16.810

Engineering Design and Rapid Prototyping

Lecture 9

Structural Testing

Instructor(s)

Prof. Olivier de Weck

January 18, 2005

16.810 Outline

- Structural Testing
  - Why testing is important
  - Types of Sensors, Procedures ....
  - Mass, Static Displacement, Dynamics
- Test Protocol for 16.810 (Discussion)
  - Application of distributed load
  - Wing trailing edge displacement measurement
  - First natural frequency testing

Data Acquisition and Processing for Structural Testing

(1) Sensor Overview:

Accelerometers, Laser sensors , Strain Gages ,

Force Transducers and Load Cells, Gyroscopes

(2) Sensor Characteristics & Dynamics:

FRF of sensors, bandwidth, resolution, placement issues

(3) Data Acquistion Process:

Excitation Sources, Non-linearity, Anti-Alias Filtering, Signal Conditioning

(4) Data Post-Processing:

FFT, DFT, Computing PSD's and amplitude spectra,

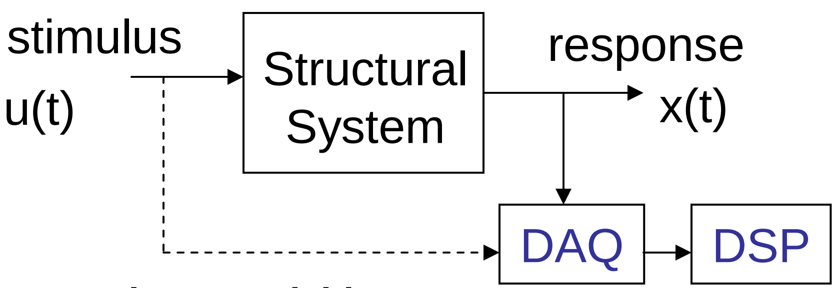
statistical values of a signal such as RMS, covariance etc.

(5) Introduction to System Identification

ETFE, DynaMod Measurement Models

Why is Structural Testing Important?

- Product Qualification Testing
- Performance Assessment
- System Identification
- Design Verification
- Damage Assessment
- Aerodynamic Flutter Testing
- Operational Monitoring
- Material Fatigue Testing



DAQ = data acquisition
DSP = digital signal processing

Example: Ground Vibration Testing

F-22 Raptor #01 during ground vibration tests at Edwards Air Force Base, Calif., in April 1999

16.810 I. Sensor Overview

This Sensor morphology is useful for classification of typical sensors used in structural dynamics.

Sensor Morphology Table

Type	Linear	Rotational	
Bandwidth	Low	Medium	High
Derivative	Position	Rate	Acceleration
Reference	Absolute	Relative	
Quantity	Force/Torque	Displacement	
Impedance	Low	High	

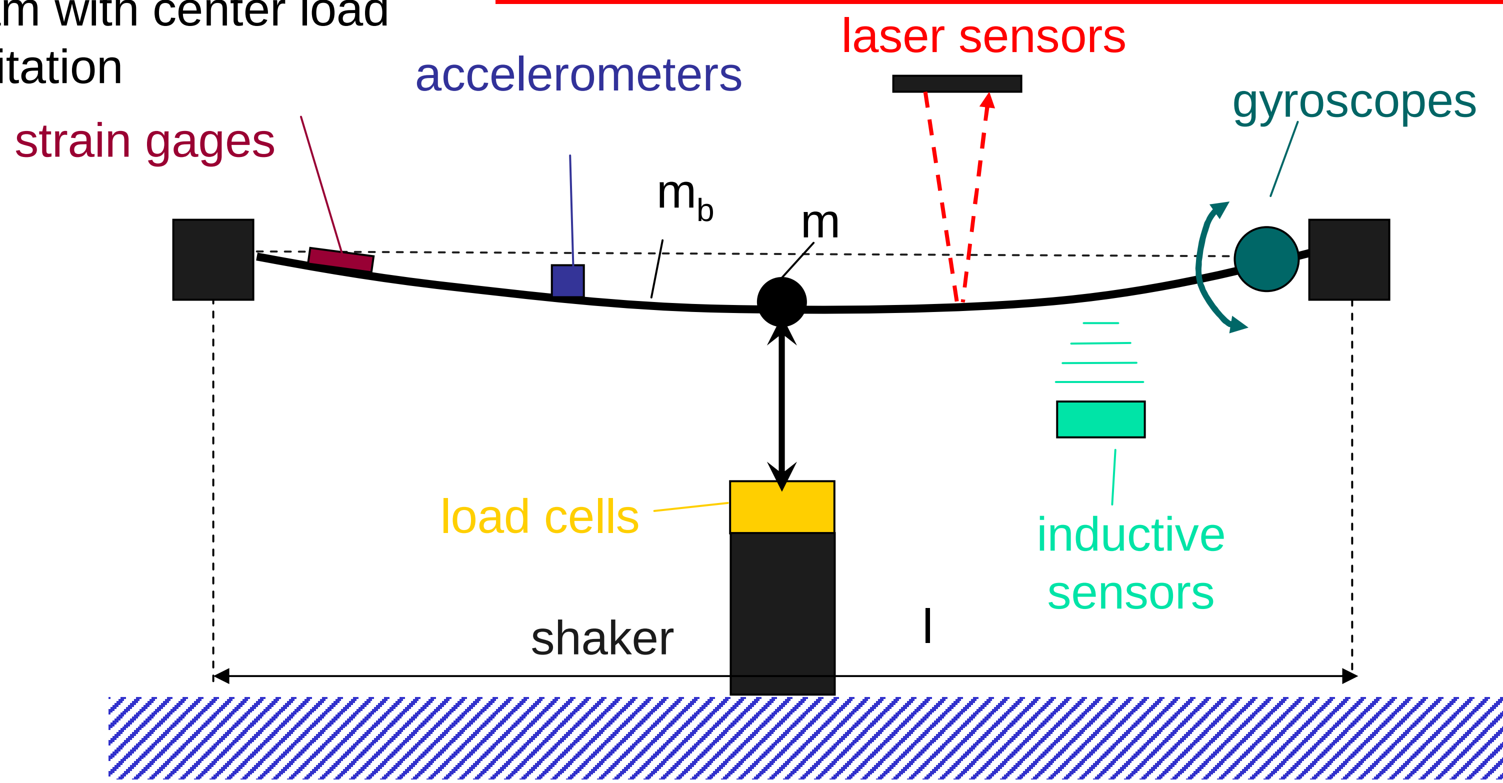
Example: uniaxial strain gage

Need units of measurement:
[m], [Nm],[μstrain],[rad] etc…

Sensor Examples for Structural Dynamics

Example: fixed-fixed beam with center load excitation

Goal: Explain what they measure and how they work

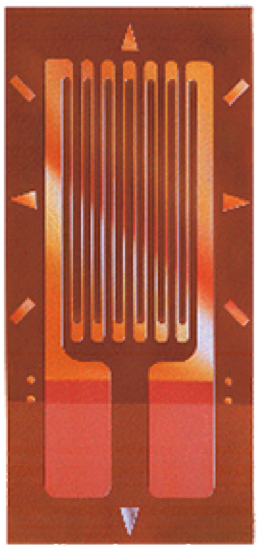


First flexible mode frequency: $$\omega_n = 14\sqrt{\frac{EI}{l^3\left(m+0.375m_b\right)}}$$

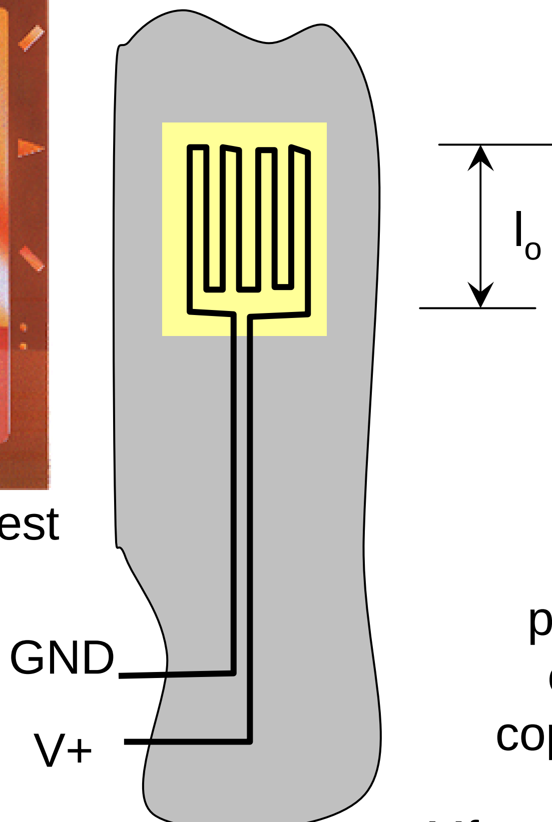
Strain Gages

Strain:

$$\varepsilon = \frac{\Delta l}{l_o}$$



bond to test article



Strain gages measure strain (differential displacement) over a finite area via a change in electrical resistance R=lρ [Ω]

Current Nominal length l_o: $$I_o = \frac{V_{in}}{l_o \rho}$$

With applied strain: $$I_\varepsilon = \frac{V_{in}}{(l_o + \Delta l)\rho}$$

<u>Implementation:</u>
Wheatstone bridge circuit

strain gages feature polyimide-encapsulated constantan grids with copper-coated solder tabs.

Mfg:

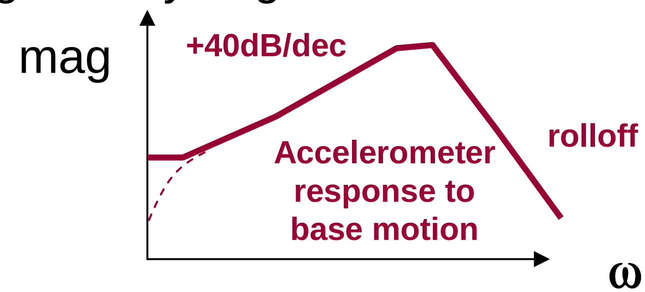
16.810 Accelerometers

Accelerometers measure linear acceleration in one, two or three axes. We distinguish:

- single vs. multi axis accelerometers
- DC versus non-DC accelerometers

$$\ddot{x}(t) \rightarrow s^2 X(s) - sx(0) - \frac{dx(0)}{dt}$$

(generally neglect initial conditions)



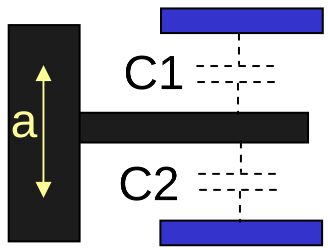
Recorded voltage

$$V_{out}(t) = K_a \ddot{x}(t) + V_0$$

Can measure: linear, centrifugal and gravitational acceleration
Use caution when double-integrating acceleration to get position (drift)

Single-Axis Accelerometer must be aligned with sensing axis.

<u>**Example:**</u> **Kistler Piezobeam (not responsive at DC)**



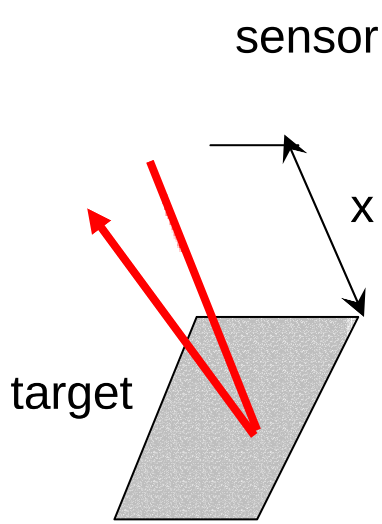
<u>**Example:**</u> **Summit capacitive accelerometer (DC capable)**

<u>Manufacturers:</u> Kistler, Vibrometer, Summit,...

Laser Displacement Sensors

Records displacement directly via slant range measurement.

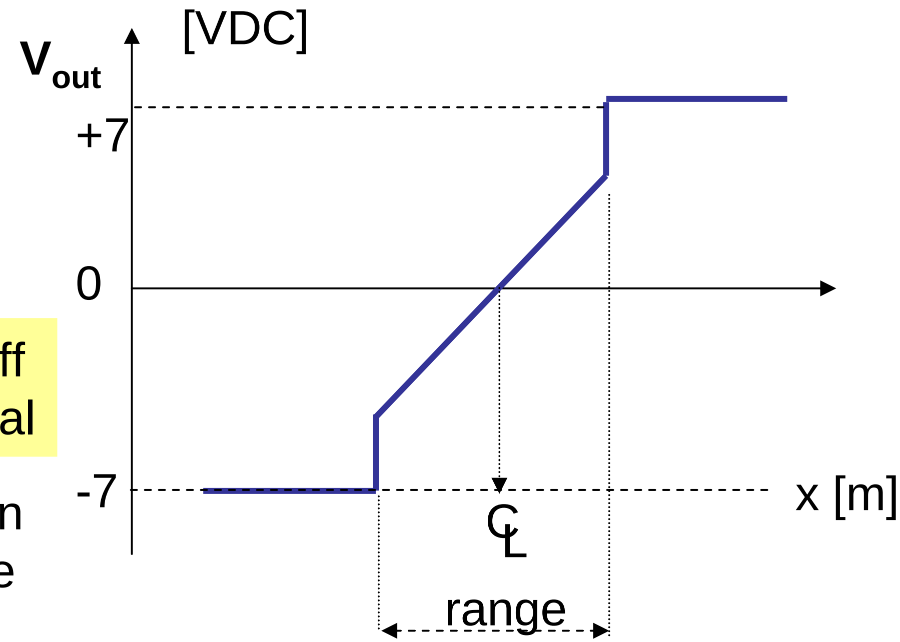
$$x(t) \rightarrow X(s)$$



Typical Settings

I: 2μm-60 ms
II: 15μm-2ms
III: 50μm-0.15ms

Resolution tradeoff spatial vs. temporal



Distance x is recorded via triangulation between the laser diode (emitter), the target and the receiver (position sensitive device - PSD).

Vibrometers include advanced processing and scanning capabilities.

Manufacturers: Keyence, MTI Instruments,...

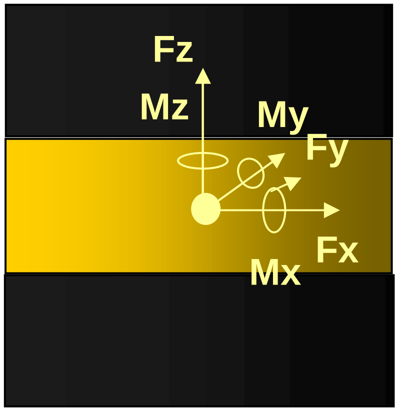
Advantages:
contact-free measurement
Disadvantages:
need reflective, flat target
limited resolution ~ 1μm

16.810 Force Transducers / Load Cells

Force Transducers/Load Cells are capable of measuring
Up to 6 DOF of force on three orthogonal axes,
and the moment (torque) about each axis, to
completely define the loading at the sensor's location

The high stiffness also results in a high resonant frequency,
allowing accurate sensor response to rapid force changes.

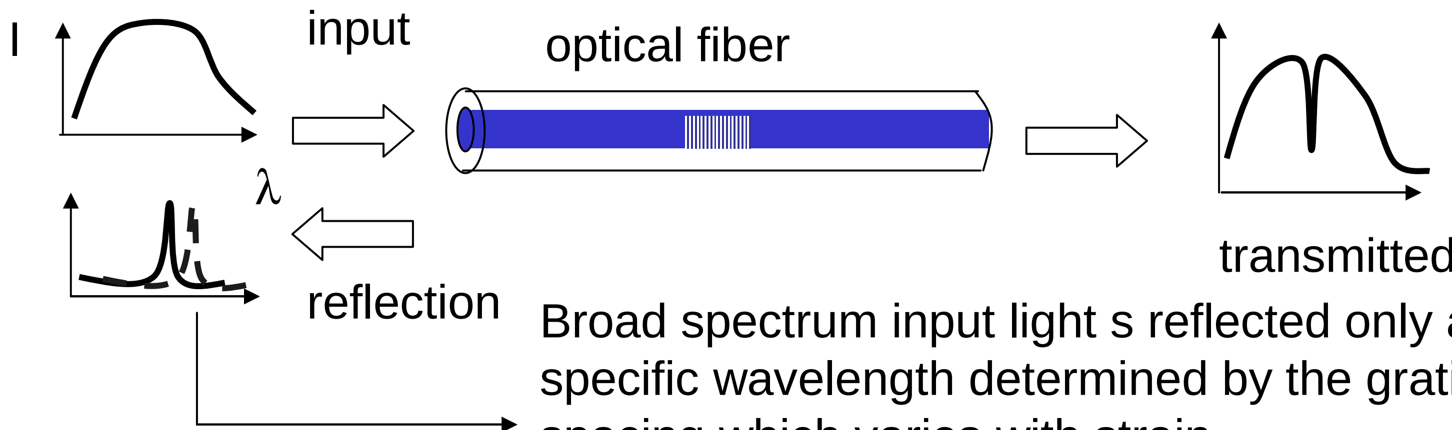
Load cells are electro-mechanical transducers
that translate force or weight into voltage.
They usually contain strain gages internally.



Manufacturers: JR3, Transducer Techniques Inc. ...

16.810 Other Sensors

- Fiber Optic strain sensors (Bragg Gratings)



Broad spectrum input light s reflected only at a specific wavelength determined by the grating spacing which varies with strain.

- Ring Laser Gyroscopes (Sagnac Effect)
- PVDF or PZT sensors

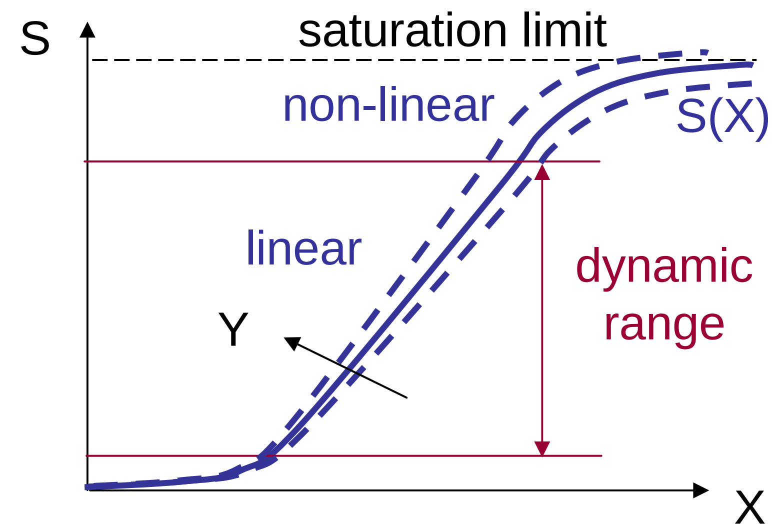
16.810 II. Sensor Characteristics & Dynamics

Goal: Explain performance characteristics (attributes of real sensors)

When choosing a sensor for a particular application we must specify the following requirements:

Sensor Performance Requirements:

- Dynamic Range and Span
- Accuracy and Resolution
- Absolute or Relative measurement
- Sensor Time Constant
- Bandwidth
- Linearity
- Impedance
- Reliability (MTBF)

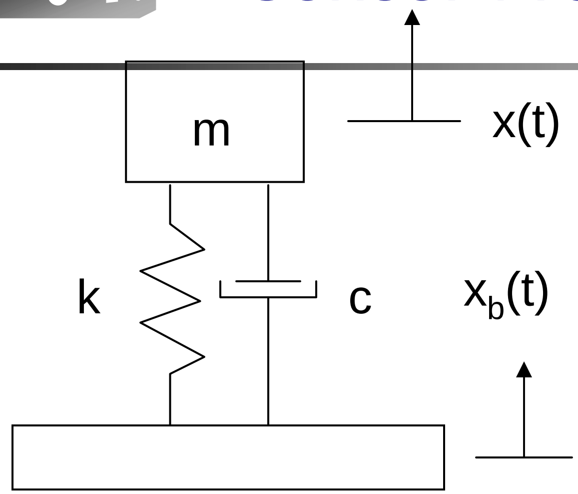


Calibration is the process of obtaining the S(X) relationship for an actual sensor. In the physical world S depends on things other than X. Consider modifying input Y (e.g. Temp)

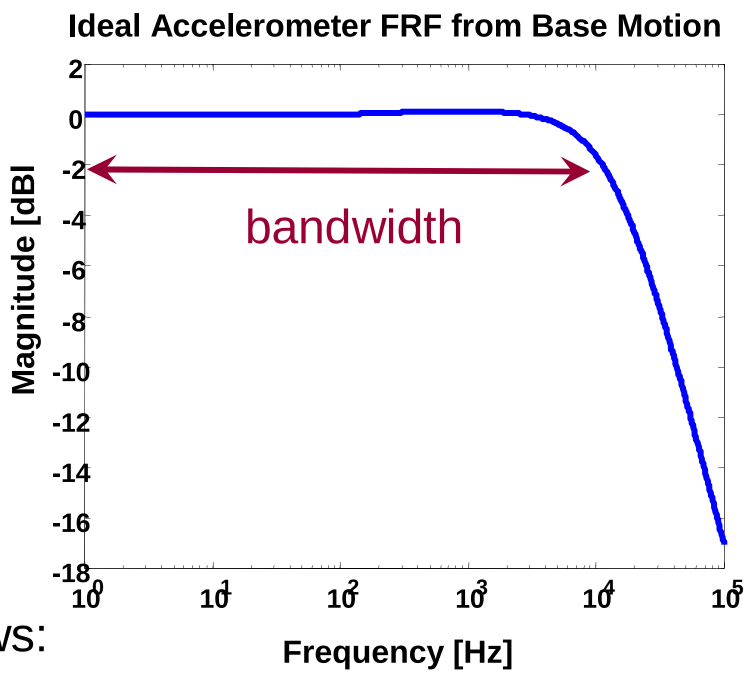
Constraints:
Power: 28VDC, 400 Hz AC, 60 Hz AC
Cost, Weight, Volume, EMI, Heat

E.g. Load cell calibration data:
X= mass (0.1 , 0.5 1.0 kg…)
S= voltage (111.3 , 563.2, 1043.2 mV)

Sensor Frequency Response Function



$$G_a(s) = \frac{s^2 X(s)}{s^2 X_b(s)} = \frac{cs+k}{ms^2+cs+k}$$



Example: Accelerometer
m = 4.5 g
k = 7.1e+05 N/m
c= 400 Ns/m

Typically specify bandwidth as follows:

Example: Kistler 8630B Accelerometer

Frequency Response +/-5%: 0.5-2000 Hz

Note: Bandwidth of sensor should be at least 10 times higher than highest frequency of signal s(t)

Sensor Time Constant

How quickly does the sensor respond to input changes ?

First-Order Instruments

$$a_1 \frac{dy}{dt} + a_o y = b_o u$$

Dividing by a_o gives:

$$\underbrace{\frac{a_1}{a_0}}_{\tau} \frac{dy}{dt} + y = \underbrace{\frac{b_o}{a_o}}_{K} u$$

In s-domain:

$$\boxed{\frac{Y(s)}{U(s)} = \frac{K}{\tau s + 1}}$$

τ : time constant

K: static sensitivity

Time for a 1/e output change

Second-Order Instruments

$$a_2 \frac{d^2 y}{dt^2} + a_1 \frac{dy}{dt} + a_o y = b_o u$$

Essential parameters are:

$$K \triangleq \frac{b_o}{a_o} \qquad \omega_n \triangleq \sqrt{\frac{a_o}{a_2}} \qquad \zeta_n \triangleq \frac{a_1}{2\sqrt{a_o a_2}}$$

static sensitivity

natural frequency

damping ratio

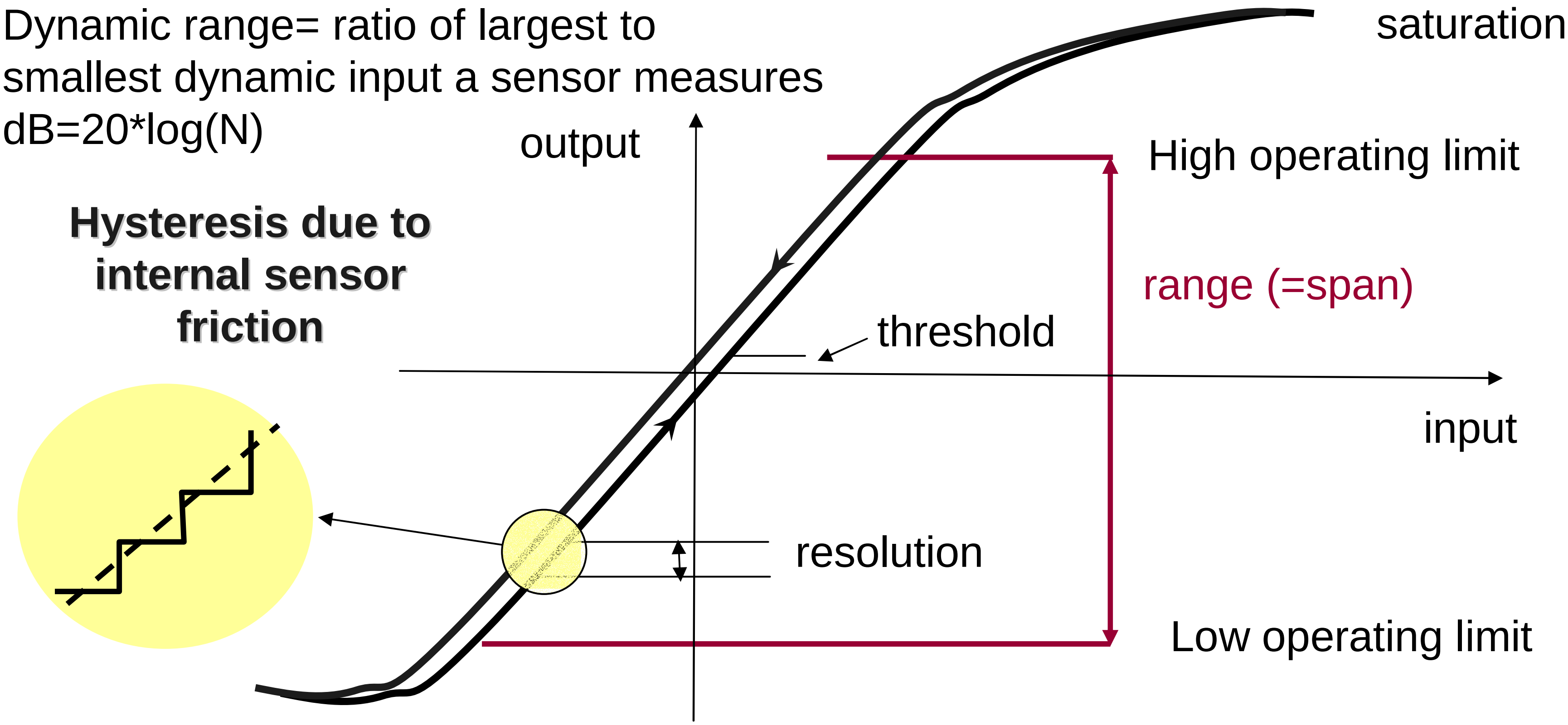
In s-domain:

$$\boxed{\frac{Y(s)}{U(s)} = \frac{K}{s^2 + 2\zeta_n \omega_n s + \omega_n^2}}$$

Time constant here is: $\tau = 1/\zeta\omega_n$

16.810 Sensor Range & Resolution

Dynamic range= ratio of largest to smallest dynamic input a sensor measures
dB=20*log(N)



Resolution = <u>smallest input increment that gives rise to a measurable output change</u>. Resolution and accuracy are NOT the same thing !

Threshold= smallest measurable input

16.810 Accuracy

Accuracy=lack of errors

Measurement theory = essentially error theory

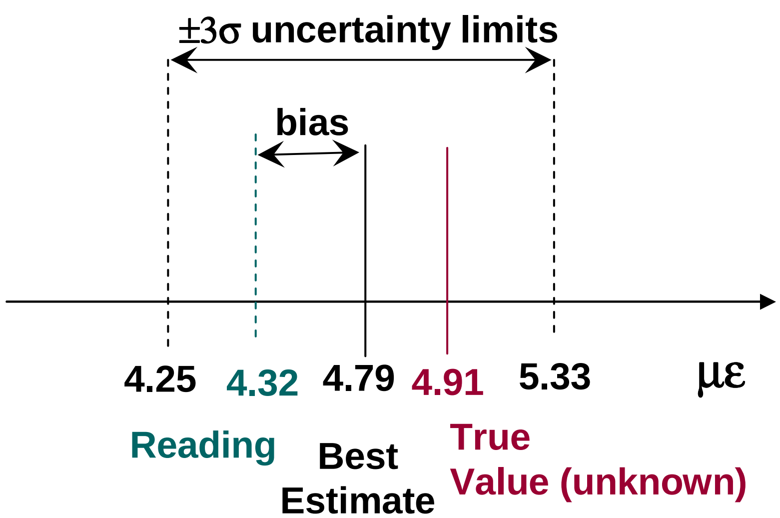
Total error = random errors & systematic errors

(IMPRECISION)

- Temperature fluctuations
- external vibrations
- electronic noise (amplifier)

(BIAS)

- Invasiveness of sensor
- Spatial and temporal averaging
- human bias
- parallax errors
- friction, magnetic forces (hysteresis)



3σ accuracy quoted as:

"4.79 ± 0.54 με"

Probable error accuracy:

$e_p = 0.674\sigma$

"4.79 ± 0.12 με"

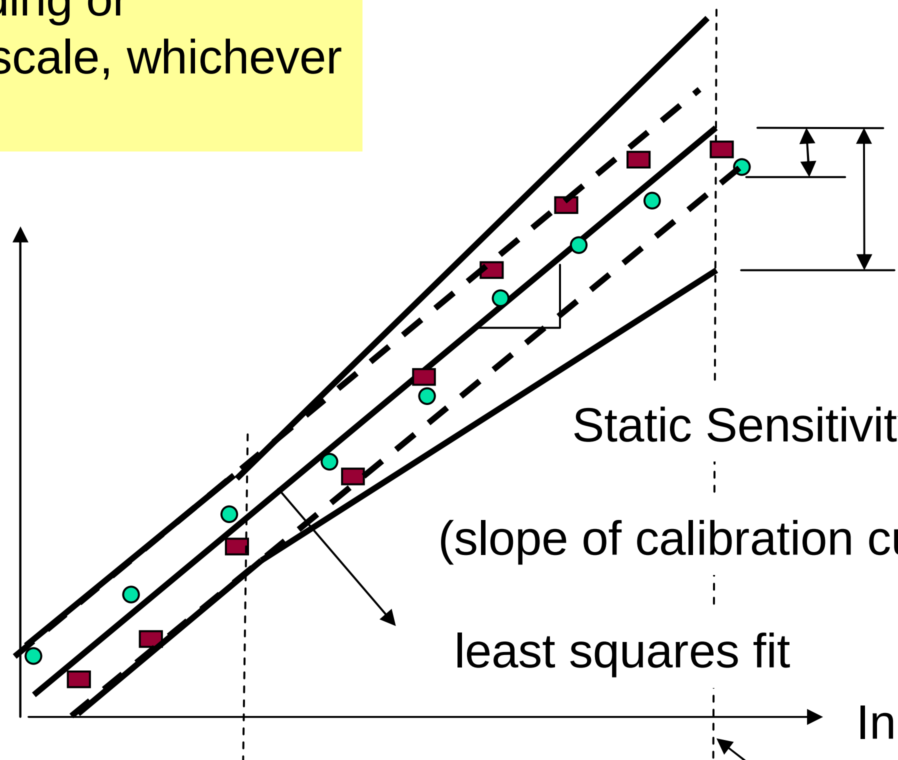
Note: Instrument standard used for calibration should be ~ 10 times more accurate than the sensor itself (National Standards Practice)

Linearity

"Independent Linearity":

+/- A percent of reading or
+/- B percent of full scale, whichever is greater

Usually have largest errors at full scale deflection of sensor



B% of full scale

A% of reading

$$\text{Static Sensitivity} = \frac{dS}{dX} \quad \left[\frac{\mathrm{mV}}{\mathrm{kg}}\right]$$

(slope of calibration curve)

least squares fit

Point at which A% of reading = B% of full scale input

Full scale

Increasing values
decreasing values

16.810 Placement Issues

Need to consider the <u>dynamics of the structure</u> to be tested before choosing where to place sensors:

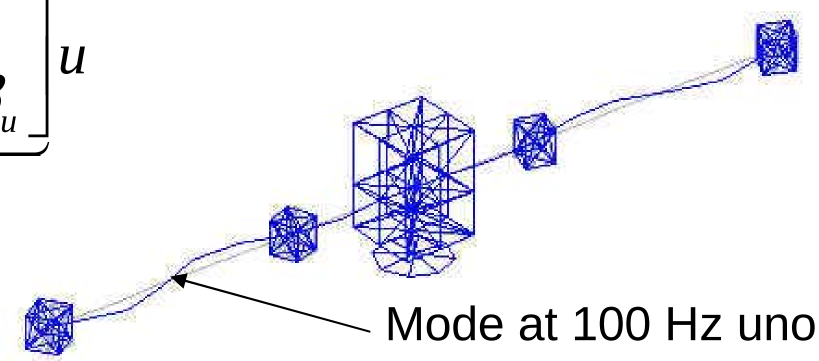
$$q = \underbrace{\begin{bmatrix} 0 & I \\ -\Omega^2 & -2Z\Omega \end{bmatrix}}_{A} q + \underbrace{\begin{bmatrix} 0 \\ \Phi^T \beta_u \end{bmatrix}}_{B} u$$

$$y = \underbrace{\begin{bmatrix} \beta_y \Phi & 0 \end{bmatrix}}_{C} q + \underbrace{\begin{bmatrix} 0 \end{bmatrix}}_{D} u$$

Observability determined by product of mode shape matrix Φ and output influence coefficients β_y

TPF for SCI Architecture; Apertures : 4 Date: 02-Sep-2000 mode 60 (100.0484 Hz)

Example: TPF SCI Architecture



Mode at 100 Hz unobservable if sensor placed at this "node"

Observability gramian:

$$W_o \rightarrow A^T W_o + W_o A + C^T C = 0$$

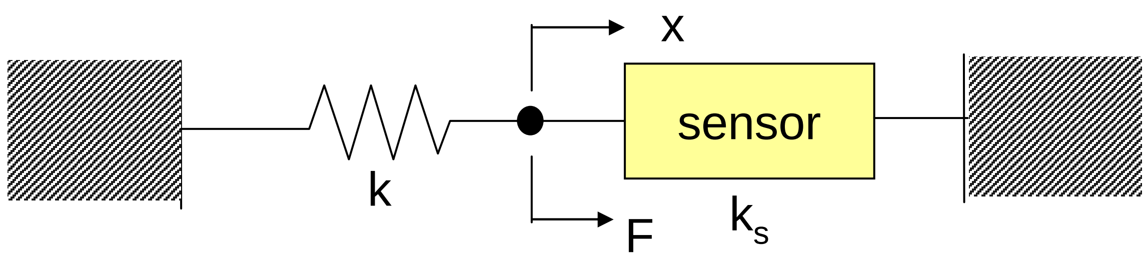
<u>Other considerations:</u>

- Pole-zero pattern if sensor used for control (collocated sensor-actuator pair)
- Placement constraints (volume, wiring, surface properties etc…)

Invasiability / Impedance

How does the measurement/sensor influence the physics of the system ?

Remember Heisenberg's uncertainty principle: $\Delta x \Delta p \geq \hbar$



$$q_{i1} \cdot q_{i2} = P \quad [\mathrm{W}]$$

Power drain: $P = q_{i1}^2 / Z_{gi}$

Impedance characterizes "loading" effect of sensor on the system.
Sensor extracts power/energy -> Consider "impedance" and "admittance"

Want to measure F

Generalized input impedance: $Z_{gi} \triangleq \dfrac{q_{i1}}{q_{i2}}$ $\dfrac{\text{Effort variable}}{\text{Flow variable}} = \dfrac{\text{Force}}{\text{Velocity}}$

$\boxed{Z_{gi} \propto k_s}$

Error due to measurement:

$$q_{i1m} = \frac{1}{Z_{go}/Z_{gi} + 1} q_{i1u}$$

"measured" → q_{i1m} ; "undisturbed" → q_{i1u}

<u>Load Cell:</u> High Impedance = k_s large vs. <u>Strain Gage:</u> Low Impedance= k_s small

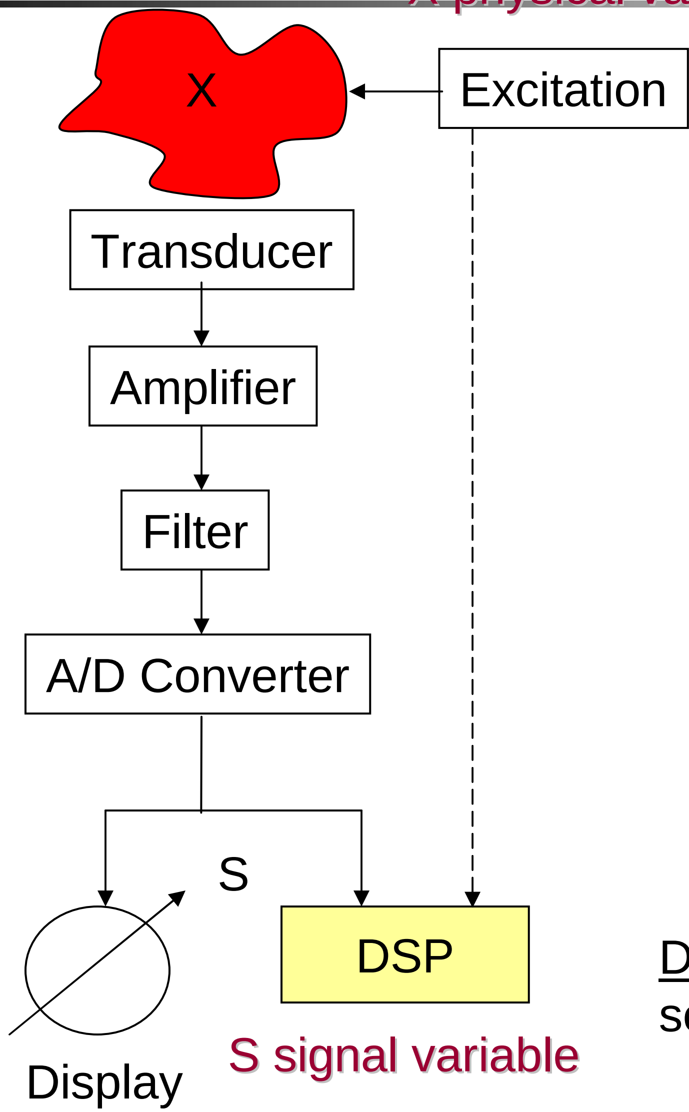
Conclusion: Impedance of sensors lead to errors that must be modeled in a high accuracy measurement chain (I.e. include sensor impedance/dynamics)

III. Data Acquisition Process

Typical setup

X physical variable

Goal: Explain the measurement chain



S signal variable

Excitation source provides power to the structural system such that a dynamic response is observable in the first place

Transducer "transforms" the physical variable X to a measured signal

Amplifier is used to increase the measurement signal strength

Filter is used to reject unwanted noise from the measurement signal

Analog to Digital converter samples the continuous measurement signal in time and in amplitude

Digital Signal Processing turns raw digital sensor data into useful dynamics information

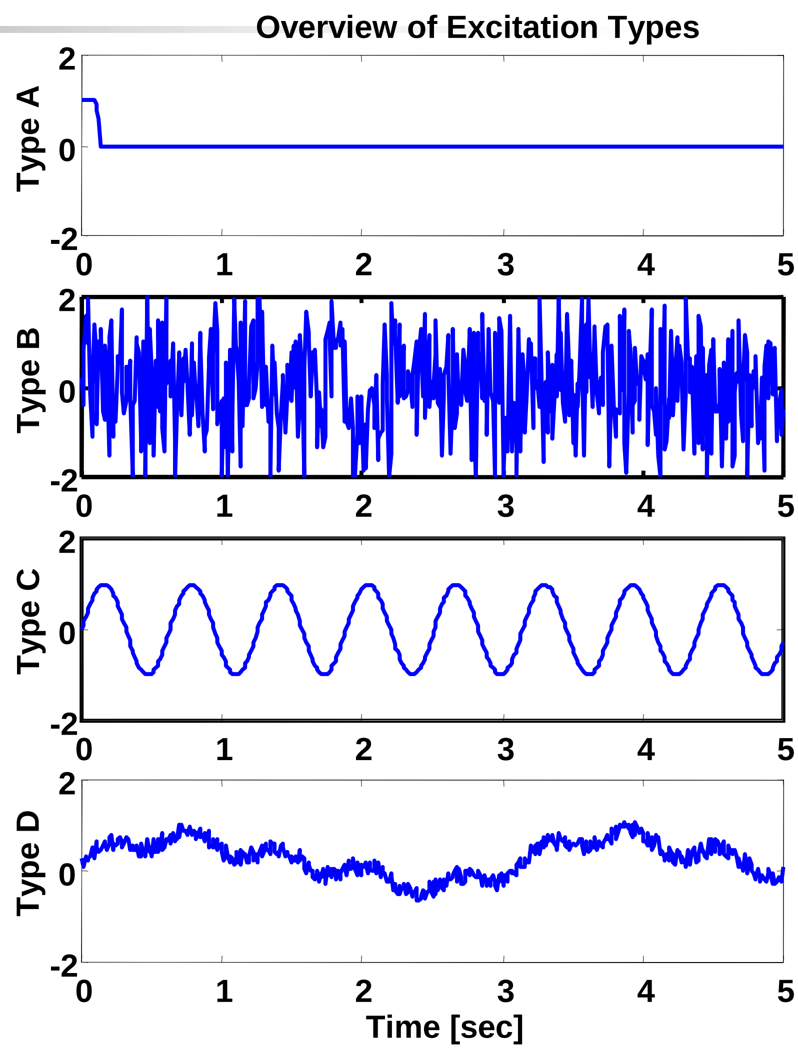
System Excitation Types

<u>Type A</u> : Impulsive Excitation
(Impulse Hammers)

<u>Type B:</u> Broadband Noise
(Electromechanical Shakers)

<u>Type C:</u> Periodic Signals
(Narrowband Excitation)

<u>Type D:</u> Environmental
(Slewing, Wind Gusts, Road, Test track, Waves)



Excitation Sources

$$u(t) = F(t) = F_o \delta(t)$$

Wide band excitation at various energy levels can be applied to a structure using impulse force hammers. They generate a nearly perfect impulse.

$$u(t) \longrightarrow \boxed{G(\omega)} \longrightarrow y(t)$$

Impulse Response h(t)

$$y(t) = \int_{-\infty}^{t} u(\tau) h(t-\tau) d\tau$$ (convolution integral)

$$Y(\omega) = \underbrace{U(\omega)}_{F_o \cdot 1} H(\omega) \longrightarrow G(\omega) = H(\omega)$$

(no noise)

Broadband

The noise-free response to an ideal impulse contains all the information about the LTI system dynamics

Shaker can be driven by periodic or broadband random current from a signal generator.

$$S_{yy}(\omega) = G(j\omega) S_{uu}(\omega) G^H(j\omega) \longrightarrow$$

Record S_{yy}, S_{uu} and solve for G

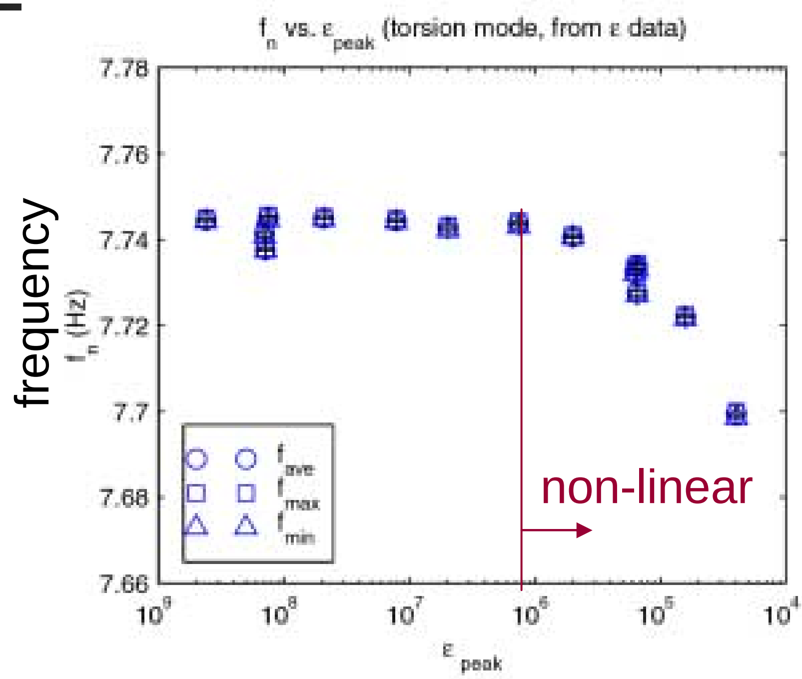
Input PSD

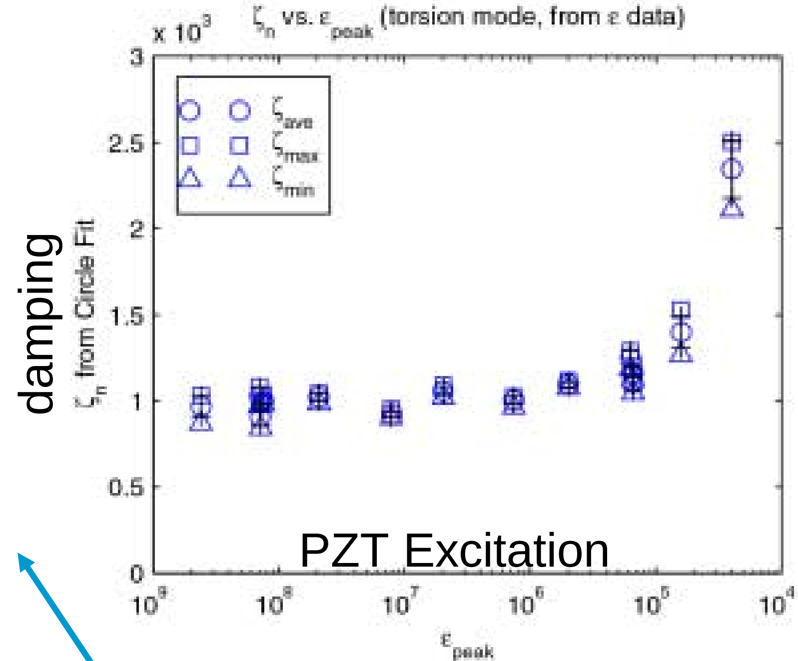
Output PSD

Excitation Amplitude / Non-Linearity

Example from MODE Experiment in μ-dynamics (torsion mode):

Plots Courtesy
Mitch Ingham

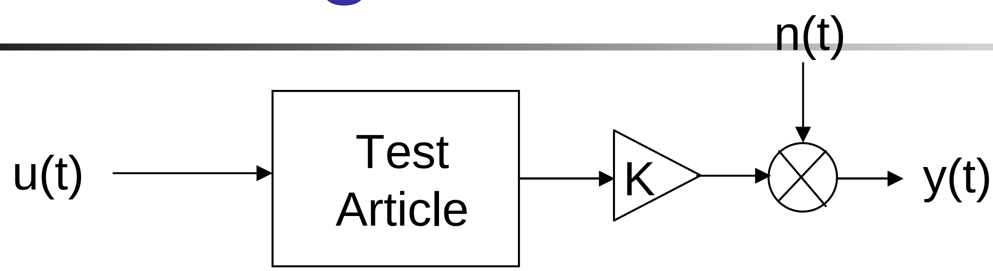




Conclusion: Linearity is only preserved for relatively small amplitude excitation (geometrical or material non-linearity, friction, stiction etc…)

Excitation amplitude selection is a tradeoff between introducing non-linearity (upper bound) and achieving good signal-to-noise ratio (SNR) (lower bound).

16.810 Signal Conditioning and Noise



When we amplify the signal, we introduce measurement noise n(t), which corrupts the measurement y(t) by some amount.

Consider Signal to Noise Ratio (SNR) = $\dfrac{\text{Power Content in Signal}}{\text{Power Content in Noise}} = \displaystyle\int_{-\infty}^{+\infty} \frac{S_{yy}(\omega)}{S_{nn}(\omega)}\, d\omega$

$$Y(s) = KG(s)U(s) + N(s)$$

Look at PSD's: $$\frac{S_{yy}(\omega)}{S_{yy}(\omega)} = \left|KG(j\omega)\right|^2 + \underbrace{\frac{S_{nn}}{S_{uu}}}_{\text{Noise contribution}}$$

Solve for system dynamics via Cross-correlation uy

$$G(j\omega) \cong \frac{S_{uy}(\omega)}{S_{uu}(\omega)}$$

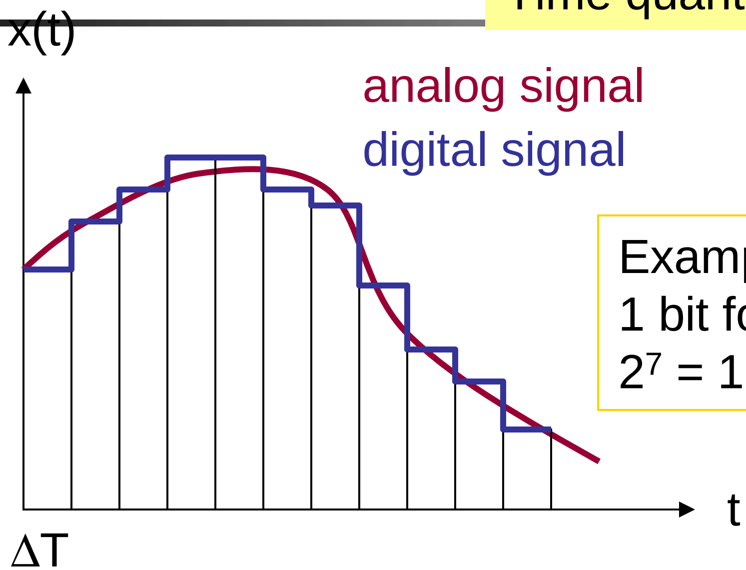
Quality estimate via coherence function → $C_{yu}(\omega)$

Decrease noise effect by:

- Increasing S_{uu} (limit non-linearity)
- Increasing K (also increases S_{nn})
- Decreasing Snn (best option)

16.810 A/D Quantization

Time quantization: f_s



Example: 8 bits
1 bit for 1 sign
2^7 = 128 levels

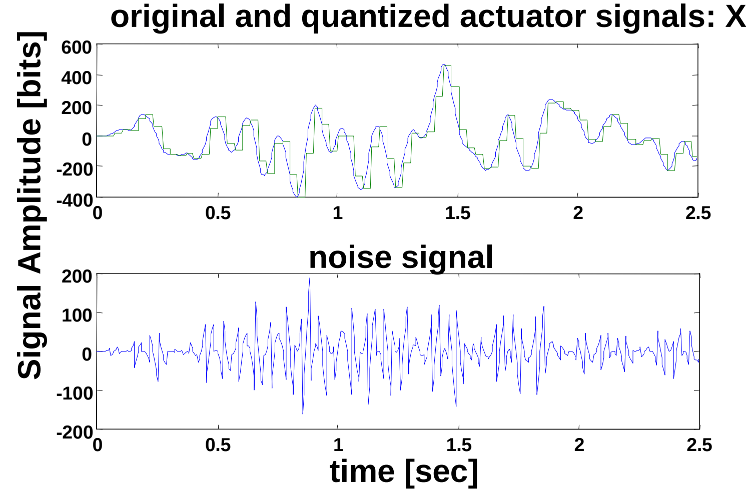
Amplitude quantization: #bits & range

Sampling Frequency: $f_s = \dfrac{1}{\Delta T}$

$$t_k = k \cdot \Delta T$$

$$x(t) \longrightarrow \boxed{A/D} \longrightarrow \hat{x}(k)$$

Figure courtesy Alissa Clawson

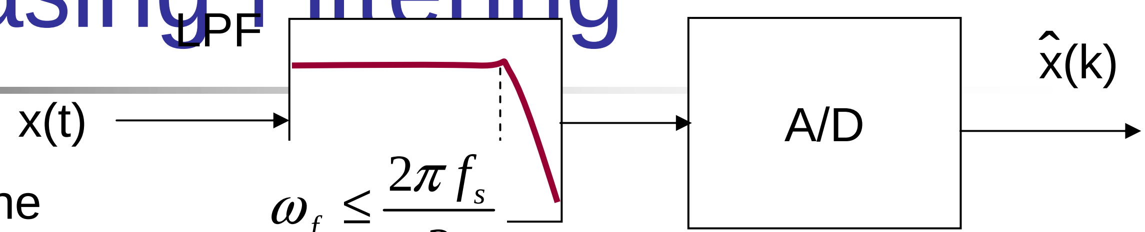


<u>Nyquist Theorem:</u> In order to recover a signal x(t) exactly it is necessary to sample the signal at a rate greater than <u>twice</u> the highest frequency present.

<u>Rule of thumb:</u> Sample 10 times faster than highest frequency of interest !

Anti-Aliasing Filtering

VERY IMPORTANT !

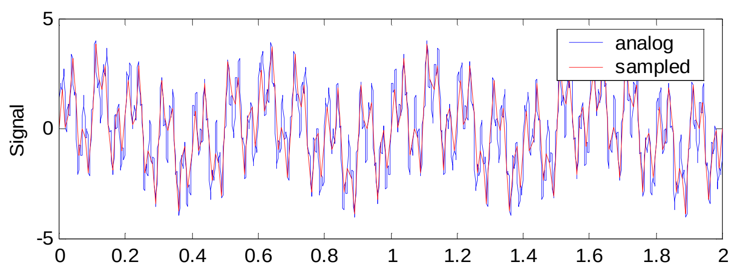


$$\omega_f \leq \frac{2\pi f_s}{2}$$

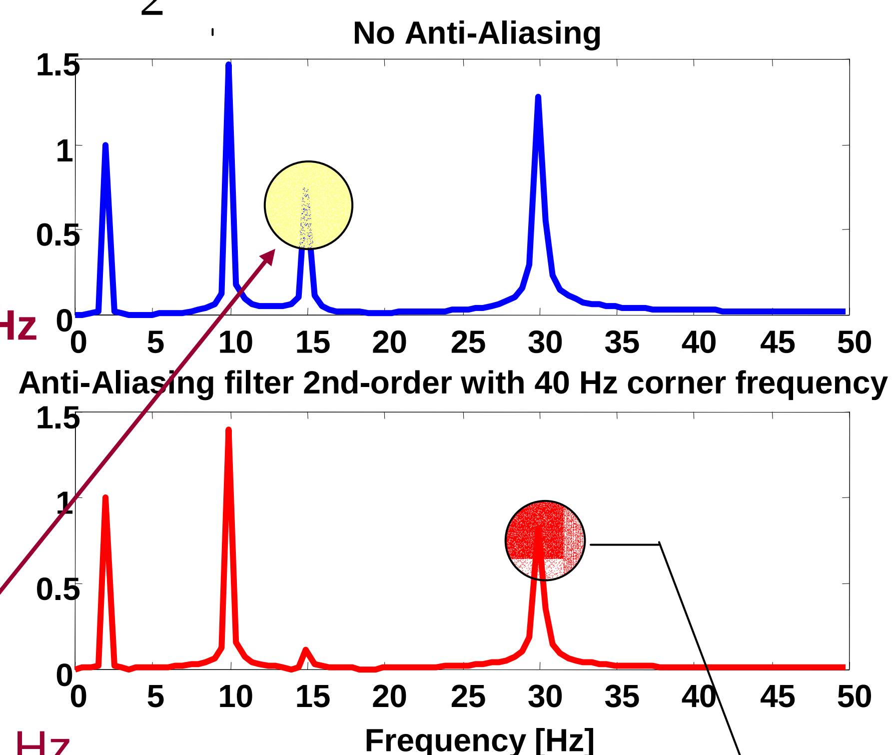
Filtering should be done on the analog signal, e.g. 4-th order Butterworth

Sample signal x(t)

Want f < 50 Hz



Fs=100Hz



Amplitudes =[1 1.5 1.5 0.75];
frequencies =[2 10 30 85];

85 Hz signal is "folded" down from the Nyquist frequency (50 Hz) to 15 Hz

Small attenuation

Solution: Use a low pass filter (LPF) which avoids signal corruption by frequency components above the Nyquist frequency

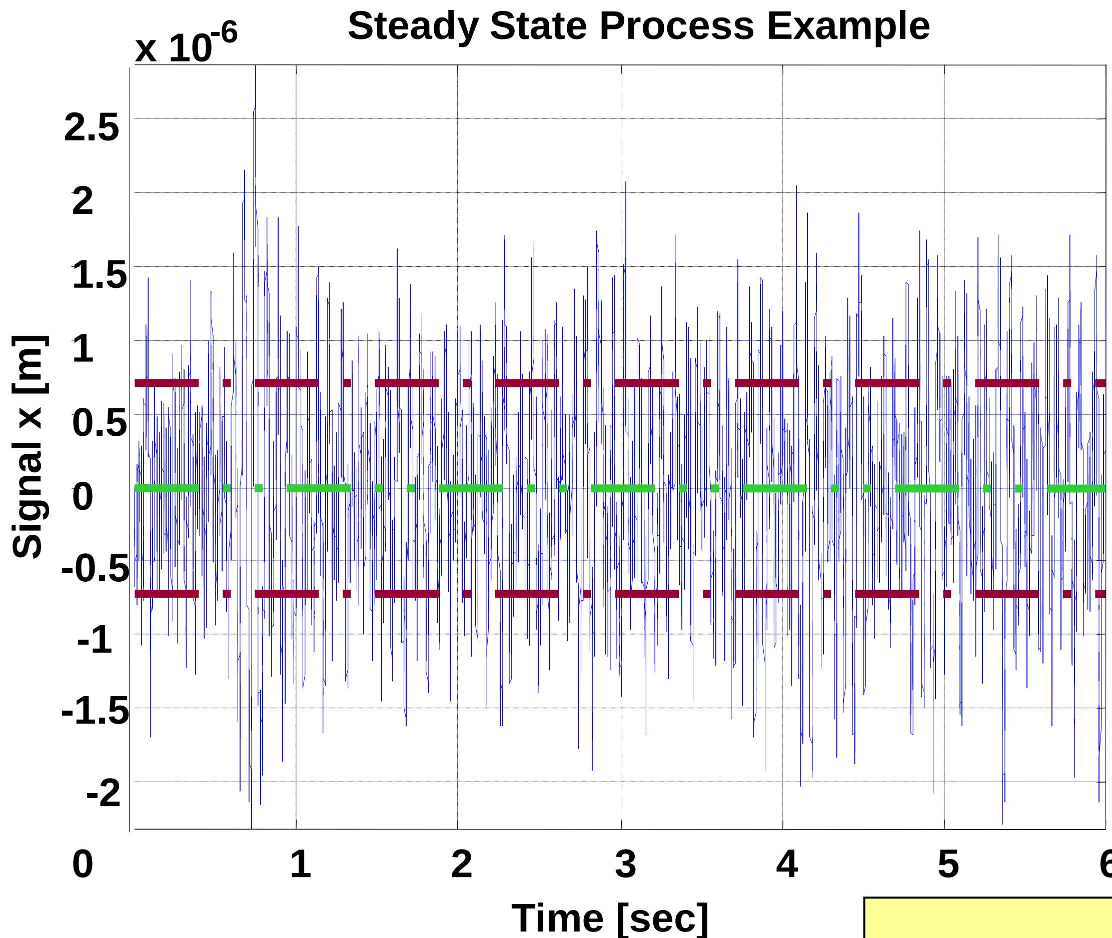
IV. Data Post-Processing

Goal: Explain what we do after data is obtained

Stationary processes ($E[x]$, $E[x^2]$,…) are time invariant	→	Analyze in frequency-domain
Transient processes	→	Analyze in time-domain (T_s, Percent overshoot etc.)
Impulse response	→	Fourier transform of $h(t) \to H(\omega)$

The FFT (Fast Fourier Transform) is the workhorse of DSP (Digital Signal Processing).

Metrics for steady state processes



Mean Value:

$$\mu_x = E[x] = \frac{1}{T}\int_{-T/2}^{T/2} x(t)dt$$

(central tendency metric)

Discrete: $\mu_x = \frac{1}{N}\sum_{k=1}^{N} x_k$

Variance:

$$\sigma_x^2 = E[(x-\mu_x)^2] = E[x^2] - \mu_x^2$$

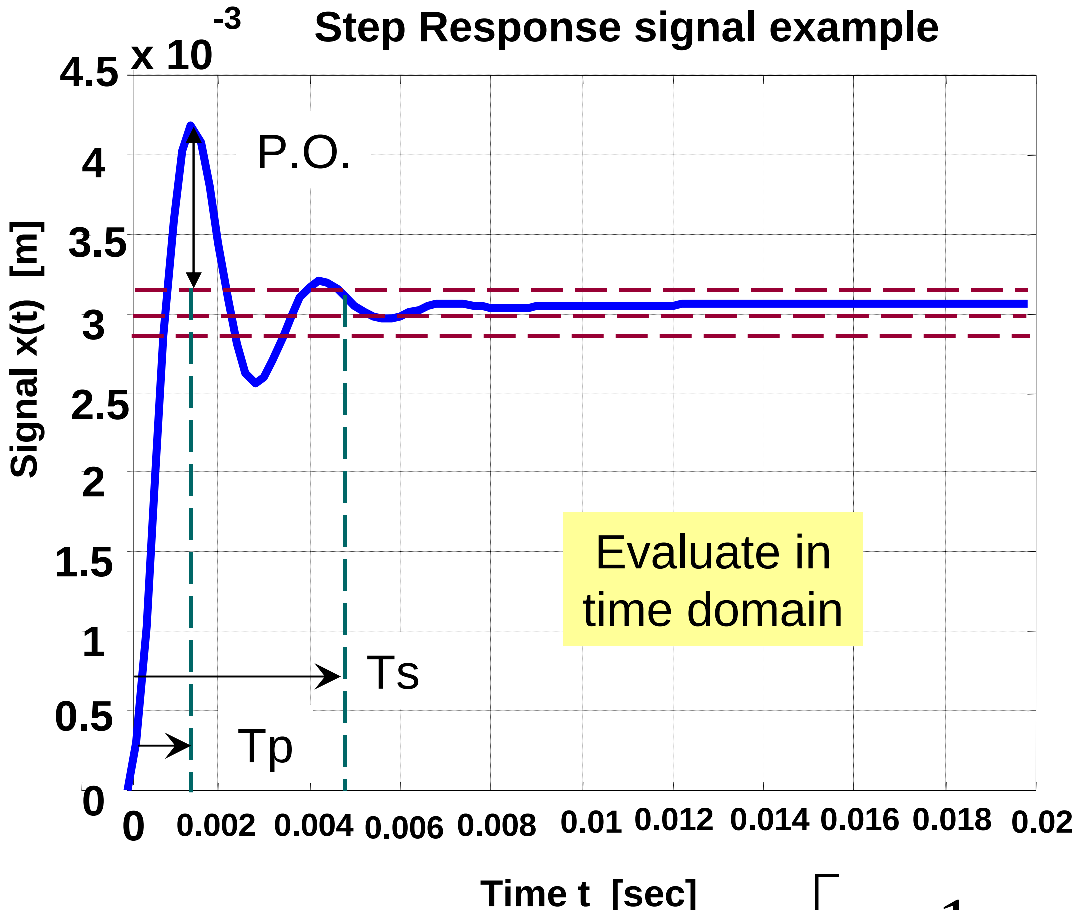
(dispersion metric)

Rarely interested in higher moments.

Root-mean-square (RMS) = $\sqrt{E[x^2]}$

Equal to σ_x only for zero mean

Metrics for transient processes



<u>Example:</u> Step Response (often used to evaluate performance of a controlled structural system)

Peak Time: $$T_p = \frac{\pi\alpha}{\omega_n}$$

Settling Time: $$T_s = \frac{4}{\zeta\omega_n}$$

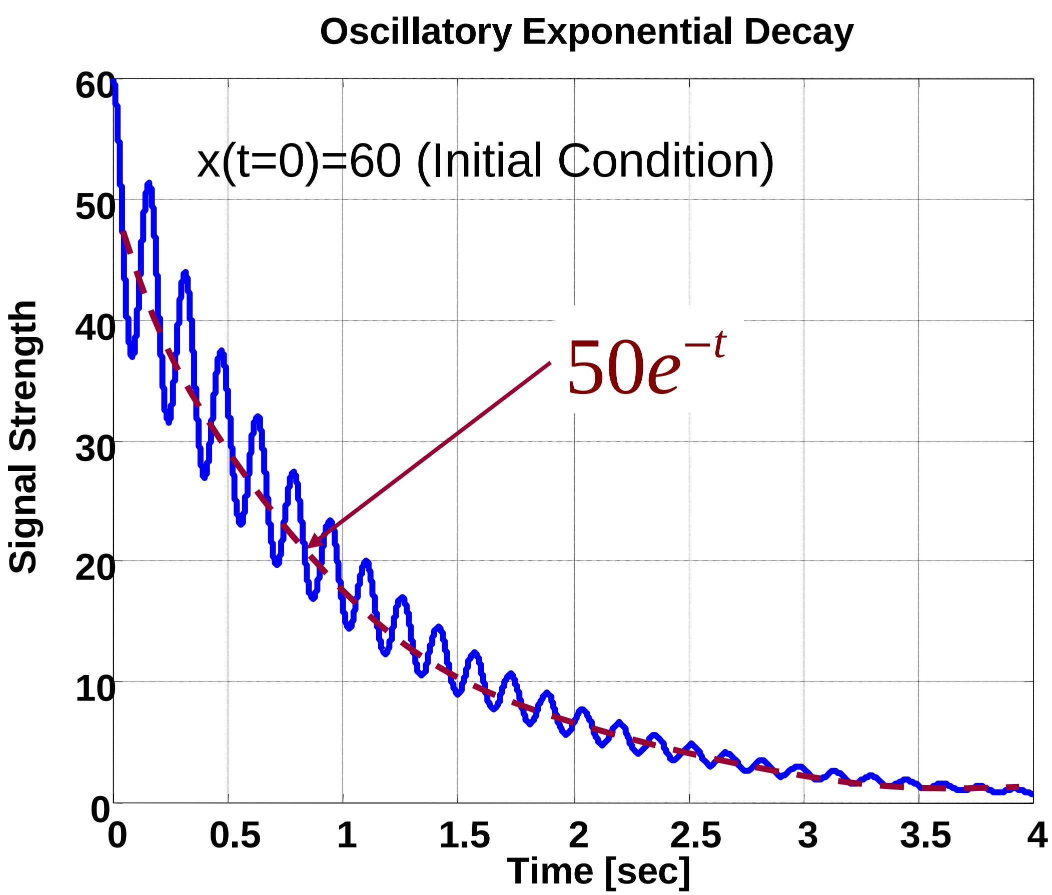
Percent Overshoot:
$$P.O. = 100\exp(-\pi\zeta\alpha)$$

Damping term: $$\alpha = \frac{1}{\sqrt{1-\zeta^2}}$$

$\zeta<1$

If assume one dominant pair of complex poles:
$$x(t) = x_o\left[1 - \frac{1}{\alpha}e^{-\zeta\omega_n t}\sin\left(\omega_n\alpha t + \tan^{-1}\left(\frac{1}{\alpha\zeta}\right)\right)\right]$$

Metrics for impulse response/decay from Initial Conditions



$$x(t) = \underbrace{50\exp(-t)} + \underbrace{10\exp((-1+40j)t)}$$

<u>Example</u>: Decay process or impulse response

Impulse response (time domain)

$$x(t) = \int_{-\infty}^{+\infty} u(\tau)h(t-\tau)d\tau$$

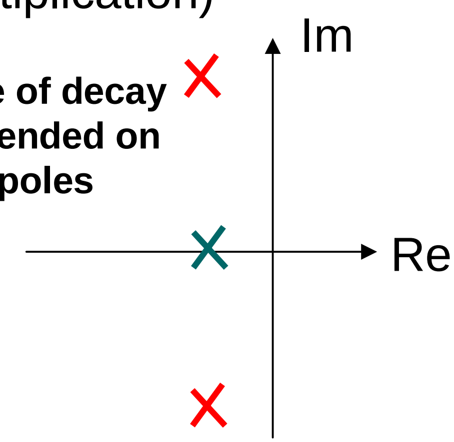
(convolution operation)

Laplace domain:

$$Y(s) = H(s)U(s)$$

(multiplication)

Rate of decay depended on poles



16.810 FFT and DFT

Fourier series: $$x(t) = \sum c_n e^{i\omega_n t}$$

Discrete Fourier Transform:

$$X_k = \sum_{r=0}^{N-1} x_r e^{-i2\pi f_k t_r}$$

$$f_k = \frac{k}{T} \quad , \quad t_r = r\frac{T}{N}$$

Approximates the continuous Fourier transform:

$$X(\omega) = \int_0^T x(t) e^{-i\omega t} dt$$

k = 0,1,..,N-1
r = 0,1,…,N-1

k and r are integers
N = # of data points
T= time length of data

Note:
X_k are complex

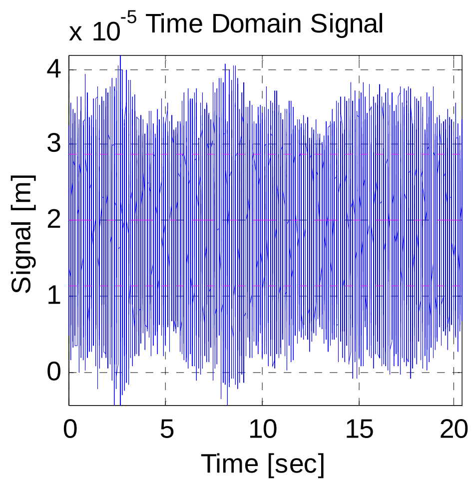
The Power Spectral Density (PSD) Function gives the frequency content of the power in the signal:

$$W_k = \frac{2\Delta T}{N} X_k \cdot X_k^H$$

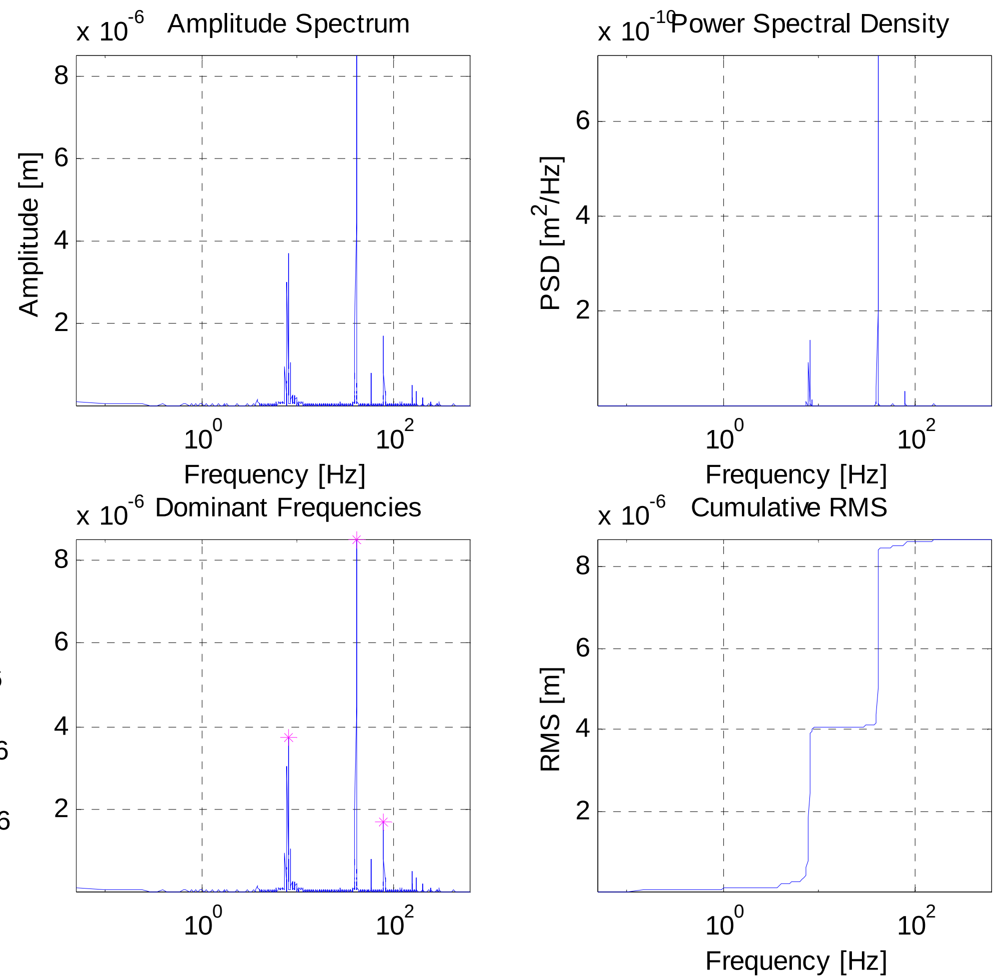
FFT - faster algorithm if N = power of 2 (512, 1024,2048,4096 …..)

Amplitude Spectra and PSD

Example: processing of Laser displacement sensor data from SSL testbed



SUMMARY OF RESULTS
MEAN of time signal: 2.0021e-005
RMS of time signal: 8.6528e-006
RMS of PSD (with fft.m): 8.6526e-006
RMS of AS (with fft.m): 8.6526e-006
RMS of cumulative RMS: 8.6526e-006
Dominant Frequency [Hz]: 40.8234
Dominant Magnitude [m]: 8.5103e-006



MATLAB coding

Time domain: Given signal x and time vector t , N samples, dt=const.

```
dt=t(2)-t(1);       % sampling time interval dt
fmax=(1/(2*dt));    % upper frequency bound [Hz] Nyquist
T=max(t);           % time sample size [sec]
N=length(t);        % length of time vector
x_mean=mean(x);     % mean of signal
x_rms=std(x);       % standard deviation of signal
```

(assume zero mean)

should match

Amplitude Spectrum:

```
X_k = abs(fft(x)); % computes periodogram of x
AS_fft = (2/N)*X_k; % compute amplitude spectrum
k=[0:N-1];          % indices for FT frequency points
f_fft=k*(1/(N*dt));     % correct scaling for frequency vector
f_fft=f_fft(1:round(N/2)); % only left half of fft is retained
AS_fft=AS_fft(1:round(N/2)); % only left half of AS is retained
```

Power Spectral Density:

```
PSD_fft=(2*dt/N)*X_k.^2; % computes one-sided PSD in Hertz
PSD_fft=PSD_fft(1:length(f_fft)); % set to length of freq vector
rms_psd=sqrt(abs(trapz(f_fft,PSD_fft))); % compute RMS of PSD
```

V. System Identification

Goal: Explain example of data usage after processing

Goal: Create a mathematical model of the system based on input and output measurements alone.

Input time histories
$u_i(t)$, i=1,2,…n

Output time histories
$x_j(t)$, j=1,2,…m

Estimator

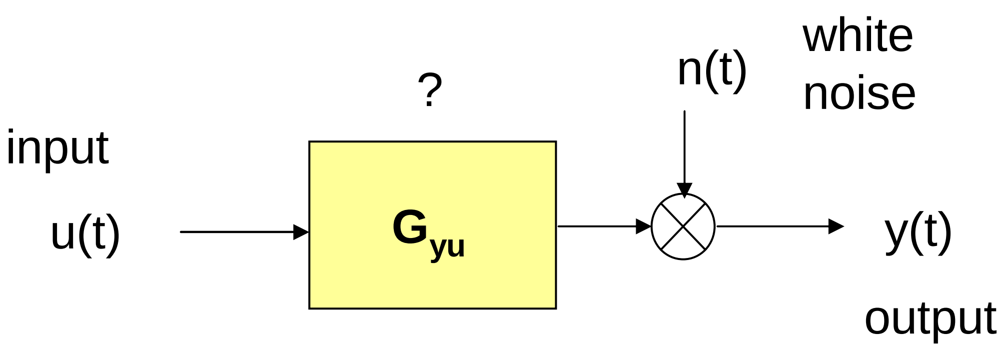
Transfer functions

Transfer matrix: G(s)

State space system

$$\dot{q} = Aq + Bu$$

$$y = Cq + Du$$



Want to obtain G_{yu} from:

$$Y(j\omega) = G(j\omega)U(j\omega) + V(j\omega)$$

G_{yu} is the actual plant we are trying to identify in the presence of noise

Empirical Transfer Function Estimate (ETFE)

$$\hat{G}_{kl}(j\omega) = \frac{Y_k(j\omega)}{U_l(j\omega)}$$

Obtain an estimate of the transfer function from the l-th input to the j-th output

$$\underbrace{\hat{G}_{kl}(j\omega)}_{\text{Estimated TF}} = \underbrace{G_{kl}(j\omega)}_{\text{True TF}} + \underbrace{\frac{N(j\omega)}{U_l(j\omega)}}_{\text{Noise}}$$

What are the consequences of neglecting the contributions by the noise term ?

Compute: $S_{yu} = E[Y(s)U^*(s)]$ $\quad S_{UU} = E[UU^*]$, $S_{YY} = E[YY^*]$

Quality Assessment of transfer function estimate via the **coherence function**:

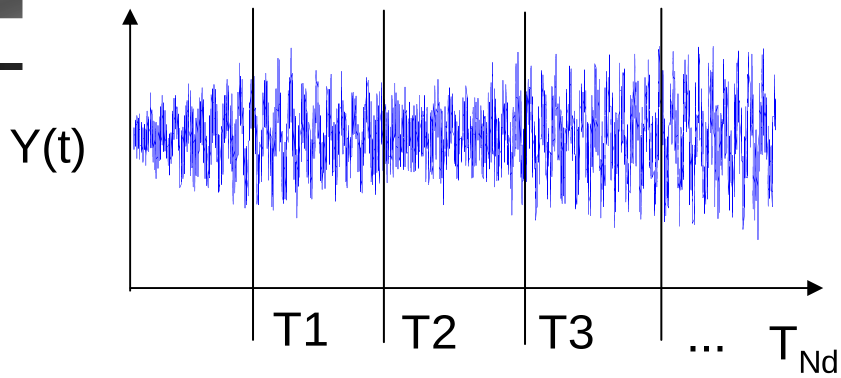
$$C_{yu}^2 = \frac{\left|S_{yu}\right|^2}{S_{yy}S_{uu}}$$

$C_{yu} \to 1$ Implies small noise (Snn ~ 0)

$C_{yu} \to 0$ Implies large noise Poor Estimate

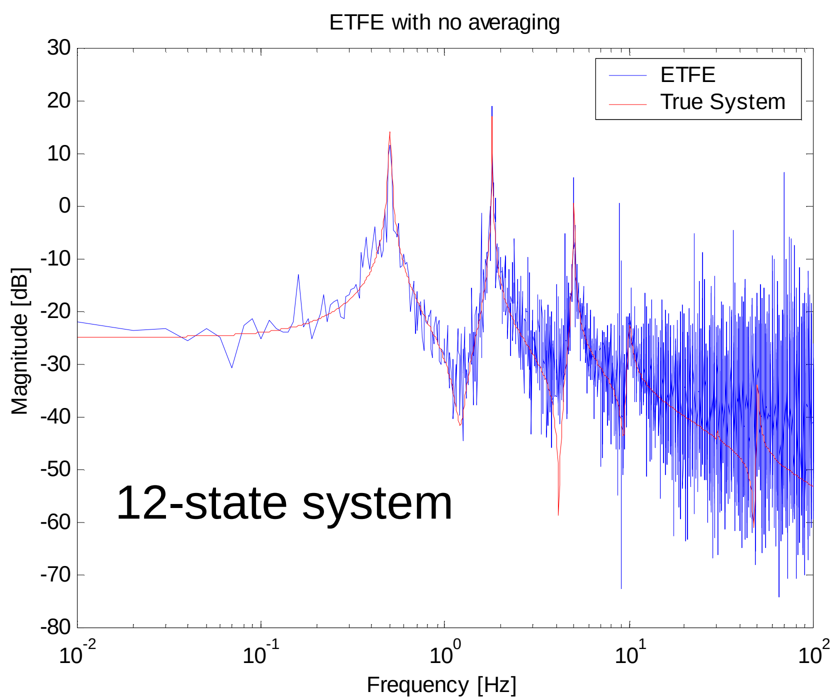
Typically we want $C_{yu} > 0.8$

Averaging

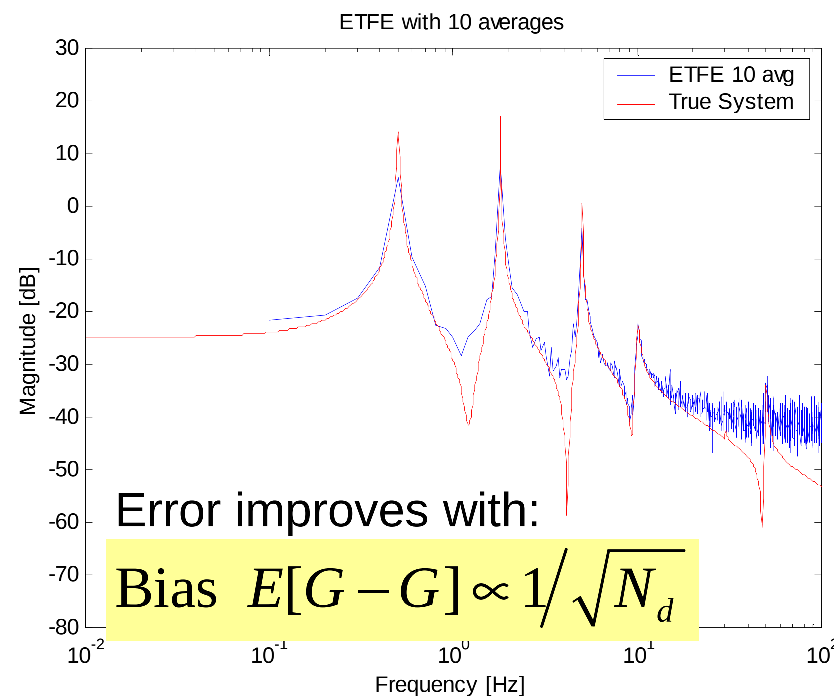


data subdivided in N_d parts

$$\hat{G}(s) = \frac{\frac{1}{N_d}\sum_{i=1}^{N_d} Y_i(s)U_i(-s)}{\frac{1}{N_d}\sum_{i=1}^{N_d} \left|U_i(s)\right|^2}$$



12-state system



Error improves with:

Bias $E[G-G] \propto 1/\sqrt{N_d}$

Model Synthesis Methods

Example: Linear Least Squares

Polynomial form: $$G(s) = \frac{b_{n-1}s^{n-1} + \ldots + b_o}{s^n + a_{n-1}s^{n-1} + \ldots + a_o} = \frac{B(j\omega,\theta)}{A(j\omega,\theta)}$$

We want to obtain an estimate of the polynomial coefficient of G(s)

$$\theta^T = \begin{bmatrix} a_o & a_1 & \ldots & a_{n-1} & b_o & \ldots & b_{n-1} \end{bmatrix}$$

Define a cost function: $$J = \frac{1}{N}\sum_{k=1}^{N} \frac{1}{2}\left[\hat{G}(j\omega_k) - \frac{B(j\omega_k,\theta)}{A(j\omega_k,\theta)}\right]^2$$

J is quadratic in θ: can apply a gradient search technique to minimize cost J

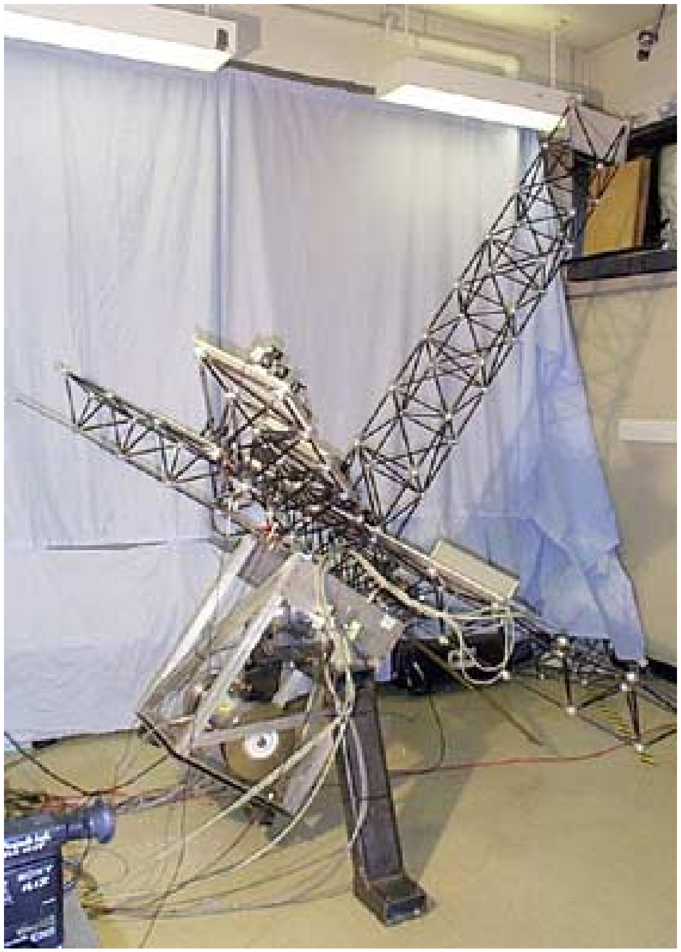
Search for: $$\frac{\partial J}{\partial \theta} = 0 \rightarrow \theta_{optim}$$

Simple method but two major problems

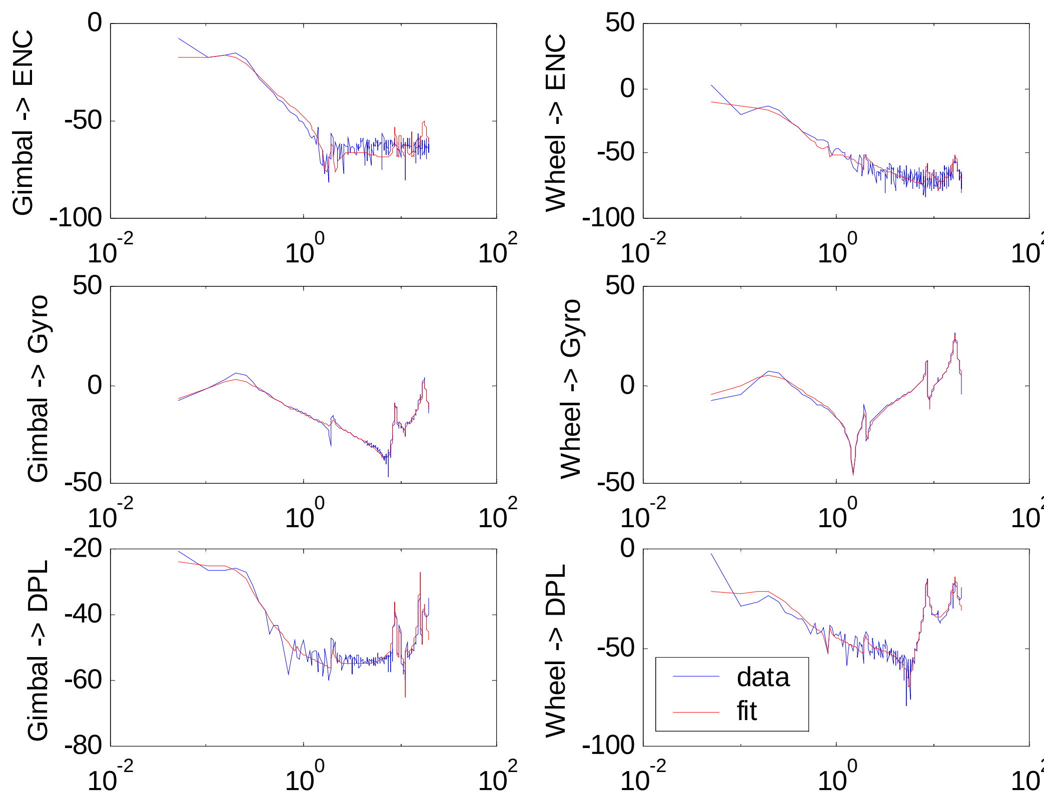
- Sensitive to order n
- Matches poles well but not zeros

Other Methods: ARX, logarithmic NLLS, FORSE

State Space Measurement Models



Measurement models obtained for MIT ORIGINS testbed (30 state model)



Software used: DynaMod by Midé Technology Corp.

Summary

Upfront work before actual testing / data acquisition is considerable:

- What am I trying to measure and why ?
- Sensor selection and placement decisions need to be made
- Which bandwidth am I interested in ?
- How do I excite the system (caution for non-linearity) ?

The topic of signal conditioning is crucial and affects results :

- Do I need to amplify the native sensor signal ?
- What are the estimates for noise levels ?
- What is my sampling rate ΔT and sample length T (Nyquist, Leakage) ?
- Need to consider Leakage, Aliasing and Averaging

Data processing techniques are powerful and diverse:

- FFT and DFT most important (try to have 2^N points for speed)
- Noise considerations (how good is my measurement ? -> coherence)