

# CS/EE/ME 75(a)

Nov. 26, 2019

Today:

- Dec. 4 Class: Brett Lopez & “flight control stack”
- Tonight: Brief review of
  - estimation,
  - odometry,
  - inertial navigation,
  - SLAM, pose graph

# State Estimation & Mapping

Some Important questions for robot operation and SubT

- Where am I? How am I oriented?
- How fast am I moving?
- Where can I move: obstacles, or unobstructed directions of motion?
- What is the local geometry of my environment?
- What is the *global* geometry of my environment?
- How do I store information about the environment that I'm working in?
- Have I been here before?
- How do I best localize the “targets”?

State Estimation & Mapping subsystems address these questions, but not always perfectly.

# Estimation & Optimal (Kalman) Filtering

## Observer

Process Dynamics

Measurement Equation

- Given  $\dot{x} = f(x, u)$        $y = h(x)$
- Calculate, infer, deduce the state  $x$  from measurements  $y$
- E.g. the *Luenberger Observer*       $\dot{x} = Ax + Bu + L(y - Cx)$

## Estimator

- Given  $\dot{x} = f(x, u) + \xi$        $y = h(x) + \omega$ 
  - $\xi$  represents *process noise/uncertainty* (e.g., gust or unmodeled effects)
  - $\omega$  represents *measurement noise/uncertainty*
- *Estimate* (in an *optimal*) way the state  $x$  based on
  - measurements  $y$
  - dynamic and measurement models
  - noise model(s).

# Estimation Overview (continued)

## Noise & Uncertainty Models for Estimation

$$\dot{x} = f(x, u) + \xi \quad y = h(x) + \omega(t)$$

- Set-based :  $\xi \in \Xi \quad \omega \in \Omega$
- **Stochastic**  $\xi$  and  $\omega$  are random processes governed by  $p(\xi)$  and  $p(\omega)$

## Why Estimation ?

- **MANY** important problems can be posed as estimation problems. *E.g.:*
  - Inertial Navigation
  - Localization, Mapping, SLAM
  - Sensor Processing and Fusion
  - Tracking and Prediction
  - Parameter Estimation

Specialized estimation  
techniques & literatures

# Landmark-based Localization & Mapping

**Localization:** A robot explores an static environment where there are known *landmarks*.

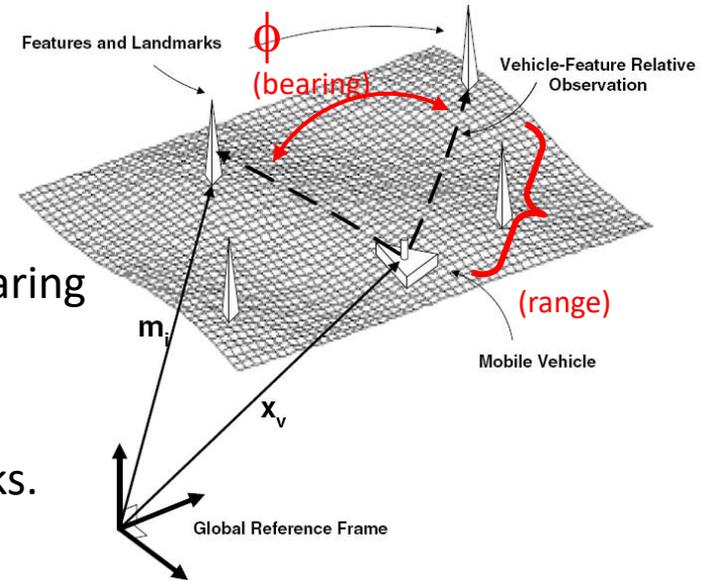
- radio beacons (Lojack)
- UWB ranging
- bar-code decals

**Goal:** Estimate the robot's position given range/bearing measurements

**Mapping:** A robot explores an unknown static environment where there are identifiable landmarks.

- doors, windows, light fixtures
- linoleum floor patterns

Build a *map* (estimate all landmark positions), assuming robot has GPS-like localization



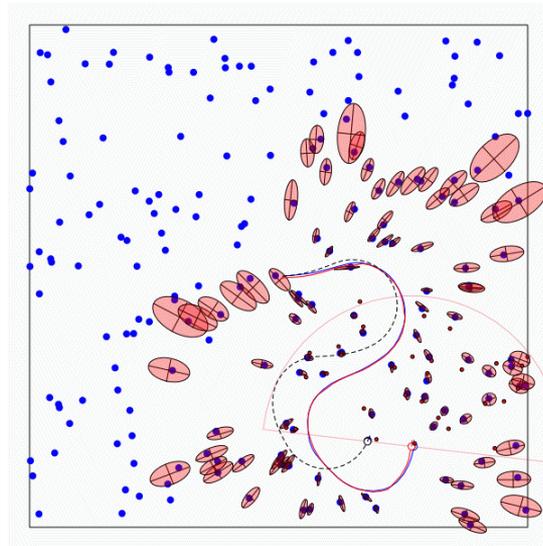
# SLAM: Simultaneous Localization & Mapping

## Given:

- Robot motion model:  $\dot{x} = f(x, u) + \xi$
- The robot's controls,  $u$
- Measurements (e.g., range, bearing ) of nearby features:  $y = h(x) + \omega$

## Estimate:

- Map of landmarks ( $x_L$ )
- Robot's current *pose*,  $x_R$ , & its path
- Uncertainties in estimated quantities

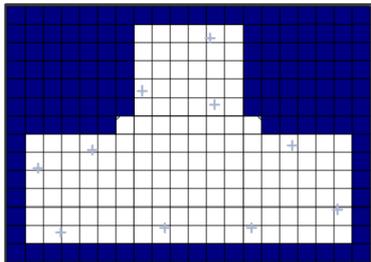


$$\vec{x} = \begin{bmatrix} \vec{x}_R \\ \vec{x}_{L_1} \\ \vdots \\ \vec{x}_{L_N} \end{bmatrix} = \left. \begin{array}{l} \text{Robot state} \\ \text{Landmark positions} \end{array} \right\}$$

# Three Major Map Models

## Grid-Based:

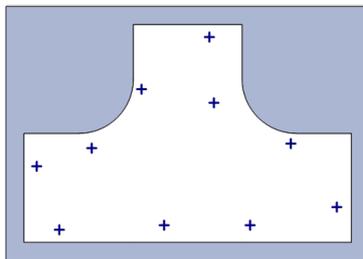
Collection of discretized  
obstacle/free-space pixels



Elfes, Moravec,  
Thrun, Burgard, Fox,  
Simmons, Koenig,  
Konolige, etc.

## Feature-Based:

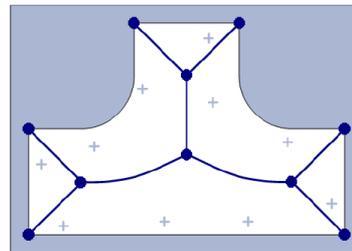
Collection of landmark  
locations and correlated  
uncertainty



Smith/Self/Cheeseman,  
Durrant-Whyte, Leonard,  
Nebot, Christensen, etc.

## Topological:

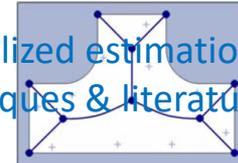
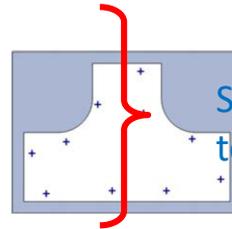
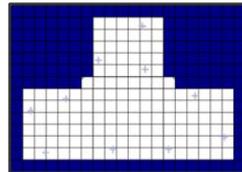
Collection of nodes and  
their interconnections



Kuipers/Byun,  
Chong/Kleeman,  
Dudek, Choset,  
Howard, Mataric, etc.

# Three Major Map Models

	Grid-Based	Feature-Based	Topological
Resolution vs. Scale	Discrete localization	Arbitrary localization	Localize to nodes
Computational Complexity	Grid size and resolution	Landmark covariance ( $N^2$ )	Minimal complexity
Exploration Strategies	Frontier-based exploration	No inherent exploration	Graph exploration

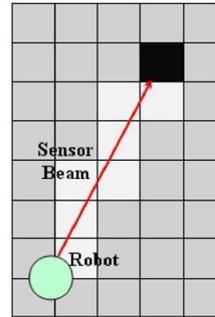
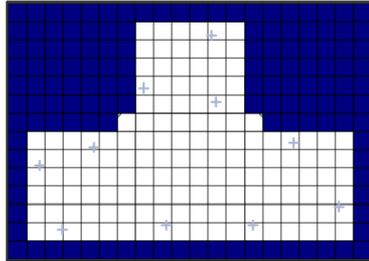
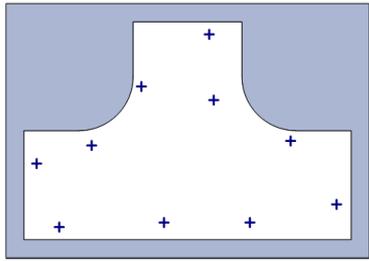


Specialized estimation techniques & literatures

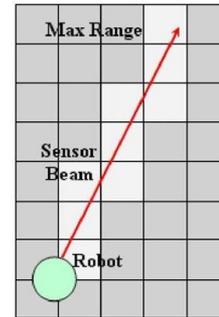
# Gmapping

**Occupancy Grid:** “map” is a grid of “cells”:  $\{x_{i,j}^m\}$

- $x_{i,j}^m = 0$  if cell (i,j) is empty;  $x_{i,j}^m = 1$  if cell (i,j) is occupied
- $p(x_{k+1}^r, \{x_{i,j}^m\}_{k+1} | x_{1:k}^r, \{x_{i,j}^m\}_k, y_{1:k+1})$  (estimate cell occupancy probability)



(a)

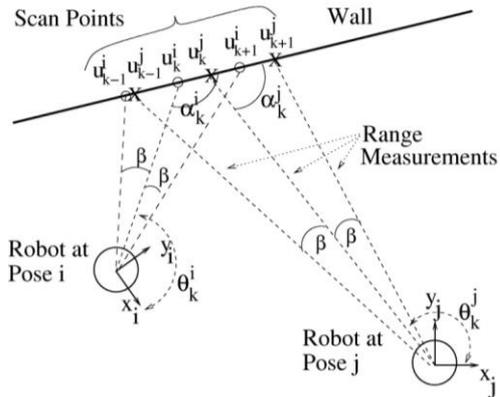
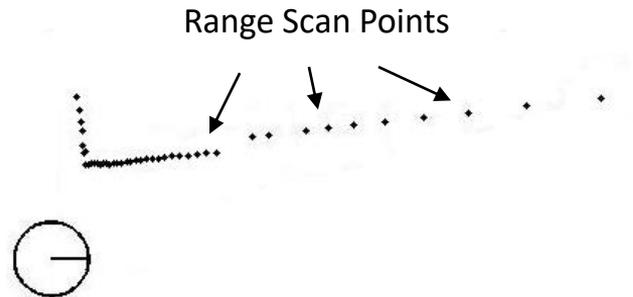


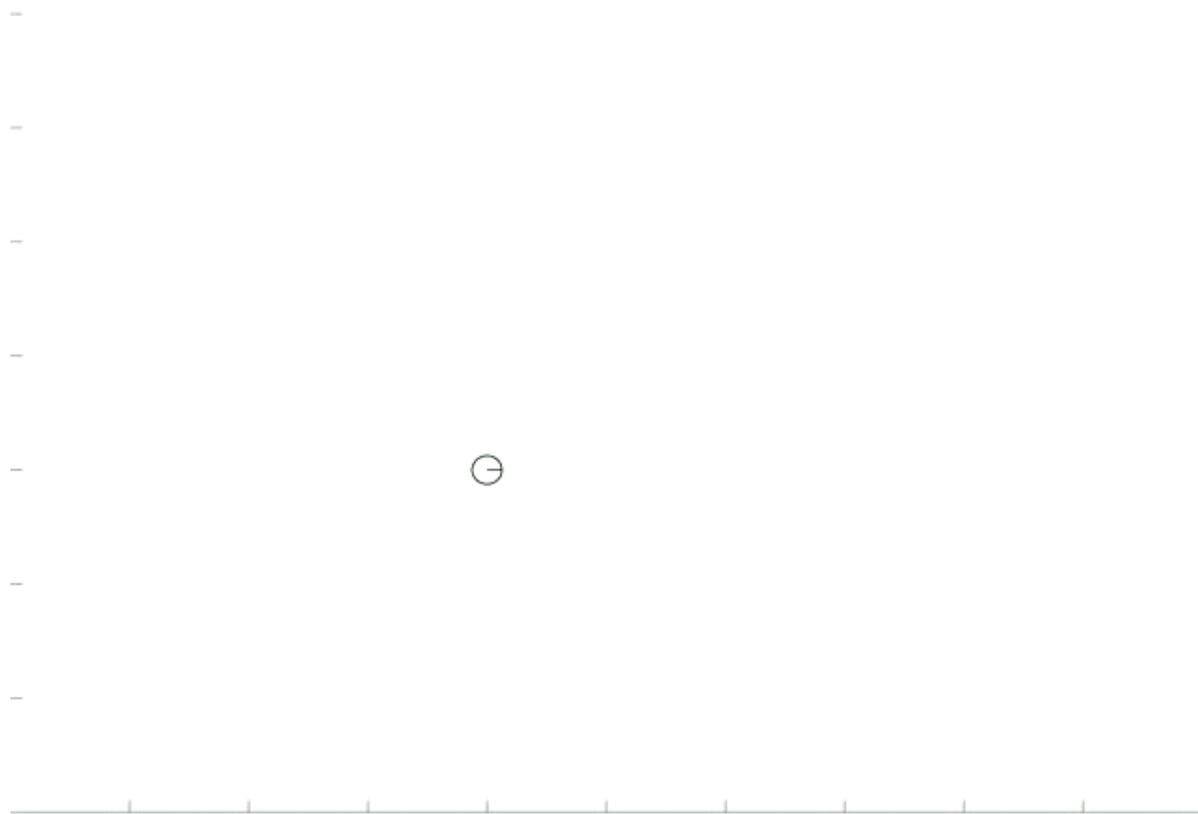
(b)

**Gmapping:**

- Uses a *Rao-Blackwellized* particle filter for estimator
- Actually computes  $p(x_{1:T}^r, \{x_{i,j}^m\} | x_{1:k}^r, x_k^m, y_{1:k+1})$

# Line-Based SLAM: LADAR





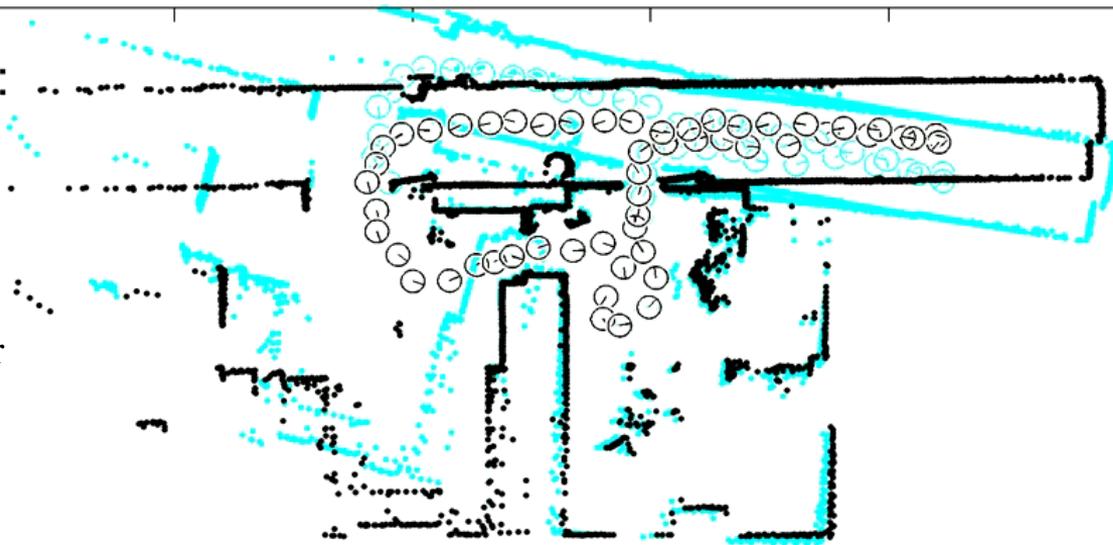
Lab Data :

53 Poses

32.8 meters

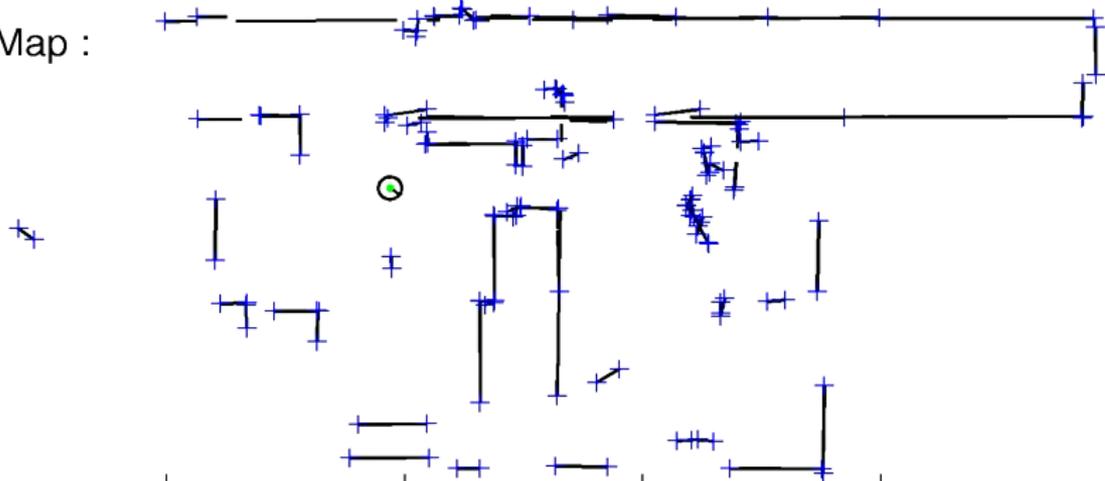
Raw Points

Kalman Filter  
Based SLAM  
Algorithm



Merged Line Map :

76 lines total

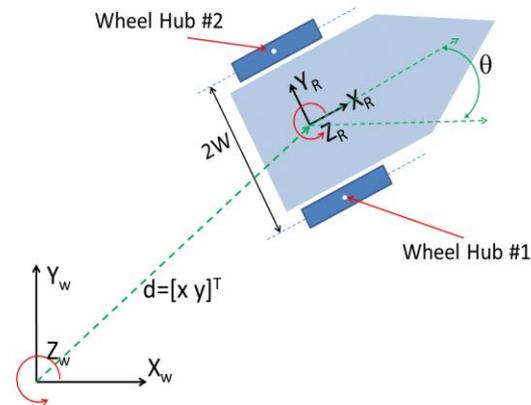


# Odometry & “Wheel Odometry”

**Definition:** Use of on-board sensors to estimate the change in a moving vehicle’s position/orientation over time.

- **Wheel Odometry:** use motion of the robot wheels to estimate robot displacement. Need a “kinematic model”
- **Inertial Odometry:** use sensors that measure inertial data (acceleration and rates of rotation) to estimate robot displacement.
- **Visual odometry:** use vision information to estimate robot displacement
  - Monocular & stereo cameras
  - Lidar
  - RGB-D
- **Visual/Inertial Odometry (VIO):** “Fuse” data from a vision sensor and the inertial sensors to get better estimates of displacement

# Example: differential drive robot

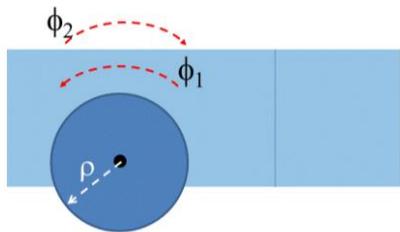


We can derive (see notes on syllabus)

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \frac{\rho}{2} \begin{bmatrix} (\dot{\phi}_2 - \dot{\phi}_1) \cos \theta \\ (\dot{\phi}_2 - \dot{\phi}_1) \sin \theta \\ -(\dot{\phi}_2 + \dot{\phi}_1)/W \end{bmatrix}$$

Which is equivalent to:

$$\begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \frac{\rho}{2} \begin{bmatrix} (\dot{\phi}_2 - \dot{\phi}_1) \\ 0 \\ -(\dot{\phi}_2 + \dot{\phi}_1)/W \end{bmatrix}$$

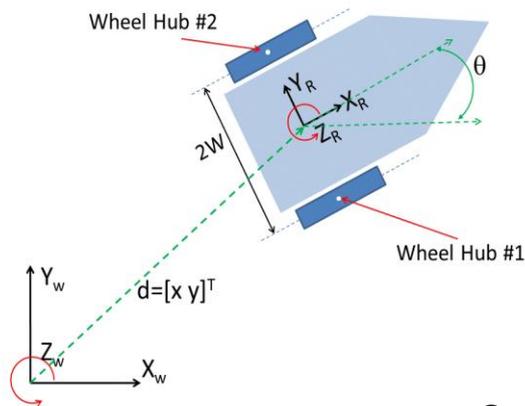


“Integrate” the kinematic equations w.r.t. time:

$$\begin{bmatrix} x(t) \\ y(t) \\ \theta(t) \end{bmatrix} = \begin{bmatrix} x(0) \\ y(0) \\ \theta(0) \end{bmatrix} + \int_0^t \begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\theta}(t) \end{bmatrix} dt = \begin{bmatrix} x(0) \\ y(0) \\ \theta(0) \end{bmatrix} + \frac{\rho}{2} \int_0^t \begin{bmatrix} (\dot{\phi}_2(t) - \dot{\phi}_1(t)) \cos \theta(t) \\ (\dot{\phi}_2(t) - \dot{\phi}_1(t)) \sin \theta(t) \\ -(\dot{\phi}_2(t) + \dot{\phi}_1(t))/W \end{bmatrix} dt$$

# Example: differential drive robot

To practically integrate these equations, we can use a *backward difference* approximation scheme:

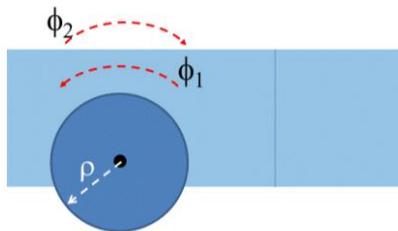


$$\dot{x}(t_k) \simeq \frac{x(t_k) - x(t_{k-1})}{t_k - t_{k-1}} = \frac{x(t_k) - x(t_{k-1})}{\Delta t}$$

$$\dot{y}(t_k) \simeq \frac{y(t_k) - y(t_{k-1})}{t_k - t_{k-1}} = \frac{y(t_k) - y(t_{k-1})}{\Delta t}$$

$$\dot{\theta}(t_k) \simeq \frac{\theta(t_k) - \theta(t_{k-1})}{t_k - t_{k-1}} = \frac{\theta(t_k) - \theta(t_{k-1})}{\Delta t}$$

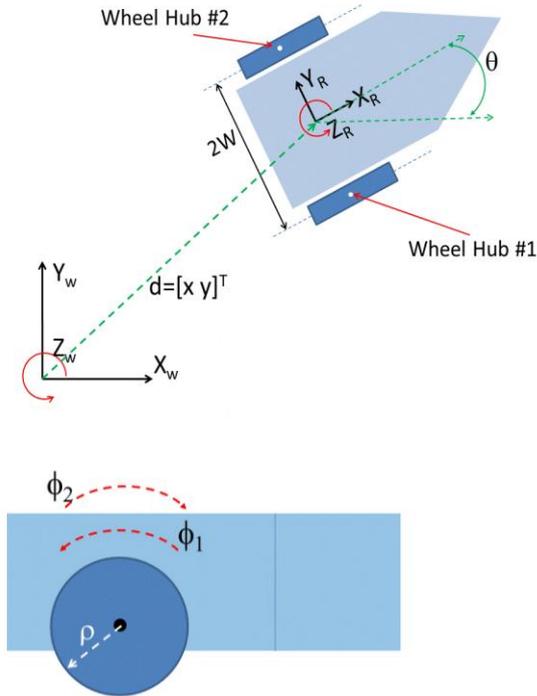
Substituting into the integration and rearranging yields:



$$\begin{bmatrix} x(t_k) \\ y(t_k) \\ \theta(t_k) \end{bmatrix} = \begin{bmatrix} x(t_{k-1}) \\ y(t_{k-1}) \\ \theta(t_{k-1}) \end{bmatrix} + \frac{\rho}{2} \begin{bmatrix} (\Delta\phi_2 - \Delta\phi_1) \cos \theta(t_{k-1}) \\ (\Delta\phi_2 - \Delta\phi_1) \sin \theta(t_{k-1}) \\ -(\Delta\phi_2 + \Delta\phi_1)/W \end{bmatrix}$$

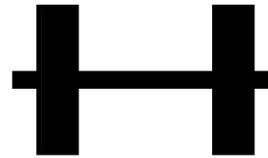
Where  $\Delta\phi_i = \phi_i(t_k) - \phi_i(t_{k-1})$

# Example: differential drive robot

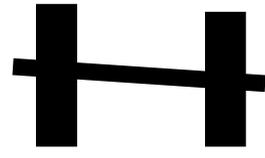


## Sources of Error:

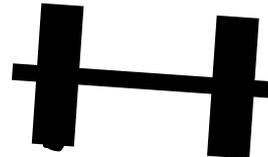
- Wheels slip on the ground (violating assumption of derivation)
- Equations of motion are an approximation (wheels don't have zero thickness)
- Backwards-difference is an approximation
- Quantization/noise error in wheel sensor measurements



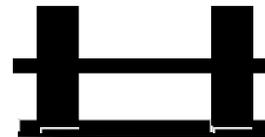
ideal case



different wheel diameters



bump



carpet

# Inertial Navigation

**Definition:** Given the vehicle's initial position and velocity, estimate the vehicle's current position and velocity relative to the starting point, using only *proprioceptors* that measure rigid body inertial properties (e.g., accelerometers and gyroscopes).

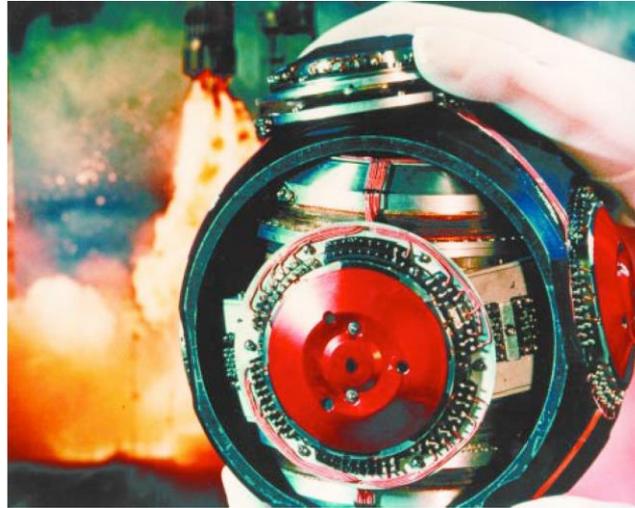
**Inertial Measurement Unit (IMU):** Contains a cluster of sensors attached to a common base.

- accelerometers (typically 3 or more along orthogonal axes) measure accelerations of the sensor's body-fixed reference frame,
- gyroscopes measure the rates of sensor rotation about three orthogonal axes.
- An optional *magnetometer* measure's the earth's magnetic field (i.e., a compass)

**Basic Concept:** Integrate accelerometer twice to obtain velocity and position. Integrate gyro readings to estimate orientation.

# Older types of IMUs

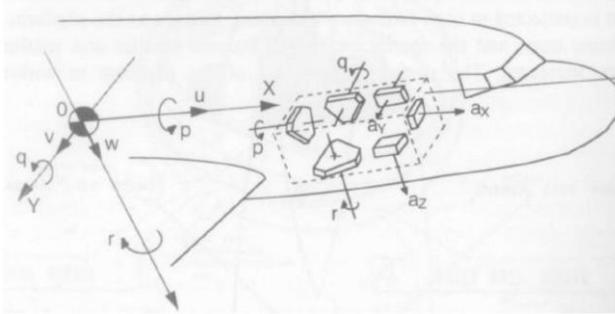
**Gimbaled:** The sensor suite is mounted on a platform in a gimbal.



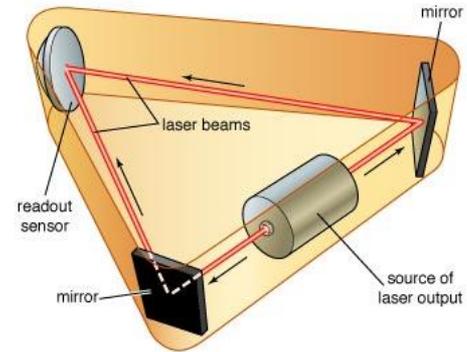
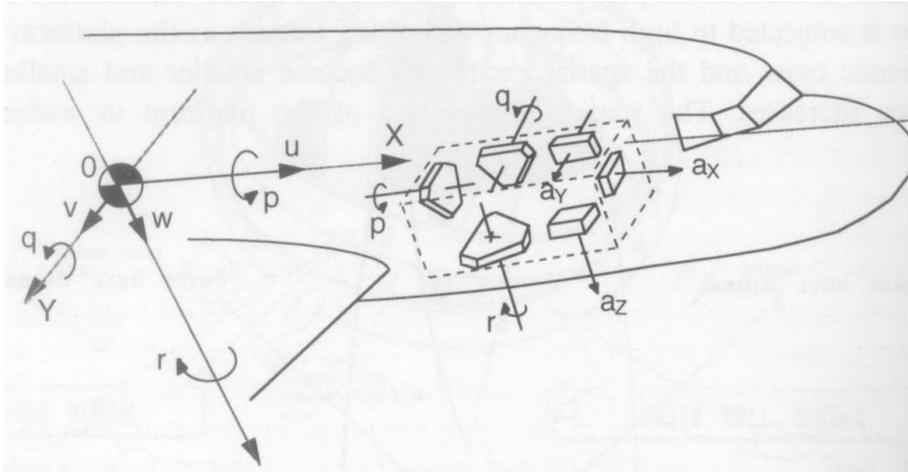
**Mechanical Gyro:** A spinning wheel will resist any change to its angular momentum vector. Maintains constant orientation if in a frictionless gimbal

# Modern IMUs

**Strapdown:** Mount sensor suite rigidly to the moving object of interest.



# Inertial Navigation



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Laser Ring Gyro  
Uses Doppler effect to  
measure rotation rate

$$x = \begin{bmatrix} p \\ \phi \\ \dot{p} \\ \dot{\phi} \\ \ddot{p} \\ \ddot{\phi} \end{bmatrix}$$

$$y = \begin{bmatrix} \dot{\phi} \\ \ddot{p} \end{bmatrix} = [0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 0]x = Hx$$

# Strapdown Gyros (1)

**The Sagnac-effect.** The inertial characteristics of light can also be utilized, by letting two beams of light travel in a loop in opposite directions. If the loop rotates clockwise, the clockwise beam must travel a longer distance before finishing the loop. The opposite is true for the counter-clockwise beam. Combining the two rays in a detector, an *interference pattern* is formed, which will depend on the angular velocity.

The loop can be implemented with 3 or 4 mirrors (*Ring Laser Gyro*), or with optical fibers (*Fiber Optic Gyro*).

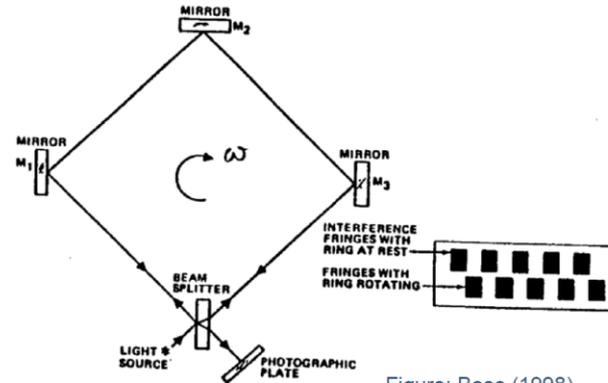
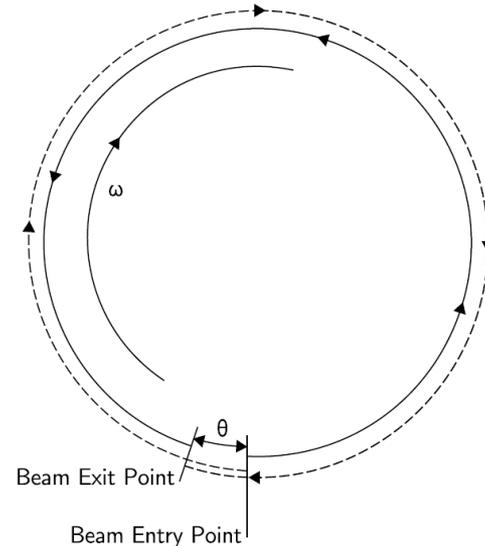


Figure: Bose (1998)

## Strapdown Gyros (2)

**The Sagnac-effect.** The inertial characteristics of light can also be utilized, by letting two beams of light travel in a loop in opposite directions. If the loop rotates clockwise, the clockwise beam must travel a longer distance before finishing the loop. The opposite is true for the counter-clockwise beam. Combining the two rays in a detector, an **interference pattern** is formed, which will depend on the angular velocity.

The loop can be implemented with 3 or 4 mirrors (*Ring Laser Gyro*), or with optical fibers (*Fiber Optic Gyro*).



# Strapdown Gyros (3)

**Coriolis Effect:** When a mass vibrating in a radial direction is rotated, the Coriolis effect will cause new vibrations perpendicular to the original vibration axis.

- Cheaper MEMS gyros use this principle (“tuning fork” or “wineglass”)
- Less accurate than ring or fiber gyro

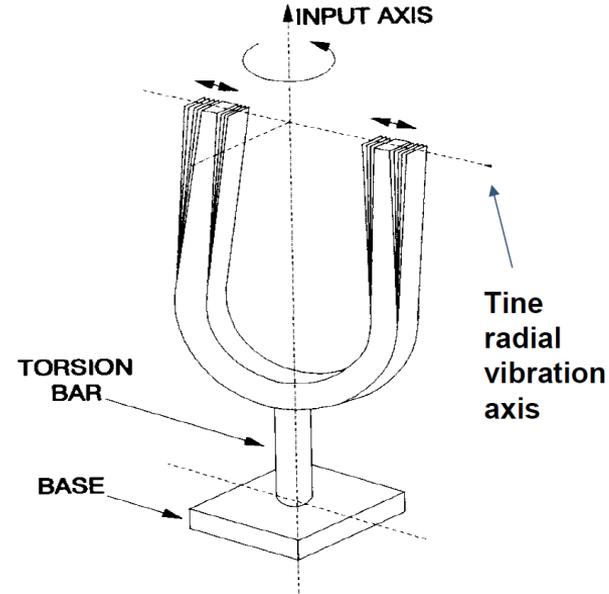
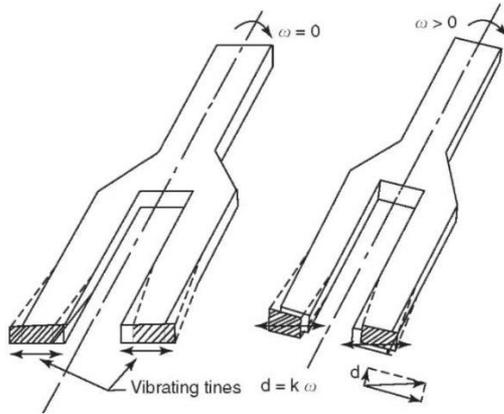
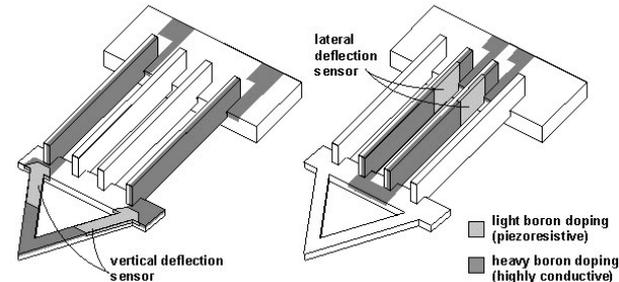


Figure: Titterton & Weston (1997)



# Accelerometers

**Vibration:** deflection of a mass on a spring yields simple acceleration signal

- Greater accuracy, dynamic range, and linearity can be realized by keeping mass close to nominal position—control forces are proportional to acceleration.

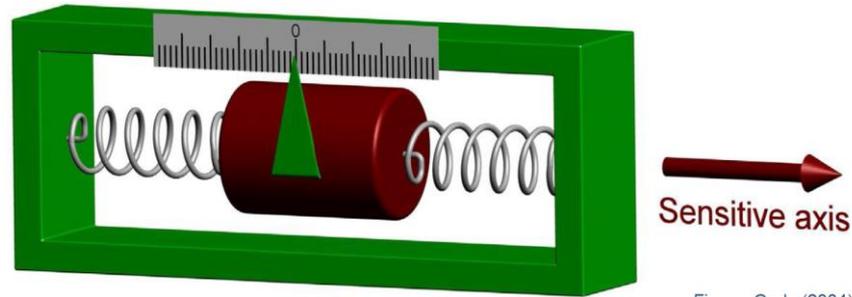
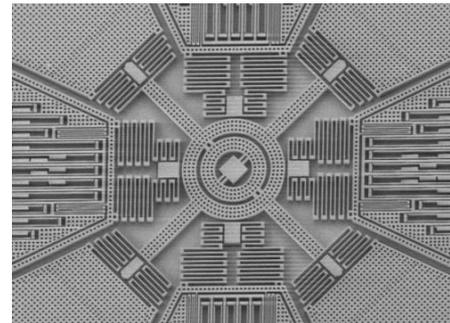
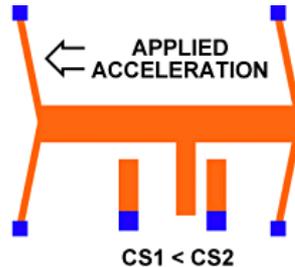
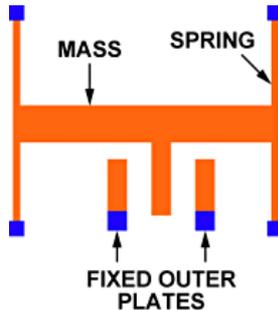
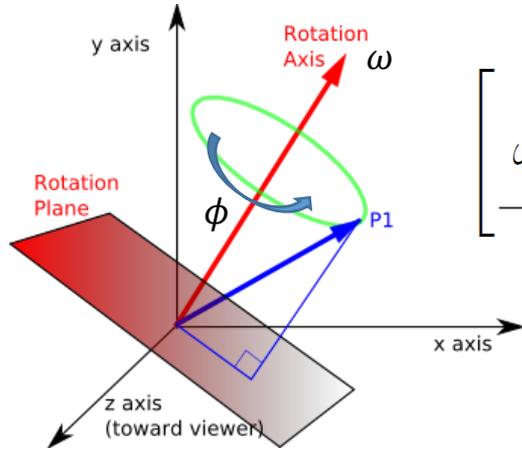


Figure: Coda (2004)



# Summary of Inertial Odometry Equations



$$\begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix}$$

$$R(\phi, \vec{\omega}) = I + (\sin \phi)\hat{\omega} + (1 - \cos \phi)\hat{\omega}^2.$$

Gyro gives us measurements of angular velocity in *body coordinates*:

$$\vec{\Omega}^1 = \begin{bmatrix} \Omega_x^1 \\ \Omega_y^1 \\ \Omega_z^1 \end{bmatrix}$$

$$\begin{aligned} R_{WB}(t_{k+1}) &= R_{WB}(t_k) e^{\Delta\phi(t_{k+1})\hat{\omega}(t_{k+1})} \\ &= R_{WB}(t_k) [I + \sin(\Delta\phi(t_{k+1}))\hat{\omega}(t_{k+1}) + (1 - \cos(\Delta\phi(t_{k+1})))\hat{\omega}^2(t_{k+1})] \end{aligned}$$

$$\Delta\phi(t_{k+1}) = \|\vec{\Omega}(t_{k+1})\|\Delta t$$

$$\hat{\omega}(t_{k+1}) = \|\vec{\Omega}(t_{k+1})\|^{-1} \vec{\Omega}(t_{k+1})$$

# Summary of Inertial Odometry Equations

Convert acceleration measured in body frame to “world” frame

$$\vec{a}^W(t) = R_{WB}(t) \vec{a}^B(t)$$

Calculate velocity of body holding the accelerometer (theory, practice)

$$\vec{v}_{WB}^W = \vec{v}_{WB}^W(t=0) + \int_0^t \vec{a}^W(\tau) d\tau \quad \vec{v}_{WB}^W(t_{k+1}) = \vec{v}_{WB}^W(t_k) + R_{WB}(t_{k+1}) \vec{a}^B(t_{k+1}) \Delta t$$

Calculate the position of the body holding the accelerometer (theory, practice)

$$\vec{p}_{WB}^W = \vec{p}_{WB}^W(t=0) + \int_0^t \vec{v}_{WB}^W(\tau) d\tau \quad \vec{p}_{WB}^W(t_{k+1}) = \vec{p}_{WB}^W(t_k) + \vec{v}_{WB}^W(t_{k+1}) \Delta t$$

# Terrestrial Navigation

**Corrections** need to be added to inertial navigation when the vehicle is operating or navigation on earth, since *earth is not an inertial system*

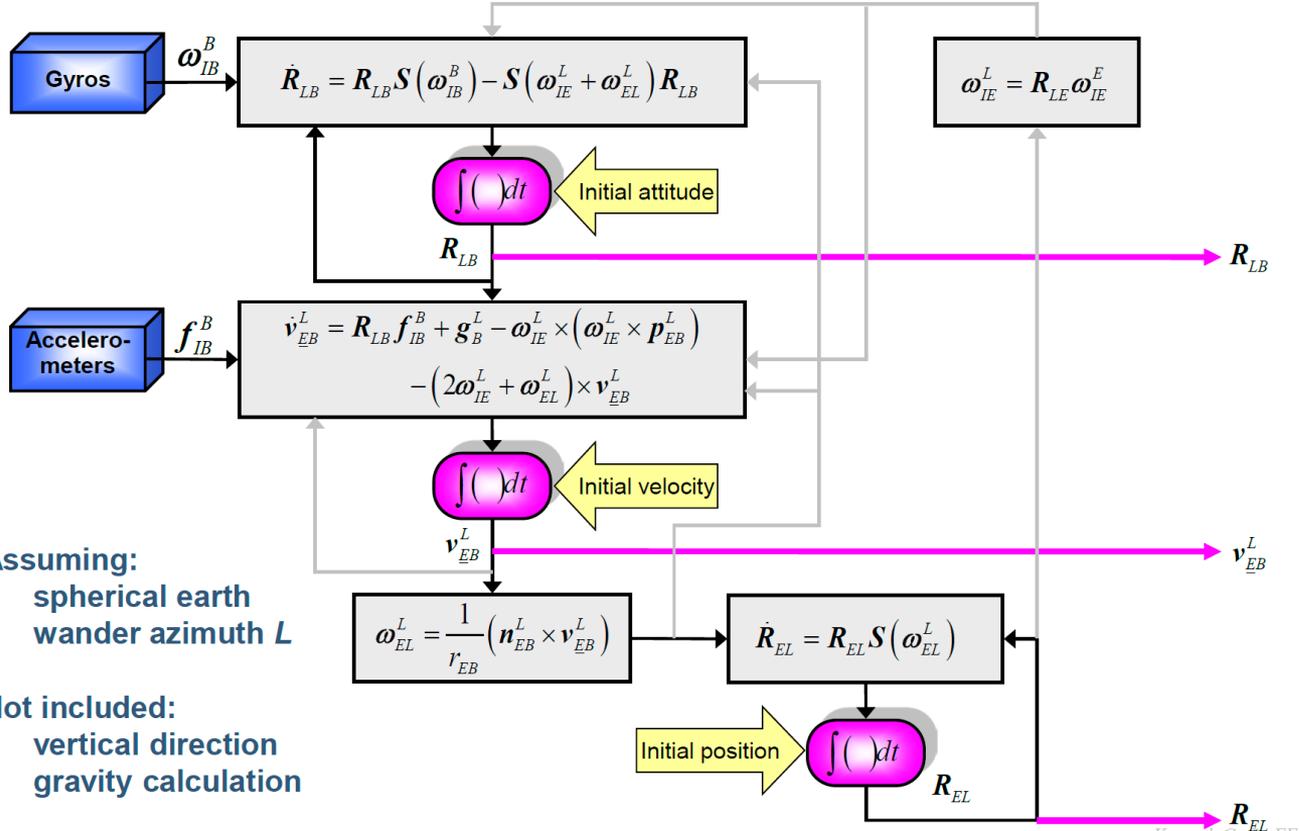
## Gyros:

- The earth rotates:  $\omega_{EB} = \omega_{IB} - \omega_{IE}$  ( $\omega_{IE}$  = earth's rotation in space)

## Accelerometers

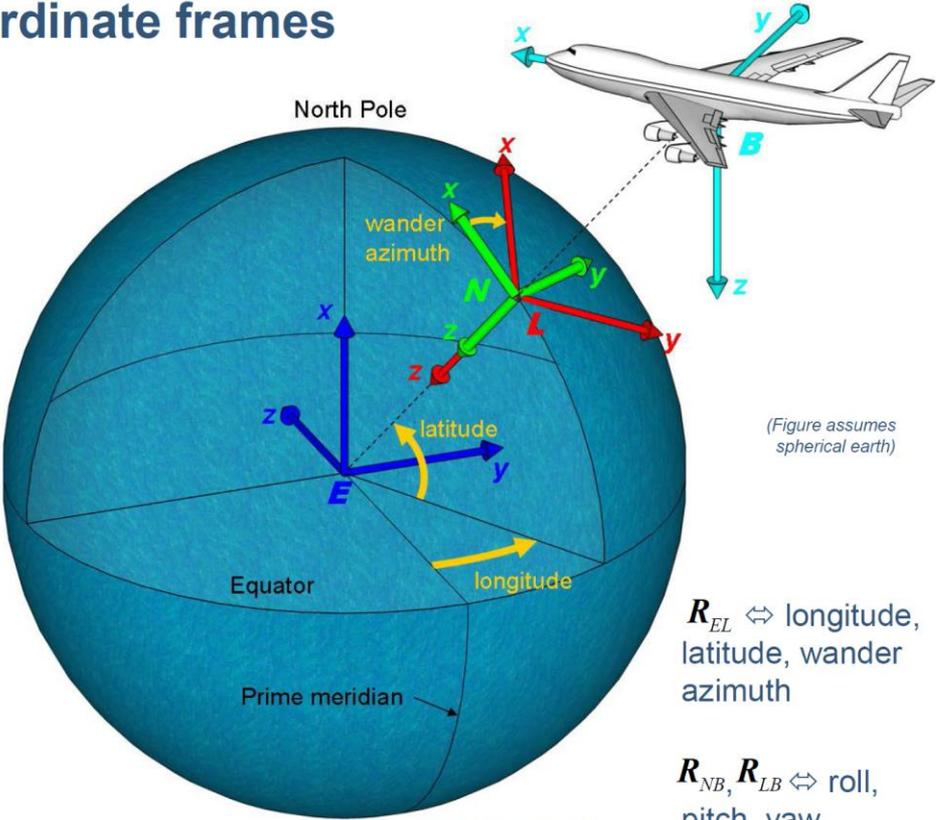
- also measure *gravitational acceleration*
  - Let  $a_{IB}$  denote the acceleration of the body measured relative to an inertial frame.
  - Let  $g_B$  denote the gravitational acceleration
  - The *specific force*,  $f_{IB}$ , measures the acceleration in an inertial frame:  $f_{IB} = a_{IB} - g$
- Also measure centrifugal and Coriolis forces due to movement in earth's rotating frame.

# Terrestrial Navigation



# Important coordinate frames

Frame symbol	Description
$I$	Inertial
$E$	Earth-fixed
$B$	Body-fixed
$N$	North-East-Down (local level)
$L$	Local level, wander azimuth (as $N$ , but not north-aligned => nonsingular)



(Figure assumes spherical earth)

$R_{EL} \Leftrightarrow$  longitude, latitude, wander azimuth

$R_{NB}, R_{LB} \Leftrightarrow$  roll, pitch, yaw

Figure: Gade (2008)

# Homework

**Team Tasks:** (all unit levels)

- Skim through the notes on the course website