

Monte Carlo Path Tracing

Today

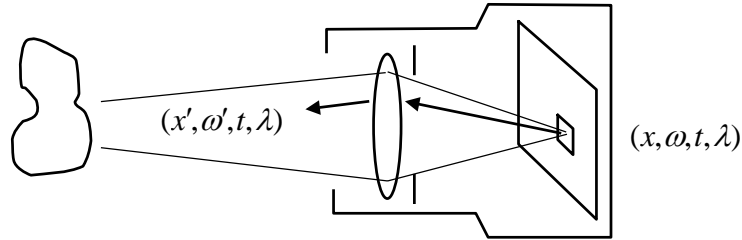
- Path tracing
- Random walks and Markov chains
- Adjoint equations
- Light ray tracing
- Bidirectional ray tracing

Next – Henrik Wann Jensen

- Irradiance caching
- Photon mapping

Path Tracing

The Measurement Equation



$$R = \iiint P(x, \lambda') S(x, \omega, t) L(T(x, \omega, \lambda), t, \lambda) d\vec{A} \bullet d\vec{\omega} dt d\lambda$$

Pixel response	$P(x, \lambda)$
Lens optics	$(x', \omega') = T(x, \omega, \lambda)$
Shutter	$S(x, \omega, t)$
Scene radiance	$L(x, \omega, t, \lambda)$

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Light Transport

Integrate over all paths of all lengths

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

Questions

- How to sample space of paths
- Find good estimators

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Path Tracing: From Camera

Step 1. Choose a ray given (x, y, u, v, t)

weight = 1;

Step 2. Trace ray

Step 3. Randomly choose to compute L_e or L_r

Step 3a. If L_e ,

return weight * L_e ;

Step 3b. If L_r ,

weight = weight * reflectance;

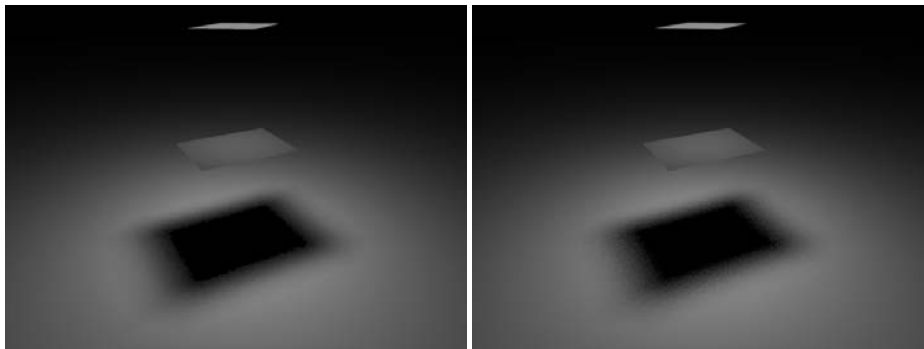
Choose new ray \sim BRDF pdf

Go to Step 2.

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Penumbra: Trees vs. Paths



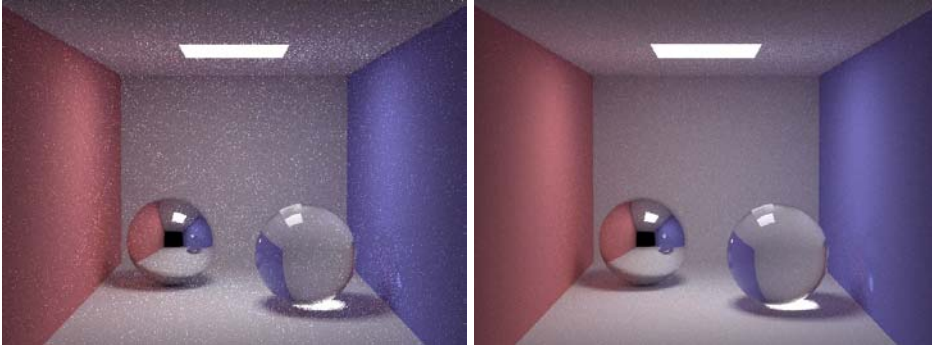
4 eye rays per pixel
16 shadow rays per eye ray

64 eye rays per pixel
1 shadow ray per eye ray

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Cornell Box: Path Tracing



10 rays per pixel

100 rays per pixel

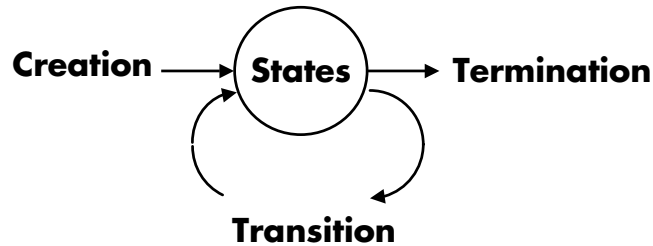
From Jensen, Realistic Image Synthesis Using Photon Maps

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Discrete Random Walk

Discrete Random Process



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

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Markov Chain

Probability of being in state i after n transitions

$$P_j^0 = p_j^0$$

$$P^0 = p^0$$

$$P_j^1 = p_j^0 + \sum_i p_{i,j} P_i^0$$

$$P^1 = p^0 + MP^0$$

\vdots

$$M_{i,j} = p_{i,j}$$

$$P_j^n = p_j^0 + \sum_i p_{i,j} P_i^{n-1}$$

$$P^n = p^0 + MP^{n-1}$$

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Equilibrium Distribution of States

Total probability of being in state i

$$P_i = \sum_{k=0}^{\infty} P_i^k = (I + M + M^2 + \dots) p^0$$

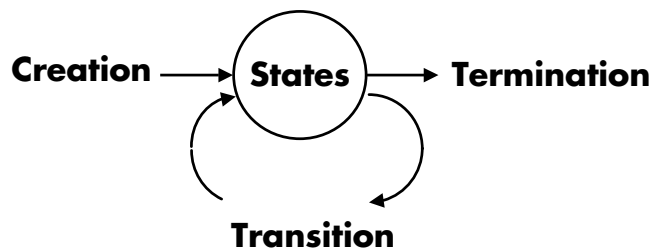
But this is the solution of the matrix equation

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

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Monte Carlo Algorithm



1. Generate random particle paths from source.
2. Undertake a discrete random walk.
3. Count how many terminate in state i

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

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Monte Carlo Algorithm: Analysis

Define a random variable on the space of paths

Path: $\alpha_k = (i_1, i_2, \dots, i_k)$

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

Monte Carlo Algorithm

Define a random variable on the space of paths

Path: $\alpha_k = (i_1, i_2, \dots, i_k)$

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

Expectation:

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

Estimator

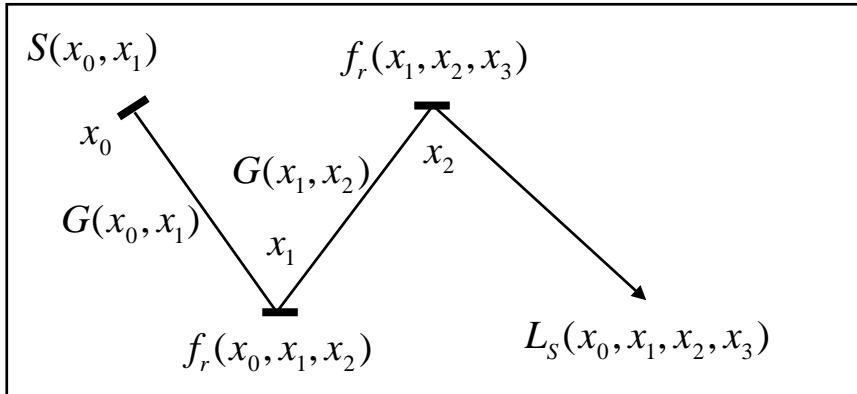
Count the number of particles terminating in state j

Estimator: $W_j(\alpha_k) = \frac{\delta_{i_k, j}}{P_{i_k}^*}$

Unbiased:
$$E[W_j] = \sum_{k=1}^{\infty} \sum_{i_k} \cdots \sum_{i_1} (p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} p_{i_k}^*) \frac{\delta_{i_k, j}}{P_j^*}$$
$$= [P^0]_j + [Mp^0]_j + [M^2 p^0]_j \cdots$$

Adjoint Formulation

Light Path

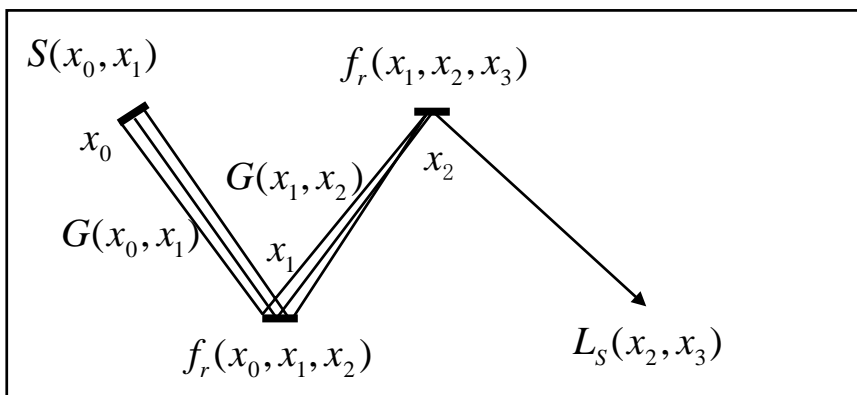


$$L_S(x_0, x_1, x_2, x_3) = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)$$

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Light Paths

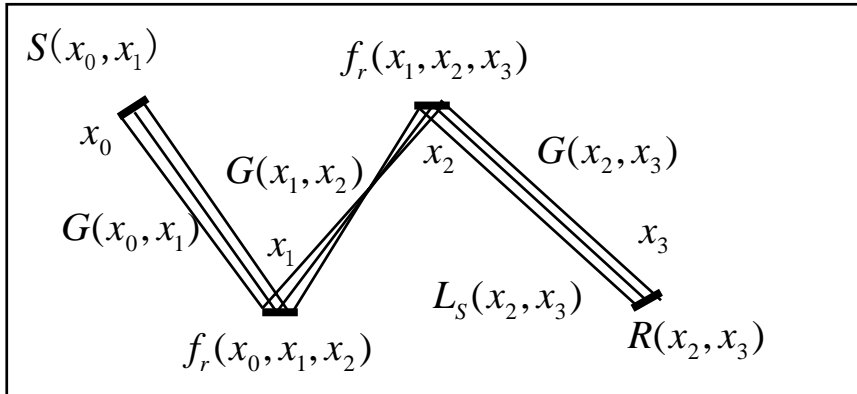


$$L_S(x_2, x_3) = \int_{M^2} \int_{M^2} L_S(x_0, x_1, x_2, x_3) dA(x_0) dA(x_1)$$

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Measurement

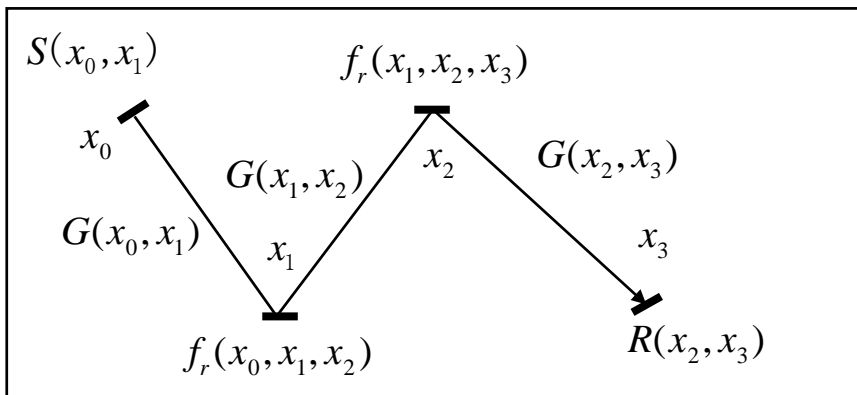


$$M = \int_{M^2} \int_{M^2} L_s(x_2, x_3) G(x_2, x_3) R(x_2, x_3) dA(x_2) dA(x_3)$$

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Symmetric Light Path

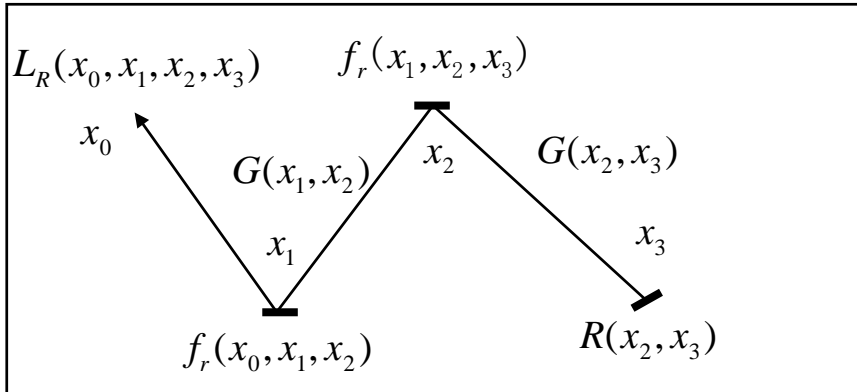


$$M = S(x_0, x_1) G(x_0, x_1) f_r(x_0, x_1, x_2) G(x_1, x_2) f_r(x_1, x_2, x_3) G(x_2, x_3) R(x_2, x_3)$$

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Symmetry

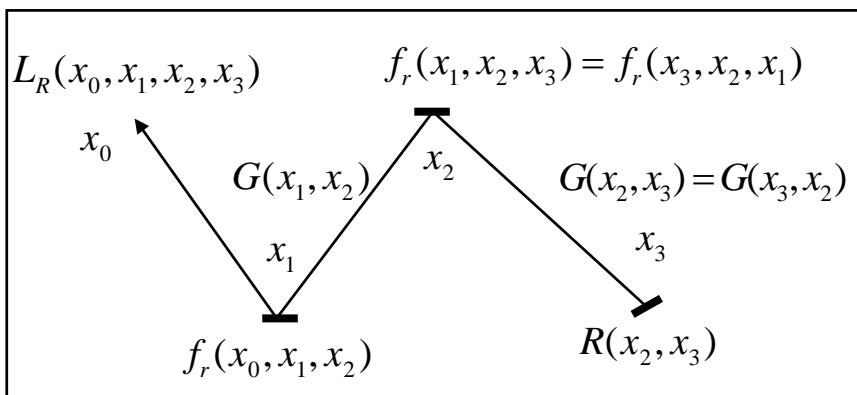


$$L_R(x_0, x_1, x_2, x_3) = f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3)$$

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Symmetry

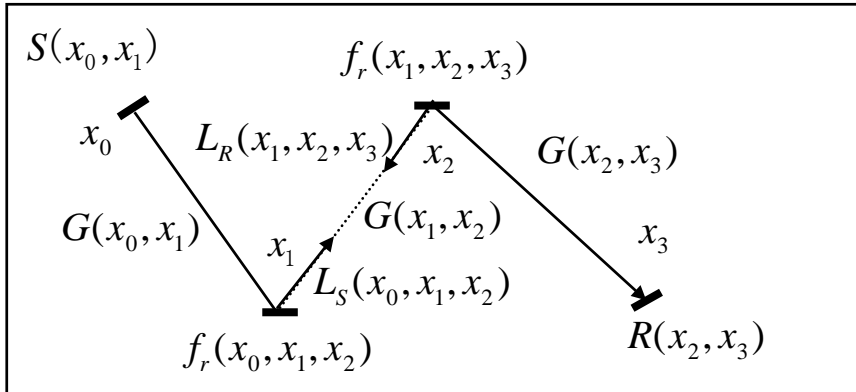


$$\begin{aligned} L_R(x_0, x_1, x_2, x_3) &= f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3) \\ &= R(x_3, x_2)G(x_3, x_2)f_r(x_3, x_2, x_1)G(x_2, x_1)f_r(x_2, x_1, x_0) \end{aligned}$$

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Importance



$$M = \int_{M^2} \int_{M^2} L_S(x_0, x_1, x_2) G(x_1, x_2) L_R(x_1, x_2, x_3) dA(x_1) dA(x_2)$$

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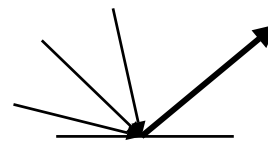
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Adjoint Equations

Original equation

$$K \circ f = \int K(x, y) f(y) dy$$

Forward direction

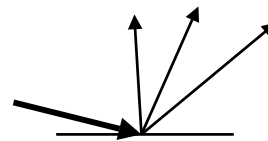


Out-Scatter

Adjoint equation

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

Backward direction



In-Scatter

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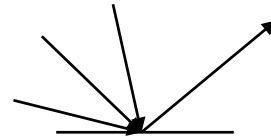
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Self-Adjoint Equations

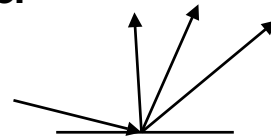
Self-adjoint

$$K^+ = K$$

Forward = backward operator



Out-Scatter



In-Scatter

Forward = Backward Estimate

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

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

Three Consequences

1. **Forward estimate equal backward estimate**
 - May use forward or backward ray tracing
2. **Adjoint solution**
 - Importance sampling paths
3. **Solve for small subset of the answer**

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Example: Linear Equations

Solve a linear system $Mx = b$

Solve for a single x_i ?

Solve the adjoint equation

Source x_i

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

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

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Light Ray Tracing

Path Tracing: From Lights

Step 1. Choose a light ray

Step 2. Trace ray

Step 3. Randomly decide whether to absorb or
reflect the ray ~ reflectance

if reflected

goto Step 2

Path Tracing: From Lights

Step 1. Choose a light ray

Choose a light source according to the
light source power distribution function.

Choose a ray from the light source
radiance (area) or intensity (point)
distribution function

weight = 1;

Step 2. Trace ray

Step 3. Randomly decide whether to absorb or
reflect the ray

if reflected

goto Step 2

Path Tracing: From Lights

Step 1. Choose a light ray

Step 2. Trace ray

Step 3. Randomly decide whether to absorb or
reflect the ray ~ reflectance

Step 3a. If reflected,

Randomly scatter ~ BRDF pdf

Go to Step 2.

Step 3b. If absorbed at the camera,

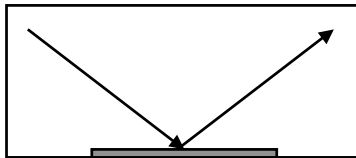
Record weight at x, y

Go to Step 1;

Bidirectional Ray Tracing

Delta Functions

Mirrors (Caustics)



Eye ray tracing: ES^*DL

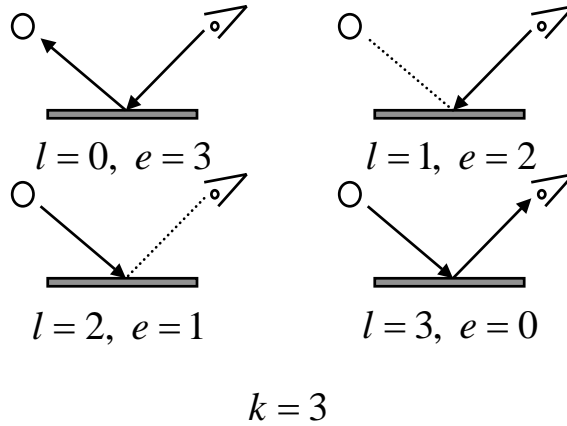
Light ray tracing: LS^*DE

ES^*DS^*L problematic (virtual point light source)

Even more problematic is $LS^*DS^*DS^*E$

Bidirectional Ray Tracing

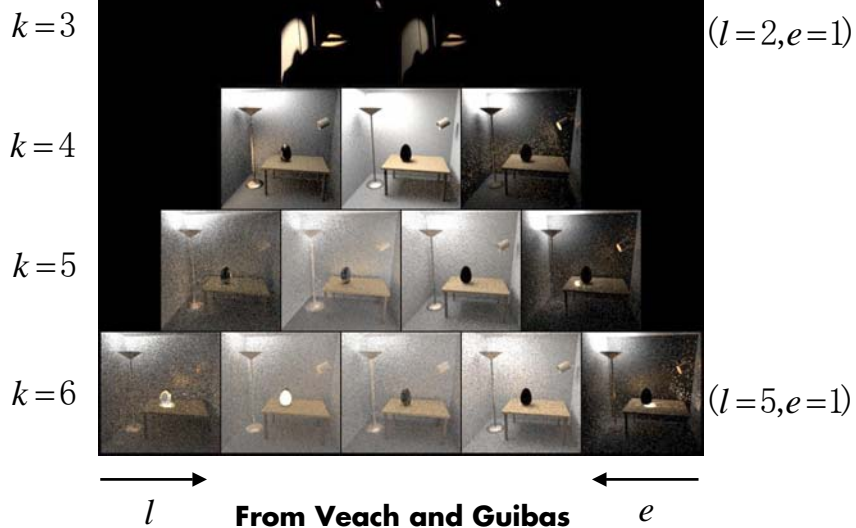
$$k = l + e$$



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Path Pyramid



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Comparison



Bidirectional ray tracing



Path tracing

From Veach and Guibas

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