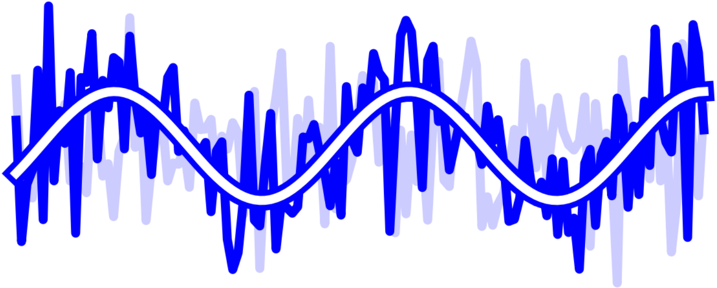
6.300: Signal Processing

Quiz Review

- Quiz #2 is in Walker (50-340) on Tuesday, 04/15 at 2:00 p.m.
- You may bring two 8.5" × 11" double-sided pages of notes.
- The review during class on Thursday, 04/10 will emphasize problem-solving strategies. Look over these slides on your own.



Slides by Titus K. Roesler (`tkr@mit.edu`)

The Story So Far

Signals

02/04 Signal Processing
02/06 Fourier Series (Sinusoids)
02/11 Fourier Series (Exponentials)
02/13 Discretization (Sampling and Quantization)
02/20 Discrete-Time Fourier Series
02/25 Continuous-Time Fourier Transform
02/27 Discrete-Time Fourier Transform
03/04 Quiz #1

Systems

03/06 Systems
03/11 Impulse Response and Convolution
03/13 Frequency Response and Filtering

The Story So Far

Discrete Fourier Transform

03/18 Discrete Fourier Transform
03/20 DFT: Frequency Resolution and Circular Convolution
04/01 Short-Time Fourier Transforms
04/03 Fast Fourier Transform (FFT)

Applications and Extensions

04/08 Communications Systems
04/10 Quiz Review
04/15 Quiz #2

(There are many more applications and extensions yet to come.)

Calculus Analogy

You wouldn't want to walk into a calculus quiz without knowing

$$\frac{d\sin(\theta)}{d\theta} = \cos(\theta)$$

by heart, right? Going back to the derivation wastes precious time!

$$\lim_{\phi \to 0} \frac{\sin(\theta + \phi) - \sin(\theta)}{\phi}$$

$$\lim_{\phi \to 0} \frac{\sin(\theta)\cos(\phi) + \sin(\phi)\cos(\theta) - \sin(\theta)}{\phi}$$

$$\lim_{\phi \to 0} \underbrace{\left[\frac{\sin(\phi)}{\phi}\right]}_{1 \text{ as } \phi \to 0} \cos(\theta) + \lim_{\phi \to 0} \underbrace{\left[\frac{\cos(\phi) - 1}{\phi}\right]}_{0 \text{ as } \phi \to 0} \sin(\theta)$$

Calculus Analogy

To do well on a calculus quiz,
you probably need to know at least a few things by heart.

common functions and their derivatives

$$\frac{d(t^n)}{dt} = nt^{n-1} \qquad \frac{d(e^{\lambda t})}{dt} = \lambda e^{\lambda t} \qquad \frac{d\sin(t)}{dt} = \cos(t)$$

differentiation rules

$$\frac{d[c_1 f(t) + c_2 g(t)]}{dt} = c_1 \frac{df}{dt} + c_2 \frac{dg}{dt} \qquad \frac{dg(f(t))}{dt} = \frac{dg}{df} \cdot \frac{df}{dt}$$

Calculus Analogy

To do well on a signal processing quiz,
you probably need to know at least a few things by heart.

common signals and their Fourier transforms

$$\delta[n-n_0] \Longleftrightarrow e^{-j\Omega n_0} \qquad e^{j\Omega_0 n} \Longleftrightarrow 2\pi\delta\big((\Omega-\Omega_0) \bmod 2\pi\big)$$

Fourier properties

$$\begin{aligned} c_1x_1[n]+c_2x_2[n] &\Longleftrightarrow c_1X_1(\Omega)+c_2X_2(\Omega) \\ x[n-n_0] &\Longleftrightarrow e^{-j\Omega n_0}X(\Omega) \\ e^{j\Omega_0 n}x[n] &\Longleftrightarrow X(\Omega-\Omega_0) \end{aligned}$$

Fourier Transforms (CT)

$$
\begin{aligned}
\textbf{time domain} \quad &\Longleftrightarrow \quad \textbf{frequency domain} \\
\delta(t) \quad &\Longleftrightarrow \quad 1 \\
\delta(t - t_0) \quad &\Longleftrightarrow \quad e^{-j\omega t_0} \\
1 \quad &\Longleftrightarrow \quad 2\pi\delta(\omega) \\
e^{j\omega_0 t} \quad &\Longleftrightarrow \quad 2\pi\delta(\omega - \omega_0)
\end{aligned}
$$

Duality: Notice the common trend in transform pairs.

$$
\begin{aligned}
x(t) \quad &\Longleftrightarrow \quad X(\omega) \\
X(t) \quad &\Longleftrightarrow \quad 2\pi x(-\omega)
\end{aligned}
$$

Fourier Transforms (DT)

All discrete-time Fourier transforms are 2π-periodic.

$$\begin{aligned} \textbf{time domain} \quad &\Longleftrightarrow \quad \textbf{frequency domain} \\ \delta[n] \quad &\Longleftrightarrow \quad 1 \\ \delta[n-n_0] \quad &\Longleftrightarrow \quad e^{-j\Omega n_0} \\ 1 \quad &\Longleftrightarrow \quad 2\pi\delta(\Omega \bmod 2\pi) \\ e^{j\Omega_0 n} \quad &\Longleftrightarrow \quad 2\pi\delta\big((\Omega-\Omega_0) \bmod 2\pi\big) \end{aligned}$$

Duality: Not so easy with discrete-time Fourier transforms. $x[n]$ is discrete in time, but $X(\Omega)$ is continuous in frequency!

Some Fourier Properties

$$
\begin{array}{rcl}
\textbf{time domain} & \Longleftrightarrow & \textbf{frequency domain} \\
c_1 x_1[n] + c_2 x_2[n] & \Longleftrightarrow & c_1 X_1(\Omega) + c_2 X_2(\Omega) \\
(x_1 * x_2)[n] & \Longleftrightarrow & X_1(\Omega) X_2(\Omega) \\
x_1[n] x_2[n] & \Longleftrightarrow & \frac{1}{2\pi}\Big(X_1 * X_2\Big)(\Omega) \\
x[-n] & \Longleftrightarrow & X(-\Omega) \\
x[nM] & \Longleftrightarrow & X(\frac{\Omega}{M}) \\
x[n - n_0] & \Longleftrightarrow & e^{-j\Omega n_0} X(\Omega) \\
e^{j\Omega_0 n} x[n] & \Longleftrightarrow & X(\Omega - \Omega_0) \\
n\, x[n] & \Longleftrightarrow & j \frac{d}{d\Omega} X(\Omega) \\
\frac{d}{dt} x(t) & \Longleftrightarrow & j\omega X(\omega)
\end{array}
$$

Check Yourself

Determine the Fourier transforms of the signals listed below.
(Apply Fourier properties to reduce the number of calculations.)

(a) $x_1(t) = e^{-t}u(t)$

(b) $x_2(t) = e^{-|t|}$

(c) $x_3(t) = 2e^{-|t|}\cos(t)$

(d) $x_4(t) = 4e^{-|t|}\cos^2(t)$

Linearity and Time-Invariance

Linearity

$$x_1[n] \rightarrow \boxed{\text{linear system}} \rightarrow y_1[n]$$

$$x_2[n] \rightarrow \boxed{\text{linear system}} \rightarrow y_2[n]$$

$$c_1 x_1[n] + c_2 x_2[n] \rightarrow \boxed{\text{linear system}} \rightarrow c_1 y_1[n] + c_2 y_2[n]$$

Time-Invariance

$$x[n] \rightarrow \boxed{\text{time-invariant system}} \rightarrow y[n]$$

$$x[n - n_0] \rightarrow \boxed{\text{time-invariant system}} \rightarrow y[n - n_0]$$

Check Yourself

Are the following systems **linear** and **time-invariant**?
(Recall: Together, additivity and homogeneity imply linearity.)

$$y[n] = \tfrac{1}{3}x[n-1] + \tfrac{1}{3}x[n] + \tfrac{1}{3}x[n+1]$$

$$y[n] = Mx[n] + B \quad \text{for constants } M \text{ and } B$$

$$y(t) = \int_0^t x(\tau)\,d\tau$$

LTI Systems

Three representations for LTI systems:

- difference equation (DT) or differential equation (CT)
- unit-sample response (DT) or impulse response (CT)
- frequency response

LTI Systems

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- difference equation (DT) or differential equation (CT)
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- frequency response

Difference Equations and Differential Equations

Impose time-domain constraints on the input and output.

$$y[n] = \tfrac{1}{2}y[n-1] + x[n]$$

$$\frac{dy(t)}{dt} = x(t) - \tfrac{1}{2}y(t)$$

LTI Systems

Three representations for LTI systems:

- difference equation (DT) or differential equation (CT)
- unit-sample response (DT) or impulse response (CT)
- frequency response

Unit-Sample Response

Characterize a system by a single time-domain signal.

$$\delta[n] \rightarrow \boxed{\textbf{LTI}} \rightarrow h[n]$$

$$x[n] \rightarrow \boxed{\textbf{LTI}} \rightarrow \sum_k h[k]x[n-k]$$

Convolution

Convolving $x[n]$ with $\delta[n-n_0]$ time-shifts $x[n]$.

$$h[n] = \delta[n-n_0] \implies (x*h)[n] = x[n-n_0]$$

Convolving $x[n]$ with a sum of scaled and time-shifted δ signals produces a sum of scaled and time-shifted $x[n]$.

$$h[n] = \sum_k h[k]\delta[n-k]$$

$$(x*h)[n] = \sum_k \underbrace{h[k]}_{\text{scale}} \underbrace{x[n-k]}_{\text{time-shift}}$$

Convolution

$(x * h)[n]$ is a superposition of scaled and time-shifted $x[n]$.

$$\vdots$$

$$
\begin{aligned}
(x * h)[n] = {} & h[0]\, x[n] + \\
& h[1]\, x[n-1] + \\
& h[2]\, x[n-2] + \\
\end{aligned}
$$

$$\vdots$$

Convolution is Commutative

$(x * h)[n]$ is a superposition of scaled and time-shifted $h[n]$.

$$\vdots$$

$$\begin{aligned}(x * h)[n] = {} & x[0]\, h[n] + \\ & x[1]\, h[n-1] + \\ & x[2]\, h[n-2] + \end{aligned}$$

$$\vdots$$

Convolution

n	$=$	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{2}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{4}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{7}}$
$x[n]$	$=$	1	1	1	1	0	0	0	0
$h[n]$	$=$	1	2	3	0	0	0	0	0

n	$=$	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{2}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{4}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{7}}$
$h[0]\,x[n-0]$	$=$	1	1	1	1	0	0	0	0
$h[1]\,x[n-1]$	$=$	0	2	2	2	2	0	0	0
$h[2]\,x[n-2]$	$=$	0	0	3	3	3	3	0	0
$(x * h)[n]$	$=$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{0}}$

Check Yourself

Consider an LTI system with unit-sample response $h[n]$.

$$\boxed{h[n] = \delta[n] + \delta[n-1] + \delta[n-2]}$$

Suppose that the input to the system is $x[n]$.

$$\boxed{x[n] = \cos\left(\frac{2\pi}{3}n\right)}$$

Determine a closed-form expression for the output $y[n]$.

LTI Systems

Three representations for LTI systems:

- difference equation (DT) or differential equation (CT)
- unit-sample response (DT) or impulse response (CT)
- frequency response

Frequency Response

Complex exponentials are eigenfunctions of LTI systems!

Characterize a system by how it shapes a signal's spectrum.

$$e^{j\Omega n} \rightarrow \boxed{\textbf{LTI}} \rightarrow H(\Omega)e^{j\Omega n}$$

$$X(\Omega) \rightarrow \boxed{\textbf{LTI}} \rightarrow H(\Omega)X(\Omega)$$

Eigenfunctions (if you're interested)

An eigenvalue-eigenvector pair $(\lambda, \boldsymbol{v})$ satisfy the eigenequation.

$$\boldsymbol{A}\boldsymbol{v} = \lambda \boldsymbol{v}$$

Likewise, eigenvalue-eigenfunction pairs satisfy eigenequations.

$$\frac{d}{dt}\{e^{\lambda t}\} = \lambda e^{\lambda t} \qquad \underbrace{\mathcal{R}\{\lambda^n\}}_{\text{right shift}} = \lambda^{-1}\lambda^n$$

Exponential functions $e^{\lambda t}$ are eigenfunctions of the d/dt operator.
eigenvalues $\lambda = j\omega \implies$ Eigenfunctions are CTFT basis functions!

Geometric sequences λ^n are eigenfunctions of the $\mathcal{R}$ (shift) operator.
eigenvalues $\lambda = e^{j\Omega} \implies$ Eigenfunctions are DTFT basis functions!

Eigenfunctions (if you're interested)

Let $P(\boldsymbol{A})$ denote a polynomial in $\boldsymbol{A}$. $P(\boldsymbol{A})$ has the same eigenvectors $\boldsymbol{v}_k$, but the corresponding eigenvalues are $P(\lambda_k)$.

$$P(\boldsymbol{A})\boldsymbol{v} = P(\lambda)\boldsymbol{v}$$

Likewise …

$$P\left(\frac{d}{dt}\right)e^{\lambda t} = P(\lambda)e^{\lambda t}$$

$$P(\mathcal{R})\lambda^n = P(\lambda^{-1})\lambda^n$$

Expressing a signal in a basis of eigenfunctions facilitates analysis.

(e.g., The homogeneous solution to a linear differential equation with constant coefficients is a linear combination of eigenfunctions that lie in the null space of the polynomial differential operator.)

Eigenfunctions (if you're interested)

How do we interpret $\boldsymbol{Ax} = \boldsymbol{b}$?

- express $\boldsymbol{x} = \sum_k c_k \boldsymbol{v}_k$ in basis spanned by eigenvectors of $\boldsymbol{A}$
- scale each eigenvector $\boldsymbol{v}_k$ by the eigenvalue λ_k
- $\boldsymbol{b} = \sum_k c_k \lambda_k \boldsymbol{v}_k$

How do we interpret $x[n] \rightarrow \boxed{\textbf{LTI}} \rightarrow y[n]$?

- express $x[n] = \frac{1}{2\pi} \int_{2\pi} X(\Omega) e^{j\Omega n} d\Omega$ in eigenfunction basis
- scale each eigenfunction $e^{j\Omega n}$ by the eigenvalue $H(\Omega)$
- $y[n] = \frac{1}{2\pi} \int_{2\pi} Y(\Omega) e^{j\Omega n} d\Omega = \frac{1}{2\pi} \int_{2\pi} H(\Omega) X(\Omega) e^{j\Omega n} d\Omega$

Check Yourself

Consider an LTI system with unit-sample response $h[n]$.

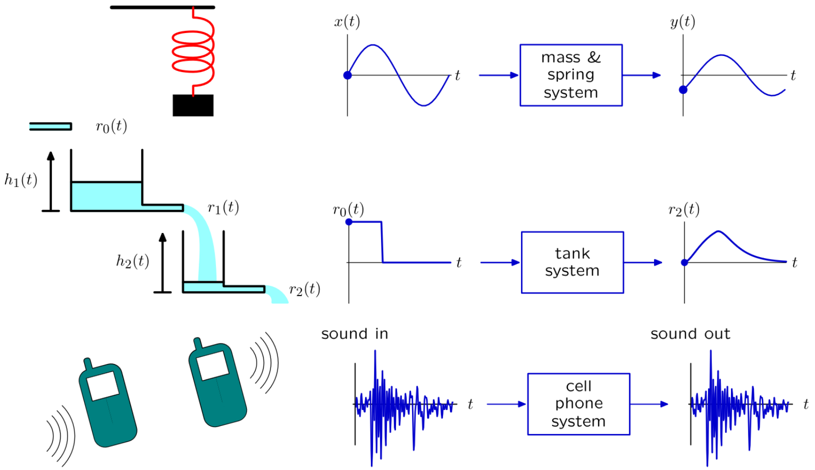
$$h[n] = \left(\tfrac{1}{2}\right)^n u[n] + \left(\tfrac{1}{3}\right)^n u[n]$$

Suppose that the input to the system is $x[n]$.

$$x[n] = (-1)^n$$

Determine a closed-form expression for the output $y[n]$.

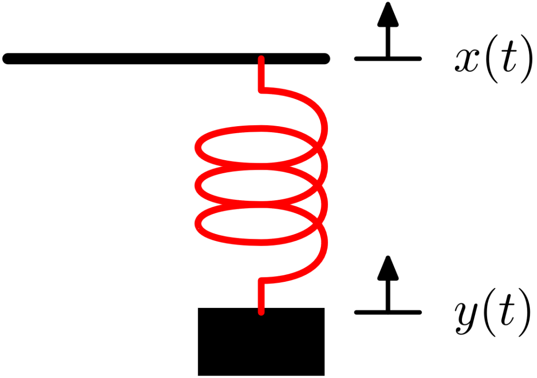
Signals and Systems



(Graphic: Denny Freeman)

Signals and Systems

Example: Mass on a Spring



(Graphic: Denny Freeman)

Signals and Systems

Example: Mass on a Spring

- **signals:** position $x(t)$ and position $y(t)$
- **parameters:** mass M and spring constant K

$$M\frac{d^2y(t)}{dt^2} = K\big(x(t) - y(t)\big)$$

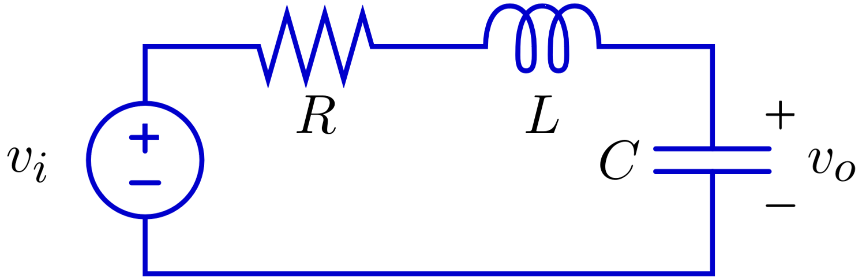
$$H(\omega) = \frac{Y(\omega)}{X(\omega)} = \frac{\omega_0^2}{\omega_0^2 - \omega^2} \qquad \omega_0 = \sqrt{\frac{K}{M}}$$

$$\cos(\omega t) \to \boxed{\textbf{LTI}} \to |H(\omega)| \cos\big(\omega t + \angle H(\omega)\big)$$

very responsive to sinusoidal oscillations at $\omega \approx \omega_0$

Signals and Systems

Example: Series RLC Circuit



(Graphic: Denny Freeman)

Signals and Systems

Example: Series RLC Circuit

- **signals:** input voltage $v_i(t)$ and output voltage $v_o(t)$
- **parameters:** resistance R, inductance L, and capacitance C

$$C\frac{d^2v_o(t)}{dt^2} = \frac{1}{L}\left(v_i(t) - RC\frac{dv_o(t)}{dt} - v_o(t)\right)$$

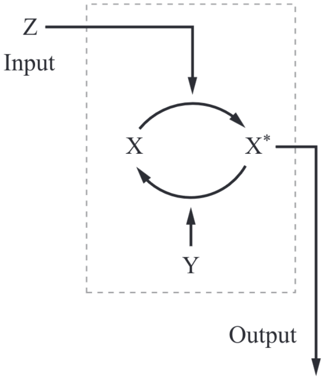
$$H(\omega) = \frac{V_o(\omega)}{V_i(\omega)} = \frac{\omega_0^2}{\omega_0^2 + \frac{1}{\tau}j\omega - \omega^2} \qquad \omega_0 = \sqrt{\frac{1}{LC}} \qquad \tau = \frac{L}{R}$$

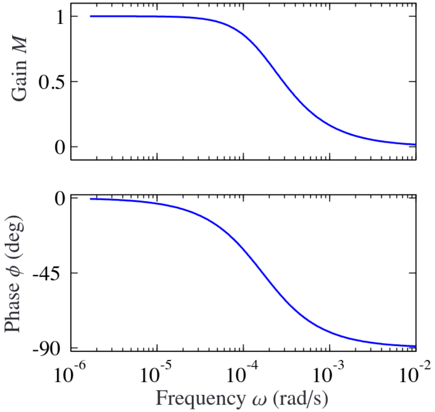
$$\cos(\omega t) \rightarrow \boxed{\textbf{LTI}} \rightarrow |H(\omega)|\cos\big(\omega t + \angle H(\omega)\big)$$

damped harmonic oscillator

Signals and Systems

Example: Phosphorylation Cycle





(*Biomolecular Feedback Systems*, D. Del Vecchio and R. M. Murray)

Signals and Systems

Example: Phosphorylation Cycle

- **signals:** kinase $x(t)$ and phosphorylated substrate $y(t)$
- **parameters:** production rate β and decay rate γ

$$\frac{dy(t)}{dt} = \beta x(t) - \gamma y(t) \iff j\omega\,Y(\omega) = \beta X(\omega) - \gamma\,Y(\omega)$$

$$H(\omega) = \frac{Y(\omega)}{X(\omega)} = \frac{\beta}{\gamma + j\omega}$$

$$\left|H(\omega)\right| = \frac{\beta}{\sqrt{\gamma^2 + \omega^2}} \qquad \angle H(\omega) = -\tan^{-1}\left(\frac{\omega}{\gamma}\right)$$

low-pass filter: unresponsive to rapidly-varying stimuli

Check Yourself

Difference Equation → Unit-Sample Response

Determine the unit-sample response $h[n]$ for the following linear constant-coefficient difference equation. Assume that the system is initially at rest: For $n < 0$, $x[n] = y[n] = 0$.

$$\boxed{y[n] = \frac{1}{2}y[n-1] + x[n]}$$

Check Yourself

Frequency Response → Unit-Sample Response

Determine the unit-sample response $h[n]$ corresponding to the frequency response $H(\Omega)$.

$$\boxed{H(\Omega) = \frac{1}{1 - \frac{1}{2}e^{-j\Omega}} + \frac{e^{-j2\Omega}}{1 - \frac{1}{3}e^{-j\Omega}}}$$

Check Yourself

Frequency Response → Difference Equation

Determine a linear difference equation with constant coefficients with frequency response $H(\Omega)$.

$$\boxed{H(\Omega) = \frac{1}{1 - \frac{1}{2}e^{-j\Omega}} + \frac{e^{-j2\Omega}}{1 - \frac{1}{3}e^{-j\Omega}}}$$

Check Yourself

Differential Equation → Impulse Response

Determine the impulse response $h(t)$ for the following linear ordinary differential equation with constant coefficients. Assume that the system is initially at rest: For $t < 0$, $x(t) = y(t) = 0$.

$$\boxed{\frac{dy(t)}{dt} = x(t) - \tfrac{1}{2}y(t)}$$

Check Yourself

Frequency Response $\rightarrow$ Differential Equation

Determine a linear ordinary differential equation with constant coefficients with frequency response $H(\omega)$.

$$\boxed{H(\omega) = \frac{1 - j\omega}{1 - 4\omega^2}}$$

LTI Systems

Three representations for LTI systems:

- difference equation (DT) or differential equation (CT)
- unit-sample response (DT) or impulse response (CT)
- frequency response

Communications Systems

Amplitude Modulation

$$x(t) \rightarrow \boxed{\textbf{AM}} \rightarrow y(t) = x(t)\cos(\omega_c t)$$

Is an amplitude modulator a linear system?
Is an amplitude modulator a time-invariant system?

Communications Systems

Amplitude Modulation

Transmission: Multiply $x(t)$ by sinusoidal carrier signal $c(t)$ and transmit the amplitude-modulated signal $y(t) = x(t)c(t)$.

Reception: Recover $x(t)$ from the amplitude-modulated signal $y(t)$ by multiplying by the carrier $c(t)$ and then low-pass filtering.

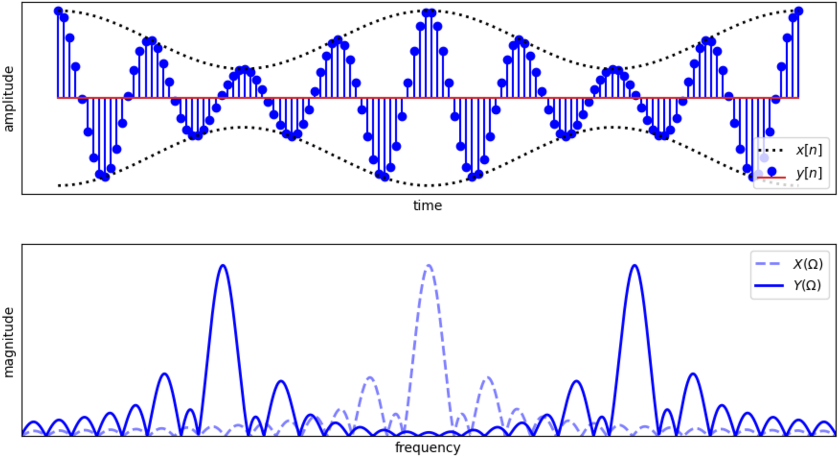
$$c(t) = \cos(\omega_c t) = \tfrac{1}{2} e^{j\omega_c t} + \tfrac{1}{2} e^{-j\omega_c t}$$

$$y(t) = x(t)c(t) \iff Y(\omega) = \tfrac{1}{2\pi}\big(X * C\big)(\omega)$$

$$Y(\omega) = \underbrace{\tfrac{1}{2} X(\omega - \omega_c) + \tfrac{1}{2} X(\omega + \omega_c)}_{\text{copies of } X(\omega) \text{ shifted outward by } \omega_c}$$

Communications Systems

Examine a finite-length window of the signal $y[n] = x[n]\cos(\Omega_c n)$.



More Modulation

We examined amplitude modulation in class. Perhaps you've heard of frequency modulation (FM) or phase modulation (PM) — but you don't need to know these for the quiz, per se.

Sinusoidal Modulation

$$y(t) = A\cos(\omega t + \phi)$$

- amplitude (AM) — time-varying amplitude $A = A(t)$
- frequency (FM) — time-varying frequency $\omega = \omega(t)$
- phase (PM) — time-varying phase $\phi = \phi(t)$

Communications: Match the signal to the channel medium by encoding the message in the carrier signal.

The Summary So Far

- Fourier transform pairs and properties
- linearity and time-invariance
- difference equations (DT) and differential equations (CT)
- unit-sample response (DT) and impulse response (CT)
- frequency response
- convolution and filtering
- modulation and communications systems

Question of the Day #1

Consider the unit-sample response $h[n]$.

$$h[n] = 2\left(\frac{1}{3}\right)^n u[n] + 5\left(\frac{1}{7}\right)^n u[n]$$

Suppose we want to express the frequency response in the form

$$H(\Omega) = \frac{A_1}{1 - p_1 e^{-j\Omega}} + \frac{A_2}{1 - p_2 e^{-j\Omega}}$$

where A_1, A_2, p_1, and p_2 are constants.

Determine values for A_1, A_2, p_1, and p_2.

Next: Discrete Fourier Transform

Discrete Fourier Transform

Quotes

'After this class, I intend to type "fft" when I need to, and try to forget the rest.'

Even if all you do after this class is type

$$\texttt{fft}(\cdots)$$

once in a while, you better know what you're doing!

- "DFT? What's that? You mean, FFT?"
- "What's with all these non-zero frequencies?"
- "Zero-padding gives me arbitrarily-good frequency resolution."
- "The FFT only works if the signal length N is a power of 2."

DT Fourier Representations

The **DTFS** is for periodic signals. No real-world periodic signals!

- finite summation over n (infinite-length periodic signals)
- frequency variable k of discrete domain

The **DTFT** may only be computed in theory.

- infinite summation over n (infinite-length aperiodic signals)
- frequency variable Ω of continuous domain

The **DFT** can be computed in practice.

- finite summation over n (finite-length aperiodic signals)
- frequency variable k of discrete domain

The **FFT** refers to a family of algorithms for computing the DFT.

The **STFT** is a "moving-window Fourier transform."

- For practical computation, use the DFT.

Discrete Fourier Transform

The DFT is a discrete-time, discrete-frequency Fourier transform.

- finite-length signals $x_w[n] = x[n]w[n]$
- discrete in time (n) N time-samples
- discrete in frequency (k) N frequency-samples

Discrete Fourier Transform

$$X[k] = \frac{1}{N}\sum_{n=0}^{N-1} x[n]e^{-jk\frac{2\pi}{N}n} \qquad \textbf{analysis}$$

$$x[n] = \sum_{k=0}^{N-1} X[k]e^{jk\frac{2\pi}{N}n} \qquad \textbf{synthesis}$$

Discrete Fourier Transform

DFT vs. Discrete-Time Fourier Series (DTFS)

The length-N DFT is equivalent to the discrete-time Fourier series of an N-periodic extension of the windowed signal $x_w[n] = x[n]w[n]$.

$$X[k] = \frac{1}{N}\sum_{n=0}^{N-1} x_w[n \bmod N]\, e^{-jk\frac{2\pi}{N}n}$$

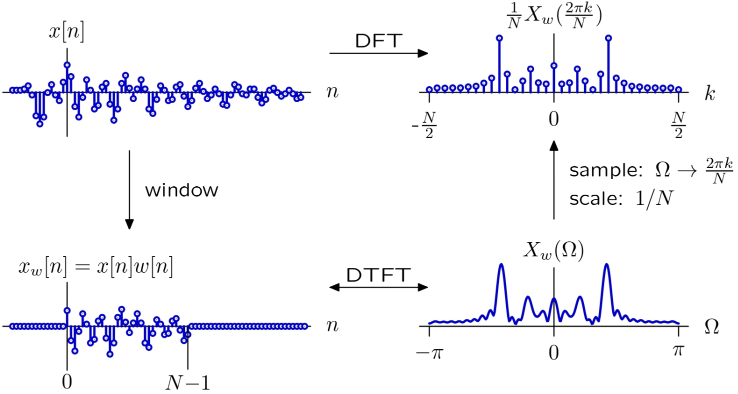
DFT vs. Discrete-Time Fourier Transform (DTFT)

$$X[k] = \tfrac{1}{N} X_w\!\left(\tfrac{2\pi}{N}k\right)$$

DFT frequency resolution: $\frac{f_s}{N}$ hertz or $\frac{2\pi}{N}$ radians

Relation Between DFT and DTFT

Graphical depiction of relation between DFT and DTFT.



While sampling and scaling are important, it is the **windowing** that most affects frequency content.

(Graphic: Denny Freeman)

Window Functions

Multiplying $x[n]$ by the window function $w[n]$ corresponds to convolving the DTFT of $x[n]$ with the DTFT of $w[n]$.

Windowing

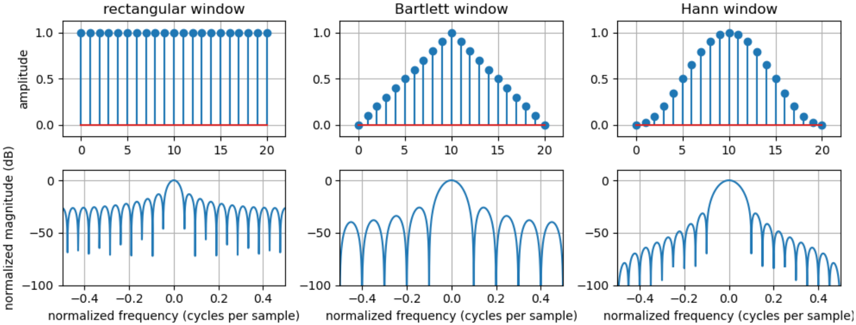
$$x_w[n] = x[n]w[n] \iff X_w(\Omega) = \tfrac{1}{2\pi}\big(X * W\big)(\Omega)$$

long time-domain $w[n] \iff$ narrow frequency-domain $W(\Omega)$

There are many window functions.

SciPy: Bartlett, Bartlett-Hann, Blackman, Blackman-Harris, Bohman, box-car, cosine, discrete prolate spheroidal sequences, Dolph-Chebyshev, exponential, flat-top, Gaussian, generalized Hamming, Hamming, Hann, Kaiser, Kaiser-Bessel, Lanczos, Nutall, Parzen, Taylor, triangular, Tukey, ...

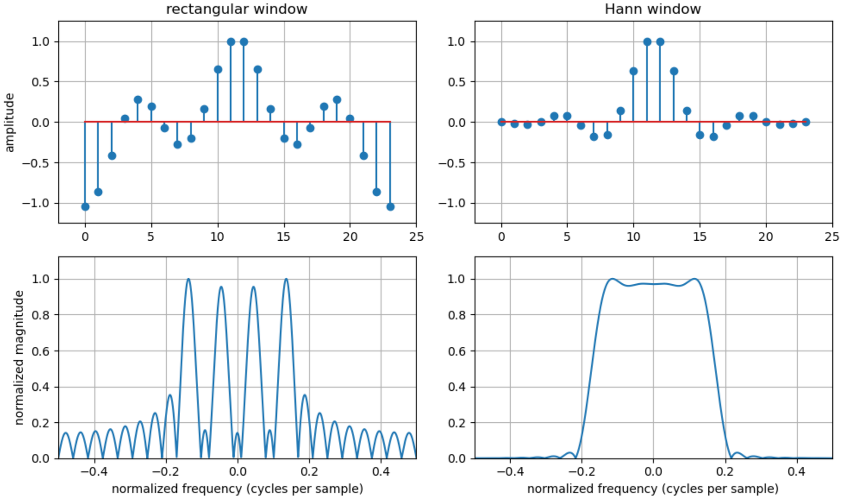
Window Functions



The window to use depends on the task at hand.

- What's most important? Narrow mainlobe? Low sidelobes?

Window Functions



DFT: Circular Convolution

Multiplication of N-point DFTs in the frequency domain corresponds to circular convolution in the time domain.

$$\begin{aligned}(x \circledast h)[n] &= N\,\mathrm{DFT}_N^{-1}\{X_N[k]H_N[k]\} \\ &= \sum_{m=0}^{N-1} x[m]h\Big[(n-m) \bmod N\Big]\end{aligned}$$

Circular convolution seems complicated, but it is really simple. You do need to know how to do regular convolution, though.

Circular Convolution

- Compute the regular (non-circular) convolution.
- Wrap the result into a length-N interval.
- Periodically extend this length-N interval.

Circular Convolution

n	$=$	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{2}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{4}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{7}}$
$x[n]$	$=$	1	1	1	1	0	0	0	0
$h[n]$	$=$	1	2	3	0	0	0	0	0

n	$=$	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{2}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{4}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{7}}$
$(x * h)[n]$	$=$	1	3	6	6	5	3	0	0
$(x \circledast h)_6[n]$	$=$	1	3	6	6	5	3	1	3
$(x \circledast h)_5[n]$	$=$	4	3	6	6	5	4	3	6
$(x \circledast h)_4[n]$	$=$	6	6	6	6	6	6	6	6

Check Yourself

Suppose that $x[n]=0$ and $h[n]=0$ for $n\notin\{0,1,2,3,\ldots,9\}$.

$$y[n]=\underbrace{\mathrm{DTFT}^{-1}\{X(\Omega)H(\Omega)\}}_{(x*h)[n]} \qquad z[n]=\underbrace{\mathrm{DFT}_5^{-1}\{X(\tfrac{2\pi}{5}k)H(\tfrac{2\pi}{5}k)\}}_{(x\circledast h)[n]}$$

n	$\boxed{\mathbf{0}}$	$\boxed{\mathbf{1}}$	$\boxed{\mathbf{2}}$	$\boxed{\mathbf{3}}$	$\boxed{\mathbf{4}}$	$\boxed{\mathbf{5}}$	$\boxed{\mathbf{6}}$	$\boxed{\mathbf{7}}$	$\boxed{\mathbf{8}}$	$\boxed{\mathbf{9}}$
$y[n]$	4	3	7	7	0	A	B	C	D	E
$z[n]$	4	3	14	13	1	4	3	14	13	1

Determine appropriate values for the constants A, B, C, D, and E. Give a few choices of $x[n]$ and $h[n]$ that produce $y[n]$.

Short-Time Fourier Transforms

Think of short-time Fourier transforms as "moving-window Fourier transforms." We analyze how a signal's spectrum changes over time.

Any Fourier transform can be a short-time Fourier transform.

Short-Time CTFT: $$X(\omega, \tau) = \int_{-\infty}^{\infty} x(t)\, \underbrace{w(t-\tau)}_{\text{window}}\, e^{-j\omega t}\, dt$$

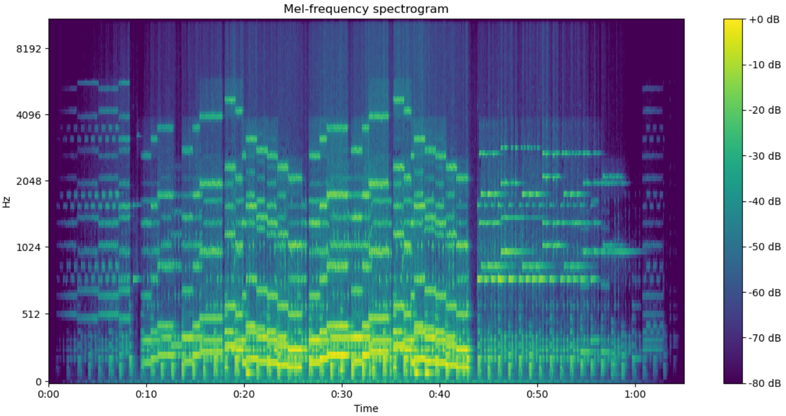
Short-Time DTFT: $$X(\Omega, m] = \sum_{n=-\infty}^{\infty} x[n]\, \underbrace{w[n-m]}_{\text{window}}\, e^{-j\Omega n}$$

Window Functions

$$x_w[n] = x[n]w[n] \iff X_w(\Omega) = \tfrac{1}{2\pi}\big(X * W\big)(\Omega)$$

Spectrograms

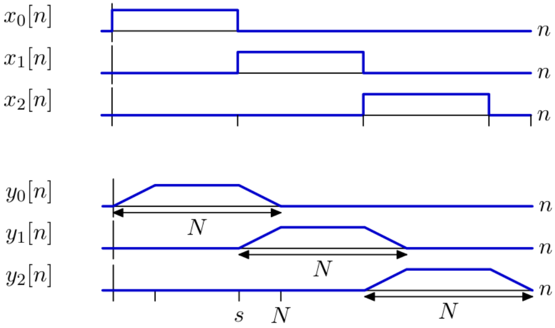
Examine the $(\text{magnitude})^2$ of a signal's time-varying spectrum.



(spectrogram of "Les Patineurs" performed on Hammond organ)

Overlap-Add Method

How can we process long signals block-by-block? Divide the input $x[n]$ into blocks — each of length s. Convolve each block with $h[n]$.



The output is $y[n] = y_0[n] + y_1[n] + y_2[n] + \cdots$ Hence *overlap-add*.

(Graphic: Denny Freeman)

Fast Fourier Transform (FFT)

Gauss, circa 1805: "…truly, that method greatly reduces the tediousness of mechanical calculations …"

Radix-2 Decimation-in-Time Algorithm

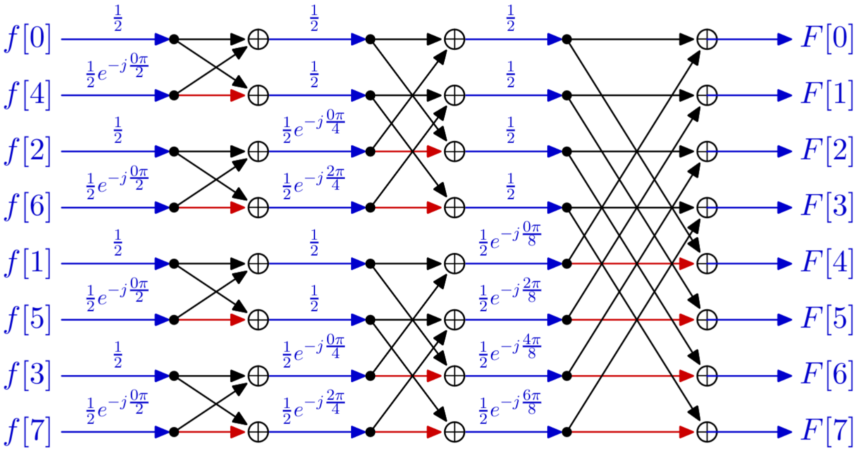
- Split a length-N DFT into a sum of two length-$(N/2)$ DFTs.

$$X_N[k] = \tfrac{1}{2}\Big(X_{N/2}^{\text{even}}[k] + W_N^k X_{N/2}^{\text{odd}}[k]\Big)$$

$$W_N = e^{-j\frac{2\pi}{N}} \ \ (N^{\text{th}} \text{ root of unity, or "twiddle factor"})$$

- Repeat (↑) until $N/2 = 1$, when we can't divide by 2 anymore.
- The DFT of a length-1 signal is the signal itself: $X[0] = x[0]$.

FFT: Decimation in Time



(Graphic: Denny Freeman)

Summary

- Fourier transform pairs and properties
- linearity and time-invariance
- difference equations (DT) and differential equations (CT)
- unit-sample response (DT) and impulse response (CT)
- frequency response
- convolution and filtering
- modulation and communications systems
- discrete Fourier transform (DFT)
- window functions
- circular convolution
- short-time Fourier transforms
- fast Fourier transform (FFT)

“Signals and Systems” Subjects

You may be interested in the following subjects.
(These certainly aren’t the only “signals and systems” subjects!)

6.200	Electrical Circuits: Modeling and Design ($\mathbb{U}$)
6.300	Signal Processing ($\mathbb{U}$)
6.301	Signals, Systems, and Inference ($\mathbb{U}$)
6.302	Fundamentals of Music Processing ($\mathbb{U}/\mathbb{G}$)
6.310	Dynamical System Modeling and Control Design ($\mathbb{U}/\mathbb{G}$)
6.430	Introduction to Computer Vision ($\mathbb{U}$)
6.480	Biomedical Systems: Modeling and Inference ($\mathbb{U}$)
6.700	Discrete-Time Signal Processing ($\mathbb{G}$)
6.741	Principles of Digital Communication ($\mathbb{U}/\mathbb{G}$)
6.880	Biomedical Signal and Image Processing ($\mathbb{U}/\mathbb{G}$)
6.862	Spoken Language Processing ($\mathbb{U}/\mathbb{G}$)
6.C27	Computational Imaging: Physics and Algorithms ($\mathbb{U}/\mathbb{G}$)

Question of the Day #2

Describe how the discrete Fourier transform is related to

- the discrete-time Fourier series and
- the discrete-time Fourier transform.

Why do we care about the discrete Fourier transform, anyway?
(No participation credit if you say, "Nobody cares.")

Discrete Fourier Transform

$$X[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-jk\frac{2\pi}{N}n} \qquad \textbf{analysis}$$

$$x[n] = \sum_{k=0}^{N-1} X[k] e^{jk\frac{2\pi}{N}n} \qquad \textbf{synthesis}$$