

Chapter 2

Surface Reflectance Overview

To provide some context for our work on acquisition and modeling of opaque surfaces, we present in this chapter a brief introduction of related methods. We first discuss various approaches for acquisition of a material's surface reflectance, and then describe interactive techniques for material modeling and editing.

2.1 Surface Reflectance Acquisition

2.1.1 *Direct Measurement*

The most direct method of acquiring surface reflectance is to densely measure the values of a reflectance function from a real material sample. This brute-force approach has been used to obtain SVBRDFs [1–3], BTFs [4, 5], and reflectance fields [6]. Dense measurements are acquired both in the angular domain of view and light directions and in the spatial domain over points on the surface. Special rigs called gonioreflectometers are needed for this capture process, and the acquired 6D datasets are of enormous size and require hours to collect and process. A compact kaleidoscope-based device was developed by Han et al. [7] for quickly measuring BTFs. This device can also be used for SVBRDF acquisition, but only with a low angular resolution.

For the case of homogeneous materials, significant time can be saved in the acquisition process by using convex or spherical objects [8, 9]. Such objects display a broad range of surface normal orientations for the given material. An image of the object therefore provides numerous BRDF measurements over the points on the surface, and substantially reduces the number of images that need to be captured to densely sample a 4D BRDF. A few devices [10, 11] have also been proposed for fast BRDF measurement, using specially designed optics and sensors that expedite the measurement process. These approaches, while efficient for homogeneous materials, cannot be applied to materials with spatial variations.

To expedite data capture for materials with spatially varying surface reflectance, several techniques employ parametric reflectance models. In [12, 13], a simple parametric model is fit to the BRDF measurements at each surface point using data taken from a sparse set of view and light directions. Though this approach is considerably more efficient than brute-force acquisition, existing research shows that simple parametric models lack the power to accurately capture the appearance of real materials [14].

Another approach is to use data-driven non-parametric models to represent surface reflectance [15], in which reflectance data is modeled more concisely in a space of possible material reflectances using dimensionality reduction tools. By exploiting data coherence in both the angular and spatial domains, data-driven nonparametric models can well reproduce the complex reflectance features of real-world materials with a manageable amount of reflectance modeling.

2.1.2 Angular Coherence

The acquisition of surface reflectance is often simplified by taking advantage of its angular coherence. This angular coherence is represented in the microfacet theory of reflectance, in which real-world surface reflectance is modeled as a result of perfect mirror reflections by many micro-scale surface facets. Only those facets with the appropriate orientation according to the lighting and viewing direction and with visibility toward both the light and viewpoint can contribute to the final surface reflectance. The reflected energy can be calculated by counting the number of microfacets that can reflect light under the given lighting condition towards the viewing direction. In determining the final reflectance, what matters is only the angular distribution of the microfacets, rather than their spatial distribution.

Microfacet theory was first used with parametric orientation distribution functions, such as a Gaussian or Beckmann distribution, or a sum of these [16–18]. Based on those pioneering works, Ashikhmin et al. [19] introduced a method to compute surface reflectance from non-parametric microfacet normal distributions.

A non-parametric microfacet normal distribution function provides more versatility for representing surface reflectance, and can reproduce the reflectance of a wide range of real-world materials. Moreover, a normal distribution function is only a 2D function instead of the 4D function of a general BRDF. This greatly reduces the data that is required to capture.

Besides the microfacet model, other non-parametric models have also been proposed to exploit the angular consistency of surface reflectance. Romeiro et al. [20] proposed a bivariate BRDF model specific to isotropic BRDFs, which are 3D functions instead of 4D because of symmetry in the reflected light distribution. With their assumptions that surface reflectance tends to be unchanged under certain rotations, 3D isotropic BRDFs can be reduced into a 2D tabulated form.

2.1.3 Spatial Coherence

Spatial coherence can be utilized in addition to angular coherence to simplify acquisition even for surfaces with spatially varying reflectance. Reflectance measurements for a given pixel can be “borrowed” from other pixels that have the same reflectance and different orientation. Lensch et al. [21] first studied this with known surface geometry as input. BRDFs from different surface points are grouped into small sets, with each set fit using a Lafortune model [22] basis. The reflectance at each point is then represented as a linear combination over this basis. Taking this a step further with unknown geometry, Goldman et al. [23] use the same linear combination approach but with an isotropic Ward model as the BRDF basis. To reconstruct both an object’s shape and its SVBRDF from sparse measurements, they iteratively solve the normal map and the reflectance by fixing the current SVBRDF or normal, respectively. By combining the angular reflectance data from multiple pixels, the number of samples needed to measure a given pixel can be significantly reduced.

Following a similar spatial linear combination model, Zickler et al. [24] represented the SVBRDF using six-dimensional radial basis functions. By assuming isotropic reflectance that varies smoothly over space, BRDF fitting at each point can be done with sparse reflectance data by using information from neighboring points. Later, Alldrin et al. [25] extended the linear combination idea using an isotropic bivariate function as the BRDF basis. With more measured data, realistic results can be reproduced with their non-parametric BRDF model.

When measuring anisotropic data, differences in the tangent direction of pixels can be used in a manner similar to surface normal variations. Samples measured with different tangent directions due to the anisotropy can be merged together to reduce the acquisition cost. In Wang et al. [26], this is done by modeling anisotropic surface reflectance from data captured from a single view and dense lighting directions. Reconstruction involves merging data from surface points having consistent reflectance properties with respect to microfacet normal distributions, and requires dense measurements over both space and lighting directions.

A different approach to using spatial coherence is to measure a set of representative BRDFs from a small number of points and then use them to represent other points with similar appearance. This was done for large outdoor scenes by Debevec et al. [27]. They measure representative BRDFs from small regions of the scene using controlled lighting, as well as images of the entire scene under natural lighting. At each scene point, the Lambertian color is recovered and its BRDF is modeled as a linear combination of two representative BRDFs whose diffuse colors are most similar to that of the point. This approach works well for the targeted application, but fails in general when surface points have similar diffuse colors but different specular reflectance. In many cases, a representative BRDF or combination of such BRDFs cannot be accurately inferred for a pixel from a small number of samples. This is addressed by Dong et al. [28] with a bootstrapping technique that efficiently captures high-resolution microfacet BRDFs sparsely over a surface with a hand-held device, and then densely acquires reflectance measurements with low angular resolution.

High-quality SVBRDFs with complex reflectance effects including anisotropic and normal variations can be well reconstructed with sparse measurements in this way.

A related technique utilizes a database of BRDFs to serve as representatives. Matusik et al. [29] modeled an isotropic BRDF as a linear combination of 100 BRDFs chosen from an existing data set. This reconstruction is obtained through a projection of about 800 measurements. Similarly, [30] represented the reflectance of human skin as a linear combination of a set of isotropic BRDFs manually selected from an existing database. Weights for each surface point are computed via non-negative matrix factorization (NMF), based on data that is densely acquired from 15 views and 300 light directions. A potential drawback of using existing data sets in comparison to directly measured BRDFs as in [28] is that the given material may not be well approximated by the predefined data.

2.2 Interactive Modeling and Editing

An alternative to direct acquisition of material reflectance models is for the user to interactively provide information within a single input image to recover the geometry and reflectance of objects. Oh et al. [31] developed a set of tools for interactively modeling the depth layers in a single image. The tools included a filter to extract the shading component in uniformly textured areas. Their method is designed for modeling the geometry of a scene or character but not materials with the rich texture and geometric details we are interested in.

Several interactive methods have been developed for modeling a bump map of structured textures [32], displacement map of tree barks [33], and stochastic/procedural volumetric textures [34] from single image input. All these methods are designed for specific kinds of textures and cannot easily be extended to model others. In industry, CrazyBump [35] is widely used by artists to generate bump maps from single images. For most texture inputs, it simply takes the image intensity as the shading map. Since image intensity is also influenced by the albedo variations of the underlying material, much manual work is needed to refine the results.

User interaction has also been employed for editing materials in a photograph to alter its appearance. Fattal et al. [36] compute a multi-scale decomposition of images under varying lighting conditions and enhance the shape and surface details of objects by manipulating its details in each scale. Fang and Hart [37] and Zelinka et al. [38] decorate an object in a photograph with synthesized texture, in which the object normals recovered via shape from shading are used to guide texture synthesis. Both methods assume the object geometry to be smooth and ignore intensity variations caused by albedo. Khan et al. [39] infer the shape and surrounding lighting of an object in a photograph and render its appearance with altered material. This method does not recover object reflectance and simply maps smoothed pixel intensities to depth. Xue et al. [40] model the reflectance of weathered surface points in a photograph as a manifold and use it for editing the weathering effects in the

image. All these methods only recover partial material information for editing object appearance under the view and lighting of the original image. New viewing and lighting conditions cannot be rendered in this way.

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