

# Robotic Perception

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# What do Inertial Sensors Measure?

- gyroscope measures angular velocity  $\tilde{\omega}$  in degrees/sec
- accelerometer measures linear acceleration  $\tilde{a}$  in m/s<sup>2</sup>
- magnetometer measures magnetic field strength  $\tilde{m}$  in uT (micro Tesla) or Gauss → 1 Gauss = 100 uT

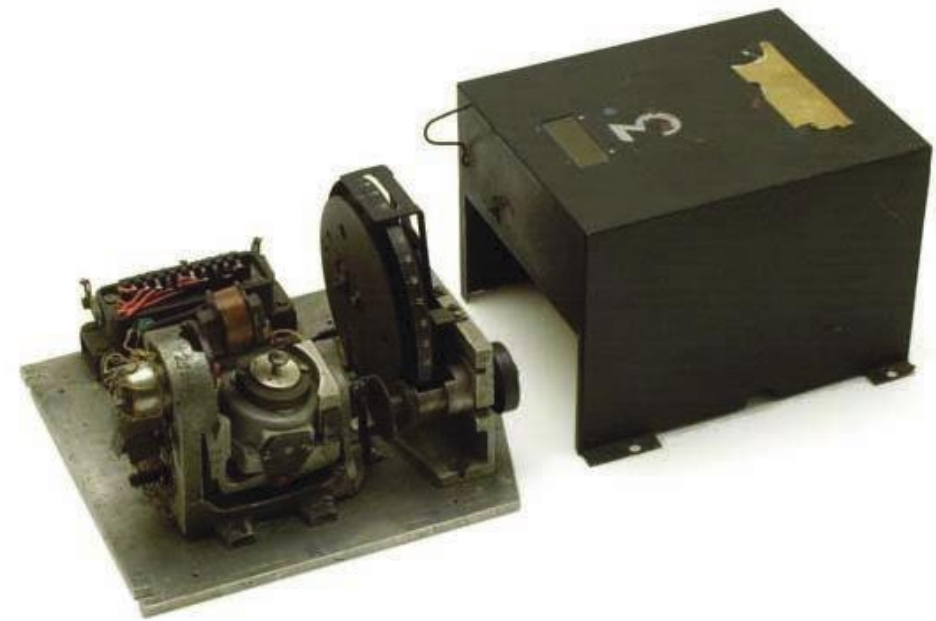
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ALL MEASUREMENTS TAKEN IN SENSOR/  
BODY COORDINATES!

# History of Gyroscopes

- critical for inertial measurements in ballistic missiles, aircrafts, drones, the mars rover, pretty much anything that moves!

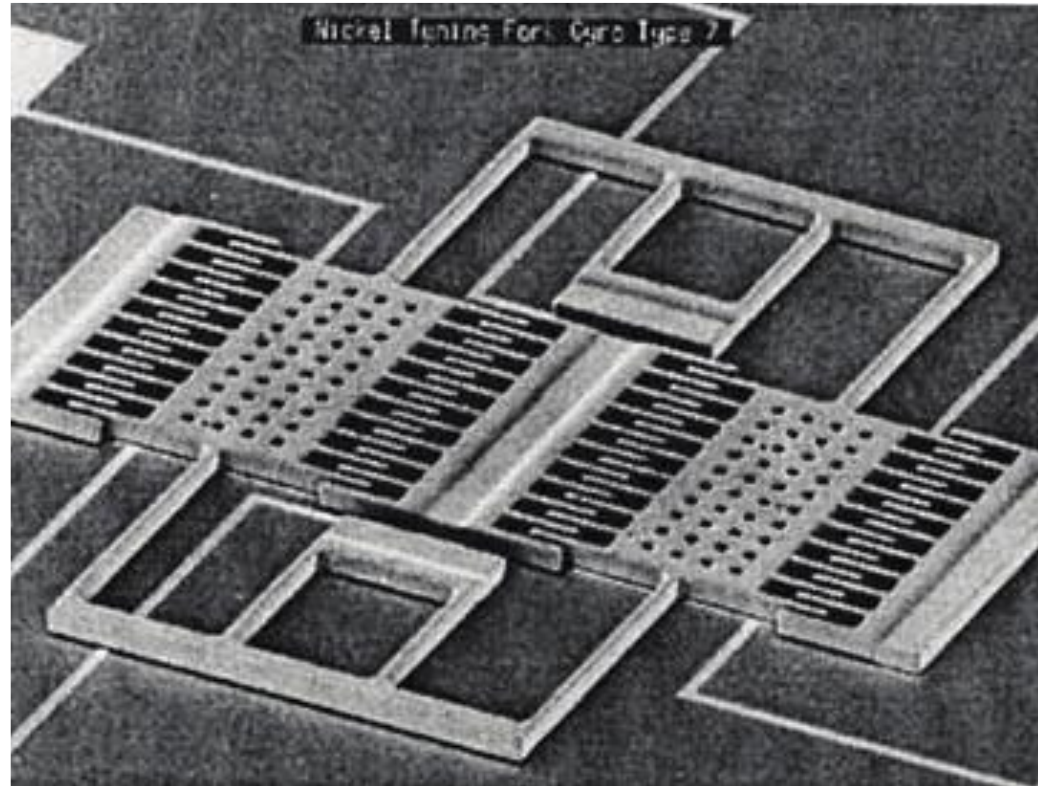
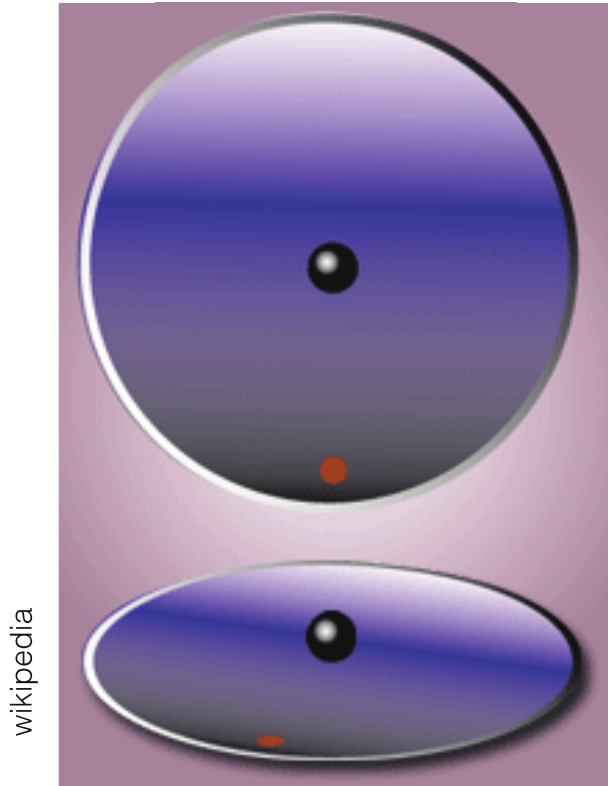


WWII era gyroscope used in the V2 rocket

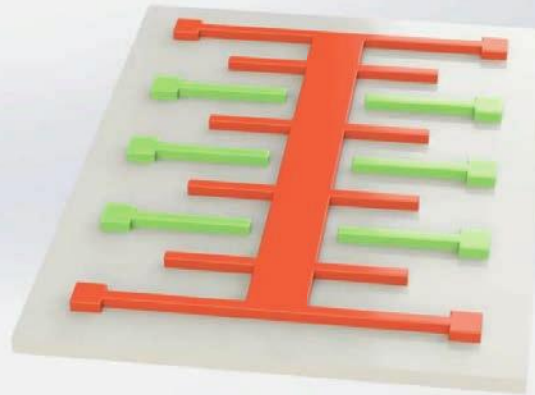
# MEMS Gyroscopes

- today, we use microelectromechanical systems (MEMS)

Coriolis Force

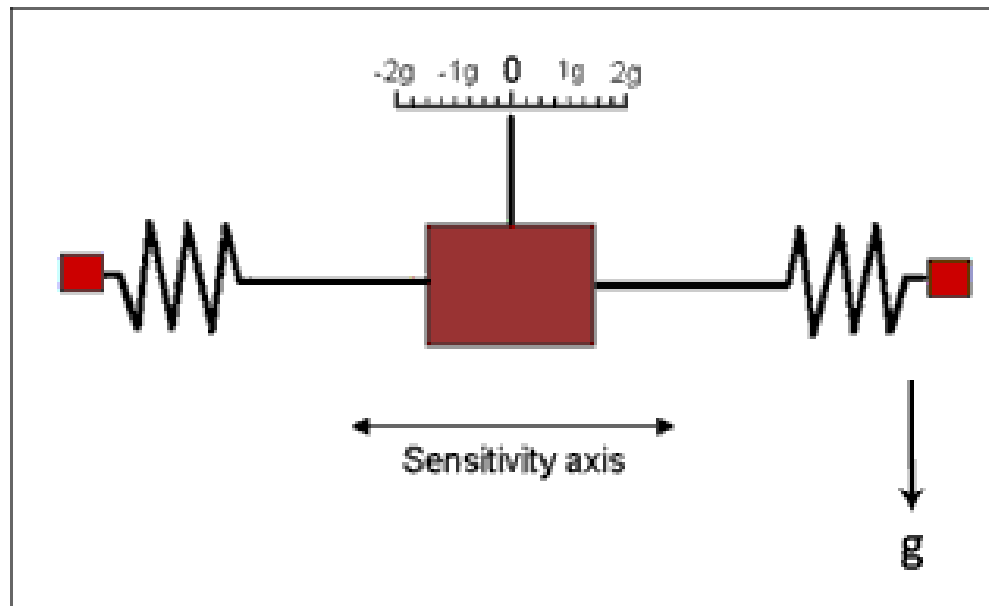


## MEMS Accelerometer



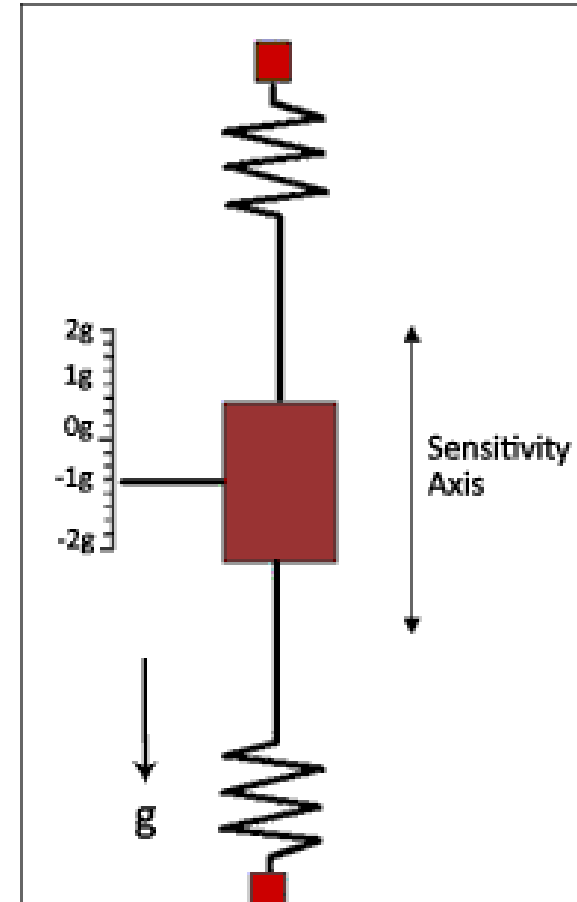
# Accelerometers

- An accelerometer is a sensor responsible for measuring inertial acceleration, also known as specific force
- An accelerometer can be thought of as a weight suspended on two sides with springs. The weight is known as the "proof mass" and the direction that the mass is allowed to move is known as the sensitivity axis.



# Specific Force

- If the accelerometer was subjected to a linear acceleration, the proof mass would attempt to remain at rest (why?)
- Acceleration would cause the proof mass to shift to one side compressing one of the springs.
- The amount of deflection in this spring is proportional to the net acceleration.
- As such an accelerometer measures both the linear acceleration due to motion and the pseudo-acceleration caused by gravity.
- It is called a pseudo-acceleration since this acceleration due to gravity doesn't necessarily result in a change in velocity or position.
- The deflection of the springs is proportional to the force acting on the proof mass, which is equivalent to the linear acceleration of the accelerometer package plus the gravitational acceleration due to gravity.
- The output of an accelerometer is affected by both linear acceleration and gravity.





# Accelerometers

- advantages:
  - points up on average with magnitude of 1g
  - accurate in long term because no drift and the earth's center of gravity (usually) doesn't move
- problem:
  - noisy measurements
  - unreliable in short run due to motion (and noise)
- complementary to gyro measurements!

# Gyroscopes

- A gyroscope is a type of sensor that measures angular rate.
- The bias of a rate gyro is the average output when the device is sitting still.
- Since the output of a gyro is integrated to find the orientation angle, constant bias errors grow linearly with time.
- You can find the constant bias error of a gyro by taking the average of the output over a long period of time while the device is not rotating.
- Once you know the constant bias you can subtract it from subsequent measurements to eliminate this form of error.

# Angle Random Walk

- Gyros will exhibit very high frequency noise that is caused by thermo-mechanical events.
- This type of noise shows up in a form known as "white noise".
- White noise is a random amount that is added to the signal that has an average amount equal to sigma and with a long term average equal to zero.
- Mathematically this is stated as a zero mean process with a standard deviation equal to sigma.

$$\sigma_{\theta}(t) = \sigma \cdot \sqrt{\delta t \cdot t}$$

# Angle Random Walk

- If we want to look at how this white noise will affect measurements over a certain period of time then we typically look this value measured at 1 second.

$$ARW = \sigma_{\theta}(1)$$

- To find error in orientation due to gyro white noise multiply ARW by the square root of the integration time (t).

# Bias Stability

- The bias of a MEMS gyro will wander or walk over time due to flicker noise in the electronics and other effects. The bias fluctuations due to flicker are usually modeled as random walk.
- A bias stability measurement tells you how stable the bias of a gyro is over a certain specified period of time. The value given in gyro datasheets is typically given in units of deg/hr or deg/s for low end gyros.

# Bias Stability

- The bias stability is calculated as the minimum average change in consecutive gyro measurements when analyzed over varying sample times.
- Allan Variance plot is constructed from the gyro raw measurements.
- Take a long sequence of data and divide it into bins equal to the sampling time period.
- The Allan Variance is then given by

$$AVAR(t) = \frac{1}{2 \cdot (n - 1)} \sum_i (a(t)_{i+1} - a(t)_i)^2$$

# Allan Deviation

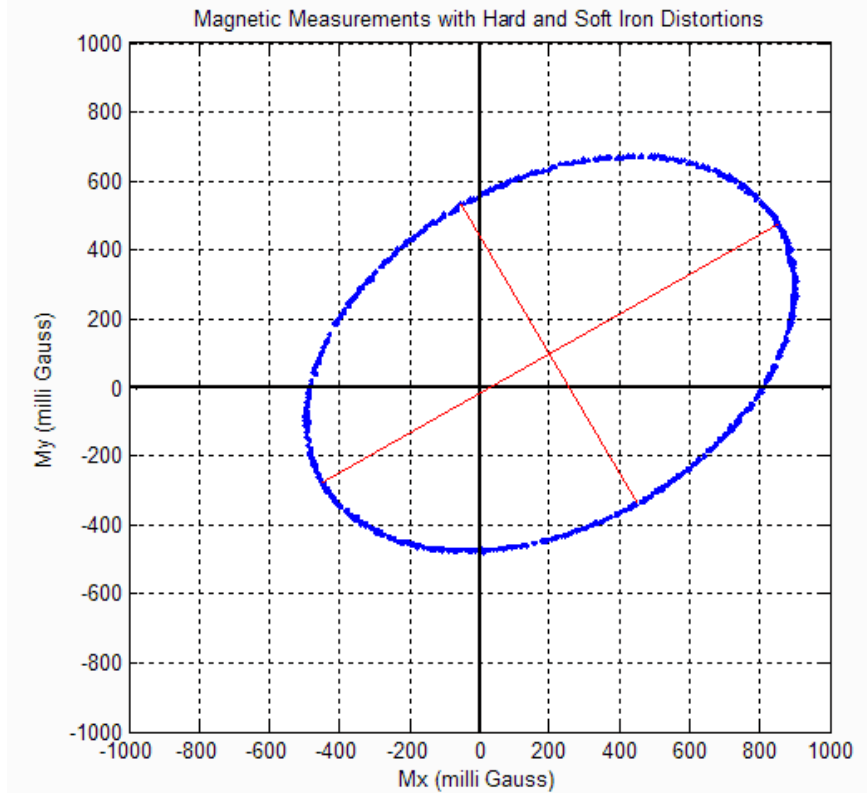
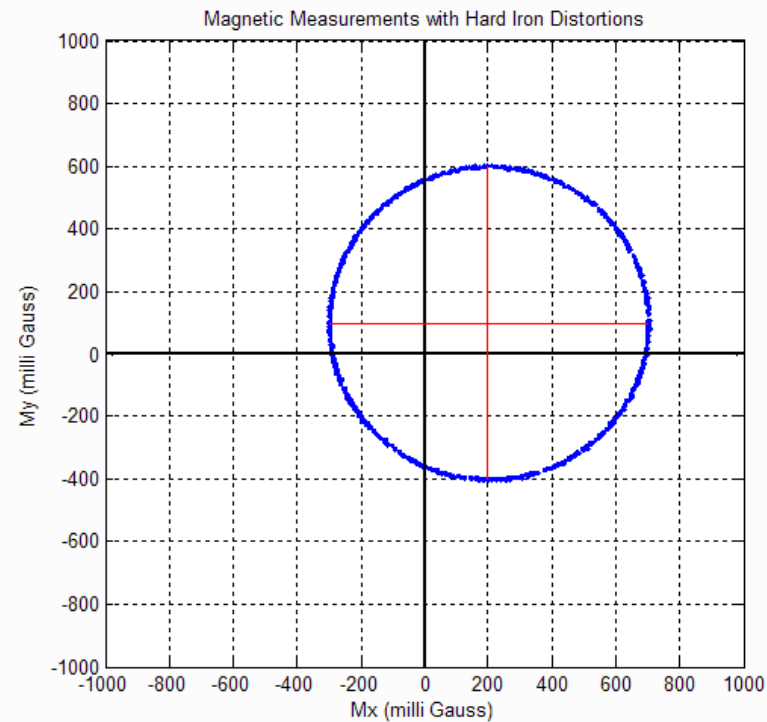
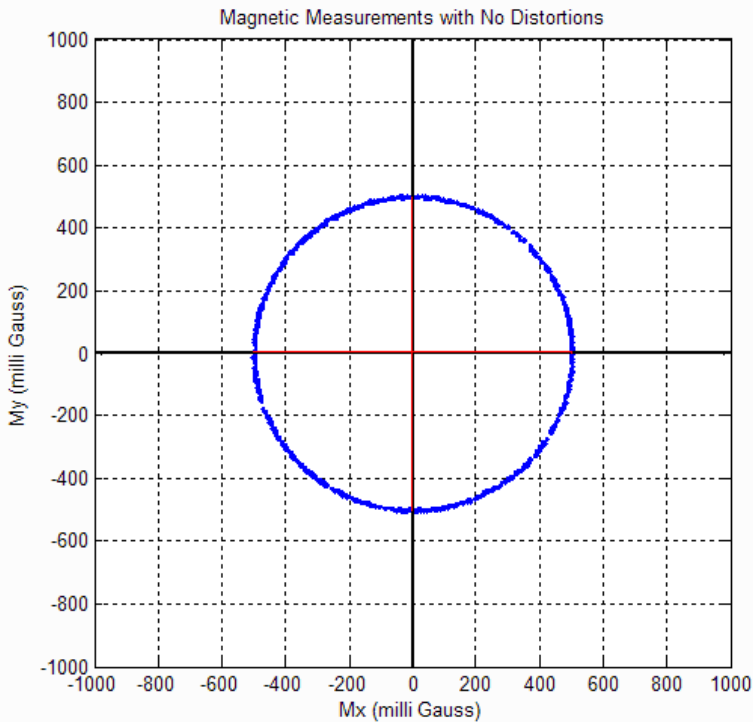
- The Allan Variance is computed for many different sampling times ranging from 0.1 to somewhere above 1000.
- The amount of data that you need to collect to perform an Allan variance plot is dependent upon where the likely minimum of the gyro bias will show up in terms of sampling rate.
- For MEMS gyros typically the minimum will occur at sampling times of less than 1000s. To capture at least 9 measurements with 1000s maximum bin size, we will need at least 9000 seconds of data.
- Typically the data is captured at 50-100Hz. This means that you will need at least 2.5 hr of data.
- Normally data is captured for 12hr at constant temperature. To maintain a constant temperature you will need to perform this test in a environmentally controlled test chamber to get optimal results.

# Magnetometers

- A magnetometer is a type of sensor that measures the strength and direction of the local magnetic field.
- The magnetic field measured will be a combination of both the earth's magnetic field and any magnetic field created by nearby objects. The magnetic field is measured in the sensor reference frame.
- Magnetic measurements will be subjected to distortion. These distortions are considered to fall in one of two categories; hard or soft iron.
- Hard iron distortions are created by objects that produce a magnetic field. A speaker or piece of magnetized iron for example will cause a hard iron distortion. If the piece of magnetic material is physically attached to the same reference frame as the sensor, then this type of hard iron distortion will cause a permanent bias in the sensor output.
- Soft iron distortions are considered deflections or alterations in the existing magnetic field. These distortions will stretch or distort the magnetic field depending upon which direction the field acts relative to the sensor. This type of distortion is commonly caused by metals such as nickel and iron.
- In most cases hard iron distortions will have a much larger contribution to the total uncorrected error than soft iron.



# Finding Hard and Soft Iron



# Errors

- Sensor calibration is a method of improving sensor performance by removing structural errors in the sensor outputs.
- Structural errors are differences between a sensors expected output and its measured output, which show up consistently every time a new measurement is taken.
- Any of these errors that are repeatable can be calculated during calibration so that during actual end-use the measurements made by the sensor can be compensated in real-time to digitally remove any errors.
- Bias
- Scale factor
- Misalignment
- Temperature Compensation

# Sensor Parameters

- This linear model consists of the following calibration parameters.
- Sensitivity of sensor X-axis to X-axis inputs ( $S_{xx}$ )
- Sensitivity of sensor Y-axis to Y-axis inputs ( $S_y$ )
- Sensitivity of sensor Z-axis to Z-axis inputs ( $S_z$ )
- Sensitivity of sensor X-axis to Y-axis inputs ( $M_{xy}$ )
- Sensitivity of sensor X-axis to Z-axis inputs ( $M_{xz}$ )
- Sensitivity of sensor Y-axis to X-axis inputs ( $M_{yx}$ )
- Sensitivity of sensor Y-axis to Z-axis inputs ( $M_{yz}$ )
- Sensitivity of sensor Z-axis to X-axis inputs ( $M_{zx}$ )
- Sensitivity of sensor Z-axis to Y-axis inputs ( $M_{zy}$ )
- Sensor X-axis offset ( $B_x$ )
- Sensor Y-axis offset ( $B_y$ )
- Sensor Z-axis offset ( $B_z$ )

# Sensor Model Equations

$$A = \begin{bmatrix} x \\ y \\ z \end{bmatrix}_I = \begin{bmatrix} 1 & M_{XY} & M_{XZ} \\ M_{YX} & 1 & M_{YZ} \\ M_{ZX} & M_{ZY} & 1 \end{bmatrix} * \begin{bmatrix} \frac{1}{S_X} & 0 & 0 \\ 0 & \frac{1}{S_Y} & 0 \\ 0 & 0 & \frac{1}{S_Z} \end{bmatrix} \left( B_D + \begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} - \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \right)$$

$$C_n = C_{n_0} + C_{n_1}\Delta T + C_{n_2}\Delta T^2 + C_{n_3}\Delta T^3$$

where  $\Delta T = [Temperature - 25] ^\circ C$

# Gyroscopes

$$\omega = \begin{bmatrix} 1 & M_{XY} & M_{XZ} \\ M_{YX} & 1 & M_{YZ} \\ M_{ZX} & M_{ZY} & 1 \end{bmatrix} * \begin{bmatrix} \frac{1}{S_X} & 0 & 0 \\ 0 & \frac{1}{S_Y} & 0 \\ 0 & 0 & \frac{1}{S_Z} \end{bmatrix} \left( \begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} - \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} - \begin{bmatrix} H_{xx} & H_{xy} & H_{xz} \\ H_{yx} & H_{yy} & H_{yz} \\ H_{zx} & H_{zy} & H_{zz} \end{bmatrix} \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \right)$$

# Accelerometer Errors

	<b>Accelerometer Bias Error</b>	<b>Pitch/Roll Error</b>	<b>Horizontal Position Error</b>			
<b>Grade</b>	<b>[mg]</b>	<b>[deg]</b>	<b>1 sec</b>	<b>5 sec</b>	<b>10 sec</b>	<b>20 sec</b>
Industrial	3	0.17	15 mm	370 mm	1.5 m	5.9 m
Automotive	125	8.2	700 mm	18 m	70 m	280 m

	<b>Accelerometer Cross-axis Error</b>	<b>Pitch/Roll Error</b>	<b>Horizontal Position Error</b>			
<b>Grade</b>	<b>[%]</b>	<b>[deg]</b>	<b>1 sec</b>	<b>5 sec</b>	<b>10 sec</b>	<b>20 sec</b>
Industrial	0.1	0.057	4.9 mm	120 mm	490 mm	2 m
Automotive	2	1.1	98 mm	2.5 m	9.8 m	39 m

	<b>Accelerometer Scale Factor Error</b>	<b>Pitch/Roll Error</b>	<b>Horizontal Position Error</b>			
<b>Grade</b>	<b>[%]</b>	<b>[deg]</b>	<b>1 sec</b>	<b>5 sec</b>	<b>10 sec</b>	<b>20 sec</b>
Industrial	0.1	0.057	4.9 mm	120 mm	490 mm	2 m
Automotive	5	2.9	240 mm	6.1 m	24 m	98 m

# Position Errors

	Accelerometer Bias Error		Horizontal Position Error [m]			
Grade	[mg]		1s	10s	60s	1hr
Navigation	0.025		0.13 mm	12 mm	0.44 m	1.6 km
Tactical	0.3		1.5 mm	150 mm	5.3 m	19 km
Industrial	3		15 mm	1.5 m	53 m	190 km
Automotive	125		620 mm	60 m	2.2 km	7900 km

	Gyro Angle Random Walk (ARW)		Horizontal Position Error [m]			
Grade	[deg/vhr]		1s	10s	60s	1hr
Navigation	0.002		0.01 mm	0.1 mm	1.3 mm	620 m
Tactical	0.07		0.1 mm	3.2 mm	46 m	22 km
Industrial	3		10 mm	0.23 m	3.3 m	1500 km
Automotive	5		20 mm	0.45 m	6.6 m	3100 km

# Gyroscopes

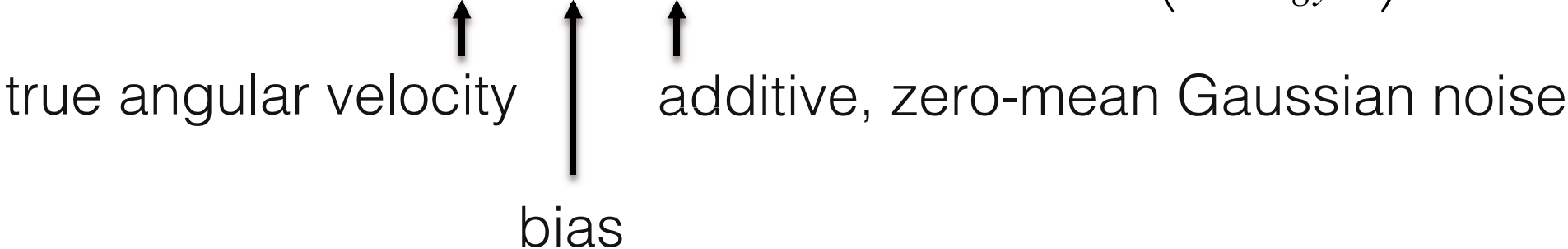
- gyro model:  $\tilde{\omega} = \omega + b + \eta$



# Gyroscopes

- gyro model:  $\tilde{\omega} = \omega + b + \eta$   $\eta \sim N(0, \sigma_{gyro}^2)$   
true angular velocity      bias      additive, zero-mean Gaussian noise

# Gyroscopes

- gyro model:  $\tilde{\omega} = \omega + b + \eta$   $\eta \sim N(0, \sigma_{gyro}^2)$   


↑ true angular velocity      ↑ bias      ↑ additive, zero-mean Gaussian noise
- 3 DOF = 3-axis gyros that measures 3 orthogonal axes, assume no crosstalk
- bias is temperature-dependent and may change over time; can approximate as a constant
- additive measurement noise

# Gyroscopes

- from gyro measurements to orientation – use Taylor expansion

$$\theta(t + \Delta t) \approx \theta(t) + \frac{\partial}{\partial t} \theta(t) \Delta t + \varepsilon, \quad \varepsilon \sim O(\Delta t^2)$$

Diagram illustrating the Taylor expansion for orientation estimation using gyro measurements:

- have: angle at last time step (points to  $\theta(t)$ )
- have: time step (points to  $\Delta t$ )
- want: angle at current time step (points to  $\theta(t + \Delta t)$ )
- $\frac{\partial}{\partial t} \theta(t) = \omega$  (points to  $\omega$ )
- have: gyro measurement (angular velocity) (points to  $\omega$ )
- approximation error! (points to  $\varepsilon$ )

# Gyro Integration aka *Dead Reckoning*

- works well for linear motion, no noise, no bias = unrealistic
- even if bias is known and noise is zero → drift (from integration)
- bias & noise variance can be estimated, other sensor measurements used to correct for drift (sensor fusion)
- accurate in short term, but not reliable in long term due to drift

# Accelerometers

- measure linear acceleration  $\tilde{a} = a^{(g)} + a^{(l)} + \eta$ ,  $\eta \sim N(0, \sigma_{acc}^2)$
- without motion: read noisy gravity vector  $a^{(g)} + \eta$  pointing UP!  
with magnitude  $9.81 \text{ m/s}^2 = 1g$
- with motion: combined gravity vector and external forces  $a^{(l)}$

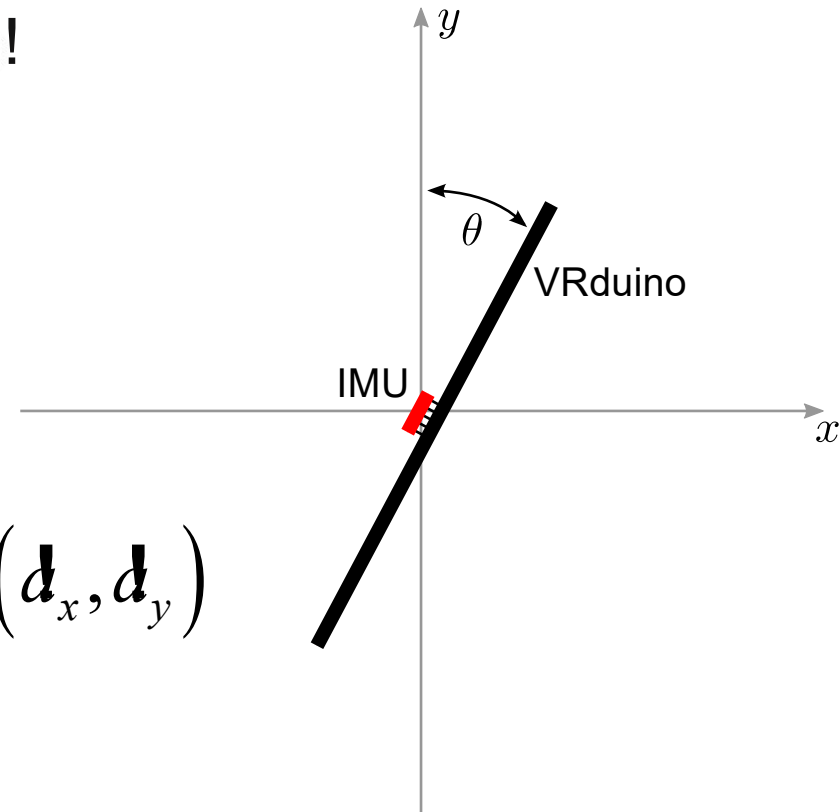
# Complimentary Filter

## Orientation Tracking in *Flatland*!

- problem: track 1 angle in 2D space!
- sensors: 1 gyro, 2-axis accelerometer!
- sensor fusion with complementary filter, i.e. linear interpolation:!

$$\theta^{(t)} = \alpha \left( \theta^{(t-1)} + \omega \Delta t \right) + (1 - \alpha) \operatorname{atan2}(d_x, d_y)$$

- no drift, no noise!!



# No external forces

## Tilt from Accelerometer!

- assuming acceleration points up (i.e. no external forces), we can compute the tilt (i.e. pitch and roll) from a 3-axis accelerometer !

$$\hat{a} = \frac{\mathbf{d}}{\|\mathbf{d}\|} = R \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} = R_z(-\theta_z) \cdot R_x(-\theta_x) \cdot R_y(-\theta_y) \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$

$$= \begin{pmatrix} -\cos(-\theta_x)\sin(-\theta_z) \\ \cos(-\theta_x)\cos(-\theta_z) \\ \sin(-\theta_x) \end{pmatrix} \Rightarrow \begin{aligned} \theta_x &= -\text{atan2}\left(\hat{a}_z, \text{sign}(\hat{a}_y) \cdot \sqrt{\hat{a}_x^2 + \hat{a}_y^2}\right) \\ \theta_z &= -\text{atan2}(-\hat{a}_x, \hat{a}_y) \text{ both in rad} \end{aligned}$$