Principles of Appearance Acquisition and Representation

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Abstract

Algorithms for scene understanding and realistic image synthesis require accurate models of the way real-world materials scatter light. This article describes recent work in the graphics community to measure the spatially- and directionally-varying reflectance and subsurface scattering of complex materials, and to develop efficient representations and analysis tools for these datasets. We describe the design of acquisition devices and capture strategies for BRDFs and BSSRDFs, efficient factored representations, and a case study of capturing the appearance of human faces.
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Measuring scattering and reflectance functions requires the ability to strike a surface with visible light and to sense its reflection in a controlled manner. Traditionally, reflectance has been measured using a gonioreflectometer. Consisting of a moving single light source and a single moving photo-detector, these devices are slow but provide highly repeatable measurements of BRDF. Over the past two decades, significant effort has been devoted to streamlining the measurement process using cameras, lighting arrays, projectors, and generalized optics in a variety of configurations. Among other things, this has enabled the collection of large BRDF databases, and the efficient measurement of higher dimensional scattering functions.

This chapter provides an overview of the acquisition process. We begin with the basic building blocks: lights sources and projectors to emit light rays; lenses and mirrors to bend them; and digital cameras to measure the radiance of rays that are scattered and reflected from a material. We then discuss the essentials of calibration and provide an overview of acquisition system designs.
1.1 Traditional BRDF Measurement: The Gonioreflectometer

For now we consider the BRDF to be a function of five dimensions—four angular dimensions and one spectral dimension. We ignore dependence on polarization and time, and we do not consider fluorescent materials. One generally measures such a BRDF by illuminating a (locally) flat surface with a collimated beam of light with direction ($\omega_i$) and placing a sensor at an output direction ($\omega_o$). The system is designed so that the input and output directions are known relative to the local coordinate system of the planar surface patch.

The classic BRDF measurement device is the four-axis gonioreflectometer. This device uses a combination of servo motors to position a source and photo-detector at various locations on a hemisphere above a planar material sample. The sensor is typically linked to a spectroradiometer or another optical assembly that permits recording of dense spectral measurements for each angular configuration of the source/sensor pair [66].

This measurement process is a lengthy one, and it can require days to measure a single material. The advantage of this approach, however, is that the system can be carefully calibrated and measurements can be quite repeatable. It also provides the ability to capture dense spectral information, which is a tremendous advantage over camera-based systems.

Acquisition time and equipment cost can be reduced if one is willing to restrict her attention to isotropic BRDFs. In this case, the angular domain is only three-dimensional, and one requires only three degrees of freedom in the acquisition system. For the gonioreflectometer recently built at Cornell University [30], this is accomplished by having two degrees of freedom in the orientation of the planar sample and one degree of freedom in the angular position of the source. Using this system, one can acquire 31 spectral samples per source/sensor configuration (roughly 10nm increments over the visible spectrum); and capturing 1000 angular samples—a very sparse sampling of the 3D angular domain—takes approximately 10 hours.
For repeatability, any measurement of reflectance should be accompanied by a precise specification of the configuration used to acquire it. For BRDF, precise guidelines for these specifications have existed for quite some time [48, 58]. Gonioreflectometers can be carefully constructed and calibrated so that precise measurement specifications are readily available, and for this reason, they are “gold standard” measurement devices for BRDF.

1.1.1 The Importance of Scale

The BRDF is a derivative quantity, so any measurement device necessarily measures it’s average over finite intervals of space and solid angle. Indeed, “truly infinitesimal elements of solid angle due not contain measureable amounts of radiant flux” ([48], p. 7). We use the term scale in this chapter to refer to the size of the angular and spatial intervals used to measure a BRDF, and the importance of determining an appropriate scale cannot be overstated.

![Fig. 1.1: BRDF measurement from a planar sample. Radiance emitted from surface patch $A_o$ into solid angle $\omega_o$ is observed by the sensor (only extreme rays are drawn). This surface must be uniformly illuminated over larger area $A_i$, the scattering properties must be uniform across $A_i$, and subsurface scattering effects must be limited to a radius of less then $r$.](image)

Consider the measurement geometry shown in Fig. 1.1, where a portion of a planar sample is observed by a sensor through an optical system. The finite area of the sensor back-projects to a finite area on the surface $A_o$, and from
each point in this area, the sensor measures the radiant flux emitted over a finite solid angle $\omega_0$. The planar sample is illuminated by a bundle of light rays covering area $A_i \supset A_o$. Selecting a measurement scale requires making choices for the values of $A_i$, $A_o$, $\omega_i$, and $\omega_o$.

Precise BRDF measurements are obtained only when the finite solid angles $\omega_i$ and $\omega_o$ are small enough for the BRDF to be relatively constant over the directions within them. Fortunately, small sensors with high sensitivity are readily available (consider a single element of a CCD array) so sufficient angular precision in $\omega_o$ is relatively easy to obtain. Sufficient precision in $\omega_o$ is also quite achievable, but choosing appropriate values for the spatial intervals $A_o$ and $A_i$ is more difficult. In order to obtain a repeatable measurement, the surface scattering effects must be statistically uniform over $A_i$, meaning that any variations must occur over very small distances relative to $A_o$. In addition, $A_i$ must be large enough to guarantee that flux incident outside of $A_i$ would not contribute significantly to the radiance reflected within $A_o$. This means that subsurface scattering and surface microstructure effects (interreflections, shadowing and masking) cannot cause measurable fractions of incident flux to be transported over distances greater than distance $r$ in Fig. 1.1.

How do we verify that these spatial scale conditions are satisfied? One approach is to use reciprocity, which tells us that the BRDF must be unchanged when the directions of the source and sensor are exchanged. By physically exchanging the input and output directions in a measurement system (with the same angular and spatial intervals), one can verify this condition. Alternatively, one can gradually increase the areas $A_o$ and $A_i$ and determine when observable changes cease to occur in the estimated BRDF value. One can also measure the distance $r$ by observing the reflection from a surface point intensely irradiated by a sharply focused beam, such as that from a laser (see Sect. 1.5). In this case, the radius of the band of diminishing radiance surrounding the intense central spot provides an estimate of $r$. Finally, one may simply choose a spatial scale and then isolate the ‘direct’ reflection component at that scale from the ‘non-direct’ one. This separation can be ac-
completed by modulating the input light rays within $\omega_1$, a procedure that is described in more detail in Sect. 1.6.1.

1.2 Image-based acquisition

Vision and graphics applications often require representations of higher dimensional appearance functions (BSSRDF, SV-BRDF, etc.) and in order to measure these functions we require techniques that are more efficient than the gonioreflectometer described in the previous section. Instead, we leverage light arrays, digital projectors and digital cameras to rapidly manipulate and sense visible light.

A camera’s sensor array contains millions of photo-sensitive elements, and by using lenses and mirrors these elements can be used to collect a large number of reflectance samples simultaneously. Similarly, lights rays output by a digital projector can be directed onto a material sample from various directions without the need for moving parts.

What are we trading for this gain in efficiency? Spectral resolution, for one. If an RGB camera is used, one obtains only three spectral measurements for each angular configuration, and these measurements are weighted averages over large, overlapping intervals of the visible spectrum. This reduced spectral information is not generally sufficient for physically-accurate color reproduction (more on this later), and it limits one’s ability to predict a material’s appearance under changes in source spectrum. Another limitation is the complexity of the required calibration procedure. In any camera-based system, we must estimate the map from pixels in the camera to output directions in the coordinate system of the sample. If we want to be precise, we also require the exitant solid angle that is subtended by each pixel. Finally, we require radiometric information including the optical fall-off in the camera’s lens system and the camera’s radiometric response function. The complexity and fragility of the calibration reduces the accuracy and repeatability of the measurements, but the significant efficiency gains often make this trade worthwhile. And for higher dimensional appearance functions, there is often no viable alternative.
When using a camera-based system for BRDF measurement, one must pay particular attention to scale. As depicted in Fig. 1.1, it is essential that the spatial intervals \( A_0 \) observed by each pixel are large enough to satisfy the requirement for statistical uniformity in the material. In general, this means that high-resolution images must be appropriately downsampled to obtain valid BRDF measurements.

1.2.1 Camera calibration

A camera must be calibrated both geometrically and radiometrically. The purpose of the former is to recover the mapping from the camera’s pixels to rays in a three-dimensional world coordinate system. The purpose of the latter is to recover the mapping from each pixel’s intensity values to scene radiance values.

Geometric calibration involves the recovery of a camera’s extrinsic parameters (position and orientation relative to a world coordinate system) and intrinsic parameters (focal length, radial distortion parameters, etc.). Free and reliable tools for geometric camera calibration are readily available [49, 3]. For a small number of cameras with similar fields of view, the most practical procedure uses multiple images of a planar checkerboard pattern [72]. For camera arrays with a wider set of views, synchronous imaging of a small moving point light source, such as an LED, is a better alternative.

Radiometric camera calibration involves two stages. First, one must determine the radiometric response function of the camera. This is the non-linear mapping that often exists between the irradiance incident on the image plane and the recorded intensity. Standard methods for doing this exist, and they usually involve imaging a calibration target or capturing multiple exposures of a static scene [11, 42]. A second step is required to recover the optical fall-off of the lens system. An imaging system that uses an ideal thin lens exhibits a relationship between scene radiance and image irradiance that falls-off as \( \cos^4 \alpha \), where \( \alpha \) is the angle between the principle incoming ray and the optical axis. In a real camera, the optical fall-off includes vignetting effects and
must be measured for each zoom and aperture setting. It can be measured, for example, by capturing an image of a cloudy sky through a diffuser.

A severe limitation that comes with the use of digital cameras for reflectometry is their small dynamic range. In order to measure high radiance values at specular peaks while maintaining sufficient signal to noise ratios in darker regions, one must acquire several images with different exposures and merge them into a single high dynamic range (HDR) image [11, 42]. This task is relatively straight-forward once the radiometric camera response is known.

1.2.2 Light source calibration

Individual light sources are often used to create incident light fields for appearance acquisition, and most commonly, these sources are modeled in one of two ways. They are either modeled as far-field sources that emit parallel rays or near-field points sources that are ideal in the sense of having zero volume. In either case, the sources must be calibrated to determine the incident light field that they create.

In the near field case, this requires estimating the position of the source and the (usually relative) radiance it emits in the sphere of directions about that position. A typical calibration procedure uses the reflections from mirrored-spheres to recover the source position, and a single image a diffuse planar surface (i.e., a material such as Spectralon®) whose position is known relative to the camera and source. In the far-field case, a single image of a diffuse plane provides all the required information.

The position of a near-field source and the direction of a far-field source can be recovered by placing shiny spheres in the scene and observing the points of mirror reflection. Since most sources do not emit light uniformly, one must also measure the non-uniformity output non-uniformity in a coordinate system that is rigidly associated with the source. On typically does this by imaging a planar surface made from a highly diffuse material such as Spectralon® whose position is known relative to a camera and source.
In some cases, linear light sources and area light sources have proven effective, in which cases alternative calibration procedures are required [16].

1.2.3 Projector calibration

When a projector is used as a light source, one must again estimate the mapping between a set of input pixel values to the projector and the light field it creates. This calibration includes radiometric and geometric stages, much like that of a camera. The usual approach is to project patterns onto a diffuse planar surface and observe them using a calibrated camera. An important part of this calibration is measuring the ‘black level’ of the projector, meaning the radiance emitted when projecting an ‘all black’ image.

1.2.4 Colorimetric calibration

As described above, camera-based acquisition systems typically provide only coarse spectral appearance information. If a single light source and RGB camera are used, then one obtains three spectral measurements of reflectance, each of which represents a weighted integral over the visible spectrum. (This is ideally obtained using separate color filters and a monochrome camera, but for efficiency reasons, it is often obtained by demosaicking a single image captured through a color filter array.) Using the linear color space transformation that is appropriate for the camera’s RGB sensor, the trichromatic measurements can be mapped to a standard linear color space; and when the spectral power distribution of the illuminant is known, these measurements can also be linearly transformed to estimate appearance information as would be obtained under a chosen ‘canonical’ illuminant. While re-lighting using linear transforms in three-dimensional color space is only an approximation of full-spectrum re-lighting, it provides sufficient visual accuracy for many vision and graphics applications. In fact, diagonal transforms—independent scalings of each color channel—are sufficient in many cases [14, 13, 6].

When a projector is used as a light source, the procedure is complicated by the existence of its three spectral filters. DLP projectors use a rotating color wheel
to project colors, so in order to make an accurate appearance measurement
under such a projector’s ‘white’, one should set the camera’s exposure time
to be an even multiple of the filter wheel’s rotational period.

Colorimetric calibration becomes more important when multiple cameras and
multiple light sources (or projectors) are used. In this case, any difference in
the spectral characteristics of the devices can manifest itself as noise in ag-
ggregated reflectance measurements. To compensate for these differences, one
captures images of a colorful scene under different camera/source pairs, and
then estimates linear or diagonal mappings that make these images as simi-
lar as possible. If a color standard is used, such as a Munsell Color Checker,
these mappings can be related to a standard color space.

1.2.5 Object shape

If the materials being measured exist on arbitrarily-shaped surfaces, the shape
of these surfaces must be known in the same coordinate system defined by
the geometric calibration of the cameras and sources. From the perspective
of measuring reflectance, three-dimensional surface reconstruction and align-
ment can thus be viewed as another calibration step. In this context, one of
the requirements of a 3D reconstruction system is that it recovers shape in
a manner that is not biased by the material properties of the surface being
measured. Indeed, we do not want the calibration of the measurement system
to depend on the signal (reflectance) being measured.

A common approach to recovering shape for general materials is to use struc-
tured lighting from lasers or projectors [2, 24], possibly in conjunction with
stereo cameras [9, 71]. For the purposes of appearance capture, one disadvan-
tage of these approaches for appearance capture is that the recovered shape
must be aligned with the images used for reflectometry, which means that
any alignment errors are manifested in noisy reflectance samples. Another
disadvantage is that they do not directly estimate surface normals, which are
ultimately required for measuring reflectance. Estimating surface normals
from a range-scan requires differentiation of the discrete shape, and this is an
additional source of noise for reflectance measurements.
By directly estimating surface normals from the same images being used for reflectometry, these two sources of noise can be reduced. Surface normals can be estimated using photometric stereo, but in its classic formulation [70], this violates the requirement of being independent of reflectance. Developing photometric stereo methods that place fewer restrictions on surface reflectance continues to be an active area of research (see [34, 19, 1, 23, 45] for some recent examples). Surface normal estimates that are truly independent from surface reflectance can be obtained by exploiting Helmholtz reciprocity. This approach relies on the acquisition of reciprocal pairs of images—images for which the positions of the light source and camera are swapped [74]. The disadvantage of this approach is that it requires correspondence between images captured from different viewpoints to compute surface normals. Practically, this means that the resolution of the recovered normal field is typically lower than that of the input images. Photometric stereo, on the other hand, provides per-pixel normals whenever the underlying reflectance assumptions are satisfied.

Current best practice is to recover coarse geometry using structured lighting or a laser range scanner, and then combine this with surface normal estimates obtained photometrically from the same images being used for reflectometry (e.g. [32, 64]). This approach leverages the fact that range scanners provide accurate low-frequency geometry while photometric methods provide good high-frequency detail. A convenient algorithm for combining the two has been developed by Nehab et al. [46]. It is also conceivable that accurate low-frequency shape could be obtained without active lighting using multi-view stereo techniques[56].

### 1.3 Acquiring BRDF, SVBRDF and 6D reflectance fields

Here we provide an overview of some existing designs for measuring BRDF, SVBRDF and non-local reflectance fields. These are functions defined over domains of three to six angular and spatial dimensions.
1.3. Acquiring BRDF, SVBRDF and 6D reflectance fields

In designing an acquisition system, there are four competing factors that need to be considered: acquisition time; precision; cost; and material diversity. Here, diversity refers to the breadth of materials that are to be considered. It is possible to build an efficient system for measuring BRDF using spherical material samples, for example, but not every material can be ‘painted on’ to a sphere.

Fig. 1.2:

1.3.1 Planar material samples

As described earlier, the gonoreflectometer is the traditional device for measuring BRDF of planar material samples. More efficient acquisition is obtained by replacing the single photodetector of a gonioreflectometer with an array of photodetectors. A camera’s sensor array contains millions of photo-
sensitive elements, and by using lenses and mirrors these elements can be used to collect a large number of reflectance samples simultaneously.

An early example is Ward’s measurement system [63], in which the radiance emitted by a planar sample is reflected from a half-silvered hemisphere and captured by a camera through a fish-eye lens. With this configuration, a single image provides a dense sampling of the hemisphere of output directions. The two degrees of freedom (DOF) in the incident direction are obtained by a one-DOF rotation of the source arm and one-DOF rotation of the planar sample. A very nice property of this system is that it allows the measurement of retro-reflection directions, meaning those for which the incident and reflected directions are equal. This is not possible with the gonioreflectometers described in the previous section. Using this system, Ward claimed that an anisotropic BRDF could be measured in ten minutes.

One way to reduce calibration requirements and improve repeatability is to develop acquisition systems with few moving parts. One way to do this is to replace a single moving point source with a large number of fixed sources (e.g. [35, 17]), and another is to use a single projector with appropriate lenses and mirrors [18]. The design of Ghosh et al. [18] includes a projector and camera that are virtually co-located using a half-mirror, and whose input and output rays are directed toward a planar sample by a pair of rotationally symmetric mirrors. This allows the 4D BRDF domain to be densely sampled in minutes without motion in the acquisition system.

The ability to simultaneously control the entire input hemisphere of lighting directions enables different choices for an illumination basis. Instead of sequentially activating one light source (or one of the projector’s pixels), we may simultaneously activate many to produce patterns corresponding to spherical harmonics, for example. The advantage of this approach is that it reduces the dynamic range requirements for the sensor and increases the signal to noise ratio in the measurements. Examples include the work of Schechner et al. [55] who use the Hadamard basis to sample the space of illuminations from a discrete set of point sources, and Ghosh et al. [18], who use an orthogonal basis defined over a radially symmetric zone of the input hemisphere.
1.3.2 Image-based measurement of curved samples

An alternative approach to using curved mirrors is to use a curved material samples instead of a planar one [37, 31]. Since the surface normal varies from point to point on the surface, a single image under directional lighting provides a very dense (near continuous) sampling of a two-dimensional slice of the BRDF domain. A sphere can be used for isotropic surfaces [39], and for anisotropic surfaces, one can use a cylinder. In the anisotropic case, the process can be made more efficient by cutting multiple strips of an anisotropic material at different orientations relative its tangent direction pasting these onto a single cylinder [47]. The cylinder provides one degree of freedom in its surface normal, and two more degrees of freedom are obtained by rotating the cylinder and the source. The fourth and final degree of freedom comes from the number of ‘strips’, which is typically coarsely sampled. BRDF measurement systems that use curved samples have the advantage of requiring only one-dimensional rotation stages in the acquisition system.

Unlike measurement systems based on planar materials, each dense 2D slices obtained from images of a curved sample do not correspond to fixed input or output directions. The sampling pattern of a curved sample is best understood using an alternative BRDF parameterization, such as Marschner’s[36] or the halfway/difference parameterization of Rusinkiewicz [52], that align the per-image 2D slices with the coordinate axes. For orthographic camera projection and distant lighting—or more generally, when scene relief is relatively small—a single image of a curved surface provides BRDF samples lying in a plane of constant difference angle ($\theta_d$), since this angle is independent of the surface normal. In the special case of isotropic materials, this means that while each (orthographic) image provides only one sample of the $\theta_d$ dimension, it represents a nearly continuous sampling of $\theta_h$ and $\phi_d$. As a result, a set of images provides dense sampling of $(\theta_h, \phi_d)$ but only as many samples of $\theta_d$ as there are images. Conveniently, this irregular sampling obtained from image-based data corresponds well with the behavior of general BRDFs, which vary slowly in the sparsely sampled $\theta_d$-dimension, at least away from grazing angles [44]. At the same time, by imaging curved sur-
faces, one efficiently obtains high sampling rates of the half-angle $\theta_h$, which are necessary to recover high-frequency variation (e.g., due to specular highlights) that is generally observed in this dimension.

Instead of using spheres or cylinders as curved material samples, one can use arbitrary shapes as long as the geometry is known in the coordinate systems of the camera and light source. This is important for live materials such as human skin and the skins of fruits that cannot be ‘painted on’ to a plane, sphere or cylinder.

In this approach, one usually captures the shape using a reconstruction system (laser scanner, structured-lighting, photometric stereo, etc.) and then aligns this shape with the acquired images [38]. This obviously introduces additional sources of error and bias, and with all of these sources of error, BRDF measurements from captured, arbitrary shapes is often prohibitively noisy. Practical considerations for reflectometry using arbitrary shapes are discussed in Sect. 1.2.5, where we see that the simultaneous recovery and shape and reflectance remains an important research topic.

### 1.4 Spatially-varying Reflectance: SVBRDF

Next we allow spatial variation in the reflectance function, which increases the dimension by two. Note that despite allowing spatial variation, we maintain our assumption regarding spatial scale and sub-surface scattering. Namely, we assume that the surface area observed by each photo detector is large enough that sub-surface scattering effects are negligible and that the surface is \textit{locally} homogeneous. This guarantees that the appearance of each small surface element can be represented by a BRDF.

Since cameras are used for the measurement of SVBRDF, essentially all acquisition systems to date have considered only sparse spectral sampling (RGB). For this reason, we can effectively ignore the spectral dimension in this section. Even with this simplification, we are left with the formidable task of measuring a function of five or six dimensions.
1.4. Spatially-varying Reflectance: SVBRDF

1.4.1 Planar Surfaces: The Spatial Gonioreflectometer

Acquisition of a spatially-varying BRDF can be thought of as the measurement of multiple, distinct BRDF—one at each point on a surface. SVBRDF acquisition systems are therefore closely related to the BRDF acquisitions systems just discussed.

A spatial gonioreflectometer is a good example and is exactly what the name suggests. It functions like a standard gonioreflectometer, except that the single photodetector is replaced by a camera. The example shown in the slides was built by David McAllister [40] and is similar in spirit to an earlier version by Kristen Dana [8]. In the example shown, the planar sample has spatially-varying reflectance, and its orientation is controlled by a two-axis pan/tilt head. The source can be rotated about the sample as well, which produces a three-axis spatial gonioreflectometer. Assuming a collimated source (and an orthographic camera for simplicity), each image yields a dense 2D spatial slice of the SVBRDF corresponding to fixed input and output directions. Of course, a three-axis device such as this one is useful for materials having an isotropic BRDF in each local region.

BRDF samples collected by this device are very non-uniformly distributed in the 5D domain. There is near continuous sampling of the spatial dimensions but only as many samples of the angular dimensions as there are positions of the sample and illuminant. This can be changed by modifying the acquisition system. As was the case for single BRDF, lenses and mirrors can be used to redirect input and output rays. Here the motive is not to decrease the acquisition time, however, but simply to alter the sampling pattern (and perhaps to improve precision).

One such system uses a beam splitter and a parabolic mirror to increase angular sampling rates at the expense of spatial sampling rates [7]. The parabolic mirror reflects a portion of the output hemisphere from a single small region toward the camera, thereby providing near-continuous sampling of this angular interval. The same mirror is used to direct an incident collimated beam of light toward the surface patch being observed. The direction of the inci-
dent ray is controlled by translating an aperture in front of the light source, and the surface sampling point \((x, y)\) is changed by translating the parabolic mirror. While the altered sampling pattern is interesting, the great strength of this system is that all required movements are pure translations. One expects this to be highly repeatable.

1.4.2 Curved Surfaces: domes and spherical gantries

Most interesting objects are curved instead of planar, and as is the case for homogeneous reflectance (Sect. 1.3.2), these can be handled provided that their geometry is known relative to the cameras and sources used for acquisition. In order to capture the SVBRDF of a curved surface, the acquisition system must be able to position sources and cameras over the entire sphere in order to sample the hemisphere of directions above every surface tangent plane. One device for accomplishing this task is a spherical gantry, the first example of which was built at Stanford University [29].

To acquire the SVBRDF of a curved surface, the pipeline often includes multiple steps in which the three-dimensional shape of the object is estimated and then aligned with images acquired from different viewpoints and illumination directions (see [54, 69] for early examples of this approach). As described in Sect. 1.2.5, more accurate results can be obtained by estimating or refining the object geometry with the same images that are used for reflectometry. A detailed example for human faces is presented in Chapter ??.

To get a sense of how many images are required to densely sample the SVBRDF of a regular surface, we can perform a simple counting exercise. When the shape of the object is known and the source and view directions are given, each pixel in an image provides one sample of the SVBRDF (or the BRDF at a particular surface point). Sampling the BRDF at every surface point therefore requires capturing images from the full double sphere of view and illumination directions. Obtaining \(5^\circ\) or \(1^\circ\) angular sampling rates for these spheres requires millions or hundreds-of millions of images, respectively.
1.4. Spatially-varying Reflectance: SVBRDF

To reduce measurement time is to capture the images more quickly using a system with an array of cameras that acquire in parallel and either a rapidly-moving source (e.g. [10]) or an array of sources that are activated sequentially (e.g. [35, 17, 65, 64]). This streamlines the acquisition process at the cost of an increase in calibration complexity (and fragility). Another strategy for reducing the measurement burden is to reduce the number of required images by placing restrictions on the BRDF at each surface point. This can be done by assuming a parametric model or by exploiting general reflectance phenomena such as reciprocity and isotropy, both of which are discussed in Chapter ??.

One very important consideration for reflectometry using curved surfaces is the presence of interreflections on non-convex shapes. When there is mutual illumination between distinct surface points, BRDF values can no longer be directly inferred from intensities observed on the image plane. For surfaces that are not mirror-like, mutual illumination can be removed from the images by modulating the input illumination with a moving binary pattern (see Sect. 1.6.1).

1.4.3 Six-dimensional reflectance fields and BTF

A concept that is closely related to the SVBRDF is the six dimensional reflectance field, sometimes called the non-local reflectance field. An SVBRDF is a material model that is defined very close to the interface between a surface and the surrounding air, and it seeks to describe the scattering effects that occur at and below this interface. In contrast, the 6D reflectance field is defined on an arbitrary reference surface that is not necessarily coincident with the object being modeled. It represents the existant light field $R(x_o, \omega_o)$ for every possible distant lighting environment $L(\omega_i)$, and if sampled densely, it can represent arbitrarily complex global lighting effects. This includes cast-shadows, occlusions, transparency, sub-surface and volumetric scattering, and mutual illumination. This representation is useful for objects that have significant mesostructure, or geometric structure that exists at or near the measurement scale. When the reference surface of a 6D reflectance
field is taken to be a plane, the term *bidirectional texture function* (BTF) is often used to describe the 6D reflectance field.

An SVBRDF can be considered a special case of the more general 6D reflectance field, in which the reference surface coincides with the material/air interface, the material is optically thick, and the measurement scale satisfies the conditions of Fig. 1.1. In this special case, the angular appearance at any given point will be represented by a BRDF and will therefore satisfy reciprocity and exhibit other phenomena (e.g. isotropy) that can be exploited to reduce acquisition time and cost. This will be discussed further in Chapter 

Despite their differences, 6D reflectance fields and SVBRDF are measured with the same acquisition systems. In both cases, one requires the ability to illuminate a surface with distant lighting and the ability to records the radiant exitance at every point and in every direction. All of the acquisition systems described in this section can therefore be used to measure 6D reflectance fields as well.

### 1.5 Acquiring BSSRDF and 8D reflectance fields

A general BSSRDF is a function of nine dimensions if we include the spectral dimension. Even if we ignore the dependency on wavelength, densely sampling an eight dimensional space is an extremely burdensome process. To make it tractable, we reduce the dimensionality of the BSSRDF by factoring it into a product of lower-dimensional functions. A number of factorizations have been explored. Each is targeted to a particular class of materials, and each requires an acquisitions system with particular capabilities.

The BSSRDF can be expressed as a linear combination of a single scattering term and a multiple scattering term. The former describes light that refracts below the surface and is scattered only once before refracting out [20], while the latter describes light that undergoes multiple scattering events below the surface interface. When the material is homogeneous, has a smooth surface and is highly scattering, both terms can be described with high accuracy by a parametric model with relatively few degrees of freedom. When
these conditions are satisfied, scattering within the material can be described by a diffusion process, which in turn can be approximated by a simple dipole model [26]. Accordingly, the BSSRDF can be written:

\[ S = S^{(1)}(x_o, \omega_o, x_i, \omega_i) + \frac{1}{\pi} F^i(\omega_i) R_d(||x_i - x_o||) F(o), \quad (1.1) \]

where the first and second terms represent single and multiple scattering, respectively. The multiple scattering term is parameterized by only three spectrally-varying parameters. The first is the index of refraction (usually denoted \( \eta(\lambda) \)). This is usually assumed to be constant over the visual spectrum, and it describes the Fresnel transmittance functions, \( F^i(\omega_i) \) and \( F(o) \), that govern reflection and refraction at the (smooth) material/air interface. The analytic forms of these functions can be found, for example in [50]. The other two parameters are the reduced scattering coefficient \( \sigma_s(\lambda) \) and absorption coefficient \( \sigma'_a(\lambda) \), which together define an analytic expression for \( R_d(r) \) in Eq. 1.1. (An alternative, more intuitive, parameterization uses the total diffuse reflectance and translucency or diffuse mean free path [25, 60].)

---

**Fig. 1.3:**

A variety of systems have been proposed for measuring the parameters of this model. All of them focus on the multiple-scattering term and are based on the assumption that single scattering effects (\( S^{(1)} \) in Eq. 1.1) are negligible far from the point of incidence. This is true whenever the scattering albedo is close to one [25], meaning that the material modulates radiation predominantly through scattering as opposed to absorption (see [4]). Jensen et al. [26] measure the absorption coefficient and reduced scattering coefficient using a
narrow focussed beam of illumination and a camera (Fig. ??). These measurements are made independent of the material’s index of refraction, and they provide three wide-band spectral measurements (RGB) of each parameter. Weyrich et al. [64, 65] obtain similar measurements for human skin using a linear array of optical fibers that are couple to a camera (see Chapter ??). In both systems, the index of refraction is not measured and an assumed value (typically 1.3–1.5) is used instead. Also, neither of these systems measure the phase function of the material, which is necessary to compute the single-scattering term 1.1. This can be added to the model by using a parametric phase function (e.g. the Henyey-Greenstein phase function [22]) with a manually tuned parameter.

The model of Eq. 1.1 assumes the material/air interface to be smooth. This can be relaxed to account for spatially-varying microstructure (roughness) by adding a spatially varying BRDF and generalizing the Fresnel transmittance functions. If single scattering is ignored, one can write the BSSRDF as [12]:

\[
S = \frac{1}{\pi} \rho(x_i, \omega_i) R_d(||x_i - x_o||) \rho(x_o, \omega_o),
\]

(1.2)

where

\[ \rho(x, \omega) = 1 - \int f_i(x, \omega, \omega_i) \cos \theta_i d\omega_i \]

is one minus the “directional-hemispherical reflectance factor” [48], or the fraction of incident radiant flux that is transmitted by the rough material/air interface. Note that the domain of integration in the expression above is the entire incident hemisphere.

So far, we have considered homogeneous materials with sub-surface scattering properties that do not change from point to point. Most interesting materials are not homogeneous, however, and in practice it is necessary to adapt the models of Eqs. 1.1 and 1.2 to handle inhomogeneity. Most recent approaches decompose reflectance into local (BRDF) and non-local (BSSRDF) components, and then further factor the non-local component. Accordingly, the radiant exitance is written

\[
L(x_o, \omega_o) = \int f_i(x_o, \omega_o, \omega_i) L(x_o, \omega_i) \cos \theta_i d\omega_i
\]

\[
+ \int \int f_i(x_i, \omega_i) R(x_i, x_o) f_0(x_o, \omega_o) L(x_i, \omega_i) \cos \theta_i d\omega_i dA.
\]

(1.3)
where the spatially-varying BRDF $f_r$, the spatially-varying transmittance functions $f_i$ and $f_o$, and the sub-surface term $R(x_i, x_o)$ are either tabulated functions or low-parameter analytic models.

To acquire the parameters of such a model, one usually requires an acquisition system that combines a spatial gonioreflectometer with a sub-surface measurement system. A non-parametric sub-surface function $R(x_i, x_o)$ can be measured reasonably efficiently using a projector that can illuminant multiple surface points in parallel [51]. When these surface points are sufficiently far apart, a single image—with the BRDF and transmittance effects removed—provides dense measurements of $R(x_i, \cdot)$ for many $x_i$. If acquisition time is an important consideration, the number of required measurements can be reduced by assuming a parametric form for $R(x_i, x_o)$. Below are four examples.

- Jensen et al. [26] suggest using a dipole-diffusion model with reduced scattering coefficients and absorption coefficients that vary as a function of incident point on the material interface: $\sigma_s(x_i, \lambda)$ and $\sigma_a'(x_i, \lambda)$. This is a coarse approximation, of course, since it does not model volume effects, but the parameters can be measured very efficiently. Tariq et al. [60] use a single projector-camera pair to acquire spatially-dense estimates of $\sigma_s(x_i, \lambda)$ and $\sigma_a'(x_i, \lambda)$ of a human face in under a minute.

- Weyrich et al. [64] represent the non-local reflectance of faces using a dipole-diffusion model with fixed material parameters $\sigma_s(\lambda)$ and $\sigma_a'(\lambda)$ that is then modulated by a spatially-varying scalar function: $R_d(||x_i - x_o||)M(x_o, \lambda)$. They show that for human faces, the parameters of this sub-surface model can be estimated directly from images acquired by a spatial gonioreflectometer—the same images that are used to estimate the local (spatially-varying BRDF) component. More details are presented in Chapter ??.
• Fuchs et al. [15] also use a scalar modulating function, but replace the two-parameter dipole-diffuse model with a linear combination of exponential functions:

\[ R(x_i, x_o) = M(x_o) \sum_k c_k(x_i) e^{d_k(x_i)||x_o - x_i||}. \]  

(1.4)

The parameters of this model are measured at three wavelengths by illuminating a surface at many points sequentially using three optically-coupled lasers.

• Unlike the three approaches above, which use Fresnel transmittance functions and spatially-varying parametric forms for \( R(x_i, x_o) \), Tong et al. [62] handle inhomogeneity using a spatially-uniform dipole-diffusion model \( R_d(||x_i - x_o||) \) with measured, non-parametric, and spatially-varying representations of the transmittance functions. The parameters of this model are measured by a gantry that allows both uniform directional sources and a laser to be positioned at multiple input angles while a planar surface patch is observed from multiple output angles.

1.5.1 Eight-dimensional reflectance fields

Analogous to the relationship between SVBRDF and 6D reflectance fields, a concept that is closely related to the BSSRDF is the eight-dimensional reflectance field. Unlike the BSSRDF, which is defined on the material/air interface, the 8D reflectance field is defined on an arbitrary reference surface enclosing the scene being modeled. It represents the exitant light field \( R(x_o, \omega_o) \) for every possible incident light field \( R(x_i, \omega_i) \), and if sampled densely, can theoretically represent arbitrarily-complex global lighting effects within the enclosed volume.

A BSSRDF can be considered a special case of a more general 8D reflectance field, in which the enclosing surface coincides with the material/air interface and the material is optically thick. In this special case, we can reduce the acquisition cost by exploiting the factorizations described above. The same factorizations cannot be expected to provide accurate descriptions in the more
general case, and as a result, the acquisition of general 8D reflectance fields can be extremely burdensome. It requires the use of projectors, catadioptrics and mechanics to generate incident light fields, as well as camera arrays to measure the 4D responses. Recent progress in the design and implementation of such systems are the topic of Chapter ??.

### 1.6 Separating Reflection Components

A typical image can be thought of as a linear combination of component images, with each component image resulting from a distinct reflection mechanism. As described in the previous section, one can separately consider local (or direct) reflection, which is well-described by a BRDF, and non-local effects, such as sub-surface scattering, that operate over relatively large distances. Similarly, direct reflectance can be further decomposed into diffuse and specular components, which correspond to interface and local body effects, respectively. These components differ in their dependence on wavelength, polarization, and the angular configuration of sources and sensors. For many objects, they also differ in how they change spatially across the surface.

By separating images according to these reflectance components, their different behaviors can be exploited to reduce acquisition time and cost.

#### 1.6.1 Local and Non-local Reflection

We first consider the separation of reflectance (Eq. 1.3) into local (BRDF) and non-local (BSSRDF) components. For a particular camera and source position, these spatially-varying components will make distinct contributions to the image, and under certain conditions, they can be separated by modulating the illumination by high-frequency patterns. When a surface is illuminated by a high-frequency projected pattern, the radiant exitance due to local reflections will exhibit rapid spatial variation. Non-local reflection acts as a low-pass filter, however, and the radiant exitance due this component is typically very smooth. To separate these components, we exploit this difference.
Fig. 1.4: Radiant exitance due to local and non-local reflections can be separated using high-frequency structured lighting. A checker-board illumination pattern is translated across the surface and the maximum and minimum intensities are recorded at pixel of a camera. If the pattern frequency is sufficiently high, the local and non-local contributions are trivially recovered from these measurements.

Consider the measurement geometry in Fig. 1.4, where a rough inhomogeneous material is illuminated by directional lighting that is modulated by a binary pattern. As in Fig. 1.1, the sensor records the radiant exitance over finite spatial and angular intervals. Suppose two measurements are taken, one with the binary pattern as shown, and one with the pattern inverted, and for reasons that will become clear in a moment, denote these images by $I_{\text{max}}$ and $I_{\text{min}}$, respectively. If the spatial frequency of the binary pattern is high relative to the translucency of the material (i.e., its period is much smaller than the diffuse mean free path), these two measurements can be written

\[
I_{\text{max}} = I_d + I_g / 2 \\
I_{\text{min}} = I_g / 2,
\]

where $I_d$ and $I_g$ are the direct and global (or non-direct) components of the measurement that would be created if the binary pattern contained no zeros. In other words, given these two measurements, we can compute $I_d = I_{\text{max}} - I_{\text{min}}$ and $I_g = 2I_{\text{min}}$, which provide good approximations to the two terms on the right of Eq. 1.3.
By illuminating a surface with a checkboard pattern and observing it with a camera, this same separation can be accomplished in parallel at every surface point. In practice, we shift the checkerboard pattern across the surface in order to obtain more accurate estimates of the maximum and minimum intensity at each pixel, and we compensate for the fact that the surface the radiance emitted by the projector in dark regions of the binary pattern is not exactly zero[45]. Since other global effects, such as volumetric scattering and inter-reflections between surface points, also behave as low-pass filter of illumination, this same procedure can be used to isolate the direct component from these effects as well. (This can be leveraged for a variety of applications, including the reconstruction of translucent surfaces [5], and rapid estimation of scattering parameters for human faces [60].)

Fig. 1.5: The designation of reflection being local or non-local depends on measurement scale. Shown are the separated components using the method of Nayar et al.[45] for various resolutions of the image plane and incident checkerboard pattern. The dominant mechanism of reflection goes from non-local to local as scale increases. (Figure courtesy of the Columbia University Computer Vision Lab (CAVE), http://www.cs.columbia.edu/CAVE/)
The definitions of local and non-local depend are scale-dependent, and will therefore vary with \( A_o \) and \( A_i \) in Fig. 1.4. An illustration of this scale dependence is shown in Fig. 1.5, where the separation is performed with \( A_i \) and \( A_o \) successively increased by a factor of two. At a small scale, the majority of radiant exitance is due to non-local sub-surface effects, but as the scale increases, more and more of this exitance is deemed to be local.

This scale dependence exists whenever the reflectance of a material is decomposed into local and non-local components (i.e., according to Eq. 1.3), and as a result, such an appearance model is only guaranteed to be accurate for the scale at which it is acquired. Efficient acquisition of multi-scale appearance models remains an open research problem.

### 1.6.2 Diffuse and Specular Reflection

For dielectric materials, which are non-conducting, the direct component of surface reflectance can be further decomposed. The direct component is a BRDF, and this BRDF can be written as a linear combination of diffuse and specular components. This is useful for acquisition because these components can often be isolated using color and polarization, and once they are isolated, each of these components exhibits different—and exploitable—behavior.

A depiction of the mechanisms that lead to diffuse and specular reflectance is shown in Fig. 1.6. The specular component of reflection corresponds to the portion of the incident radiant flux that is reflected at the surface boundary. For a perfectly smooth surface, this component is described by a ‘specular spike’ occurring in the mirror direction, and the reflected flux can be computed using the Fresnel equations. Rough surfaces are more common, and in these cases, the specular component takes the form of a ‘specular lobe’, whose shape is determined by the surface microstructure (recall the Cook-Torrance model from Chapter ??). The diffuse reflection component is induced by flux that penetrates the surface and multiply refracts internally before refracting back out into the air. Diffuse-reflected flux is randomly polarized, and it is distributed more or less uniformly over the output hemisphere.
The diffuse and specular components differ in their dependence on wavelength, polarization and the angular configuration of the input and output directions. For many objects, they also differ in how they change spatially across the surface, and this is shown in the example of Fig. 1.7. In general, the SVBRDF $f_t(x, \omega_i \rightarrow \omega_o)$ is a function of spatial ($x$) and angular ($\omega_i$, $\omega_o$) dimensions. The diffuse component is well-represented by a Lambertian model for a wide range of input and output angles, but for surfaces with significant texture, it can change quite quickly from point to point. Said another way, it varies slowly in the angular dimensions, but varies quickly in the spatial dimensions. The specular component is often just the opposite. It tends to exhibit rapid changes in the angular dimensions, but often changes slowly over much of an object’s surface. By separating the diffuse and specular contributions to a set of images of an object, these behaviors can be exploited to reduce the number of required input images [54, 73]. This will be discussed
Fig. 1.7: An example of an image that has been separated into diffuse and specular components using polarization. The diffuse component is approximately Lambertian but varies rapidly between surface points. The specular component exhibits more complex variations in the angular domain, but varies smoothly (if at all) across the surface.

in more detail in the next chapter; here we focus on techniques for separating the two components in an image.

Polarization The diffuse and specular components of an image are typically separated using color, polarization, or both. The polarization of light refers the orientations of the (orthogonal) planes of vibration for the electric and magnetic fields along the direction of propagation of an electromagnetic wave. A single ray can have linear, circular or elliptical polarization, with each referring to the path traced out by the electric field vector as the wave propagates. We speak of collections of light rays as being, polarized, unpolarized, or partially polarized. Polarized light is coherent in terms of it’s polarization state, whereas unpolarized (or randomly polarized) light is completely incoherent. Partially polarized light refers to a mixture of randomly-polarized and coherently polarized rays.

Before now, we have largely ignored polarization, and have focussed instead on the angular and spatial distributions of incident and reflected flux. Polar-
1.6. Separating Reflection Components

Polarization reflectance effects can be quite complicated, and a completely general description might require as many as sixteen BRDF—a four-by-four matrix in terms of Stokes parameters—for a single material ([48], p. 32). Fortunately, polarization effects for non-conducting surfaces can be described and exploited quite simply.

The simplest way to separate specular and diffuse reflections is by ‘cross-polarization’, in which linear polarizing filters are placed on the source and camera (e.g., [41]). Most light sources emit unpolarized light, and by passing this through a linear polarizing filter, one obtains linearly polarized light at half the original radiance. When linearly polarized flux is incident on a non-conducting surface, the reflected flux will be partially linearly polarized. It consists of the diffuse component, which is unpolarized, and the specular component, which maintains a linear polarization. By placing another linear polarizing filter in front of the camera and orienting it with the polarization direction of the specularly-reflected flux, one obtains an image consisting of the complete specular component and half the diffuse component: 

\[ I_1 = I_d/2 + I_s \]

Then, by rotating the camera’s filter by 90°, the specular component is blocked, and this second image contains the (attenuated) diffuse component only: 

\[ I_2 = I_d/2 \]

From these two images, the diffuse and specular components are simply given by 

\[ I_d = 2I_2 \]
\[ I_s = I_1 = I_2 \]

Figure 1.7 shows an image that was decomposed in this way.

One potential complication in this process is that the polarization plane of the specular-reflected flux depends on the material’s index of refraction (which may vary with wavelength) and the orientation of the incident polarization relative to the incident plane. This relationship is described by the Fresnel equations for a non-conductor, and by assuming an index of refraction (1.5, the refractive index of common salt and glass, is the usual choice), one can design polarized lighting arrays with optimal polarization fields [32]. For a single source, however, the simplest strategy is to polarize the incident flux in the direction orthogonal to the plane spanned by the light direction and the camera’s optical axis. This insures that the polarization of the specular-reflected flux will remain in that direction, regardless of the material’s index of refraction.
Another effect to be aware of is that diffuse reflectance can become partially polarized when the angle between the surface normal and view direction is large [67]. This means that polarization-based separation will be less accurate near the occluding contour of an observed object.

Finally, it is worth re-emphasizing that this strategy cannot be used for metallic materials or semiconductors, since reflectance in these cases is due purely to surface effects. The imaginary component of the index of refraction is non-zero in these cases, and the Fresnel equations that govern interface effects are more complicated (e.g., [50]). For example, linearly-polarized incident flux leads to elliptically-polarized reflected flux in general. The differences between the way in which different materials (especially conductors vs. dielectrics), and the way in which these vary geometrically, can be exploited in other ways than described here. This is especially useful in uncontrolled environments, where the polarization state of the illuminant cannot be controlled [68, 67].

**Wavelength/Color** If we consider the wavelength dependence of the BRDF, it becomes a function of five dimensions, \( f_r(\lambda, \omega_i \rightarrow \omega_o) \). In many cases, this function can be factored into separated functions of wavelength and geometry:

\[
f_r(\lambda, \omega_i \rightarrow \omega_o) \approx g(\lambda)f(\omega_i \rightarrow \omega_o).
\] (1.5)

This is typically a good approximation, but not always. For example, the underside of a compact disc exhibits joint angular and spectral variations caused by diffraction effects, and these cannot be described by this factored form.

As mentioned above, the BRDF of many materials, including all dielectrics, can be decomposed into two additive components: a specular (interface) component and a diffuse (body) component. Utilizing the spectral/angular factorization described above, the BRDF of such materials can be written,

\[
f_r(\lambda, \omega_i \rightarrow \omega_o) = g_d(\lambda)f_d(\omega_i \rightarrow \omega_o) + g_s(\lambda)f_s(\omega_i \rightarrow \omega_o).
\]
Additionally, since the index of refraction of many surfaces is constant over the visible spectrum [28] that function $g_s(\lambda)$ can be considered constant, and this leads to the expression

$$f_r(\lambda, \omega_i \rightarrow \omega_o) = g_d(\lambda)f_d(\omega_i \rightarrow \omega_o) + f_s(\omega_i \rightarrow \omega_o), \quad (1.6)$$

where $f_s(\omega_i \rightarrow \omega_o) = g_s f_s(\omega_i \rightarrow \omega_o)$. In this expression, the function $g_d(\lambda)$ is often referred to as the spectral reflectance of the material.

Equation 1.6 is at the core of Shafer’s dichromatic model of an image [57]. When such a surface is lit by a single illuminant and imaged by a trichromatic sensor, the observed colors can be written as linear combinations of a source color and diffuse color [57]. That is,

$$I_k = \sigma_d d_k + \sigma_s s_k, \quad (1.7)$$

where $\sigma_d$ and $\sigma_s$ are geometric scale factors that depend on the view and source configuration and

$$d_k = \int e(\lambda)g_d(\lambda)c_k(\lambda)d\lambda, \quad (1.8)$$

$$s_k = \int e(\lambda)c_k(\lambda)d\lambda. \quad (1.9)$$

Here, $e(\lambda)$ is the spectral power distribution of the incident illumination, $g_d(\lambda)$ is the spectral reflectance of the surface, and $c_k(\lambda)$ is the spectral sensitivity of a linear sensor. A typical RGB camera yields three such observations, and in this case we write $I_{RGB} = \{I_k\}_{k=R,G,B}$ and define $d = \{d_k\}_{k=R,G,B}$ and $s = \{s_k\}_{k=R,G,B}$ to be the diffuse color and source color mentioned above. Empirically, this model has shown to be suitable for a diverse set of materials, including certain types of plant leaves, cloth, wood, and the skin of fruits [28, 61, 21].

The dichromatic model provides a means of using color for separating diffuse and specular reflection components. Unlike polarization, however, one cannot achieve this separation unambiguously using color. Even when the source color $s$ is known, there is a one-parameter family of diffuse colors that satisfy Eq. 1.7, and thus a one-parameter family of possible separations. To choose a good separation from the set of possibilities, the traditional approach is to
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exploit spatial coherence in the distribution of diffuse colors on a surface (e.g. [27, 43, 57, 59, 33]) and/or the distinct angular behavior of diffuse and specular effects [53].

1.6.3 Uncontrolled environments

The separation of reflection components can be especially useful in natural environments when controlled, active illumination is difficult or impossible. Local and non-local reflections for non-conducting surfaces can be separated (at least approximately) using a simple stick occluder under direct sunlight, and diffuse/specular separation can be achieved using color information according to the dichromatic model and/or passive polarization imaging [68, 43]. In many cases, passive polarization imaging can also be used for material identification, for example to distinguish metallic from non-metallic surfaces[67, 68].
References

References


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References