Robust and Accurate Non-Parametric Estimation of Reflectance using Basis Decomposition and Correction Functions

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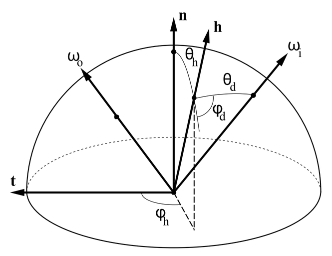
Problem Overview

- The appearance properties for opaque materials are effectively described using the *Bidirectional Reflectance Distribution Function* (BRDF).
- BRDF describes how much light from an incident direction is reflected to an outgoing direction.
- We assume that we are provided with a ✗**sparse**, ✗**irregularly** sampled set of angular BRDF measurements containing ✗**outliers**.



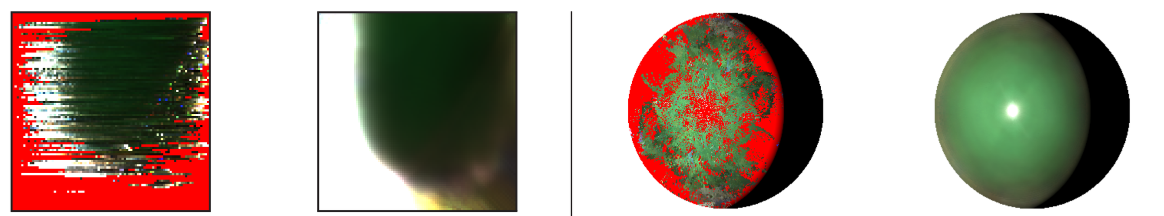
$\rho(\theta_h, \phi_h, \theta_d, \phi_d)$
anisotropic / 4D
$\rho(\theta_h, \theta_d, \phi_d)$
isotropic / 3D

✓ **Task:** *Robustly* reconstruct the complete BRDF that accurately describes the sparsely measured behavior.

Contributions

- A common approach to **non-parametric** BRDF estimation is the approximation of the sparsely measured input using *basis decomposition*.
- We **introduce the novel concept of correction functions** which greatly improves the overall fitting accuracy of such methods.
- We also **introduce a basis** to efficiently estimate novel, dense BRDF correction functions from sparse measurements.
- Our algorithm is the **first to explicitly address outliers** and **computes physically meaningful solutions.**
- Further, the method is **invariant to different error metrics** which alleviates the error-prone choice of an appropriate one for the given input.
- Real and synthetic experiments show that our method can **outperform other state-of-the-art basis decomposition methods** by an order of magnitude in the perceptual sense.

Prior Work



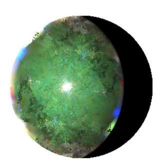
Measured BRDF data
2D projected for visualization

Desired output
2D projected for visualization

Synthesized image
Raw data only

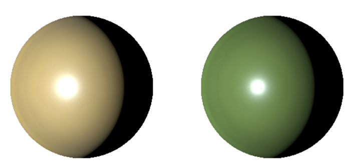
Synthesized image
Desired output

Scattered Data Interpolation
[7, 6]



✓ Measured values directly represented
✓ No error metric needed
✗ Physically implausible
✗ Noise and outliers directly represented

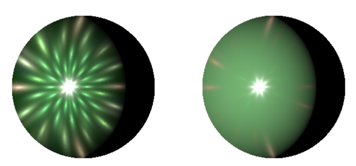
Global Basis Decomposition
[4, 6, 5, 1]



Linear 0.59 | Logarithmic 0.37

✓ Physically plausible
✓ *Relatively* robust w.r.t. outliers
✗ Dependent on error metric
✗ Low flexibility

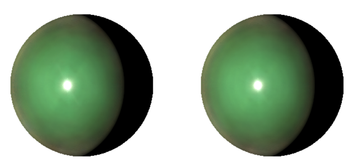
Local Basis Decomposition
[7, 6]



Linear 0.40 | Logarithmic 0.31

✓ Large flexibility
✗ Dependent on error metric
✗ Physically implausible
✗ Not robust w.r.t. outliers

Our Method



Linear 0.20 | Logarithmic 0.19

✓ Physically plausible
✓ Independent on error metric
✓ Large flexibility
✓ Robust w.r.t. outliers

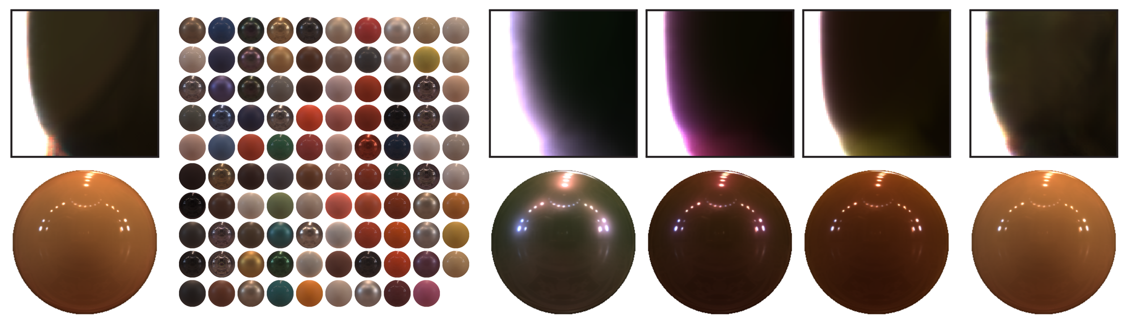
Basis Decomposition

- **Idea:** Express BRDF function using suitable basis Ψ_i:

$$\rho(\vec{x}) \approx \sum_i \alpha_i \Psi_i(\vec{x})$$

- *Global* basis: Ψ_i non-zero for a large range of parameters.
- *Local* basis: Ψ_i zero for a large range of parameters.
- Estimate *coefficients* α_i by fitting to the measurements.
- How to define a good fit? → Choose *error metric*.

✗ **Quality of result is highly dependent on this choice!**



Measured material | Global basis of 99 measured materials [3] | Linear 17.55 | Root 18.10 | Logarithmic 13.36 | Our Method 0.62

Our Method

- Operate using global bases → robust w.r.t. sparse data.
- **Key idea:** Avoid the inflexibility and reduced accuracy of a global basis by iteratively applying different *corrections* to an initial estimate.
- Explicitly **identify and exclude outliers** during iterative process to converge to true solution.

1. **Initialize** *dense* estimate ϱ from *sparse* measurements $\rho_i \approx \rho(\theta_{hi}, \theta_{di}, \phi_{di})$ using basis of 100 measured materials M_i [3]:

$$\rho(\theta_h, \theta_d, \phi_d) \approx \varrho(\theta_h, \theta_d, \phi_d) = \sum_i \alpha_i M_i(\theta_h, \theta_d, \phi_d)$$

2. Formulate a BRDF *correction function* σ that represents **the error of this estimate** using scaling factors:

$$\rho(\theta_h, \theta_d, \phi_d) = \sigma(\theta_h, \theta_d, \phi_d) \varrho(\theta_h, \theta_d, \phi_d)$$

✗ **Problem:** *Dense* σ is unknown and must be estimated!

3. Compute *sparse* set of *correction factors* σ_i:

$$\sigma_i = \frac{\rho_i}{\varrho(\theta_{hi}, \theta_{di}, \phi_{di})}$$

4. Assign a low weight to correction factors where measured input ρ_i and estimate $\varrho_i = \varrho(\theta_{hi}, \theta_{di}, \phi_{di})$ differ largely to **detect outliers**:

$$w_i = e^{-\gamma \frac{|\rho_i - \varrho_i|}{\varrho_i}}$$

5. **Estimate correction function** from σ_i using suitable global *correction basis* C_i:

$$\sigma(\theta_h, \theta_d, \phi_d) = \sum_i \beta_i C_i(\theta_h, \theta_d, \phi_d)$$

✓ Suitable correction basis is introduced within the next section.

6. **Correct** current estimate:

$$\varrho(\theta_h, \theta_d, \phi_d) := \sigma(\theta_h, \theta_d, \phi_d) \varrho(\theta_h, \theta_d, \phi_d)$$

7. **Stop** if sigma is *almost* constantly one, otherwise **continue** from 2.

Correction Basis

- Our intuition was that novel correction functions can be well described using a basis of **previously generated** correction functions.
- **Idea:** Generate *global* basis of correction functions C_i from set of 100 measured materials M_i [3]:

1. For each BRDF M_i from this database, compute an approximation using the remaining 99 materials as a basis:

$$M_i(\theta_h, \theta_d, \phi_d) \approx \varrho(\theta_h, \theta_d, \phi_d) = \sum_{j, j \neq i} \beta_i M_j(\theta_h, \theta_d, \phi_d)$$

2. Compute dense correction function C_i as:

$$C_i(\theta_h, \theta_d, \phi_d) = \frac{M_i(\theta_h, \theta_d, \phi_d)}{\varrho(\theta_h, \theta_d, \phi_d)}$$

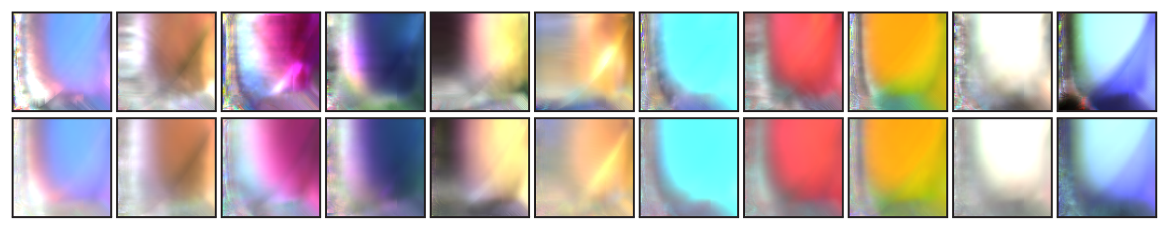
- **Characteristics** of such generated scaling correction functions C_i:

✓ Values of each correction function are distributed within a **narrow range**.
✓ Each correction function itself is a relatively **smooth function**.

→ In sharp contrast to usually rapidly changing BRDF functions!
→ Space of correction functions is **less complex** than space of BRDFs.
→ Finding *good approximations* is more easy in this space.

✗ **Open question:** Is generated basis expressive enough to model novel correction functions?

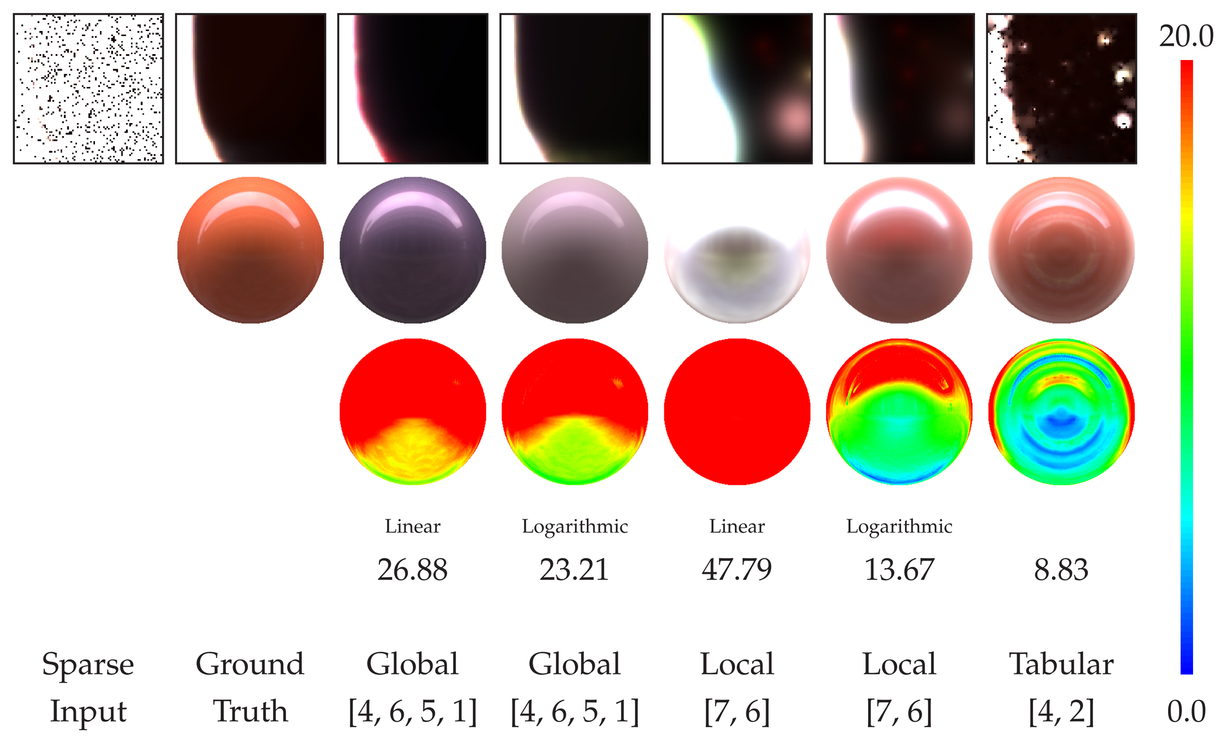
Test: How well is each C_i (top) described using the remaining 99 functions (bottom)?



✓ Average scaling deviation of only 0.076 units.
2D projected for visualization

Synthetic Evaluation

- **State-of-the-art methods:** (10% data, 40% outliers)

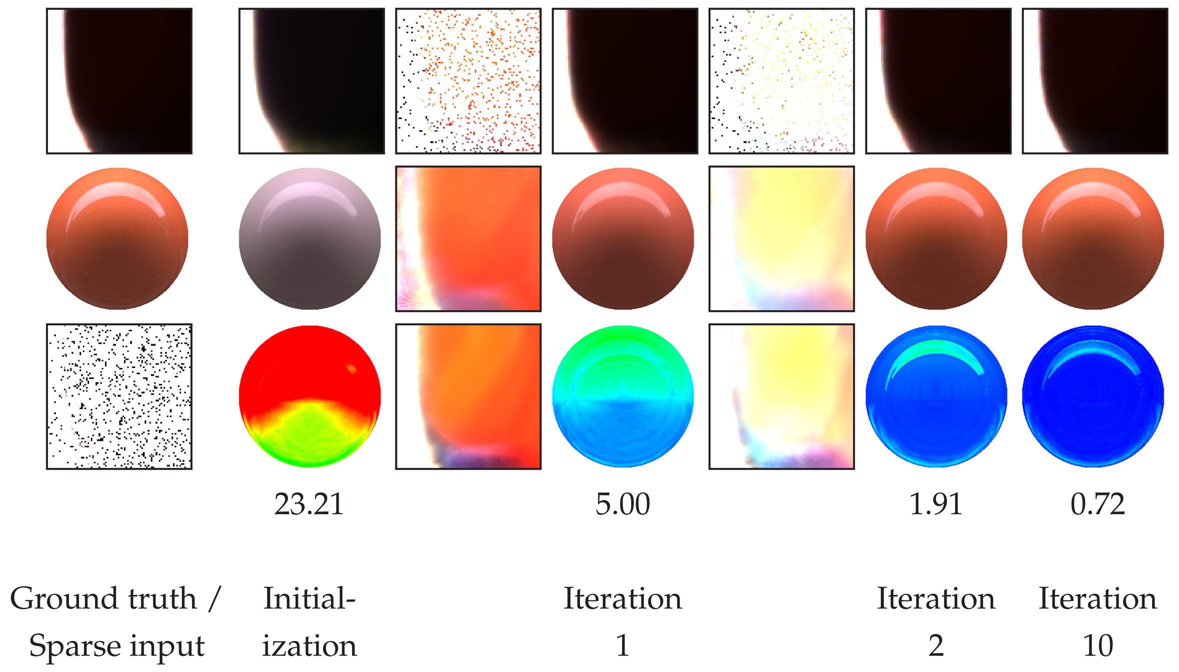


References

[1] Ali, M. A. et al. "Toward Efficient Acquisition of BRDFs with Fewer Samples". In: ACCV. 2013.
[2] Lawrence, J. et al. "Inverse Shade Trees for Non-parametric Material Representation and Editing". In: SIGGRAPH. 2006.
[3] Matusik, W. et al. "A Data-driven Reflectance Model". In: SIGGRAPH. 2003.
[4] Matusik, W. et al. "Efficient Isotropic BRDF Measurement". In: EGRW. 2003.
[5] Ren, P. et al. "Pocket Reflectometry". In: SIGGRAPH. 2011.
[6] Weistroffer, R. P. et al. "Efficient Basis Decomposition for Scattered Reflectance Data". In: EGSR. 2007.
[7] Zickler, T. et al. "Reflectance Sharing: Image-based Rendering from a Sparse Set of Images". In: EGSR. 2005.

Synthetic Evaluation (cont.)

- **Our method:** (10% data, 40% outliers)



- **Average perceptual errors:**

Data ratio (columns) / Outlier ratio (rows)

Our	1.0	0.7	0.5	0.3	0.1
0.00	0.28	0.29	0.29	0.29	0.31
0.20	0.36	0.37	0.44	0.41	0.49
0.40	0.73	0.72	0.75	0.78	0.92
0.60	2.06	2.10	2.05	2.23	2.31
0.80	4.86	4.89	4.83	4.81	4.83

Glo	1.0	0.7	0.5	0.3	0.1
0.00	4.88	4.89	4.91	4.96	5.05
0.20	6.32	6.58	6.76	7.57	7.59
0.40	7.97	8.22	7.93	8.32	9.03
0.60	9.64	9.74	9.46	9.59	9.53
0.80	11.33	11.16	11.05	11.05	10.61

Loc	1.0	0.7	0.5	0.3	0.1
0.00	4.11	4.11	4.13	4.15	4.17
0.20	6.85	6.78	6.96	7.12	7.74
0.40	9.74	9.98	9.79	10.41	11.04
0.60	12.49	12.63	12.49	12.56	13.45
0.80	15.18	15.32	15.28	15.16	15.92

Tab	1.0	0.7	0.5	0.3	0.1
0.00	0.00	0.09	0.20	0.46	2.14
0.20	17.32	15.59	17.28	14.00	12.30
0.40	26.12	26.38	24.80	24.35	22.90
0.60	33.32	34.90	32.71	32.13	28.22
0.80	39.86	41.70	40.75	38.94	34.09

✓ Outperformed other methods by an order of magnitude in the perceptual sense for outlier ratios up to 40%.

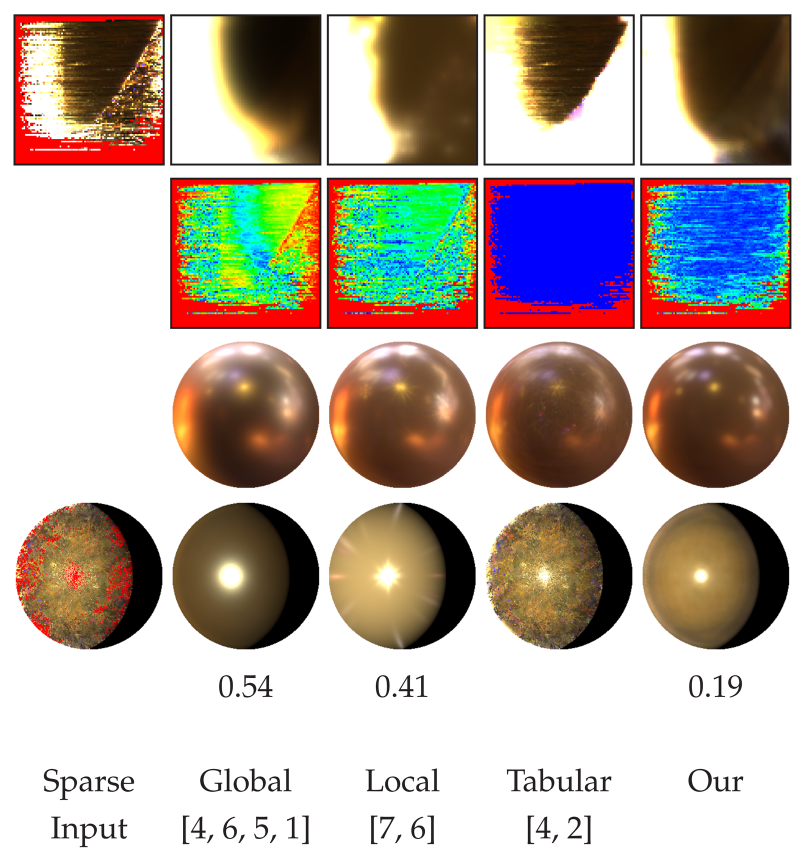
- **Sensitivity towards error metric:**

Our			Global			Local		
Linear	Root	Logarithmic	Linear	Root	Logarithmic	Linear	Root	Logarithmic
0.44	0.31	0.28	13.39	5.05	4.88	24.14	3.32	4.11

✓ Method is invariant w.r.t. different error metrics.

Real Data Evaluation

- **Evaluation using 16 newly measured materials:**



Material	Glo	Loc	Our
1	0.37	0.31	0.19
2	0.49	0.35	0.21
3	0.53	0.47	0.23
4	0.51	0.29	0.18
5	0.58	0.29	0.19
6	0.54	0.41	0.19
7	0.37	0.34	0.19
8	0.45	0.38	0.19
9	0.57	0.37	0.19
10	0.48	0.36	0.18
11	0.47	0.41	0.23
12	0.56	0.40	0.18
13	0.54	0.55	0.20
14	0.49	0.39	0.18
15	0.61	0.44	0.19
16	0.49	0.31	0.15
Avg.	0.50	0.38	0.19

(Method; color scale 0.0 – 1.0)

✓ Achieved a significantly lower perceptual error.