

# Sensor Fusion

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# Outline

- ▶ Implementing EKF for robot systems.
- ▶ Sensor fusion using GPS and accelerometer.
- ▶ Indoor sensor fusion using UWB.
- ▶ Complementary and Madgwick filter.

# A Single Link Flexible Joint Robot

$$\dot{\theta}_m(t) = \omega_m(t)$$

$$\dot{\omega}_m(t) = \frac{k}{J_m}(\theta_l(t) - \theta_m(t)) - \frac{B}{J_m}\omega_m(t) + \frac{K_\tau}{J_m}u(t)$$

$$\dot{\theta}_l(t) = \omega_l(t)$$

$$\dot{\omega}_m(t) = -\frac{k}{J_l}(\theta_l(t) - \theta_m(t)) - \frac{mgb}{J_l}\sin(\theta_l(t))$$

System parameters	Values
Motor inertia, $J_m$ (kg m <sup>2</sup> )	$3.7 \times 10^{-3}$
Link inertia, $J_l$ (kg m <sup>2</sup> )	$9.3 \times 10^{-3}$
Pointer mass, $m$ (kg)	$2.1 \times 10^{-1}$
Link length, $2b$ (m)	$3.1 \times 10^{-1}$
Torsional spring constant, $k$ (Nm rad <sup>-1</sup> )	$1.8 \times 10^{-1}$
Viscous friction coefficient, $B$ (Nm V <sup>-1</sup> )	$4.6 \times 10^{-2}$
Amplifier gain, $K_\tau$ (Nm V <sup>-1</sup> )	$8 \times 10^{-2}$

# A Single Link Flexible Joint Robot

## Assignment

1. Let us assume we can only measure the first two states. Write the system into the following nonlinear state space representation:

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{F}\mathbf{x}(t) + \mathbf{g}(\mathbf{x}) + \mathbf{D}u(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t)\end{aligned}$$

2. Use Euler discretization to transform the continuous time system in question (1) into the discrete time system:

$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{f}(\mathbf{x}_k) + \mathbf{B}u_k \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k\end{aligned}$$

3. Let us assume the error covariance matrices for model and measurement are given by  $\mathbf{Q}_F = \mathbf{I}_{4 \times 4}$  and  $\mathbf{R}_F = 4\mathbf{I}_{2 \times 2}$ , respectively, and the initial conditions for the system and estimate are given by  $\mathbf{x}_0 = (0 \ 1 \ 2 \ 0)^\top$  and  $\hat{\mathbf{x}}_0 = (1 \ 1 \ 1 \ 1)^\top$ , respectively. Implement EKF for system in question (2).

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# GPS+Accelerometer

- ▶ Accelerometer: high frequency, high accuracy, drifting.
- ▶ GPS: low frequency, low accuracy, absolute position.
- ▶ Kalman filter can be used to estimate a position using an accelerometer (predict) and a GPS (update).
- ▶ Consider the following kinematic equation:

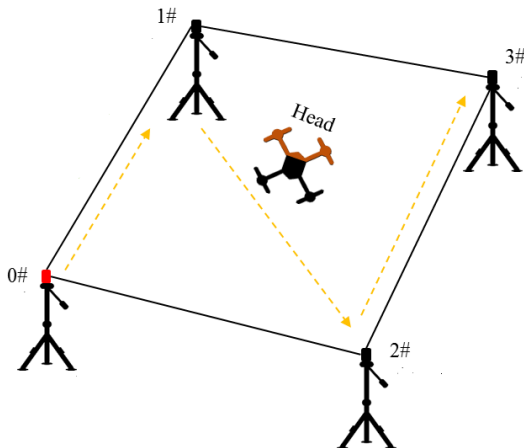
$$\begin{aligned}p_{k+1} &= p_k + \Delta t v_k + \frac{\Delta t^2}{2} a_k \\v_{k+1} &= v_k + \Delta t a_k\end{aligned}$$

Using KF, we can estimate position and velocity of an object.



# Indoor sensor fusion using UWB

How to determine position of an object using 4 ultra-wideband sensors?



# Filters

- ▶ Kalman filter
- ▶ Complementary filter
- ▶ Madgwick filter

# Inertial Measurement Unit

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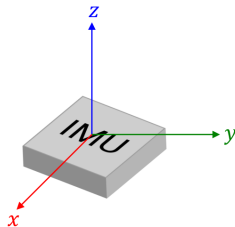
- ▶ angular velocities (gyroscope)
- ▶ linear accelerations (accelerometer)
- ▶ magnetic field (magnetometer/compass)

A combination of Gyroscope and Accelerometer is called an Inertial Measurement Unit or IMU or a 6-DoF IMU.

A combination an IMU and a Compass is called a Magnetic, Angular rate, and Gravity (MARG) sensor or Attitude and Heading Reference System (AHRS) or a 9-DoF IMU

# Inertial Measurement Unit

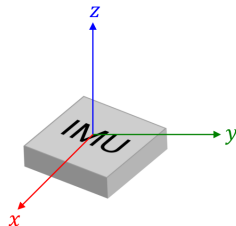
- Estimate the orientation in World frame!





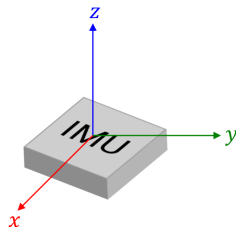
# Inertial Measurement Unit

- ▶ Estimate the orientation in World frame!
- ▶ Orientation is also called Attitude.



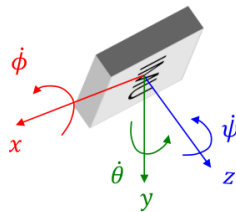
# Inertial Measurement Unit

- ▶ Estimate the orientation in World frame!
- ▶ Orientation is also called Attitude.
- ▶ Orientation can be parametrized as either Euler angles (roll, pitch and yaw) or Quaternions.



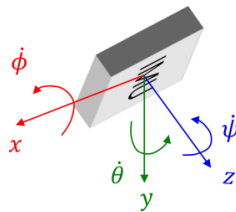
# Attitude Estimation from Gyroscope

- We want to estimate  $(\phi \quad \theta \quad \psi)^T_{t+1}$



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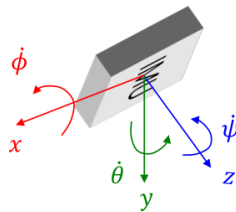
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- ▶ We estimate by numerical integration

$$\begin{pmatrix} \phi \\ \theta \\ \psi \end{pmatrix}_{t+1} = \begin{pmatrix} \phi \\ \theta \\ \psi \end{pmatrix}_{t+1} + \begin{pmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{pmatrix}_t \Delta t$$

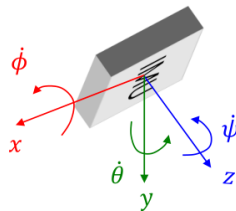


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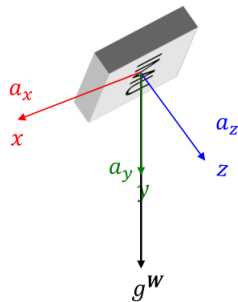
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- ▶ However! It is impossible to obtain attitude without knowing initial conditions!



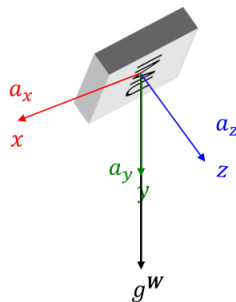
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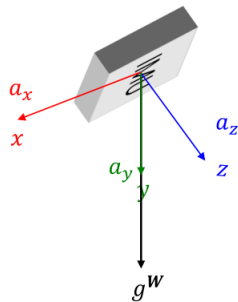
# Attitude Estimation from Accelerometer

- ▶ Let us assume that our IMU/accelerometer is only rotating.
- ▶ We want to estimate  $(\phi \quad \theta \quad \psi)_{t+1}^T$
- ▶ We have  $(a_x \quad a_y \quad a_z)_t^T$
- ▶ How to estimate the attitude?

$$\phi = \tan^{-1} \left( \frac{a_y}{\sqrt{a_x^2 + a_z^2}} \right)$$

$$\theta = \tan^{-1} \left( \frac{a_x}{\sqrt{a_y^2 + a_z^2}} \right)$$

$$\psi = \tan^{-1} \left( \frac{\sqrt{a_x^2 + a_y^2}}{a_z} \right)$$



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Both Gyroscope and Accelerometer have noise and bias!

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Both Gyroscope and Accelerometer have noise and bias!

Bias: They don't read zero at rest!

Noise: The values don't remain constant when the sensor is not moving!

# Gyroscope and Accelerometer models

Gyroscope can be modelled by

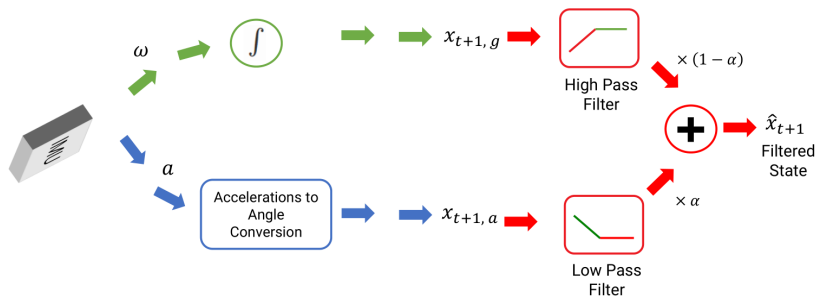
$$\omega = \hat{\omega} + b_g + n_g, \quad \dot{b}_g \sim \mathcal{N}(0, \mathbf{Q}_g)$$

Accelerometer can be modelled by

$$a = \mathbf{R}^T(\hat{a} - g) + b_a + n_a, \quad \dot{b}_a \sim \mathcal{N}(0, \mathbf{Q}_a)$$

- ▶ Bias will overshadow real values when integrating if not compensated for!
- ▶ Noise will make values drift from real value during integration!

# Complementary Filter



$$\hat{x}_{t+1} = (1 - \alpha)\hat{x}_{t+1,g} + \alpha\hat{x}_{t+1,a}$$

# Madgwick Filter

We want to model attitude estimation from the accelerometer measurements by modelling it as an optimization problem instead of direct angle computation

$$\min_{{}^I_W \hat{\mathbf{q}} \in \mathbb{R}^{4 \times 1}} f({}^I_W \hat{\mathbf{q}}, {}^W \hat{\mathbf{g}}, {}^I \hat{\mathbf{a}})$$

$$f({}^I_W \hat{\mathbf{q}}, {}^W \hat{\mathbf{g}}, {}^I \hat{\mathbf{a}}) = {}^I_W \hat{\mathbf{q}}^* \otimes {}^W \hat{\mathbf{g}} \otimes {}^I_W \hat{\mathbf{q}} - {}^I \hat{\mathbf{a}}$$

We can achieve this using Gradient Descent!

ref: S. Madgwick, et al., Estimation of IMU and MARG orientation using a gradient descent algorithm, 2011 IEEE international conference on rehabilitation robotics, Zurich, Switzerland, 2011.