#### COMP 551: Advanced Robotics Lab

# Lec02: Sensors, Pose Estimation, Simple Python Projects

James McLurkin Rice University jmclurkin@rice.edu

## Sensors

#### Sensors, sensors, everywhere

We're surrounded by sensors

You can sense anything and everything.

For example, let's say you want to sense obstacles:

#### **Lever Switch**



#### **IR Range Finder**



#### Sonar



#### Radar



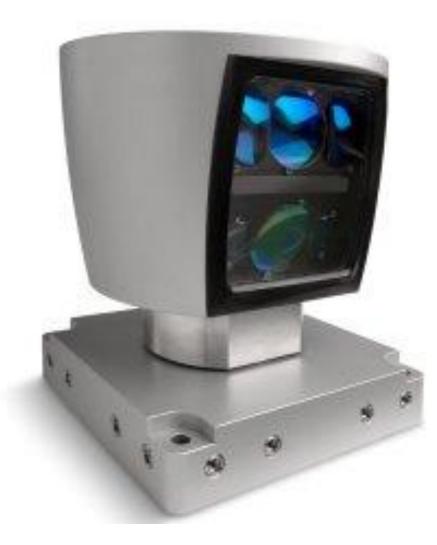
#### Lidar



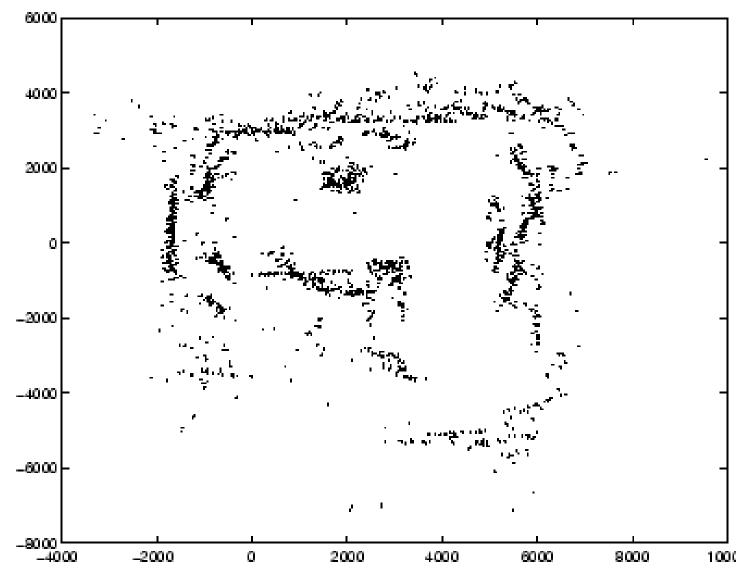
#### Lidar (smaller)



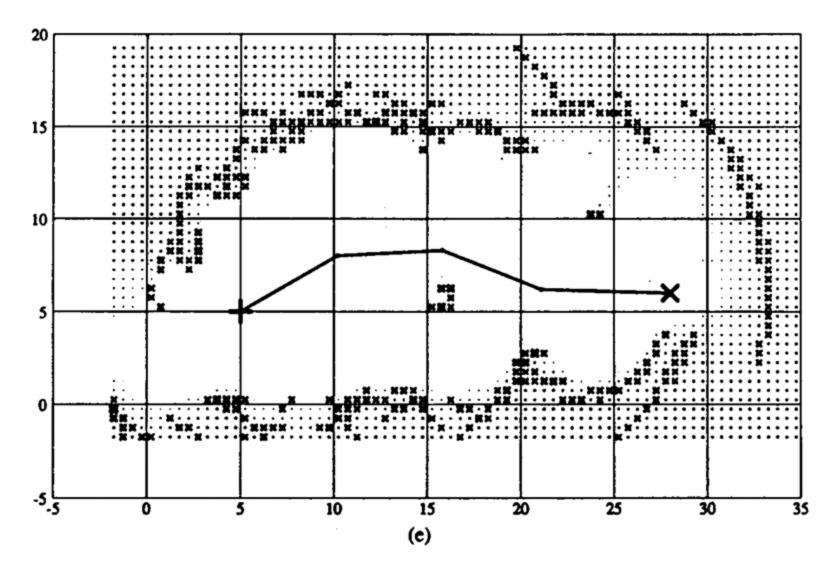
## Lidar (insane)



#### **Map from Sonar**



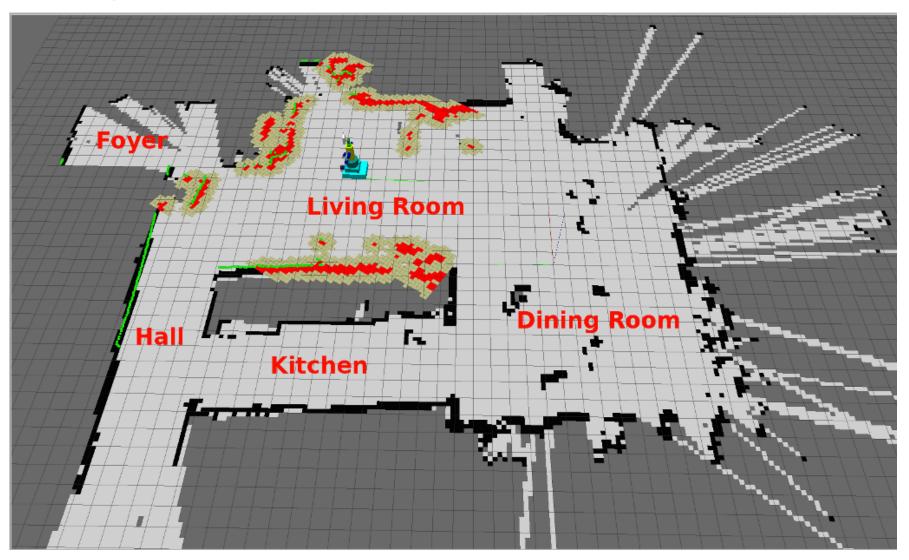
#### **Map from Sonar**



#### **Map from Lidar**



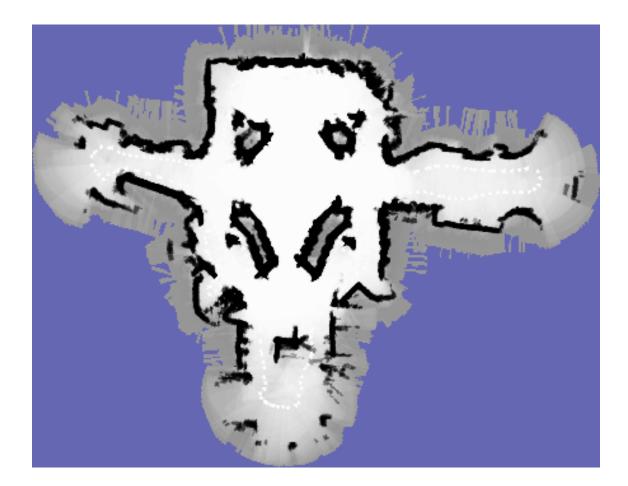
#### **Map from Lidar**



### **Occupancy Grid Mapping**

Use laser scanner to detect obstacles

Use sensor model and "better pose" to produce a map



## **Particle Filter Localization (MCL)**

#### Produce lots of estimates of current position Keep the good ones



KLD-Sampling: Adaptive Particle Filters. D. Fox. NIPS-01.

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SLAM in Large-Scale Cyclic Environments Using the Atlas Framework

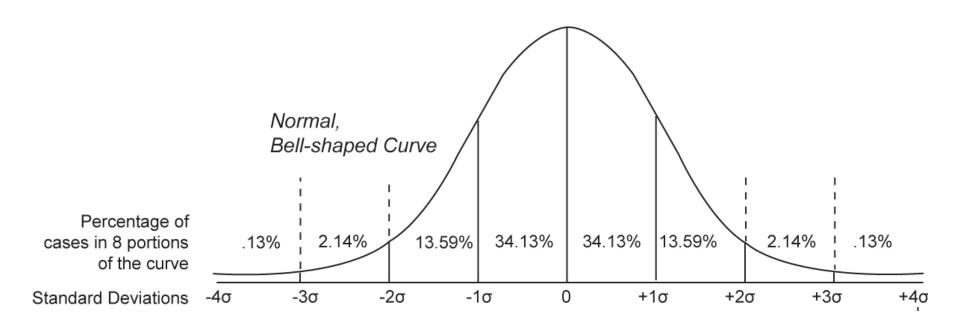
Michael Bosse, Paul Newman, John Leonard, Seth Teller

International Journal of Robotics Research February, 2004

#### **The Sensor Model**

There are many ways to sense any physical quantity
Each approach has trade-offs in cost, complexity, and accuracy
We need to understand these basic parameters of the *sensor model* in order to select the right sensors for the job
We often represent this model as a *normal distribution...*

#### **Normal Distribution**



Looks complex, but can be represented with two parameters

- This is convenient for math
- It can be easily manipulated

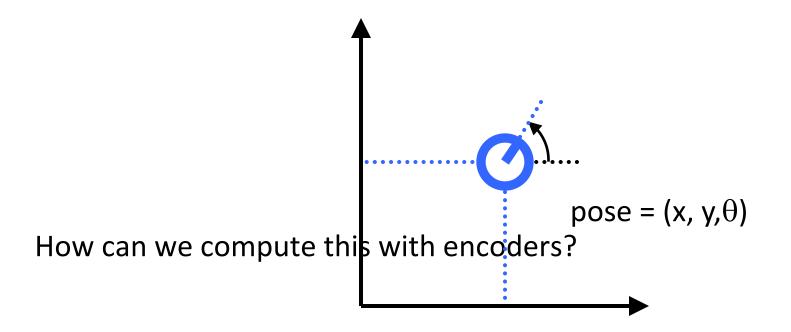
#### Surprisingly accurate

• Even when the underlying physical phenomena is not normal

# Using Sensors: Odometry

#### **Pose Estimation**

We can describe the robot's *pose* in an external reference frame: This is useful for getting the robots around in the world

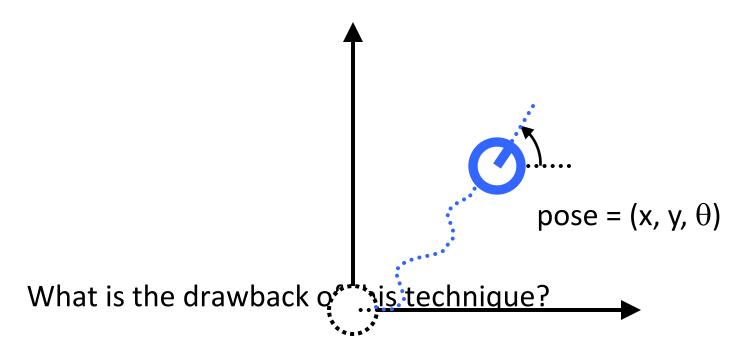


#### **Pose Estimation**

We assume the robot starts at (0, 0, 0)

We compute incremental changes to the pose using the encoders

This is called *dead reckoning* 



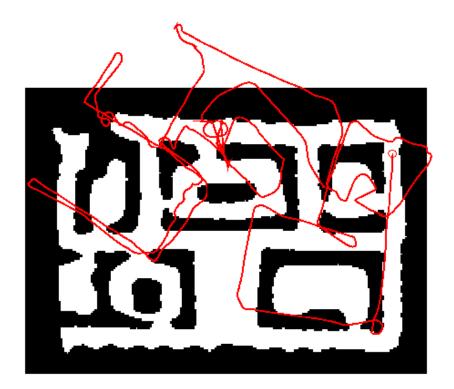
#### **Wheel Slippage**

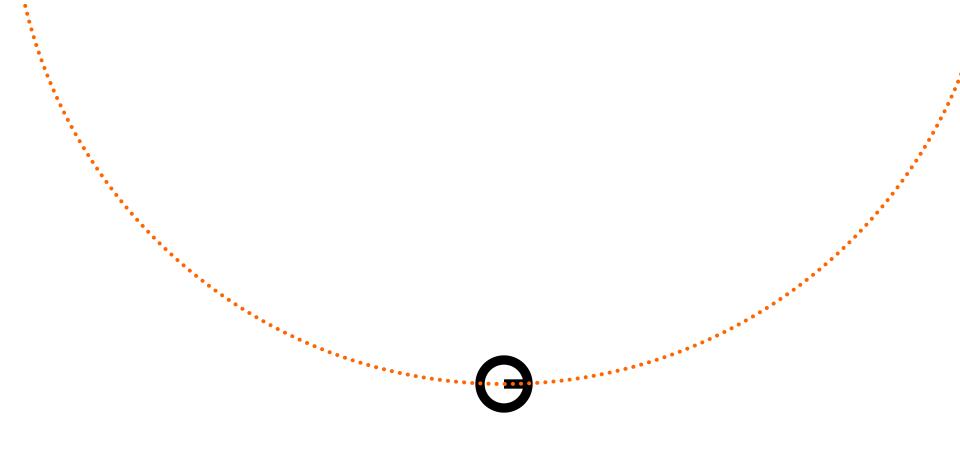
Wheels are always slipping, therefore Dead Reckoning is always accruing errors

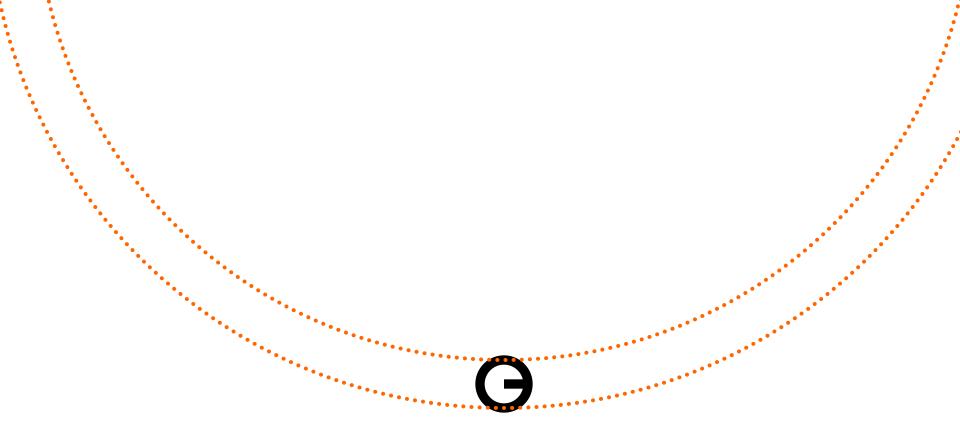
Even worse, the errors *integrate*, i.e. they increase little by little but have no bound. Soon the robot has **no idea** where it is.

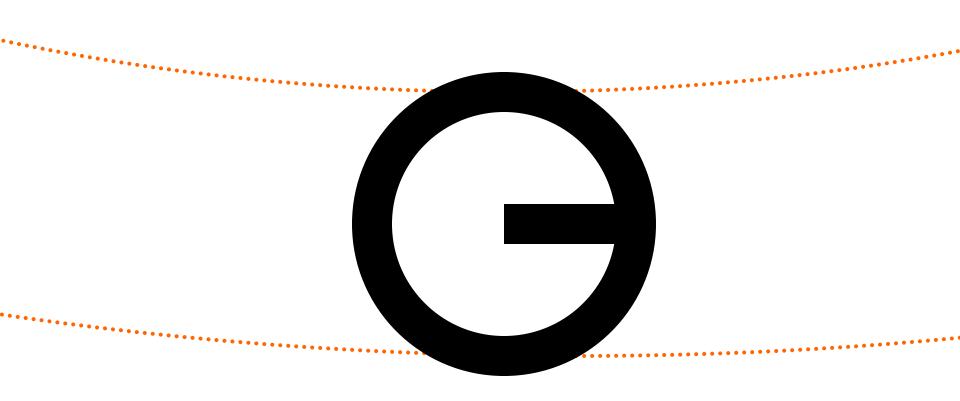
We can do better, right?

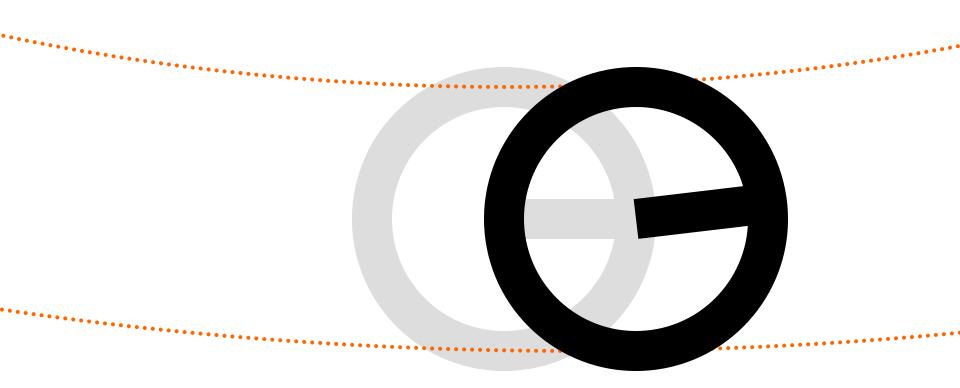


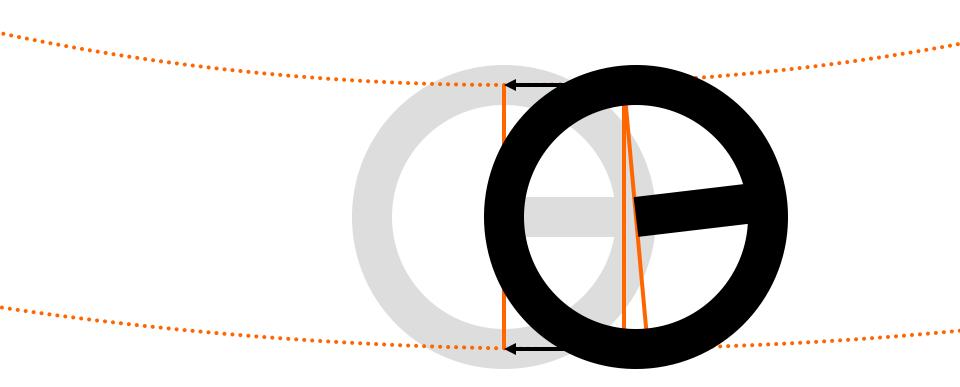




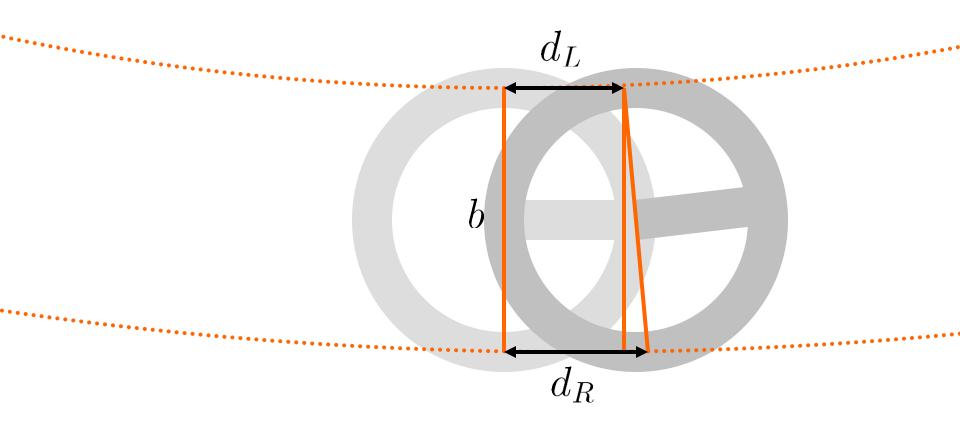




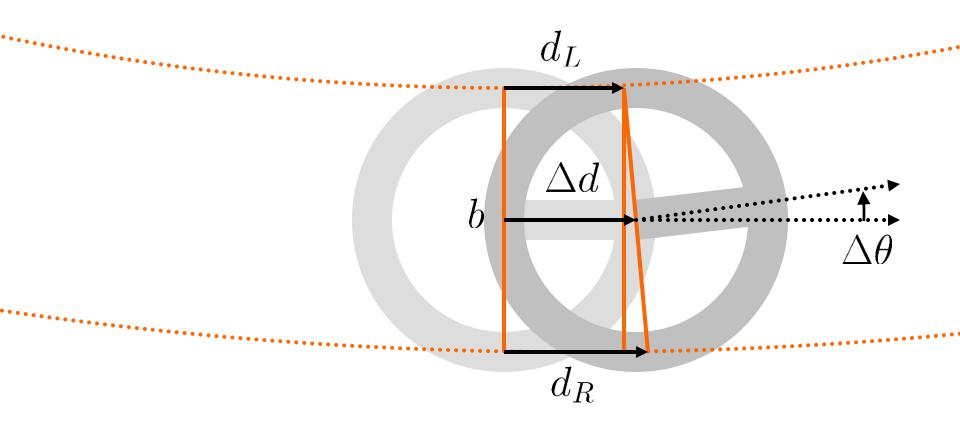




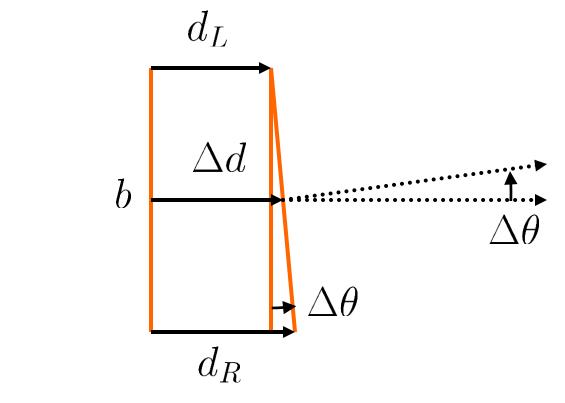
#### Parameters we know



#### Parameters we want to compute



#### **One Update Step**

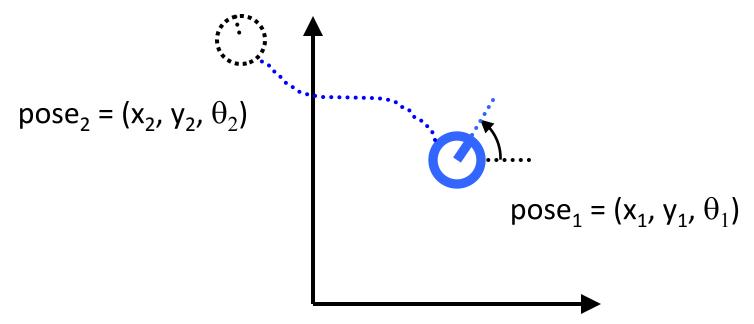


[The rest is homework]

# Using Odometry: Waypoint Navigation

## **Waypoint Navigation**

We assume that we know our current pose How can we get from one point to another? We don't want to specify  $\theta_2$ , just (x<sub>2</sub>, y<sub>2</sub>)



## **Waypoint Navigation**

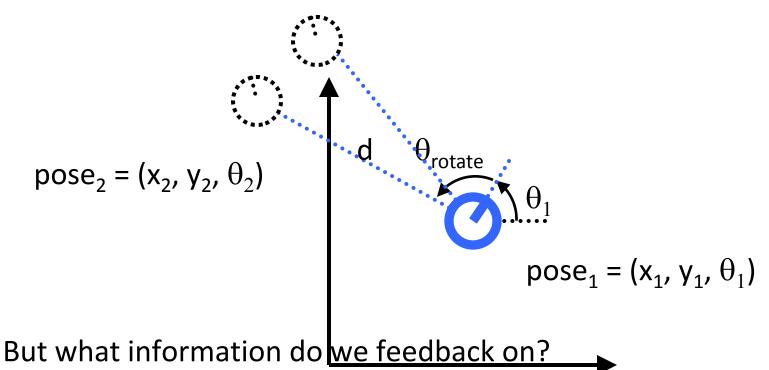
- 1. Compute  $\theta_{\text{rotate}}$  and d
- 2. Rotate, then move a fixed distance

pose<sub>2</sub> = (x<sub>2</sub>, y<sub>2</sub>, 
$$\theta_2$$
)  
will this work? Will it work well?

#### No

Small angular errors will be magnified over long d

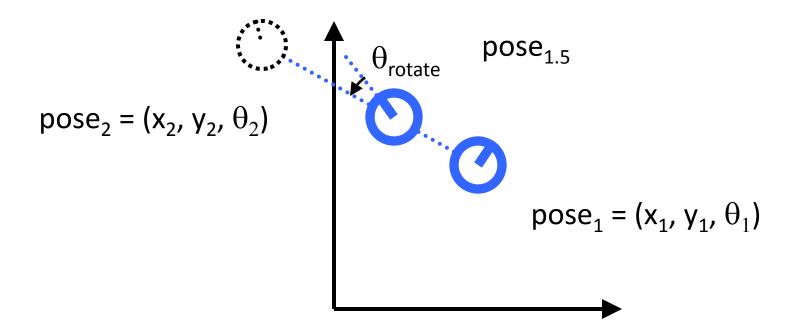
But we know how to deal with errors: a feedback controller



### Waypoint Navigation with a controller

**1**. While d > ε:

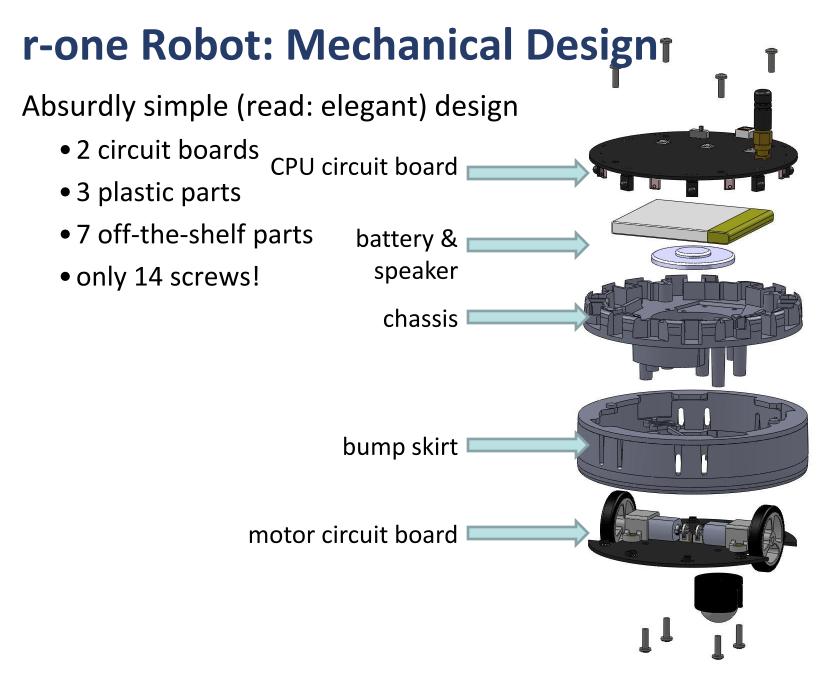
- 2. Compute  $\theta_{\text{rotate}}$  and d
- 3. Rotate while translating



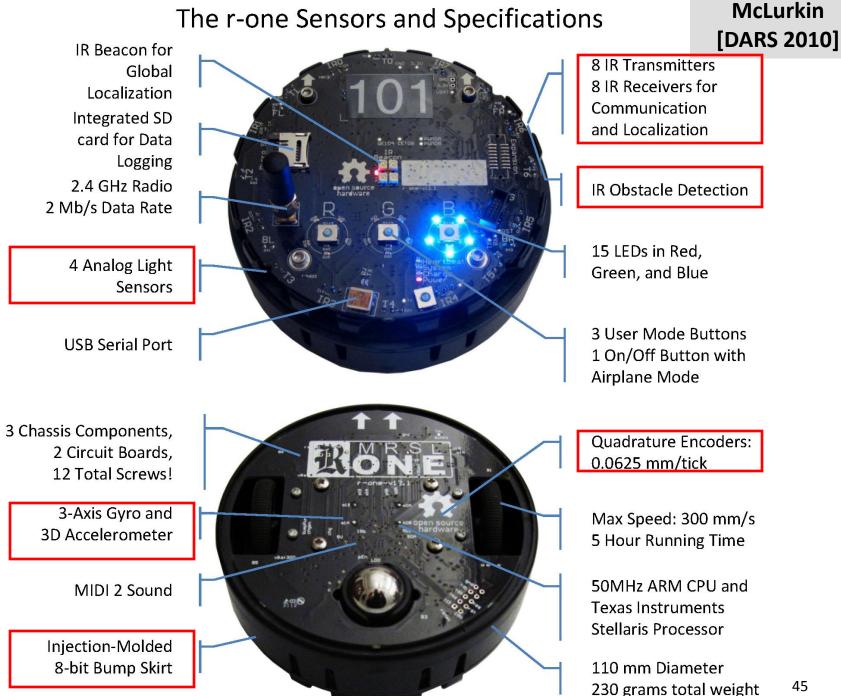
# **Topic 5:** The "r-one" robot

# Sensors and Actuators on the r-one Robot





#### The r-one Sensors and Specifications



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