A Survey of BRDF Models for Computer Graphics

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1. Introduction

To produce photo-realistic images in computer graphics, we must effectively describe the interactions between light and surfaces. In this paper, we focus on Bidirectional Reflectance Distribution Functions (BRDFs), which characterize these interactions. We survey on most BRDF representations introduced so far and we investigate their usage, importance and applications. We look at in detail their two important usages; in GPU-based real-time renderings and in renderings of metallic car paints.

2. BRDF Models

Many analytical BRDF models have been introduced over the past 35 years. These models can be divided into two categories: empirical (i.e., phenomenological) models and physically-based models.

Both empirical and physically-based analytical BRDF models are only approximations of the reflectance properties of real materials. Many of these models are based on material parameters that in principle could be measured, but in practice are difficult to acquire [1].

The alternative to directly measuring model parameters is to acquire actual samples from BRDFs using a gonioreflectometer, and then fit the measured data to a selected analytical model using various optimization techniques [1]. Although physically-based BRDF models have a stronger theoretical basis than empirical models, it is not necessarily easier to fit physically-based model parameters to measured BRDF data [2].

There are several problems in model fitting when a BRDF is represented by an analytical function [1]. First, a BRDF represented by an analytical function with computed parameters is only an approximation of real reflectance: measured BRDF values are not exactly equal to the values of the analytical model [1]. Another major problem is that the number of parameters in an analytical BRDF grows with the number of lobes used to model the BRDF. For example, when the Lafortune et al. [3] model is used to represent an anisotropic material, at least 4 non-linear parameters must be estimated for a 2-lobe (1 diffuse lobe + 1 specular lobe)

BRDF, and at least 8 parameters are necessary for a 3-lobe (1 diffuse lobe + 2 specular lobes) representation. As Lawrence et al. [4] noted, fitting a three-lobe Lafortune et al. model may be unstable, taking minutes or hours to converge in a non-linear optimizer. Furthermore, the resulting parameters may require additional manual tuning to find a good fit. Ngan et al. [5] found that in practice, fitting with four lobes (1 diffuse lobe + 3 specular lobes) is very unstable. Hence, they omitted results from the four-lobe Lafortune et al. model.

In non-linear estimation, optimization results also depend on the choice of initial values, and a globally optimal fit is not guaranteed. Another problem involved in the fitting process is that the choice of the objective function for optimization is not clear. Some researchers have applied logarithmic or cubic root transformations on the BRDF data before fitting. The pure least squares method assumes that the variances at sample points are the same. For BRDF data, the variances are hardly ever homogeneous and some weighting functions have been proposed to stabilize the corresponding variances. Lafortune et al. [3] define the objective function for fitting as the BRDF difference multiplied by the cosine of both incident and outgoing elevation angles. Ngan et al. [5] multiply the BRDF difference only by the cosine of incident elevation angle.

Unfortunately, real BRDF data are difficult to acquire and measurements are often limited in angular resolution. Datasets with higher resolution can help guide the optimization process, but they also increase the computational cost of each iteration. In general, densely acquired data is very important but finding such data is difficult.

Another method for BRDF modelling is to use the measured BRDF data directly in the rendering process. Matusik et al. [1]'s data-driven method and Lawrence et al. [4]'s importance sampling method are examples of this approach. These methods preserve the subtleties of the measured data that may be lost in a data-fitting model. Since the resulting BRDFs come directly from measured data, these approaches produce very realistic results [1]. The main disadvantage of these methods is the amount of memory required to store the BRDF data. For example, Matusik et al. [1]'s data-driven model requires about 17 MB of memory per material. Using hundreds or thousands of materials in the same scene would be impossible because of memory requirements.

The best-known reflectance model for simulating the effects of specular reflection (and one of the oldest) is the Phong model [6]. For specular surfaces, this model assumes that incoming light tends to leave the surface in a distribution centred on the direction of perfect reflection. Blinn [7] developed a variant of the Phong model that allows faster computation, since it uses the halfway direction instead of reflection direction. Ngan et al. have shown that the halfway direction representation is a more accurate way to model specular reflections. However, both models are mathematically simple, and as a result, are very commonly used.

The Fresnel effect and the microscale geometry of a surface are important factors in BRDF modelling. Torrance and Sparrow [8], Cook and Torrance [9] and Ashikhmin et al. [10] have presented BRDF models based on surfaces made up of small planar microfacets with varying angle and size. The Torrance-Sparrow and Cook-Torrance models are physically-based models that assume the microfacets on the surface form "V-cavities." In contrast, Ashikhmin et al. is an empirical model. These models account for masking and self-shadowing effects and predict off-specular reflection. A comprehensive but computationally expensive model based on physical theory was developed by He et al. [11]. Oren and Nayar [12] presented a non-Lambertian diffuse model to simulate rough and diffuse surfaces such as sand and plaster. This model is based on Lambertian diffuse microfacets and exhibits backscattering phenomena. For anisotropic surfaces, Poulin and Fournier [13] introduced a reflection and refraction model. Their model assumes that a surface consists of small cylindrical features. All of three previous models are physically-based models.

In contrast to the physically-based BRDF models, there are also a number of empirical models which do not explicitly consider the physical mechanism of the light-material interaction. Ward [2] developed a model that, while not strictly physically based, was capable of describing most significant reflection phenomena. His model obeys the most basic of physical laws (reciprocity and energy conversation) and it is relatively simple compared to most other analytical reflectance models. Ward's model can represent isotropic and anisotropic reflections. Duer [14] proposed a slight variation on Ward's model with a different normalization factor. Schröder and Sweldens [15] represented reflectance functions using spherical wavelets. Koenderink et al. [16] used Zernike polynomials for representing BRDFs. Ozturk et al. [17] used a polynomial based analytical model to represent diffuse and glossy BRDFs. Their model uses PCA transformed variables in the polynomial to represent BRDFs compactly. Lafortune et al. introduced an empirical model which can capture important phenomena such as off-specular reflection, increasing reflectance and retro-reflection. Like the Phong BRDF, this model is based on the direction of perfect reflection.

The potential benefit of using measurements of BRDFs has also gained recent attention. The measurements of Matusik et al. [1] provide a dense (90 x 90 x 180 for θh, θd, Φd values) sampling of many isotropic BRDFs (see Figure 1). The main drawback of these representations is their size, since they typically represent the full 3D isotropic BRDFs in tabular form. In Matusik's thesis, he also describes one approach for sampling these measured BRDFs, but the alternate representation requires as much storage as the original BRDFs, making it difficult to use for scenes containing many materials [4].

Figure 1. Physically based rendering of measured BRDF data.

In an effort to reduce the size of measured BRDFs while maintaining an accurate representation of their effects, several researchers have investigated techniques for factoring these large datasets into more compact, manageable form. In all cases the 4D BRDF is factored into products of 2-dimensional functions that can be represented as texture maps and used to shade a model in real-time. However, in most cases these factorizations allow only a single term approximation. More important, there are no techniques for importance sampling these representations [4]. On the other hand, Lawrence et al. [4] have developed a model based on factorization of BRDF data which is convenient for importance sampling, but this representation is not as accurate as the original measured BRDF data.

When we look at the BRDF history from neural networks side, we see that Gargan and Neelamkavil [18] have presented a model which uses neural networks for approximating reflectance functions. They used standard backpropagation networks with two or three weight layers, and it is a non-linear model. Their neural network structure is used during rendering. Recently, Kurt and Cinsdikici [19] introduced a new BRDF model which uses neural networks to represent measured BRDF data. They used SOMs and MANs to represent BRDFs.

3. Application Areas of BRDF Models

BRDF models are used in many applications, such as material design, automotive design, lighting design, architectural previsualization, and gaming. Because the computation power is increasing incredibly, new areas can come out. For example, Krivanek and Colbert [20] proposed a new real-time rendering algorithm which aims to make possible interactive material and lighting design (see Figure 2). Such a high-fidelity real-time visualization of surfaces under high-dynamic-range (HDR) image-based illumination provides an invaluable resource for various computer graphics applications.

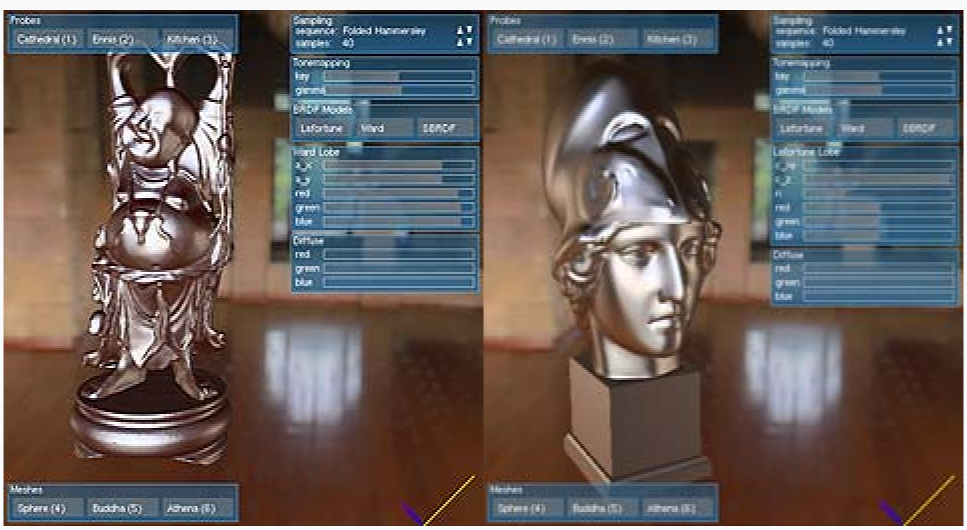

Figure 2. BRDF models can be used in GPU-based rendering algorithms. The interface is from [20]. (Follow this link to view a quicktime example)

Figure 3. BRDF models can be used in renderings of metallic car paints. The scenes are from [21].

Photo-realistic rendering of metallic car paint is another attractive problem. The ability to accurate appearance of metallic car paints under high-dynamic-range (HDR) image-based illumination opens a new way for production phase and marketing phase of automotive industry. However, modern car paints have complex effects like specular reflection, spatially varying glitter with depth impression and color shifts [21]. Consequently, Rump et al. [21] developed a new model to represent metallic car paints. They separated appearance of metallic car paint into two parts; *homogenous* BRDF part and *spatially varying* Bidirectional Texture Function (BTF) part. So, their model is first hybrid analytical and image-based representation to model metallic car paints (see Figure 3). In addition, they used both BRDF and BTF rendering techniques during rendering.

4. Conclusions

Efficient BRDF representations are very important for Computer Graphics and other related areas. Realism, simplicity, and low memory requirements are the key factors in creating effective BRDF representations. Sampling efficiency is also an important factor in designing good BRDFs. This tends to go hand-in-hand with simplicity, but not always.

Someone could encounter BRDF models in any areas like automotive industry, game, film industry and design industry. Eventually, this situation makes efficient, compact and accurate BRDF representations become attractive and important.

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was born in Izmir, Turkey, in 1981. He received B.Sc. degree in the civil engineering from Engineering Department, Dokuz Eylul University in 2002 and M.Sc. degree in computer science from International Computer Institute, Ege University in 2007. He has been a Research Assistant with the International Computer Institute since 2005. His research interests are algorithms, computer graphics with focuses on BRDF models, appearance modeling, global illumination algorithms, photorealistic rendering and digital image processing with focuses on image registration, wavelets, LPR. He is also currently a Ph.D. student in the International Computer Institute, Ege University.

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