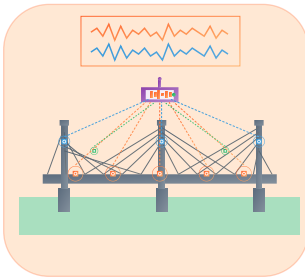




Sensing Techniques and Data Analytics

Chapter 4: Frequency Domain Analysis



Instructor:
Mohammad Talebi-Kalaleh

PhD Candidate of Structural Engineering
University of Alberta

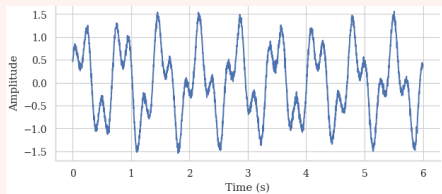
Fall 2025

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Why Frequency Domain?

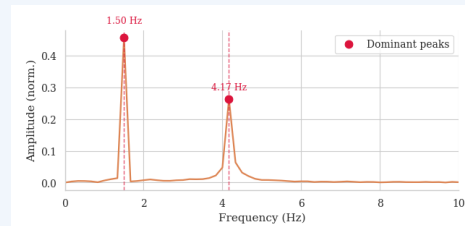
Time Domain Limitations

- ✗ Mixed frequencies overlap
- ✗ Modal properties hidden
- ✗ Noise affects entire signal
- ✗ Damage signatures unclear



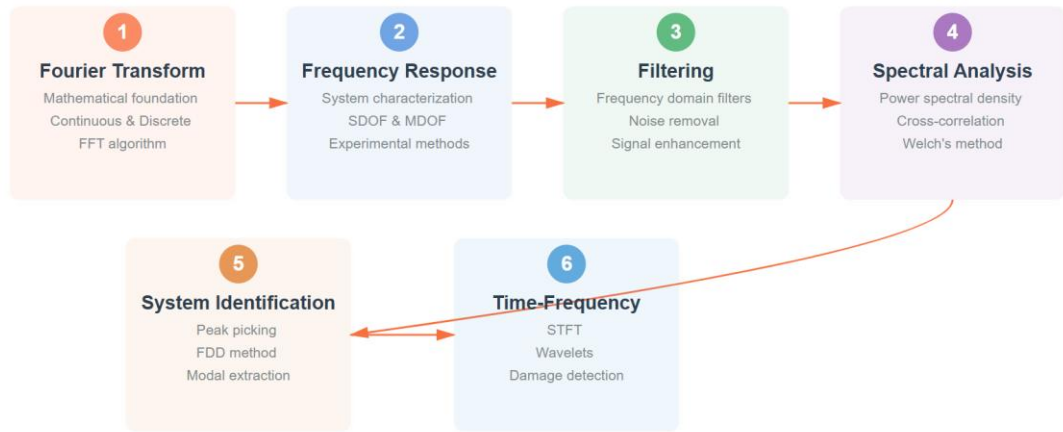
Frequency Domain Benefits

- ✓ Separate frequency components
- ✓ Clear modal identification
- ✓ Target specific frequencies
- ✓ Damage patterns visible



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Overview



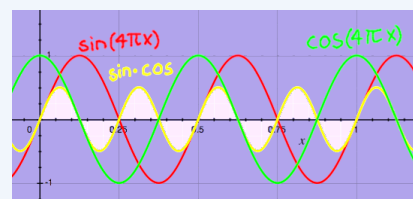
Inner Product: Measuring Signal Similarity

Mathematical Definition

$$\langle f, g \rangle = \frac{1}{T} \int f(t) \times g^*(t) dt$$

- Measures total overlap between signals
 - Large value = high similarity
 - Zero value = orthogonal (no similarity)

Visual Example



Why This Matters for Fourier Transform

1. Fourier Transform compares your signal with sine/cosine waves at all frequencies
2. High inner product = that frequency is strongly present in your signal
3. This reveals the frequency content of your structural response

Foundation for understanding frequency decomposition

Fourier Transform: Decomposing Signals

Any Signal = Sum of Sine and Cosine Waves

Fourier Transform finds the amplitude and phase of each frequency component

Forward Transform

Time \rightarrow Frequency

$$X(f) = \frac{1}{2\pi} \int x(t) e^{-j2\pi f t} dt$$

- $x(t)$ = time signal
- $X(f)$ = frequency spectrum
- $e^{-j2\pi f t}$ = complex sinusoid

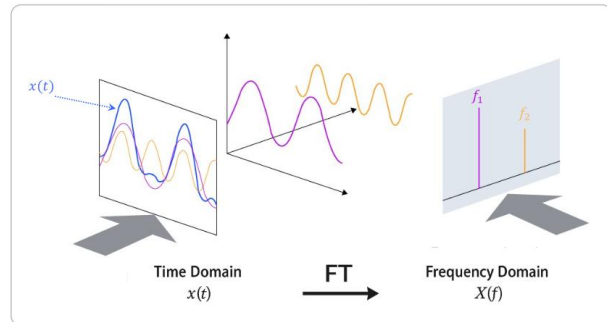
Inverse Transform

Frequency \rightarrow Time

$$x(t) = \int X(f) e^{j2\pi f t} df$$

- Sums all frequency components
- Rebuilds signal from spectrum
- Perfect reconstruction

$$e^{j2\pi f t} = \cos(2\pi f t) + j \sin(2\pi f t)$$



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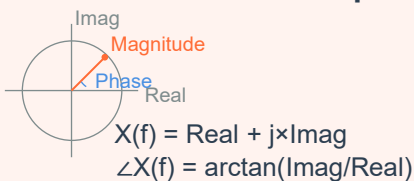
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Magnitude and Phase

Fourier Transform Output



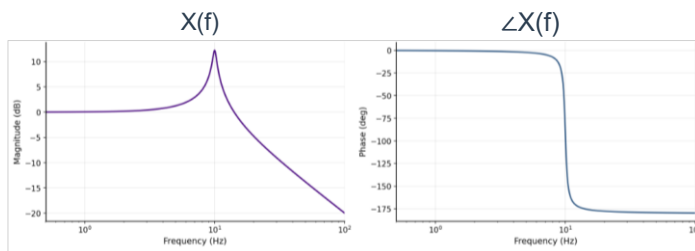
What They Tell Us

Magnitude $|X(f)|$

How much of each frequency is present

Phase $\angle X(f)$

When each frequency reaches its peak



$$|X(f)|_{dB} = 10 \log_{10}(|X(f)|)$$

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Key Fourier Transform Properties

1 Linearity

$$FT\{ax(t) + by(t)\} = aX(f) + bY(f)$$

Combine signals → Combine their spectra

2 Time Shifting

$$FT\{x(t - \tau)\} = X(f) \times e^{-j2\pi f\tau}$$

Time delay → Phase shift in frequency

3 Convolution Theorem

$$FT\{x(t) * h(t)\} = X(f) \times H(f)$$

Convolution in time → Multiplication in frequency

4 Differentiation

$$FT\{dx/dt\} = j2\pi f \times X(f)$$

Derivative → Multiply by frequency

Why These Properties Matter

- Design filters and analyze system responses efficiently
- Simplify complex calculations (convolution → multiplication)




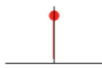

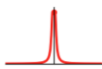

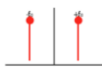

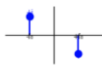
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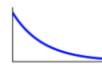
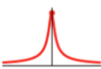
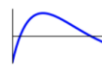
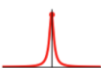
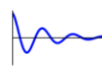
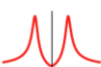
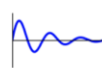
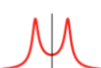
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Common Fourier Transform Pairs

Time Domain $x(t)$	Time Plot	Frequency Domain $X(f)$	Frequency Plot
$\delta(t)$		$\frac{1}{2\pi}$	
1		$\frac{1}{2\pi}\delta(f)$	
t		$\frac{j}{(2\pi f)^2}$	
$\cos(2\pi f_0 t)$		$\frac{1}{4\pi}[\delta(f - f_0) + \delta(f + f_0)]$	
$\sin(2\pi f_0 t)$		$\frac{j}{4\pi}[\delta(f - f_0) - \delta(f + f_0)]$	

Time Domain $x(t)$	Time Plot	Frequency Domain $X(f)$	Frequency Plot
$e^{-at}u(t)$		$\frac{1}{2\pi(a + j2\pi f)}$	
$te^{-at}u(t)$		$\frac{1}{2\pi(a + j2\pi f)^2}$	
$e^{-at}\cos(\omega_0 t)u(t)$		$\frac{1}{4\pi}\left[\frac{1}{a + j2\pi(f - f_0)} + \frac{1}{a + j2\pi(f + f_0)}\right]$	
$e^{-at}\sin(\omega_0 t)u(t)$		$\frac{1}{4\pi}\left[\frac{1}{a + j2\pi(f - f_0)} - \frac{1}{a + j2\pi(f + f_0)}\right]$	

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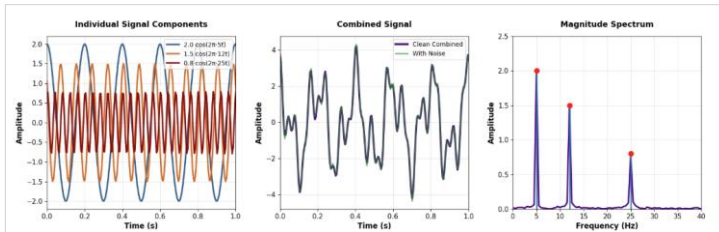
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Storage Efficiency in Frequency Domain

Example:

$$x(t) = 2\cos(2\pi \times 5t) + 1.5\cos(2\pi \times 12t) + 0.8\cos(2\pi \times 25t)$$

Three modes: 5 Hz, 12 Hz, 25 Hz



Time Domain Storage

Sampling: 200 Hz
Duration: 10 seconds

2000 data points

Store every sample value

Frequency Domain Storage

Frequencies: [5, 12, 25] Hz
Amplitudes: [2.0, 1.5, 0.8]
Phases: [0, 0, 0]

9 values only!

222× reduction

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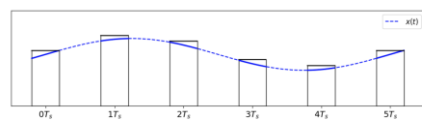
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From Continuous to Discrete

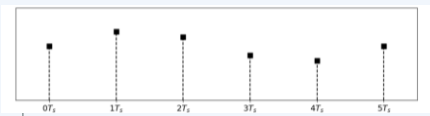
Digital processing requires discrete samples

Continuous Signal



$x(t)$ - Infinite values

Sampled Signal



$x[n]$ - Discrete samples at T_s intervals

$$x_s(t) = \sum_{n=0}^{N-1} x[n] \delta(t - nT_s),$$

Key Sampling Parameters

Sampling Rate (fs)

Samples per second

Sampling Period (Ts)

$T_s = 1/f_s$

N Samples

Total data points

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Discrete Fourier Transform (DFT)

$$X_s(f) = \frac{1}{2\pi} \int_0^T x_s(t) e^{-j2\pi ft} dt = \frac{1}{N \times T_s} \sum_{n=0}^{N-1} x[n] e^{-j2\pi f n T_s} \times T_s$$

DFT Mathematical Definition

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N}, \quad k = 0, 1, \dots, N-1$$

$k = 0, 1, 2, \dots, N-1$ (frequency bins)

Input

n: Sample index (time)
N: Number of samples
x[n]: Sampled signal

Output

Complex values (mag + phase)
k: Frequency bin index
X[k]: Frequency spectrum

Frequencies

Resolution: F_s/N Hz
 F_s : Sampling frequency
 $f[k] = k \times F_s/N$

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Python FFT Implementation

```

1 import numpy as np
2
3 # Forward FFT: Time domain → Frequency domain
4 X = np.fft.fft(x)
5
6 # Create frequency axis
7 freq = np.fft.fftfreq(len(x), 1/fs)
8
9 # Inverse FFT: Frequency domain → Time domain
10 x_reconstructed = np.fft.ifft(X)
11
12 # For real signals, use rfft for efficiency (positive frequencies only)
13 X_real = np.fft.rfft(x)
14 freq_real = np.fft.rfftfreq(len(x), 1/fs)
15
16 # Inverse of real FFT
17 x_from_rfft = np.fft.irfft(X_real)

```

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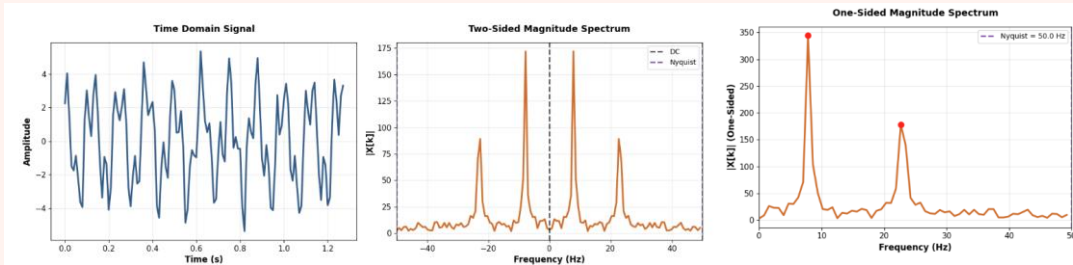
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DFT Symmetry and Nyquist Frequency

For Real Signals: Conjugate Symmetry



Nyquist Frequency

$$f_{\text{Nyquist}} = f_s/2$$

Maximum detectable frequency
Example: $f_s = 200 \text{ Hz} \rightarrow f_{\text{Nyquist}} = 100 \text{ Hz}$

What This Means

- ✓ Half the FFT output is useful
- ✓ Must sample $> 2 \times$ highest frequency
- ✓ Only plot 0 to $f_s/2$
- ✓ Prevents aliasing

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Frequency Response Function (FRF)

System Characterization in Frequency Domain

$$x(t) = g(t) * u(t) = \int_0^t g(t - \tau) u(\tau) d\tau \quad \longrightarrow \quad X(f) = G(f) \cdot U(f)$$

$$\text{FRF} = \text{Output} / \text{Input} = X(f) / U(f) = G(f)$$



FRF Reveals

Natural frequencies, damping, mode shapes

Independent of Input

System property only

FRF = Complete system description

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