Realistic Image Synthesis

Introduction
Which One is Real?
What?

• Goal: Create photorealistic images
• Applications
  • Movies and games
  • Design and architecture
  • Visualization and simulation
  • Optimization, inverse rendering
  • AI and machine learning
Who?

• Instructors
  • Philipp Slusallek
    • [http://graphics.cg.uni-saarland.de/slusallek/](http://graphics.cg.uni-saarland.de/slusallek/)
  • Karol Myszkowski
  • Gurpreet Singh

• Teaching Assistant
  • Pascal Grittmann
    • [https://graphics.cg.uni-saarland.de/people/grittmann.html](https://graphics.cg.uni-saarland.de/people/grittmann.html)

• Tutor
  • NN
Administrative information

• Type
  • Advanced lecture
  • 9 credit points

• Prerequisites
  • Interest in math, physics
  • Basic programming experience in C++
  • Core lecture “Computer Graphics” recommended but not required

• Web-page: https://graphics.cg.uni-saarland.de/courses/ris-2024/

• MS Teams (Join via link on the webpage)
  • Announcements, Q&A, …
  • Assignments posted and submitted
Grading

• Exam admission requires
  • 50% of the total points across all assignments
  • 30% of the maximum points in every assignment

• Final grade
  • Assignments: 50%
  • Final exam: 50%
Assignments

• Irregular rhythm
  • Sometimes 1 week, sometimes 2

• Type
  • A few theoretical assignments
  • Mostly practical ones

• Teamwork
  • Can be done in groups of two
    • Make sure you understand everything your partner worked on!

• Published, handed-in, and graded via MS Teams
Reading materials

- More listed on the website
Applications

Where are the things you will learn here used?
Movies: Visual Effects (VFX)

Game of Thrones

© HBO

Avatar: The Way of Water

© 20th Century Studios
Movies: Animated Films

The Lion King (2019) © Disney

The Sea Beast © Netflix
Video Games

Cyberpunk 2077 © CD Projekt RED

Valheim © Iron Gate Studios
Simulation

© Thomas Angus / ICL
Design and Engineering

© Autodesk

© IES

© MIT

Realistic Image Synthesis 2024 - Lecture 1: Introduction
Product Visualization and Advertisement

© IKEA

© Nissan
Architecture

© Pixelcraft Work
Artificial Intelligence
Course overview

What will you learn?
Course Overview

• Core concepts
  • Rendering equation
  • Radiosity
  • Probability theory and Monte Carlo integration
  • BRDFs and path tracing
  • Advanced sampling

• Bidirectional and adaptive algorithms
  • Bidirectional methods
  • Markov chain Monte Carlo
  • Path guiding

• Advanced effects
  • Volume rendering
  • Radar / Spectral

• Perception and imaging
  • HDR and tone mapping
  • Perception and modern display technology

• Machine learning
  • Denoising
  • Differentiable rendering
Rendering Equation

\[ L_o(x, \omega_o) = L_e(x, \omega_o) + \int_{\Omega} L_i(x, \omega_i) f_r(\omega_o, x, \omega_i) \cos \theta_i \, d\omega_i \]

- Outgoing light
- Emitted light
- Incident light (recursively given by the same equation)
- Projection
- Integral over all directions (computes reflected light)
- BSDF: Material properties
Monte Carlo Integration and Path Tracing

\[
\int_{X} f(x) \, dx \approx \frac{1}{n} \sum_{i=1}^{n} \frac{f(x_i)}{p(x_i)}
\]
Advanced Sampling
Bidirectional Methods
Adaptive / Learned Sampling

Initial training samples

Guided samples
Volume Rendering

http://coclouds.com
http://wikipedia.org
http://commons.wikimedia.org
HDR and Tone Mapping

Luminance

LDR screen

“HDR” screen
Denoising

Noisy image and features

Denoiser

Denoised image
Differentiable Rendering

© Jakob et al. (https://mitsuba.readthedocs.io/)
Beyond this course

How and where can you apply what you will learn?
Reflection & Refraction

- Visualization of a car headlight
  - It reflects and refracts light almost entirely from the environment. Up to 50 rays per path are needed to render this image faithfully (800k triangles).
Instant Global Illumination

• Real-time simulation of indirect lighting ("many-light method")
Real-Time Photon Mapping

- Real-time performance with procedural textures and density estimation. Interleaved sampling allows to reduce computation by a factor of 10.
Photon Mapping

- Car headlight used as a light source

  Photons are emitted and traced until they hit a wall. Density estimation is used to reconstruct the illumination. The results run at 3 FPS with 250k photons on a cluster of 25 cores (in 2004). Visualization without running the simulation achieves even 11 FPS (lower center) and compare well to a real photograph (lower right).
Light Transport Simulation

• Volkswagen’s large Corporate Visualization Center in Wolfsburg using ray tracing technology developed in Saarbrücken (Spin-off “inTrace”).
Massive Models

- The original CAD model of a Boeing 777 consisting of 365 million polygons (30 GB). Ray tracing was the first method to allow real-time visualization of such models.
Massive Models

• Visualization of large outdoor scenes (300x300m2) with 365k plants and several billion triangles.
Massive Models

- Much larger outdoor scene (80x80 km²) with realistic lighting and full vegetation (90*10^{12} triangles)
High-Performance Simulation

• Advanced rendering techniques in games
Physically-Based Image Synthesis with Real-Time Ray Tracing

Technical Oscar
Feb 2021
Custom Ray Tracing Processor [Siggraph’05]

In EVERY GPU starting 2022
AnyDSL Compiler Framework

- Computer Vision DSL
- Physics DSL
- Ray Tracing DSL
- Parallel Runtime DSL
- Layered DSLs
- Impala Language & Unified Program Representation
- AnyDSL Compiler Framework (Thorin)
- Various Backends (via LLVM)

- CPUs
- GPUs
- FPGAs
- Accels

Developer
Importance Caching

- Iliyan Georgiev, et al. [Eurographics 2012]
Monte-Carlo vs Density Estimation

- Vertex Connection & Merging, Ilijan Georgiev [SiggraphAsia´12]
  - Formulating Density Estimation algorithms as a Monte-Carlo (MC) techniques
A Quick Glance at (Some of) Our Current Research

- Goal: General, robust, and efficient rendering algorithms
- “One algorithm to render them all”

- Methodology: Adapt the algorithm to the scene based on statistics from initial samples
  - Learn better sample distributions
  - Optimize parameter values and sample counts
  - Adapt weighting functions and combinations
Motivation

Performance  ---  Accuracy

© Ronan Bekerman

Realistic Image Synthesis 2024 - Lecture 1: Introduction
Adapting Parameters and Sample Counts

Grittmann et al. – Efficiency-aware multiple importance sampling
SIGGRAPH 2022
Lightweight Bidirectional Methods

Grittmann et al. – Efficient caustic rendering with lightweight photon mapping
EGSR 2018
What Should Path Guiding Learn?

Rath et al. – Variance-aware path guiding. SIGGRAPH 2020
Path Termination and Splitting

Rath et al. – EARS: Efficiency-aware Russian roulette and splitting
SIGGRAPH 2022
Optimal MIS

Kondapaneni et al. – Optimal multiple importance sampling
SIGGRAPH 2019
Fixing MIS for Bidirectional Methods

Grittmann et al. – Variance-aware multiple importance sampling
SIGGRAPH Asia 2019
Fixing MIS for Bidirectional Methods – Part II

Grittmann et al. – Correlation-aware multiple importance sampling
Eurographics 2021
Identifying Guiding Targets not on Surfaces

Rath et al. – Focal Path Guiding
Siggraph 2023
Learning Compact Scene Representations

Weier, et al. – Rendering with mixed geometric and neural representations. Siggraph 2023 + 2024
Other Research From Saarbrücken

- Some more examples from my research group
DFKI-ASR: Agents and Simulated Reality

How to design AI systems that can provide guarantees and that humans can understand and trust?

How can synthetic data from parametric models and simulations be used for training, validating, and certifying AI systems?

How can AI-systems be realized technically in a reliable and efficient way?
Digital Reality

- Training and Validation in Reality
  - E.g. driving millions of miles to gather data
  - Difficult, costly, and non-scalable
  - Even millions of miles does not get you a reliable AI system
    - Issue of long-tail distributions (critical scenarios)
Digital Reality

- Training and Validation in the Digital Reality
  - Arbitrarily scalable (given the right platform)
  - But: Where to get the models and the training data from?
Digital Reality: AI to Certify AI
Digital Reality: AI to Certify AI

Coverage of Variability via Directed Search

Concrete Instances of Scenarios

Reasoning

Relevant Scenarios

Partial Models (Rules)

Configuration & Learning

Modeling & Learning

Reality

Car

Digital Reality

Car
Digital Reality: AI to Certify AI

Training, Validation, and Certification of AI Systems ➔ Trusted AI
Digital Reality: AI to Certify AI

- Relevant Scenarios
  - Coverage of Variability via Directed Search
- Concrete Instances of Scenarios
  - Adaptation to the Simulated Environment (e.g., used sensors)
- Partial Models (Rules)
  - Configuration & Learning
- Continuous Validation & Adaptation
  - Modeling & Learning
- Reality Car
  - Validation / Adaptation / Certification
- Simulation / Rendering
  - Synthetic Sensor Data, Labels, ...
- Digital Reality Car
  - Continuous Validation & Adaptation
  - Reasoning

Model Learning

Simulation & Learning
Digital Reality: AI to Certify AI

Coverage of Variability via Directed Search

Relevant Scenarios

Concrete Instances of Scenarios

Model Learning

Continuous Learning Loop
Not just for Automated Driving:
Works for any AI System where we can model its interaction with the environment

Validation / Adaptation / Certification
Radar Simulation

Bridging the gap between radar simulation & modern computer graphics
Our resulting method is over 1,000x faster than existing commercial software, while still achieving better accuracy

Ours Method: 33 seconds
(Physical Optics + Monte Carlo)

EM.Illumina: 13.4 hours
(Physical Optics + Finite Elements)
Autonomous Driving: Training using Synthetic Sensor Data and Realistic Models (TÜV, VDA, ZF, Conti, …)
Motion Modeling and Synthesis

Gosh et al. – Using action descriptions to drive motion synthesis via learned models
Eurographics 2023
Collaborative Robotics and Simulated Reality (VW, Airbus, …)
Models of the World

• Long history in motion research (>50 years)
  • E.g. Gunnar Johansson's Point Light Walkers (1974)

• Humans can easily identify more than what we see
  • Identify the person with high probability
  • Perceive properties like gender, age, weight, mood, ...
  • Based on minimal information

• Can we teach machines the same?
  • Currently, only bottom-up analysis
  • Neuroscience: Humans strongly perceive also top-down
Models & AI: Relationship Between Humans and AI

- **Human Perceived Reality**
- **AI Perceived Reality**
- **Physical Reality**

Problem Domain (entirely part of reality)
Models & AI: Relationship Between Humans and AI

Reality

Human Perceived Reality
AI Perceived Reality
Physical Reality

Problem Domain
( entirely part of reality)

Human
H-WorldModel

Machine
M-WorldModel

(M-WorldModel)
Models & AI: Relationship Between Humans and AI

- Human Perceived Reality
- AI Perceived Reality
- Physical Reality

Reality

Digital Reality

Problem Domain (entirely part of reality)
Models & AI: Relationship Between Humans and AI

- **Human Perceived Reality**
- **AI Perceived Reality**
- **Physical Reality**

**Reality**

**Communication about H- vs M-Model !!**

**Perception & Interaction**

**Problem Domain**
(entirely part of reality)

**Human**
- H-WorldModel

**Machine**
- M-WorldModel

**Model Alignment & Explainable AI**
Neuro-Explicit AI Models (1)

- Need to move from ChatGPT to ActGPT
  - Not just words (or pixels) but modeling the physical world
    - 3D structures, motion, masses & forces, illumination, surface properties, ...
  - Need vectors, representing these properties and their relationships/context

- Neuro-explicit AI models
  - We already know how the world works (physics, chemistry, ...) – no need to re-learn
  - Use explicit models as the core (differential equations, simulations, logic models, ...)
  - Use neural models to learn and model the difference to the real world

- Key Role for Trusted AI
  - Need for guarantees about the behavior of physical/embedded AI systems
  - ChatGT hallucinating text is already really bad
  - But a hallucinating robot can (literally) wreak havoc
CERTAIN: Trusted AI should give Guarantees for...

- Functionality
- Transparency and Explainability
- Fairness and Impartiality
- Robustness and Reliability
- Safety, Security, Privacy
- Responsibility and Accountability
- Safety, Security, Privacy
- Responsibility and Accountability
Guarantees for Trusted AI

<table>
<thead>
<tr>
<th>By Design</th>
<th>By Tools</th>
<th>By Insight</th>
<th>By Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Intrinsic Correctness</td>
<td>• Modelling and Simulating the Real World</td>
<td>• Explanations, Reasons</td>
<td>• Human Experience, Influence, Control</td>
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<tr>
<td>• Deductive Arguments &amp; Proofs</td>
<td>• Systematic Testing with Synthetic Data</td>
<td>• Causality</td>
<td>• Reinforcement Learning from Human Feedback (RLHF)</td>
</tr>
<tr>
<td>• (Physical) Laws, Rules &amp; Constraints</td>
<td>• Monitoring, Auditing</td>
<td>• Transparency, Accountability, Visualization</td>
<td>• Useable Trust, Trust Calibration</td>
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Neuro-explicit AI Models

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<thead>
<tr>
<th>Ethics</th>
<th>Standards</th>
<th>Data</th>
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Ultimate Goal: Can we Teach Computers to “Understand” and Simulate the World Around Us?

- Relevant Scenarios
  - Coverage of Variability via Directed Search
  - Concrete Instances of Scenarios
    - Adaptation to the Simulated Environment (e.g. used sensors)
- Partial Models (Rules)
  - Configuration & Learning
- Continuous Validation & Adaptation
  - Modeling & Learning
- Reality
  - Car
- Digital Reality
  - Car

Reasoning:
- Simulation & Learning
- Validation / Adaptation / Certification

Model Learning:
- Continuous Validation & Adaptation