

Digital Signal Processing

Statistics, Probability and Noise Part 1

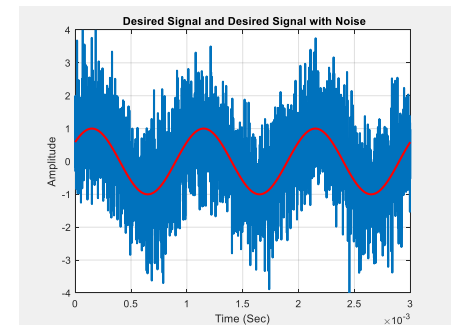
Today's Key Points

- Input signals often contain both the desired information and some level of noise.
- Statistics are used to characterize these signals
 - Mean, Standard Deviation, Variance
- The signal to noise ratio (SNR) is used to compare the signal level to the noise level

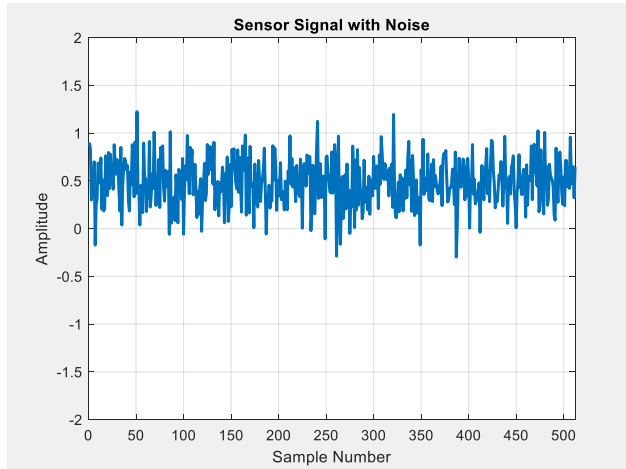
Signal Visualization

The Domain of a Signal

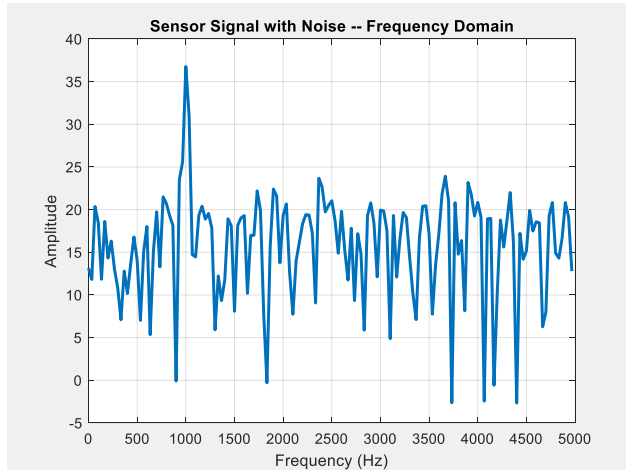
- On a graph the dependent value is on the y-axis
- The independent value on the x-axis
- The independent value (x-axis) is sometimes described as the “domain” of the signal
 - Time, Spatial, Frequency for example
- In many cases we'll use the sample number on the x-axis.
 - We'll still refer to this as the time domain



Signal Domains

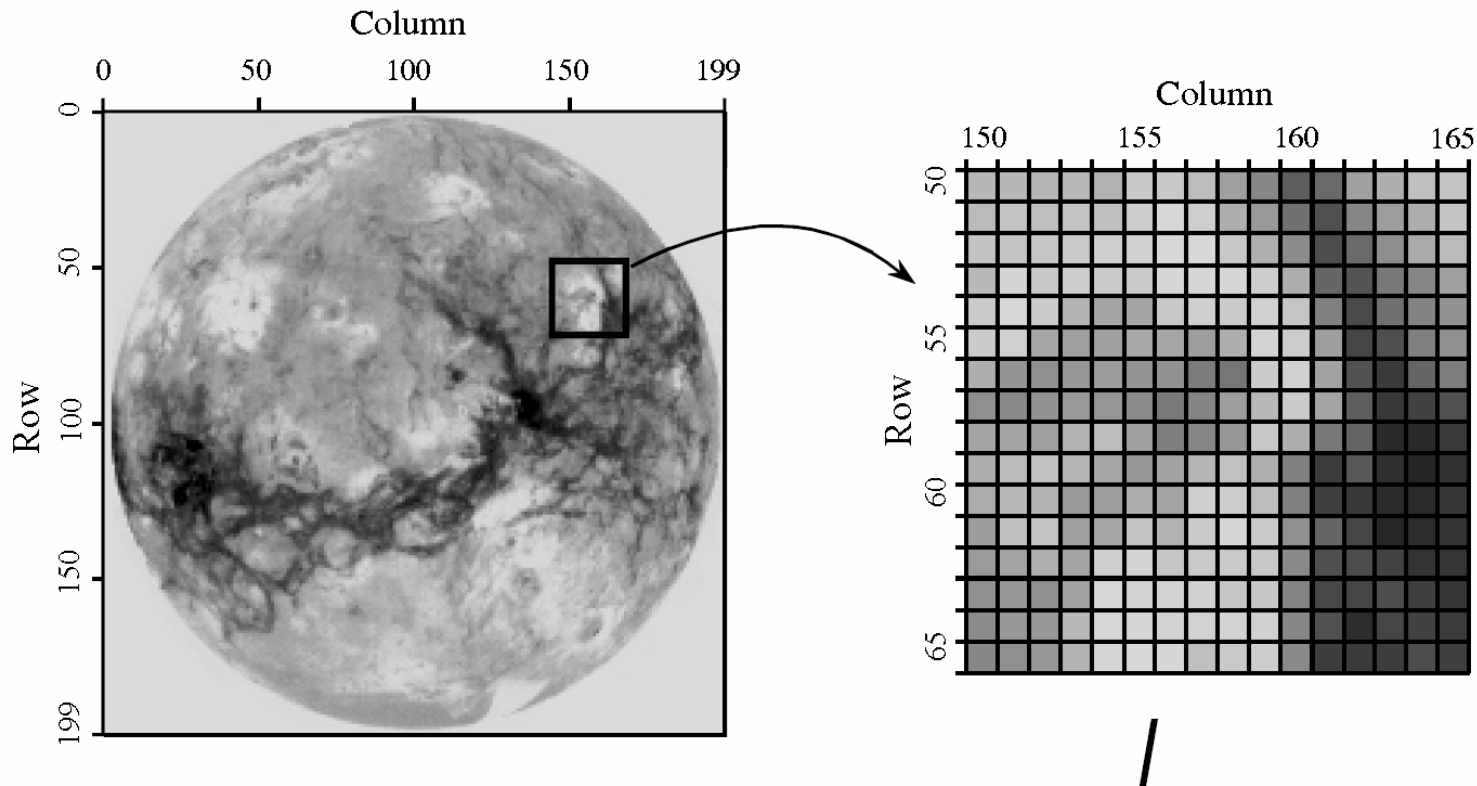


Time Domain – The independent value is time or samples



Frequency Domain – The independent value is Frequency

Signal Domains



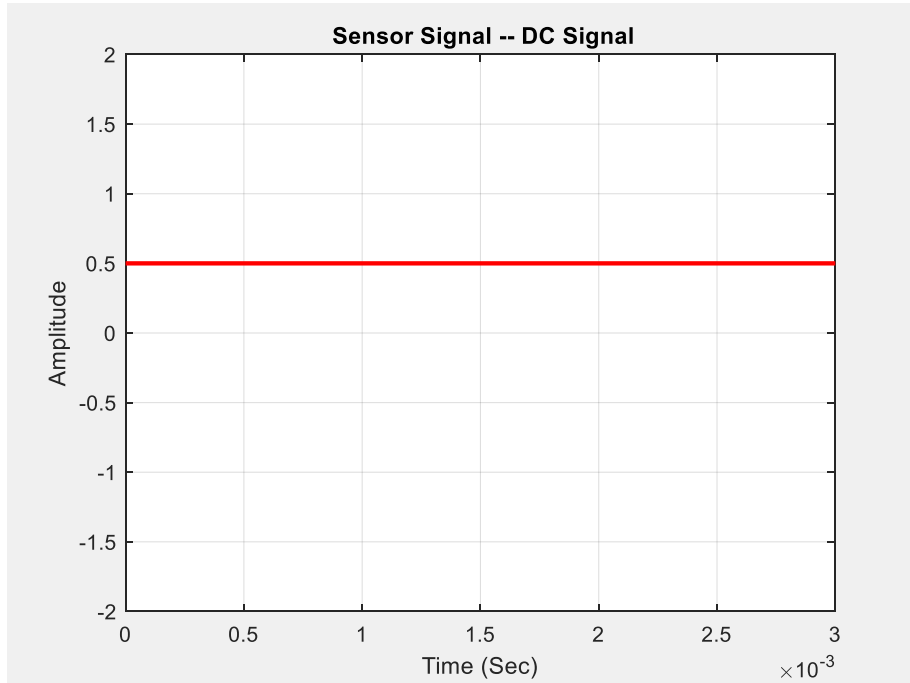
Spatial Domain – The independent value is distance

Introduction to Noise

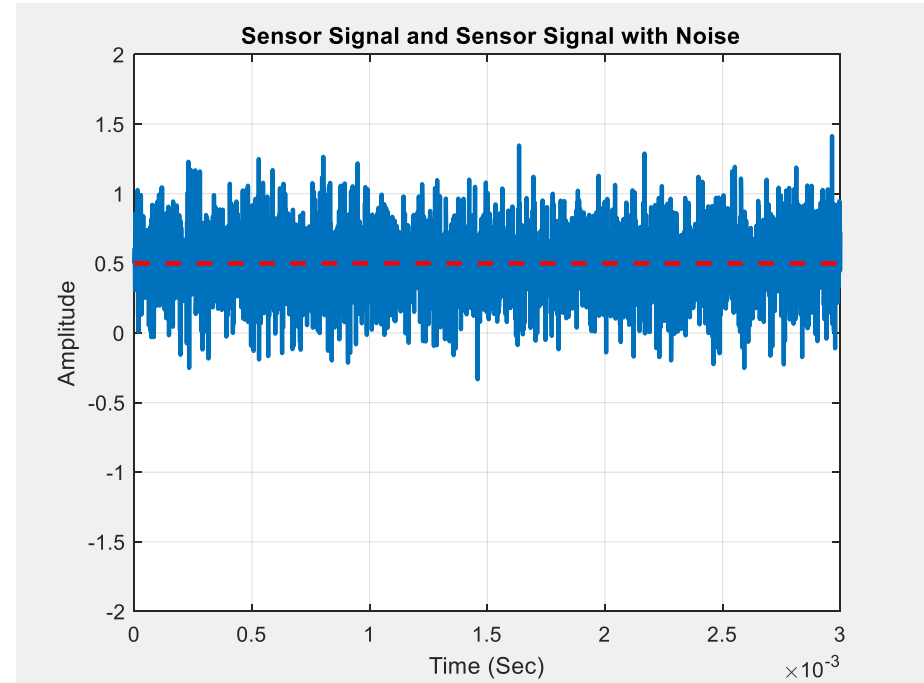
- Noise may come from many different sources
- External Noise
 - Noise inherent on the incoming signal from the analog world
 - For example noise from temperature sensors, voltage sources, strain gauges, microphones, etc..
- Internal Noise
 - Noise added by the Analog to Digital conversion process
 - Noise added by digital calculations in software or hardware
- Noise is random, or at least assumed to be random

Signal and Noise Examples

Sensor Signal



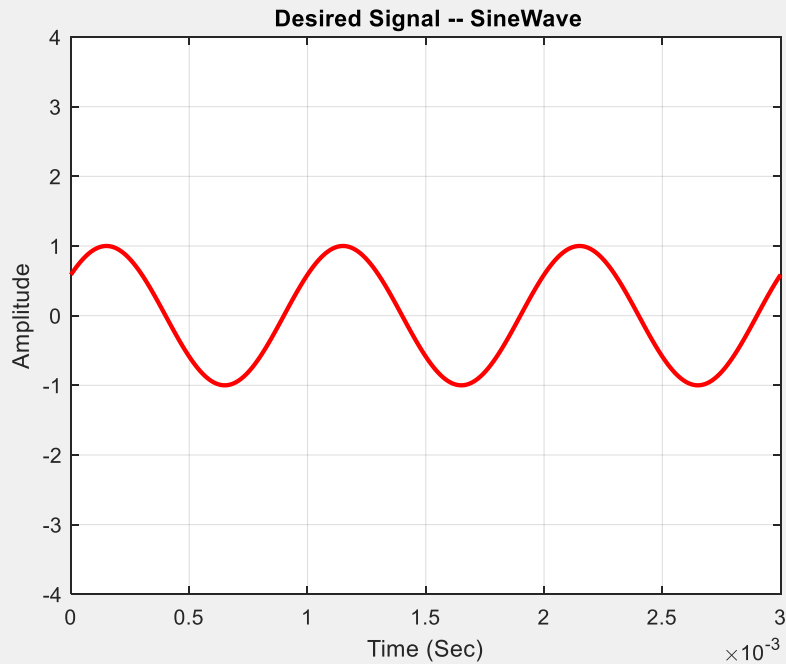
Sensor Signal
Fixed DC Value = 0.5V



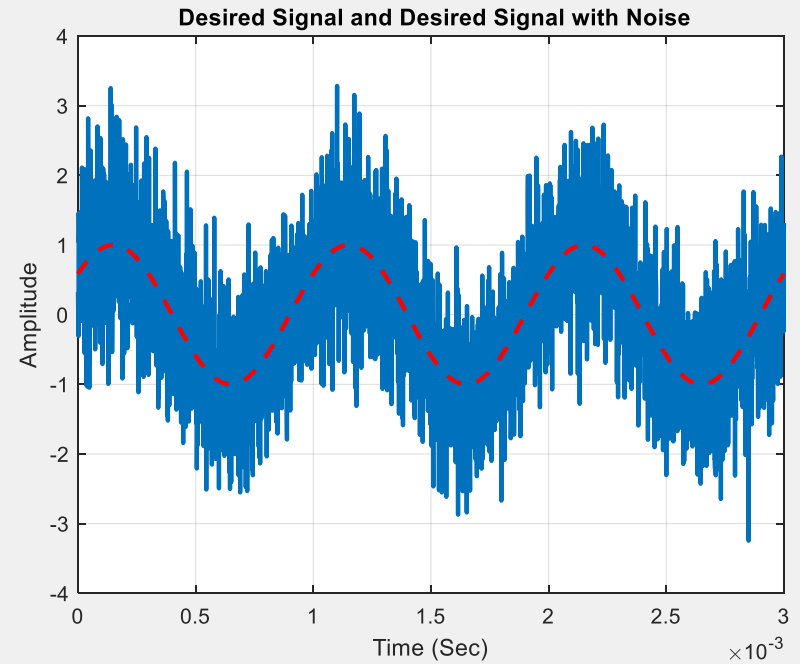
Sensor Signal with Noise

Signal and Noise Example

Sinewave Signal



Desired Signal
1 kHz Sinewave



Desired Signal with Noise

Using Statistics to Characterize Signals and Noise

- Common Statistics Used to Describe Noise and Signals
 - Mean, Standard Deviation, Variance
 - Each statistic has its own purpose and its own properties
- A set of measurements of signal can be displayed using histograms to help visualize how much random noise is present.

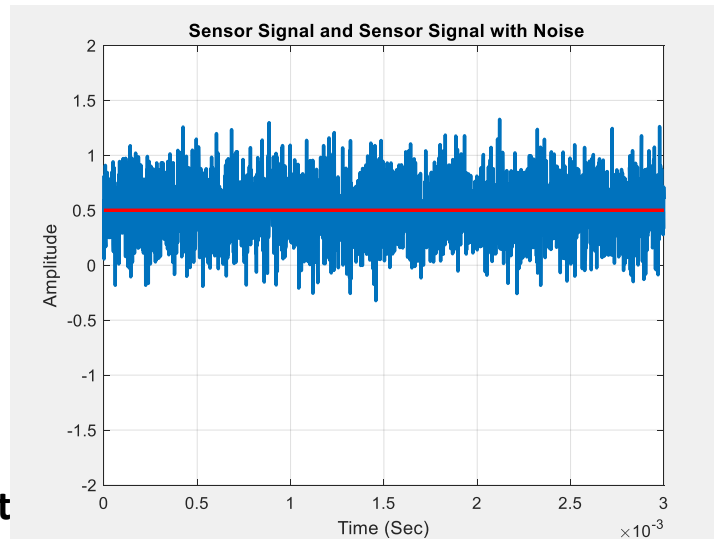
Mean

- The sample mean is the average of all the sample values.

$$\hat{\mu} = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

This is an estimate of the true mean

- In electronics it is the DC value of the signal



Mean = 0.5

Variance

- The sum of the squared difference of the signal from the mean divided by $N - 1$.

$$\hat{\sigma}^2 = \frac{1}{N - 1} \sum_{i=0}^{N-1} (x_i - \hat{\mu})^2$$

- Represents the power of the signal variations around the mean

Standard Deviation

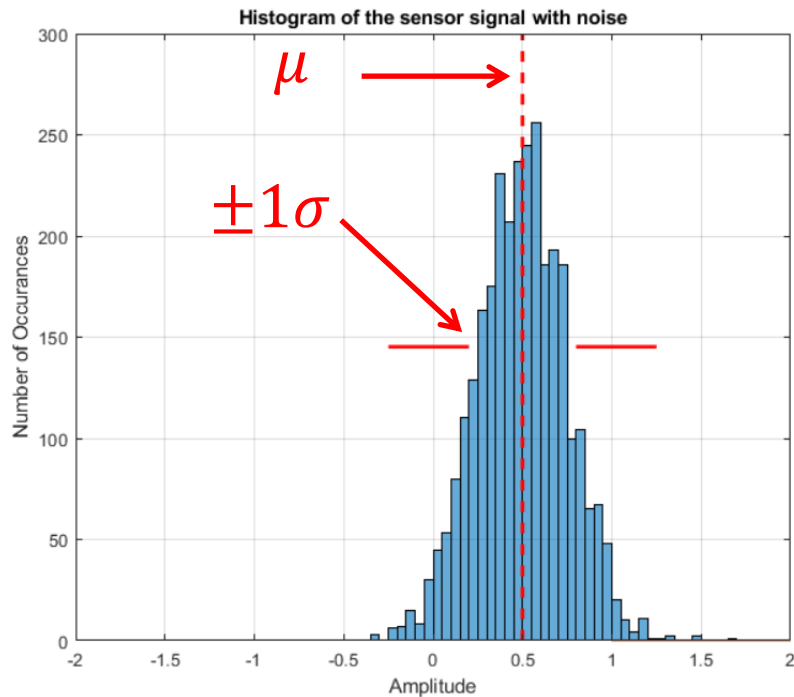
- Standard deviation is the square root of the variance

$$\hat{\sigma} = \sqrt{\hat{\sigma}^2} = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2}$$

- A measure of the how far the signal varies from the mean
 - Has the same units as the signal (e.g. volts)
 - Akin to the RMS value of an electrical signal

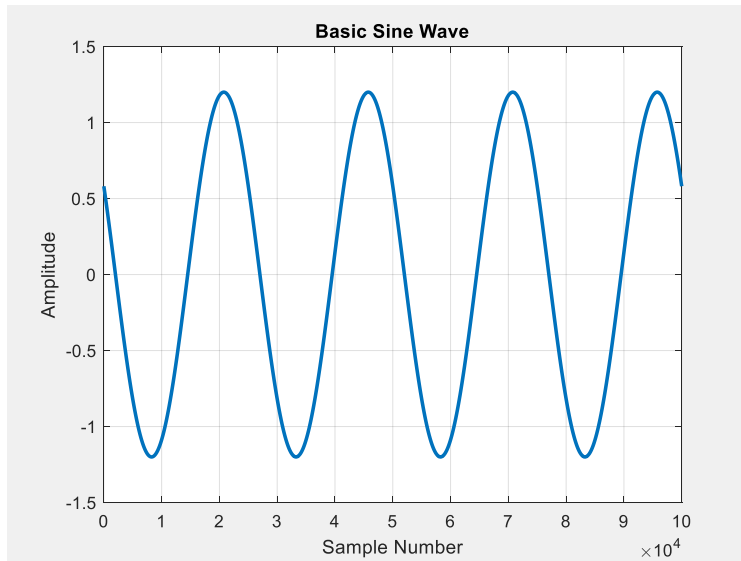
Histograms

- Some statistical parameters can be estimated from a histogram of the data
 - Mean
 - Standard Deviation



Electrical Analogy

- If an electrical signal has only an AC component, then the RMS (root mean square) of that signal is the same as its standard deviation.



$$V_{peak} = 1.2V$$

$$V_{RMS} = \frac{V_{peak}}{\sqrt{2}} = 0.8485$$

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2}$$

Examples of Common Signals and Their Standard Deviations

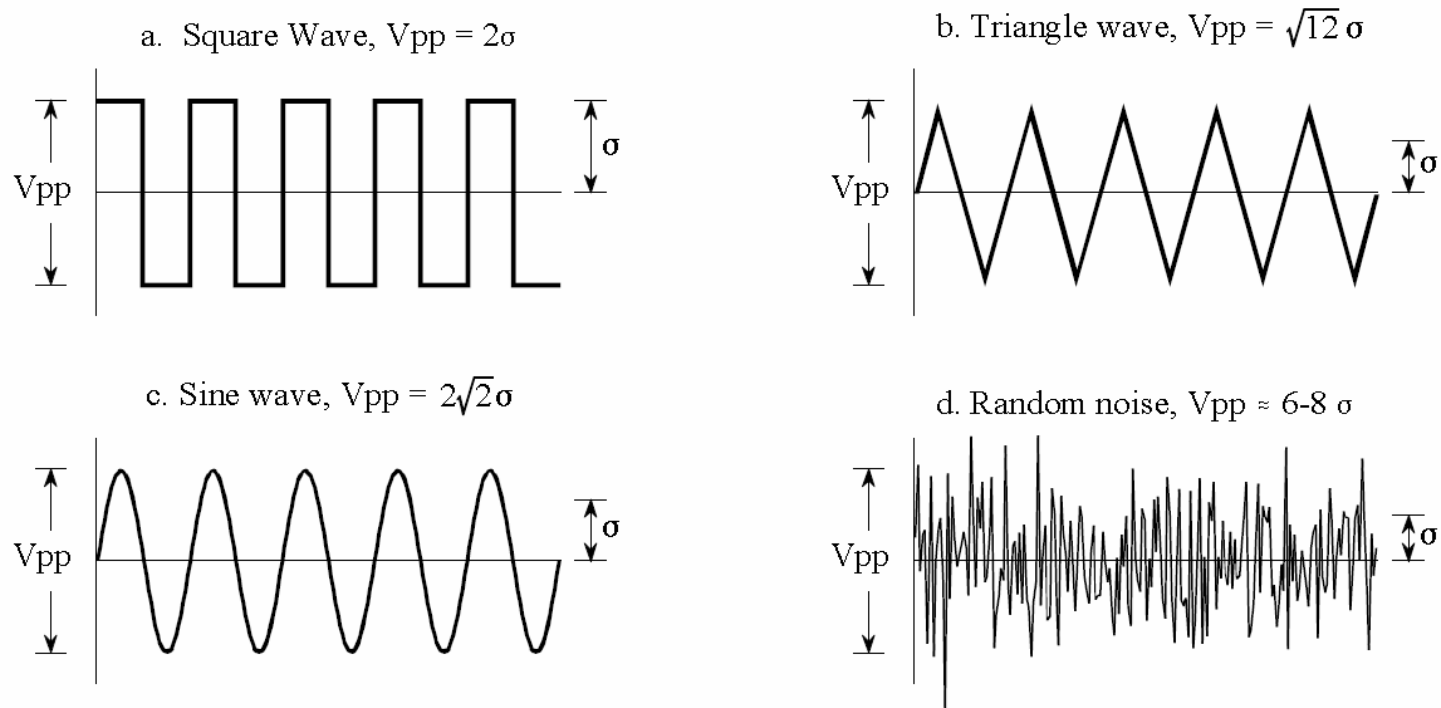
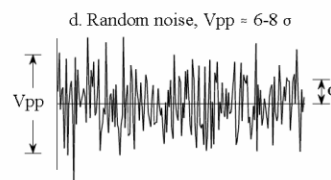
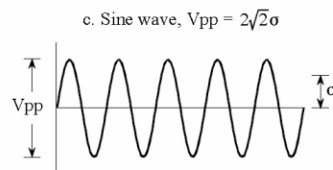
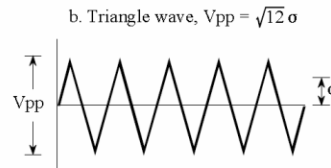
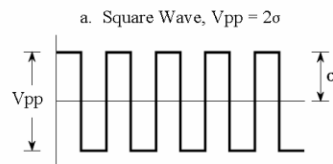


FIGURE 2-2

Ratio of the peak-to-peak amplitude to the standard deviation for several common waveforms. For the square wave, this ratio is 2; for the triangle wave it is $\sqrt{12} = 3.46$; for the sine wave it is $2\sqrt{2} = 2.83$. While random noise has no *exact* peak-to-peak value, it is *approximately* 6 to 8 times the standard deviation.

In Class Problem:

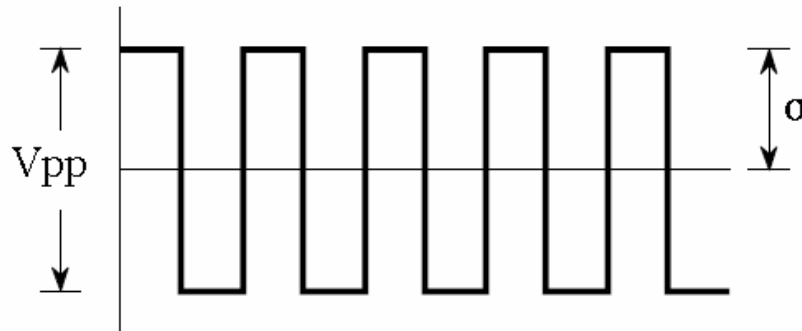
- What is the power in the fluctuation for each of these signals?
- A) Square wave with $V_{pp} = 2$
- B) Sine wave with $V_{pp} = 2.828$
- C) Triangular wave with $V_{pp} = 3.464$
- D) Random noise with $V_{pp} = 7$



In Class Problem:

- A) Square Wave with $V_{pp} = 2$

a. Square Wave, $V_{pp} = 2\sigma$



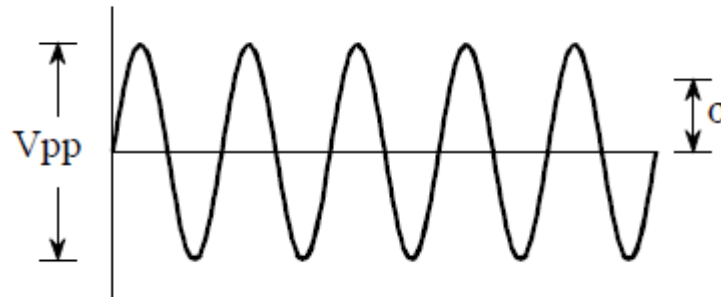
$$V_{pp} = 2\sigma \qquad \sigma = \frac{V_{pp}}{2}$$

$$\sigma = \frac{2}{2} = 1 \qquad \sigma^2 = 1^2 = 1$$

In Class Problem:

- B) A Sine Wave with $V_{pp} = 2.828$

c. Sine wave, $V_{pp} = 2\sqrt{2}\sigma$



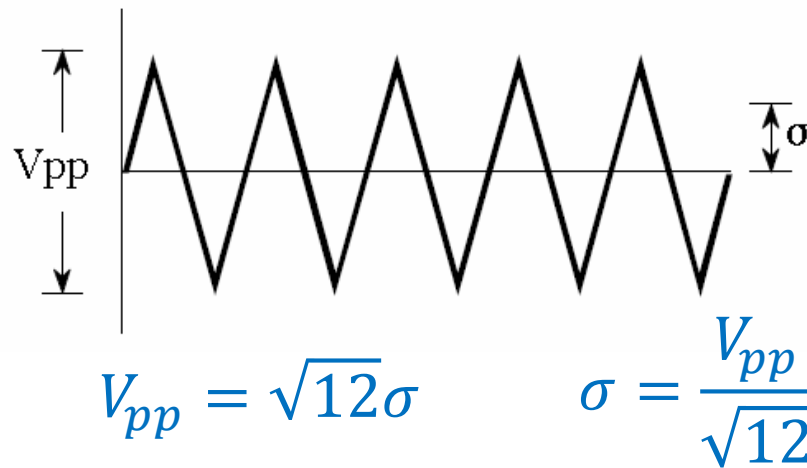
$$V_{pp} = 2\sqrt{2}\sigma \quad \sigma = \frac{V_{pp}}{2\sqrt{2}}$$

$$\sigma = \frac{2.828}{2\sqrt{2}} = 1 \quad \sigma^2 = 1^2 = 1$$

In Class Problem:

- C) Triangle Wave with $V_{pp} = 3.464$

b. Triangle wave, $V_{pp} = \sqrt{12} \sigma$

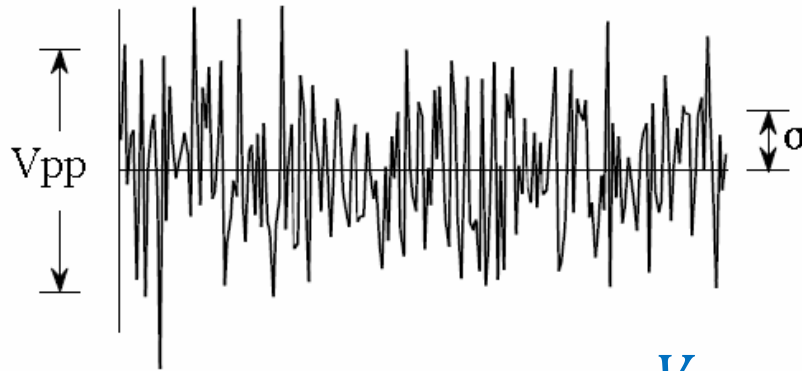


$$\sigma = \frac{3.464}{\sqrt{12}} = 1 \quad \sigma^2 = 1^2 = 1$$

In Class Problem:

- D) Random Noise with $V_{pp} = 7$

d. Random noise, $V_{pp} \approx 6-8 \sigma$



$$V_{pp} = 6\sigma \text{ to } 8\sigma \quad \sigma \sim \frac{V_{pp}}{7}$$

$$\sigma = \frac{7}{7} = 1 \quad \sigma^2 = 1^2 = 1$$

Computing Statistics on a Sample

- When computing $\hat{\sigma}$ or $\hat{\mu}$ we use a set of values that are a sample of N values $x = 6.3, 4.5, 8.9, 10.2, \dots$

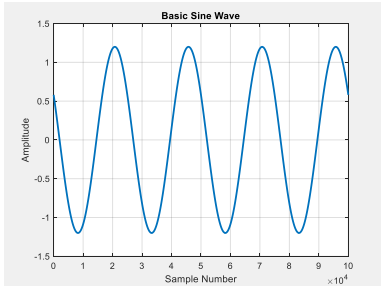
$$\hat{\mu} = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

Sum up all the samples
Divide by N

$$\hat{\sigma}^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \hat{\mu})^2$$

Find $\hat{\mu}$
Sum up all the samples - $\hat{\mu}$ squared
Divide by N-1

Compute the SD using MATLAB



Compute the mean

Compute the variance

$$V_{RMS} = \frac{1.2}{\sqrt{2}} = 0.8485$$

Compute the Variance Using all the Samples Recursively

```

32
33 % Compute the standard deviation using the standard equation using all the
34 % samples at once
35
36 % Compute an estimate of the mean
37
38 N = length( basicSineWave );
39 meanSum = 0;
40 for i = 1:N
41     meanSum = meanSum + basicSineWave(i);
42 end
43
44 meanEstimate = meanSum / N;
45
46 varSum = 0;
47 for i = 1:N
48     varSum = varSum + (basicSineWave(i) - meanEstimate )^2;
49 end
50
51 varEstimate = varSum / (N-1);
52 stdEstimate = sqrt(varEstimate);
53
54 resultStr = sprintf('Variance Estimate -- %2.4f\nSD Estimate - %2.4f', varEstimate,
55 disp(resultStr)
    
```

$$\mu = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

$$\sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2$$

Compute the standard deviation

Variance Estimate -- 0.7200
SD Estimate - 0.8485

Computed SD matches RMS value of 0.8485

Mean and SD Calculations With Limited Precision

- A problem occurs when the mean is much greater than the variation.
- The difference $(x_i - \mu)$ is a very small number and round off error can occur

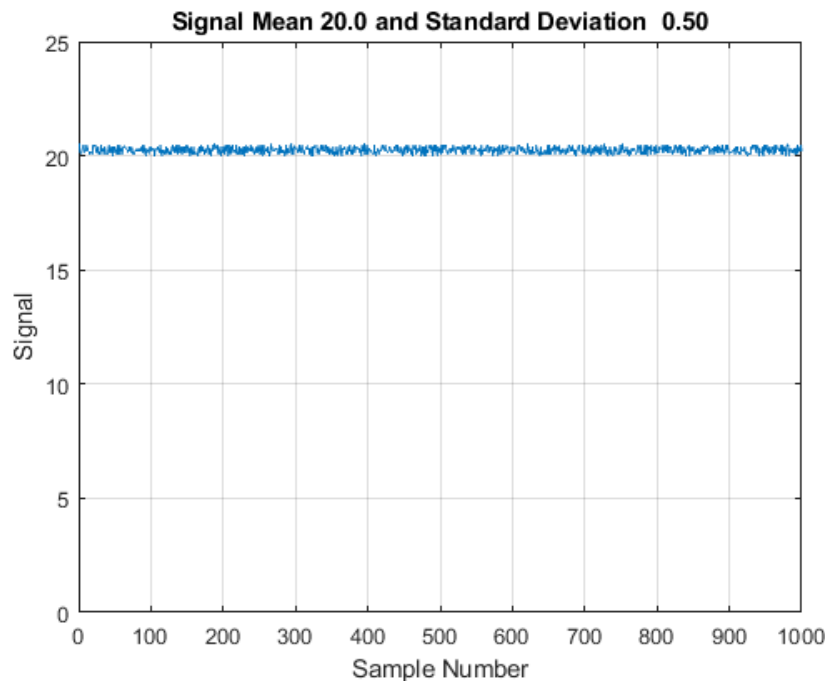
$$\hat{\sigma}^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \hat{\mu})^2$$

Potential Round off error
when this difference is small

- Occurs when the mean is much greater than the standard deviation

Mean and SD Calculations With Limited Precision

- When the mean is much larger than the standard deviation then there are small differences between the mean and each sample



$$\hat{\sigma}^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \hat{\mu})^2$$

Potential Round off error
when this difference is small

Issues with Mean and SD Calculations – Efficiency

- What happens if we get one more sample?
- Or we want to keep updating variance for each new sample?

Must save all the samples
and recompute the mean for
each new sample x_i



Must recompute σ^2
including for each new
sample x_i

$$\mu = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

$$\sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2$$

- May require significant memory storage and computation time!

Computing Running Variance A Better Way

- Refactor the variance equation as

$$\sigma^2 = \frac{1}{N-1} \left[\sum_{i=0}^{N-1} x_i^2 - \frac{1}{N} \left(\sum_{i=0}^{N-1} x_i \right)^2 \right]$$
$$\sigma^2 = \frac{1}{N-1} \left[\text{sum of squares} - \frac{\text{sum}^2}{N} \right]$$

- Keep a running value of sum of squares, the mean and the total number of samples

Alternative Calculation Using Running Statistics

$$\sigma^2 = \frac{1}{N-1} \left[\sum_{i=0}^{N-1} x_i^2 - \frac{1}{N} \left(\sum_{i=0}^{N-1} x_i \right)^2 \right]$$

Need to store only N, (sum of squares) and sum

$$\sigma^2 = \frac{1}{N-1} \left[\text{sum of squares} - \frac{\text{sum}^2}{N} \right]$$

- More computationally efficient, requires less memory

MATLAB Example for Calculating Running Statistics

Compute the estimate using the running variance formula

$$N = N + 1$$

$$Sum = \sum_{i=0}^{N-1} x_i$$

$$SS = \sum_{i=0}^{N-1} x_i^2$$

$$\sigma^2 = \frac{1}{N-1} \left[\sum_{i=0}^{N-1} x_i^2 - \frac{1}{N} \left(\sum_{i=0}^{N-1} x_i \right)^2 \right]$$

```
N = 0;
sumOfValues = 0;
sumSquareOfValues = 0;

varData = zeros( length( basicSineWave ), 1);

for i = 1:length( basicSineWave)

    N = N + 1;
    sumOfValues = sumOfValues + basicSineWave(i);
    sumSquareOfValues = sumSquareOfValues + basicSineWave(i)^2;

    runningVar = ( sumSquareOfValues - ( sumOfValues^2 / N ) ) / (N-1);
    varData(i) = runningVar;

end

runningVarEstimate = runningVar;
runningStdEstimate = sqrt( varEstimate );
```

In Class Problem: Running Statistics

- If you have $N-1$ samples and a new sample x_i is acquired, how many calculations (multiply, add, divide, square root) are required to compute the new variance using :
 - 1) The standard calculation
 - 2) The running variance calculation
- What impact does this have on calculation time?

The Standard Calculation

- Recompute the mean
 $N - 1$ additions, 1 divide

$$\mu = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

- Recompute the variance

$$\sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2$$

$N - 1$ subtractions, N multiplies, $N - 1$ more additions, 1 divide

$3N - 2$ additions (and subtractions), N multiplies, 2 divides

The Running Variance

$$\sigma^2 = \frac{1}{N-1} \left[\sum_{i=0}^{N-1} x_i^2 - \frac{1}{N} \left(\sum_{i=0}^{N-1} x_i \right)^2 \right]$$

Running Sum of Squares

1 multiply (square), 1 addition

Running Sum

1 addition

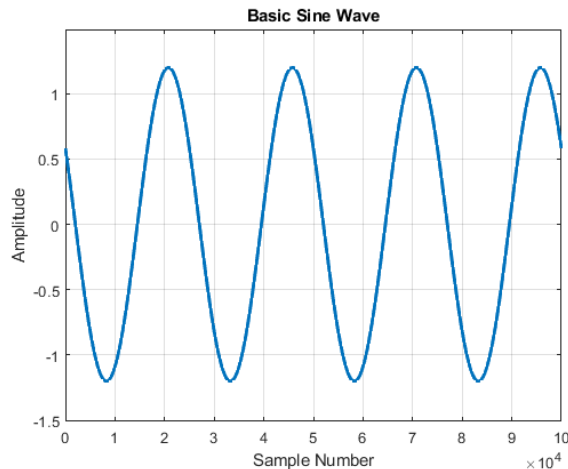
Running Variance

1 multiply (square), 1 divide, 1 addition, 1 divide

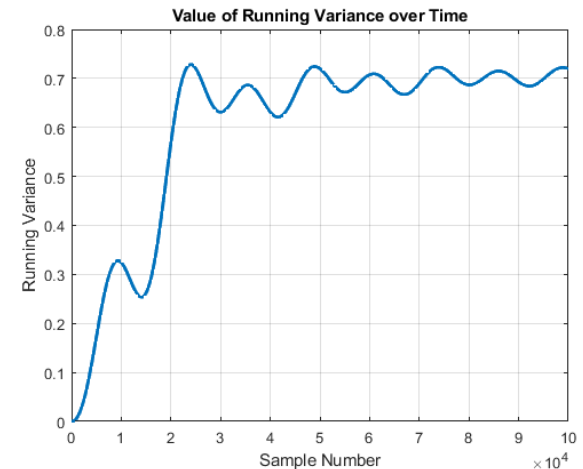
Total = 2 multiplies, 3 additions, 2 divides

Why Do We Care?

- In the breathing rate detection system the variance will be used to determine the strength of a signal
 - Need to compute a running variance efficiently



Running variance of a
sinusoidal signal



Signal to Noise Ratio

- We've defined how to quantify a signal in terms of mean and variance
- Let's apply this to describing how clean or noisy a signal is.

Signal to Noise Ratio (SNR)

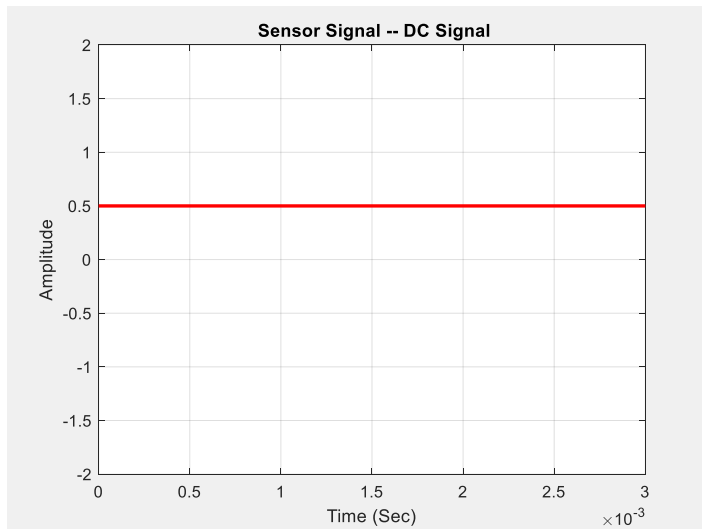
- Crudely --
 - We'll call the part we want "signal of interest"
 - We'll call the parts we don't want "noise"
- In many cases we are interested knowing how large the signal of interest is relative to the noise in the signal.
- We express this as a ratio of the signal to the noise or SNR

$$SNR = \frac{\textit{Level of the Signal of Interest}}{\textit{Level of the Noise}}$$

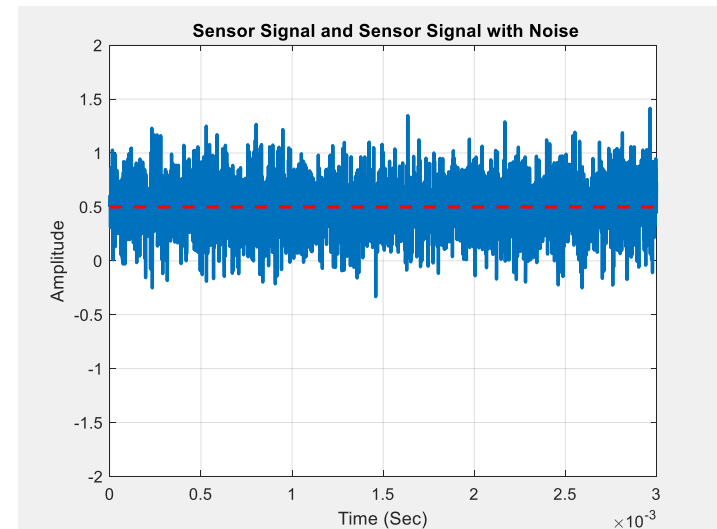
SNR has no units. It is a ratio

Signal to Noise Ratio

- In some cases, the mean describes what is being measured
- The standard deviation represents the noise.



Sensor Signal Alone
Fixed DC Value = 0.5V



Sensor Signal with Noise
 $\mu = 0.5, \sigma = 0.25$

Signal to Noise Ratio (SNR)

- The text describes the SNR as the mean μ divided by the standard deviation σ .
- This is the definition often used in imaging

SNR as a numerical ratio

$$SNR = \frac{\mu}{\sigma}$$

Signal Amplitude μ

Noise Amplitude σ

Power Signal to Noise Ratio

- In communications, the ratio of the signal power to the noise power defines the signal to noise ratio

$$SNR = \frac{P_{signal}}{P_{noise}}$$

Power SNR

$$SNR = \frac{\mu^2}{\sigma^2}$$

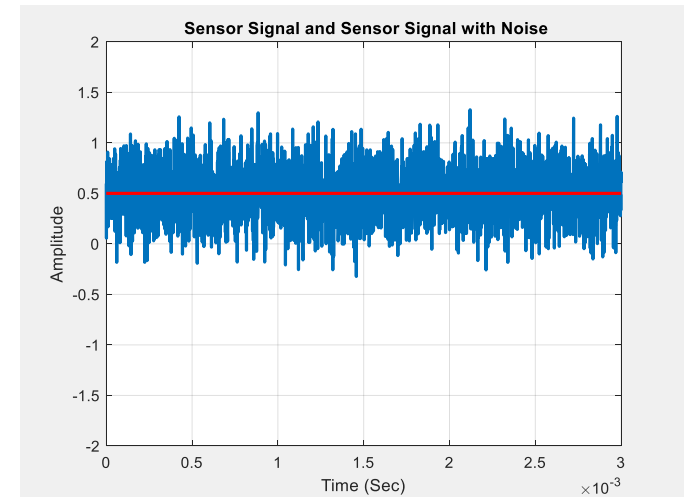
Signal Power μ^2

Noise Power σ^2

SNR Example

- A signal from a sensor has a mean value $\mu = 0.5$ and a standard deviation of $\sigma = 0.25$
- What is the SNR?

$$SNR = \frac{\mu}{\sigma} = \frac{0.5}{0.25} = 2$$



Sensor Signal with Noise
 $\mu = 0.5, \sigma = 0.25$

Signal to Noise Ratio in Decibels

- Often the SNR is expressed in decibels

$$SNR = \frac{\mu}{\sigma} = 2 \quad \text{SNR as a numerical ratio}$$

$$SNR_{dB} = 20 \times \log_{10} \frac{\mu}{\sigma} = 6.02 \text{ dB} \quad \text{SNR in decibels}$$

$$\text{Power } SNR = \frac{\mu^2}{\sigma^2} = 4 \quad \text{SNR as a numerical ratio}$$

$$\text{Power } SNR_{dB} = 10 \times \log_{10} \frac{\mu^2}{\sigma^2} = 6.02 \text{ dB} \quad \text{SNR in decibels}$$

- We'll use $SNR = \mu/\sigma$ unless specifically called out

Coefficient of Variation

- Another metric is the coefficient of variation (CV) expressed in %

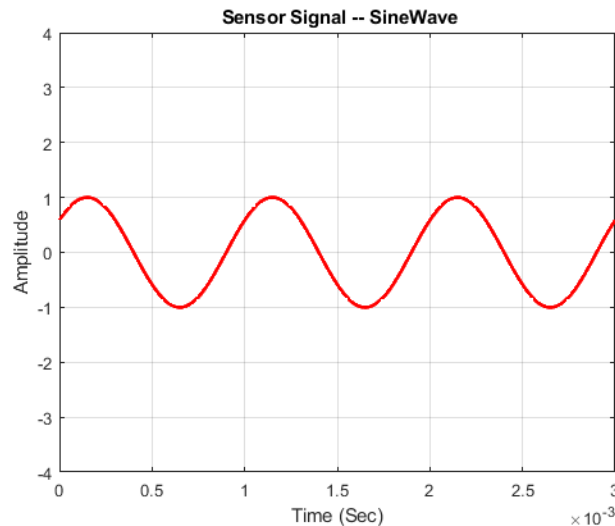
$$CV = \frac{\sigma}{\mu} \times 100$$

- Example: A signal has a mean of 6 lumens and a standard deviation of .18 lumens. Calculate the CV in %

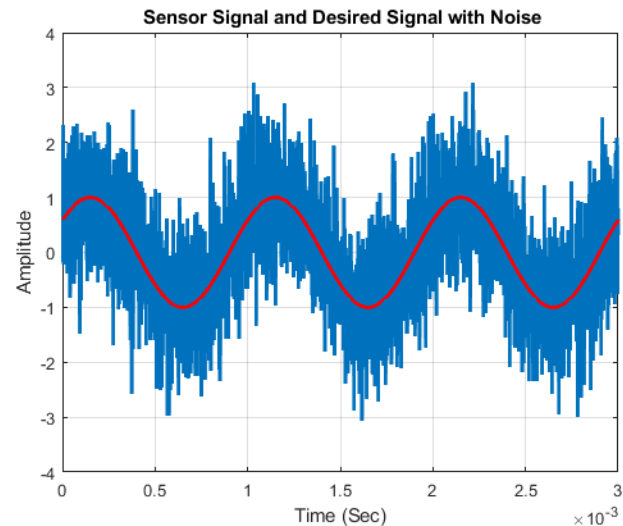
$$CV = \frac{\sigma}{\mu} \times 100 = \frac{.18}{6} \times 100 = 3.0\%$$

What about a Sinusoidal Signal?

- In some cases, the standard deviation best describes what is being measured
- The standard deviation represents the noise.



Sensor Signal Alone
Sinusoid $\sigma = 0.707V$



Sensor Signal with Noise
 $\sigma_{signal} = 0.707, \sigma_{noise} = 0.75$

Signal to Noise Ratio (SNR)

- In this case use the ratio of the power of the signal to the power of the noise for SNR

SNR as a numerical ratio

$$SNR = \frac{\sigma_{signal}^2}{\sigma_{noise}^2}$$

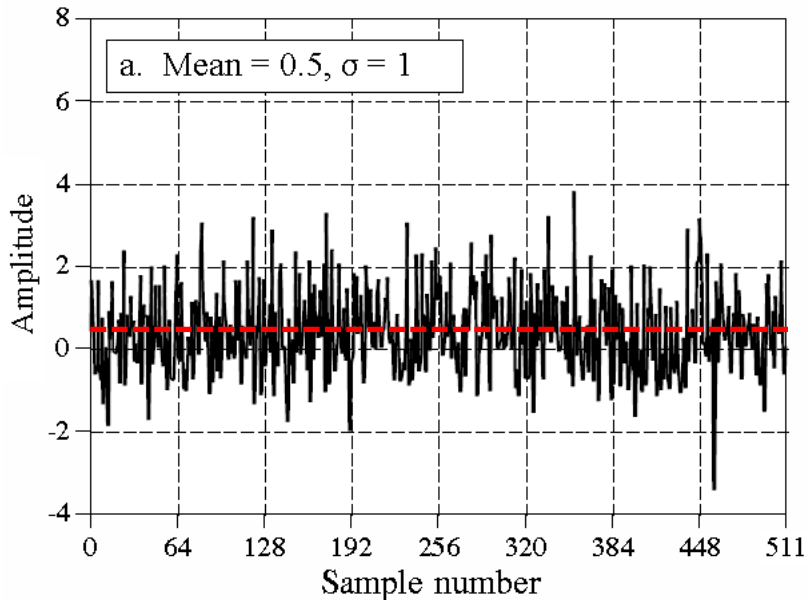
Signal Power

Noise Power

SNR in decibels

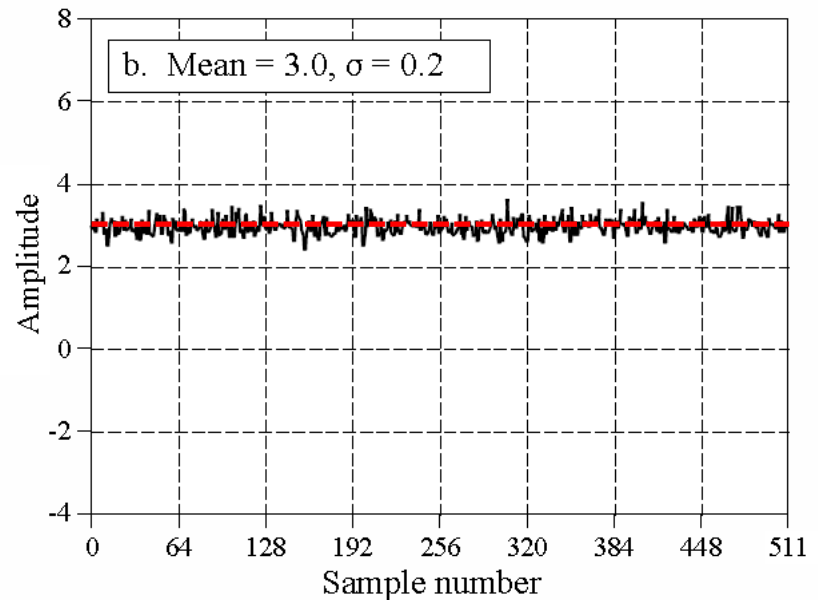
$$SNR_{dB} = 10 \log_{10} \left(\frac{\sigma_{signal}^2}{\sigma_{noise}^2} \right)$$

SNR Examples



$$SNR = \frac{0.5}{1} = .5$$

$$SNR_{dB} = 20 \log_{10} .5 = -6 \text{ dB}$$

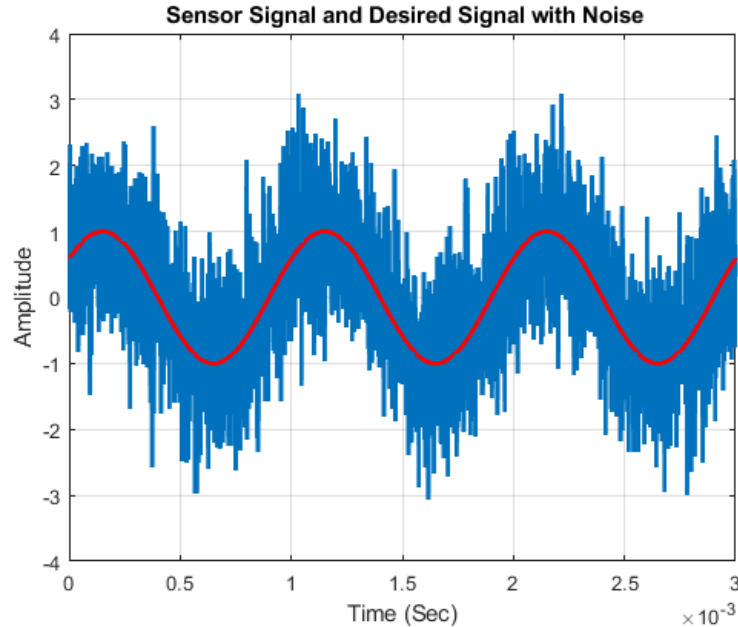


$$SNR = \frac{3.0}{.2} = 15$$

$$SNR_{dB} = 20 \log_{10} 15 = 23.52$$

SNR Examples

Sensor Signal with Noise
 $\sigma_{signal} = 0.707, \sigma_{noise} = 0.75$



$$SNR = \sigma_{signal}^2 / \sigma_{noise}^2$$

$$SNR = \left(\frac{0.707^2}{0.75^2} \right) = 0.89$$

$$SNR_{dB} = 10 \log_{10} 0.89 = -.51 \text{ dB}$$

In Class Problem

- The mean of a signal with noise is 3 volts
- The standard deviation of the signal is .35 volts
- Calculate the SNR as a numerical ratio and in decibels
- Calculate the coefficient of variation in %

In Class Problem

- The mean of a signal with noise is 3 volts
- The standard deviation of the signal is .35 volts
- Calculate the SNR as a numerical ratio and in decibels
- Calculate the coefficient of variation in %

$$SNR = \frac{\mu}{\sigma} = \frac{3}{.35} = 8.571$$

$$SNR_{dB} = 20 \times \log_{10} SNR = 20 \times \log_{10} 8.571$$

$$SNR_{dB} = 18.66 \text{ dB}$$

$$CV = \frac{\sigma}{\mu} \times 100 = \left(\frac{.35}{3} \right) 100 = 11.67\%$$