

Lecture 9: Monte Carlo Rendering

Chapters 4 and 5 in Advanced GI

Fall 2004
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Homework

- HW 1out, due Oct 5
- Assignments done separately
 - Might revisit this policy for later assignments

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Stochastic Ray Tracing

- Parameters?
 - # starting rays per pixel
 - # random rays for each surface point (branching factor)
- Path Tracing
 - Branching factor == 1

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Algorithm so far ...

- Shoot # viewing rays through each pixel
- Shoot # indirect rays, sampled over hemisphere
 - Path tracing shoots only 1 indirect ray
- Terminate recursion using Russian Roulette

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Performance/Error

- Want better quality with smaller number of samples
 - Fewer samples/better performance
 - Stratified sampling
 - Quasi Monte Carlo: well-distributed samples
- Faster convergence
 - Importance sampling: next-event estimation

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Stratified Sampling

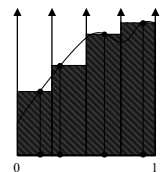
- Samples could be arbitrarily close
- Split integral in subparts

$$I = \int_{x_1} f(x) dx + \dots + \int_{x_N} f(x) dx$$

- Estimator

$$\bar{I}_{strat} = \frac{1}{N} \sum_{i=1}^N \frac{f(\bar{x}_i)}{p(\bar{x}_i)}$$

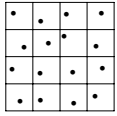
- Variance: $\sigma_{strat} \leq \sigma_{sec}$



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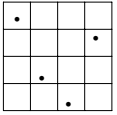
Higher Dimensions

- Stratified grid sampling:



→ N^d samples

- N-rooks sampling:

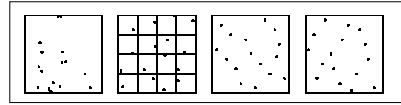


→ N samples

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Quasi Monte Carlo

- Eliminates randomness to find well-distributed samples
- Samples are deterministic but “appear” random



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Performance/Error

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Next Event Estimation

$$L(x \rightarrow \Theta) = L_e + L_{direct} + L_{indirect}$$

$$= L_e + \int_{\Omega_x} f_r \cdot \cos + \int_{\Omega_x} f_r \cdot \cos$$

- So ... sample direct and indirect with separate MC integration

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How to sample direct illumination

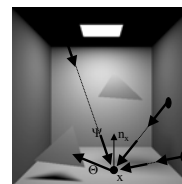
- Sampling a single light source
- Sampling for many lights

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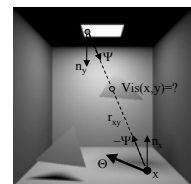
Direct Illumination

$$L(x \rightarrow \Theta) = \int_{A_{source}} f_r(x, -\Psi \leftrightarrow \Theta) \cdot L(y \rightarrow \Psi) \cdot G(x, y) \cdot dA_y$$

$$G(x, y) = \frac{\cos(n_x, \Theta) \cos(n_y, \Psi) Vis(x, y)}{r_{xy}^2}$$



hemisphere integration



area integration

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Estimator for direct lighting

- Pick a point on the light's surface with pdf

$$p(y)$$

- For N samples, direct light at point x is:

$$E(x) = \frac{1}{N} \sum_{i=1}^N \frac{f_r L_{source} \frac{\cos \theta_x \cos \theta_{\bar{y}_i}}{r_{x\bar{y}_i}^2} Vis(x, \bar{y}_i)}{p(\bar{y}_i)}$$

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PDF for sampling light

- Uniform

$$p(y) = \frac{1}{Area_{source}}$$

- Pick a point uniformly over light's area
 - Can stratify samples

- Estimator:

$$E(x) = \frac{Area_{source}}{N} \sum_{i=1}^N f_r L_{source} \frac{\cos \theta_x \cos \theta_{\bar{y}_i}}{r_{x\bar{y}_i}^2} Vis(x, \bar{y}_i)$$

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Different pdfs

- Uniform

$$p(y) = \frac{1}{Area_{source}}$$

- Solid angle sampling
 - Removes cosine and distance from integrand
 - Better when significant foreshortening

$$E(x) = \frac{1}{N} \sum_{i=1}^N \frac{f_r L_{source} \frac{\cos \theta_x \cos \theta_{\bar{y}_i}}{r_{x\bar{y}_i}^2} Vis(x, \bar{y}_i)}{p(\bar{y}_i)}$$

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Parameters

- How to distribute paths within light source?
 - Uniform
 - Solid angle
 - What about light distribution?
- How many paths ("shadow-rays")?
 - Total?
 - Per light source? (~intensity, importance, ...)

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Formulation over all lights

- When M is large, each direct lighting sample is very expensive
- We would like to importance sample the lights
- Instead of M integrals

$$L(x \rightarrow \Theta) = \sum_{i=1}^M \int_{A_{source}} f_r(x, -\Psi \leftrightarrow \Theta) \cdot L_{source}(y \rightarrow -\Psi) \cdot G(x, y) \cdot dA_y$$

- Formulation over 1 integration domain

$$L(x \rightarrow \Theta) = \int_{A_{all\ lights}} f_r(x, -\Psi \leftrightarrow \Theta) \cdot L_{source}(y \rightarrow -\Psi) \cdot G(x, y) \cdot dA_y$$

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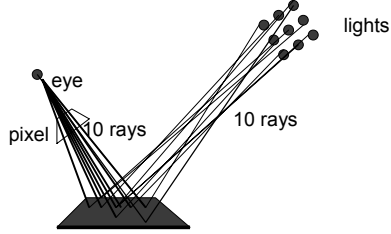
Why?

- Do not need a minimum of M rays/sample
- Can use only one ray/sample
- Still need N samples, but 1 ray/sample
- Ray is distributed over the whole integration domain
 - Can importance sample the lights

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Anti-aliasing

- Can piggy-back on the anti-aliasing of pixel



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How to sample the lights?

- A discrete pdf $p_L(k_i)$ picks the light k_i
- A surface point is then picked with pdf $p(y_i|k_i)$

- Estimator with N samples:

$$E(x) = \frac{1}{N} \sum_{i=1}^N \frac{f_r L_{source} G(x, \bar{y}_i)}{p_L(k_i) p(y_i | k_i)}$$

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Strategies for picking light

– Uniform $p_L(k) = \frac{1}{M}$

– Area $p_L(k) = \frac{A_k}{\sum A_k}$

– Power $p_L(k) = \frac{P_k}{\sum P_k}$

Don't take visibility into account

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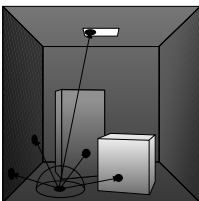
Research on many lights

- Ward '91
- Shirley, Wang, Zimmerman '94
- Fernandez, Bala, Greenberg '02
- Wald and Slusallek '03

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Alternative direct paths

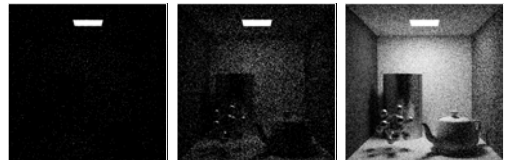
- Shoot paths at random over hemisphere; check if they hit light source



- paths not used efficiently
- noise in image
- might work if light source occupies large portion on hemisphere

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Alternative direct paths



1 path / point

16 paths / point

256 paths / point

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Direct paths

- Different path generators produce different estimators and different error characteristics
- Direct illumination general algorithm:

```

compute_radiance (point, direction)
  est_rad = 0;
  for (i=0; i<n; i++)
    p = generate_path;
    est_rad += energy_transfer(p) / probability(p);
  est_rad = est_rad / n;
  return(est_rad);
  
```

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Stochastic Ray Tracing

- Sample area of light source for direct term
- Sample hemisphere with random rays for indirect term
- Optimizations:
 - Stratified sampling
 - Importance sampling
 - Combine multiple probability density functions into a single PDF

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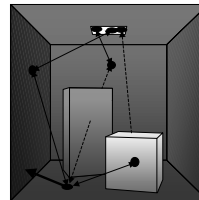
Indirect Illumination

- Paths of length > 1
- Many different path generators possible
- Efficiency depends on:
 - BRDFs along the path
 - Visibility function
 - ...

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Indirect paths - surface sampling

- Simple generator (path length = 2):
 - select point on light source
 - select random point on surfaces



- per path:
 - 2 visibility checks

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Indirect paths - surface sampling

- Indirect illumination (path length 2):

$$L(x \rightarrow \Theta) = \int_{A_{\text{source}}} \int_{A_d} L(y \rightarrow \Psi_1) f_r(z, -\Psi_1 \leftrightarrow \Psi_2) G(z, y) f_r(x, -\Psi_2 \leftrightarrow \Theta) G(z, x) dA_d dA_s$$

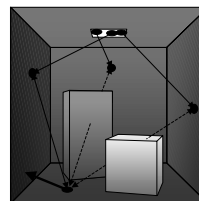
$$\langle L(x \rightarrow \Theta) \rangle = \frac{1}{N} \sum_{i=1}^N \frac{L(y_i \rightarrow \Psi_{1i}) f_r(z_i, -\Psi_{1i} \leftrightarrow \Psi_{2i}) G(z_i, y_i) f_r(x, -\Psi_{2i} \leftrightarrow \Theta) G(z_i, x)}{p_s(y_i) p_r(z_i)}$$

- 2 visibility values cause noise
 - which might be 0

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Indirect paths - source shooting

- Shoot ray from light source, find hit location
- Connect hit point to receiver

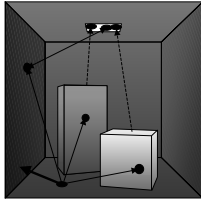


- per path:
 - 1 ray intersection
 - 1 visibility check

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Indirect paths - receiver gathering

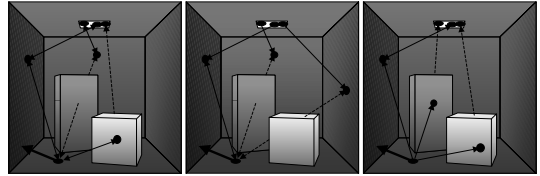
- Shoot ray from receiver point, find hit location
- Connect hit point to random point on light source



- per path:
- 1 ray intersection
 - 1 visibility check

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Indirect paths



Surface sampling

Source shooting

Receiver gathering

- 2 visibility terms;
can be 0

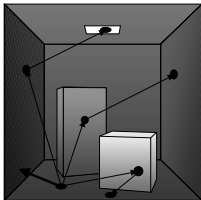
- 1 visibility term
- 1 ray intersection

- 1 visibility term
- 1 ray intersection

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More variants ...

- Shoot ray from receiver point, find hit location
- Shoot ray from hit point, check if on light source



- per path:
- 2 ray intersections
 - L_e might be zero

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Indirect paths

- Same principles apply to paths of length > 2
 - generate multiple surface points
 - generate multiple bounces from light sources and connect to receiver
 - generate multiple bounces from receiver and connect to light sources
 - ...
- Estimator and noise characteristics change with path generator

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Indirect paths

```
compute_radiance (point, direction)
  est_rad = 0;
  for (i=0; i<n; i++)
    q = generate_indirect_path;
    est_rad += energy_transfer(q) / p(q);
  est_rad = est_rad / n;
  return(est_rad);
```

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Stochastic Ray Tracing

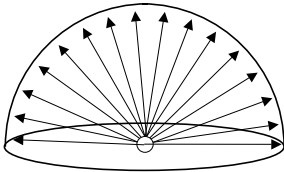
- Sample area of light source for direct term
- Sample hemisphere with random rays for indirect term
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Sampling strategies

- Uniform sampling over the hemisphere

$$L(x \rightarrow \Theta) = \int_{\Omega_x} L(x \leftarrow \Psi) \cdot f_r(\Psi \leftrightarrow \Theta) \cdot \cos(\Psi, n_x) \cdot d\omega_\Psi$$



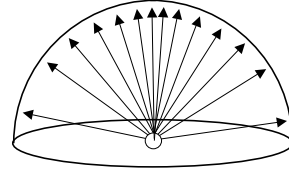
$$p(\Theta) = 1/(2\pi)$$

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Sampling strategies

- Sampling according to the cosine factor

$$L(x \rightarrow \Theta) = \int_{\Omega_x} L(x \leftarrow \Psi) \cdot f_r(\Psi \leftrightarrow \Theta) \cdot \cos(\Psi, n_x) \cdot d\omega_\Psi$$



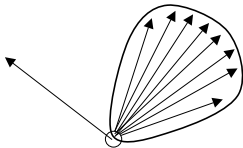
$$p(\Theta) = \cos \theta / \pi$$

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Sampling strategies

- Sampling according to the BRDF

$$L(x \rightarrow \Theta) = \int_{\Omega_x} L(x \leftarrow \Psi) \cdot f_r(\Psi \leftrightarrow \Theta) \cdot \cos(\Psi, n_x) \cdot d\omega_\Psi$$



$$p(\Theta) \sim f_r(\Theta \leftrightarrow \Psi)$$

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Example: sample according to BRDF

- Discrete pdf q_1, q_2, q_3 $q_1 + q_2 + q_3 = 1$

$$L_{\text{indirect}} = L_{\text{diffuse}} + L_{\text{specular}}$$

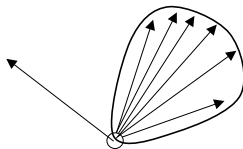
$$\langle L_{\text{indirect}} \rangle = \begin{cases} \frac{L(x \leftarrow \Psi_i) k_d \cos(N, \Psi_i)}{q_1 p_1(\Psi_i)} & | \xi < q_1 \\ \frac{L(x \leftarrow \Psi_i) k_s \cos^n(R, \Psi_i) \cos(N, \Psi_i)}{q_2 p_2(\Psi_i)} & | q_1 \leq \xi < q_2 \\ 0 & | \text{otherwise} \end{cases}$$

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Sampling strategies

- Sampling according to the BRDF times the cosine

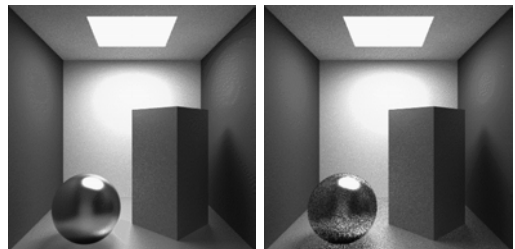
$$L(x \rightarrow \Theta) = \int_{\Omega_x} L(x \leftarrow \Psi) \cdot f_r(\Psi \leftrightarrow \Theta) \cdot \cos(\Psi, n_x) \cdot d\omega_\Psi$$



$$p(\Theta) \sim f_r(\Theta \leftrightarrow \Psi) \cos \theta$$

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Comparison



With importance sampling
(brdf on sphere)

Without importance sampling

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