

# Restoring Illumination and View Dependent Data from Sparse Samples

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## Abstract

Capturing appearance of material with respect to illumination and viewing directions is crucial to achieve realistic visual experience in virtual environments. The capturing process is time demanding or requires a specific shape of the captured material. Therefore, we propose a method of such a data reconstruction from very sparse measurements, whose placement allows for continuous and fast acquisition, from which can benefit future acquisition setups. The proposed approach was tested on a number of view- and illumination- dependent samples and showed a promising performance in terms of whole data-space reconstruction speed and visual quality.

## 1 Introduction

Although view- and illumination-dependent data are due to their ability to digitally represent realism of material appearance demanded in many applications, their measurement is costly and time consuming. The standard acquisition procedures of such data require either time consuming measurement or require specific shape of a measured sample [3, 4]. A *bidirectional reflectance distribution function* (BRDF) is one example of such data. BRDF describes distribution of energy reflected to a viewing direction when illuminated from a specific direction. However, it imposes restrictions on reciprocity and energy conservation. More general view and illumination data is an apparent BRDF (ABRDF), which can be obtained by measuring local effects in rough material structure (accounting for occlusions, masking, subsurface scattering) and thus do not generally fulfill these restrictions. If we process individual color channels separately, the ABRDF can be represented by a four-dimensional function  $ABRDF(\theta_i, \varphi_i, \theta_v, \varphi_v)$ . ABRDF can be considered as the most general data representation of a reflectance of opaque materials dependent on local illumination  $\mathbf{I}$  and view  $\mathbf{V}$ . Its typical parameterization by elevation  $\theta$  and azimuthal  $\varphi$  angles

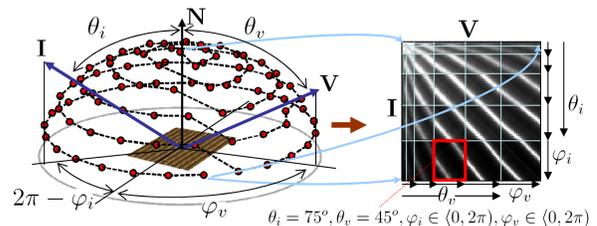


Figure 1. Data parameterization.

[8] is shown in Fig. 1. Highlighted rectangular area on the right represents toroidal subspace with constant elevations  $\theta_i/\theta_v$  but varying  $\varphi_i/\varphi_v$ .

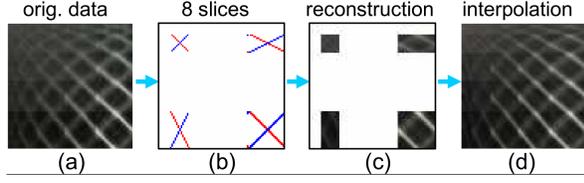
Although there are techniques available for BRDF reconstruction from sparse data by taking several images of known geometry from different illumination/viewing directions [9, 2], we are not aware of any work that would allow full ABRDF space reconstruction from predefined intuitively obtainable sparse samples. In this paper we propose a novel method of ABRDF reconstruction based on a set of sparse samples.

Main motivation of our work is an accurate restoration of whole ABRDF space, from such sparse samples that can be measured quickly and intuitively (unlike a uniform hemisphere sampling) without need of an expensive conventional measurement setups. Contrary to parametric BRDF models, e.g., [5] the method do not have any data restrictions and require considerably less input samples to reconstruct whole ABRDF.

The paper is further structured as follows. Section 2 explains principle of the proposed method. Section 3 shows results of the performed experiments, while Section 4 concludes the papers.

## 2 The Reconstruction Method

A principle of the proposed method is explained in Fig. 2. Firstly, the sparse samples of the material's ABRDF (a) are measured at predefined locations (azimuthal angles) (b). Then four ABRDF subspaces are reconstructed from values of the slices (c), and finally the remaining values are interpolated (d).



**Figure 2. An example of ABRDF reconstruction:** (a) original, (b) sparse-sampling by 8 slices, (c) reconstructions of elevations where the slices were measured, (d) missing data interpolation.

### 1. Acquisition of slices

In the first step, a small subset of ABRDF values is measured with the intent of capturing as much information about material reflectance behavior as possible. We selected such illumination/view azimuthal angles that form a couple of perpendicular slices in a space of illumination/view azimuthal angles  $\varphi_i/\varphi_v$  (see Fig. 3-a). Due to this selection, the slices are orthogonal to the most prominent features of a majority of the materials: a specular reflection and an anisotropic reflection (see the first row in Fig. 5). These features are often constant in the direction perpendicular to the slices and thus can be reliably represented by the marginal values of the slices. The slice aligned with the direction of the specular highlights is called *axial slice*  $s_A$  (red), i.e.,  $\varphi_i - \varphi_v = \alpha$  holds for azimuthal angles (where  $\alpha = 15$  to avoid the same location of camera and light). The axial slice records the material's anisotropic properties (mutual position of light and camera is fixed while the sample rotates), i.e., for isotropic samples it is almost a constant value. The slice perpendicular to the highlights is called *diagonal slice*  $s_D$  (blue), i.e.,  $\varphi_i + \varphi_v = 2\pi + \alpha$  holds for azimuthal angles. The diagonal slice captures the shape of the specular peaks (light and camera travel in mutually opposite directions over the sample). The slices are measured from ABRDF  $B$  (Fig. 3-a) as

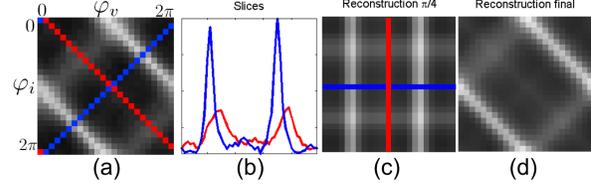
$$\begin{aligned} s_A(\varphi_i) &= B(\theta_i, \theta_v, \varphi_i, \varphi_v = \varphi_i - \alpha) , \\ s_D(\varphi_v) &= B(\theta_i, \theta_v, \varphi_i = 2\pi - \varphi_v + \alpha, \varphi_v) . \end{aligned} \quad (1)$$

An example of measurement of the slices from ABRDF data at fixed elevations  $\theta_i/\theta_v$  is shown in Fig. 3-a,b.

### 2. Reconstruction from slices

ABRDF toroidal subspace reconstruction is performed for elevation angles at which the slices were captured and can be explained as a combination of two slices (i.e., sets of marginal values) as shown in Fig. 3. The reconstruction of point  $\hat{B}$  in ABRDF subspace starts as a sum of values from the slices.

$$v(\varphi_i, \varphi_v) = s_A(\varphi_{i,R}) + s_D(\varphi_{v,R}) , \quad (2)$$



**Figure 3. Reconstruction of BRDF values from two slices:** (a) original data with slices placements, (b) data profiles in the slices, (c) reconstruction from slices ( $\frac{\pi}{4}$  rotated), (d) final reconstruction.

$$\begin{bmatrix} \varphi_{i,R} \\ \varphi_{v,R} \end{bmatrix} = \begin{bmatrix} \cos \pi/4 & -\sin \pi/4 \\ \sin \pi/4 & \cos \pi/4 \end{bmatrix} \begin{bmatrix} \varphi_i \\ \varphi_v \end{bmatrix} \quad (3)$$

Note that azimuths  $\varphi_i, \varphi_v$  had to be rotated for  $\pi/4$  (Fig. 3-c) to account for the slant of slices with respect to the  $\varphi_i, \varphi_v$  coordinate system (Fig. 3-a). As sum of slices (2) changes a dynamic range, the summed value  $v$  is mapped back to a dynamic range of original slices

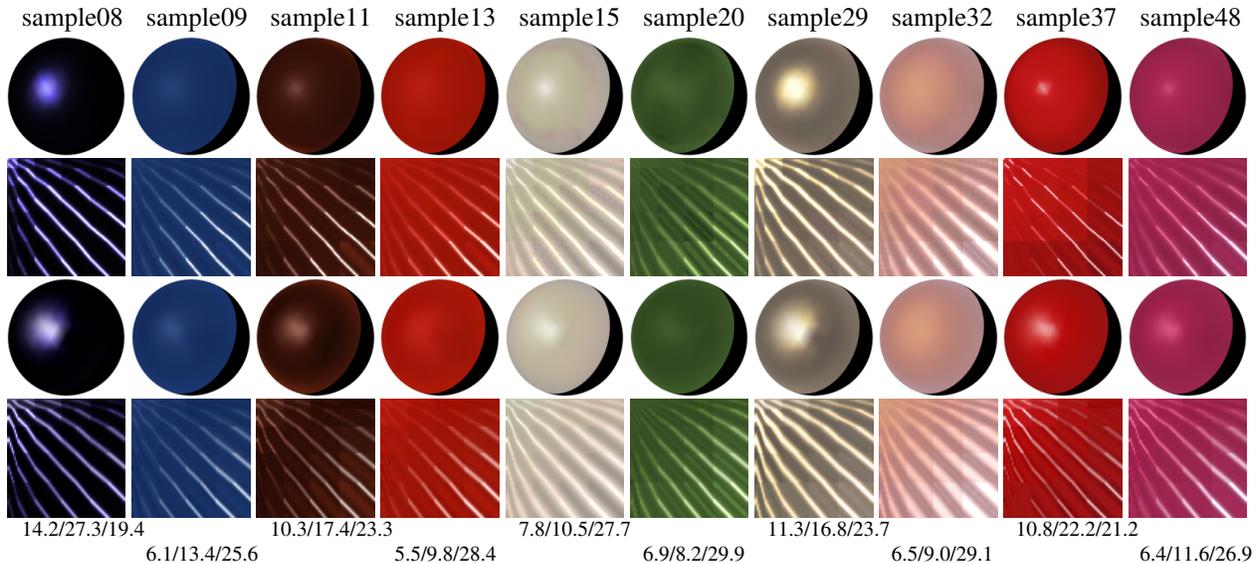
$$\begin{aligned} \hat{B}(\theta_i, \theta_v, \varphi_i, \varphi_v) &= v(\varphi_i, \varphi_v) \cdot (M - m) + m , \\ m &= \min(s_A \cup s_D) \quad M = \max(s_A \cup s_D) . \end{aligned} \quad (4)$$

Since the axial slice always has a constant value for isotropic samples, the slices do not have to be combined and reconstruction can be performed using the diagonal slice alone as

$$\hat{B}(\theta_i, \theta_v, \varphi_i, \varphi_v) = s_D(\varphi_{v,R}) . \quad (5)$$

### 3. Interpolation of missing values

At this point, the four ABRDF subspaces have been reconstructed as shown in Fig. 2-c. These subspaces correspond to elevation angles  $\theta_i/\theta_v$  at which the slices were taken/measured (to cover the most of the elevations we used  $30^\circ/30^\circ$ ,  $30^\circ/75^\circ$ ,  $75^\circ/30^\circ$ ,  $75^\circ/75^\circ$ ). However, the data for the remaining elevations are still unknown and must to be estimated. The BRDF parametric models, e.g., [5], cannot be used to solve this problem as they impose restrictions on data properties (reciprocity, energy conservation, etc.), require many more samples, lengthy fitting, and depend on initial values. We tried to fit measured samples using the anisotropic parametric BRDF model, however we were unable to find stable parameters providing any reasonable fitting for most of the tested ABRDFs. Therefore, the interpolation was performed by means four-dimensional radial basis functions [6] separately in each color channel. We tested several parameterizations of illumination and viewing directions, e.g.  $[\theta_i, \phi_i, \theta_v, \phi_v]$ ,  $[\theta_h, \phi_h, \theta_d, \phi_d]$  from [7], and finally used "onion" parameterization according to [1] applied to both illumination and view directions  $[\alpha_i, \beta_i, \alpha_v, \beta_v]$ . This parameterization has shown the lowest reconstruction error



**Figure 4. Comparison of MERL isotropic BRDFs (the first row), with their reconstruction from the slices (the second row). Below are the difference values in CIE  $\Delta E$ / RMSE/ PSNR.**

due to specular highlights alignments near 0 value of parameter  $\beta_i$ . After the interpolation all missing values for arbitrary directions are filled (Fig. 2-d).

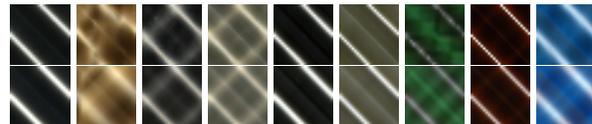
### 3 Tests and Results

In this section we show results of experiments with isotropic and anisotropic BRDF datasets.

First, we tested our method on reconstruction of 55 isotropic BRDF samples (resampled to  $81 \times 81$  directions) from the MERL BRDF database [3]. Example results of ten reconstructed BRDFs with corresponding visualization on a sphere are shown in Fig. 4. As the BRDFs are isotropic, their axial slices are always constant; therefore the reconstruction was performed using only diagonal slices. The advantage of isotropic reconstruction is that half as many slices  $s_D$  have to be obtained (in our case, 102 samples instead of 204 needed for anisotropic data). Mean reconstruction errors of all 55 BRDFs (8bits/channel) were: CIE  $\Delta E=9.1$ , RMSE=15.7, and PSNR= 24.9.

In the second experiment we used nine bidirectional texture function (BTF) samples (eight from Bonn University BTF database [8]<sup>1</sup> and one from Volumetric Surface Texture Database<sup>2</sup>) in our experiments (aluminum profile, corduroy, dark and light fabrics, dark and light leatherettes, lacquered wood, knitted wool, and Lego<sup>2</sup>). Their angular resolution was  $81 \times 81$  illumination and view directions distributed uniformly over the hemisphere (Fig. 1). The BTF samples represent spatially

varying ABRDF and due to their rough structure, exhibit strong anisotropic effects caused by occlusions, masking, subsurface scattering and therefore represent a challenging dataset to test the proposed method. We averaged all BTF pixels to obtain average ABRDF. Examples of ABRDF subspace reconstruction from two slices are shown in Fig. 5 and prove the ability of the proposed approach to represent a variety of anisotropic materials.



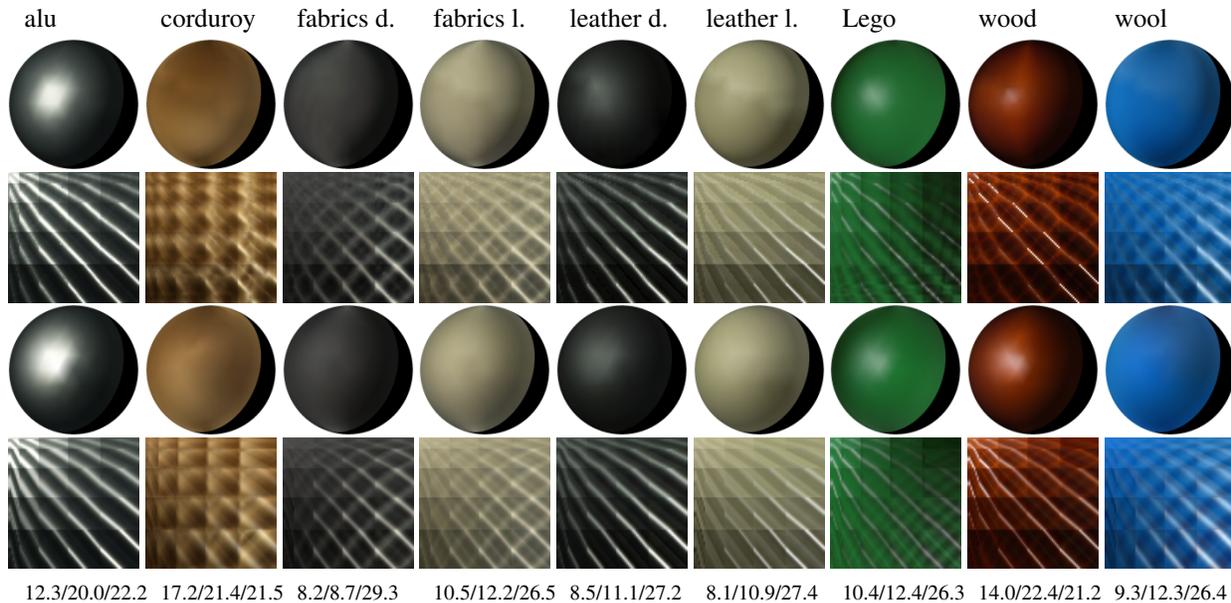
**Figure 5. Comparison of the material's ABRDF toroidal subset at elevation  $75^\circ$  (the first row), with its reconstruction from the slices (the second row).**

The results of complete reconstruction of original ABRDFs from 204 sparse samples again with sphere visualizations are shown in Fig. 6, together with reconstruction errors in terms of CIE  $\Delta E$ , RMSE, PSNR. Generally, the proposed model provides promising reconstruction even of such challenging datasets.

To sum up, for angular resolution  $81 \times 81 = 6561$  directions of original ABRDF only 102 samples for isotropic and 204 samples for anisotropic dataset were used to obtain sufficient data for reconstruction. Although this represents compression ratio of original data  $\approx 1:32$ , the main advantage is the reconstruction of the data that allow arbitrarily dense directional sampling of

<sup>1</sup><http://btf.cs.uni-bonn.de/>

<sup>2</sup><http://vision.ucsd.edu/kriegman-grp/research/vst/>



**Figure 6. Comparison of the material’s ABRDF (the first row), with reconstruction and interpolation from slices (the second row). Below are the difference values in CIE  $\Delta E$ / RMSE/ PSNR.**

ABRDF even for a majority of originally unmeasured directions. Reconstruction and interpolation of single ABRDF from the slices is very fast and takes  $\approx 1$  second on Intel Xeon 2.67GHz (using 3 cores).

## 4 Conclusions

A novel reconstruction model of view- and illumination-dependent material appearance from very sparse data is proposed. It uses intuitive continuous sparse sampling of material appearance: rotation of the sample below fixed light and sensor, and mutually opposite movement of the light and sensor with regards to the sample. The model does not impose any restrictions on data and is capable of reconstruction anisotropic non-reciprocal ABRDF data without limitation of input dynamic range. Additionally, due to the final interpolation step it allows arbitrary dense angular modeling of original data. We tested isotropic and anisotropic BRDFs of rough surfaces with encouraging results. We can conclude that the method allows very promising approximation of material appearance given the extremely sparse dataset (204 samples). In our future work we would like to extend and test the sparse reconstruction to handle also spatially varying data, i.e., SVBRDF and BTF. We believe that this result will contribute to future development of simple and cheap acquisition setups of illumination- and view-dependent data.

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