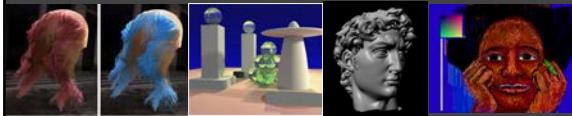


Advanced Computer Graphics

CSE 163 [Spring 2018], Lecture 3

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<http://www.cs.ucsd.edu/~ravir>



To Do

- Sign up for Piazza
- Assignment 1, Due Apr 27.
 - Anyone need help finding partners?
 - Any issues with skeleton code?
 - Please START EARLY

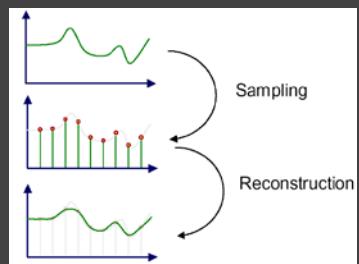
Outline

- Basic ideas of sampling, reconstruction, aliasing
- Signal processing and Fourier analysis
- Implementation of digital filters (second part of homework): next lecture
- Section 14.10 of FvDFH 2nd edition (should read)
 - Readings: Chapter 13 (color) and 14.10

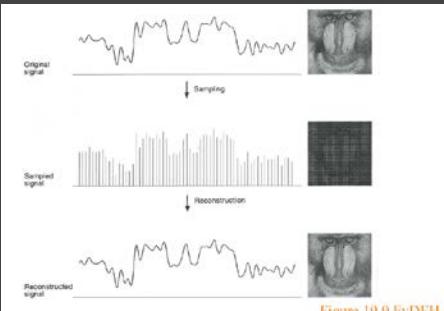
Some slides courtesy Tom Funkhouser

Sampling and Reconstruction

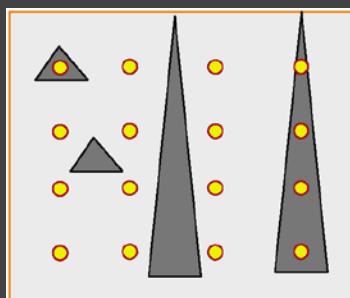
- An image is a 2D array of samples
- Discrete samples from real-world continuous signal



Sampling and Reconstruction

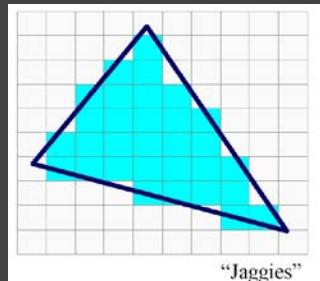


(Spatial) Aliasing



(Spatial) Aliasing

- Jaggies probably biggest aliasing problem



Sampling and Aliasing

- Artifacts due to undersampling or poor reconstruction
- Formally, high frequencies masquerading as low
- E.g. high frequency line as low freq jaggies

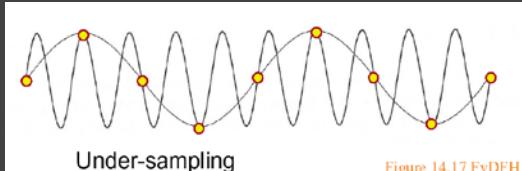
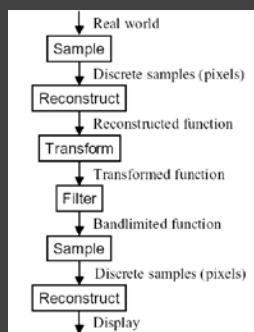


Figure 14.17 FvDFH

Image Processing pipeline



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Motivation

- Formal analysis of sampling and reconstruction
- Important theory (signal-processing) for graphics
- Also relevant in rendering, modeling, animation
- Note: Fourier Analysis useful for understanding, but image processing often done in spatial domain

Ideas

- Signal (function of time generally, here of space)
- Continuous: defined at all points; discrete: on a grid
- High frequency: rapid variation; Low Freq: slow variation
- Images are converting continuous to discrete. Do this sampling as best as possible.
- Signal processing theory tells us how best to do this
- Based on concept of frequency domain Fourier analysis

Sampling Theory

Analysis in the frequency (not spatial) domain

- Sum of sine waves, with possibly different offsets (phase)
- Each wave different frequency, amplitude

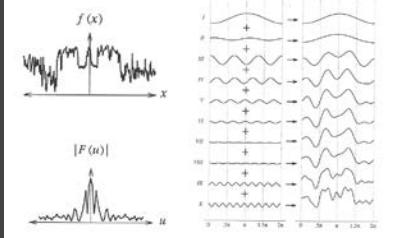


Figure 2.6: Wohlberg

Fourier Transform

- Tool for converting from spatial to frequency domain

$$f(x) = \sum_{u=-\infty}^{+\infty} F(u) e^{2\pi i u x}$$

$$e^{2\pi i u x} = \cos(2\pi u x) + i \sin(2\pi u x)$$

- Or vice versa
- $i = \sqrt{-1}$

- One of most important mathematical ideas
- Computational algorithm: Fast Fourier Transform
 - One of 10 great algorithms scientific computing
 - Makes Fourier processing possible (images etc.)
 - Not discussed here, but look up if interested

Fourier Transform

- Simple case, function sum of sines, cosines

$$f(x) = \sum_{u=-\infty}^{+\infty} F(u) e^{2\pi i u x}$$

$$F(u) = \int_0^1 f(x) e^{-2\pi i u x} dx$$

- Continuous infinite case

Forward Transform: $F(u) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i u x} dx$

Inverse Transform: $f(x) = \int_{-\infty}^{+\infty} F(u) e^{2\pi i u x} du$

Fourier Transform

- Simple case, function sum of sines, cosines

$$f(x) = \sum_{u=-\infty}^{+\infty} F(u) e^{2\pi i u x}$$

$$F(u) = \int_0^1 f(x) e^{-2\pi i u x} dx$$

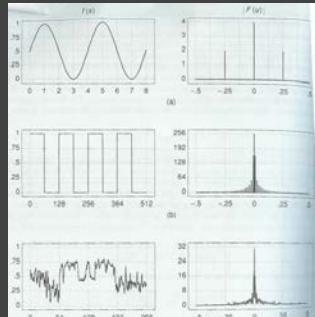
- Discrete case

$$F(u) = \sum_{x=0}^{x=N-1} f(x) [\cos(2\pi u x / N) - i \sin(2\pi u x / N)], \quad 0 \leq u \leq N-1$$

$$f(x) = \frac{1}{N} \sum_{u=0}^{u=N-1} F(u) [\cos(2\pi u x / N) + i \sin(2\pi u x / N)], \quad 0 \leq x \leq N-1$$

Fourier Transform: Examples 1

Single sine curve (+constant DC term)



$$f(x) = \sum_{u=-\infty}^{+\infty} F(u) e^{2\pi i u x}$$

$$F(u) = \int_0^1 f(x) e^{-2\pi i u x} dx$$

Fourier Transform Examples 2

Forward Transform: $F(u) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i u x} dx$

Inverse Transform: $f(x) = \int_{-\infty}^{+\infty} F(u) e^{2\pi i u x} du$

- Common examples

$f(x)$	$F(u)$
$\delta(x - x_0)$	$e^{-2\pi i u x_0}$
1	$\delta(u)$
e^{-ax^2}	$\sqrt{\frac{\pi}{a}} e^{-\pi^2 u^2 / a}$

Fourier Transform Properties

$$\text{Forward Transform: } F(u) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i u x} dx$$

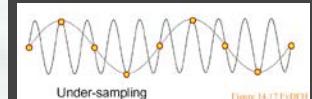
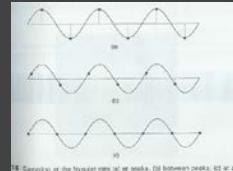
$$\text{Inverse Transform: } f(x) = \int_{-\infty}^{+\infty} F(u) e^{2\pi i u x} du$$

- Common properties

- Linearity: $F(af(x) + bg(x)) = aF(f(x)) + bF(g(x))$
- Derivatives: [integrate by parts] $F(f'(x)) = \int_{-\infty}^{\infty} f'(x) e^{-2\pi i u x} dx = 2\pi i u F(u)$
- 2D Fourier Transform
Forward Transform: $F(u,v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) e^{-2\pi i u x - 2\pi i v y} dx dy$
- Convolution (next)
Inverse Transform: $f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{+\infty} F(u,v) e^{2\pi i u x + 2\pi i v y} du dv$

Sampling Theorem, Bandlimiting

- A signal can be reconstructed from its samples, if the original signal has no frequencies above half the sampling frequency – Shannon
- The minimum sampling rate for a bandlimited function is called the Nyquist rate



14.17 Sampling at the Nyquist rate (a), (b) between peaks, (c) at twice the Nyquist rate. (Courtesy of George Wolberg, Technical University of Denmark.)

Sampling Theorem, Bandlimiting

- A signal can be reconstructed from its samples, if the original signal has no frequencies above half the sampling frequency – Shannon
- The minimum sampling rate for a bandlimited function is called the Nyquist rate
- A signal is bandlimited if the highest frequency is bounded. This frequency is called the bandwidth
- In general, when we transform, we want to filter to bandlimit before sampling, to avoid aliasing

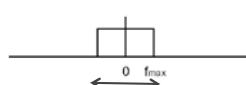
Antialiasing

- Sample at higher rate
 - Not always possible
 - Real world: lines have infinitely high frequencies, can't sample at high enough resolution
- Prefilter to bandlimit signal
 - Low-pass filtering (blurring)
 - Trade blurriness for aliasing

Ideal bandlimiting filter

- Formal derivation is homework exercise

- Frequency domain



- Spatial domain

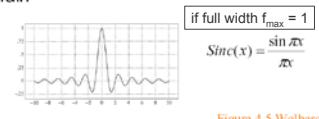


Figure 4.5 Wolberg

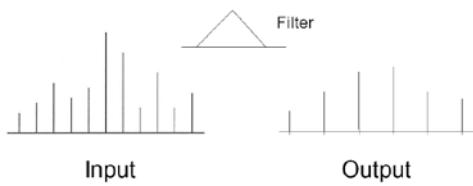
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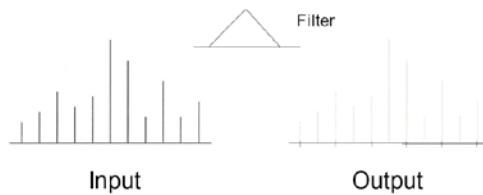
Convolution 1

- Spatial domain: output pixel is weighted sum of pixels in neighborhood of input image
 - Pattern of weights is the “filter”



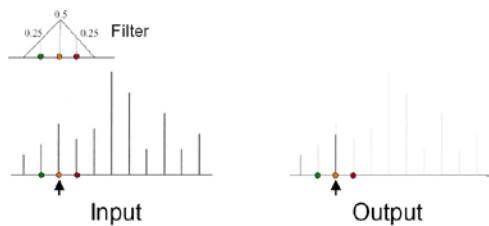
Convolution 2

- Example 1:



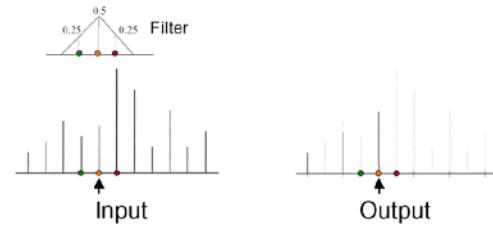
Convolution 3

- Example 1:



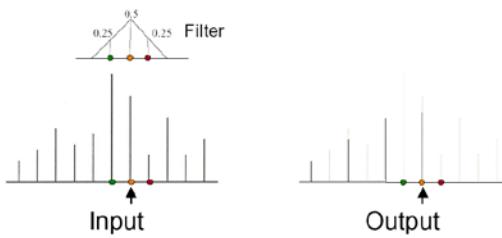
Convolution 4

- Example 1:



Convolution 5

- Example 1:



Convolution in Frequency Domain

$$\text{Forward Transform: } F(u) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i u x} dx$$

$$\text{Inverse Transform: } f(x) = \int_{-\infty}^{+\infty} F(u) e^{2\pi i u x} du$$

- Convolution (f is signal ; g is filter [or vice versa])

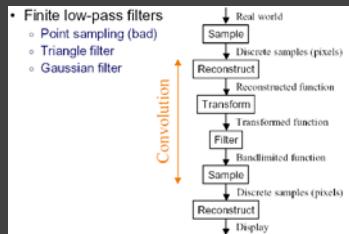
$$h(y) = \int_{-\infty}^{+\infty} f(x) g(y - x) dx = \int_{-\infty}^{+\infty} g(x) f(y - x) dx$$

$$h = f^* g \text{ or } f \otimes g$$

- Fourier analysis (frequency domain multiplication) $H(u) = F(u)G(u)$

Practical Image Processing

- Discrete convolution (in spatial domain) with filters for various digital signal processing operations
- Easy to analyze, understand effects in frequency domain
 - E.g. blurring or bandlimiting by convolving with low pass filter



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