Advanced Computer Graphics Sampling Strategies for Solving the Rendering Equation

Matthias Teschner

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Outline

- Context
- Some concepts
- Direct illumination
- Indirect illumination

Goal and Governing Equation

- Computation of incident radiance at a sensor $L(s \leftarrow \omega_s)$
- Incident radiance at sensor position s is equal to exitant radiance at scene position p with $p = r_c(s, \omega_s)$:

$$L(\boldsymbol{s} \leftarrow \boldsymbol{\omega}_s) = L(\boldsymbol{p} \rightarrow \boldsymbol{\omega}_{\boldsymbol{o}})$$

– Raycast operator r_c , conservation of radiance

- Exitant radiance at scene position p is computed as:

$$L(\boldsymbol{p} \to \boldsymbol{\omega}_o) = L_e(\boldsymbol{p} \to \boldsymbol{\omega}_o) + \int_{\Omega} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\boldsymbol{\omega}_i$$

Rendering equation

Goal and Governing Equation



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Monte Carlo Integration

$$\begin{split} L(\boldsymbol{p} \rightarrow \boldsymbol{\omega}_{o}) &= L_{e}(\boldsymbol{p} \rightarrow \boldsymbol{\omega}_{o}) + \int_{\Omega} f_{r}(\boldsymbol{p}, \boldsymbol{\omega}_{i} \leftrightarrow \boldsymbol{\omega}_{o}) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_{i}) \cos(\boldsymbol{\omega}_{i}, \boldsymbol{n}_{p}) d\boldsymbol{\omega}_{i} \\ \text{is approximated with} \\ L(\boldsymbol{p} \rightarrow \boldsymbol{\omega}_{o}) &= L_{e}(\boldsymbol{p} \rightarrow \boldsymbol{\omega}_{o}) + \sum_{i=1}^{N} f_{r}(\boldsymbol{p}, \boldsymbol{\omega}_{i} \leftrightarrow \boldsymbol{\omega}_{o}) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_{i}) \cos(\boldsymbol{\omega}_{i}, \boldsymbol{n}_{p}) \frac{1}{Np(\boldsymbol{\omega}_{i})} \\ \text{Minor domby complete directions in } \end{split}$$

– N randomly sampled directions ω_i

– According to a probability density function $p(\boldsymbol{\omega}_i)$

Monte Carlo Integration

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$$\int_{\Omega} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\boldsymbol{\omega}_i$$
$$\approx \sum_{i=1}^N f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \frac{1}{Np(\boldsymbol{\omega}_i)}$$



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Monte Carlo Integration – Error

- Estimated sample size is not equal to the actual sample size due to random sample selection
- Sample contributions are randomly over- or underestimated





Uniform sampling of a 3D hemisphere Estimated sample size Uniform random sampling of a 3D hemisphere Actual sample size

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Monte Carlo Integration - Error

- Variance, noise: resulting radiance values are randomly too dark or too bright
- If a Monte Carlo approximation converges for growing sample numbers to the correct result, the scheme is unbiased, otherwise biased

Monte Carlo Integration - Variance



1024 samples per pixel

[Pharr et al., Physically Based Rendering]

Rendering Equation – Recursive Problem

 Solving the rendering equation requires N samples, where many samples require the solution of another rendering equation



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Need of a Sampling Strategy

- Sample processing is expensive
 - Ray-scene intersection tests
- Samples differ in terms of relevance
- Important samples, e.g.
 - Towards / from visible light sources
 - From / towards sensors
 - Towards / from bright parts of a scene
- Less important samples, e.g.
 - After increasing number of bounces
 - Towards / from dark parts in a scene

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Stratification

- Subdivision of the integration domain, e.g.
- $L(\boldsymbol{p} \to \boldsymbol{\omega}_o) = L_e(\boldsymbol{p} \to \boldsymbol{\omega}_o) + \int_{\Omega} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\omega_i$

$$= L_e(\boldsymbol{p} \to \boldsymbol{\omega}_o) + \int_{\Omega_{\text{direct}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\boldsymbol{\omega}_i \\ + \int_{\Omega_{\text{indirect}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\boldsymbol{\omega}_i$$

- Integral over Ω_{direct} can directly be computed using L_e
- Integral over $\Omega_{indirect}$ requires the recursive computation of L

Stratification



Two sample sets for two parts of the integration domain

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Stratification

Subdivision into non-overlapping strata

- Allows the usage of an individual technique for each stratum
- Allows / requires the individual sampling of each stratum
- Avoids sample clustering in a part of the integration domain

Importance Sampling

- Probability density function
 - Should be proportional to the integrand $p(\boldsymbol{\omega}_i) \propto f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$
 - Product of functions
 - Incident radiance expensive to compute
 - Optimal PDF $p(\boldsymbol{\omega}_i) = \frac{f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)}{\int_{\Omega} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\omega_i}$

 - Irrelevant: If the integral would be known, we are done.

Importance Sampling

- Large integrand values
 - More samples with smaller size and reduced sampling inaccuracies to improve accuracy, i.e. minimize variance / noise
- Small integrand values
 - Less samples with larger size and larger sampling errors to improve efficiency

Multiple Importance Sampling MIS

- Combine sample sets from different PDFs
 - $$\begin{split} &\int_{\Omega} f(x) dx \approx \sum_{j=1}^{M} f(X_j) \frac{1}{Mp(X_j)} & \text{Monte Carlo with } M \text{ samples} \\ &= \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} f(X_j) \frac{1}{Mp(X_j)} & \text{Summing up } N \text{ MC estimates and dividing by } N \\ &= \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N_i} f(X_{i,j}) \frac{1}{N_i p_i(X_{i,j})} & \text{Using individual PDFs } p_i \text{ with individual sample counts } N_i \text{ for each of the } N \text{ MC estimates} \\ &= \sum_{j=1}^{N_1} \frac{1}{N} f(X_{1,j}) \frac{1}{N_1 p_1(X_{1,j})} + \sum_{j=1}^{N_2} \frac{1}{N} f(X_{2,j}) \frac{1}{N_2 p_2(X_{2,j})} + \ldots + \sum_{j=1}^{N_N} \frac{1}{N} f(X_{N,j}) \frac{1}{N_N p_N(X_{N,j})} \\ &\text{Replacing weight } 1/N \text{ with individual weighting functions } w_i \end{split}$$

$$= \sum_{j=1}^{N_1} w_1(X_{1,j}) f(X_{1,j}) \frac{1}{N_1 p_1(X_{1,j})} + \sum_{j=1}^{N_2} w_2(X_{2,j}) f(X_{2,j}) \frac{1}{N_2 p_2(X_{2,j})} + \dots$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N_i} w_i(X_{i,j}) f(X_{i,j}) \frac{1}{N_i p_i(X_{i,j})} = \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p_i(X_{i,j})}$$

$$\sum_{j=1}^{j} w_i(X_{i,j}) \frac{1}{p_i(X_{i,j})}.$$

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Multiple Importance Sampling MIS

$$\int_{\Omega} f(x) dx \approx \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p_i(X_{i,j})}$$

- Use N PDFs p_i
- Generate N_i samples $X_{i,j}$ from PDF p_i
- Weight all contributions with functions $w_i(x): \Omega \to \mathbb{R}$
 - Constraints for weighting functions

 $f(x) \neq 0 \Rightarrow \sum_{i} w_{i}(x) = 1 \quad \text{wint} \\ p_{j}(x) = 0 \Rightarrow w_{j}(x) = 0 \quad \text{if} \\ \Rightarrow \sum_{i \neq j} w_{i}(x) = 1 \end{cases}$

The weights have to add up to one everywhere on Ω . The weights are irrelevant, if a sample has zero contribution. If any of the PDFs is zero for some x, the weights for all other PDFs have to sum up to one.

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MIS – Example Weightings

$$\begin{split} \int_{\Omega} f(x) dx &\approx \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j})) \frac{f(X_{i,j})}{p_i(X_{i,j})} \\ w_i(x)) &\in \{0,1\} \qquad \sum_i w_i(x) = 1 \\ X_{i,j} &\in \Omega_{\text{indirect}} \Rightarrow w_1(X_{i,j}) = 1 \land w_2(X_{i,j}) = 0 \\ X_{i,j} &\in \Omega_{\text{direct}} \Rightarrow w_1(X_{i,j}) = 0 \land w_2(X_{i,j}) = 1 \end{split}$$

$$\overset{\text{Ligh}}{- \text{Realizes stratification}}$$

- E.g. generate samples from p_1 and p_2
- Use a sample from p_1 , if it is in $\Omega_{indirect}$ and discard it if it is in Ω_{direct}
- Use a sample from p_2 , if it is in $\Omega_{\rm direct}$ and discard it if it is in $\Omega_{\rm indirect}$



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MIS – Example Weightings

$$\int_{\Omega} f(x) dx \approx \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p_i(X_{i,j})}$$

 $w_i(X_{i,j}) = \frac{1}{N}$

– Compute N MC estimates with PDFs p_i and average them

$$w_i(X_{i,j})) = \frac{p_i(X_{i,j})}{\sum_{k=1}^N p_k(X_{i,j})}$$

- Balance heuristic [Eric Veach 1995, 1997]
- Larger weight to more accurate samples with smaller size
- Good, if any of the p_i is large for large f, but no p_i is proportional to f everywhere
- If any p_i is perfectly proportional to f, the balance heuristic is not optimal

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MIS – Example Weightings

$$\int_{\Omega} f(x) dx \approx \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p_i(X_{i,j})}$$
$$w_i(X_{i,j}) = \frac{p_i(X_{i,j})^{\beta}}{\sum_{k=1}^{N} p_k(X_{i,j})^{\beta}} \quad \beta = 2$$

- Power heuristic [Eric Veach 1995, 1997]
- Popular choice in MIS
- Other alternatives
 - Cutoff heuristic
 - Maximum heuristic

MIS – Adaptive Sample Counts

$$\int_{\Omega} f(x) dx \approx \sum_{i=1}^{N} \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p_i(X_{i,j})}$$

- Fixed sample counts N_i can be replaced by randomly selecting a PDF p_i from a discrete PDF p(i)
- One-sample estimator
 - Generate I_k from p Choose a PDF
 - Generate X_k from p_{I_k} Draw a sample from that PDF $\int_{\Omega} f(x) dx \approx \frac{1}{N} \sum_{k=1}^{N} \frac{w_{I_k}(X_k) f(X_k)}{p(I_k) p_{I_k}(X_k)} \approx \frac{w_{I_1}(X_{I_1}) f(X_1)}{p(I_1) p_{I_1}(X_1)}$
 - Relevant, e.g. in path tracing

MIS - Example

- Diffuse material under direct illumination L_e
 - Regular importance sampling with a PDF $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$ $\int_{\Omega} \frac{\rho_d}{\pi} L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\boldsymbol{\omega}_i \approx \sum_{i=1}^N \frac{\rho_d}{\pi} L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \frac{1}{Np_1(\boldsymbol{\omega}_i)}$
- Mixed material under L_e
 - Multiple importance sampling with two PDFs p_1 and p_2 with $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$ and $p_2(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e$

$$\int_{\Omega} \left(\frac{\rho_d}{\pi} + \rho_g \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e\right) L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \mathrm{d}\boldsymbol{\omega}_i \quad r \text{-reflection direction}$$

$$\approx \frac{1}{N} \sum_{i=1}^N \frac{w_{I_i}(\boldsymbol{\omega}_i)}{p(I_i)p_{I_i}(\boldsymbol{\omega}_i)} \left(\frac{\rho_d}{\pi} + \rho_g \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e\right) L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$$

 $I_i \in \{1,2\}$ from p , e.g. $p(1) = p(2) = rac{1}{2}$, $oldsymbol{\omega}_i$ from p_{I_i}

MIS - Example





Importance sampling for a diffuse surface

Using samples from one PDF

Multiple importance sampling for mixed material

Using two sample sets from two PDFs

Weighted averaging of two MC estimates

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Problem



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Hemisphere Dominated by L_e

- BRDF sampling
- Sampling directions from a PDF proportional to the BRDF
- Diffuse: $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$ $\sum_{i=1}^{N} \frac{\rho_d}{\pi} L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \frac{1}{Np_1(\boldsymbol{\omega}_i)}$



- Mixed: $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \quad p_2(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e$ $\frac{1}{N} \sum_{i=1}^{N} \frac{w_{I_i}(\boldsymbol{\omega}_i)}{p(I_i)p_{I_i}(\boldsymbol{\omega}_i)} \left(\frac{\rho_d}{\pi} + \rho_g \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e\right) L_e \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$
- Majority of samples hit a light source, only few misses with zero contribution

Small Light Source

- Majority of samples would miss in case of BRDF sampling, inefficient
- Light sampling
 - Use area form of the rendering equation
 - Sample positions on the light source instead of directions

 $\int_{\Omega_{\text{direct}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) d\omega_i$



 $= \int_{A_{\text{direct}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x} \rightarrow -\boldsymbol{\omega}_i) V(\boldsymbol{p}, \boldsymbol{x}) \frac{\cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \cos(-\boldsymbol{\omega}_i, \boldsymbol{n}_x)}{r_{px}^2} \mathrm{d}x$ University of Freiburg – Computer Science Department – 29

Light Sampling

$$\int_{A_{\text{direct}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x} \to -\boldsymbol{\omega}_i) V(\boldsymbol{p}, \boldsymbol{x}) \frac{\cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p) \cos(-\boldsymbol{\omega}_i, \boldsymbol{n}_x)}{r_{px}^2} \mathrm{d}x$$

 $= \int_{A_{\text{direct}}} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x} \to -\boldsymbol{\omega}_i) G(\boldsymbol{p}, \boldsymbol{x}) dx$

$$\approx \sum_{i=1}^{N} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x}_i \rightarrow -\boldsymbol{\omega}_i) G(\boldsymbol{p}, \boldsymbol{x}_i) \frac{1}{Np(\boldsymbol{x}_i)}$$

- E.g., uniform light sampling $p(x_i) = \frac{1}{A_{\text{direct}}}$
- Area of the light source A_{direct}
- Position x_i is sampled, direction ω_i is computed as $\omega_i = \frac{x_i - p}{\|x_i - p\|}$

Many Small Light Sources

- N_l light sources with areas $A_{\text{direct},j}$
- Uniform sampling of all light sources $\sum_{j=1}^{N_l} \sum_{i=1}^{N} f_r(\boldsymbol{p}, \boldsymbol{\omega}_{j,i} \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x}_{j,i} \rightarrow -\boldsymbol{\omega}_{j,i}) G(\boldsymbol{p}, \boldsymbol{x}_{j,i}) \frac{1}{Np_j(\boldsymbol{x}_{j,i})}$



Adaptive Sample Counts

- Random light source selection from a discrete PDF p
- One-sample estimator
 - Generate I_k from p
 - Generate positions \boldsymbol{x}_k from p_{I_k}
 - Compute $\boldsymbol{\omega}_k = rac{\boldsymbol{x}_k \boldsymbol{p}}{\|\boldsymbol{x}_k \boldsymbol{p}\|}$
 - MC estimator
 - $\sum_{k=1}^{N} f_r(\boldsymbol{p}, \boldsymbol{\omega}_k \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x}_k \rightarrow -\boldsymbol{\omega}_k) G(\boldsymbol{p}, \boldsymbol{x}_k) \frac{1}{N p(I_k) p_{I_k}(\boldsymbol{x}_k)} \\ \approx f_r(\boldsymbol{p}, \boldsymbol{\omega}_1 \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x}_1 \rightarrow -\boldsymbol{\omega}_1) G(\boldsymbol{p}, \boldsymbol{x}_1) \frac{1}{p(I_1) p_{I_1}(\boldsymbol{x}_1)}$
 - Relevant, e.g. in path tracing



Choose a PDF

Draw a sample from that PDF

Light Source Sampling

- Random light source selection
 - Based on relevance for $\int_{\Omega_{direct}} \dots$
 - Discrete PDF p should be proportional to
 - Projected light source area
 - Light source power
- Sampling of each light source
 - Proportional to spatial power distribution

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Problem



- $\int_{\Omega_{direct}}$ can already be computed
- Assume, $\int_{\Omega_{indirect}}$ can also be computed



Multiple importance sampling for mixed material and a small light source

Using three sample sets from three PDFs Weighted averaging of three MC estimates Relevant for recursive raytracing to compute $\int_{\Omega_{direct}} \dots + \int_{\Omega_{indirect}} \dots$

– Three PDFs

- BRDF PDFs $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$ $p_2(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e$
- Light PDF $p_3(\boldsymbol{x}_i) = rac{1}{A_{ ext{direct}}}$
- Discrete PDF for PDF selection, e.g. $p(1) = p(2) = p(3) = \frac{1}{3}$

F = 0

Select $I_i \in \{1, 2, 3\}$ from p Generate N samples $I_i \in \{1, 2\} \land \omega_i \in \Omega_{\text{indirect}} \Rightarrow$ If a sample direction from p_1 or p_2 does not hit the light source, it contributes to $\int_{\Omega_{\text{indirect}}} \cdots$ $F = F + \frac{w_{I_i}(\omega_i)}{p(I_i)p_{I_i}(\omega_i)} f_r(\boldsymbol{p}, \omega_i \leftrightarrow \omega_o) L(\boldsymbol{p} \leftarrow \omega_i) \cos(\omega_i, \boldsymbol{n}_p)$ $I_i \in \{3\} \Rightarrow F = F + \frac{w_3(\boldsymbol{\omega}(\boldsymbol{x}_i))}{p(3)p_3(\boldsymbol{x}_i)} f_r(\boldsymbol{p}, \omega_i \leftrightarrow \omega_o) L_e(\boldsymbol{x}_i \rightarrow -\omega_i) G(\boldsymbol{p}, \boldsymbol{x}_i)$ $F = \frac{1}{N}F$ A sample position from p_3 contributes to $\int_{\Omega_{\text{direct}}} \cdots$. If not, then V=G=0. University of Freiburg – Computer Science Department – 37

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– MIS weights

- E.g.
$$\boldsymbol{\omega} \in \Omega_{\text{indirect}} \Rightarrow w_1(\boldsymbol{\omega}) = w_2(\boldsymbol{\omega}) = 0.5$$

 $\boldsymbol{\omega} \in \Omega_{\text{direct}} \Rightarrow w_1(\boldsymbol{\omega}) = w_2(\boldsymbol{\omega}) = 0$
 $\boldsymbol{\omega}(\boldsymbol{x}) \in \Omega_{\text{direct}} \Rightarrow w_3(\boldsymbol{\omega}(\boldsymbol{x})) = 1$
 $\boldsymbol{\omega}(\boldsymbol{x}) \in \Omega_{\text{indirect}} \Rightarrow w_3(\boldsymbol{\omega}(\boldsymbol{x})) = 0$
 $F = 0$
Select $I_i \in \{1, 2, 3\}$ from p
 $I_i \in \{1, 2\} \land \boldsymbol{\omega}_i \notin \Omega_{\text{direct}} \Rightarrow$
 $F = F + \frac{w_{I_i}(\boldsymbol{\omega}_i)}{p(I_i)p_{I_i}(\boldsymbol{\omega}_i)} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L(\boldsymbol{p} \leftarrow \boldsymbol{\omega}_i) \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$
 $I_i \in \{3\} \Rightarrow F = F + \frac{1}{p(3)p_3(\boldsymbol{x}_i)} f_r(\boldsymbol{p}, \boldsymbol{\omega}_i \leftrightarrow \boldsymbol{\omega}_o) L_e(\boldsymbol{x}_i \rightarrow -\boldsymbol{\omega}_i) G(\boldsymbol{p}, \boldsymbol{x}_i)$
 $F = \frac{1}{N}F$
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- If a ray in direction ω does not hit a light source:
 - $\boldsymbol{\omega} \in \Omega_{\mathrm{indirect}}$
- If a ray in direction ω hits a light source: $\omega \in \Omega_{ ext{direct}}$
- If a light source position x is visible from a surface point p, the respective direction $\omega(x)$ is in $\Omega_{
 m direct}$
- If a light source position x is not visible from a surface point p, the respective direction $\omega(x)$ is in $\Omega_{
 m indirect}$



Multiple importance sampling for mixed material and many small light sources

Three PDFs

- BRDF PDFs $p_1(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{\omega}_i, \boldsymbol{n}_p)$ $p_2(\boldsymbol{\omega}_i) \propto \cos(\boldsymbol{r}(\boldsymbol{n}_p, \boldsymbol{\omega}_i), \boldsymbol{\omega}_o)^e$
- k light sources $p_3(I_k) = \frac{1}{k} p_{I_k+3}(x_i) = \frac{1}{A_{I_k}} I_k \in \{1, \dots, k\}$
- Discrete PDF for PDF selection, e.g. $p(1) = p(2) = p(3) = \frac{1}{3}$

F = 0

Select
$$I_i \in \{1, 2, 3\}$$
 from p Generate N samples
 $I_i \in \{1, 2\} \land \omega_i \in \Omega_{\text{indirect}} \Rightarrow$ If a sample direction from p_1 or p_2 does not
hit the light source, it contributes to $\int_{\Omega_{\text{indirect}}} \cdots$
 $F = F + \frac{w_{I_i}(\omega_i)}{p(I_i)p_{I_i}(\omega_i)} f_r(p, \omega_i \leftrightarrow \omega_o) L(p \leftarrow \omega_i) \cos(\omega_i, n_p)$
 $I_i \in \{3\} \Rightarrow F = F + \frac{w_3(\omega(x_i))}{p(3)p_3(I_k)p_{I_k+3}(x_i)} f_r(p, \omega_i \leftrightarrow \omega_o) L_e(x_i \rightarrow -\omega_i)G(p, x_i)$
 $F = \frac{1}{N}F$ A sample position from p_3 contributes to $\int_{\Omega_{\text{direct}}} \cdots$
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Computation of $\int_{\Omega_{indirect}}$

- Notation:
$$L^1 = \int_{\Omega_d^1} f_r^1 \cos^1 L_e^1 + \int_{\Omega_i^1} f_r^1 \cos^1 L^2$$

 $L^2 = \int_{\Omega_d^2} f_r^2 \cos^2 L_e^2 + \int_{\Omega_i^2} f_r^2 \cos^2 L^3$
 $L^3 = \dots$



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Recursive Formulation

$$\begin{split} L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} L^{2} \\ L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \left(\int_{\Omega_{d}^{2}} f_{r}^{2} \cos^{2} L_{e}^{2} + \int_{\Omega_{i}^{2}} f_{r}^{2} \cos^{2} L^{3} \right) \\ L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \left(\int_{\Omega_{d}^{2}} f_{r}^{2} \cos^{2} L_{e}^{2} + \int_{\Omega_{i}^{2}} f_{r}^{2} \cos^{2} \left(\int_{\Omega_{d}^{3}} f_{r}^{3} \cos^{3} L_{e}^{3} + \int_{\Omega_{i}^{3}} f_{r}^{3} \cos^{3} L^{4} \right) \right) \\ - \text{Recursion is terminated by setting } \int_{\Omega_{i}^{k}} = 0 \ , \ \text{e.g.} \\ L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \left(\int_{\Omega_{d}^{2}} f_{r}^{2} \cos^{2} L_{e}^{2} + \int_{\Omega_{i}^{2}} f_{r}^{2} \cos^{2} \left(\int_{\Omega_{d}^{3}} f_{r}^{3} \cos^{3} L_{e}^{3} \right) \right) \\ L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \int_{\Omega_{d}^{2}} f_{r}^{2} \cos^{2} L_{e}^{2} + \int_{\Omega_{i}^{2}} f_{r}^{2} \cos^{2} \int_{\Omega_{d}^{3}} f_{r}^{3} \cos^{3} L_{e}^{3} + \dots \end{split}$$

Emitted lightEmitted lightEmitted lightEmitted lightafter oneafter twoafter threeafter morebouncebouncesbouncesbounces

Path Tracing

$$\begin{split} L^{1} &= \int_{\Omega_{d}^{1}} f_{r}^{1} \cos^{1} L_{e}^{1} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \int_{\Omega_{d}^{2}} f_{r}^{2} \cos^{2} L_{e}^{2} + \int_{\Omega_{i}^{1}} f_{r}^{1} \cos^{1} \int_{\Omega_{i}^{2}} f_{r}^{2} \cos^{2} \int_{\Omega_{d}^{3}} f_{r}^{3} \cos^{3} L_{e}^{3} + \dots \\ L^{1} &\approx \frac{1}{N_{d,1}} \sum_{i=1}^{N_{d,1}} \frac{f_{r}^{1} \cos^{1} L_{e}^{1}}{pdf_{d}^{1}} + \frac{1}{N_{i,1}} \sum_{i=1}^{N_{i,1}} \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \left(\frac{1}{N_{d,2}} \sum_{i=1}^{N_{d,2}} \frac{f_{r}^{2} \cos^{2}}{pdf_{d}^{2}} L_{e}^{2} \right) + \dots \\ - \text{Taking one sample everywhere} \\ L^{1} &\approx \frac{f_{r}^{1} \cos^{1}}{pdf_{d}^{1}} L_{e}^{1} + \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \frac{f_{r}^{2} \cos^{2}}{pdf_{d}^{2}} L_{e}^{2} + \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \frac{f_{r}^{2} \cos^{2}}{pdf_{d}^{2}} L_{e}^{3} + \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \frac{f_{r}^{2} \cos^{3}}{pdf_{d}^{2}} L_{e}^{4} + \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \frac{f_{r}^{2} \cos^{2}}{pdf_{d}^{2}} L_{e}^{3} + \frac{f_{r}^{1} \cos^{1}}{pdf_{i}^{1}} \frac{f_{r}^{2} \cos^{3}}{pdf_{d}^{3}} L_{e}^{3} + \dots \end{split}$$

Path tracing with next event estimation

Path Tracing with Next Event Estimation



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General Path Tracing

 $L^1 = 0$

Generate a sample towards p_1

$$\beta = 1 \qquad L_e > 0 \Rightarrow L^1 = L^1 + \beta L_e$$

Generate a sample from p_1 into the entire hemisphere with pdf₁ towards p_2

$$\beta = \beta \cdot \frac{f_r^1 \cos^1}{\mathrm{pdf}^1} \quad L_e > 0 \Rightarrow L^1 = L^1 + \beta L_e$$

Generate a sample from p_2 into the entire hemisphere with pdf₂ towards p_3

$$\beta = \beta \cdot \frac{f_r^2 \cos^2}{\mathrm{pdf}^2} \quad L_e > 0 \Rightarrow L^1 = L^1 + \beta L_e$$

Generate a sample towards p_4

$$\beta = \beta \cdot \frac{f_r^3 \cos^3}{\mathrm{pdf}^3} \quad L_e > 0 \Rightarrow L^1 = L^1 + \beta L_e$$

Terminate, if e.g. throughput β smaller than user-defined threshold University of Freiburg – Computer Science Department – 47

 p^4 p^2 p^1 p^3

Assumes reflective light sources.

General Path Tracing



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Jittered Path Sampling per Pixel

- Various strategies
 - Random
 - Stratified
 - Quasi random (low-discrepancy sequences)
- Regular sampling would cause aliasing



n samples / paths per pixel.

Image Reconstruction

- Convolution with a normalized kernel function / filter W $L(\boldsymbol{x}_i) = \int_A L(\boldsymbol{x}')W(\|\boldsymbol{x}_i - \boldsymbol{x}'\|)d\boldsymbol{x}'$ $L(\boldsymbol{x}_i) \approx \sum_j L(\boldsymbol{x}_j)W(\|\boldsymbol{x}_i - \boldsymbol{x}_j\|)A(\boldsymbol{x}_j)$ - E.g., box filter: W = const
 - $x_{j} \text{uniform samples in one pixel } i$ $A = \frac{\text{area of pixel}}{N} \sum_{j} W = \frac{1}{\text{area of pixel}}$ $\sum_{j} W \cdot A = \frac{\text{area of pixel}}{N} \cdot \frac{1}{\text{area of pixel}}$ $L(x_{i}) = \sum_{j} L(x_{j}) \cdot W \cdot A = \frac{1}{N} \sum_{j} L(x_{j})$ $L(x_{i}) = \sum_{j} L(x_{j}) \cdot W \cdot A = \frac{1}{N} \sum_{j} L(x_{j})$ $L(x_{i}) = \sum_{j} W \cdot A = \frac{1}{N} \sum_{j} W \cdot A$

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9 pixels with *N* samples. Pixel *i* with representative position *x_i* and samples / paths at positions *x_j*

Path Tracing – Maximum Path Length

- Fixed, user-defined
- Adaptive with Russian Roulette
 - Minimum fixed length, user-defined
 - Termination probability q for additional segments

- Random sample
$$\xi$$
:
 $F' = \begin{cases} \frac{F-qc}{1-q} & \xi > q \\ c & \text{otherwise} \end{cases}$
Typically $c=0$

- Intuition
 - Some samples are discarded
 - Remaining samples are amplified to account for missing contributions

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 $E[F'] = (1-q)\frac{E[F]-qc}{1-q} + qc$

= E[F]

Russian Roulette - Motivation

Fixed path length

- Biased estimator
- Always too small / dark, but consistent
- Converges to correct result
- Completely misses effects that require longer paths
- Example: All paths with zero contribution

Adaptive path length with Russian Roulette

- Unbiased estimator
- Converges to correct result
- Arbitrarily long paths potentially capture more effects than fixed path lengths, although with low quality
 - Example: Most samples with zero contribution Some very long paths with non-zero contr.





Adaptive sample counts at intersections



Without splitting

Splitting

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Path Tracing – Degrees of Freedom

$$- L = \prod_{i=1}^{N} \frac{f_r^i \cos^i}{\mathrm{pdf}^i} L_e^N$$

- Path length, e.g. Russian Roulette
- PDFs at each intersection, e.g. MIS with light and material sampling
- Next event estimation, i.e. light sampling at each intersection
- Number of samples at each intersection, i.e. splitting

Current Variants

- Bidirectional path generation
 - Motivation: Samples from the light source into the scene are as important as samples from the sensor into the scene
 - Symmetric setting
- Metropolis sampling
 - Path mutations instead of random sampling
 - Small mutations in case of relevant paths
 - Large mutations in case of less relevant paths