and rough multi-layered surfaces. They have presented an arbitrarily layered micro-facet surface model considering energy absorption and the Fresnel reflectance at each layer, and also the facet distribution of each layer under an assumption that the size of any microfacet is much larger than the thickness of a layer. In their model, the reflectance of a layer is modeled by using a microfacet reflectance model. However, their model is not developed in a quantitative manner based on radiometric quantities but by intuition to some extent.

Our two-layer model is similar to the work by Weidlich in terms of the physical structure of a surface, but our model is derived based on radiometric quantity and provides a compact model by focusing on metallic paint used in industry. The derivation in Sect. 3 provides an extension to theories applied to develop the previous physically-based models for a single layer surface reflectance. And we show that our two-layer model satisfies the rule of Helmholtz reciprocity. We also present how real reflectance of metallic paint is described using our model.

2.2 Model Fitting to the Measured BRDF

In our research, it is extremely important to determine the values of model parameters of an analytical model that correspond to the target material we want to represent. For complex materials like metallic paint, it is really hard to find the values of model parameters either heuristically or by a trial-and-error approach. In the case of a physically based model that uses physical parameters, the values of some model parameters are known or can be determined by measurement, but the reflectance property of metallic paint is dependent upon many physical parameters as shown in Ershov model [8], that it is difficult to determine all the model parameters in practice. An alternative to determine model parameters is to estimate them by fitting the selected model to the measured data.

For model fitting methods, several researchers including Günter et al. [5] and Rump et al. [7] have fitted the measured data to a Cook-Torrance model with 2 or 3 lobes to represent the homogeneous BRDF part of car paints, but their research basically follows the study of Ngan et al. [6]. Ngan analyzed various analytical models using Matusik’s 100 isotropic BRDF data sets which include metallic paints. In his experiments, physically based models show better fitting performance than empirical models such as Phong model. He also showed that multiple specular terms are required to represent complex materials like metallic paints, but fitting with more than three specular lobes often diverges due to instability in optimization.

He also presented a robust fitting method that estimates each term of Ashikhmin’s generalized microfacet BRDF model [19] using the measured BRDF data. He used a non-parametric function for the facet distribution of the model. But, it showed higher fitting errors than that of the well-known parametric model, the Cook-Torrance model, for 54 cases out of the 100 material samples. We judge that their low performance in fitting is mainly caused by the limitation of Ashikhmin’s model which can only deal with the reflectance of a single-layered surface.

Ershov presents a method that determines the parameters of a BRDF model for metallic paints using the measured data [20]. But many physical parameters are coupled in his model so that it is difficult to optimize the model based on a measure-and-fit method. He simplifies the model by assuming that the refractive index of the binder is known and skipping the glossy term of single scattering on the binder surface. His method therefore is limited to estimation, not an optimization using the measured data.

Our model is also highly nonlinear like the other multi-layer surface models. We use an optimization method similar to Ngan to increase the performance of fitting to the measured data. However, unlike the single lobe based Ashikhmin model used by Ngan [6], our model consists of one diffuse term and two specular lobes. To solve this optimization problem, we use an iterative Gauss-Seidel relaxation method (See Sect. 4).

3. The Reflectance Model for Metallic Paints

Metallic paints consist of a binder with color pigments and metallic flakes in it. The light propagation in metallic paints depends on not only multiple scattering among the constituent elements but also various manufacturing factors such as layer thickness, microfacet distributions of binder and metallic flakes, sizes and densities of color pigments and metallic flakes, etc. It requires an extremely complex model and expensive computation to describe the reflectance of metallic paints with the full consideration of all the light scattering with numerous manufacturing parameters.

As the starting point to develop our model, we simplify the structure of metallic paint considering both optical and geometrical properties of color pigments and metallic flakes. We assume that pigment particles are isotropic and have a spherical shape, so that the scattered light of a large number of tiny color pigments can be modeled to give a perfect diffuse reflection due to their multiple scattering in arbitrary directions. The size of flake particles is much greater than light wavelengths, and we assume that they are imbedded in the paint layer as disk-like particles. The reflected light on the flakes therefore shows a specular property which can be described by a reflection on a surface that follows a certain microfacet distribution. The subsurface particles uniformly distributed in a very thin coating layer have two reflectance properties that correspond to two independent basis functions, namely the diffuse and the specular terms, of the single layer reflectance model based on the microfacet theory.
described in Sect. 2.1. Accordingly, we simplify both color pigments and metallic flakes as one layer that follows a microfacet distribution. Based on these assumptions, we propose a two-layer structure for metallic paint that consists of a binder layer and a subsurface-particle layer with the surface of each layer following a microfacet distribution. Figure 1 schematically shows the composition of metallic paint and our two-layer surface model.

In the remainder of this section, we first present a microfacet reflectance model employed in our work to represent the reflectance of each layer. Then we describe our proposed model by applying it to the two-layer structure.

The notations for vectors and angles used in this paper are summarized in Table 1.

### Table 1 Vectors and angles used in BRDF descriptions.

| Symbol | Description |
|--------|-------------|
| \(\vec{l}\) | the opposite direction of the incoming light direction to a surface |
| \(\vec{v}\) | outgoing light direction from a surface |
| \(\vec{n}\) | surface normal |
| \(\vec{h}\) | the half vector between \(\vec{l}\) and \(\vec{v}\) |
| \(\theta_i\) | the angle between \(\vec{l}\) and \(\vec{n}\) |
| \(\theta_o\) | the angle between \(\vec{v}\) and \(\vec{n}\) |
| \(\theta_g\) | the angle between \(\vec{n}\) and \(\vec{h}\) |
| \(\theta_f\) | the angle between \(\vec{l}\) and \(\vec{h}\) |
| \(\theta_i\) | the angle between \(\vec{v}\) and \(\vec{h}\) |
| \(\theta_\text{ref}\) | the refracted angle in the binder layer when the angle observed in the air is \(\theta\) |

### 3.1 Single Layer Microfacet Reflectance Model

We use the Cook-Torrance model [9] as the microfacet model to represent the reflectance of a metallic paint layer since it is well-known for its good fitting performance to opaque materials. The model is expressed as the summation of two components: the diffuse term and the specular term. The specular term is modeled by single scattering of microfacets. And the diffuse term is modeled by a constant under an assumption that the outgoing radiance of diffusion reflection is linearly proportional to the incident irradiance with no angular dependency. The formula then becomes

\[
f_{c-T}(\hat{\vec{l}}, \vec{n}, \vec{v}) = d^2 + s \frac{G(\hat{\vec{l}}, \vec{n}, \vec{v})D(\theta_i)F(\theta_g)}{\pi \cos \theta_i \cos \theta_o} \tag{1}
\]

Here \(d\) and \(s\) are the diffuse coefficient and the specular coefficient respectively. \(\rho\) is the diffuse bidirectional reflectance. \(D\) and \(G\) are the micro-facet distribution function and the geometric attenuation term, respectively. And \(F\) is the Fresnel reflectance.

In the original Cook-Torrance model, there is one constraint for the diffuse and specular coefficients, that is, \(d+s = 1\) for energy conservation. But we do not consider this constraint since our measured data has relative values and it is not normalized. We intend to make our model more flexible to perform data fitting so that we modify some variables and functions in the model from their original form. See Sect. 4 for more details of our model.

### 3.2 Our Proposed Two-Layer Microfacet Reflectance Model

When outgoing radiance \(dL_o\) is reflected in the viewing direction \(\vec{v}\) from a surface point of metallic paint due to the incident light with radiance \(L_i\) and in the incident direction of \(-\vec{l}\), \(dL_o\) can be decomposed into two components: the radiance \(dL_{o,1}\) directly reflected from the surface of a binder and the radiance \(dL_{o,2}\) due to the reflection at the subsurface layer (See Fig. 2). By the definition of BRDF, the total reflectance \(f\) can be expressed as follows.

\[
f = \frac{dL_o}{L_i \cos \theta_i d\omega_i} = \frac{dL_{o,1} + dL_{o,2}}{L_i \cos \theta_i d\omega_i} \tag{2}
\]

Not only the reflected light from the surface of a binder but also the penetrating light into the surface can proceed to many directions according to its microfacet distribution. The huge diversity in the directions of penetrating light into a surface leads to highly expensive and complex computation for subsurface scattering. Fortunately, however, metallic paints generally have a smooth coating surface, and angular variation of the penetrating light is insignificant. In order to simplify the problem, we consider them a beam that represents the average surface normal for all microfacet surfaces when the light enters a material through a surface.

The radiometric quantity of radiance is defined by the radiant flux per unit projected area and per unit solid angle. Thus, the incident flux \(\Phi_i\) upon a small surface patch \(dA\) radiated from a small light source with the incident radiance \(L_i\) and the solid angle \(d\omega_i\) is given by \[10\]

\[
\Phi_i = L_i \cdot \cos \theta_i \cdot dA \cdot d\omega_i \tag{3}
\]

And the incident flux \(\Phi_i\) into the sublayer which penetrates through the patch \(dA\) has the following relationship with \(\Phi_i\)
using the Fresnel reflectance.

$$\Phi_i = (1 - F_{\text{air}\rightarrow\text{binder}}(\theta_i)) \cdot \Phi_i$$  \hfill (4)

When light travels through a medium (not vacuum), a part of light is absorbed that is proportional to its travelled distance. But in Eq. (4), we do not consider the attenuation of light for the purpose of simplicity since it is insignificant for a thin layer surface [8].

The transmitted beam which penetrates from the air to the binder proceeds to a certain refracted direction that follows the Snell’s law. Inside the binder medium, the incident light into the subsurface layer will have radiance \( \bar{L}_1 \) and solid angle \( d\bar{\omega}_1 \) that are changed due to refraction. Similar to Eq. (3), the flux incident \( \Phi_i \) can be expressed in terms of \( \bar{L}_1 \) and \( d\bar{\omega}_1 \) as follows.

$$\Phi_i = \bar{L}_1 \cdot \cos \bar{\theta}_i \cdot dA \cdot d\bar{\omega}_1$$  \hfill (5)

By combining Eqs. (3), (4) and (5), the relationship between two incident radiance, \( L_i \) and \( L_i \) are expressed as follows.

$$L_i \cdot \cos \theta_i \cdot d\omega_i = \frac{\bar{L}_1 \cdot \cos \bar{\theta}_i \cdot d\bar{\omega}_1}{(1 - F_{\text{air}\rightarrow\text{binder}}(\theta_i))}$$  \hfill (6)

Applying the same process shown in Eqs. (3), (4) and (5) to the case of reflection, the relationship between two outgoing radiance at each medium, \( dL_{\omega,2} \) and \( dL_{\omega,2} \) are given by

$$dL_{\omega,2} = (1 - F_{\text{binder}\rightarrow\text{air}}(\theta_o)) \cdot dL_{\omega,2} \cdot \frac{\cos \theta_o \cdot d\bar{\omega}_o}{\cos \theta_o \cdot d\bar{\omega}_o}$$  \hfill (7)

Here, \( d\omega_o \) and \( d\bar{\omega}_o \) are the solid angles of detector at air and binder medium, respectively.

In the unit hemisphere domain based on a spherical coordinate system \( (\theta, \varphi) \), the solid angle \( d\omega_o \) subtended by an infinitesimal patch of size \( d\theta_o \) in the polar angle and \( d\varphi_o \) in the azimuth angle and its corresponding refracted solid angle \( d\bar{\omega}_o \) formed by \( (d\bar{\theta}_o, d\bar{\varphi}_o) \) can be expressed as follows.

$$d\omega_o = \sin \theta_o d\theta_o d\varphi_o$$

$$d\bar{\omega}_o = \sin \bar{\theta}_o d\bar{\theta}_o d\bar{\varphi}_o$$  \hfill (8)

From Snell’s law, we can calculate the following relationships [17].

$$\frac{d\theta_o d\varphi_o}{d\bar{\theta}_o d\bar{\varphi}_o} = \frac{d\theta_o}{d\bar{\theta}_o} = \frac{\eta_{\text{binder}} \cos \bar{\theta}_o}{\cos \theta_o}$$  \hfill (9)

Here \( \eta_{\text{binder}} \) is the refractive index of the binder.

Combining Eq. (8), Eq. (9) and Snell’s law, the ratio of \( d\omega_o \) to \( d\bar{\omega}_o \) is given by

$$\frac{d\bar{\omega}_o}{d\omega_o} = \frac{1}{\eta_{\text{binder}}} \frac{\cos \theta_o}{\cos \bar{\theta}_o}$$  \hfill (10)

Applying both Eq. (10) and Helmholtz reciprocity \( (F_{\text{binder}\rightarrow\text{air}}(\theta_o) = F_{\text{air}\rightarrow\text{binder}}(\theta_o)) \) to Eq. (7), it becomes as follows.

$$dL_{\omega,2} = (1 - F_{\text{air}\rightarrow\text{binder}}(\theta_o)) \cdot dL_{\omega,2} \cdot \frac{1}{\eta_{\text{binder}}}$$  \hfill (11)

The total reflectance shown in Eq. (2), combined with Eqs. (6) and (11) yields,

$$f = f_1 + f_2 \frac{1}{\eta_{\text{binder}}} T$$  \hfill (12)

Here,

$$f_1 = \frac{dL_{\omega,1}}{L_1 \cos \theta_o d\omega_o}$$

$$f_2 = \frac{dL_{\omega,2}}{L_2 \cos \theta_o d\omega_o}$$

$$T = (1 - F_{\text{air}\rightarrow\text{binder}}(\theta_o))(1 - F_{\text{air}\rightarrow\text{binder}}(\theta_o))$$

Weidlich’s model [18] described the reflectance on a multi-layer surface, but it does not include the term \( \frac{1}{\eta_{\text{binder}}} \) in Eq. (12) since they used an intuitive approach.

As mentioned earlier, the reflectance of corresponding medium in each layer is expressed by using a microfacet based reflectance model. In Eq. (12), \( f_1 \) represents the reflectance of the top (binder) layer that takes place in the air medium and \( f_2 \) represents the reflectance of the bottom (subsurface particles) layer in the binder. Applying Cook-Torrance model shown in Eq. (1) to \( f_1 \) and \( f_2 \) respectively, we have the following BRDF model for the two-layer surface.

$$f(\hat{l}, \hat{n}, \hat{v}) = d_1 \frac{\rho_1}{\pi} + d_2 \frac{g_1(\hat{l}, \hat{n}, \hat{v}) \rho_1}{\pi \cos \theta_o \cos \theta_i}$$

$$+ \left( d_2 \frac{\rho_2^2}{\pi} + d_2 \frac{g_2(\hat{l}, \hat{n}, \hat{v}) \rho_2}{\pi \cos \theta_o \cos \theta_i} \right) T$$  \hfill (13)

Here, the subscript ‘1’ or ‘2’ represents the terms of reflectance on the binder surface and those of reflectance on the subsurface, respectively.

Note that diffuse reflectance of sublayer \( d_2 \frac{\rho_2^2}{\pi} \) in Eq. (13) does not include \( -\frac{1}{\eta_{\text{binder}}} \) term. As described in Sect. 3.1, the outgoing radiance of diffuse reflection is assumed to be linearly proportional to incident irradiance with no angular dependency. So, \( -\frac{1}{\eta_{\text{binder}}} \) term caused by directionality of incoming and outgoing light beams need not be considered.

We can simplify Eq. (13) considering further properties of metallic paints used in the industry. First of all, the binder layer consists of a uniform and transparent material and has a smooth surface although it is not mirror-like. We can therefore neglect both the diffuse term \( d_1 \frac{\rho_1}{\pi} \) and geometric attenuation factor \( G_1 \) for the reflectance of a surface. Second, aluminum flake are generally used as metallic flakes but its Fresnel reflectance shows little variation for the incident direction. As such, we can neglect angular dependence of \( F_2(\bar{\theta}_o) \) and treat it as a constant using the Fresnel reflectance at normal incidence in the binder medium \( F_2(0^\circ) \).

In summary, we develop a following model as the governing equation for metallic paints in our study.

$$f(\hat{l}, \hat{n}, \hat{v}) = d_1 \frac{D_1(\hat{l}, \hat{n}, \hat{v})}{\pi \cos \theta_o \cos \theta_i}$$

$$+ \left( d_2 \frac{\rho_2^2}{\pi} + d_2 \frac{g_2(\hat{l}, \hat{n}, \hat{v}) \rho_2}{\pi \cos \theta_o \cos \theta_i} \right) T$$  \hfill (14)
4. Data Modeling Using Hybrid Basis Functions

The proposed model is basically a multi-lobe model that consists of one diffuse lobe and two specular lobes. Also basis functions or lobes of the model are coupled by the refractive index or the Fresnel’s reflectance of the binder. The model becomes highly nonlinear and this causes several problems such as the local maximum and divergence problem when we fit our model to the measured data based on a traditional optimization method. In this section, we describe an optimizing method based on the sampled microfacet distribution functions that increases the flexibility and robustness of data fitting.

4.1 Model Parameters for Data Fitting

When a measured BRDF for the incident vector \( \vec{t} \) and reflectance vector \( \vec{r} \) is given for the surface normal vector \( \vec{n} \), four angular variables of our model, \( \theta_i, \theta_o, \phi_i, \phi_o \) are easily computed by inner product among input vectors. Also, their corresponding refraction angles, \( \theta_i, \theta_o, \phi_i, \phi_o \) can be determined by using the Snell’s law using \( \eta_{\text{binder}} \). Further details about these angular variables are described in [17]. For the geometric attenuation factor of the sub-layer \( G_2 \), we use the equation based on symmetric V-shaped grooves in [9] that explicitly expresses it by using the four refraction angles. Thus, the unknowns in our governing Eq. (14) are three determinable coefficient terms of \( s_1, d_2 \rho_2 \) and \( s_2 F_2(0^\circ) \), and three 1-D functions of \( D_1, F_1 \) and \( D_2 \).

Among these unknowns, the Fresnel term is a fully physical quantity which describes the reflectance of a perfectly smooth surface according to the incident light angle. When the material is dielectric, the Fresnel term for unpolarized incident light can be expressed using the following formula [17].

\[
F(\theta) = \frac{1}{2} \left( \cos \theta - c \right)^2 \left\{ 1 + \frac{(c \cos \theta + c - 1)^2}{(c \cos \theta - c + 1)^2} \right\}
\]

(15)

Where,

\[
c^2 = \eta_2^2 - \cos^2 \theta - 1
\]

Since the microfacet distribution can have an arbitrary shape, we represent the microfacet distribution functions using arbitrary curves, similar to Ngan’s approach [6]. Applying a general technique of ‘piecewise linearization’ of a non-linear curve, we can formulate \( D_1 \) and \( D_2 \) as follows.

\[
D_1(\theta_i) = \frac{\theta_i}{\theta_{oi} - \theta_{hi}} d_{1,k} + \frac{\theta_{hi} - \theta_i}{\theta_{oi} - \theta_{hi}} d_{1,k+1}
\]

\[
D_2(\theta_o) = \frac{\theta_o}{\theta_{mo} - \theta_{ho}} d_{2,m} + \frac{\theta_{ho} - \theta_o}{\theta_{mo} - \theta_{ho}} d_{2,m+1}
\]

(16)

Where, \( \theta_{hi} \leq \theta_i < \theta_{hi+1} \) and \( \theta_{ho} \leq \theta_o < \theta_{ho+1} \). \( k = 1, 2, \ldots, M_1 - 1 \) and \( m = 1, 2, \ldots, M_2 - 1 \). \( d_{1,1}, d_{1,2}, \ldots, d_{1,M_1} \) and \( d_{2,1}, d_{2,2}, \ldots, d_{2,M_2} \) are arbitrary fixed functions, called the sampling nodes of the \( D_1 \) and \( D_2 \) terms, respectively. And \( M_1 \) and \( M_2 \) are the number of sampling nodes of the piecewise linear approximation for \( D_1 \) and \( D_2 \) respectively.

In Eq. (16), \( \theta_{hi} \) denotes the value of the angle \( \theta_i \) that corresponds to \( D_1 \) term. When the basis functions of the \( D_1 \) are uniformly sampled for \( \theta_i \), \( \theta_{hi} \) becomes \( \frac{\pi (k-1)}{2(M_1-1)} \). Also, \( \theta_{ho} \) denotes the value of the angle \( \theta_o \) that corresponds to \( D_2 \) term.

Equation (16) is rewritten as a more generalized form in Eq. (17).

\[
\begin{align*}
D_1(\theta_i) &= \sum_{k=1}^{M_1} a_k(\theta_i) d_{1,k} \\
D_2(\theta_o) &= \sum_{m=1}^{M_2} b_m(\theta_o) d_{2,m}
\end{align*}
\]

(17)

4.2 Optimization with a Known Fresnel Term

Since the Fresnel coefficient or the index of refraction is a fundamental property in optics, the values are known for several materials. If the Fresnel term of the binder is known, our governing Eq. (14) is represented as a linear simultaneous equation for \( s_1 D_1(\theta_i), s_2 F_2(0^\circ)D_2(\theta_o) \) and \( d_2 \rho_2 \). Considering the measurement error, the governing equation for the measured BRDF can be expressed as follows.

\[
f_j = \sum_{k=1}^{M_1} \alpha_{j,k} x_k + \sum_{m=1}^{M_2} \beta_{j,m} y_m + \gamma_j z + E_j
\]

(18)

Here, \( j = 1, \ldots, N \). \( f_j \) denotes the value of the measured BRDF and \( E_j \) is the noise term. \( N \) is the number of data. The angle expression \( \theta \) denotes the angle \( \theta_i \) that corresponds to the \( j \)th measured data. In Eq. (18), unknown variables for model fitting to the measured data are \( x_k, y_m \) and \( z \).

If we model \( E_j \) as zero-mean independent Gaussian random variables with variance \( \sigma_j \), the maximum-likelihood of the Eq. (18) leads to the following objective function that needs to be minimized.

\[
\Theta = \sum_{j=1}^{N} \frac{1}{\sigma_j^2} \left( f_j - \sum_{k=1}^{M_1} \alpha_{j,k} x_k - \sum_{m=1}^{M_2} \beta_{j,m} y_m - \gamma_j z \right)^2
\]

(19)

Generally, an objective function is minimized by setting the gradient with respect to its variable equal to zero. However, our problem consists of three variables, \( x_k, y_m \) and \( z \), so that we apply the principle of Gauss-Seidel relaxation to determine the solution. The Gauss-Seidel relaxation minimizes an objective function with respect to a single variable first, and uses these new values to minimize subsequent variables [23]. The solution therefore takes an iterative form as...
Here, the upper script \(^{(i)}\) represents the number of iterations. \(A\) and \(B\) are \(N\) by \(M\) matrices that have the following relationships.

\[
A = [w_j \alpha_{j,k}], \quad B = [w_j \beta_{j,m}]
\]  

(21)

And \(w_j\) is the weight factor having the relationship of \(w_j = 1/\sigma_j^2\) considering the noise term. The measurement error is potentially proportional to the change of BRDF values in the local area. Generally, the BRDF value changes rapidly near the grazing angle (\(\theta_h = 0^\circ\)) or the specular angle (\(\theta_s = 90^\circ\)). Considering this sensitivity in measurement error, we choose the following as the weight factor.

\[
w_j = (\sin \theta_h + 0.1)(\cos \theta_s + 0.1)/1.21
\]  

(22)

We need to be cautious when the measured data does not exist in the interval made by two adjacent basis functions, in which case singularity occurs and the solution diverges. This type of problem can be resolved by eliminating columns having the bins with zero values.

The objective function in Eq. (19) is quadratic with respect to unknowns \(x_k\), \(y_m\) and \(z\). A linear least square sense can be considered for optimization. But, the SVD method of the well-known general least square optimization can lead to a ‘negative solution’ in a multi-variable problem [2]. Besides, the SVD method has drawbacks such as an expensive computation time and a huge memory space. The main strength of this iterative method is preventing negative solutions which give invalid physical meanings of the unknowns. According to Eq. (20), a variable \(p\) among three unknowns, \(x_k\), \(y_m\) and \(z\) can have a negative value when one of the rest variables has an over-estimated value. We can easily reduce the over-estimated value in the subsequent iteration by replacing the negative value of the unknown variable by a positive.

If \(p < 0\) then set \(q\) as \(‘qp’\), \(0 < q < 1\)

(23)

Here, \(q\) is a user-defined constant to prevent divergence. In our experiments, we set \(q\) as 0.3 and can obtain a converged solution within 10 iterations.

4.3 Optimization with Unknown Fresnel Term

But the Fresnel term is not known for most materials. Since it also depends on the wavelength of light, it is required to find the Fresnel term that is appropriate to the RGB system. Thus it must be estimated from the measured data. Fortunately, the Fresnel term is fully defined by a single parameter of the reflectance at normal incidence whose value is bounded by zero to one. And Fresnel reflectance shows a monotonic behavior with respect to the Fresnel reflectance at normal incidence. Due to the characteristics of the Fresnel term, a simple line search algorithm can be used. In our method, we determine the Fresnel reflectance at normal incidence of the binder \(F_1(0^\circ)\) that gives the lowest fitting error using the method given in Sect. 4.2 while narrowing down the sampling interval and search range as shown in Fig. 3.

5. Experimental Analysis

5.1 Acquisition of BRDFs

Recently image-based measurement devices using a curved sample have been developed due to the simple system setup and quick acquisition time [3], [5], [21]. We have also built an image-based measurement device that uses a hemi-sphere sample to measure isotropic BRDF as shown in Fig. 4. Our measurement system uses a Cannon Mark II digital camera as a detector which produces high resolution images (3504 \(\times\) 2336 pixels) and has a sufficient range of exposure time (1/8000 to 8 Sec.). As a light source, we use a 50 W halogen lamp. A color filter is used to make the light source close to the standard light of D65. A diffuse filter, a condenser lens, and an iris with a small aperture are additionally used to generate an unpolarized beam that is spatially uniform.

When using a digital camera as a detector for a measurement system, both geometric and radiometric calibrations are needed. We perform a geometric calibration using Tsai’s camera calibration method using a planar feature pattern [22], in which the geometric relationship is found between the digital camera, the sample and the light source.

For radiometric calibration, we use Robertson’s method [23]. We take a total of 18 photographs with exposure times ranging from 1/4000 to 2 seconds for each light position to generate an HDR image as the radiance map of the material sample.

For the experiment, we choose 14 material samples that include glossy (or solid) paints of black, grey, white, green, blue, red and orange, and their corresponding metallic paints containing the flake size of 20 \(\mu\)m and the volume density of 5 percents, as shown in Fig. 5. Each glossy and metallic paint sample is covered uniformly observing different flake size and volume density by a professional paint studio. We measure each paint sample using the light source with every
10 degree interval from 10 to 140 degrees. Though our data are not measured uniformly in the 3D domain of an isotropic BRDF, a sufficient amount of data is obtained in the entire domain using high resolution camera and for many normal directions of the hemisphere sample.

5.2 Model Fitting

To evaluate the performance of our model, we have selected a Cook-Torrance model with 2 specular lobes and the Ershov’s model which have been used for representing metallic paints based on measured data in previous studies [5], [7], [20]. We test the two-layer model described in Sect. 3 with the Gaussian functions as the microfacet distributions in order to observe the difference in fitting performance between parametric and non-parametric functions. We use the well known Levenberg-Marquardt algorithm, a nonlinear optimization method, to fit the measured data to the above mentioned models expressed as a parametric form.

Ershov model is also highly nonlinear since it is a multi-layer model with basis functions that are coupled by physical parameters. To avoid the divergence problem, we heuristically set search range for several parameters in Ershov model but this can lead to a local minimum. To make a fair comparison, we have fit the measured data to Ershov model using two methods: the general method based on Levenberg-Marquardt algorithm and our fitting method based on the sampled microfacet distribution functions described in Sect. 4.

In our experiments, we use a data set with 8,000 incoming and outgoing light directions per a material sample with no preprocessing. The radiance of a material sample is measured and it is equal to $\text{BRDF} \cdot \cos \theta_i$ assuming a uniform directional light source. The amount of error of the BRDF becomes significant near 90° of $\theta_i$ and when the value of $\cos \theta_i$ becomes very small, so that the value of $\cos \theta_i$ is less than 0.1 is not used.

The fitting errors of our proposed model and two other models for fourteen material samples are given in Table 2. For the glossy paints, single specular lobe models are used and the reflectance term of metallic flakes is neglected. Table 2 shows that our proposed two-layer model with hybrid basis functions has the lowest errors for both glossy and metallic paints. The superior performance of the proposed method is primarily due to the use of a multilayer structure and non-parametric basis functions which provide a high degree of freedom. Ershov’s model shows relatively higher fitting errors than ours even when the sampled microfacet distributions are applied to it. It is because the specular term in his model does not appropriately represent the reflectance at the binder surface and also the specular reflection based on the R-V coordinate system causes errors since the coordinate system does not follow the microfacet theory.

### Table 2 The fitting errors of the proposed model and other BRDF models.

| Materials         | Cook-Torrance with parametric basis | Ershov with parametric basis | Ershov with hybrid basis | The two-layer with parametric basis | Our proposed two-layer with hybrid basis |
|-------------------|-------------------------------------|------------------------------|--------------------------|-------------------------------------|-----------------------------------------|
| Glossy black      | 0.142                               | 0.145                        | 0.107                    | 0.146                               | 0.074                                   |
| Glossy grey       | 0.136                               | 0.138                        | 0.085                    | 0.134                               | 0.082                                   |
| Glossy white      | 0.121                               | 0.123                        | 0.082                    | 0.106                               | 0.081                                   |
| Glossy red        | 0.142                               | 0.137                        | 0.104                    | 0.134                               | 0.101                                   |
| Glossy green      | 0.137                               | 0.141                        | 0.092                    | 0.141                               | 0.095                                   |
| Glossy blue       | 0.143                               | 0.153                        | 0.126                    | 0.148                               | 0.120                                   |
| Glossy orange     | 0.123                               | 0.123                        | 0.087                    | 0.119                               | 0.078                                   |
| **Average error** | **0.135**                           | **0.137**                    | **0.098**                | **0.112**                           | **0.090**                               |
| Metallic black    | 0.182                               | 0.244                        | 0.158                    | 0.225                               | 0.119                                   |
| Metallic silver   | 0.165                               | 0.243                        | 0.151                    | 0.242                               | 0.099                                   |
| Metallic white    | 0.142                               | 0.160                        | 0.107                    | 0.151                               | 0.093                                   |
| Metallic red      | 0.196                               | 0.238                        | 0.180                    | 0.229                               | 0.117                                   |
| Metallic green    | 0.193                               | 0.285                        | 0.139                    | 0.274                               | 0.101                                   |
| Metallic blue     | 0.184                               | 0.258                        | 0.145                    | 0.238                               | 0.103                                   |
| Metallic gold     | 0.152                               | 0.257                        | 0.169                    | 0.243                               | 0.118                                   |
| **Average error** | **0.175**                           | **0.241**                    | **0.150**                | **0.229**                           | **0.107**                               |
addition, the fitting errors of metallic paints are bigger than that of glossy paints; it is due to more complex reflectance property of metallic paints. Among analytical models using parametric basis functions, our two-layer model using Gaussian distribution functions gives the lowest fitting errors for glossy paints. But for metallic paints, the Cook-Torrance model with two lobes gives the lowest fitting errors. We think that the degree of the freedom of the models causes these fitting results. The Cook-Torrance model lacks in considering the layered structure but it is relatively flexible compared to the Ershov model and the two-layer model. Differently to the Cook-Torrance model, the diffuse and specular lobes of the Ershov model and the two-layer model are coupled by the Fresnel effect of the binder.

Figure 6 shows the fitting between three different models for the measured data of white metallic paint. The three models are Cook-Torrance model with two specular lobes, Ershov model based on non-parametric facet distribution functions and our proposed model. As shown by the figure, our proposed model fits the measured data much better than the other two models in all BRDF domains.

Figure 7 shows the determined microfacet distribution functions of our model for the metallic red paint. The estimated facet distribution shows partially bad continuity due to discreteness of non-parametric basis, linear interpolation used for data modeling and the noise in the measured data. As shown in Fig. 7, fluctuations often occur at the inflection area of the facet distribution of the sublayer. In our experiment, they strongly appear when the sampling rate of the functions is insufficient. We use 150 for $M_1$ and 200 for $M_2$ since the size of error almost converges above these values.

Figure 8 shows the sampling nodes of the non-parametric microfacet distribution functions for the red channel shown in Fig. 7 and their Gaussian approximations by curve fitting. The error of the fitted Gaussian function to the non-parametric microfacet distribution function of the binder surface (the upper layer) is about 10 percent, but the error of the sublayer is about 40 percent. Experimentally we found that the non-parametric microfacet distribution functions of both layers obtained by the proposed method can be approximated to less than 5 percent of curve fitting errors by using a Gaussian mixture function which combines more than two Gaussians with each Gaussian allowing shifting effects.

$$D(\theta) = \sum_i u_i e^{-\frac{(\theta - \epsilon_i)^2}{m_i^2 - \nu_i}}$$

However, it is too much nonlinear to apply the two-layer
model using Gaussian mixture functions as the microfacet distributions to data fitting through a general non-linear optimization method.

For our method, the computing time for optimization is highly dependent on the number of samples of nonparametric terms, but for a general non-linear optimization of an analytical model, it is highly sensitive to initial parameter values or a search range. It is hard to compare the performance of these two types of methods objectively. However, we observe that our optimization method consistently gives a stable result for all the material samples compared to the general method for parametric models.

5.3 Rendering Results

Using a BRDF model, we can compute a radiance map or a HDR image of a given virtual object under a certain illuminating condition. But in order to display a radiance map or a scene in a general display device using the LDR image format, the relationship between a radiance value and its corresponding pixel value needs to be established. This is generally called a tone-mapping. In our tone-mapping, the relationship is obtained by fitting the measured radiance of the color checker as shown in Fig. 4 to the reference values provided by GretagMacBeth under an assumption that the color temperature of the lighting environment is D65.

\[
\begin{pmatrix}
R \\
G \\
B
\end{pmatrix} = \begin{pmatrix}
\frac{1}{2.06} & & \\
\frac{1}{2.04} & & \\
\frac{1}{1.97} & & 
\end{pmatrix}
\]

Fig. 8 Estimated non-parametric nodes of microfacet distributions and their Gaussian approximations for the red metallic paint (red channel): (a) top layer, (b) subsurface layer.

Fig. 9 Rendering results of a sphere model using 11 directional light sources. (Top-to-bottom: metallic black, metallic silver and metallic white paint. Left-to-right: (a) Using the measured radiance data (ground truth), (b) Cook-Torrance model, (c) Ershov model, (d) Ershov model with the hybrid basis, (e) our two-layer model with Gaussian facet distribution functions and (f) our proposed two-layer model with the hybrid basis).

Fig. 10 Rendering results of a sphere model for 14 glossy and metallic paints.

Here, \((R, G, B)\) and \((r, g, b)\) represent the pixel value in the LDR level and the radiance value in the HDR level, respectively.

Figure 9 shows the rendering results of a sphere using directional light for several metallic paints. The proposed model represents the glossy appearance quite well as expected by its superior fitting performance. Observing the highlighted area of a sphere, we can confirm that the half vector based coordinates (e.g., the Cook Torrance model and our two-layer model) represents specular reflection better than the R-V coordinates (e.g., Ershov model).

Figure 10 shows the rendering results of a sphere model
of 14 glossy and metallic paints under global illumination using a well-known RNL environment map by Paul Debevec [24]. To compute each pixel, we sample about 1,500 directions of incoming light using importance sampling with respect to the BRDF model. Different from the rendering results under a small number of lights as shown in Fig. 9, visual artifacts disappear under global illumination although there still exists bad continuity in the microfacet distribution.

6. Conclusion and Future Work

In this paper, we present a novel method that can accurately represent the reflectance of metallic paints by a two-layer reflectance model using arbitrary microfacet distribution functions. The reflectance model is quantitatively derived by applying a well-known microfacet reflectance model to a two-layer structure. The microfacet distribution terms in the model are handled as a piecewise linear non-parametric form to increase its degree of freedom. Our results show that the proposed method can accurately represent the actual BRDF better than the previous methods based on the multi-lobe Cook-Torrance model or Ershov model used in other studies. The proposed hybrid model also gives better results than the two-layer model using parametric microfacet distribution functions.

In our model, we avoid expensive computation needed in subsurface scattering by simplifying the metallic paints to a two-layer structure and also approximating the direction and intensity of the transmitted beam into a sublayer assuming a smooth binder surface. We do not consider the interference effect due to the multiple reflections between air and the binder layer and between the binder layer and the layer containing subsurface particles. Due to these approximations, our model can represent complex reflectance properties in real time.

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