

Overview

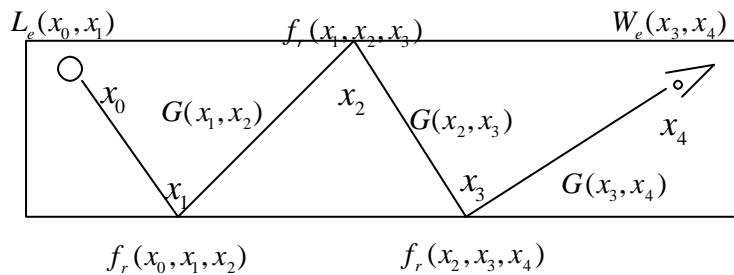
Tuesday

- Direct lighting
- Sampling distributions and shapes
- Importance and multiple importance sampling

Today

- Markov chains and path tracing
- Forward and backward tracing (adjoint equations)
- Bidirectional ray tracing
- Density estimation and photon tracing

Light Paths



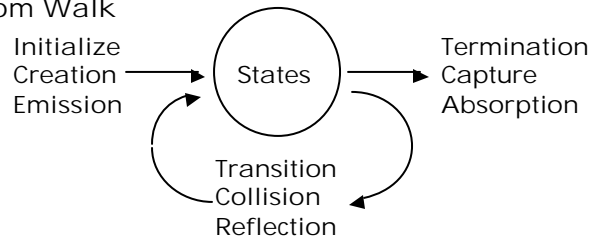
$$M = \sum_{k=1}^{\infty} \int_{M^2} \int_{M^2} \dots \int_{M^2} L_e(x_0, x_1) G(x_0, x_1) f_r(x_0, x_1, x_2) \dots f_r(x_{k-2}, x_{k-1}, x_k) G(x_{k-1}, x_k) W_e(x_{k-1}, x_k) dA_0 dA_1 \dots dA_k$$

Light transport: Integrate over paths with k bounces

- Sample space of paths
- Find good estimators

Particle Simulation

Discrete Random Walk



von Neumann and Ulam; Forsythe and Leibler ('50)

1. Generate random particle paths from source (receiver).
2. Count how many terminate in state i .

Wasow ('52)

1. Generate random particle paths from source (receiver).
2. Count how many pass through state i .

Markov Process

Assign probabilities to each process

- Creation: p_i^0 : probability of particle being created in state i
- Transition: $p_{i,j}$: probability of transition from state $i \rightarrow j$
- Termination: p_i^* : probability of termination in state i

$$p_i^* = 1 - \sum_j p_{i,j}$$

Compute steady state probability of being in state i

$$\begin{aligned} P_i^0 &= p_i^0 \\ P_i^1 &= \sum_j p_{j,i} P_j^0 \\ &\vdots \\ P_i^n &= \sum_j p_{j,i} P_j^{n-1} \end{aligned}$$

$$P_i = \sum_{k=0}^{\infty} P_i^k$$

But this is the solution of

$$(I - M)P = p^0$$

Random Walk Algorithm

Define a random variable on the space of paths

Path: $\mathbf{a}_k = (i_1, i_2, \dots, i_k)$

Expectation: $E[W] = \sum_{\mathbf{a}} P(\mathbf{a})W(\mathbf{a}) = \sum_{k=1}^{\infty} \sum_{\mathbf{a}_k} P(\mathbf{a}_k)W(\mathbf{a}_k)$

Count the number of particles terminating in state j

Estimator: $W_j(\mathbf{a}_k) = \frac{d_{i_k, j}^*}{p_{i_k}^*}$

Probability: $P(\mathbf{a}_k) = p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} p_{i_k}^*$

$$E[W_j] = \sum_{k=1}^{\infty} \sum_{i_k} \cdots \sum_{i_1} (p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} p_{i_k}^*) \frac{d_{i_k, j}^*}{p_j^*}$$

$$= [p^0]_j + [Mp^0]_j + [M^2 p^0]_j \cdots$$

CS348B Lecture 14

Pat Hanrahan, Spring 2000

Collision Estimator

Count the number of particles passing through state j

Weight: $W_j(\mathbf{a}_k) = \sum_{m=1}^k d_{i_m, j}$

$$E[W_j] = \sum_{k=1}^{\infty} \sum_{i_k} \cdots \sum_{i_1} (p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} p_{i_k}^*) \left(\sum_{m=1}^k d_{i_m, j} \right)$$

$$= \sum_{m=1}^{\infty} \sum_{i_m} \cdots \sum_{i_1} (p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{m-1}, i_m}) d_{i_m, j} \underbrace{\left(\sum_{k=m}^{\infty} \sum_{i_{m+1}} \cdots \sum_{i_k} p_{i_m, i_{m+1}} \cdots p_{i_{k-1}, i_k} p_{i_k}^* \right)}_{\text{Probability that particle terminates}=1.0}$$

Is this better?

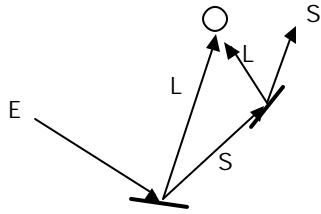
$$V[W_j^c] \leq V[W_j^a] \quad \text{iff} \quad p_j^* \leq \frac{\Pr[j \text{ never returns to } j]}{2 - \Pr[j \text{ never returns to } j]}$$

CS348B Lecture 14

Pat Hanrahan, Spring 2000

Path Tracing

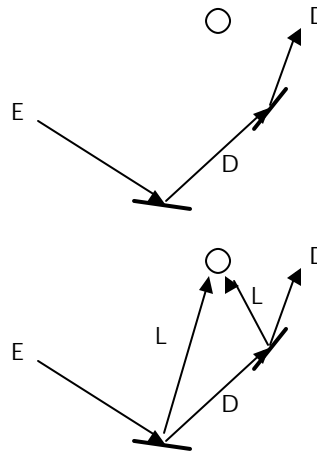
Classic ray tracing
[Whitted 1980]



Bias towards the lights ...
Careful to not count twice!

CS348B Lecture 14

Path Tracing
[Kajiya 1986]



Pat Hanrahan, Spring 2000

Classic Path Tracing: Random Walk

1. Generate particle

$$w_0 = \frac{L_e(x_0, x_1)G(x_0, x_1)}{p_0(x_0, x_1)}$$

2. Test for termination

q_i probability of continuation

q_i^* probability of termination

3. Find intersection

$$w_{i+1} = w_i \frac{1}{q_i} \frac{f_r(x_{i-1}, x_i, x_{i+1})G(x_i, x_{i+1})}{p_i(x_i, x_{i+1})}$$

4. Repeat 2

CS348B Lecture 14

Pat Hanrahan, Spring 2000

Classic Path Tracing

This process yields a set of path samples

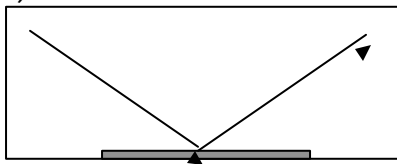
Final estimator

$$w_i = \frac{L_e(x_0, x_1)G(x_0, x_1)}{p_0(x_0, x_1)} W_e(x_{i-1}, x_i) \prod_{j=1}^{i-1} \frac{1}{q_j} \frac{f_r(x_{j-1}, x_j, x_{j+1})G(x_j, x_{j+1})}{p_j(x_j, x_{j+1})}$$

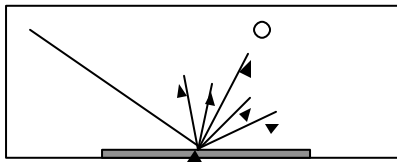
$$E[M] = \frac{1}{N} \sum_{i=1}^N w_i$$

Delta Functions

Mirrors (Caustics)



Point lights



LS*DS*E particularly problematic

Russian Roulette and Splitting

Previous estimators just counted particles

- Termination causes noise

Instead weight the particles by probabilities

- Weighting better, but terminate those with small weights

Russian Roulette

if ($w < wc$)

terminate with probability $1-wc$

if survive, $w=w/wc$

$$E[w] = (1-wc)*0 + wc*(w/wc) = w$$

Splitting

if ($w > wn$)

split into n particles with $w=w/n$

Forward=Backward Estimate

Inner product / Estimated quantity

$$KL = S$$

$$K^+L^+ = R = S^+$$

Justification for eye ray tracing

$$\langle S^+, L \rangle = \langle K^+L^+, L \rangle = \langle L^+, KL \rangle = \langle L^+, S \rangle$$

Self-adjoint

$$K(y, x) = K(x, y) \Rightarrow K^+ = K$$

Adjoint Equations

Estimated quantity

$$\langle f, g \rangle = \int f(x)g(x)dx$$

Original equation

$$Kg = \int K(x, y)g(y)dy$$

Estimated quantity

$$\begin{aligned}\langle f, Kg \rangle &= \int f(x)\left(\int K(x, y)g(y)dy\right)dx \\ &= \int\left(\int f(x)K(x, y)dx\right)g(y)dy \\ &= \langle K^+f, g \rangle\end{aligned}$$

Adjoint equation

$$K^+f = \int K(x, y)f(x)dx$$

Three Consequences

1. Forward estimate equal backward estimate
2. Solve for small subset of the answer
3. Importance sampling paths

Example

Solve a linear system

$$Mx = b$$

Solve for a single x_i ?

von Neumann and Ulam: Solve the adjoint equation

Source x_i

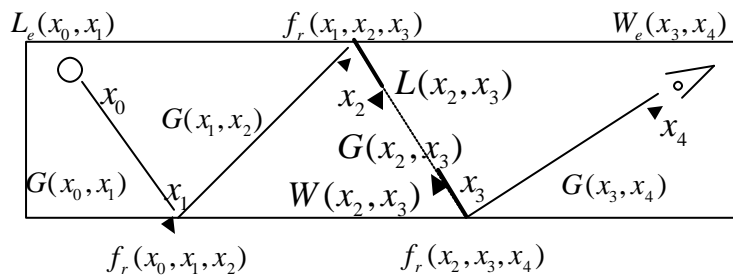
Estimator $\langle (x_i + Mx_i + M^2x_i + \dots), b \rangle$

More efficient than solving the whole system of equations

Applicable to image synthesis! Don't solve if not seen

"Importance"

Importance is the adjoint solution

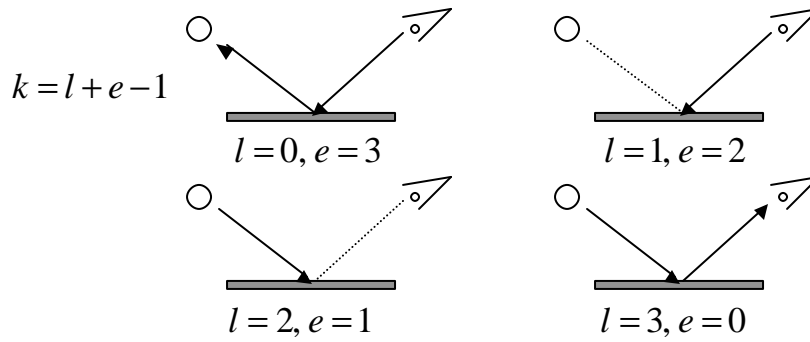


$$L(x_m, x_{m+1}) = \int \int \dots \int_{M^2 M^2 M^2} L_e(x_0, x_1) G(x_0, x_1) f_r(x_0, x_1, x_2) \dots G(x_{m-1}, x_m) f_r(x_{m-1}, x_m, x_{m+1}) dA_0 dA_1 \dots dA_{m-1}$$

$$W(x_m, x_{m+1}) = \int \int \dots \int_{M^2 M^2 M^2} f_r(x_m, x_{m+1}, x_{m+2}) G(x_{m+1}, x_{m+2}) \dots f_r(x_m, x_{m+1}, x_{m+2}) G(x_{k-1}, x_k) W_e(x_{k-1}, x_k) dA_{m+2} dA_{m+3} \dots dA_k$$

$$M = \int \int_{M^2 M^2} L(x_m, x_{m+1}) G(x_m, x_{m+1}) W(x_m, x_{m+1}) dA_m dA_{m+1}$$

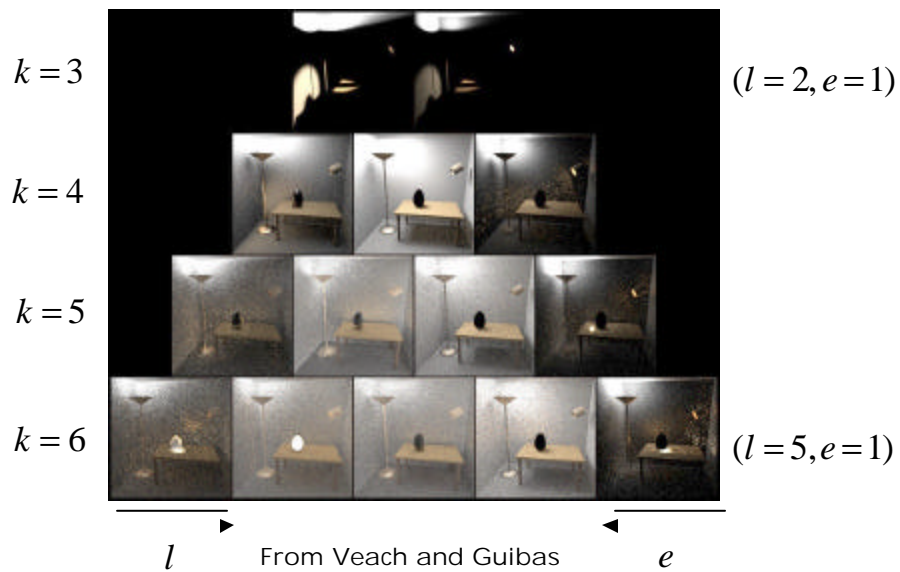
Bidirectional Ray Tracing



CS348B Lecture 14

Pat Hanrahan, Spring 2000

Path Pyramid



CS348B Lecture 14

Pat Hanrahan, Spring 2000

Comparison



Bidirectional ray tracing



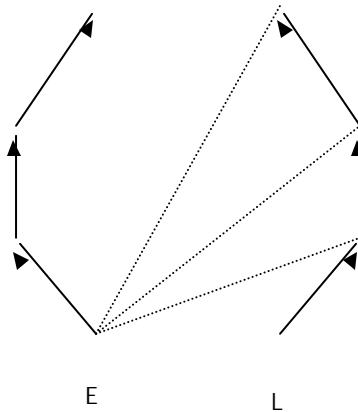
Path tracing

From Veach and Guibas

CS348B Lecture 14

Pat Hanrahan, Spring 2000

Tree of Paths



Efficiently generate a collection of bidirectional paths

CS348B Lecture 14

Pat Hanrahan, Spring 2000