Welcome!

Lecture 8 - “Variance Reduction”
Today's Agenda:

- Introduction
- Stratification
- Next Event Estimation
- Importance Sampling
- MIS
Introduction

Previously in Advanced Graphics
Introduction
Introduction

Today in Advanced Graphics:

- Stratification
- Next Event Estimation
- Importance Sampling
- Multiple Importance Sampling
- Resampled Importance Sampling*

Aim:

- to get a better image with the same number of samples
- to increase the efficiency of a path tracer
- to reduce variance in the estimate

Requirement:

- produce the correct image

*: If time permits
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Stratification

Uniform Random Sampling

To sample a light source, we draw two random values in the range 0..1.

The resulting 2D positions are not uniformly distributed over the area.

We can improve uniformity using *stratification*: one sample is placed in each stratum.
Uniform Random Sampling

To sample a light source, we draw two random values in the range 0..1.

The resulting 2D positions are not uniformly distributed over the area.

We can improve uniformity using **stratification**: one sample is placed in each stratum.

For 4x4 strata:

\[
\text{stratum}_x = (\text{idx} \mod 4) \times 0.25 \quad \text{if} \quad \text{idx} = 0..15
\]

\[
\text{stratum}_y = (\text{idx} / 4) \times 0.25
\]

\[
r_0 = \text{Rand()} \times 0.25
\]

\[
r_1 = \text{Rand()} \times 0.25
\]

\[
P = \text{vec2}( \text{stratum}_x + r_0, \text{stratum}_y + r_1 )
\]
Stratification
Stratification

Use Cases

Stratification can be applied to any Monte Carlo process:

- Anti-aliasing (sampling the pixel)
- Depth of field (sampling the lens)
- Motion blur (sampling time)
- Soft shadows (sampling area lights)
- Diffuse reflections (sampling the hemisphere)

However, there are problems:

- We need to take one sample per stratum
- Stratum count: higher is better, but with diminishing returns
- Combining stratification for e.g. depth of field and soft shadows leads to correlation of the samples, unless we stratify the 4D space - which leads to a very large number of strata: the curse of dimensionality.
Troubleshooting Path Tracing Experiments

When experimenting with stratification and other variance reduction methods you will frequently produce incorrect images.

Tip:

Keep a simple reference path tracer without any tricks. Compare your output to this reference solution frequently.
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```plaintext
L (depth < POW2DEPTH)

\( c = \text{ inside } \) ? \( \text{ INSIDE} \) : \( \text{ OUTSIDE} \)

\( r = \text{ NT } \cdot \text{ (0, 0, 1) } \)
\( n = \text{ NT } \cdot \text{ norm} \cdot \text{ (0, 0, 1) } \)
\( n = \text{ LNF } \cdot \text{ norm} \cdot \text{ (0, 0, 1) } \)
\( n \)

\( n = \text{ NT } \cdot \text{ (0, 0, 1) } \)
\( r = \text{ NT } \cdot \text{ norm} \cdot \text{ (0, 0, 1) } \)
\( E = \text{ diffuse} \)
\( E = \text{ true} \)
\( \text{ ref} \) \& \& \( \text{ depth} < \text{ POW2DEPTH} \)
\( \text{ ref} \) \& \& \( \text{ diffuse} \)
\( \text{ true} \)

\( \text{ NADENIPHER} \)
\( \text{ Survive } = \text{ SurviveProbability}(\text{ diffuse} \) estimation --> doing it properly, check)
\( \text{ radiance } = \text{ SampleLight}(\text{ Brand }, \text{ R }, \text{ RLIGHT}) \)
\( \text{ radiance } = \text{ SampleLight}(\text{ Brand }, \text{ R }, \text{ RLIGHT}) \)
\( \text{ radiance } + \text{ radiance} ) > \text{ R } \& \& \text{ (color} \text{ R} \text{)}
\( \text{ true} \)
\( \text{ Refractive } = \text{ EvaluateRefract} (\text{ L, N }) \) * \text{ Pencil}:
\( \text{ atc factor } = \text{ diffuse } = \text{ INV23} \)
\( \text{ weight } = \text{ Mi2} (\text{ directfr }, \text{ refract}) \)
\( \text{ weight } = \text{ Mi2} (\text{ directfr }, \text{ refract}) \)
\( \text{ E } = \text{ (weight } \cdot \text{ cosThetaMax) } / \text{ directPDF } \) * (radiance)
\( \text{ random walk } = \text{ done properly, closely following specular diffuse)

\( \text{ E = } \text{ bpdf } \times \text{ pdfd } \times \text{ pdfd}\)
Next Event Estimation

Recall the rendering equation:
\[ L_o(x, \omega_o) = L_E(x, \omega_o) + \int_{\Omega} f_r(x, \omega_o, \omega_i) L_i(x, \omega_i) \cos \theta_i \ d\omega_i \]

Also recall that we had two ways to sample direct illumination:

- Integrating over the hemisphere
- Integrating over the lights

Can we apply this to the full rendering equation, instead of just direct illumination?
Incoming direct light

\[ \int_{\Omega} L_d(x, \omega_i) \, d\omega_i \]

\[ = \text{intensity} \ast \pi \ast 2 \]

\[ \approx \frac{2\pi}{N} \sum_{i=1}^{N} L_d(p, \Omega_i) \]

\[ x \]

\[ -\frac{1}{2}\pi \]

\[ \frac{1}{2}\pi \]
Incoming direct light

\[ I = \int_{\Omega} L_d(x, \omega_i) \, d\omega_i \]

\[ = \text{intensity} \times \pi \times 2 \]

\[ = \frac{2\pi}{N} \sum_{i=1}^{N} L_d(p, \Omega_i) \]
Incoming direct light

\[ \int_{\Omega} L_d(x, \omega_i) \, d\omega_i \approx \frac{2\pi}{N} \sum_{i=1}^{N} L_d(p, \Omega_i) \]

\[ = (B - A) \cdot \text{intensity} + (D - C) \cdot \text{intensity} \]

\[ = \int_{A..B} L_d(x, \omega_i) \, d\omega_i + \int_{C..D} L_d(x, \omega_i) \, d\omega_i \]
Incoming direct + indirect light
Incoming direct + indirect light

\[-\frac{1}{2}\pi\]
Next Event Estimation

Observation: light travelling via any vertex on the path consists of indirect light and direct light for that vertex.

Next Event Estimation: sampling direct and indirect separately.
Next Event Estimation

Per surface interaction, we trace *two* random rays.

- Ray A returns (via point $x$) the energy reflected by $y$ (estimates indirect light for $x$).
- Ray B returns the direct illumination on point $x$ (estimates direct light on $x$).
- Ray C returns the direct illumination on point $y$, which will reach the sensor via ray A.
- Ray D leaves the scene.
Next Event Estimation

When a ray for indirect illumination stumbles upon a light, the path is terminated and no energy is transported via ray D:

This way, we prevent accounting for direct illumination on point $y$ twice.
Next Event Estimation

We thus split the hemisphere into two distinct areas:

1. The area that has the projection of the light source on it;
2. The area that is not covered by this projection.

We can now safely send a ray to each of these areas and sum whatever we find there.

(or: we integrate over these non-overlapping areas and sum the energy we receive via both to determine the energy we receive over the entire hemisphere)

Area 1:
Send a ray directly to a random light source. Reject it if it hits anything else than the targeted light.

Area 2:
Send a ray in a random direction on the hemisphere. Reject it if it hits a light source.
Next Event Estimation

Color Sample(Ray ray)
{
    // trace ray
    I, N, material = Trace(ray);
    BRDF = material.albedo / PI;
    // terminate if ray left the scene
    if(ray.NOHIT) return BLACK;
    // terminate if we hit a light source
    if(material.isLight) return BLACK;
    // sample a random light source
    L, Nl, dist, A = RandomPointOnLight();
    Ray lr(I, L, dist);
    if(N.L > 0 && Nl.N-L > 0) if(!Trace(lr))
    {
        solidAngle = (Nl.N-L) * A / dist^2;
        Ld = lightColor * solidAngle * BRDF * N.L;
    }
    // continue random walk
    R = DiffuseReflection(N);
    Ray r(I, R);
    Ei = Sample(r) * (N.R);
    return PI * 2.0f * BRDF * Ei + Ld;
}
Advanced Graphics – Variance Reduction

NEE

\begin{verbatim}
C
L (depth < ZBuffers)
R = 0.5 + \text{random} \in [0, 1)
T = \text{random} \in [0, 1)
N = \text{random} \in [0, 1)
\end{verbatim}

\begin{verbatim}
if (T < \text{Inside}) \text{ If } T < 0.5 \text{ Then } E = \text{ diffuse} \text{ Else } E = \text{ Lambertian}
\end{verbatim}

\begin{verbatim}
if (R < \text{diffuse}) = \text{true};
if (R < \text{refr}) = \text{false};
\end{verbatim}

\begin{verbatim}
\text{survive} = \text{SurvivalProbability} \times \text{diffuse};
\end{verbatim}

\begin{verbatim}
\text{radiance} = \text{SampleLight} \times \text{Lambertian} \times \text{diffuse} \times \text{survive} \times \text{area} \times \text{weight};
\end{verbatim}

\begin{verbatim}
\text{if } (E < \text{ weight} \times \text{cosTheta} / \text{directPdf}) \text{ Then SampleDiffuse( diffuse, N, r1, r2, N, E, \text{refr} );}
\end{verbatim}

\begin{verbatim}
\text{else Set} = \text{SampleDirect( diffuse, N, N, \text{refr} );}
\end{verbatim}

\begin{verbatim}
\text{Next} = \text{SampleEmissive( N, \text{refr} );}
\end{verbatim}

\begin{verbatim}
\text{if } (N < \text{weight}) \text{ Then Set = \text{SampleSoft( diffuse, N, \text{refr} );}
\end{verbatim}

\begin{verbatim}
\text{else E} = \text{ Set } \times \text{Lambertian} ;
\end{verbatim}

\begin{verbatim}
\text{end}
\end{verbatim}

Next Event Estimation

Some vertices require special attention:

- If the first vertex after the camera is emissive, its energy can't be reflected to the camera.
- For specular surfaces, the BRDF to a light is always 0.

Since a light ray doesn't make sense for specular vertices, we will include emission from a vertex directly following a specular vertex.

The same goes for the first vertex after the camera: if this is emissive, we will also include this.

*This means we need to keep track of the type of the previous vertex during the random walk.*
Color Sample( Ray ray, bool lastSpecular )
{
    // trace ray
    I, N, material = Trace( ray );
    BRDF = material.albedo / PI;
    // terminate if ray left the scene
    if (ray.NOHIT) return BLACK;
    // terminate if we hit a light source
    if (material.isLight)
        if (lastSpecular) return material.emissive;
        else return BLACK;
    // sample a random light source
    L, Nl, dist, A = RandomPointOnLight();
    Ray lr( I, L, dist );
    if (N.L > 0 && Nl.--L > 0) if (!Trace( lr ))
        {
            solidAngle = ((Nl.--L) * A) / dist^2;
            Ld = lightColor * solidAngle * BRDF * N.L;
        }
    // continue random walk
    R = DiffuseReflection( N );
    Ray r( I, R );
    Ei = Sample( r, false ) * (N.R);
    return PI * 2.0f * BRDF * Ei + Ld;
}
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Importance Sampling

Importance Sampling for Monte Carlo

Monte Carlo integration:

\[
V_A = \int_A^B f(x) \, dx = E(f(X)) \approx \frac{B - A}{N} \sum_{i=1}^{N} f(X)
\]

Example 1: rolling two dice \(D_1\) and \(D_2\), the outcome is \(6D_1 + D_2\). What is the expected value of this experiment? (average die value is 3.5, so the answer is of course \(3.5 \times 6 + 3.5 = 24.5\))

Using Monte Carlo:

\[
V = \frac{1}{N} \sum_{i=1}^{N} f(D_1) + g(D_2) \quad \text{where:} \quad D_1, D_2 \in \{1,2,3,4,5,6\}, \quad f(x) = 6x, \quad g(x) = x
\]
Importance Sampling for Monte Carlo

Changing the experiment slightly: each sample is one roll of one die.

Using Monte Carlo:

\[
V = \frac{1}{N} \sum_{i=1}^{N} f(T, D) \cdot 0.5
\]

where: \( D \in \{1,2,3,4,5,6\} \), \( T \in \{0,1\} \), \( f(t, d) = (5t + 1) \cdot d \)

\[0.5: \text{Probability of using die } T.\]
Importance Sampling

Importance Sampling for Monte Carlo

What happens when we don't pick each die with the same probability?

```cpp
for( int i = 0; i < 1000; i++ )
{
    int D = IRand( 6 ) + 1;
    float r = Rand(); // uniform 0..1
    int T = (r < 0.8f) ? 0 : 1;
    float p = (T == 0) ? 0.8f : 0.2f;
    float f = (float)((5 * T + 1) * D) / p;
    total += f;
    rolls++;
}
```

- we get the correct answer;
- we get lower variance.
Importance Sampling

Importance Sampling for Monte Carlo

Example 2: sampling two area lights.

Sampling the large light with a greater probability yields a better estimate.
Importance Sampling

Importance Sampling for Monte Carlo

Example 3: sampling an integral.

Considering the previous experiments, which stratum should be sample more often?
Importance Sampling for Monte Carlo

Example 3: sampling an integral.

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Importance Sampling

Importance Sampling for Monte Carlo

Example 3: sampling an integral.

Considering the previous experiments, which stratum should be sample more often?

When using 8 strata and a uniform random distribution, each stratum will be sampled with a 0.125 probability. When using 8 strata and a non-uniform sampling scheme, the sum of the sampling probabilities must be 1. Good sampling probabilities are obtained by simply following the function we’re sampling. Note: we must normalize. We don’t have to use these probabilities; any set of non-zero probabilities will work, but with greater variance. This includes any approximation of the function we’re sampling, whether this approximation is good or not.
Importance Sampling

Importance Sampling for Monte Carlo

Example 3: sampling an integral.

Considering the previous experiments, which stratum should be sample more often?

If we go from 8 to infinite strata, the probability of sampling a stratum becomes 0. This is where we introduce the PDF, or *probability density function*. On a continuous domain, the probability of sampling a specific $X$ is 0. However, we can say that the probability of choosing *any* $X$ in the domain is 1, and the probability of choosing $X$ in the first half of the domain is 0.5. We get this 0.5 by integrating a function $p(x)$ over the domain [0,0.5). Function $p(x)$ is the *probability density*. 
Importance Sampling for Monte Carlo

Example 4: sampling the hemisphere.
Importance Sampling

Importance Sampling for Monte Carlo

Example 4: sampling the hemisphere.
Importance Sampling

Importance Sampling for Monte Carlo

Monte Carlo without importance sampling:

\[ E(f(X)) \approx \frac{1}{N} \sum_{i=1}^{N} f(X) \]

With importance sampling:

\[ E(f(X)) \approx \frac{1}{N} \sum_{i=1}^{N} \frac{f(X_i)}{p(X_i)} \]

Here, \( p(x) \) is the probability density function (PDF).
Importance Sampling

Probability Density Function

Properties of a valid PDF $p(x)$:

1. $p(x) > 0$ for all $x \in D$ where $f(x) \neq 0$
2. $\int_D p(x) d\mu(x) = 1$

*Note: $p(x)$ is a density, not a probability; it can (and will) exceed 1 for some $x$.*

Applied to direct light sampling:

$p(x) = C$ for the part of the hemisphere covered by the light source

$\Rightarrow C = 1 / \text{solid angle to ensure } p(x) \text{ integrates to 1}$

$\Rightarrow$ Since samples are divided by $p(x)$, we multiply by $(1/(1/\text{solid angle}))$: 

$$L_o(p, \omega_i) \approx \text{lights} \times \frac{1}{N} \sum_{i=1}^{N} f_r(p, \omega_o, P) L_d'(p, P) V(p \leftrightarrow P) \frac{\Delta t_i}{d} \cos \theta_i \cos \theta_o \frac{1}{\| p - P \|^2}$$
Importance Sampling

Probability Density Function

Applied to hemisphere sampling:

Light arriving over the hemisphere is cosine weighted.

➔ Without further knowledge of the environment, the ideal PDF is the cosine function.

\[
PDF: \quad p(\theta) = \cos \theta
\]

Question: how do we normalize this?

\[
\int_{\Omega} \cos \theta \, d\theta = \pi \quad \Rightarrow \quad \int_{\Omega} \frac{\cos \theta}{\pi} \, d\theta = 1
\]

Question: how do we chose random directions using this PDF?
Importance Sampling

Cosine-weighted Random Direction

Without deriving this in detail:

A cosine-weighted random distribution is obtained by generating points on the unit disc, and projecting the disc on the unit hemisphere. In code:

```c
float3 CosineWeightedDiffuseReflection()
{
    float r0 = Rand(), r1 = Rand();
    float r = sqrt( r0 );
    float theta = 2 * PI * r1;
    float x = r * cosf( theta );
    float y = r * sinf( theta );
    return float3( x, y, sqrt( 1 - r0 ) );
}
```

Note: you still have to transform this to tangent space.
Importance Sampling

```cpp
Color Sample(Ray ray) {
    // trace ray
    I, N, material = Trace(ray);
    // terminate if ray left the scene
    if (ray.NOHIT) return BLACK;
    // terminate if we hit a light source
    if (material.isLight) return emittance;
    // continue in random direction
    R = DiffuseReflection(N);
    Ray r(I, R);
    // update throughput
    BRDF = material.albedo / PI;
    PDF = 1 / (2 * PI);
    Ei = Sample(r) * (N ∙ R) / PDF;
    return BRDF ∙ Ei;
}
```
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END of “Variance Reduction”
next lecture: “Various”