Learning Efficient Illumination Multiplexing for Joint Capture of Reflectance and Shape

Kaizhang Kang, Cihui Xie, Cheng’an He, Mingqi Yi, Minyi Gu, Zimin Chen, Kun Zhou and Hongzhi Wu

State Key Lab of CAD&CG, Zhejiang University / Yale University / ZJU-FaceUnity Joint Lab of Intelligent Graphics
Introduction

- Realistic Digital Models are **Important**

---

Culture Heritage

© The Palace Museum

e-Commerce


Visual Effects

© Paramount Pictures
Introduction

• Realistic Digital Models are Important
Introduction

• Realistic Digital Models are Important

• Acquisition of Physical Objects is Crucial in Graphics/Vision
Introduction

• Realistic Digital Models are Important
• Acquisition of Physical Objects is Crucial in Graphics/Vision
• Efficient, Joint Capture of Reflectance & Shape is Challenging
  1. High-dimensional Unknowns
  2. Reflectance & Shape Tightly Coupled in Measurements
  3. Limited Number of Samples in Practice
Introduction

• Realistic Digital Models are Important
• Acquisition of Physical Objects is Crucial in Graphics/Vision
• Efficient Acquisition of Reflectance & Shape is Challenging

• Our Goal
  • Optimize Physical Acquisition Efficiency in Joint Capture of Reflectance & Shape
Our Framework

• Map Physical Acquisition & Computational Reconstruction to a Deep Neural Network
  • Automatic Optimization of Illumination w.r.t Joint Acquisition Efficiency
  • Breaks Mutual Dependency between Reflectance & Shape
Our Framework

• Map Physical Acquisition & Computational Reconstruction to a Deep Neural Network

• Carefully Designed Network Architecture
  • Shares Information between Reflectance & Shape Estimation
  • Combines Domain-Specific Knowledge with Deep Learning
Our Framework

• Map Physical Acquisition & Computational Reconstruction to a Deep Neural Network

• Carefully Designed Network Architecture

• Flexible / Adaptable
  • Setup’s Geometry
  • Properties of Appearance
Related Work

• Geometry Reconstruction with a Diffuse Assumption
  • Structured Lighting [Scharstein and Szeliski 2003]
    / Structure-from-Motion [Schonberger et al. 2016]
    • Diffuse-dominant Reflectance Assumption
  • Photometric Stereo [Woodham 1980]
    • Latest Work Limited to Isotropic Reflectance [Ikehata 2018]
Related Work

• Geometry Reconstruction with a Diffuse Assumption

• Reflectance Capture on a Known/Pre-acquired Shape
  • Direct Sampling [Dana et al. 1999; Lawrence et al. 2006]
  • Reflectance Prior [Dong et al. 2010; Aittala et al. 2015; Wu et al. 2016]
Related Work

• Geometry Reconstruction with a Diffuse Assumption
• Reflectance Capture on a Known/Pre-acquired Shape
• Joint Acquisition of Reflectance & Shape
  • Reflectance Prior [Holroyd et al. 2010; Zhou et al. 2013; Nam et al. 2018]
  • Illumination Prior [Tunwattanapong et al. 2013; Xia et al. 2016]
  • Alternating Optimization [Nam et al. 2018]
  • Physical Efficiency not Optimized
Related Work

• Geometry Reconstruction with a Diffuse Assumption
• Reflectance Capture on a Known/Pre-acquired Shape
• Joint Acquisition of Reflectance & Shape

• Deep-Learning-Assisted Modeling
  • Reflectance Modeling [Li et al. 2017; Deschaintre et al. 2018]
  • Shape Modeling [Kendall et al. 2017; Yao et al. 2018]
  • Joint Modeling [Li et al. 2018]
  • Focus on Shape / Reflectance Reconstruction from Highly Sparse Input
  • Physical Acquisition Process Not Optimized
Hardware Prototype

Exterior

Main Circuit Board

Lit Sphere
Hardware Prototype

- Back
- Left
- Top
- Right
- Front
- Bottom

32 × 32

LEDs
Top
LEDs

Diffuser
Sample
Turntable

Camera

Back
Front

Top
Bottom

Bottom

32 × 32
Hardware Prototype

• 80cm x 80cm x 80cm
• Single Camera
• 24,576 LEDs
• 20,000+ FPS for Binary Lighting Patterns

• High-precision Control / Synchronization via FPGA
Lumitexel
Lumitexel

Sample

Camera
Lumitexel

Sample → Camera → Lumitexel

0.5
0.3
Lumitexel

Sample

Camera

Lumitexel

0.5
0.3
0.2
Lumitexel

Camera

Sample

0.5
0.3
0.2
0.0

Lumitexel
Lumitexel

Sample

Camera

+ Most Informative
- Expensive to Capture
Illumination Multiplexing

Sample

Camera

Lumitexel

0.5
0.3
0.2
0.0
0.0
0.0
0.0
0.0

Lighting Pattern

0.8
Illumination Multiplexing

Sample

Camera

Lumitexel

<table>
<thead>
<tr>
<th>Lighting Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
</tr>
<tr>
<td>1.0</td>
</tr>
</tbody>
</table>

Sample diagram showing the interaction between the sample and the camera, with lumitexel values and lighting pattern.
Illumination Multiplexing

Sample

Camera

Lumitexel

Lighting Pattern

0.5
0.3
0.2
0.0
0.0
0.0
0.0
0.5
0.8
1.0
Illumination Multiplexing

Camera

Sample

Lumitexel

Lighting Pattern

0.5
0.3
0.2
0.0
0.0
0.0
0.0
0.0
0.0

0.8
1.0
0.5
0.0
0.0
0.4
1.0
0.3
0.9

* = 0.8

Measured Radiance
Illumination Multiplexing

• What are Optimal Lighting Patterns for Efficient, Joint Capture of Reflectance & Shape?
• How to Reconstruct Reflectance & Shape from Measurements under Such Patterns?
Our Pipeline
Our Pipeline
Our Network

• 1 Encoder
  • Physical Capture
• 4 Decoders
  • Computational Reconstruction
• Asymmetric
• Mixed-Domain
• Per-Pixel
Our Network

- 1 Encoder
  - Physical Capture
- 4 Decoders
  - Computational Reconstruction
- Asymmetric
- Mixed-Domain
- Per-Pixel
Our Network

- 1 Encoder
  - Physical Capture
- 4 Decoders
  - Computational Reconstruction
- Asymmetric
- Mixed-Domain
- Per-Pixel
Our Network

• 1 Encoder
  • Physical Capture
• 4 Decoders
  • Computational Reconstruction
• Asymmetric
• Mixed-Domain
• Per-Pixel
Loss Function

\[ L = \lambda_d L_d(m_d) + \lambda_s L_s(m_s) + \lambda_n L_n(n) + \lambda_p L_p(p). \]

Diffuse Lumitexel
\[ L_d(m_d) = \sum_l [m_d(l) - \tilde{m}_d(l)]^2, \]

Specular Lumitexel
\[ L_s(m_s) = \sum_l [\log(1 + m_s(l)) - \log(1 + \tilde{m}_s(l))]^2, \]

Normal
\[ L_n(n) = ||n - \tilde{n}||_2, \]

Approximate Position
\[ L_p(p) = ||p - \tilde{p}||_2, \]
Training

• 200 Million Synthetic Lumitexels
  • Random Position / Local Frame / BRDF Parameters (Anisotropic GGX)
  • Based on Calibration Data

• To Increase Robustness
  • Add Gaussian Noise to Simulated Measurements
  • 10% Dropout Rate to fc Layers
Geometry Reconstruction

Diffuse Maps

Normal Maps

Multi-view Stereo

Point Cloud
Geometry Reconstruction

Multi-view Stereo

Point Cloud

Diffuse Maps

Normal Maps
Geometry Reconstruction

- Diffuse Maps
- Normal Maps
- Multi-view Stereo
- Point Cloud
- Screened Poisson Reconstruction
- Rough Shape
Geometry Reconstruction

Multi-view Stereo

Screened Poisson Reconstruction

Shape Refinement

Diffuse Maps

Normal Maps

Point Cloud

Rough Shape

Detailed Shape
Reflectance Reconstruction

• Input:
  • Decoded Lumitexel
  • 3D Position

• Output:
  • BRDF Parameters (Diffuse / Specular Albedo, Roughnesses, Normal, Tangent)

• Non-linear Optimization using L-BFGS-B
Results
Statistics

- Training: 70 hours
- # Lighting Patterns: 16(isotropic)~32(anisotropic)
- Per-view Acquisition: 7~15 seconds
- Total Acquisition (24 views): 6 minutes
- Decoding: 15 minutes
- Shape Reconstruction: 45 minutes
- Reflectance Fitting: 2 hours
Lighting Patterns
Network Results

(a)
Network Results

(a) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
(b) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
(c) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
(d) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
(e) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
(f) Input Lumitexel, Ground-Truth, Network Output, Fitting Result
<table>
<thead>
<tr>
<th>Diffuse Albedos</th>
<th>Specular Albedos</th>
<th>Normals</th>
<th>Tangents</th>
<th>Roughnesses</th>
<th>Geometry</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Diffuse Albedos" /></td>
<td><img src="image2" alt="Specular Albedos" /></td>
<td><img src="image3" alt="Normals" /></td>
<td><img src="image4" alt="Tangents" /></td>
<td><img src="image5" alt="Roughnesses" /></td>
<td><img src="image6" alt="Geometry" /></td>
</tr>
<tr>
<td><img src="image7" alt="Diffuse Albedos" /></td>
<td><img src="image8" alt="Specular Albedos" /></td>
<td><img src="image9" alt="Normals" /></td>
<td><img src="image10" alt="Tangents" /></td>
<td><img src="image11" alt="Roughnesses" /></td>
<td><img src="image12" alt="Geometry" /></td>
</tr>
<tr>
<td><img src="image13" alt="Diffuse Albedos" /></td>
<td><img src="image14" alt="Specular Albedos" /></td>
<td><img src="image15" alt="Normals" /></td>
<td><img src="image16" alt="Tangents" /></td>
<td><img src="image17" alt="Roughnesses" /></td>
<td><img src="image18" alt="Geometry" /></td>
</tr>
</tbody>
</table>
Validation Results
Limitations

• No Explicit Modeling of Inter-reflection / Self-shadowing
• Cannot Recover Appearance Substantially Deviated from Training Samples
• Cannot Reconstruct Details not Observed from Sampled Views
Conclusions & Future Work

• Deep-Learning-Based Framework for Efficient, High-quality Acquisition of Unknown Reflectance & Shape
Conclusions & Future Work

• Deep-Learning-Based Framework for Efficient, High-quality Acquisition of Unknown Reflectance & Shape

• High-quality **Photometric Stereo for General Anisotropic Reflectance under Controlled Illumination**
  • Average Normal Prediction Error 3.8°
Conclusions & Future Work

• Deep-Learning-Based Framework for Efficient, High-quality Acquisition of Unknown Reflectance & Shape
• High-quality Photometric Stereo for General Anisotropic Reflectance under Controlled Illumination

• Inspire More Research on Differentiable Acquisition
• Apply to Existing / Novel Setups
• Exploit View Coherence
• Handle Other Types of Appearance
Acknowledgements

• Anonymous Reviewers
• Yue Dong(MSRA), Xiaohe Ma, Lijian Ge, Jingke Wang, Tong Yang(ZJU)
• Design Connected EOOD (www.designconnected.com)
• National Key Research & Development Program of China (2018YFB1004300)
• National Science Foundation of China (61772457 & U1609215)
Thank you / Merci / Gracias / 謝謝

- Email: cocoa_kang@zju.edu.cn

- Project Website:
Design Considerations

• Approximate Positions
  • Sufficient for Diffuse Albedo Computation
  • Insufficient for Geometry Reconstruction

• Per-Pixel Normal Prediction v.s. Fitting
  • Breaks the Mutual Dependency of Reflectance and Shape Reconstruction

• Lumitexel Prediction v.s. BRDF Parameter Regression

• No Spatial Aggregation in Our Network
  • Exploit State-of-the-Art Related Work
  • Avoid Combinatorial Explosion in Training Data