


Translucent Material Parameter Estimation

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Outline

- Introduction: Essential ideas
- Problem and Goals
- Method
- Results
- Hopefully: Live example or a video

Introduction

Physics-Based Differentiable Rendering
A Comprehensive Introduction. SIGGRAPH
2020 Course, Zhao et al.[1]



Scene description: geometry,
materials, lights, etc.

Rendering



$$f(x) = y$$



“Inverse Rendering”

$$x = f^{-1}(y)$$



Difficulties

- Physics-based (inverse) rendering
 - Scattering effects, complex materials, global illumination

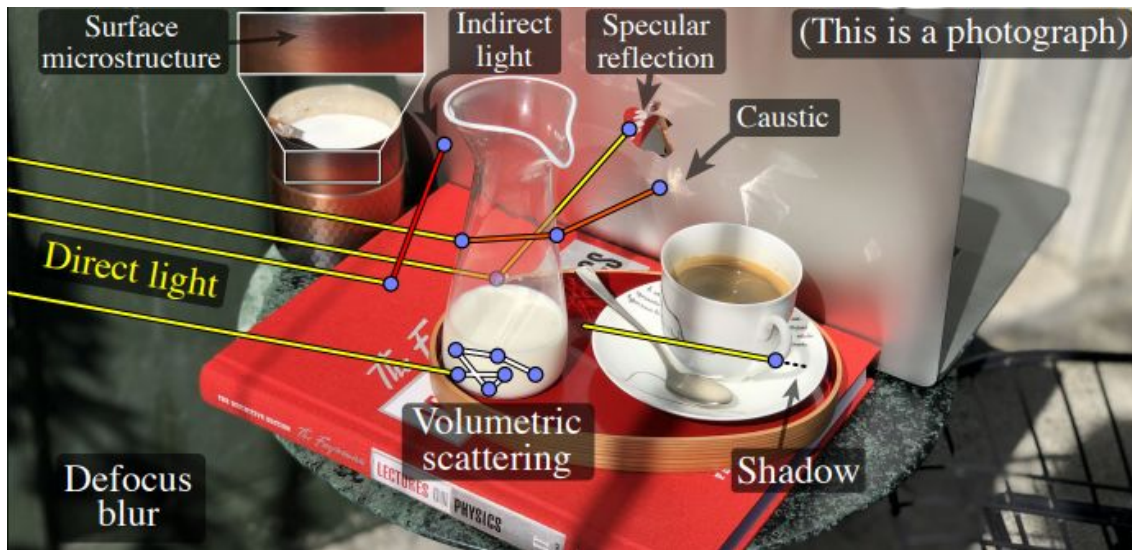


Image from Zhao et al. [1]

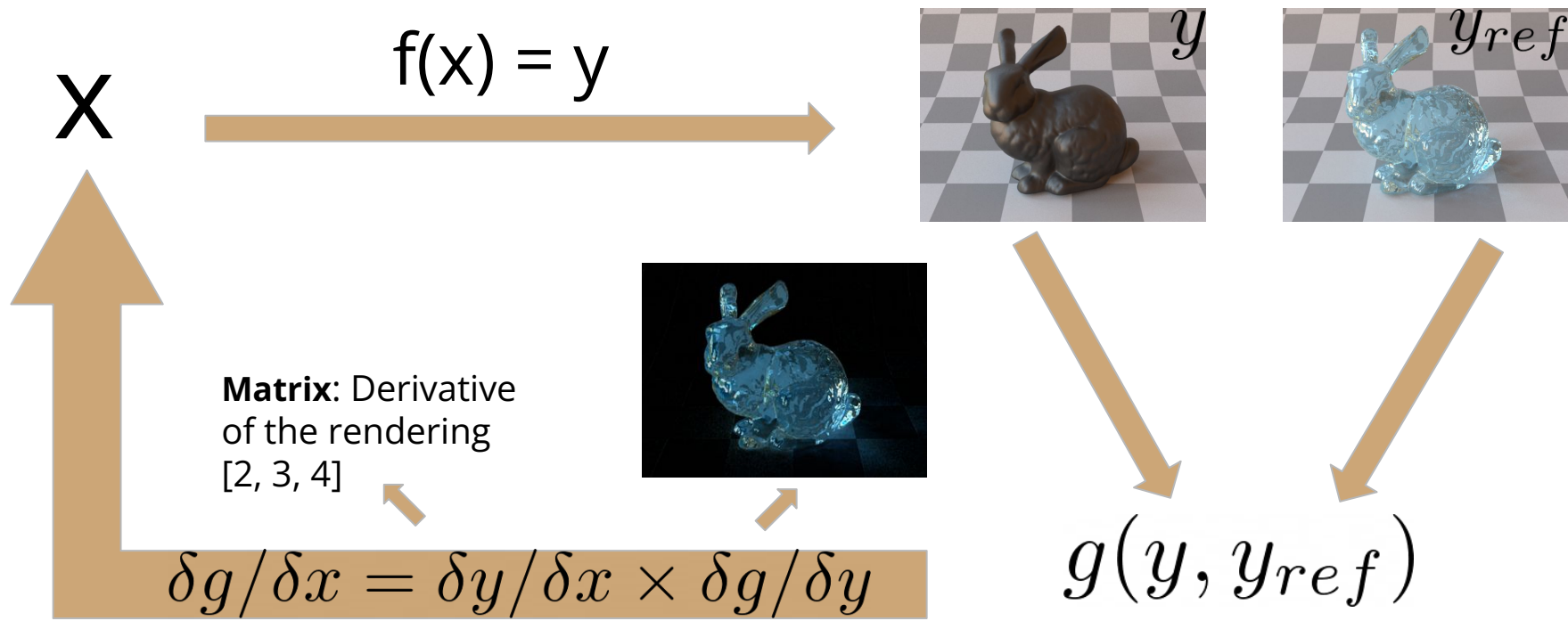
Objective Function

$$g(\text{img}) = \left\| \text{Rendering} - \text{Target} \right\|^2$$

Rendering Target

minimize $g(f(x))$

Differentiable Rendering



Problem and Goals (1)

- Main task: Translucent material parameter estimation
- But also:
 - A tool for inverse rendering
 - A gradient based optimization algorithm
 - A workflow for data acquisition
 - A naive approach for geometry and material reconstruction



Optimized material from synthetic (left) and real-world (right) alginate [5] data. Dragon model by Delatronic [14]

Problem and Goals (2)

Material parameters of interest:

- (1) Disney Principled BSDF with integrated subsurface scattering [7, 8]
- (2) Volumetric rendering: Rough dielectric BSDF [9] with homogeneous participating medium [6]

The diagram illustrates the mapping of physical material properties to a set of variables x . Five labels are positioned above the variable set, with arrows pointing from each label to a specific element in the set:

- Albedo** points to c
- Roughness** points to α
- Specular transmission** points to σ_s
- Index of refraction** points to η
- Extinction coefficient** points to σ_t

$$x = \{c, \alpha, \sigma_s, \eta, \sigma_t\}$$

Problem and Goals (3)

- Estimate material parameters: $x = \{c, \alpha, \sigma_s, \eta, \sigma_t\}$
- By defining the task as an optimization problem

$$\min g(y(x)), \text{ s.t. } h(x) \leq 0,$$

where h defines additional constraints and g is either

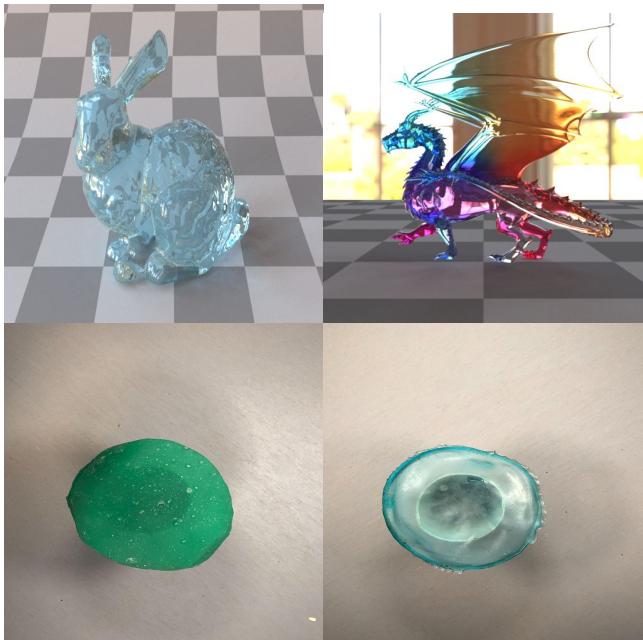
- the L2 norm $g(y) = ||y - y_{ref}||^2$, or
- the dual buffer method by Deng et al. [13]:

$$g(y_1, y_2) = (y_1 - y_{ref}) \cdot (y_2 - y_{ref})$$

Problem and Goals (4)

Requirements

- (1) a (set of) reference image(s)
- (2) a Mitsuba scene



Example reference images we used in our project. Top: Synthetic test cases. Bottom: Real-World alginate materials [5].

```
<scene version="3.0.0">
  <!-- Integrator -->
  <integrator type='integrator'>
    <integer name="max_depth" value="$max_depth"/>
  </integrator>
  <!-- Sensor -->
  <sensor type="perspective" id="sensor">
    ...
  </sensor>
  <!-- BSDFs -->
  <bsdf type="diffuse" id="white">
    <rgb name="reflectance" value="0.885809, 0.698859, 0.666422"/>
  </bsdf>
  <bsdf type="dielectric" id="glass"/>
  <!-- Light -->
  <shape type="obj" id="light">
    <string name="filename" value="meshes/cbox_luminaire.obj"/>
    <ref id="white"/>
    <emitter type="area">
      <rgb name="radiance" value="18.387, 13.9873, 6.75357"/>
    </emitter>
  </shape>
  <!-- Shapes -->
  <shape type="obj" id="floor">
    <string name="filename" value="meshes/cbox_floor.obj"/>
    <ref id="white"/>
  </shape>
  <shape type="sphere" id="glasssphere">
    <ref id="glass"/>
  </shape>
</scene>
```

Example (simple) Mitsuba scene [5].

Method (1)

Using our tool:

1. Load a scene file which includes material parameters x_0 .
2. Load a (set of) reference image(s).
3. Select \mathcal{X} , which gets assigned to initialized ADAM optimizer.
4. (Optional) Select optimization hyperparameters (e.g. iteration count).
5. Start the optimization loop.

The screenshot shows the 'Material Optimizer' application window. It features a 'File' menu, a 'Load reference image/s' input field, and a table of material parameters. The table has columns for parameter names, values, learning rates, and clamping limits. Below the table are input fields for 'Minimum Error', 'Samples per pixel during optimization', 'Loss function', and 'Iteration Count'. A 'Start Optimization' button is located at the bottom right.

	Value	Learning Rate	Min. Clamp Value	Max. Clamp Value	Optimize
gray.reflectance.value	0.8500000238418579, 0.8500000238418579, 0.8500000238418579	0.03	0.001	0.999	<input type="checkbox"/>
white.reflectance.value	0.8858090043067932, 0.6988589763641357, 0.6664220094680786	0.03	0.001	0.999	<input type="checkbox"/>
green.reflectance.value	0.10542099922895432, 0.37797999382019043, 0.07642500102519989	0.03	0.001	0.999	<input type="checkbox"/>
red.reflectance.value	0.5700680017471313, 0.043013498187065125, 0.04437059909105301	0.03	0.001	0.999	<input type="checkbox"/>
mirror.eta.value	0.0	0.03	0.001	4.1	<input type="checkbox"/>
mirror.k.value	1.0	0.03	0.001	4.1	<input type="checkbox"/>
mirror.specular_reflectance.value	1.0	0.03	0.001	0.999	<input type="checkbox"/>
light.emitter.radiance.value	18.386999130249023, 13.987299919128418, 6.753570079803467	0.03	0.001	10000.0	<input type="checkbox"/>
light.vertex_positions	mi.Float(length=12)	0.03	-10.0	10.0	<input type="checkbox"/>
floor.vertex_positions	mi.Float(length=12)	0.03	-10.0	10.0	<input type="checkbox"/>

Minimum Error

Samples per pixel during optimization

Loss function

Iteration Count

User interface of our tool.

Method (2)

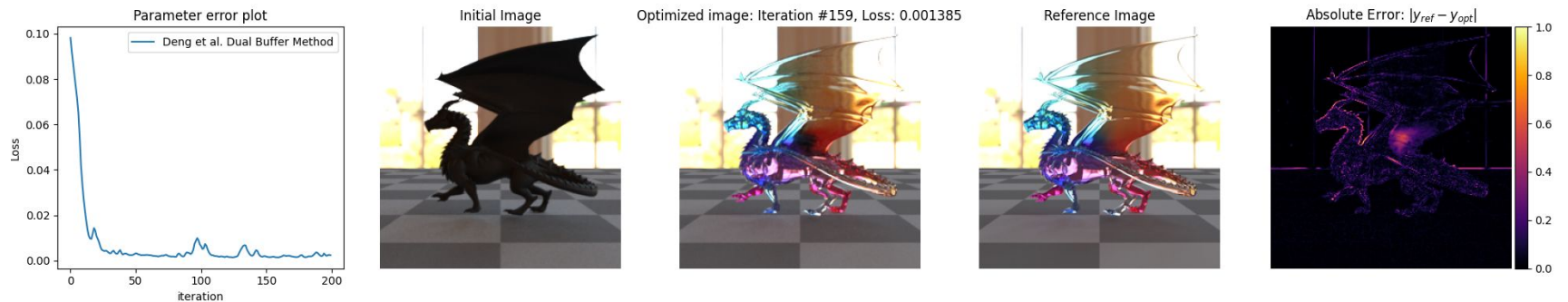
Optimization loop

Our tool initializes $\mathcal{X}_i = \mathcal{X}_0$, and runs for each camera pose (i.e. reference image):

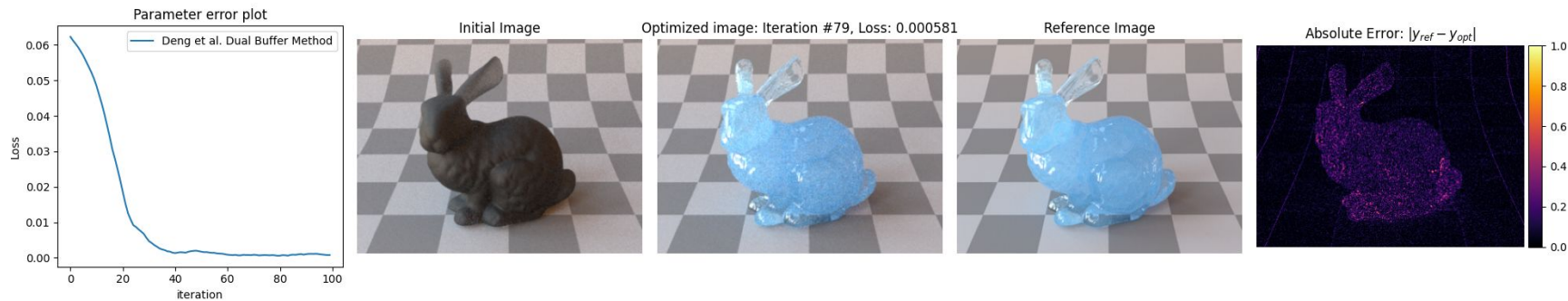
1. Perform a differentiable rendering step with respect to \mathcal{X}_i resulting in an image y_i .
2. Evaluate the objective function $g(y_i)$.
3. Back-propagate $\delta g / \delta y$ using Mitsuba 3, to obtain $\delta g / \delta x_i$.
4. Take an ADAM optimization step to find updated parameters \tilde{x}_{i+1} .
5. Ensure legal values for \mathcal{X}_{i+1} by clamping \tilde{x}_{i+1} using box constraints.
6. Update the scene with \mathcal{X}_{i+1} .
7. Repeat until either the loss tolerance or the maximal iterations is reached.

Results: Synthetic Data

Disney Principled BSDF with integrated subsurface scattering [7, 8]

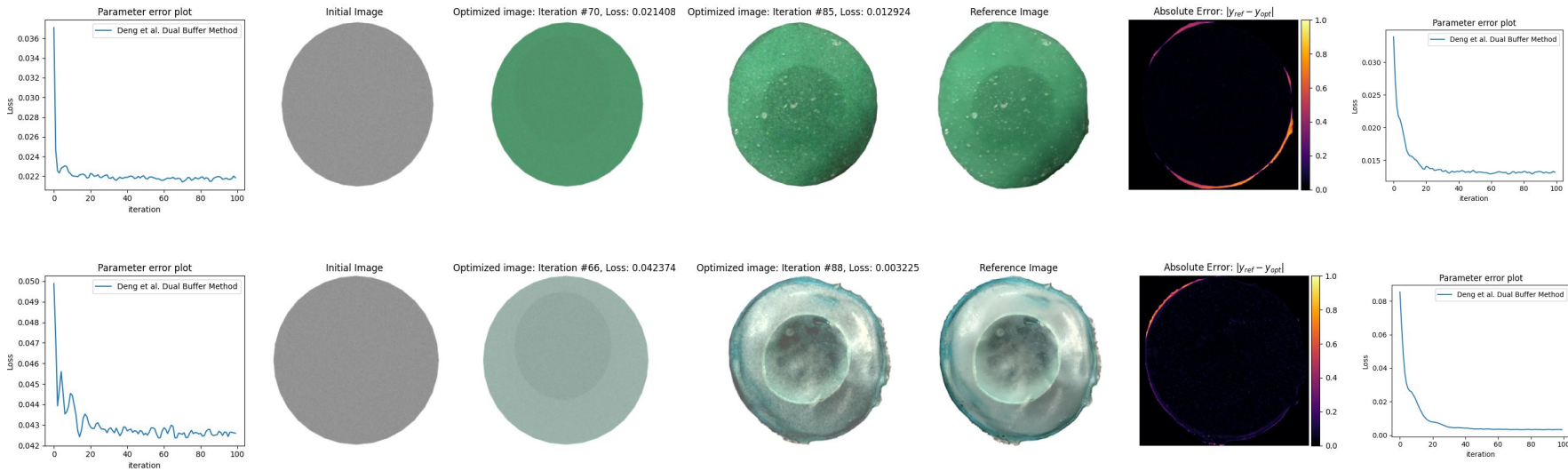


Rough dielectric BSDF [9] with homogeneous participating medium [6]



Results: Alginate [5] specimens (real-world)

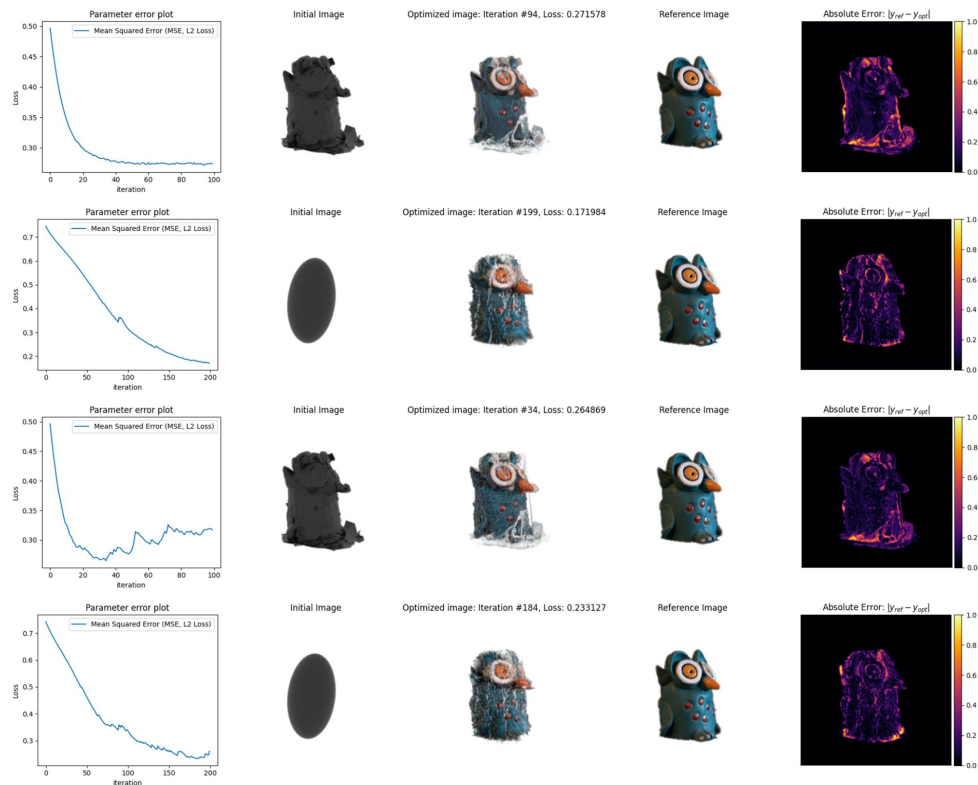
Disney Principled BSDF with integrated subsurface scattering [7, 8]



Plots Left/Right: Parameter error plot from the first/second optimization.

Images–Left to right: (1) Initial image. (2/3) Optimized image from the first and second part of the optimization. (4) Reference. (5) Absolute error.

Results: Bird statue (real-world)

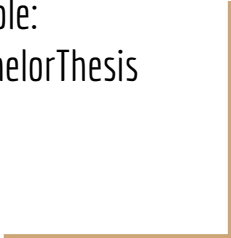


Geometry and material estimation. Rows: (1) Material estimation using reconstructed mesh from Metashape [16] (2) Texture and geometry estimation. (3) Material and geometry estimation using reconstructed mesh from Metashape. (4) Geometry and material estimation.



Thank you for
your attention

Thesis/paper/code available:
<https://github.com/sapo17/BachelorThesis>



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References (4)

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References (5)

[12] <baptiste.nicolet@epfl.ch>, B. N. Mitsuba blender add-on.
<https://github.com/mitsuba-renderer/mitsuba-blender>, 2022

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References (6)

- [15] Kingma, D. P., and Ba, J. Adam: A method for stochastic optimization, 2014.
- [16] AgiSoft. Agisoft metashape standard, 2022. <https://www.agisoft.com/>.