### **Monte Carlo Path Tracing**

### **Today**

- Path tracing starting from the eye
- Path tracing starting from the lights
- Which direction is best?
- Bidirectional ray tracing
- Random walks and Markov chains

#### **Next**

- **■** Irradiance caching
- **■** Photon mapping

CS348B Lecture 14

Pat Hanrahan, Spring 2010

## The Rendering Equation

$$L(x,\omega) = L_e(x,\omega) + \int_{H^2} f_r(x,\omega') \to \omega L(x^*(x,\omega'), -\omega') \cos \theta' d\omega'$$

$$L = L_{e} + K \circ L$$

CS348B Lecture 14

## **Solving the Rendering Equation**

### **Rendering Equation**

$$L = L_e + K \circ L$$
$$(I - K) \circ L = L_e$$

### **Solution**

$$L = (I - K)^{-1} \circ L_e$$

$$= (I + K + K^2 + K^3 + \cdots) \circ L_e$$

$$= (I + K(I + K(I + K \cdots))) \circ L_e$$

CS348B Lecture 14

Pat Hanrahan, Spring 2010

### **Successive Gathers**





 $K \circ L_e$ 



 $K \circ K \circ L_{\rho}$ 



 $K \circ K \circ K \circ L_a$ 





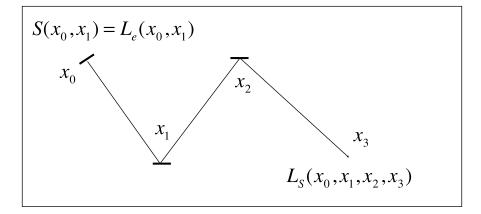




 $L_e + K \circ L_e$   $L_e + \cdots K^2 \circ L_e$   $L_e + \cdots K^3 \circ L_e$ 

CS348B Lecture 14

## **Light Path**



CS348B Lecture 14

Pat Hanrahan, Spring 2010

## **Light Path**

$$S(x_{0},x_{1}) \qquad f_{r}(x_{1},x_{2},x_{3})$$

$$X_{0} \qquad X_{1} \qquad X_{2}$$

$$G(x_{0},x_{1}) \qquad X_{1} \qquad X_{1}$$

$$f_{r}(x_{0},x_{1},x_{2}) \qquad L_{S}(x_{0},x_{1},x_{2},x_{3})$$

$$L_{S}(x_{0}, x_{1}, x_{2}, x_{3}) = S(x_{0}, x_{1})G(x_{0}, x_{1})f_{r}(x_{0}, x_{1}, x_{2})G(x_{1}, x_{2})f_{r}(x_{1}, x_{2}, x_{3})$$

CS348B Lecture 14

### **Solving the Rendering Equation**

### One path

$$L_s(x_0, x_1, x_2, x_3) = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)$$

Solution is the integral over all paths

$$L(x_{k-1},x_k)$$

$$= \sum_{k=1}^{\infty} \int_{M^2} \cdots \int_{M^2} L_S(x_0, \dots, x_{k-2}, x_{k-1}, x_k) dA(x_0) \cdots dA(x_{k-2})$$

**Solve using Monte Carlo Integration** 

Question: How to generate a random path?

CS348B Lecture 14

Pat Hanrahan, Spring 2010

## Path Tracing from the Eye

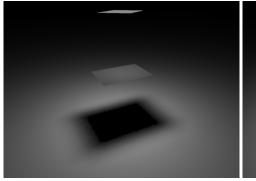
## **Path Tracing: From Camera**

```
Step 1. Choose a camera ray r given the
  (x, y, u, v, t) sample
    weight = 1;
Step 2. Find ray-surface intersection
Step 3.
  if hit light
    return weight * Le(r);
else
    weight *= reflectance(r)
    Choose new ray r' ~ BRDF(O|I)
    Go to Step 2.
```

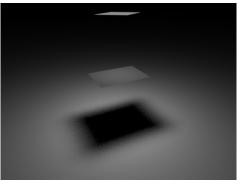
CS348B Lecture 14

Pat Hanrahan, Spring 2010

### Penumbra: Trees vs. Paths

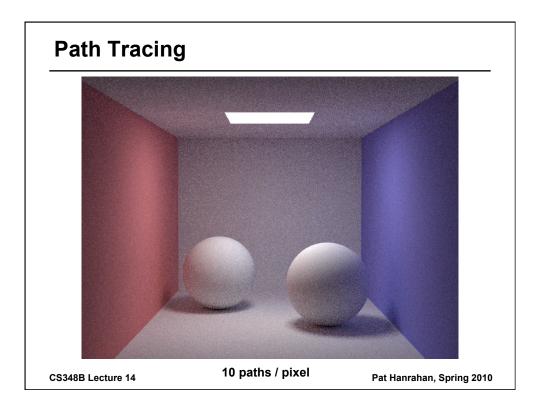


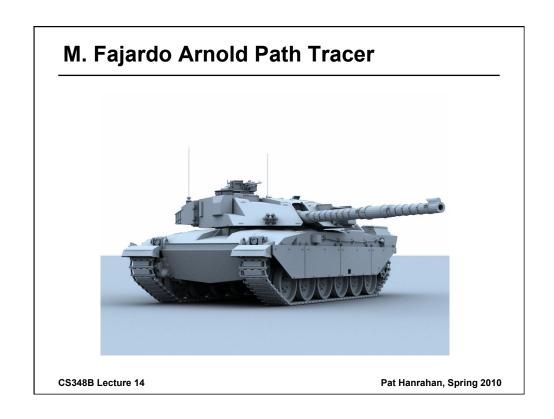
4 eye rays per pixel 16 shadow rays per eye ray



64 eye rays per pixel 1 shadow ray per eye ray

CS348B Lecture 14





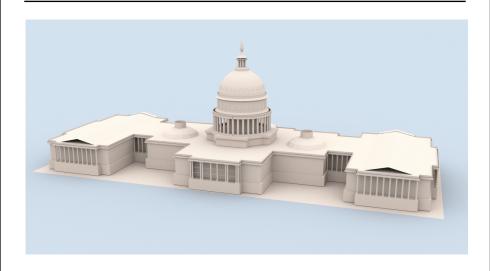
# M. Fajardo Arnold Path Tracer



CS348B Lecture 14

Pat Hanrahan, Spring 2010

# M. Fajardo Arnold Path Tracer



CS348B Lecture 14



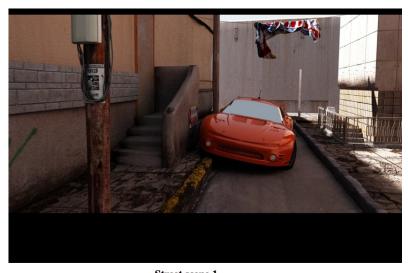


# M. Fajardo Arnold Path Tracer



CS348B Lecture 14

## M. Fajardo Arnold Path Tracer



Street scene 1
1536x654, 16 paths/pixel, 2 bounces, 250,000 faces, 18 min., dual PIII-800
CS348B Lecture 14
Pat Hanrahan, Spring 2010

## **How Many Bounces?**

Avoid paths that carry little energy

Terminate when the weight is low

Photons with similar power is a good thing Think of importance sampling Integrand is f(x)/p(x) which is constant

CS348B Lecture 14

### **Russian Roulette**

Terminate photon with probability pAdjust weight of the result by 1/(1-p)

$$E(X) = p \cdot 0 + (1-p) \frac{E(X)}{1-p} = E(X)$$

Intuition:

Reflecting from a surface with R=.5

100 incoming photons with power 2 W

- 1. Reflect 100 photons with power 1 W
- 2 Reflect 50 photons with power 2 W

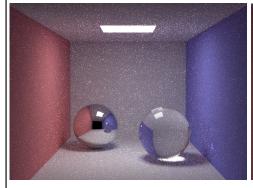
CS348B Lecture 14

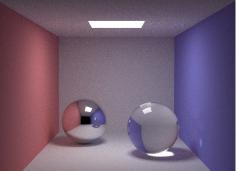
Pat Hanrahan, Spring 2010

### **Path Tracing: Include Direct Lighting**

```
Step 1. Choose a camera ray r given the
  (x,y,u,v,t) sample
  weight = 1;
  L = 0
Step 2. Find ray-surface intersection
Step 3.
  L += weight * Sum (fr * Le(light))
  weight *= reflectance(x)
  Choose new ray r' ~ BRDF pdf(r)
  Go to Step 2.
CS348B Lecture 14
Pat Hanrahan, Spring 2010
```

## **Variance Decreases with N**





10 rays per pixel

100 rays per pixel

From Jensen, Realistic Image Synthesis Using Photon Maps

CS348B Lecture 14

Pat Hanrahan, Spring 2010

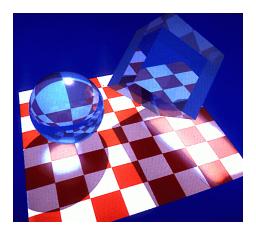
# **Fixed Sampling (Not Random Enough)**



CS348B Lecture 14

# **Light Ray Tracing**

# Early Example [Arvo, 1986]



"Backward" ray tracing

CS348B Lecture 14

### **Path Tracing: From Lights**

```
Step 1. Choose a light ray.
  Choose a ray from the light source
  distribution function
  x ~ p(x)
  d ~ p(d|x)
  r = (x, d)
  weight = Φ;
```

CS348B Lecture 14

Pat Hanrahan, Spring 2010

### **Path Tracing: From Lights**

```
Step 1. Choose a light ray

Step 2. Find ray-surface intersection

Step 3. Reflect or transmit

u = Uniform()

if u < reflectance(x)

Choose new direction d ~ BRDF(O|I)

goto Step 2

else u < reflectance(x)+transmittance(x)

Choose new direction d ~ BTDF(O|I)

goto Step 2

else // absorption=1-reflectance-transmittance

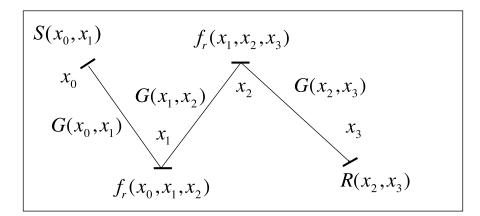
terminate on surface; deposit energy

CS348B Lecture 14

Pat Hanrahan, Spring 2010
```

## **Bidirectional Path Tracing**

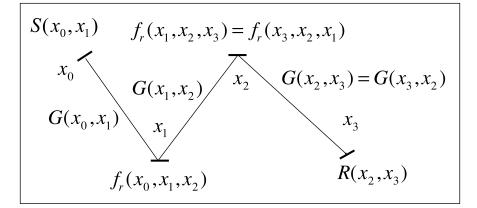
## **Symmetric Light Path**



$$M = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3)$$

CS348B Lecture 14

## Symmetric Light Path

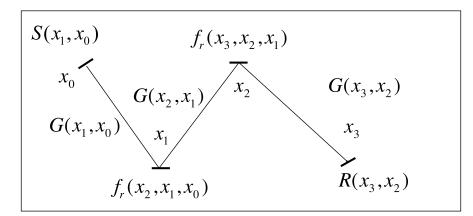


$$M = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3)$$

CS348B Lecture 14

Pat Hanrahan, Spring 2010

## **Symmetric Light Path**



$$M = R(x_3, x_2)G(x_3, x_2)f_r(x_3, x_2, x_1)G(x_2, x_1)f_r(x_2, x_1, x_0)G(x_1, x_0)S(x_1, x_0)$$

CS348B Lecture 14

## **Bidirectional Ray Tracing**

$$k = l + e$$

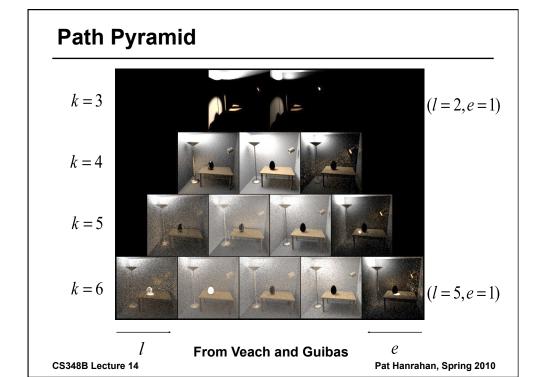
$$l = 0, e = 3$$

$$l = 1, e = 2$$

$$l = 3, e = 0$$

$$k = 3$$

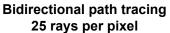
CS348B Lecture 14



## Comparison

#### Same amount of time







Path tracing 56 rays per pixel

From Veach and Guibas

CS348B Lecture 14

Pat Hanrahan, Spring 2010

### Which Direction?

Solve a linear system Mx = b

Solve for a single  $x_i$ ?

Solve the reverse equation

Source  $\chi$ 

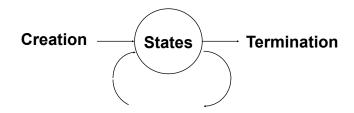
Estimator  $\langle (x_i + Mx_i + M^2x_i + \cdots), b \rangle$ 

More efficient than solving for all the unknowns [von Neumann and Ulam]

CS348B Lecture 14

### **Discrete Random Walk**

### **Discrete Random Process**



Transition

### Assign probabilities to each process

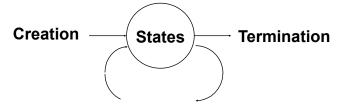
 $p_i^0$ : probability of creation in state i

 $p_{i,j}$ : probability of transition from state  $i \rightarrow j$ 

 $p_i^*$ : probability of termination in state i  $p_i^* = 1 - \sum_j p_{i,j}$ 

CS348B Lecture 14

### **Discrete Random Process**



**Transition** 

Equilibrium number of particles in each state

$$P_i = \sum_j p_{i,j} P_j + p_i^0 \qquad M_{i,j} = p_{i,j}$$

$$P = MP + p^0$$

CS348B Lecture 14

Pat Hanrahan, Spring 2010

## **Equilibrium Distribution of States**

Total probability of being in states P

Solve this equation

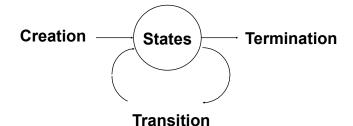
$$(I - M)P = p^{0}$$

$$P = (I - M)^{-1} p^{0}$$

$$= (I + M + M^{2} + \cdots)p^{0}$$

CS348B Lecture 14

### **Discrete Random Walk**



- 1. Generate random particles from sources.
- 2. Undertake a discrete random walk.
- 3. Count how many terminate in state i

[von Neumann and Ulam; Forsythe and Leibler; 1950s]

CS348B Lecture 14

Pat Hanrahan, Spring 2010

## **Monte Carlo Algorithm**

Define a random variable on the space of paths

**Path:**  $\alpha_{k} = (i_{1}, i_{2}, ..., i_{k})$ 

**Probability:**  $P(\alpha_k)$ 

**Estimator:**  $W(\alpha_k)$ 

**Expectation:** 

$$E[W] = \sum_{k=1}^{\infty} \sum_{\alpha_k} P(\alpha_k) W(\alpha_k)$$

CS348B Lecture 14

## **Monte Carlo Algorithm**

Define a random variable on the space of paths

Probability: 
$$P(\alpha_{\scriptscriptstyle k}) = p_{\scriptscriptstyle i_1}^{\scriptscriptstyle 0} \times p_{\scriptscriptstyle i_1,i_2} \cdots p_{\scriptscriptstyle i_{k-1},i_k} \times p_{\scriptscriptstyle i_k}^*$$

Estimator: 
$$W_{j}(\alpha_{k}) = \frac{\delta_{i_{k},j}}{p_{i_{k}}^{*}}$$

CS348B Lecture 14

Pat Hanrahan, Spring 2010

### **Estimator**

Count the number of particles terminating in state j

$$E[W_{j}] = \sum_{k=1}^{\infty} \sum_{i_{k}} \cdots \sum_{i_{1}} (p_{i_{1}}^{0} p_{i_{1}, i_{2}} \cdots p_{i_{k-1}, i_{k}} p_{i_{k}}^{*}) \frac{\delta_{i_{k}, j}}{p_{j}^{*}}$$

$$= \left[ p^{0} \right]_{j} + \left[ M p^{0} \right]_{j} + \left[ M^{2} p^{0} \right]_{j} \cdots$$

CS348B Lecture 14

## **Equilibrium Distribution of States**

Total probability of being in states P

$$P = (I + M + M^2 + \cdots)p^0$$

Note that this is the solution of the equation

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

Thus, the discrete random walk is an unbiased estimate of the equilibrium number of particles in each state

CS348B Lecture 14