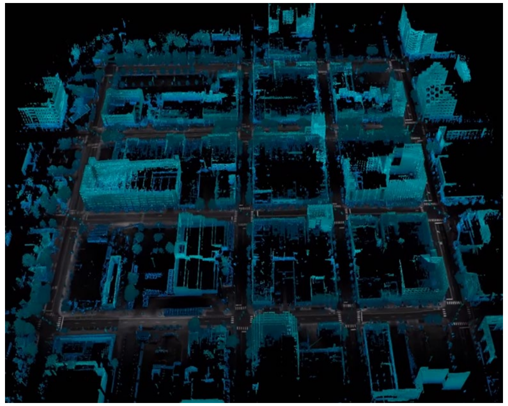
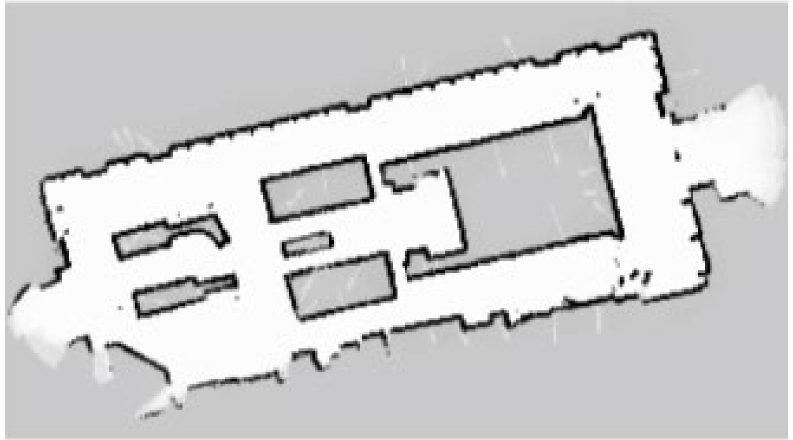
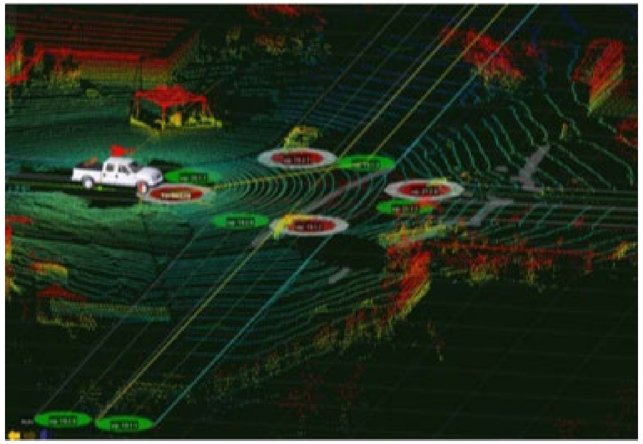
BYU Electrical & Computer Engineering





L1: INTRODUCTION

ECEN 633: Robotic Localization and Mapping (FALL 2023)

A Little About Me

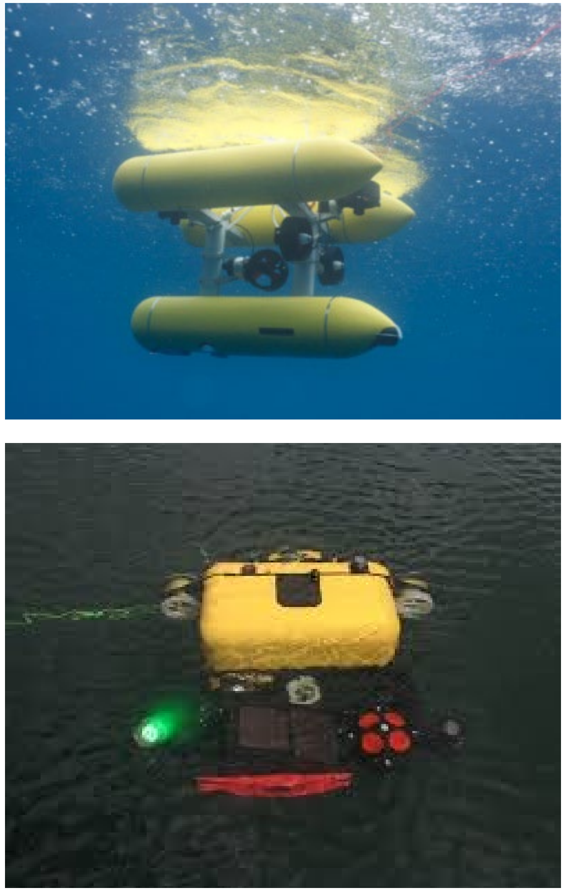
BS – Electrical Engineering

MS/Ph.D. - Robotics

Carnegie Mellon
THE ROBOTICS INSTITUTE

Postdoc – Field Robotics

My Family



Marine and General Robotic Navigation, Mapping, SLAM, and Perception

Challenges in Robotics

- Actuator Design
- Physical compone… …on
- Non-line…
- S…
- Es…
- Mo…
- High…
- Huma… …on

Intra-robot Communications
Inter-robot Communications
Data logging/playback
Efficiency
Timing Synchronization
Simulation
Visualization
Ground Truth
Testing/Evaluation

Calibration
Segmentation
Object Classification
Place Recognition
Outlier Rejection
Data Association

Pose Estimation
Tracking
Intent Estimation
Data Fusion
Environment Modeling
Mapping

Obstacle Avoidance
What motions are useful?
Which motions are best?
Which motions are safe?

Slide courtesy of Ryan Eustice

Why I Bring this Up?

- First:
  - Jumping into robotics is difficult
  - Jumping into research in robotics is even harder

- Second:
  - We can't cover everything in this course

- My goal in this course is to help you become familiar and gain experience with a set of ***Fundamental & Essential*** algorithms focused on mobile robotic
  - State Estimation,
  - Localization and Mapping, and
  - Perception

Research!

Topic Overview

State Estimation:

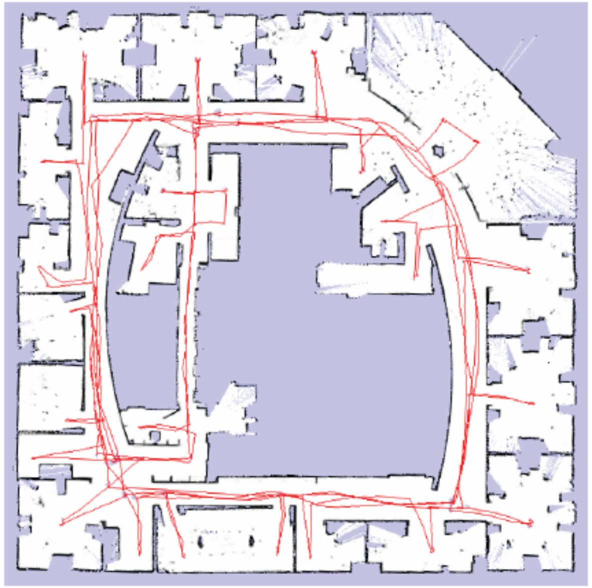
- Mapping
- Localization
- Simultaneous Localization and Mapping

Perception:

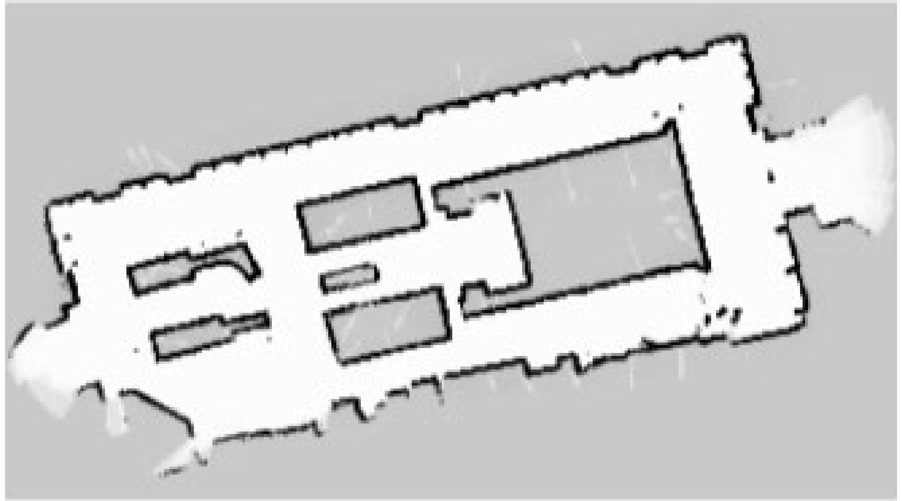
- Sensor Types/Models
- Working with Data

State Estimation: Mapping

- Given:
  - A robot's pose (position/orientation) at specific points in time
  - Data observed by the robot's sensors at those points in time
- Estimate:
  - A map/model of the environment

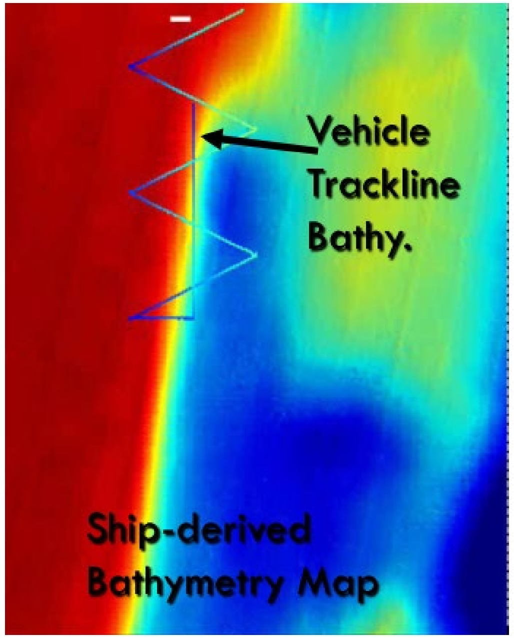


International LiDAR Mapping Forum



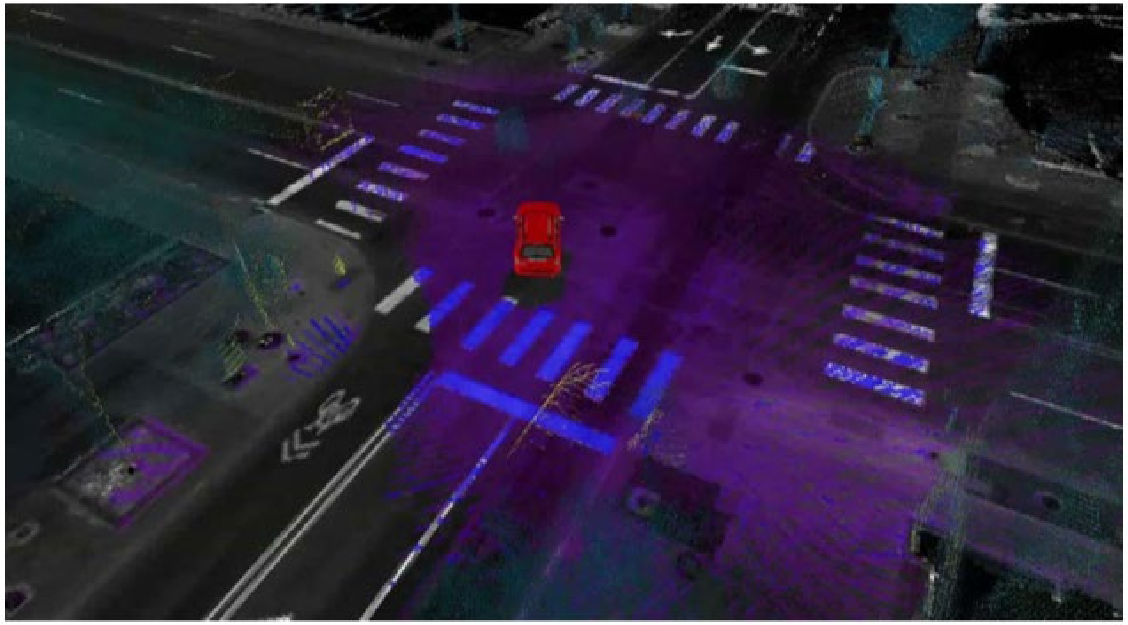
State Estimation: Localization

- Given:
  - A map/model of the environment
  - Data observed by the robot's sensors at specific points in time
- Estimate:
  - The robot's pose (position/orientation) at a specific point in time (or at a sequence of points in time)



Courtesy of Ryan Eustice

Autonomous Driving

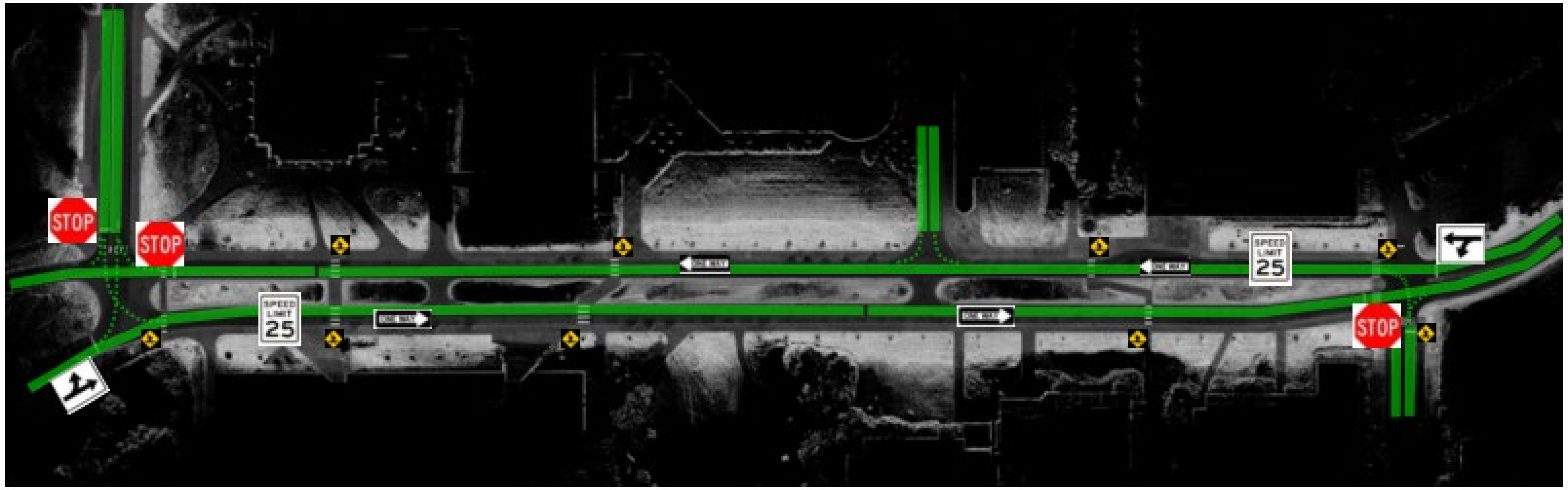


How do you and I drive?

www.drivecrossroadsford.com

Localization into a Prior Map

- Simplify the Problem
  - Build Prior Map
  - Annotate map with lanes, signs, lights, rules, etc ...
  - Localize into that prior map with cm accuracy
  - Just look for differences from the map



Bonisteel Blvd, University of Michigan

Slide courtesy of Ryan Eustice

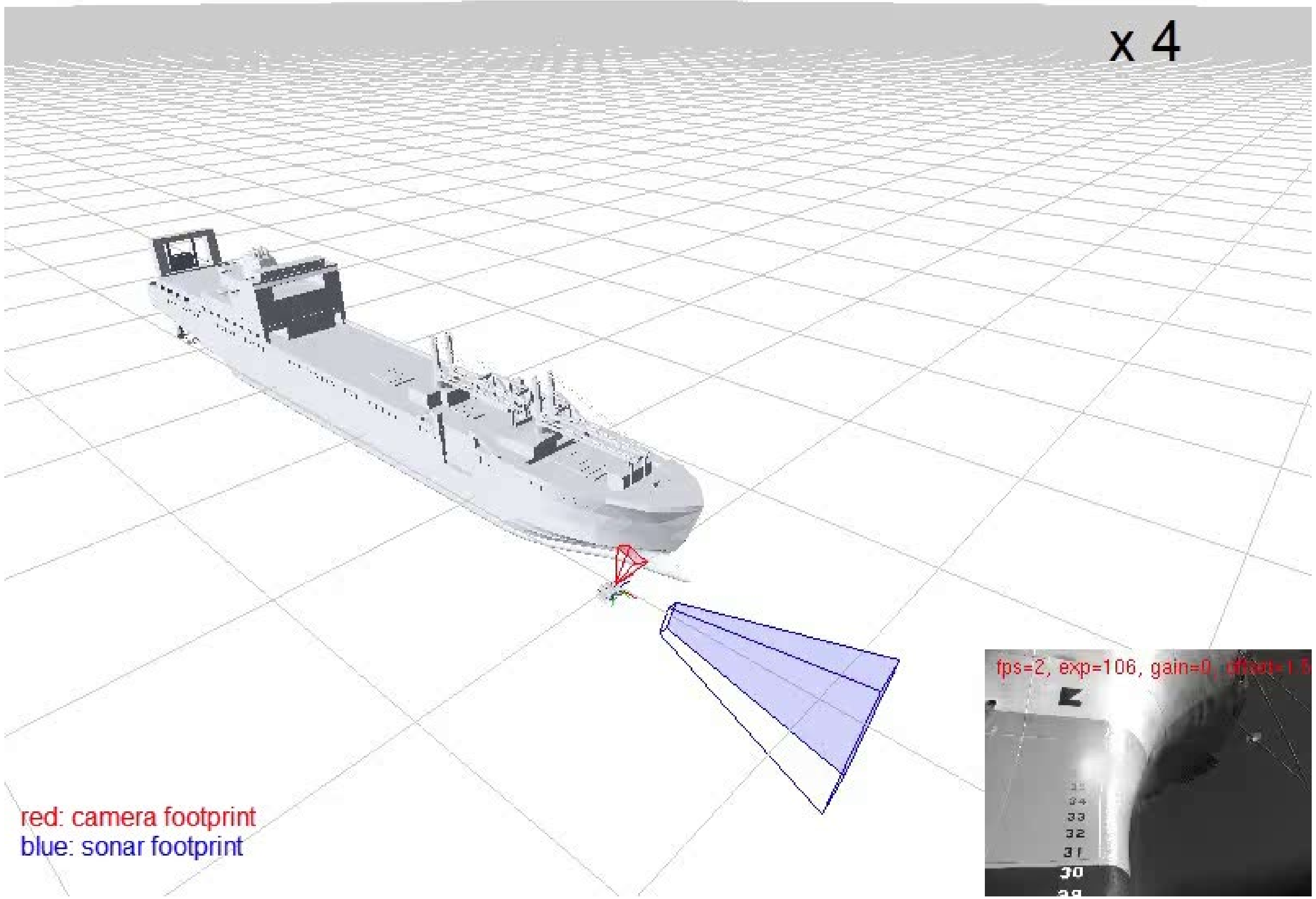
Localization into a Prior Map

Courtesy of Ryan Eustice

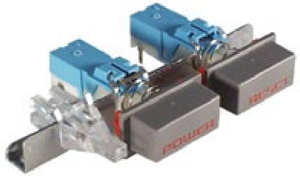
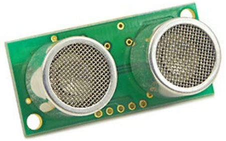
Localization into a Prior Map

Courtesy of Ryan Eustice

State Estimation: Simultaneous Localization and Mapping



Perception: Sensing

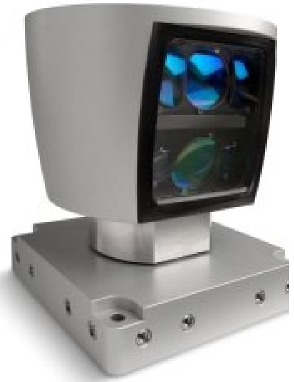


$5

$200

$0.02

$2000



$75000

$4000

Courtesy of Ed Olson

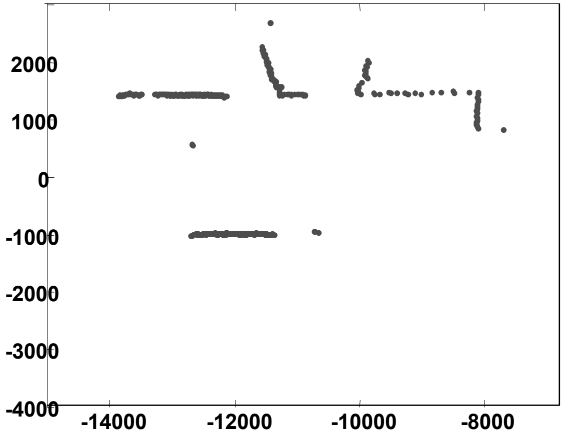
Perception: Data

Camera image

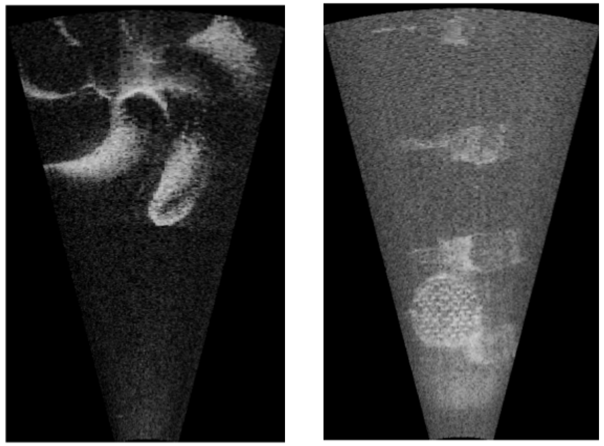
RGB-D image

LiDAR scan

2D laser scan



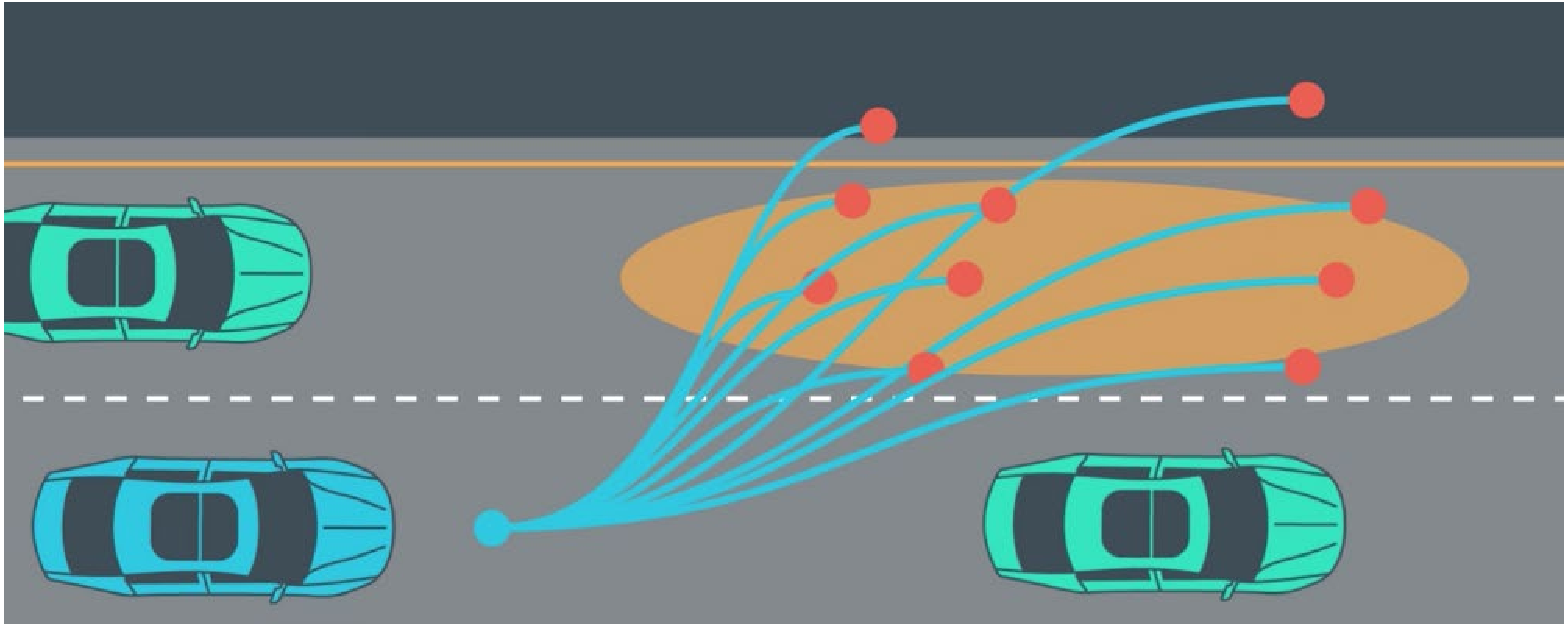
Multi-beam sonar (profiling and imaging)



Courtesy of Michael Kaess

Path Planning

Udacity



Course Purpose

- After taking this course, students will be **prepared to begin contributing to research** relating to mobile robotic
  - localization,
  - mapping,
  - SLAM, and
  - perception.
- Students will be able to **analyze** specific instances of common mobile robotic system challenges such as localization, mapping, SLAM, and navigation planning and then **evaluate** and **apply** ***historical and modern solutions*** to solve them.

Learning Outcomes

1. Students will be able to ***analyze*** and ***succinctly describe*** localization, mapping, and navigation problems including what is known, what needs to be found, and what conditions must be met.

2. Students will be able to ***select*** appropriate solutions to these problems.

3. Students will be able to correctly ***implement*** and ***apply*** historical and modern solutions to these problems.

4. Students will be able to ***analyze*** research papers proposing solutions to these problems and ***evaluate*** whether a given solution can be successfully applied to a given situation.

Course Basics

- Lecture: MW 8:00-9:15 am, 340 CTB
  - In-person
- Office Hours:
  - MW 9:30-10:30 am
  - Other Times By Appointment
  - In my Office (450E EB) or pre-determined location (will be announced)
- Textbooks:
  - S. Thrun, W. Burgard, D. Fox. *Probabilistic Robotics.* Third Printing.
    - **Must correct based on Errata at:** http://www.probabilistic-robotics.org
  - M. Spong, S. Hutchinson, and M. Vidyasagar *Robot Modeling and Control. 2e.*
  - T. Barfoot. *State Estimation for Robotics.*
    - Older Available at: http://asrl.utias.utoronto.ca/~tdb/bib/barfoot_ser17.pdf
    - Newer Version Available Now at Same Place

Course Basics

- Prerequisites:
  - Linear Algebra
    - Matrix Theory
    - Vector Spaces
    - Linear Transformations
    - Matrix Decompositions
  - Probability Theory (Will Review):
    - Axioms of Probability
    - Conditional Probability
    - Discrete/Continuous Random Variables
    - Expectation
    - Conditional Expectation
    - Independence
    - Conditional Independence
    - Multivariate Distributions

Course Basics

- Learning Suite
  - Schedule
  - Reading/Assignments/Grades etc.

Course Breakdown

- Course Breakdown:
  - Citizenship 5%
  - Minisets and Reading 13%
  - Paper analysis outlines and presentations 7%
  - Coding problem sets 20%
  - Midterm Exam 25%
  - Final project, paper, and presentation 30%

Citizenship (5%)

- Slack
- If you have questions, please post them on Slack
- Link under content tab on Learning Suite

- You are expected to participate in both:
  - In-class discussion
  - By answering questions on Slack

- If you actively participate in both these arenas, you will earn the full 5%.

Weekly Schedule

- Monday/Wednesday: Lectures
  - Reading before class
  - Asked in Mini-set Self Grading quiz if you have completed the reading

Mini-sets and Reading (13%)

- Assigned Reading
  - Must be completed each day before class
- Weekly “mini-sets” of problems
  - **Purpose:** Give you hands-on experience with theory and math behind the methods we discuss
  - Closely follow lecture material
  - Will be representative of questions on midterm exam
  - Due: Tuesday nights at 11:59 pm (submitted via learning suite)
- Grading:
  - 3% Completion
  - 10% Self-graded – Solutions released Wednesday morning at 12:05 AM
    - Half points for a correct initial submission/half points for correction after seeing solution.
  - Lowest two will be dropped
- **This is a graduate course – it is your responsibility to make sure you understand this material. It is essential that you learn it and it will be on the exam.**

Paper Analysis (7%)

- Bi-weekly Outlines (4%)
- Outline Presentation (3%)
  - Once per semester
  - **Sign up at link under content on Learning Suite!**
  - Also, add your email to gain access to the labs/coding assignments hosted on bitbucket.
  - Please Signup before this Friday.
- Purpose: The purpose of this assignment is to give you experience extracting the essential pieces of information from a research paper.

- Details about outline/presentation are available on Learning Suite

Coding Problem Sets (20%)

- Approx. every two weeks
- Purpose: The purpose of these assignments will be to give you hands on experience implementing fundamental algorithms relevant to the topics we will be discussing in class.

- **You MUST participate in all coding problem sets.**

- Details will be available on Learning Suite under assignments and in the syllabus.

Midterm Exam(25%)

- 1 Midterm Exam (25% of Grade)

- Midterm – Take Home Exam – w/ a time limit
  - Written Portion
  - Coding Portion

- Purpose: To help both you and I evaluate how will you are understanding the material.

Final Project, Paper, and Presentation (30%)

- Groups of 3-4

- You need to select a project that is closely related to the course; specifically, your project must either:
  1. Build on and extend existing robotics research relating to mobile robotic perception, localization, mapping, or SLAM, or
  2. Implement an existing paper or system that builds on what we have covered in the course and evaluates it on real-world data.

- Project proposal due: Nov. 11
- Final paper due: Dec. 8
- Presentation: Last 2 Days of Class

- More details to come (And currently on Learning Suite)

Integrity

- BYU Honor Code

- Encouraged to work together
- Discussing concepts together is strongly encouraged.

- BUT you must do your own work (code and write up)
- Please do not post your solutions online or make available to others.

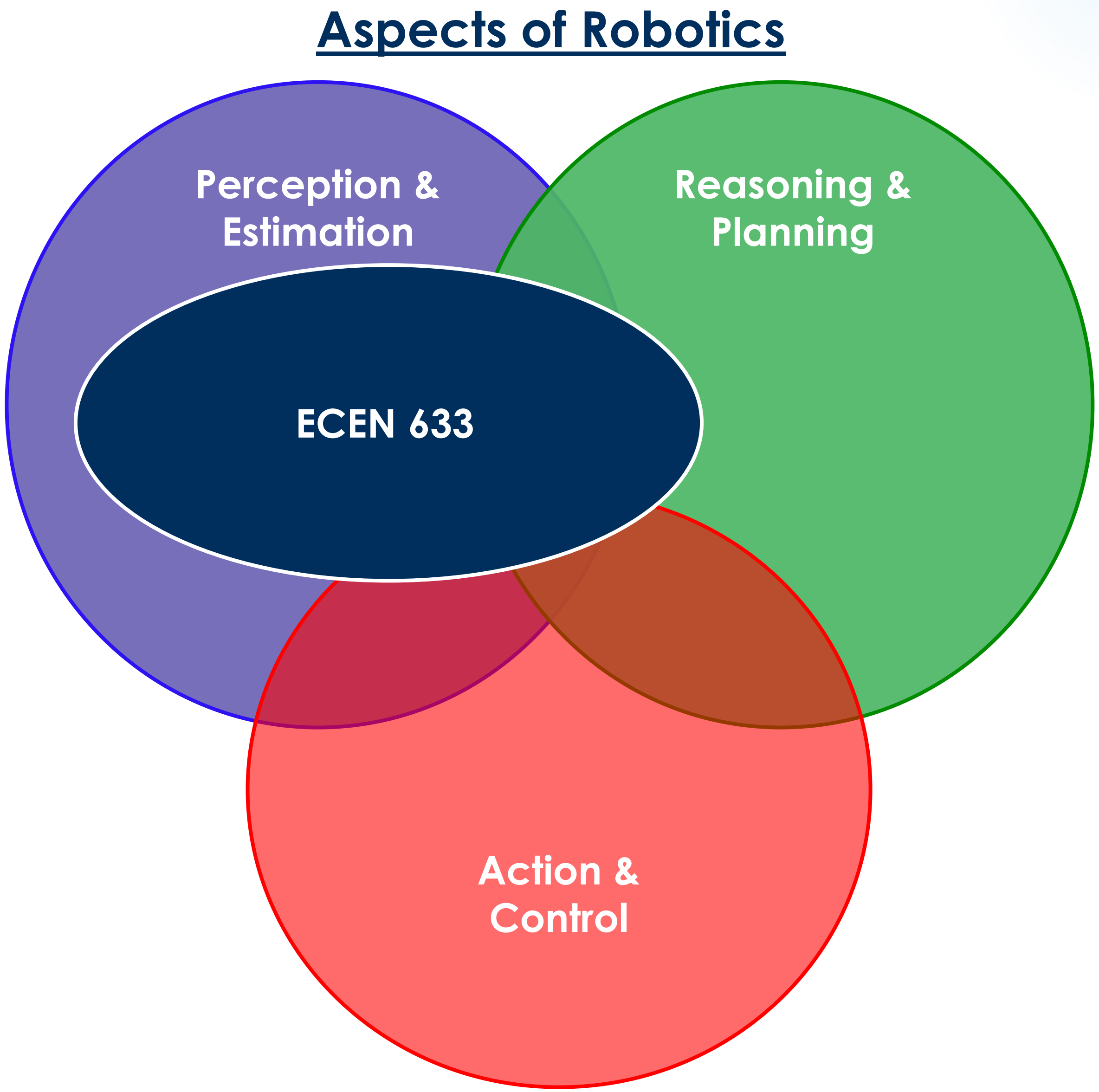
Health and Covid

- Class is in-person
- Attendance is Required
- One of the major strengths of a BYU education is in-person interactions with faculty and other students. We want to preserve this as much as possible.

- Will Try Record Lectures for Review/Courtesy, But you Need to Be in Class

Questions on Course Organization?

What topics will we cover?



Fundamental Topics Covered in the Course

State Estimation

- **Fundamental Problems**
  - Mapping
  - Localization
  - Simultaneous Localization and Mapping
- **Fundamental/Modern Solutions & Important Concepts**
  - Modeling Uncertainty
  - Occupancy Grids
  - Bayes Filtering
  - Kalman Filtering, EKF, UKF
  - Particle Filtering
  - Information Filters
  - Least Squares Estimation
  - Graph-Optimization Based Solutions
  - Robust Optimization
  - SLAM Front-ends
  - Semantic Mapping

Perception

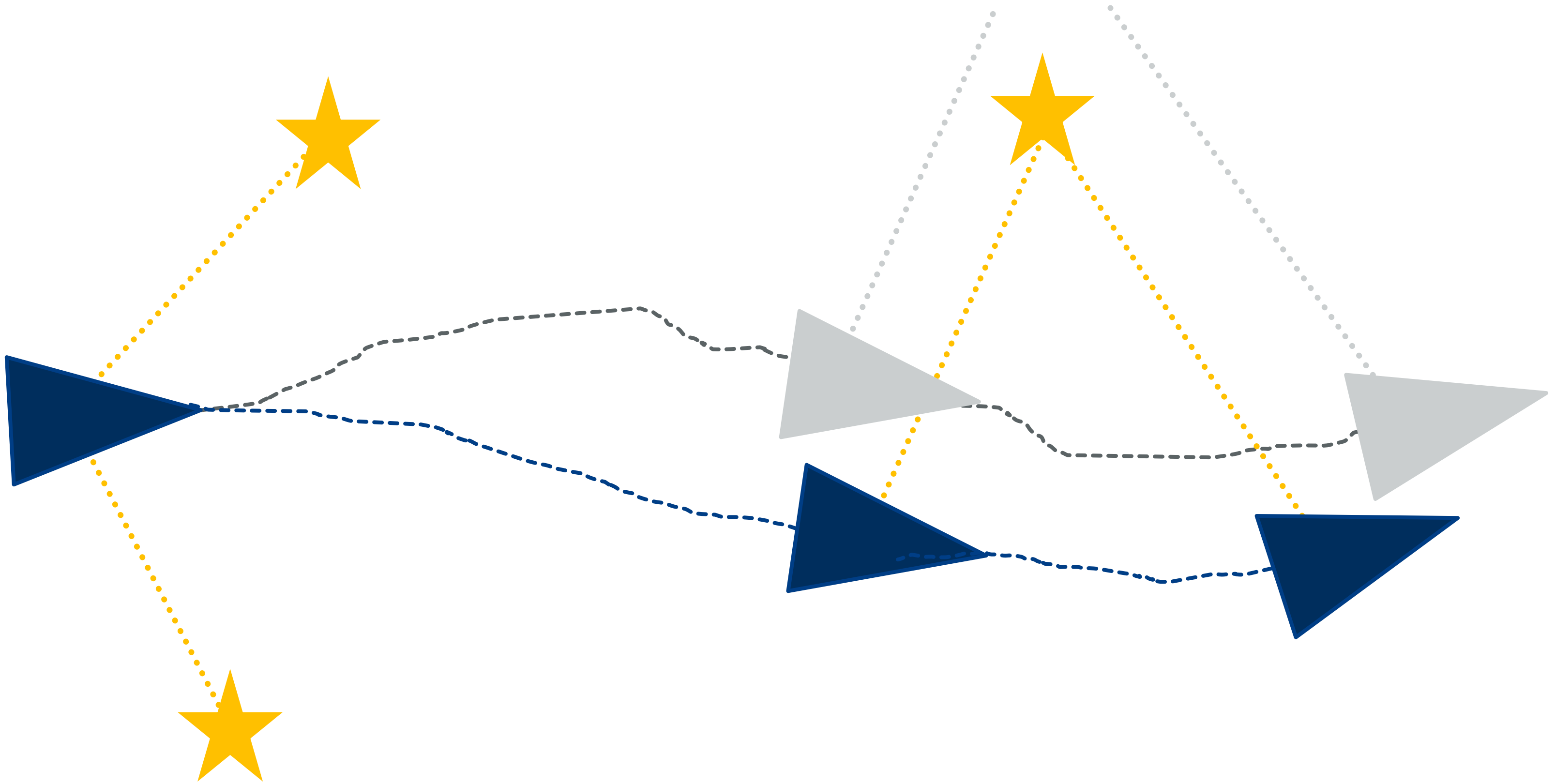
- Optical Cameras
- Feature Detection/Matching
- Place Recognition
- LiDAR
- Point Cloud Alignment/Scan Matching
- Sonar
- Sensor Calibration
- Data Association

Planning (If time allows)

- Motion Planning
- Sampling Based Planning
- MDPs/POMDPs

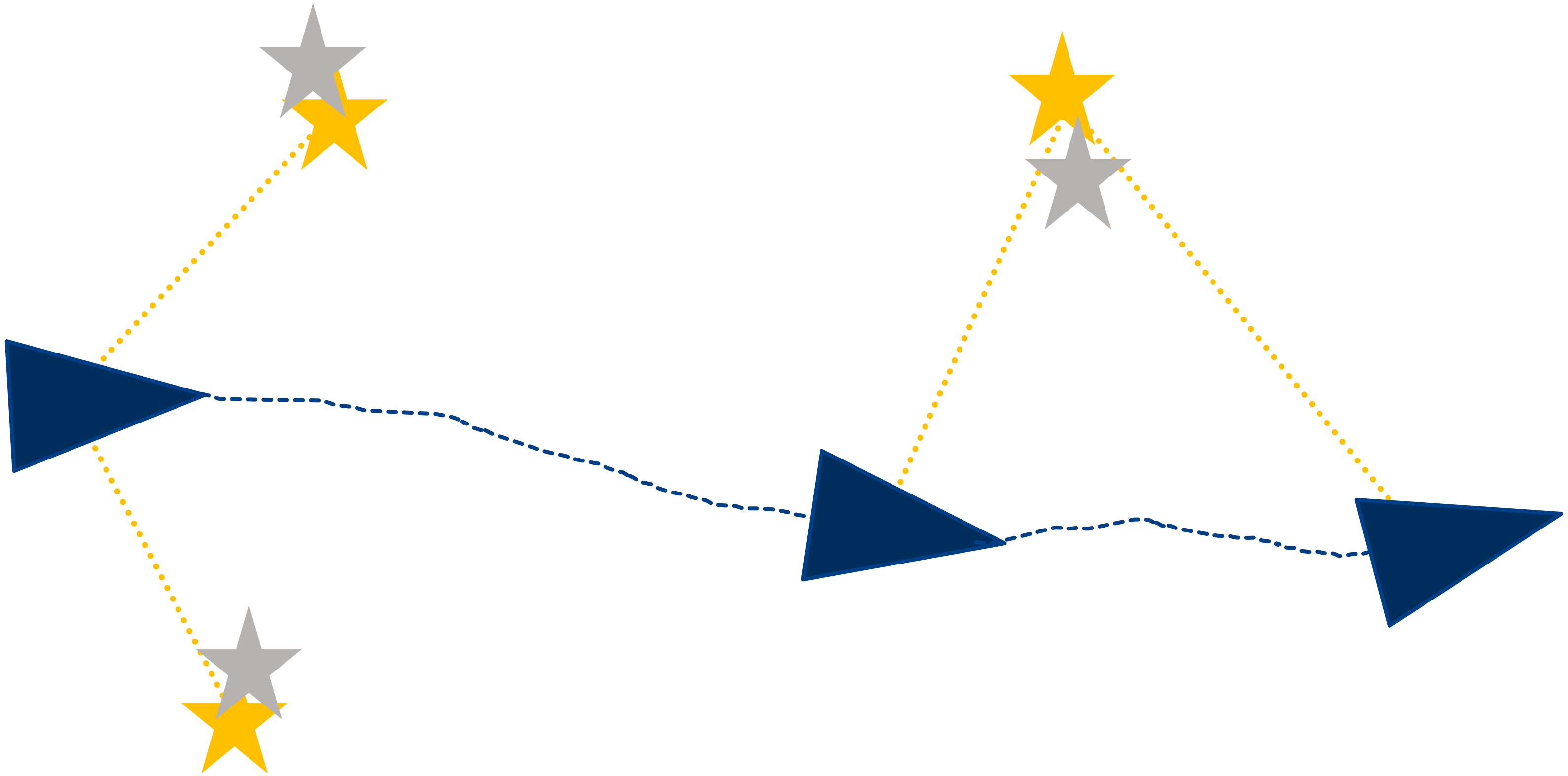
Simultaneous Localization and Mapping (SLAM)

- Localization Example



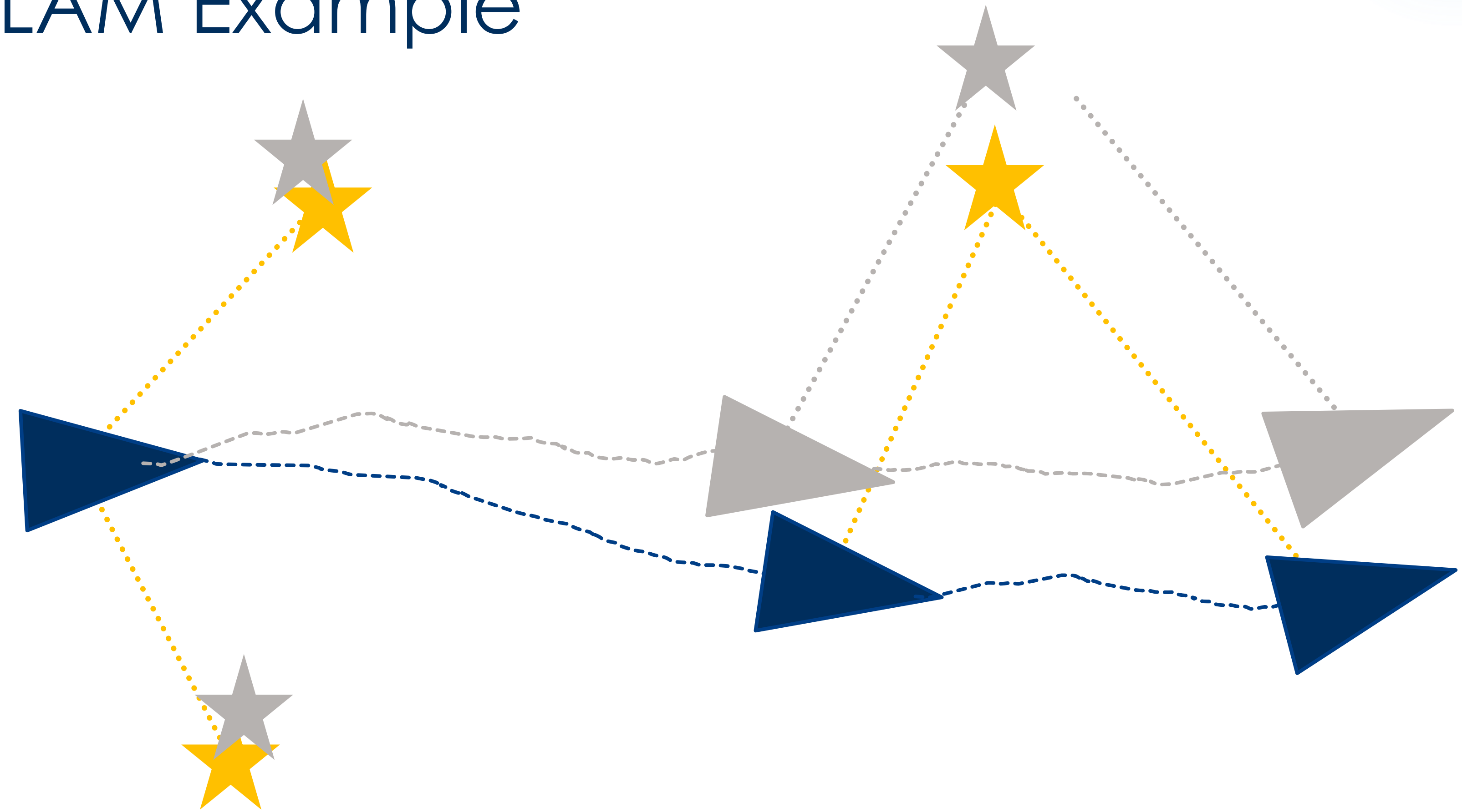
Simultaneous Localization and Mapping (SLAM)

- Mapping Example



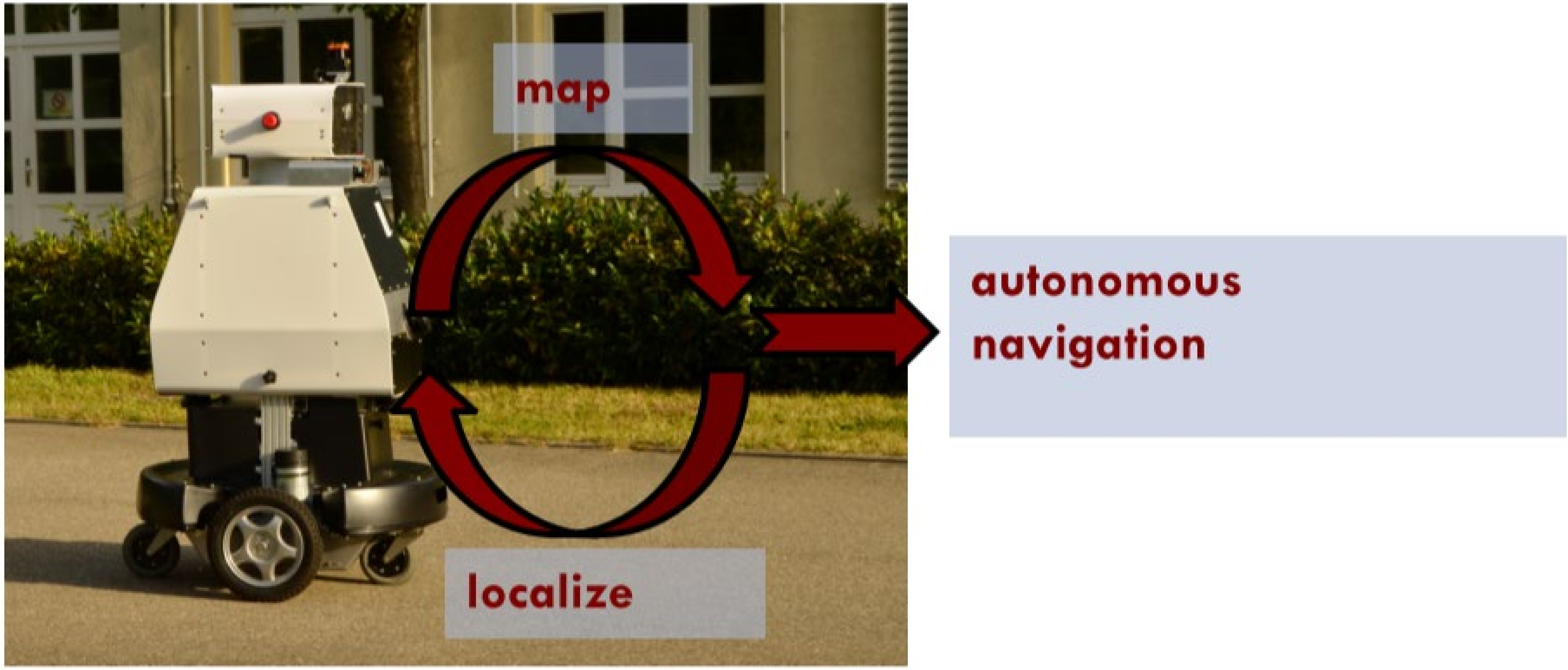
Simultaneous Localization and Mapping (SLAM)

- SLAM Example



Simultaneous Localization and Mapping (SLAM)

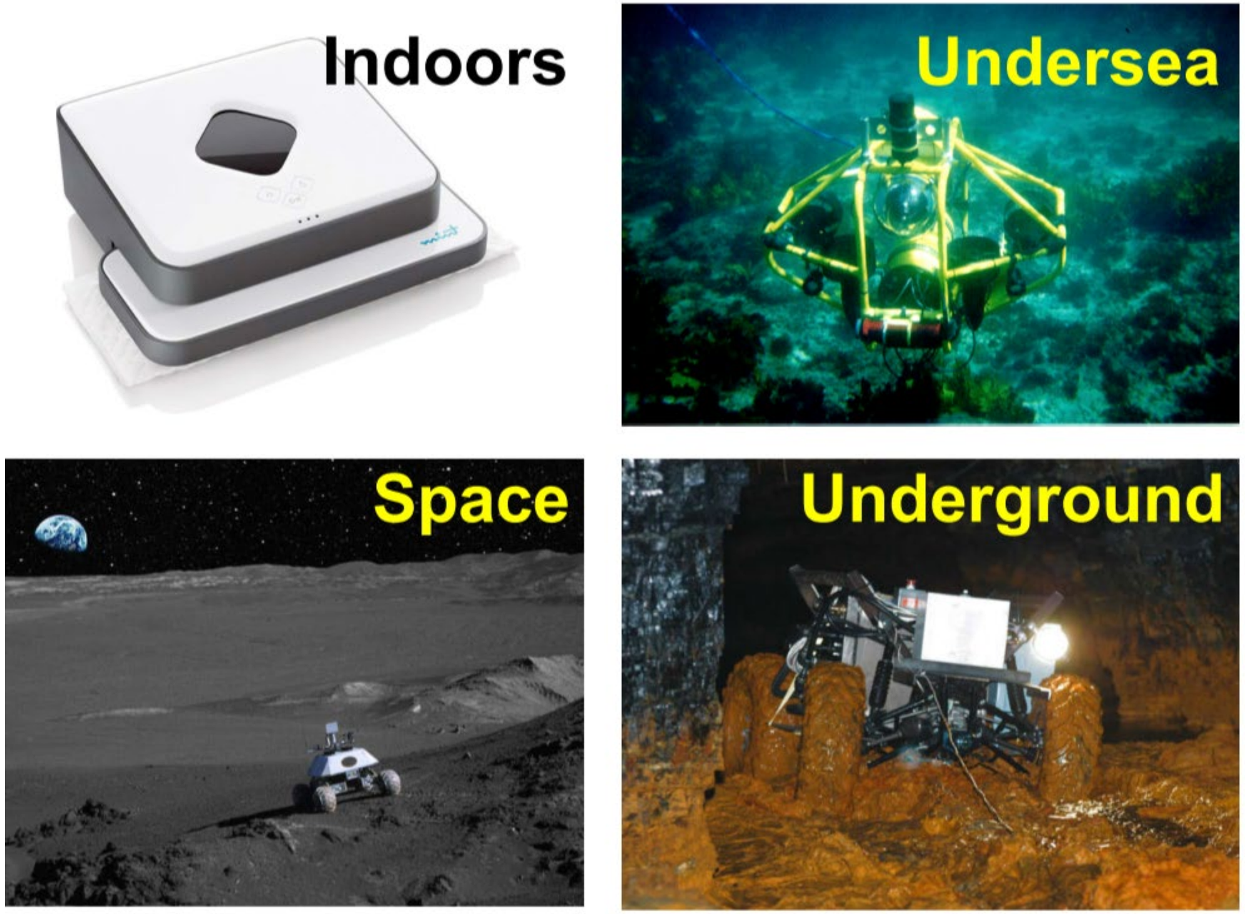
- Chicken in the Egg Problem



Courtesy: C. Stachniss

Simultaneous Localization and Mapping (SLAM)

- Essential for Autonomous Navigation in Unknown Environments



Courtesy: Evolution Robotics, H. Durrant-Whyte, NASA, S. Thrun

What makes all these problems difficult?

Uncertainty

Uncertainty: / Scale:	Continuous	Discrete
Local	Sensor noise	Data association
Global	Navigation drift	Loop closing

Courtesy of John Leonard

How do we model uncertainty?

Probability Theory!

(Review Starts Now)