Sampling and Reconstruction

Digital Image Synthesis

Yung-Yu Chuang

10/26/2005

with slides by Pat Hanrahan, Torsten Moller and Brian Curless
Sampling theory

- Sampling theory: the theory of taking discrete sample values \((grid\ of\ color\ pixels)\) from functions defined over continuous domains \((incident\ radiance\ defined\ over\ the\ film\ plane)\) and then using those samples to reconstruct new functions that are similar to the original (reconstruction).

**Sampler**: selects sample points on the image plane

**Filter**: blends multiple samples together
Aliasing

- Reconstruction generates an approximation to the original function. Error is called aliasing.

**sampling**

**sample value**

**reconstruction**

**sample position**
Sampling in computer graphics

• Artifacts due to sampling - Aliasing
  – Jaggies
  – Moire
  – Flickering small objects
  – Sparkling highlights
  – Temporal strobing (such as Wagon-wheel effect)

• Preventing these artifacts - Antialiasing
Jaggies

Retort sequence by Don Mitchell

Staircase pattern or jaggies
Moire pattern

- Sampling the equation
  \[ \sin(x^2 + y^2) \]
Fourier transforms

- Most functions can be decomposed into a weighted sum of shifted sinusoids.
- Each function has two representations
  - Spatial domain - normal representation
  - Frequency domain - spectral representation
- The *Fourier transform* converts between the spatial and frequency domain

\[
\begin{align*}
F(\omega) &= \int_{-\infty}^{\infty} f(x)e^{-i\omega x} \, dx \\
\Leftrightarrow f(x) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega)e^{i\omega x} \, d\omega
\end{align*}
\]
Fourier analysis

**spatial domain**

\[ \cos(2\pi ax) \]

**frequency domain**

\[ \cos(2\pi bx) \]
Fourier analysis

**spatial domain**

- $II(x)$

**frequency domain**

- $\text{sinc}(s)$
- $\text{gauss}(x; \sigma)$
- $\text{gauss}(s; 1/\sigma)$
- $\text{gauss}(x; 1/\sigma)$
- $\text{gauss}(s; \sigma)$
Fourier analysis

spatial domain

frequency domain
Convolution

- **Definition**

\[ h(x) = f \otimes g = \int f(x')g(x - x') \, dx' \]

- **Convolution Theorem**: Multiplication in the frequency domain is equivalent to convolution in the space domain.

\[ f \otimes g \leftrightarrow F \times G \]

- **Symmetric Theorem**: Multiplication in the space domain is equivalent to convolution in the frequency domain.

\[ f \times g \leftrightarrow F \otimes G \]
1D convolution theorem example

\[ f(x) \quad \ast \quad h(x) \Downarrow \quad g(x) \]

\[ F(s) \quad \times \quad H(s) \Downarrow \quad G(s) \]
2D convolution theorem example

\[ f(x, y) \ast h(x, y) \rightarrow g(x, y) \]

\[ F(s_x, s_y) \ast H(s_x, s_y) \rightarrow G(s_x, s_y) \]
The delta function

- Dirac delta function, zero width, infinite height and unit area

\[ \delta(x) \]
Sifting and shifting

Sifting:

\[ f(x) \delta(x - a) = f(a) \delta(x - a) \]

Shifting:

\[ f(x) \ast \delta(x - a) = f(x - a) \]
Shah/impulse train function

**spatial domain**

\[ III(x) = \sum_{n=-\infty}^{\infty} \delta(x - nT) \]

**frequency domain**

\[ III(s) = \sum_{n=-\infty}^{\infty} \delta(s - ns_0), \quad s_0 = 1/T \]
Sampling

band limited
The reconstructed function is obtained by interpolating among the samples in some manner.
In math forms

\[ \tilde{F} = (F(s) \ast \Pi I(s)) \times \Pi(s) \]

\[ \tilde{f} = (f(x) \times \Pi I(x)) \ast \text{sinc}(x) \]

\[ \tilde{f}(x) = \sum_{i=-\infty}^{\infty} \text{sinc}(x - i) f(i) \]
Reconstruction filters

The sinc filter, while ideal, has two drawbacks:

- It has large support (slow to compute)
- It introduces ringing in practice

The box filter is bad because its Fourier transform is a sinc filter which includes high frequency contribution from the infinite series of other copies.
Aliasing

increase sample spacing in spatial domain

decrease sample spacing in frequency domain

Aliasing
Aliasing

high-frequency details leak into lower-frequency regions
Sampling theorem

This result is known as the Sampling Theorem and is due to Claude Shannon who first discovered it in 1949:

A signal can be reconstructed from its samples without loss of information, if the original signal has no frequencies above $\frac{1}{2}$ the sampling frequency.

For a given bandlimited function, the minimum rate at which it must be sampled is the Nyquist frequency.
Sampling theorem

- For band limited function, we can just increase the sampling rate.
- However, few of interesting functions in computer graphics are band limited, in particular, functions with discontinuities.
- It is because the discontinuity always falls between two samples and the samples provides no information about this discontinuity.
Aliasing

- Prealiasing: due to sampling under Nyquist rate
- Postaliasing: due to use of imperfect reconstruction filter
Antialiasing

- Antialiasing = Preventing aliasing

1. Analytically prefilter the signal
   - Not solvable in general
2. Uniform supersampling and resample
3. Nonuniform or stochastic sampling
Antialiasing (Prefiltering)
It is blurred, but better than aliasing
Uniform Supersampling

- Increasing the sampling rate moves each copy of the spectra further apart, potentially reducing the overlap and thus aliasing.
- Resulting samples must be resampled (filtered) to image sampling rate.

\[
\text{Pixel} = \sum_s w_s \cdot \text{Sample}_s
\]
Point vs. Supersampled

Point 4x4 Supersampled

Checkerboard sequence by Tom Duff
Analytic vs. Supersampled

Exact Area

4x4 Supersampled
Distribution of Extrafoveal Cones

- Monkey eye cone distribution
- Fourier transform

Yellot theory
- Aliases replaced by noise
- Visual system less sensitive to high freq noise
Non-uniform Sampling

• Intuition

• Uniform sampling
  – The spectrum of uniformly spaced samples is also a set of uniformly spaced spikes
  – Multiplying the signal by the sampling pattern corresponds to placing a copy of the spectrum at each spike (in freq. space)
  – Aliases are coherent, and very noticeable

• Non-uniform sampling
  – Samples at non-uniform locations have a different spectrum; a single spike plus noise
  – Sampling a signal in this way converts aliases into broadband noise
  – Noise is incoherent, and much less objectionable
Antialiasing (nonuniform sampling)

- The impulse train is modified as

\[
\sum_{i=-\infty}^{\infty} \delta\left(x - \left(iT + \frac{1}{2} - \xi\right)\right)
\]

- It turns regular aliasing into noise. But random noise is less distracting than coherent aliasing.
Jittered Sampling

Add uniform random jitter to each sample
Jittered vs. Uniform Supersampling

4x4 Jittered Sampling  4x4 Uniform
Antialiasing (adaptive sampling)

- Take more samples only when necessary. However, in practice, it is hard to know where we need supersampling. Some heuristics could be used.

- It makes a less aliased image, but may not be more efficient than simple supersampling particular for complex scenes.
Application to ray tracing

• Sources of aliasing: object boundary, small objects, textures and materials
• Good news: we can do sampling easily
• Bad news: we can’t do prefiltering
• Key insight: we can never remove all aliasing, so we develop techniques to mitigate its impact on the quality of the final image.
Prefer noise over aliasing

reference

aliasing

noise
Creating good sample patterns can substantially improve a ray tracer’s efficiency, allowing it to create a high-quality image with fewer rays.

Because evaluating radiance is costly, it pays to spend time on generating better sampling.

- core/sampling.*, samplers/*
- random.cpp, stratified.cpp, bestcandidate.cpp, lowdiscrepancy.cpp,
An ineffective sampler
A more effective sampler
Sampler

Sampler(int xstart, int xend,
        int ystart, int yend, int spp);

bool GetNextSample(Sample *sample);

int TotalSamples()
{
    samplesPerPixel * 
    (xPixelEnd - xPixelStart) * 
    (yPixelEnd - yPixelStart);
}

Render() in core/scene.cpp,
    used for generating eye rays

while (sampler->GetNextSample(sample)) {
    ...
}

Sample

Struct Sample {
    store required information for one eye ray sample
    Sample(Surface Integrator *surf,
            Volume Integrator *vol,
            const Scene *scene);

    float imageX, imageY;
    float lensU, lensV;
    float time;
    // Integrator Sample Data
    vector<u_int> n1D, n2D;
    float **oneD, **twoD;
    ...
}

Sample is allocated once in Render(). Sampler is called to fill in the information for each eye ray. The integrator can ask for multiple 1D and/or 2D samples, each with an arbitrary number of entries, e.g. depending on #lights.
Different types of lights require different number of samples, usually 2D samples.

- Sampling BRDF requires 2D samples.
- Selection of BRDF components requires 1D samples.
Sample

```cpp
Sample::Sample(SurfaceIntegrator *surf,
                VolumeIntegrator *vol, const Scene *scene) {
    // calculate required number of samples
    // according to integration strategy
    surf->RequestSamples(this, scene);
    vol->RequestSamples(this, scene);

    // Allocate storage for sample pointers
    int nPtrs = n1D.size() + n2D.size();
    if (!nPtrs) {
        oneD = twoD = NULL;
        return;
    }
    oneD = (float **) AllocAligned(nPtrs*sizeof(float *));
    twoD = oneD + n1D.size();
```
// Compute total number of sample values needed
int totSamples = 0;
for (u_int i = 0; i < n1D.size(); ++i)
    totSamples += n1D[i];
for (u_int i = 0; i < n2D.size(); ++i)
    totSamples += 2 * n2D[i];
// Allocate storage for sample values
float *mem = (float *)AllocAligned(totSamples *
    sizeof(float));
for (u_int i = 0; i < n1D.size(); ++i) {
    oneD[i] = mem;
    mem += n1D[i];
}
for (u_int i = 0; i < n2D.size(); ++i) {
    twoD[i] = mem;
    mem += 2 * n2D[i];
}
Random sampler

RandomSampler::RandomSampler(...) { Just for illustration; does not work well in practice

...// Get storage for a pixel's worth of stratified samples imageSamples = (float *)AllocAligned(5 * xPixelSamples * yPixelSamples * sizeof(float));
  lensSamples = imageSamples + 2 * xPixelSamples * yPixelSamples;
  timeSamples = lensSamples + 2 * xPixelSamples * yPixelSamples;

// prepare samples for the first pixel
for (i=0; i<5*xPixelSamples*yPixelSamples; ++i)
  imageSamples[i] = RandomFloat();

// Shift image samples to pixel coordinates
for (o=0; o<2*xPixelSamples*yPixelSamples; o+=2) {
  imageSamples[o] += xPos;
  imageSamples[o+1] += yPos; }
samplePos = 0;
}
Random sampler

```cpp
bool RandomSampler::GetNextSample(Sample *sample) {
  if (samplePos == xPixelSamples * yPixelSamples) {
    // Advance to next pixel for sampling
    if (++xPos == xPixelEnd) {
      xPos = xPixelStart;
      ++yPos;
    }
    if (yPos == yPixelEnd)
      return false;
  }
  for (i=0; i < 5*xPixelSamples*yPixelSamples; ++i)
    imageSamples[i] = RandomFloat();

  // Shift image samples to pixel coordinates
  for (o=0; o<2*xPixelSamples*yPixelSamples; o+=2)
    { imageSamples[o] += xPos;
      imageSamples[o+1] += yPos; }
  samplePos = 0;
}
```
Random sampler

// Return next sample point according to samplePos
sample->imageX = imageSamples[2*samplePos];
sample->imageY = imageSamples[2*samplePos+1];
sample->lensU = lensSamples[2*samplePos];
sample->lensV = lensSamples[2*samplePos+1];
sample->time = timeSamples[samplePos];

// Generate samples for integrators
for (u_int i = 0; i < sample->n1D.size(); ++i)
    for (u_int j = 0; j < sample->n1D[i]; ++j)
        sample->oneD[i][j] = RandomFloat();
for (u_int i = 0; i < sample->n2D.size(); ++i)
    for (u_int j = 0; j < 2*sample->n2D[i]; ++j)
        sample->twoD[i][j] = RandomFloat();

++samplePos;
return true;
Random sampling

a pixel

completely random
Stratified sampling

- Subdivide the sampling domain into non-overlapping regions (\textit{strata}) and take a single sample from each one so that it is less likely to miss important features.
Stratified sampling

- completely random
- stratified uniform
- stratified jittered

turn aliasing into noise
Comparison of sampling methods

256 samples per pixel as reference

1 sample per pixel (no jitter)
Comparison of sampling methods

1 sample per pixel (jittered)

4 samples per pixel (jittered)
Stratified sampling

reference  random  stratified jittered
High dimension

- D dimension means $N^D$ cells.
- Solution: make strata separately and associate them randomly, also ensuring good distributions.
if (samplePos == xPixelSamples * yPixelSamples) {
    // Advance to next pixel for stratified sampling
    ...
    // Generate stratified samples for (xPos, yPos)
    StratifiedSample2D(imageSamples,
        xPos, yPos, jitterSamples);
    StratifiedSample2D(lensSamples,
        xPos, yPos, jitterSamples);
    StratifiedSample1D(timeSamples,
        xPos, yPos, jitterSamples);

    // Shift stratified samples to pixel coordinates
    ...
    // Decorrelate sample dimensions
    Shuffle(lensSamples, xPixelSamples*yPixelSamples, 2);
    Shuffle(timeSamples, xPixelSamples*yPixelSamples, 1);
    samplePos = 0;
}
Stratified sampling

```c
void StratifiedSample1D(float *samp, int nSamples, bool jitter) {
    float invTot = 1.f / nSamples;
    for (int i = 0; i < nSamples; ++i) {
        float delta = jitter ? RandomFloat() : 0.5f;
        *samp++ = (i + delta) * invTot;
    }
}

void StratifiedSample2D(float *samp, int nx, int ny, bool jitter) {
    float dx = 1.f / nx, dy = 1.f / ny;
    for (int y = 0; y < ny; ++y) {
        for (int x = 0; x < nx; ++x) {
            float jx = jitter ? RandomFloat() : 0.5f;
            float jy = jitter ? RandomFloat() : 0.5f;
            *samp++ = (x + jx) * dx;
            *samp++ = (y + jy) * dy;
        }
    }
}
```

n stratified samples within [0..1]
nx*ny stratified samples within [0..1]X[0..1]
void Shuffle(float *samp, int count, int dims) {
    for (int i = 0; i < count; ++i) {
        u_int other = RandomUInt() % count;
        for (int j = 0; j < dims; ++j)
            swap(samp[dims*i + j], samp[dims*other + j]);
    }
}
// Return next _StratifiedSampler_ sample point
sample->imageX = imageSamples[2*samplePos];
sample->imageY = imageSamples[2*samplePos+1];
sample->lensU = lensSamples[2*samplePos];
sample->lensV = lensSamples[2*samplePos+1];
sample->time = timeSamples[samplePos];

// what if integrator asks for 7 stratified 2D samples
// Generate stratified samples for integrators
for (u_int i = 0; i < sample->n1D.size(); ++i)
    LatinHypercube(sample->oneD[i], sample->n1D[i], 1);
for (u_int i = 0; i < sample->n2D.size(); ++i)
    LatinHypercube(sample->twoD[i], sample->n2D[i], 2);

++samplePos;
return true;
Latin hypercube sampling

- Integrators could request an arbitrary $n$ samples. $nx1$ or $1xn$ doesn’t give a good sampling pattern.

A worst case for stratified sampling LHS can prevent this from happening.
void LatinHypercube(float *samples,
    int nSamples, int nDim) {

    // Generate LHS samples along diagonal
    float delta = 1.f / nSamples;
    for (int i = 0; i < nSamples; ++i)
        for (int j = 0; j < nDim; ++j)
            samples[nDim*i+j] = (i+RandomFloat())*delta;

    // Permute LHS samples in each dimension
    for (int i = 0; i < nDim; ++i) {
        for (int j = 0; j < nSamples; ++j) {
            u_int other = RandomUInt() % nSamples;
            swap(samples[nDim * j + i],
                 samples[nDim * other + i]);
        }
    }
}
Stratified sampling
Stratified sampling

This is better because `StratifiedSampler` could generate a good LHS pattern for this case.

1 camera sample and 16 shadow samples per pixel

16 camera samples and each with 1 shadow sample per pixel
Low discrepancy sampling

When $B$ is the set of AABBs with a corner at the origin, this is called star discrepancy

$$D_N^*(P) = D_N(B, P)$$

$D_N^*(P)$ is a measure of the difference between the volume of a shape estimated by the number of sample points and the real volume of the shape. It is used to assess the quality of a sample set in terms of how well it represents the underlying distribution.
1D discrepancy

\[ x_i = \frac{i}{N} \quad \Rightarrow \quad D_N^*(x_1, ..., x_n) = \frac{1}{N} \]

\[ x_i = \frac{i - 0.5}{N} \quad \Rightarrow \quad D_N^*(x_1, ..., x_n) = \frac{1}{2N} \]

\[ x_i = \text{general} \quad \Rightarrow \quad D_N^*(x_1, ..., x_n) = \frac{1}{2N} + \max_{1 \leq i \leq N} \left| x_i - \frac{2i - 1}{2N} \right| \]

Uniform is optimal! However, we have learnt that irregular patterns are perceptually superior to uniform samples. Fortunately, for higher dimension, the low-discrepancy patterns are less uniform and works reasonably well as sample patterns in practice.
Radical inverse

- A positive number \( n \) can be expressed in a base \( b \) as

\[
n = a_k \ldots a_2 a_1 = a_1 b^0 + a_2 b^1 + a_3 b^2 + \ldots
\]

- A radical inverse function in base \( b \) converts a nonnegative integer \( n \) to a floating-point number in \([0,1)\)

\[
\Phi_b(n) = 0.a_1 a_2 \ldots a_k = a_1 b^{-1} + a_2 b^{-2} + a_3 b^{-3} + \ldots
\]

```cpp
inline double RadicalInverse(int n, int base) {
    double val = 0;
    double invBase = 1. / base, invBi = invBase;
    while (n > 0) {
        int d_i = (n % base);
        val += d_i * invBi;
        n /= base;
        invBi *= invBase;
    }
    return val;
}
```
van der Corput sequence

- The simplest sequence $x_i = \Phi_2(i)$
- Recursively split 1D line in half, sample centers
- Achieve minimal possible discrepancy

\[
D_N^*(P) = O\left(\frac{\log N}{N}\right)
\]

<table>
<thead>
<tr>
<th>(i)</th>
<th>binary form of (i)</th>
<th>radical inverse</th>
<th>(x_i)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0.0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0.1</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0.01</td>
<td>0.25</td>
</tr>
<tr>
<td>3</td>
<td>11</td>
<td>0.11</td>
<td>0.75</td>
</tr>
<tr>
<td>4</td>
<td>100</td>
<td>0.001</td>
<td>0.125</td>
</tr>
<tr>
<td>5</td>
<td>101</td>
<td>0.101</td>
<td>0.625</td>
</tr>
<tr>
<td>6</td>
<td>110</td>
<td>0.011</td>
<td>0.375</td>
</tr>
</tbody>
</table>
Halton sequence

- Use relatively prime numbers as bases for each dimension recursively split the dimension into $p_d$ parts, sample centers

$$x_i = (\Phi_2(i), \Phi_3(i), \Phi_5(i), ..., \Phi_{p_d}(i))$$

- Achieve best possible discrepancy for N-D

$$D_N^*(P) = O\left(\frac{(\log N)^d}{N}\right)$$

- Can be used if N is not known in advance

- All prefixes of a sequence are well distributed so as additional samples are added to the sequence, low discrepancy will be maintained
Hammersley sequence

- Similar to Halton sequence.
- Slightly better discrepancy than Halton.
- Needs to know $N$ in advance.

$$x_i = \left( \frac{i - 1/2}{N}, \Phi_{b_1}(i), \Phi_{b_2}(i), \ldots, \Phi_{b_{d-1}}(i) \right)$$
Folded radical inverse

• It can be used to improve Hammersley and Halton, called Hammersley-Zaremba and Halton-Zaremba.

\[ \Phi_b(n) = \sum_{i=1}^{\infty} \left( (a_i + i - 1) \mod b \right) \frac{1}{b^i} \]
Radial inverse

Halton

Hammersley

Better for that there are fewer clumps.
Folded radial inverse

Halton

Hammersley

The improvement is more obvious
Low discrepancy sampling

stratified jittered, 1 sample/pixel

Hammersley sequence, 1 sample/pixel
(0, 2)-sequences

- A useful low-discrepancy sequence in 2D is to use the van der Corput sequence in one dimension and a Sobol sequence in the other.
- It is stratified in a very general way.
- To generate different sequences for different pixels, pbrt scrambles the (0,2)-sequence by permuting the original sequence.
- Divide the square into half, swap two halves with 50% probability. Repeat until below numerical precision.
(0, 2)-sequences
Implementation of \((0,2)\)-sequences

- We use binary base; scramble equals XOR
- Assume the same scramble decision for the same level
(0,2)-sequences

```c
void Sample02(u_int n, u_int scramble[2],
              float sample[2]) {
    sample[0] = VanDerCorput(n, scramble[0]);
    sample[1] = Sobol2(n, scramble[1]);
}

float VanDerCorput(u_int n, u_int scramble) {
    n = (n << 16) | (n >> 16);
    n = ((n&0xff00ff00) << 8) | ((n&0x00ff00ff) >> 8);
    n = ((n&0x0f0f0f0f) << 4) | ((n&0xf0f0f0f0) >> 4);
    n = ((n&0x33333333) << 2) | ((n&0xcccccccc) >> 2);
    n = ((n&0x55555555) << 1) | ((n&0xaaaaaaaaa) >> 1);
    n ^= scramble;
    return (float)n / (float)0x100000000LL;
}

float Sobol2(u_int n, u_int scramble) {
    for (u_int v = 1<<31; n != 0; n >>= 1, v ^= v >> 1)
        if (n & 0x1) scramble ^= v;
    return (float)scramble / (float)0x100000000LL;
}
```
LDSampler

- pbrt uses (0,2)-sequence instead of Hammersley because it is prone to aliasing.
- LDSampler uses (0,2)-sequences for position and lens, van der Corput with scramble for time.

```c
// Generate low-discrepancy samples for pixel
LDSHuffleScrambled2D(1, pixelSamples, imageSamples);
LDSHuffleScrambled2D(1, pixelSamples, lensSamples);
LDSHuffleScrambled1D(1, pixelSamples, timeSamples);
for (u_int i = 0; i < sample->n1D.size(); ++i)
  LDSHuffleScrambled1D(sample->n1D[i], pixelSamples, oneDSamples[i]);
for (u_int i = 0; i < sample->n2D.size(); ++i)
  LDSHuffleScrambled2D(sample->n2D[i], pixelSamples, twoDSamples[i]);
```

copy to oneD and twoD of Sample
void LDShuffleScrambled1D(int nSamples, int nPixel, float *samples) {
    u_int scramble = RandomUInt();
    for (int i = 0; i < nSamples * nPixel; ++i)
        samples[i] = VanDerCorput(i, scramble);
    for (int i = 0; i < nPixel; ++i)
        Shuffle(samples + i * nSamples, nSamples, 1);
    Shuffle(samples, nPixel, nSamples);
}

void LDShuffleScrambled2D(int nSamples, int nPixel, float *samples) {
    u_int scramble[2] = { RandomUInt(), RandomUInt() };
    for (int i = 0; i < nSamples * nPixel; ++i)
        Sample02(i, scramble, &samples[2*i]);
    for (int i = 0; i < nPixel; ++i)
        Shuffle(samples + 2 * i * nSamples, nSamples, 2);
    Shuffle(samples, nPixel, 2 * nSamples);
}
Best candidate sampling

- Stratified sampling doesn’t guarantee good sampling across pixels.
- *Poisson disk pattern* addresses this issue. The Poisson disk pattern is a group of points with no two of them closer to each other than some specified distance.
- It can be generated by *dart throwing*. It is time-consuming.
- *Best-candidate* algorithm by Dan Mitchell. It randomly generates many candidates but only inserts the one farthest to all previous samples.
Best candidate sampling

stratified jittered

best candidate

*It avoids holes and clusters.*
Best candidate sampling

- Because of it is costly to generate best candidate pattern, pbrt computes a “tilable pattern” offline (by treating the square as a rolled torus).
- \texttt{tools/samplepat.cpp} → \texttt{sampler/sampleddata.cpp}
Best candidate sampling

stratified jittered, 1 sample/pixel

best candidate, 1 sample/pixel
Best candidate sampling

stratified jittered, 4 sample/pixel

best candidate, 4 sample/pixel
Comparisons

reference  low-discrepancy  best candidate
Some recent progresses

- Fast Poisson Disk Sampling
- Recursive Wang Tiles for Real-Time Blue Noise

- Good topic for your final project
Fast Poisson-Disk Sampling
Fast Poisson-Disk Sampling
Recursive Wang Tiles for Blue Noise

- 32,965 points, 22.75ms
  1,449,011 points per second

- 34,897 points, 15.7ms
  2,222,739 points per second

- 22,748 points, 11.67ms
  1,949,272 points per second
Reconstruction filters

• Given image samples, we can do the following to compute pixel values.
  1. reconstruct a continuous function $L'$ from samples
  2. prefilter $L'$ to remove frequency higher than Nyquist limit
  3. sample $L'$ at pixel locations

• Because we will only sample $L'$ at pixel locations, we do not need to explicitly reconstruct $L$’s. Instead, we combine the first two steps.
Reconstruction filters

- Ideal reconstruction filters do not exist because of discontinuity in rendering. We choose nonuniform sampling, trading off noise for aliasing. There is no theory about ideal reconstruction for nonuniform sampling yet.
- Instead, we consider an interpolation problem

\[
I(x, y) = \frac{\sum_i f(x-x_i, y-y_i)L(x_i, y_i)}{\sum_i f(x-x_i, y-y_i)}
\]

final value

filtered sampled radiance

\((x, y)\)

\((x_i, y_i)\)
Filter

- provides an interface to $f(x,y)$
- Film stores a pointer to a filter and use it to filter the output before writing it to disk.

```
Filter::Filter(float xw, float yw)
Float Evaluate(float x, float y);
```

width, half of support

\[ x, y \text{ is guaranteed to be within the range;} \]
\[ \text{range checking is not necessary} \]

- filters/* (box, gaussian, mitchell, sinc, triangle)
Box filter

- Most commonly used in graphics. It’s just about the worst filter possible, incurring postaliasing by high-frequency leakage.

```cpp
Float BoxFilter::Evaluate(float x, float y)
{
    no need to normalize since the weighted sum is divided by the total weight later.
    return 1.;
}
```

![Sinc function](image1)

![Box filter response](image2)
Triangle filter

```cpp
Float TriangleFilter::Evaluate(float x, float y)
{
    return max(0.f, xWidth-fabsf(x)) *
            max(0.f, yWidth-fabsf(y));
}
```

Sinc²

![Triangle filter diagram]
Gaussian filter

- Gives reasonably good results in practice

```cpp
Float GaussianFilter::Evaluate(float x, float y)
{
    return Gaussian(x, expX)*Gaussian(y, expY);
}
```

Gaussian essentially has a infinite support; to compensate this, the value at the end is calculated and subtracted.
Mitchell filter

- parametric filters, tradeoff between ringing and blurring
- Negative lobes improve sharpness; ringing starts to enter the image if they become large.
Mitchell filter

\[
h(x) = \frac{1}{6} \begin{cases} 
(12 - 9B - 6C)x^3 + (-18 + 12B + 6C)x^2 + (6 - 2B) & |x| < 1 \\
(-B - 6C)x^3 + (6B + 30C)x^2 + (-12B - 48C)x + (8B + 24C) & 1 < |x| < 2 \\
\text{otherwise} & 
\end{cases}
\]

- Separable filter
- Two parameters, B and C, B+2C=1 suggested

FFT of a cubic filter. Mitchell filter is a combination of cubic filters with $C^0$ and $C^1$ Continuity.
Windowed sinc filter

\[ \text{Lanczos } w(x) = \frac{\sin \frac{\pi x}{\tau}}{\pi x / \tau} \]
Comparisons

Box

Mitchell
Comparisons

windowed sinc

Mitchell
Comparisons

\begin{tabular}{c c c}
box & Gaussian & Mitchell \\
\end{tabular}