



Computer
Graphics
Charles
University

PRINCIPLED KERNEL PREDICTION FOR SPATIALLY VARYING BSSRDFs

Oskar Elek and Jaroslav Krivánek
Charles University, Prague

DiSTRO



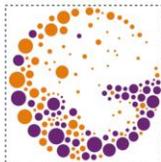
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 642841.



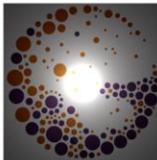
FACULTY
OF MATHEMATICS
AND PHYSICS
Charles University

• Oskar Elek • oskar.elek@gmail.com • cgg.mff.cuni.cz/~oskar •
• Computer Graphics Group • Charles University in Prague •

Prediction of **spatially varying BSSRDF** kernels from optical parameters



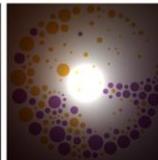
Scattering albedo
texture (here 2.5D)



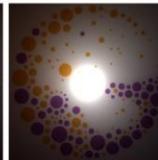
Local approaches



Parameter
aggregation



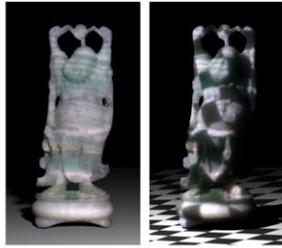
Ours



Path tracing
reference

- We got interested in this while working on color and texture reproduction in 3D printing
- These are preliminary, proof-of-concept results
- The main point of presenting this is to incite further discussion based on preliminary, proof-of-concept results

Not tackling SV-BSSRDF acquisition / compression / editing



[Peers et al. @ SIGGRAPH 2006]



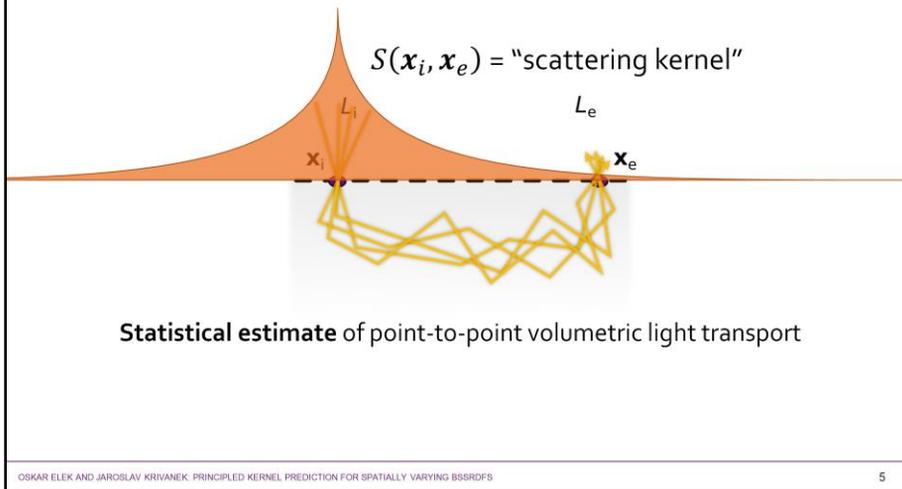
[Song et al. @ SIGGRAPH 2009]

- This largely is a separate problem, the above papers are a good starting point
- We actually compare to the factorized model proposed in these works though

BSSRDF and SV-BSSRDF

Uses and challenges

BSSRDF: Background



- Basic description what sub-surface scattering is and how to estimate it using a BSSRDF
- The BSSRDF can be derived from first principles or empirically (e.g. by fitting to simulated/acquired data)
- Roughly speaking, it's a volumetric counterpart to a BRDF
- Mention that for simplicity, we are going to operate on flat, half-infinite objects with properties defined by 2D textures (extruded vertically)

BSSRDF: Background

Great for (quasi-)homogeneous materials with well **localized light transport**...



[Jensen et al. @ SIGGRAPH 2001]



[Donner et al. @ SIGGRAPH 2005]



[Frisvad et al. @ ACM ToG 2014]

- Works well for **homogeneous** volumetric materials with **transport on a small scale** (smaller than some basic feature size)
- Stone, skin, plastic, wax...

BSSRDF: Background



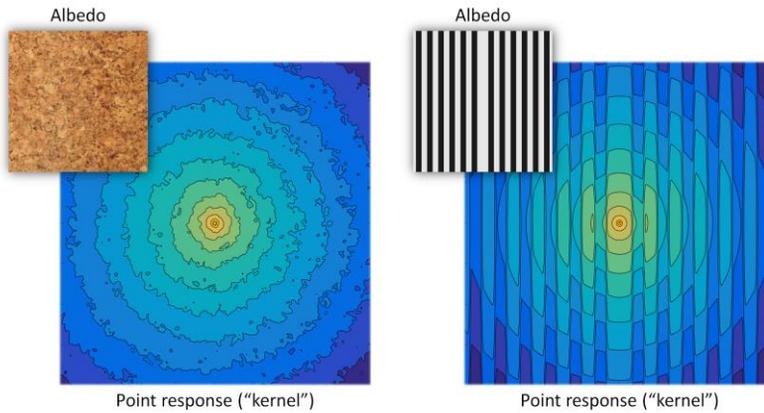
...but not so great when the **transport scale exceeds the feature scale**



[Elek, Sumin et al. @ SIGGRAPH Asia 2017]

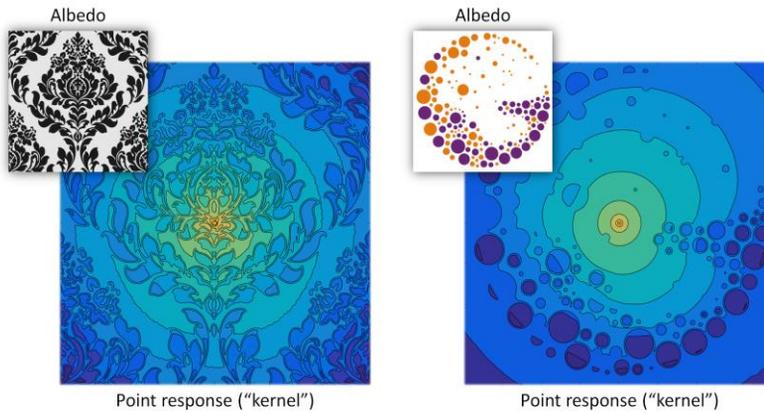
- But less so when the geometric or optical features have higher frequency than the transport
- This is what got us involved, since we've been interested in fabricating detailed color textures
- The above (**proportion between the scale of transport and material features**) is the key consideration of our work

SV-BSSRDF: Kernel Shape



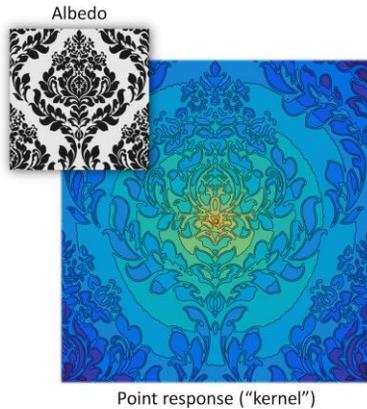
- For heterogeneous materials, however, the kernel is a rather messy function
- It can be reasonably behaved for materials with regular or random structure...

SV-BSSRDF: Kernel Shape



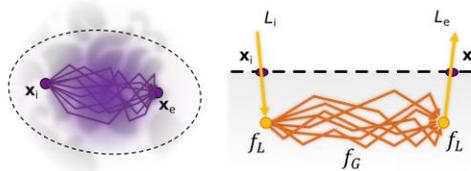
- ...but for those with lots of explicit features, both the local and global structure determines the transport
- And again: this problem becomes more apparent for transport 'larger' than the feature size

SV-BSSRDF: Kernel Shape



Two key ideas:

1. Data-driven **parameter aggregation**
2. Decomposition of transport into **local and global**



- The two key ideas that we employ here are:
- 1) statistically characterize the (unweighted) path distribution that connects x_i and x_e by an **aggregation kernel**
- 2) split the transport into **local and global factors** to account for both overall energy distribution and sensitivity to local features (essentially equivalent to single/multiple scattering decomposition)

Methodology

Step-by-step walkthrough

Method Outline



Preprocessing:

- i. Derive a basis (homogeneous) BSSRDF
- ii. For each (x_i, x_e) estimate the transport path distribution connecting them
- iii. Fit a generic parametric model to the distribution (e.g. Gaussian mixture)

Runtime:

- 1) Use standard MC to select x_e
- 2) For given (x_i, x_e) aggregate the material properties using the kernel from iii.
- 3) Separate the transport kernel into the local and global components
- 4) Use point-evaluated properties to compute the local components
- 5) Use the aggregate properties from 3) to compute the global component

- What follows is a generic outline of the proposed methodology, a scheme if you will
- Most of the steps are currently only proof-of-concept implementations; later we discuss how to generalize them in future
- **Preprocessing:** understanding the light transport overall
- **Runtime:** accounting for the specific parameter distribution in applying the model

Method Outline

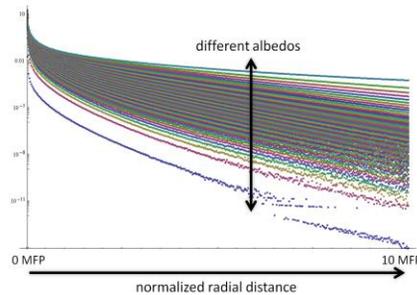


Preprocessing:

- i. Derive a basis (homogeneous) BSSRDF
- ii. For each (x_i, x_e) estimate the transport path distribution connecting them
- iii. Fit a generic parametric model to the distribution (e.g. Gaussian mixture)

Runtime:

- 1) Use standard MC to select x_e
- 2) For given (x_i, x_e) aggregate the material properties using the kernel from iii.
- 3) Separate the transport kernel into the local and global components
- 4) Use point-evaluated properties to compute the local components
- 5) Use the aggregate properties from 3) to compute the global component



BSSRDF kernel:

$$S \cong \sum_i A_i \cdot e^{-r \cdot B_i}$$

Also see [Christensen and Burley @ SIGGRAPH Talks 2015]

- To obtain as accurate as possible homogeneous BSSRDF, we fit to a brute-force analog MC simulated data
- Then fit a mixture of negative exponentials (i=1..6) parametrized by MFP-normalized radial distance and albedo (fixing IOR=1.5 and scattering isotropy g=0.3)
- Similar to Christensen, who however assume index-matched materials

Method Outline

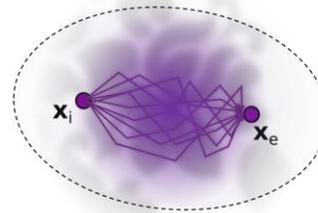


Preprocessing:

- i. Derive a basis (homogeneous) BSSRDF
- ii. For each $(\mathbf{x}_i, \mathbf{x}_e)$ estimate the transport path distribution connecting them
- iii. Fit a generic parametric model to the distribution (e.g. Gaussian mixture)

Runtime:

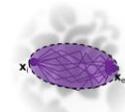
- 1) Use standard MC to select \mathbf{x}_e
- 2) For given $(\mathbf{x}_i, \mathbf{x}_e)$ aggregate the material properties using the kernel from iii.
- 3) Separate the transport kernel into the local and global components
- 4) Use point-evaluated properties to compute the local components
- 5) Use the aggregate properties from 3) to compute the global component



Distribution of unweighted sub-surface paths



Line: [d'Eon and Irving @ SIGGRAPH 2011]



Ellipse: [Sone et al. @ EG Shorts 2017]

- We want to explicitly account for the material distribution around \mathbf{x}_i and \mathbf{x}_e , but still do this in a principled way
- Idea: statistically average unweighted (i.e. as if in a homogeneous medium) transport paths and describe the distribution (density) by a **generic aggregation kernel**
- This doesn't rely on any heuristics, as opposed to previous approaches

Method Outline

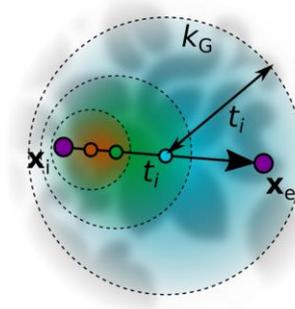


Preprocessing:

- i. Derive a basis (homogeneous) BSSRDF
- ii. For each (x_i, x_e) estimate the transport path distribution connecting them
- iii. Fit a generic parametric model to the distribution (e.g. Gaussian mixture)

Runtime:

- 1) Use standard MC to select x_e
- 2) For given (x_i, x_e) aggregate the material properties using the kernel from iii.
- 3) Separate the transport kernel into the local and global components
- 4) Use point-evaluated properties to compute the local components
- 5) Use the aggregate properties from 3) to compute the global component



Aggregation kernel:

$$K = \sum k_G$$

'Transport' albedo:

$$\alpha_t = \int K(x)$$

- Currently we use uniform sampling within the illuminated area (discussion about IS later)
- The aggregation kernel is a 3-component GMM, evaluated in constant time using a Gaussian pyramid (as opposed to MC integration of Sone2017)
- This yields the 'transport' parameters (now just the albedo)

Method Outline

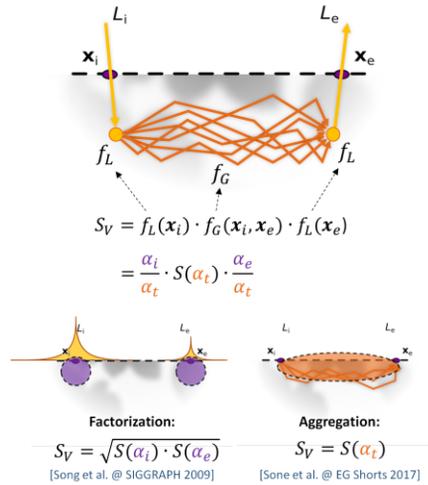


Preprocessing:

- i. Derive a basis (homogeneous) BSSRDF
- ii. For each (x_i, x_e) estimate the transport path distribution connecting them
- iii. Fit a generic parametric model to the distribution (e.g. Gaussian mixture)

Runtime:

- 1) Use standard MC to select x_e
- 2) For given (x_i, x_e) aggregate the material properties using the kernel from iii.
- 3) Separate the transport kernel into the local and global components
- 4) Use point-evaluated properties to compute the local components
- 5) Use the aggregate properties from 2) to compute the global component



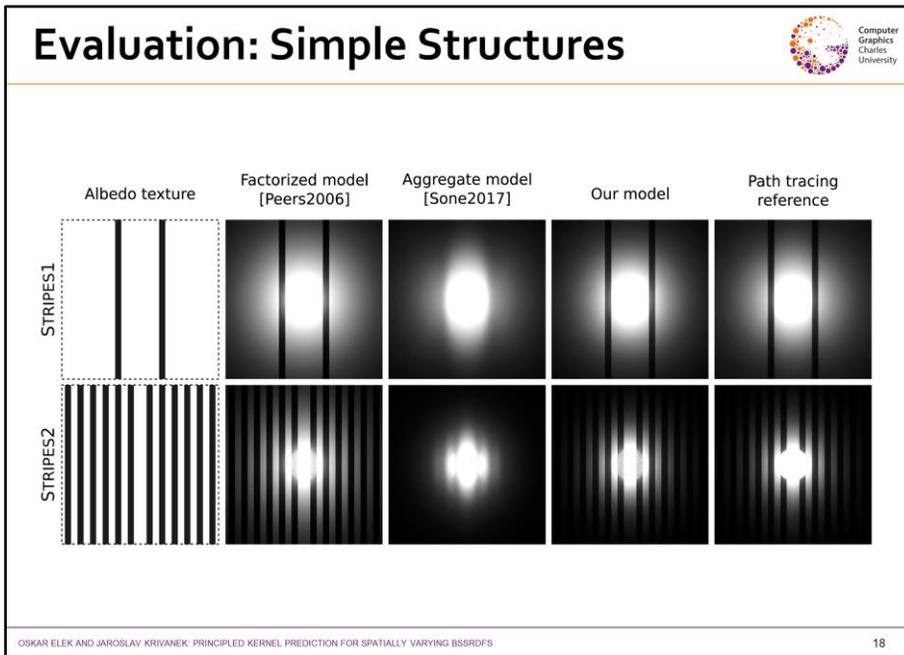
OSKAR ELEK AND JAROSLAV KRIVANEK: PRINCIPLED KERNEL PREDICTION FOR SPATIALLY VARYING BSSRDFS

- To rephrase, the idea is to account for both the local material properties at x_i/x_e , and the global distribution in their surroundings
- Currently we simply read out the local albedos, but rigorously averaging the distribution of single-scattering sites would be better
- Why is this advantageous? Both evaluated alternatives – factorization and aggregation – miss either the global or local features
- This is not to talk down factorization! It’s just not meant for this in first place – we merely use it as a stand-in for other local heuristics...

Evaluation

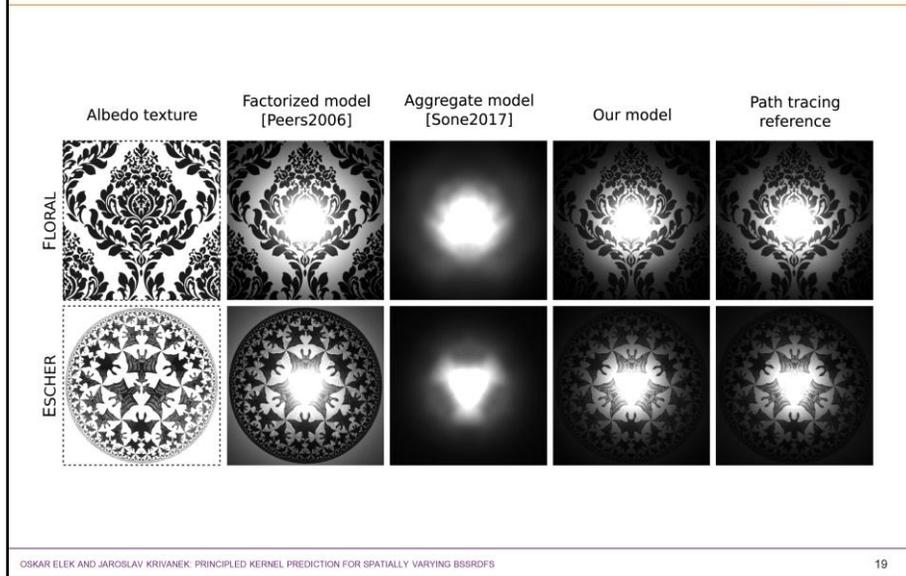
Overall quality and detail preservation

Evaluation: Simple Structures



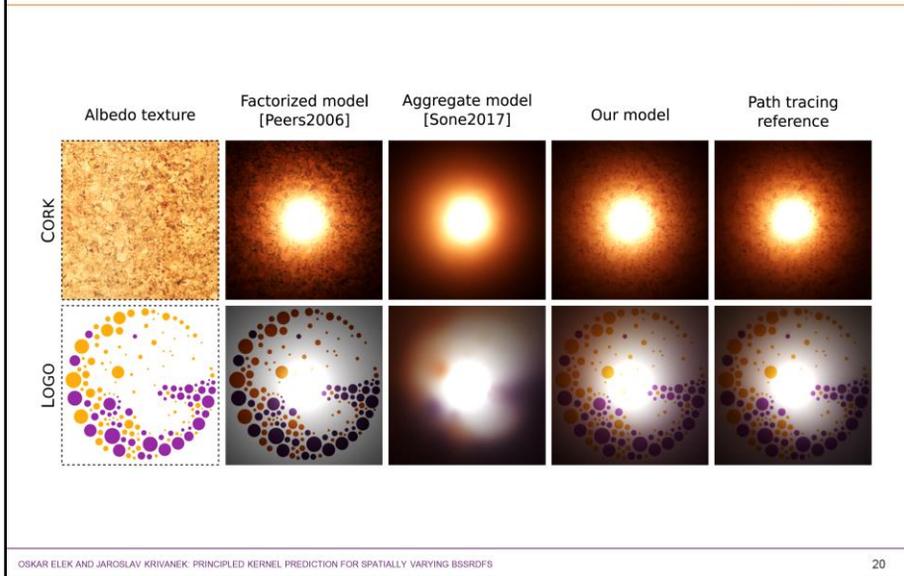
- Simple canonical scene: flat textured object, constant optical density, cone light with radius 1 MFP

Evaluation: Complex Structures



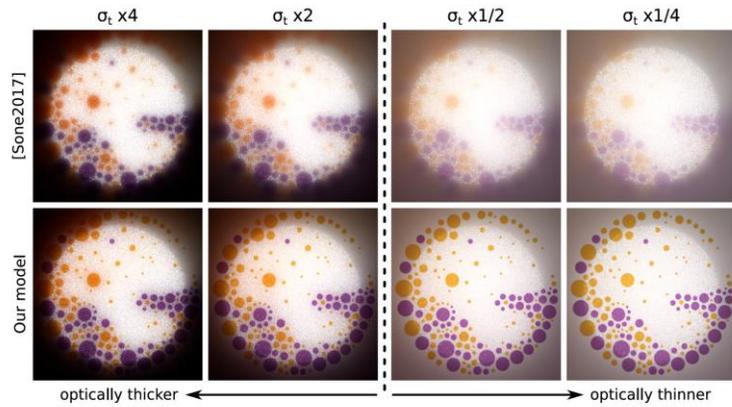
- Simple canonical scene: flat textured object, constant optical density, cone light with radius 1 MFP

Evaluation: Color Features



- Simple canonical scene: flat textured object, constant optical density, cone light with radius 1 MFP

Evaluation: Feature Preservation



- Same scene as before, but the light radius is 4 MFP and we vary optical density

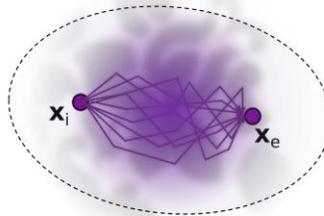
Discussion

What follows?

Future Work



- Principled aggregation kernel
 - Currently only a manual fit



Paper: At the moment, the parameter aggregation kernel is fit manually, as a proof of concept. A better course of action would be numerically fitting a meta-parametric model to the distributions of (contribution-weighted) sub-surface paths for every pair of surface points and required medium parametrizations. Such a meta-model would then output the aggregation kernel on-the-fly, for instance again in the form of a Gaussian mixture model.

Future Work



- Principled aggregation kernel
- Spatial variation of all material parameters
 - Currently only scattering albedo



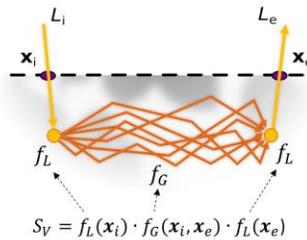
[Hasan et al. @ SIGGRAPH 2010]

Paper: While the aggregation of other medium properties beyond the scattering albedo is desirable, arguably the most relevant is handling the optical density. We conjecture that rather than using a simple average [SHK17], it should be used as a scaling factor during the albedo aggregation. This of course needs to be verified by future experiments.

Future Work



- Principled aggregation kernel
- Spatial variation of all material parameters
- Importance sampling
 - Currently only uniform sampling of incident illumination



OSKAR ELEK AND JAROSLAV KRIVANEK: PRINCIPLED KERNEL PREDICTION FOR SPATIALLY VARYING BSSRDFS

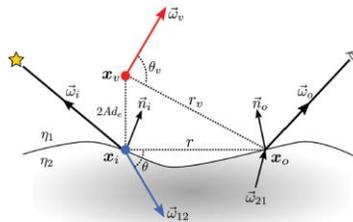
25

Paper: Our implementation currently uses a uniform distribution of sample points during the evaluation, resulting in significant noise even after 1k samples. The main challenge in deriving an efficient importance-sampling scheme for the proposed model is that rather than given explicitly, the SV-BSSRDF is implicitly defined by the pair of sampling points. One possible approach to tackle this circular dependence could be a multi-level sampling scheme, where the sample point were found iteratively, based on increasingly more accurate estimates of the transport kernel.

Future Work



- Principled aggregation kernel
- Spatial variation of all material parameters
- Importance sampling
- General 3D geometry and parameter distributions
 - Current solution limited to 2.5D objects



[Frisvad et al. @ ACM ToG 2014]

Paper: Since the basis BSSRDF determines the accuracy of the global transport, research in this direction is highly relevant. Also, to make the aggregation work for more general geometries and full 3D material parameters distributions, additional investigation of higher-dimensional aggregation kernels and surface-adaptive sampling techniques [FHK14,SHK17] is, too, warranted.



Computer
Graphics
Charles
University

PRINCIPLED KERNEL PREDICTION FOR SPATIALLY VARYING BSSRDFs

Oskar Elek and Jaroslav Krivánek
Charles University, Prague

DiSTRO



This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 642841.

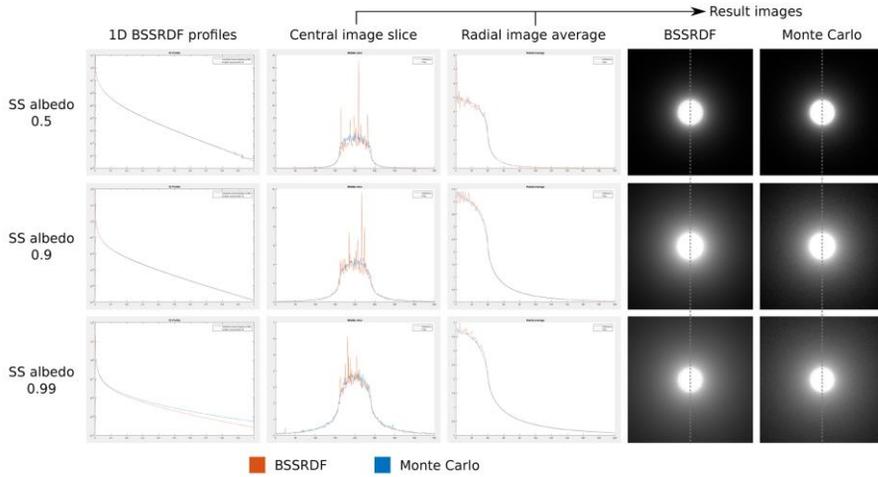


FACULTY
OF MATHEMATICS
AND PHYSICS
Charles University

• Oskar Elek • oskar.elek@gmail.com • cgg.mff.cuni.cz/~oskar •
• Computer Graphics Group • Charles University in Prague •

Extra Slides

Basis BSSRDF



Full Results

