

Monte Carlo I

Previous lecture

- Analytical illumination formula

This lecture

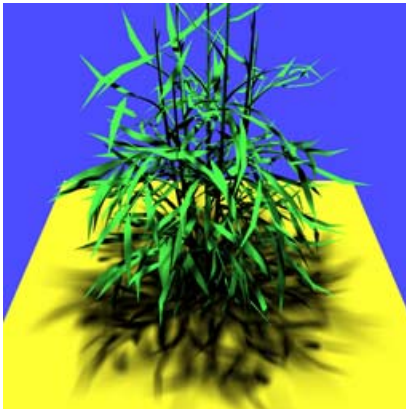
- Review random variables and probability
- Monte Carlo integration
- Sampling from distributions
- Sampling from shapes
- Variance and efficiency

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Lighting and Soft Shadows

$$E(x) = \int_{H^2} L_i(x, \omega) \cos \theta d\omega$$



Challenges

- Visibility and blockers
- Varying light distribution
- Complex source geometry

Source: Agrawala, Ramamoorthi, Heirich, Moll, 2000

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Monte Carlo Algorithms

Advantages

- Easy to implement
- Easy to think about (but be careful of statistical bias)
- Robust when used with complex integrands and domains (shapes, lights, ...)
- Efficient for high dimensional integrals
- Efficient solution method for a few selected points

Disadvantages

- Noisy
- Slow (many samples needed for convergence)

Random Variables

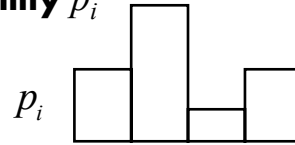
X is chosen by some random process

$X \sim p(x)$ probability distribution function (PDF)

Discrete Probability Distributions

Discrete events X_i with probability p_i

$$p_i \geq 0 \quad \sum_{i=1}^n p_i = 1$$



Cumulative PDF

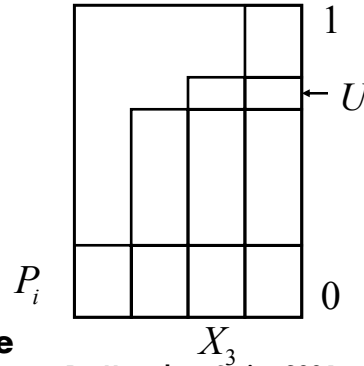
$$P_j = \sum_{i=1}^j p_i$$

Construction of samples

To randomly select an event,

Select X_i if $P_{i-1} < U \leq P_i$

Uniform random variable



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Continuous Probability Distributions

PDF $p(x)$

$$p(x) \geq 0$$

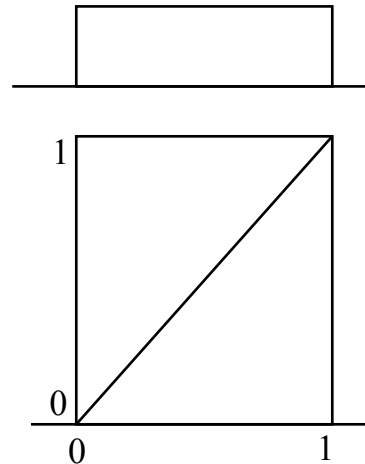
CDF $P(x)$

$$P(x) = \int_0^x p(x) dx$$

$$P(x) = \Pr(X < x) \quad P(1) = 1$$

$$\Pr(\alpha \leq X \leq \beta) = \int_{\alpha}^{\beta} p(x) dx = P(\beta) - P(\alpha)$$

Uniform



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Sampling Continuous Distributions

Cumulative probability distribution function

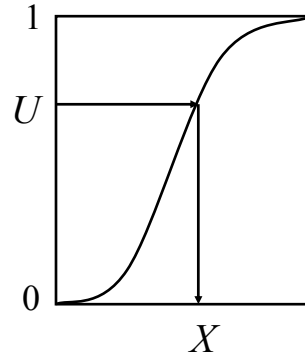
$$P(x) = \Pr(X < x)$$

Construction of samples

$$\text{Solve for } X = P^{-1}(U)$$

Must know:

1. The integral of $p(x)$
2. The inverse function $P^{-1}(x)$



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Example: Power Function

Assume

$$p(x) = (n+1)x^n$$

$$P(x) = x^{n+1}$$

$$X \sim p(x) \Rightarrow X = P^{-1}(U) = \sqrt[n+1]{U}$$

$$\int_0^1 x^n dx = \frac{x^{n+1}}{n+1} \Big|_0^1 = \frac{1}{n+1}$$

Trick

$$Y = \max(U_1, U_2, \dots, U_n, U_{n+1})$$

$$\Pr(Y < x) = \prod_{i=1}^{n+1} \Pr(U_i < x) = x^{n+1}$$

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Sampling a Circle

$$A = \int_0^{2\pi} \int_0^1 r \, dr \, d\theta = \int_0^1 r \, dr \int_0^{2\pi} d\theta = \left(\frac{r^2}{2} \right) \Big|_0^1 \theta \Big|_0^{2\pi} = \pi$$

$$p(r, \theta) \, dr \, d\theta = \frac{1}{\pi} r \, dr \, d\theta \Rightarrow p(r, \theta) = \frac{r}{\pi}$$

$$p(r, \theta) = p(r)p(\theta)$$

$$p(\theta) = \frac{1}{2\pi}$$

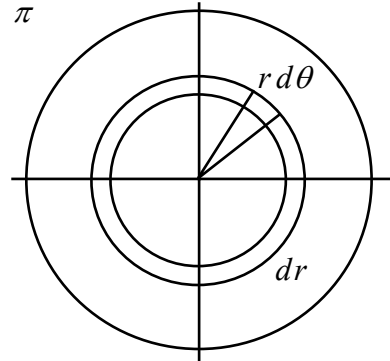
$$\theta = 2\pi U_1$$

$$P(\theta) = \frac{1}{2\pi} \theta$$

$$p(r) = 2r$$

$$r = \sqrt{U_2}$$

$$P(r) = r^2$$



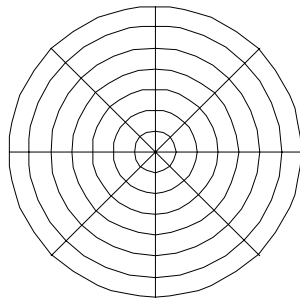
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Sampling a Circle

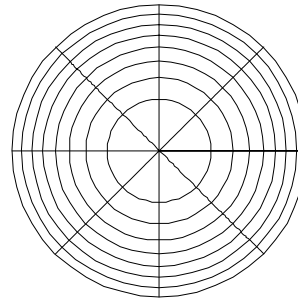
WRONG \neq Equi-Areal

RIGHT = Equi-Areal



$$\theta = 2\pi U_1$$

$$r = U_2$$



$$\theta = 2\pi U_1$$

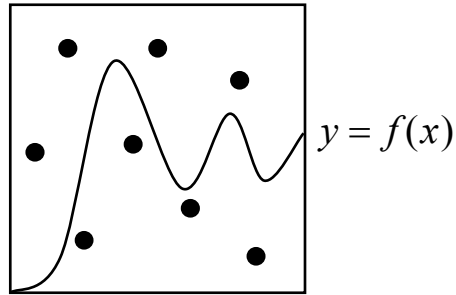
$$r = \sqrt{U_2}$$

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Rejection Methods

$$I = \int_0^1 f(x) dx$$
$$= \iint_{y < f(x)} dx dy$$



Algorithm

Pick U_1 and U_2

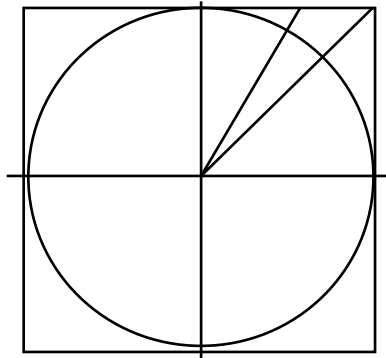
Accept U_1 if $U_2 < f(U_1)$

Wasteful? Efficiency = Area / Area of rectangle

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Sampling a Circle: Rejection



```
do {  
    X=1-2*U1  
    Y=1-2*U2  
while( X2+ Y2 >1 )
```

May be used to pick random 2D directions

Circle techniques may also be applied to the sphere

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Monte Carlo Integration

Definite integral $I(f) \equiv \int_0^1 f(x) dx$

Expectation of f $E[f] \equiv \int_0^1 f(x)p(x) dx$

Random variables $X_i \sim p(x)$
 $Y_i = f(X_i)$

Estimator $F_N = \frac{1}{N} \sum_{i=1}^N Y_i$

Unbiased Estimator

$E[F_N] = I(f)$

Properties

$$E[\sum_i Y_i] = \sum_i E[Y_i]$$

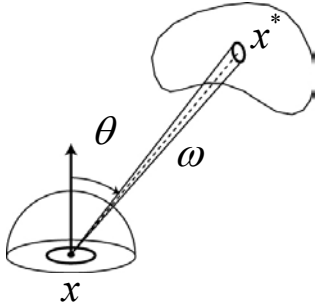
$$E[aY] = aE[Y]$$

$$\begin{aligned} E[F_N] &= E\left[\frac{1}{N} \sum_{i=1}^N Y_i\right] \\ &= \frac{1}{N} \sum_{i=1}^N E[Y_i] = \frac{1}{N} \sum_{i=1}^N E[f(X_i)] \\ &= \frac{1}{N} \sum_{i=1}^N \int_0^1 f(x)p(x) dx \\ &= \frac{1}{N} \sum_{i=1}^N \int_0^1 f(x) dx \\ &= \int_0^1 f(x) dx \end{aligned}$$

Assume uniform probability distribution for now

Direct Lighting - Directional Sampling

$$E(x) = \int_{\Omega} L(x, \omega) \cos \theta d\omega$$



Ray intersection $x^*(x, \omega)$

Sample ω uniformly by Ω

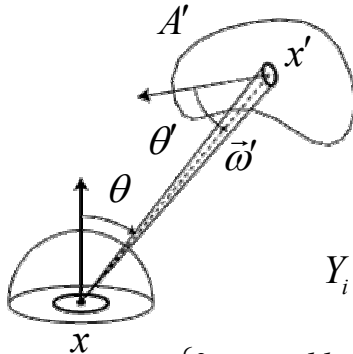
$$Y_i = L(x^*(x, \omega_i), -\omega_i) \cos \theta_i 2\pi$$

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Direct Lighting - Area Sampling

$$E(x) = \int_{\Omega} L_i(x, \omega) \cos \theta d\omega = \int_{A'} L_o(x', \omega') V(x, x') \frac{\cos \theta \cos \theta'}{|x - x'|^2} dA'$$



Ray direction $\omega' = x - x'$

Sample x' uniformly by A'

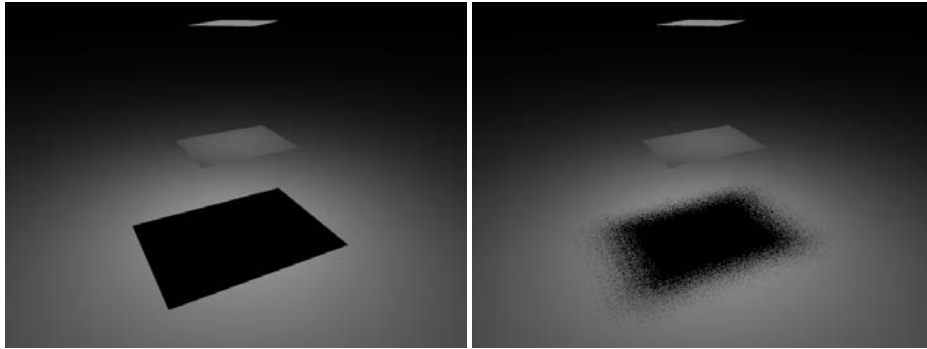
$$Y_i = L_o(x'_i, \omega'_i) V(x, x'_i) \frac{\cos \theta_i \cos \theta'_i}{|x - x'_i|^2} A$$

$$V(x, x') = \begin{cases} 0 & \text{-visible} \\ 1 & \text{visible} \end{cases}$$

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Examples



4 eye rays per pixel
1 shadow ray per eye ray

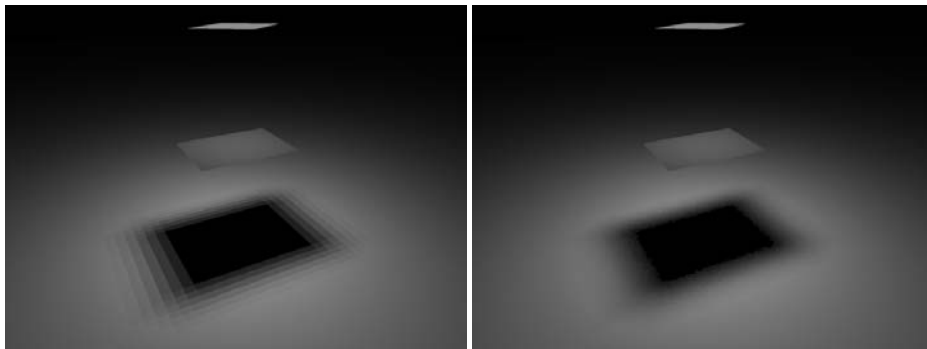
Fixed

Random

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Examples



4 eye rays per pixel
16 shadow rays per eye ray

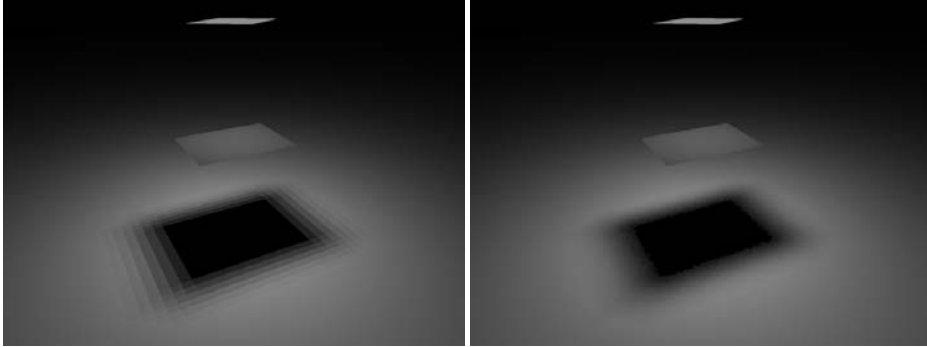
Uniform grid

Stratified random

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Examples



4 eye rays per pixel
64 shadow rays per eye ray

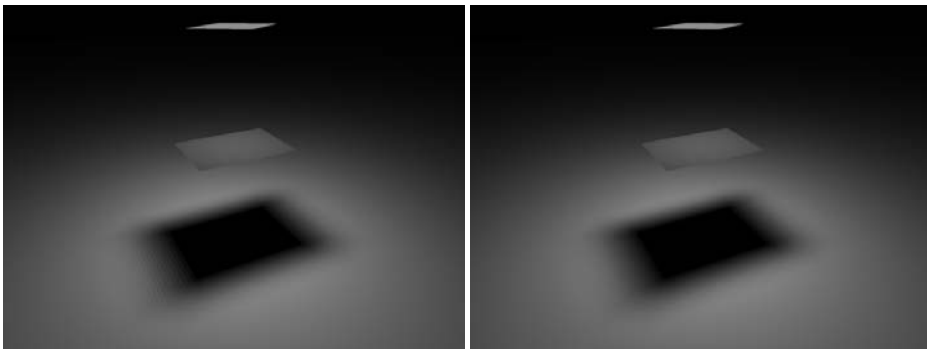
Uniform grid

Stratified random

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Examples



4 eye rays per pixel
100 shadow rays per eye ray

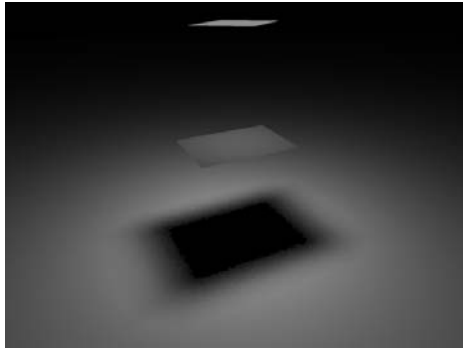
Uniform grid

Stratified random

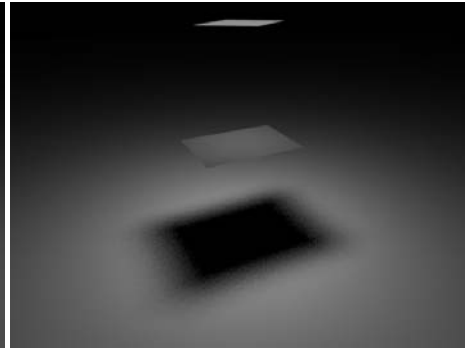
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Examples



**4 eye rays per pixel
16 shadow rays per eye ray**



**64 eye rays per pixel
1 shadow ray per eye ray**

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Variance

Definition

$$\begin{aligned}V[Y] &\equiv E[(Y - E[Y])^2] \\ &= E[Y^2 - 2YE[Y] + E[Y]^2] \\ &= E[Y^2] - E[Y]^2\end{aligned}$$

Properties

$$V[\sum_i Y_i] = \sum_i V[Y_i]$$

$$V[aY] = a^2 V[Y]$$

Variance decreases with sample size

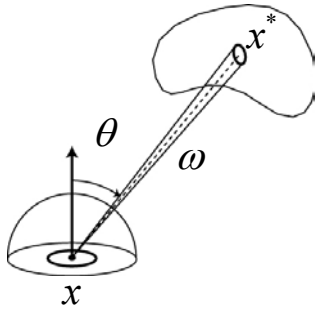
$$V\left[\frac{1}{N} \sum_{i=1}^N Y_i\right] = \frac{1}{N^2} \sum_{i=1}^N V[Y_i] = \frac{1}{N} V[Y]$$

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Direct Lighting – Directional Sampling

$$E(x) = \int_{\Omega} L(x, \omega) \cos \theta d\omega$$



Ray intersection $x^*(x, \omega)$

Sample ω uniformly by Ω

$$Y_i = L(x^*(x, \omega_i), -\omega_i) \cos \theta 2\pi$$

Sample ω uniformly by $\tilde{\Omega}$

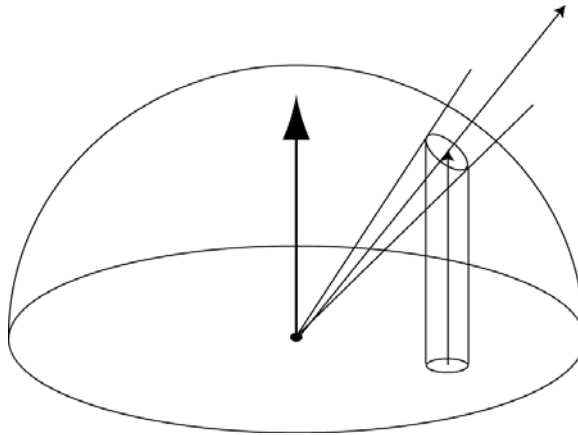
$$Y_i = L(x^*(x, \omega_i), -\omega_i) \pi$$

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Sampling Projected Solid Angle

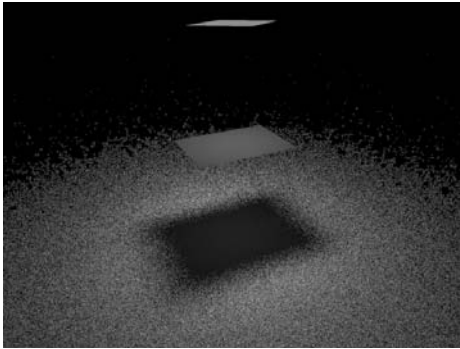
Generate cosine weighted distribution



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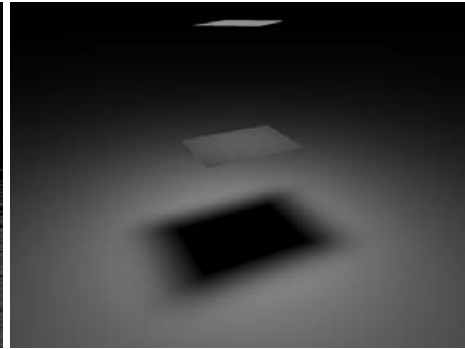
Examples



Projected solid angle

**4 eye rays per pixel
100 shadow rays**

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Area

**4 eye rays per pixel
100 shadow rays**

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Variance Reduction

Efficiency measure

$$Efficiency \propto \frac{1}{Variance \bullet Cost}$$

Techniques

- Importance sampling
- Sampling patterns: stratified, ...

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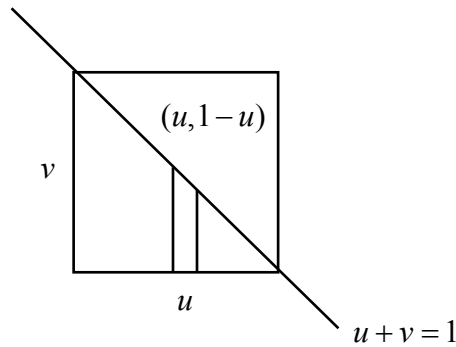
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Sampling a Triangle

$$u \geq 0$$

$$v \geq 0$$

$$u + v \leq 1$$



$$A = \int_0^1 \int_0^{1-u} dv du = \int_0^1 (1-u) du = -\frac{(1-u)^2}{2} \Big|_0^1 = \frac{1}{2}$$

$$p(u, v) = 2$$

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Sampling a Triangle

Here u and v are not independent! $p(u, v) = 2$

Conditional probability

$$p(u) \equiv \int p(u, v) dv \quad p(u | v) \equiv \frac{p(u, v)}{p(u)}$$

$$p(u) = 2 \int_0^{1-u} dv = 2(1-u)$$

$$P(u_0) = \int_0^{u_0} 2(1-u) du = (1-u_0)^2$$

$$u_0 = 1 - \sqrt{U_1}$$

$$p(v | u) = \frac{1}{(1-u)}$$

$$v_0 = \sqrt{U_1} U_2$$

$$P(v_0 | u_0) = \int_0^{v_0} p(v | u_0) dv = \int_0^{v_0} \frac{1}{(1-u_0)} dv = \frac{v_0}{(1-u_0)}$$

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