

ECE276A: Sensing & Estimation in Robotics

Lecture 1: Introduction

Instructor:

Nikolay Atanasov: natanasov@ucsd.edu

Teaching Assistants:

Qiaojun Feng: qif007@eng.ucsd.edu

Arash Asgharivaskasi: aasghari@eng.ucsd.edu

UC San Diego

JACOBS SCHOOL OF ENGINEERING
Electrical and Computer Engineering

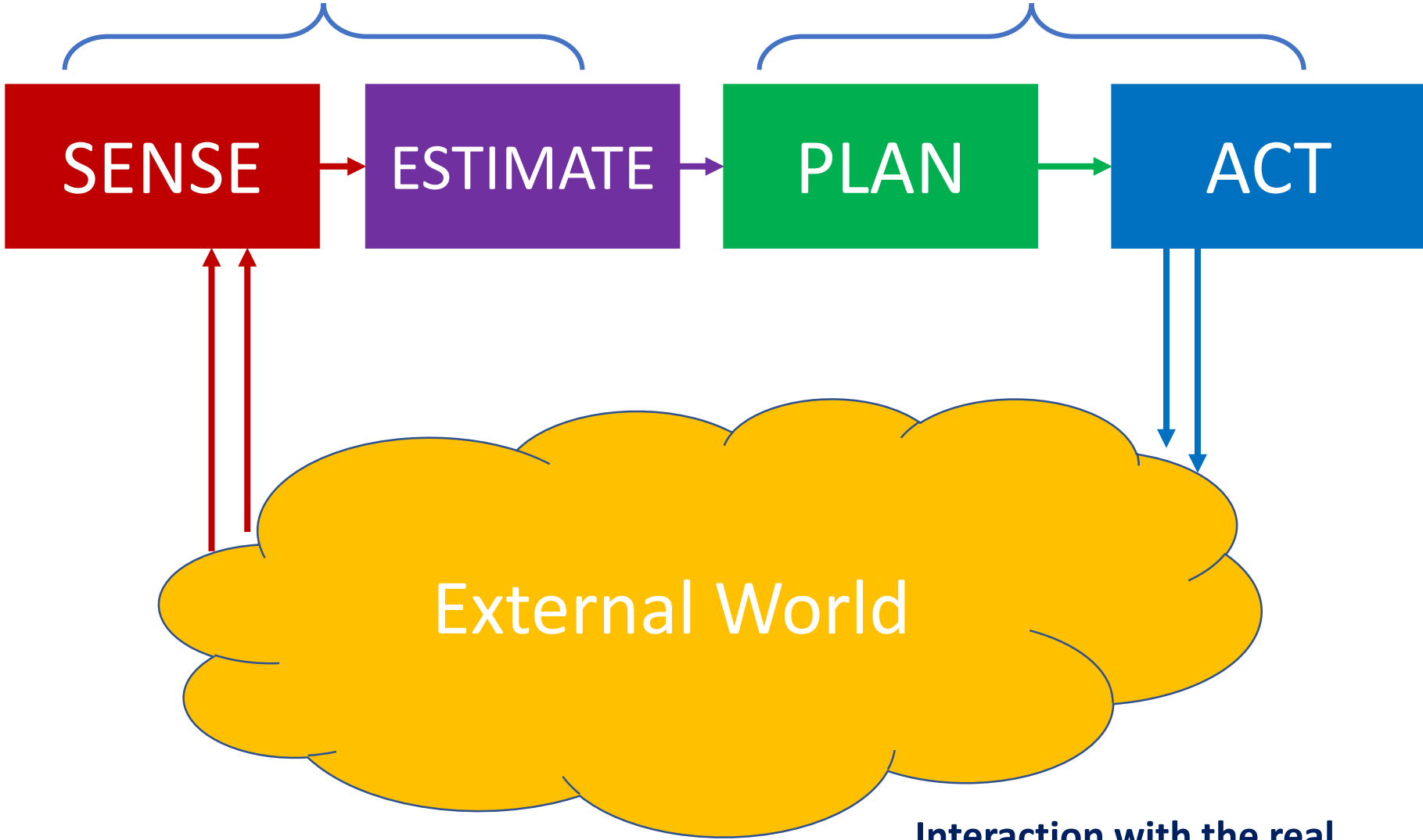
Robot Autonomy

- Robot autonomy is a research area relying on tools from:
 - **Computer Vision & Signal Processing:** algorithms to deal with real world signals in real time (e.g., filtering sound signals, convolving images with edge detectors, recognizing objects)
 - **Probability Theory:** the ability to deal with uncertainty caused by sensor and actuator noise, computation and communication delays, and environment changes is critical in robotics
 - **Estimation & Control Theory:** algorithms to estimate robot and world states and plan and execute robot actions
 - **Optimization Theory:** algorithms to choose the best robot behavior according to a suitable performance criterion
 - **Machine Learning:** algorithms to improve performance based on previous results and data (supervised, unsupervised, and reinforcement learning)

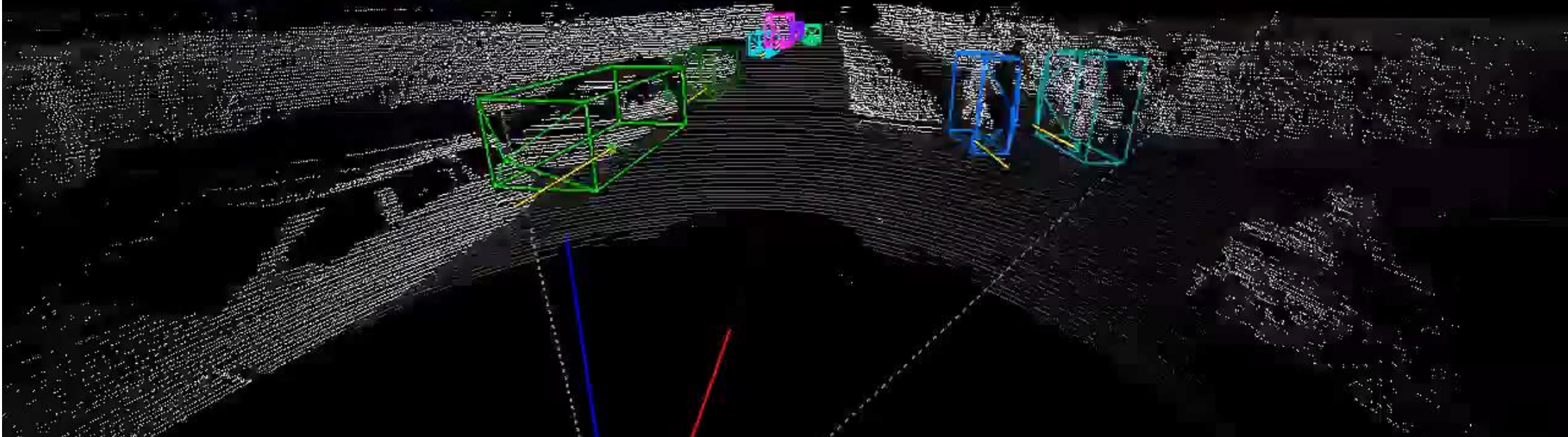
Robot Autonomy

CSE252A-B; ECE276A

ECE276B-C; MAE281A-B



Interaction with the real world introduces uncertainty!

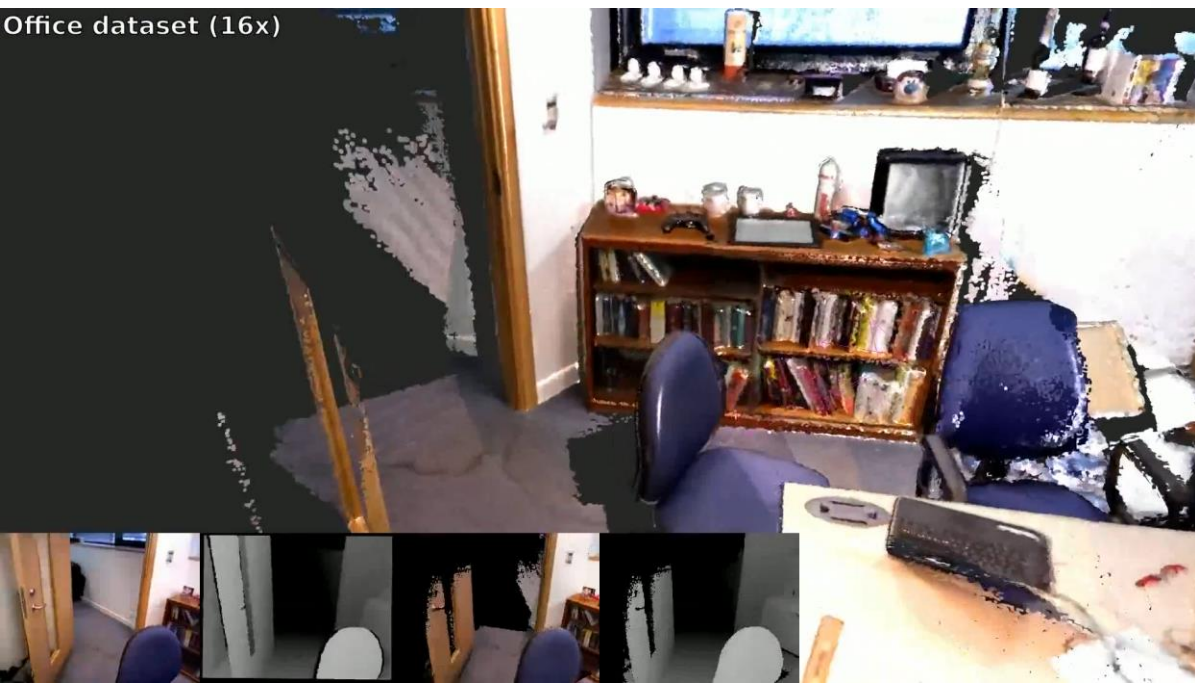




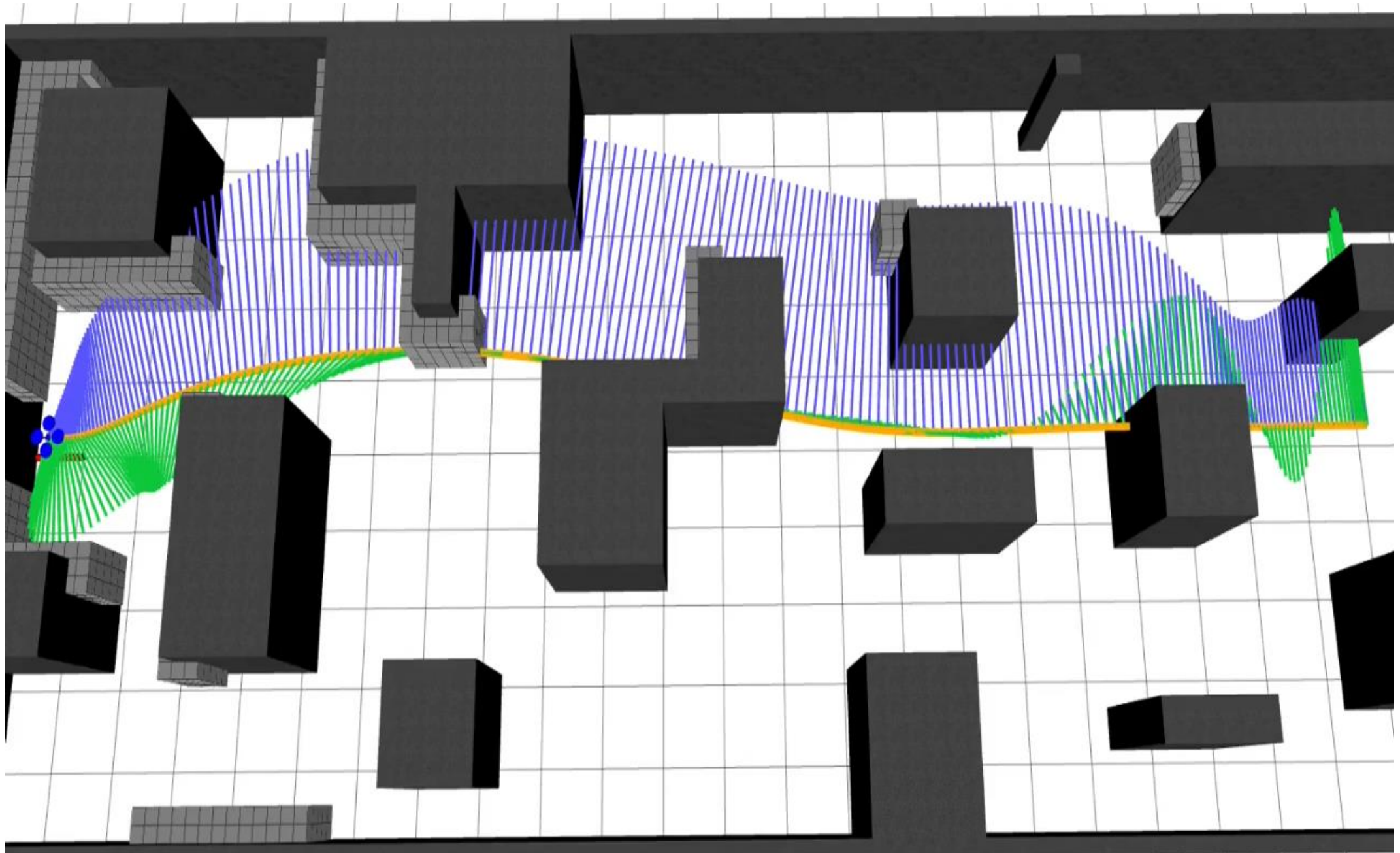
ESTIMATE

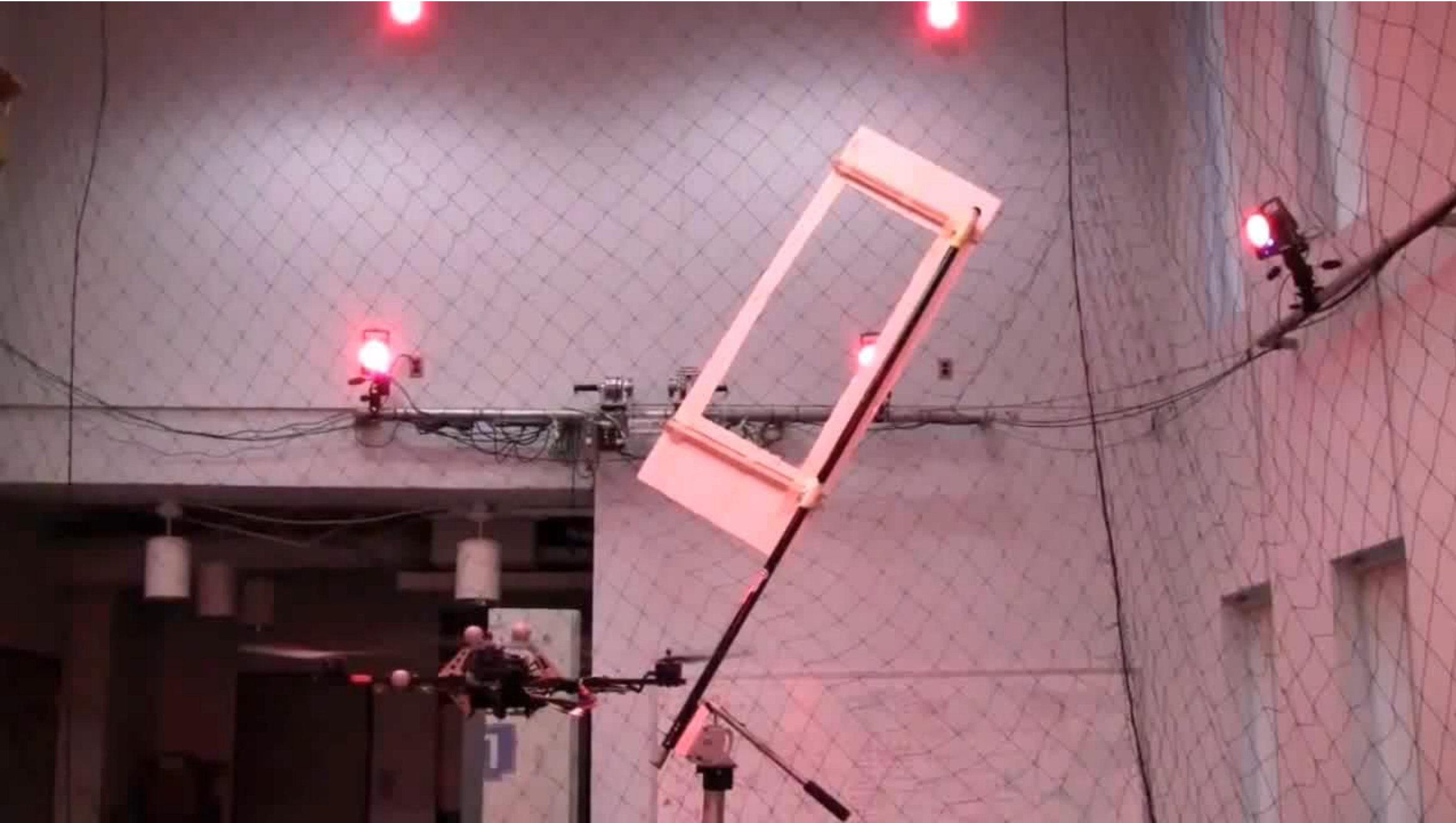
Forster, Carlone, Dellaert,
Scaramuzza, RSS'15

Office dataset (16x)



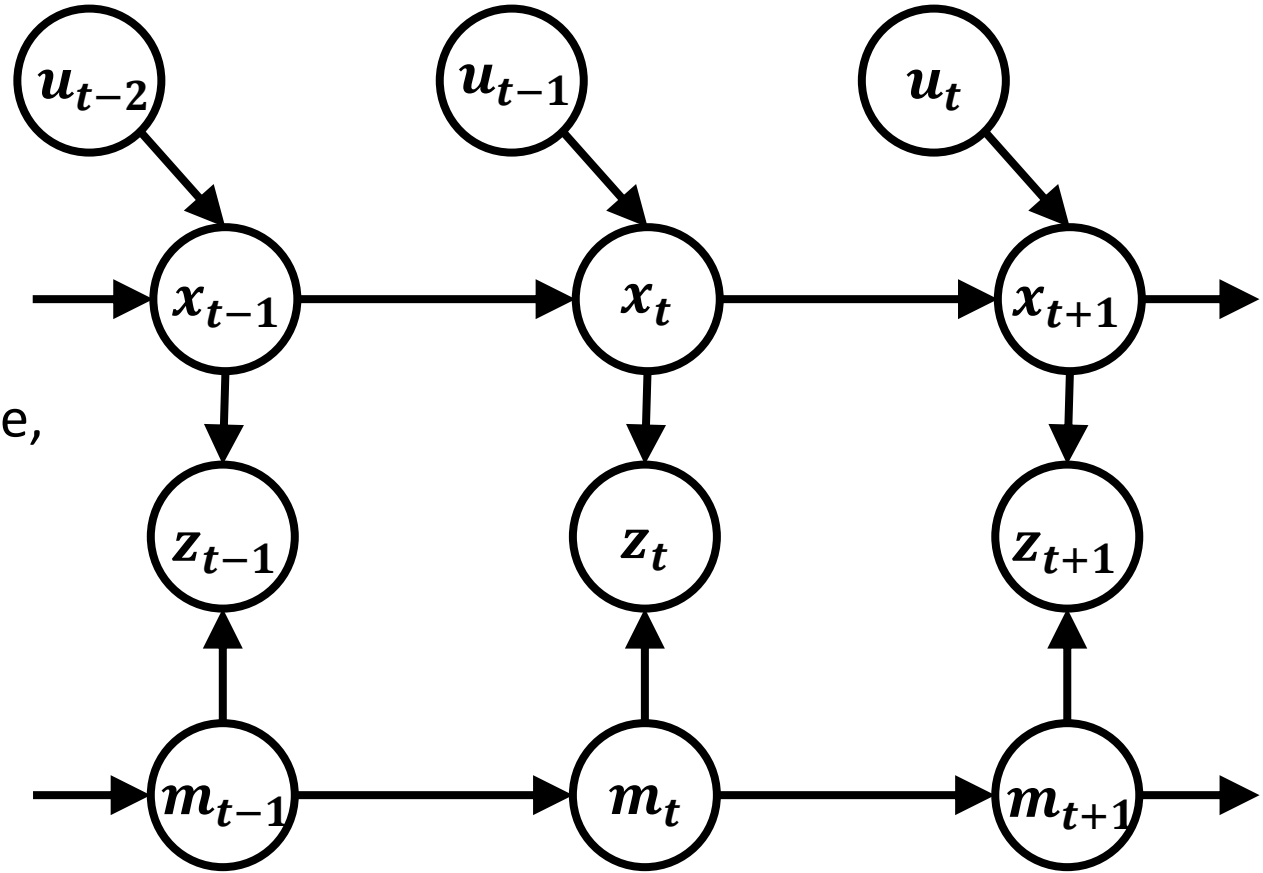
Whelan, Leutenegger, Salas-
Moreno, Glocker, Davison, RSS'15





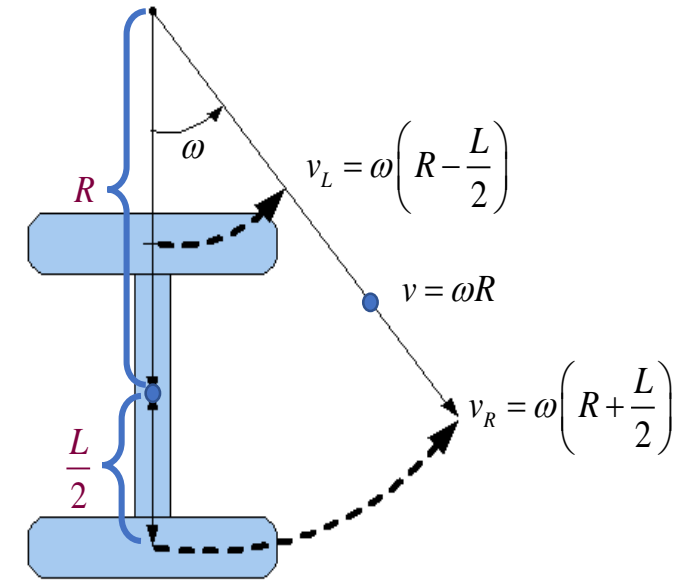
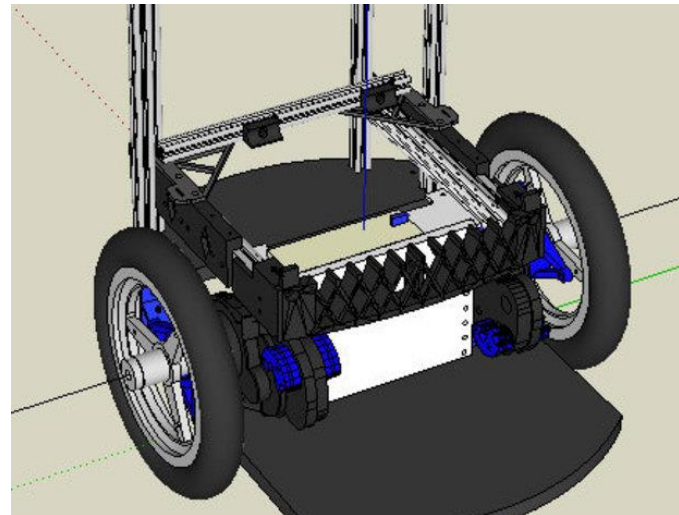
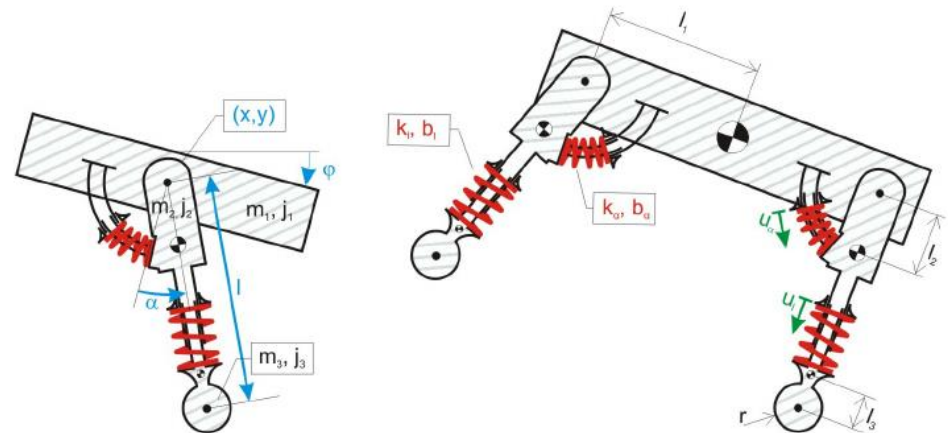
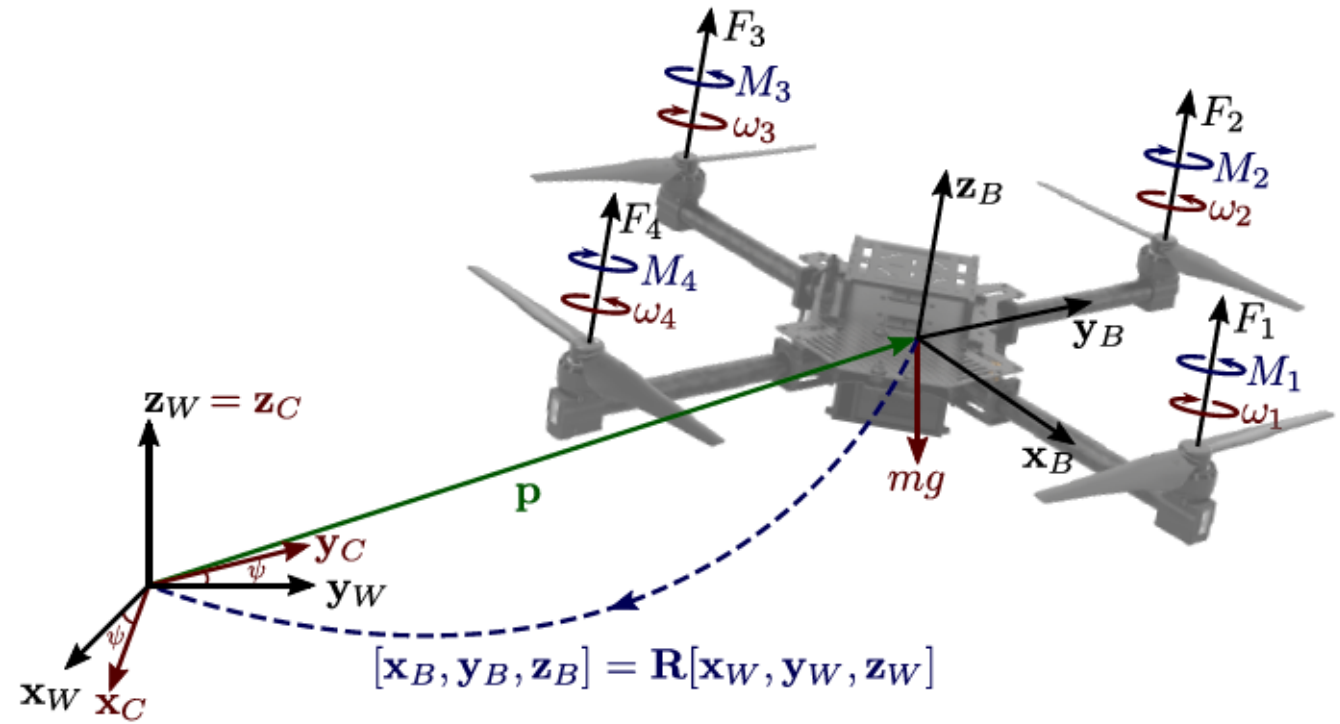
Structure of Robotics Problems

- **Time:** t (discrete or continuous)
- **Robot state:** x_t (e.g., position, orientation, velocity)
- **Environment state:** m_t (e.g., map of free space, locations of objects)
- **Control input:** u_t (e.g., quadrotor thrust and moment of rotation)
- **Observation:** z_t (e.g., image, laser scan, radio signal, inertial measurements)
- **Motion Model:** $p(x_{t+1}|x_t, u_t)$ --- describes the motion of the robot to a new state x_{t+1} after applying control input u_t at state x_t
- **Observation Model:** $p(z_t|x_t, m_t)$ --- describes the observation z_t of the robot depending on its state x_t and the map m_t of the environment



Motion Models

- Based on **kinematics or dynamics**:
 - Differential drive model (roomba)
 - Ackermann drive model (car, bicycle)
 - Quadrotor model
 - Legged locomotion model
- Based on **odometry**:
 - use of sensory data to estimate change in the robot pose over time
 - Only available in retrospect
 - Useful for localization and mapping but cannot be used for planning and control



Observation Models

- **Position Sensor:** directly measures position (e.g., GPS, laser scanner, IR sensor, RGBD camera)
- **Velocity/Acceleration/Force Sensor:** measures linear acceleration or angular velocity or pressure or force (accelerometer, gyroscope, inertial measurement unit (IMU), tactile sensor)
- **Bearing Sensor:** measures angles to 3-D points (e.g., magnetometer, camera, microphone)
- **Range Sensor:** measures distances to 3-D points (e.g., radio)



FLIR RGB Camera



VectorNav IMU



Ublox GPS
and Compass



Beaglebone
Radio



Garmin Single-beam Lidar



Hokuyo
2D Lidar



HDL-64E



HDL-32E



VLP-16

Velodyne
3D Lidar

ECE 276A: Sensing & Estimation in Robotics

- The course will cover theoretical topics in:
 - **Sensing**: image formation, classification, projective geometry, rotations, features, optical flow
 - **Estimation**: maximum likelihood estimation, probabilistic models, Bayesian filtering, localization, mapping, Hidden Markov models
- Course website: <https://natanaso.github.io/ece276a>
- Includes information about:
 - Schedule: **reading materials** and assignments
 - Homework + Grades: **GradeScope (SIGN UP!)**
 - Discussion: **Piazza (SIGN UP!)**
 - 2-3 TA sessions per week: **TBD**
- Main Reference (**available online!**):
 - State Estimation for Robotics: Barfoot
- Additional References (not required):
 - An Invitation to 3-D Vision: Ma, Kosecka, Soatto & Sastry
 - Probabilistic Robotics: Thrun, Burgard & Fox
 - Bayesian Filtering and Smoothing: Sarkka

A Warning About Prerequisites

- This is a challenging course
- I want everyone to learn about robotics so the prerequisites are not strictly enforced
- As graduate students, I expect you to be mature and make a careful evaluation for yourselves whether you are prepared to take the course
- Prerequisites:
 - **Probability Theory**: if you have not had a good course on probability theory it is too early to take ECE276A
 - **Linear Algebra**: if you have not had a good course on linear algebra, it is too early to take ECE276A
 - **Programming experience**: if you have not written a program of reasonable complexity before, it is too early to take ECE276A
- You will enjoy the course more and learn more if you have the right background
- Every year many people ignore this and have an unpleasant experience
- Since the class is very large, I **will not make personal exceptions** such as late drops or incompletes

Grading

- Assignments:
 - 3 theoretical homeworks (16% of the final grade)
 - 3 programming assignments in **python** with project reports (18% of the final grade each)
 - Final exam (30% of final grade)
- An **example project report will be provided** with the first project. Pay special attention to the problem formulation section.
- There is sufficient time to complete every assignment if you start **early**
- Late submissions will not be accepted because our schedule is tight
- Letter grades will be assigned based on the class performance, i.e., there will be a “curve”
- Piazza is a great place for discussion so I encourage you to use it
- In the past, people have been selfish in using Piazza – asking many questions but rarely helping others. This year, I will give extra credit to people who provide good answers on Piazza

Collaboration and Academic Integrity

- An important element of academic integrity is fully and correctly acknowledging any materials taken from the work of others – provide references for papers and acknowledge in writing people you discuss with
- You are encouraged to work with other students and to discuss the assignments in general terms but the work you turn in should be completely your own
- Every assignment in this course is **individual**
- **Cheating will not be tolerated.** There are automated tools for detecting plagiarism so it is unlikely that you will get away with it
- Instances of academic dishonesty will be penalized via grade reduction and may be referred to the Office of Student Conduct for adjudication

Syllabus Snapshot

Date	Lecture	Material	Assignment
Jan 06	Introduction		
Jan 08	Probability Theory Review	Barfoot-Ch2	
Jan 13	Unconstrained Optimization	Barfoot-Ch4.3.1, Matrix-calculus	
Jan 15	Supervised Learning	Mitchell-NaiveBayesLogReg	HW1, PR1
Jan 20	Unsupervised Learning	Tomasi-EM	
Jan 22	Rotations	Barfoot-Ch6.1-6.3	
Jan 27	Motion and Observation Models	Barfoot-Ch6.4	
Jan 29	Bayes Filter, Particle Filter	Barfoot-Ch4.2	
Feb 03	Particle Filter SLAM	Thrun-Ch7-9	HW2, PR2
Feb 05	TBD		
Feb 10	Kalman Filter	Barfoot-Ch3.3	
Feb 12	EKF, UKF	Barfoot-Ch4.2	
Feb 17	SO(3) and SE(3) Groups I	Barfoot-Ch7.1	
Feb 19	SO(3) and SE(3) Groups II	Barfoot-Ch7.3	HW3
Feb 24	SO(3) and SE(3) Kinematics	Barfoot-Ch7.2	PR3
Feb 26	Visual Features, Optical Flow	Image-Features	
Mar 02	Visual-Inertial SLAM		
Mar 04	Localization and Odometry from Point Features		
Mar 09	TBD		
Mar 11	Hidden Markov Models	Rabiner-HMM	
Mar 16	Final Exam		

Report Structure

1. Introduction

It is important to monitor the humidity of plants and choose optimal watering times. In this paper, we present an approach to select the best watering time in the week from given historical humidity data.

2. Problem Formulation

Let $f: \mathbb{R} \rightarrow \mathbb{R}$ be the average historical weekly humidity.

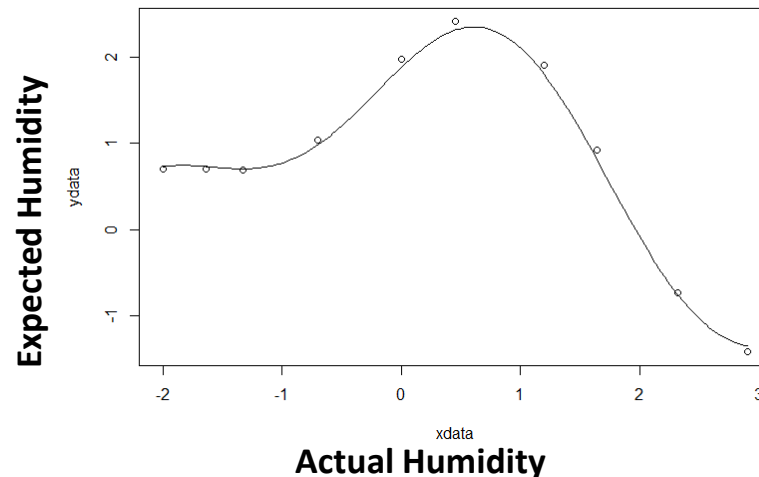
Problem: Find a watering time $t^* \in \mathbb{R}$ such that $t^* = \underset{t}{\operatorname{argmin}} f(t)$

3. Technical Approach

The minimum of a function appears at one of its critical points $\{s \in \mathbb{R} \mid f'(s) = 0\}$. We find all the roots of f' and select the smallest one as the optimal watering time.

4. Results and Discussion

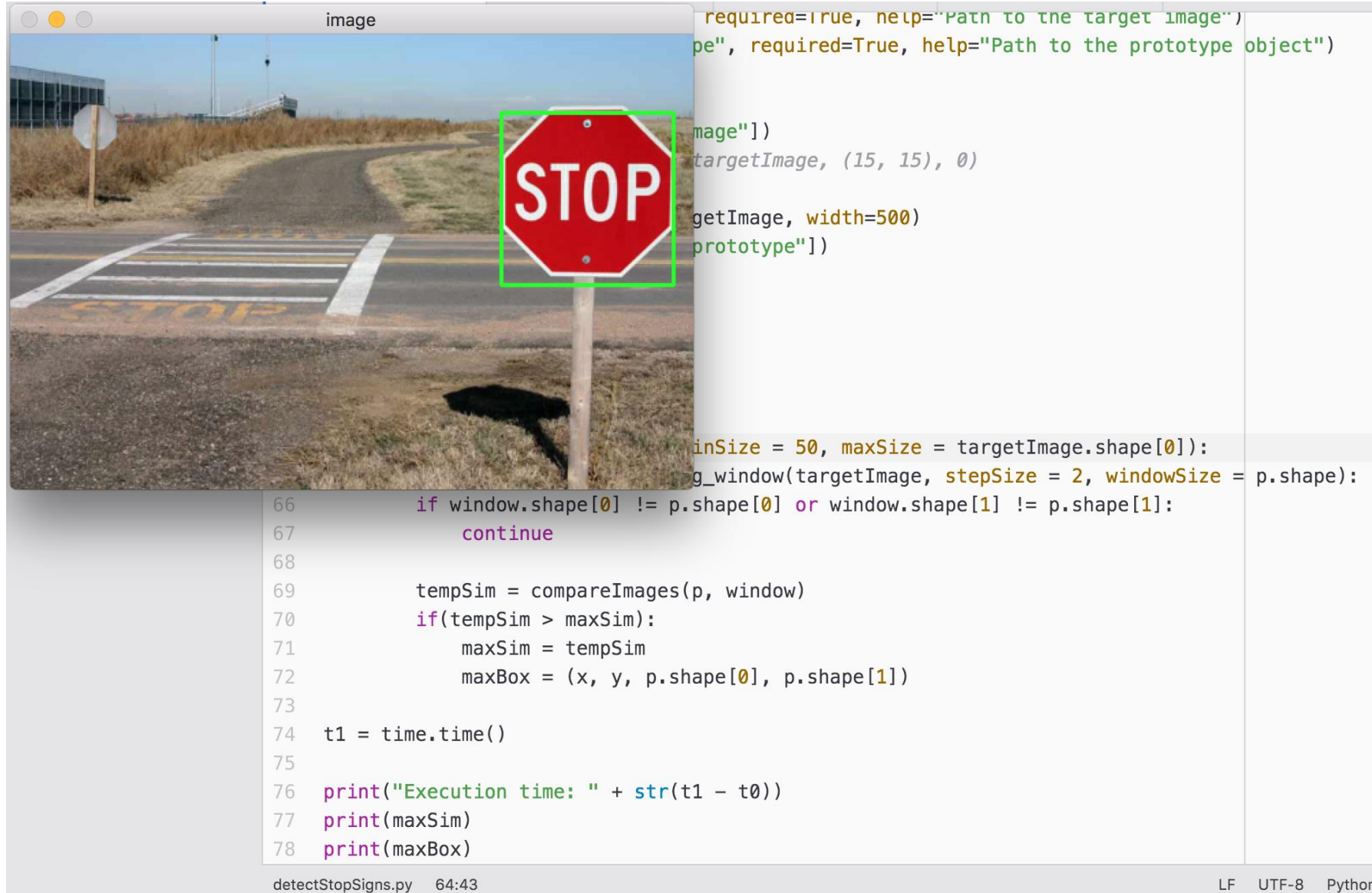
The method performs well as shown in Fig. 1. The performance could be improved if real-time humidity measurements are used to update f .



Project 1: Color Classification

Data from Michael Basilyan,
<https://github.com/mbasilyan/Stop-Sign-Detection>

- Train a color classification model and use it to detect stop signs!



```
required=True, help="Path to the target image")
    p = argparse.ArgumentParser("Path to the prototype object")

    p.add_argument("image")
    p.add_argument("targetImage", (15, 15), 0)

    p.add_argument("width", width=500)
    p.add_argument("prototype")

    minSize = 50, maxSize = targetImage.shape[0]:
    for y in range(0, p.shape[0] - minSize, stepSize):
        for x in range(0, p.shape[1] - minSize, stepSize):
            window = img_window(targetImage, stepSize = 2, windowSize = p.shape):
                if window.shape[0] != p.shape[0] or window.shape[1] != p.shape[1]:
                    continue

            tempSim = compareImages(p, window)
            if(tempSim > maxSim):
                maxSim = tempSim
                maxBox = (x, y, p.shape[0], p.shape[1])

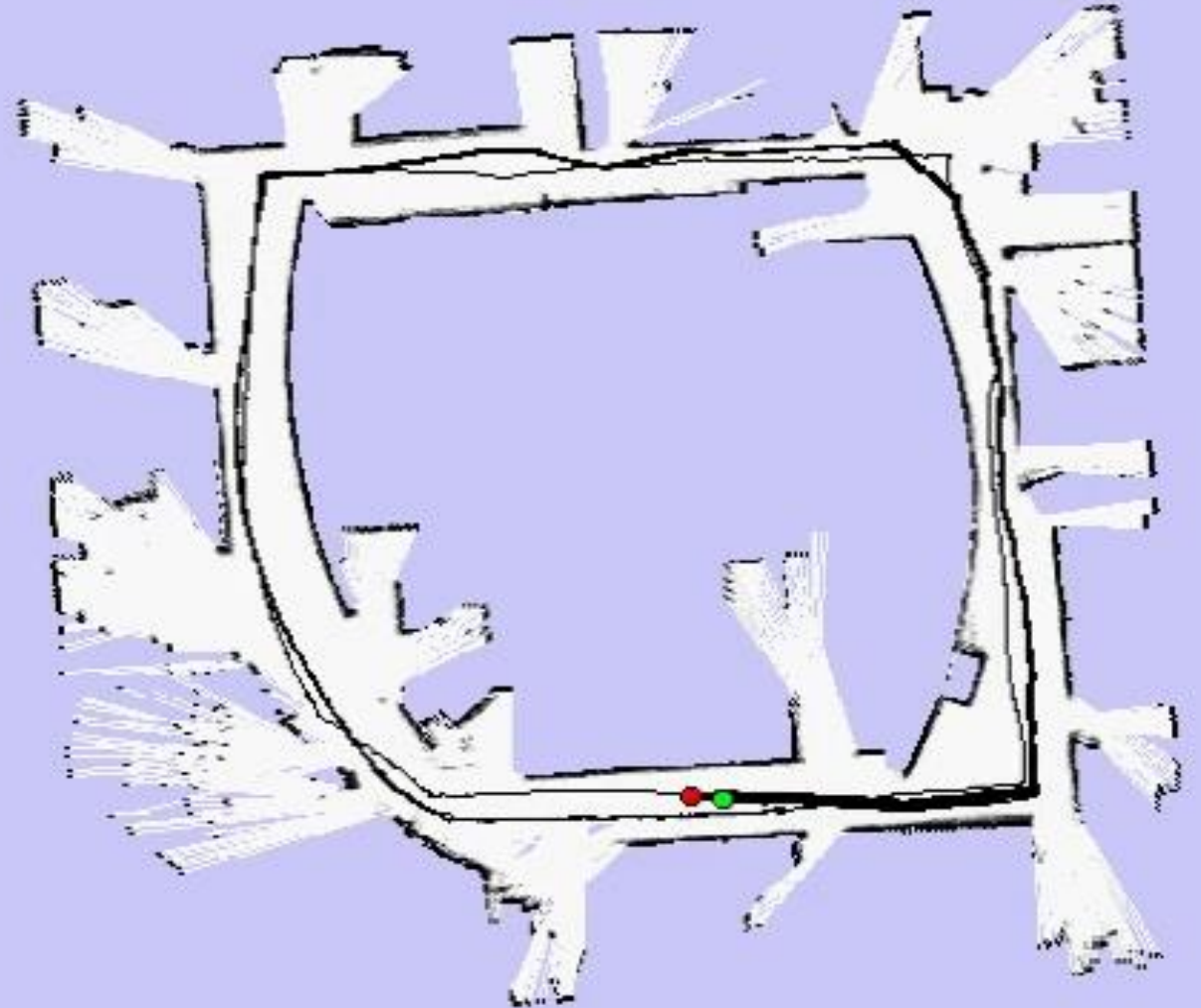
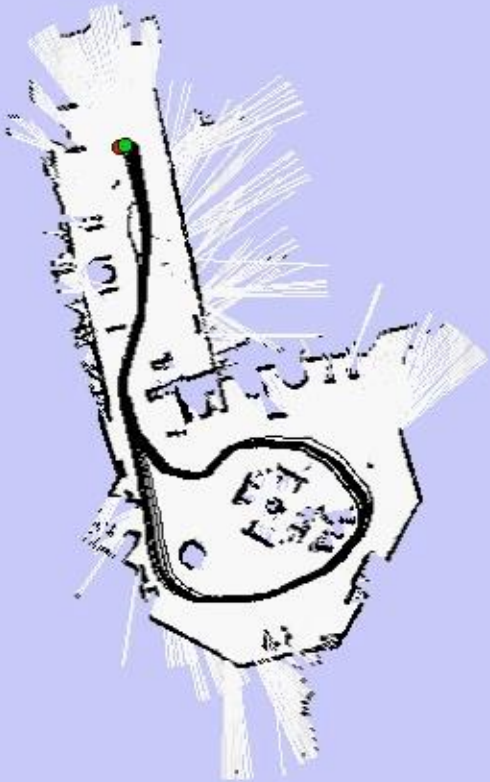
    t1 = time.time()
    print("Execution time: " + str(t1 - t0))
    print(maxSim)
    print(maxBox)
```

detectStopSigns.py 64:43

LF UTF-8 Python

Project 2: Particle Filter SLAM

- **FastSLAM** (Montemerlo et al., AAAI'02): one of the early successful demonstrations of *simultaneous localization and mapping (SLAM)* using a lidar



Project 3: Visual Inertial SLAM

OrbSLAM, Mur-Artal, Montiel, Tardos, TRO'15

- Kalman Filter to track the 3-D pose of a moving body based on IMU and camera measurements



TRACKING - KFs: 456 , MPs: 34546 , Tracked: 353

