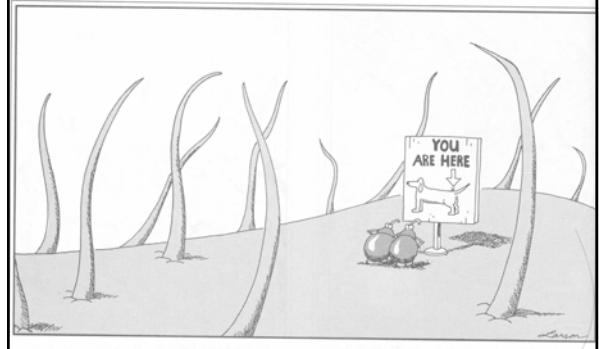


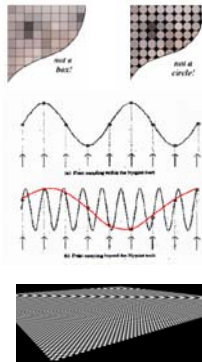
Sampling and Monte-Carlo Integration

Sampling and Monte-Carlo Integration



Last Time

- Pixels are samples
- Sampling theorem
- Convolution & multiplication
- Aliasing: spectrum replication
- Ideal filter
 - And its problems
- Reconstruction
- Texture prefiltering, mipmaps



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Quiz solution: Homogeneous sum

- $(x_1, y_1, z_1, 1) + (x_2, y_2, z_2, 1)$
 $= (x_1+x_2, y_1+y_2, z_1+z_2, 2)$
 $\approx ((x_1+x_2)/2, (y_1+y_2)/2, (z_1+z_2)/2)$
- This is the average of the two points
- General case: consider the homogeneous version of (x_1, y_1, z_1) and (x_2, y_2, z_2) with w coordinates w_1 and w_2
- $(x_1 w_1, y_1 w_1, z_1 w_1, w_1) + (x_2 w_2, y_2 w_2, z_2 w_2, w_2)$
 $= (x_1 w_1 + x_2 w_2, y_1 w_1 + y_2 w_2, z_1 w_1 + z_2 w_2, w_1 + w_2)$
 $\approx ((x_1 w_1 + x_2 w_2)/(w_1 + w_2), (y_1 w_1 + y_2 w_2)/(w_1 + w_2), (z_1 w_1 + z_2 w_2)/(w_1 + w_2))$
- This is the weighted average of the two geometric points

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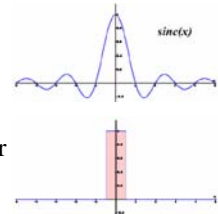
Today's lecture

- Antialiasing in graphics
- Sampling patterns
- Monte-Carlo Integration
- Probabilities and variance
- Analysis of Monte-Carlo Integration

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Ideal sampling/reconstruction

- Pre-filter with a perfect low-pass filter
 - Box in frequency
 - Sinc in time
- Sample at Nyquist limit
 - Twice the frequency cutoff
- Reconstruct with perfect filter
 - Box in frequency, sinc in time
- And everything is great!



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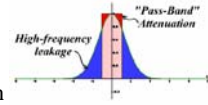
Difficulties with perfect sampling

- Hard to prefilter
- Perfect filter has infinite support
 - Fourier analysis assumes infinite signal and complete knowledge
 - Not enough focus on local effects
- And negative lobes
 - Emphasizes the two problems above
 - Negative light is bad
 - Ringing artifacts if prefiltering or supports are not perfect

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At the end of the day

- Fourier analysis is great to understand aliasing
- But practical problems kick in
- As a result there is no perfect solution
- Compromises between
 - Finite support
 - Avoid negative lobes
 - Avoid high-frequency leakage
 - Avoid low-frequency attenuation
- Everyone has their favorite cookbook recipe
 - Gaussian, tent, Mitchell bicubic

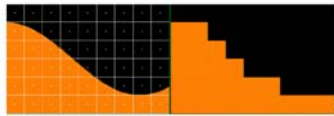


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The special case of edges

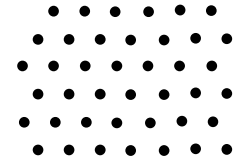
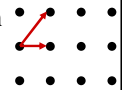
- An edge is poorly captured by Fourier analysis
 - It is a local feature
 - It combines all frequencies (sinc)
- Practical issues with edge aliasing lie more in the jaggies (tilted lines) than in actual spectrum replication

Jagged boundaries



Anisotropy of the sampling grid

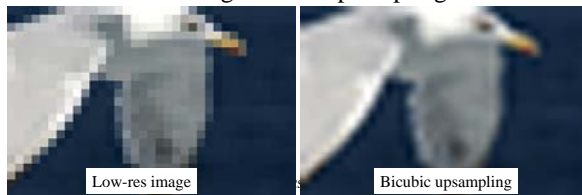
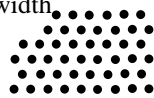
- More vertical and horizontal bandwidth
 - E.g. $\sqrt{2}$ less bandwidth in diagonal
- A hexagonal grid would be better
 - Max anisotropy $\cos 30^\circ = \sqrt{3}/4 = 0.86$
 - But less practical



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Anisotropy of the sampling grid

- More vertical and horizontal bandwidth
- A hexagonal grid would be better
 - But less practical
- Practical effect: vertical and horizontal direction show when doing bicubic upsampling



Philosophy about mathematics

- Mathematics are great tools to model (i.e. describe) your problems
- They afford incredible power, formalism, generalization
- However it is equally important to understand the practical problem and how much the mathematical model fits

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Questions?

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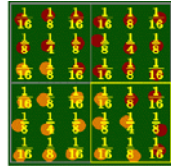
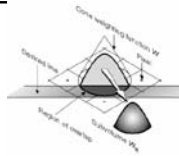
Today's lecture

- Antialiasing in graphics
- **Sampling patterns**
- Monte-Carlo Integration
- Probabilities and variance
- Analysis of Monte-Carlo Integration

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Supersampling in graphics

- Pre-filtering is hard
 - Requires analytical visibility
 - Then difficult to integrate analytically with filter
- Possible for lines, or if visibility is ignored
- usually, fall back to supersampling



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Uniform supersampling

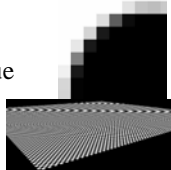
- Compute image at resolution $k \times \text{width}$, $k \times \text{height}$
- Downsample using low-pass filter (e.g. Gaussian, sinc, bicubic)



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Uniform supersampling

- Advantage:
 - The first (super)sampling captures more high frequencies that are not aliased
 - Downsampling can use a good filter
- Issues
 - Frequencies above the (super)sampling limit are still aliased
- Works well for edges, since spectrum replication is less an issue
- Not as well for repetitive textures
 - But mipmapping can help



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Multisampling vs. supersampling

- Observation:
 - Edge aliasing mostly comes from visibility/rasterization issues
 - Texture aliasing can be prevented using prefiltering
- **Multisampling idea:**
 - Sample rasterization/visibility at a higher rate than shading/texture
- In practice, same as **supersampling**, except that all the subpixel get the same color if visible

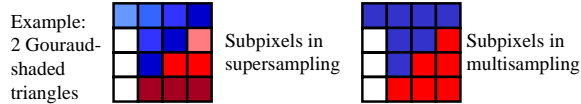
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Multisampling vs. supersampling

```

For each triangle
  For each pixel
    Compute pixelcolor //only once for all subpixels
    For each subpixel
      If (all edge equations positive &&
          zbuffer[subpixel] > currentz )
        Then Framebuffer[subpixel]=pixelcolor
  
```

- The subpixels of a pixel get different colors only at edges of triangles or at occlusion boundaries



Questions?

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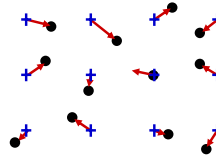
Uniform supersampling

- Problem: supersampling only pushes the problem further: The signal is still not bandlimited
- Aliasing happens

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Jittering

- Uniform sample + random perturbation
- Sampling is now non-uniform
- Signal processing gets more complex
- In practice, adds noise to image
- But noise is better than aliasing Moiré patterns



Jittered supersampling

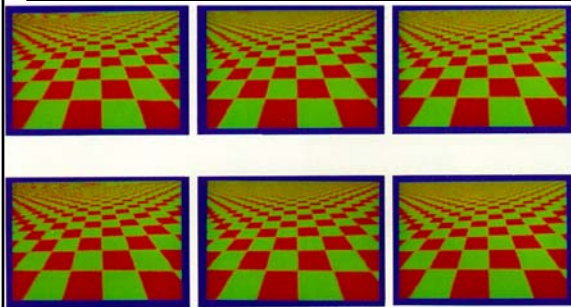


Figure 11
Jittered sampling of a slowly moving texture with jitter of 0, 0.5, and 1 from left to right and oversampling rates of 1 and 2 from top to bottom.

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Jittering

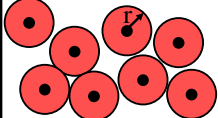
- Displaced by a vector a fraction of the size of the subpixel distance
- Low-frequency Moiré (aliasing) pattern replaced by noise
- Extremely effective
- Patented by Pixar!
- When jittering amount is 1, equivalent to stratified sampling (cf. later)

Poisson disk sampling and blue noise

- Essentially random points that are not allowed to be closer than some radius r
- Dart-throwing algorithm:


```
Initialize sampling pattern as empty
Do
  Get random point P
  If P is farther than r from all samples
    Add P to sampling pattern
Until unable to add samples for a long time
```

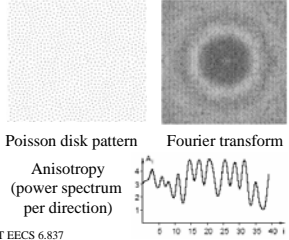
From Hiller et al.



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Poisson disk sampling and blue noise

- Essentially random points that are not allowed to be closer than some radius r
- The spectrum of the Poisson disk pattern is called blue noise:
- No low frequency
- Other criterion: Isotropy (frequency content must be the same for all direction)



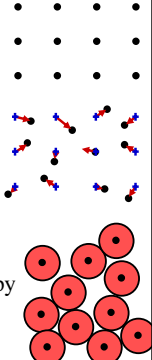
Poisson disk pattern Fourier transform

Anisotropy (power spectrum per direction)

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Recap

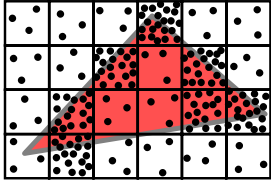
- Uniform supersampling
 - Not so great
- Jittering
 - Great, replaces aliasing by noise
- Poisson disk sampling
 - Equally good, but harder to generate
 - Blue noise and good (lack of) anisotropy



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Adaptive supersampling

- Use more sub-pixel samples around edges

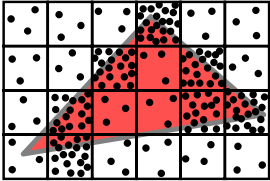


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Adaptive supersampling

- Use more sub-pixel samples around edges

Compute color at small number of sample
If their variance is high
Compute larger number of samples

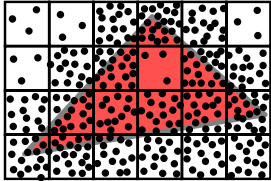


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Adaptive supersampling

- Use more sub-pixel samples around edges

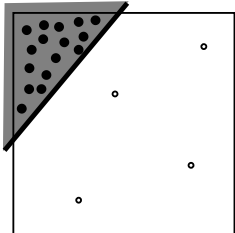
Compute color at small number of sample
If variance **with neighbor pixels** is high
Compute larger number of samples



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Problem with non-uniform distribution

- Reconstruction can be complicated

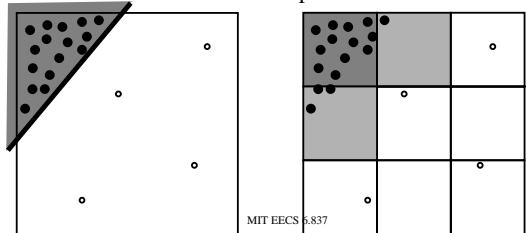


80% of the samples are black
Yet the pixel should be light grey

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Problem with non-uniform distribution

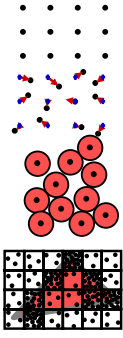
- Reconstruction can be complicated
- Solution: do a multi-level reconstruction
 - Reconstruct uniform sub-pixels
 - Filter those uniform sub-pixels



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Recap

- Uniform supersampling
 - Not so great
- Jittering
 - Great, replaces aliasing by noise
- Poisson disk sampling
 - Equally good, but harder to generate
 - Blue noise and good (lack of) anisotropy
- Adaptive sampling
 - Focus computation where needed
 - Beware of false negative
 - Complex reconstruction



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Questions?

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Today's lecture

- Antialiasing in graphics
- Sampling patterns
- **Monte-Carlo Integration**
- Probabilities and variance
- Analysis of Monte-Carlo Integration

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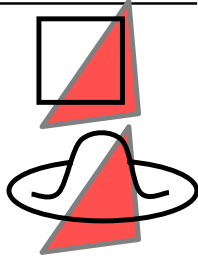
Shift of perspective

- So far, Antialiasing as signal processing
- Now, Antialiasing as integration
- Complementary yet not always the same

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Why integration?

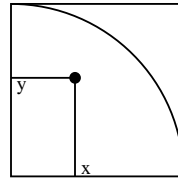
- Simple version:
compute pixel coverage
- More advanced:
Filtering (convolution)
is an integral
pixel = $\int \text{filter} * \text{color}$
- And integration is useful in tons of places in graphics



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Monte-Carlo computation of π

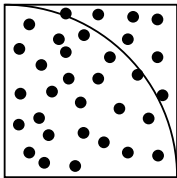
- Take a square
- Take a random point (x,y) in the square
- Test if it is inside the $\frac{1}{4}$ disc ($x^2+y^2 < 1$)
- The probability is $\pi/4$



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Monte-Carlo computation of π

- The probability is $\pi/4$
- Count the inside ratio $n = \# \text{ inside} / \text{total} \# \text{ trials}$
- $\pi \approx n * 4$
- The error depends on the number of trials



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Why not use Simpson integration?

- Yeah, to compute π ,
Monte Carlo is not very efficient
- But convergence is independent of dimension
- Better to integrate high-dimensional functions
- For d dimensions, Simpson requires N^d domains

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Dumbest Monte-Carlo integration

- Compute 0.5 by flipping a coin
- 1 flip: 0 or 1 \Rightarrow average error = 0.5
- 2 flips: 0, 0.5, 0.5 or 1 \Rightarrow average error = 0.25
- 4 flips: 0 (*1), 0.25 (*4), 0.5 (*6), 0.75 (*4), 1 (*1)
 \Rightarrow average error = 0.1875
- Does not converge very fast
- Doubling the number of samples does not double accuracy

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Questions?

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Today's lecture

- Antialiasing in graphics
- Sampling patterns
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- **Probabilities and variance**
- Analysis of Monte-Carlo Integration

**BEWARE:
MATHS INSIDE**

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Review of probability (discrete)

- Random variable can take discrete values x_i
- Probability p_i for each x_i

$$0 \leq p_i \leq 1$$

If the events are mutually exclusive, $\sum p_i = 1$

- Expected value $E(x) = \sum_{i=1}^n p_i x_i$
- Expected value of function of random variable
– $f(x_i)$ is also a random variable

$$E[f(x)] = \sum_{i=1}^n p_i f(x_i)$$

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Ex: fair dice

$$\begin{aligned} E(x_{dice}) &= \sum_{i=1}^6 p_i x_i \\ &= \sum_{i=1}^6 \frac{1}{6} x_i \\ &= \frac{1}{6}(1 + 2 + 3 + 4 + 5 + 6) \\ &= 3.5 \end{aligned}$$

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Variance & standard deviation

- Variance σ^2 :
Measure of deviation from expected value
- Expected value of square difference (MSE)
 $\sigma^2 = E[(x - E[x])^2] = \sum_i (x_i - E[x])^2 p_i$

- Also

$$\sigma^2 = E[x^2] - (E[x])^2$$

- Standard deviation σ :
square root of variance (notion of error, RMS)

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Questions?

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Continuous random variables

- Real-valued random variable x
- Probability density function (PDF) $p(x)$
– Probability of a value between x and $x+dx$ is $p(x) dx$
- Cumulative Density Function (CDF) $P(y)$:
– Probability to get a value lower than y

$$P(y) = Pr(x \leq y) = \int_{-\infty}^y p(x) dx$$

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Properties

- $p(x) \geq 0$ but can be greater than 1 !!!!

$$\int_{-\infty}^{\infty} p(x) dx =$$

$$p(x) =$$

$$Pr(a \leq x \leq b) =$$

- P is positive and non-decreasing

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Properties

- $p(x) \geq 0$ but can be greater than 1 !!!!

$$\int_{-\infty}^{\infty} p(x) dx = 1$$

$$p(x) = \frac{dP(x)}{dx}$$

$$Pr(a \leq x \leq b) = P(b) - P(a) = \int_a^b p(z) dz$$

- P is positive and non-decreasing

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Example

- Uniform distribution between a and b
- Dirac distribution

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Expected value

$$E[x] = \int_{-\infty}^{\infty} xp(x) dx$$

$$E[f(x)] = \int_{-\infty}^{\infty} f(x)p(x) dx$$

- Expected value is linear

$$E[f_1(x) + a f_2(x)] = E[f_1(x)] + a E[f_2(x)]$$

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Variance

$$\sigma^2 = E[(x - E[x])^2] = \int_{-\infty}^{\infty} (x - E[x])^2 p(x) dx$$

- Variance is not linear !!!!
- $\sigma^2[x+y] = \sigma^2[x] + \sigma^2[y] + 2 \text{Cov}[x,y]$
- Where Cov is the covariance
 - $\text{Cov}[x,y] = E[xy] - E[x] E[y]$
 - Tells how much they are big at the same time
 - Null if variables are independent
- But $\sigma^2[ax] = a^2 \sigma^2[x]$

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