ROB 537:
Learning-Based Control

Week 3, Lecture 1
Neural Networks for Control

Announcements:
Paper topics due TODAY
HW 2 Due on 10/16

Reading: Papers on Neurocontrol
Miikkulaininen
Shepherd

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Problem Definitions

- Do we know what are good robot actions?
  - YES: Supervised learning
    Drive around with the training "on" to generate input/output pairs
  - NO: Unsupervised learning (critic based learning) Explore parameters till you find "right behavior"
- Online/Offline ?
  - Offline: train/search for a complete solution before implementing
  - Online: take action, evaluate, take next action etc.

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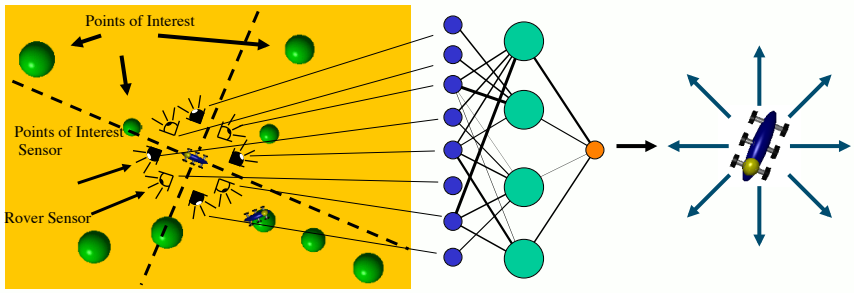
Example: Robot Control



- Robots observe environment through some sensors
- Sensors are inputed into a neural network
- Output of neural network determines direction/velocity of rover

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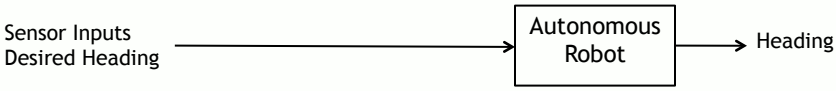
Robot Control



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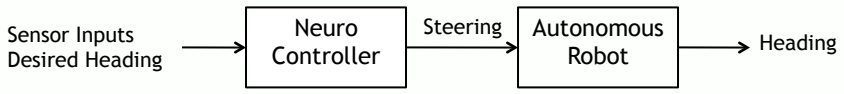
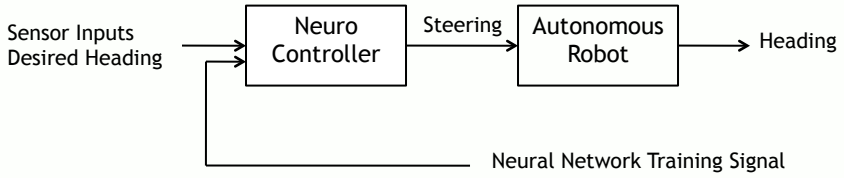
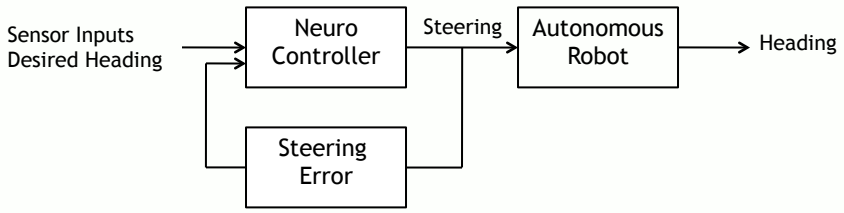
Robot Control



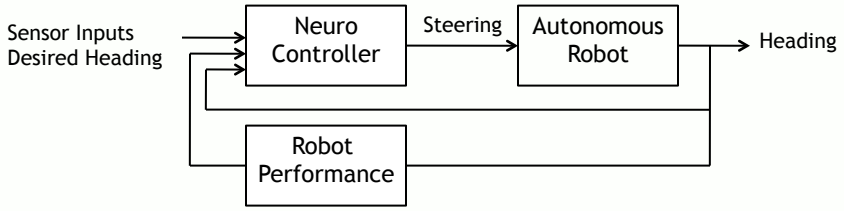
Robot Control



Robot Control : Learn with a Teacher



Robot Control : Learn without a Teacher



Neural Networks for Nonlinear Control

- Motivation:
  - Control a system with nonlinear dynamics
    - Robot
    - Satellite
    - Air vehicle
- Do we know what the good control strategies are?
  - Yes: "teach" neural network those strategies
    - Drive a car and record good driver actions for each state
    - Fly a helicopter and record good pilot actions for each state
  - No: have a neural network discover those strategies
    - Let car drive around and provide feedback on performance

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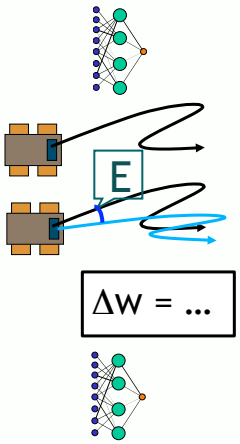
Neuro-Control with a Teacher

1. Initialize a neural network
2. Let neural network pick heading
3. Compute heading error using teacher
4. Use error to update neural network weights
5. Go to step 2



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Unsupervised Learning

- What if we don't have a teacher?
- Unsupervised learning: learning without a set of labeled examples
- Each input results in an outcome (measured by a reward)
- Training:

?

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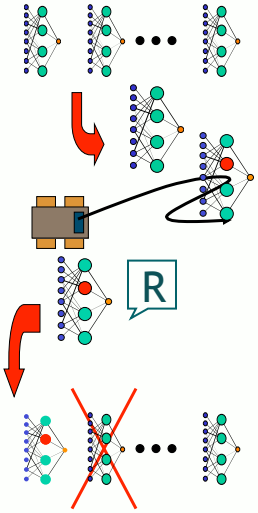
Neuro-Control without a Teacher

1. At t=0 initialize N neural networks
2. Pick a network using ε−greedy alg (ε=.1)
3. Randomly modify network parameters
4. Use network on this agent for T steps
5. Evaluate network performance
6. Re-insert network into pool
7. Remove worst network from pool
8. Go to step 2



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Example: Quadrotor Control

- Benefits of quadrotors:
  - Operate in dangerous & challenging environments
  - Overcome resource limitations
  - Maneuverability - over airplanes
  - Mechanical simplicity - over helicopters
- Drawbacks:
  - Highly non-linear dynamics
  - Unintuitive control (difficult for a human)
  - Stability problems – as opposed to airplanes
  - Control problems – as opposed to helicopters

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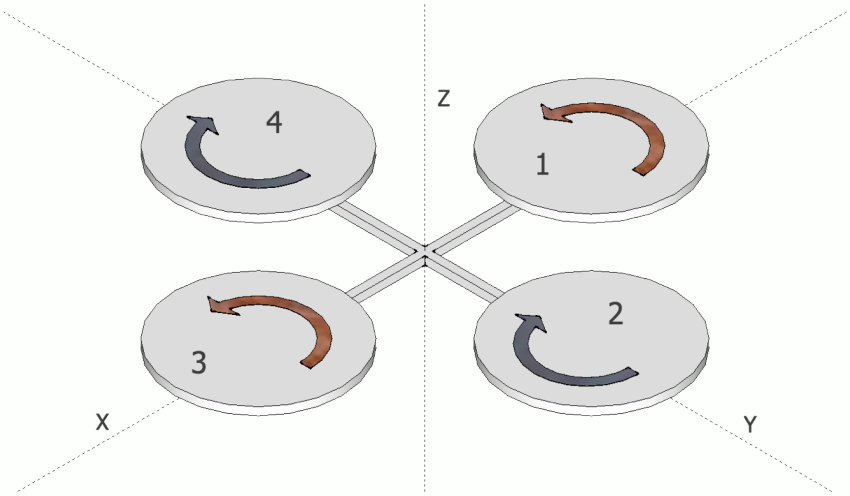
Background — Quadrotor Control



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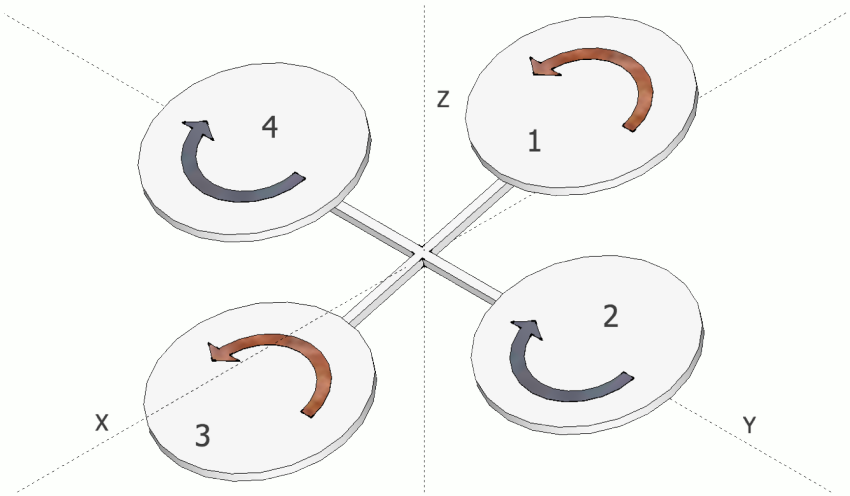

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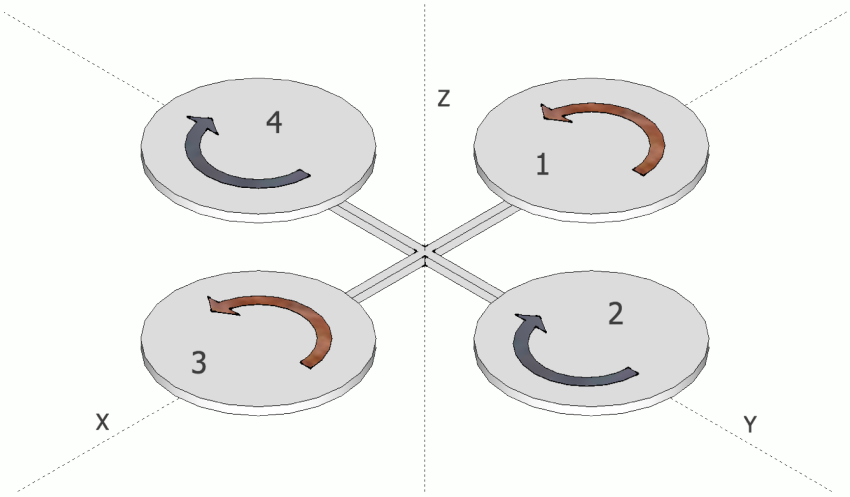

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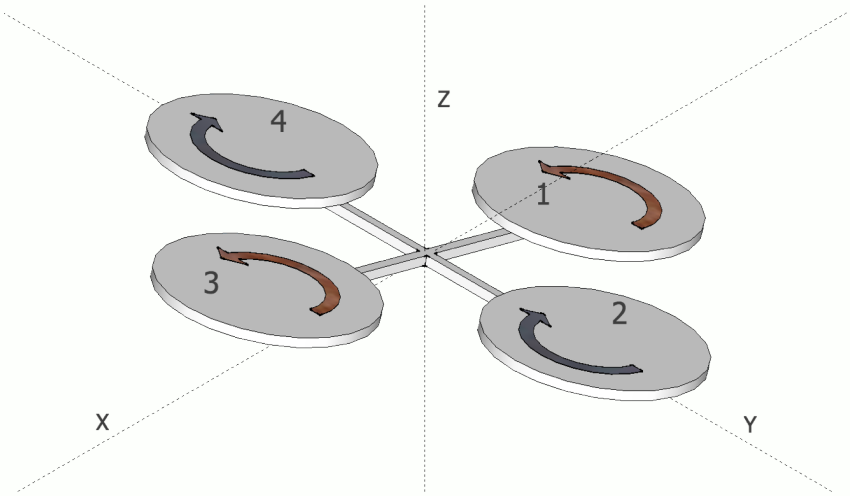

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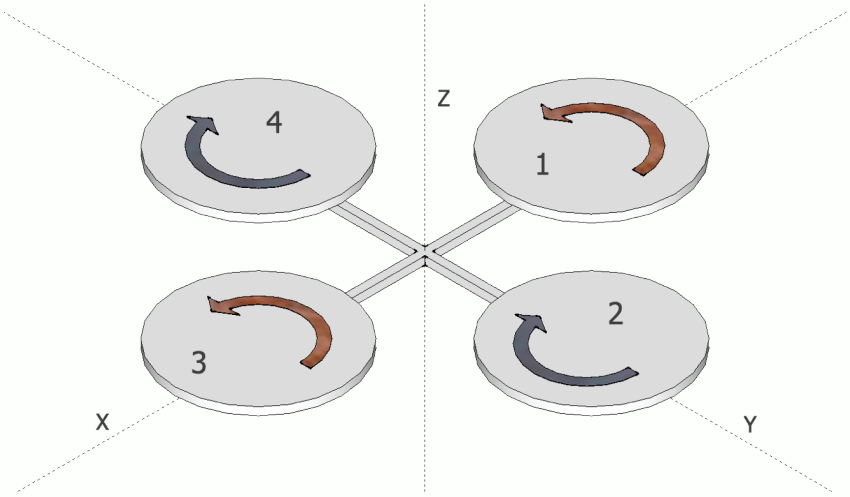

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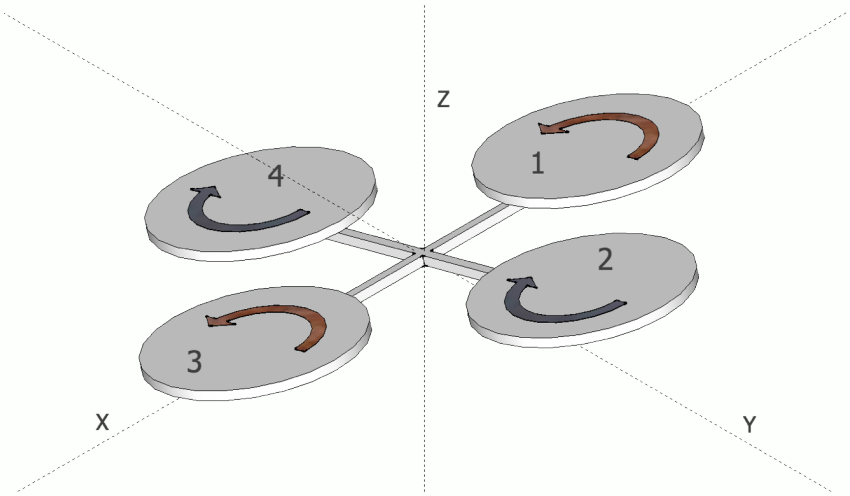

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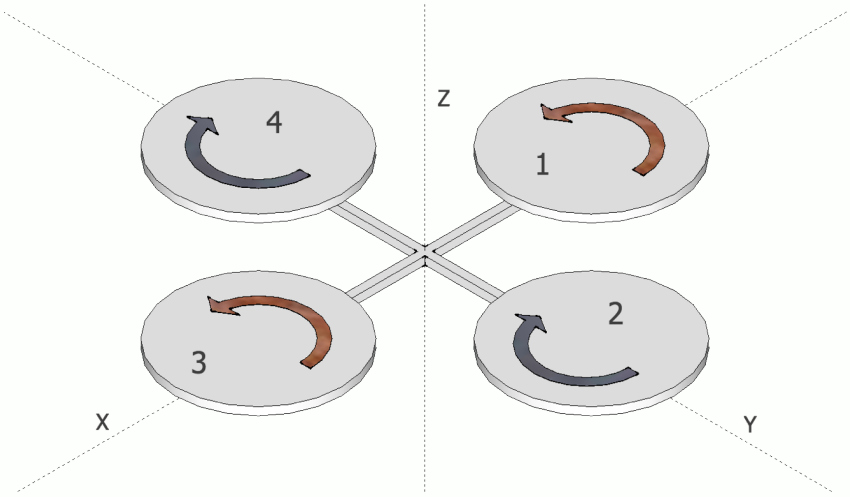

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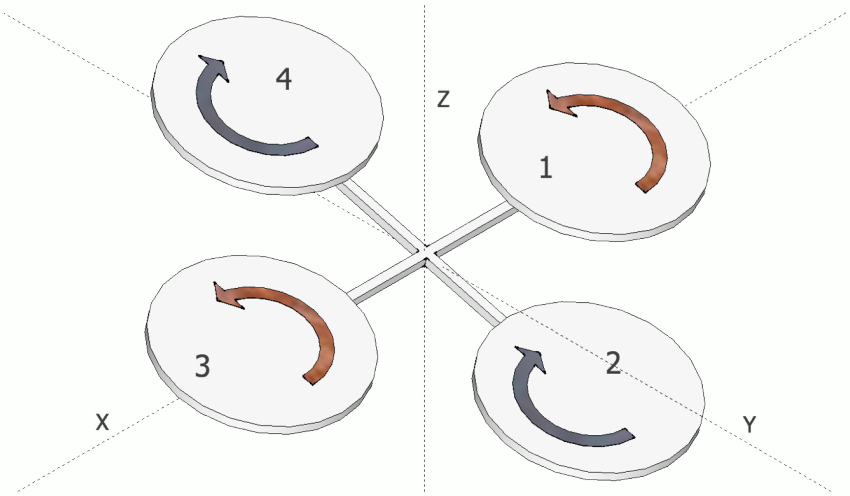

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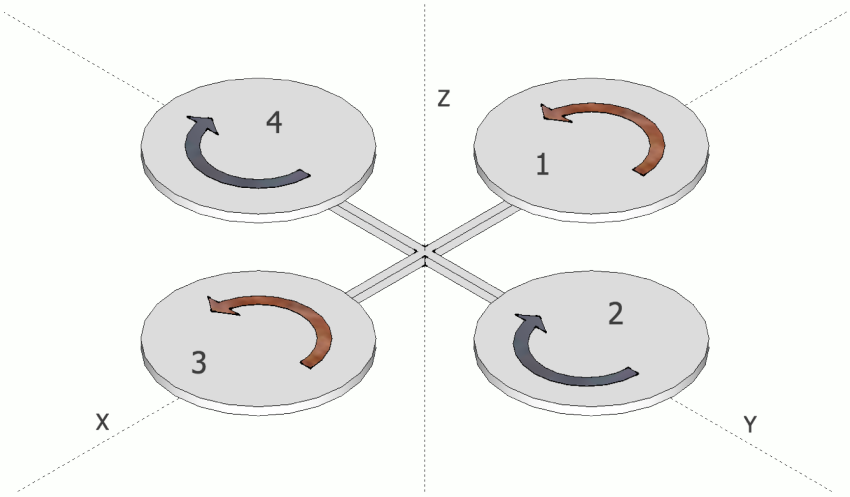

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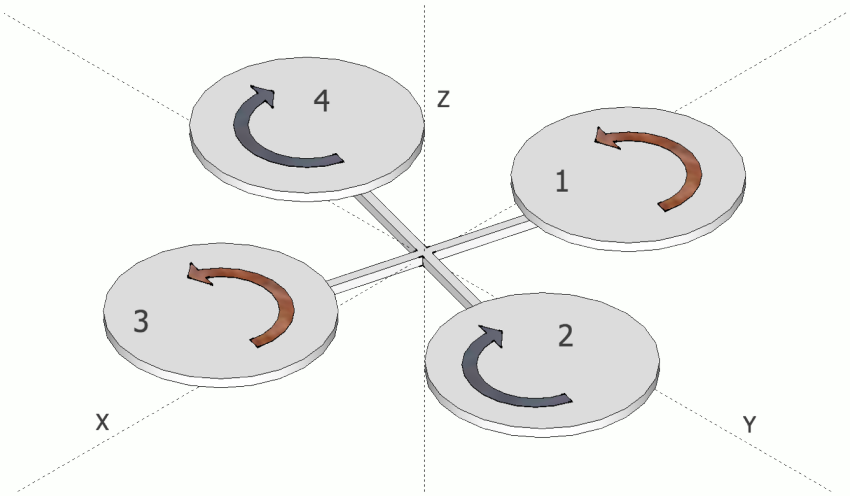

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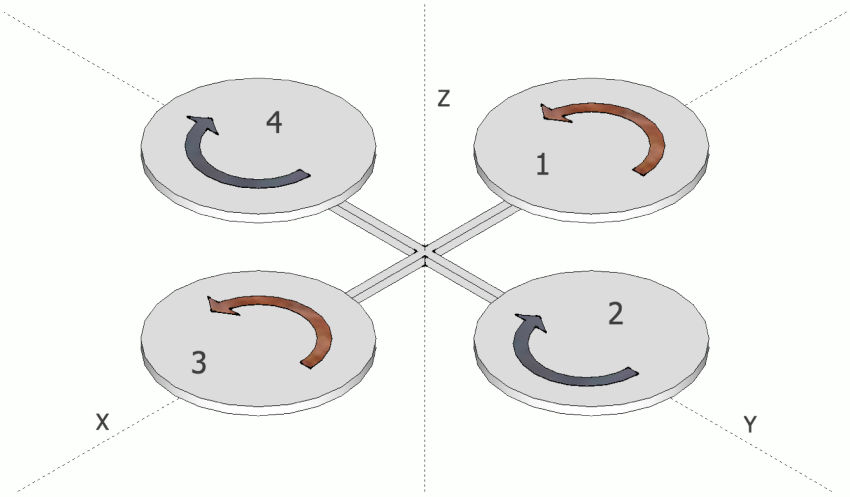

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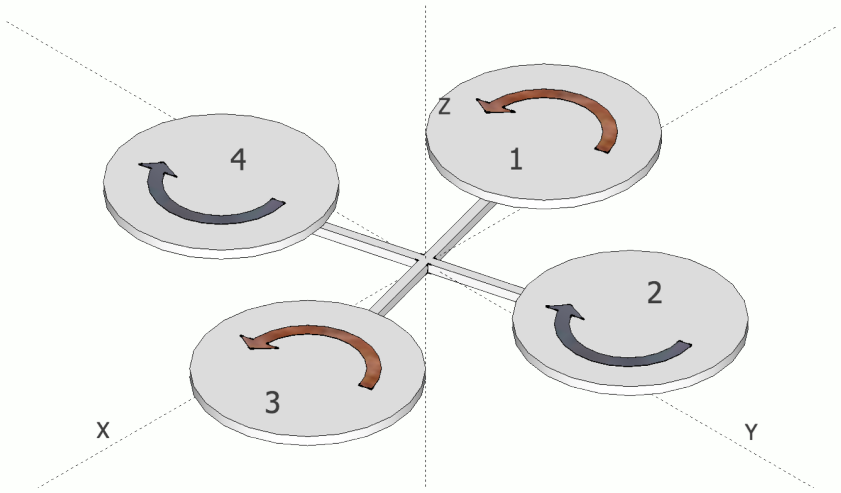

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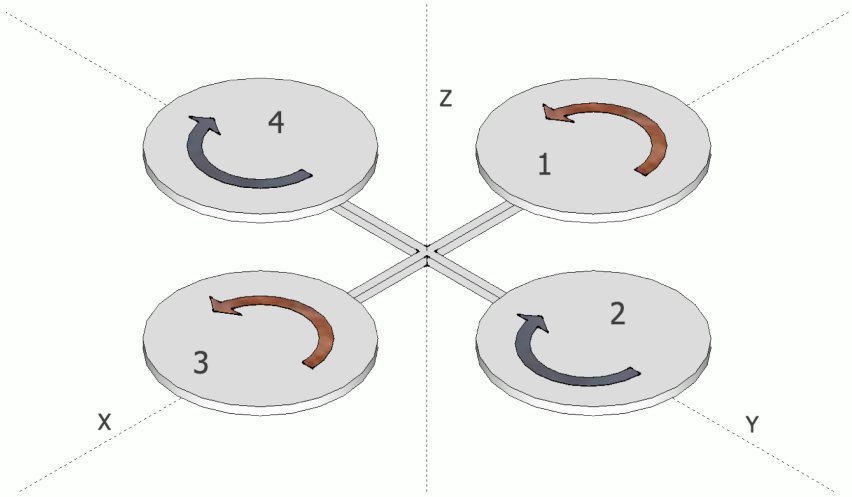

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Controller Formulation

- Break problem down into solvable units
  - Top Level: Position controller - for waypoint navigation
  - Middle Level: Attitude controller - for maintaining stability
  - Low level: Pitch/Yaw controller – for specific rotor movement
  - All following results from:

J. Shepherd III and K. Tumer, **Robust Neuro-Control for A Micro Quadrotor**. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pp. 1131–1138, Portland, OR, July 2010.

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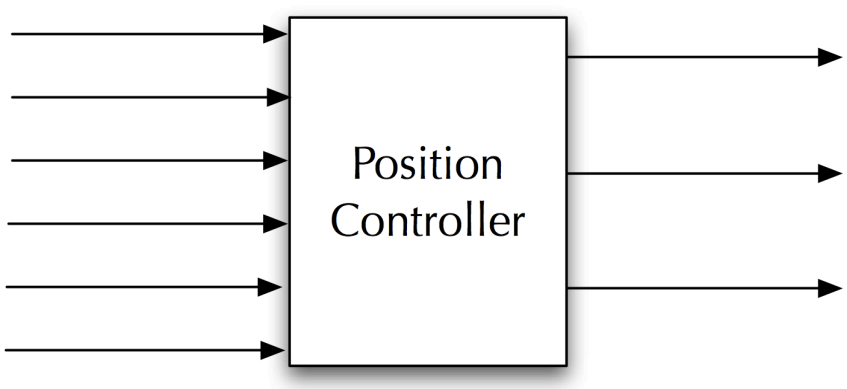
Position Controller Formulation



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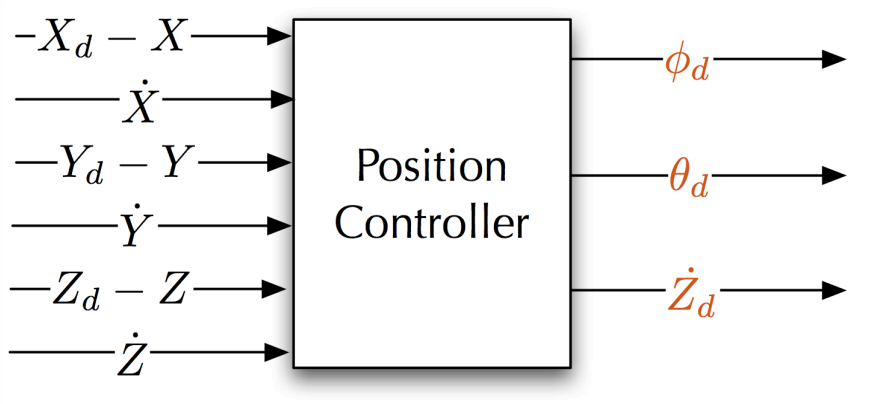
Position Controller Formulation



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Position Controller Training

- Fitness based on distance traveled and distance to goal:

$$F = 10000 - d_g + (100 - d_t)^2$$

Arbitrary

- Stability criteria
  - Erratic motion resulted in a fitness set to 0
- 15000 iterations to train :
  - Select - Mutate - Evaluate
  - Evaluate position controller multiple grid points
  - Run with neuro-controller for 10 seconds

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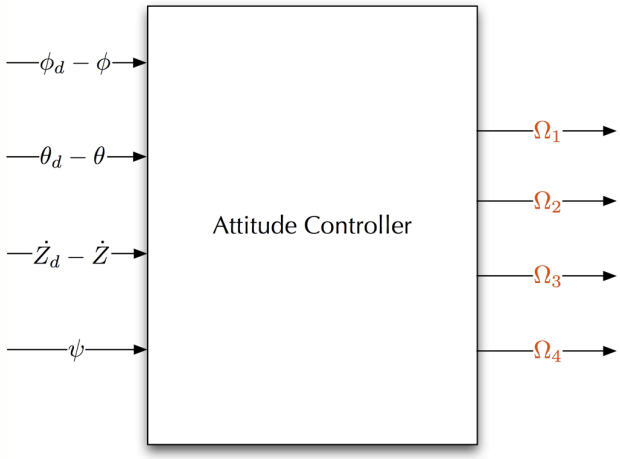
Attitude Controller Formulation



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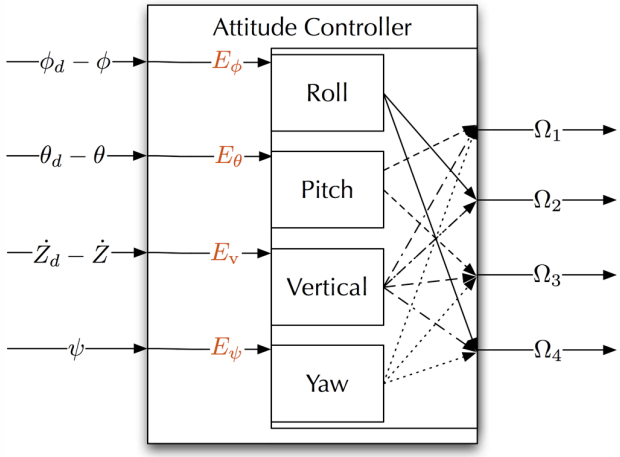
Attitude Controller Formulation



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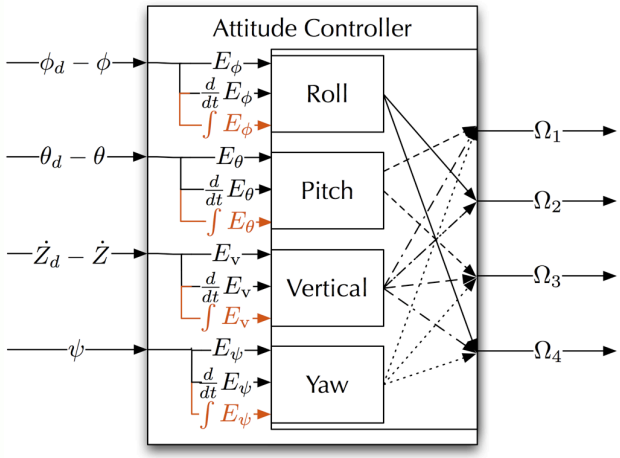
Attitude Controller Formulation



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Attitude Controller - Two Step Training

- Step 1: Supervised
  - Population of 100 controllers
  - Control quadrotor for 10s
  - Fitness based on matching PID results

$$F = e^{-\sum |A_{nn} - A_{pid}|}$$

  - Run for 3000 iterations

Arbitrary

- Step 2: Unsupervised
  - Create new population from best controllers from step 1
  - Add 20% weight mutation
  - Fitness based directly on achieved angle
  - Run for another 1000 iterations

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Experiments

1. Navigation
   - Set of waypoints given, controller performance measured
2. Robustness to disturbances
   - Modeled as a discrete change in the crafts current orientation
     - Sudden at 30° pitch
   - Time to recover, and range of ability to recover compared
3. Robustness to noise
   - Random sensor and actuator noise added.
   - Average distance craft traveled around the desired hold point compared
4. Robustness to design parameters
   - Craft physical parameters (size, weight, thrust & drag coefficients)
   - Time to perform move compared (mostly binary result).

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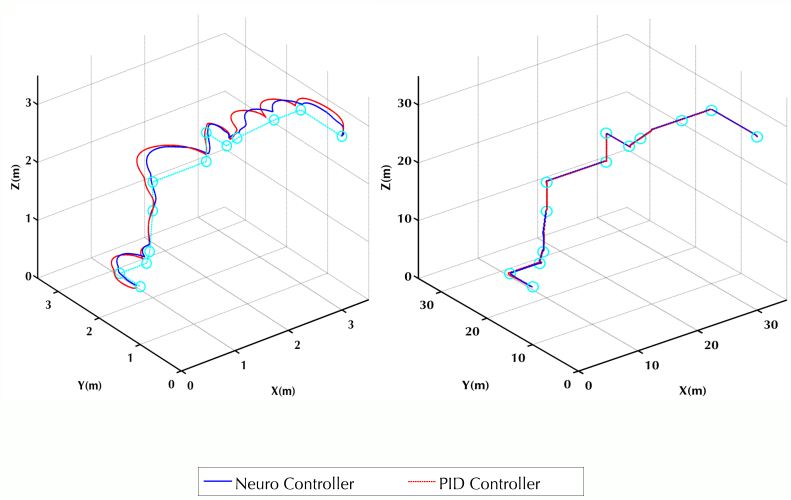
1. Navigation Results



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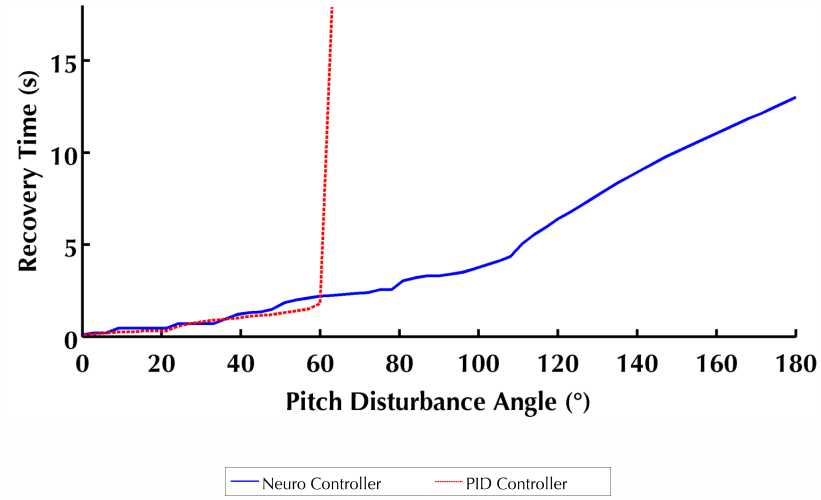
2. Robustness to Disturbances



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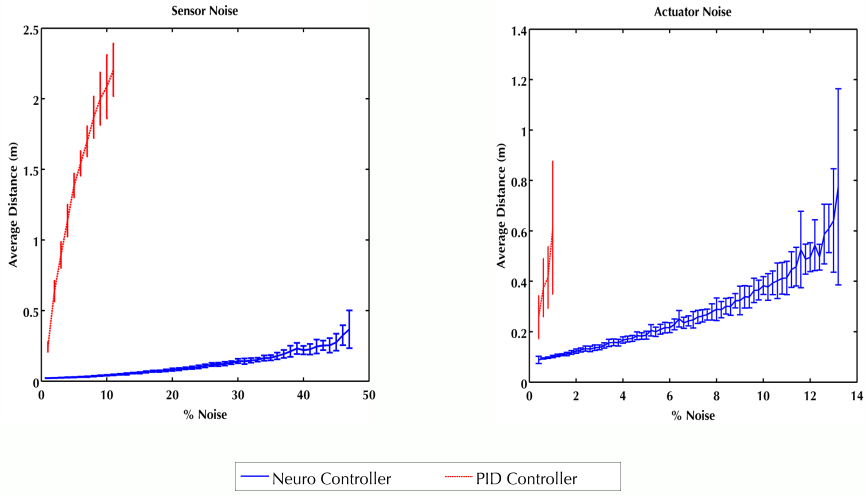
3. Robustness to Sensor/Actuator Noise



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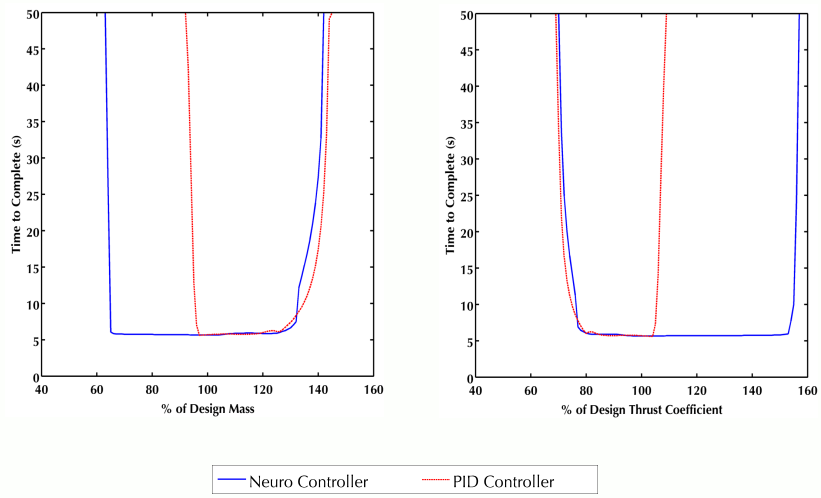
4. Robustness to Design Parameters



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Conclusions — Controller Development/Performance

- Developed a hierarchy of adaptive controllers
  - Divided problem
  - Applied relevant model information
- Produced Quadrotor control that Overcame Disturbances
  - Up to 180° flip
- Handled sensor and actuator Noise
  - 4 times better than PID for sensor noise
  - 8 times better than PID for actuator noise
- Provided insensitivity to Design Parameter
  - Mass & Thrust changes of ±30%

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Learning in Theory

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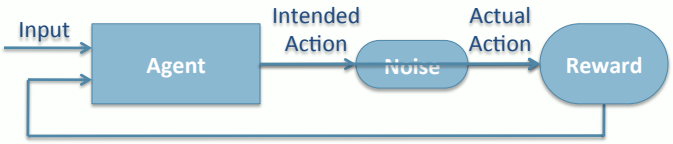
Learning in the Real World



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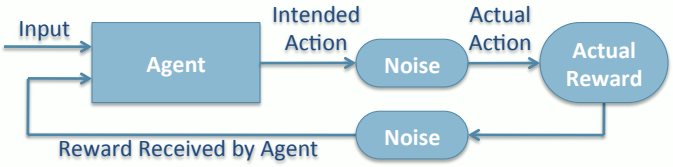
Learning in the Real World



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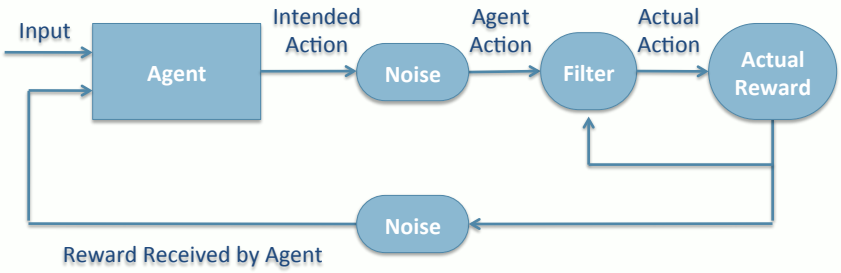
Human in the Loop: Suggestion Agents



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Agent-Based Air Traffic Management

- Agents : Control traffic like metering lights
- Two control structures
  - Fully agent controlled Traffic
  - Agents suggest actions to human air traffic controllers
- In both cases, system reward is blend of delay and congestion

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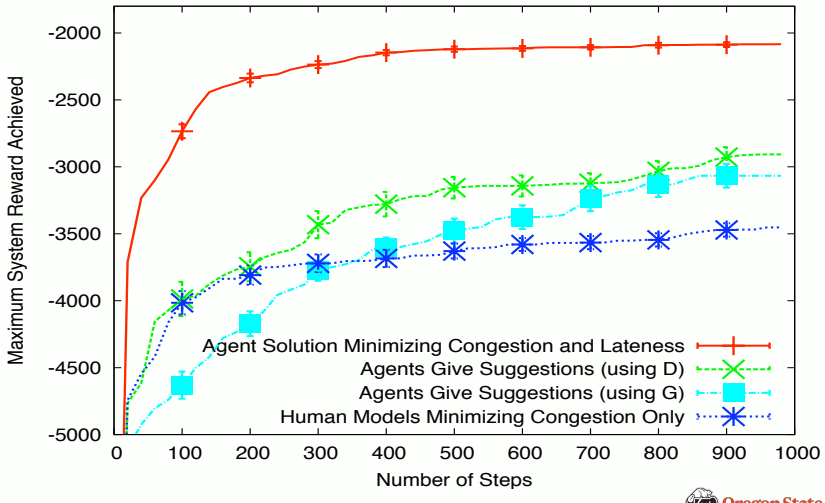
Traffic Agents vs. Suggestion Agents



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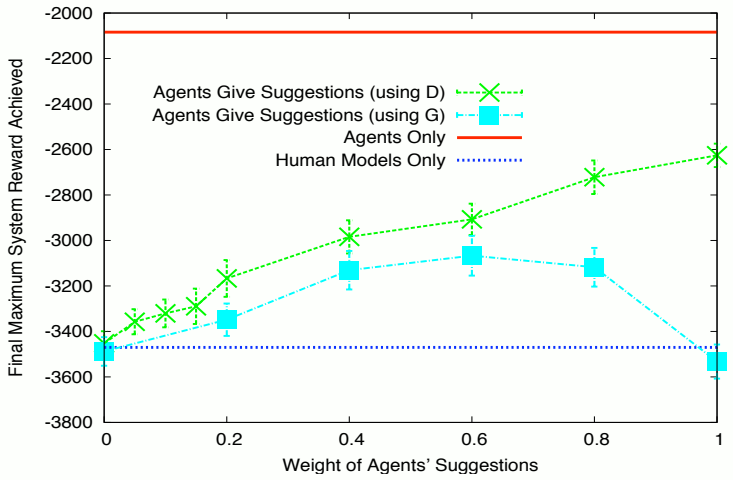
Suggestion Agents



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Cautionary Tale

- What are your systems learning?

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