

Computer Vision

Spring 2006 15-385,-685

Instructor: S. Narasimhan

Wean 5403

T-R 3:00pm – 4:20pm

Announcements

- Homework 1 is due today in class.
- Homework 2 will be out later this evening (due in 2 weeks).
- Start homeworks early.
- Post questions on bboard.

Image Processing and Filtering

Lecture #5

Image as a Function

- We can think of an **image** as a function, f ,
- $f: \mathbb{R}^2 \rightarrow \mathbb{R}$
 - $f(x, y)$ gives the **intensity** at position (x, y)
 - Realistically, we expect the image only to be defined over a rectangle, with a finite range:
 - $f: [a, b] \times [c, d] \rightarrow [0, 1]$
- A color image is just three functions pasted together. We can write this as a “vector-valued” function:

$$f(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

Image as a Function

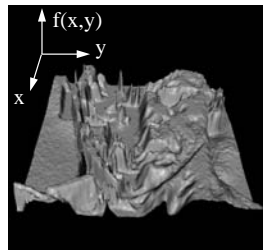
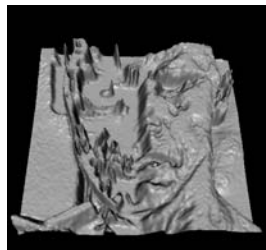
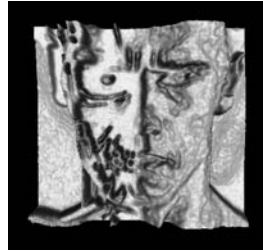


Image Processing

- Define a new image g in terms of an existing image f
 - We can transform either the domain or the range of f
- Range transformation:

$$g(x, y) = t(f(x, y))$$

What kinds of operations can this perform?

Image Processing

- Some operations preserve the range but change the domain of f :

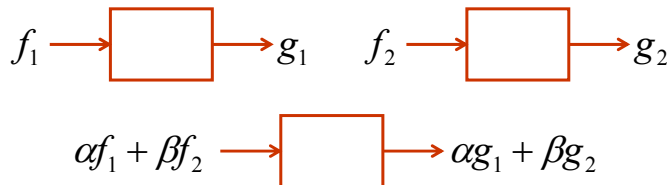
$$g(x, y) = f(t_x(x, y), t_y(x, y))$$

What kinds of operations can this perform?

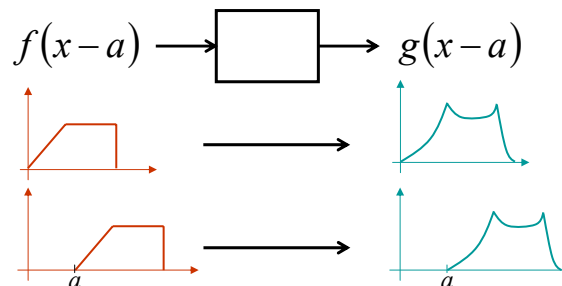
- Still other operations operate on both the domain and the range of f .

Linear Shift Invariant Systems (LSIS)

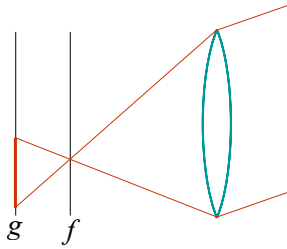
Linearity:



Shift invariance:



Example of LSIS



Defocused image (g) is a processed version of the focused image (f)

Ideal lens is a LSIS $f(x) \rightarrow \boxed{\text{LSIS}} \rightarrow g(x)$

Linearity: Brightness variation

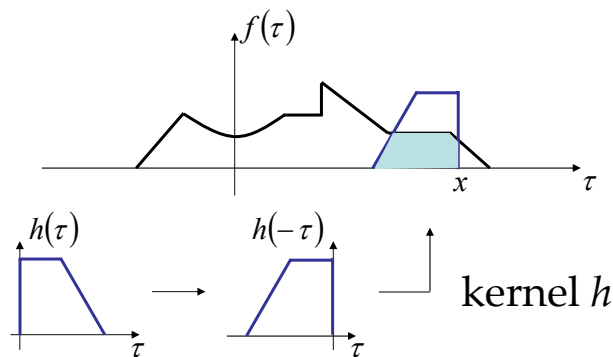
Shift invariance: Scene movement

(not valid for lenses with non-linear distortions)

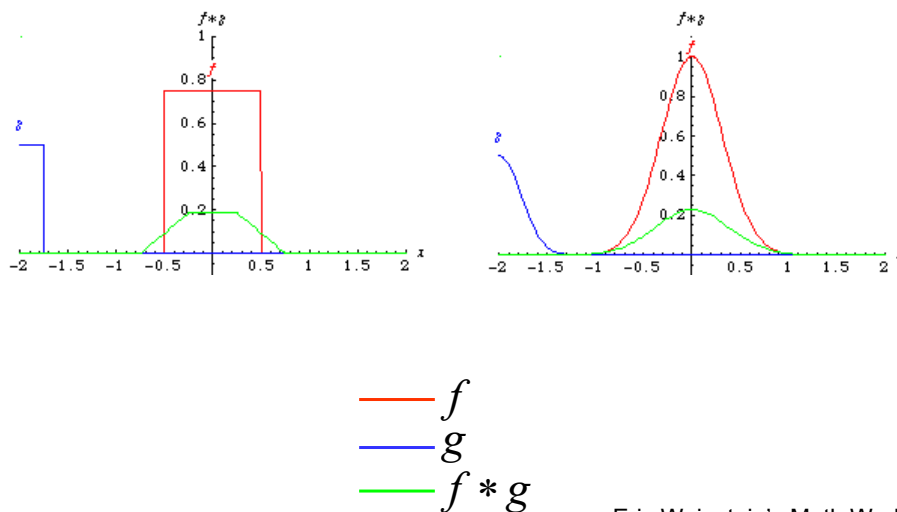
Convolution

LSIS is doing convolution; convolution is linear and shift invariant

$$g(x) = \int_{-\infty}^{\infty} f(\tau)h(x-\tau)d\tau \quad g = f * h$$

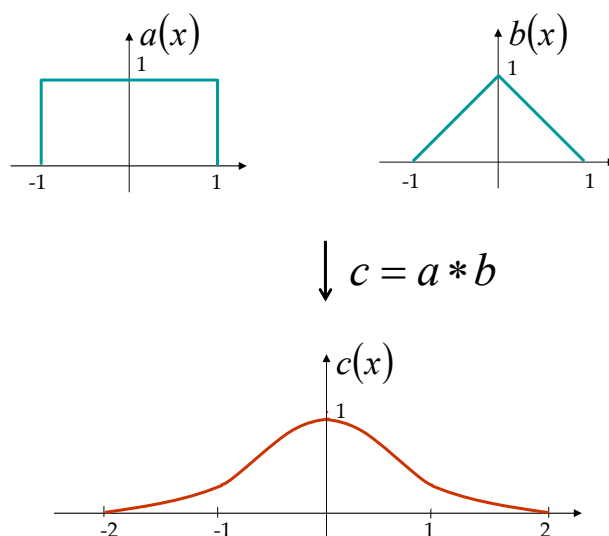


Convolution - Example



Eric Weinstein's Math World

Convolution - Example



Convolution Kernel – Impulse Response

$$f \longrightarrow \boxed{h} \longrightarrow g \quad g = f * h$$

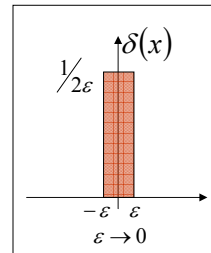
- What h will give us $g = f$?

Dirac Delta Function (Unit Impulse)

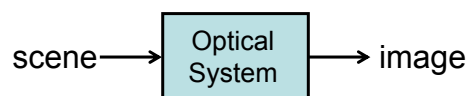
Sifting property:

$$\begin{aligned} \int_{-\infty}^{\infty} f(x) \delta(x) dx &= \int_{-\infty}^{\infty} f(0) \delta(x) dx \\ &= f(0) \int_{-\infty}^{\infty} \delta(x) dx = f(0) \end{aligned}$$

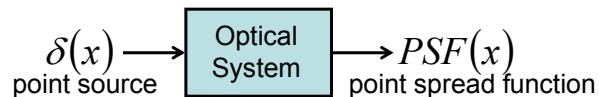
$$\begin{aligned} g(x) &= \int_{-\infty}^{\infty} f(\tau) \delta(x - \tau) d\tau = f(x) \\ &= \int_{-\infty}^{\infty} \delta(\tau) h(x - \tau) d\tau = h(x) \end{aligned}$$



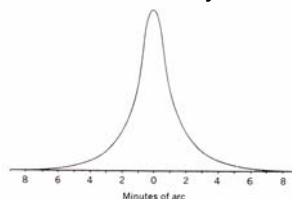
Point Spread Function



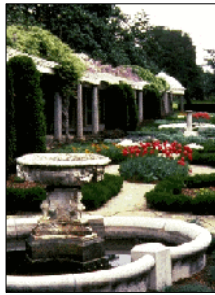
- Ideally, the optical system should be a Dirac delta function.
- However, optical systems are never ideal.



- Point spread function of Human Eyes



Point Spread Function



normal vision



myopia



hyperopia



astigmatism

Images by Richmond Eye Associates

Properties of Convolution

- Commutative

$$a * b = b * a$$

- Associative

$$(a * b) * c = a * (b * c)$$

- Cascade system

$$f \longrightarrow \boxed{h_1} \longrightarrow \boxed{h_2} \longrightarrow g$$

$$= f \longrightarrow \boxed{h_1 * h_2} \longrightarrow g$$

$$= f \longrightarrow \boxed{h_2 * h_1} \longrightarrow g$$

How to Represent Signals?

- Option 1: Taylor series represents any function using polynomials.

$$f(x) = f(\alpha) + f'(\alpha)(x - \alpha) + \frac{f''(\alpha)}{2!}(x - \alpha)^2 + \frac{f^{(3)}(\alpha)}{3!}(x - \alpha)^3 + \dots + \frac{f^{(n)}(\alpha)}{n!}(x - \alpha)^n + \dots$$

- Polynomials are not the best - unstable and not very physically meaningful.
- Easier to talk about “signals” in terms of its “frequencies” (how fast/often signals change, etc).

Jean Baptiste Joseph Fourier (1768-1830)

- Had crazy idea (1807):
- Any** periodic function can be rewritten as a weighted sum of **Sines** and **Cosines** of different frequencies.
- Don't believe it?
 - Neither did Lagrange, Laplace, Poisson and other big wigs
 - Not translated into English until 1878!
- But it's true!
 - called **Fourier Series**
 - Possibly the greatest tool used in Engineering

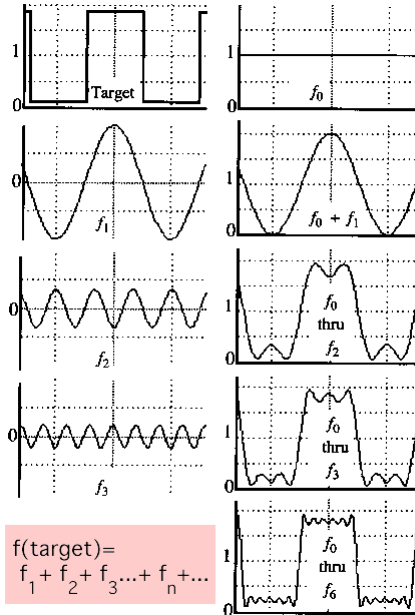


A Sum of Sinusoids

- Our building block:

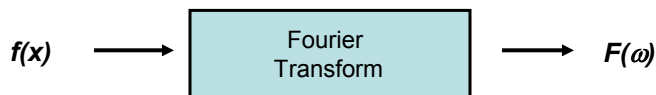
$$A \sin(\omega x + \phi)$$

- Add enough of them to get any signal $f(x)$ you want!
- How many degrees of freedom?
- What does each control?
- Which one encodes the coarse vs. fine structure of the signal?



Fourier Transform

- We want to understand the frequency ω of our signal. So, let's reparametrize the signal by ω instead of x :



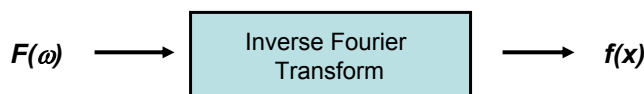
- For every ω from 0 to inf, $F(\omega)$ holds the amplitude A and phase ϕ of the corresponding sine $A \sin(\omega x + \phi)$

– How can F hold both? Complex number trick!

$$F(\omega) = R(\omega) + iI(\omega)$$

$$A = \pm \sqrt{R(\omega)^2 + I(\omega)^2}$$

$$\phi = \tan^{-1} \frac{I(\omega)}{R(\omega)}$$



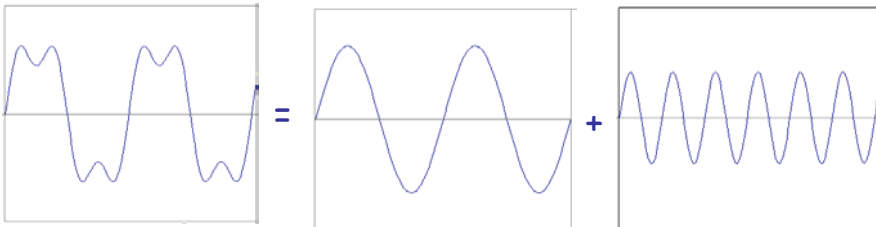
Time and Frequency

- example : $g(t) = \sin(2\pi f t) + (1/3)\sin(2\pi(3f) t)$



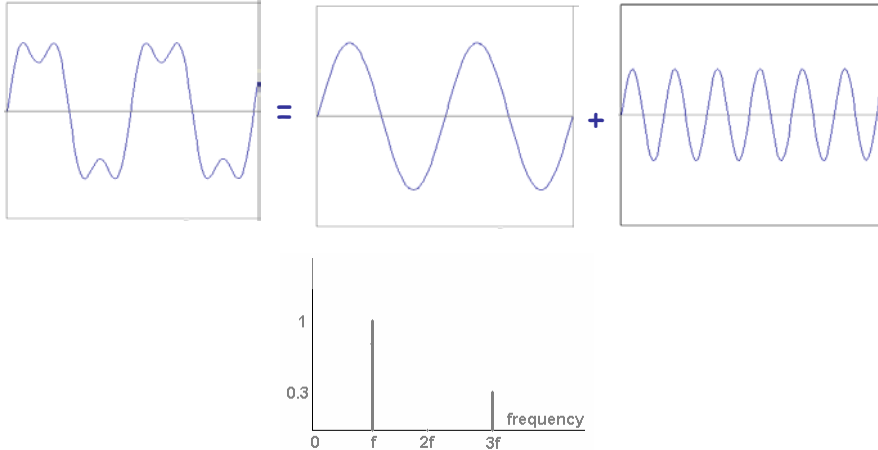
Time and Frequency

- example : $g(t) = \sin(2\pi f t) + (1/3)\sin(2\pi(3f) t)$



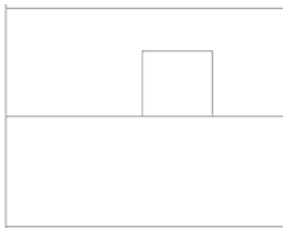
Frequency Spectra

- example : $g(t) = \sin(2\pi f t) + (1/3)\sin(2\pi(3f) t)$

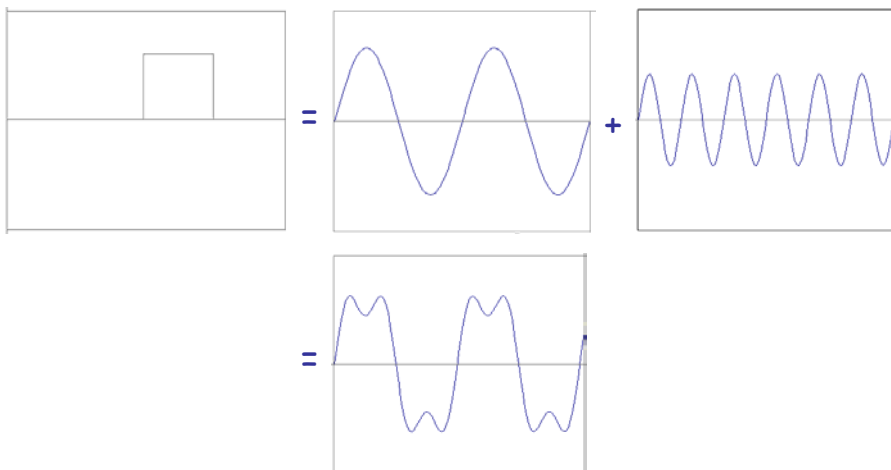


Frequency Spectra

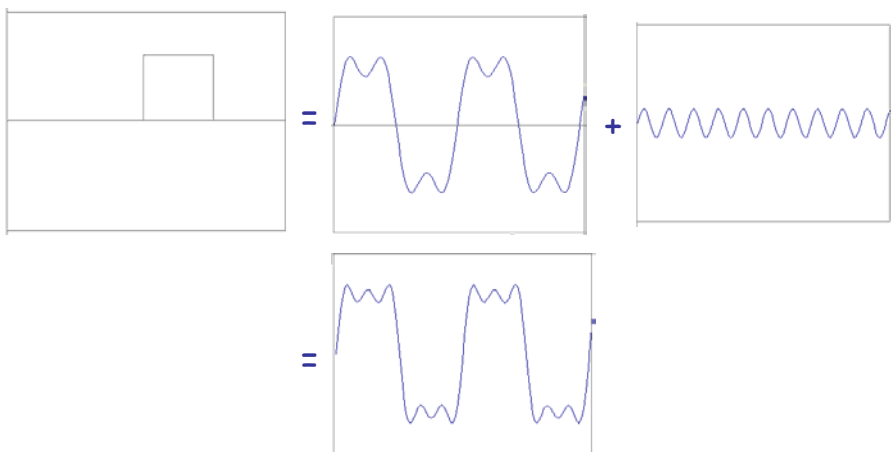
- Usually, frequency is more interesting than the phase



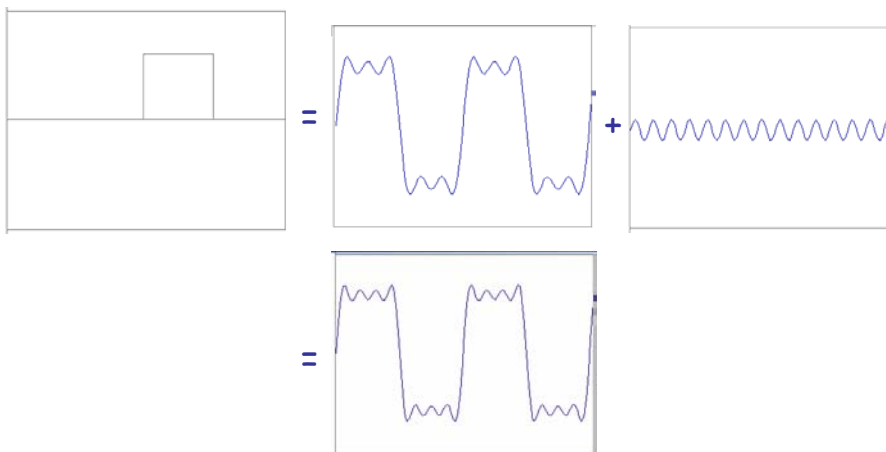
Frequency Spectra



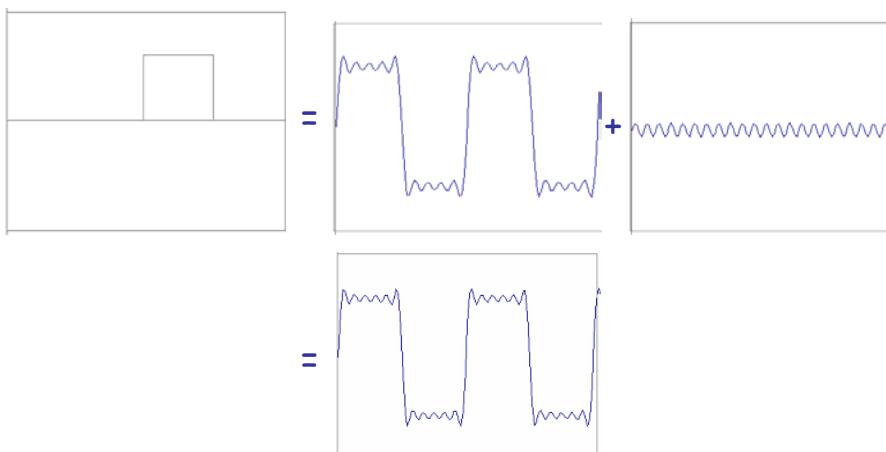
Frequency Spectra



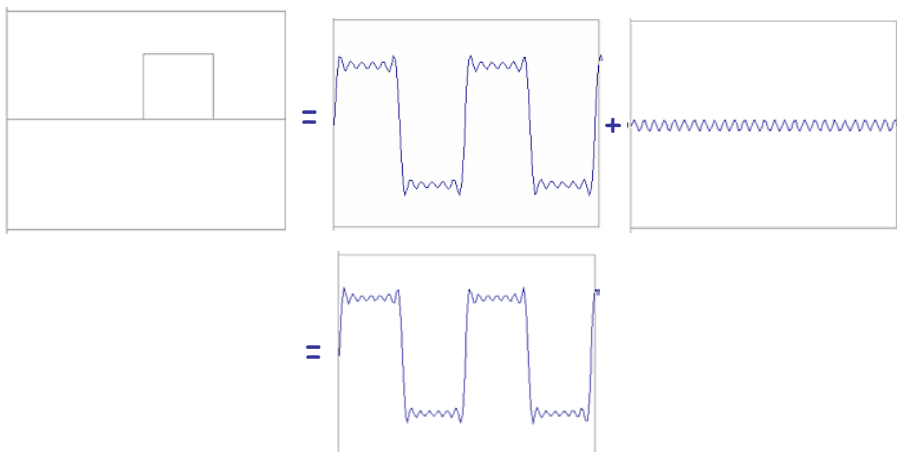
Frequency Spectra



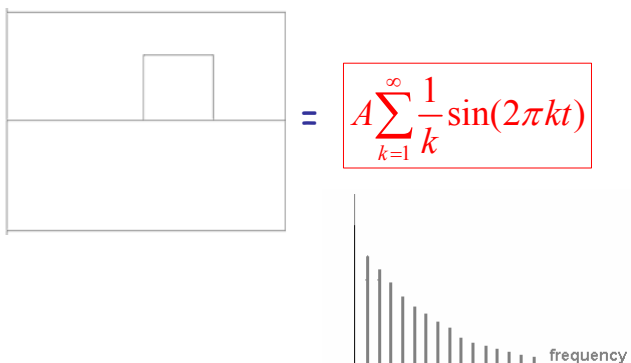
Frequency Spectra



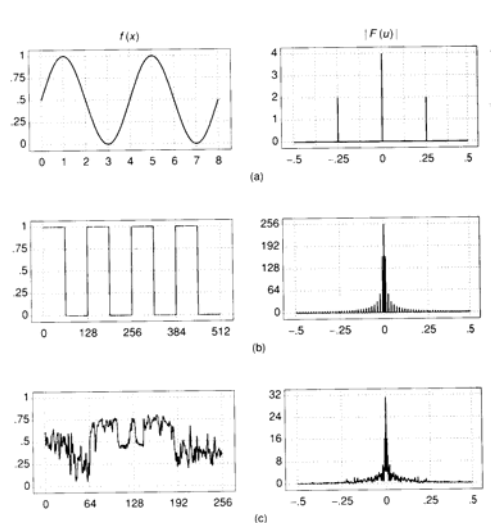
Frequency Spectra



Frequency Spectra

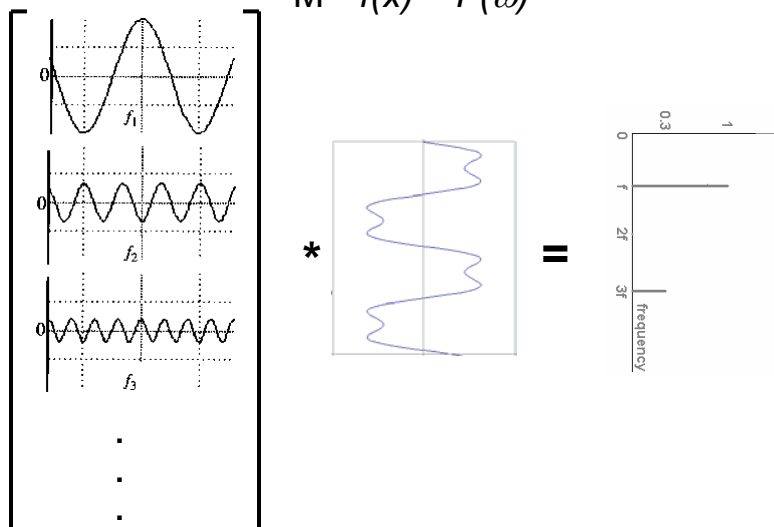


Frequency Spectra

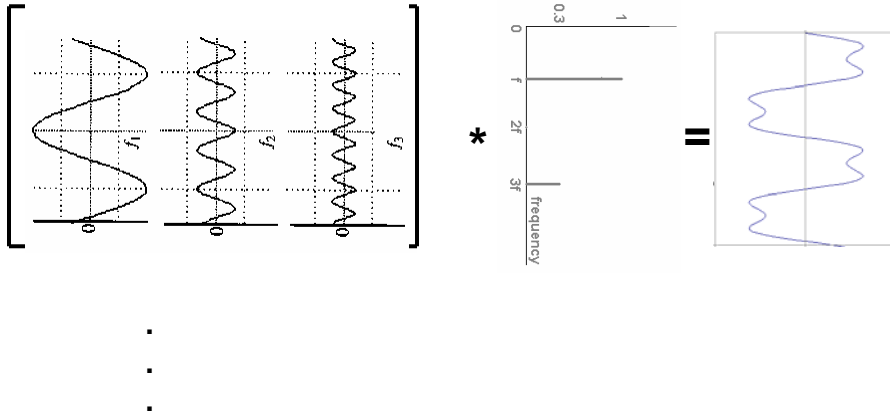


FT: Just a change of basis

$$M * f(x) = F(\omega)$$



$$M^{-1} * F(\omega) = f(x)$$



Represent the signal as an infinite weighted sum of an infinite number of sinusoids

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi ux} dx$$

Note: $e^{ik} = \cos k + i \sin k$ $i = \sqrt{-1}$

Arbitrary function \longrightarrow Single Analytic Expression

Spatial Domain (x) \longrightarrow Frequency Domain (u)
(Frequency Spectrum $F(u)$)

Inverse Fourier Transform (IFT)

$$f(x)=\int_{-\infty}^{\infty}F(u)e^{i2\pi ux}dx$$

Fourier Transform

- Also, defined as:

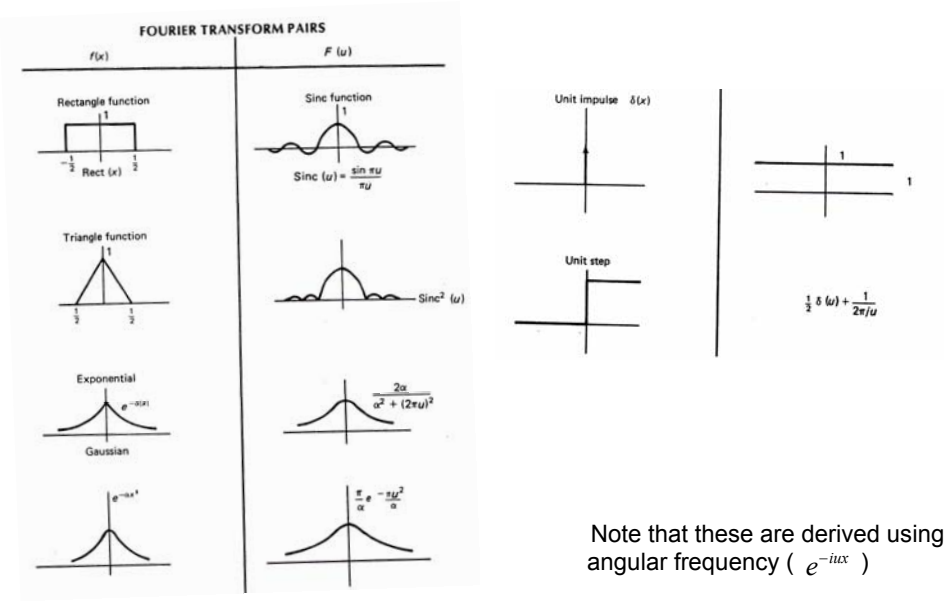
$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-iux} dx$$

Note: $e^{ik} = \cos k + i \sin k$ $i = \sqrt{-1}$

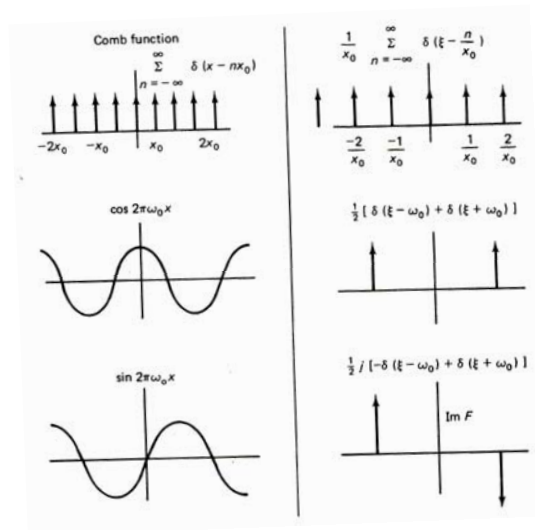
- Inverse Fourier Transform (IFT)

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(u) e^{iux} dx$$

Fourier Transform Pairs (I)



Fourier Transform Pairs (I)



Note that these are derived using angular frequency ($e^{-i\omega x}$)

Fourier Transform and Convolution

Let $g = f * h$

Then $G(u) = \int_{-\infty}^{\infty} g(x) e^{-i2\pi u x} dx$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau) h(x - \tau) e^{-i2\pi u x} d\tau dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [f(\tau) e^{-i2\pi u \tau} d\tau] [h(x - \tau) e^{-i2\pi u (x - \tau)} dx]$$

$$= \int_{-\infty}^{\infty} [f(\tau) e^{-i2\pi u \tau} d\tau] \int_{-\infty}^{\infty} [h(x') e^{-i2\pi u x'} dx']$$

$$= F(u)H(u)$$

Convolution in spatial domain

\Leftrightarrow Multiplication in frequency domain

Fourier Transform and Convolution

Spatial Domain (x)		Frequency Domain (u)
$g = f * h$	\longleftrightarrow	$G = FH$
$g = fh$	\longleftrightarrow	$G = F * H$

So, we can find $g(x)$ by Fourier transform

$$\begin{array}{ccccc}
 g & = & f & * & h \\
 \uparrow & & \downarrow & & \downarrow \\
 \boxed{\text{IFT}} & & \boxed{\text{FT}} & & \boxed{\text{FT}} \\
 \downarrow & & \downarrow & & \downarrow \\
 G & = & F & \times & H
 \end{array}$$

Properties of Fourier Transform

	Spatial Domain (x)	Frequency Domain (u)
Linearity	$c_1 f(x) + c_2 g(x)$	$c_1 F(u) + c_2 G(u)$
Scaling	$f(ax)$	$\frac{1}{ a } F\left(\frac{u}{a}\right)$
Shifting	$f(x - x_0)$	$e^{-i2\pi x_0 u} F(u)$
Symmetry	$F(x)$	$f(-u)$
Conjugation	$f^*(x)$	$F^*(-u)$
Convolution	$f(x) * g(x)$	$F(u)G(u)$
Differentiation	$\frac{d^n f(x)}{dx^n}$	$(i2\pi u)^n F(u)$

Note that these are derived using frequency ($e^{-i2\pi x u}$)

Properties of Fourier Transform

Parseval's theorem:

$$\int_{-\infty}^{\infty} |f(x)|^2 dx = \int_{-\infty}^{\infty} |F(\xi)|^2 d\xi$$

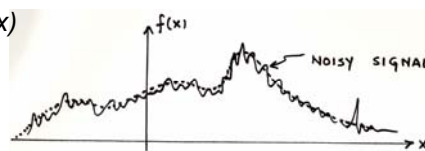
$$\int_{-\infty}^{\infty} f(x) g^*(x) dx = \int_{-\infty}^{\infty} F(\xi) G^*(\xi) d\xi$$

$f(x)$	$F(\xi)$
Real (R)	Real part even (RE) Imaginary part odd (IO)
Imaginary (I)	RO, IE
RE, IO	R
RE, IE	I
RE	RE
RO	IO
IE	IE
IO	RO
Complex even (CE)	CE
CO	CO

Example use: Smoothing/Blurring

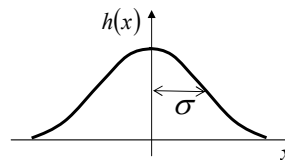
- We want a smoothed function of $f(x)$

$$g(x) = f(x) * h(x)$$



- Let us use a Gaussian kernel

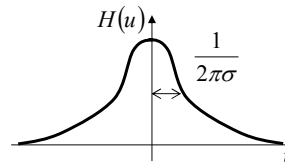
$$h(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2} \frac{x^2}{\sigma^2}\right]$$



- Then

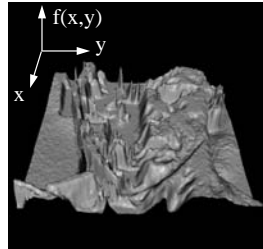
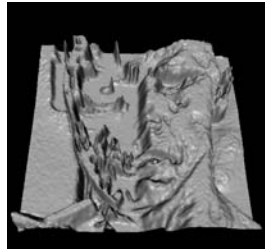
$$H(u) = \exp\left[-\frac{1}{2} (2\pi u)^2 \sigma^2\right]$$

$$G(u) = F(u)H(u)$$



$H(u)$ attenuates high frequencies in $F(u)$ (Low-pass Filter)!

Image as a Discrete Function



Digital Images

The scene is

- **projected** on a 2D plane,
- **sampled** on a regular grid, and each sample is
- **quantized** (rounded to the nearest integer)

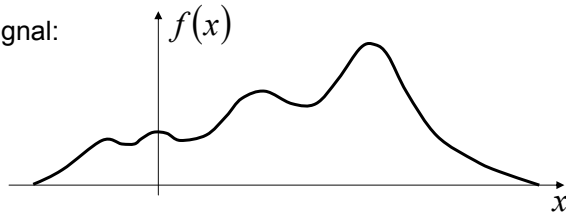
$$f(i, j) = \text{Quantize}\{f(i\Delta, j\Delta)\}$$

Image as a matrix

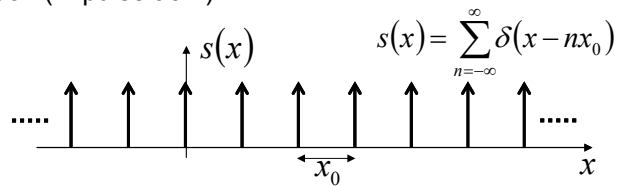
	$j \rightarrow$							
$i \downarrow$	62	79	23	119	120	105	4	0
	10	10	9	62	12	78	34	0
	10	58	197	46	46	0	0	48
	176	135	5	188	191	68	0	49
	2	1	1	29	26	37	0	77
	0	89	144	147	187	102	62	208
	255	252	0	166	123	62	0	31
	166	63	127	17	1	0	99	30

Sampling Theorem

Continuous signal:



Shah function (Impulse train):

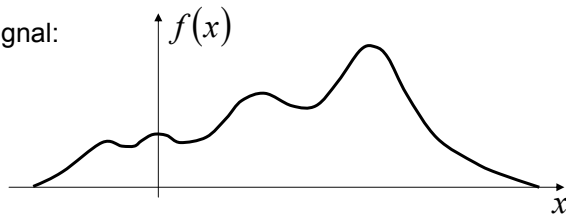


Sampled function:

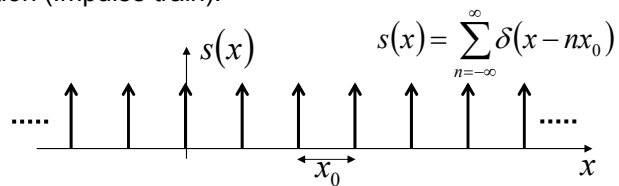
$$f_s(x) = f(x)s(x) = f(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0)$$

Sampling Theorem

Continuous signal:



Shah function (Impulse train):



Sampled function:

$$f_s(x) = f(x)s(x) = f(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0)$$

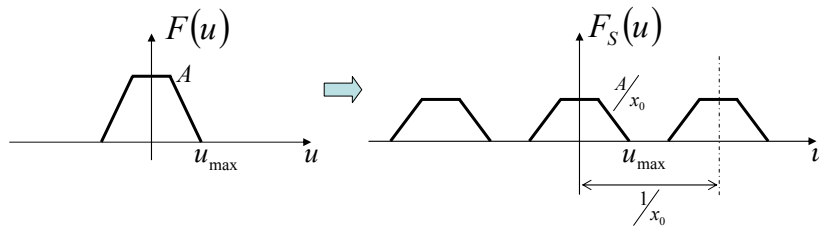
Sampling Theorem

Sampled function:

$$f_s(x) = f(x)s(x) = f(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0)$$

Sampling frequency $\frac{1}{x_0}$

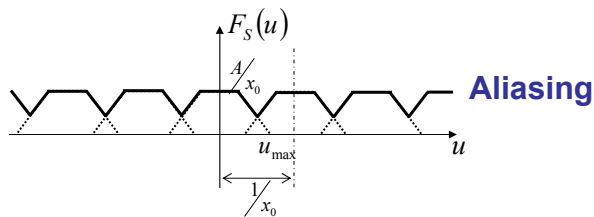
$$F_s(u) = F(u) * S(u) = F(u) * \frac{1}{x_0} \sum_{n=-\infty}^{\infty} \delta\left(u - \frac{n}{x_0}\right)$$



Only if $u_{\max} \leq \frac{1}{2x_0}$

Nyquist Theorem

If $u_{\max} > \frac{1}{2x_0}$



When can we recover $F(u)$ from $F_s(u)$?

Only if $u_{\max} \leq \frac{1}{2x_0}$ (Nyquist Frequency)

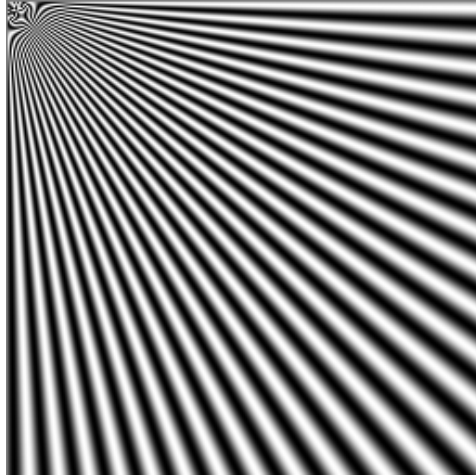
We can use

$$C(u) = \begin{cases} x_0 & |u| < 1/2x_0 \\ 0 & \text{otherwise} \end{cases}$$

Then $F(u) = F_s(u)C(u)$ and $f(x) = \text{IFT}[F(u)]$

Sampling frequency must be greater than $2u_{\max}$

Aliasing



Announcements

- Homework 1 is due today in class.
- Homework 2 will be out later this evening.
- Start homeworks early.
- Post questions on bboard.

Next Class

- Image Processing and Filtering (continued)
- Horn, Chapter 6