Realistic Material Modeling for Product Design

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Abstract

In 21st century, the aesthetic quality of an industrial product plays an important role in its commercial success. Many factors affect the aesthetic quality such as the design of the product and the materials used for product appearance. In this paper, a realistic material modeling method that can provide a photorealistic view of the industrial products coated with metallic paints is introduced. An image-based BRDF (Bi-directional Reflectance Distribution Function) measurement system is developed to acquire BRDFs of a given surface. Then, the acquired data are fitted to various analytic BRDF models for determining appropriate parameters for these models. The performance of these models is analyzed in terms of their ability to model the appearance of the product based on the fitting results. Finally, the rendering results are shown for several industrial products on a hardware accelerated rendering system.

Keywords: aesthetic design, material appearance, reflectance measurement system, BRDF model

1 Introduction

In this world of global competition, design and modeling technology of an industry plays a major role on the quality and the development period of a product. As the consumer demands are increasingly becoming diverse, the aesthetic quality and the development period of a product strongly affect the commercial success. In the 21st industrial environment where demands for complicated and aesthetic outlook of products are increasing, the importance of modeling technology which can ensure aesthetic quality of the designed products in early stages of product development is even further growing. Therefore, incorporating computer graphics technology that ensures the aesthetic quality of a product in the early stage of development is crucial.

In computer graphics, the aesthetic quality of a material is determined by the function which can formulate how rays of incident light reflect from its surface. The commonly used function to describe this phenomenon is called BRDF. BRDF describes the reflectance of a surface under the assumption that all light transport occurs at a single point, which is simplified to the 4D function from the 12D general light scattering case [Nicodemus et al. 1977]. To model the appearance of a surface, we need to determine BRDFs of it. There are mainly two ways to determine BRDFs of a surface: analytical BRDF models and direct measurement. Analytical reflection models are usually simple and easy to use. Over the past few decades, numerous analytical BRDF models have been proposed. However, selecting a BRDF model from these wide range of models and choosing the appropriate parameter values which faithfully represent the reflection properties of a real world surface is a difficult task. On the other hand, BRDFs of a surface also can be measured by traditional device called a gonio-reflectometer. But, its use is far from widespread due to the high cost of measurement time and the required equipment. Direct rendering using the measured BRDFs also requires mass storage.

In this paper, we focus on the realistic representation of metallic painted surfaces that are widely used in automobiles, appliances and other industries due to their deluxe. First, an image-based measurement system that can measure isotropic BRDFs of a surface is developed. After acquiring the BRDFs of metallic paint sample using this system, various analytical BRDF models are fitted to the measured data using nonlinear optimization technique to determine the appropriate parameters of these models. Several well-known BRDF models are analyzed in terms of their ability to approximate the appearance of metallic painted surface based on the fitting results.

2 Background

2.1 Analytical BRDF models

Over the past few decades, numerous analytical reflection models have been proposed to approximate the reflectance of various classes of real-world materials. They can be roughly divided into two classes: empirical and physically-based models. Empirical models seek to emulate the characteristics of material reflection qualitatively, while physically-based model derive quantities from basic principles of physics. Among the wide ranges of existing models, empirical models such as Phong[Phong 1975], Blinn-Phong[Blinn 1977], Ward[Ward 1992], Lafortune [Lafortune et al. 1997] and physically-based models such as Cook-Torrance[Cook et al. 1981], He-Torrance-Sillion-Greenberg[He et al. 1991], Oren-Nayar[Oren et al. 1994], Ashikhmin et al.[Ashikhmin et al. 2000] are popular. A BRDF model is typically composed of two components, the diffuse term and the specular term. The diffuse term generally describes the aggregate effects of multiple reflections. As a result, it is mostly independent of the light and view direction. While the diffuse term of the above-mentioned models are the same, researchers in those models tried to come up with a new specular term for better representation of material reflectance.

2.2 Measured data based BRDF modeling

Several researchers have used the measured data based modeling approach for different purposes. Matusik[Matusik et al. 2003] and Ngan[Ngan et al. 2005] evaluated the existing BRDF models and determined the appropriate parameters by fitting these model to the measured data. They then used these parameters to model the appearance of hundred different types of materials. Recently,

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Günther et al. [Günther 2005] used the same approach for realistic rendering of a car paint. At first, they measured BRDFs of car paint using an image-based measurement system. Then they fitted a multi-lobe Cook-Torrance model to the measured data using a non-linear optimization technique. Finally, they used a real-time ray tracing technique to render the image. In this paper, we model the appearance of metallic paints, with varying composition of microstructure.

3 BRDF acquisition

BRDFs of a surface are usually acquired using a traditional device called a gonio-reflectometer. Researchers have been proposing many efficient gonio-reflectometers for the last few years. Nowadays image-based measurement systems such as the one proposed by Marschner et al.[Marschner et al. 2000] have become popular. Inspired by Marschner et al., we have built an image-based measurement system for measuring isotropic BRDF as shown in figure 1. The main parts of this system are a digital camera as a detector, a light source, a precise computer-controlled turntable and a hemisphere-shape material sample for the acquisition target.

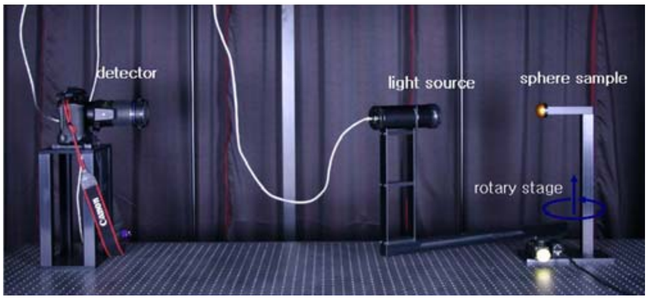


Figure 1. Image-based measurement system.

Each hemisphere sample is covered with uniformly distributed metallic paints of varying composition of microstructure by a professional painting studio. Among the various microstructural components, the flake plays the major role on the metallic painted appearance. Therefore, we use metallic paint sample with varying flake density and size, as shown in figure 2. The light source is mounted on an arm to the turntable which facilitates the light to orbit the measurement sample placed at the center of rotation. In the image of the hemisphere sample taken using the detector, every pixel is in effect a BRDF measurement. The whole system is placed in a dark room, whose walls and ceiling are covered with black fabric.

Figure 2. Metallic painted hemisphere samples differing in their composition of microstructure.

During acquisition, the light source moves in increment of 1 degree from the point exactly in front of the camera to the position exactly the opposite from the camera. For each position of the light, we take 10 images with different exposure time and combine them to generate one high dynamic range radiance map, which records the BRDF data for this light position.

In this system, a camera calibration method is used for determining the relationship between the camera coordinate and the sample coordinate[Tsai 1987]. And photometric calibration is performed to estimate radiance flux (or electromagnetic flux) using a digital camera[Robertson 2003].

4 Fitting BRDF model to measured data

A core part of our modeling process is to fit analytical BRDF models to the measured BRDF data. The acquired BRDF data described in section 3 are processed using a standard parameterization method [Rusinkiewicz 1998] for fitting. Selected BRDF models to fit and the data fitting algorithm are presented in the following sections.

4.1 BRDF models for fitting

As we presented in section 2, there exist a wide range of BRDF models. Since no model is perfect for all type of surfaces, determining the best model from such a variety of models with appropriate parameters for a target material is a challenging task. Among the models presented in section 2, we have selected three BRDF models based on the result of Ngan et al.[Ngan et al. 2005], who evaluated the performance of BRDF models presented in section 2 in terms of their ability to fit measured data of 100 types of materials which includes plastic, fabric, paint, etc. Ngan et al. found that Cook-Torrance and Ashikhmin et al.'s models perform the best in most cases. They also concluded that the half-vector based Blinn-Phong model performs better than the reflection-vector based Phong model. We adopted their two best-performed physically-based models, Cook-Torrance and Ashikhmin et al. model, and one empirical model, Blinn-Phong, for our analysis.

Table 1. The parameters of BRDF models to be determined from fitting

BRDF Models	**Features**	**Parameters** (to be determined)
Blinn-Phong	Empirical	k_d, k_s, p_0
Cook-Torrance	Physically-based	k_d, k_s, p_0, p_1
Ashikhmin	Physically-based	k_d, k_s, p_0, p_1

To evaluate the performance of the selected models, we assumed that the diffuse contribution of the three models to be ideal diffuse. For each color channel, the three models can be expressed with two parameters, k_d and k_s, for diffuse and specular color and a variable number of parameters p_0, p_1, p_2, etc. for specular lobe. Table 1 shows the required parameters of the three BRDF models which need to be determined from fitting. Readers are referred to the respective papers for the equation of the models and the parameters.

4.2 Fitting algorithm

Since the BRDF models presented above are nonlinear expressions, the fitting process requires non-liner optimization. We apply a constrained nonlinear optimization technique based on a sequential quadratic programming technique. We use a standard nonlinear Levenberg-Marquardt [Marquardt 1963] algorithm for that purpose. The goal of the optimization is to minimize the error metric *E(p)* which is defined as the root mean squared error between the measured BRDF, M and the BRDF of the target model, K weighted by the cosine of exitant angle, θ_v given parameter vector, **p** :

$$\text{minimize},\ E(p) = \sqrt{\sum\ [M(\omega_i,\omega_o)\cos\theta_v - K(\omega_i,\omega_o;p)\cos\theta_v]^2}$$

Like any other nonlinear optimization technique, the quality of fitting is dependent on a good initial guess of the parameters to be determined. To ensure that the optimization converges to the global minimum, we visually inspect the fitting quality of the result and when necessary, restart the optimization from a different set of initial guesses.

The result of the optimization process described above is the fitted parameters and visual representation of the fitting. In order to judge the results appropriately and to determine the difference between different fittings it is necessary to make a quanitative comparison of the resulting fitting to each other. We use signal-to-noise (SNR) ratio for that purpose. The higher the SNR value the better the model fit. There are various different metrics to calculate the SNR. The one which is commonly applied in graphics and computer vision to compare images is calculated as follows:

$$mean\ \ squared\ \ error\ ,MSE\ =\frac{1}{N}\sum_{i}^{N}(m_i-s_i)^2$$

$$Variance,VAR=\frac{1}{N}\sum_{i}^{N}(m_i-\overline{m})^2$$

$$SNR=10\log_{10}(\frac{VAR}{MSE})$$

Here, s_i is the BRDF model predicted value; m_i is the measured value, *m-bar* is the mean of the measured values in the dataset and N is the number of samples in the set. We performed a comparison of the results using the SNR as a measure of accuracy.

5 Results

We first present the fitting results in section 5.1. Then we provide rendering results based on the fitted parameters as well as real measured data in section 5.2.

5.1 Fitting result

After fitting the BRDF models to the measured data of all coated samples which have varying composition of their microstructure, we perform a comparison of BRDF models in terms of their ability to approximate the reflectance of coating materials. A sample figure of the BRDF model fitting comparison is shown in figure 3.

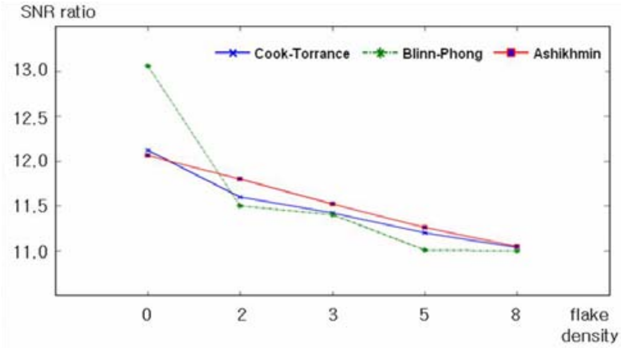
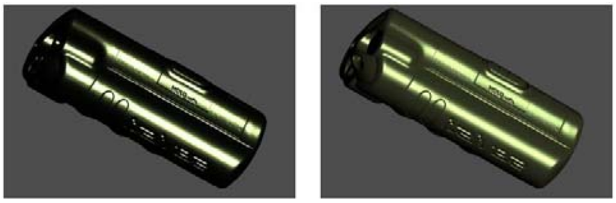


Figure 3. Microstructure-based BRDF model fitting comparison

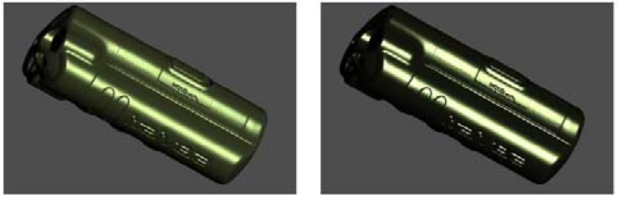
The x-axis denotes the different samples having varying composition of microstructural components especially flake density variation, and the y-axis shows the goodness of fit or SNR ratio. Our comparison shows that when the density of flake of a coated sample increases while keeping the composition of other components the same, the SNR ratio decreases. In our other fitting analysis, it shows that when the average flake size of a coating microstructure increases while keeping the composition of other components the same, the SNR ratio of every model also decreases. The most probable reason for these phenomena is that none of the existing BRDF models take account of the effect of microstructural composition on the appearance of coated surfaces. In our study, Ashikhmin model performs the best among the three models presented in the figure in terms of SNR ratio. The fitting capability of Blinn-Phong and Cook-Torrance models for coated samples are almost the same.

5.2 Rendering results

We render various products coated with metallic paints having different composition of microstructure on a hardware-accelerated rendering system. We compare the rendering results of three BRDF models with their respective fitted parameters and the results of measured data shown in figure 4. We can see from these figures that, Ashikhmin model can best approximate the appearance with real measured data while Cook-Torrance and Blinn-Phong shows discrepancies. It is because the fitting performance of Ashikhmin et al.'s model is better than others as we have seen in fitting analysis. Though Ashikhmin model shows best performance in terms of approximating the appearance of the coated samples, there is a subtle discrepancy with the measured rendering results. Figure 5 shows rendering result of a *MP3 player* with gold metallic coating using Ashikhmin model. The coating has different flake density with the fixed average flake size.

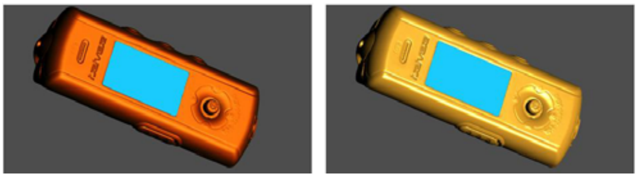


(a) Measured (b) Blinn-Phong model



(c) Cook-Torrance model (d) Ashikhmin model

Figure 4. Rendering results of a *MP3 player* with BRDF models for metallic coating having 8% flake density and the average flake size of 25 microns.



(a) Flake density: 0% (b) Flake density: 2%

(c) Flake density: 3% (d) Flake density: 5%

Figure 5. Rendering results of a *MP3 player* with gold metallic coating using Ashikhmin BRDF model.

6 Conclusion and future work

In this paper, we have proposed a method that can model material reflectance properties. It is based on the measured data and provides a photorealistic view of a product. Our analysis and rendering results suggest that physically based Ashikhmin model performs better than other models for most cases. Our results also show that the performance of Blinn-Phong and Cook-Torrance model are almost the same, but they cannot accurately model the appearance of metallic paint surfaces. Since the existing models have limitations in accurately representing some materials, there is a need to build new BRDF models in future. For metallic painted materials, our future work will include to represent the phenomena of spatially varying components caused by metallic flakes.

7 Acknowledgments

This research was supported by ICRC at GIST funded by the Ministry of Science and Technology, and by RBRC at GIST funded by the Ministry of Information and Communication.

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