

Robot Localization and Mapping

16-833

Michael Kaess

February 1, 2021

Robot Autonomy Needs Localization & Mapping



Space
[JPL]

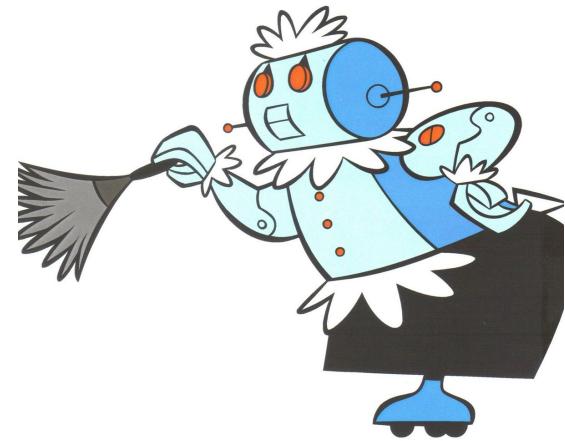
Transportation
[ArgoAI]



Drones
[Skydio]



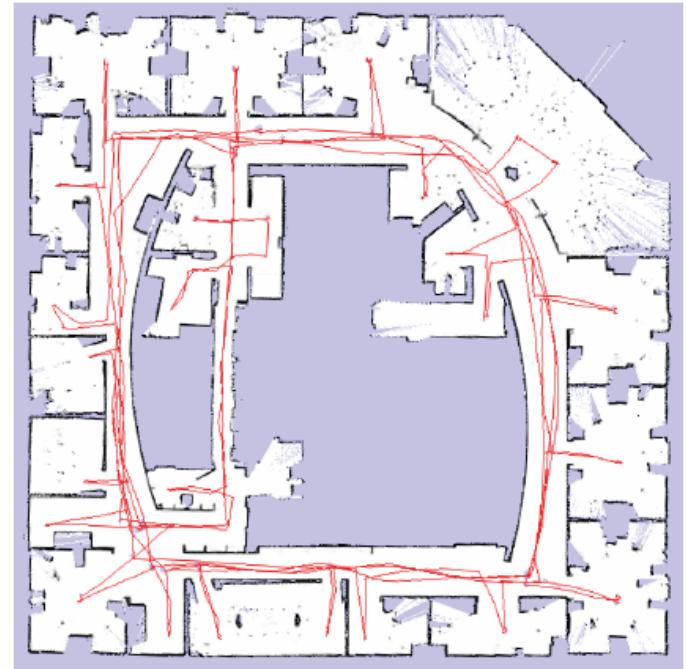
Underwater
[MIT]



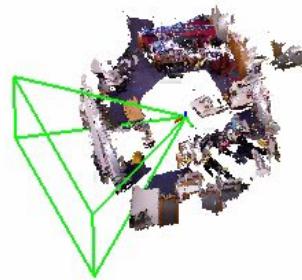
Rosie the Robot Maid
[The Jetsons, 1960s]

SLAM

- Simultaneous Localization and Mapping
 - CML (Concurrent Mapping and Localization)
 - FBN (Feature-based Navigation)
 - SMAL
- Chicken-and-egg problem:
 - Given a suitable map it's easy (relatively speaking) to localize
 - Given the exact robot pose, it's easy to build the map



SLAM Example

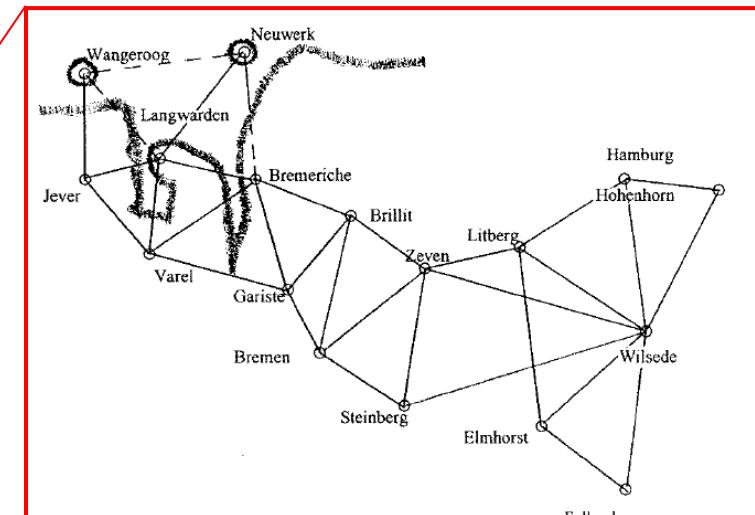


History of SLAM



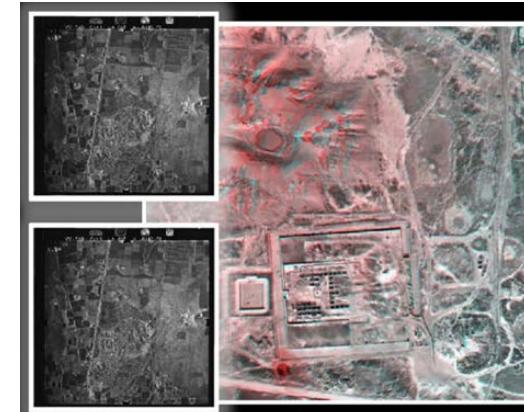
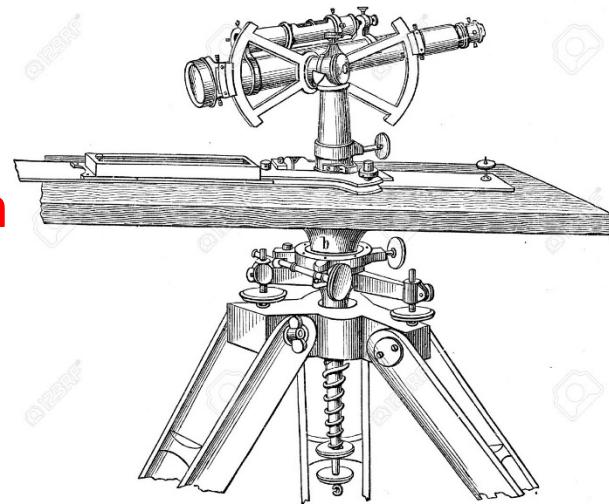
Carl Friedrich Gauss

1828: Triangulation of Kingdom of Hanover



A Brief History of SLAM

- Geodesy (2000-3000 years old)
 - “Geodesy is the science of accurately measuring and understanding the Earth geometric shape, orientation in space, and gravity field” (NOAA)
 - Using survey tools (now GPS...)
- Photogrammetry (since about 1850)
 - “Photogrammetry is the science of making measurements from photographs, especially for recovering the exact positions of surface points.” (Wikipedia)
 - Typically using imagery from satellites or planes

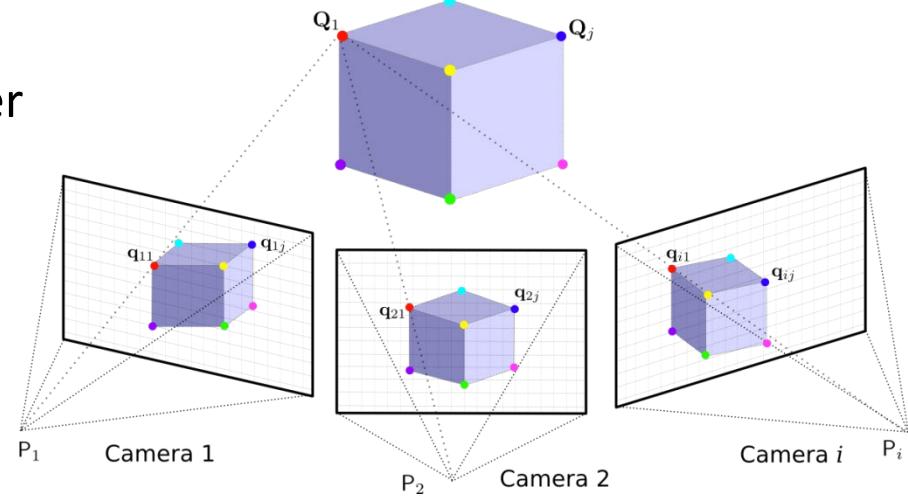


A Brief History of SLAM

- Computer Vision: (traditionally offline)

- Structure from Motion / Bundle adjustment

- Brown 1976
 - Bill Triggs 1999: seminal paper



- SLAM in Robotics: (online!)

- Sonar

- Several papers around 1989

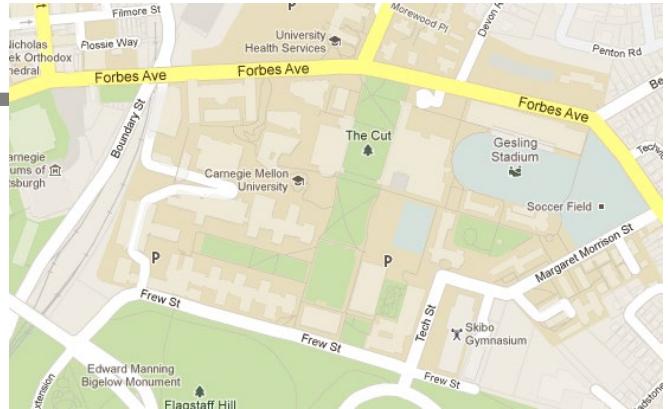
- Laser

- Vision

- Andrew Davison, PhD thesis 1998 (first real-time)

SLAM – Challenges

- Prior maps not always available (home, search-and-rescue, exploration)
- Environments change over time
- Difficult to map even if GPS is available
 - Google's driverless car uses pre-generated and manually annotated maps
 - Without GPS even more challenging
- High processing requirements for large-scale environments



Robot Localization and Mapping

- Motivation
- Class Logistics
- Overview

Course Basics

- Lecture: MW 2:20pm - 3:40pm, REMOTE
- TAs: Wei Dong, Ceci Morales, Jay Patrikar
- TA Office Hours: TBD
- Pre-requisites: Python, Matlab?, probability theory, linear algebra
- Resources:
 - Piazza: Discussion
<https://piazza.com/cmu/spring2021/16833a>
 - Canvas: Course material, assignments, grades

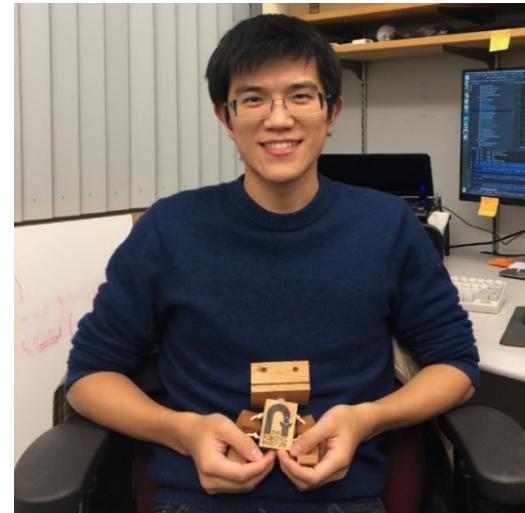
16-833 TA: Wei Dong

Email:

weidong@andrew.cmu.edu

Advised by:

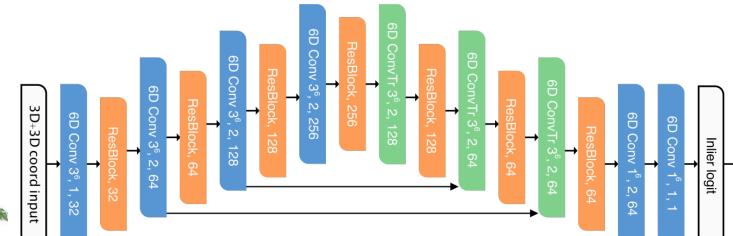
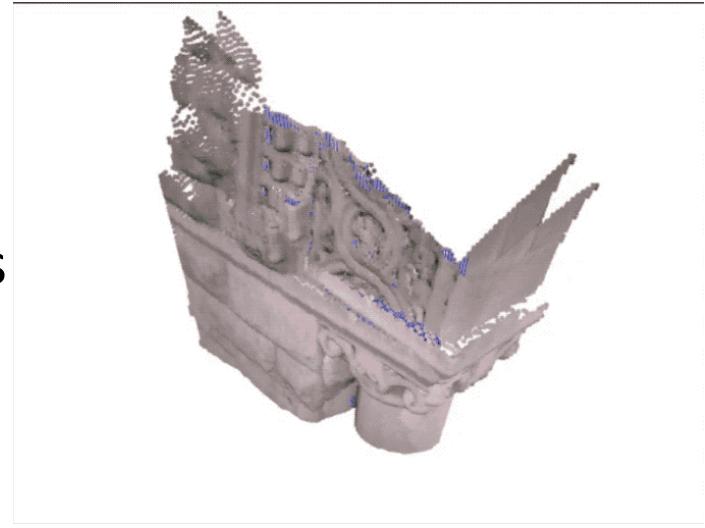
Prof. Michael Kaess



Please post your questions on Piazza first so
that everyone benefits

Research Interests

- Dense 3D reconstruction
- Learn to register 3D point clouds
- GPU accelerated 3D perception



16-833 TA: Ceci Morales

Email:

cgmorale@andrew.cmu.edu

Advised by:

Prof. Artur Dubrawski

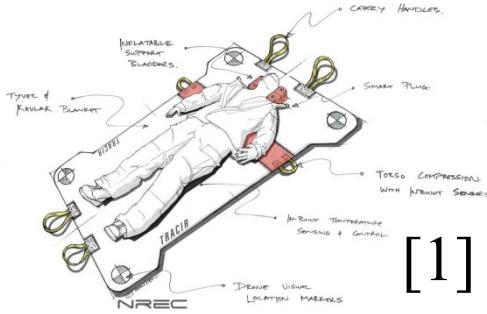


Please reach out and introduce yourself and your research! I would love to get to know you all 😊

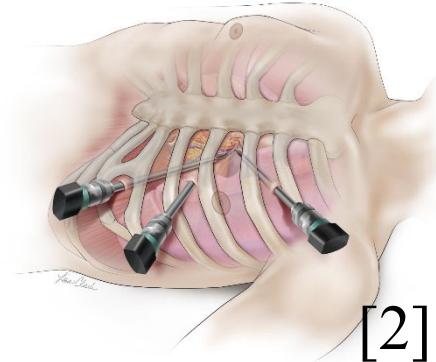
16-833 TA: Ceci Morales

Research Interests

- Diagnosis and treatment of lethal diseases
- Minimally Invasive Surgeries
- Accessible Healthcare



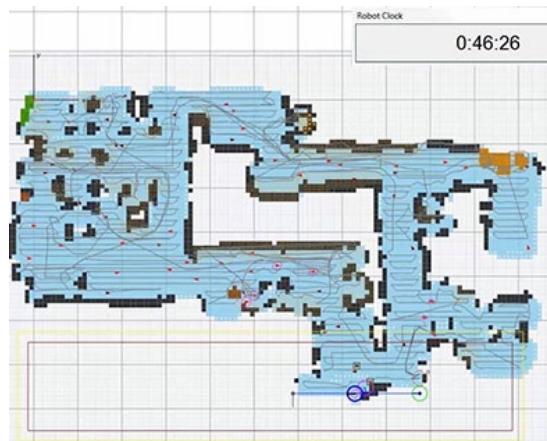
[1]



[2]

Professional Experience

- Director of all GT Systems and Lead of a SLAM group at iRobot
 - Please reach out if you have any questions about SLAM in industry



[1] <https://www.cmu.edu/news/stories/archives/2019/may/trauma-care-system.html>

[2] <https://www.sts.org/>

16-833 TA: Jay Patrikar

Email:

jpatrika@andrew.cmu.edu

Advised by:

Prof. Sebastian Scherer

Website: jaypatrikar.me



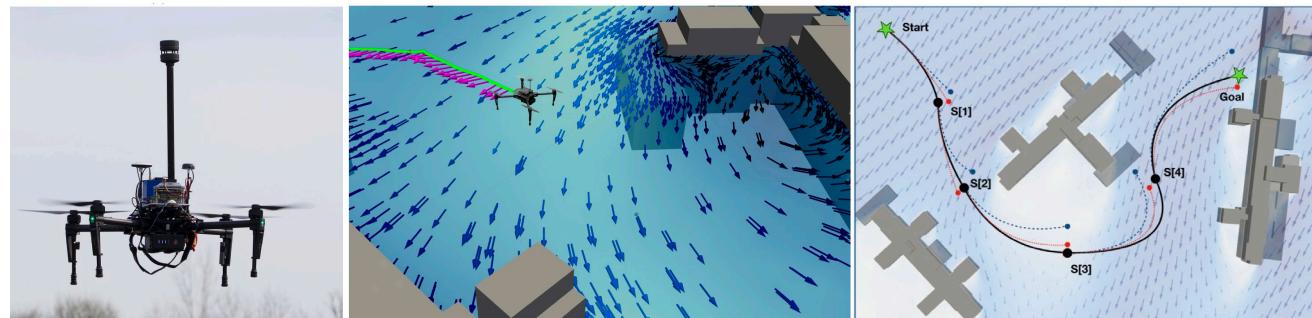
16-833 TA: Jay Patrikar

Research Interests

- Long-Range Object Detection and Triangulation



- Wind Estimation and Kinodynamic Path Planning for UAVs



Michael Kaess

Associate Research Professor

kaess@cmu.edu

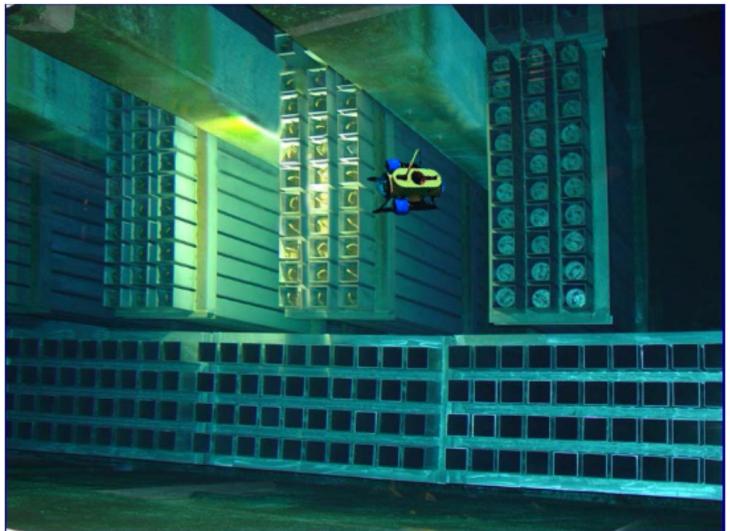
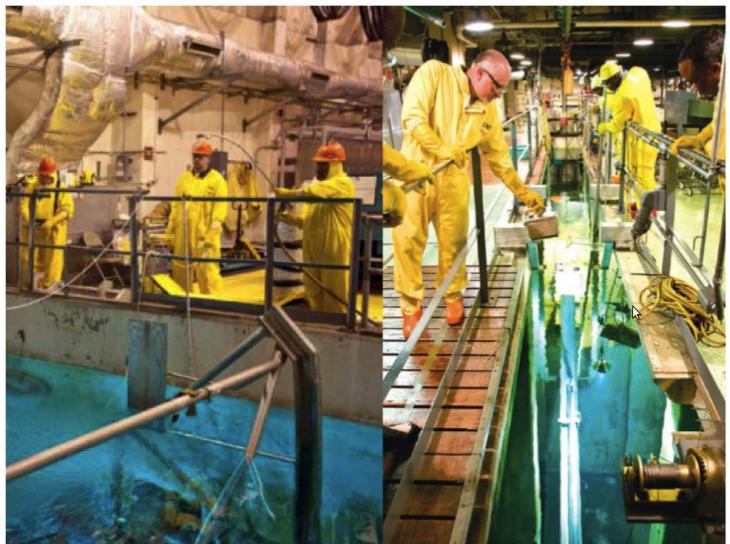
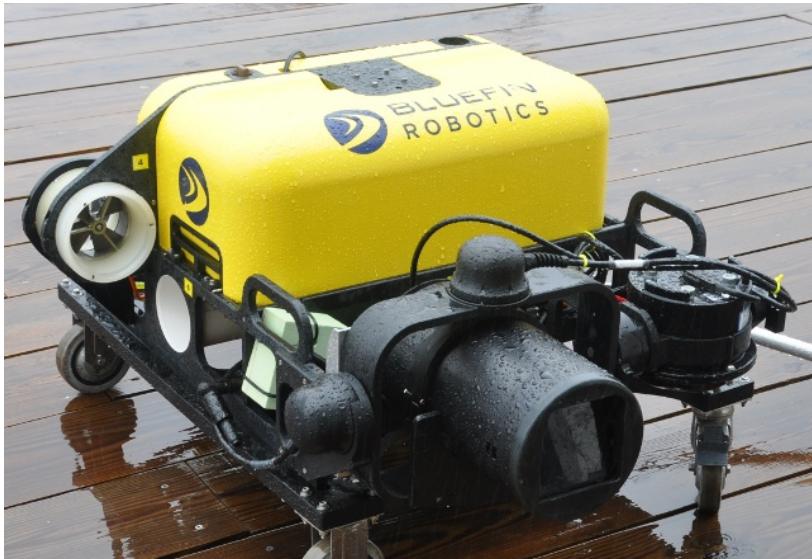
Research Interests:

- Localization and Mapping
- Robust and Large-scale Inference
- Inertial Fusion
- Underwater Robotics

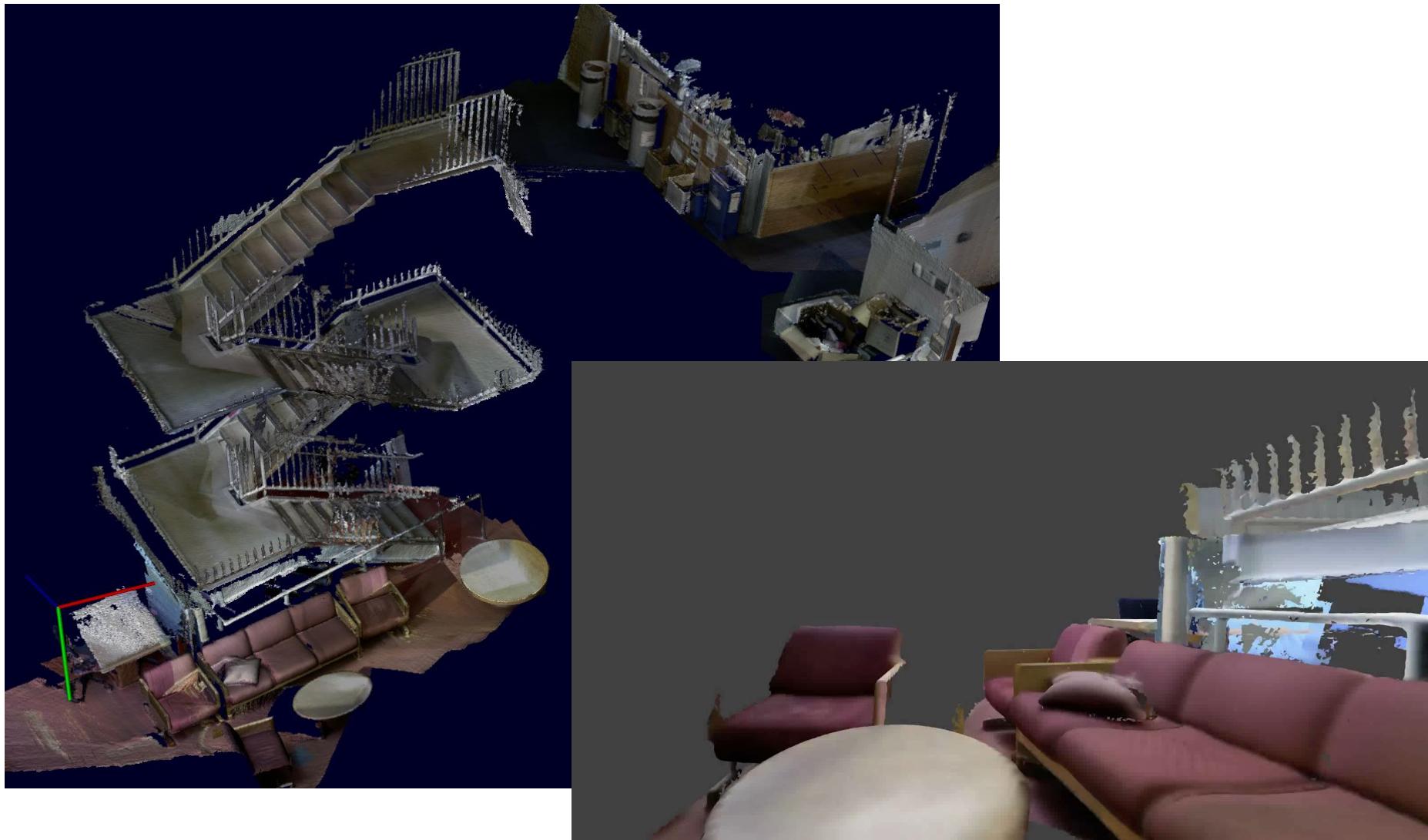


Underwater Robotics

Working in challenging and dangerous environments



Real-time Dense 3D Modeling



GPS-denied Navigation

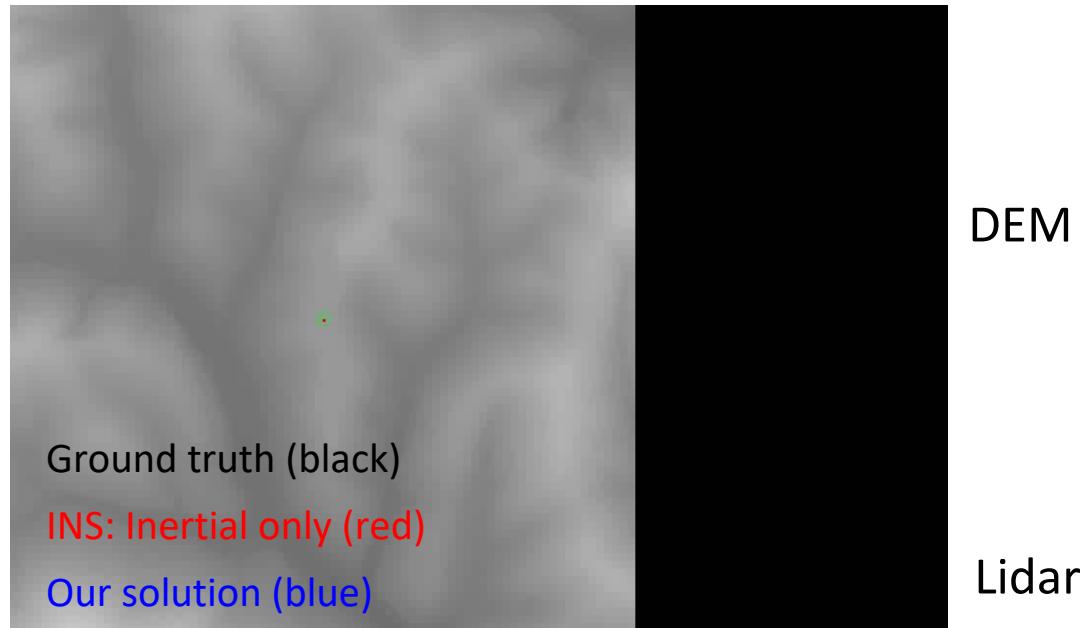
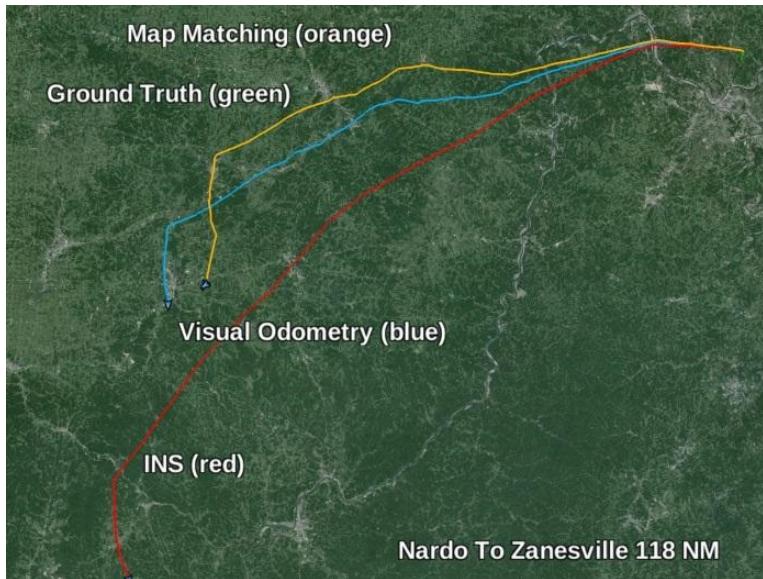
Low and bounded navigation drift without GPS

Lidar localization against digital elevation model (DEM)

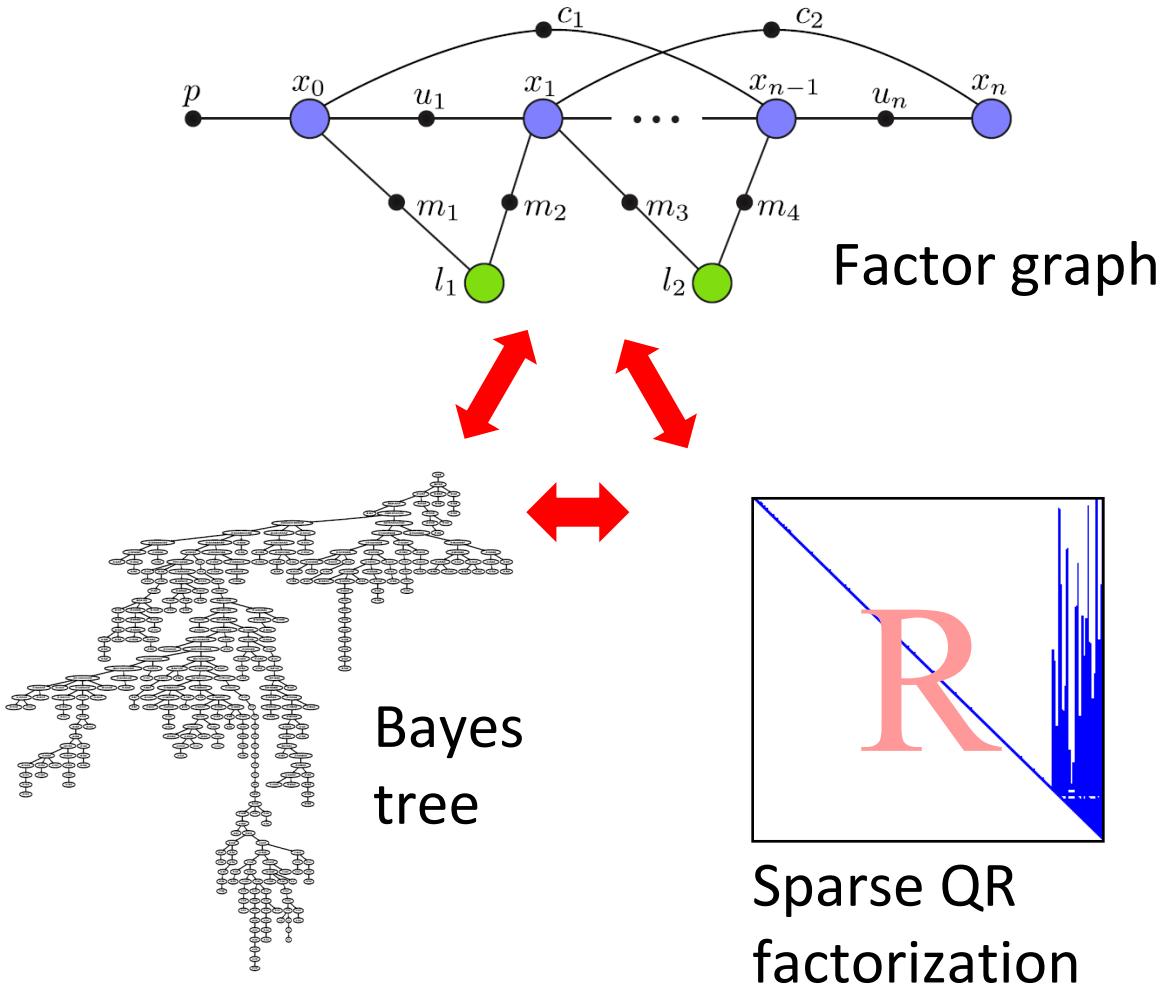
Fusing with inertial data to provide low drift navigation

Flight distance 118nm = **218km**

Landing position error < **40m**



Efficient and Robust Inference



Topics

- Probabilities, Gaussians, Covariances
- Particle filter
- Kalman filter, EKF
- Simultaneous localization and mapping
- Least-squares
- Nonlinear least-squares
- Graphical-model-based inference
- Rigid-body transformations and manifolds
- Data association
- SLAM systems including front-ends

Resources

- Book: “Probabilistic Robotics”, Thrun, Burgard, Fox, 2005
- “Factor Graphs for Robot Perception”, Dellaert and Kaess, Foundations and Trends in Robotics, vol. 6, no. 1-2, pp. 1-139, Aug. 2017 (pdf on Canvas)

Assignments

- 60% Four Problem Sets
 - Particle Filters
 - EKF
 - Smoothing / Nonlinear Optimization
 - Dense Mapping
- 10% Participation
 - Quiz (optional)
 - Reading
- 30% Course Project
 - Proposal (5%)
 - Midterm report (5%)
 - Presentation (10%)
 - Report (10%)

Course Project

- The topic of the final project should be closely related to the course. It should be either of the following:
 - An algorithmic or theoretical contribution that extends the current state-of-the-art
 - An implementation of a state-of-the-art algorithm using real-world data and/or robots.
- Team: 3-5 students
- Deliverables:
 - Presentation in class
 - Paper (IEEE style, 6-8 pages)
 - Source code

Programming Language

- Official language of the course is Python
 - Assignments in Python (or Matlab)
 - If you're new to Python (or Matlab), team up with someone more familiar with it
- Course Project
 - Your choice of programming language

Late Submission Policy

- Before deadline: 100% (get some good sleep!)
 - Within 48 hours after the deadline: 50%
 - After 48 hours: 0% (still must submit something!)
-
- To help with unexpected situations, you have a total of **4 late days** that can be used on any of the 4 homework assignments

Integrity

- All encouraged to work together BUT you must do your own work (code and write up)
- If you work with someone, please include their name in your write up and inside any code that has been discussed
- If we find highly identical write-ups or code without proper accreditation of collaborators, we will take action according to university policies. **You will fail the course!**
- I reserve the right to use automated software to find duplicate code and writeup in submissions

Health

Take care of yourself. Do your best to maintain a healthy lifestyle this semester by eating well, exercising, avoiding drugs and alcohol, getting enough sleep and taking some time to relax. This will help you achieve your goals and cope with stress.

All of us benefit from support during times of struggle. You are not alone. There are many helpful resources available on campus and an important part of the college experience is learning how to ask for help. Asking for support sooner rather than later is often helpful.

If you or anyone you know experiences any academic stress, difficult life events, or feelings like anxiety or depression, we strongly encourage you to seek support. Counseling and Psychological Services (CaPS) is here to help: call [412-268-2922](tel:412-268-2922) and visit their website at <http://www.cmu.edu/counseling/>. Consider reaching out to a friend, faculty or family member you trust for help getting connected to the support that can help.

Robot Localization and Mapping

- Motivation
- Class Logistics
- **Overview**

Perception: Sensors



\$0.02



\$5



\$200



\$2000



\$75000



\$4000



Courtesy E. Olson

Perception: Sensor Data

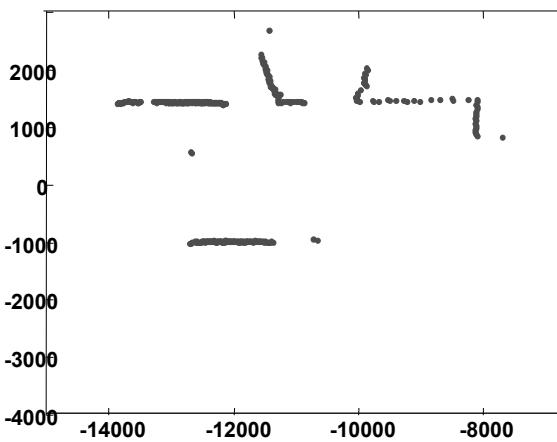
Camera image



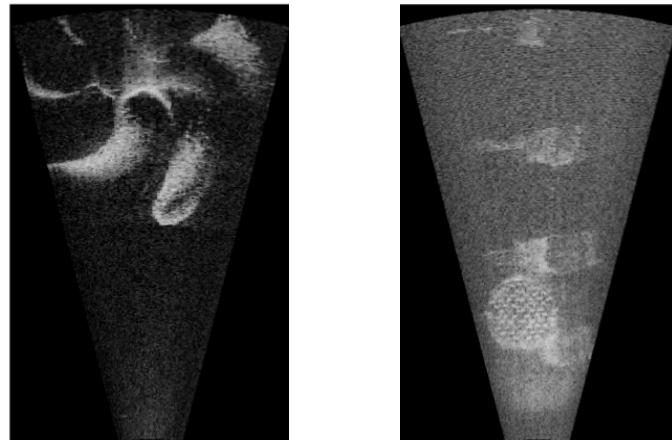
RGB-D image



2D laser scan



Multi-beam sonar (profiling and imaging)



Localization and Mapping

- State Estimation
 - Most common example: GPS + Inertial
- Localization
 - Estimating robot's location/orientation given a prior map
- Mapping
 - Building a map given known robot location and orientation
- Simultaneous Localization and Mapping

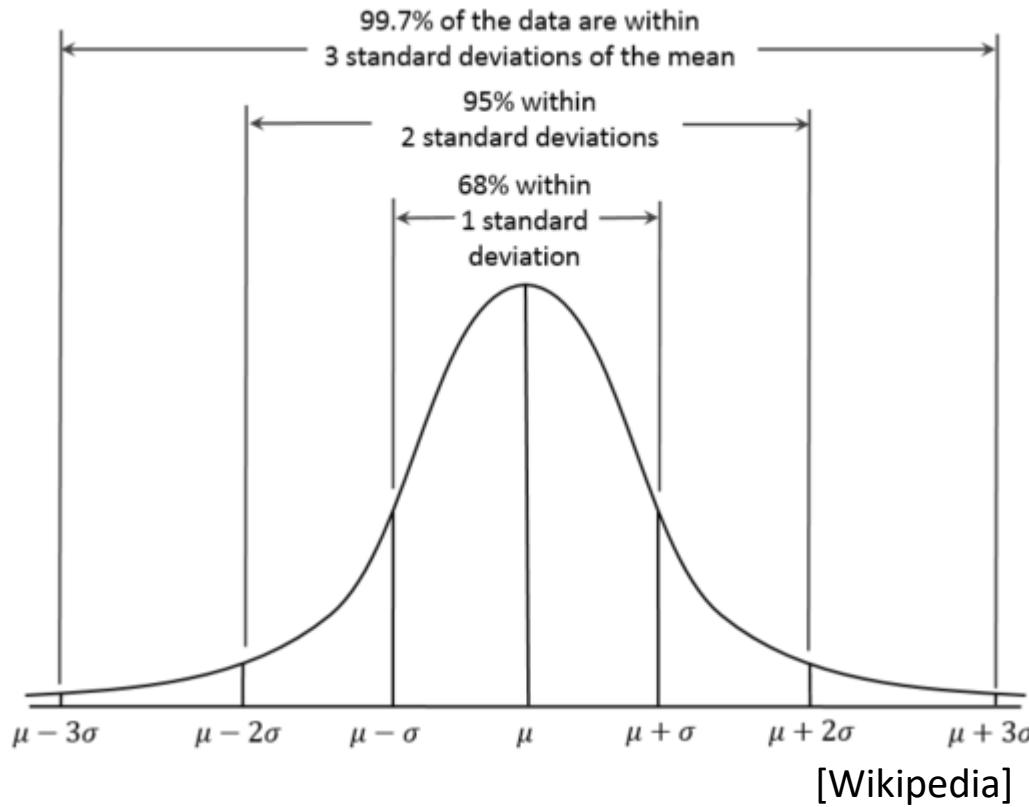
- Static vs Dynamic
- Tracking

State

- Position
 - Orientation
 - Velocity
 - Sensor calibration
-
- Current pose vs trajectory
 - Discrete vs continuous trajectory
 - 2D vs 3D

Uncertainty in State Estimate

- Normal density

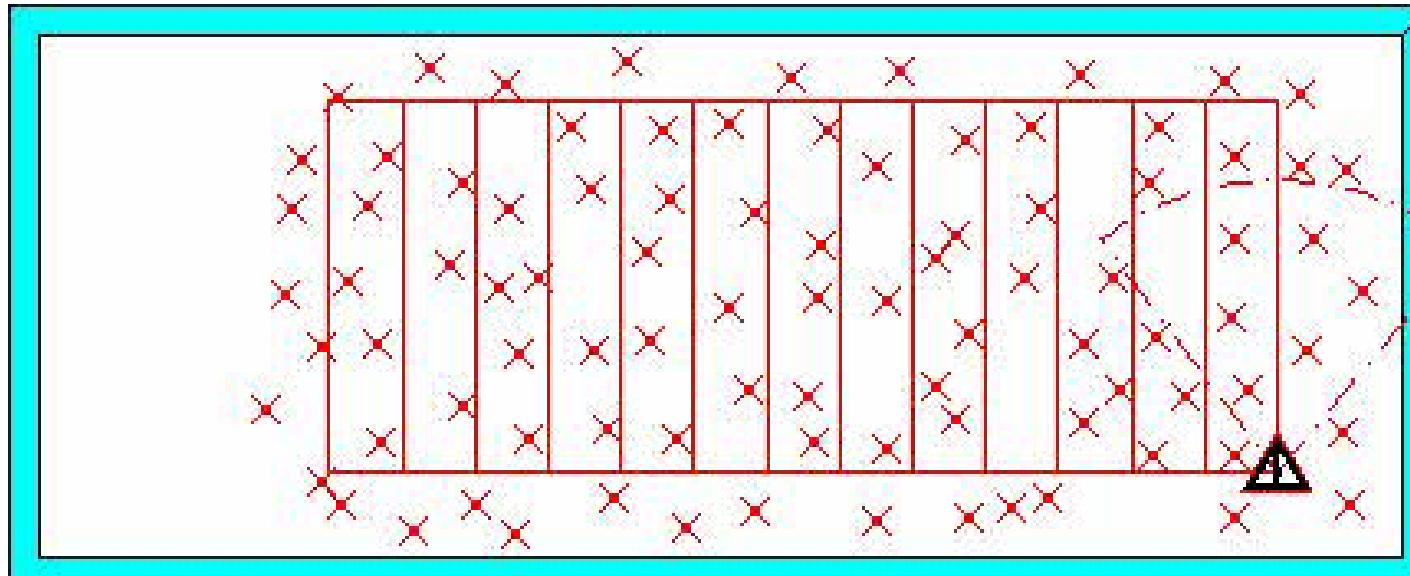


Choices for Map Representation

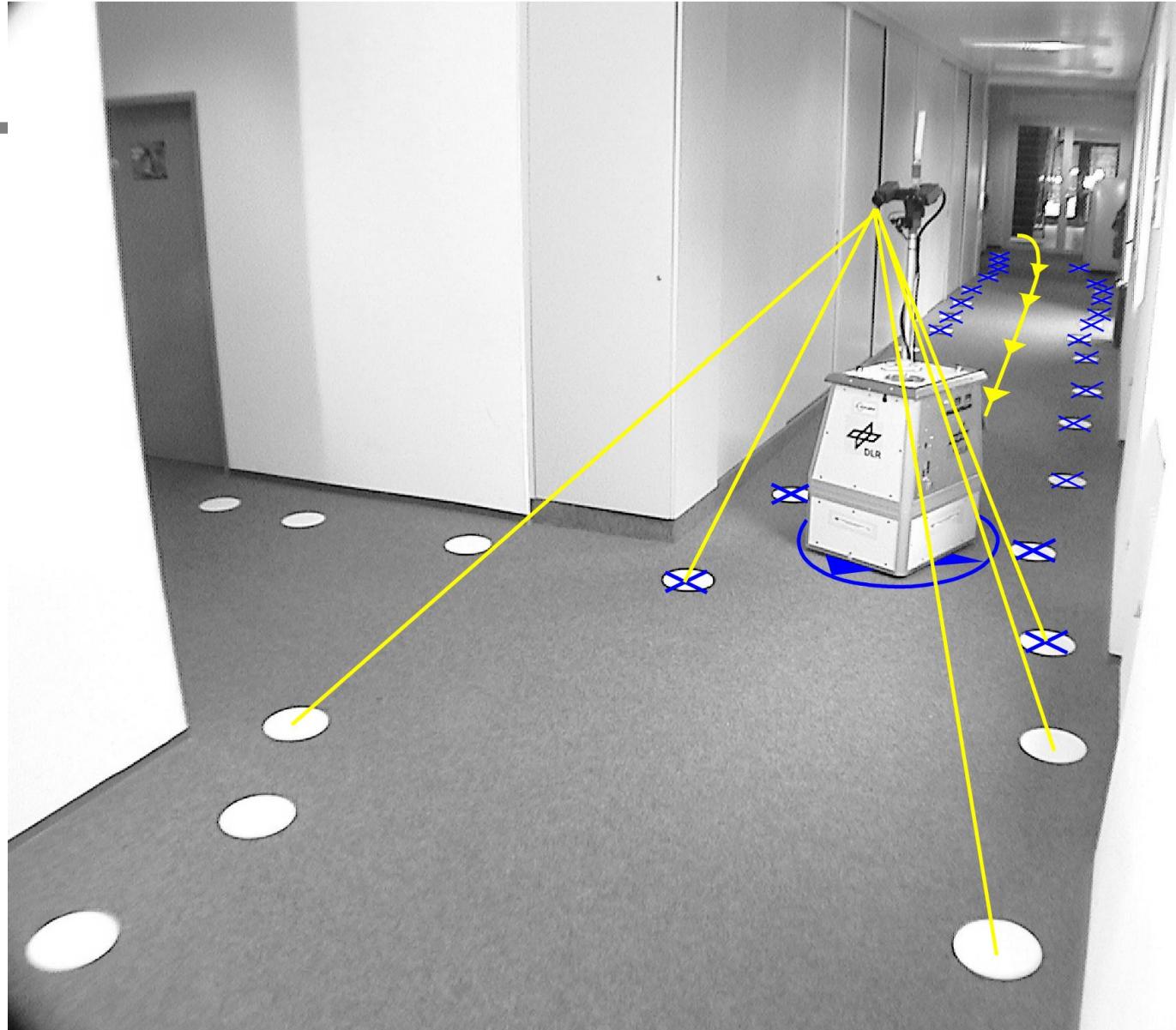
- Features / landmarks
- Occupancy grid
- Poses + raw sensor data
- Point cloud
- Surfaces: triangle mesh, planar patches, implicit representation
- Topological

Feature-based SLAM: Points

- 1. Move
- 2. Sense
- 3. Associate measurements with known features
- 4. Update state estimates for robot and previously mapped features
- 5. Find new features from unassociated measurements
- 6. Initialize new features



Courtesy J. Leonard



http://www.informatik.uni-bremen.de/~ufrese/slamvideos1_e.html Courtesy U. Frese

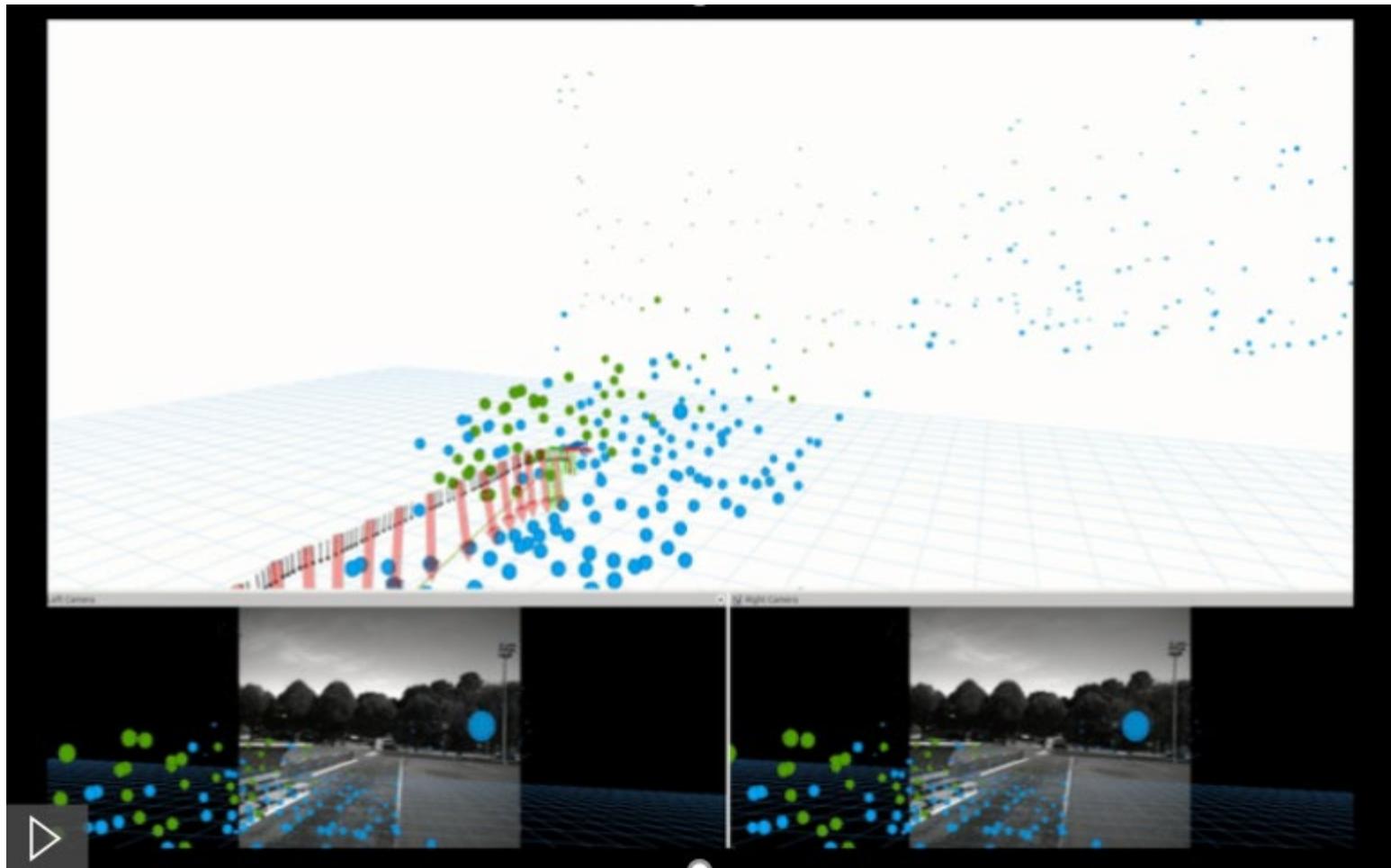


Mapping

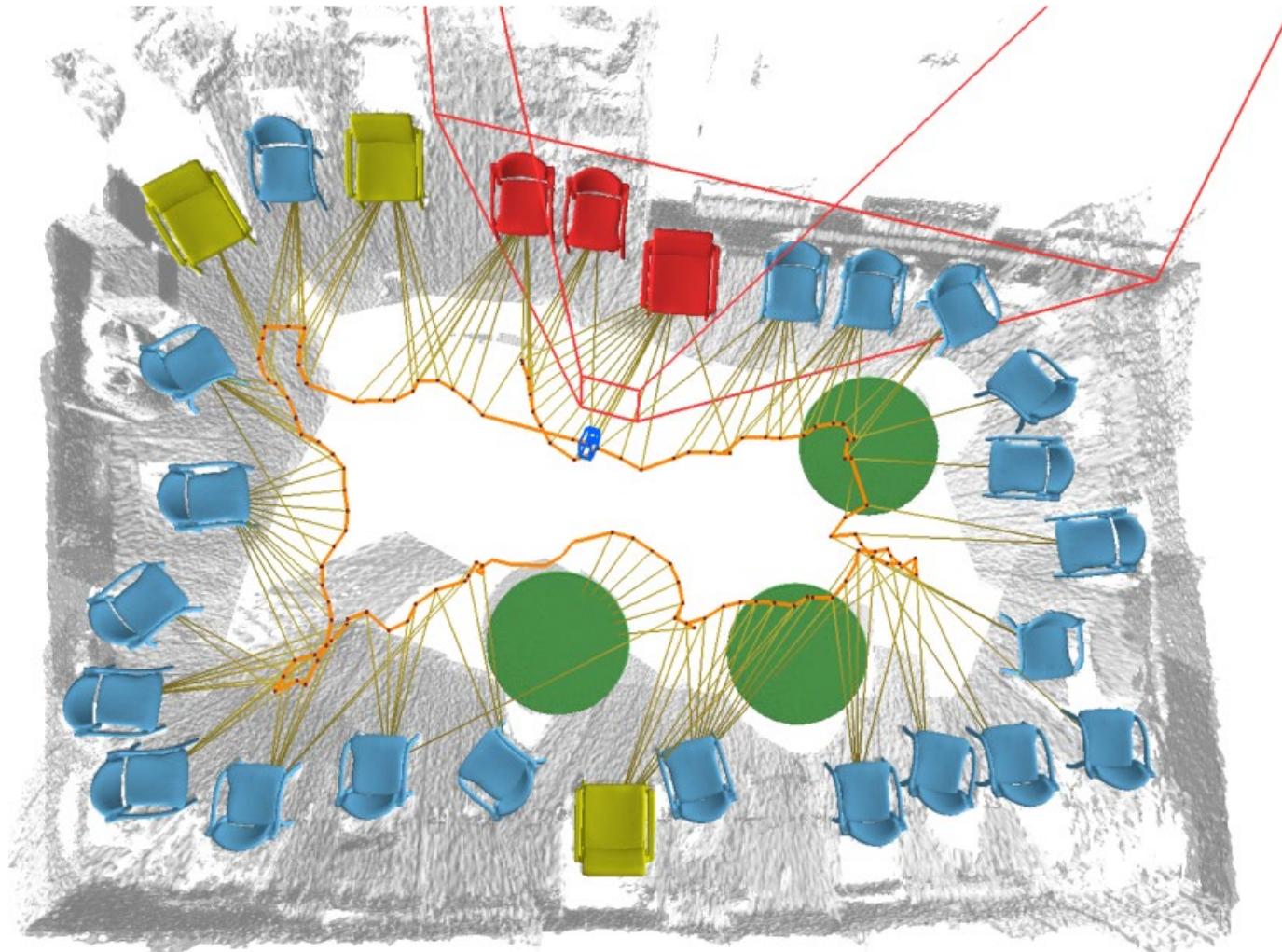
http://www.informatik.uni-bremen.de/~ufrese/slamvideos1_e.html

Courtesy U. Frese

Features: Interest Points from Vision



Features: Chairs



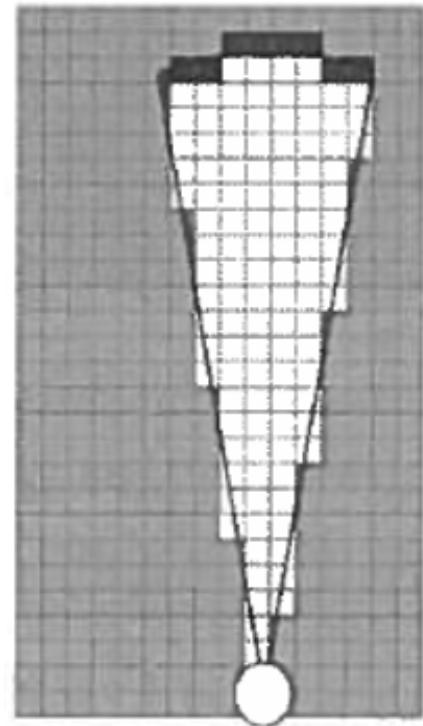
SLAM++, Salas-Moreno et al, CVPR 2013

Choices for Map Representation

- Features / landmarks
- **Occupancy grid**
- Poses + raw sensor data
- Point cloud
- Surfaces: triangle mesh, planar patches, implicit representation
- Topological

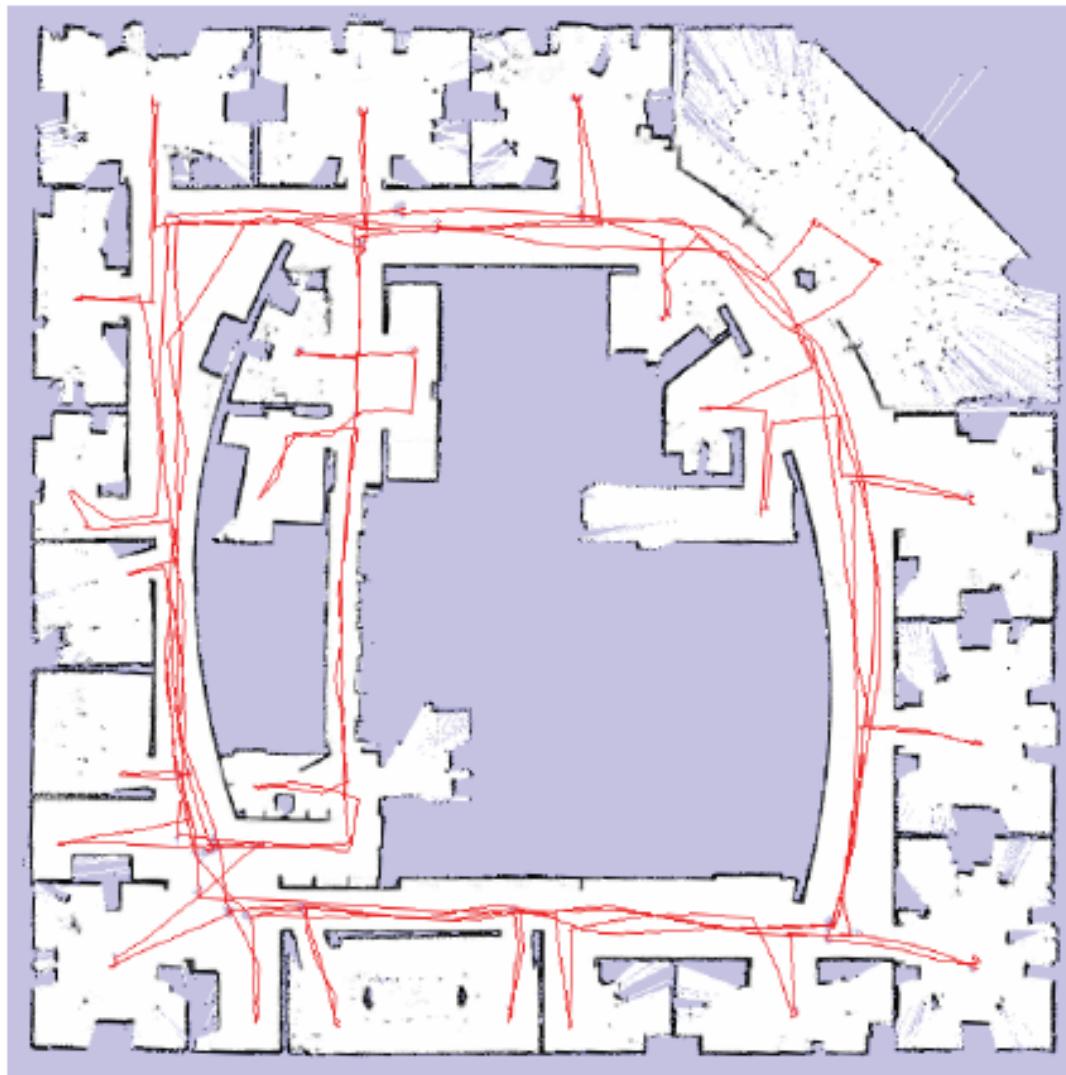
Occupancy Grid Map

- Discretize space into grid cells
- For each cell independently estimate probability of being occupied
- Efficient implementation using “log-odds”



[Moravec, Elfes, “High resolution maps from wide angle sonar”, ICRA 1985]

Occupancy Grid Laser Map

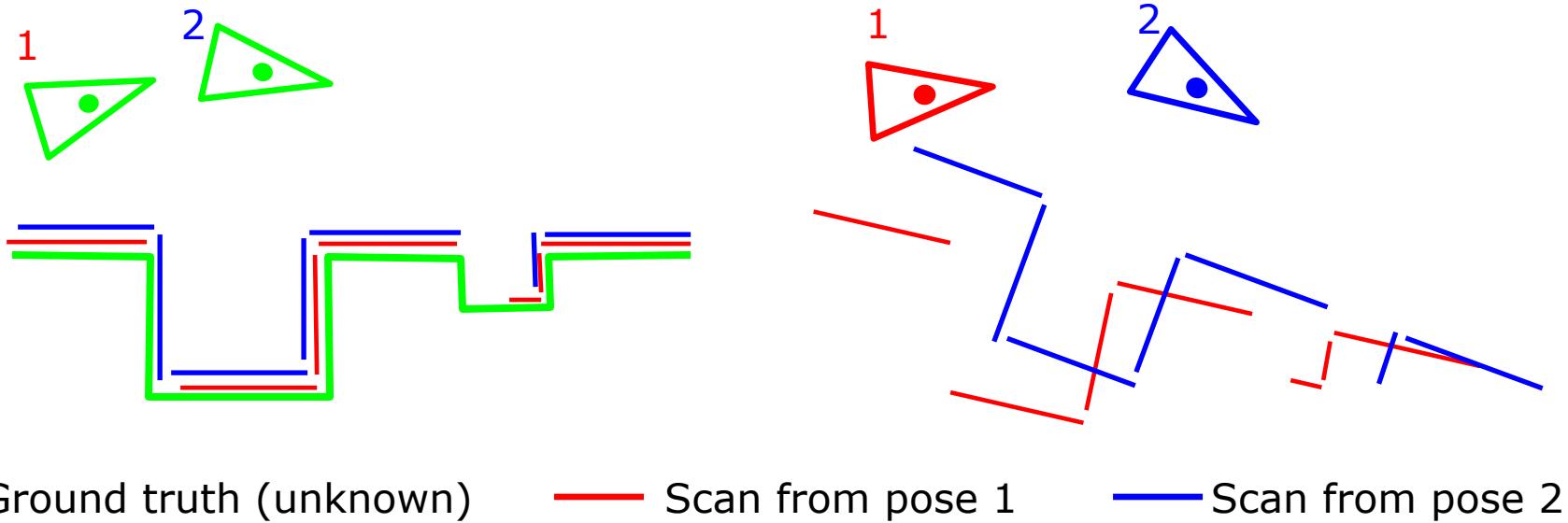


Choices for Map Representation

- Features / landmarks
- Occupancy grid
- **Poses + raw sensor data**
- Point cloud
- Surfaces: triangle mesh, planar patches, implicit representation
- Topological

Representation: Poses and Scans

- Robot scans, moves, scans again
- Short-term odometry error causes misregistration of scans
- Scan matching is the process of bringing these scans into alignment



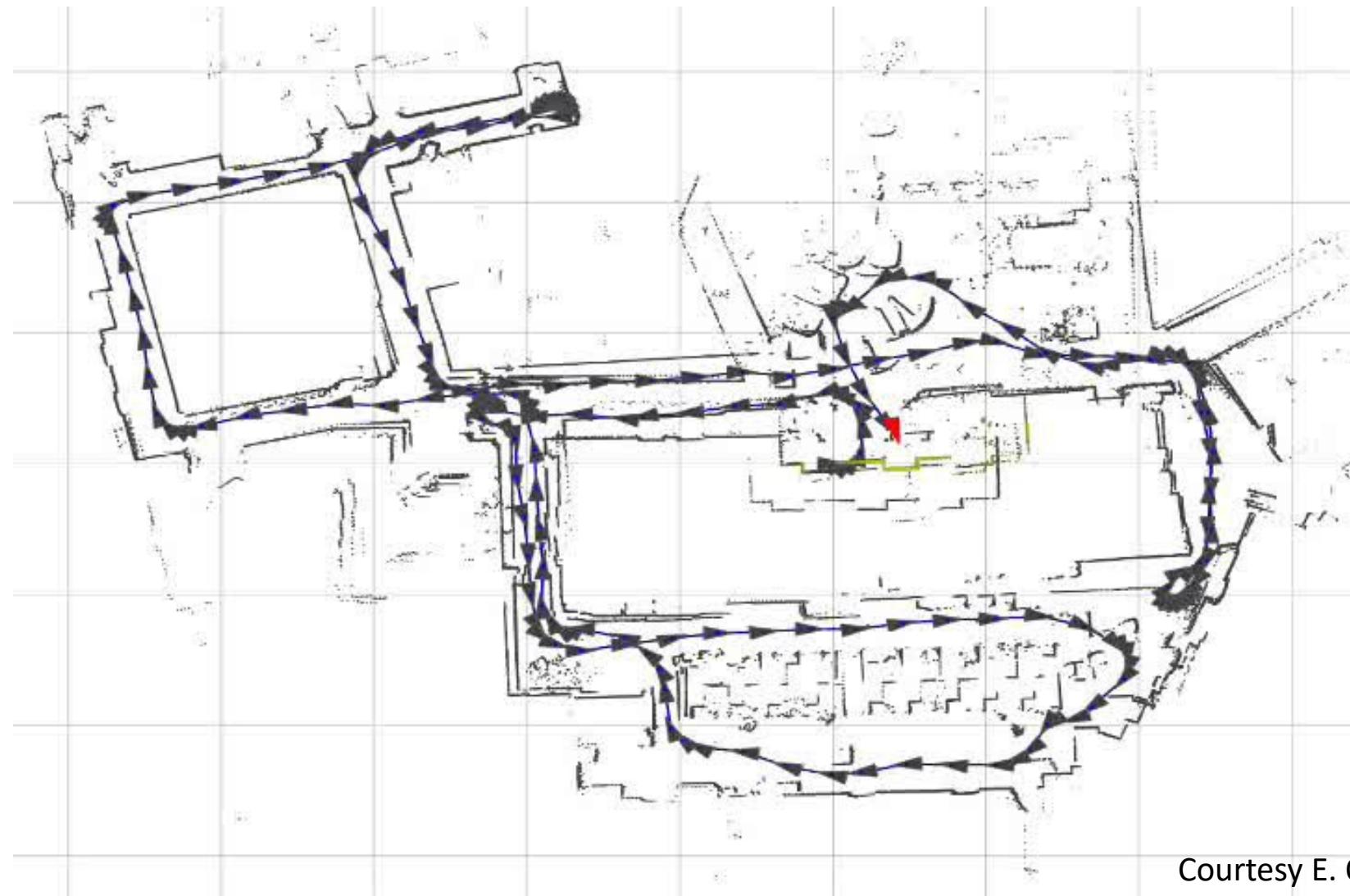
Courtesy J. Leonard

SLAM Based on Laser Scan Matching



Olsen 2005

SLAM Based on Laser Scan Matching

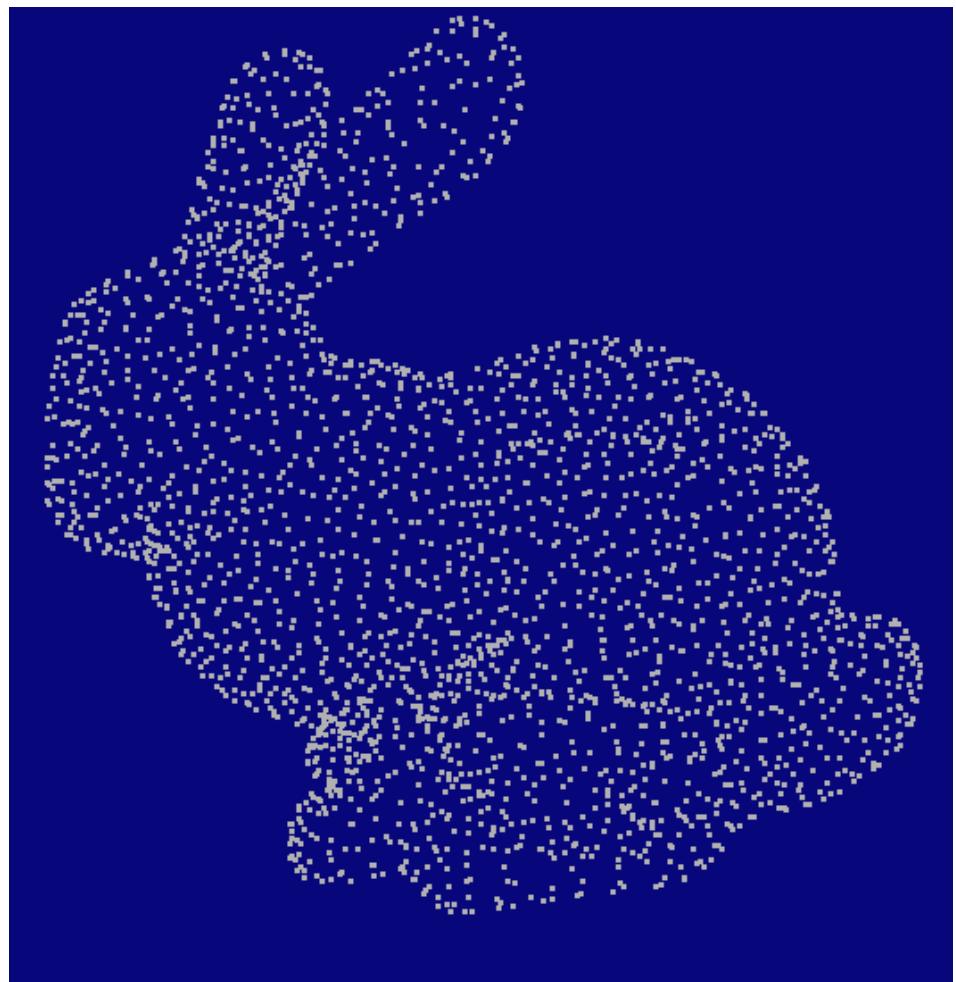
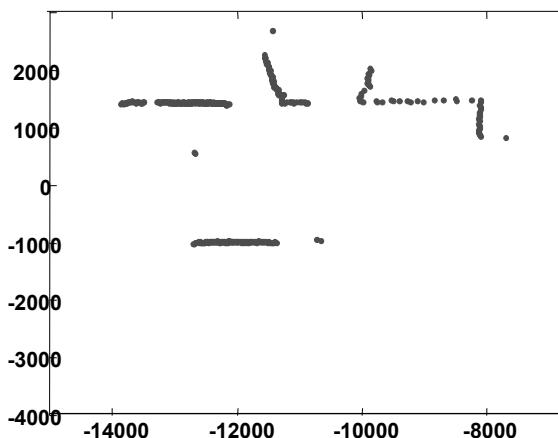


Courtesy E. Olson

Choices for Map Representation

- Features / landmarks
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- **Point cloud**
- Surfaces: triangle mesh, planar patches, implicit representation
- Topological

Point Cloud



Point Cloud Example

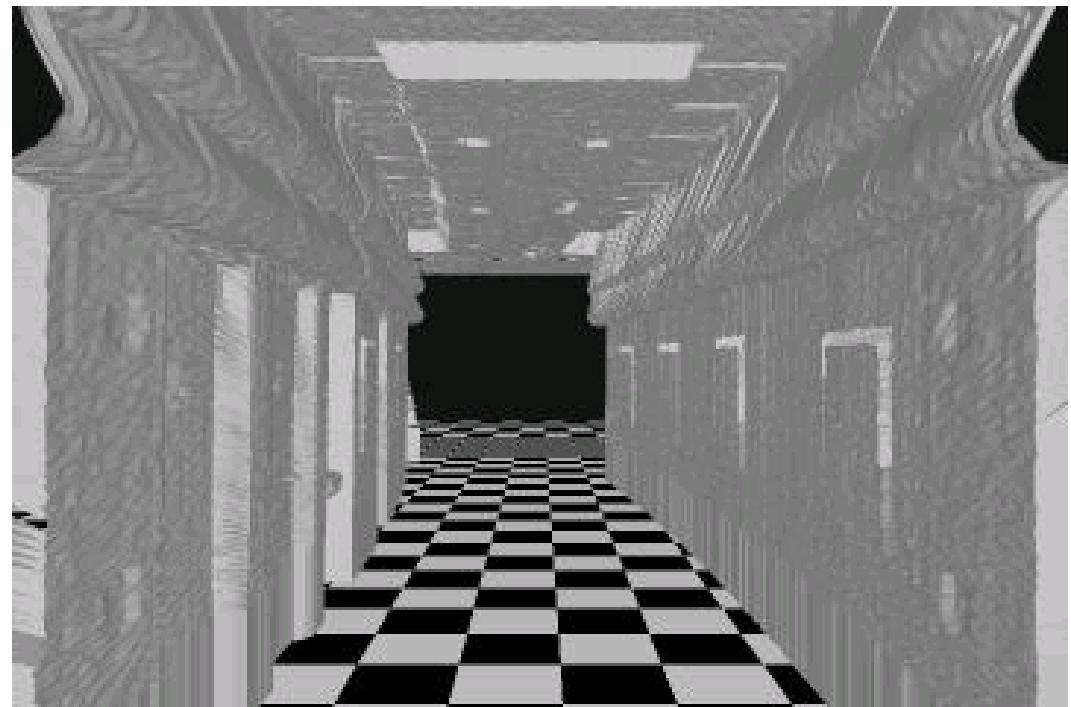
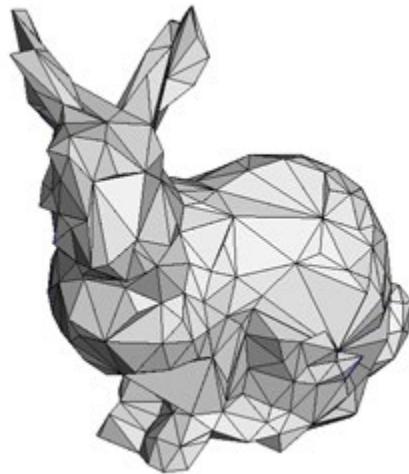


FRC machine shop, courtesy Ji Zhang

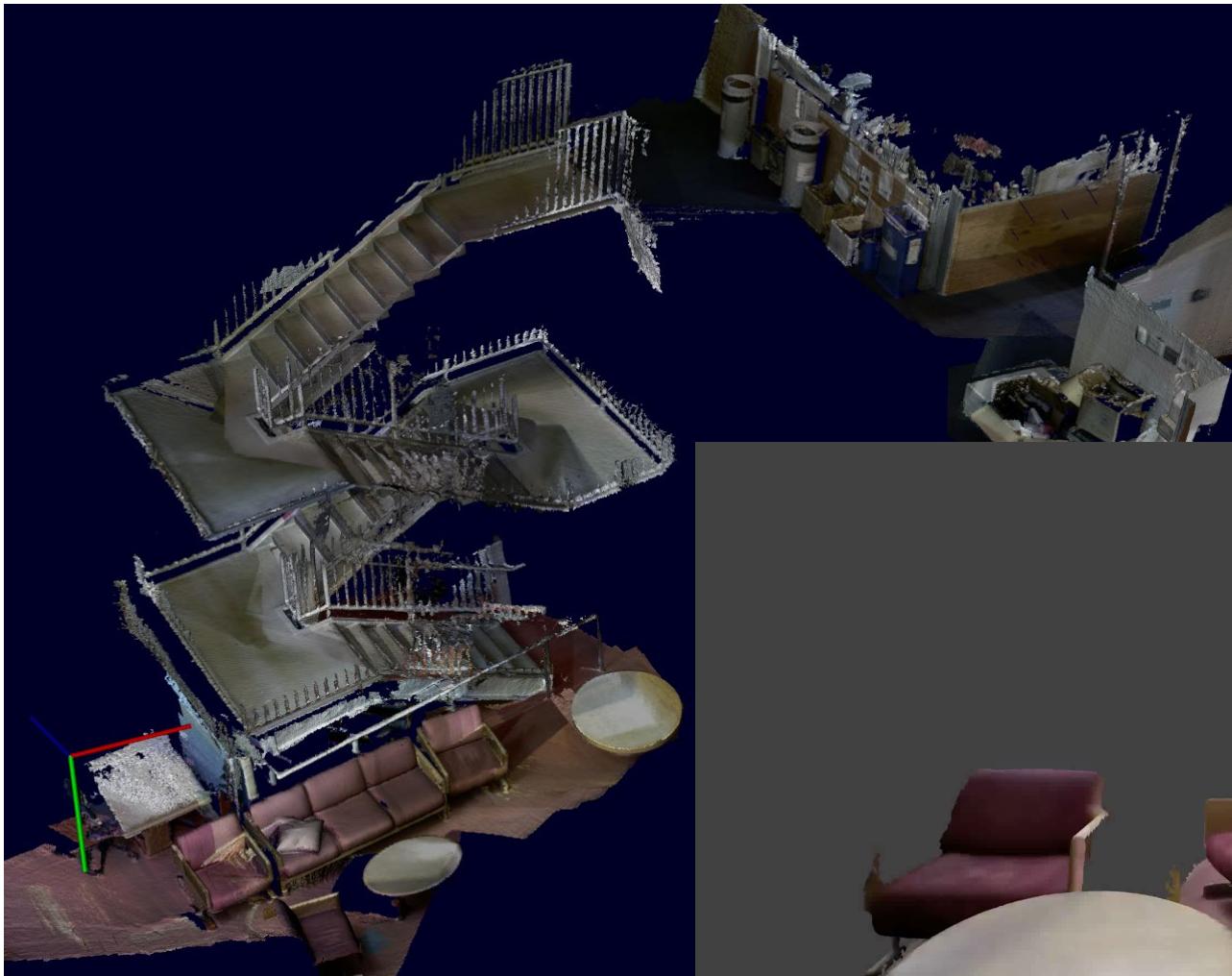
Choices for Map Representation

- Features / landmarks
- Occupancy grid
- Poses + raw sensor data
- Point cloud
- **Surfaces: triangle mesh, planar patches, implicit representation**
- Topological

Triangle Mesh



Surface Representations: Triangle Mesh



- Handheld RGB-D sensor (\$180)
- Real-time with GPU processing

Surface Representations: Implicit and Planar

Implicit (Signed Distance Function)

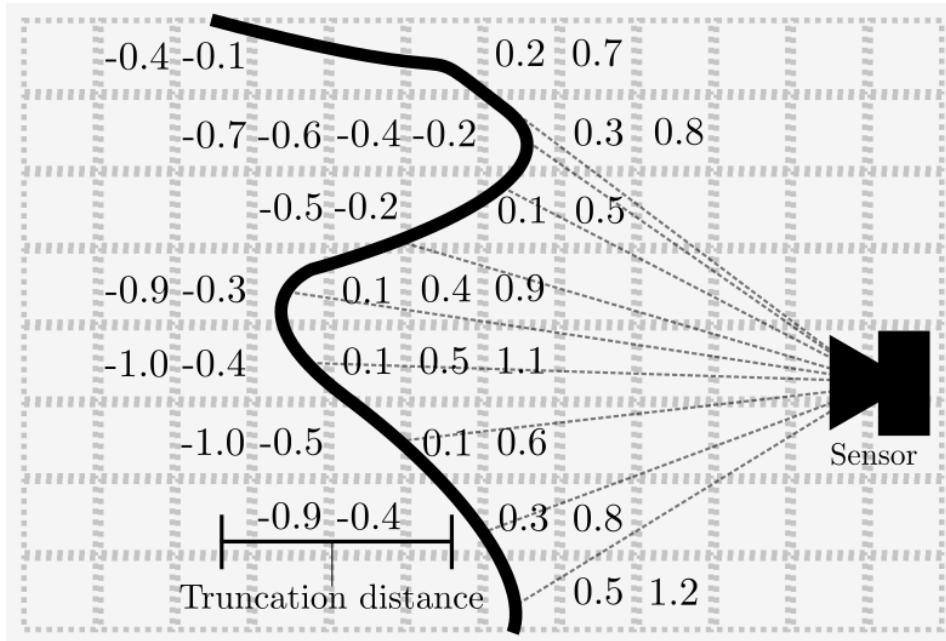
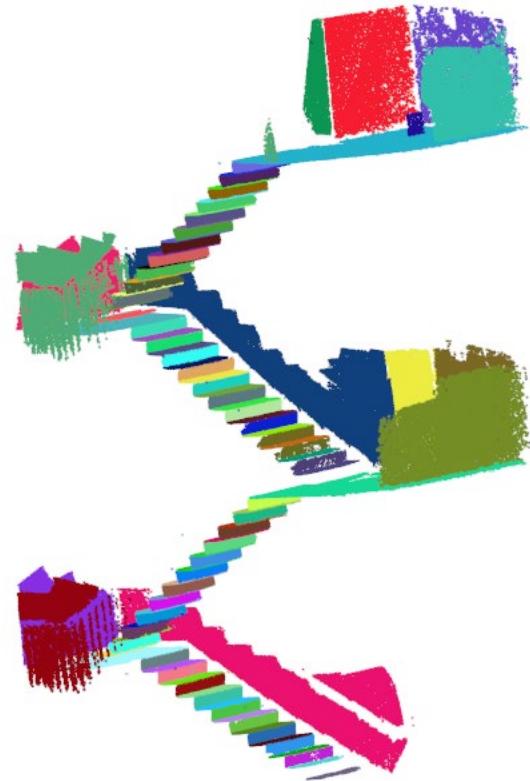


Figure 1: Two dimensional example of the structure of the truncated signed distance function representation of an implicit surface. Shown are example signed distance values stored at voxels within the truncation distance of the observed surface, with rays cast from the observing sensor.

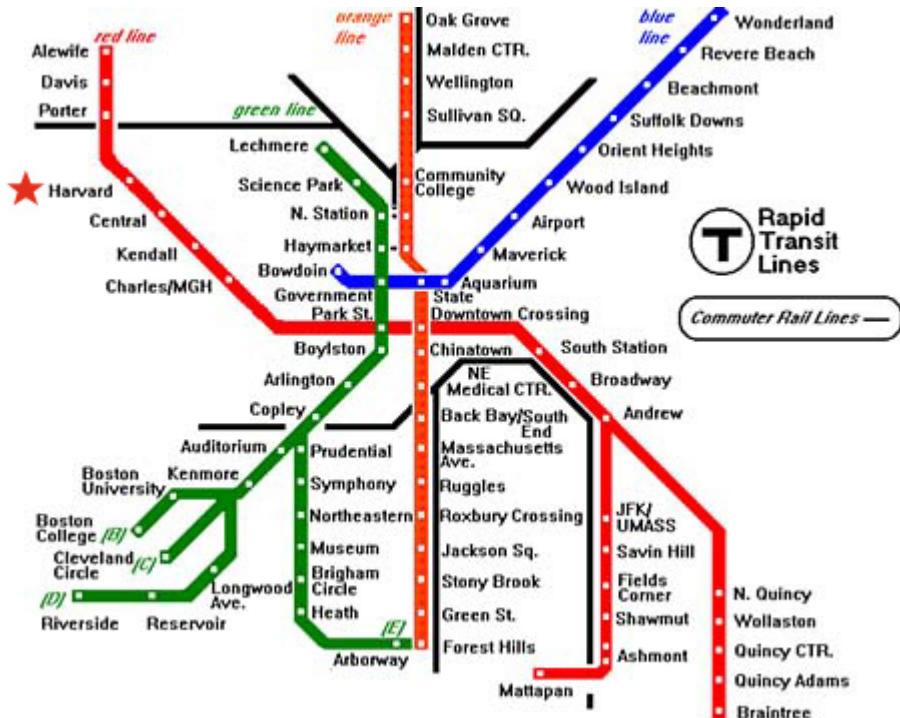
Planar surface patches



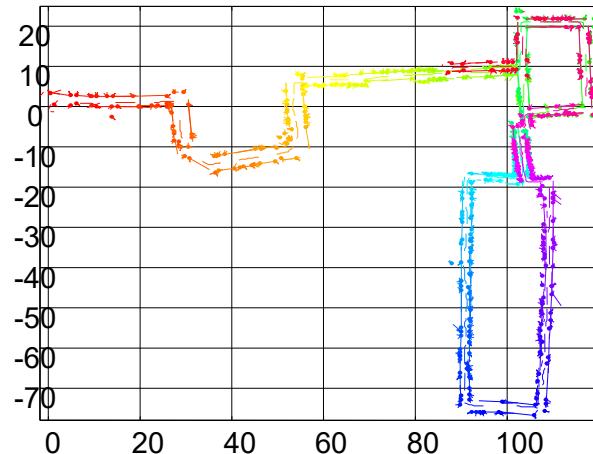
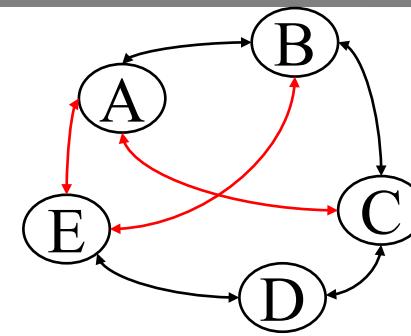
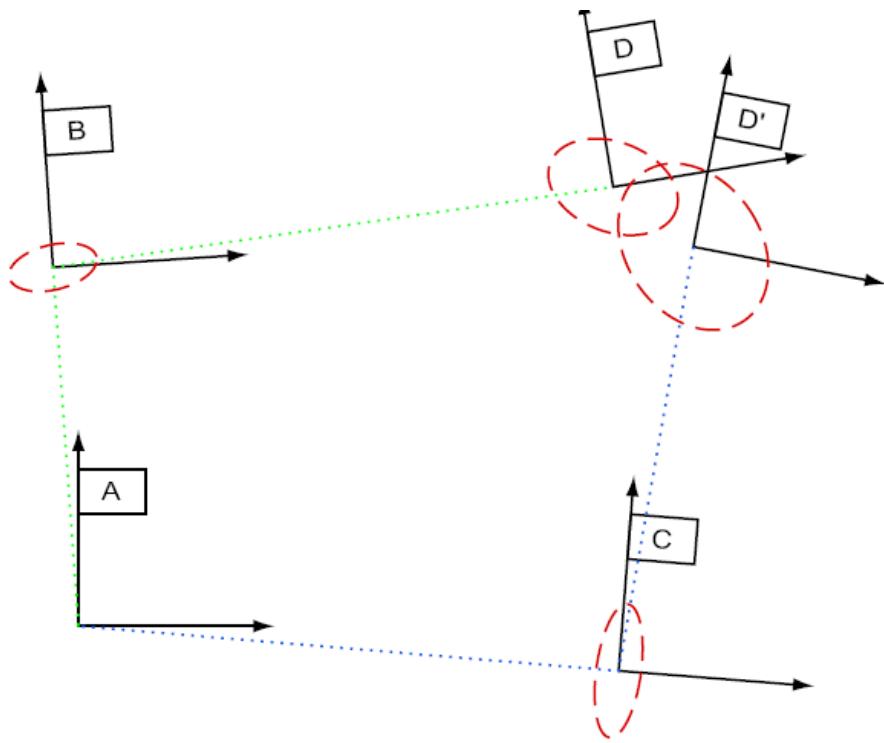
Choices for Map Representation

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Topologic vs. Geometric Maps



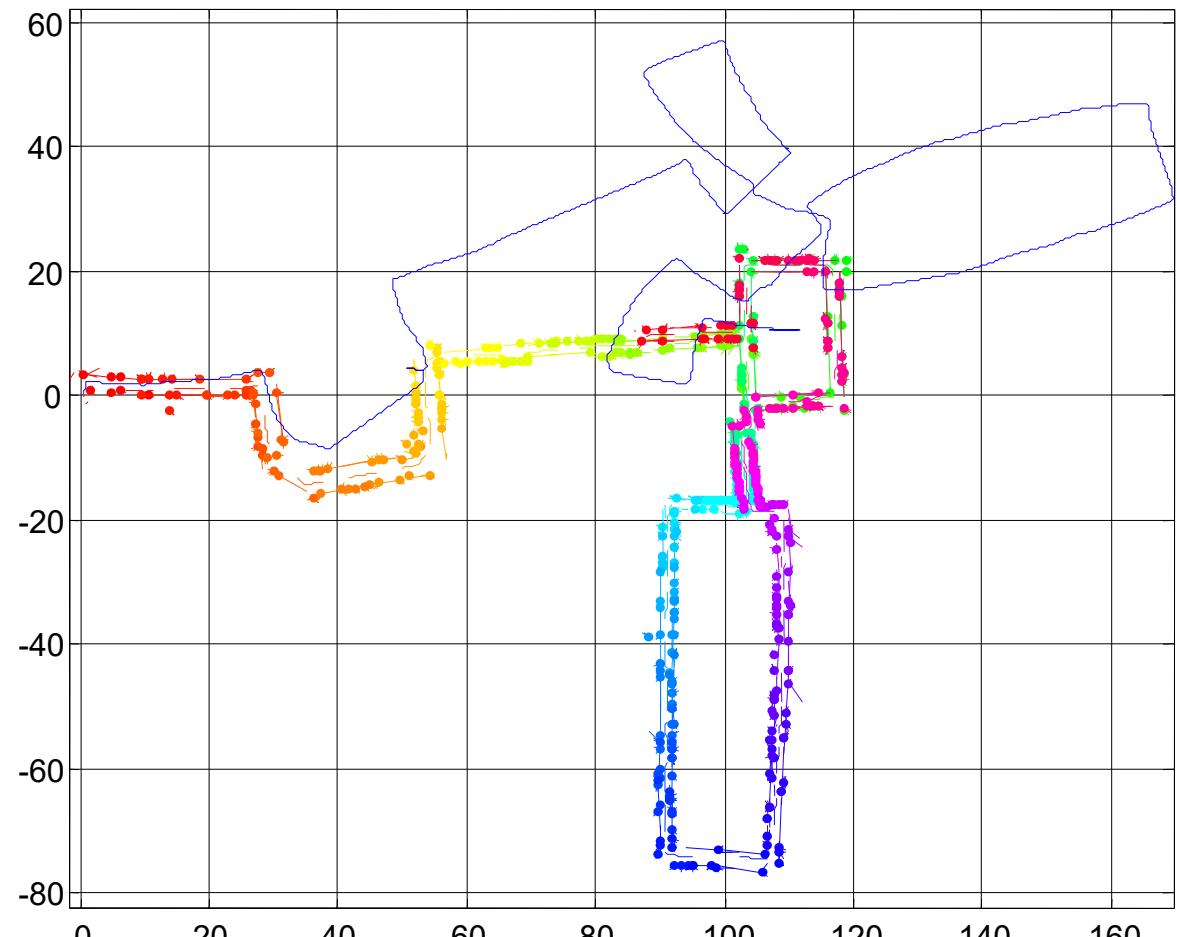
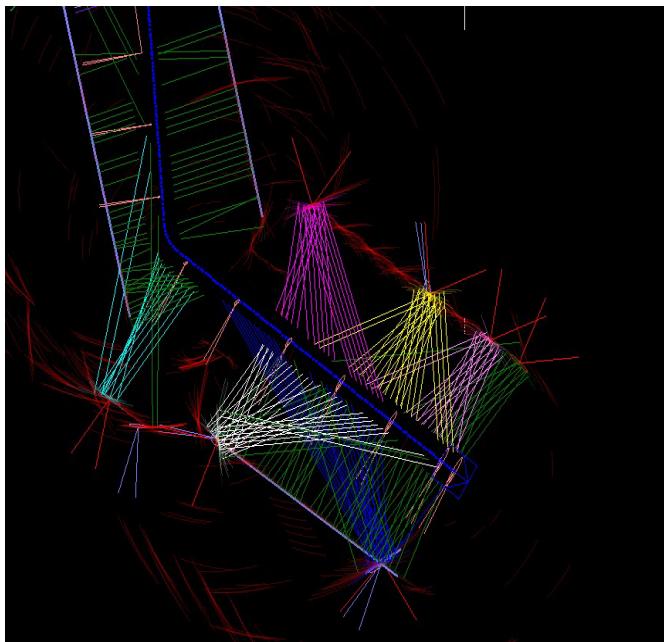
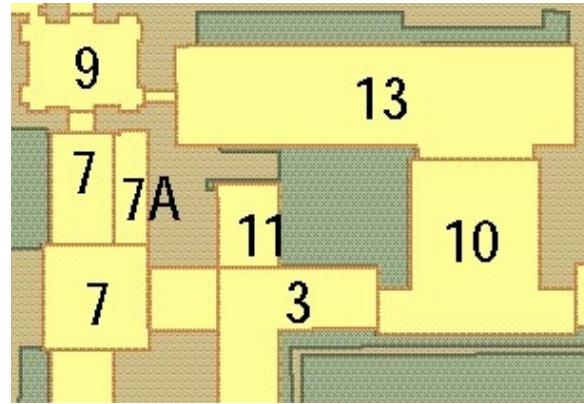
SLAM using Hybrid Metric/Topological Maps



- Geometry: rigid frames, submaps
- Topology: map adjacencies
- Hybrid: uncertain transforms

Bosse, Newman, Leonard & Teller, 2004

Example of a globally optimized map



Bosse, Newman, Leonard & Teller, 2004

Summary

- SLAM is a challenging problem
- Sensors
- State Estimation / Localization / Mapping / SLAM
- Map Representations

Next Lecture

- Probability Review