Workshop on Material Appearance Modeling (2017)
H. Rushmeier and R. Klein (Editors)

Towards sparse and multiplexed acquisition of material BTFs

D. den Brok[1] and M. Weinmann[1] and R. Klein[1]

[1]Institute of Computer Science II, University of Bonn, Germany

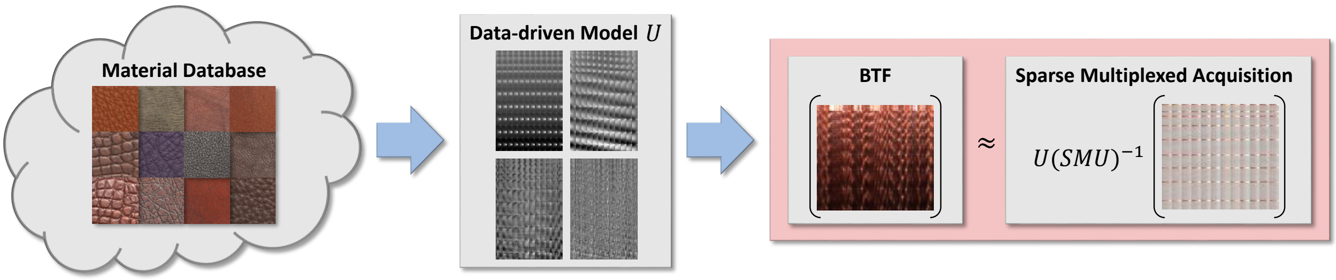


Figure 1: *Sketch of the proposed method: given a database of traditionally measured BTFs, a data-driven linear model is derived in a novel way that allows for both existing paradigms under consideration to be used separately as well as, for the first time, simultaneously.*

Abstract

We present preliminary results on our effort to combine sparse and illumination-multiplexed acquisition of bidirectional texture functions (BTFs) for material appearance. Both existing acquisition paradigms deal with a single specific problem: the desire to reduce either the number of images to be obtained while maintaining artifact-free renderings, or the shutter times required to capture the full dynamic range of a material's appearance. These problems have so far been solved by means of data-driven models. We demonstrate that the way these models are derived prevents combined sparse and multiplexed acquisition, and introduce a novel model that circumvents this obstruction. As a result, we achieve acquisition times on the order of minutes in comparison to the few hours required with sparse acquisition or multiplexed illumination.

Categories and Subject Descriptors (according to ACM CCS): I.4.1 [Image Processing and Computer Vision]: Digitization and Image Capture—Reflectance

1. Introduction

Photo-realistic reproduction of material appearance is of great importance im many applications in fields like virtual prototyping, advertisement and entertainment. While analytical reflectance models such as bidirectional reflectance distribution functions (BRDFs) [NRH*77] have become widely used due to their capability of modeling the reflectance at a surface point depending on the incident and outgoing light directions, such models face serious limitation when it comes to faithfulness, in particular when reproducing non-local effects like self-shadowing and interreflections. For this reason, data-driven reflectance models like the bidirectional texture function (BTF) are the first choice in such cases.

One of the main challenges of data-driven models is presented by the dense sampling of view and light directions necessary to accurately capture high-frequency characteristics of the light exchange on the material surface. The resulting high sampling rate leads to intolerably time-consuming acquisition on the order of many hours or even days [SSW*14]. In the context of image based acquisition devices this problem is even more challenging since for the accurate acquisition of the full dynamic range of the material's reflectance behavior capturing HDR images is with possibly excessive exposure times is inevitable.

Several approaches to mitigate these problems were proposed in the literature. Sparse acquisition techniques are applied where only a small subset of the desired dense sampling is actually measured, and the remaining data is interpolated by means of a model learned from an existing database (e.g. [dBSHK14, NJR15]). A common technique to accelerate the capturing of HDR images by increasing the amount of light on the sample and decreasing the dynamic range caused by shadows (cf. Fig. 2) is illumination multiplexing, i.e. illuminating the material with illumination patterns comprised of several simultaneous light sources and exploiting the linearity of

DOI: 10.2312/mam.20171326

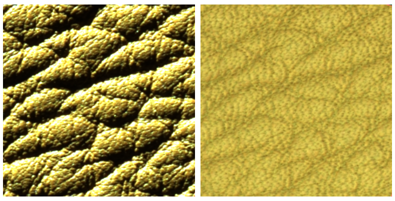


Figure 2: *Material sample as illuminated by single light source (left) and illumination pattern (right).*

the superposition of light to reconstruct the desired images by solving an appropriate linear system, a process that is, however, known to be detrimental to the signal-to-noise ratio (SNR). The models used in sparse BTF acquisition have been shown to also help mitigate the noise problems [dBSK15]. Although both methods significantly reduce acquisition times, the process still takes in the range of hours. Therefore, the question arises whether the two paradigms - sparse acquisition and illumination multiplexing - can be combined in order to speed up the acquisition further. So far, this has been impossible: the linear bases used as models in the above approaches rely heavily on range-reduction techniques applied to the training data which do not commute with multiplexing. Therefore, de-multiplexing has to be performed prior to fitting the measured data to the model, but this requires images for *all* illumination patterns, which we wish to avoid in sparse acquisition.

In this paper, we investigate whether accurate reflectance acquisition, simultaneously exploiting sparse acquisition and multiplexed illumination, is possible. Specifically, we propose a different approach to dynamic range reduction in model learning: rather than the *absolute* L_2 error on non-linearly transformed data as a metric, we minimize the *relative* L_2 error on untransformed data, which ultimately allows for sparse multiplexed acquisition of BTFs. As demonstrated by our results, combining sparse and multiplexed acquisition allows for a reduction of the acquisition time from the order of hours/days required for brute-force measurements to only several minutes.

2. Related work

Related work can be categorized according to techniques that focus on the acquisition and modeling of material appearance and techniques that focus on sparse reflectance acquisition or multiplexed acquisition, respectively.

Acquisition and modeling of material appearance As detailed surveys on acquisition and modeling of material appearance can be found in the literature [HF13, WK15], we only briefly discuss two of the reflectance models that are widely used for the depiction of materials in industry and cultural heritage. Spatially varying bidirectional reflectance distribution functions (SVBRDFs) [NRH*77] and bidirectional texture functions (BTFs) [DvGNK99] both capture the spatially varying material characteristics under varying viewing and illumination conditions. Unlike SVBRDFs, BTFs are not necessarily defined with respect to the material's actual surface but can also be defined on an approximate surface geometry and do not impose restrictions regarding energy conservation on the per-texel BRDFs and simply encode the *appearance* of the material at one particular coordinate on the reference geometry. In contrast, SVBRDFs do not accurately capture the light exchange for such materials. Consequently, one typically retreats to image-based representations that can be evaluated by doing a possibly interpolated table look-up. For the purpose of modeling, it is convenient to represent BTFs as matrices $\mathbf{B} \in \mathbf{R}^{n_{lv} \times n_{tx}}$, where n_{lv} and n_{tx} denote the number of light/view combinations and texels, respectively (cf. Fig. 3).

Basis acquisition and computation Given a database $\mathbf{D}$ of measured BTFs, where the separate BTFs are concatenated along the second dimension, a straight-forward approach to modeling is the use of matrix factorization techniques like the (truncated) singular value decomposition (SVD), e.g. $\mathbf{D} \approx \mathbf{U}\Sigma\mathbf{V}^T$. Matusik et al. [MPBM03a] have shown that the dynamic range of reflectance data, determined by the huge difference in brightness between specular highlights and diffuse reflection which may amount to several orders of magnitude, leads to severe overfitting of the highlights. A number of metrics have since been proposed to overcome this problem, most of which based on some logarithmic scaling of the data, the most recent being the one proposed by Nielsen et al. [NJR15].

Sparse acquisition Techniques for sparse reflectance acquisition aim at taking only a suitable subset of the total amount of images used by conventional dense-sampling approaches. Instead of the full measurement $\mathbf{B}$, the matrix product $\mathbf{SB}$ is obtained, where $\mathbf{S} \in \{0,1\}^{n_s \times n_{lv}}$ with $\mathbf{SS}^t = \mathbf{1}$ denotes a binary sparse measurement matrix that selects the desired rows, i.e. textures, of $\mathbf{B}$. Assuming that $\mathbf{B}$ can be approximated well by a linear basis $\mathbf{U}$, an approximation $\mathbf{B} \approx \mathbf{UV}$ is given by

$$\mathbf{V} = \operatorname{argmin}_{\tilde{\mathbf{V}}} \|\mathbf{SU}\tilde{\mathbf{V}} - \mathbf{SB}\|_F^2 + \|\mathbf{R}\tilde{\mathbf{V}}\|_F^2, \qquad (1)$$

where $\|\mathbf{R}\tilde{\mathbf{V}}\|_F^2$ represents an optional Tihonov regularization that penalizes implausible solutions. In their work on sparse BRDF acquisition, Nielsen et al. [NJR15] use $\mathbf{R} = \Sigma^{-1}$, where Σ denotes the diagonal matrix of singular values corresponding to the singular vectors in $\mathbf{U}$, which penalizes large deviations from the training set's distribution of basis coefficients.

Sparse acquisition has been successfully used in the context of (SV)BRDFs of various kinds [MPBM03a, MPBM03b, NJR15, VF16, YXM*16]. Furthermore, Peers et al. [PML*09] investigate the acquisition of reflectance fields based on compressed sensing, and sparse reconstruction of light fields has been considered based on dictionary-based techniques [MWBR13]. Closely related to our approach is the technique presented by den Brok et al. [dBSHK14], where sparse BTF acquisition is achieved based on linear models derived from a database of small BTF patches.

Multiplexed illumination In illumination-multiplexing techniques, the material is illuminated by multiple light sources at once, following certain illumination patterns. As the amount of light illuminating the scene is increased, and less shadows occur when light is coming from different directions, the shutter times used for image acquisition can be reduced. This corresponds to measuring $\mathbf{MB}$, where $\mathbf{M} \in \{0,1\}^{n_p \times n_{lv}}$ represents a multiplexing matrix that specifies the n_p illumination patterns used during acquisition. If $\mathbf{M}$ is chosen to be an invertible matrix, it is possible to reconstruct $\mathbf{B}$

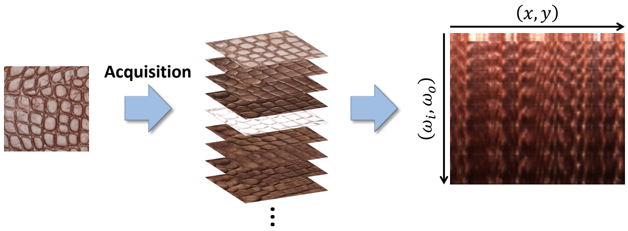


Figure 3: *Representation of a discretized BTF as a matrix.* (x, y) *denotes the spatial coordinates in the BTF patch, i.e. there are* n_{tx} *columns in the matrix. The number of rows* n_{lv} *corresponds to the number of view-light configurations* (ω_i, ω_o).

from **MB**. However, the reconstruction suffers from noise as, for imaging systems like BTF acquisition setups, the measurements are distorted by Poisson noise [HS79]. Den Brok et al. [dBSK15] introduced this technique to BTF acquisition, demonstrating significantly reduced acquisition times in comparison to single-light acquisition. Noise contained in the demultiplexed reconstruction is mitigated by projecting the noisy BTF onto a linear subspace **U** obtained from a database of conventionally measured BTFs:

$$\mathbf{V} = \text{argmin}_{\tilde{\mathbf{V}}} \|\mathbf{U}\tilde{\mathbf{V}} - \mathbf{M}^{\dagger}(\mathbf{MB})\|_F^2 \quad (2)$$

where $\mathbf{M}^{\dagger}$ denotes the pseudo-inverse of **M**.

Other techniques that rely on multiplexed illumination include the acquisition of time-varying light fields of human faces [WGT*05], continuous per-point spectral reflectance reconstruction from spectral measurements, programmable aperture photography of light fields [LLW*08] and the recovery of dense and accurate light transports from objects by using orthogonal illumination based on a Walsh-Hadamard matrix which allows to consider ambient illumination in addition to directly reflected light [MT16].

3. Our approach

While the aforementioned techniques individually enable significant speed-ups of the acquisition process, they are still far from what we are used from, e.g., SVBRDF acquisition. Considering the gains provided by the individual techniques, the question arises whether the combination of these approaches is possible, in particular as they deal with orthogonal problems. For this purpose, we propose to pose the combination of the different paradigms of sparse acquisition and multiplexed acquisition as an optimization problem

$$\mathbf{V} = \text{argmin}_{\tilde{\mathbf{V}}} \|\mathbf{SMU}\tilde{\mathbf{V}} - \mathbf{SMB}\|_F^2 + \|\mathbf{R}\tilde{\mathbf{V}}\|_F^2, \quad (3)$$

where the first summand represents the data term and the second summand an optional regularization term as described in Section 2. This corresponds to obtaining a possibly small number of images of the material sample lit by and viewed from selected illumination patterns and camera positions, respectively. It turns out that the obstacle is the very idea which makes the previous approaches practical in their domains: the application of a logarithmic scaling to the data. The basis **U** typically is a basis for log-space data, but we cannot infer $\mathbf{M}\log(\mathbf{B})$ from the measurement **MB**, because in general $\log(\mathbf{MB}) \neq \mathbf{M}\log(\mathbf{B})$.

Relative error metric Inspired by Ruiters et al. [RSK12], we therefore modify the metric used when computing the basis by assigning per-entry weights **W** to the L_2 errors instead of modifying the data. The optimization problem to be solved then becomes

$$\mathbf{U}, \mathbf{V} = \text{argmin}_{\tilde{\mathbf{U}}, \tilde{\mathbf{V}}} \|\mathbf{W} \odot (\tilde{\mathbf{U}}\tilde{\mathbf{V}} - \mathbf{D})\|_F, \quad (4)$$

where $\odot$ denotes the entry-wise matrix product. By taking **W** as the entry-wise inverse of **D**, this is equivalant to minimizing the *relative* L_2 error instead of the absolute one, which dampens the influence of highlights in a fashion similar to the logarithmic scaling, but without any change to the input data.

Basis computation We assume the availability of a database $\mathbf{D} \in \mathbf{R}^{n_{lv} \times n_{tx} \cdot n}$ of n fully measured material BTFs. To the best of our knowledge, there is no canonical way to solve Eq. 4; we chose an alternating least-squares approach: Let c be the approximate rank of **D** and **d**, **w** be the vectors of entries of **D** and **W**, respectively. We initialize $\mathbf{U} \in \mathbf{R}^{n_{lv} \times c}$ with random values drawn uniformly from the interval $(-\frac{1}{2}, \frac{1}{2})$. Then, we may determine $\mathbf{V} \in \mathbf{R}^{c \times n_{tx}}$ by solving for its vector **v** of entries as

$$\mathbf{v} = \text{argmin}_{\tilde{\mathbf{v}}} \|\text{diag}(\mathbf{w})\,\text{diag}(\mathbf{U}, \ldots, \mathbf{U})\,\tilde{\mathbf{v}} - \text{diag}(\mathbf{w})\,\mathbf{d}\|_2, \quad (5)$$

where $\text{diag}(\mathbf{U}, \ldots, \mathbf{U})$ is a block-diagonal matrix of n_{tx} copies of **U**. Given a new estimate of **V**, **U** can be obtained analogously. These alternating optimizations are iterated until convergence, after which the columns of **U** are normalized. Optionally, for reasons of efficiency, this method may be applied on a per-material basis and the resulting bases merged similar to what has been done in previous work [dBSHK14].

Sampling strategy It remains to determine a sparse measurement matrix $\mathbf{S} \in \{0, 1\}^{n_s \times n_p}$. Following Matusik et al. [MPBM03a], we propose to minimize the condition number $\kappa(\mathbf{SMU}\Sigma)$, because this is a good indicator that redundant sample coordinates have been avoided. A greedy strategy is to start with a random subsampling and iteratively test whether exchanging a random coordinate with another leads to a smaller condition number, and, if so, keeping the new coordinate, until convergence or a time-limit is reached.

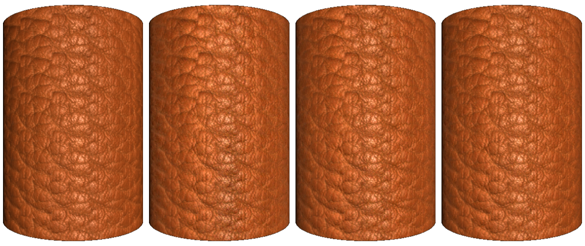
Reconstruction Once a sparse, multiplexed measurement **SMB** has been obtained, determining an approximation $\mathbf{B} \approx \mathbf{UV}$ is straight-forward:

$$\mathbf{V} = \left((\mathbf{SMU})^t(\mathbf{SMU}) + \mathbf{R}^t\mathbf{R}\right)^{-1}(\mathbf{SMU})^t(\mathbf{SMB}), \quad (6)$$

where **R** is an appropriate regularization matrix. We take $\mathbf{R} = \lambda \cdot \Sigma^{-1}$, where λ is a free parameter determining the regularization's weight.

4. Evaluation

We evaluate our approach on a material database of 12 pieces of leather. BTFs for the materials were captured by means of a semi-parallel setup consisting of 11 cameras, 198 LEDs, and a sample holder placed on a turntable which is rotated in increments of 30° during measurement, described in detail by Schwartz



(a) *Reference.* **(b)** $n_s = 100$. **(c)** $n_s = 200$. **(d)** $n_s = 400$.

Figure 4: *Comparison of reconstructions from sparse, illumination-multiplexed measurements for a leather BTF.*

et al. [SSW*14] The resulting measured BTFs each consist of $198 \times 11 \times 12 = 26136$ HDR RGB images of size 128×128. We randomly select one leather as a test material $\mathbf{B}_{\text{test}}$. The remaining materials are used for training the models. Computations are performed using MATLAB 2015b on a modern desktop-grade machine. We compute and merge per-material bases as explained in Section 3, assuming a rank of $c = 256$. The algorithm converges quickly; we allowed for 15 iterations, reached after about two hours. We inspect the projections $\mathbf{U}^T\mathbf{B}_{\text{test}}$ for various numbers $d_{\text{class}} \in \{256, 512, \ldots, 2048\}$ of columns of $\mathbf{U}$ perceptually and find that $d_{\text{class}} = 1024$ is an adequate choice. We determine a sampling strategy optimized for our setup from the basis for $n_s \in \{100, 200, 400\}$ as described in Sec. 3, where the setup's parallel nature is taken into account, i.e. each sample corresponds to 11 images. Cf. Fig. 4 for renderings of the reconstructed test leather BTF. Acquisition of the ground truth took roughly a day, whereas sparse multiplexed acquisition took about 10, 20 or 40 minutes, depending on the chosen sparsity, in close reach of the realm of industrial-grade SVBRDF acquisition devices. While reconstruction for $n_s = 100$ exhibits annoying artificats, we observe perceptually good reconstruction results for $n_s \in \{200, 400\}$.

5. Conclusion & Future work

We demonstrated that using a novel linear model for material BTFs, obtained by minimizing the relative L_2 error, it is possible to obtain high-resolution, high-dynamic-range material BTFs from sparse, illumination-multiplexed measurements. It remains to be seen whether the results extend to a wider range of materials, and a more quantitative analysis is desirable. Moreover, our model should also lend itself to each previous use case individually; it would thus be interesting to compare its performance against that of the prior art.

References

[dBSHK14] DEN BROK D., STEINHAUSEN H. C., HULLIN M. B., KLEIN R.: Patch-based sparse reconstruction of material BTFs. *Journal of WSCG 22*, 2 (June 2014), 83–90. 1, 2, 3

[dBSK15] DEN BROK D., STEINHAUSEN H. C., KLEIN R.: Fast multiplexed acquisition of high-dynamic-range material appearance. In *Vision, Modeling & Visualization* (Aachen, Germany, 2015), Bommes D., Ritschel T., Schultz T., (Eds.), Eurographics Association, pp. 151–158. 2, 3

[DvGNK99] DANA K. J., VAN GINNEKEN B., NAYAR S. K., KOENDERINK J. J.: Reflectance and texture of real-world surfaces. *ACM Trans. Graph. 18*, 1 (Jan. 1999), 1–34. 2

[HF13] HAINDL M., FILIP J.: *Visual Texture: Accurate Material Appearance Measurement, Representation and Modeling*. Advances in Computer Vision and Pattern Recognition. Springer-Verlag, London, 2013. 2

[HS79] HARWIT M., SLOANE N.: *Hadamard transform optics*. Academic Press, 1979. 3

[LLW*08] LIANG C.-K., LIN T.-H., WONG B.-Y., LIU C., CHEN H. H.: Programmable aperture photography: Multiplexed light field acquisition. *ACM Trans. Graph. 27*, 3 (Aug. 2008), 55:1–55:10. 3

[MPBM03a] MATUSIK W., PFISTER H., BRAND M., MCMILLAN L.: A data-driven reflectance model. *ACM Trans. Graph. 22*, 3 (July 2003), 759–769. 2, 3

[MPBM03b] MATUSIK W., PFISTER H., BRAND M., MCMILLAN L.: Efficient isotropic BRDF measurement. In *Proceedings of the 14th Eurographics Workshop on Rendering* (Aire-la-Ville, Switzerland, Switzerland, 2003), EGRW '03, Eurographics Association, pp. 241–247. 2

[MT16] MIYAGAWA I., TANIGUCHI Y.: Dense light transport for relighting computation using orthogonal illumination based on walsh-hadamard matrix. *IEICE Transactions on Information and Systems E99-D*, 4 (2016), 1038–1051. 3

[MWBR13] MARWAH K., WETZSTEIN G., BANDO Y., RASKAR R.: Compressive light field photography using overcomplete dictionaries and optimized projections. *ACM Trans. Graph. 32*, 4 (July 2013), 46:1–46:12. 2

[NJR15] NIELSEN J. B., JENSEN H. W., RAMAMOORTHI R.: On optimal, minimal BRDF sampling for reflectance acquisition. *ACM Trans. Graph. 34*, 6 (November 2015), 186:1–186:11. 1, 2

[NRH*77] NICODEMUS F. E., RICHMOND J. C., HSIA J. J., GINSBERG I. W., LIMPERIS T.: *Geometrical considerations and nomenclature for reflectance*. National Bureau of Standards Monograph #160, U.S. Department of Commerce, 1977. 1, 2

[PML*09] PEERS P., MAHAJAN D. K., LAMOND B., GHOSH A., MATUSIK W., RAMAMOORTHI R., DEBEVEC P.: Compressive light transport sensing. *ACM Trans. Graph. 28*, 1 (Feb. 2009), 3:1–3:18. 2

[RSK12] RUITERS R., SCHWARTZ C., KLEIN R.: Data driven surface reflectance from sparse and irregular samples. *Computer Graphics Forum (Proc. of Eurographics) 31*, 2 (May 2012), 315–324. 3

[SSW*14] SCHWARTZ C., SARLETTE R., WEINMANN M., RUMP M., KLEIN R.: Design and implementation of practical bidirectional texture function measurement devices focusing on the developments at the university of bonn. *Sensors 14*, 5 (Apr. 2014). 1, 4

[VF16] VAVRA R., FILIP J.: Minimal Sampling for Effective Acquisition of Anisotropic BRDFs. *Computer Graphics Forum (PACIFIC GRAPHICS 2016)*, 7 (2016), 299 – 309. 2

[WGT*05] WENGER A., GARDNER A., TCHOU C., UNGER J., HAWKINS T., DEBEVEC P.: Performance relighting and reflectance transformation with time-multiplexed illumination. *ACM Trans. Graph. 24*, 3 (July 2005), 756–764. 3

[WK15] WEINMANN M., KLEIN R.: Advances in geometry and reflectance acquisition (course notes). In *SIGGRAPH Asia 2015 Courses* (New York, NY, USA, 2015), SA '15, ACM, pp. 1:1–1:71. 2

[YXM*16] YU J., XU Z., MANNINO M., JENSEN H. W., RAMAMOORTHI R.: Sparse Sampling for Image-Based SVBRDF Acquisition. In *Workshop on Material Appearance Modeling* (2016), Klein R., Rushmeier H., (Eds.), The Eurographics Association. 2