DeepBRDF: A Deep Representation for Manipulating Measured BRDF

Bingyang Hu\(^1\)  \hspace{2cm} Jie Guo\(^{1*}\)  \hspace{2cm} Yanjun Chen\(^1\)

Mengtian Li\(^1\)  \hspace{2cm} Yanwen Guo\(^1\)

\(^1\)State Key Lab for Novel Software Technology, Nanjing University

*guojie@nju.edu.cn
Material Appearance

+ Material
A real material’s surface reflectance function is a very complex function of 16 variables.

$$Y_{r}^{GRF} = GRF(\lambda_i, x_i, y_i, z_i, t_i, \theta_i, \varphi_i, \lambda_v, x_v, y_v, z_v, t_v, \theta_v, \varphi_v, \theta_l, \varphi_l)$$
• Bidirectional Reflectance Distribution Function
• BRDF $f_r$ describes surface reflection at a point $x$ for light incident from direction $\omega_i = (\theta_i, \varphi_i)$ reflected into direction $\omega_r = (\theta_r, \varphi_r)$

$$f_r(\omega_i \rightarrow \omega_r) \equiv \frac{L_r(\omega_r)}{L_i(\omega_i) \cos \theta_i \, d\omega_i}$$
Material Appearance

Raymond et al. – Multi-Scale Rendering of Scratched Materials using a Structured SV-BRDF Model. 2016
Material Appearance

Heitz et al. - Multiple-Scattering Microfacet BSDFs with the Smith Model, SIGGRAPH 2016
Material Apperance

Vincent Schussler et al. - Microfacet-based normal mapping for robust Monte Carlo path tracing, SIGGRAPH Asia 2017
Material Appearance

Yan et al. – Rendering Specular Microgeometry with Wave Optics, SIGGRAPH 2018
BRDF Acquisition

- Lamp
- Sample
- Controlled turntable
- Qimaging Retiga 1300
  (10-bit 1300x1300 firewire camera)
Measured BRDF

MERL BRDFs

UTIA BRDFs
Measured BRDF
Measured BRDF

+ Accurate

- Memory footprint
- Computational cost

Reduce the dimensionality
Related Work

A data-driven reflectance model

[Matusik 2003]
Related Work

A data-driven reflectance model [Matusik 2003]

On Optimal, Minimal BRDF Sampling for Reflectance Acquisition [Nielsen 2015] (IPCA)
Related Work

An intuitive control space for material appearance

[Starrano et al. 2016]

On Optimal, Minimal BRDF Sampling for Reflectance Acquisition

[Nielsen 2015](IPCA)
An intuitive control space for material appearance

[Serrano et.al 2016]

Connecting measured BRDFs to analytic BRDFs by data-driven diffuse-specular separation.

[Sun et.al 2018]
Related Work

An intuitive control space for material appearance
[Serrano et.al 2016]

Connecting measured BRDFs to analytic BRDFs by data-driven diffuse-specular separation.
[Sun et.al 2018]

Linear dimensionality reducer
Related Work

Fitting measured BRDF to analytic models
Related Work

Fitting measured BRDF to analytic models

Measured  Ward  Blinn-Phong  Lafortune

[Ngan 2005] Experimental Analysis of BRDF Models
- The fitting process is time-consuming and unstable.
  - For some materials, they are not accurate.
Our Approach

- Deep learning based dimensionality reducer to explore a nonlinear low-dimensional manifold for measure BRDFs
Basic Idea

DeepBRDF

MERL BRDF Database

Encoder

Latent vector

Decoder

BRDF Editing

Parameter Tweaking

Diffuse
Specular
Roughness

Decoder

Latent vector

BRDF Recovery

CNN

Latent vector
Network Architecture
\[ \rho = \ln\left(\frac{\rho + \epsilon}{\rho_{ref} + \epsilon} + 1\right) \]
Loss Function

\[ \mathcal{L} = \sum_{\mathbf{X} \in \mathcal{D}_{\text{train}}} \| \text{mask}(g_{\theta}(f_{\theta}(\mathbf{X})) - \text{mask}(\mathbf{X}) \| \]
Loss Function

$L_1$ loss

- RelAE: 0.102
- RelAE: 0.032
- RelAE: 0.025
- RelAE: 0.033

$L_2$ loss

- RelAE: 0.024
- RelAE: 0.024
- RelAE: 0.018
- RelAE: 0.017

Reference

- SPECULAR-MAROON-PHENOLIC
- COLOR-CHANGING-PAINT1
- GOLD-METALLIC-PAINT2
- ALUM-BRONZE
Geometric Interpretation
Quality Analysis

- Visual quality comparisons against PCA and improved PCA (IPCA)
- Quantitative evaluation in terms of RelAE is provided for each reconstructed result
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Quality Analysis

- Reconstruction error comparison of our DeepBRDF against PCA and IPCA with varying dimensions.
From left to right in each group of closeups, we compare the method of Sun et al. [SJR18], ours and the reference, with corresponding RelAE.
Evaluation on other BRDF data (not in MERL dataset)
Applications

- Measured BRDF editing
- Single Image BRDF Recovery
Measured BRDF Editing

Measured BRDF

Low-dim. representation

DeepBRDF ($\mathbf{Y}$)
(10D Latent Vector)

Perceptual appearance

Attributes

Diffuse albedo ($\alpha_d$)
Specular albedo ($\alpha_s$)
roughness ($g$)
Train a Back Propagation (BP) regression network to establish the relationship between $Y$ (latent vector) and $\alpha (\alpha_s \in \mathbb{R}^3, \alpha_d \in \mathbb{R}^3, g \in \mathbb{R})$.
Linear interpolation between *RED-METALLIC-PAINT* and *RED-FABRIC* using IPCA and our DeepBRDF, respectively.
Measured BRDF Editing

- Editing diffuse albedo
Measured BRDF Editing

- Editing the roughness of RED-PLASTIC
• Editing the roughness of *SPECULAR-YELLOWPHENOLIC* with IPCA-based representation (bottom row) and DeepBRDF-based representation (top row)
Single Image BRDF Recovery

Image → ? → BRDF
Single Image BRDF Recovery

Image \rightarrow \text{DeepBRDF} \rightarrow \text{Decoder} \rightarrow \text{BRDF}
A new CNN is trained to map the input image to the latent space of DeepBRDF.
Comparison with the method of Ye et al. [YLD*18] in homogeneous BRDF recovery.
Single Image BRDF Recovery

- BRDF recovery results for real-world images.
We have presented DeepBRDF, a deep-learning-based representation for Measured BRDF.

We have apply the DeepBRDF to edit measured BRDFs.

We have apply the DeepBRDF to the task of single image BRDF recovery.
Thank you!

Q&A