SIGNALS AND SYSTEMS

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Signal Analysis

Signal and Vectors

Any vector A in 3 dimensional space can be expressed as

 $A = A_1a + A_2b + A_3c$

- a, b, c are vectors that do not lie in the same plane and are not collinear
- A1, A2, and A3 are linearly independent
- No one of the vectors can be expressed as a linear combination of the other 2
- a, b, c is said to form a basis for a 3 dimensional vector space
- To represent a time signal or function X(t) on a T interval (to to to+T) consider a set of time function independent of $x(t) \cdot _1(t), \cdot _2(t), \cdot _3(t) \cdot _N(t)$

Signal and Vectors

• X(t) can expanded as

$$x_{a}(t) \cdot \underbrace{\stackrel{N}{\bullet}}_{n \cdot 0} x_{n \cdot n}(t)$$

• N coefficients Xn are independent of time and subscript xa is an approximation

Signals and Vectors

- Signal **g** can be written as N dimensional vector $\mathbf{g} = [g(t_1) g(t_2) \dots g(t_N)]$
- Continuous time signals are straightforward generalization of finite dimension vectors
 N. .
 t · [a,b]
- In vector (dot or scalar), inner product of two realvalued vector g and x:
 - $\langle g, x \rangle = ||g|| \cdot ||x|| \cos \theta$ θ angle between vector **g** and **x**
 - Length of a vector x:

$$||X||_2 = \langle X.X \rangle$$

Analogy between Signal Spaces and Vector Spaces

- Consider two vectors V1 and V2 as shown in Fig. If V1 is to be
- represented in terms of V2

 $V_1 = C_{12}V_2 + V_e$

• where Ve is the error.

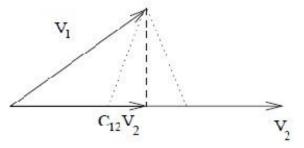
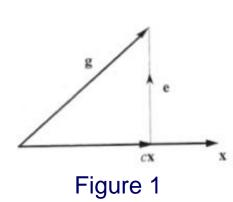


Figure : Representation in vector space

Component of a Vector in terms of another vector.

Vector **g** in Figure 1 can be expressed in terms of vector **x**



$$\mathbf{g} = \mathbf{C}\mathbf{X} + \mathbf{e}$$

$$\mathbf{e} = \mathbf{g} - \mathbf{c} \mathbf{x}$$
 (error vector)

 Figure 2 shows infinite possibilities to express vector g in terms of vector x

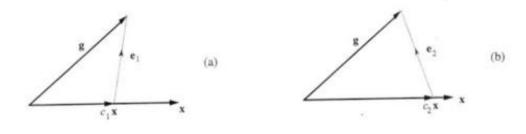


Figure 2

 $g = C_1 X + e_1 = C_2 X + e_2$

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 Let f1(t) and f2(t) be two real signals. Approximation of f1(t) by f2(t) over a time interval t1 < t < t2 can be given by

$$f_e(t) = f_1(t) - C_{12}f_2(t)$$

where fe(t) is the error function.

 The goal is to find C12 such that fe(t) is minimum over the interval considered. The energy of the error signal ε given by

$$\varepsilon = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} [f_1(t) - C_{12} f_2(t)]^2 dt$$

To find C12,



$$\frac{\partial \varepsilon}{\partial C_{12}} = 0$$

Solving the above equation we get

$$C_{12} = \frac{\frac{1}{t_2 - t_1} \int_{t_1}^{t_2} f_1(t) \cdot f_2(t) dt}{\frac{1}{t_2 - t_1} \int_{t_1}^{t_2} f_2^2(t) dt}$$

- The denominator is the energy of the signal f2(t).
- When f1(t) and f2(t) are orthogonal to each other
 C12 = 0.

Scalar or Dot Product of Two Vectors $\mathbf{g} \cdot \mathbf{x} = |\mathbf{g}| |\mathbf{x}| \cos \theta$

- • is the angle between vectors **g** and **x**.
- The length of the component **g** along **x** is: $c|\mathbf{x}| = |\mathbf{g}| \cos \theta$
- Multiplying both sides by $|\mathbf{x}|$ yields: $c|\mathbf{x}|^2 = |\mathbf{g}||\mathbf{x}|\cos\theta = \mathbf{g}\cdot\mathbf{x}$
- Where: $|\mathbf{x}|^2 = \mathbf{x} \cdot \mathbf{x}$

• Therefore:
$$c = \frac{\mathbf{g} \cdot \mathbf{x}}{\mathbf{x} \cdot \mathbf{x}} = \frac{1}{|\mathbf{x}|^2} \mathbf{g} \cdot \mathbf{x}$$

- If g and x are **Orthogonal** (perpendicular): $\mathbf{g} \cdot \mathbf{x} = \mathbf{0}$
- Vectors g and x are defined to be Orthogonal if the dot product of the two vectors are zero.

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Components and Orthogonality of Signals

- Concepts of vector component and orthogonality can be extended to CTS
- If signal g(t) is approximated by another signal x(t) as :

$$g(t) \simeq cx(t)$$
 $t_1 \leq t \leq t_2$

 The optimum value of c that minimizes the energy of the error signal is:

$$C = \frac{1}{E_x} \int_{t_1}^{t_2} g(t) x(t) dt$$

- We define **real** signals g(t) and x(t) to be orthogonal over the interval [t₁, t₂], if: $\int_{t_2}^{t_2} g(t)x(t) dt = 0$
- We define complex signals* x1(t) and x2(t) to be orthogonal over the interval [t1, t2]:

$$\int_{t_1}^{t_2} x_1(t) x_2^*(t) \, dt = 0 \quad \text{or} \quad \int_{t_1}^{t_2} x_1^*(t) x_2(t) \, dt = 0$$

Example

 For the square signal g(t) find the component in g(t) of the form sin t. In order words, approximate g(t) in terms of sin t so that the energy of the error signal is minimum

 $g(t) \simeq c \, \sin t \qquad 0 \le t \le 2\pi$

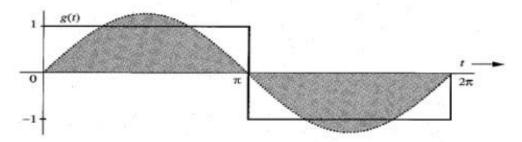
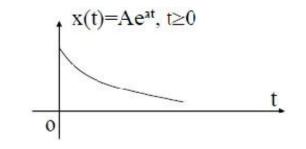


Figure 2.17 Approximation of a square signal in terms of a single sinusoid.

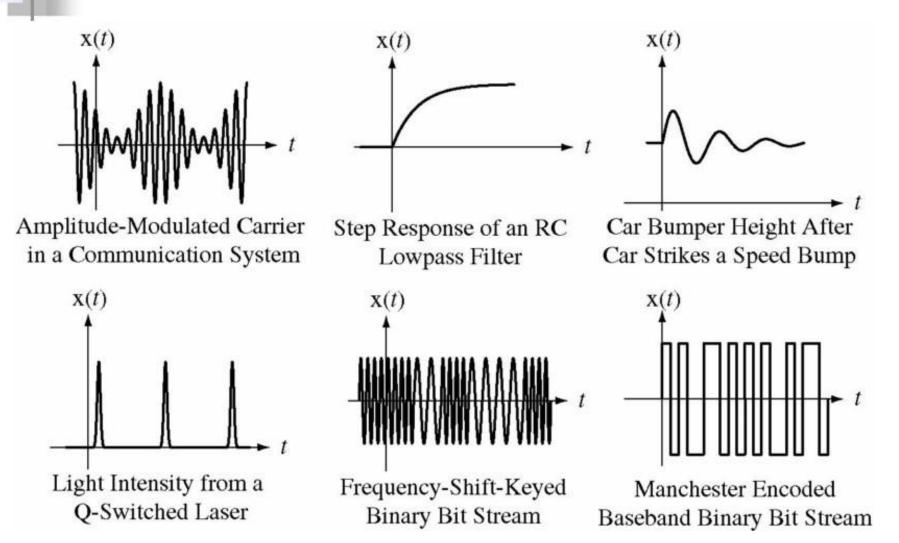
$$x(t) = \sin t \quad \text{and} \quad E_x = \int_0^{2\pi} \sin^2 t \, dt = \pi$$
$$c = \frac{1}{\pi} \int_0^{2\pi} g(t) \sin t \, dt = \frac{1}{\pi} \left[\int_0^{\pi} \sin t \, dt + \int_{\pi}^{2\pi} -\sin t \, dt \right] = \frac{4}{\pi}$$
$$g(t) \simeq \frac{4}{\pi} \sin t$$

Introduction to Signals

- A Signal is the function of one or more independent variables that carries some information to represent a physical phenomenon.
- A continuous-time signal, also called an analog signal, is defined along a continuum of time.

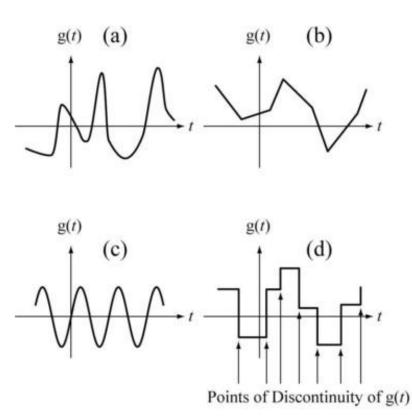


Typical Continuous-Time Signals



Continuous vs Continuous-Time Signals

All continuous signals that are functions of time are **continuous-time** but not all continuous-time signals are continuous



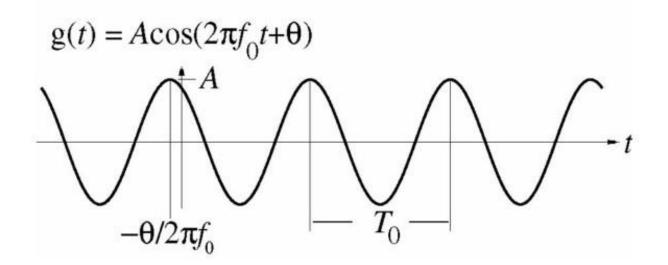
Continuous-Time Sinusoids

$$g(t) = A\cos(2pt/T_0 + q) = A\cos(2pf_0t + q) = A\cos(w_0t + q)$$

Amplitude

Period Phase Shift (s) (radians) Cyclic Frequency (Hz)

Radian Frequency (radians/s)



Elementary Signals

Sinusoidal & Exponential Signals

- Sinusoids and exponentials are important in signal and system analysis because they arise naturally in the solutions of the differential equations.
- Sinusoidal Signals can expressed in either of two ways :

cyclic frequency form- A sin $2\Pi f_0 t = A \sin(2\Pi/T_0)t$

radian frequency form- A sin $\omega_0 t$

 $\omega_{\circ}=2\Pi f_{o}=2\Pi/\mathsf{T}_{o}$

 $T_o = Time Period of the Sinusoidal Wave$

Sinusoidal & Exponential Signals Contd.

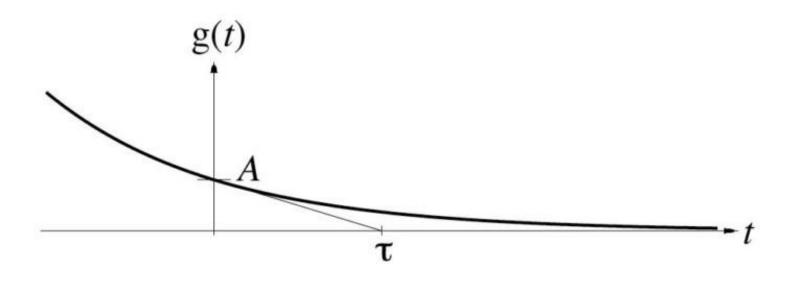
$$\begin{aligned} \mathbf{x}(t) &= \mathbf{A} \sin \left(2 \Pi f_o t + \theta \right) \\ &= \mathbf{A} \sin \left(\omega_o t + \theta \right) \end{aligned} \ \begin{aligned} & \text{Sinusoidal signal} \\ \mathbf{x}(t) &= \mathbf{A} e_{at} \end{aligned} \ \begin{aligned} & \text{Real Exponential} \\ &= \mathbf{A} e_{j\omega t} \end{aligned} \ \begin{aligned} &= \mathbf{A} [\cos \left(\omega_o t \right) + j \sin \left(\omega_o t \right)] \end{aligned} \ \end{aligned}$$

 θ = Phase of sinusoidal wave A = amplitude of a sinusoidal or exponential signal f_0 = fundamental cyclic frequency of sinusoidal signal ω_0 = radian frequency

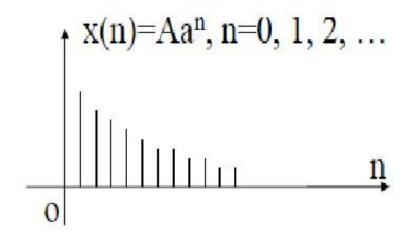
Continuous-Time Exponentials

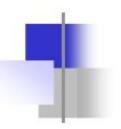
$$g(t) = Ae_{-t/t}$$

Amplitude Time Constant (s)



A discrete-time signal is defined at discrete times.

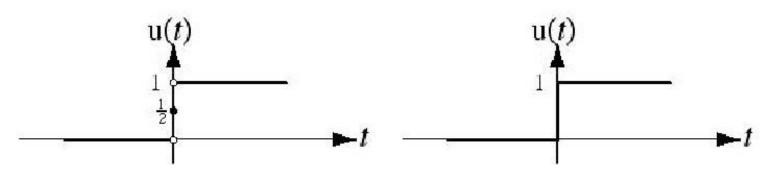


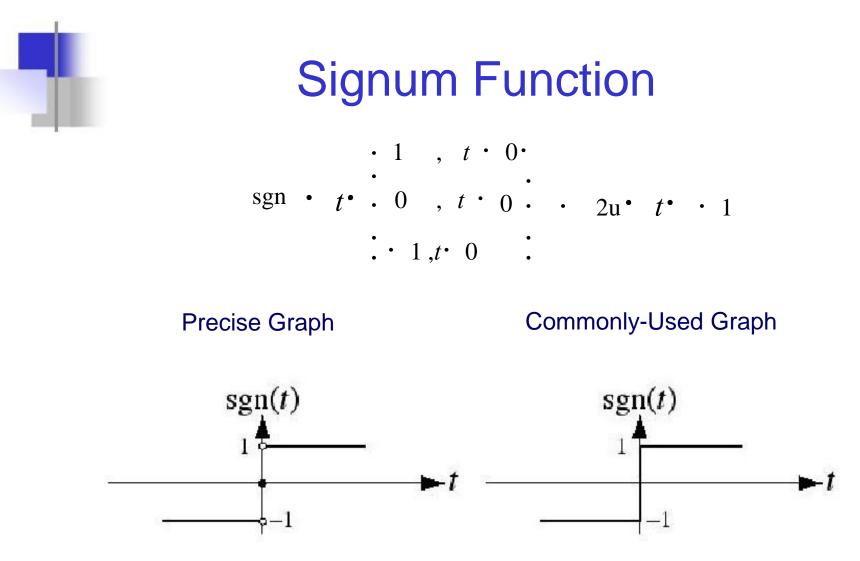


Unit Step Function

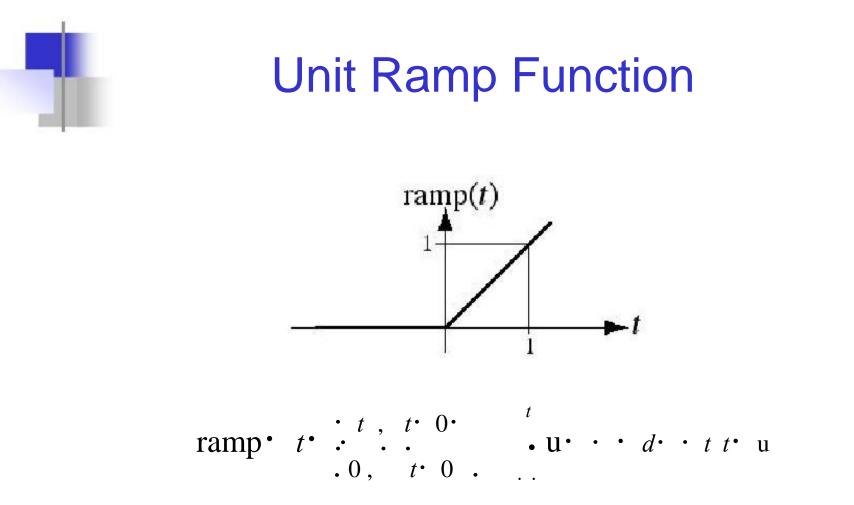


Commonly-Used Graph



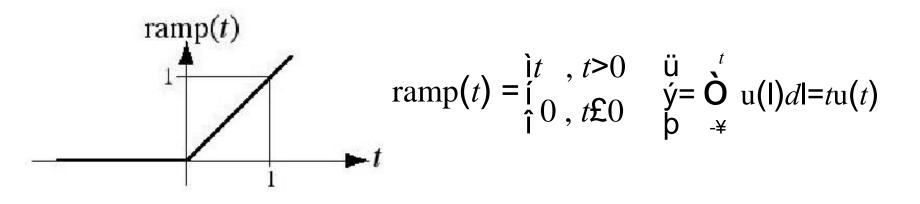


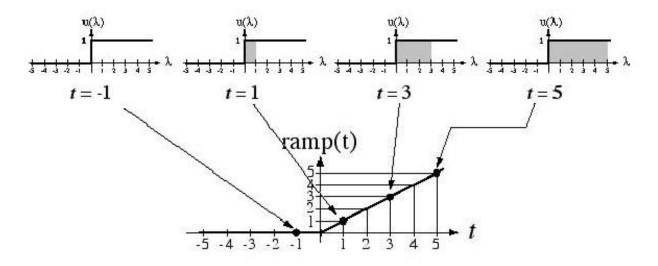
The signum function, is closely related to the unit-step function.



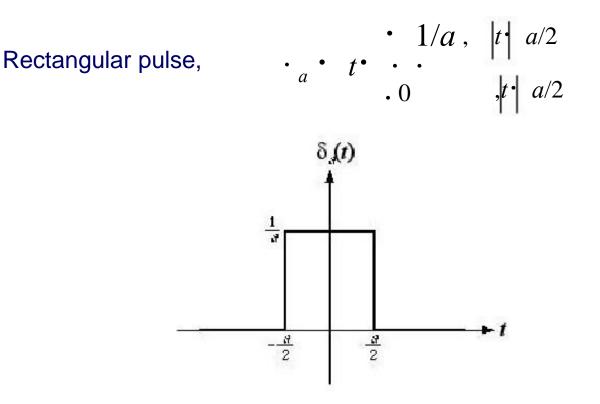
The unit ramp function is the integral of the unit step function.
It is called the unit ramp function because for positive t, its slope is one amplitude unit per time.

The Unit Ramp Function



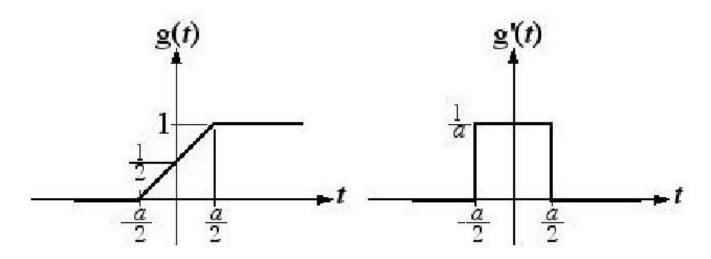


Rectangular Pulse or Gate Function



Unit Impulse Function

As *a* approaches zero, $g \cdot t \cdot$ approaches a unit step and $g \cdot$ approaches a unit impulse $t \cdot$

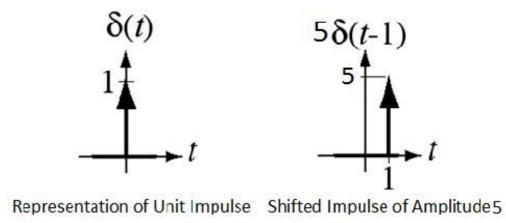


Functions that approach unit step and unit impulse

So unit impulse function is the **derivative** of the unit step function or unit step is the integral of the unit impulse function

Representation of Impulse Function

The area under an impulse is called its strength or weight. It is represented graphically by a vertical arrow. An impulse with a strength of one is called a unit impulse.



Properties of the Impulse Function

The Sampling Property

• •

•
$$g t \cdot \cdots t \cdot \frac{b}{b} \cdot dt \cdot g \cdot \frac{d}{b} \cdot dt$$

The Scaling Property

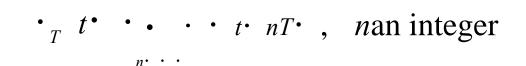
$$\cdot \ a \ t \cdot \ t \cdot \ \frac{1}{|a|} \cdot \cdot \ t \cdot$$

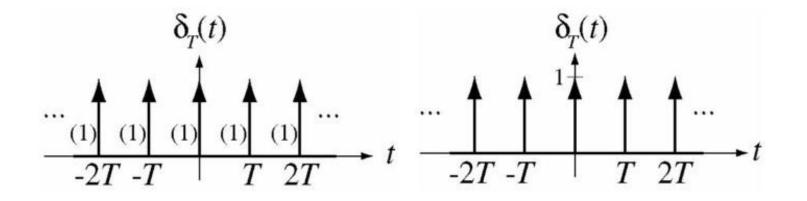
The Replication Property

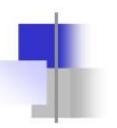
 $g(t) \otimes \, \delta(t) = g \, (t)$

Unit Impulse Train

The unit impulse train is a sum of infinitely uniformlyspaced impulses and is given by

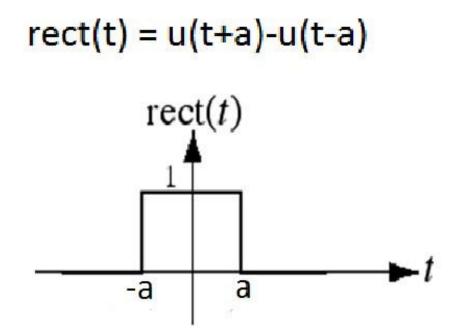






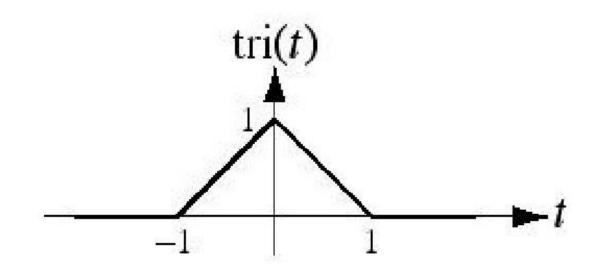
The Unit Rectangle Function

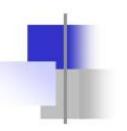
The unit rectangle or gate signal can be represented as combination of two shifted unit step signals as shown



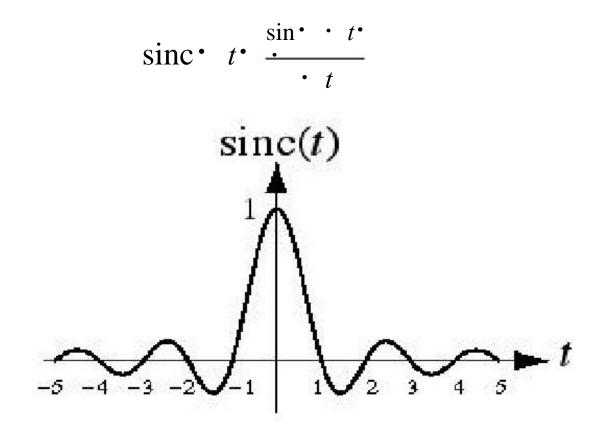
The Unit Triangle Function

A triangular pulse whose height and area are both one but its base width is not, is called unit triangle function. The unit triangle is related to the unit rectangle through an operation called **convolution**.





Sinc Function



Discrete-Time Signals

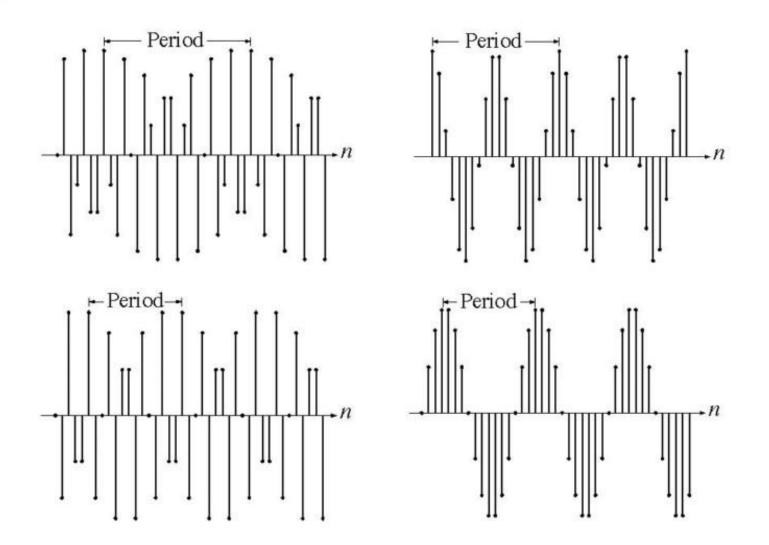
- **Sampling** is the acquisition of the values of a continuous-time signal at discrete points in time
- x(*t*) is a continuous-time signal, x[*n*] is a discrete-time signal
 - $\mathbf{x} \cdot \mathbf{n} \cdot \mathbf{x} \mathbf{n} T_s$ where T_s is the time between samples

Discrete Time Exponential and Sinusoidal Signals

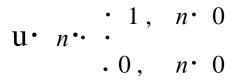
- DT signals can be defined in a manner analogous to their continuous-time counter part
 - - $x[n] = a_n$ Discrete Time Exponential Signal
 - n = the discrete time
 - A = amplitude
 - θ = phase shifting radians,

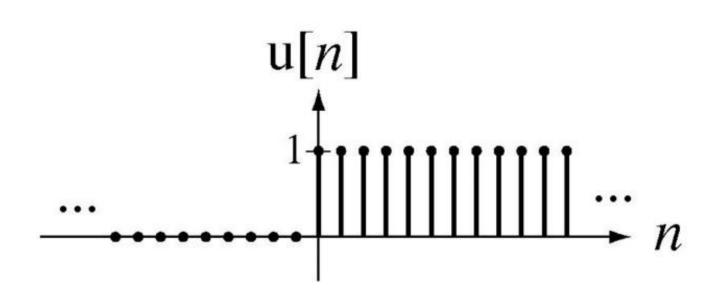
 N_0 = Discrete Period of the wave 1/N₀ = F₀ = $\Omega_0/2 \Pi$ = Discrete Frequency

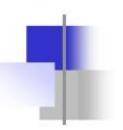
Discrete Time Sinusoidal Signals



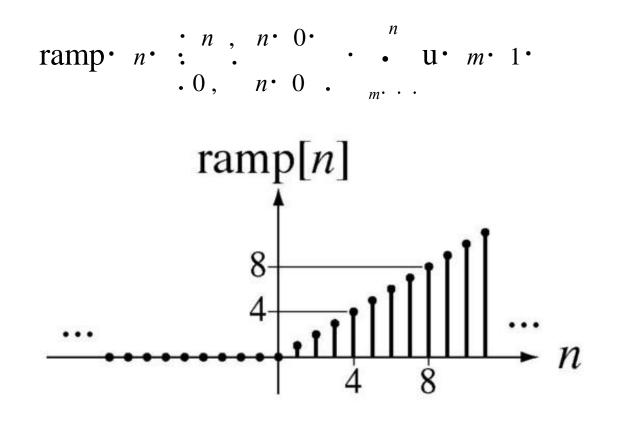
Discrete Time Unit Step Function or Unit Sequence Function



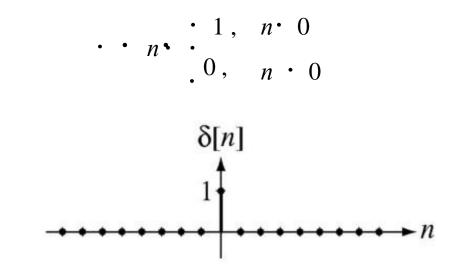




Discrete Time Unit Ramp Function



Discrete Time Unit Impulse Function or Unit Pulse Sequence





Unit Pulse Sequence Contd.

- The discrete-time unit impulse is a function in the ordinary sense in contrast with the continuous-time unit impulse.
- It has a sampling property.
- It has no scaling property i.e. $\delta[n] = \delta[an] \text{ for any non-zero finite integer } "a"$

Operations of Signals

- Sometime a given mathematical function may completely describe a signal .
- Different operations are required for different purposes of arbitrary signals.
- The operations on signals can be Time Shifting
 - **Time Scaling**
 - Time Inversion or Time Folding

Time Shifting

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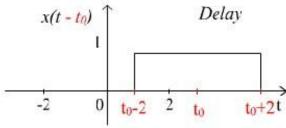
• The original signal x(t) is shifted by an amount t_o .

0

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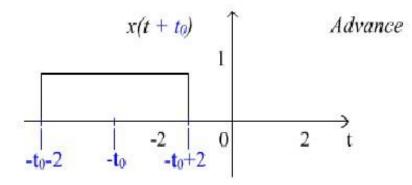
• X(t) · X(t-to) · Signal Delayed · Shift to the right

-2



Time Shifting Contd.

X(t) X(t+to)
 Signal Advanced
 Shift to the left

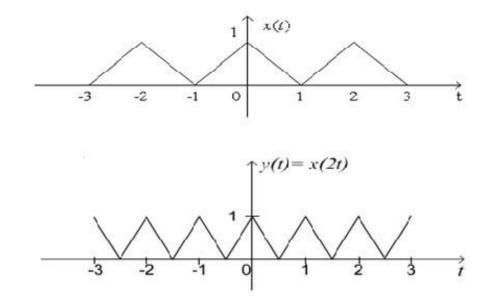


Time Scaling

- For the given function x(t), x(at) is the time scaled version of x(t)
- For a > 1,period of function x(t) reduces and function speeds up. Graph of the function shrinks.
- For a < 1, the period of the x(t) increases and the function slows down.
 Graph of the function expands.

Time scaling Contd.

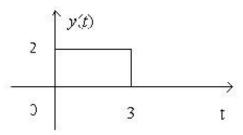
Example: Given x(t) and we are to find y(t) = x(2t).

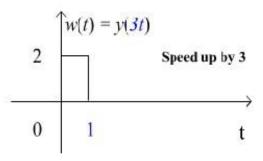


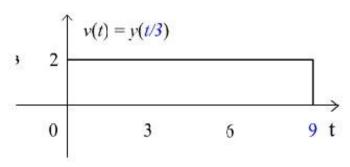
The period of x(t) is 2 and the period of y(t) is 1,

Time scaling Contd.

- Given *y*(*t*),
 - find w(t) = y(3t)and v(t) = y(t/3).



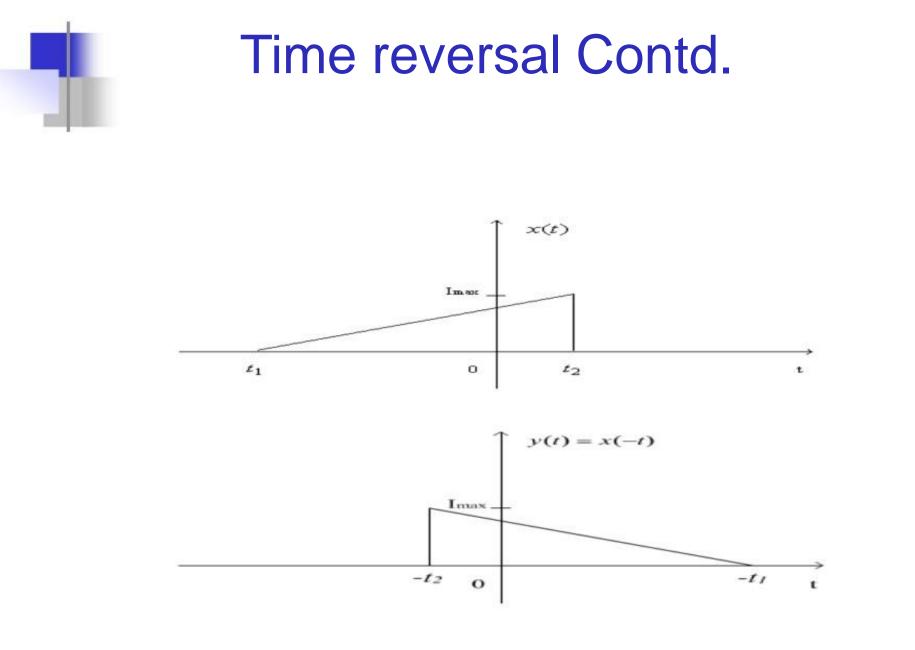




Time Reversal

- Time reversal is also called time folding
- In Time reversal signal is reversed with respect to time i.e.

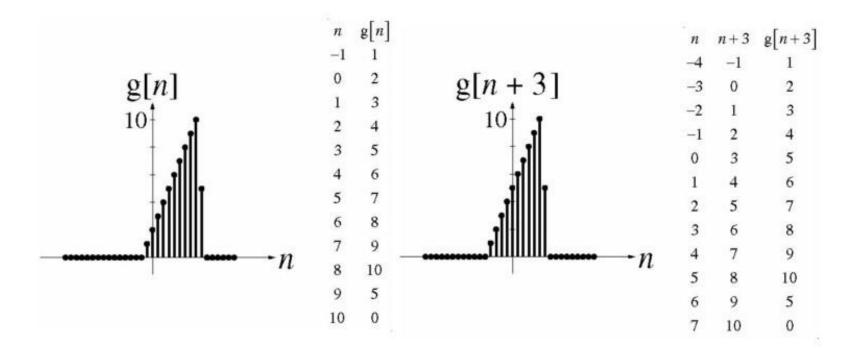
y(t) = x(-t) is obtained for the given function



Operations of Discrete Time Functions

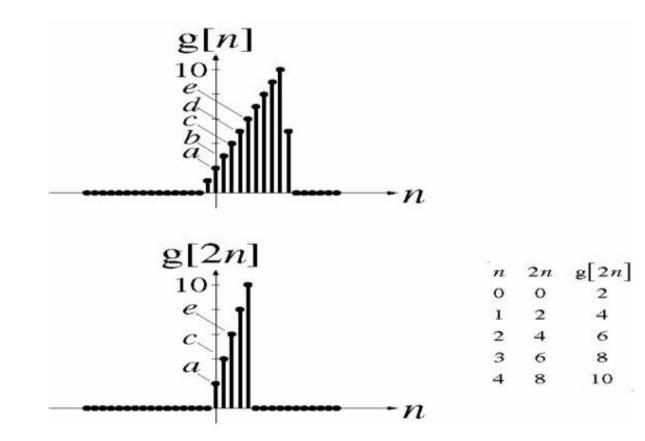
Timeshifting

n• *n*• *n*₀, *n*₀ an integer



Operations of Discrete Functions Contd. Scaling; Signal Compression

 $n \cdot Kn K$ an integer > 1



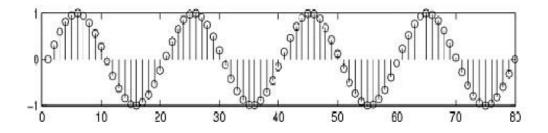
Classification of Signals

- Deterministic & Non Deterministic
 Signals
- Periodic & A periodic Signals
- Even & Odd Signals
- Energy & Power Signals

Deterministic & Non Deterministic Signals

Deterministic signals

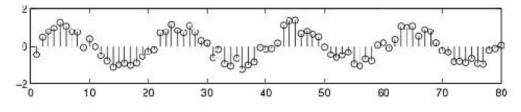
- Behavior of these signals is predictable w.r.t time
- There is no uncertainty with respect to its value at any time.
- These signals can be expressed mathematically.
 For example x(t) = sin(3t) is deterministic signal.



Deterministic & Non Deterministic Signals Contd.

Non Deterministic or Random signals

- Behavior of these signals is random i.e. not predictable w.r.t time.
- There is an uncertainty with respect to its value at any time.
- These signals can't be expressed mathematically.
- For example Thermal Noise generated is non deterministic signal.



Periodic and Non-periodic Signals

- Given x(t) is a continuous-time signal
- x (t) is periodic iff x(t) = x(t+T_o) for any T and any integer
- Example
 - $x(t) = A \cos(wt)$
 - $x(t+T_o) = A \cos[w \cdot t+T_o] = A \cos(wt+wT_o) = A \cos(wt+2 \cdot) = A \cos(wt)$
 - Note: $T_o = 1/f_o$; w· 2· f_o

Periodic and Non-periodic Signals Contd. • For non-periodic signals $x(t) \neq x(t+T_0)$

- A non-periodic signal is assumed to have a period T = ∞
- Example of non periodic signal is an exponential signal

Important Condition of Periodicity for Discrete Time Signals

A discrete time signal is periodic if

x(n) = x(n+N)

 For satisfying the above condition the frequency of the discrete time signal should be ratio of two integers

i.e.
$$f_o = k/N$$

Sum of periodic Signals

- X(t) = x1(t) + X2(t)
- $X(t+T) = x1(t+m_1T_1) + X2(t+m_2T_2)$
- $m_1T_1=m_2T_2 = T_o = Fundamental period$
- Example: cos(t · /3)+sin(t · /4)
 - T1=(2·)/(·/3)=6; T2 =(2·)/(·/4)=8;
 - T1/T2=6/8 = $\frac{3}{4}$ = (rational number) = m2/m1
 - $m_1T_1=m_2T_2$ · Find m1 and m2·
 - $-6.4 = 3.8 = 24 = T_o$

Sum of periodic Signals - may not always be periodic!

$$x(t)$$
 $x_1(t)$ $x_2(t)$ $\cos \sin \sqrt{2t}$

T1= $(2 \cdot)/(1)=2 \cdot ;$ T2 = $(2 \cdot)/(sqrt(2));$ T1/T2= sqrt(2);

- Note: T1/T2 = sqrt(2) is an irrational number

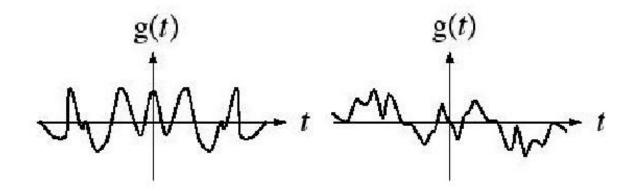
- X(t) is aperiodic

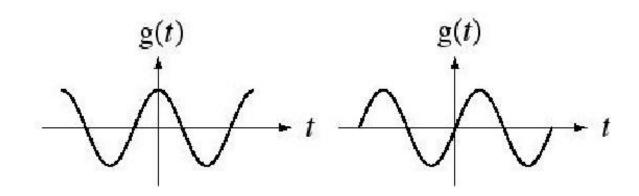
Even and Odd Signals

Even Functions

Odd Functions







Even and Odd Parts of Functions

Theeven part of a function is $g_e \cdot t \cdot \frac{g \cdot t \cdot g \cdot t}{2}$.

Theodd part of a function is
$$g_o \cdot t \cdot \frac{g \cdot t \cdot g \cdot g \cdot t}{2}$$

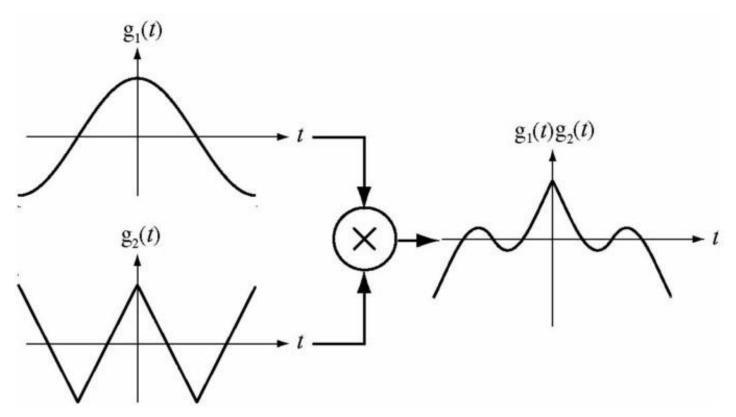
A function whose even part is zero, is odd and a function whose odd part is zero, is even.

Various Combinations of even and odd functions

Function type	Sum	Difference	Product	Quotient
Both even	Even	Even	Even	Even
Both odd	Odd	Odd	Even	Even
Even and odd	Neither	Neither	Odd	Odd

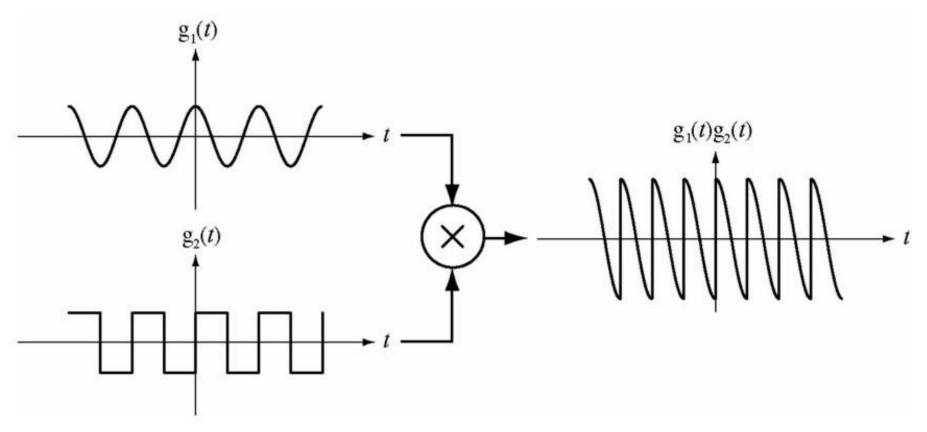
Product of Even and Odd Functions

Product of Two Even Functions



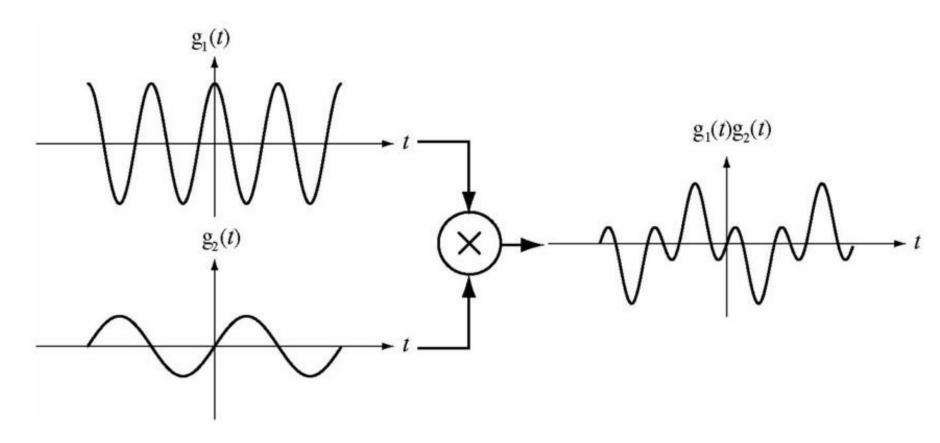
Product of Even and Odd Functions Contd.

Product of an Even Function and an Odd Function

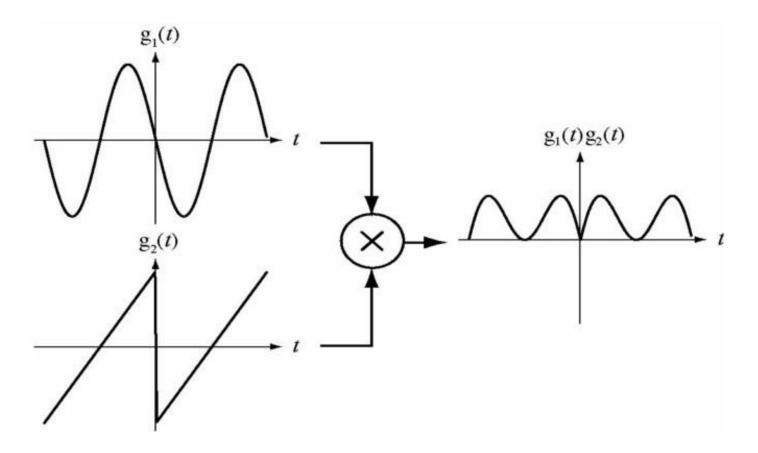


Product of Even and Odd Functions Contd.

Product of an Even Function and an Odd Function



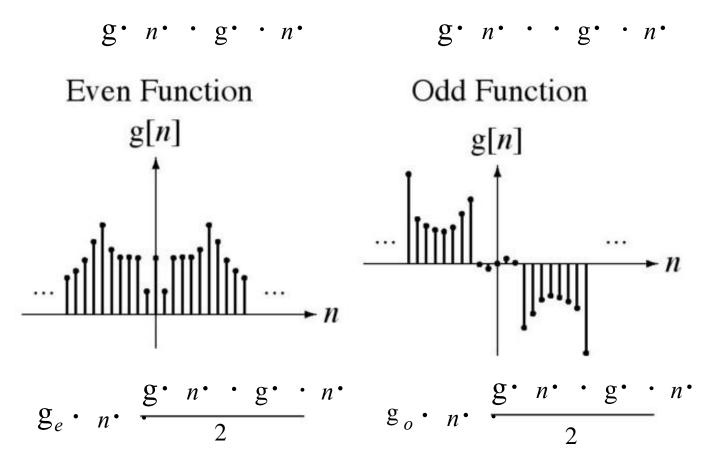
Product of Even and Odd Functions Contd. Product of Two Odd Functions



Derivatives and Integrals of Functions

Function type	Derivative	Integral
Even	Odd	Odd + constant
Odd	Even	Even

Discrete Time Even and Odd Signals

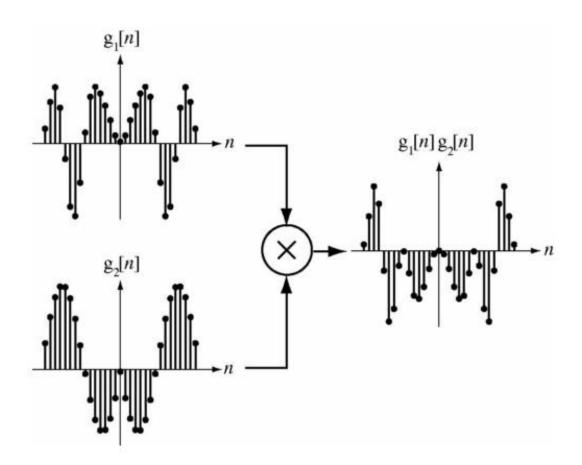


Combination of even and odd function for DT Signals

Function type	Sum	Difference	Product	Quotient
Both even	Even	Even	Even	Even
Both odd	Odd	Odd	Even	Even
Even and odd	Even or Odd	Even or odd	Odd	Odd

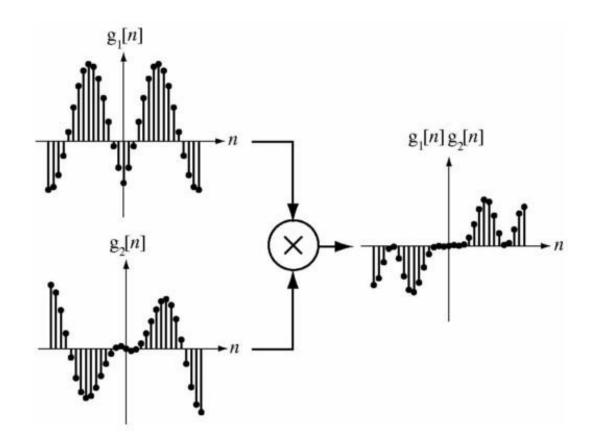
Products of DT Even and Odd Functions

Two Even Functions



Products of DT Even and Odd Functions Contd.

An Even Function and an Odd Function



Proof Examples

• Prove that product of two even signals is even.

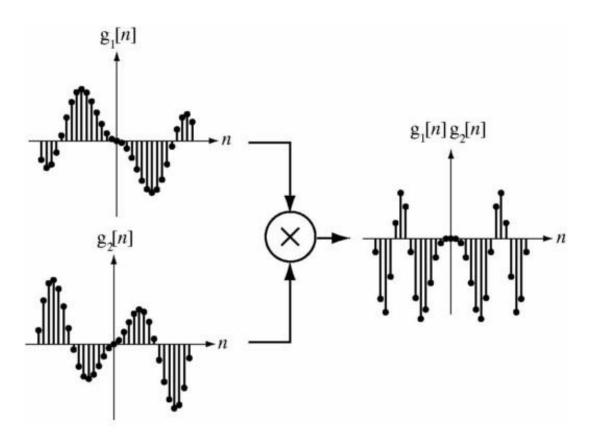
Change t· -t x t)· x t)· x(t)· $_2$ $x(\cdot t)$ · $x(\cdot_1 t)$ · $x(\cdot t)$ · x_1t)· x t)· x(t)

• Prove that product of two odd signals is odd.

 What is the product of an even signal and an odd signal? Prove it! $x(t) \cdot x(t) \cdot x_{2}(t) \cdot x_{2}(t) \cdot x(t) \cdot$

Products of DT Even and Odd Functions Contd.

Two Odd Functions



Energy and Power Signals Energy Signal

 A signal with finite energy and zero power is called Energy Signal i.e.for energy signal

0<E<∞ and P =0

• Signal energy of a signal is defined as the area under the square of the magnitude of the signal.

$$E_{\mathbf{x}} \cdot \mathbf{y}^2 \cdot t = \mathbf{x} \cdot \mathbf{x}^2 \cdot \mathbf{x}$$

• The units of signal energy depends on the unit of the signal.

Energy and Power Signals Contd. Power Signal

 Some signals have infinite signal energy. In that caseit is more convenient to deal with average signal power.

• For power signals

 $0 < P < \infty$ and $E = \infty$

• Average power of the signal is given by

$$P_{\mathbf{x}} \cdot \lim_{T \cdot \cdot} \frac{1}{T} \int_{T/2}^{T/2} |\mathbf{x} \cdot t|^2 dt$$

Energy and Power Signals Contd.

- For a periodic signal $\mathbf{x}(t)$ the average signal power is $P_{\mathbf{x}} = \frac{1}{\tau} \cdot \frac{1}{\tau} \cdot t |^{2} dt$
- T is any period of the signal.
- Periodic signals are generally power signals.

Signal Energy and Power for DT Signal

•A discrtet time signal with finite energy and zero power is called Energy Signal i.e.for energy signal

0<E<∞ and P =0

•The **signal energy** of a for a discrete time signal x[n] is

$$E_{\mathbf{x}} \cdot \cdot |\mathbf{x} \cdot \mathbf{n}|^2$$

Signal Energy and Power for DT Signal Contd.

The average signal power of a discrete time power signal x[*n*] is

$$P_{\mathbf{x}} \cdot \lim_{N \to \infty} \frac{1}{2N} \frac{1}{n \cdot \cdot N} |\mathbf{x} \cdot n|^2$$

For a periodic signal x[n] the average signal power is

$$P_{\mathbf{x}} \cdot \frac{1}{N_{n}} \cdot |\mathbf{x} \cdot \mathbf{n}|^2$$

• The notation • means the sum over any set of • $n \cdot \langle N \rangle$

. consecutive n's exactly N in length.



What is System?

- Systems process input signals to produce output signals
- A system is combination of elements that manipulates one or more signals to accomplish a function and produces some output.

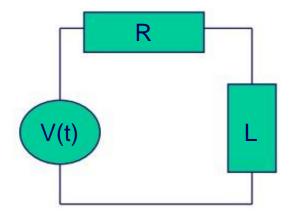
Examples of Systems

- A circuit involving a capacitor can be viewed as a system that transforms the source voltage (signal) to the voltage (signal) across the capacitor
- A communication system is generally composed of three sub-systems, the transmitter, the channel and the receiver. The channel typically attenuates and adds noise to the transmitted signal which must be processed by the receiver
- Biomedical system resulting in biomedical signal processing
- Control systems

System - Example

- Consider an RL series circuit
 - Using a first order equation:

$$V(t) \cdot L \quad \frac{di(t)}{dt}$$
$$V(t) \cdot V_{R} \cdot V_{L}(t) \cdot i(t) \cdot R \cdot \frac{di(t)}{dt}$$



Mathematical Modeling of Continuous Systems

Most continuous time systems represent how continuous signals are transformed via **differential equations**.

E.g. RC circuit

System indicatin<u> $dv_c(t)$ </u> velocity $\frac{1}{RC}v(t)$ $\frac{1}{RC}v(t)$

$$m \frac{dv(t)}{dt} \cdot \cdot v t) \cdot f(t)$$

Mathematical Modeling of Discrete Time Systems

Most discrete time systems represent how discrete signals are transformed via **difference equations** e.g. bank account, discrete car velocity system

$$y[n] \cdot 1.01y[n \cdot 1] \cdot x[n]$$

$$v[n]$$
 · $\frac{m}{m \cdot \cdot \cdot} v[n \cdot 1]$ · $\frac{\cdot}{m \cdot \cdot \cdot} f[n]$

Order of System

 Order of the Continuous System is the highest power of the derivative associated with the output in the differential equation

For example the order of the system shown is
1.

$$m \frac{dv(t)}{dt} \cdot \cdot v t \cdot f(t)$$

Order of System Contd.

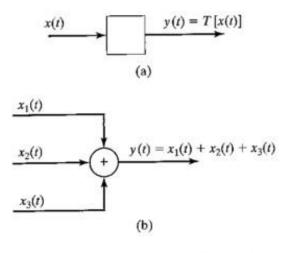
- Order of the Discrete Time system is the highest number in the difference equation by which the output is delayed
- For example the order of the system shown is 1.

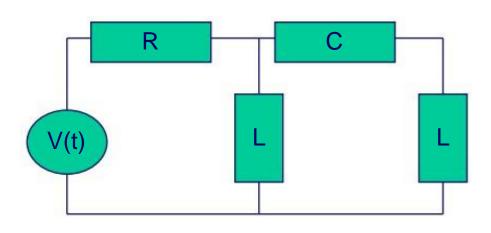
 $y[n] \cdot 1.01y[n \cdot 1] \cdot x[n]$

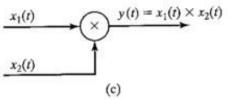
Interconnected Systems

- Parallel
- Serial (cascaded)
- Feedback



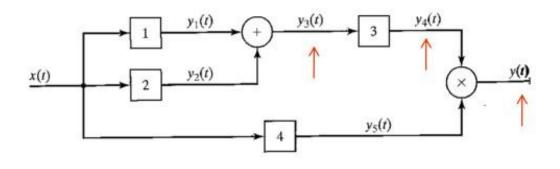






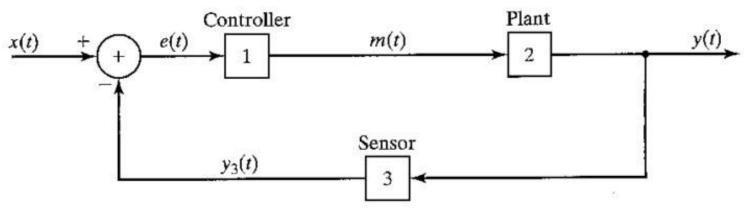
Interconnected System Example

- Consider the following systems with 4 subsystem
- Each subsystem transforms it input signal
- The result will be:
 - -y3(t)=y1(t)+y2(t)=T1[x(t)]+T2[x(t)]
 - -y4(t)=T3[y3(t)]=T3(T1[x(t)]+T2[x(t)])
 - $-y(t) = y4(t)^* y5(t) = T3(T1[x(t)]+T2[x(t)])^* T4[x(t)]$



Feedback System

- Used in automatic control
 - e(t)=x(t)-y3(t)=x(t)-T3[y(t)]=
 - y(t) = T2[m(t)] = T2(T1[e(t)])
 - · y(t)=T2(T1[x(t)-y3(t)])=T2(T1([x(t)] T3[y(t)])) =
 - =T2(T1([x(t)] -T3[y(t)]))



Types of Systems

- Causal & Anticausal
- Linear & Non Linear
- Time Variant & Time-invariant
- Stable & Unstable
- Static & Dynamic
- Invertible & Inverse Systems

Causal & Anticausal Systems

- Causal system : A system is said to be *causal* if the present value of the output signal depends only on the present and/or past values of the input signal.
- Example: y[n]=x[n]+1/2x[n-1]

Causal & Anticausal Systems Contd.

- Anticausal system : A system is said to be *anticausal* if the present value of the output signal depends only on the future values of the input signal.
- Example: *y*[*n*]=*x*[*n*+1]+1/2*x*[*n*-1]

Linear & Non Linear Systems

- A system is said to be linear if it satisfies the principle of superposition
- For checking the linearity of the given system, firstly we check the response due to linear combination of inputs
- Then we combine the two outputs linearly in the same manner as the inputs are combined and again total response is checked
- If response in step 2 and 3 are the same, the system is linear othewise it is non linear.

Time Invariant and Time Variant Systems

 A system is said to be *time invariant* if a time delay or time advance of the input signal leads to a identical time shift in the output signal.

 $y_{t}^{t} \cdot Hx(t \cdot t_{0}) \}$ $\cdot H\{S^{t0}x(t)\}\} \cdot HS^{t0}x(t)\}$ $y_{0}^{t} \cdot S^{t0}y(t)\}$ $\cdot S^{t0}\{Hx(t)\}\} \cdot S^{t0}Hx(t)\}$

Stable & Unstable Systems

• A system is said to be *bounded-input bounded-output stable* (BIBO stable) iff every bounded input results in a bounded output.

i.e.

•
$$t ||x|t|| \cdot M ||x|t|| \cdot M ||x|t|| \cdot M ||x|t||$$

Stable & Unstable Systems Contd.

Example

- y[n]=1/3(x[n]+x[n-1]+x[n-2])

$$y[n] \cdot \frac{1}{3} |x[n] \cdot x[n \cdot 1] \cdot x[n \cdot 2]$$

$$\cdot \frac{1}{3} (|x[n]| \cdot |x[n \cdot 1]| \cdot |x[n \cdot 2]|)$$

$$\cdot \frac{1}{3} (M_{x} \cdot M_{x} \cdot M_{x}) \cdot M_{x}$$

Stable & Unstable Systems Contd.

Example: The system represented by y(t) = A x(t) is unstable ; A>1 Reason: let us assume x(t) = u(t), then at every instant u(t) will keep on multiplying with A and hence it will not be bonded.

Static & Dynamic Systems

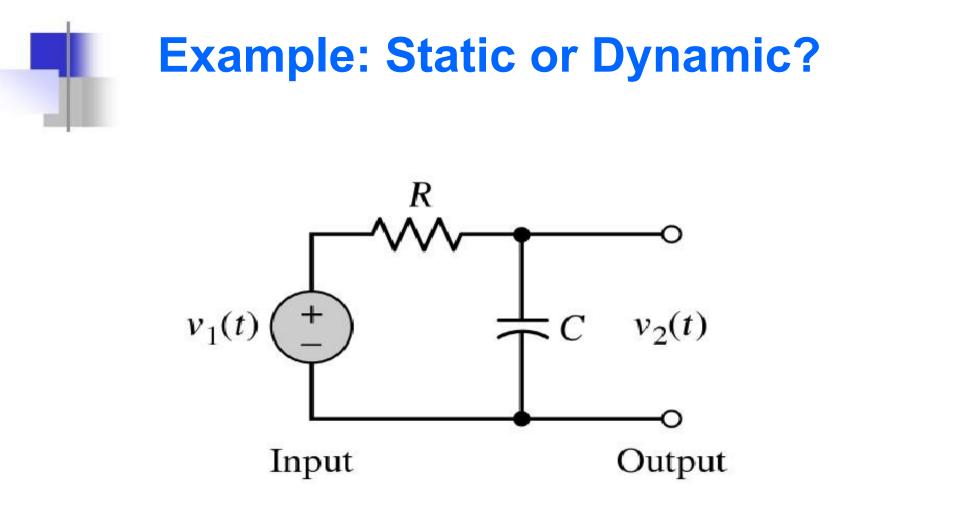
- A static system is memoryless system
- It has no storage devices
- its output signal depends on present values of the input signal
- For example

$$i(t) = \frac{1}{R}v(t)$$

Static & Dynamic Systems Contd.

- A dynamic system possesses memory
- It has the storage devices
- A system is said to possess *memory* if its output signal depends on past values and future values of the input signal

$$i(t) = \frac{1}{L} \int_{-\infty}^{t} v(\tau) d\tau$$
$$y[n] = x[n] + x[n-1]$$



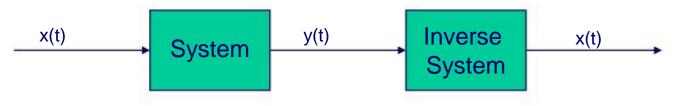
Example: Static or Dynamic?

Answer:

- The system shown above is RC circuit
- R is memoryless
- C is memory device as it stores charge because of which voltage across it can"t change immediately
- Hence given system is dynamic or memory system

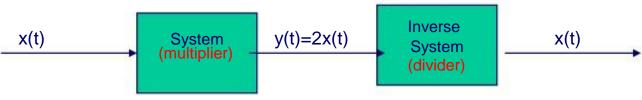
Invertible & Inverse Systems

• If a system is invertible it has an Inverse System



- Example: y(t)=2x(t)
 - System is invertible must have inverse, that is:
 - For any x(t) we get a distinct output y(t)
 - Thus, the system must have an Inverse

• x(t)=1/2 y(t)=z(t)





LTI Systems

- LTI Systems are *completely characterized* by its unit sample response
- The output of any LTI System is a convolution of the input signal with the unit-impulse response, *i.e.* v[n] = x[n] * h[n]

$$=\sum_{k=-\infty}^{+\infty}x[k]h[n-k]$$

Properties of Convolution

Commutative Property

 $x[n]^*h[n]$ · $h[n]^*x[n]$

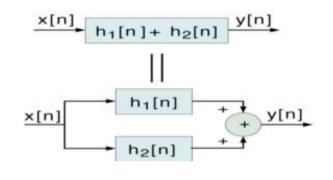
Distributive Property

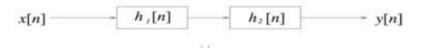
 $x[n]^*(h_1[n] \cdot h_2[n]) \cdot (x[n]^*h_1[n]) \cdot (x[n]^*h_2[n])$

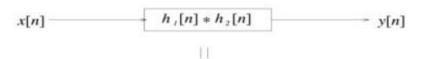
Associative Property

 $x[n]*h_{1}[n]*h_{2}[n] \cdot (x[n]*h_{1}[n])*h_{2}[n] \cdot (x[n]*h_{2}[n])*h_{1}[n]$

$$x[n] \xrightarrow{y[n]} = \frac{h[n]}{x[n]} \xrightarrow{y[n]}$$









Useful Properties of (DT) LTI Systems

Causality:

$$h[n] \cdot 0 \quad n \cdot 0$$

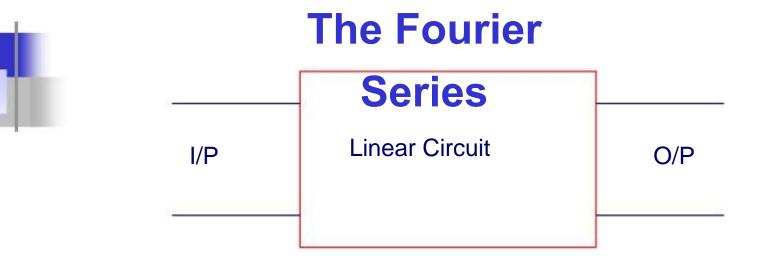
• Stability: $|h[k]| \cdot \cdot$

Bounded Input \leftrightarrow Bounded Output

for
$$|x[n] \cdot | x_{\max} \cdot \cdot$$

 $|y[n] \cdot | | \cdot x[k]h[n \cdot k] \cdot x | \max_{k \cdot \cdot \cdot} h[n \cdot k] \cdot |$

Periodic Functions and Fourier Series



Sinusoidal Inputs



Nonsinusoidal Inputs



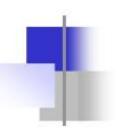
Nonsinusoidal Inputs



Sinusoidal Inputs







The Fourier



Joseph Fourier 1768 to 1830

Fourier studied the mathematical theory of heat conduction. He established the partial differential equation governing heat diffusion and solved it by using infinite series of trigonometric functions.

The Fourier Series

Fourier proposed in 1807

A periodic waveform *f*(*t*) could be broken down into an *infinite series of simple sinusoids* which, when added together, would construct the *exact form* of the original waveform.

Consider the periodic function

$$f(t) \cdot f(t \cdot nT) ; n \cdot 1, 2, 3, \cdot$$

T = Period, the smallest value of T that satisfies the above Equation.

The Fourier Series

The expression for a *Fourier Series* is

$$ft) \cdot a = \begin{pmatrix} N & & N \\ \bullet & a_n \cos N & 0 \\ n \cdot 1 & & n \cdot 1 \end{pmatrix} = \begin{pmatrix} N & & N \\ \bullet & b_n \sin N & 0 \\ n \cdot 1 & & n \cdot 1 \end{pmatrix}$$

$$a_{0}, a_n, \text{ and } b \text{ are real and are called} \qquad \text{and} \qquad W_0 \cdot \frac{2 \cdot}{T}$$
Fourier Trigonometric Coefficients
Or, alternative form

$$ft \cdot C = \frac{N}{0} \cdot \cdot C_n \cos(nW = t \cdot \cdot n)$$

$$n \cdot 1$$

 $C_0 \cdot a_0$ and C_n are the Complex Coefficients

Fourier Series = a finite sum of harmonically related sinusoids

The Fourier Series

$$ft \cdot C = \frac{N}{0} \cdot C_n \cos(nWt \cdot \frac{1}{0} \cdot \frac{1}{n}) = \frac{N}{n}$$

 C_0 is the average (or DC) value of f(t)

For n = 1 the corresponding sinusoid is called **the fundamental**

 $C \cos(Wt \cdot \cdot 0) = 1$

For n = k the corresponding sinusoid is called **the kth harmonic term** $C_{k} \cos(k W t_{0} \cdot)_{k}$

Similarly, wo is call the **fundamental frequency** *kwo* is called the *kth harmonic frequency*

The Fourier Series

 N^{\bullet}

Definition

A **Fourier Series** is an accurate representation of a periodic signal and consists of the sum of sinusoids at the fundamental and harmonic frequencies.

The waveform *f*(*t*) depends on the *amplitude* and *phase* of every harmonic components, and we can generate any non-sinusoidal waveform by an appropriate combination of sinusoidal functions.

The Fourier Series (Dirichlet's Conditions)

To be described by the Fourier Series the waveform f(t) must satisfy the following mathematical properties:

1. *f*(*t*) is a **single-value function** except at possibly a finite number of points.

- 2. The integral for any *t*o.
- 3. *f(t)* has a finite number of *discontinuities* within the period *T*.
 4. *f(t)* has a finite number of *maxima* and *minima* within the period *T*.

$$\begin{bmatrix} t_0 \cdot T \\ \bullet \\ t_0 \end{bmatrix} f(t) dt$$

In practice, f(t) = v(t) or i(t) so the above 4 conditions are always satisfied.

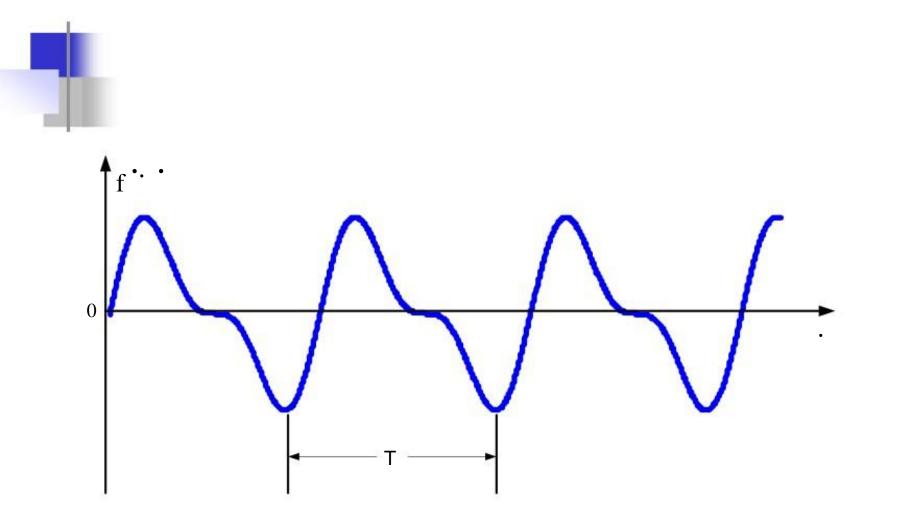
Periodic Functions

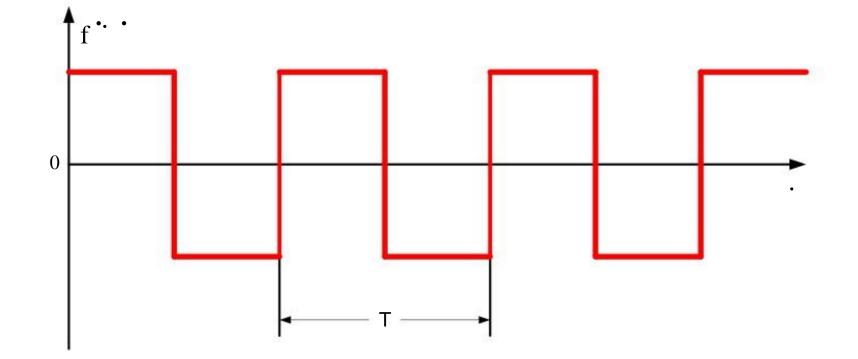
A function $f \cdot \cdot \cdot \cdot$ is periodic

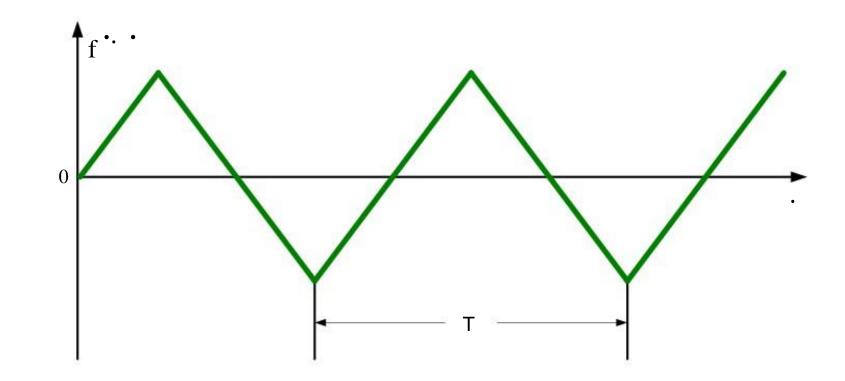
if it is defined for all real *

and if there is some positive number,

T such that $f \cdot \cdot \cdot T \cdot \cdot f \cdot \cdot \cdot f$









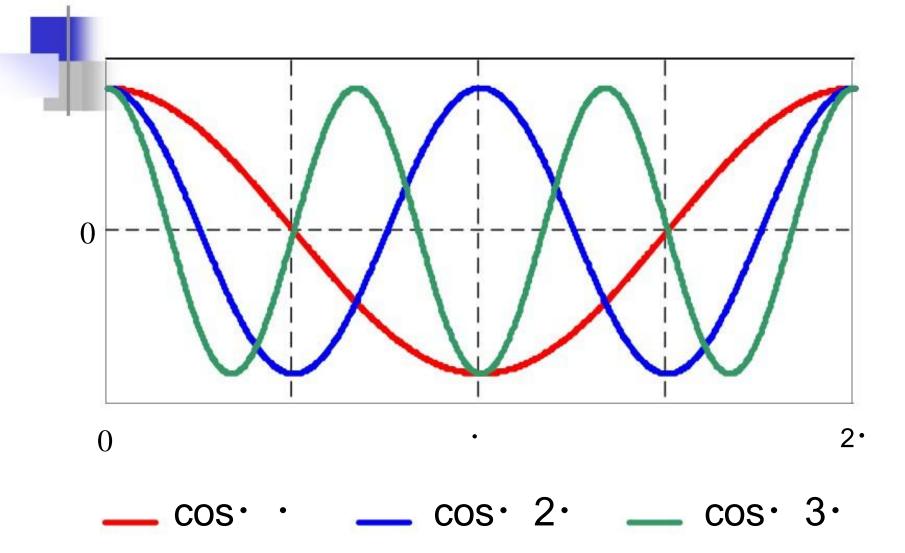
f • • • be a periodic function with peri²d

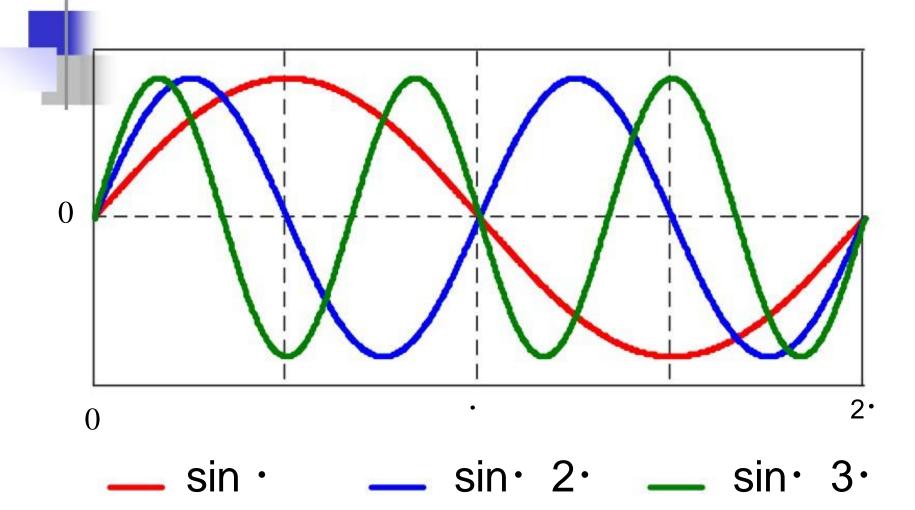
The function can be represented by a trigonometric series as:

$$f \cdot \cdot \cdot \cdot \cdot_0 a \cdot \cdot a_n \cos n \cdot \cdot \cdot \cdot \cdot b_n \sin n \cdot 1$$

are we talking about?

$\cos \cdot , \cos 2 \cdot , \cos 3 \cdot \cdot$ and $\sin \cdot , \sin 2 \cdot , \sin 3 \cdot \cdot$





We want to determine the coefficients, a_n and b_n

Let us first remember some useful integrations.

. cosn cosm d.

- $\cdot \frac{1}{2} \cdot \cdot \cos \cdot n \cdot m \cdot \cdot d \cdot \cdot \frac{1}{2} \cdot \cdot \cos \cdot n \cdot m \cdot \cdot d \cdot$
 - .
 - cos n · cosm d · 0 n · m
 - ••
 - •
 - $\circ \cos n \cdot \cos m d \cdot \cdot n \cdot m$
 - · •

sinn cosm d.

$\cdot \frac{1}{2} \cdot \frac{$

sinn cosm d 0

· .

•

for all values of *m*.

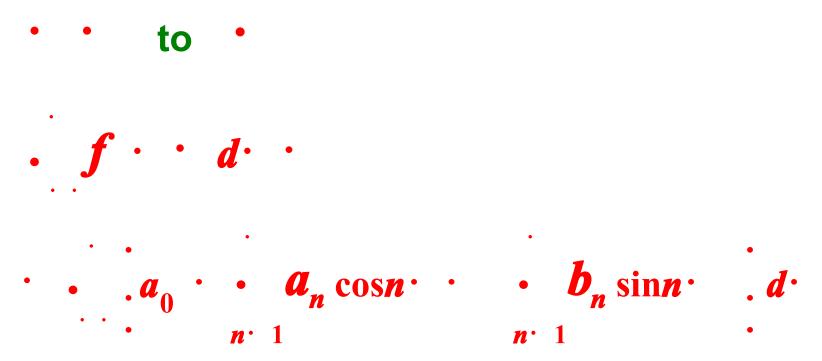
sinn sinm d

- $\cdot \frac{1}{2} \cdots \cos \cdot n \cdot m d \cdot \cdot \frac{1}{2} \cdots \cos \cdot n \cdot m \cdot d \cdot$

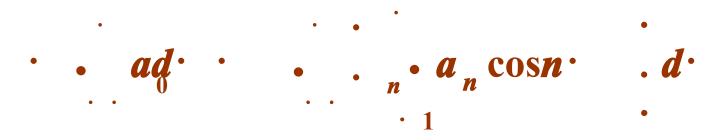
 - $sinn \cdot sin m \cdot d \cdot \cdot 0 n \cdot m$
 - •••
 - · ·
 - sinn·sin m·d··· n· m
 - · •

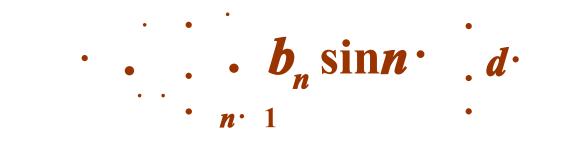
Determine \boldsymbol{a}_0

Integrate both sides of (1) from

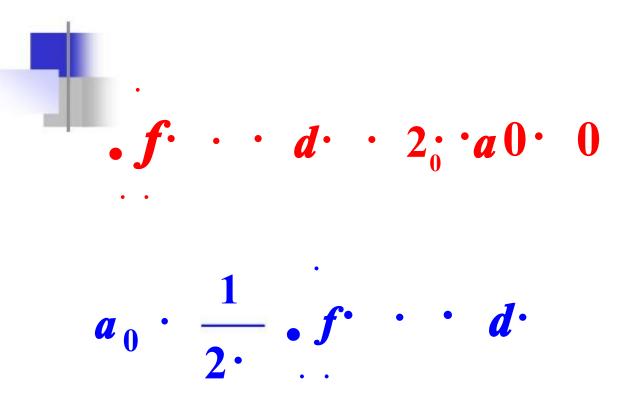












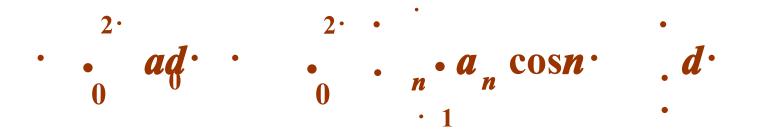
 a_0 is the average (dc) value of the function, f.

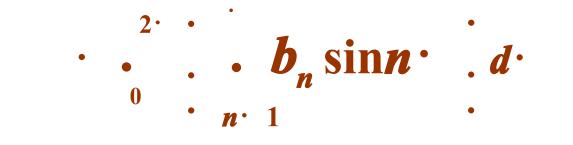
You may integrate both sides of (1) from 0 to 2 instead.

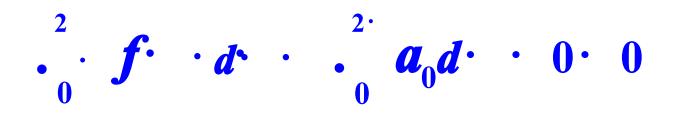


It is alright as long as the integration is performed over one period.

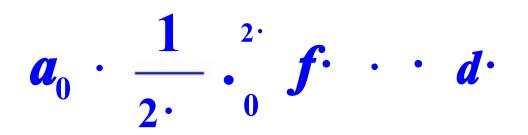








 $\int_{0}^{\cdot} f \cdots d \cdots 2 \cdot a_{0} \cdot 0 \cdot 0$





Multiply (1) by COSm.

and then Integrate both sides from

• • • •

• •

$$f \cdot cosm \cdot d$$

Let us do the integration on the right-hand-side one term at a time.

First term,

- $\bullet a_0 cosm \cdot d \cdot \cdot 0$
- •

Second term,

 $\begin{array}{c} \cdot & \cdot \\ & a_{nCOS} \ n \cdot \ cosm \cdot \ d \cdot \\ & \cdot \cdot \\ & n \cdot \ 1 \end{array}$

Second term,

• • $a_n \cos n \cdot \cos n \cdot d \cdot \cdot a_m$

Third term,









Multiply (1) by *sinm*.

and then Integrate both sides from

• • to •





Let us do the integration on the right-hand-side one term at a time.

First term,

• $a_0 sinm \cdot d \cdot \cdot 0$

Second term,

• • $a_n \cos n \cdot \sin m \cdot d$. • $n \cdot 1$

Second term,

• $a_n \cos n \cdot \sin n \cdot d \cdot \cdot 0$

Third term,



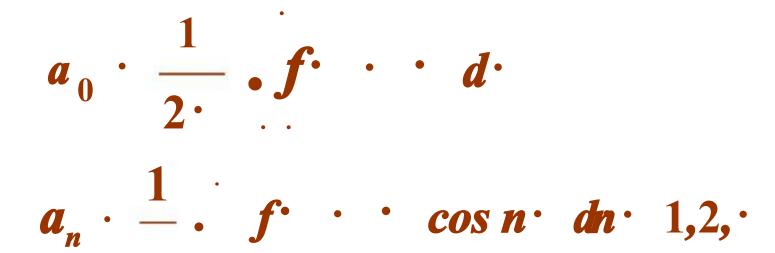


• $f \cdot \cdot \sin m \cdot d \cdot \cdot b_m$



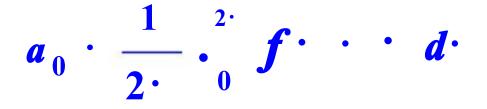


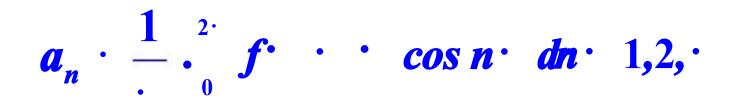
We can write **n** in place of **m**:





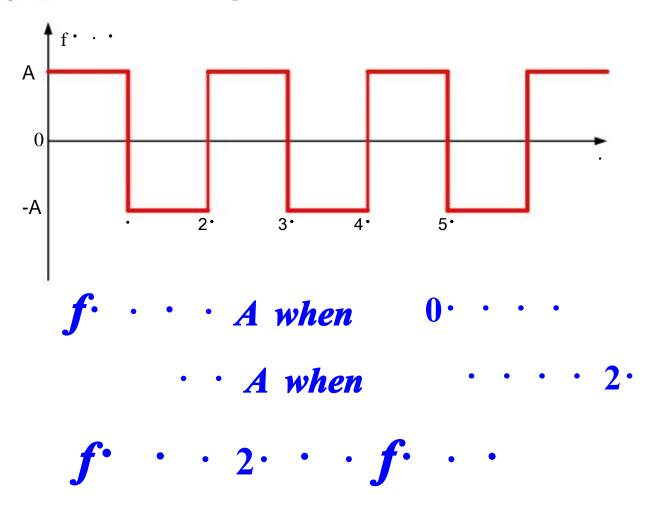
The integrations can be performed from 0_{to} $2 \cdot instead.$

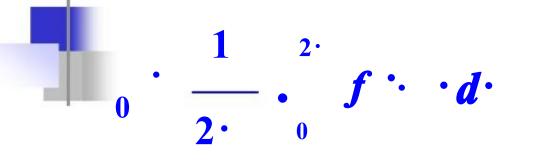






Example 1. Find the Fourier series of the following periodic function.





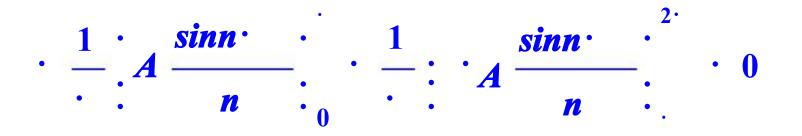


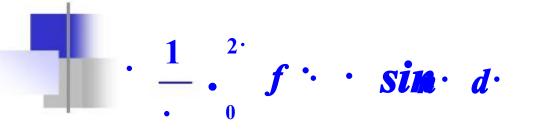


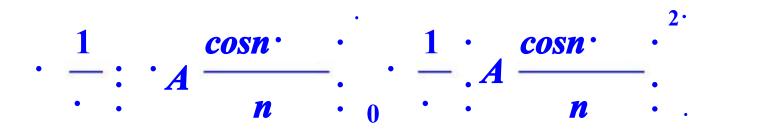
• 0

 $\prod_{n} \cdot \frac{1}{\ldots} \int_{0}^{2} f \cdot cos n \cdot d$

$$\cdot \frac{1}{\cdot} \cdot \int_{0}^{\cdot} A \cos n \cdot d \cdot \cdot \cdot \int_{0}^{2 \cdot} \cdot \cdot A \cdot \cos d \cdot d \cdot$$





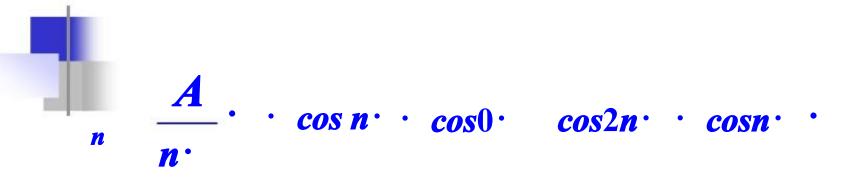




$n \cdot \frac{A}{n} \cdot \cos n \cdot \cos 0 \cdot \cos 2n \cdot \cos n \cdot \cos$

$$\cdot \frac{A}{n} \cdot 1 \cdot 1 \cdot 1 \cdot 1 \cdot$$

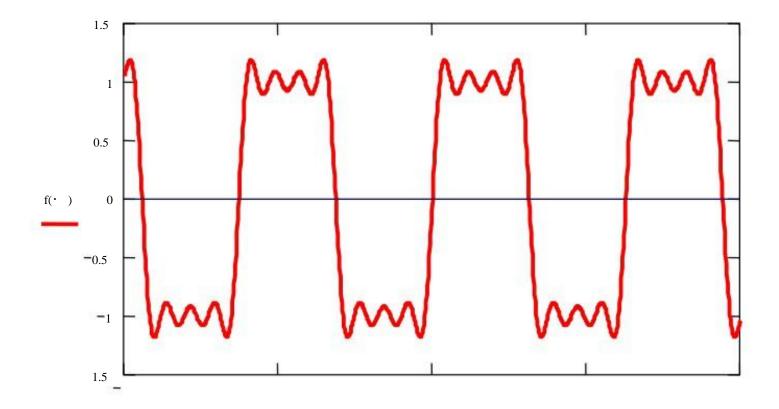




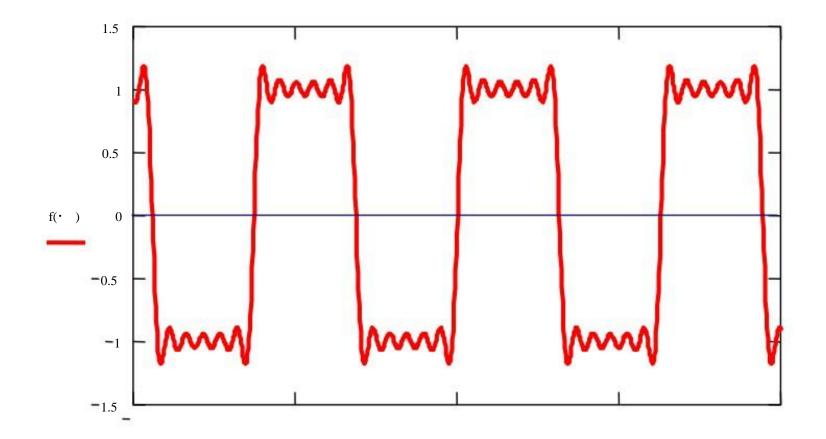
- $\cdot \mathbf{A} \cdot \mathbf{11} \cdot \mathbf{1} \cdot \mathbf{1} \cdot \mathbf{n} \cdot \mathbf{n}$
- 0 when n is even

In writing the Fourier series we may not be able to consider infinite number of terms for practical reasons. The question therefore, is - how many terms to consider?

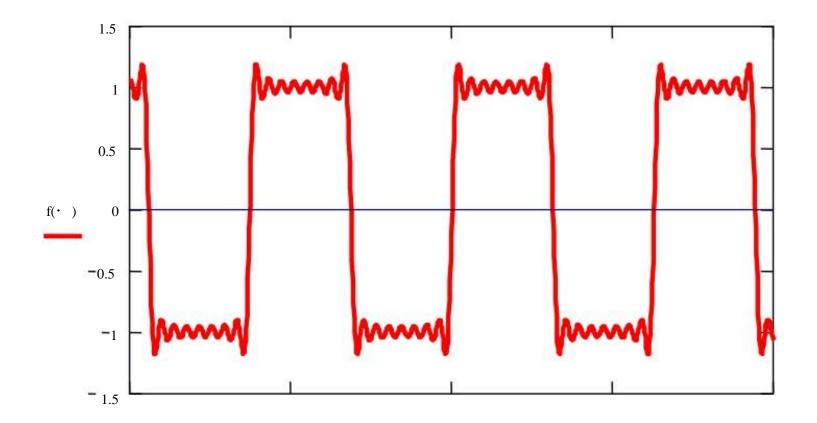
When we consider 4 terms as shown in the previous slide, the function looks like the following.



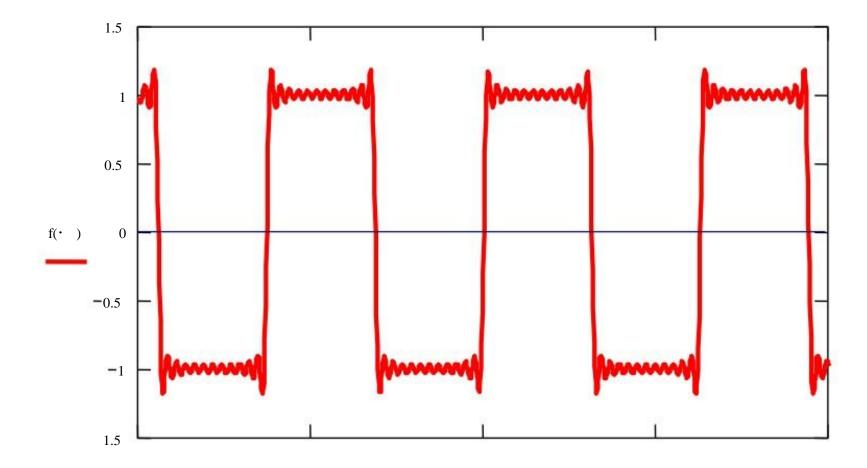
When we consider 6 terms, the function looks like the following.



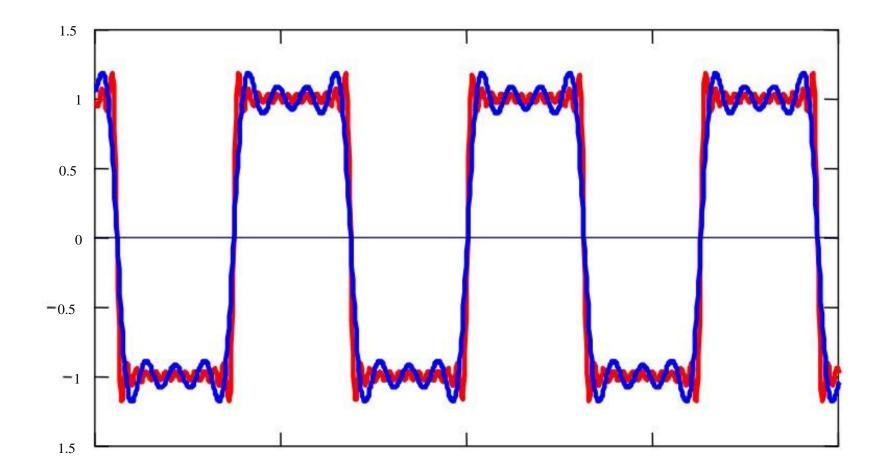
When we consider 8 terms, the function looks like the following.



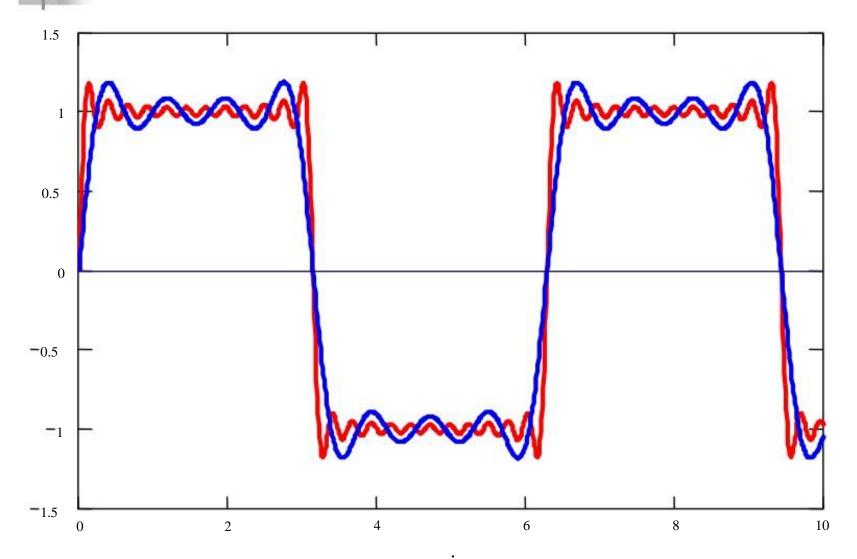
When we consider 12 terms, the function looks like the following.



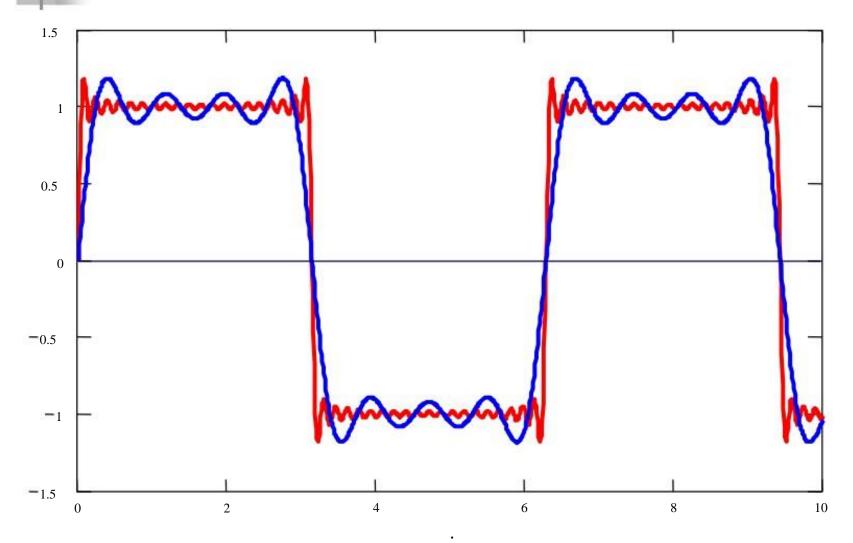
The red curve was drawn with 12 terms and the blue curve was drawn with 4 terms.



The red curve was drawn with 12 terms and the blue curve was drawn with 4 terms.

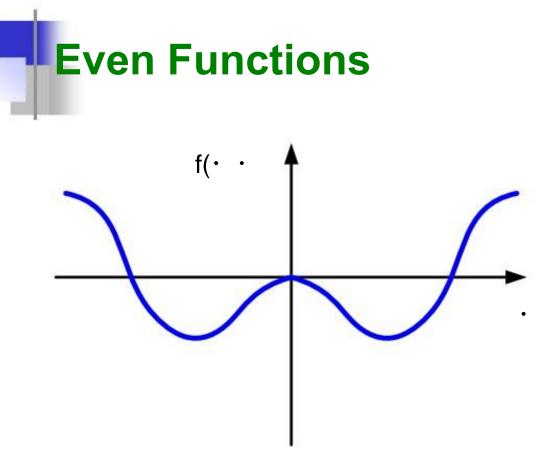


The red curve was drawn with 20 terms and the blue curve was drawn with 4 terms.



Even and Odd Functions

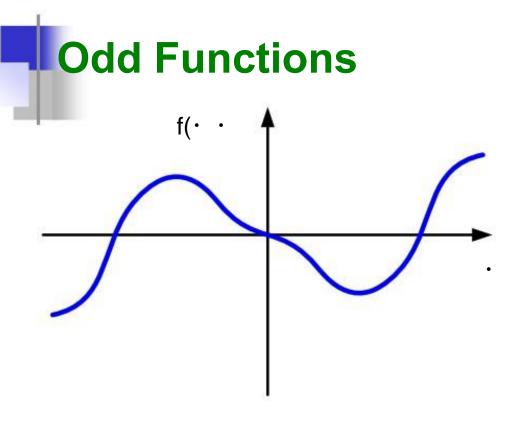
(We are not talking about even or odd numbers.)



The value of the function would be the same when we walk equal distances along the X-axis in opposite directions.

Mathematically speaking -



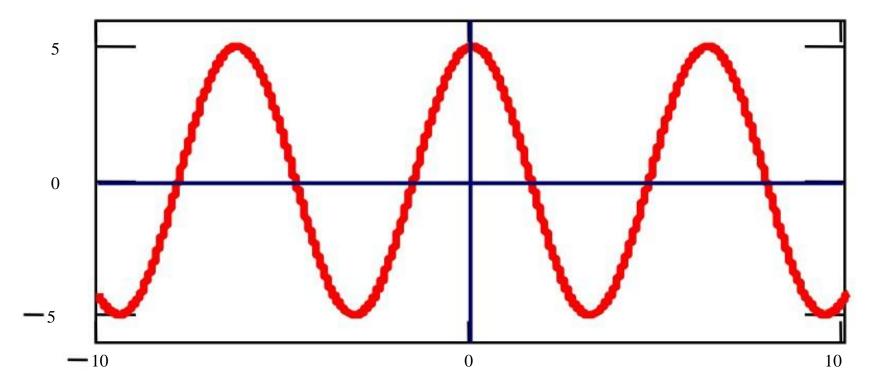


The value of the function would change its sign but with the same magnitude when we walk equal distances along the X-axis in opposite directions.

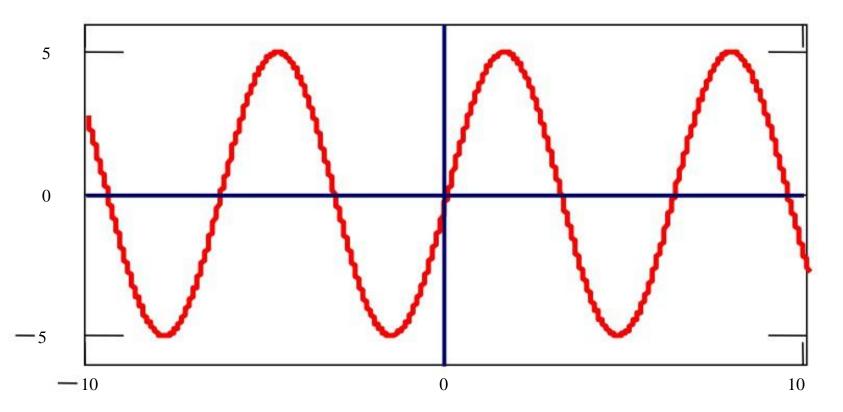
Mathematically speaking -

f · · · · · f · · ·

Even functions can solely be represented by cosine waves because, cosine waves are even functions. A sum of even functions is another even function.



Odd functions can solely be represented by sine waves because, sine waves are odd functions. A sum of odd functions is another odd function.



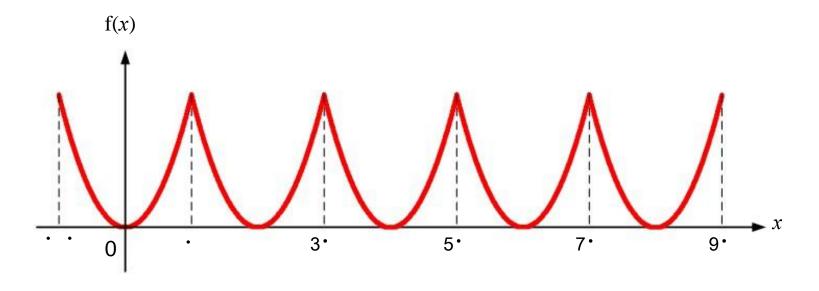
The Fourier series of an even function f · · · is expressed in terms of a cosine series.

The Fourier series of an odd function $f \cdot \cdot \cdot$

is expressed in terms of a sine series.

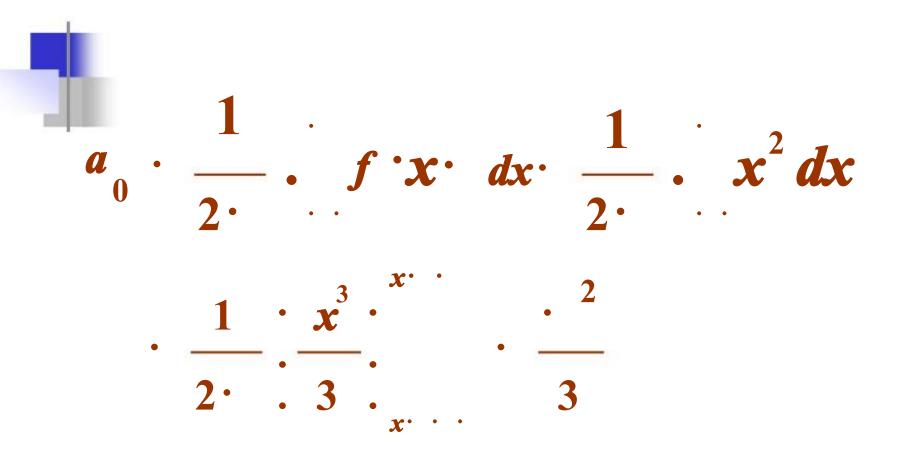
$$f \cdot \cdot \cdot \cdot b_n \sin n \cdot \frac{1}{n \cdot 1}$$

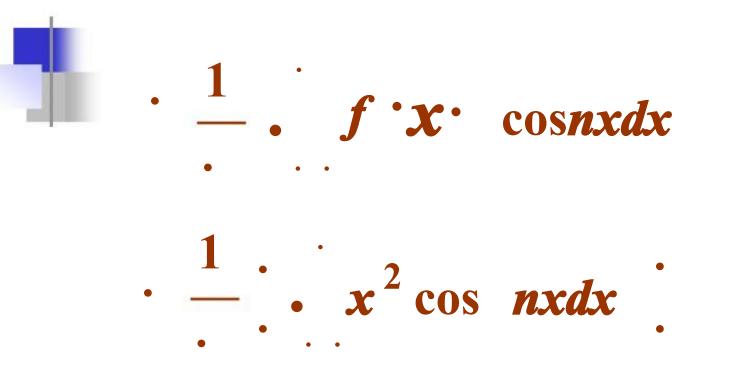
Example 2. Find the Fourier series of the following periodic function.



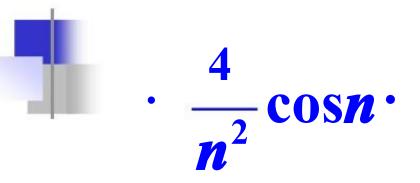


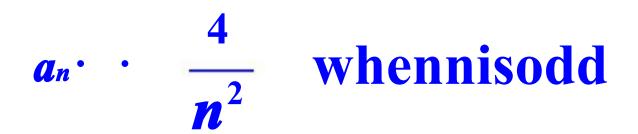






Use integration by parts. Details are shown in your class note.

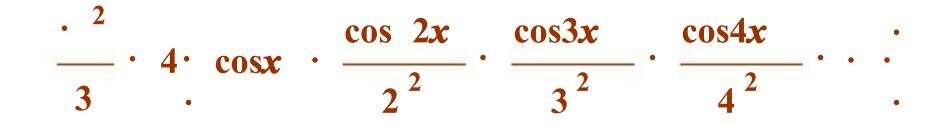






This is an even function. Therefore, $b_n \cdot 0$

The corresponding Fourier series is



Functions Having Arbitrary Period

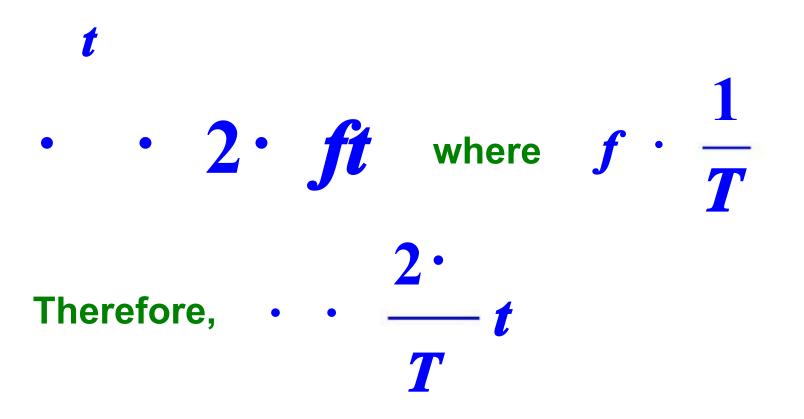
Assume that a function $f \cdot t$ has period, T. We can relate angle (\cdot) with time (t) in the following manner.

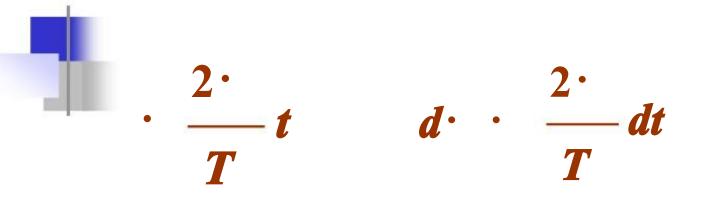
••• W **t**

W is the angular velocity in radians per second.

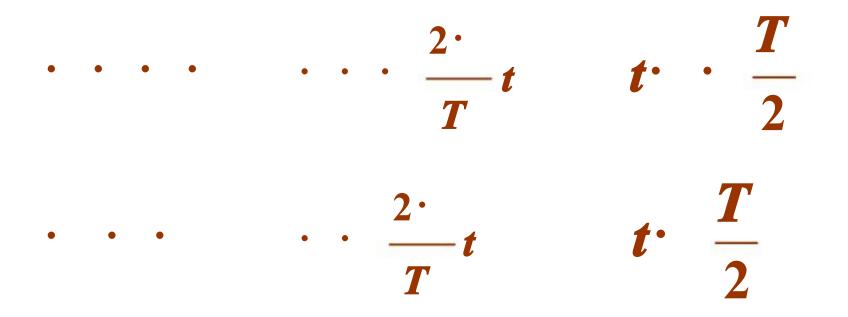


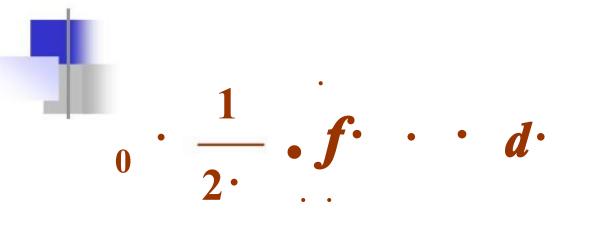
f is the frequency of the periodic function,





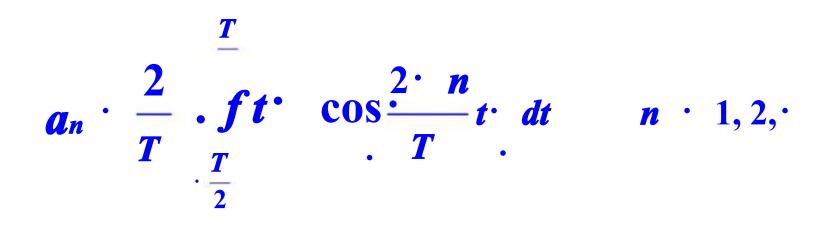
Now change the limits of integration.



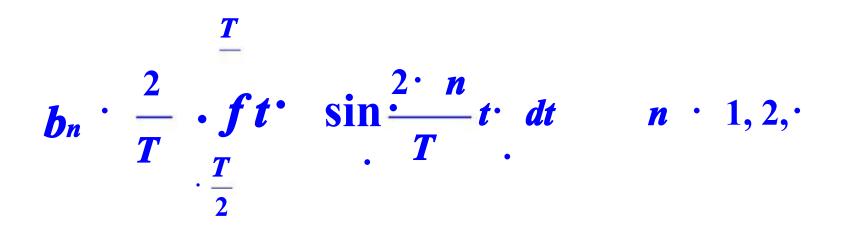


 $a_0 \cdot \frac{1}{T} \cdot \frac{T}{2} t$ $\cdot \frac{T}{2}$

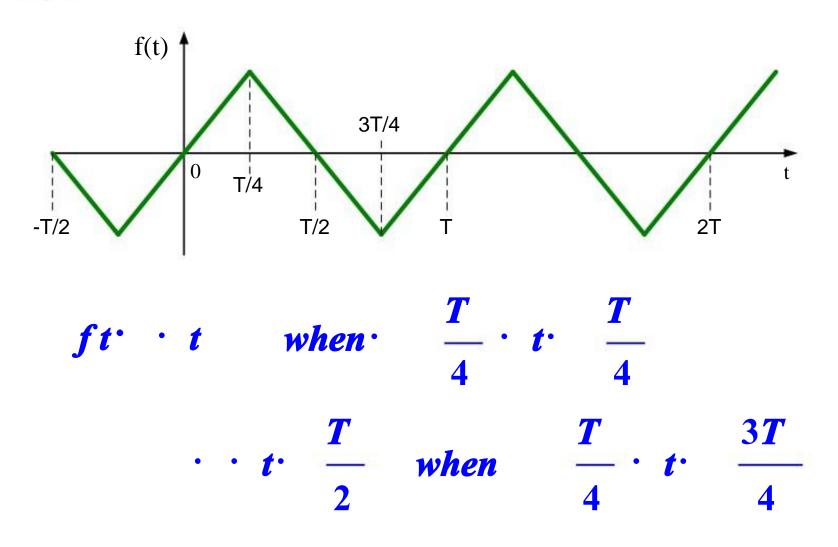




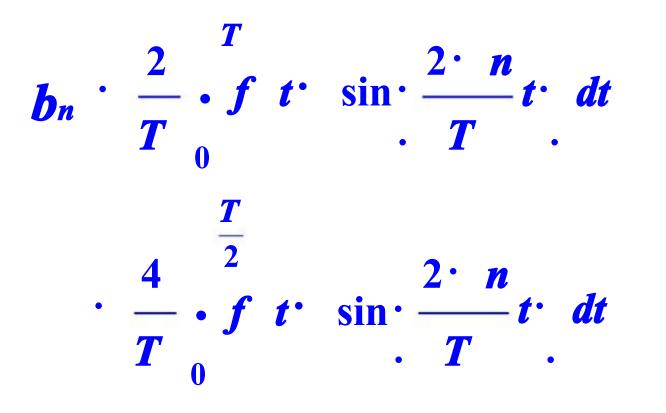
 $n \cdot \frac{1}{f} \cdot \frac{f}{f} \cdot$

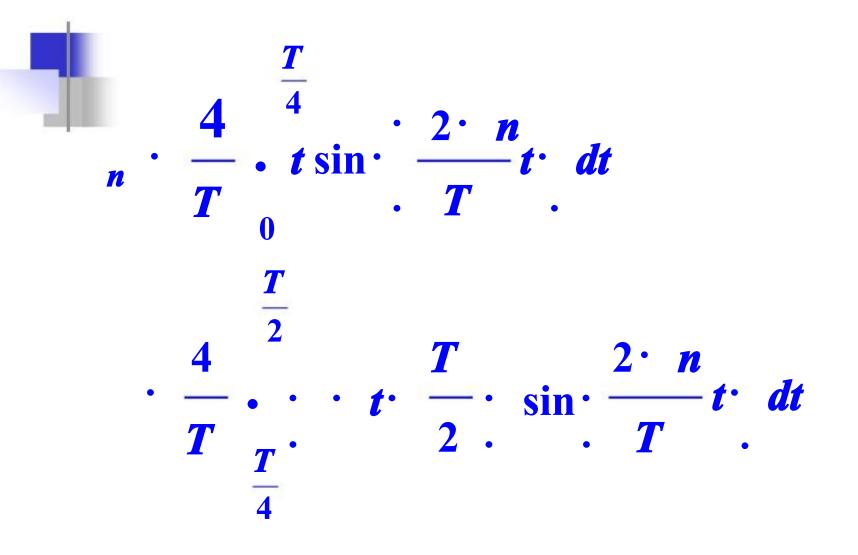


Example 4. Find the Fourier series of the following periodic function.

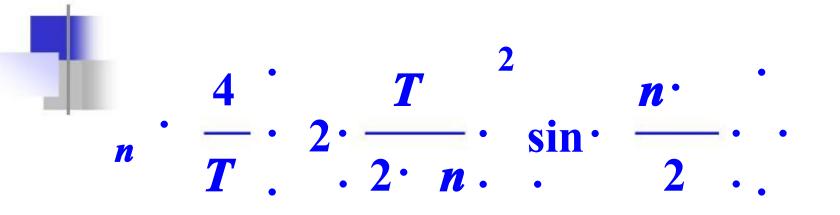


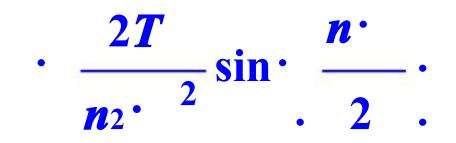
This is an odd function. Therefore, $a_n \cdot 0$





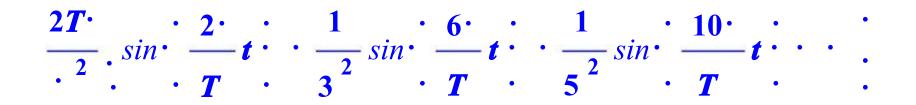
Use integration by parts.



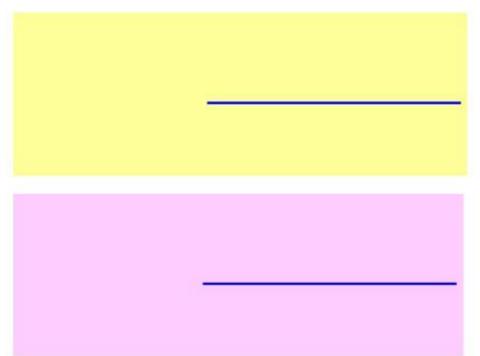


 $b_n \cdot 0$ when *n* is even.

Therefore, the Fourier series is



Let us utilize the Euler formulae.



The **1**th harmonic component of (1) can be expressed as:

 $\cdot b_n \sin n$ $a_n \cos n$. $\frac{e^{jn} \cdot e^{jn}}{2} \cdot \frac{b_n}{2} \frac{e^{jn} \cdot e^{jn}}{2}$ 2*i* • e^{• jn•} $\frac{e^{jn} \cdot e^{jn}}{\cdots} \cdot \frac{e^{jn}}{ib_n} \cdot \frac{e^{jn}}{\cdots}$ a •

 $\cos n \cdot \cdot b$ sin*n* · $a_n^{i} jb$ <u>n</u>.e. jn. · jn· ۲ 2 •

Denoting

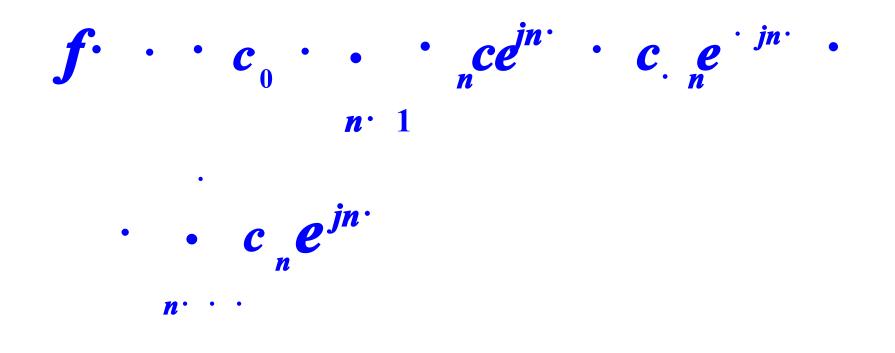


and $\boldsymbol{C}_0 \cdot \boldsymbol{a}_0$

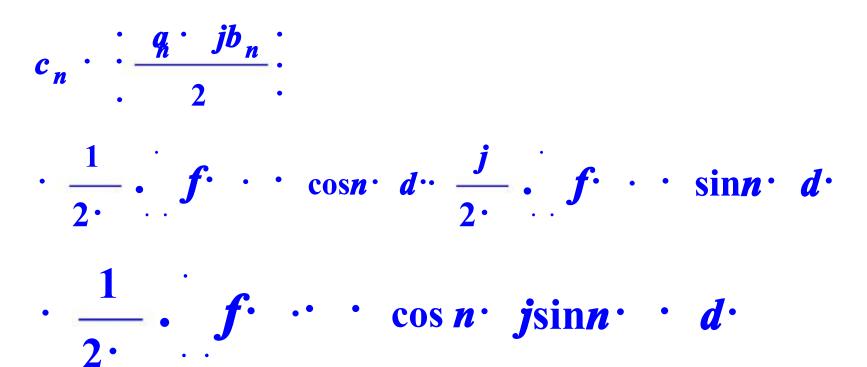
$a_n \cos n \cdot \cdot b_n \sin n \cdot$

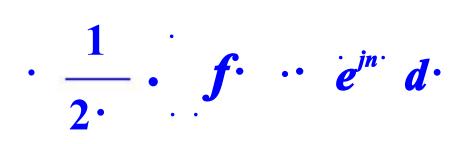
 $\cdot c_n e^{jn} \cdot c_n e^{jn}$

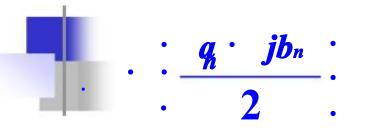
The Fourier series for $f \cdot \cdot \cdot$ can be expressed as:

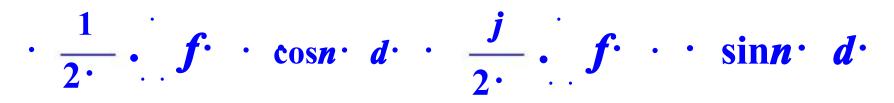


The coefficients can be evaluated in the following manner.

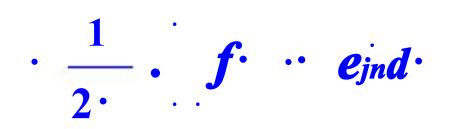


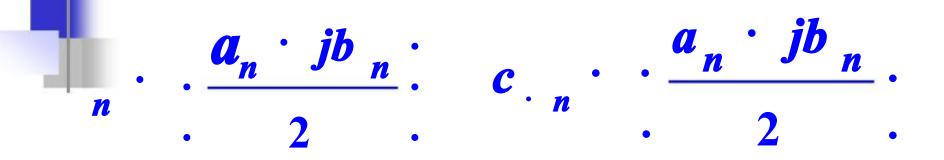




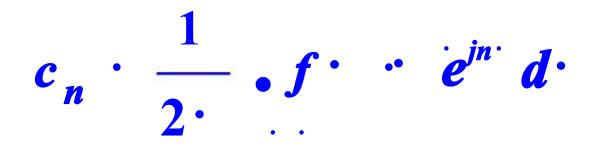








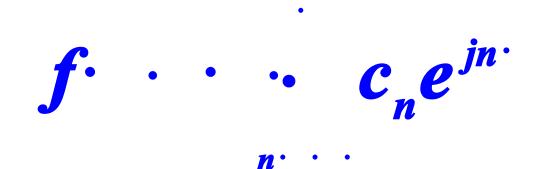
Note that C_n is the complex conjugate of C_n Hence we may write that



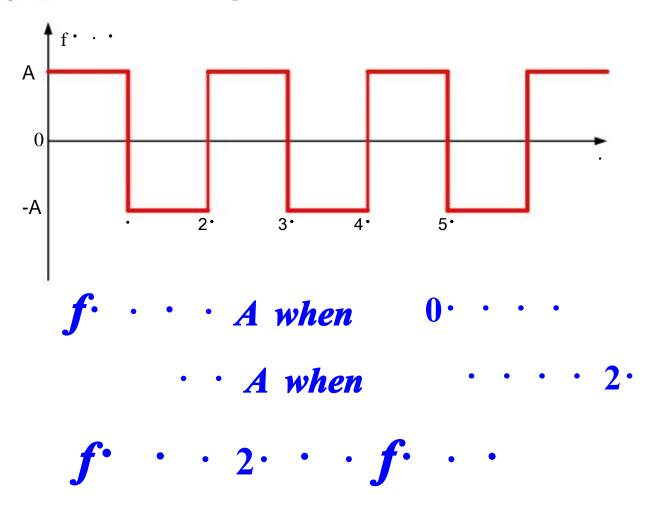
n· 0,· 1,· 2,·

The complex form of the Fourier series of

f withperiod *is*:



Example 1. Find the Fourier series of the following periodic function.

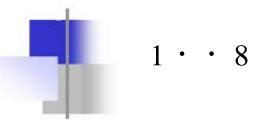


-

5

$$f(x)$$
A if $0 \cdot x \cdot \cdot$ \cdot A if $\cdot x \cdot 2 \cdot \cdot$ 0 otherwise

A0• 0



An
$$\cdot \frac{1}{\cdot} \cdot \frac{2}{\cdot} f(x) \cdot \cos(n \cdot x) dx$$

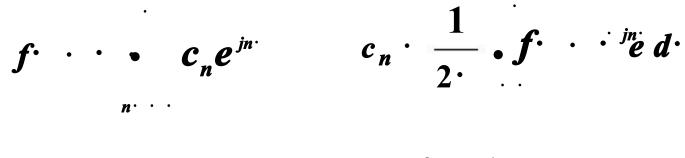
A1 · 0	A2• 0	A3•	0	A4• 0
A5 \cdot 0	A6• 0	A7•	0	A8• 0

$$n \cdot \frac{1}{\cdot} \cdot \frac{2}{\cdot} f(x) \cdot \frac{1}{\cdot} \sin(n \cdot x) dx$$

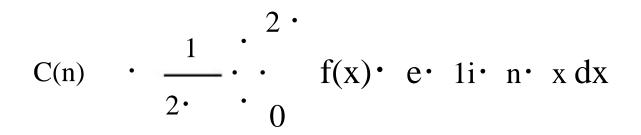
 $B1 \cdot 6.366$ $B2 \cdot 0$ $B3 \cdot 2.122$ $B4 \cdot 0$
 $B5 \cdot 1.273$ $B6 \cdot 0$ $B7 \cdot 0.909$ $B8 \cdot 0$



Complex Form



$$\boldsymbol{n} \cdot \boldsymbol{0}, \cdot \boldsymbol{1}, \cdot \boldsymbol{n}$$



$$\mathbf{C}(\mathbf{n}) \cdot \frac{1}{2 \cdot \cdot \cdot} \cdot \frac{2 \cdot \cdot}{\mathbf{0}} \mathbf{f}(\mathbf{x}) \cdot \mathbf{e} \cdot \mathbf{1} \mathbf{i} \cdot \mathbf{n} \cdot \mathbf{x} \, \mathrm{d} \mathbf{x}$$

() \cdot 0C(1) \cdot \cdot 3.183iC(2) \cdot 0C(3) \cdot \cdot 1.061iC(4) \cdot 0C(5) \cdot \cdot 0.637iC(6) \cdot 0C(7) \cdot \cdot 0.455i

 $C(\cdot 1) \cdot 3.183i$ $C(\cdot 2) \cdot 0$ $C(\cdot 3) \cdot 1.061i$
 $C(\cdot 4) \cdot 0$ $C(\cdot 5) \cdot 0.637i$ $C(\cdot 6) \cdot 0$ $C(\cdot 7) \cdot 0.455i$

The Fourier Series

Recall from calculus that sinusoids whose frequencies are integer multiples of some fundamental frequency $f_0 = 1/T$ form an **orthogonal** set of functions.

$$\frac{2}{T} \cdot \int_{0}^{T} \sin \frac{2 \cdot nt}{T} \cos \frac{2 \cdot mt}{T} dt \cdot 0; \qquad \cdot n, m$$

and

$$\frac{2}{T} \cdot \int_{0}^{T} \sin \frac{2 \cdot nt}{T} \sin \frac{2 \cdot mt}{T} dt \cdot \frac{2}{T} \cdot \int_{0}^{T} \cos \frac{2 \cdot nt}{T} \cos \frac{2 \cdot mt}{T} dt$$
$$\cdot \int_{0}^{T} \int_{0}^{T} \sin \frac{2 \cdot mt}{T} dt$$
$$\cdot \int_{0}^{T} \int_{0}^{T} \sin \frac{2 \cdot mt}{T} dt$$

The Fourier Series

The Fourier Trigonometric Coefficients can be obtained from

$$a_{0} \cdot \frac{1}{T} \cdot t_{0} \cdot T ft)dt \quad \text{average value over one period}$$

$$a_{n} \cdot \frac{2}{T} \cdot t_{0} \cdot T ft)\cos n W_{0}tdt \quad n > 0$$

$$b_{n} \cdot \frac{2}{T} \cdot t_{0} \cdot T ft)\sin n W_{0}tdt \quad n > 0$$

The Fourier Series

To obtain ak

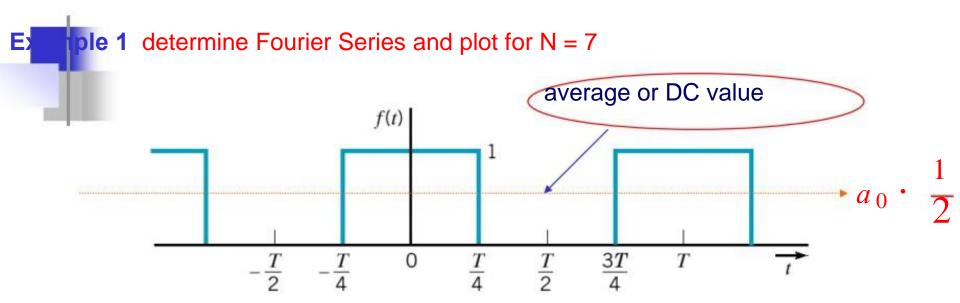
$$\int_{0}^{T} f(t) \cos k W_{0} t dt \cdot \int_{0}^{T} a_{0} \cos k W t dt$$

$$\int_{0}^{N} \int_{0}^{T} (a_{n} \cos n W_{0} t \cdot b_{n} \sin n W t_{0}) \cos k W t dt$$

The only nonzero term is for n = k

•
$$\int_{0}^{T} ft \cos kW$$
 0t dt • $a k \cdot \frac{T}{2}$.

Similar approach can be used to obtain *b*_k



$$a_{0} \cdot \frac{1}{T} \cdot \int_{0}^{t_{0} \cdot T} f(t) dt$$

$$\cdot \frac{1}{T} \cdot \int_{T/2}^{T/2} f(t) dt \cdot \frac{1}{T} \cdot \int_{T/4}^{T/4} 1 dt \cdot \frac{1}{2}$$

Example 1(cont.)

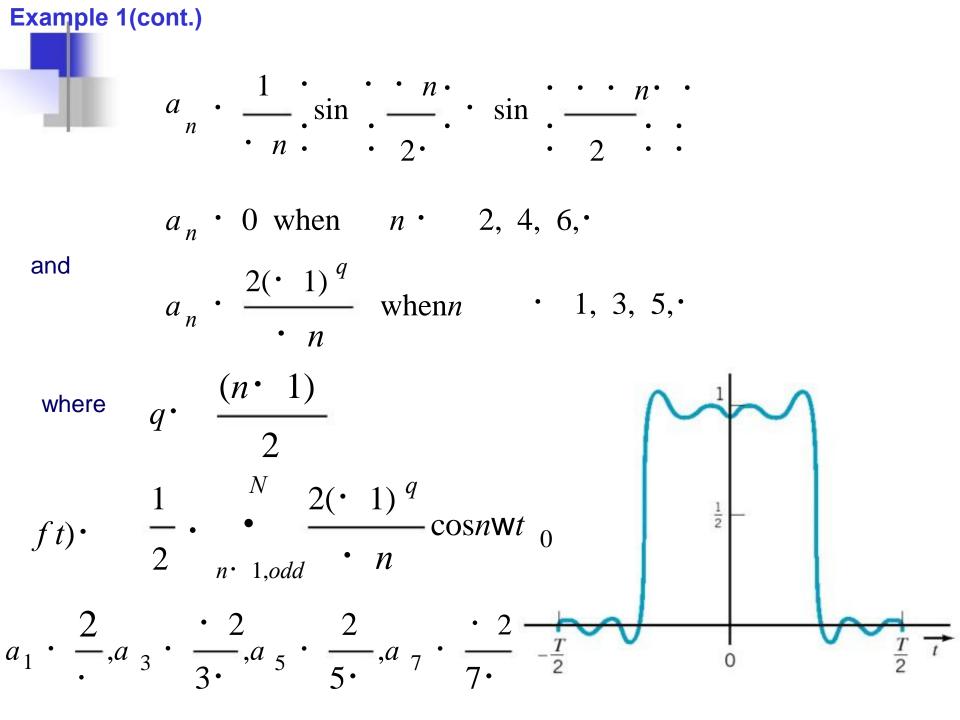
An even function exhibits symmetry around the vertical axis at t = 0 so that f(t) = f(-t).

$$b_n \cdot \frac{2}{T} \cdot \int_{t_0}^{t_0 \cdot T} f(t) \sin n wt \, dt_0$$
$$\cdot \frac{2}{T} \cdot \int_{T/4}^{T/4} 1 \sin n wt \, dt \cdot 0$$

Determine only an

٠

$$a_{n} \cdot \frac{2}{T} \cdot \frac{T/4}{T/4} \operatorname{1} \operatorname{cosn} Wt_{0} dt$$
$$\cdot \frac{2}{TW_{0}n} \operatorname{sin} W_{0}t \Big|_{\cdot T/4}^{T/4}$$

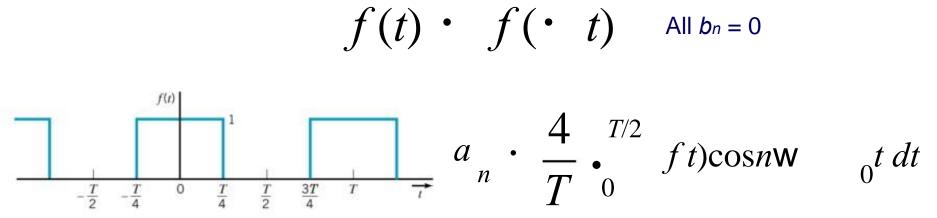


Symmetry of the Function

Four types

- 1. Even-function symmetry
- 2. Odd-function symmetry
- 3. Half-wave symmetry
- 4. Quarter-wave symmetry

Even function



Symmetry of the Function Odd function $f(t) \cdot \cdot f(\cdot t) \text{ All } a_n = 0$ $\int_{T/2}^{T/0} \int_{T/2}^{T/2} f(t) \sin nW = \int_{0}^{T/2} t dt$

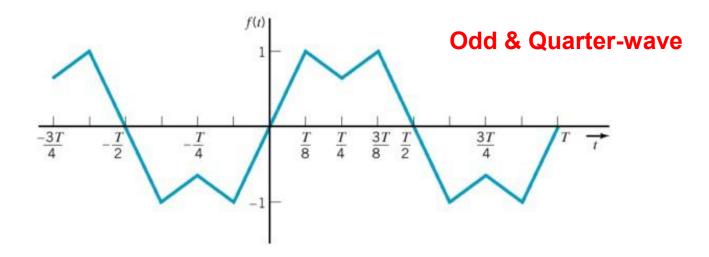
Half-wave symmetry

$$f(t) \cdot \cdot f(t \cdot \frac{T}{2})$$

 a_n and $b_n = 0$ for even values of n and $a_0 = 0$

Symmetry of the Function

Quarter-wave symmetry



All $a_n = 0$ and $b_n = 0$ for even values of n and $a_0 = 0$

$$b_n \cdot \frac{8}{T} \cdot \int_0^{T/4} ft \sin n W = \int_0^t dt$$
; for odd *n*

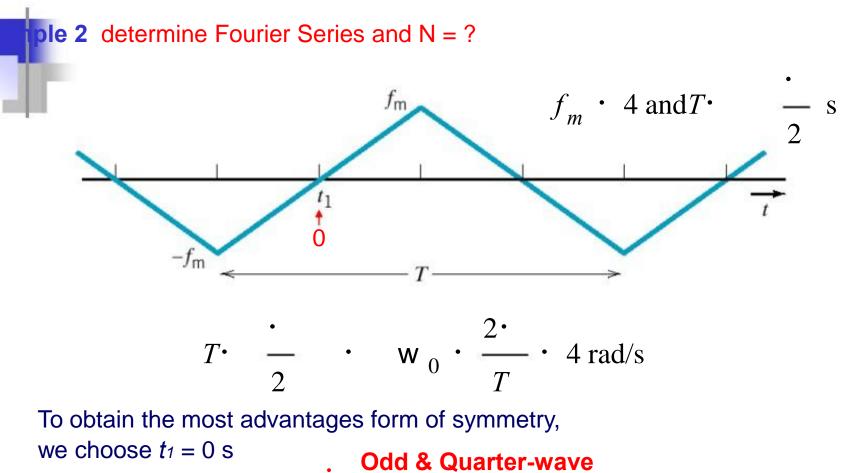
Symmetry of the Function

For Even & Quarter-wave

All $b_n = 0$ and $a_n = 0$ for even values of n and $a_0 = 0$

$$a_n \cdot \frac{8}{T} \cdot \int_0^{T/4} ft \cos n W = \int_0^T dt$$
; for odd *n*

Table 15.4-1 gives a summary of Fourier coefficientsand symmetry.

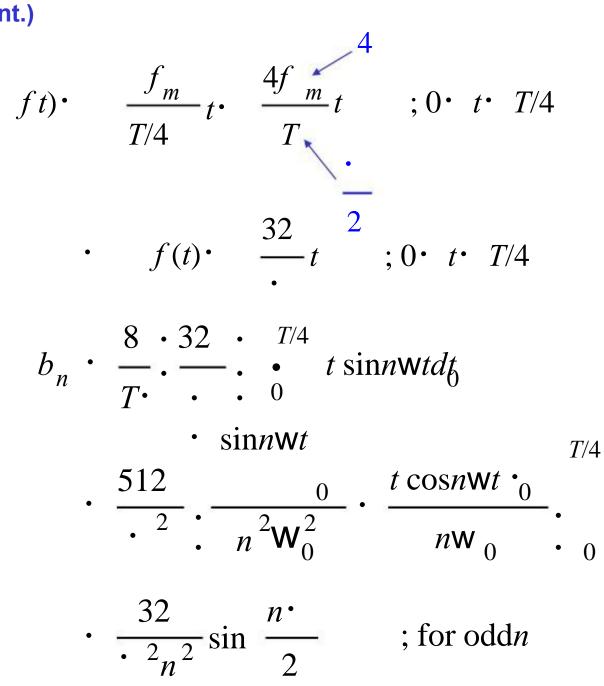


All $a_n = 0$ and $b_n = 0$ for even values of n and $a_0 = 0$

E

$$b_n \cdot \frac{8}{T} \cdot \int_0^{T/4} ft \sin n W = \int_0^t dt$$
; for odd *n*

Example 2(cont.)



Example 2(cont.)

The Fourier Series is

 $f(t) \cdot 3.24 \qquad \stackrel{N}{\underset{n \in 1}{\stackrel{1}{\frac{\pi_2}{2}}} \sin \frac{n \cdot n}{2} \sin n \cdot \frac{n \cdot n}{2} \sin n \cdot$

The first 4 terms (upto and including N = 7)

$$ft) \cdot 3.24(\sin 4t \cdot \frac{1}{9} \sin 12t \cdot \frac{1}{25} \sin 20t \cdot \frac{1}{49} \sin 28t)$$
Next harmonic is for N = 9 which has magnitude
$$3.24/81 = 0.04 < 2\% \text{ of } b_1(=3.24)$$

Therefore the first 4 terms (including N = 7) is enough for the desired approximation

Exponential Form of the Fourier Series ft · C $_{0}$ · · C $_{n}\cos(nWt_{0} \cdot)_{n}$ *n*• 1 C_0 is the average (or DC) value of f(t) and $\mathbf{C}_n \cdot \frac{(a_n \cdot jb)_n}{\mathbf{\gamma}} \cdot C_n \cdot n$ $C_n \cdot |\mathbf{C}_n| \cdot \frac{\sqrt{a_n^2 \cdot b_n^2}}{2}$ where $\cdot \quad \tan^{-1} \cdot \frac{b_n}{m} \cdot ; \text{ if } a_n \cdot 0$ • *a*_n• and $\frac{180}{2} \cdot \tan \frac{1}{n} \cdot \frac{b_n}{a} = \frac{b_n}{n} \cdot \frac{b_n}{a} = \frac{1}{n} \cdot \frac{b_n}{a} = \frac{1$

Exponential Form of the Fourier Series

 $a_n \cdot 2C_n \cos \cdot and \qquad b_n \cdot 2C_n \sin \cdot n$ Writing $\cos(nW_0 \cdot \cdot n)$ on tial form using $N \cdot \cdot \cdot$

$$ft) \cdot C = \underset{n \cdot \cdots \\ n \cdot 0}{\circ} \cdot C e_n^{jn \otimes t_0} \cdot C e_n^{jn \otimes t_0}$$

where the *complex coefficients* are defined as

$$\mathbf{C}_{n} \cdot \frac{1}{T} \cdot \int_{t_{0}}^{t_{0} \cdot T} f(t) e^{-\int f(t) \cdot dt} dt \cdot C e^{-\int r \cdot n}$$

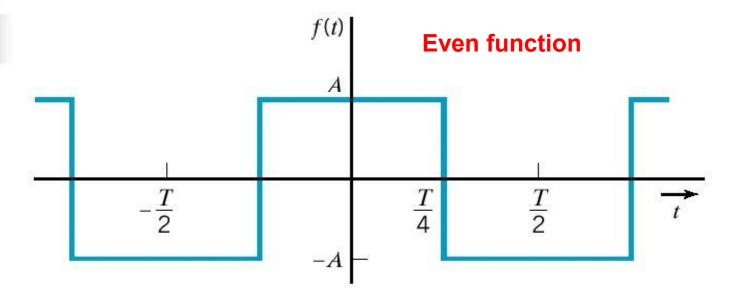
$$\mathbf{C} \cdot \mathbf{C} \cdot \mathbf{C} \cdot \mathbf{C}$$

complex $n \cdot n$

And

ple 3 determine complex Fourier Series

E



The average value of f(t) is zero

 $\cdot C_0 \cdot 0$

$$C_{n} \cdot \frac{1}{T} \cdot t_{0} \cdot T_{t_{0}} f(t) e^{-\int f(t) dt} dt$$
We select
$$t_{0} \cdot \cdot \frac{T}{2} e^{f(t)} f(t) e^{-\int f(t) dt} f(t) e^{-\int f(t) dt} dt$$

Example 3(cont.)

$$\mathbf{C}_{n} = \frac{1}{T} \cdot \frac{T/2}{\cdot T/2} f(t) e^{-t j n w 0 t} dt$$

$$\cdot \frac{1}{T} \cdot \frac{T/2}{\cdot T/2} \cdot A e^{-t m t} dt \cdot \frac{1}{T} \cdot \frac{T/4}{\cdot T/4} A e^{-t m t} dt \cdot \frac{1}{T} \cdot \frac{T/2}{T/4} \cdot A e^{-t m t} dt$$

$$\cdot \frac{A}{mT} \cdot e^{m t} \left| \frac{T/4}{T/2} \cdot e^{-m t} \right|_{-T/4}^{T/4} \cdot e^{-m t} \left| \frac{T/2}{T/4} \cdot \frac{A}{T/4} \cdot \frac{A}{T/4}$$

• $A \frac{\sin x}{x}$ where $x \cdot \frac{n}{2}$

Example 3(cont.)

Since f(t) is even function, all C_n are real and = 0 for n even

For n = 1

$$\mathbf{C}_1 \cdot \frac{A \sin \cdot /2}{\cdot /2} \cdot \frac{2A}{\cdot} \cdot \mathbf{C}_{\cdot 1}$$

For n = 2

$$\mathbf{C}_2 \cdot A \xrightarrow{\sin \cdot} \cdot 0 \cdot \mathbf{C}_{\cdot 2}$$

For n = 3

$$\mathbf{C}_3 \cdot \frac{A \sin(3 \cdot /2)}{3 \cdot /2} \cdot \frac{2A}{3 \cdot} \cdot \mathbf{C}_{\cdot 3}$$

Example 3(cont.)

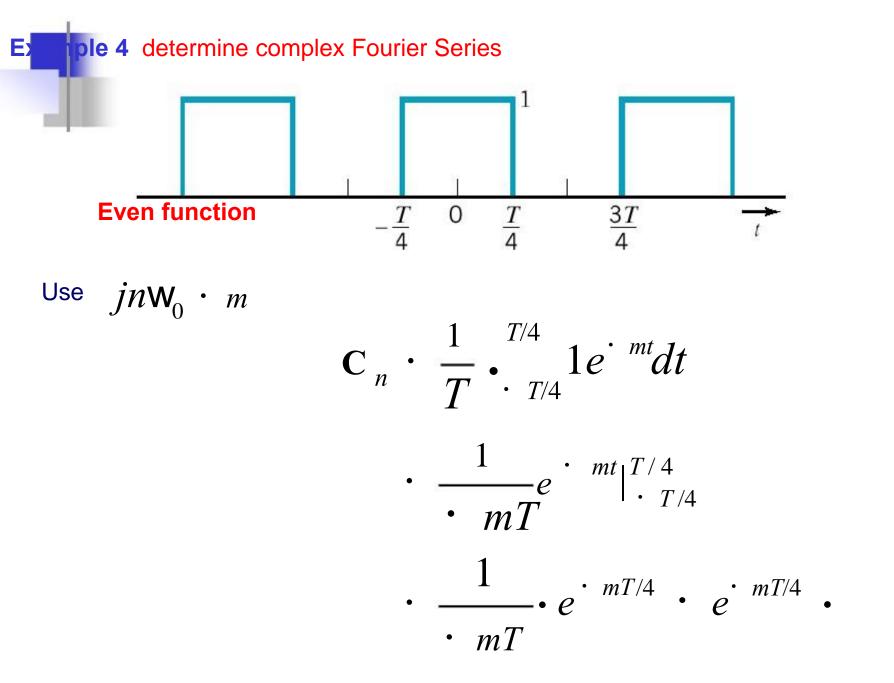
The complex Fourier Series is

$$f(t) \cdot \cdot \cdot \frac{2A}{3 \cdot} e^{-j3wot} \cdot \frac{2A}{2} e^{-jwot} \cdot \frac{2A}{2} e^{jwot} \cdot \frac{2A}{3 \cdot} e^{j3wot}$$

$$\cdot \frac{2A}{3 \cdot} e^{jwot} \cdot e^{-jwot} \cdot \frac{2A}{3 \cdot} e^{j3wot} \cdot e^{-j3wot} \cdot \frac{2A}{3 \cdot} e^{j3wot}$$

$$\cdot \frac{4A}{2} \cos wt \cdot_{0} + \frac{4A}{3 \cdot} \cos 3wt \cdot_{0} \cdot \frac{e^{jx} \cdot e^{-jx} \cdot 2\cos x}{e^{jx} \cdot e^{jx} \cdot 2j\sin x}$$

$$\cdot \frac{4A}{2} \cdot \frac{(\cdot 1)^{q}}{n} \cos nWt = q \cdot \frac{n \cdot 1}{2}$$
For real $f(t) \cdot |C_{n}| \cdot |C_{-n}|$



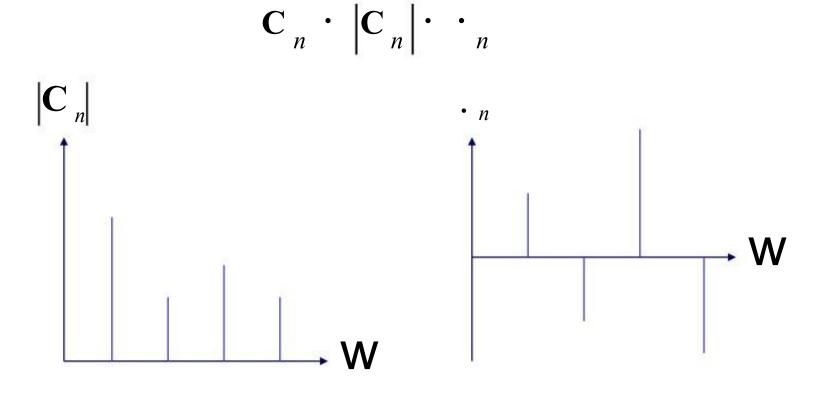
Example 4(cont.)

$\mathbf{C}_{n} \cdot \frac{1}{i \cdot jn2} \cdot e^{jn \cdot 2} \cdot e^{jn \cdot 2} \cdot e^{jn \cdot 2} \cdot \frac{1}{i \cdot jn2} \cdot \frac{1}{i \cdot j$

To find Co

$$C_{0} \cdot \frac{1}{T} \cdot \int_{0}^{T} f(t) dt$$
$$\cdot \frac{1}{T} \cdot \int_{T/4}^{T/4} 1 dt \cdot \frac{1}{2}$$

The complex Fourier coefficients

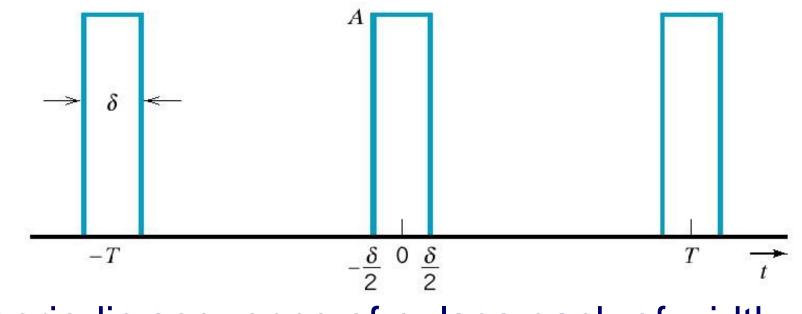


Amplitude spectrum

Phase spectrum

The Fourier Spectrum is a graphical display of the amplitude and phase of the complex Fourier coe at the fundamental and harmonic frequencies.

Example

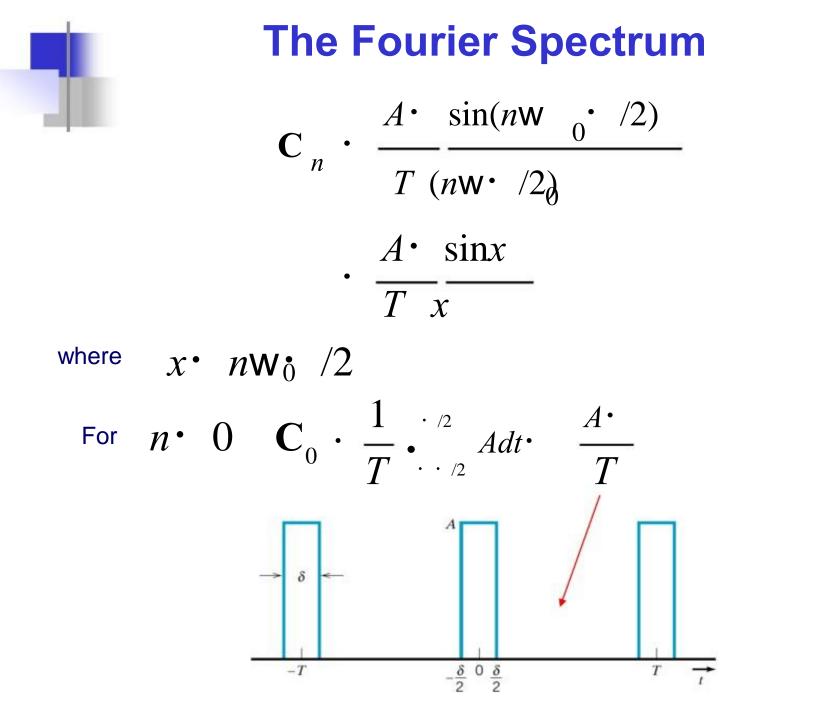


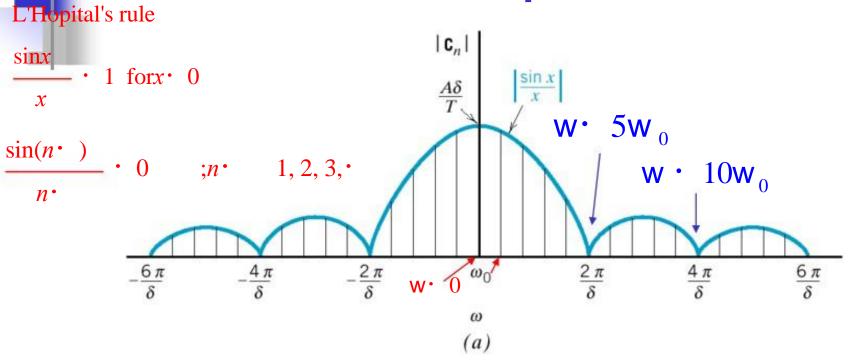
A periodic sequence of pulses each of width ·

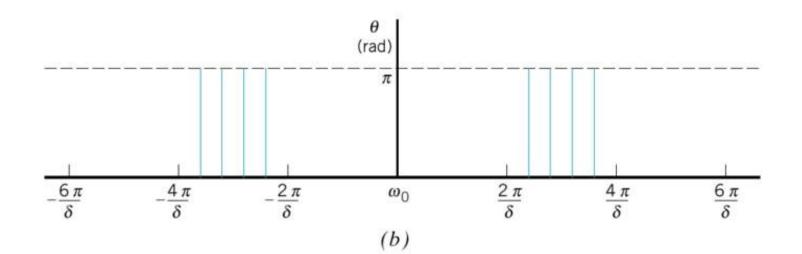
The Fourier coefficients are

For
$$n \cdot 0$$

 $C_n \cdot \frac{1}{T} \cdot \frac{T/2}{T/2} A e^{-\frac{1}{2}jnw0t} dt$
 $C_n \cdot \frac{A}{T} \cdot \frac{T/2}{T/2} e^{-\frac{1}{2}jnwt_0} dt$
 $\cdot \frac{A}{T} \cdot \frac{A}{T} \cdot \frac{e^{jnw0\cdot/2}}{T} \cdot e^{jnw0\cdot/2} \cdot e^{jnw0\cdot/2} \cdot \frac{2A}{jnw0T} \cdot \frac{NW_0}{2} \cdot \frac{2A}{T}$







The Truncated Fourier Series

A practical calculation of the Fourier series requires that we truncate the series to a *finite* number of terms.

$$f(t) \cdot \begin{pmatrix} N \\ \bullet \\ n \end{pmatrix} \cdot \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} p \\ n \end{pmatrix} \begin{pmatrix} n \\ N \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} p \\ n \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} p \\ n \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix} P \\ n \end{pmatrix} \begin{pmatrix} N \\ n \end{pmatrix} \begin{pmatrix}$$

The error for *N* terms is

•
$$t$$
)• $f(t)$ • $S_N(t)$

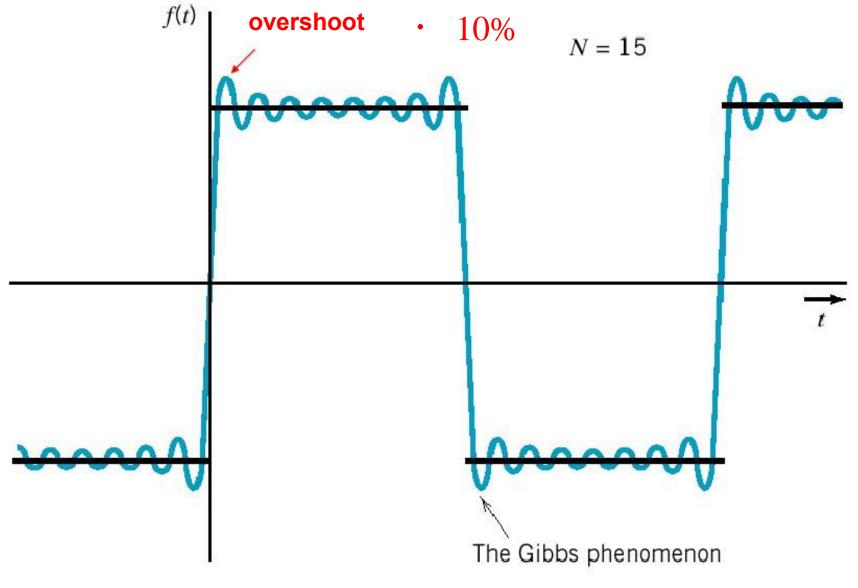
We use the mean-square error (MSE) defined as

$$MSE \cdot \quad \frac{1}{T} \cdot \frac{T}{0} \cdot \frac{2}{t} dt$$

MSE is minimum when C_n = Fourier series" coefficients



The Truncated Fourier Series

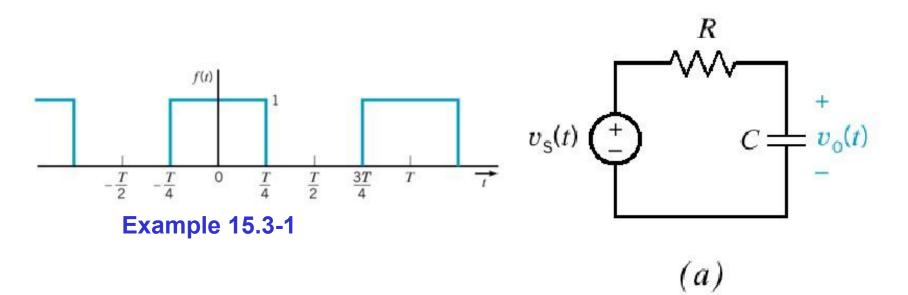


Circuits and Fourier Series

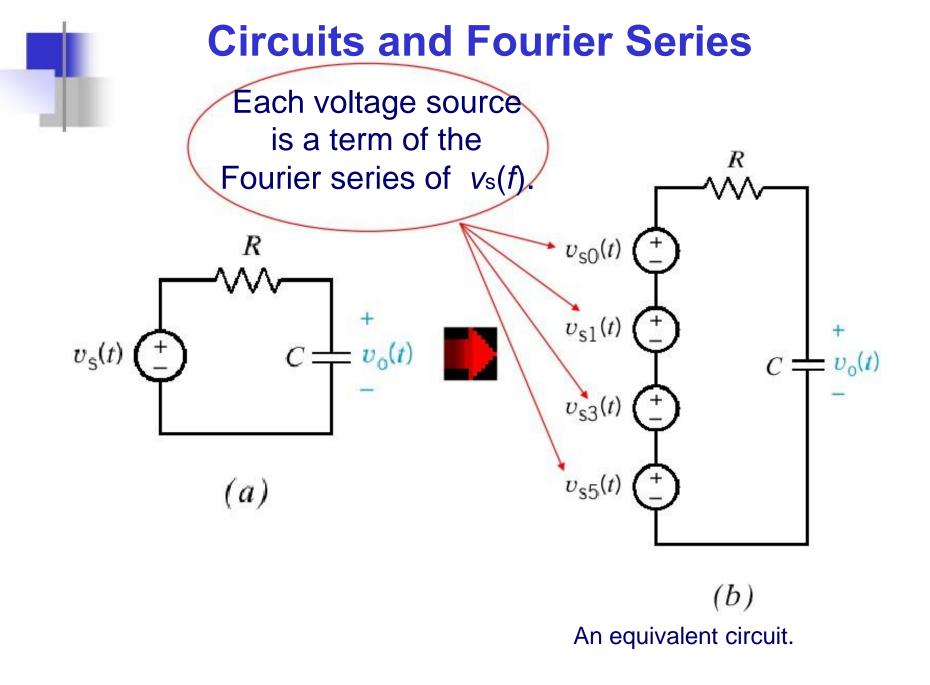
It is often desired to determine the response of a circuit excited by a periodic signal $v_{s}(t)$.

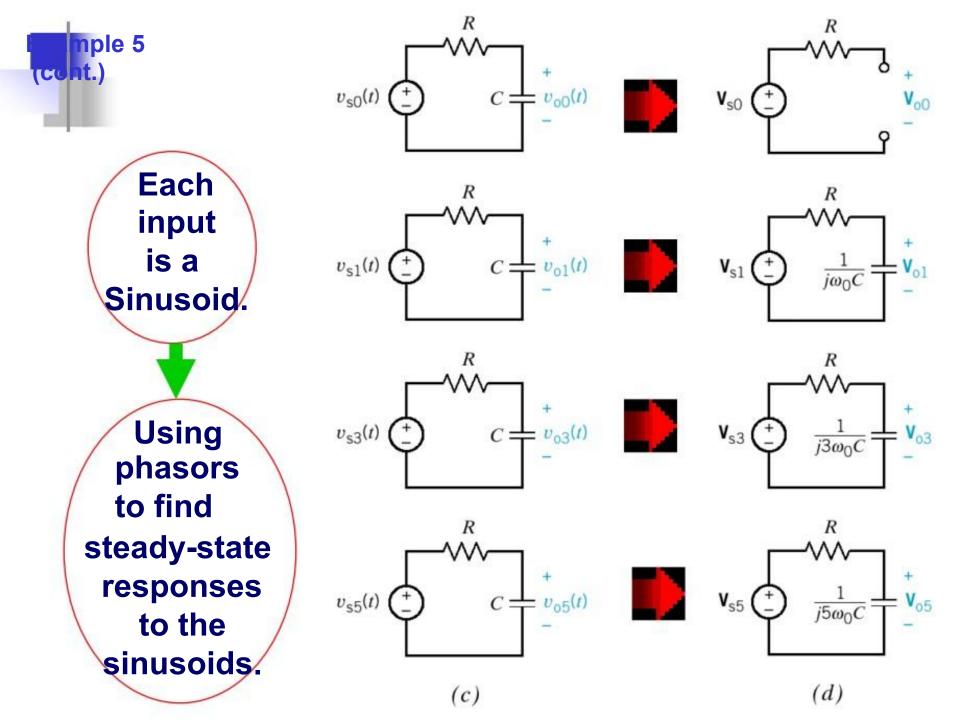
Example 15.8-1 An RC Circuit vo(t) = ?

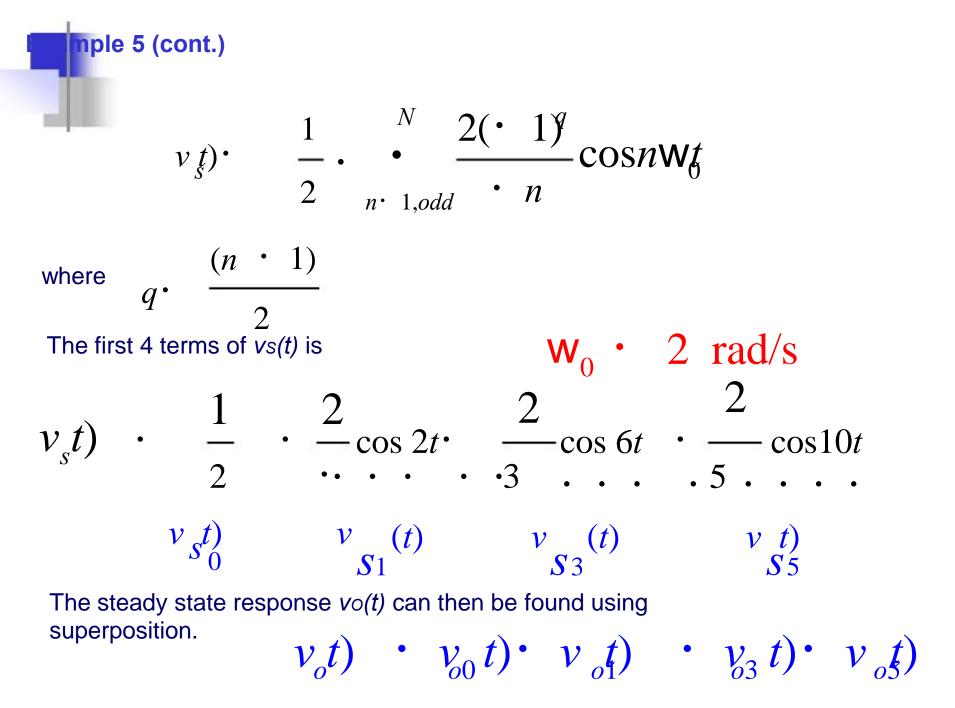
$$R \cdot 1 \cdot , C \cdot 2F, T \cdot \cdot sec$$



An *RC* circuit excited by a periodic voltage $v_{s}(t)$.







nple 5 (cont.)

The impedance of the capacitor is

 $\mathbf{Z}_{C} \cdot \frac{1}{jn \mathbf{W}_{0}C} \quad ; \text{for} n \cdot 0, 1, 3, 5, \cdot$ We can find 1 $\frac{jn W_0 C}{1} V_{sn} ; \text{for} n \cdot 0, 1, 3, 5, \cdot$ \mathbf{V}_{on} R. jn CW_0 $\frac{1 \cdot jn w_0 CR}{4}$

mple 5 (cont.)

The steady-state response can be written as

$$v_{on}t) \cdot |\mathbf{V}_{on}| \cos(n\mathbf{W}_0 t \cdot \cdot \mathbf{V}_{on})$$

$$\cdot \frac{|\mathbf{V}_{sn}|}{\sqrt{1 \cdot 16n^2}} \cos(n\mathbf{W}t_0 \cdot \mathbf{V}_{sn} \cdot \tan^{-1}4n)$$

In this example we have

$$\begin{aligned} \left| \mathbf{V}_{s0} \right| \cdot \frac{1}{2} \\ \left| \mathbf{V}_{sn} \right| \cdot \frac{2}{n} \quad \text{for} n \cdot 1, 3, 5 \\ \cdot \mathbf{V}_{sn} \cdot \mathbf{0} \quad \text{for} n \cdot 0, 1, 3, 5 \end{aligned}$$

$$\begin{aligned} & \text{ple 5 (cont.)} \\ & _{o0}(t) \cdot \frac{1}{2} \\ & v_{on}t) \cdot \frac{2}{n \cdot \sqrt{1 \cdot .16n^{2}}} \cos(n2t \cdot \tan^{-1}4n) \quad ; \text{for}n \cdot 1, 3, 5 \\ & \ddots & \ddots & n \cdot \sqrt{1 \cdot .16n^{2}} \dots \dots \dots \\ & v_{o1}t) \quad \cdot 0.154 \cos(2t \cdot .76 \cdot .) \\ & v_{o3}t) \quad \cdot 0.018 \cos(6t \cdot .85 \cdot .) \\ & v_{o5}t) \quad \cdot 0.006 \cos(10t \cdot .87 \cdot .) \\ & \cdot & v_{f}t) \quad \cdot \frac{1}{2} \cdot 0.154 \cos(2t - .76 \cdot .) \cdot 0.018 \cos(6t \cdot .85 \cdot .) \\ & \cdot & 0.006 \cos(10t - .87 \cdot .) \end{aligned}$$

Properties of Fourier Series

$$xt \cdot \cdot FS \cdot \cdot q$$

· Linearity

$$xt \cdot \cdot FS \cdot a_{k}, y_{t} \cdot \cdot FS \cdot b_{k}$$

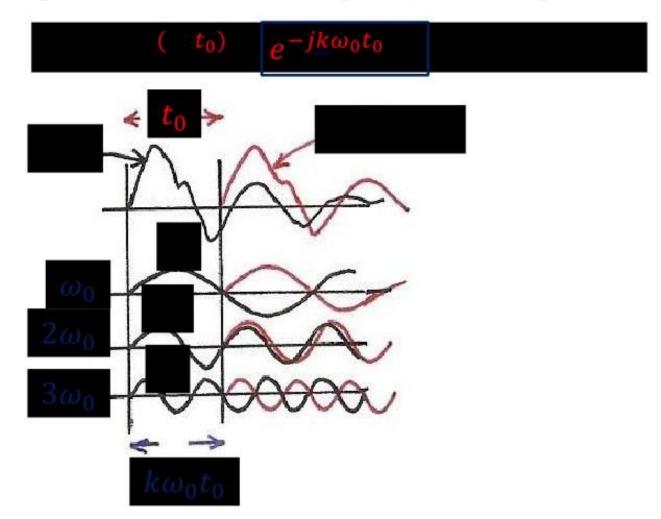
$$Axt \cdot \cdot Byt \cdot \cdot FS \cdot Aa_{k} \cdot Bb_{k}$$

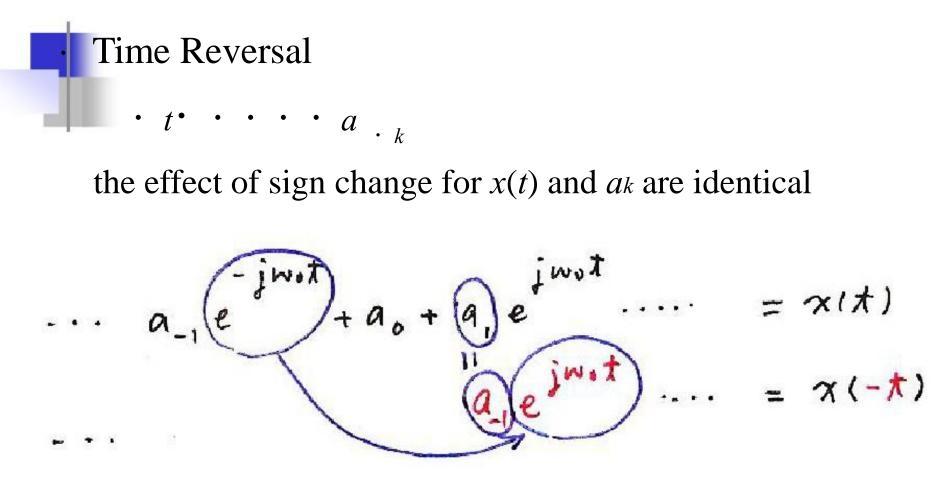




 $x \cdot t \cdot t_0 \cdot \cdots \cdot e^{-jkw0t0} a_k$

phase shift linear in frequency with amplitude unchanged





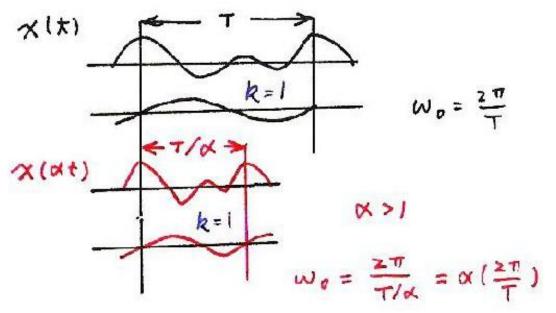
unique representation for orthogonal basis

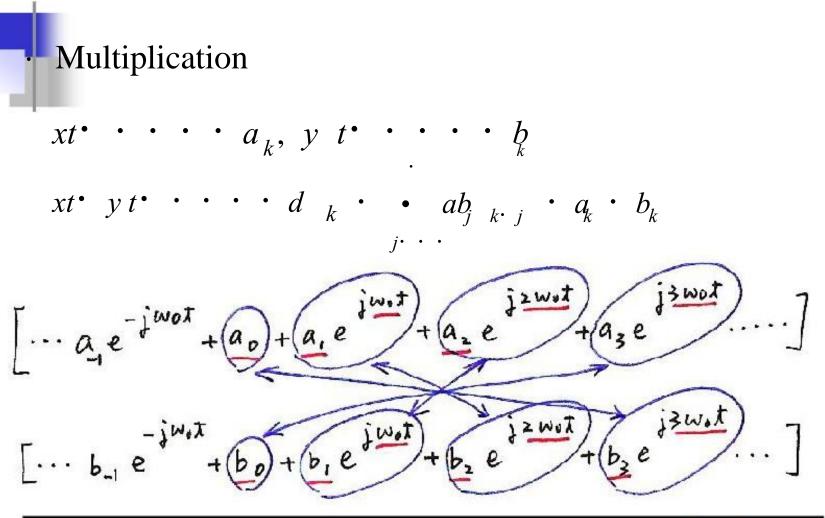
Time Scaling

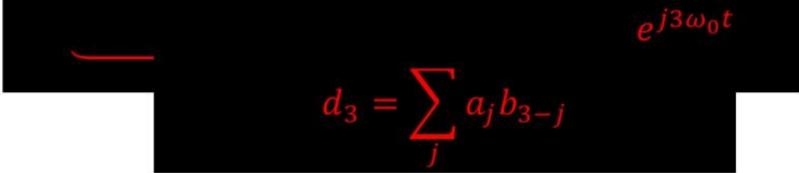
- :positive real number
- $x \cdot t^{\bullet}$:periodic with period T/α and fundamenta frequency $\alpha\omega_0$

$$x \cdot \cdot t \cdot \cdot a_k e^{jk \cdot \cdot \cdot y \cdot t}$$

ak unchanged, but $x(\alpha t)$ and each harmonic component are different



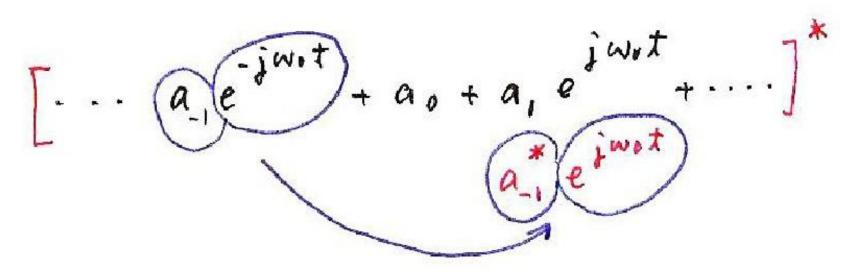






$$x^{\cdot} t^{\bullet} \cdot a^{\cdot} a_{\cdot k}$$

 $a_{k} \cdot a_{k}$, if $x \cdot t$ real



unique representation

• Differentiation

$$\frac{dxt}{dt} \cdot \cdot \cdot jk \mathbf{W} \quad {}_{0}a_{k}$$

$$\frac{d}{dt} (a_{k} e^{jkw_{0}t}) = \underbrace{jkw_{0}}_{kw_{0}t} e^{jkw_{0}t} \qquad k=1 \qquad k=2 \qquad k=3 \qquad k=$$

Parseval's Relation

$$\frac{1}{T} \cdot \left| xt \cdot \right|^2 dt \cdot \left| a_k \right|^2$$



total average power in a period T

$$\frac{1}{T} \cdot \left| a_k e^{jkw_0 t} \right|^2 dt \cdot \left| a_k \right|^2$$

average power in the *k*-th harmonic component in a period *T*

Continuous-Time Signal Analysis: The Fourier Transform

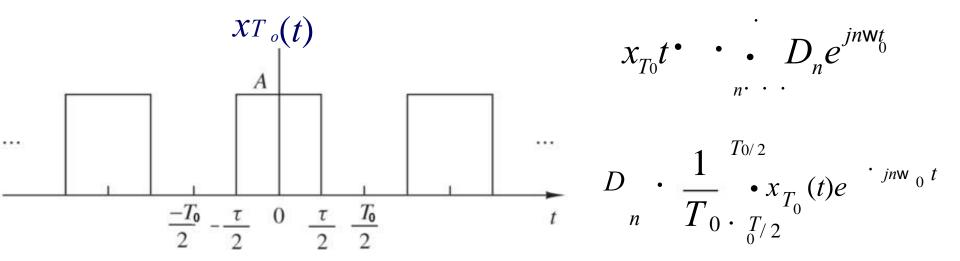
Chapter Outline

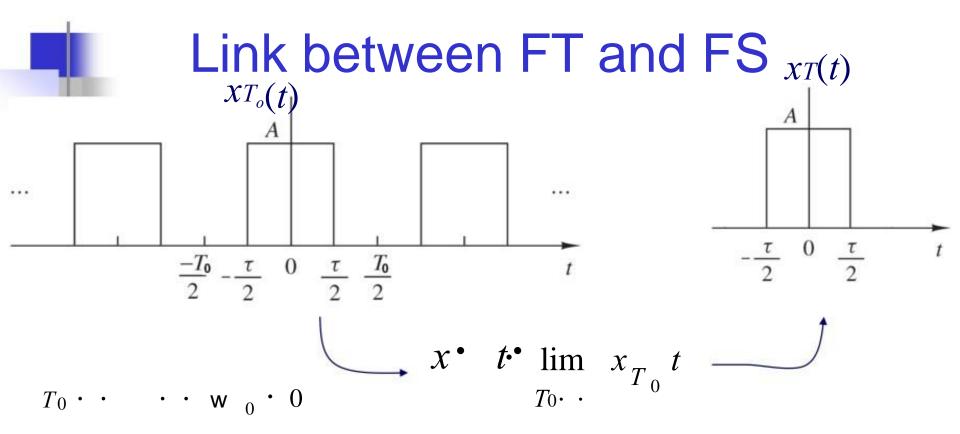
- Aperiodic Signal Representation by Fourier Integral
- Fourier Transform of Useful Functions
- Properties of Fourier Transform
- Signal Transmission Through LTIC Systems
- Ideal and Practical Filters
- Signal Energy
- Applications to Communications
- Data Truncation: Window Functions

Link between FT and FS

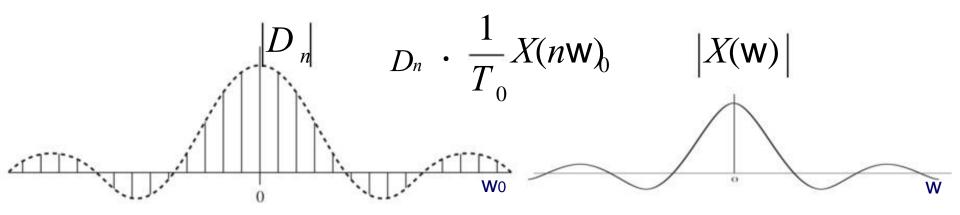
Fourier series (FS) allows us to represent periodic signal in term of sinusoidal or exponentials ejnwot.

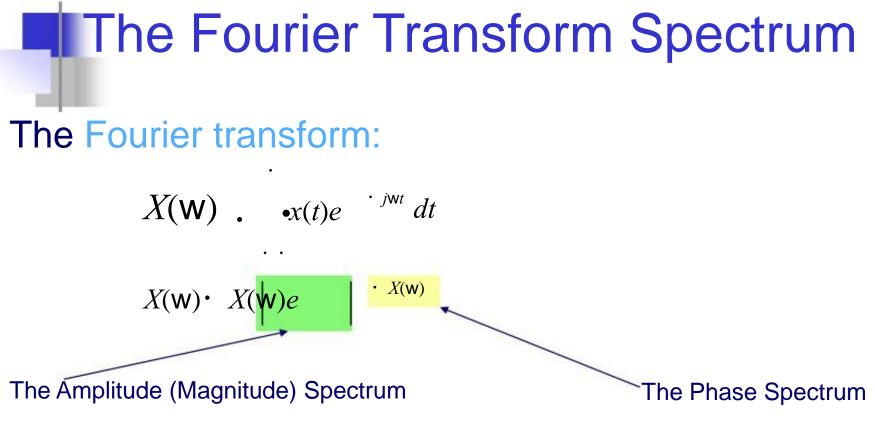
Fourier transform (FT) allows us to represent aperiodic (not periodic) signal in term of exponentials ejwt.





As T₀ gets larger and larger the fundamental frequency w₀ gets smaller and smaller so the spectrum becomes continuous.



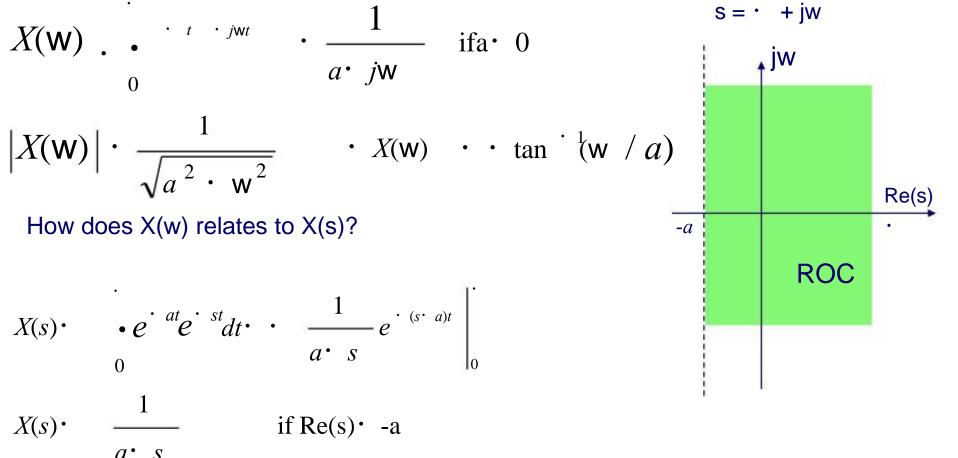


The amplitude spectrum is an even function and the phase is an odd function.

The Inverse Fourier transform:

$$x(t) \cdot \frac{1}{2 \cdot} \cdot X(\mathbf{W}) e_{jwt} d\mathbf{W}$$

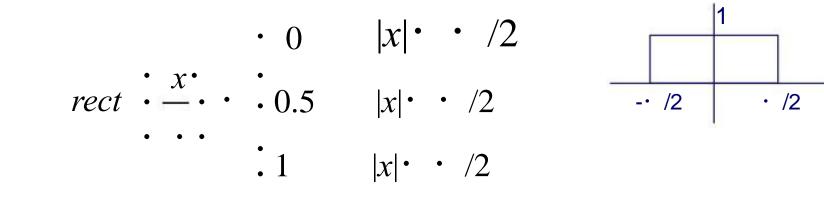
Find the Fourier transform of $x(t) = e_{-at}u(t)$, the magnitude, and the spectrum Solution:



Since the jw-axis is in the region of convergence then FT exist.

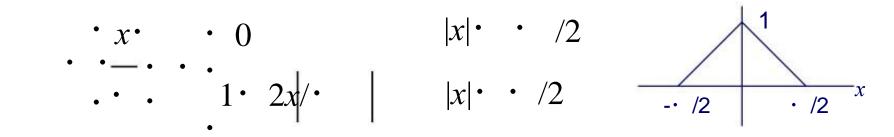
Useful Functions

Unit Gate Function



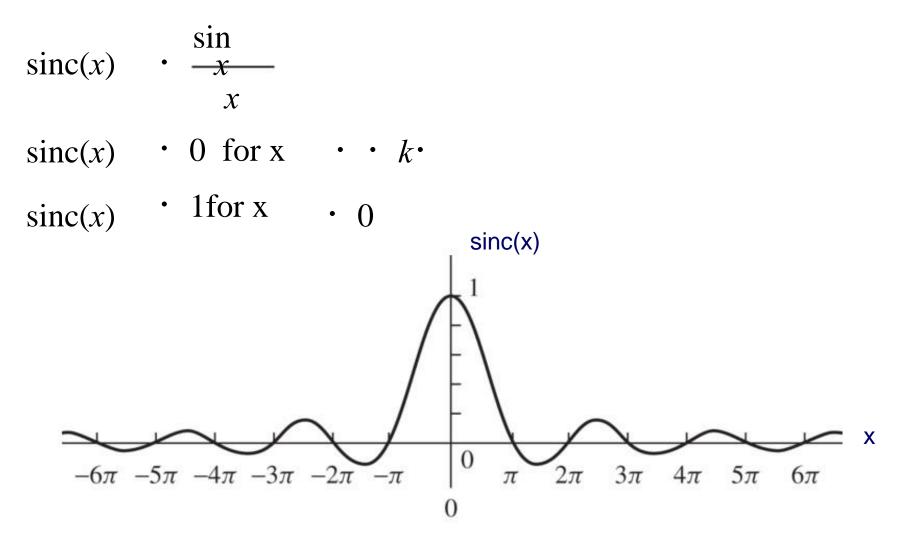
X

Unit Triangle Function



Useful Functions

Interpolation Function



Find the FT, the magnitude, and the phase spectrum of $x(t) = rect(t/\cdot)$.

Answer

$$X(w)$$
 · $/2$
· $rect(t / \cdot)e^{i jwt} dt \cdot sinc(w \cdot / 2)$
· $/2$

What is the bandwidth of the above pulse?

The spectrum of a pulse extend from 0 to $\cdot\,$. However, much of the spectrum is concentrated within the first lobe (w=0 to 2 $\cdot\,$ / $\cdot\,$)

Find the FT of the unit impulse \cdot (t). Answer

$$X(\mathbf{w})$$
 · · $(t)e^{ijwt} dt$ · 1

• •

Find the inverse FT of \cdot (w).

Answer

$$x(t)$$
 $\cdot \frac{1}{2 \cdot \cdot} \cdot (\mathbf{W}) e^{j\mathbf{W}t} d\mathbf{W} \cdot \frac{1}{2 \cdot}$

so thespectrumof a constantisan impulse

$$1 \cdot 2 \cdot \cdot (w)$$

Find the inverse FT of \cdot (w-w $_{0}$). Answer

$$x(t) \cdot \frac{1}{2 \cdot \ldots} \cdot (\mathbf{w} \cdot \mathbf{w}_{0}) e^{-j\mathbf{w}t} d\mathbf{w} \cdot \frac{1}{2 \cdot e^{-j\mathbf{w}0t}}$$

sothespectrum f a complex exponent is a shifted impulse

 $e^{jWt_0} \cdot 2 \cdot \cdot (W \cdot W_0)$ and $e^{jWt_0} \cdot 2 \cdot \cdot (W \cdot W)_0$

Find the FT of the everlasting sinusoid cos(wot). Answer

$$\cos \mathbf{W}_0 t \cdot \frac{1}{2} \cdot \overset{j w_b}{e} \cdot e^{j w_b} \cdot$$

$$\frac{1}{2} \cdot e^{jw_0 t} \cdot e^{jw_0 t} \cdot \cdots \cdot (w \cdot w) \cdot (w \cdot w)$$

Find the FT of a periodic signal. Answer

 $x(t) \cdot \underbrace{De}_{n}^{n \cdot \cdot \cdot} W_{0} \cdot 2 \cdot /T_{0}$

TaketheFT of both sideand use linearity property of FT

 $X(\mathbf{w}) \cdot 2 \cdot \cdots \cdot D_n \cdot (\mathbf{w} \cdot n\mathbf{w}) = 0$

Find the FT of the unit impulse train t_{T0} (Answer

$$\cdot_{T_0}(t) \cdot \frac{1}{T_{0n}} \cdot e^{jn W 0t}$$

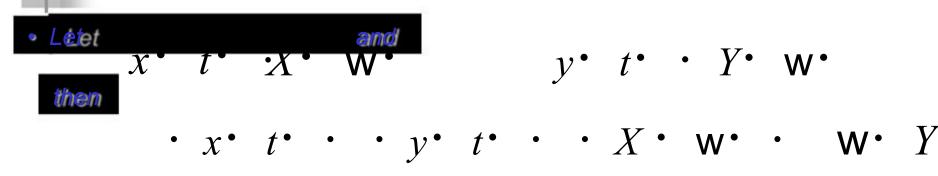
$$X(W) \cdot \frac{2 \cdot e^{n \cdot t}}{T_{0n} \cdot t} \cdot (W \cdot nW)_0$$

TABL	E Fourier Tr	Fourier Transforms			
No.	<i>x(t)</i>	$X(\omega)$	and a second		
1	$e^{-at}u(t)$	$\frac{1}{a+j\omega}$	<i>a</i> > 0		
2	$e^{at}u(-t)$	$\frac{1}{a-j\omega}$	a > 0		
3	$e^{-a t }$	$\frac{2a}{a^2+\omega^2}$	a > 0		
4	$te^{-at}u(t)$	$\frac{1}{(a+j\omega)^2}$	a > 0		
5	$t^n e^{-at} u(t)$	$\frac{n!}{(a+j\omega)^{n+1}}$	a > 0		
6 7 8 9	$\delta(t)$	1			
7	1	$2\pi\delta(\omega)$			
8	ejwot	$2\pi\delta(\omega-\omega_0)$			
9	$\cos \omega_0 t$	$\pi[\delta(\omega-\omega_0)+\delta(\omega+\omega_0)]$			
0	$\sin \omega_0 t$	$j\pi[\delta(\omega+\omega_0)-\delta(\omega-\omega_0)]$			
1	<i>u</i> (<i>t</i>)	$\pi\delta(\omega) + \frac{1}{j\omega}$			
2	sgn t	$\frac{2}{j\omega}$	÷		

TABL	E Fourier Trans	Fourier Transforms		
No.	x(t)	X(ω)		
13	$\cos \omega_0 t u(t)$	$\frac{\pi}{2}[\delta(\omega-\omega_0)+\delta(\omega+\omega_0)]+\frac{j\omega}{\omega_0^2-\omega^2}$		
14	$\sin \omega_0 t u(t)$	$\frac{\pi}{2j}[\delta(\omega-\omega_0)-\delta(\omega+\omega_0)]+\frac{\omega_0}{\omega_0^2-\omega^2}$		
15	$e^{-at}\sin\omega_0 tu(t)$	$\frac{\omega_0}{(a+j\omega)^2+\omega_0^2}$	<i>a</i> > 0	
16	$e^{-at}\cos\omega_0 tu(t)$	$\frac{a+j\omega}{(a+j\omega)^2+\omega_0^2}$	a > 0	
17	$\operatorname{rect}\left(\frac{t}{\tau}\right)$	$\tau \operatorname{sinc}\left(\frac{\omega\tau}{2}\right)$		
18	$\frac{W}{\pi}$ sinc (Wt)	$\operatorname{rect}\left(\frac{\omega}{2W}\right)$		
19	$\Delta\left(\frac{t}{\tau}\right)$	$\frac{\tau}{2}\operatorname{sinc}^2\left(\frac{\omega\tau}{4}\right)$		
20	$\frac{W}{2\pi}\operatorname{sinc}^{2}\left(\frac{Wt}{2}\right)$	$\Delta\left(\frac{\omega}{2W}\right)$		
21	$\sum_{n=-\infty}^{\infty} \delta(t-nT)$	$\omega_0 \sum_{n=-\infty}^{\infty} \delta(\omega - n\omega_0)$	$\omega_0 = \frac{2\pi}{T}$	
22	$e^{-t^2/2\sigma^2}$	$\sigma\sqrt{2\pi}e^{-\sigma^2\omega^2/2}$		

Properties of the Fourier Transform







then

$$x \cdot at \cdot \frac{1}{|a|} X \cdot \frac{w}{a}$$

Compression in the time domain results in expansion in the frequency domain

Internet channel A can transmit 100k pulse/sec and channel B can transmit 200k pulse/sec. Which channel does require higher bandwidth?

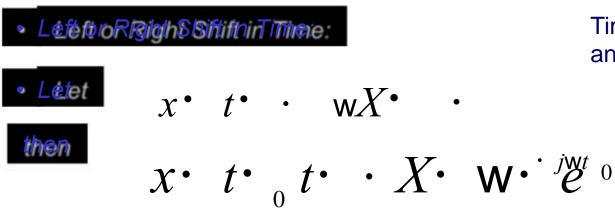
Properties of the Fourier Transform

• TimeRevesabl:

• Let
$$x \cdot t \cdot \cdot wX^{\bullet}$$

them $x(\cdot t) \cdot X(\cdot w)$

Example: Find the FT of eatu(-t) and e-a|t|

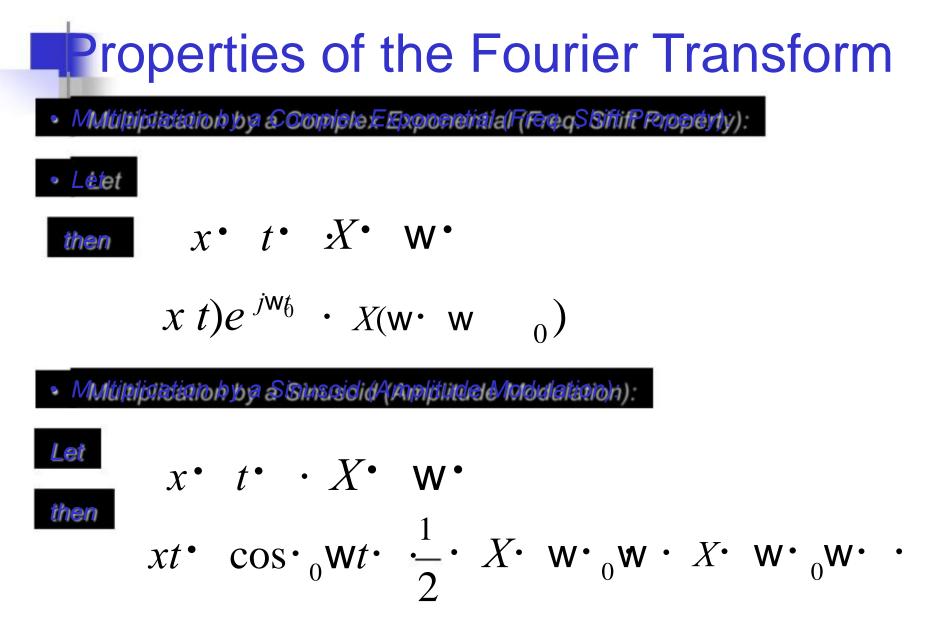


Example: if x(t) = sin(wt) then what is the FT of $x(t-t_0)$?

Example: Find the FT of

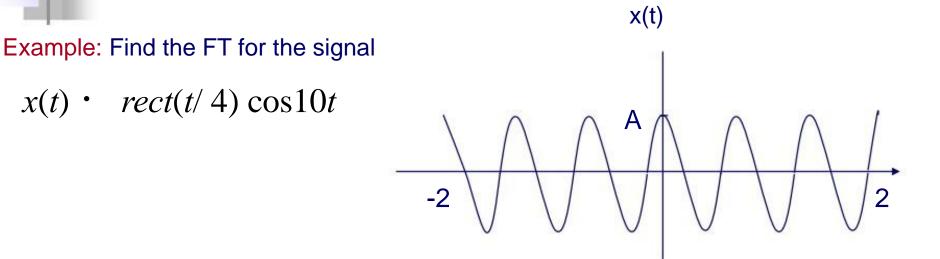
$$e^{at}$$

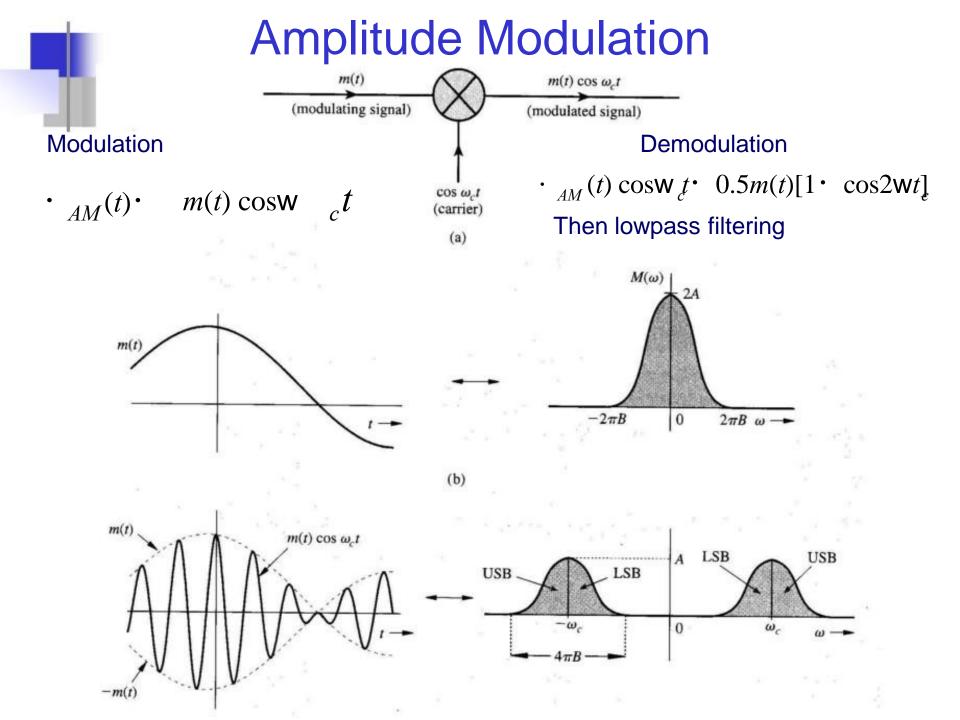
Time shift effects the phase and not the magnitude.



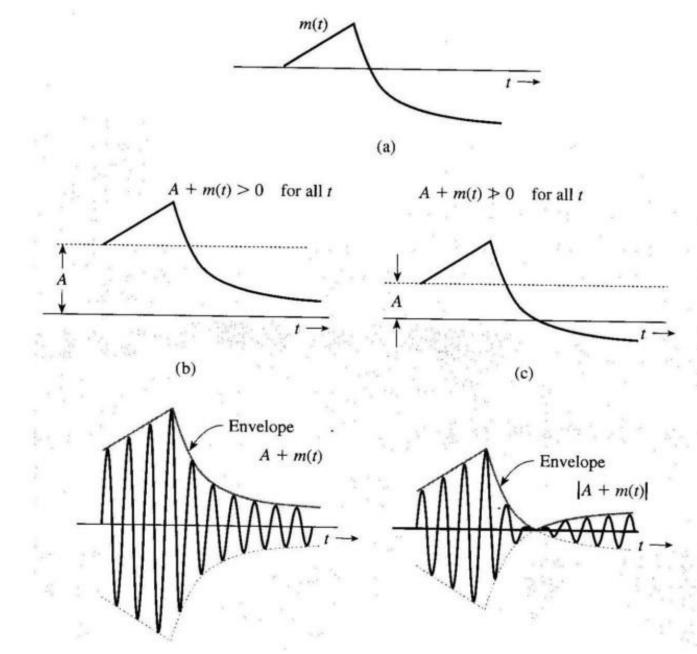
coswot is the carrier, x(t) is the modulating signal (message), x(t) coswot is the modulated signal.

Example: Amplitude Modulation

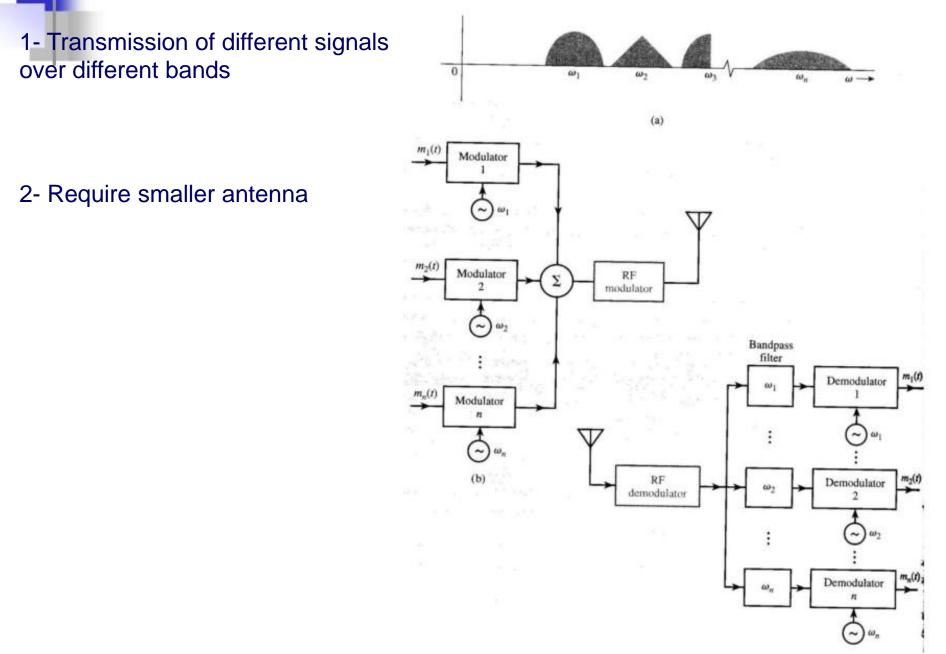




Amplitude Modulation: Envelope Detector



Applic. of Modulation: Frequency-Division Multiplexing



Properties of the Fourier Transform Differentiation in this Erequency Dominian • Letet $x \bullet t \bullet \cdot X \bullet W \bullet$ $t^n x t$ (j) $n \frac{d^n}{dw^n} X(W)$ then DDifferentiation in the Time Domaia ... $x \bullet t \bullet \bullet wX \bullet$ $\frac{d^n}{dt^n} x t \cdot (j \mathbf{W})^n X(\mathbf{W})$ then

Example: Use the time-differentiation property to find the Fourier Transform of the triangle pulse $x(t) = \cdot (t/\cdot)$

Properties of the Fourier Transform

Intrageration in the Time Domain

٠

$$t \bullet \cdot X \bullet W \bullet$$

•
$$x(\cdot)d\cdot \cdot \frac{1}{jW}X(w)\cdot \cdot X(0)\cdot (w)$$

Convolution and Multiplication in the Time Dominin:

Let

$$x t \cdot \cdot X \cdot W \cdot$$

 $1, t \bullet V \bullet M/\bullet$

Then

$$x(t) \cdot y(t) \cdot X(\mathbf{W})Y(\mathbf{W})$$

$$x_{1}t)x(t)_{2} \quad \frac{1}{2} \cdot X(\mathbf{W}) \cdot X_{2}(\mathbf{W})$$

Frequency convolution

Example

Find the system response to the input $x(t) = e_{-at} u(t)$ if the system impulse response is $h(t) = e_{-bt} u(t)$.

Properties of the Fourier Transform

• Parseval's Theorem $\min(x(t))$ is not maripulie and has FX(w) then it is an energy signals:

$$E \cdot \cdot |xt \cdot|^2 dt \cdot \frac{1}{2 \cdot} \cdot |X \cdot w|^2 dw$$

Real signal has even spectrum X(w) X(-w),

 $E \cdot \frac{1}{\cdot} |X \cdot w|^2 dW$

Example

Find the energy of signal $x(t) = e_{-at} u(t)$. Determine the frequency w so that the energy contributed by the spectrum components of all frequencies below w is 95% of the signal energy Ex.

Answer: w=12.7a rad/sec

Properties of the Fourier Transform

٠

• DDalálytý Sisnihalábyly)



 $x \bullet t \bullet \bullet wX \bullet$



 $X(t) \cdot 2 \cdot x(\cdot W)$

TABLE Fourier Transform Operations		
Operation	<i>x</i> (<i>t</i>)	$X(\omega)$
Scalar multiplication	kx(t)	$kX(\omega)$
Addition	$x_1(t) + x_2(t)$	$X_1(\omega) + X_2(\omega)$
Conjugation	$x^*(t)$	$X^*(-\omega)$
Duality	X(t)	$2\pi x(-\omega)$
Scaling (a real)	x(at)	$\frac{1}{ a } X\left(\frac{\omega}{a}\right)$
Time shifting	$x(t-t_0)$	$X(\omega)e^{-j\omega t_0}$
Frequency shifting (ω_0 real)	$x(t)e^{j\omega_0 t}$	$X(\omega-\omega_0)$
Time convolution	$x_1(t) \ast x_2(t)$	$X_1(\omega)X_2(\omega)$
Frequency convolution	$x_1(t)x_2(t)$	$\frac{1}{2\pi}X_1(\omega) * X_2(\omega)$
Time differentiation	$\frac{d^n x}{dt^n}$	$(j\omega)^n X(\omega)$
Time integration	$\int_{0}^{t} x(u) du$	$\frac{X(\omega)}{j\omega} + \pi X(0)\delta(\omega)$

Sampling Theorem

A real signal whose spectrum is bandlimited to B Hz [X(w)=0 for $|w| > 2 \cdot B$] can be reconstructed exactly from its samples taken uniformly at a rate $f_s > 2B$ samples per second. When $f_s = 2B$ then f_s is the Nyquist rate.

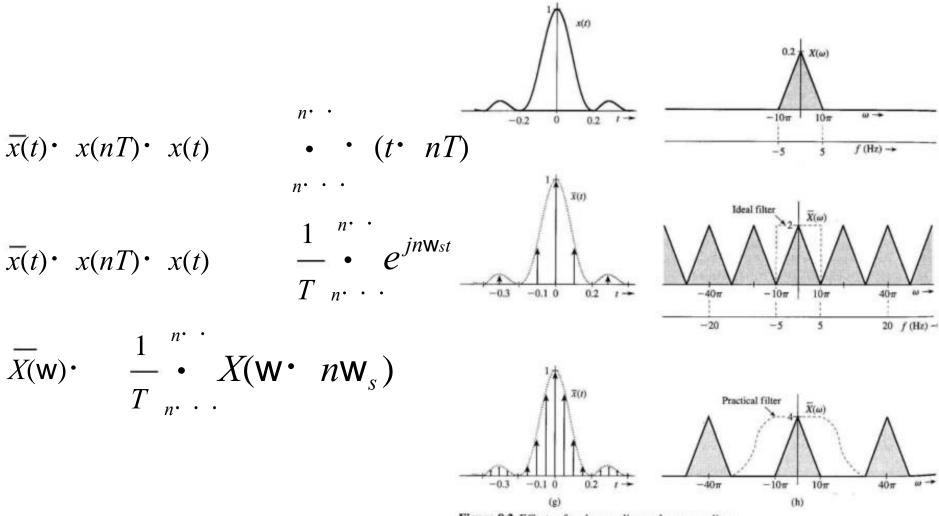
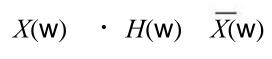


Figure 8.2 Effects of undersampling and oversampling.

Reconstructing the Signal from the Samples

0.3



 $x(t) \cdot h(t) * x(nT)$

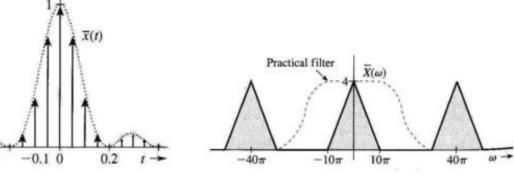
$$x(t) \cdot h(t)^* \cdot x(nT) \cdot (t \cdot nT)$$

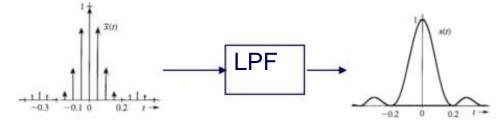
$$n$$

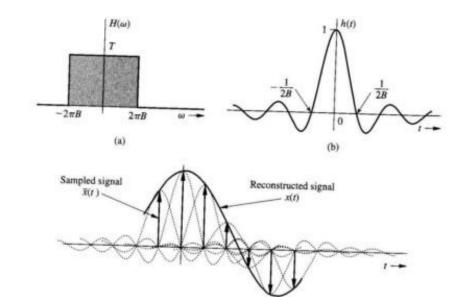
$$x(t) \cdot x(nT)h(t \cdot nT)$$

$$x(t)$$
 • $x(nT)h(t \cdot nT)$

$$x(t) \cdot \cdot x(nT) \operatorname{sinc}(2 \cdot B(t \cdot nT))$$







Example

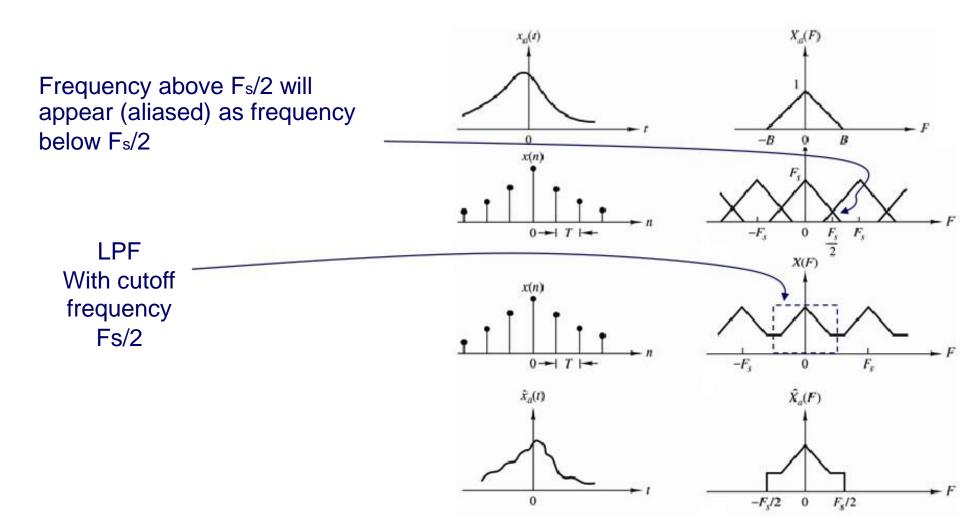
Determine the Nyquist sampling rate for the signal $x(t) = 3 + 2\cos(10 \cdot) + \sin(30 \cdot)$.

Solution

The highest frequency is $f_{max} = 30 \cdot /2 \cdot = 15$ Hz The Nyquist rate = $2 f_{max} = 2^*15 = 30$ sample/sec

Aliasing

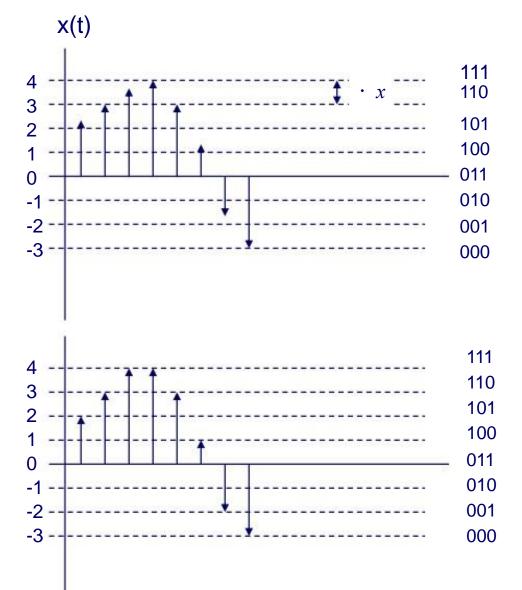
If a continuous time signal is sampled below the Nyquist rate then some of the high frequencies will appear as low frequencies and the original signal can not be recovered from the samples.

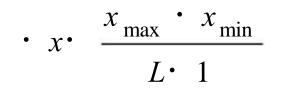


Quantization & Binary Representation

L· 2^{n}

L : number of levels n : Number of bits Quantization error = $\cdot x/2$





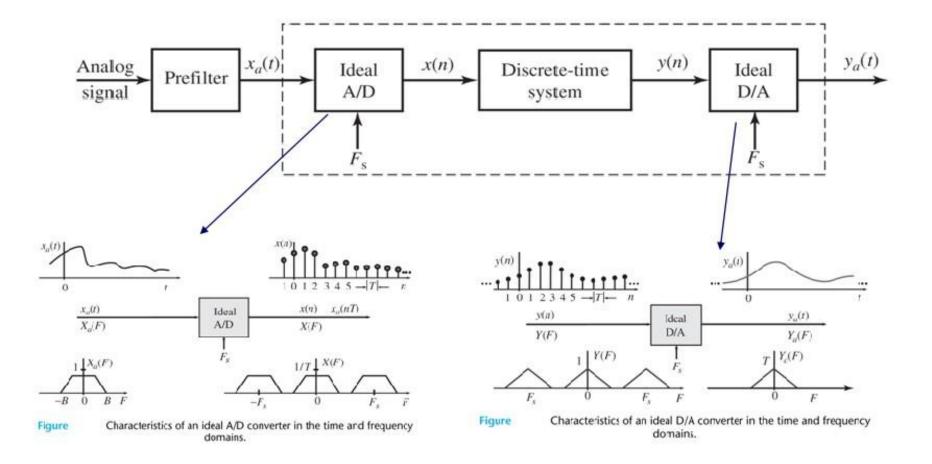


A 5 minutes segment of music sampled at 44000 samples per second. The amplitudes of the samples are quantized to 1024 levels. Determine the size of the segment in bits.

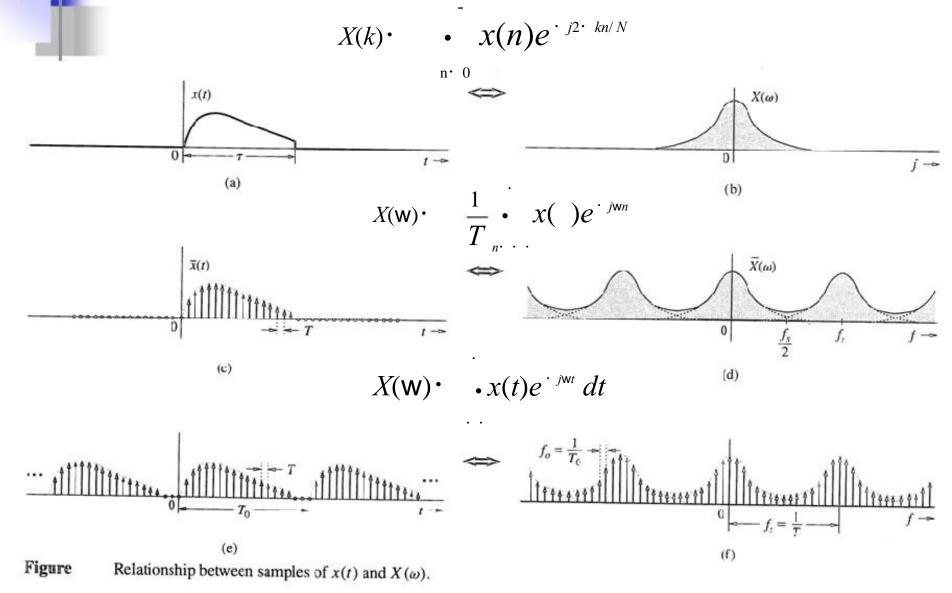
Solution

```
# of bits per sample = ln(1024) { remember L=2n }
n = 10 bits per sample
# of bits = 5 * 60 * 44000 * 10 = 13200000 = 13.2 Mbit
```

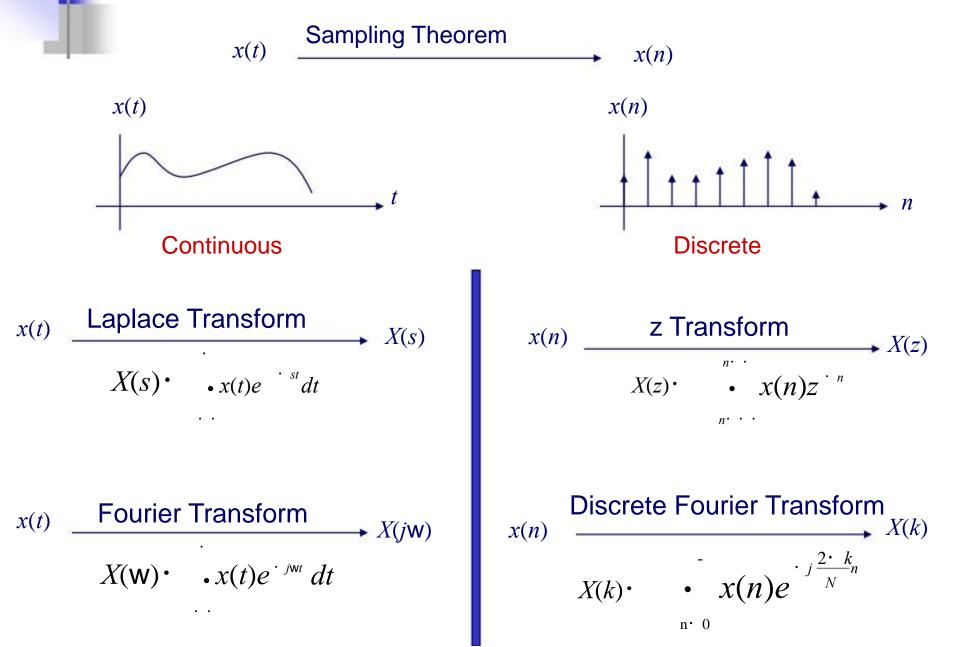
Discrete-Time Processing of Continuous-Time Signals



Discrete Fourier Transform



Link between Continuous and Discrete



- Fourier, Laplace, and z-transforms change from the time-domain representation of a signal to the frequency-domain representation of the signal
- The resulting two signals are equivalent representations of the same signal in terms of time or frequency

 In contrast, The Hilbert transform does not involve a change of domain, unlike many other transforms

 Strictly speaking, the Hilbert transform is not a transform in this sense

- First, the result of a Hilbert transform is **not equivalent to the original signal**, rather it is a completely different signal

- Second, the Hilbert transform does **not involve a domain change**, i.e., the Hilbert transform of a signal x(t) is another signal denoted byx(t)in the same domain (i.e.,time domain)

- The Hilbert transform of a signal x(t) is a signal x(t) whose frequency components lag the frequency components of x(t) by 90.
 - x(t) has exactly the same frequency components present in x(t) with the same amplitude-except there is a 90 \cdot phase delay
 - The Hilbert transform of $x(t) = Acos(2 \cdot fot + \cdot)$ is $Acos(2 \cdot fot + \cdot - 90 \cdot) = Asin(2 \cdot fot + \cdot)$

- A delay of \cdot /2 at all frequencies
 - e_{j2} for will become $e^{j2 \cdot f_0 t \cdot \frac{1}{2}} \cdot \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2}$
 - - At positive frequencies, the spectrum of the signal is multiplied by -*j*
 - At negative frequencies, it is multiplied by +j
 - This is equivalent to saying that the spectrum (Fourier transform) of the signal is multiplied by
 - -*j*sgn(*f*).

• Assume that x(t) is real and has no DC component : $X(f)|_{f=0} = 0$,

then F x t · · · jsgn(f)X(f)

$$F^{\cdot 1} \cdot j \operatorname{sgn}(f) \cdot \frac{1}{\cdot t}$$

$$\hat{f}(t) \cdot \frac{1}{\cdot t} \cdot x(t) \cdot \frac{1}{\cdot \cdot \cdot} \cdot \frac{x(\cdot)}{t \cdot \cdot \cdot} d\cdot$$

- The operation of the Hilbert transform is equivalent to a convolution, i.e., filtering

Example

Determine the Hilbert transform of the signal x(t) = 2sinc(2t)

Solution

• We use the frequency-domain approach . Using the scaling property of the Fourier transform, we have

 $F \cdot x(t) \cdot 2 \frac{1}{2} \cdot \frac{f}{2} \cdot \cdots \cdot \frac{1}{2} \cdot \cdots \cdot \frac{1}{$

- In this expression, the first term contains all the negative frequencies and the second term contains all the positive frequencies
- To obtain the frequency-domain representation of the Hilbert transform of *x(t)*, we use the relation F · x(t) · = -jsgn(f)F[x(t)], which results in

$$F \cdot x(t) \cdot j \cdot \frac{1}{j} \cdot \frac{1}{2} \cdot j \cdot \cdot f \cdot \frac{1}{2}$$

Taking the inverse Fourier transform, we have

$$x(t) \cdot j e_{j} \cdot j \sin ct \cdot j e^{-j \cdot t} \sin ct \cdot j e^{-j \cdot t} \sin ct \cdot j e^{-j \cdot t} \cdot e^{-j \cdot t} \sin ct$$

$$\cdot j \cdot 2j \sin(\cdot t) \sin ct \cdot 2\sin(\cdot t) \sin ct$$

- Obviously performing the Hilbert transform on a signal is equivalent to a 90 phase shift in all its frequency components
- Therefore, the only change that the Hilbert transform performs on a signal is changing its phase
- The amplitude of the frequency components of the signal do not change by performing the Hilbert-transform

x(t)

transform changes cosines into sines, the Hilbert transform of a signal x(t) is orthogonal to x(t)

 Also, since the Hilbert transform introduces a 90 · phase shift, carrying it out twice causes a 180 · phase shift, which can cause a sign reversal of the original signal

Evenness and Oddness

- The Hilbert transform of an even signal is odd, and the Hilbert transform of an odd signal is even
- Proof
 - If x(t) is even, then X(f) is a real and even function
 - Therefore, -jsgn(f)X(f) is an imaginary and odd function
 - Hence, its inverse Fourier transform x(t) will be odd
 - If x(t) is odd, then X(f) is imaginary and odd
 - Thus -jsgn(f)X(f) is real and even
 - Therefore, x(t) is even

Sign Reversal

Applying the Hilbert-transform operation to a signal twice causes a sign reversal of the signal, i.e.,
 x t) · · x(t)

– Proof

 $F[X(t)] \cdot jsgn(f) \cdot X(f)$

 $F[x (t)] \cdot \cdot X(f)$

• X(f) does not contain any impulses at the origin

• Energy

• The energy content of a signal is equal to the energy content of its Hilbert transform

- Proof

• Using Rayleigh's theorem of the Fourier transform,

$$E_{x} \cdot \left| x(t) \right|^{2} dt \cdot \left| X(f) \right|^{2} df$$

$$E_{x} \cdot \left| \left| \left| f(t) \right|^{2} dt \cdot \left| f(t) \right|^{2} dt \cdot \left| f(t) \right|^{2} df \cdot \left| f(t) \right|^{2} df \cdot \left| f(t) \right|^{2} df$$

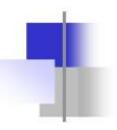
• Using the fact that $|-jsgn(f)|_2 = 1$ except for f = 0, and the fact that X(f) does not contain any impulses at the origin completes the proof

Orthogonality

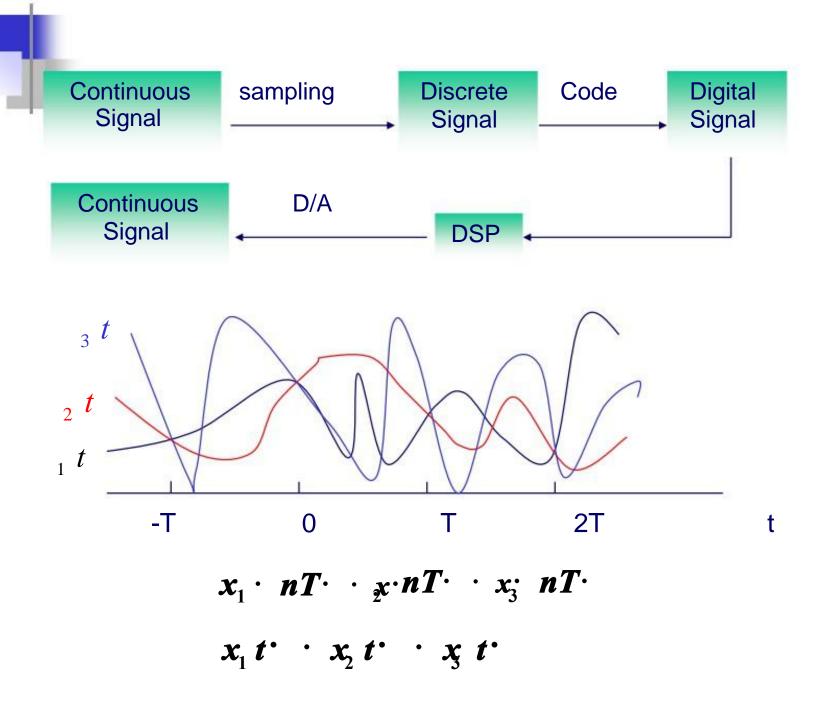
- The signal x(t) and its Hilbert transform are orthogonal
- Proof
 - Using Parseval's theorem of the Fourier transform, we obtain

$$\begin{array}{cccc} x(t)^{*}(t)dt \cdot & X(f)[\cdot j \operatorname{sgn}(f)X(f)] * df \\ & \ddots & j \bullet_{-}^{0} \left| X(f) \right|^{2} df \cdot j & \bullet_{0}^{-} \left| X(f) \right|^{2} df \cdot 0 \end{array}$$

• In the last step, we have used the fact that X(f) is Hermitian; $|X(f)|_2$ is even



Sampling and reconstruction



Sampling: Time Domain

- Many signals originate as continuoustime signals, e.g. conventional music or voice
- By sampling a continuous-time signal at isolated, equally-spaced points in time, we obtain a sequence of nusmbtrs sampled rTs *n* · {..., -2, -1, 0, 1, 2,...} s **s**(*t*) T_{s} is the sampling period. $t \cdot nT_s$ $s_{sampled} t \cdot \cdot s(t) \cdot \cdot \cdot$ Sampled analog waveform

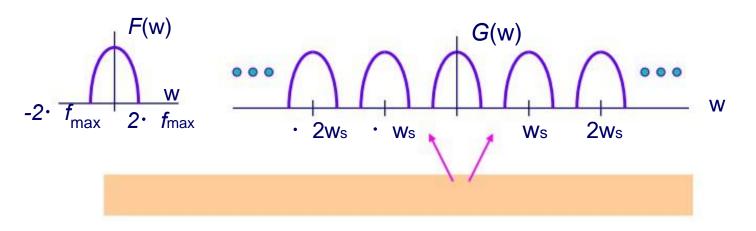
impulse train

Sampling: Frequency Domain

- Replicates spectrum of continuous-time signal At offsets that are integer multiples of sampling frequency
- Fourier series of impulse train where $w_s = 2 \cdot f_s$

• Example

Modulation by cos(ws t) Modulation by cos(2



Shannon Sampling Theorem

• A continuous-time signal x(t) with frequencies no higher than f_{max} can be reconstructed from its samples $x[n] = x(n T_s)$ if the samples are taken at a rate f_s which is greater than 2 f_{max} .

Nyquist rate = $2 f_{max}$

Nyquist frequency = $f_s/2$.

- What happens if $f_s = 2f_{max}$?
- Consider a sinusoid $sin(2 \cdot fmax t)$ Use a sampling period of $T_s = 1/f_s = 1/2f_{max}$. Sketch: sinusoid with zeros at t = 0, $1/2f_{max}$, $1/f_{max}$, ...

Shannon Sampling Theorem

Assumption

- Continuous-time signal has no frequency content above *f*max
- Sampling time is exactly the same between any two samples
- Sequence of numbers obtained by sampling is represented in exact precision
- Conversion of sequence to continuous time is ideal

In Practice

Why 44.1 kHz for Audio CDs?

• Sound is audible in 20 Hz to 20 kHz range:

 $f_{\text{max}} = 20 \text{ kHz}$ and the Nyquist rate 2 $f_{\text{max}} = 40 \text{ kHz}$

- What is the extra 10% of the bandwidth used? Rolloff from passband to stopband in the magnitude response of the anti-aliasing filter
- Okay, 44 kHz makes sense. Why 44.1 kHz? At the time the choice was made, only recorders capable of storing such high rates were VCRs.
 NTSC: 490 lines/frame, 3 samples/line, 30 frames/s = 44100 samples/s

PAL: 588 lines/frame, 3 samples/line, 25 frames/s = 44100 samples/s

Sampling

- As sampling rate increases, sampled waveform looks more and more like the original
- Many applications (e.g. communication systems) care more about frequency content in the waveform and not its shape
- Zero crossings: frequency content of a sinusoid Distance between two zero crossings: one half period.
 With the sampling theorem satisfied, sampled sinusoid crosses zero at the right times even though its

waveform shape may be difficult to recognize

Aliasing

- Analog sinusoid $x(t) = A \cos(2 \cdot f_0 t + \cdot)$
- Sample at $T_s = 1/f_s$ $x[n] = x(T_s n) =$ $A \cos(2 \cdot \cdot f_0 T_s n + \cdot)$
- Keeping the sampling period same, sample
 y(t) = A cos(2 · (f₀ + lf_s)t + ·)
 where *I* is an integer

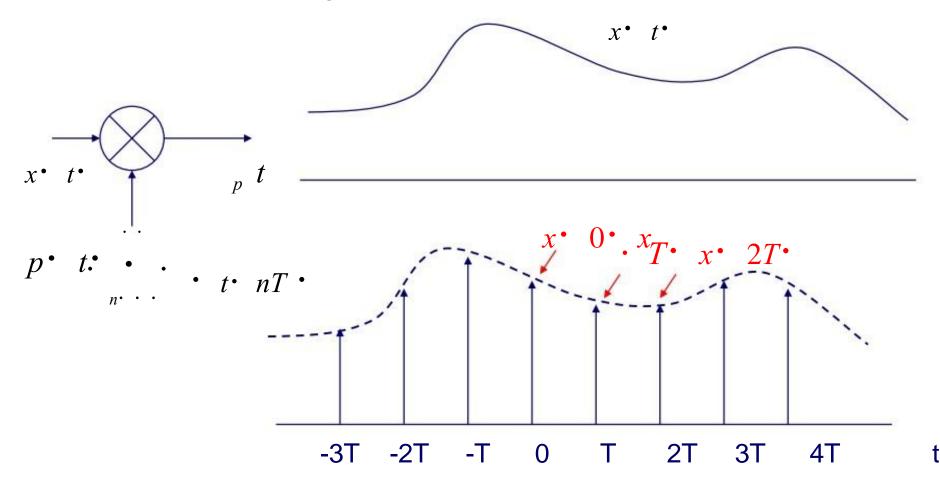
 $y[n] = y(T_s n)$ $= A \cos(2 \cdot (f_0 + lf_s)T_s n + \cdot)$ $= A \cos(2 \cdot f_0T_s n + 2 \cdot \cdot lf_sT_s n + \cdot)$ $= A \cos(2 \cdot f_0T_s n + 2 \cdot \cdot l n + \cdot)$ $= A \cos(2 \cdot f_0T_s n + \cdot)$ = x[n]Here, $f_sT_s = 1$ Since *l* is an integer, $\cos(x + 2 \cdot l) = \cos(x)$

 y[n] indistinguishable from x[n]

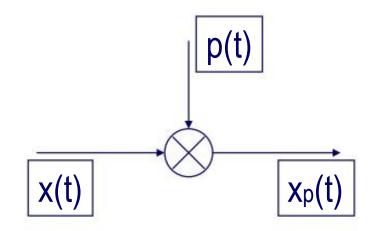
Frequencies $f_0 + I f_s$ for $I \cdot 0$ are aliases of frequency f_0



Impulse-Train Sampling







$$\begin{array}{c} x_p t \end{pmatrix} \cdot x t p(t) \\ \vdots \\ x_p(jw) \cdot \frac{1}{2} \left[X(jw)^* P(jw) \right] \end{array}$$

where p(t) · · $_{T}(t)$ · · (t · nT)

• •

Time domain:

 $x_p(t) \cdot x(t) \cdot \cdot T(t) \cdot x(nT) \cdot (t \cdot nT)$

 $n \cdot \cdot \cdot$

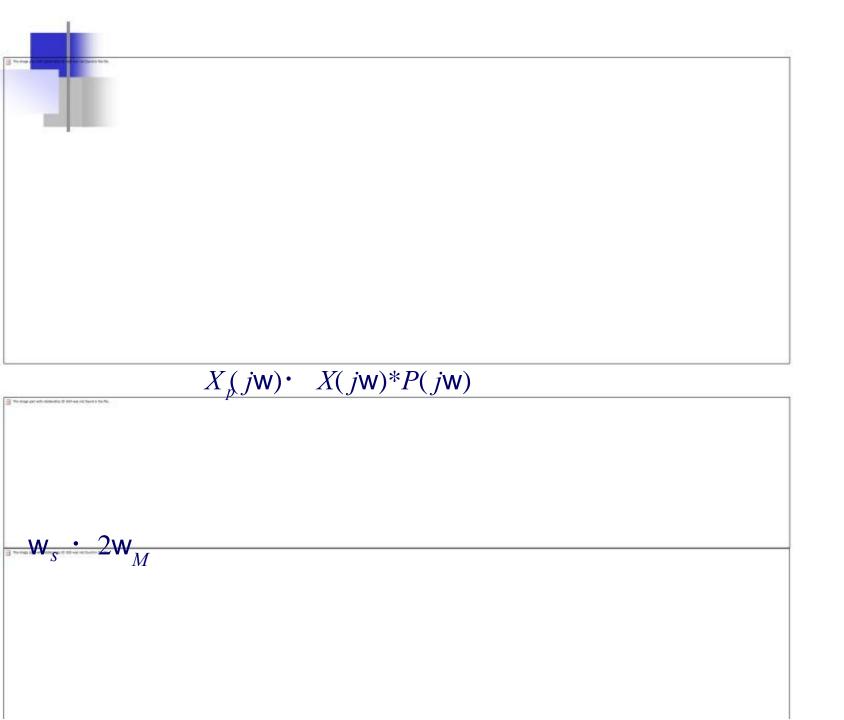
• •





Frequency domain:

$$\begin{aligned} x(t) \cdot \cdot F \cdot X(jw) \\ p(t) \cdot F \cdot x_{k} \cdot \frac{1}{T} & (Periodic \ signal) \\ p(t) \cdot F \cdot P(jw) \cdot 2 \cdot a_{k} \cdot (w \cdot kw)_{s} \cdot w_{s} \cdot (w \cdot kw)_{s} \\ k \cdot \cdots k \\ x_{p}(t) \cdot F \cdot X_{p}(jw) \cdot \frac{w_{s}}{2 \cdot k} \cdot X(w \cdot kw)_{s} \cdot \frac{1}{T} \cdot X(w \cdot kw)_{s} \end{aligned}$$



Sampling Theorem:Letbe a band-limited signal with
 $x \cdot t^{*}$ is uniquely determined by its samples $X \cdot j W \cdot 0, |w| |w|_{M}$
 $x \cdot nT, n \cdot 0, \cdot 1, \cdot$ if $x \cdot t \cdot where$ $x \cdot nT, n \cdot 0, \cdot 1, \cdot$ $w_{s} \cdot 2w_{M}$ $W_{s} \cdot \frac{2 \cdot}{T}$

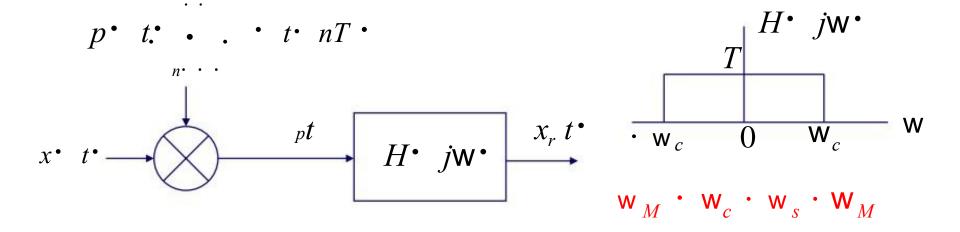
 $2W_M$: Nyquisy Rate

(Minimum distortionless sampling frequency)

W_M:NyquistFrequency

(Maximum distortionless sampled signal frequency)

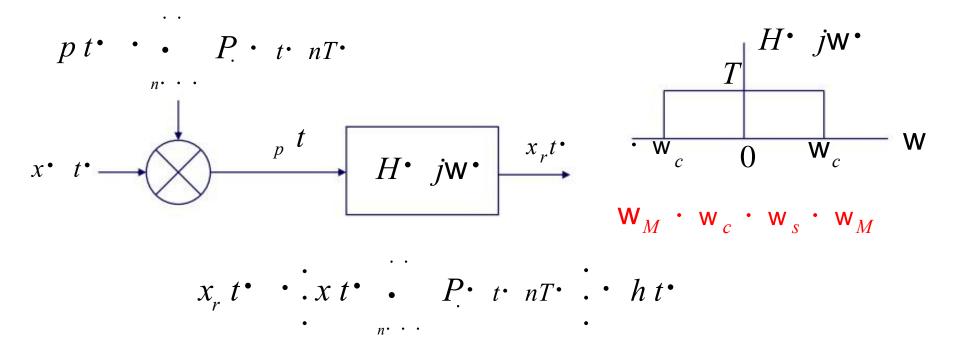
The reconstruction of the signal



$$x t \cdot \cdot \cdot x \cdot nT \cdot S \cdot W \cdot t \cdot nT \cdot \cdot$$

• •

Natural Sampling



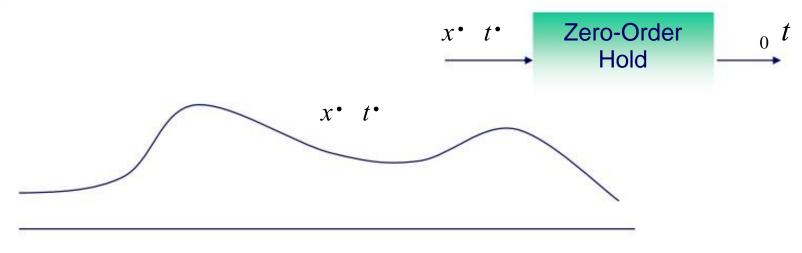
Difficult:

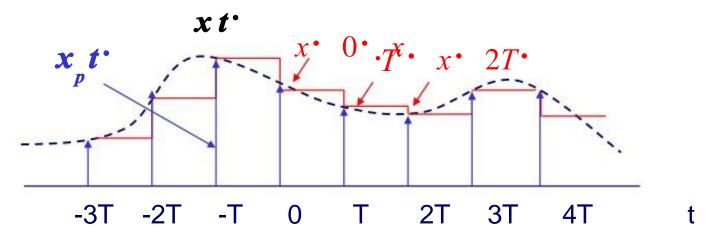
1 ILPF is unpractical;

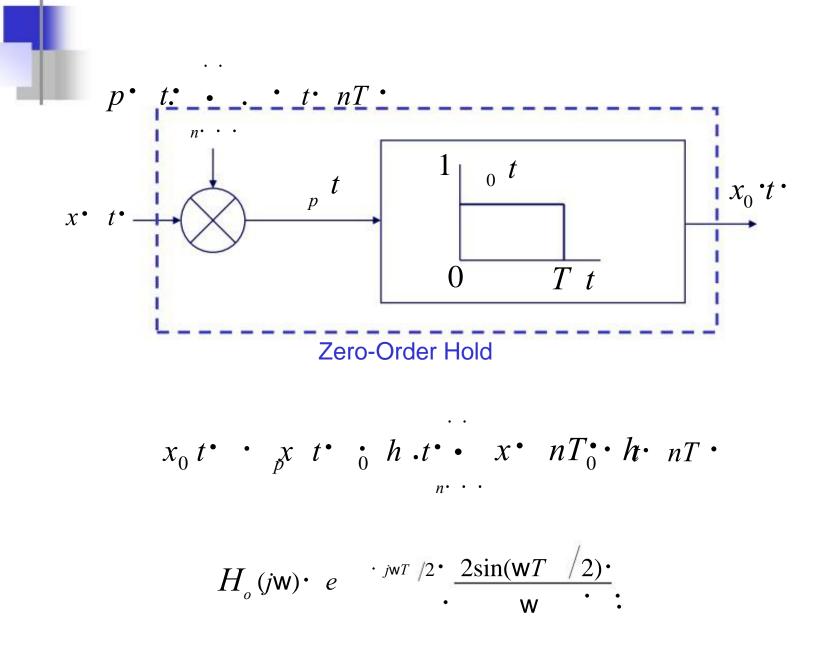
2 narrow, large-amplitude pulses are difficult to generate and transmit.

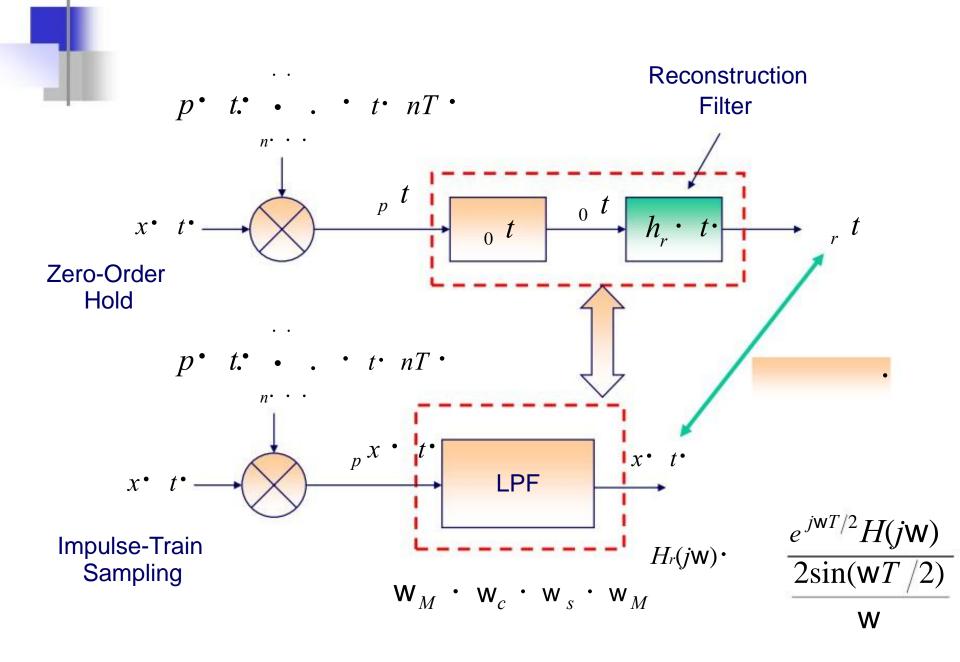


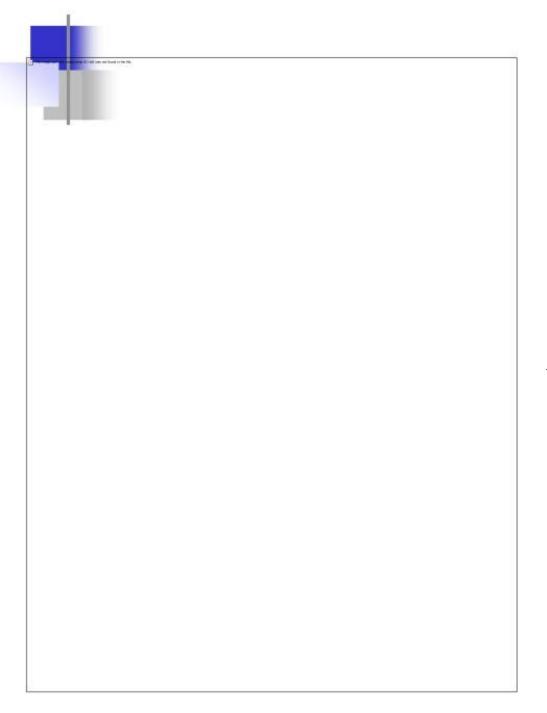
Sampling with a Zero-Order Hold











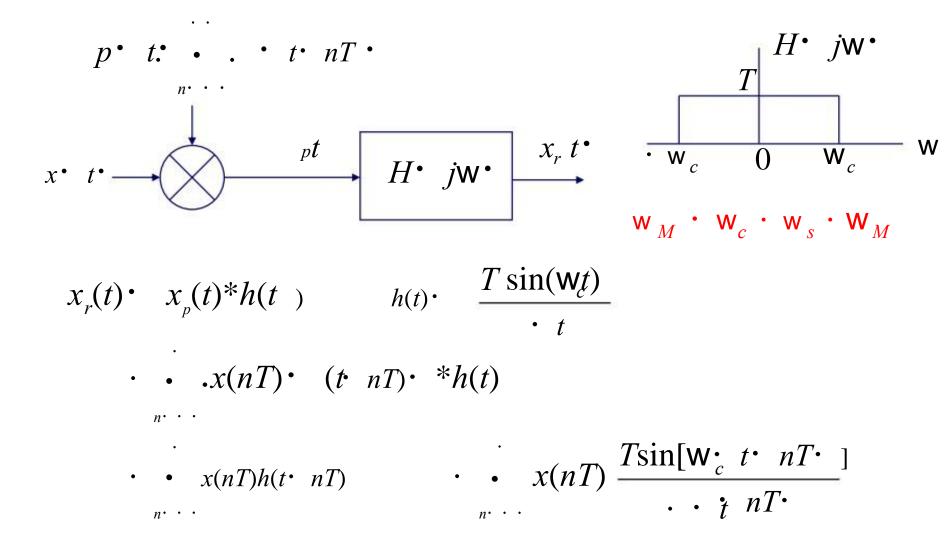
 $H_r(jW)$ ·

 $\frac{e^{jwT/2}H(jW)}{2\sin(wT/2)}$

W

Reconstruction

Band-limited interpolation







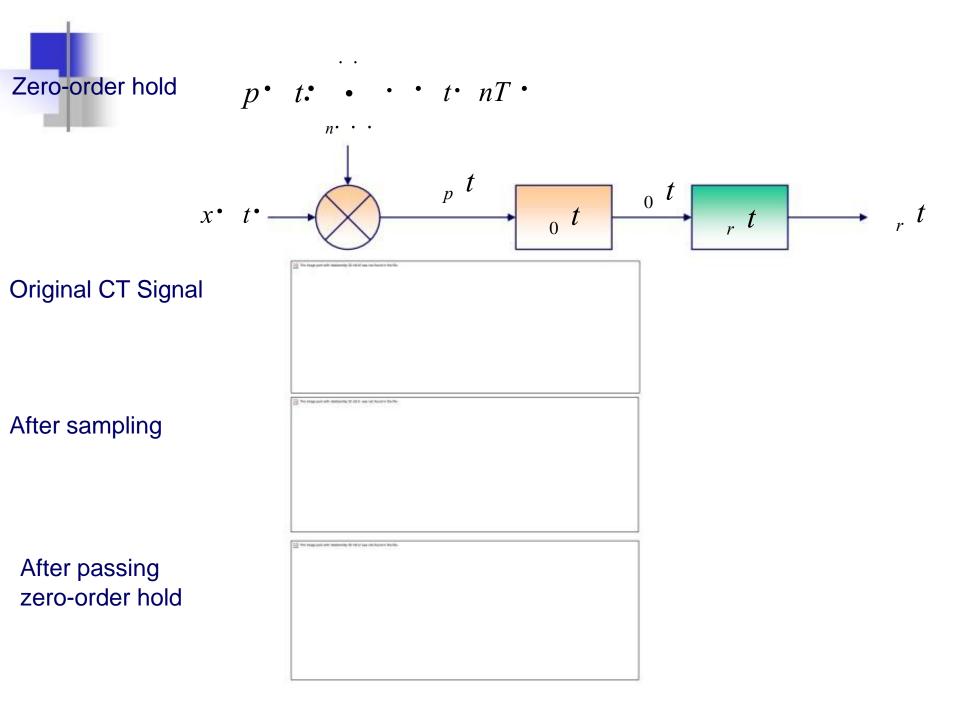
After sampling

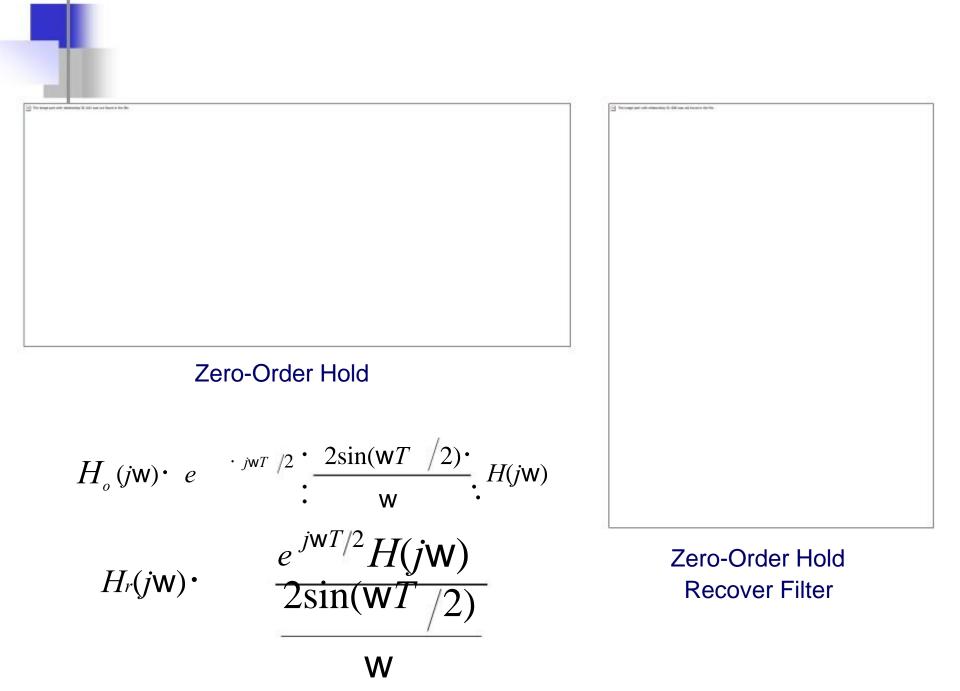
[2] The map part with statement (in mit) was not been in the bi-

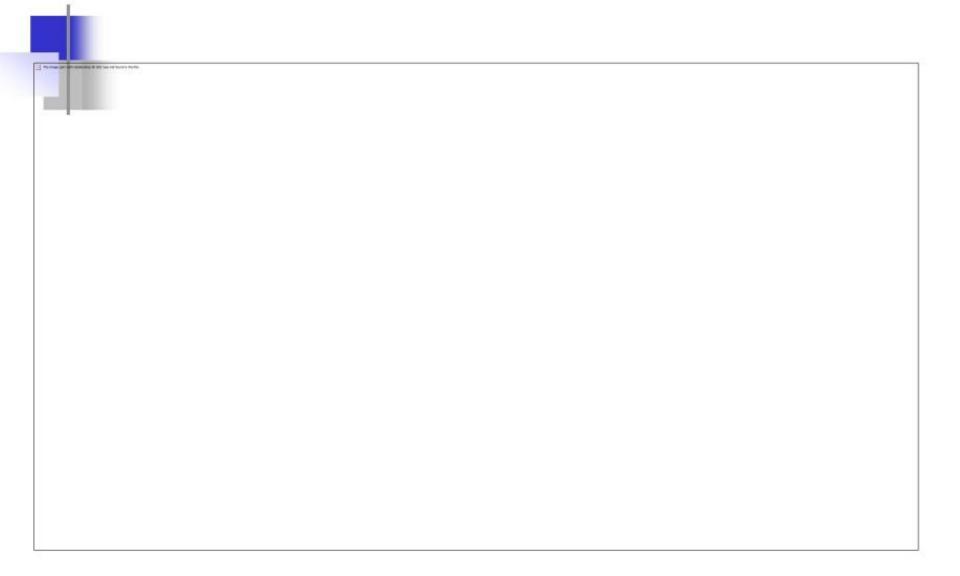
The map per site address in the second site in



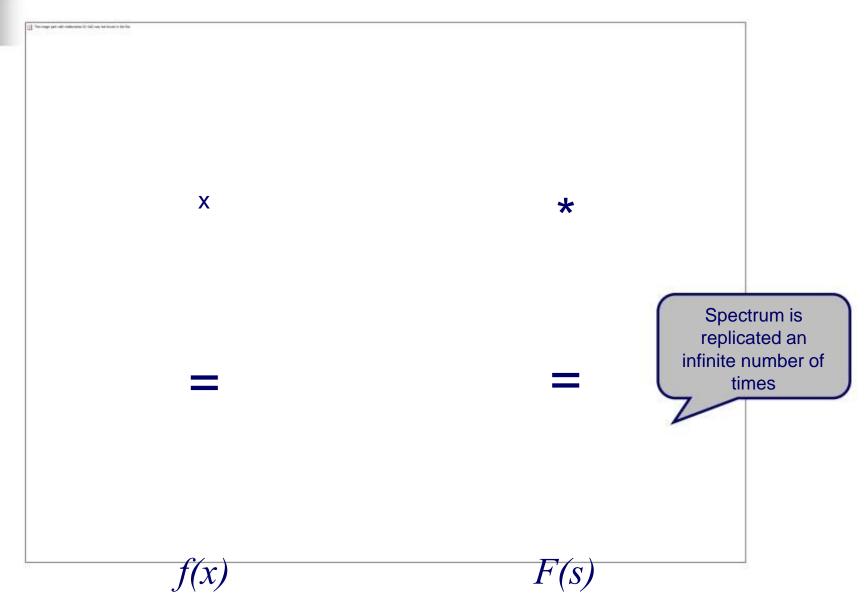
The LPF smoothes out shape and fill in the gaps



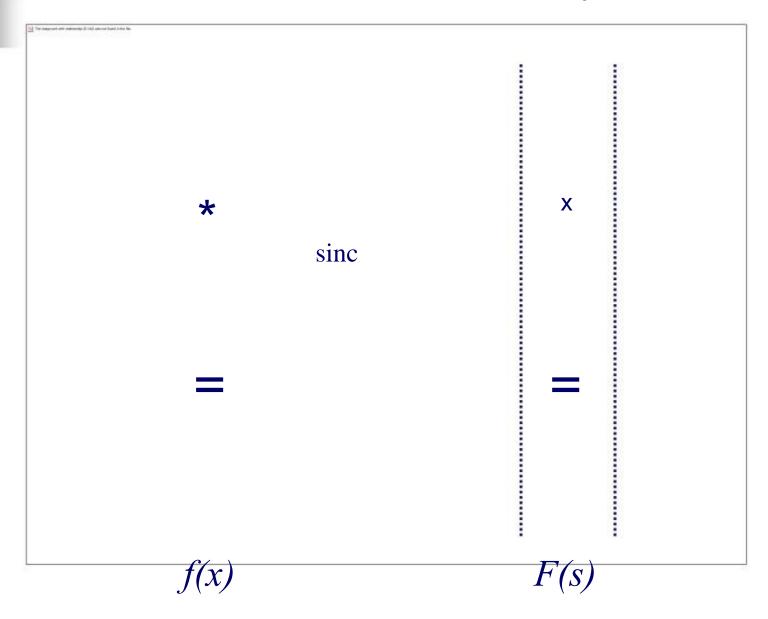




Sampling theory

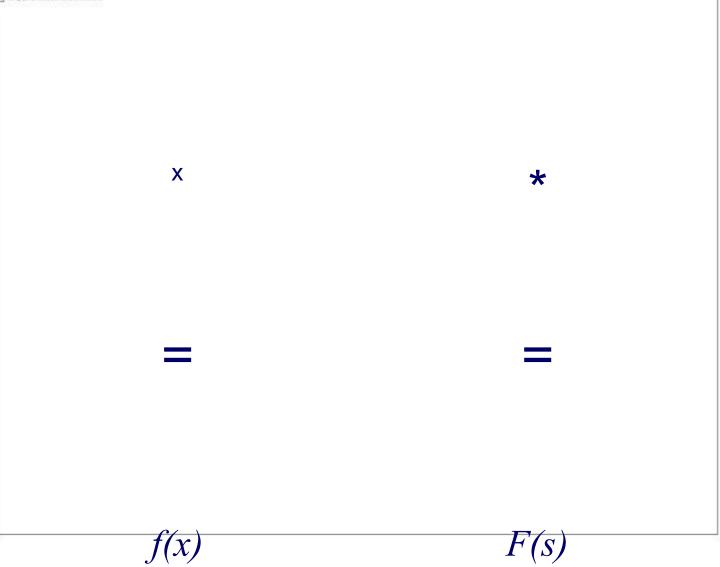


Reconstruction theory

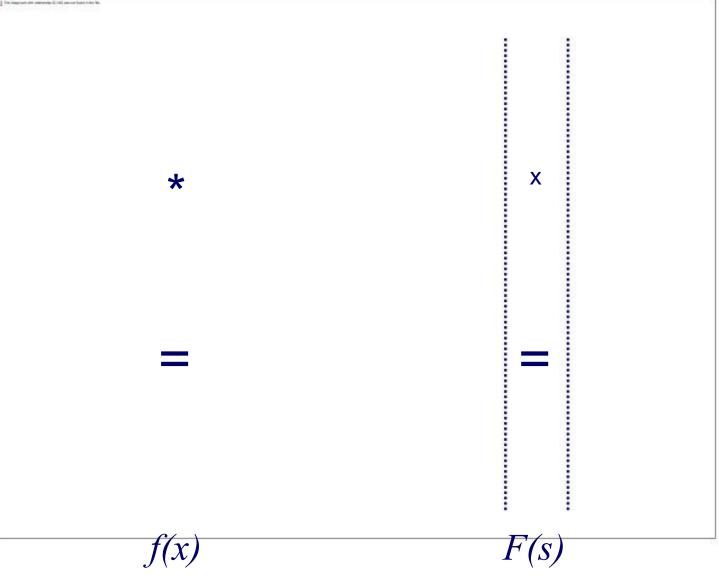


Sampling at the Nyquist rate

The range part with residences 20 GeV was not more in the fire.

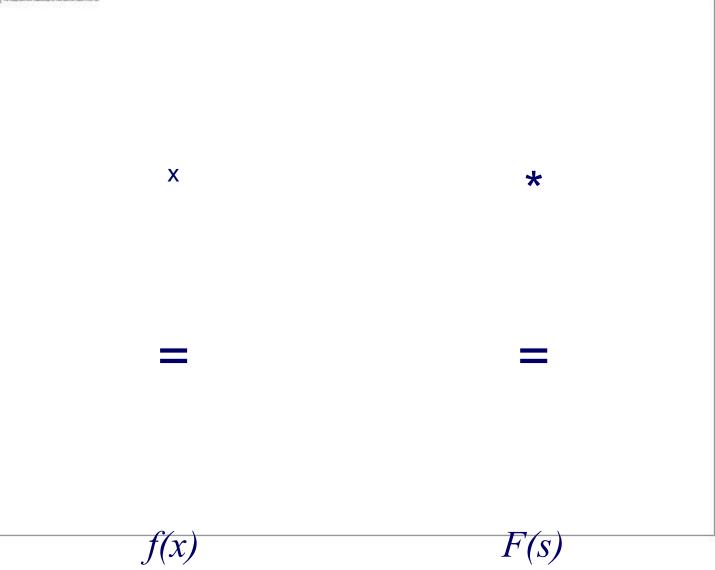


Reconstruction at the Nyquist rate

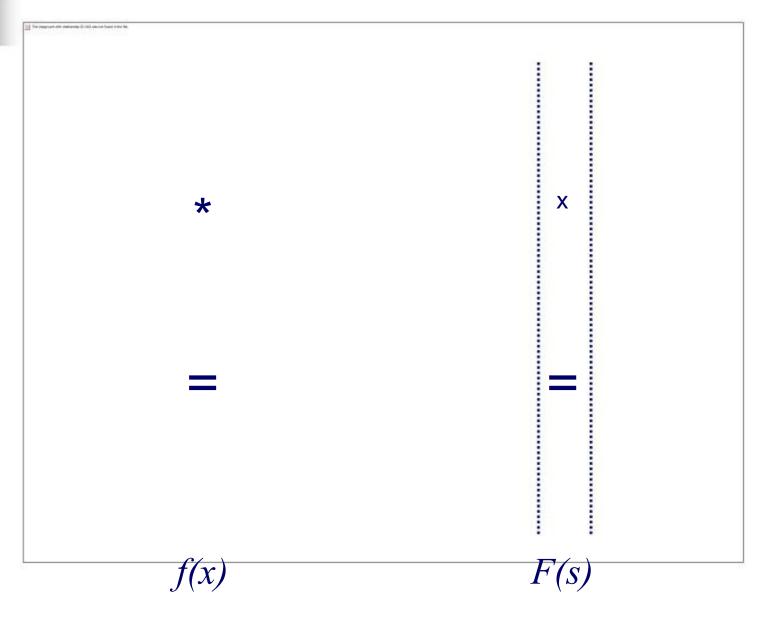


Sampling below the Nyquist rate

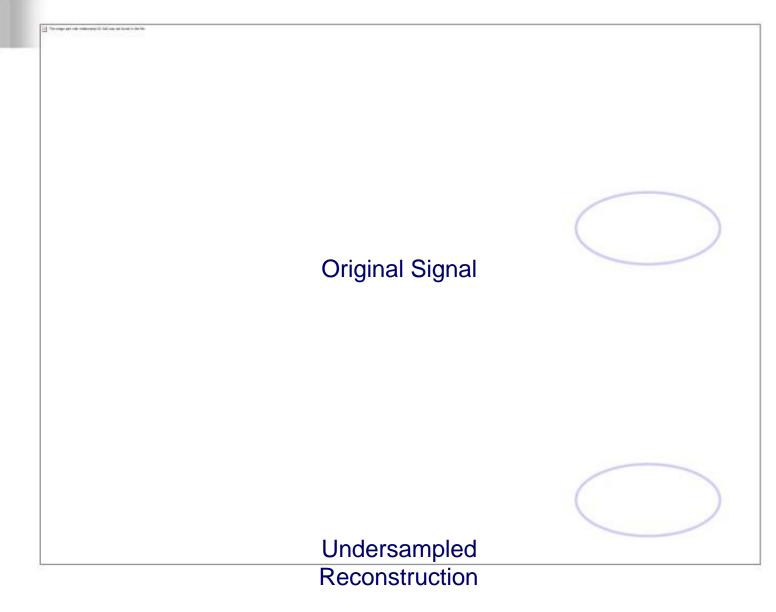
The program with manager (2 mill operate band to be.)



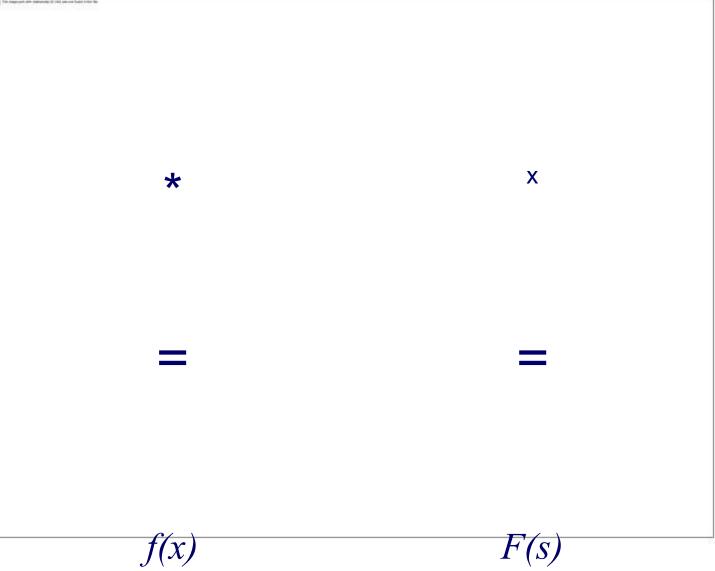
Reconstruction below the Nyquist rate



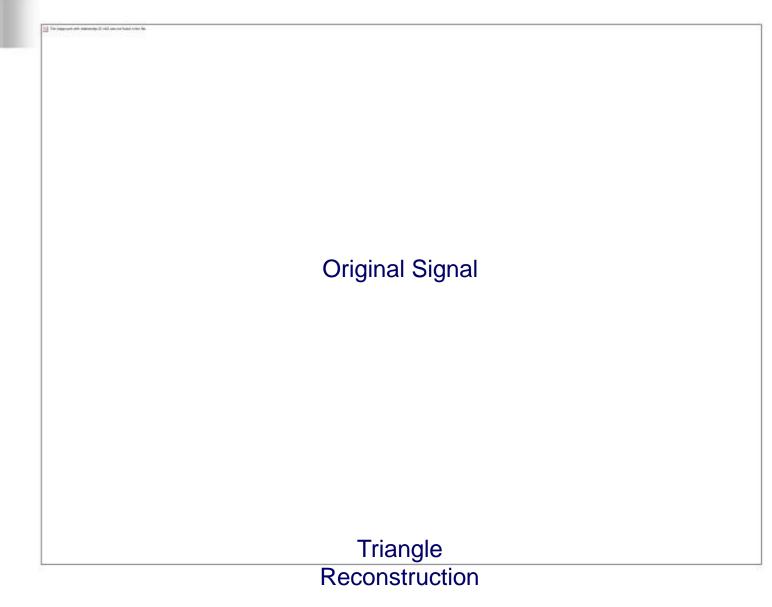
Reconstruction error



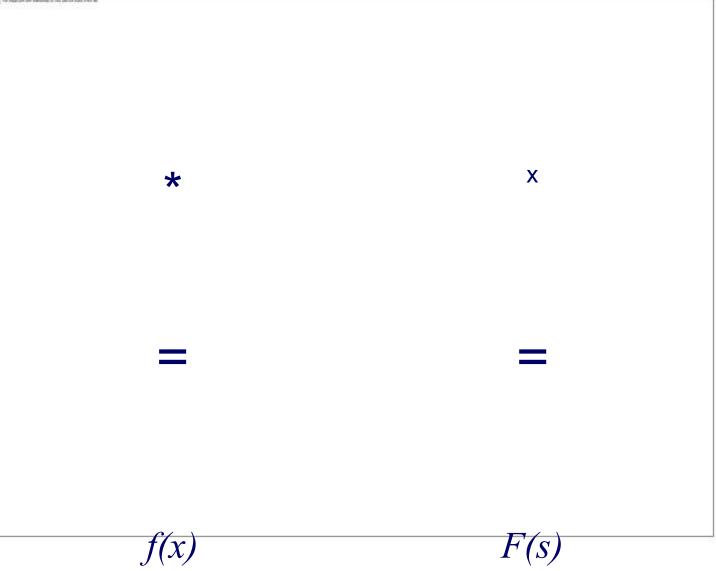
Reconstruction with a triangle function



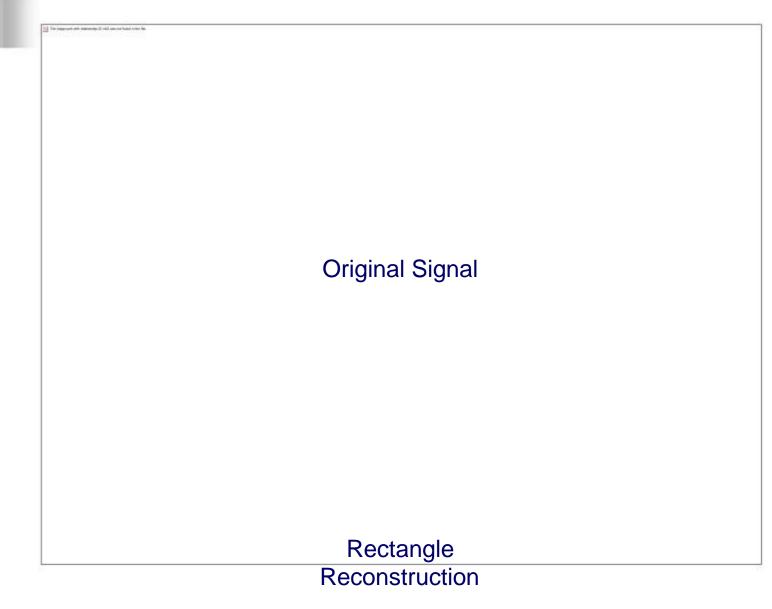
Reconstruction error



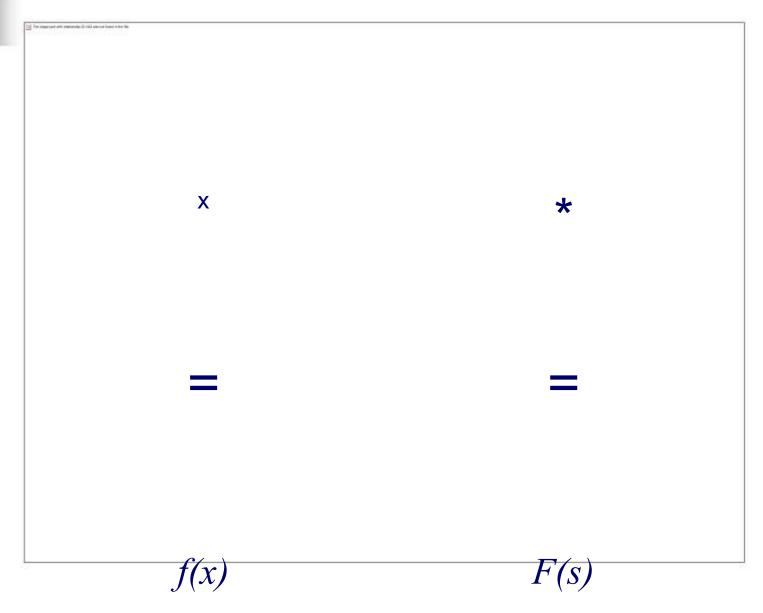
Reconstruction with a rectangle function



Reconstruction error

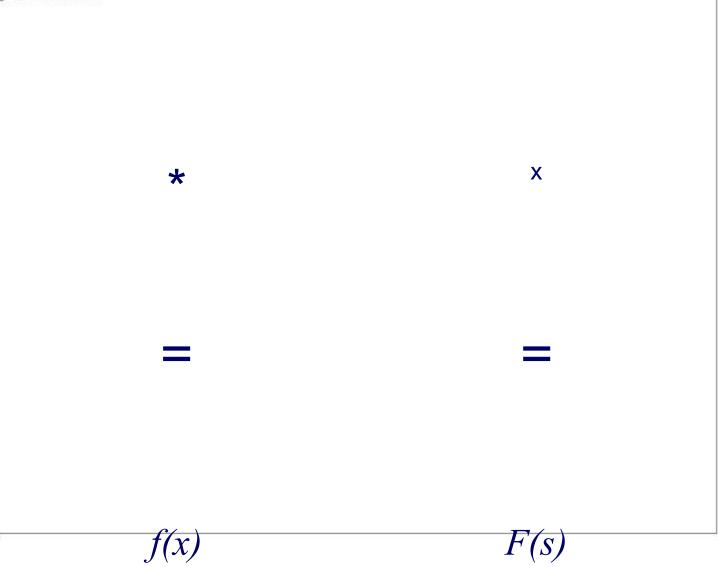


Sampling a rectangle



Reconstructing a rectangle (jaggies)

The maps part with million page 20 (bill value for fixmer (c) the firm



Sampling and reconstruction

Aliasing is caused by

- Sampling below the Nyquist rate,
- Improper reconstruction, or
- Both

We can distinguish between

- Aliasing of fundamentals (demo)
- Aliasing of harmonics (jaggies)

Time-Domain System Analysis

Impulse Response

Let a system be described by

$$a_2 \mathbf{y} \mathbf{\phi} \mathbf{\phi}(t) + a_1 \quad \mathbf{y} \mathbf{\phi}(t) + a_0 \mathbf{y}(t) = \mathbf{x}(t)$$

and let the excitation be a unit impulse at time t = 0. Then the

zero-state response y is the impulse response h.

$$a_2 \operatorname{h} \phi \phi(t) + a_1 \operatorname{h} \phi(t) + a_0 \operatorname{h}(t) = \operatorname{d}(t)$$

Since the impulse occurs at time t = 0 and nothing has excited the system before that time, the impulse response before time t = 0 is zero (because this is a causal system). After time t = 0the impulse has occurred and gone away. Therefore there is no longer an excitation and the impulse response is the homogeneous solution of the differential equation.

Impulse Response

 $_{2} h \phi \phi(t) + a_{1} h \phi(t) + a_{0} h(t) = d(t)$

What happens at time, t = 0? The equation must be satisfied at all times. So the left side of the equation must be a unit impulse. We already know that the left side is zero before time t = 0because the system has never been excited. We know that the left side is zero after time t = 0 because it is the solution of the homogeneous equation whose right side is zero. These two facts are both consistent with an impulse. The impulse response might have in it an impulse or derivatives of an impulse since all of these occur only at time, t = 0. What the impulse response does have in it depends on the form of the differential equation.

Continuous-time LTI systems are described by differential equations of the general form,

$$()(t) + a_{n-1}y_{(n-1)}(t) + \cdot + a_1 \qquad y\phi(t) + a_0 y(t)$$

$$()(t) + b_{m-1}x_{(m-1)}(t) + \cdot + b_1 \qquad x\phi(t) + b_0 x(t)$$

For all times, t < 0:

If the excitation x (t) is an impulse, then for all time t < 0it is zero. The response y(t) is zero before time t = 0because there has never been an excitation before that time.

For all time t > 0:

The excitation is zero. The response is the homogeneous solution of the differential equation.

At time t = 0:

The excitation is an impulse. In general it would be possible for the response to contain an impulse plus derivatives of an impulse because these all occur at time t = 0 and are zero before and after that time. Whether or not the response contains an impulse or derivatives of an impulse at time t = 0 depends on the form of the differential equation

$$() (t) + a_{n-1}y_{(n-1)}(t) + \cdot + a_1 \qquad y\phi(t) + a_0 y(t) \\ () (t) + b_{m-1}x_{(m-1)}(t) + \cdot + b_1 \qquad x\phi(t) + b_0 x(t)$$

 $() (t) + a_{n-1}y_{(n-1)}(t) + \cdot + a_1 \qquad y \notin (t) + a_0 y(t)$ $() (t) + b_{m-1}x_{(m-1)}(t) + \cdot + b_1 \qquad x \notin (t) + b_0 x(t)$

Case 1: m < n

If the response contained an impulse at time t = 0 then the *n*th derivative of the response would contain the *n*th derivative of an impulse. Since the excitation contains only the *m*th derivative of an impulse and m < n, the differential equation cannot be satisfied at time t = 0. Therefore the response cannot contain an impulse or any derivatives of an impulse.

Case 2: m = n

In this case the highest derivative of the excitation and response are the same and the response could contain an impulse at time t = 0 but no derivatives of an impulse. Case 3: m > n

In this case, the response could contain an impulse at time t = 0 plus derivatives of an impulse up to the (m - n)th derivative.

Case 3 is rare in the analysis of practical systems.

Example

Let a system be described by $y\phi(t) + 3y(t) = x(t)$. If the excitation x is an impulse we have $h\phi(t) + 3h(t) = d(t)$. We know that h(t) = 0 for t < 0 and that h(t) is the homogeneous solution for t > 0 which is $h(t)=Ke_{-3t}$. There are more derivatives of y than of x. Therefore the impulse response cannot contain an impulse. So the impulse response is $h(t) = Ke_{-3t} u(t)$.

Example

To find the constant K integrate $h'(t)+3h(t)=\delta(t)$ over the infinitesimal range 0^- to 0^+ .

$$\int_{0^{-}}^{0^{+}} h'(t) dt + 3 \int_{0^{-}}^{0^{+}} h(t) = \int_{0^{-}}^{0^{+}} \delta(t)$$

$$\frac{h(0^{+}) - h(0^{-}) + 3 \int_{0^{-}}^{0^{+}} Ke^{-3t} u(t) dt = u(0^{+}) - u(0^{-})$$

$$K + 3K \left[\frac{e^{-3t}}{-3} \right]_{0}^{0^{+}} = K + 3K \left[(-1/3) - (-1/3) \right] = 1$$

$$K = 1 \Rightarrow h(t) = e^{-3t} u(t)$$

Example

To check the solution, put it into the differential equation to see whether it is satisfied.

$$\frac{d}{dt} \left(e^{-3t} u(t) \right) + 3e^{-3t} u(t) = \delta(t)$$

$$e^{-3t} \delta(t) - 3e^{-3t} u(t) + 3e^{-3t} u(t) = \delta(t)$$

$$\underbrace{e^{-3t} \delta(t)}_{=e^0 \delta(t) = \delta(t)} = \delta(t) \Rightarrow \delta(t) = \delta(t) \quad \text{Check.}$$

Example

Let a system be described by 4y'(t) + 3y(t) = x'(t). The homogeneous solution is $y_h(t) = Ke^{-3t/4}$ and that is the form of the impulse response for t > 0. The number of y derivatives and the number of x derivatives are the same. Therefore the impulse response has an impulse in it and its form is $h(t) = Ke^{-3t/4} u(t) + K_{\delta}\delta(t)$. Integrate between 0^- and 0^+ .

$$\begin{cases}
4 \int_{0^{-}}^{0^{+}} \mathbf{h}'(t) dt + 3 \int_{0^{-}}^{0^{+}} \mathbf{h}(t) dt = \int_{0^{-}}^{0^{+}} \delta'(t) dt \\
\left\{ 4 \left[\underbrace{\mathbf{h}(0^{+})}_{=K} - \underbrace{\mathbf{h}(0^{-})}_{=0} + K_{\delta} \left(\underbrace{\delta(0^{+})}_{=0} - \underbrace{\delta(0^{-})}_{=0} \right) \right] \\
+ 3 \int_{0^{-}}^{0^{+}} Ke^{-3t/4} \mathbf{u}(t) dt + 3K_{\delta} \left[\underbrace{\mathbf{u}(0^{+})}_{=1} - \underbrace{\mathbf{u}(0^{-})}_{=0} \right] \right\} = \underbrace{\delta(0^{+})}_{=0} - \underbrace{\delta(0^{-})}_{=0} \\$$

Example

$$4K+3K_{\delta}=0$$

Now integrate again over the same infinitesimal interval.

$$4\int_{0}^{0^{+}} \int_{-\infty}^{t} h'(\lambda) d\lambda dt + 3\int_{0^{-}}^{0^{+}} \int_{0^{-}}^{t} Ke^{-3\lambda/4} u(\lambda) d\lambda dt + 3\int_{0^{-}}^{0^{+}} \int_{0^{-}}^{t} K_{\delta} \delta(\lambda) d\lambda dt = \int_{0^{-}}^{0^{+}} \int_{0^{-}}^{t} \delta'(\lambda) d\lambda dt$$

$$4\int_{0}^{0^{+}} h(t) dt - 4K \int_{0^{-}}^{0^{+}} (1 - e^{-3t/4}) u(t) dt + 3K_{\delta} \int_{0^{-}}^{0^{+}} u(t) dt = \int_{0^{-}}^{0^{+}} \delta(t) dt$$

$$4K_{\delta} = 1 \rightarrow K_{\delta} = 1/4 \rightarrow 4K + 3/4 = 0 \rightarrow K = -3/16$$

$$h(t) = (-3/16)e^{-3t/4} u(t) + (1/4)\delta(t)$$

Example
$$h(t) = (-3 / 16)e_{-3t/4} u(t) + (1 / 4)d(t)$$

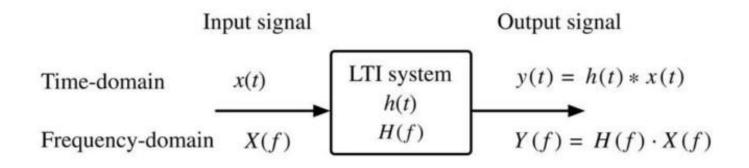
The original differential equation is

 $4h\phi(t)+3h(t)=d\phi(t).$

Substituting the solution we get

$$\frac{1}{4} \frac{d}{dt} \frac{\dot{e}(-3/16)e_{-3t/4}}{\ddot{e}} u(t) + (1/4)d(t)\dot{u} \\
\hat{u}\ddot{y} = d\phi(t) \\
\hat{u}\ddot{y} = d\phi(t)$$

Signal Transmission Through a Linear System

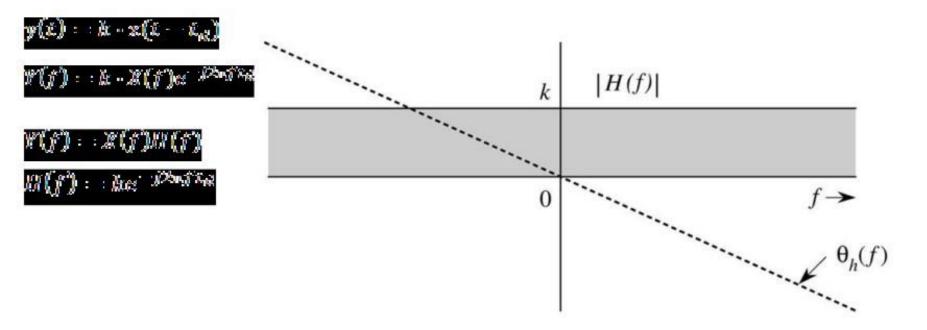


H(f): Transfer function/frequency response

Signal transmission through a linear time-invariant system.

Distortionless transmission:

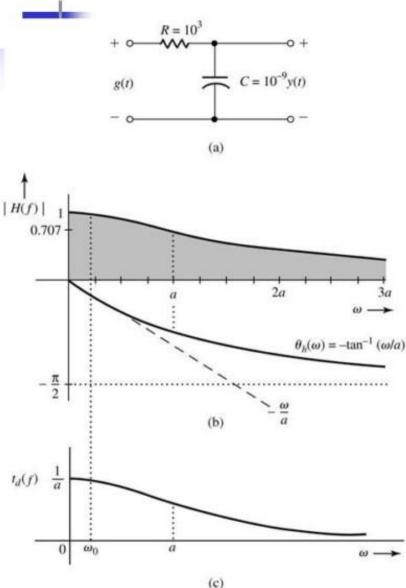
a signal to pass without distortion delayed ouput retains the waveform

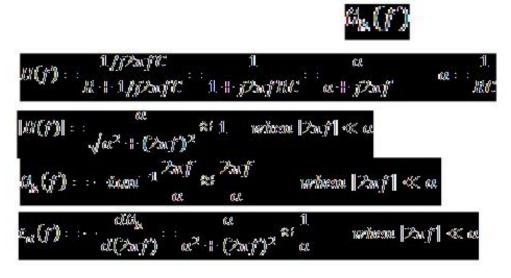


Linear time invariant system frequency response for distortionless transmission.

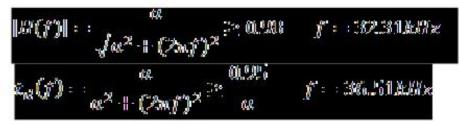


and td(f).





What is the requirement on the bandwidth of *g*(*t*) if amplitude variation within 2% and time delay variation within 5% are tolerable?

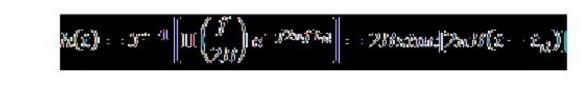


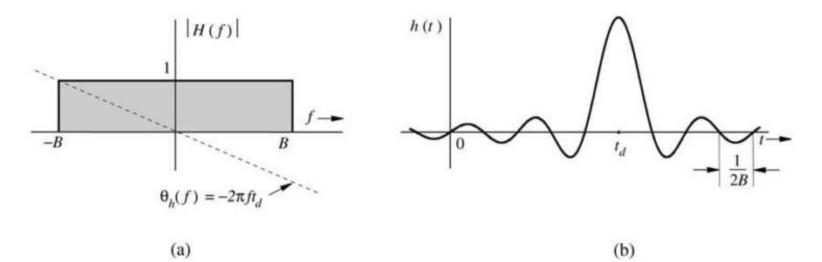
(a) Simple RC filter. (b) Its frequency response and time delay.

Ideal filters: allow distortionless transmission of a certain band of frequencies and suppress all the remaining frequencies.

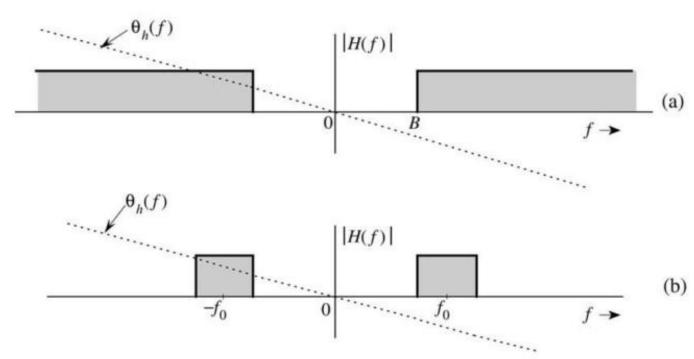






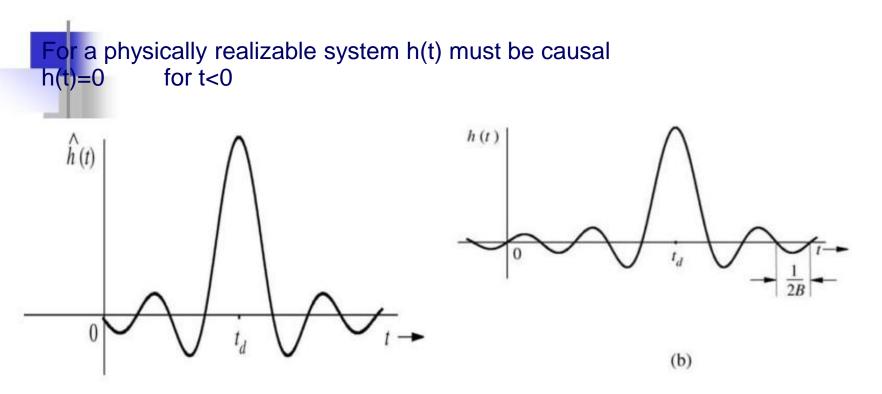


(a) Ideal low-pass filter frequency response and (b) its impulse response.



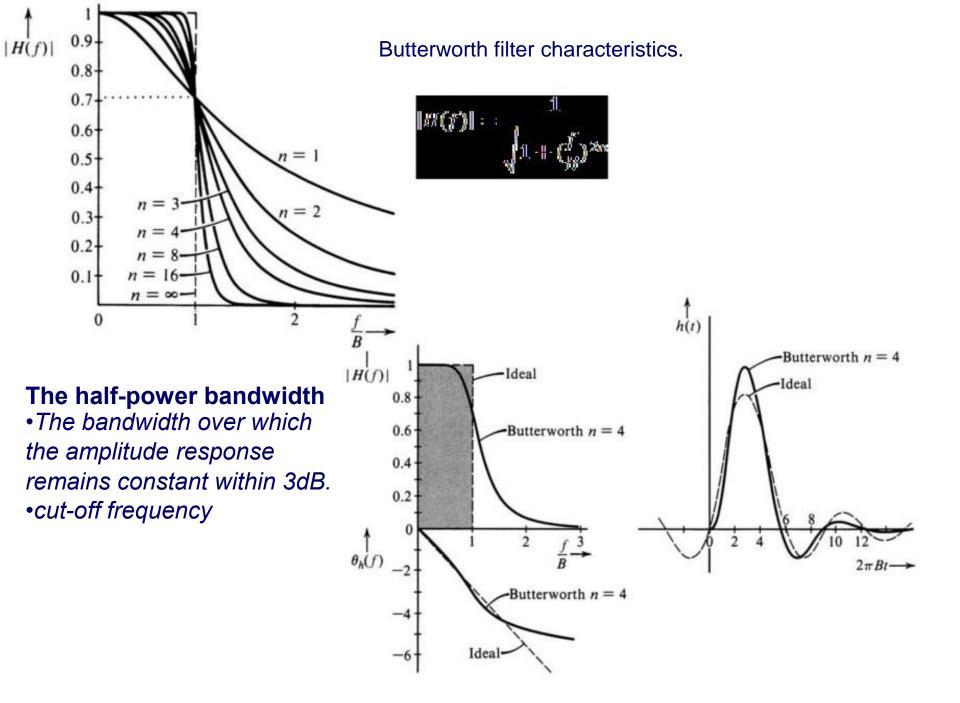
Ideal high-pass and bandpass filter frequency responses.

Paley-Wiener criterion



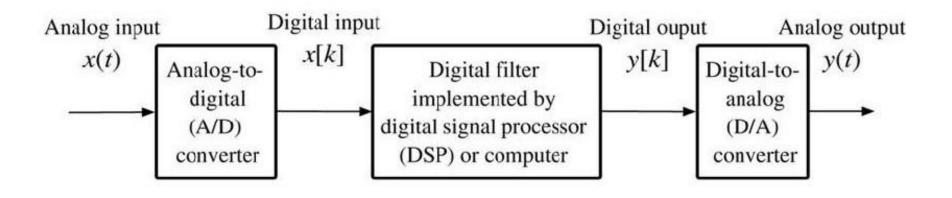
Approximate realization of an ideal low-pass filter by truncating its impulse response.





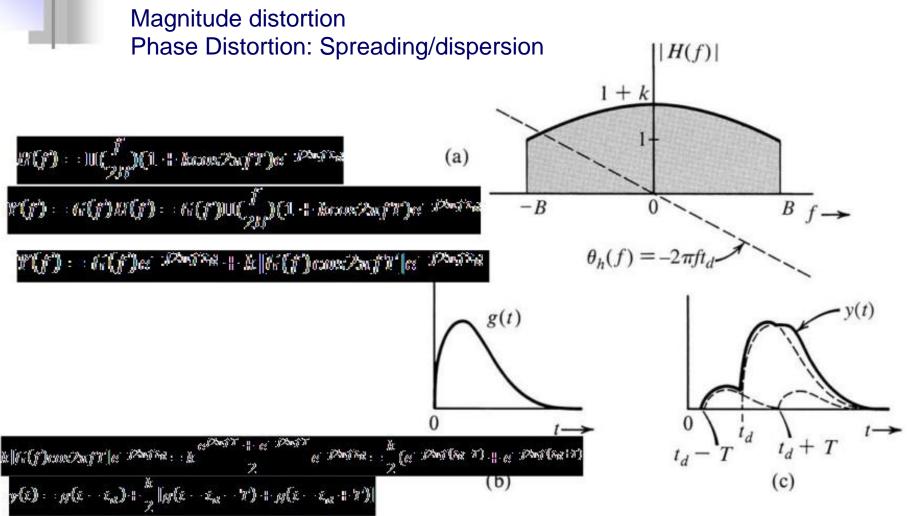
Digital Filters

Sampling, quantizing, and coding

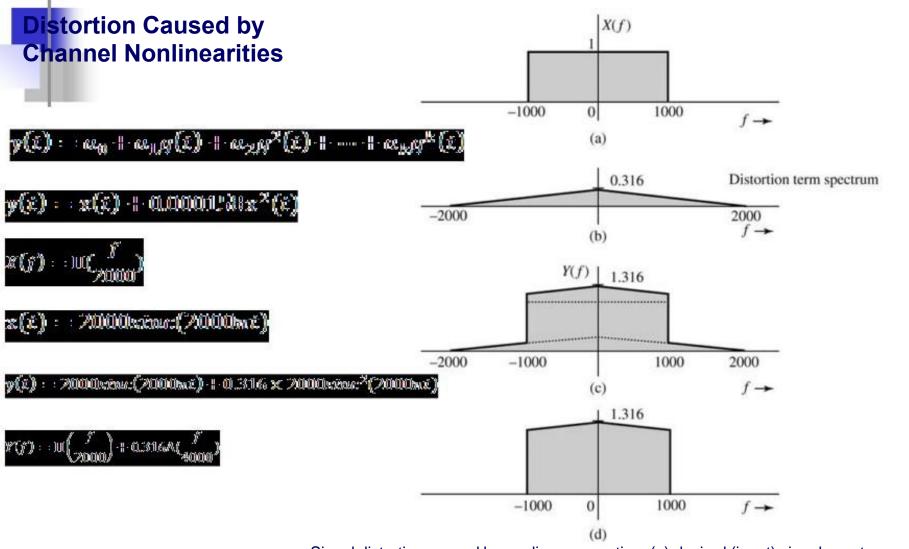


Basic diagram of a digital filter in practical applications.

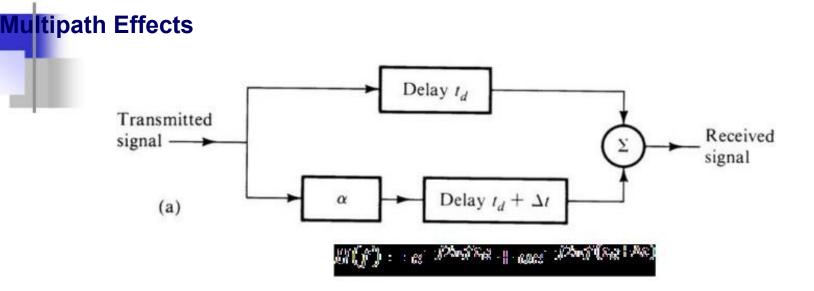
Linear Distortion

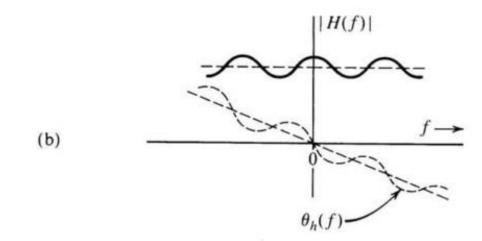


Pulse is dispersed when it passes through a system that is not distortionless.



Signal distortion caused by nonlinear operation: (a) desired (input) signal spectrum; (b) spectrum of the unwanted signal (distortion) in the received signal; (c) spectrum of the received signal (d) spectrum of the received signal after low-pass filtering.

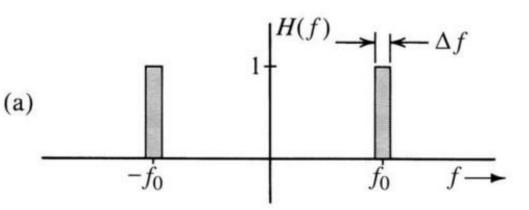




Multipath transmission.

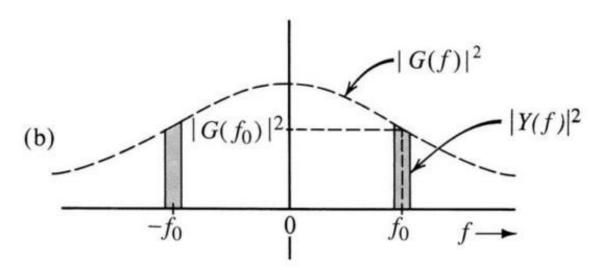
Signal Energy: Parseval's Theorem





Energy Spectral Density





Interpretation of the energy spectral density of a signal.

Essential Bandwidth: the energy content of the components of frequeicies greater than B Hz is negligible.

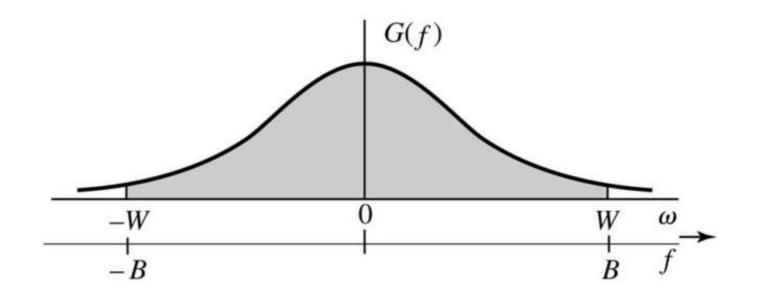
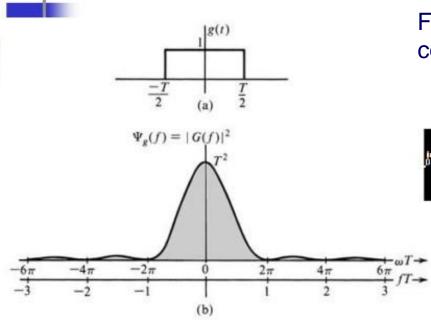
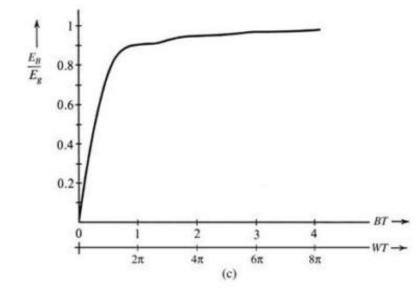
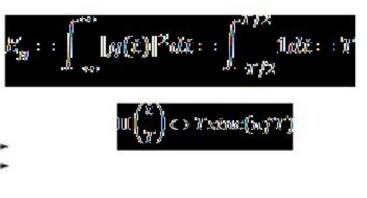


Figure Estimating the essential bandwidth of a signal.



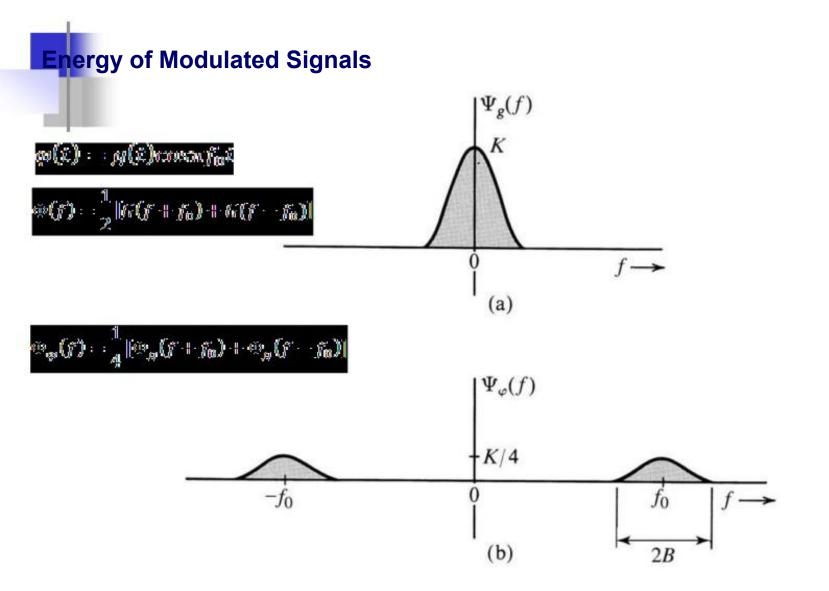


Find the essential bandwidth where it contains at least 90% of the pulse energy.



 $\mathfrak{M}_{\mathfrak{N}}(\mathfrak{i})::\mathfrak{T}^{\mathcal{R}}$ andalo. $\mathfrak{T}(\mathfrak{a},\mathfrak{f}\mathfrak{T})$





Energy spectral densities of (a) modulating and (b) modulated signals.

Determine the ESD of



Autocorrelation Function

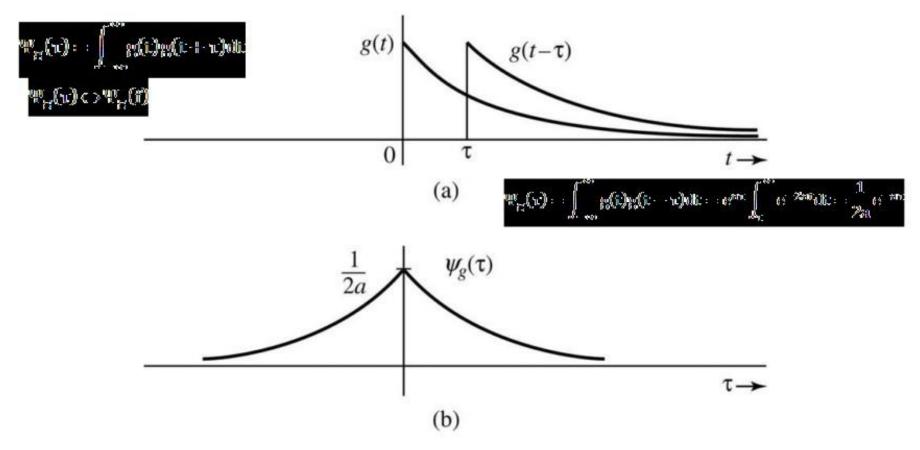
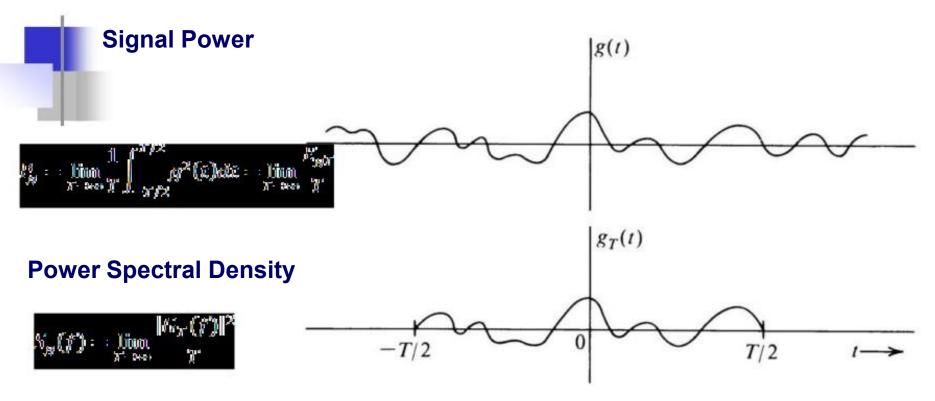


Figure Computation of the time autocorrelation function.



Limiting process in derivation of PSD.

Time Autocorrelation Function of Power Signals

PSD of Modulated Signals

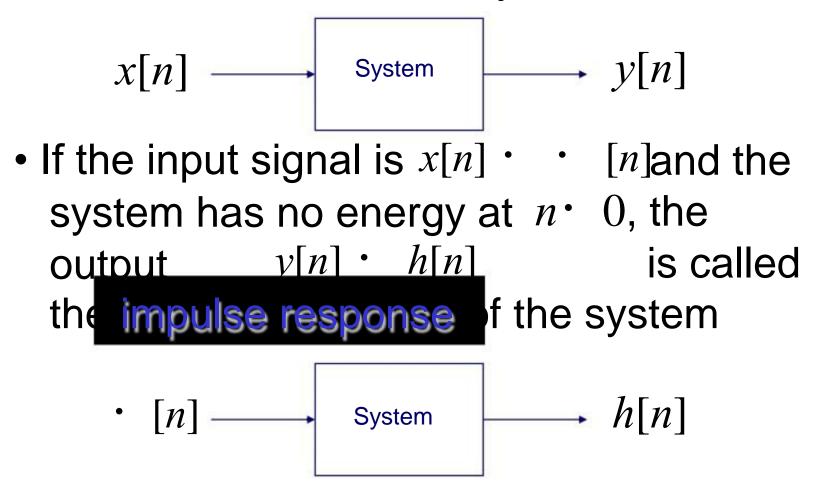






DT Unit-Impulse Response

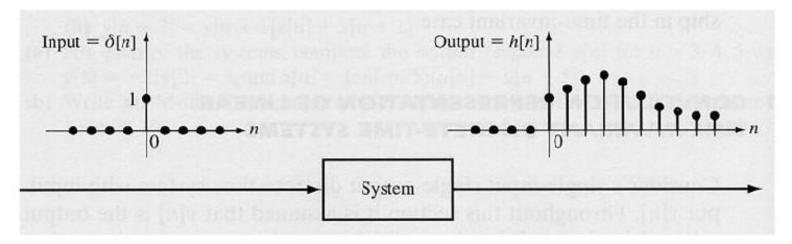
• Consider the DT SISO system:





- Consider the DT system described by $y[n] \cdot ay[n \cdot 1] \cdot bx[n]$
- Its impulse response can be found to be

$$h[n] \cdot \cdot (\cdot \ a)b, \quad n \cdot 0, 1, 2, \cdot 0, \quad n \cdot \cdot 1, \cdot 2, \cdot 3, \cdot$$

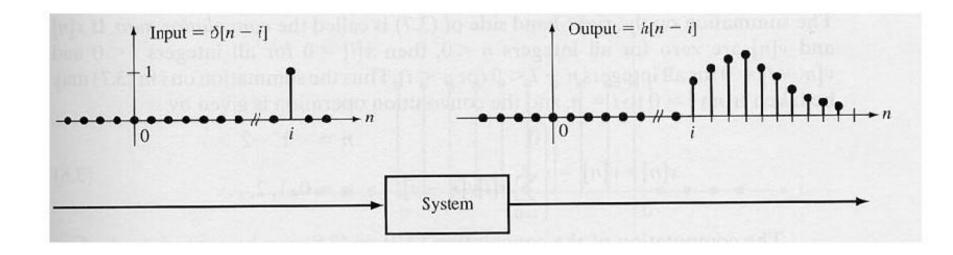


Representing Signals in Terms of Shifted and Scaled Impulses

- Let *x*[*n*] be an arbitrary input signal to a DT LTI system
- Suppose that $x[n] \cdot 0$ for $n \cdot 1, \cdot 2, \cdot$
- This signal can be represented as
- x[n] · x[0] · [n] · x[1] · $[n \cdot 1]$ · x[2] · $[n \cdot 2]$ · ·

•
$$xi$$
]• $[n \cdot i]$, $n \cdot 0, 1, 2, \cdot i \cdot 0$

Exploiting Time-Invariance and Linearity



$$y[n] \cdot xi]h[n \cdot i], \qquad n \cdot 0$$

The Convolution Sum

This particular summation is called the convolution sum

$$y[n] \cdot xi]h[n \cdot i]$$

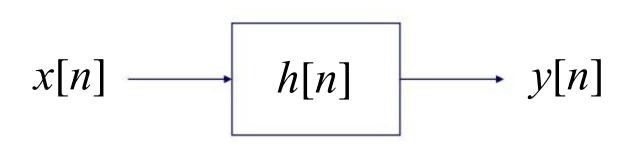
• Equation v[n] · x[n] · h[n] is called the convolution representation of the system

 $x | n | \cdot h | n |$

• Remark: a DT LTI system is completely described by its impulse response *h*[*n*]

Block Diagram Representation of DT LTI Systems

 Once the impulse response n(n) provides the complete description of a DT LTI system, we write



The Convolution Sum for Noncausal Signals

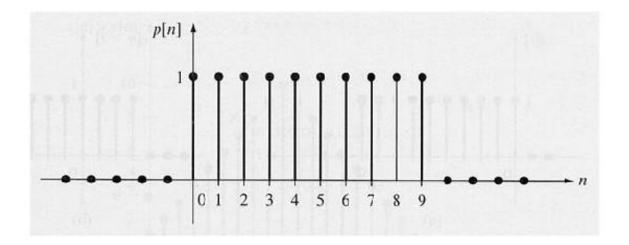
and v[n] that are not zero for negative times noncausal signals

 Then, their convolution is expressed by the two-sided series

$$y[n] \cdot \cdot xi v[n \cdot i]$$

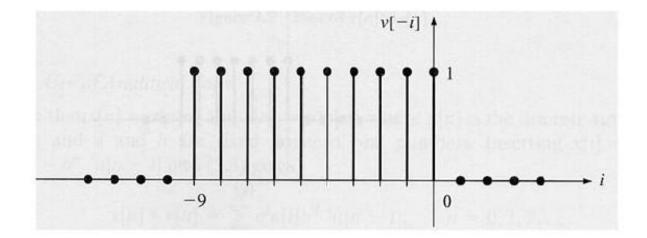
Example: Convolution of Two Rectangular Pulses

 Suppose that both x[n] and v[n] are equal to the rectangular pulse p[n] (causal signal) depicted below

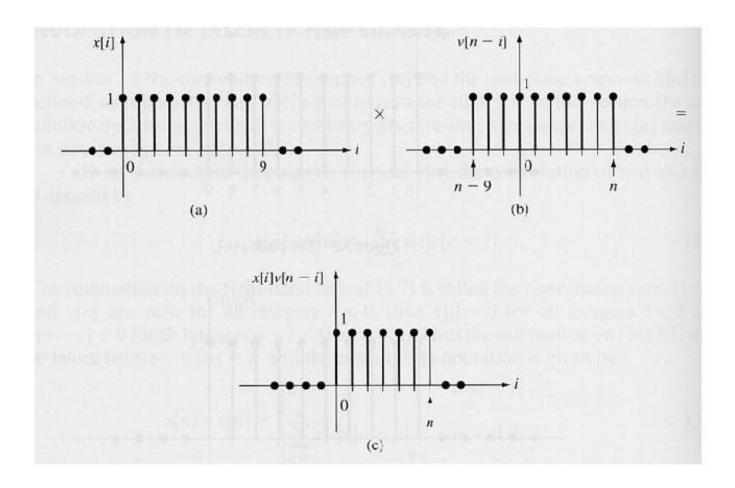


The Folded Pulse

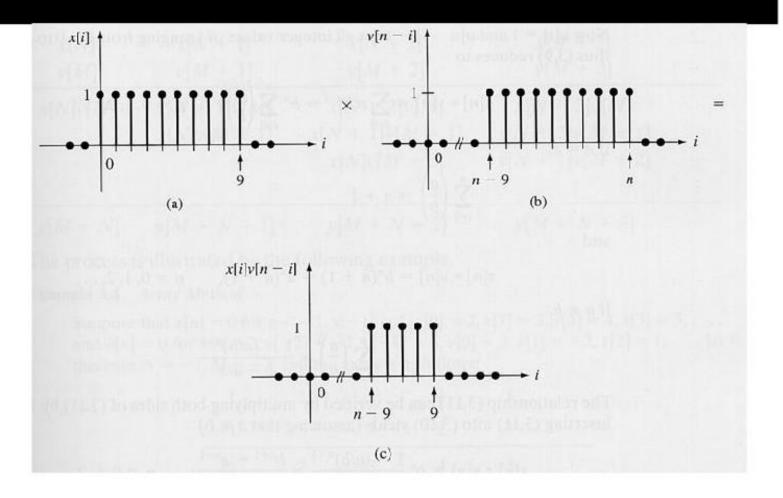
• The signal $v[\cdot i]$ is equal to the pulse p[i] folded about the vertical axis



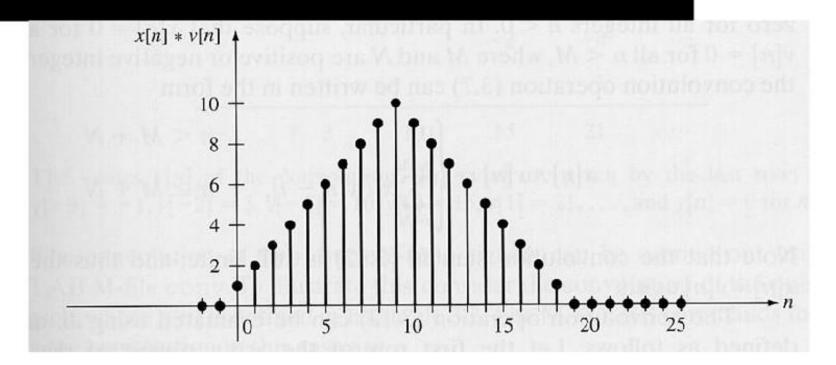
Sliding v[n-ii]over x[i]

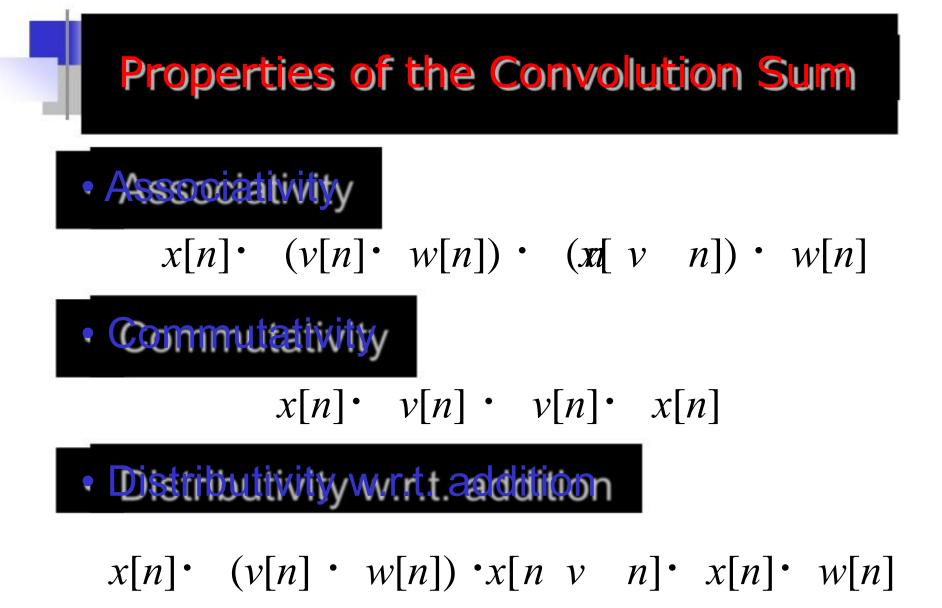


Sliding v[m-ii]over xi]] - Cont'd



$\mathsf{Plot} \ \mathsf{off} x[n] * v[n]$





Properties of the Convolution Sum - Cont'd

• Shiftproperty: efine
then

$$w[n \cdot q] \cdot x_q[n] \cdot v[n] \cdot x[n \cdot q]$$

 $w[n \cdot q] \cdot x_q[n] \cdot v[n] \cdot x[n] \cdot v[n]$
• Convolution with the unit impulse
 $x[n] \cdot \cdot [n] \cdot x[n]$

$$x[n] \cdot \cdot_q[n] \cdot x[n \cdot q]$$

Example: Computing Convolution with Matlab

Consider the DT LTI system

$$x[n] \longrightarrow h[n] \longrightarrow y[n]$$

• impulse response:

h[n] · sin(0.5n), n · 0

• input signal:

 $x[n] \cdot \sin(0.2n), n \cdot 0$

Example: Computing Convolution with Matlab - Contfd

0.3 0.5 0.4 0.2 $h[n] \cdot \sin(0.5n), n \cdot 0$ [w]4 (a) -0.2 -0.4 -0.5 -0.3 10 5 15 20 25 30 35 40 0.8 0.5 0.4 02 $x[n] \cdot \sin(0.2n), n \cdot 0$ (b) -0.2 -0.4 -0.5 -0.8 10 15 20 15 30 35

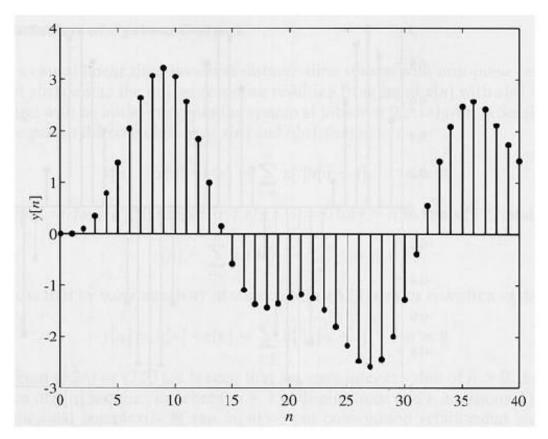
Example: Computing Convolution with Matlab – Contfd

• Matlab code:

n=0:40; x=sin(0.2*n); h=sin(0.5*n); y=conv(x,h); stem(n,y(1:length(n)))

Example: Computing Convolution with Matlab – Contfd

 $y[n] \cdot x[n] \cdot h[n]$



CT Unit-Impulse Response • Consider the CT SISO system: x(t)System $\longrightarrow \mathcal{V}(t)$ • If the input signal is $x(t) \cdot (t)$ and the system has no energy at $t \cdot 0^+$, the is called output $v(t) \cdot h(t)$ the impulse response of the system • $(t)_{-}$ $\bullet h(t)$ System

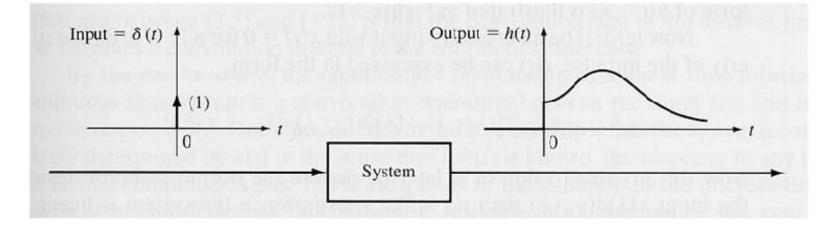
Exploiting Time-Invariance

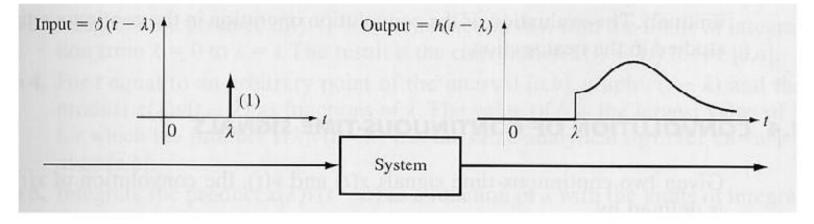
- Let x[n] be an arbitrary input signal with $x(t) \cdot 0$, for $t \cdot 0$
- Using the sifting property · (t), we may write

$$x(t)$$
 • $x(\cdot)$ • $(t \cdot \cdot) d \cdot , t \cdot 0$

• Exploiting time-invariance is • $(t \cdot \cdot \cdot)$ System $h(t \cdot \cdot \cdot)$

Exploiting Time-Invariance





Exploiting Linearity

• Exploiting linearity, is

$$y(t)$$
 • $x(\cdot)h(t \cdot \cdot)d \cdot , t \cdot 0$

• If the integrand $x(\cdot)h(t \cdot \cdot)$ does not contain an impulse $| \cdot \cdot 0 ed at$, the lower limit of the integral can be taken to be 0, i.e.,

$$y(t) \cdot \cdot x(\cdot \cdot)h(t \cdot \cdot \cdot)d \cdot , \quad t \cdot 0$$

The Convolution Integral

This particular integration is called the convolution integral

$$y(t)$$
 • $x(\cdot)h(t \cdot \cdot)d \cdot , t \cdot 0$

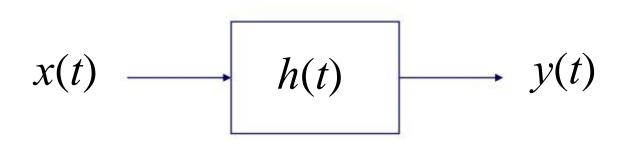
 $x(t) \cdot h(t)$

• Equation v(t) • x(t) • h(t) is called the convolution representation of the system

• Remark: a CT LTI system is completely described by its impulse response *h*(*t*)

Block Diagram Representation of CT LTI Systems

the complete description of a CT LTI system, we write

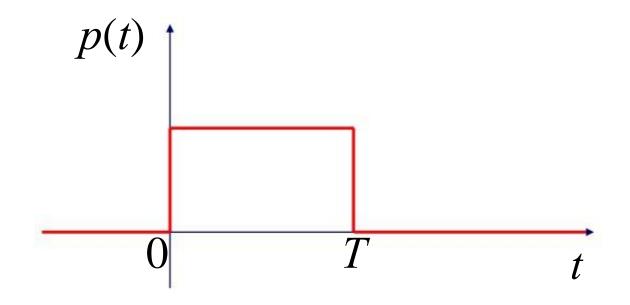


Example: Analytical Computation of the Convolution Integral

ouppose that

wnere

p(t) is the rectangular pulse depicted in figure $x(t) \cdot h(t) \cdot p(t)$,



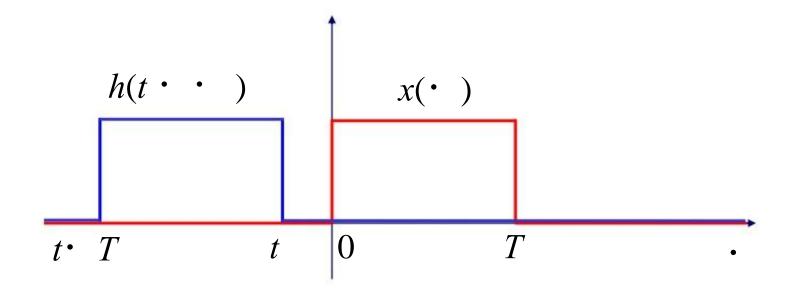


In order to compute the convolution integral

$$y(t) \cdot \cdot x(\cdot \cdot)h(t \cdot \cdot \cdot)d \cdot \cdot t \cdot 0$$

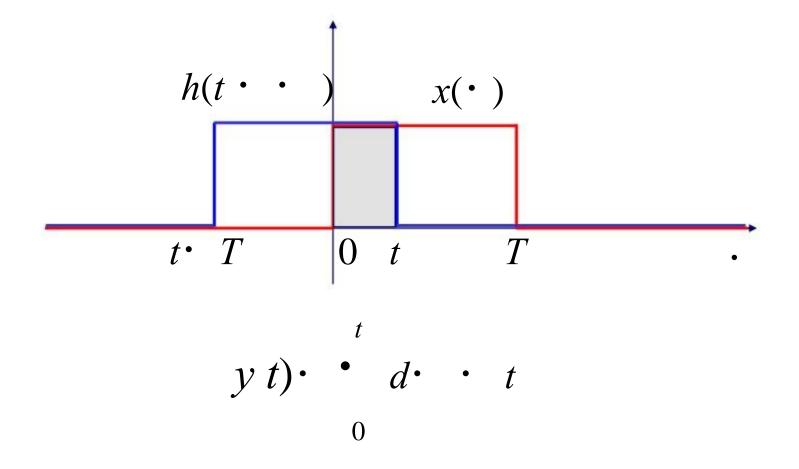
we have to consider four cases:

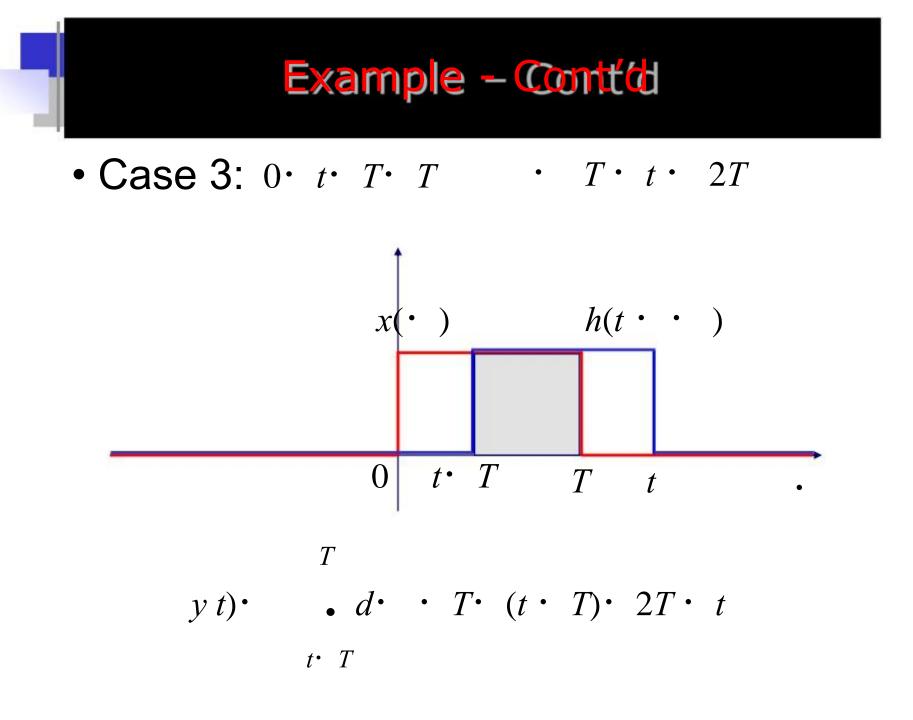
Example – Contťd

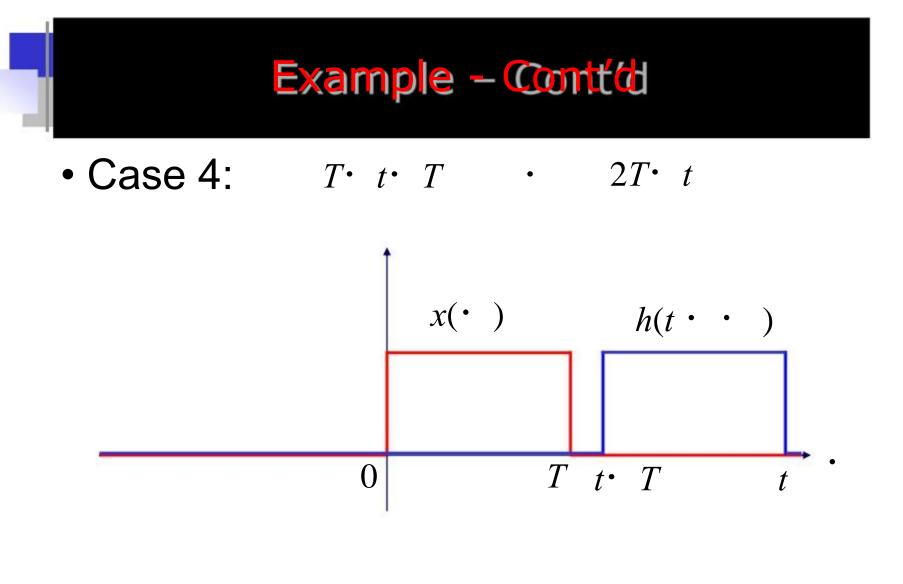


 $y(t) \cdot 0$

Example – Contťd

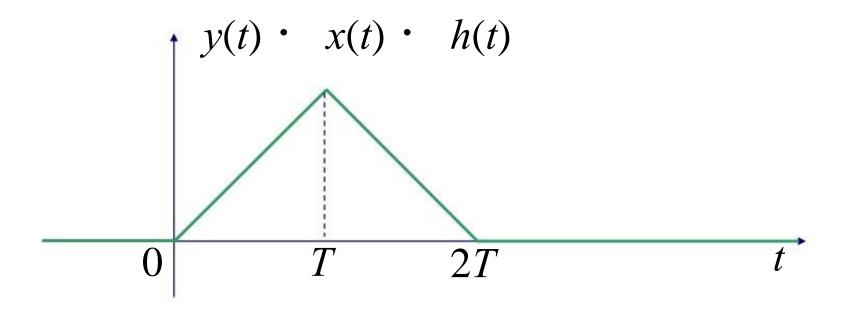






 $y(t) \cdot 0$

Example - Contfd



Properties of the Convolution Integral • Associativity $x(t) \cdot (v(t) \cdot w(t)) \cdot (x(t) \cdot v(t)) \cdot w(t)$ • Commutativity $x(t) \cdot v(t) \cdot v(t) \cdot x(t)$ • Distributivity/writt addition $x(t) \cdot (v(t) \cdot w(t)) \cdot x(t) \cdot v(t) \cdot x(t) \cdot w(t)$

Properties of the **Convolution Integral - Cont'd** • $x \underset{q}{t}$)• $x(t \cdot q)$ • Shiftproperty: efine $v_d t$ · $v(t \cdot q)$ $w(t) \cdot x(t) \cdot v(t)$ then $w(t \cdot q) \cdot x_a t$ $v t \cdot x t$ $v_a t$ Convolution with the unit impulse $x(t) \cdot \cdot (t) \cdot x(t)$ Convolution with the shifted unit impulse

$$x t$$
) · · $q t$) · $xt q()$

Properties of the Convolution Integral - Cont'd

- Derivative property: the signal x(t) is differentiable, then it is $\frac{d}{dt} \cdot x(t) \cdot v(t) \cdot \frac{dx(t)}{dt} \cdot v(t)$
 - If both x(t) and v(t) are differentiable,
 then it is also

$$\frac{d^2}{dt^2} \cdot x t \cdot v t \cdot \frac{dx t}{dt} \cdot \frac{dv t}{dt}$$

Propertiestof the Convolutioneintegrat/d Cont/d

Integentionation pertopertoperto;

$$\begin{array}{c} \cdot & t \\ \cdot & x^{(1)} \\ \cdot & x^{(\cdot)} \\ \cdot & \cdot \\ \cdot & t \\ \cdot & t \\ \cdot & v^{(1)} \\ \cdot & \cdot \\ \cdot & v(\cdot) \\ \cdot & \cdot \\ &$$

then

$$(x \cdot v)^{(\cdot 1)}(t) \cdot x^{(\cdot 1)}(t) \cdot v(t) \cdot x(t) \cdot v^{(\cdot 1)}(t)$$

Representation of a CT LTI System in Terms of the Unit-Step Response

Let g(t) be the response of a system
 with impulse response h(t) whenx(t) • u(t)
 with no initial energy at timet • 0, i.e.,

$$u(t) \longrightarrow h(t) \longrightarrow g(t)$$

• Therefore, it is

$$g(t) \cdot h(t) \cdot u(t)$$

Representation of a CT LTI System in Terms of the Unit-Step Response - Contfd

Differentiating both sides

$$\frac{dg t}{dt} \cdot \frac{dh t}{dt} \cdot u t \cdot h t \cdot \frac{du t}{dt}$$

Recalling that

$$\frac{du t}{dt} \cdot \cdot (t)$$
 and $h(t) \cdot h(t) \cdot \cdot (t)$

it is
$$\frac{dg(t)}{dt} \cdot h(t)$$
 or $g(t) \cdot \cdot \cdot \cdot \cdot h(t) d \cdot 0$



Definitions of the components/Keywords:

Convolution of two signals:

Let x(t) and h(t) are two continuous signals to be convolved.

The convolution of two signals is denoted by

is the variable of integration.

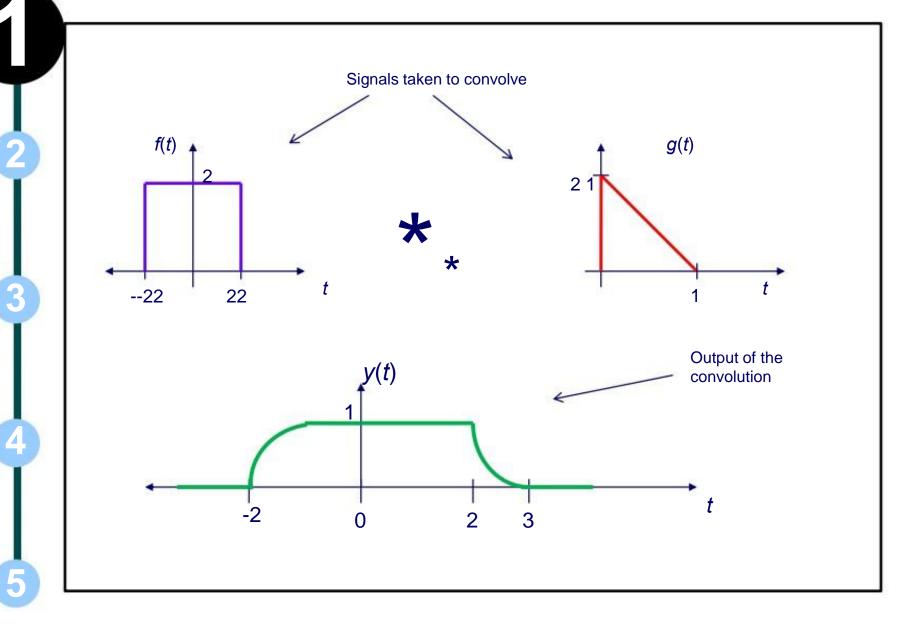
which means

where •

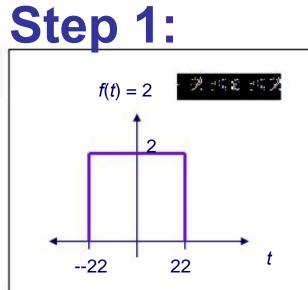


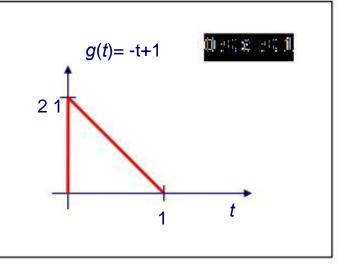


Master Layout

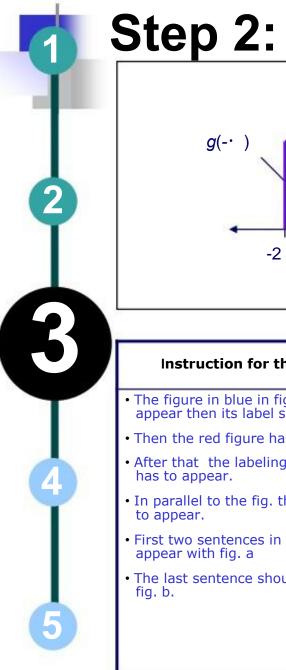


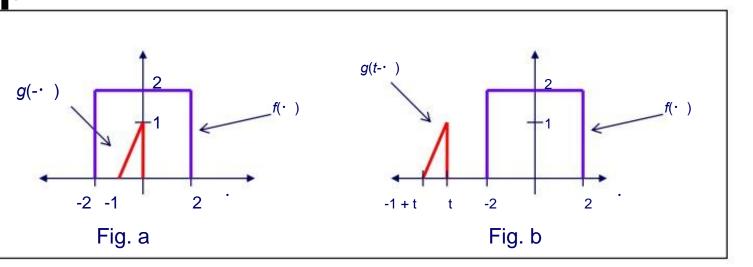






Instruction for the animator	Text to be displayed in the working area (DT)
 The first point in DT has to appear before the figures. Then the blue figure has to appear. After that the red figure has to appear. After the figures, the next point in DT has to appear. 	 <i>f(t)</i> and <i>g(t)</i> are the two continuous signals to be convolved. The convolution of the signals is denoted by which means where • is a dummy variable.

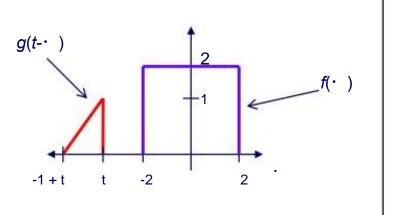




Text to be displayed in the working area (DT)
• The signal f(* *) is shown
• The reversed version of g(•) i.e., g(-• • • is shown
• The shifted version of g(-••• <i>i.e., g(t-•</i>) is shown

Step 3: Calculation of *y(t)* in five stages

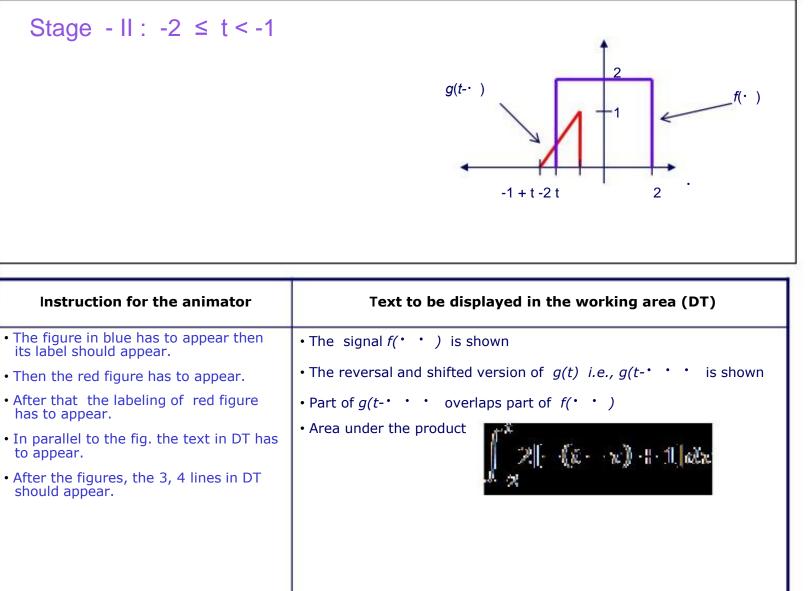
Stage - I : t < -2



Instruction for the animator	Text to be displayed in the working area (DT)
• The figure in blue has to appear then its label should appear.	• The signal f(• •) is shown
• Then the red figure has to appear.	• The reversal and shifted version of $g(t)$ <i>i.e.</i> , $g(t- \cdot \cdot$
 After that the labeling of red figure has to appear. 	 Two functions do not overlap Area under the product of the functions is zero
• In parallel to the fig. the text in DT has to appear.	
• After the figures, the 3, 4 lines in DT should appear.	

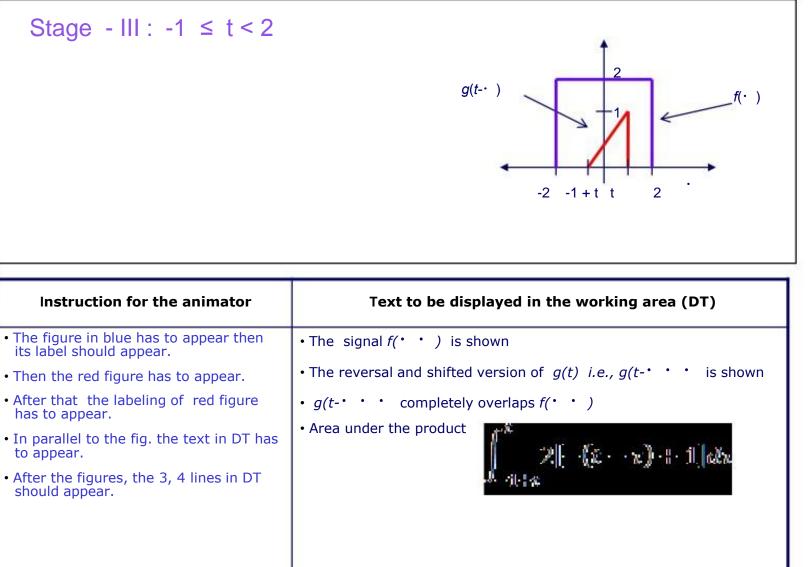


Step 4:





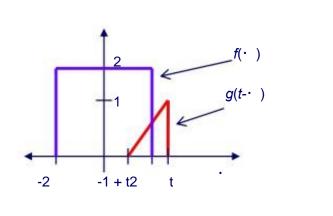
Step 5:





Step 6:

Stage - IV : $2 \le t < 3$

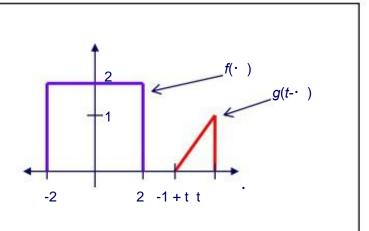


Text to be displayed in the working area (DT)		
• The signal f(• •) is shown		
 The reversal and shifted version of g(t) i.e., g(t-• • • is shown Part of g(t-• • • overlaps part of f(• •) 		
• Area under the product $2 + \frac{2}{2} + \frac{2}{$		
.⊈ jtt‡sc		



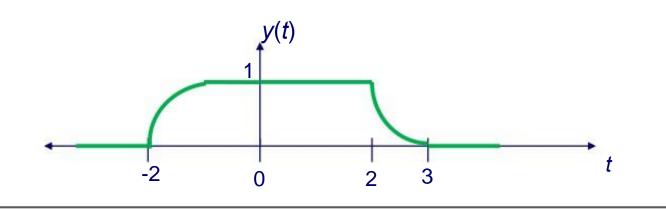
Step 7:



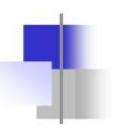


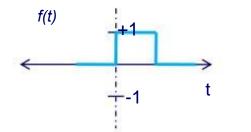
Instruction for the animator	Text to be displayed in the working area (DT)	
• The figure in blue has to appear then its label should appear.	• The signal f(* *) is shown	
• Then the red figure has to appear.	• The reversal and shifted version of $g(t)$ <i>i.e.</i> , $g(t- \cdot \cdot$	
 After that the labeling of red figure has to appear. 	 Two functions do not overlap Area under the product of the functions is zero 	
• In parallel to the fig. the text in DT has to appear.		
• After the figures, the 3, 4 lines in DT should appear.		

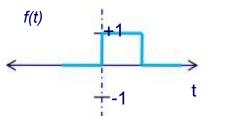
Step 8: Output of Convolution

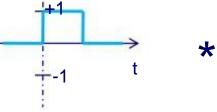


Instruction for the animator	Text to be displayed in the working area (DT)		
 The figure in green has to appear then its label should appear. 	• The signal $y(t)$ is shown		
 In parallel to the fig. the text in DT has to appear. 		• 0	for $t \cdot 2$
 After the figure, the equations in DT should appear . 		-	
		$\cdot t^2 \cdot 2t$	for $2 \cdot t \cdot \cdot 1$
	$y(t) \cdot f(t)^* g(t) \cdot \cdot 1$		for $1 \cdot t \cdot 2$
		$t^2 \cdot 6t \cdot 9$	for $2 \cdot t \cdot 3$
		· 0	for $t \cdot 3$



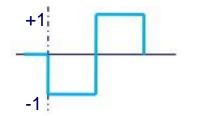


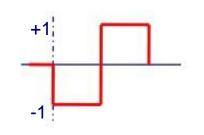


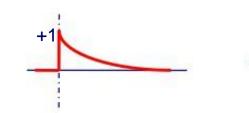


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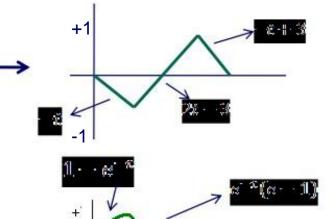


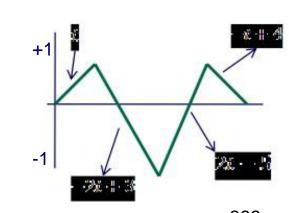


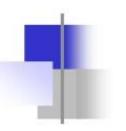


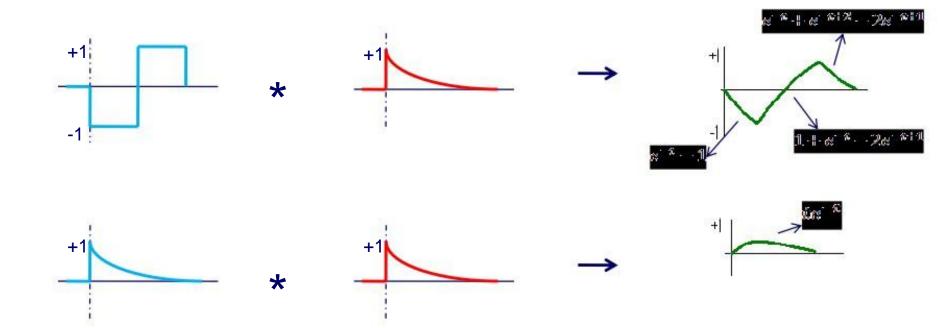
+1

-1









Correlation and Auto-Correlation of Signals

Objectives

- Develop an intuitive understanding of the crosscorrelation of two signals.
- Define the meaning of the auto-correlation of a signal.
- Develop a method to calculate the cross-correlation and auto-correlation of signals.
- Demonstrate the relationship between auto-correlation and signal power.
- Demonstrate how to detect periodicities in noisy signals using auto-correlation techniques.
- Demonstrate the application of cross-correlation to sonar or radar ranging

Correlation

- Correlation addresses the question: "to what degree is signal A similar to signal B."
- An intuitive answer can be developed by comparing deterministic signals with stochastic signals.
 - Deterministic = a predictable signal equivalent to that produced by a mathematical function
 - Stochastic = an unpredictable signal equivalent to that produced by a random process

Three Signals

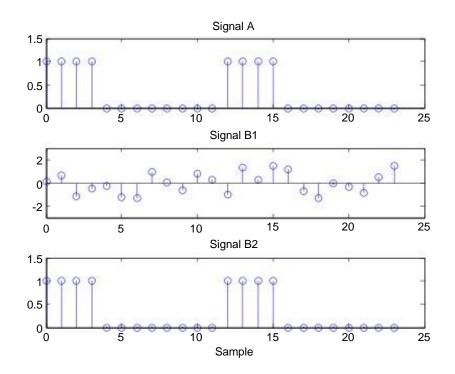
>> n=0:23;

- >> A=[ones(1,4),zeros(1,8),ones(1,4),zeros(1,8)];
- >> subplot (3,1,1),stem(n,A);axis([0 25 0 1.5]);title('Signal A')
- >> B1=randn(size(A)); %The signal B1 is Gaussian noise with the same length as A
- >> subplot(3,1,2),stem(n,B1);axis([0 25 -3 3]);title('Signal B1')

>> B2=A;

>> subplot(3,1,3),stem(n,B2); axis([0 25 0 1.5]);title('Signal B2');xlabel('Sample')

By inspection, A is "correlated" with B2, but B1 is "uncorrelated" with both A and B2. This is an intuitive and visual definition of "correlation."



Quantitative Correlation

- We seek a quantitative and algorithmic way of assessing correlation
- A possibility is to multiple signals sample-bysample and average the results. This would give a relatively large positive value for identical signals and a near zero value for two random signals.

$$r_{12} \cdot \frac{1}{N} \int_{n \cdot 0}^{N \cdot 1} x_{l}[n] x[n]$$

Simple Cross-Correlation

 Taking the previous signals, A, B1(random), and B2 (identical to A):

>> A*B1'/length(A)

ans =

-0.0047

>> A*B2'/length(A)

ans =

0.3333

The small numerical result with A and B1 suggests those signals are uncorrelated while A and B2 are correlated.

Simple Cross-Correlation of Random Signals

>> n=0:100;

- >> noise1=randn(size(n));
- >> noise2=randn(size(n));

>> noise1*noise2'/length(noise1)

ans =

0.0893

Are the two signals correlated?

With high probability, the result is expected to be

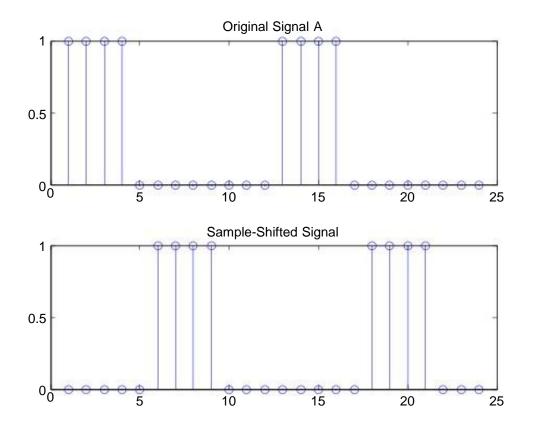
 $\leq \pm 2/\sqrt{N} = \pm 0.1990$

for two random (uncorrelated) signals

We would conclude these two signals are *uncorrelated*.



The Flaw in Simple Cross-Correlation



In this case, the simple cross-correlation would be zero despite the fact the two signals are obviously "correlated."

Sample-Shifted Cross-Correlation

- Shift the signals k steps with respect to one another and calculate r₁₂(k).
- All possible k shifts would produce a vector of values, the "full" cross-correlation.
- The process is performed in MATLAB by the command **xcorr**
- **xcorr** is equivalent to **conv** (convolution) with one of the signals taken in reverse order.

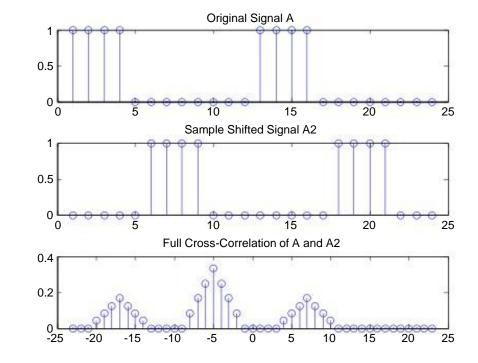
$$r_{12}(k) \cdot \frac{1}{N} \cdot x_{1}[n] x[n \cdot k]$$

Full Cross-Correlation

>> A=[ones(1,4),zeros(1,8),ones(1,4),zeros(1,8)];

- >> A2=filter([0,0,0,0,0,1],1,A);
- >> [acor,lags]=xcorr(A,A2);
- >> subplot(3,1,1),stem(A); title('Original Signal A')
- >> subplot(3,1,2),stem(A2); title('Sample Shifted Signal A2')
- >> subplot(3,1,3),stem(lags,acor/length(A)),title('Full Cross-Correlation of A and A2')

Signal A2 shifted to the left by 5 steps makes the signals identical and $r_{12} = 0.333$

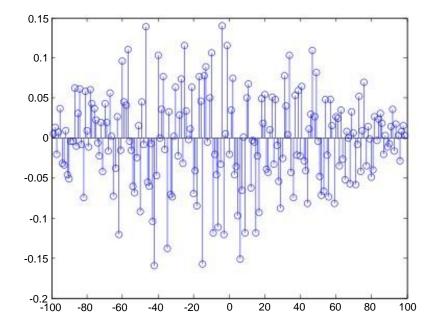


Full Cross-Correlation of Two Random Signals

>> N=1:100;

- >> n1=randn(size(N));
- >> n2=randn(size(N));
- >> [acor,lags]=xcorr(n1,n2);
- >> stem(lags,acor/length(n1));

The crosscorrelation is random and shows no peak, which implies no correlation



Auto-Correlation

• The cross-correlation of a signal with itself is called the *auto-correlation*

$$r_{11}(k) \cdot \frac{1}{N} \frac{N \cdot 1}{n \cdot 0} x_1[n] x[n \cdot k]$$

• The "zero-lag" auto-correlation is the same as the mean-square *signal power*.

$$r(0) \cdot \qquad \frac{1}{N} \cdot x[n] x[n] \cdot \qquad \frac{1}{N} \cdot x^{N-1} x[n] x[n] \cdot \qquad \frac{1}{N} \cdot x^{N-1} x^{2}[n]$$

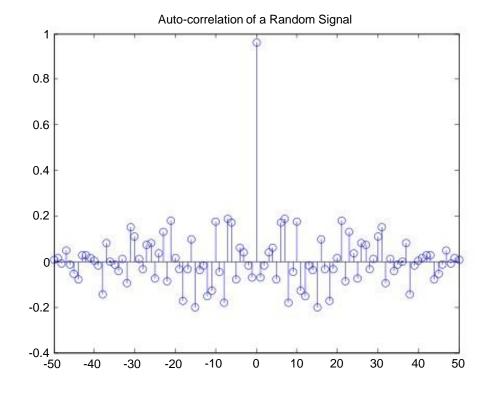
Auto-Correlation of a Random Signal

>> n=0:50;

- >> N=randn(size(n));
- >> [rNN,k]=xcorr(N,N);

>> stem(k,rNN/length(N));title('Auto-correlation of a Random Signal')

Mathematically, the auto-correlation of a random signal is like the impulse function

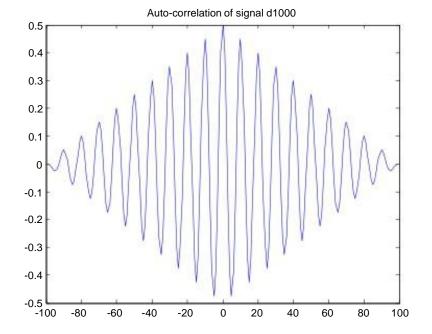


Auto-Correlation of a Sinusoid

>> n=0:99;

- >> omega=2*pi*100/1000;
- >> d1000=sin(omega*n);
- >> [acor_d1000,k]=xcorr(d1000,d1000);
- >> plot(k,acor_d1000/length(d1000));
- >> title('Auto-correlation of signal d1000')

The autocorrelation vector has the same frequency components as the original signal

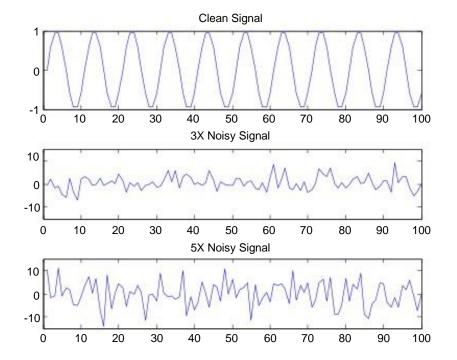


Identifying a Sinusoidal Signal Masked by Noise

>> n=0:1999;

- >> omega=2*pi*100/1000;
- >> d=sin(omega*n);
- >> d3n=d+3*randn(size(d)); % The sinusoid is contaminated with 3X noise
- >> d5n=d+5*randn(size(d)); % The sinusoid is contaminated with 5X noise.
- >> subplot(3,1,1),plot(d(1:100)),title('Clean Signal')
- >> subplot(3,1,2),plot(d3n(1:100)),title('3X Noisy Signal'), axis([0,100,-15,15])
- >> subplot(3,1,3),plot(d5n(1:100)),title('5X Noisy Signal'), axis([0,100,-15,15])

It is very difficult to "see" the sinusoid in the noisy signals



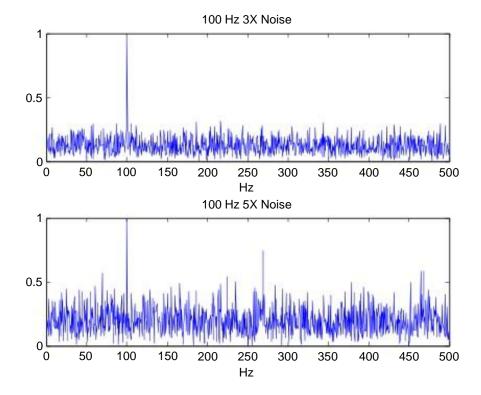
Identifying a Sinusoidal Signal Masked by Noise (Normal Spectra)

>> n=0:1999;

- >> omega=2*pi*100/1000;
- >> d=sin(omega*n);
- >> d3n=d+3*randn(size(d)); % The sinusoid is contaminated with 3X noise
- >> d5n=d+5*randn(size(d)); % The sinusoid is contaminated with 5X noise.
- >> subplot(2,1,1),fft_plot(d3n,1000);title('100 Hz 3X Noise')

>> subplot(2,1,2),fft_plot(d5n,1000);title('100 Hz 5X Noise')

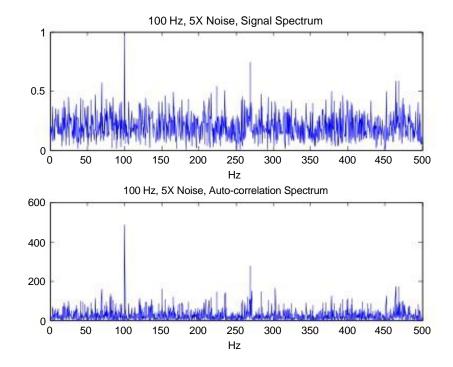
Normal spectra of a sinusoid masked by noise: High noise power makes detection less certain



Identifying a Sinusoidal Signal Masked by Noise (Auto-correlation Spectra)

>> acor3n=xcorr(d3n,d3n); >> acor5n=xcorr(d5n,d5n); >> subplot(2,1,1),fft_plot(d3n,1000);title('100 Hz, 3X Noise, Signal Spectrum') >> subplot(2,1,2),fft_plot(acor3n,1000);title('100 Hz, 3X Noise, Auto-correlation Spectrum') >> figure, subplot(2,1,1),fft_plot(d5n,1000);title('100 Hz, 5X Noise, Signal Spectrum') >> subplot(2,1,2),fft_plot(acor5n,1000);title('100 Hz, 5X Noise, Auto-correlation Spectrum')

The <u>auto-</u> <u>correlation</u> of a noisy signal provides greater S/N in detecting dominant frequency components compared to a normal FFT

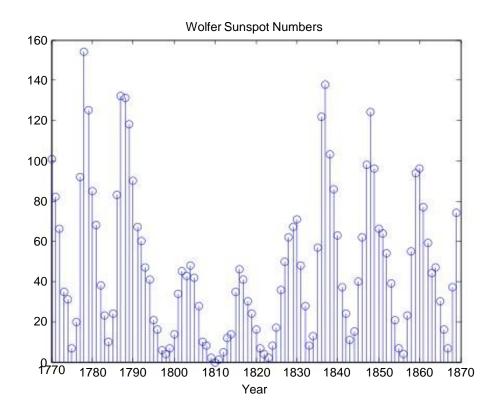


Detecting Periodicities in Noisy Data: Annual Sunspot Data

>> load wolfer_numbers

- >> year=sunspots(:,1);
- >> spots=sunspots(:,2);

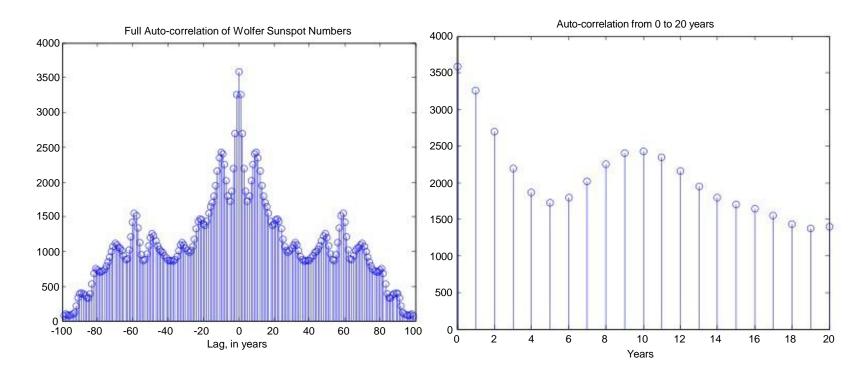
>> stem(year,spots);title('Wolfer Sunspot Numbers');xlabel('Year')



Detecting Periodicities in Noisy Data: Annual Sunspot Data

- >> [acor,lag]=xcorr(spots);
- >> stem(lag,acor/length(spots));
- >> title('Full Auto-correlation of Wolfer Sunspot Numbers')
- >> xlabel('Lag, in years')
- >> figure, stem(lag(100:120),acor(100:120)/length(spots));
- >> title('Auto-correlation from 0 to 20 years')
- >> xlabel('Years')

Autocorrelatio n has detected a periodicity of 9 to 11 years

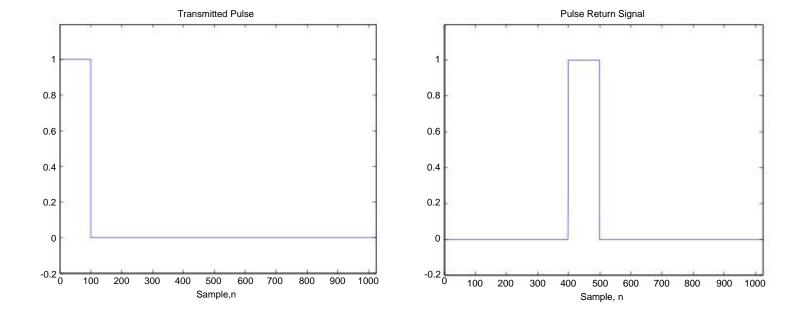


>> x=[ones(1,100),zeros(1,924)];

- >> n=0:1023;
- >> plot(n,x); axis([0 1023 -.2, 1.2])
- >> title('Transmitted Pulse');xlabel('Sample,n')
- >> h=[zeros(1,399),1]; % Impulse response for z-400 delay
- >> x_return=filter(h,1,x); % Put signal thru delay filter
- >> figure,plot(n,x_return); axis([0 1023 -.2, 1.2])

>> title('Pulse Return Signal');xlabel('Sample, n')

Simulation of a transmitted and received pulse (echo) with a 400 sample delay



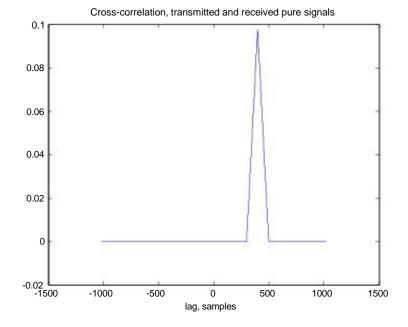
>> [xcor_pure,lags]=xcorr(x_return,x);

>> plot(lags,xcor_pure/length(x))

>> title('Cross-correlation, transmitted and received pure signals')

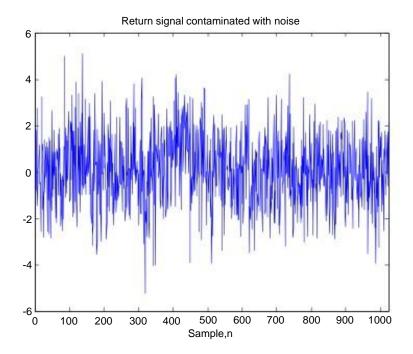
>> xlabel('lag, samples')

The cross-correlation of the transmitted and received signals shows they are correlated with a 400 sample delay



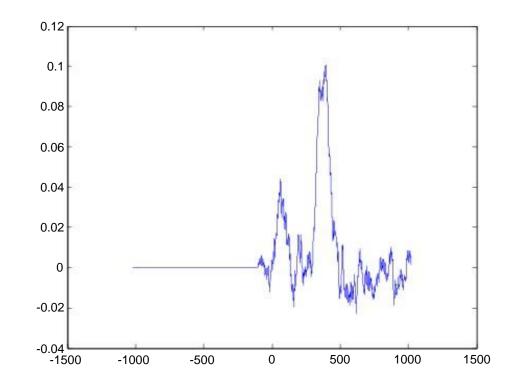
>> x_ret_n=x_return+1.5*randn(size(x_return));
>> plot(n,x_ret_n); axis([0 1023 -6, 6]) %Note change in axis range
>> title('Return signal contaminated with noise')
>> xlabel('Sample,n')

The presence of the return signal in the presence of noise is almost impossible to see



>> [xcor,lags]=xcorr(x_ret_n,x);
>> plot(lags,xcor/length(x))

Crosscorrelation of the transmitted signal with the noisy echo clearly shows a correlation at a delay of 400 samples



Summary

- Cross-correlation allows assessment of the degree of similarity between two signals.
 - Its application to identifying a sonar/radar return echo in heavy noise was illustrated.
- Auto-correlation (the correlation of a signal with itself) helps identify signal features buried in noise.

The Laplace Transform

Generalizing the Fourier Transform

The CTFT expresses a time-domain signal as a linear combination of **complex sinusoids** of the form $e^{j\omega t}$. In the generalization of the CTFT to the Laplace transform, the complex sinusoids become **complex exponentials** of the form e^{st} where *s* can have any complex value. Replacing the complex sinusoids with complex exponentials leads to this definition of the Laplace transform.

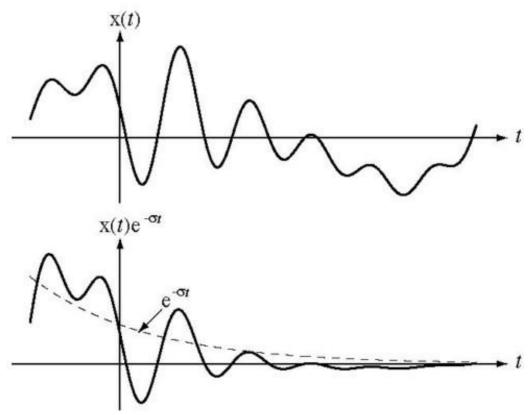
$$L (x(t)) = X(s) = \int_{-\infty}^{\infty} x(t) e^{-st} dt$$
$$x(t) \xleftarrow{\ } X(s)$$

Generalizing the Fourier Transform

The variable *s* is viewed as a generalization of the variable ω of the form $s = \sigma + j\omega$. Then, when σ , the real part of *s*, is zero, the Laplace transform reduces to the CTFT. Using $s = \sigma + j\omega$ the

Laplace transform is $X(s) = \int_{-\infty}^{\infty} x(t) e^{-(\sigma + j\omega)t} dt \qquad \bigwedge$ $= \mathsf{F} \left[x(t) e^{-\sigma t} \right]$

which is the Fourier transform of $x(t)e^{-\sigma t}$



Generalizing the Fourier Transform

e extra factor e_{-st} is sometimes called a **convergence factor** because, when chosen properly, it makes the integral converge for some signals for which it would not otherwise converge. For example, strictly speaking, the signal A u(t) does not have a CTFT because the integral does not converge. But if it is multiplied by the convergence factor, and the real part of sis chosen appropriately, the CTFT integral will converge.

Complex Exponential Excitation

If a continuous-time LTI system is excited by a complex exponential $x(t) = Ae^{st}$, where A and s can each be any complex number, the system response is also a complex exponential of the same functional form except multiplied by a complex constant. The response is the convolution of the excitation with the impulse response and that is

$$\mathbf{y}(t) = \int_{-\infty}^{\infty} \mathbf{h}(\tau) \mathbf{x}(t-\tau) d\tau = \int_{-\infty}^{\infty} \mathbf{h}(\tau) A e^{s(t-\tau)} d\tau = \underbrace{A e^{st}}_{\mathbf{x}(t)} \int_{-\infty}^{\infty} \mathbf{h}(\tau) e^{-s\tau} d\tau$$

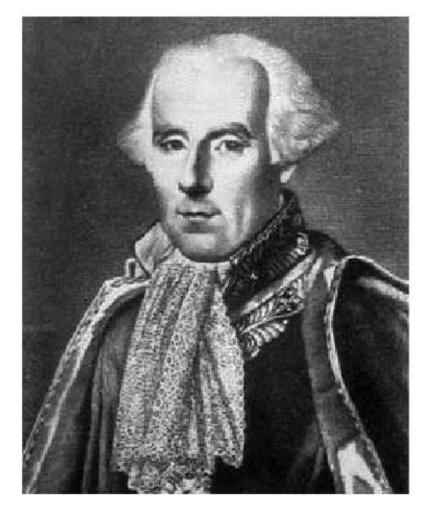
The quantity $H(s) = \int_{-\infty}^{\infty} h(\tau) e^{-s\tau} d\tau$ is called the **Laplace transform** of h(t).

Complex Exponential Excitation

Let
$$\mathbf{x}(t) = \underbrace{(6+j3)}_{A} e^{\overline{(3-j2)}t} = (6.708 \angle 0.4637) e^{(3-j2)t}$$

and let $h(t) = e^{-4t} u(t)$. Then $H(s) = \frac{1}{s+4}$, $\sigma > -4$ and, in this case, $s = 3 - j2 = \sigma + j\omega$ with $\sigma = 3 > -4$ and $\omega = -2$. $y(t) = x(t)H(s) = \frac{6+j3}{2-j2}e^{(3-j2)t} = (0.6793 \angle 0.742)e^{(3-j2)t}$.

Pierre-Simon Laplace



3/23/1749 - 3/2/1827

The Transfer Function

e x(t) be the excitation and let y(t) be the response of a system with impulse response h(t). The Laplace transform of y(t) is

The Transfer Function Let x(t) = u(t) and let $h(t) = e_{-4t} u(t)$. Find y(t). \dot{o} ()u(t-t)dty(*t*) -¥ $y(t) \quad \bigcup_{i=0}^{i} \dot{O} \quad (t) = e_{-4t} \quad \dot{O} = e_{-4t} \quad dt = e_{-4t} \quad \frac{e_{4t} - 1}{4} = 1 - e_{-4t} \quad (t > 0)$, t < 0ï0î y(t) ()u(t)X(s)=1/s, $H(s)=\frac{1}{s+4} PY(s)=\frac{1}{s}, \frac{1}{s+4}=\frac{1}{s}, \frac{1}{s+4}=\frac{1}{4}$ ()u(t)

Cascade-Connected Systems

If two systems are cascade connected the transfer function of the overall system is the product of the transfer functions of the two individual systems.

$$X(s) \rightarrow H_{1}(s) \rightarrow X(s)H_{1}(s) \rightarrow H_{2}(s) \rightarrow Y(s)=X(s)H_{1}(s)H_{2}(s)$$
$$X(s) \rightarrow H_{1}(s)H_{2}(s) \rightarrow Y(s)$$



A very common form of transfer function is a ratio of two polynomials in *s*,

and the second se

$$H(s) = \frac{Y(s)}{X(s)} = \frac{\sum_{k=0}^{N} b_k s^k}{\sum_{k=0}^{N} a_k s^k} = \frac{b_N s^N + b_{N-1} s^{N-1} + \dots + b_1 s + b_0}{a_N s^N + a_{N-1} s^{N-1} + \dots + a_1 s + a_0}$$

The transfer function can be conceived as the product of two transfer functions,

$$H_{1}(s) = \frac{Y_{1}(s)}{X(s)} = \frac{1}{a_{N}s^{N} + a_{N-1}s^{N-1} + \dots + a_{1}s + a_{0}}$$

and

$$H_{2}(s) = \frac{Y(s)}{Y_{1}(s)} = b_{N}s^{N} + b_{N-1}s^{N-1} + \dots + b_{1}s + b_{0}$$

$$X(s) \rightarrow H_{1}(s) = \frac{1}{a_{N}s^{N} + a_{N-1}s^{N-1} + \dots + a_{1}s + a_{0}} \rightarrow Y_{1}(s) \rightarrow H_{2}(s) = b_{N}s^{N} + b_{N-1}s^{N-1} + \dots + b_{1}s + b_{0} \rightarrow Y(s)$$

From

$$H_1(s) = \frac{Y_1(s)}{X(s)} = \frac{1}{a_N s^N + a_{N-1} s^{N-1} + \dots + a_1 s + a_0}$$

we get

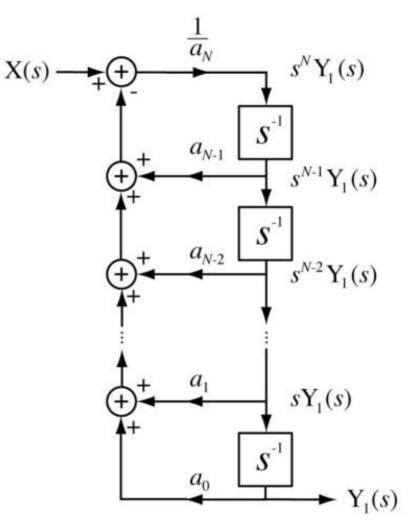
$$X(s) = [a_N s^N + a_{N-1} s^{N-1} + \dots + a_1 s + a_0] Y_1(s)$$

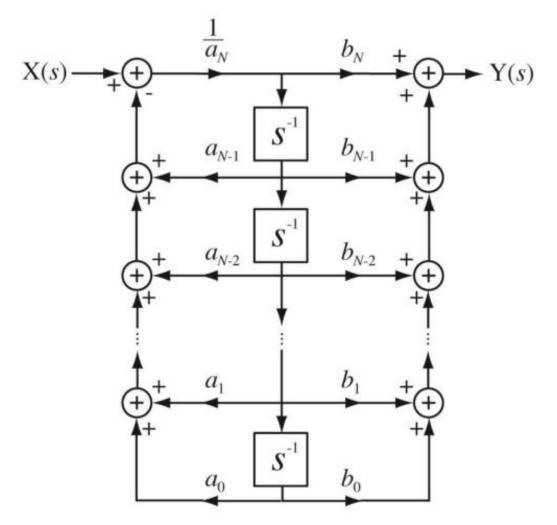
or

$$X(s) = a_N s^N Y_1(s) + a_{N-1} s^{N-1} Y_1(s) + \dots + a_1 s Y_1(s) + a_0 Y_1(s)$$

Rearranging

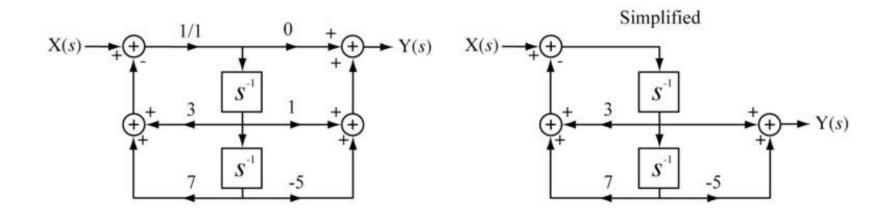
$$s^{N} Y_{1}(s) = \frac{1}{a_{N}} \{ X(s) - [a_{N-1}s^{N-1} Y_{1}(s) + \dots + a_{1}s Y_{1}(s) + a_{0} Y_{1}(s)] \}$$





A system is defined by $y \notin (t) + 3y \notin (t) + 7y(t) = x \notin (t) - 5x(t)$.

$$H(s) = \frac{s-5}{s_2 + 3s + 7}$$



Inverse Laplace Transform

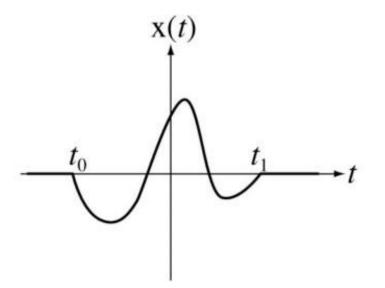
There is an inversion integral

$$y(t) = \frac{1}{j^{2}p} \mathop{\stackrel{s}{\overset{}}}_{s-j^{*}} Y(s) e_{st} ds , s = s + jw$$

for finding y(t) from Y(s), but it is rarely used in practice. Usually inverse Laplace transforms are found by using tables of standard functions and the properties of the Laplace transform.

Time Limited Signals

If x(t) = 0 for $t < t_0$ and $t > t_1$ it is a **time limited** signal. If x(t) is also bounded for all t, the Laplace transform integral converges and the Laplace transform exists for all s.

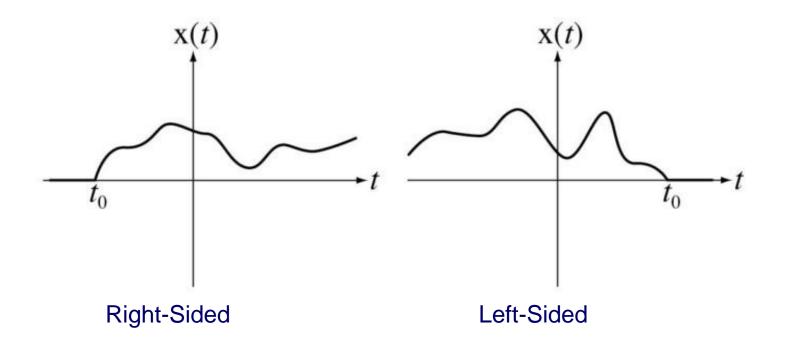




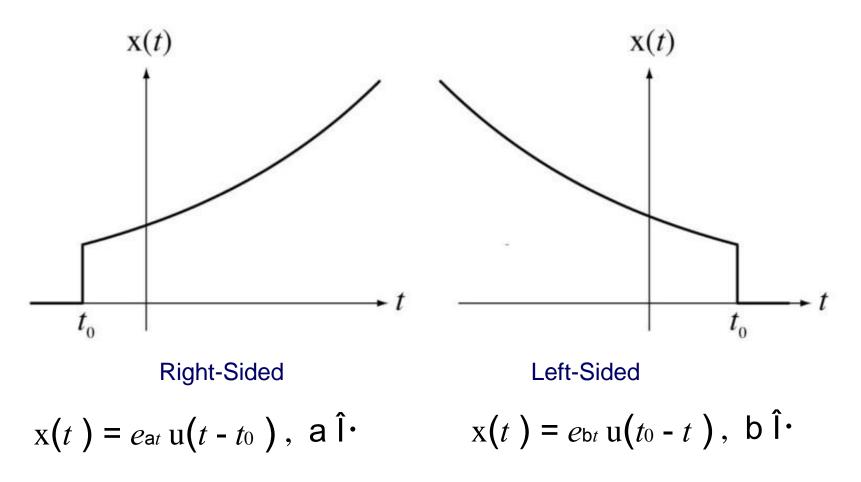
Let
$$x(t) = rect(t) = u(t + 1 / 2) - u(t - 1 / 2).$$

$$X(s) = \overset{*}{\overset{*}{O}} rect(t) e_{-st} dt = \overset{'}{\overset{*}{O}} e_{-st} dt = e_{-s/2} - e_{-s/2} = e_{-s/2} - e_{-s/2}$$

Right- and Left-Sided Signals



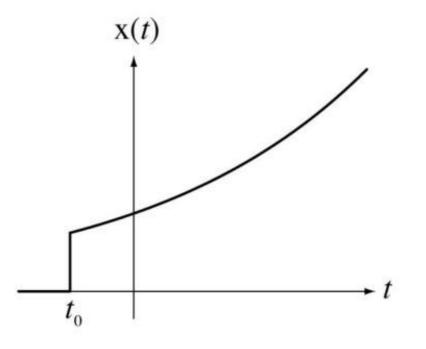
Right- and Left-Sided Exponentials



Right-Sided Exponential

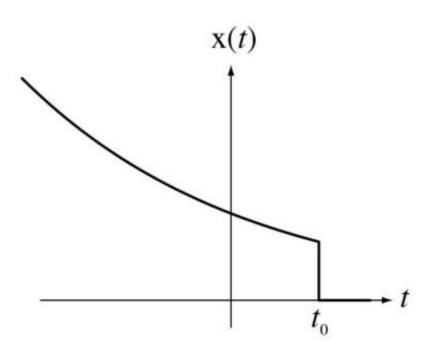
 $x(t) = e_{at} u(t - t_0), a \hat{I} \cdot$ $x(t) = e_{at} u(t - t_0), a \hat{I} \cdot$ $y = \hat{I} \cdot \hat{I} \cdot$

transform integral converges.

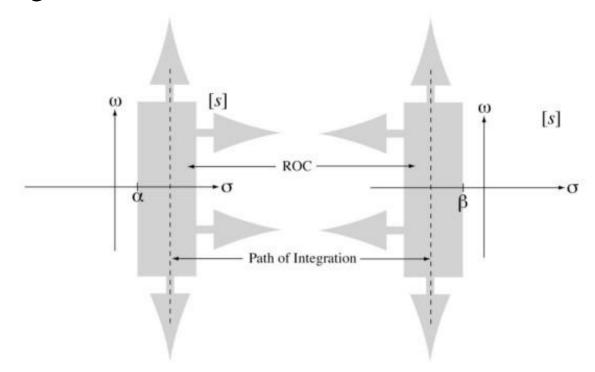


Left-Sided Exponential

 $x(t) = e_{bt} u(t_0 - t), b \hat{i}$ $X(s) = \overset{t_0}{\overset{t_0}{\overset{t_0}{\overset{t_0}{}}} e_{(b-s)t}e_{-jwt}dt$ If s < b the asymptotic behavior of $e_{(b-s)t}e_{-jwt}$ as $t \otimes -¥$ is to approach zero and the Laplace transform integral converges.



The two conditions s > a and s < b define the **region of convergence** (**ROC**) for the Laplace transform of right- and left-sided signals.



Any right-sided signal that grows no faster than an exponential in positive time and any left-sided signal that grows no faster than an exponential in negative time has a Laplace transform. If $x(t) = x_r(t) + x_l(t)$ where $x_r(t)$ is the right-sided part and $x_{l}(t)$ is the left-sided part and $ifx_{r}(t) < |K_{r}e_{at}|$ and $x_{l}(t) < K_{l}e_{bt}$ and a and b are as small as possible, then the Laplace-transform integral converges and the Laplace transform exists for a < s < b. Therefore if a < b the ROC is the region a < b. If a > b, there is no ROC and the Laplace transform does not exist.

Laplace Transform Pairs

The Laplace transform of $g_1(t) = Ae_{at} u(t)$ is

 $G_1(s) = \overset{\stackrel{\stackrel{\scriptstyle}{\bullet}}{\overset{\scriptstyle}{\bullet}} A e_{at} u(t) e_{-st} dt = A \overset{\stackrel{\scriptstyle}{\bullet} e_{-(s-a)t} dt \qquad \overset{\scriptstyle}{\overset{\scriptstyle}{\bullet}} \overset{\scriptstyle}{\overset{\scriptstyle}{\bullet}} \overset{\scriptstyle}{\overset{\scriptstyle}{\bullet}} \overset{\scriptstyle}{\overset{\scriptstyle}{\bullet}} () t e_{-jwt} dt = A \underbrace{A}_{s-a}$ This function has a **pole** at s = a and the ROC is the region to the right of that point. The Laplace transform of $g_2(t) = Ae_{bt} u(-t)$ is $G_{2}(s) = \overset{\mathsf{Y}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}{{}}}{\overset{\mathsf{O}}{\overset{\mathsf{O}}}{\overset{\mathsf{O}}}}{\overset{$ This function has a pole at s = b and the ROC is the region to the left of that point.

Region of Convergence

The following two Laplace transform pairs illustrate the importance of the region of convergence.

$$e^{-\alpha t} \mathbf{u}(t) \xleftarrow{\mathsf{L}} \frac{1}{s+\alpha} , \ \sigma > -\alpha$$
$$-e^{-\alpha t} \mathbf{u}(-t) \xleftarrow{\mathsf{L}} \frac{1}{s+\alpha} , \ \sigma < -\alpha$$

The two time-domain functions are different but the algebraic expressions for their Laplace transforms are the same. Only the ROC's are different.

Region of Convergence

Some of the most common Laplace transform pairs (There is more extensive table in the book.)

$$\delta(t) \xleftarrow{ \sqcup} 1 , \text{ All } \sigma$$

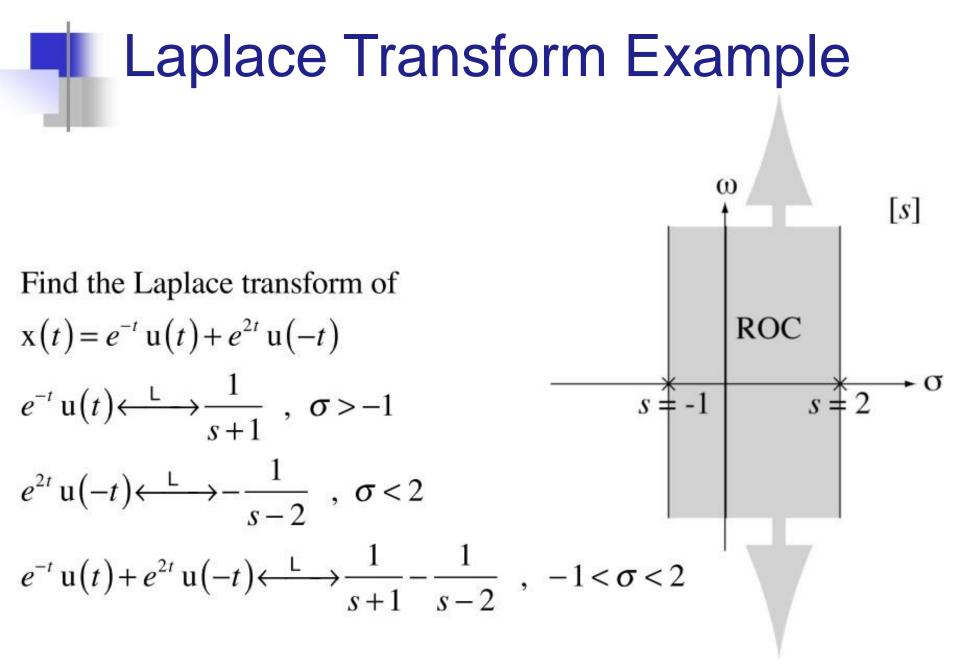
$$u(t) \xleftarrow{ \sqcup} 1/s , \sigma > 0 \qquad -u(-t) \xleftarrow{ \sqcup} 1/s , \sigma < 0$$

$$\operatorname{ramp}(t) = t u(t) \xleftarrow{ \sqcup} 1/s^{2} , \sigma > 0 \qquad \operatorname{ramp}(-t) = -t u(-t) \xleftarrow{ \sqcup} 1/s^{2} , \sigma < 0$$

$$e^{-\alpha t} u(t) \xleftarrow{ \sqcup} 1/(s+\alpha) , \sigma > -\alpha \qquad -e^{-\alpha t} u(-t) \xleftarrow{ \sqcup} 1/(s+\alpha) , \sigma < -\alpha$$

$$e^{-\alpha t} \sin(\omega_{0}t) u(t) \xleftarrow{ \sqcup} \frac{\omega_{0}}{(s+\alpha)^{2} + \omega_{0}^{2}} , \sigma > -\alpha \qquad -e^{-\alpha t} \sin(\omega_{0}t) u(-t) \xleftarrow{ \sqcup} \frac{\omega_{0}}{(s+\alpha)^{2} + \omega_{0}^{2}} , \sigma < -\alpha$$

$$e^{-\alpha t} \cos(\omega_{0}t) u(t) \xleftarrow{ \sqcup} \frac{s+\alpha}{(s+\alpha)^{2} + \omega_{0}^{2}} , \sigma > -\alpha \qquad -e^{-\alpha t} \cos(\omega_{0}t) u(-t) \xleftarrow{ \sqcup} \frac{s+\alpha}{(s+\alpha)^{2} + \omega_{0}^{2}} , \sigma < -\alpha$$



Laplace Transform Example

Find the inverse Laplace transform of

$$X(s) = \frac{4}{s+3} - \frac{10}{s-6}, -3 < s < 6$$

The ROC tells us that $\frac{4}{s+3}$ must inverse transform into a $\frac{10}{10}$

right-sided signal and that $\frac{1}{s-6}$ must inverse transform into a left-sided signal.

$$x(t) = 4e_{-3t} u(t) + 10e_{6t} u(-t)$$

Laplace Transform Example

Find the inverse Laplace transform of

$$X(s) = \frac{4}{s+3} - \frac{10}{s-6}$$
, s > 6

The ROC tells us that both terms must inverse transform into a right-sided signal.

$$x(t) = 4e_{-3t} u(t) - 10e_{6t} u(t)$$

Laplace Transform Example

Find the inverse Laplace transform of

$$X(s) = \frac{4}{s+3} - \frac{10}{s-6}$$
, s < -3

The ROC tells us that both terms must inverse transform into a left-sided signal.

$$x(t) = -4e_{-3t}u(-t) + 10e_{6t}u(-t)$$

MATLAB System Objects

A MATLAB system object is a special kind of variable in MATLAB that contains all the information about a system. It can be created with the tf command whose syntax is

sys = tf(num,den)

where num is a vector of numerator coefficients of powers of *s*, den is a vector of denominator coefficients of powers of *s*, both in descending order and Sys is the system object.

MATLAB System Objects

For example, the transfer function

$$H_1(s) = \frac{s^2 + 4}{s^5 + 4s^4 + 7s^3 + 15s^2 + 31s + 75}$$

can be created by the commands

H1 = tf(num, den);

»H1

Transfer function:

$$s^{2} + 4$$

s ^ 5 + 4 s ^ 4 + 7 s ^ 3 + 15 s ^ 2 + 31 s + 75

The inverse Laplace transform can always be found (in principle at least) by using the inversion integral. But that is rare in engineering practice. The most common type of Laplace-transform expression is a ratio of polynomials in s,

$$G(s) = \frac{b_M s^M + b_{M-1} s^{M-1} + \dots + b_1 s + b_0}{s^N + a_{N-1} s^{N-1} + \dots + a_1 s + a_0}$$

The denominator can be factored, putting it into the form,

$$G(s) = \frac{b_M s^M + b_{M-1} s^{M-1} + \dots + b_1 s + b_0}{(s - p_1)(s - p_2) \cdots (s - p_N)}$$

For now, assume that there are <u>no repeated poles</u> and that N > M, making the fraction **proper** in s. Then it is possible to write the expression in the **partial fraction** form,

$$G(s) = \frac{K_1}{s - p_1} + \frac{K_2}{s - p_2} + \dots + \frac{K_N}{s - p_N}$$

where

$$\frac{b_M s^M + b_{M-1} s^{M-1} + \dots + b_1 s + b_0}{(s - p_1)(s - p_2) \cdots (s - p_N)} = \frac{K_1}{s - p_1} + \frac{K_2}{s - p_2} + \dots + \frac{K_N}{s - p_N}$$

The *K*'s can be found be any convenient method.

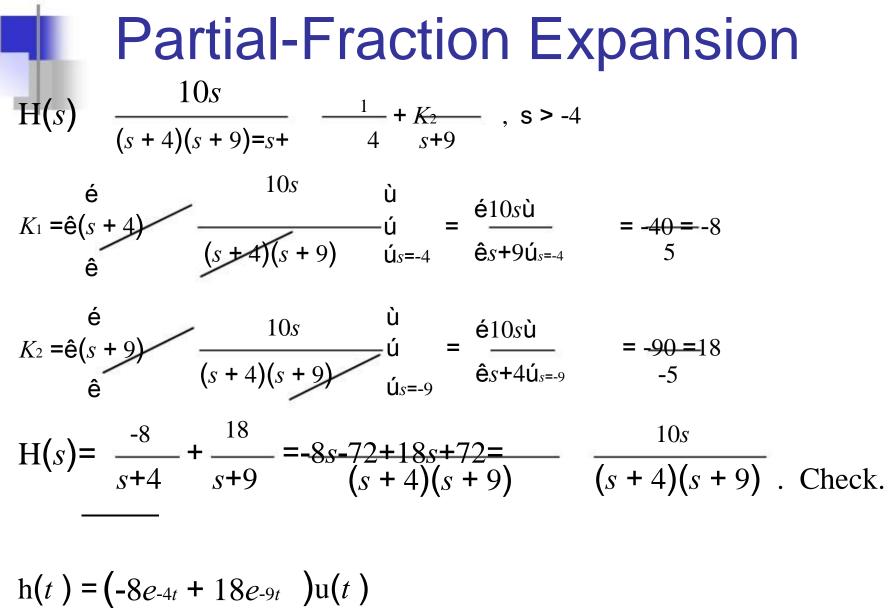
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Multiply both sides by $s - p_1$

$$(s - p_1) \frac{b_M s^M + b_{M-1} s^{M-1} + \dots + b_1 s + b_0}{(s - p_1)(s - p_2) \cdots (s - p_N)} = \begin{bmatrix} K_1 + (s - p_1) \frac{K_2}{s - p_2} + \dots \\ + (s - p_1) \frac{K_N}{s - p_N} \end{bmatrix}$$

$$K_1 = \frac{b_M p_1^M + b_M p_1^{M-1} + \dots + b_1 p_1 + b_0}{(p_1 - p_2) \cdots (p_1 - p_N)}$$

All the *K*'s can be found by the same method and the inverse Laplace transform is then found by table look-up.



If the expression has a repeated pole of the form,

$$G(s) = \frac{b_M s^M + b_{M-1} s^{M-1} + \dots + b_1 s + b_0}{(s - p_1)^2 (s - p_3) \cdots (s - p_N)}$$

the partial fraction expansion is of the form,

$$G(s) = \frac{K_{12}}{(s-p_1)^2} + \frac{K_{11}}{s-p_1} + \frac{K_3}{s-p_3} + \dots + \frac{K_N}{s-p_N}$$

and K_{12} can be found using the same method as before. But K_{11} cannot be found using the same method.

Instead K_{11} can be found by using the more general formula

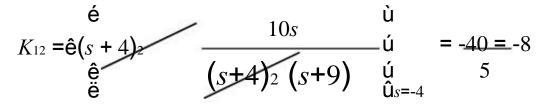
$$K_{qk} = \frac{1}{(m-k)!} \frac{d^{m-k}}{ds^{m-k}} \left[\left(s - p_q \right)^m H(s) \right]_{s \to p_q} , \quad k = 1, 2, \cdots, m$$

where *m* is the order of the *q*th pole, which applies to repeated poles of any order.

If the expression is not a proper fraction in *s* the partialfraction method will not work. But it is always possible to **synthetically divide** the numerator by the denominator until the remainder is a proper fraction and then apply partial-fraction expansion.

$$H(s) = \frac{10s}{(s+4)_2(s+9)} \frac{12}{(s+4)_2} + \frac{K_{11}}{s+4} + \frac{K_{22}}{s+9} , s > 4$$

Repeated Pole



Using

$$K_{qk} = \frac{1}{(m-k)!} \frac{d_{m-k}}{ds_{m-k}} \stackrel{\text{é}}{=} (s-p_q)_m H(s) \qquad \overset{\text{ù}}{u}_{s \otimes p_q}, k = 1, 2, \cdot, m$$
$$K_{11} = \frac{1}{(2-1)!} \frac{d_{2-1}}{ds_{2-1}} \stackrel{\text{é}}{=} (s+4)_2 H(s) \overset{\text{u}}{u}_{s \otimes -4} = d_{ds} \stackrel{\text{é}}{=} \frac{d_{ds}}{ds} \stackrel{\text{é}}{=} \frac{d_{ds}}{u_{s \otimes -4}} \stackrel{\text{e}}{=} d_{ds} \stackrel{\text{e}}{=} \frac{d_{ds}}{u_{s \otimes -4}}$$

$$\begin{aligned} & \stackrel{e}{=} \stackrel{e}{=} \stackrel{(s+9)10 - 10s\dot{u}}{(s+9)_2} \quad \stackrel{i}{=} \stackrel{=}{=} \stackrel{=}{=} \stackrel{18}{-5} \\ & K_2 = -18 - \frac{5}{-5} \quad PH(s) = \quad \frac{(s+84)_2 + 1}{-5} \quad \frac{8/5}{s+4} + \frac{-18/5}{s+9} - 4 \end{aligned}$$

$$H(s) = \frac{-8s - 72 + \frac{18}{5}(s_2 + 13s + 36) - 18}{(s + 4)_2(s + 9)}(s_2 + 8s + 16), s > -4$$

$$H(s) = \frac{10s}{(s+4)_2(s+9)}$$
, $s > -4$

$$h(t) = \overset{\text{@}}{\underset{\text{ς}}{\text{$-8te-4t$} + 18$}} - \underbrace{\begin{array}{c} & \text{$\ddot{0}$} \\ - & e-4t - 18e^{-9t} \\ 5 & 5 & \\ \hline & & \div u(t) \end{array}}$$

$$H(s) = \frac{10s^{2}}{(s+4)(s+9)}, s > -4 \neg \text{Improper in s}$$

$$H(s) = \frac{10s^{2}}{s_{2}+13s+36}, s > -4$$

$$Synthetic Division @ s_{2}+13s+36$$

$$10$$

$$10s_{2}$$

$$10s_{2}$$

$$10s_{2} + 130s + 360$$

$$-130s + 360$$

$$-130s - 360$$

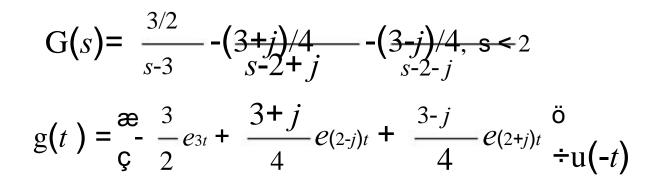
$$H(s) = 10 - \frac{130s + 360}{(s+4)(s+9) = 10} - \hat{e}_{s+4} \qquad \hat{e}_{-32} + \frac{162\dot{u}}{s+9\dot{u}}, s > -4$$

 $h(t) = 10d(t) - \acute{e}_{162e-9t} - 32e_{-4t} \dot{u}u(t) \hat{u}$

Inverse Laplace Transform Example

Method 1

$$G(s) = \frac{s}{(s-3)(s-2+j)}, \ s < 2$$
$$G(s) = \frac{(s-3)(s-2+j)(s-2-j)}{(s-2-j)}, \ s < 2$$



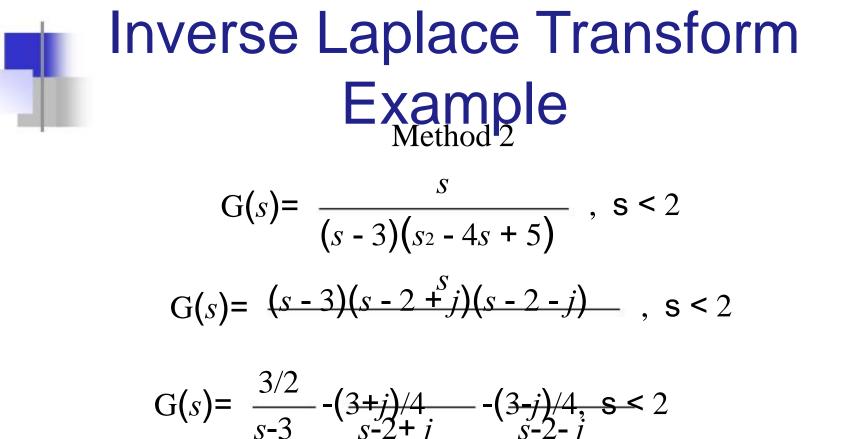
Inverse Laplace Transform Example

$$g(t) = \stackrel{\text{@}}{\underset{\text{ς}}{\text{$=$}}} \frac{3}{2}e_{3t} + \frac{3+j}{4}e_{(2-j)t} + \frac{3-j}{4}e_{(2+j)t} \stackrel{\text{"o}}{\underset{\text{\doteq}}{\text{$=$}}} u(-t)$$

This looks like a function of time that is complex-valued. But, with the use of some trigonometric identities it can be put into the form

$$g(t) = (3/2) \{ e_{2t} \ddot{e}_{cos}(t) + (1/3) \sin(t) \hat{u} - e_{3t} \} u(-t)$$

which has only real values.



 $G(s) = \frac{3/2}{s-3} - \frac{1}{4s_2} \frac{6s - 10}{-4s+5} = \frac{3/2}{s-3} - \frac{6}{4(s-2)_2 + 1}, \ s < 2$

Inverse Laplace Transform Example M ethod 2 $G(s) = \frac{3/2}{s-3} - \frac{6}{4(s-2)_2+1} , s < 2$

The denominator of the second term has the form of the Laplace transform of a damped cosine or damped sine but the numerator is not yet in the correct form. But by adding and subtracting the correct expression from that term and factoring we can put it into the form

$$G(s) = \frac{3/2}{s-3} - \frac{3\acute{e}}{2} \frac{s-2}{\ddot{e}(s-2)_2 + 1 + (s-2)_2 + 1} \frac{1/3}{\acute{u}} \quad \dot{u} \quad s < 2$$

Inverse Laplace Transform Example

M ethod 2

$$G(s) = \frac{3/2}{s-3} - \frac{3\acute{e}}{2} \frac{s-2}{\acute{e}} \frac{1/3}{(s-2)_2 + 1 + (s-2)_2 + 1} \frac{\acute{u}}{\acute{u}}, \ s < 2$$

This can now be directly inverse Laplace transformed into

$$g(t) = (3/2) \{ e_{2t} \ddot{e}_{\cos}(t) + (1/3) \sin(t) \hat{u} - e_{3t} \} u(-t)$$

which is the same as the previous result.

Inverse Laplace Transform Example

M ethod 3

When we have a pair of poles p_2 and p_3 that are complex conjugates

we can convert the form $G(s) = \frac{A}{s-3} + \frac{K_2}{s-p_2} + \frac{K_3}{s-p_3}$ into the form $G(s) = \frac{A}{s-3} + \frac{(K_2 + K_3) - K_3 p_2 - K_2 p_3}{s_2 - (p_1 + p_2) s + p_1 p_2} = A + \frac{Bs + C}{s-3s_2 - (p_1 + p_2) s + p_1 p_2}$

In this example we can find the constants A, B and C by realizing that

$$G(s) = \frac{s}{(s-3)(s_2-4s+5)} \quad \frac{-3}{s-3} + \frac{-3}{s_2-4s+5} \quad , \ s < 2$$

is not just an equation, it is an **identity**. That means it must be an equality for any value of *s*.

Inverse Laplace Transform Example Method 3

A can be found as before to be 3/2. Letting s = 0, the

identity becomes 0 ° $-3/2_3 + C_5$ and C = 5/2. Then, letting s = 1, and solving we get B = -3/2. Now

$$G(s) = \frac{3/2}{s-3} + (-3/2)s + 5/2 + 5 , s < 2$$

or

$$G(s) = \frac{3/2}{s-3} - \frac{3}{2s_2} \frac{s-5/3}{-4s+5} , s < 2$$

This is the same as a result in Method 2 and the rest of the solution is also the same. The advantage of this method is that all the numbers are real.

Use of MATLAB in Partial Fraction Expansion

MATLAB has a function residue that can be very helpful in partial fraction expansion. Its syntax is [r,p,k] = residue(b,a) where b is a vector of coefficients of descending powers of s in the numerator of the expression and a is a vector of coefficients of descending powers of s in the denominator of the expression, r is a vector of residues, p is a vector of finite pole locations and k is a vector of so-called direct terms which result when the degree of the numerator is equal to or greater than the degree of the denominator. For our purposes, residues are simply the numerators in the partial-fraction expansion.

Let g(t) and h(t) form the transform pairs, $g(t) \xleftarrow{\ } G(s)$ and $h(t) \xleftarrow{\ } H(s)$ with ROC's, ROC_G and ROC_H respectively.

Linearity $\alpha g(t) + \beta h(t) \xleftarrow{\ } \alpha G(s) + \beta H(s)$ ROC $\supseteq \operatorname{ROC}_{G} \cap \operatorname{ROC}_{H}$ Time Shifting $g(t-t_{0}) \xleftarrow{\ } G(s)e^{-st_{0}}$ ROC = ROC_G *s*-Domain Shift $e^{s_{0}t} g(t) \xleftarrow{\ } G(s-s_{0})$ ROC = ROC_G shifted by s_{0} , (*s* is in ROC if $s - s_{0}$ is in ROC_G)

Time Scaling

Time Differentiation

 $g(at) \leftarrow (1/|a|) G(s/a)$ $ROC = ROC_G$ scaled by a (s is in ROC if s / a is in ROC₆) $\frac{d}{dt}g(t) \xleftarrow{} g(s)$ $ROC \supseteq ROC_G$ $-tg(t) \xleftarrow{\ } \frac{d}{ds}G(s)$ $ROC = ROC_{c}$

s-Domain Differentiation

Convolution in Time

Time Integration

$$g(t) * h(t) \xleftarrow{ } G(s)H(s)$$

ROC \supseteq ROC_G \cap ROC_H
$$\int_{-\infty}^{t} g(\tau) d\tau \xleftarrow{ } G(s) / s$$

ROC \supseteq ROC_G $\cap (\sigma > 0)$

If g(t) = 0, t < 0 and there are no impulses or higher-order singularities at t = 0 then

Initial Value Theorem:
$$g(0^+) = \lim_{s \to \infty} sG(s)$$
Final Value Theorem: $\lim_{t \to \infty} g(t) = \lim_{s \to 0} sG(s)$ if $\lim_{t \to \infty} g(t)$ exists

Final Value Theorem $\lim_{t\to\infty} (t) = \lim_{s\to 0} s G(s)$ This theorem only applies if the limit $\lim_{t \to \infty} g(t)$ actually exists. It is possible for the limit $\lim sG(s)$ to exist even though the limit $\lim g(t)$ does not exist. For example $t \rightarrow \infty$ $\mathbf{x}(t) = \cos(\omega_0 t) \xleftarrow{\ } \mathbf{X}(s) = \frac{s}{s^2 + \omega_0^2}$ $\lim_{s \to 0} s X(s) = \lim_{s \to 0} \frac{s^2}{s^2 + \omega_s^2} = 0$ but $\lim_{t\to\infty}\cos(\omega_0 t)$ does not exist.

Final Value Theorem

The final value theorem applies to a function G (*s*) if all the poles of sG(s) lie in the open left half of the *s* plane. Be sure to notice that this does not say that all the poles of G (*s*) must lie in the open left half of the *s* plane. G (*s*) could have a single pole at *s* = 0 and the final value theorem would still apply.

Use of Laplace Transform Properties

Find the Laplace transforms of x(t) = u(t) - u(t-a) and x(2t) = u(2t) - u(2t-a). From the table $u(t) \xleftarrow{\ } 1/s, \sigma > 0$. Then, using the time-shifting property $u(t-a) \xleftarrow{\ } e^{-as} / s, \sigma > 0$. Using the linearity property $u(t) - u(t-a) \xleftarrow{\ } (1-e^{-as}) / s, \sigma > 0$. Using the time-scaling property

$$\mathbf{u}(2t) - \mathbf{u}(2t-a) \xleftarrow{\mathsf{L}} \frac{1}{2} \left[\frac{1-e^{-as}}{s} \right]_{s \to s/2} = \frac{1-e^{-as/2}}{s}, \, \sigma > 0$$

Use of Laplace Transform Properties

Use the *s*-domain differentiation property and $u(t) \leftarrow \frac{L}{1/s}, \sigma > 0$

to find the inverse Laplace transform of $1/s^2$. The s-domain

differentiation property is
$$-tg(t) \xleftarrow{\ } \frac{d}{ds}(G(s))$$
. Then

$$-t \operatorname{u}(t) \xleftarrow{ \mathsf{L}} \frac{d}{ds} \left(\frac{1}{s}\right) = -\frac{1}{s^2}.$$
 Then using the linearity property
$$t \operatorname{u}(t) \xleftarrow{ \mathsf{L}} \frac{1}{s^2}.$$

In most practical signal and system analysis using the Laplace transform a modified form of the transform, called the **unilateral Laplace transform**, is used. The unilateral Laplace transform is defined by $G(s) = \dot{O}_{0}^{*} g(t) e_{-st} dt$. The only difference between this version and the previous definition is the change of the lower integration limit from - 4 to 0. With this definition, all the Laplace transforms of causal functions are the same as before with the same ROC, the region of the *s* plane to the right of all the finite poles.

The unilateral Laplace transform integral excludes negative time. If a function has non-zero behavior in negative time its unilateral and bilateral transforms will be different. Also functions with the same positive time behavior but different negative time behavior will have the same unilateral Laplace transform. Therefore, to avoid ambiguity and confusion, the unilateral Laplace transform should only be used in analysis of causal signals and systems. This is a limitation but in most practical analysis this limitation is not significant and the unilateral Laplace transform actually has advantages.

The main advantage of the unilateral Laplace transform is that the ROC is simpler than for the bilateral Laplace transform and, in most practical analysis, involved consideration of the ROC is unnecessary. The inverse Laplace transform is unchanged. It is

$$g(t) = \frac{1}{j^2 p_{s-j}} \overset{s+j}{\to} G(s) e_{+st} ds$$

Some of the properties of the unilateral Laplace transform are different from the bilateral Laplace transform.

Time-Shifting

Time Scaling

First Time Derivative

Nth Time Derivative

Time Integration

$$g(t-t_{0}) \xleftarrow{\mathsf{L}} G(s)e^{-st_{0}}, t_{0} > 0$$

$$g(at) \xleftarrow{\mathsf{L}} (1/|a|)G(s/a), a > 0$$

$$\frac{d}{dt}g(t) \xleftarrow{\mathsf{L}} sG(s) - g(0^{-})$$

$$\frac{d^{N}}{dt^{N}}(g(t)) \xleftarrow{\mathsf{L}} s^{N}G(s) - \sum_{n=1}^{N} s^{N-n} \left[\frac{d^{n-1}}{dt^{n-1}}(g(t))\right]_{t=0^{-}}$$

$$\int_{0^{-}}^{t} g(\tau)d\tau \xleftarrow{\mathsf{L}} G(s)/s$$

The time shifting property applies only for shifts to the right because a shift to the left could cause a signal to become non-causal. For the same reason scaling in time must only be done with positive scaling coefficients so that time is not reversed producing an anti-causal function. The derivative property must now take into account the initial value of the function at time t = 0 and the integral property applies only to functional behavior after time t = 0. Since the unilateral and bilateral Laplace transforms are the same for causal functions, the bilateral table of transform pairs can be used for causal functions.

The Laplace transform was developed for the solution of differential equations and the unilateral form is especially well suited for solving differential equations with initial conditions. For example,

$$\frac{d^2}{dt_2}\ddot{\operatorname{ex}}(t)\hat{\operatorname{u}} + 7\frac{d}{dt}\ddot{\operatorname{ex}}(t)\hat{\operatorname{u}} + 12\operatorname{x}(t)=0$$

with initial conditions $\mathbf{x}(0) = 2$ and $\frac{d}{dt}(\mathbf{x}(t))_{t=0} = -4$.

Laplace transforming both sides of the equation, using the new derivative property for unilateral Laplace transforms,

$$s_2 X(s) - s_1(0) - \frac{d}{dt} (x(t))_{t=0} + 7_{\ddot{e}}$$
 $\dot{u}_{t+1} = 0$



Solving for X(s)

 $X(s) = \frac{s x(0^{-}) + 7 x(0^{-}) + \frac{d}{dt}(x(t))_{t=0^{-}}}{s^{2} + 7s + 12}$ or $X(s) = \frac{2s + 10}{s^{2} + 7s + 12} = \frac{4}{s+3} - \frac{2}{s+4}$. The inverse transform yields $x(t) = (4e^{-3t} - 2e^{-4t})u(t)$. This solution solves the differential equation with the given initial conditions.

If the transfer function of a stable system is H(s), the frequency response is $H(j\omega)$. The most common type of transfer function is of the form,

$$H(s) = A \frac{(s-z_1)(s-z_2)\cdots(s-z_M)}{(s-p_1)(s-p_2)\cdots(s-p_N)}$$

Therefore $H(j\omega)$ is

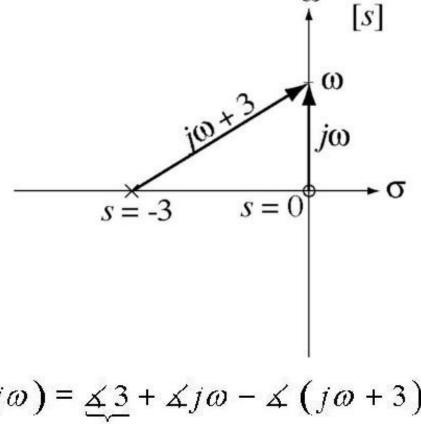
$$H(j\omega) = A \frac{(j\omega - z_1)(j\omega - z_2)\cdots(j\omega - z_M)}{(j\omega - p_1)(j\omega - p_2)\cdots(j\omega - p_N)}$$

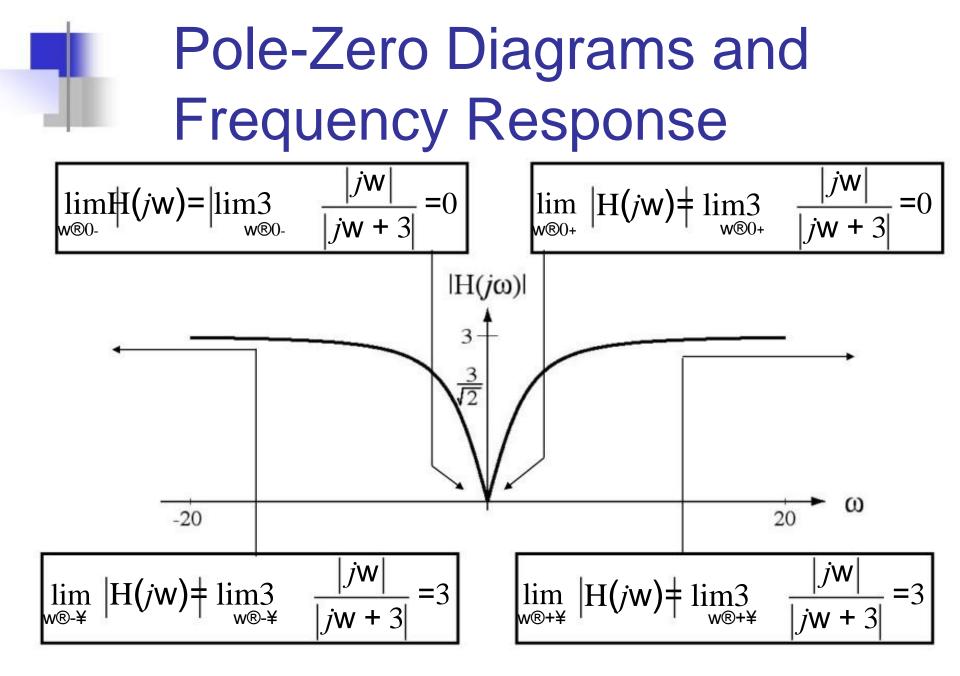


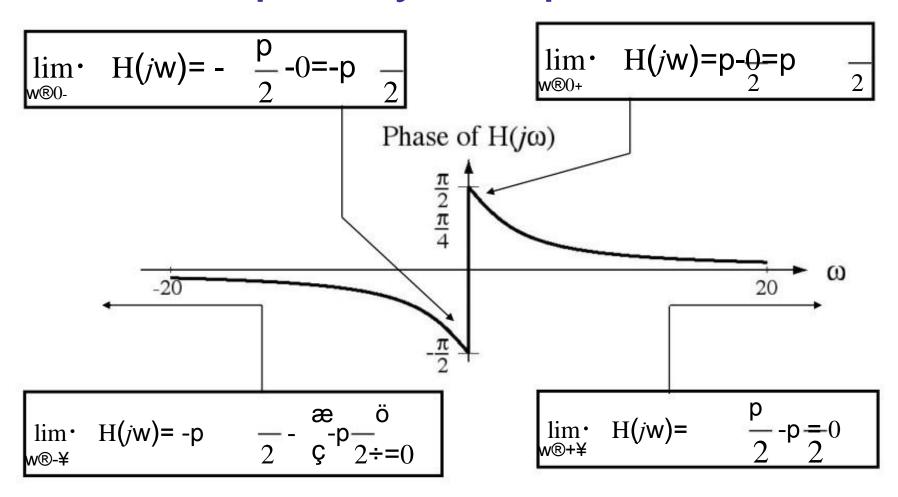
Let H(s) =
$$\frac{3s}{s+3}$$
.
H(j ω) = $3\frac{j\omega}{j\omega+3}$

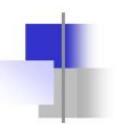
The numerator $j\omega$ and the denominator $j\omega + 3$ can be conceived as vectors in the *s* plane.

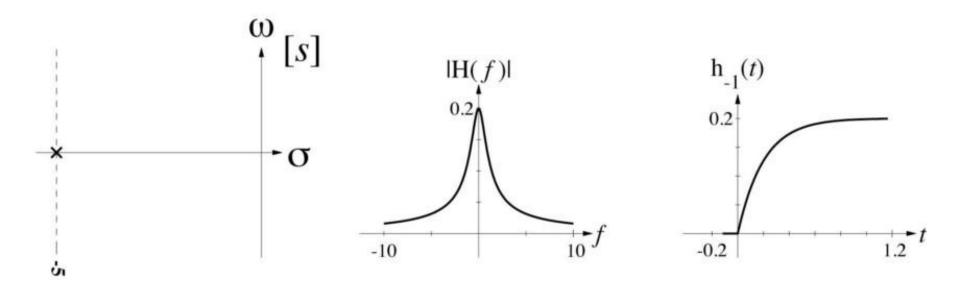
$$\left| H(j\omega) \right| = 3 \frac{|j\omega|}{|j\omega+3|} \qquad \measuredangle H(j\omega) = \cancel{43} + \cancel{4}j\omega - \cancel{4}(j\omega+3)$$

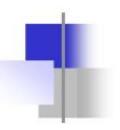


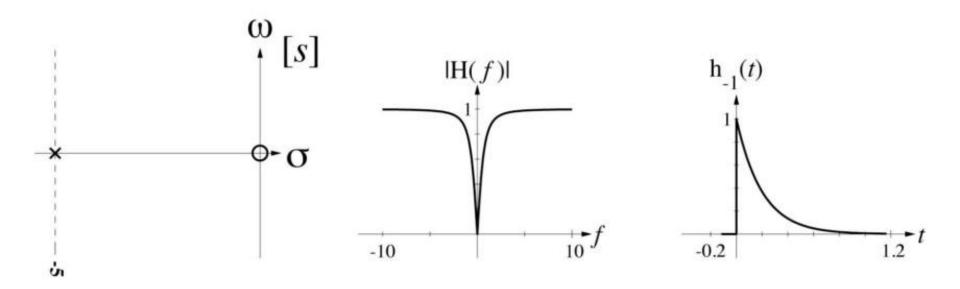


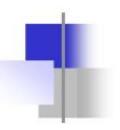


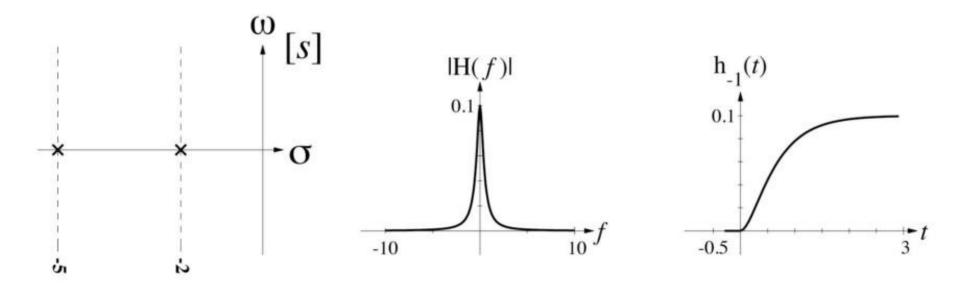


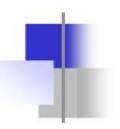


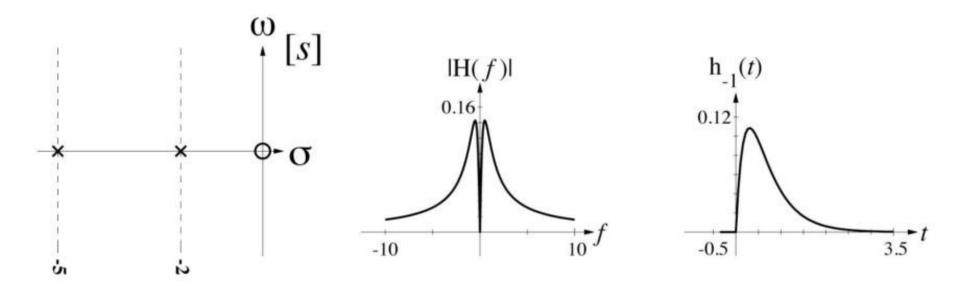


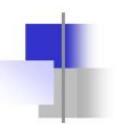


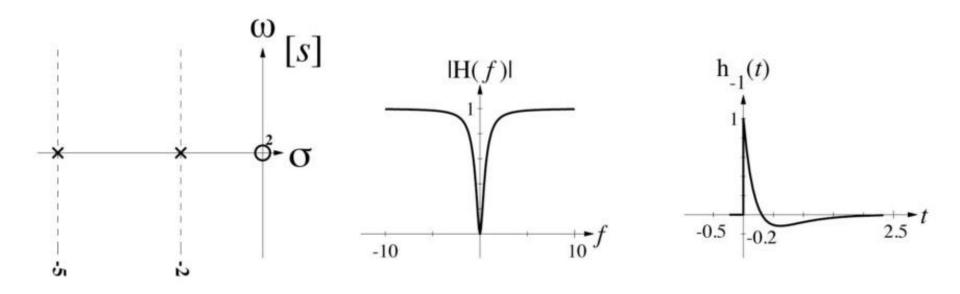


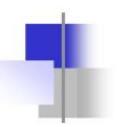


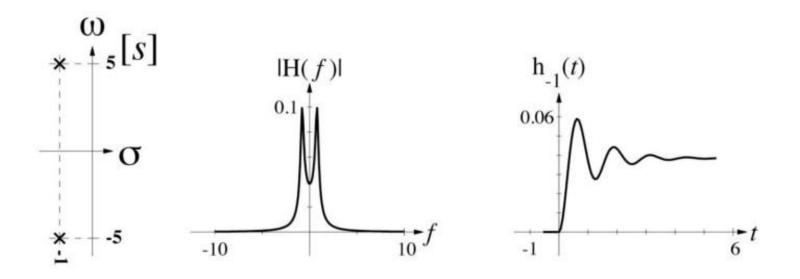


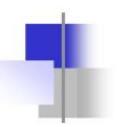


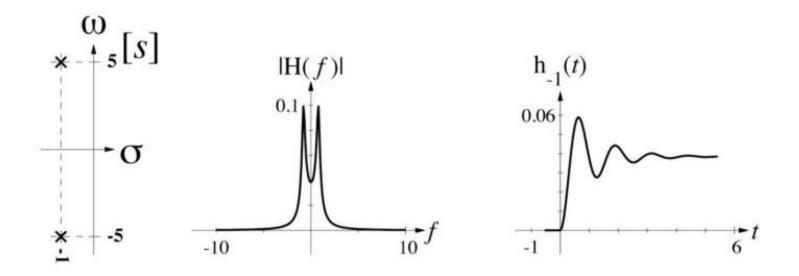


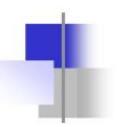


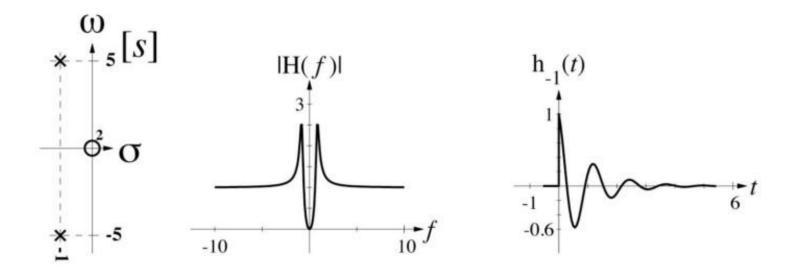












The *z* Transform

Generalizing the DTFT

The forward DTFT is defined by $X(e_{jW}) = \overset{\sharp}{a}_{n=-\frac{1}{2}} x[n]e_{-jWn}$ in which

W is discrete-time radian frequency, a real variable. The quantity e_{jWn} is then a complex sinusoid whose magnitude is always one and whose phase can range over all angles. It always lies on the unit circle in the complex plane. If we now replace e_{jW} with a variable *z* that can

have any complex value we define the *z* transform $X(z) = \overset{\sharp}{\underset{n=-1}{a}} x[n]_{z-n}$

The DTFT expresses signals as linear combinations of complex sinusoids. The z transform expresses signals as linear combinations of complex exponentials.

Complex Exponential Excitation

Let the excitation of a discrete-time LTI system be a complex exponential of the form Az^n where z is, in general, complex and A is any constant. Using convolution, the response y[n] of an LTI system with impulse response h[n] to a complex exponential excitation x[n] is

$$\mathbf{y}[n] = \mathbf{h}[n] * Az^{n} = A \sum_{m=-\infty}^{\infty} \mathbf{h}[m] z^{n-m} = \underbrace{Az^{n}}_{=\mathbf{x}[n]} \sum_{m=-\infty}^{\infty} \mathbf{h}[m] z^{-m}$$

The response is the product of the excitation and the z transform of

$$h[n]$$
 defined by $H(z) = \sum_{m=-\infty}^{\infty} h[n] z^{-n}$.

The Transfer Function

If an LTI system with impulse response h[n] is excited by a signal, x[n], the *z* transform Y(z) of the response y[n] is

$$Y(z) = \sum_{n=-\infty}^{\infty} y[n] z^{-n} = \sum_{m=-\infty}^{\infty} (h[n] * x[n]) z^{-n} = \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} h[m] x[n-m] z^{-n}$$
$$Y(z) = \sum_{m=-\infty}^{\infty} h[m] \sum_{m=-\infty}^{\infty} x[n-m] z^{-n}$$

Let q = n - m. Then

$$Y(z) = \sum_{m=-\infty}^{\infty} h[m] \sum_{q=-\infty}^{\infty} x[q] z^{-(q+m)} = \sum_{\substack{m=-\infty\\ =H(z)}}^{\infty} h[m] z^{-m} \sum_{\substack{q=-\infty\\ =X(z)}}^{\infty} x[q] z^{-q}$$
$$Y(z) = H(z) X(z)$$

H(z) is the transfer function.

Systems Described by Difference Equations

The most common description of a discrete-time system is a difference equation of the general form

$$\sum_{k=0}^{N} a_{k} y[n-k] = \sum_{k=0}^{M} b_{k} x[n-k].$$

It was shown in Chapter 5 that the transfer function for a system of this type is

$$H(z) = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=0}^{N} a_k z^{-k}} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_M z^{-M}}{a_0 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_N z^{-N}}$$

or

$$H(z) = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=0}^{N} a_k z^{-k}} = z^{N-M} \frac{b_0 z^M + b_1 z^{M-1} + \dots + b_{M-1} z + b_M}{a_0 z^N + a_1 z^{N-1} + \dots + a_{N-1} z + a_N}$$

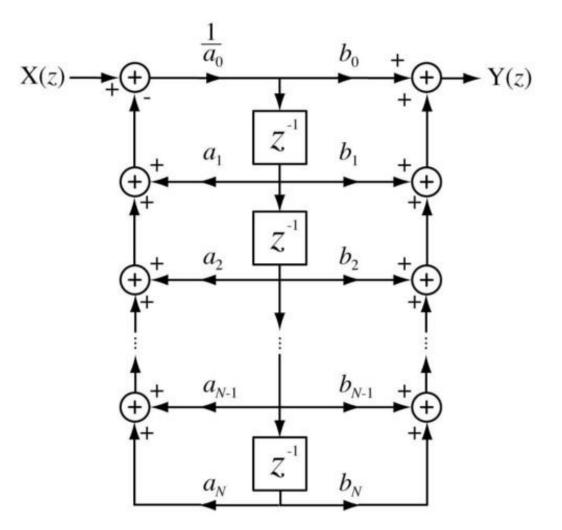
Direct Form II Realization

Direct Form II realization of a discrete-time system is similar in form to Direct Form II realization of continuous-time systems

A continuous-time system can be realized with integrators, summing junctions and multipliers

A discrete-time system can be realized with delays, summing junctions and multipliers

Direct Form II Realization



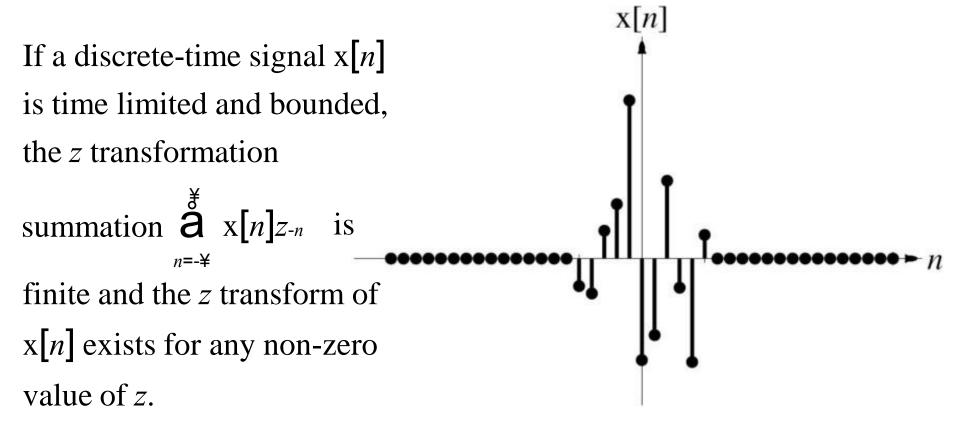
The Inverse z Transform

The inversion integral is

$$\mathbf{x}[n] = \frac{1}{j2\pi} \oint_{\mathbf{C}} \mathbf{X}(z) z^{n-1} dz.$$

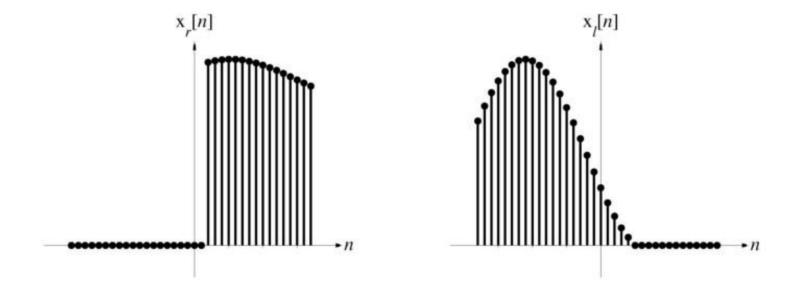
This is a contour integral in the complex plane and is beyond the scope of this course. The notation $x[n] \xleftarrow{z} X(z)$ indicates that x[n] and X(z) form a "z-transform pair".

Time Limited Signals

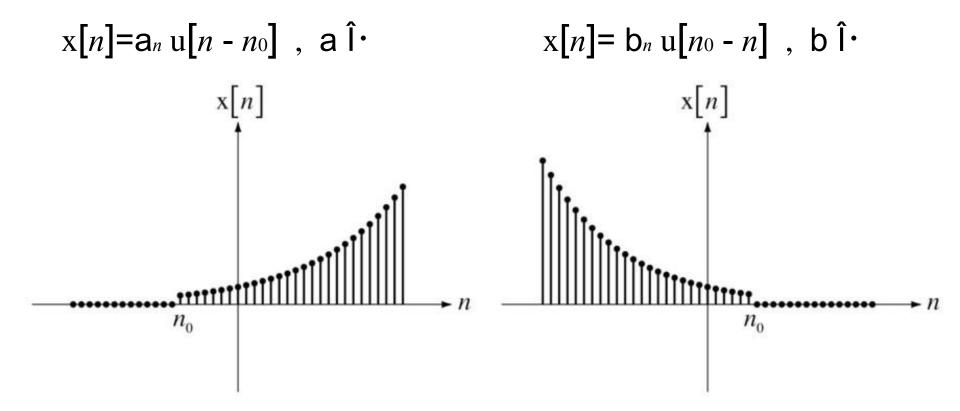


Right- and Left-Sided Signals

A right-sided signal $x_r[n]$ is one for which $x_r[n] = 0$ for any $n < n_0$ and a left-sided signal $x_l[n]$ is one for which $x_l[n] = 0$ for any $n > n_0$.



Right- and Left-Sided Exponentials



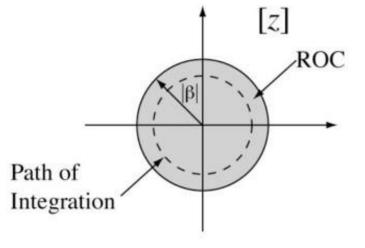
The *z* transform of $x[n] = a_n u[n - n_0]$, a \hat{l} . is $X(z) = a_{a_n}^* u[n - n_0] z_{-n} = a(a_{z_{-1}}^*)$ n=-¥n=n0if the series converges and it converges if $z \ge a$. The path of integration of [z]the inverse z transform must lie in the ROC region of the z plane outside a circle of Path of radiusa Integration

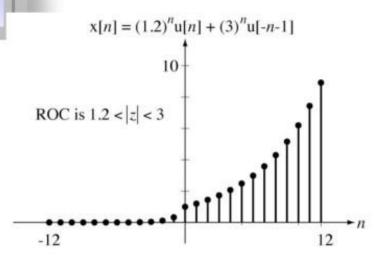
The *z* transform of $x[n] = b_n u[n_0 - n]$, bî is

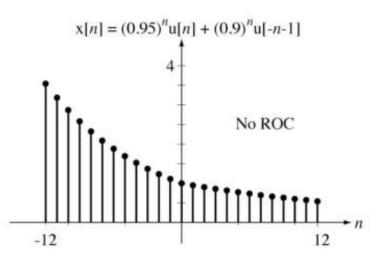
$$X(z) = \overset{n_0}{a} \overset{n_0}{b_{nZ-n}} = \overset{n_0}{a} (b_{Z-1})^n = \overset{*}{\underset{n=-n_0}{a}} (b_{-1Z})^n$$

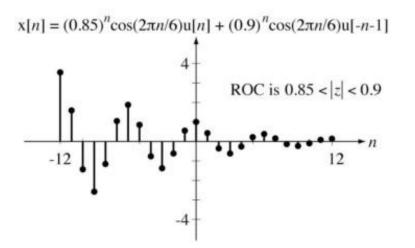
if the series converges and it converges if $|z| < |b|$. The path

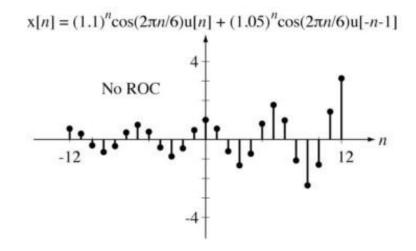
of integration of the inverse *z* transform must lie in the region of the *z* plane inside a circle of radius |b|











Some Common z Transform P_{All_z}

 $u[n] \xleftarrow{z}{\longrightarrow} \frac{z}{z-1} = \frac{1}{1-z^{-1}}, |z| > 1$, $-\mathbf{u}[-n-1] \xleftarrow{z}{z-1}, |z| < 1$ $\alpha^{n} \mathbf{u}[n] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}} , |z| > |\alpha| , \qquad -\alpha^{n} \mathbf{u}[-n-1] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}} , |z| < |\alpha|$ $n\mathbf{u}[n] \xleftarrow{z}{(z-1)^2} = \frac{z^{-1}}{(1-z^{-1})^2} , \ |z| > 1 \qquad , \qquad \qquad -n\mathbf{u}[-n-1] \xleftarrow{z}{(z-1)^2} = \frac{z^{-1}}{(1-z^{-1})^2} , \ |z| < 1$ $n\alpha^{n} \mathbf{u}[n] \xleftarrow{z}{(z-\alpha)^{2}} = \frac{\alpha z^{-1}}{(1-\alpha z^{-1})^{2}} , \quad |z| > |\alpha| , \qquad -n\alpha^{n} \mathbf{u}[-n-1] \xleftarrow{z}{(z-\alpha)^{2}} = \frac{\alpha z^{-1}}{(1-\alpha z^{-1})^{2}} , \quad |z| < |\alpha|$ $\sin(\Omega_0 n)\mathbf{u}[n] \xleftarrow{z}{\longrightarrow} \frac{z\sin(\Omega_0)}{z^2 - 2z\cos(\Omega_0) + 1} , |z| > 1 , -\sin(\Omega_0 n)\mathbf{u}[-n-1] \xleftarrow{z}{\longrightarrow} \frac{z\sin(\Omega_0)}{z^2 - 2z\cos(\Omega_0) + 1} , |z| < 1$ $\cos(\Omega_0 n) \mathbf{u}[n] \xleftarrow{z}{z^2 - 2z\cos(\Omega_0)} \mathbf{u}[n] \xleftarrow{z}{z^2 - 2z\cos(\Omega_0)} \mathbf{u}[n] \mathbf$ $\alpha^{n}\sin(\Omega_{0}n)\mathbf{u}[n] \xleftarrow{z}{z} \frac{z\alpha\sin(\Omega_{0})}{z^{2}-2\alpha z\cos(\Omega_{0})+\alpha^{2}} , |z| > |\alpha| , -\alpha^{n}\sin(\Omega_{0}n)\mathbf{u}[-n-1] \xleftarrow{z}{z} \frac{z\alpha\sin(\Omega_{0})}{z^{2}-2\alpha z\cos(\Omega_{0})+\alpha^{2}} , |z| < |\alpha|$ $\alpha^{n}\cos(\Omega_{0}n)\mathbf{u}[n] \xleftarrow{z}{z^{2}-2\alpha z} \cos(\Omega_{0}) \downarrow \qquad (|z| > |\alpha| \quad , \quad -\alpha^{n}\cos(\Omega_{0}n)\mathbf{u}[-n-1] \xleftarrow{z}{z^{2}-2\alpha z} \cos(\Omega_{0}) \downarrow = \alpha^{2} \quad , \quad |z| < |\alpha|$ $\alpha^{|\alpha|} \xleftarrow{z} \frac{z}{z-\alpha} - \frac{z}{z-\alpha^{-1}}$, $|\alpha| < |z| < |\alpha^{-1}|$

$$u[n-n_0] - u[n-n_1] \xleftarrow{z}{z-1} (z^{-n_0} - z^{-n_1}) = \frac{z^{n_1-n_0-1} + z^{n_1-n_0-2} + \dots + z+1}{z^{n_1-1}} , |z| > 0$$

Given the z-transform pairs $g[n] \xleftarrow{z} G(z)$ and $h[n] \xleftarrow{z} H(z)$ with ROC's of ROC_G and ROC_H respectively the following properties apply to the *z* transform.

Linearity	$\alpha g[n] + \beta h[n] \xleftarrow{z}{\longrightarrow} \alpha G(z) + \beta H(z)$ ROC = ROC _G \cap ROC _H
Time Shifting	$g[n - n_0] \xleftarrow{Z} z^{-n_0} G(z)$ ROC = ROC _G except perhaps $z = 0$ or $z \to \infty$
Change of Scale in z	$\alpha^{n} g[n] \xleftarrow{Z} G(z / \alpha)$ ROC = $ \alpha ROC_{G}$

Time Reversal

Time Expansion

 $g[-n] \xleftarrow{Z} G(z^{-1})$ $ROC = 1/ROC_{G}$ $\begin{cases} g[n/k] , n/k \text{ and integer} \\ 0 , \text{ otherwise} \end{cases} \xleftarrow{Z} G(z^{k})$ $ROC = (ROC_{G})^{1/k}$

Conjugation

$$g^*[n] \xleftarrow{Z} G^*(z^*)$$

ROC = ROC_G

z-Domain Differentiation $-ng[n] \xleftarrow{z} z \frac{d}{dz} G(z)$ ROC = ROC_G

Convolution

$$g[n] * h[n] \xleftarrow{z} H(z)G(z)$$

First Backward Difference

$$g[n] - g[n-1] \xleftarrow{Z} (1-z^{-1})G(z)$$

ROC \supseteq ROC_G $\cap |z| > 0$

Accumulation

$$\sum_{m=-\infty}^{n} g[m] \xleftarrow{z}{z-1} G(z)$$

ROC \supseteq ROC_G $\cap |z| > 1$

Initial Value Theorem

Final Value Theorem

If g[n]=0, n < 0 then $g[0] = \lim_{z \to \infty} G(z)$ If g[n]=0, n < 0, $\lim_{n \to \infty} g[n] = \lim_{z \to 1} (z-1)G(z)$ if $\lim_{n \to \infty} g[n]$ exists.

For the final-value theorem to apply to a function G(z) all the finite poles of the function (z - 1)G(z) must lie in the open interior of the unit circle of the *z* plane. Notice this does not say that all the poles of G(z) must lie in the open interior of the unit circle. G(z) could have a single pole at z = 1 and the final-value theorem could still apply.

The Inverse z Transform

Synthetic Division

For rational z transforms of the form

$$H(z) = \frac{b_{MZM} + b_{M-1ZM-1} + \cdot + b_{1Z} + b_{0}}{a_{NZN} + a_{N-1ZN-1} + \cdot + a_{1Z} + a_{0}}$$

we can always find the inverse *z* transform by synthetic division. For example,

$$H(z) = \frac{(z-1.2)(z+0.7)(z+0.4)}{(z-0.2)(z-0.8)(z+0.5)} , |z| \ge 0.8$$
$$H(z) = \frac{z_3 - 0.1z_2 - 1.04z - 0.336}{z_3 - 0.5z_2 - 0.34z + 0.08} , |z| \ge 0.8$$



Synthetic Division

$$\frac{1+0.4z^{-1}+0.5z^{-2}\cdots}{z^3-0.5z^2-0.34z+0.08)z^3-0.1z^2-1.04z-0.336}$$

$$\frac{z^3-0.5z^2-0.34z+0.08}{0.4z^2-0.7z-0.256}$$

$$\frac{0.4z^2-0.2z-0.136-0.032z^{-1}}{0.5z-0.12+0.032z^{-1}}$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

The inverse z transform is

$$\delta[n] + 0.4\delta[n-1] + 0.5\delta[n-2] \cdots \xleftarrow{z} 1 + 0.4z^{-1} + 0.5z^{-2} \cdots$$



Synthetic Division

We could have done the synthetic division this way.

$$\begin{array}{r} -4.2 - 30.85z - 158.613z^{2} \cdots \\ 0.08 - 0.34z - 0.5z^{2} + z^{3} \\ \hline -0.336 - 1.04z - 0.1z^{2} + z^{3} \\ \underline{-0.336 + 1.428z + 2.1z^{2} - 4.2z^{3}} \\ -2.468z - 2.2z^{2} + 5.2z^{3} \\ \underline{-2.468z + 10.489z^{2} + 15.425z^{3} - 30.85z^{4}} \\ \underline{-12.689z^{2} - 10.225z^{3} + 30.85z^{4}} \\ \vdots & \vdots & \vdots \\ -4.2\delta[n] - 30.85\delta[n+1] - 158.613\delta[n+2] \cdots \underbrace{z}{} - 4.2 - 30.85z - 158.613z^{2} \cdots \\ \text{but with the restriction } |z| > 0.8 \text{ this second form does not converge and is} \end{array}$$

therefore not the inverse z transform.



The Inverse z Transform

Synthetic Division

We can always find the inverse *z* transform of a rational function with synthetic division but the result is not in closed form. In most practical cases a closed-form solution is preferred.

Partial Fraction Expansion

Partial-fraction expansion works for inverse z transforms the same way it does for inverse Laplace transforms. But there is a situation that is quite common in inverse z transforms which deserves mention. It is very common to have z-domain functions in which the number of finite zeros equals the number of finite poles (making the expression improper in z) with at least one zero at z = 0.

$$H(z) = \frac{z^{N-M}(z-z_1)(z-z_2)\cdots(z-z_M)}{(z-p_1)(z-p_2)\cdots(z-p_N)}$$

Partial Fraction Expansion

Dividing both sides by z we get

$$\frac{\mathrm{H}(z)}{z} = \frac{z^{N-M-1}(z-z_1)(z-z_2)\cdots(z-z_M)}{(z-p_1)(z-p_2)\cdots(z-p_N)}$$

and the fraction on the right is now proper in z and can be expanded in partial fractions.

$$\frac{\mathrm{H}(z)}{z} = \frac{K_1}{z - p_1} + \frac{K_2}{z - p_2} + \dots + \frac{K_N}{z - p_N}$$

Then both sides can be multiplied by z and the inverse transform can be found.

$$H(z) = \frac{zK_1}{z - p_1} + \frac{zK_2}{z - p_2} + \dots + \frac{zK_N}{z - p_N}$$
$$h[n] = K_1 p_1^n u[n] + K_2 p_2^n u[n] + \dots + K_N p_N^n u[n]$$

An LTI system has a transfer function

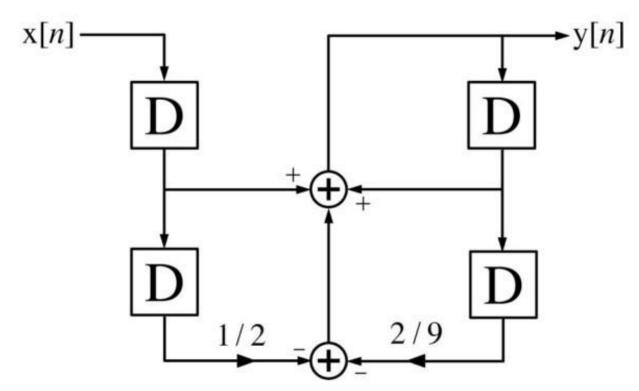
$$H(z) = \frac{Y(z)}{X(z)} \frac{-1/2}{z_2 z - z + 2/9} , |z| \ge 2/3$$

Using the time-shifting property of the *z* transform draw a block diagram realization of the system.

 $Y(z)(z_2 - z + 2 / 9) = X(z)(z - 1 / 2)$ $z_2 Y(z) = z X(z) - (1 / 2)X(z) + zY(z) - (2 / 9)Y(z)$ $Y(z) = z_{-1} X(z) - (1 / 2)z_{-2} X(z) + z_{-1}Y(z) - (2 / 9)z_{-2} Y(z)$

 $Y(z) = z_{-1} X(z) - (1/2) z_{-2} X(z) + z_{-1} Y(z) - (2/9) z_{-2} Y(z)$ Using the time-shifting property

y[n] = x[n-1] - (1/2)x[n-2] + y[n-1] - (2/9)y[n-2]

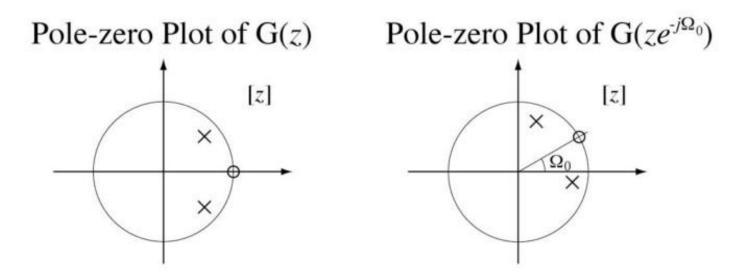


z-Transform PropertiesLet $g[n] \xleftarrow{z} G(z) = \frac{z-1}{(z-0.8e^{-j\pi/4})(z-0.8e^{+j\pi/4})}$. Draw a

pole-zero diagram for G(z) and for the *z* transform of $e^{j\pi n/8}g[n]$. The poles of G(z) are at $z = 0.8e^{\pm j\pi/4}$ and its single finite zero is at z = 1. Using the change of scale property

$$e^{j\pi n/8}g[n] \longleftrightarrow^{\mathbb{Z}} G(ze^{-j\pi/8}) = \frac{ze^{-j\pi/8} - 1}{(ze^{-j\pi/8} - 0.8e^{-j\pi/4})(ze^{-j\pi/8} - 0.8e^{+j\pi/4})}$$
$$G(ze^{-j\pi/8}) = \frac{e^{-j\pi/8}(z - e^{j\pi/8})}{e^{-j\pi/8}(z - 0.8e^{-j\pi/8})e^{-j\pi/8}(z - 0.8e^{+j3\pi/8})}$$
$$G(ze^{-j\pi/8}) = e^{j\pi/8}\frac{z - e^{j\pi/8}}{(z - 0.8e^{-j\pi/8})(z - 0.8e^{+j3\pi/8})}$$

 $G(ze_{-jp/8})$ has poles at $z = 0.8e_{-jp/8}$ and $0.8e_{+j3p/8}$ and a zero at $z = e_{jp/8}$. All the finite zero and pole locations have been rotated in the *z* plane by p /8 radians.



Using the accumulation property and $u[n] \xleftarrow{z}{z-1} \frac{z}{z-1}$, |z| > 1

show that the *z* transform of n u[n] is $\frac{z}{(z-1)^2}$, |z| > 1.

$$n\mathbf{u}[n] = \sum_{m=0}^{n} \mathbf{u}[m-1]$$

$$u[n-1] \xleftarrow{z}{z^{-1}} z^{-1} \frac{z}{z-1} = \frac{1}{z-1} , |z| > 1$$
$$nu[n] = \sum_{m=0}^{n} u[m-1] \xleftarrow{z}{z^{-1}} \left(\frac{z}{z-1}\right) \frac{1}{z-1} = \frac{z}{(z-1)^2} , |z| > 1$$

Inverse z Transform Example

Find the inverse z transform of

$$X(z) = \frac{z}{z - 0.5} - \frac{z}{z + 2} , \ 0.5 < |z| < 2$$

Right-sided signals have ROC's that are outside a circle and left-sided signals have ROC's that are inside a circle. Using

$$\alpha^{n} \mathbf{u}[n] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}} , |z| > |\alpha|$$
$$-\alpha^{n} \mathbf{u}[-n-1] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}} , |z| < |\alpha|$$

We get

$$(0.5)^{n} u[n] + (-2)^{n} u[-n-1] \xleftarrow{z} X(z) = \frac{z}{z-0.5} - \frac{z}{z+2} , \ 0.5 < |z| < 2$$

Inverse z Transform Example

Find the inverse z transform of

$$X(z) = \frac{z}{z-0.5} - \frac{z}{z+2}$$
, $|z| > 2$

In this case, both signals are right sided. Then using

$$\alpha^n \operatorname{u}[n] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}} , |z| > |\alpha|$$

We get

$$\left[(0.5)^n - (-2)^n \right] \mathbf{u}[n] \xleftarrow{\mathbf{z}} \mathbf{X}(z) = \frac{z}{z - 0.5} - \frac{z}{z + 2} \quad , \quad |z| > 2$$

Inverse z Transform Example

Find the inverse z transform of

$$X(z) = \frac{z}{z - 0.5} - \frac{z}{z + 2} , |z| < 0.5$$

In this case, both signals are left sided. Then using

$$-\alpha^n \operatorname{u}[-n-1] \xleftarrow{z}{z-\alpha} = \frac{1}{1-\alpha z^{-1}}, |z| < |\alpha|$$

We get

$$-\left[(0.5)^n - (-2)^n \right] u \left[-n - 1 \right] \xleftarrow{z} X(z) = \frac{z}{z - 0.5} - \frac{z}{z + 2} , |z| < 0.5$$



Just as it was convenient to define a unilateral Laplace transform it is convenient for analogous reasons to define a unilateral *z* transform

$$\mathbf{X}(z) = \mathbf{a}_{n=0}^{*} [n]_{Z-n}$$

Properties of the Unilateral z Transform

If two causal discrete-time signals form these transform pairs,

 $g[n] \xleftarrow{z} G(z)$ and $h[n] \xleftarrow{z} H(z)$ then the following properties hold for the unilateral *z* transform.

Time Shifting

Delay:
$$g[n-n_0] \xleftarrow{Z} z^{-n_0} G(z), n_0 \ge 0$$

Advance: $g[n+n_0] \xleftarrow{Z} z^{n_0} \left(G(z) - \sum_{m=0}^{n_0-1} g[m] z^{-m} \right), n_0 > 0$

Accumulation:

$$\sum_{m=0}^{n} g[m] \xleftarrow{z}{z-1} G(z)$$

Solving Difference Equations

The unilateral z transform is well suited to solving difference equations with initial conditions. For example,

y[n+2]-
$$\frac{3}{2}$$
y[n+1]+ $\frac{1}{2}$ y[n]=(1/4)_n, for n ³0
y[0]=10 and y[1]=4

z transforming both sides,

$$\begin{array}{cccc} z_2 & \acute{e}Y(z) - y[0] - z_{-1}y[1] \grave{u} - & & & \\ \ddot{e} & & & \\ \ddot{u} & & & \\ & & & & \\ & & & \\ & & & \\ & & & \\ & & & & \\ & & & \\ & & & & \\ & & & \\ & &$$

the initial conditions are called for systematically.

Solving Difference Equations

Applying initial conditions and solving,

$$Y(z)=z$$
 $\frac{\approx 16/3}{cz-1/4} + \frac{4}{z-1/2} + \frac{2/3\ddot{o}}{z-1\div}$

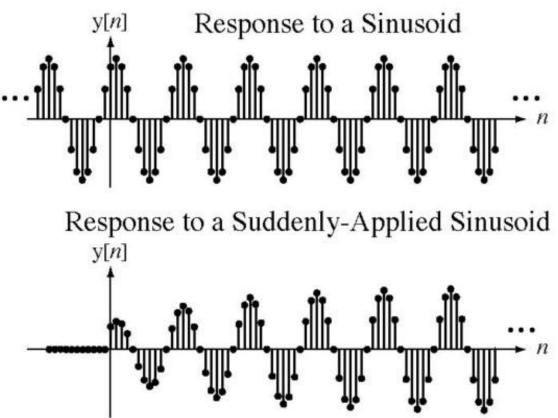
and

$$y[n] = \stackrel{\acute{e}16 \And 1\ddot{o}}{\stackrel{e}{e} - - +4}_{\ddot{e} 3cc} \stackrel{\ast}{+4} \stackrel{\ast}{-} \stackrel{\ast}{-} \stackrel{\ast}{+4} \frac{2\dot{u}}{\stackrel{\circ}{-}}_{\dot{u}} [n]$$

This solution satisfies the difference equation and the initial conditions.

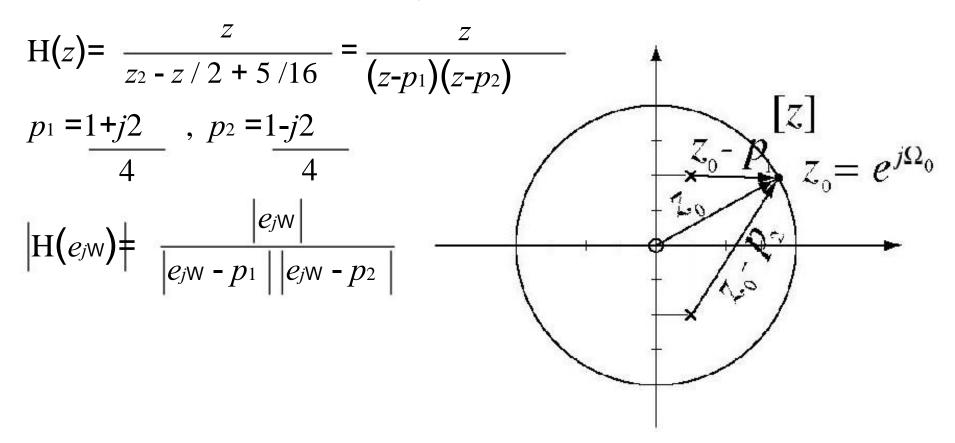
Pole-Zero Diagrams and Frequency Response

For a stable system, the response to a sinusoid applied at time t = 0 approaches the response to a true sinusoid (applied for all time).



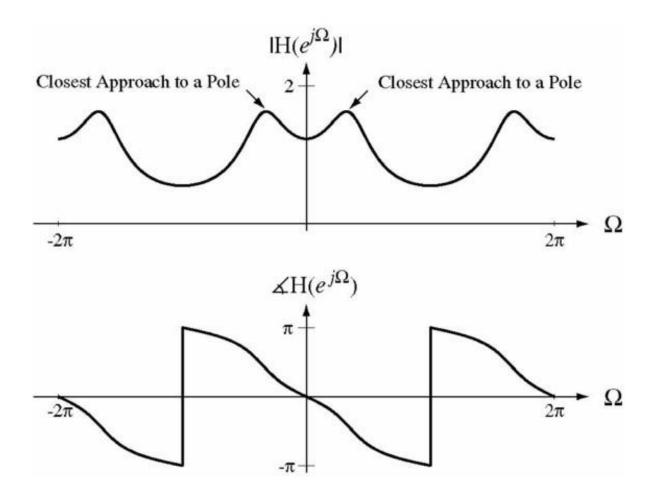


Let the transfer function of a system be





Pole-Zero Diagrams and Frequency Response



A system with transfer function $H(z) = \frac{z}{(z - 0.3)(z + 0.8)}, |z| \ge 0.8$

is excited by a unit sequence. Find the total response. Using *z*-transform methods,

$$Y(z) = H(z)X(z) = \frac{z}{(z - 0.3)(z + 0.8)}, z - 1, |z| \ge 1$$

$$Y(z) = \frac{z^2}{(z - 0.3)(z - 0.8)}, \frac{1169}{z - 0.3} + \frac{0.3232}{z + 0.8} + \frac{0.7937}{z - 1}, |z| \ge 1$$

$$y[n] = \stackrel{\text{é}-0.1169}{\text{e}} (0.3)_{n-1} + 0.3232 (-0.8)_{n-1} + 0.7937 \hat{u} \qquad \hat{u}u[n-1]$$

Using the DTFT,

$$\mathbf{H}\left(e^{j\Omega}\right) = \frac{e^{j\Omega}}{\left(e^{j\Omega} - 0.3\right)\left(e^{j\Omega} + 0.8\right)}$$

$$\mathbf{Y}\left(e^{j\Omega}\right) = \mathbf{H}\left(e^{j\Omega}\right)\mathbf{X}\left(e^{j\Omega}\right) = \frac{e^{j\Omega}}{\left(e^{j\Omega} - 0.3\right)\left(e^{j\Omega} + 0.8\right)} \times \underbrace{\left(\frac{1}{1 - e^{-j\Omega}} + \pi\delta_{2\pi}\left(\Omega\right)\right)}_{\text{DTFT of a Unit Sequence}}$$

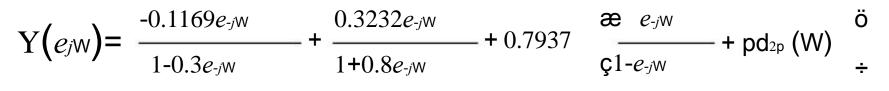
$$\begin{split} \mathbf{Y}\left(e^{j\Omega}\right) &= \frac{e^{j\Omega}}{\left(e^{j\Omega} - 0.3\right)\left(e^{j\Omega} + 0.8\right)\left(e^{j\Omega} - 1\right)} + \pi \frac{e^{j\Omega}}{\left(e^{j\Omega} - 0.3\right)\left(e^{j\Omega} + 0.8\right)}\delta_{2\pi}\left(\Omega\right) \\ \mathbf{Y}\left(e^{j\Omega}\right) &= \frac{-0.1169}{e^{j\Omega} - 0.3} + \frac{0.3232}{e^{j\Omega} + 0.8} + \frac{0.7937}{e^{j\Omega} - 1} + \frac{\pi}{\left(1 - 0.3\right)\left(1 + 0.8\right)}\delta_{2\pi}\left(\Omega\right) \end{split}$$

Using the equivalence property of the impulse and the periodicity of both $\delta_{2\pi}(\Omega)$ and $e^{j\Omega}$

$$Y(e^{j\Omega}) = \frac{-0.1169e^{-j\Omega}}{1-0.3e^{-j\Omega}} + \frac{0.3232e^{-j\Omega}}{1+0.8e^{-j\Omega}} + \frac{0.7937e^{-j\Omega}}{1-e^{-j\Omega}} + 2.4933\delta_{2\pi}(\Omega)$$

Then, manipulating this expression into a form for which the inverse DTFT is direct

$$Y(e^{j\Omega}) = \frac{-0.1169e^{-j\Omega}}{1 - 0.3e^{-j\Omega}} + \frac{0.3232e^{-j\Omega}}{1 + 0.8e^{-j\Omega}} + 0.7937 \left(\frac{e^{-j\Omega}}{1 - e^{-j\Omega}} + \pi \delta_{2\pi}(\Omega)\right)$$
$$\underbrace{-0.7937\pi\delta_{2\pi}(\Omega) + 2.4933\delta_{2\pi}(\Omega)}_{=0}$$



Finding the inverse DTFT,

 $y[n] = \begin{array}{l} e^{-0.1169} \quad (0.3)_{n-1} + 0.3232 \ (-0.8)_{n-1} + 0.7937 u \\ \\ \hat{u}u[n-1] \end{array}$ The result is the same as the result using the *z* transform, but the effort and the probability of error are considerably greater.

System Response to a Sinusoid

A s tem with transfer function

$$H(z) = \frac{z}{z - 0.9}$$
, $|z| \ge 0.9$

is excited by the sinusoid x[n] = cos(2p n / 12). Find the response.

The *z* transform of a true sinusoid does not appear in the table of *z* transforms. The *z* transform of a <u>causal</u> sinusoid of the form x[n] = cos(2pn/12)u[n] does appear. We can use the DTFT to find the response to the true sinusoid and the result is y[n]=1.995cos(2pn/12-1.115).

System Response to a Sinusoid

Using the *z* transform we can find the response of the system to a causal sinusoid x[n] = cos(2p n / 12)u[n] and the response is $y[n]=0.1217(0.9)_n u[n]+1.995cos(2pn / 12 - 1.115)u[n]$ Notice that the response consists of two parts, a transient response $0.1217(0.9)_n u[n]$ and a forced response 1.995 cos(2p n / 12 - 1.115)u[n] that, except for the unit sequence factor, is exactly the same as the forced response we found using the DTFT.

System Response to a Sinusoid

This type of analysis is very common. We can generalize it to say that if a system has a transfer function $H(z) = \frac{N(z)}{D(z)}$ that the response to a

causal cosine excitation $\cos(\Omega_0 n)u[n]$ is

$$\mathbf{y}[n] = \underbrace{\mathbb{Z}^{-1}\left(z\frac{N_{1}(z)}{D(z)}\right)}_{\text{Natural or Transient Response}} + \underbrace{|\mathbf{H}(p_{1})| \cos\left(\Omega_{0}n + \measuredangle \mathbf{H}(p_{1})\right)\mathbf{u}[n]}_{\text{Forced Response}}$$

where $p_1 = e^{j\Omega_0}$. This consists of a natural or transient response and a forced response. If the system is stable the transient response dies away with time leaving only the forced response which, except for the u[n] factor is the same as the forced response to a true cosine. So we can use the z transform to find the response to a true sinusoid.