

ECE276A: Sensing & Estimation in Robotics

Lecture 1: Introduction

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JACOBS SCHOOL OF ENGINEERING
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Robotics Overview

- Robot Autonomy is an amalgam of several research areas:
 - **Computer Vision & Signal Processing:** algorithms to deal with real world signals in real time (e.g., filter sound signals, convolve images with edge detectors, recognize objects)
 - **Probability Theory:** the ability to deal with uncertainty is critical in robotics
 - Sensor noise & actuator slippage
 - Environment changes (outdoor sun, moving to different rooms, people)
 - Real-time operation and delays
 - **Estimation & Control Theory:** algorithms to estimate robot and world states and plan and execute robot actions
 - **Optimization:** algorithms to choose the best robot behavior according to a suitable criterion from a set of available alternatives
 - **Machine Learning:** algorithms to improve performance based on previous results and data (supervised, unsupervised, and reinforcement learning)

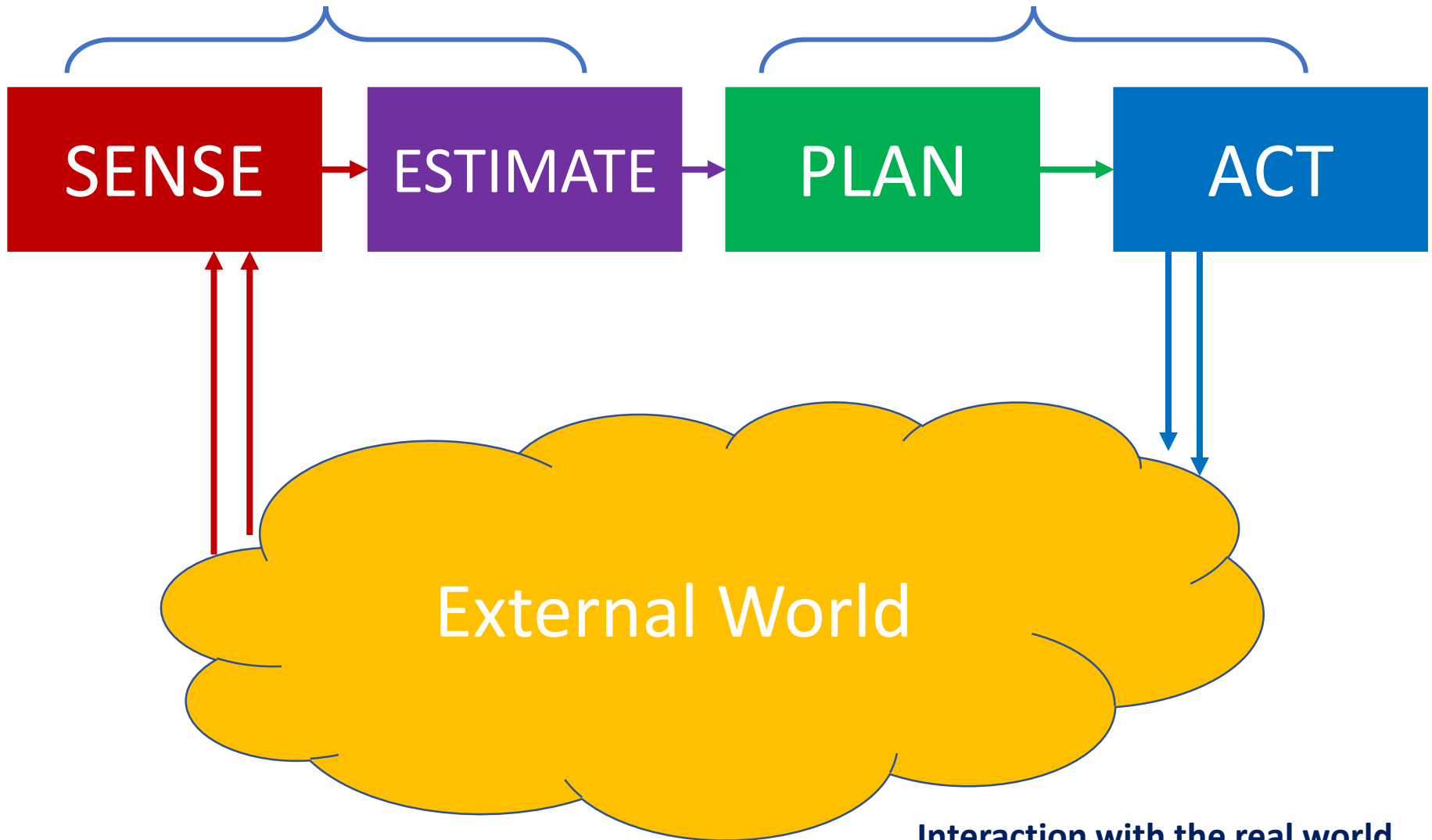
Main themes

- **Noise:** how to model uncertainty using probability distributions
- **Perception:** how to recognize objects and geometry in the environment
- **Estimation:** how to estimate robot and environment state variables given uncertain measurements
- **Planning/Sequential decision making:** how to choose the most appropriate action at each time
- **Control/Dynamics:** how to control forces that act on the robot and the resulting acceleration; how to take world changes in time into account
- **Learning:** how to incorporate prior experience to improve robot performance

Robotics Overview

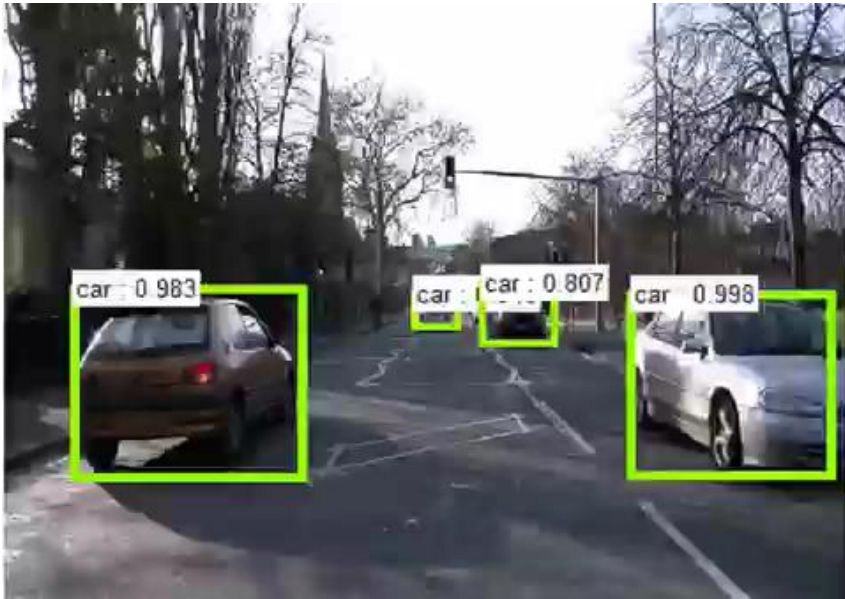
CSE252A-B; CSE291; ECE276A

ECE276B-C; MAE281A-B



**Interaction with the real world
introduces uncertainty!**

SENSE

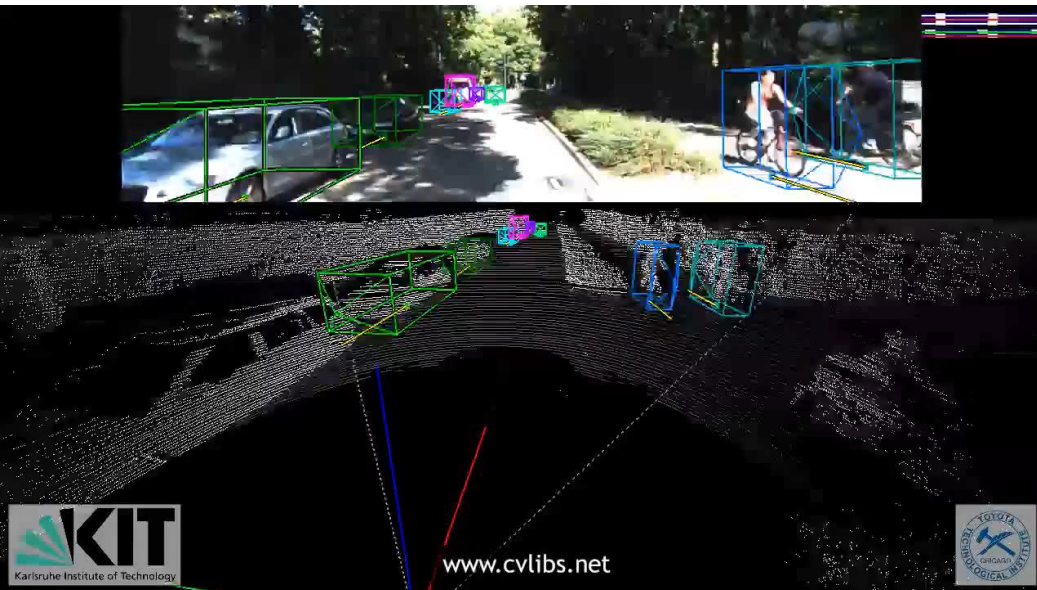


Ren, He, Girshick, Sun, NIPS'15

Zhu, Zhou,
Daniilidis,
ICCV'15



Newcombe, Fox, Seitz, CVPR'15



Geiger, Lenz, Urtasun, CVPR'12



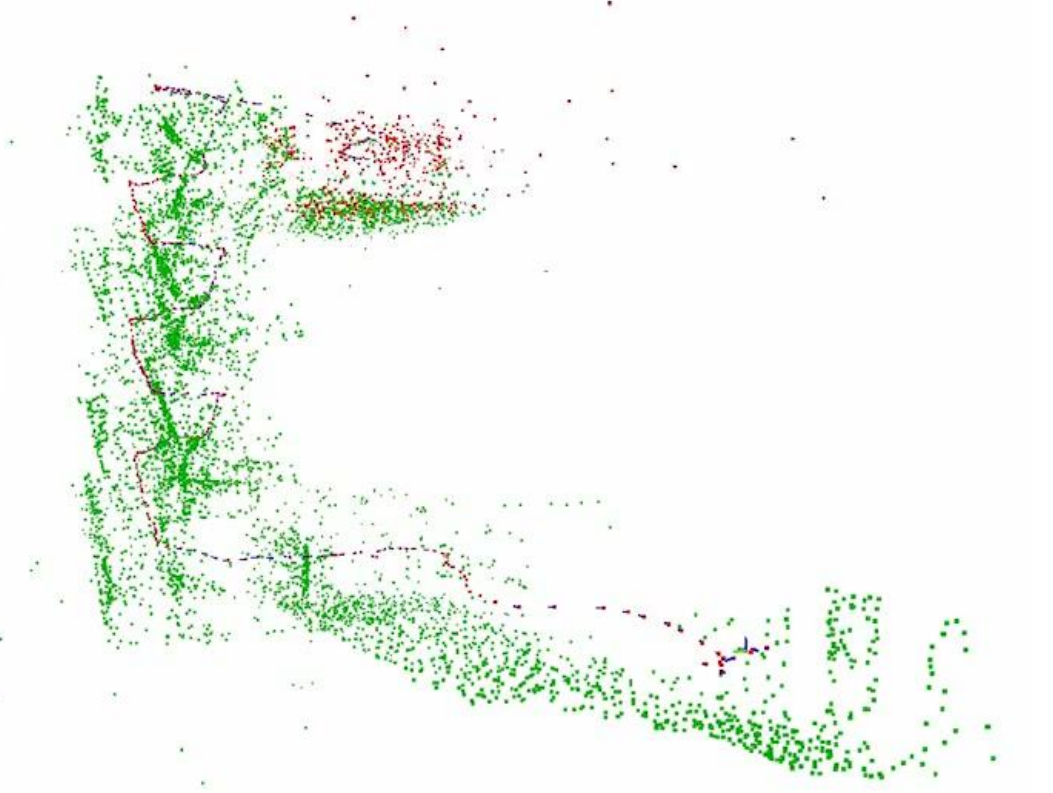
Long, Shelhamer, Darrell, CVPR'15

ESTIMATE

Goal: determine the robot pose over time and build a map of the environment



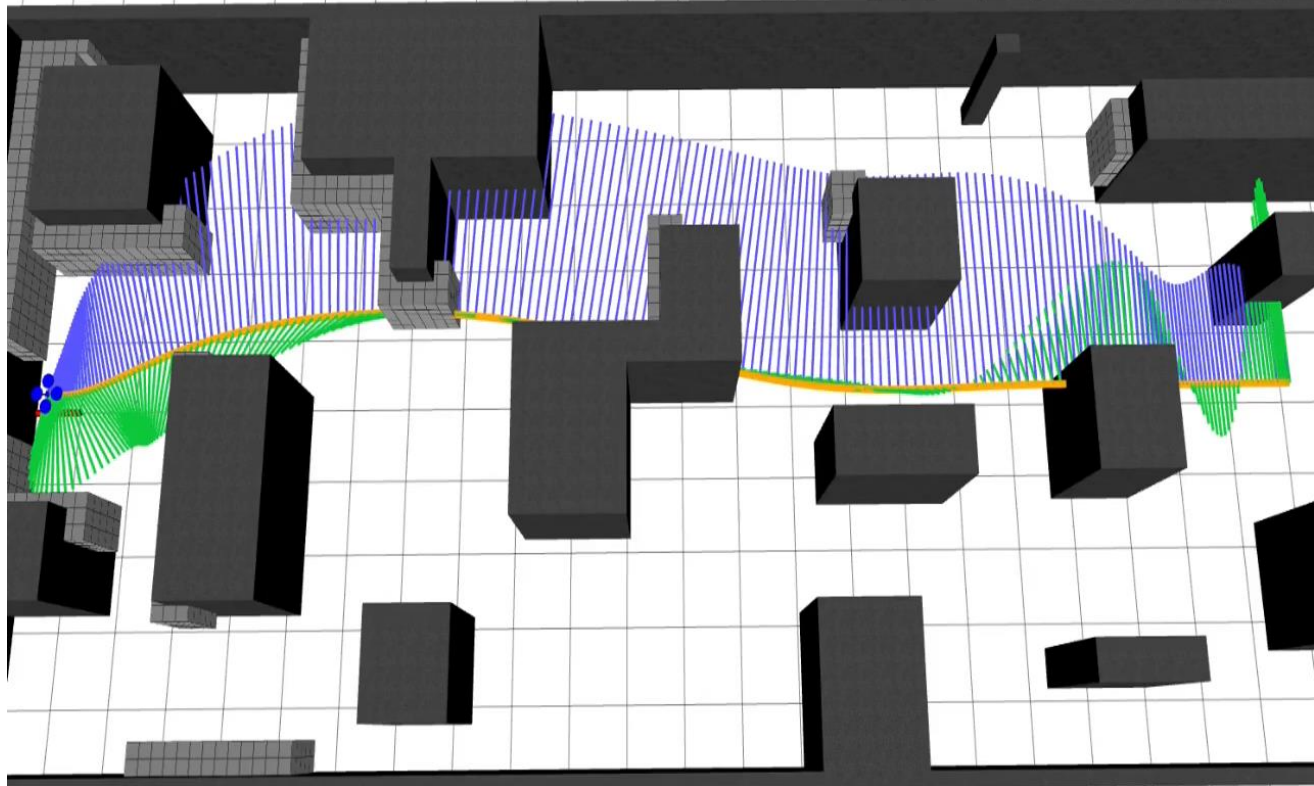
Whelan, Leutenegger, Salas-Moreno, Glocker, Davison, RSS'15



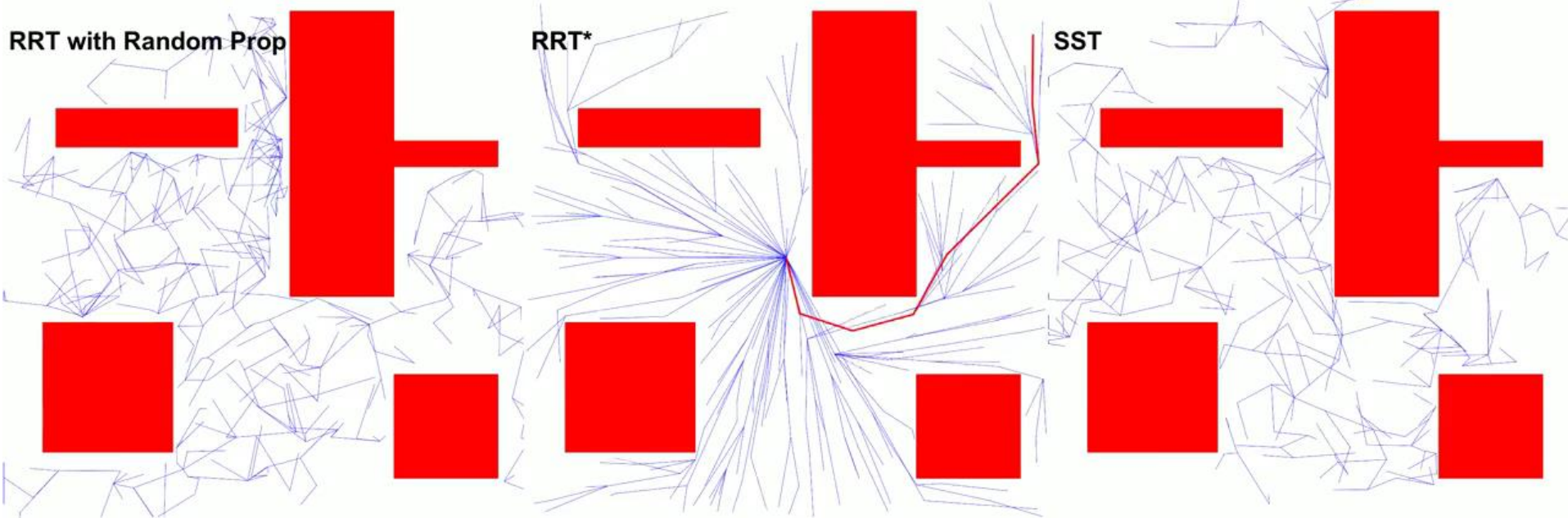
Forster, Carlone, Dellaert, Scaramuzza, RSS'15

PLAN

Liu, Atanasov, Mohta,
Kumar, IROS'17



Li, Littlefield, Bekris, IJRR'16



ACT



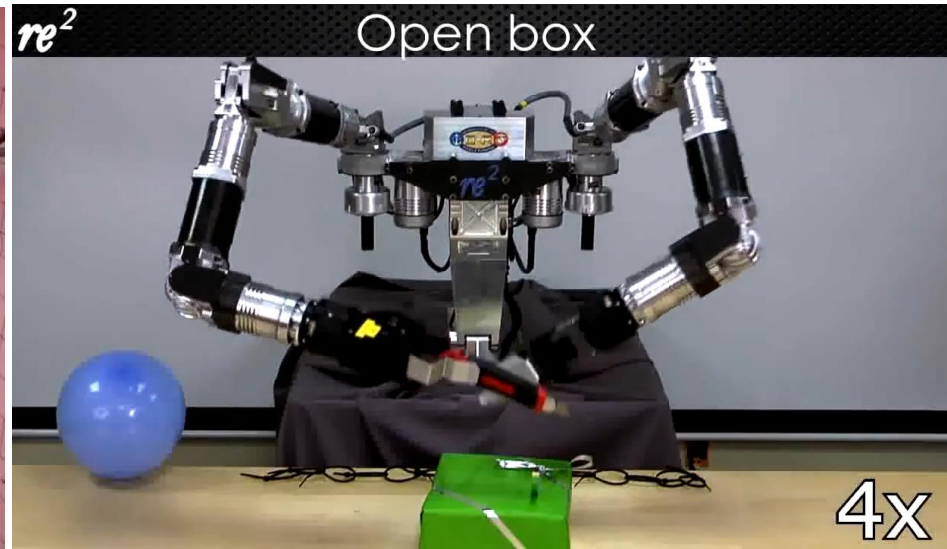
JPL-Caltech, DARPA Robotics Challenge, 2015



Boston Dynamics



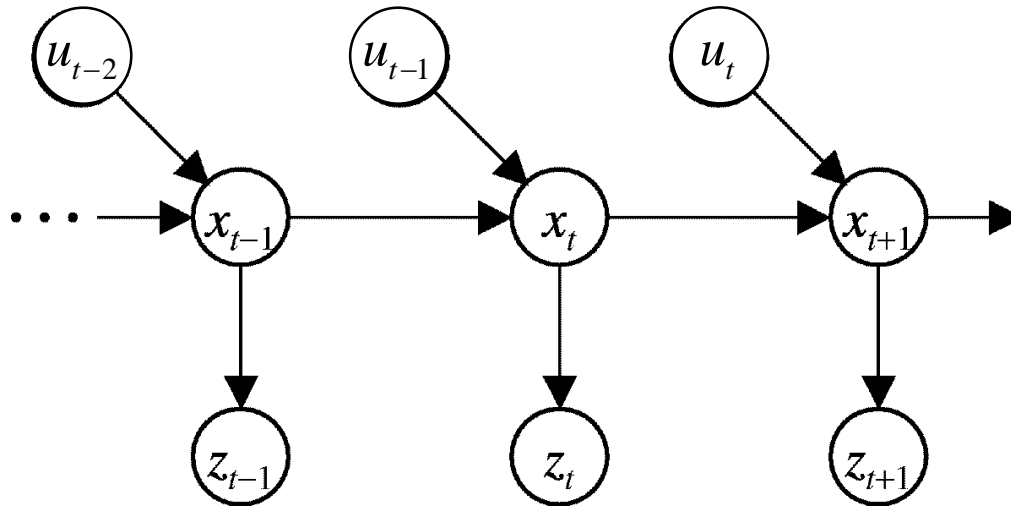
Mellinger, Michael, Kumar, IJRR'12



RE2 Robotics, Inc.

Structure of Robotics Problems

- **Time:** t (can be discrete or continuous)
- **Robot state:** x_t (e.g., position, orientation, velocity, etc.)
- **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 and Observation Models

- **Common Actuators:**

- Steering, throttle for wheeled robots
- Thrust for quadrotors
- Joint angles for legged robots and articulated robot arms
- Pan-tilt heads

- **Common Sensors:**

- Images from cameras
- Distances from IR, sonar, laser range finders
- Tactile bump switches
- Magnetic sensors
- Acceleration and angular velocity from inertial measurement units
- Sounds from microphones

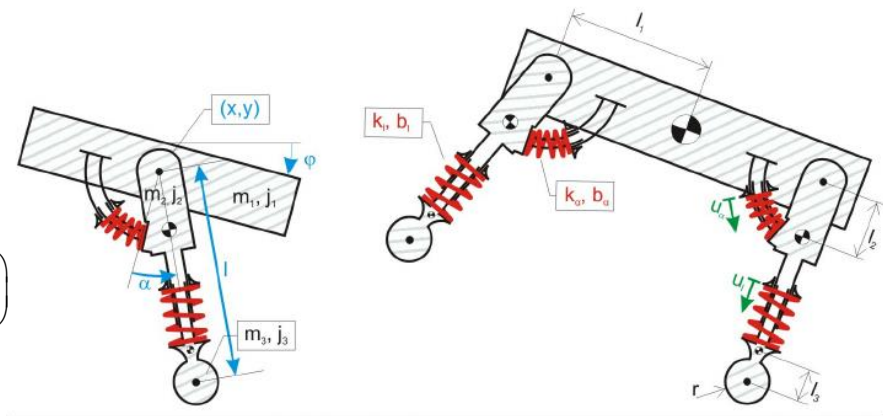
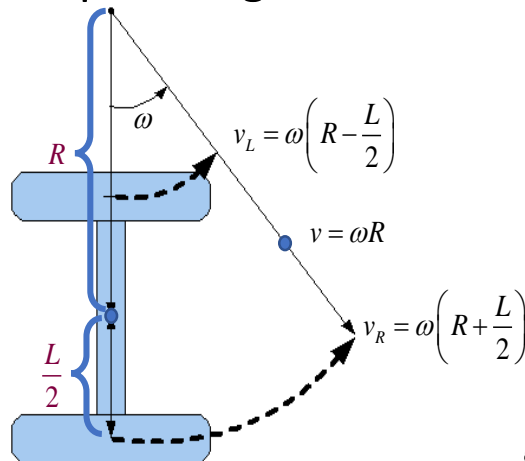
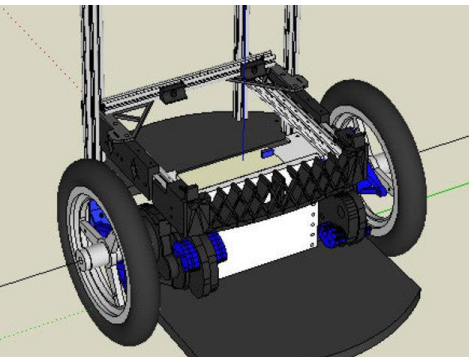
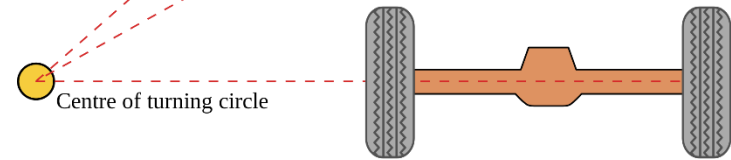
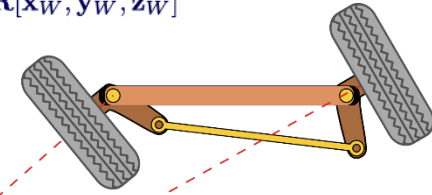
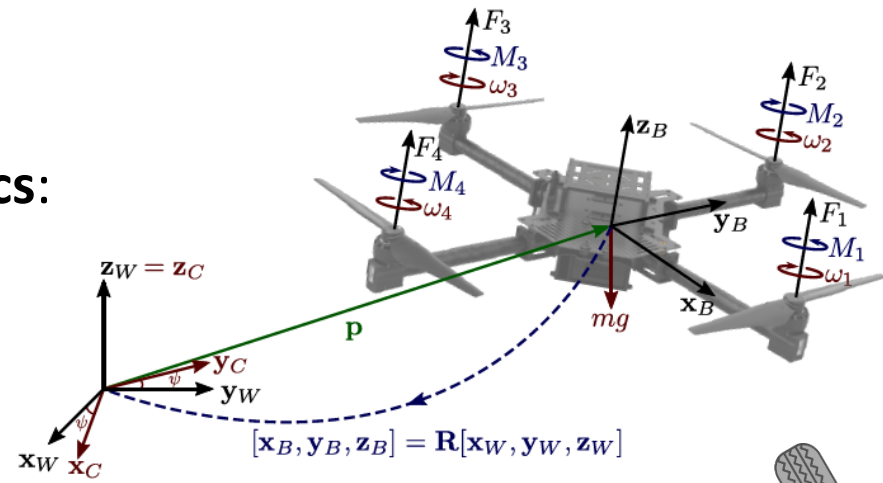
Motion Models

- Based on **robot kinematics or dynamics**:

- Differential drive model (roomba)
- Ackermann drive model (car, bicycle)
- Quadrotor model
- Legged locomotion model

- Based on **odometry**:

- Odometry**: the 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 the sensor position (e.g., GPS)
- **Velocity/Acceleration Sensor:** measures linear acceleration or angular velocity (accelerometer, gyroscope, inertial measurement unit (IMU))
- **Bearing Sensor:** measures angles to 3-D points (e.g., magnetometer, camera)
- **Range Sensor:** measures distances to 3-D points (e.g., radio, laser)



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 links to:
 - Homework + Grades: **GradeScope (SIGN UP!)**
 - Discussion: **Piazza (SIGN UP!)**
 - TA sessions: **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
 - Nonlinear Gaussian Filtering: Theory, Algorithms, and Applications: Huber

Grading

- Four assignments:
 - Project 1: Color Segmentation (20% of final grade)
 - Project 2: Particle Filter SLAM (25% of final grade)
 - Project 3: Visual Inertial SLAM (25% of final grade)
 - Final Exam (30% of final grade)
- Letter grades will be assigned based on the class performance, i.e., there will be a “curve”
- Each project includes:
 - theoretical homework
 - programming assignment in **python**
 - project report
- A test set will be released for each project a few days before the deadline. Your report should include results on **both** the test set and the training set
- An **example project report will be posted on Piazza**. Pay special attention to the problem formulation section.

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 weakly humidity.

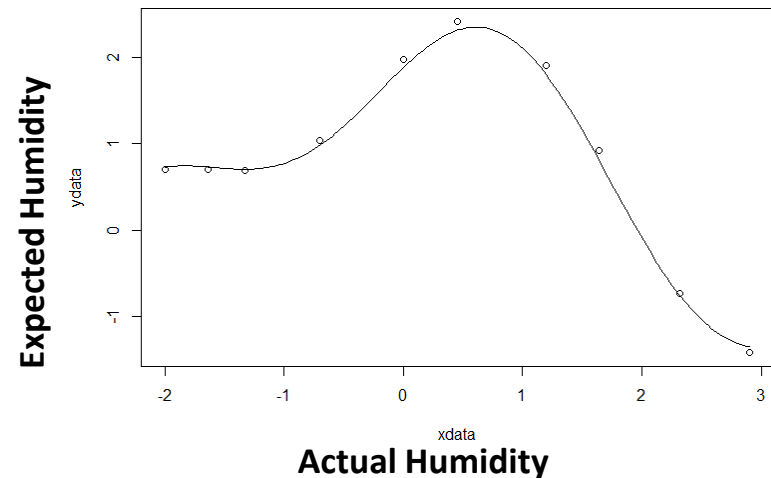
Problem: Find a watering time $t^* \in \mathbb{R}$ such that $t^* = \underset{t}{\operatorname{argmin}} f(t)$

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 .

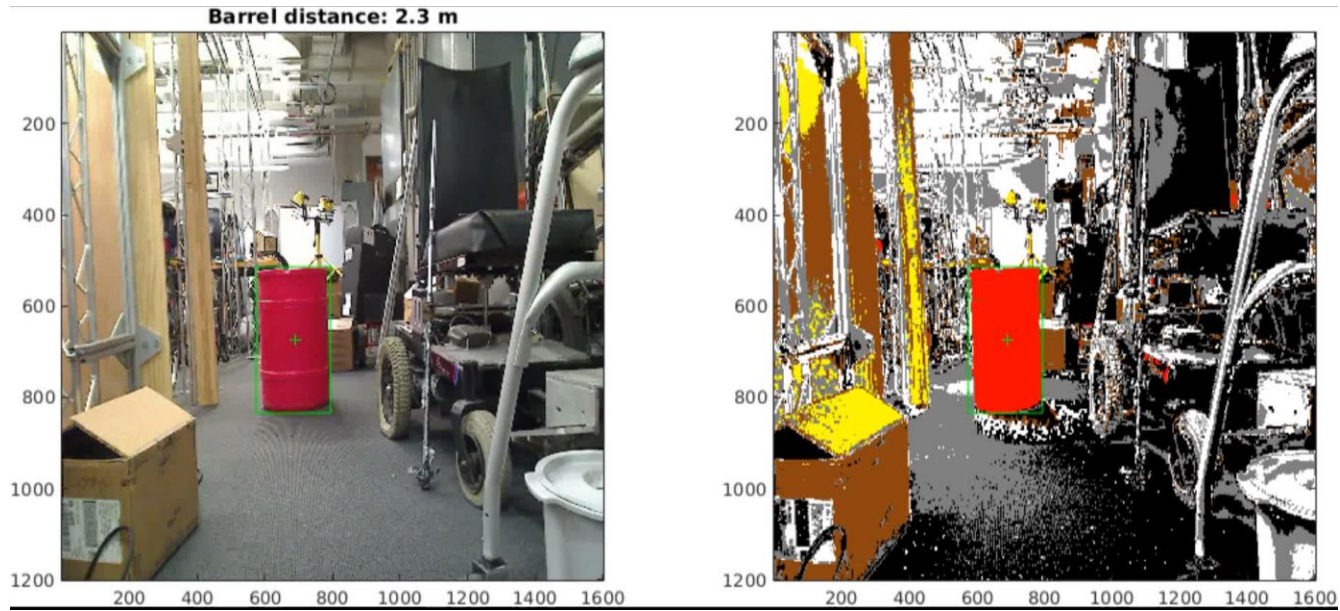


Syllabus Snapshot

Date	Lecture	Materials	Assignments
Jan 08	Introduction, Linear Algebra, Probability Theory	Barfoot-Ch2, Matrix-calculus	
Jan 10	Estimation Theory, Color Vision		
Jan 15	Supervised Learning	Mitchell-NaiveBayesLogReg	
Jan 17	Unsupervised Learning	Tomasi-EM	
Jan 22	Bayes Filter, Particle Filter	Barfoot-Ch4.2	
Jan 24	Rotations	Barfoot-Ch6.1-6.3	
Jan 29	Motion and Observation Models	Barfoot-Ch6.4	
Jan 31	Particle Filter SLAM	Thrun-Ch7-9	
Feb 05	Kalman Filter	Barfoot-Ch3.3	
Feb 07	EKF, UKF	Barfoot-Ch4.2	
Feb 12	SE(3) Geometry	Barfoot-Ch7.1	
Feb 14	SE(3) Kinematics and Probability	Barfoot-Ch7.2-7.3	
Feb 19	Visual Features, Optical Flow	Image-Features, Shi-Good-Features-To-Track	
Feb 21	Visual-Inertial SLAM		
Feb 26	Localization and Odometry from Point Features		
Feb 28	Robust Estimation: RANSAC, Hough, IRLS	Barfoot-Ch5.3	
Mar 05	Batch Estimation, Factor Graphs	Barfoot-Ch4.3, Ch3.1-3.2	
Mar 07	Pose Estimation	Barfoot-Ch8	
Mar 12	Pose-and-Point Estimation	Barfoot-Ch9	
Mar 14	Hidden Markov Models	Rabiner-HMM	

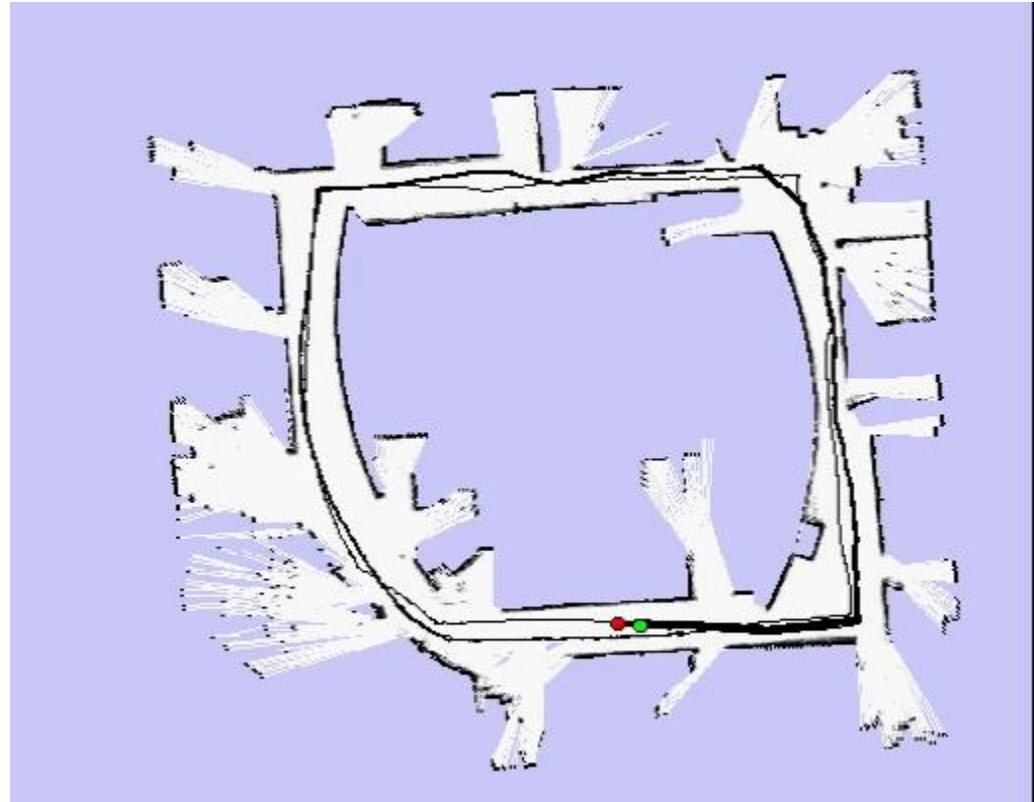
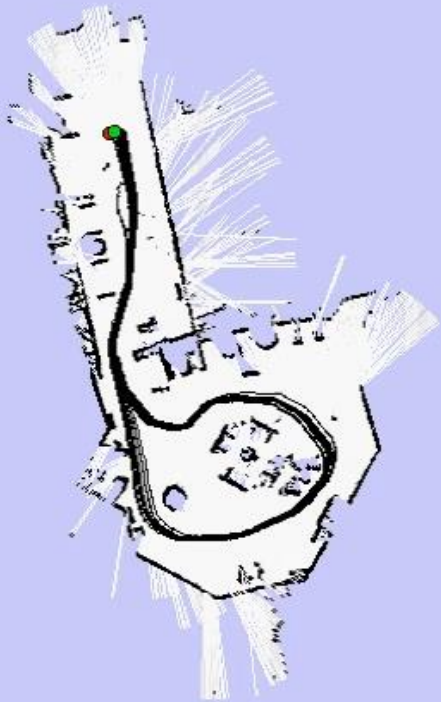
Project 1: Color Segmentation

- Train a color classification model and use it to detect an object of interest



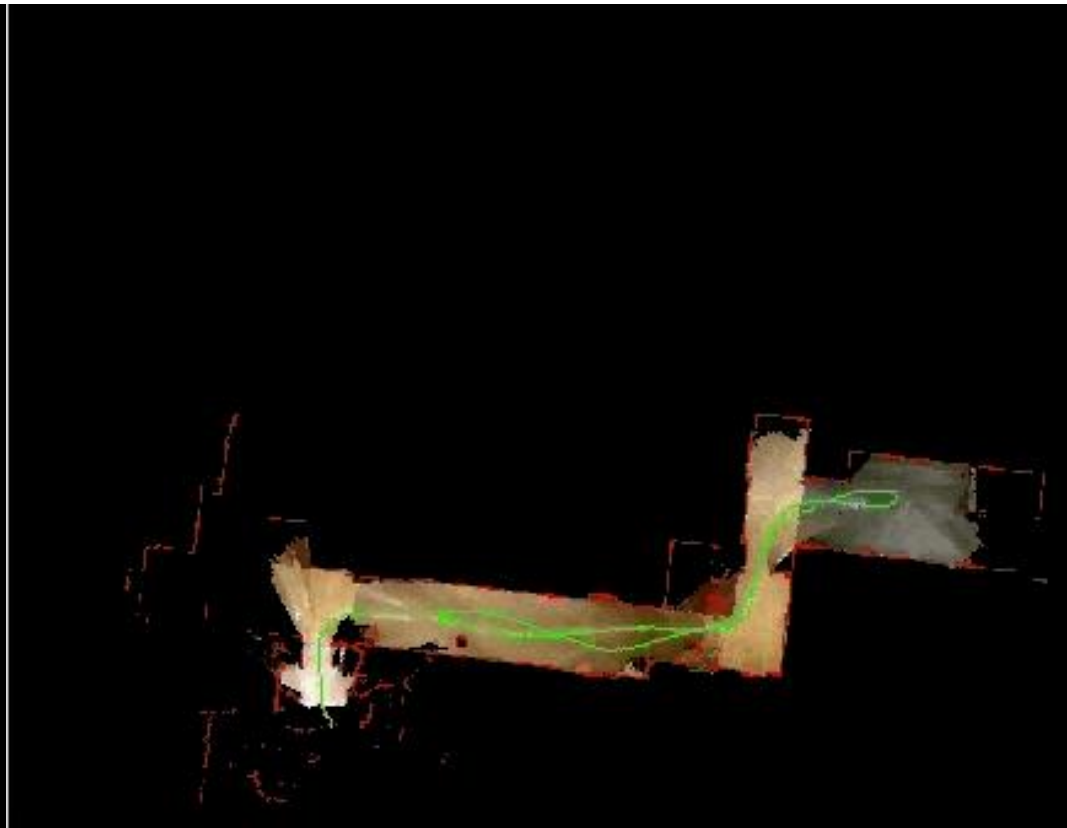
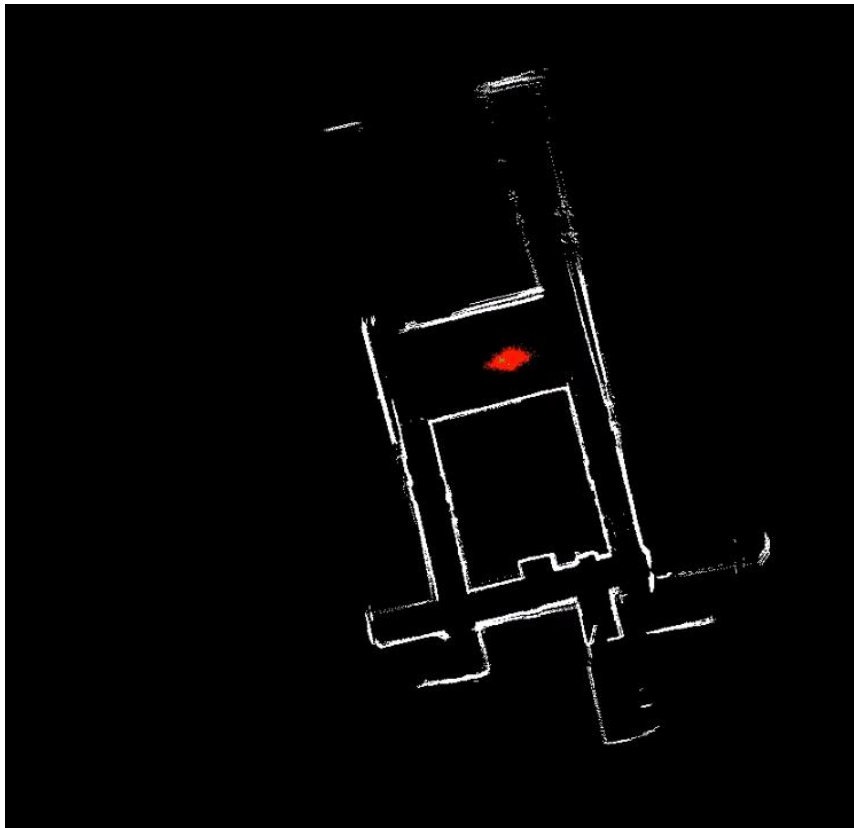
Project 2: Particle Filter SLAM

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

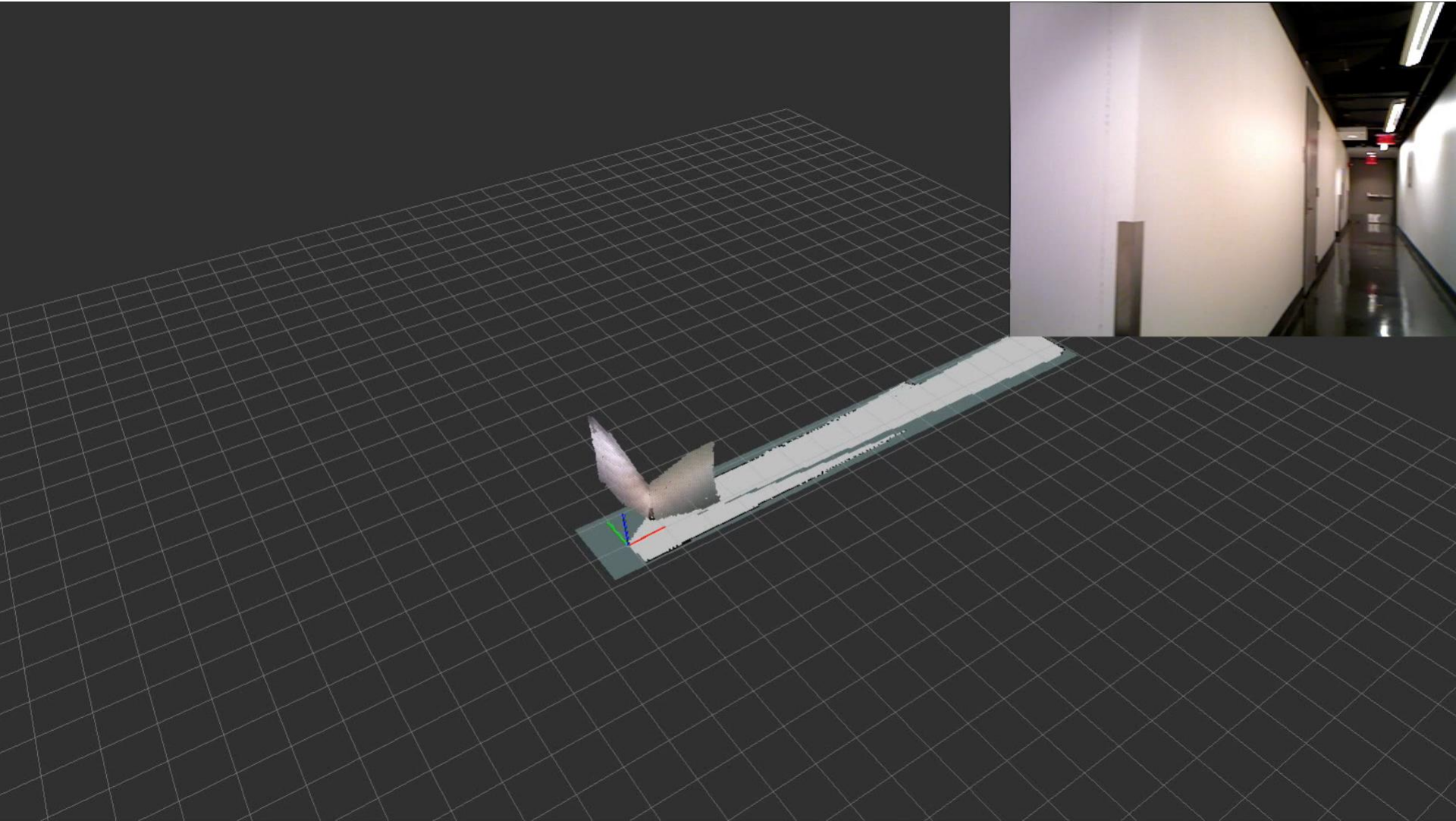


Project 2: Particle Filter SLAM

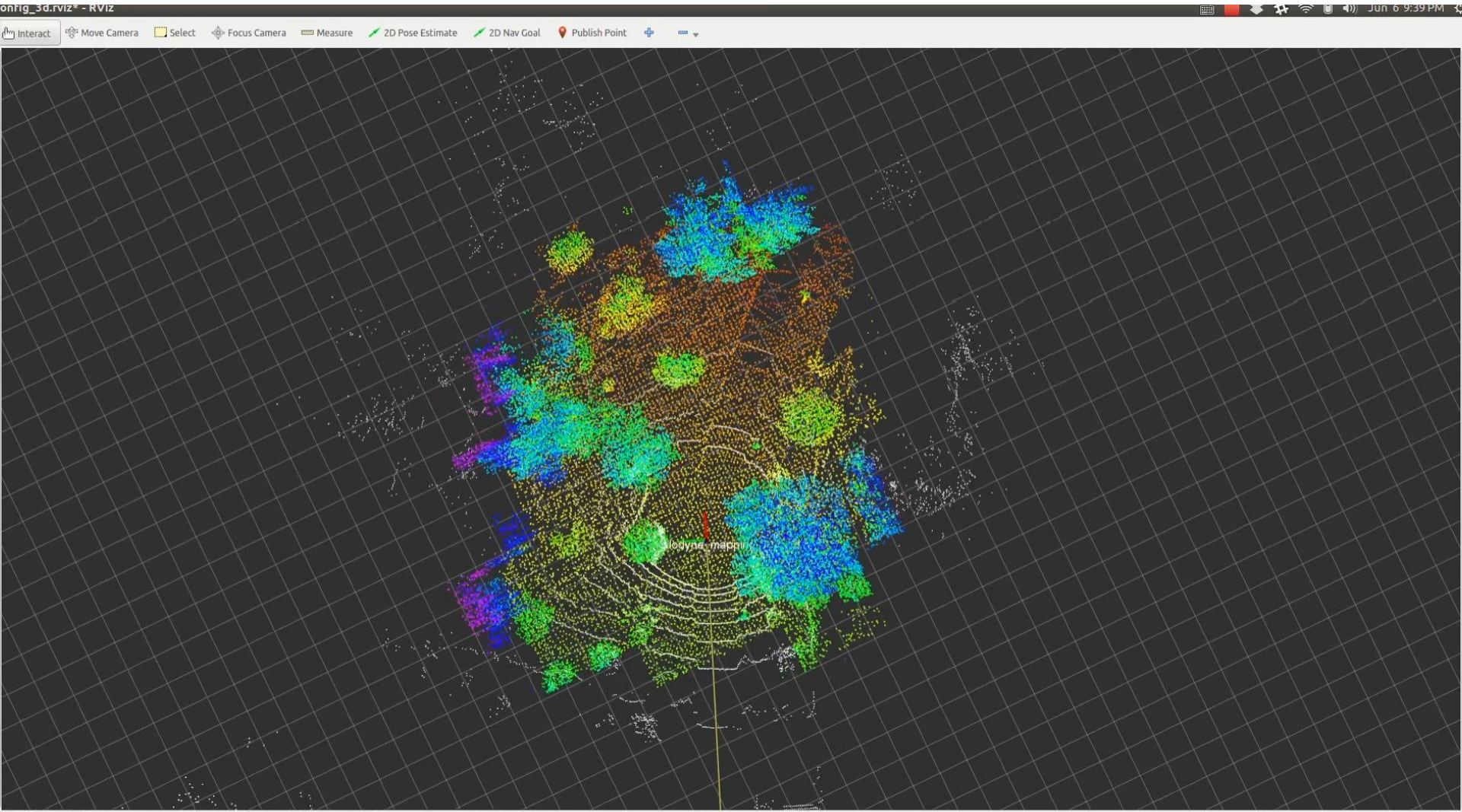
- Implement robot localization & mapping using odometry, IMU, laser, and RGBD measurements



Project 2: Lidar and RGBD SLAM



Project 2: Lidar Odometry and Mapping

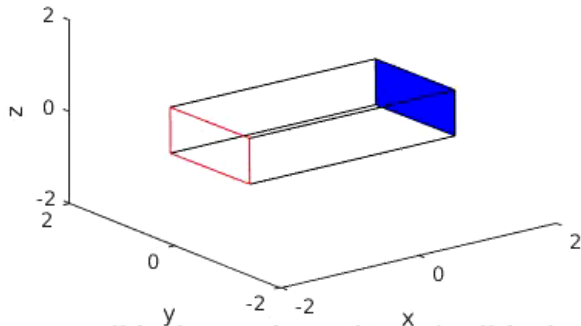


Reset | Left-Click: Rotate. Middle-Click: Move X/Y. Right-Click/Mouse Wheel: Zoom. Shift: More options.

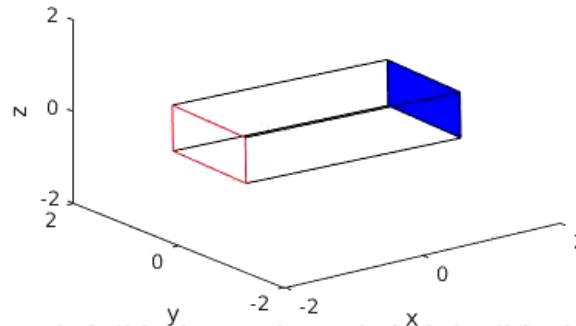
Project 3: Orientation Tracking

- use a Kalman filter to track the 3-D orientation of a rotating body based on IMU measurements and construct a panorama using RGB images

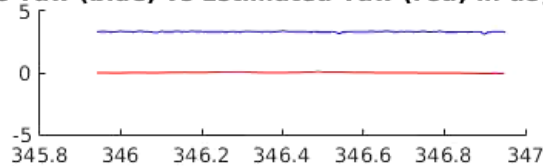
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yaw = -0.24, pitch = -0.06, roll = 0.31



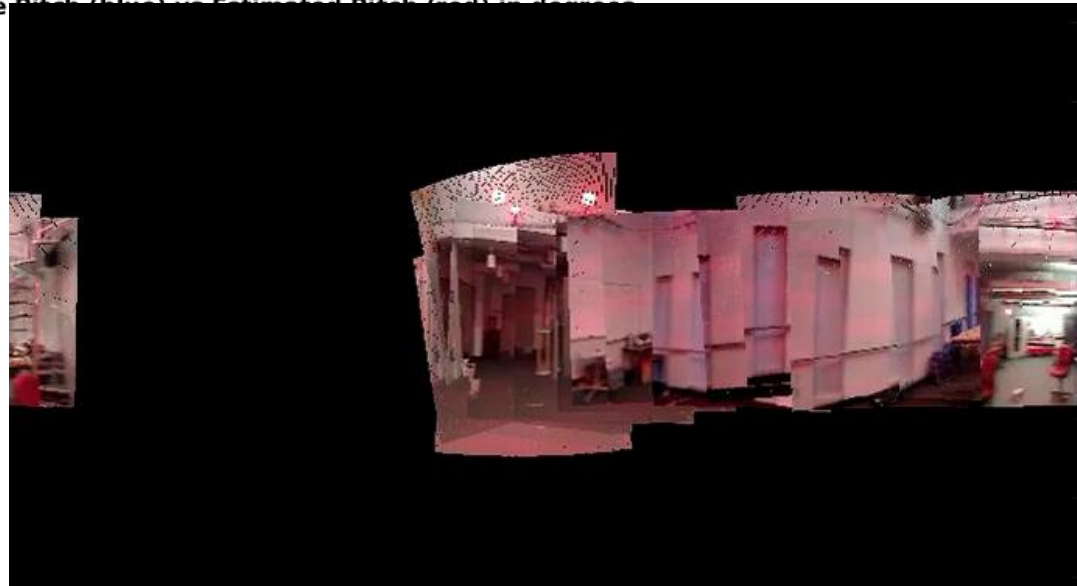
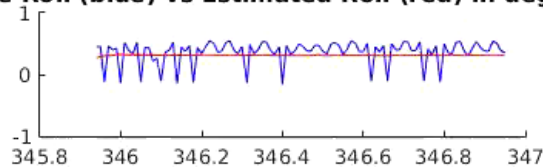
grav = [-0.00,-0.01,1.01]
yaw = 3.35, pitch = 0.37, roll = 0.39



True Yaw (blue) vs Estimated Yaw (red) in degrees



True Roll (blue) vs Estimated Roll (red) in degrees



Project 3: Visual Inertial SLAM

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

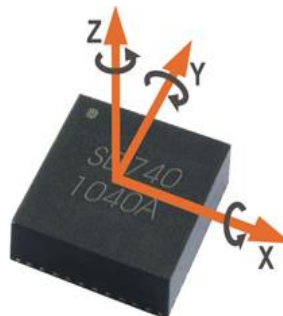


Project 3: Visual Inertial SLAM



Harris
corners, SIFT,
SURF, FAST,
BRISK, ORB,
etc.

\mathcal{Y}



linear acceleration
& angular velocity

\mathcal{I}

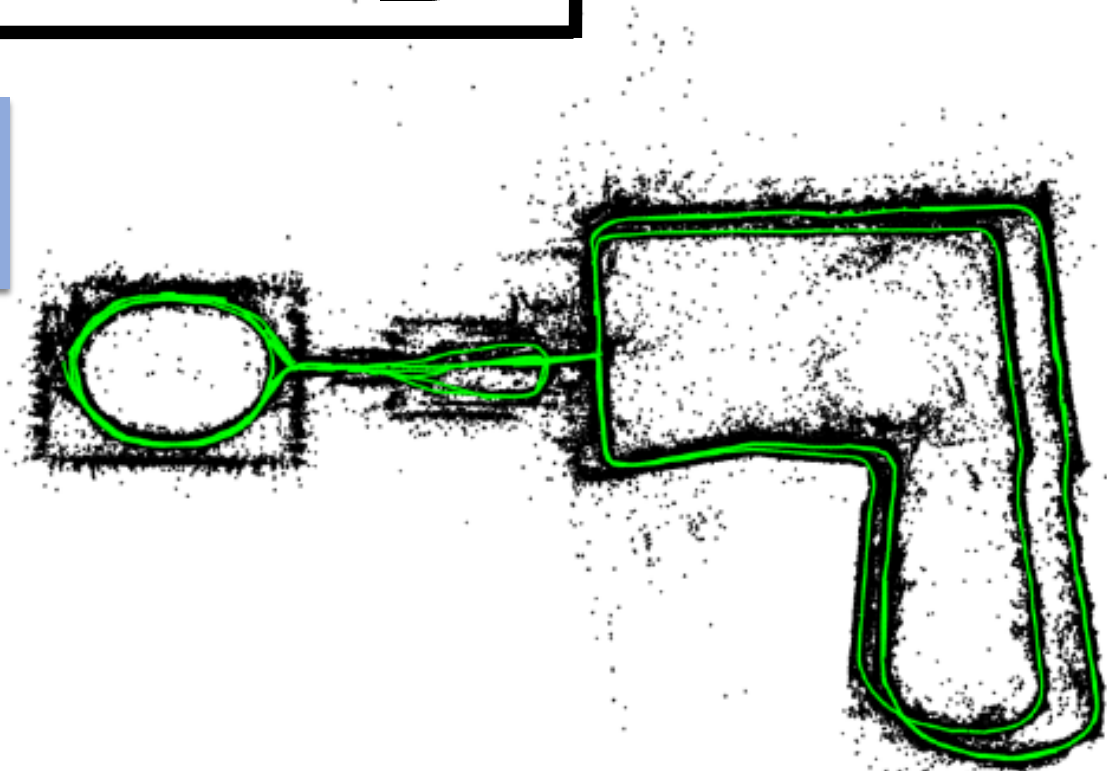
Optimization Problem

sensor
states

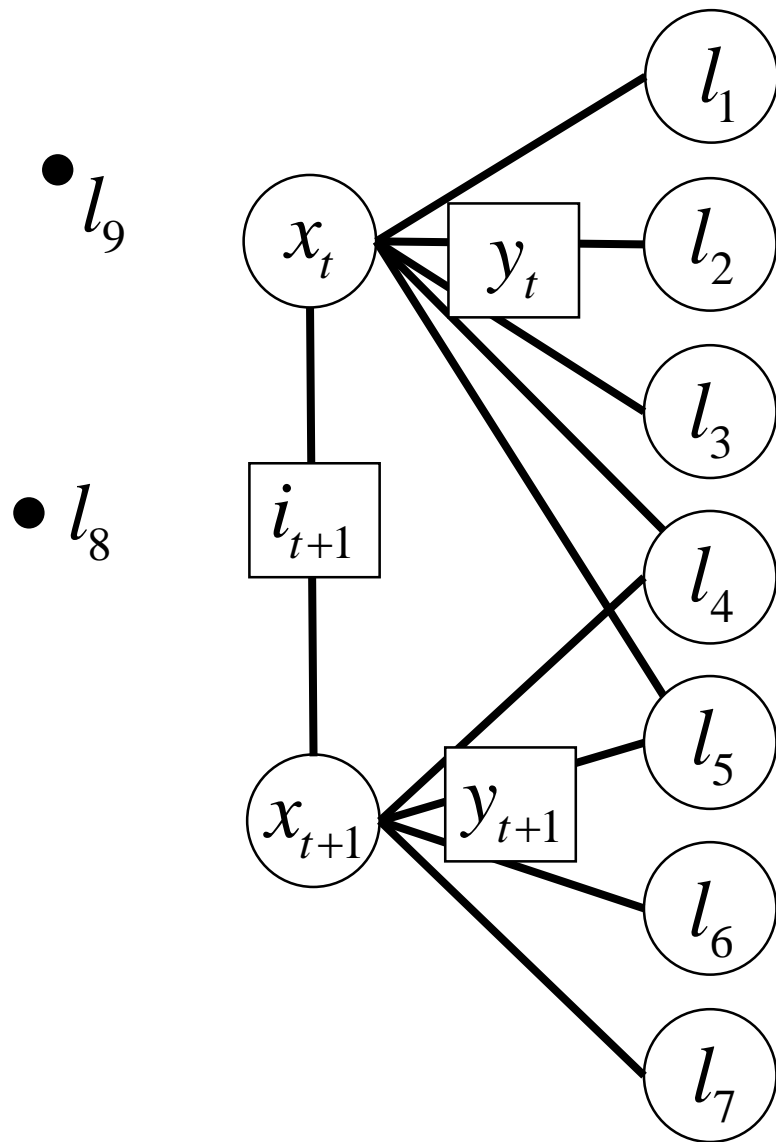
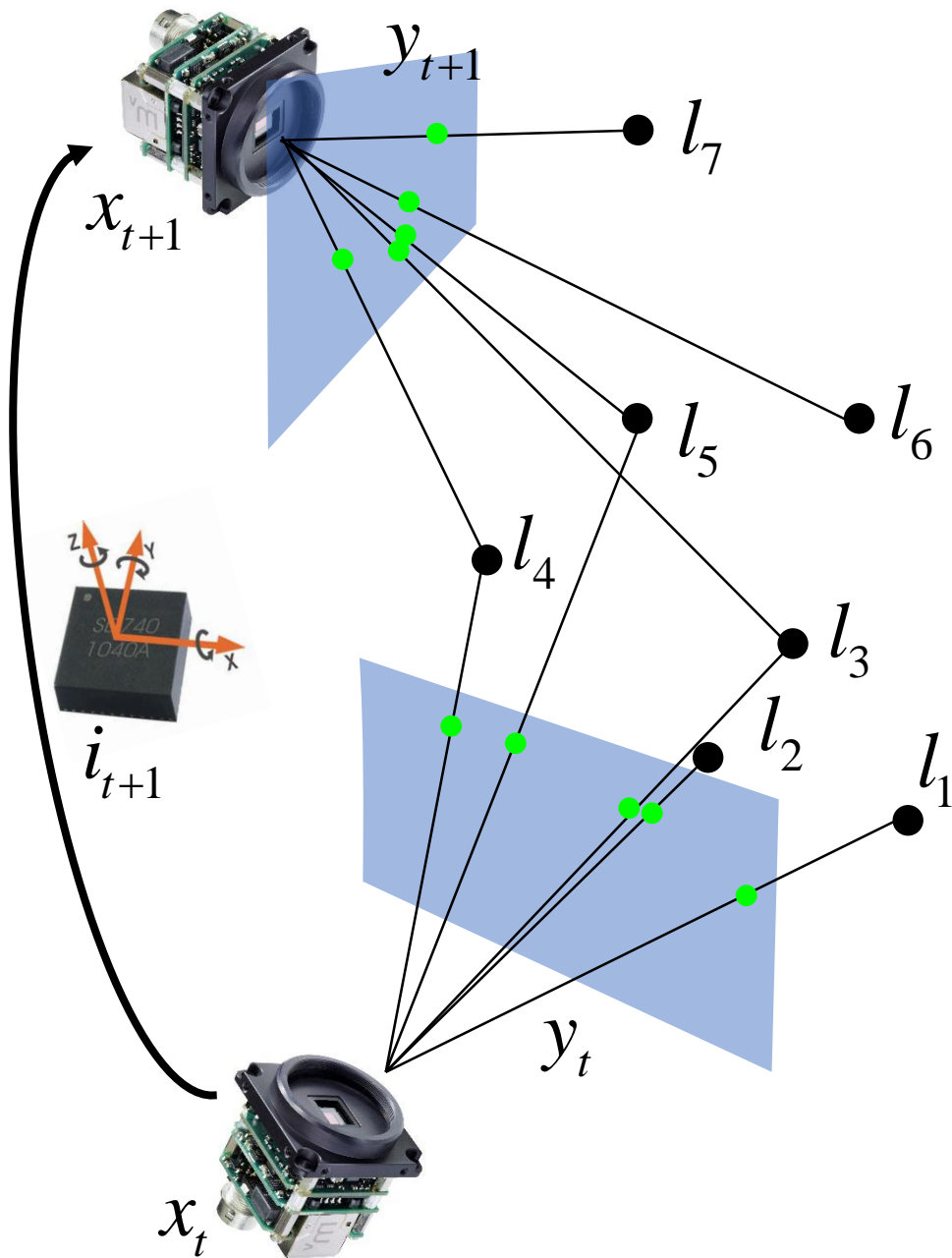
\mathcal{X}

landmark
map

\mathcal{L}



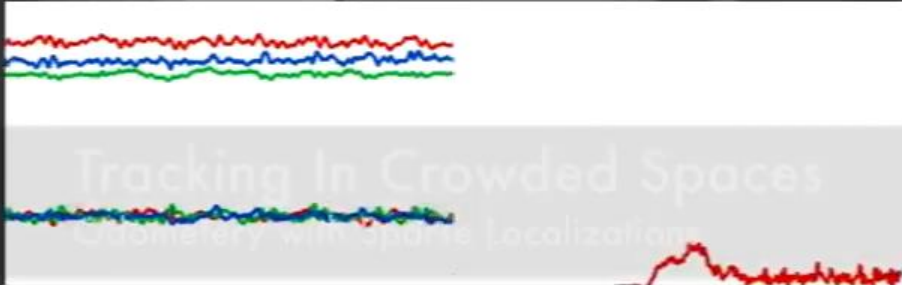
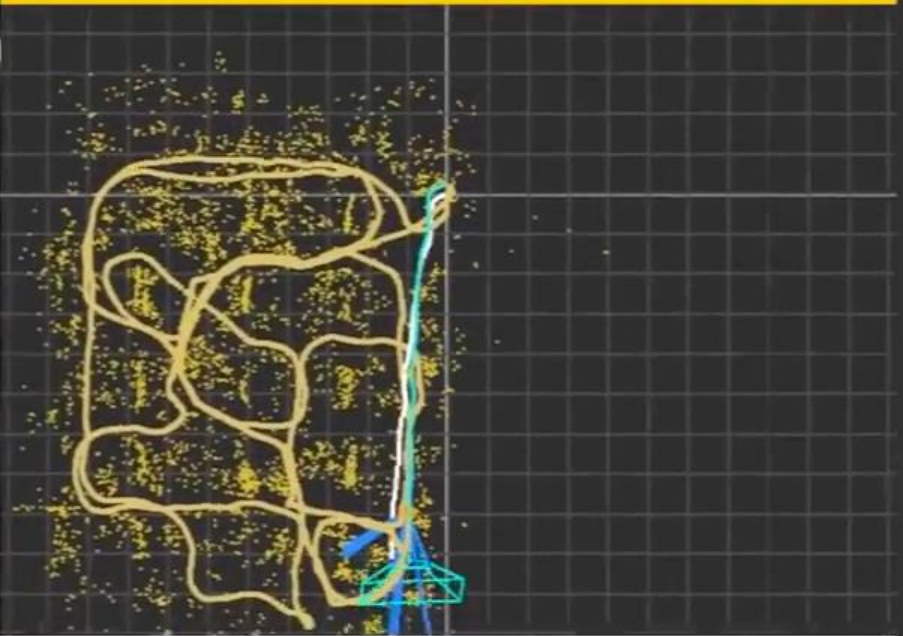
Project 3: Visual Inertial SLAM



Google Project Tango



Top-down view graph plot grid size: 1 m



Time is: 363.63

FPS: 31.66

Position (m): 0.09, 0.03, -0.24

Path length (m): 129.5

Number of loop closures: 0

Distance to origin (m):

Loop closure: 0.3 (0.2 % of path)

Open loop: 9.3 (92.8 % of path)

Number of keyframes: 1681