Neural BRDF Representation and Importance Sampling

Alejandro Sztrajman    Gilles Rainer    Tobias Ritschel    Tim Weyrich

University College London, UK
Despite its limitations, the BRDF is the most widely used reflectance parameterisation.

Traditionally, two prevailing modelling paradigms:

• Analytic BRDFs
  – closed-form reflectance functions

• Data-driven BRDFs
  – measured
  – discrete reflectance values
Why data-driven representations?

Polar plot of a Phong BRDF for multiple fixed incident azimuth angles (15, 30, 45, 60, 75).

Polar plot of a real-world measured BRDF from the MERL dataset, for multiple fixed incident azimuth angles (15, 30, 45, 60, 75).
Representing measured reflectance data

GT (Tabular)
- Accurate
- Large storage (~34 MB)
- Requires interpolation

Analytic Model (here: GGX)
- Requires costly and unstable optimisation
- Often inaccurate
- Very low storage (0.03 KB)
- Fast built-in interpolation

Sztajman, Rainer, Ritschel, Weyrich: Neural BRDF Representation and Importance Sampling
Representation objectives

• Expressive enough for measured data
• Compactness (low storage)
• Practical for rendering
  – fast evaluation
  – no angular interpolation artefacts
  – no spatial interpolation artefacts (SVBRDFs)
  – suitable for importance sampling

Sztrajman, Rainer, Ritschel, Weyrich: Neural BRDF Representation and Importance Sampling
Past representations for measured data

- Analytic model fits
  - [Marschner et al. 1999], [Ngan et al. 2005], [Bagher et al. 2012], [Löw et al. 2012], ...

- Data volume compression
  - PCA [Matusik et al. 2003]
  - matrix factorisation [Lawrence et al. 2004], [Ngan et al. 2006], [Nielsen et al. 2015]

- Non-parametric
  - [Bagher et al. 2016], [Dupuy & Jakob 2018]

- Neural
  - [Maximov et al. 2019], [Hu et al. 2020], [Rainer et al. 2019/2020]
Our neural BRDF representation

- Directly encodes a BRDF
  - maps hemispherical directions to reflectance
  - Rusinkiewicz parameterisation
  - exponential activation

- Training:
  - image-based loss (cosine-weighted)
  - sampled uniformly in Rusinkiewicz space (denser near highlights)
  - convergence in 10 secs to 3 mins
Neural BRDF

GT (Tabular)
- Accurate
- Large storage (34 MB)
- Requires interpolation

Analytic Model (GGX)
- Requires costly and unstable optimisation
- Often inaccurate
- Very low storage (0.03 KB)
- Fast built-in interpolation

NBRDF (Ours)
- Costly but stable training
- Accurate
- Very low storage (2.7 KB)
- Fast built-in interpolation

Sztrajman, Rainer, Ritschel, Weyrich: Neural BRDF Representation and Importance Sampling
MERL materials in different BRDF representations

Inset values: SSIM

Average SSIM over all MERL materials:
Reconstruction error

Average image-based losses of BRDF representations for all MERL materials:

<table>
<thead>
<tr>
<th>Method</th>
<th>MAE</th>
<th>RMSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>NBRDF Adaptive Sampling</td>
<td>0.0028 ± 0.0034</td>
<td>0.0033 ± 0.0038</td>
<td>0.995 ± 0.008</td>
</tr>
<tr>
<td>NBRDF Uniform Sampling</td>
<td>0.0072 ± 0.0129</td>
<td>0.0078 ± 0.0134</td>
<td>0.984 ± 0.029</td>
</tr>
<tr>
<td>NPF [BSN16]</td>
<td>0.0056 ± 0.0046</td>
<td>0.0062 ± 0.0047</td>
<td>0.990 ± 0.008</td>
</tr>
<tr>
<td>Low et al. [LKYU12] (ABC)</td>
<td>0.0080 ± 0.0070</td>
<td>0.0088 ± 0.0075</td>
<td>0.986 ± 0.012</td>
</tr>
<tr>
<td>Bagher et al. [BSH12] (SGD)</td>
<td>0.0157 ± 0.0137</td>
<td>0.0169 ± 0.0145</td>
<td>0.974 ± 0.027</td>
</tr>
<tr>
<td>Dupuy et al. [DHI+15]</td>
<td>0.0174 ± 0.0143</td>
<td>0.0190 ± 0.0151</td>
<td>0.976 ± 0.021</td>
</tr>
<tr>
<td>GGX</td>
<td>0.0189 ± 0.0118</td>
<td>0.0206 ± 0.0126</td>
<td>0.969 ± 0.024</td>
</tr>
</tbody>
</table>
Compression and speed

Reconstruction Error vs Representation Size

Average SSIM error vs Memory footprint (log scale) for multiple BRDF representations. NBRDFs (in blue) shown for multiple network sizes. *(675 is second from the right)*

High Compression and Fast Evaluation

<table>
<thead>
<tr>
<th>Material Representation</th>
<th>Rays/sec ($\times 10^6$)</th>
<th>Memory (KB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bagher et al. [BSH12]</td>
<td>10.64</td>
<td>0.13</td>
</tr>
<tr>
<td>RGL [DJ18]</td>
<td>10.66</td>
<td>48.0</td>
</tr>
<tr>
<td>NBRDF + PhongIS (Ours)</td>
<td>12.50</td>
<td>2.70</td>
</tr>
<tr>
<td>Cook-Torrance</td>
<td>13.59</td>
<td>0.03</td>
</tr>
<tr>
<td>Dupuy et al. [DHI15]</td>
<td>14.05</td>
<td>2.16</td>
</tr>
<tr>
<td>Low et al. [LKYU12]</td>
<td>15.13</td>
<td>0.03</td>
</tr>
<tr>
<td>GGX</td>
<td>16.82</td>
<td>0.03</td>
</tr>
<tr>
<td>NPF [BSN16]</td>
<td>–</td>
<td>3.20</td>
</tr>
</tbody>
</table>

Rays traced per second in Mitsuba renderer, and memory footprint, for different material representations.
Anisotropic materials

• Neural BRDF reconstruction of materials from the EPFL/RGL dataset [Dupuy and Jakob 2018]
  - additional DOF requires $5 \times$ sample count for training
  - slight increase in visual differences (average SSIM of $0.981 \pm 0.016$)
Representation objectives

- Expressive enough for measured data
- Compactness (low storage)
- Practical for rendering
  - fast evaluation
  - no angular interpolation artefacts
- no spatial interpolation artefacts (SVBRDFs)
- suitable for importance sampling

Sztrajman, Rainer, Ritschel, Weyrich: Neural BRDF Representation and Importance Sampling
Hyper-network: NBRDF autoencoder

- Input and output are Neural BRDF network weights
- Latent representation are 32-value vectors
  - a more compact NBRDF parameterisation
  - ideally, suited for NBRDF interpolation
- Training
  - with NBRDFs of the MERL database
  - image-based loss in NBRDF output domain
    - evaluates GT and predicts output NBRDF’s output
    - implemented as differentiable rendering loss
NBRDF embedding in latent space

• Evaluation by t-SNE clustering
  – of MERL materials encoded by hyper-network
  – test-set materials outlined in red

• Materials cluster according to common reflectance properties
  – suggests favourable outcome
NBRDF interpolation

Plausible interpolation between NBRDF embeddings

- enables creation of new materials
- desirable property for extension to Neural SVBRDFs
Representation objectives

☑ Expressive enough *for measured data*

☐ Compactness (low storage)

☐ Practical for rendering
  ☑ fast evaluation
  ☑ no angular interpolation artefacts
  ☑ no spatial interpolation artefacts (SVBRDFs)
  ☑ suitable for importance sampling

Sztrajman, Rainer, Ritschel, Weyrich: Neural BRDF Representation and Importance Sampling
Importance sampling

• Indispensable for efficient path tracing

• Requires sampling from a PDF
  – via uniform sampling of its CDF$^{-1}$...
  – ... which would not be readily available for measured data and/or an NBRDF :-(

• Key insight [Lawrence et al. 2004]
  – importance sampling converges even if the PDF differs from the BRDF
  – provides room to *pick a PDF whose CDF$^{-1}$ is known* :-(
Importance sampling

• General approach
  – choose any parametric BRDF model with known CDF\(^{-1}\)
  – fit that model to the NBRDF
  – choose its CDF\(^{-1}\) for importance sampling

• How to do so efficiently?

• Neural implementation
  – network to predict analytic parameters from (embedded) NBRDF
  – only predicting parameters relevant for IS
  – we tested Phong and GGX
  – Phong performed best; CDF\(^{-1}\) defined by two parameters
Importance sampling of a kitchen scene using 64 SPP. Most materials in the scene have been replaced by MERL materials within our test set.
Importance sampling

Average RMSE errors (log scale) vs SPP/render time.
Representation objectives

- Expressive enough for measured data
- Compactness (low storage)
- Practical for rendering
  - fast evaluation
  - no angular interpolation artefacts
  - no spatial interpolation artefacts (SVBRDFs)
  - suitable for importance sampling
Summary

• Neural representation for measured BRDF data (NBRDF)
  – isotropic + anisotropic
  – higher fidelity than other representations
  – storage- and compute-efficient

• Hyper-network autoencoder with a differentiable rendering loss
  – creates compact embedding of NBRDFs with good interpolation properties

• Learnt mapping between embedded NBDRFs and an invertible analytic BRDF/CDF, enabling importance sampling

• Improves viability of measured BRDFs for practical applications
Subsequent / concurrent work

• “A compact representation of measured BRDFs using neural processes” [Zheng et al. 2022; concurrent]
  – autoencoder representation for BRDFs
  – (lower) 7-dimensional representation, but much larger decoder

• “Neural layered BRDFs” [Fan et al. 2022]
  – also directly trains a latent space of BRDFs that share one decoder
Supplemental material

See https://reality.cs.ucl.ac.uk/projects/reflectance-remapping/sztrajman2021neural.html for...

- reconstruction results for both MERL and EPFL/RGL databases
- our NBRDF training implementation (Keras)
- a Mitsuba plugin to render NBRDFs
- a dataset of pretrained NBRDFs for materials from the MERL, EPFL/RGL and Nielsen et al. databases
- an interactive WebGL demo
Neural BRDF Representation and Importance Sampling

Alejandro Sztrajman     Gilles Rainer     Tobias Ritschel     Tim Weyrich

University College London, UK