



Secure Autonomous Systems

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<https://bit.ly/secureauto-spring24>

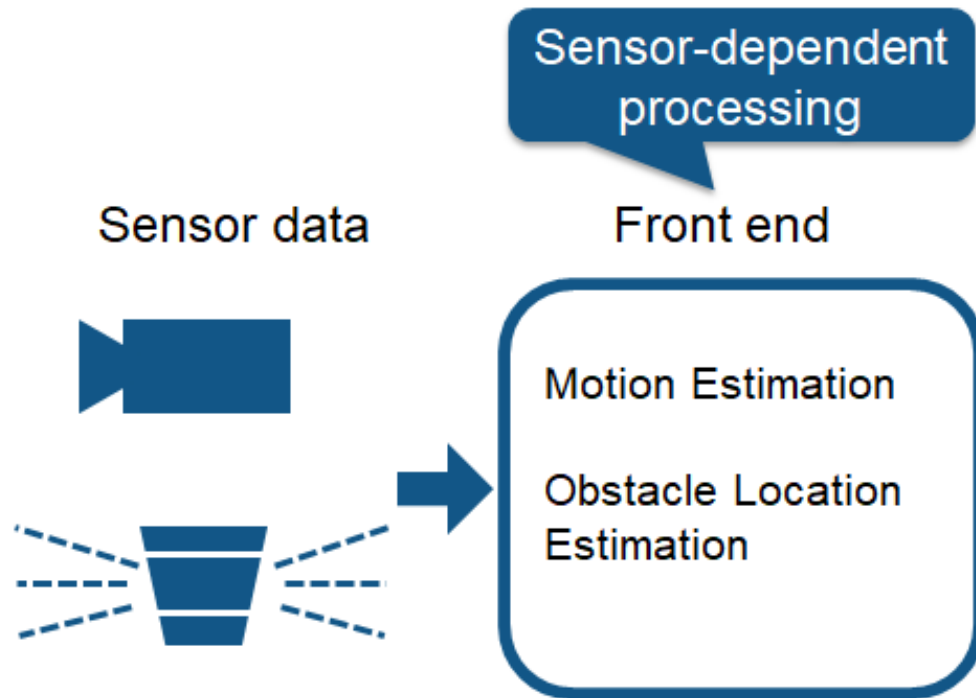


SLAM Processing Workflow

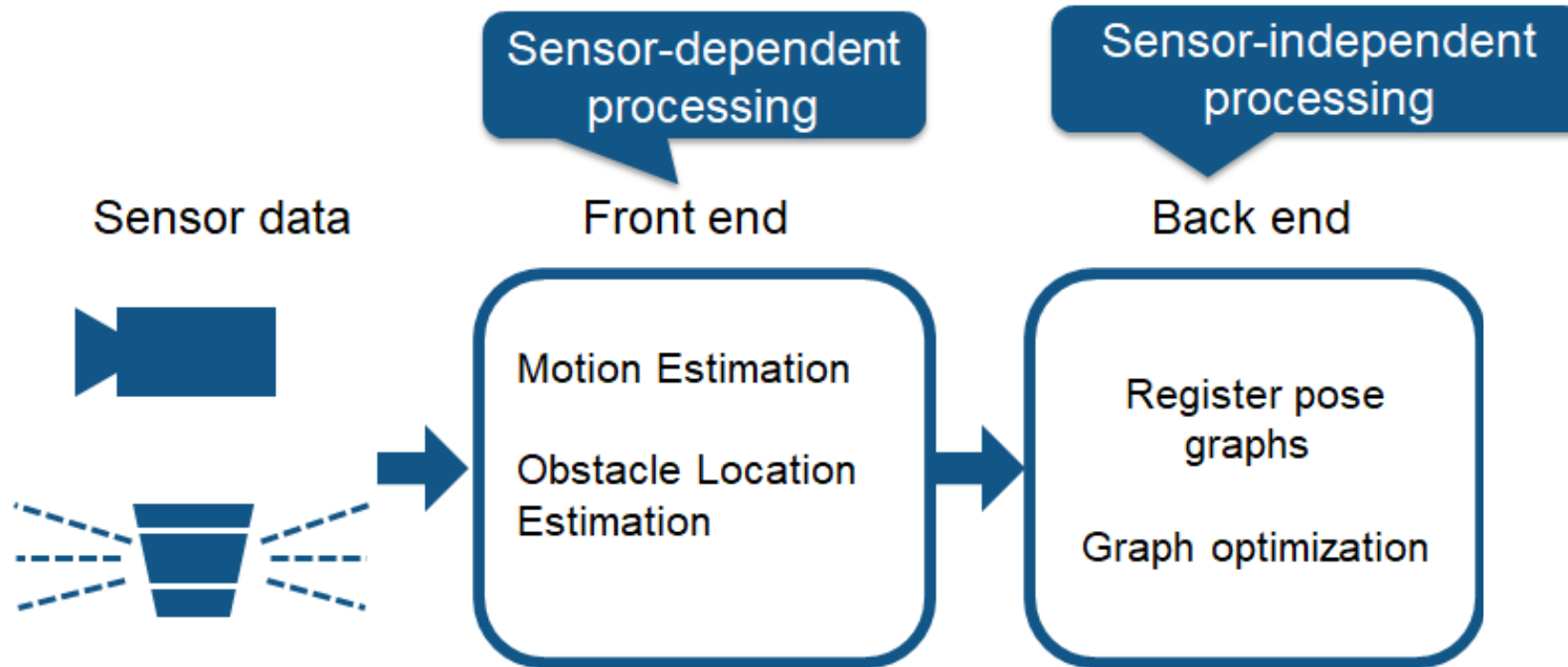
Sensor data



SLAM Processing Workflow

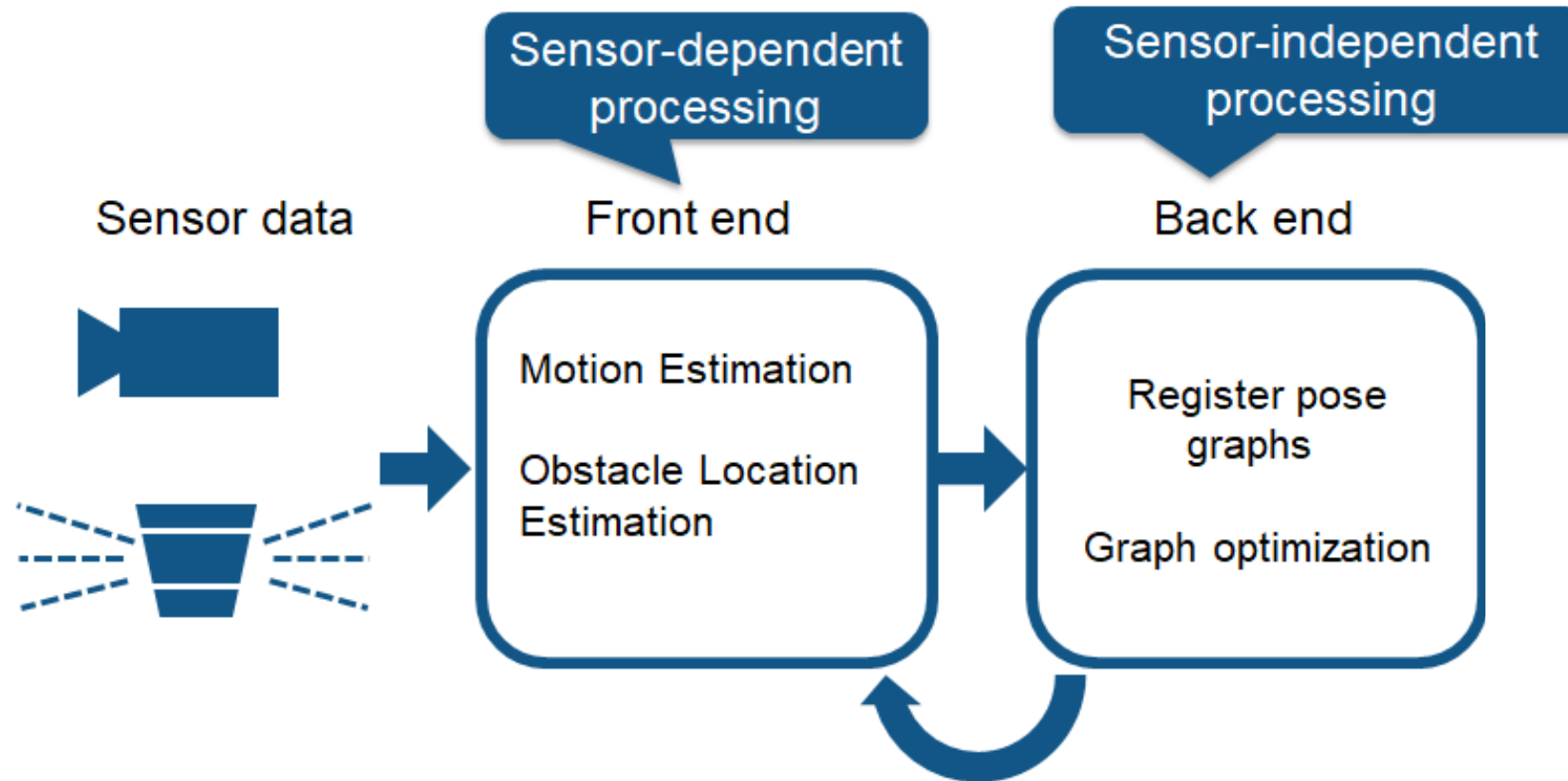


SLAM Processing Workflow

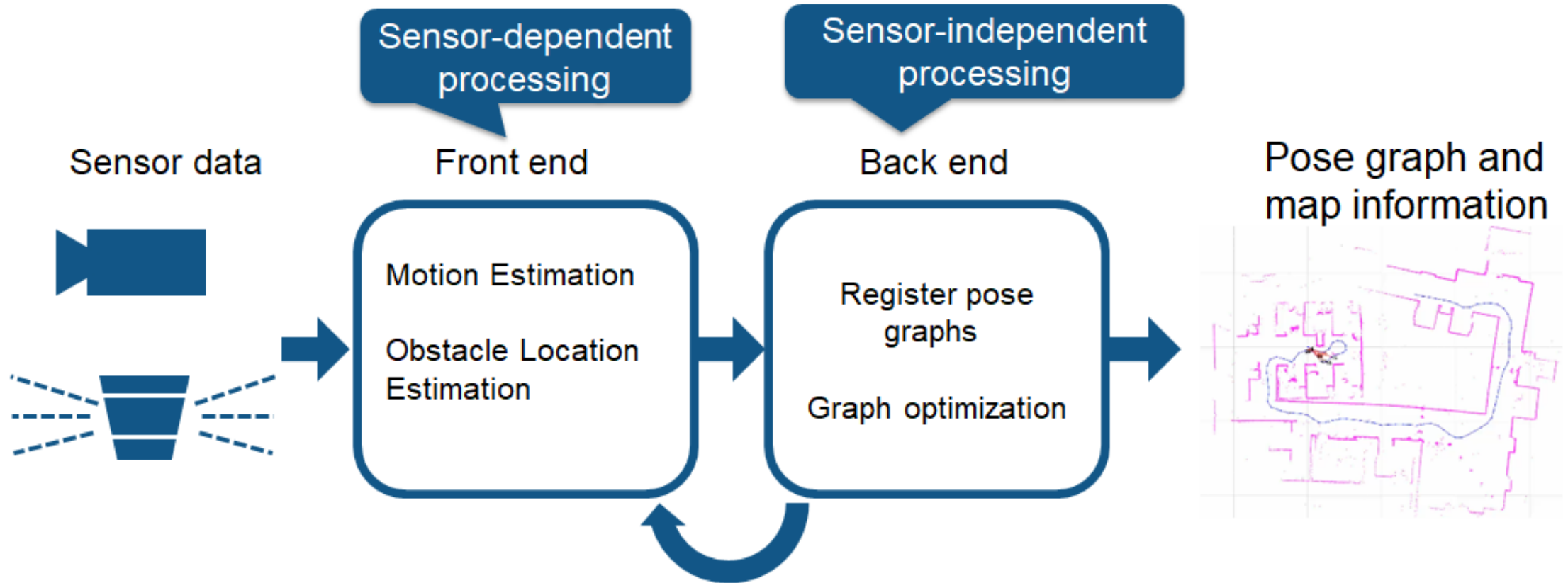


“pose” → position+orientation

SLAM Processing Workflow

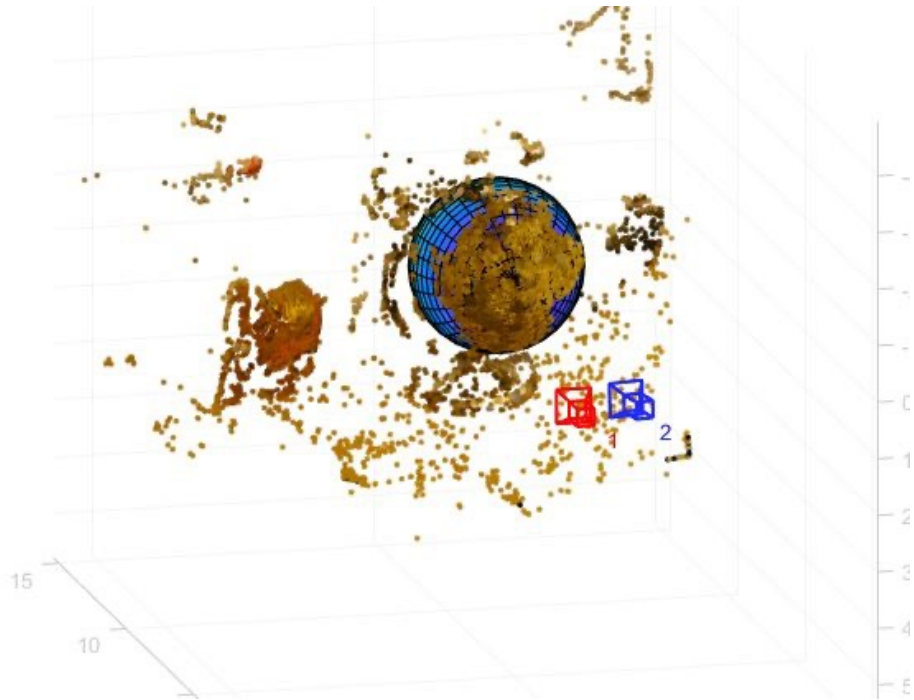


SLAM Processing Workflow

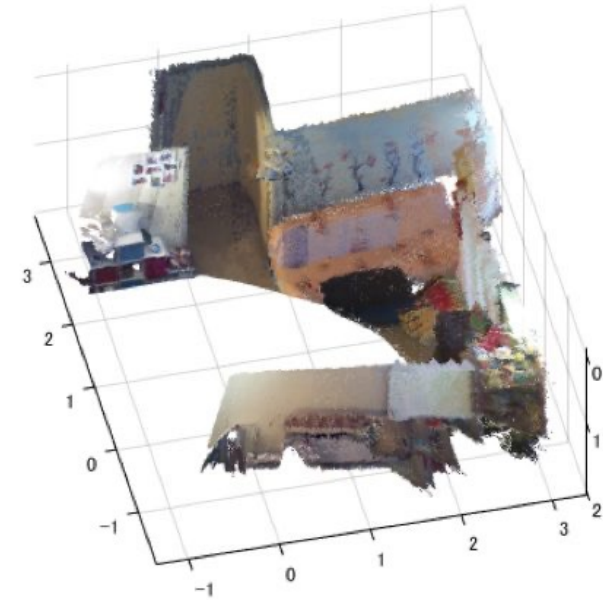


Types of SLAM

- Visual SLAM (**vSLAM**) uses **cameras**
 - Sparse methods match feature points of images [PTAM, ORB_SLAM]
 - Dense methods use overall brightness of images [DTAM, LSD- SLAM, DSO, SVO]



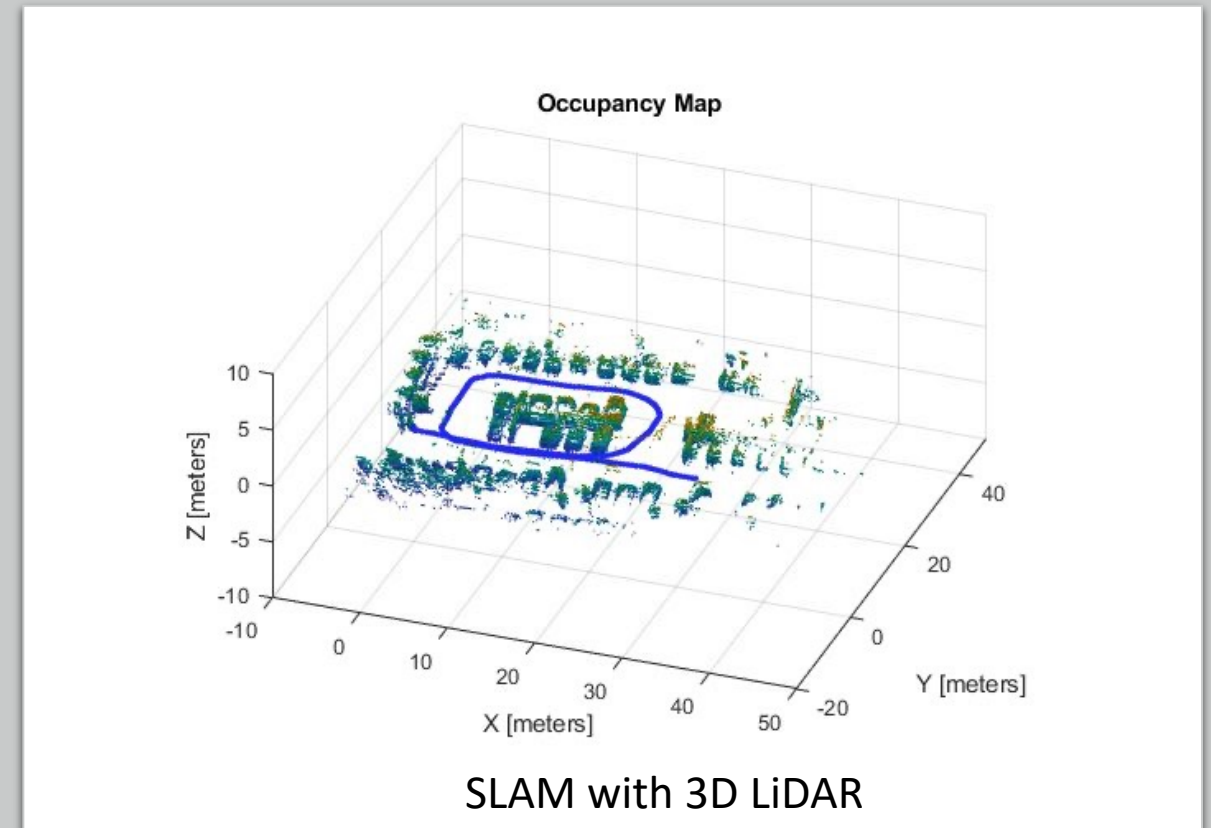
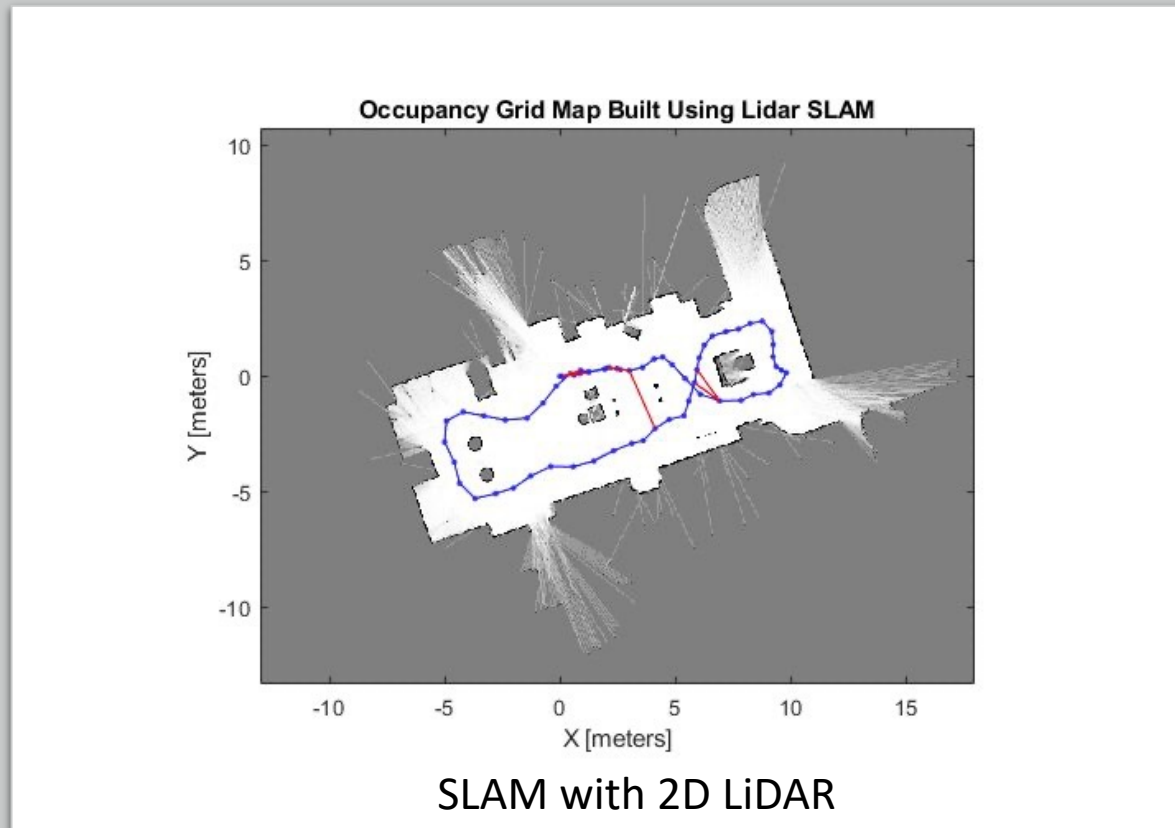
Structure from Motion



Point cloud registration

Types of SLAM | LiDAR SLAM

- Laser point cloud provides **high-precision distance measurements**
- Not as finely detailed as camera images
- Environments with fewer obstacles → less precision
- May require **fusion** with other sensors (e.g., GPS, odometry)



SLAM Components



LANDMARK
ASSOCIATION



DATA
ASSOCIATION



STATE
ESTIMATION



STATE UPDATE



LANDMARK
UPDATE



SLAM Details | The Hardware

- Mobile robot → e.g., indoor robot
- Range measurement device → e.g., LiDAR, RADAR, Sonar, etc.



SLAM Steps | Details

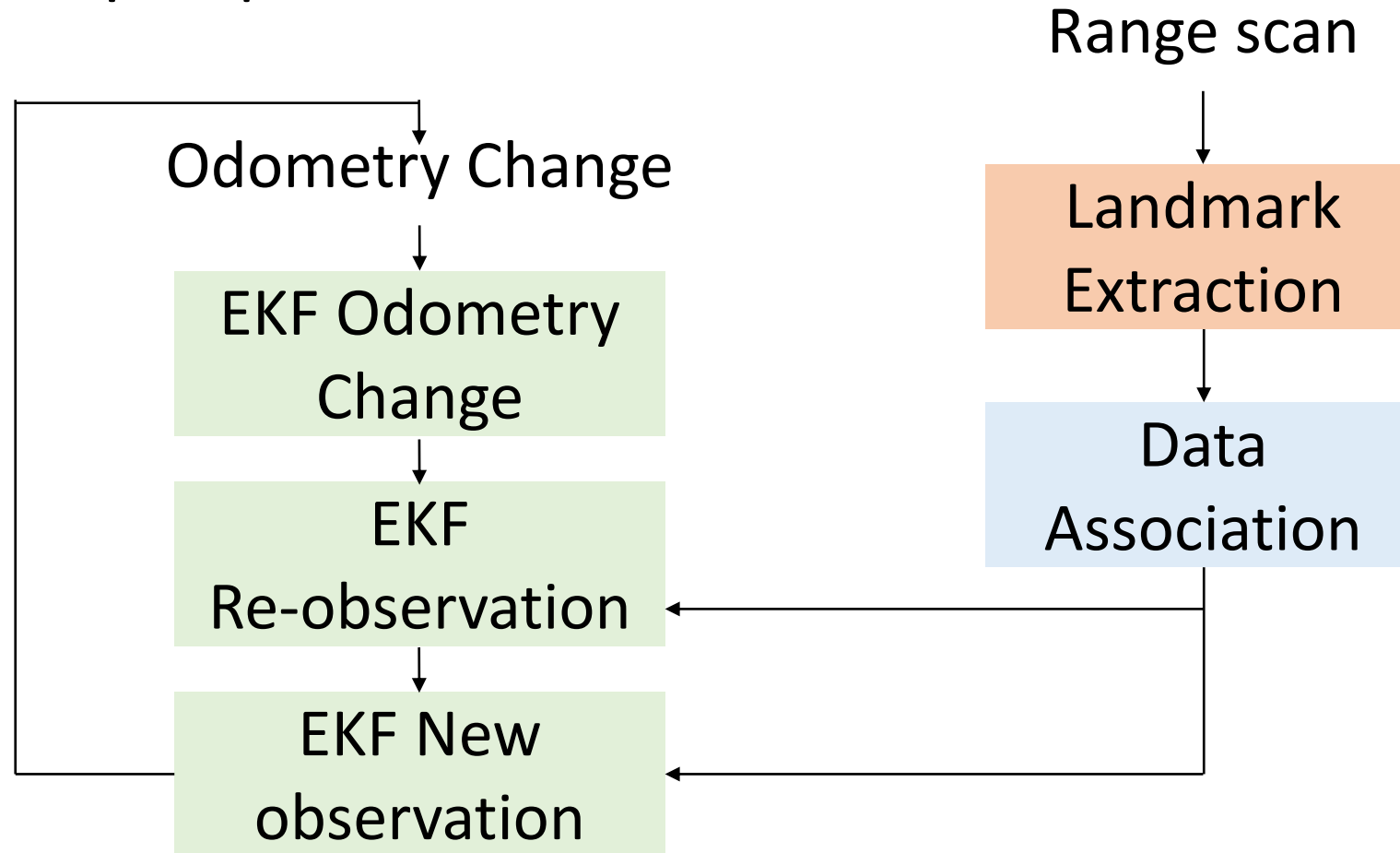
- Use **environment** to **update** position of robot
- Odometry can be erroneous
- Use range measurement devices to correct position
 - Extract features from environment
 - re-observing when robot moves around

EKF

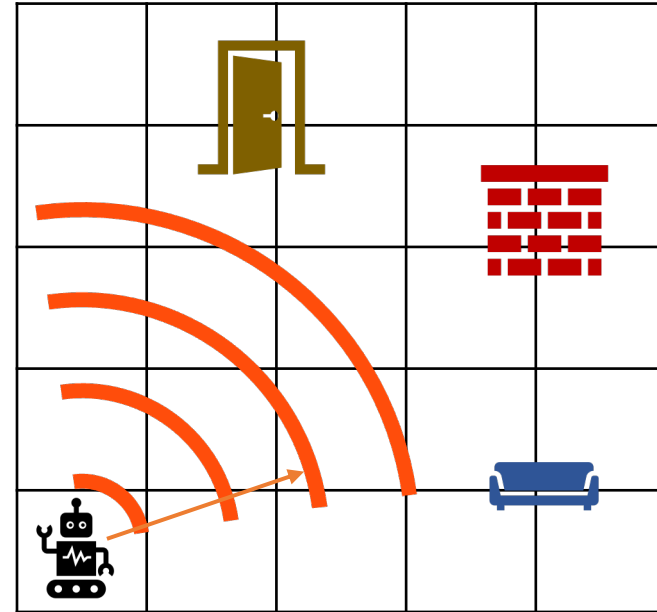
- “features” → **landmarks**

EKF tracks **uncertainty** in position and landmarks

SLAM Steps | Outline

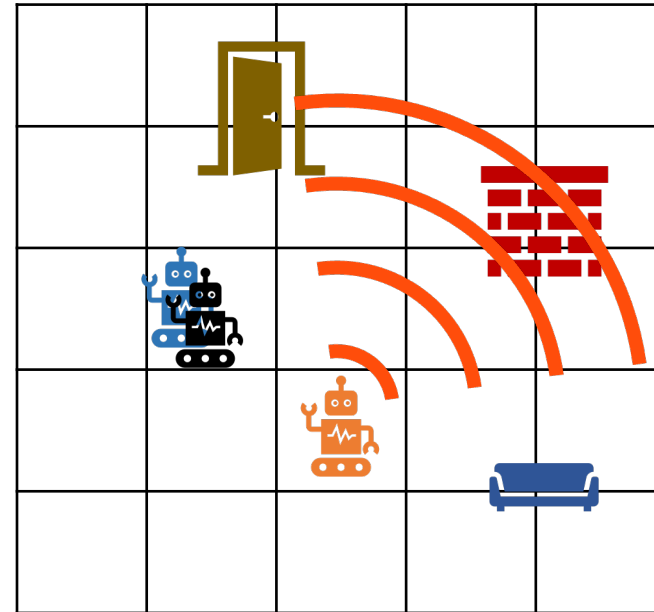


SLAM Steps | Abstract View



SLAM Steps | Abstract View

Robot trusts sensors more than odometry!



Mismatch in position!

SLAM | Data



LiDAR, RADAR, etc. provide data about surroundings



Odometry data provides **approximate** position of robot



Challenge → **synchronizing** the timing of both

LiDAR has a higher rate than odometry



Solution → **Extrapolate** the data

Easier to extrapolate odometry data

SLAM | Landmarks

- ↗ Features that can be **re-observed** and **distinguished from environment**
- 📍 Used by robot to find out where it is → **localize** itself
- 🌳 Types of landmarks depend on the environment

Landmarks should be:

- **Re-observable** and viewable from different angles & positions
- **Unique** enough to be identifiable between time steps
- **Plentiful** in the environment
- **Stationary**

SLAM | Indoor Landmarks



- Lots of straight lines
- Well defined corners

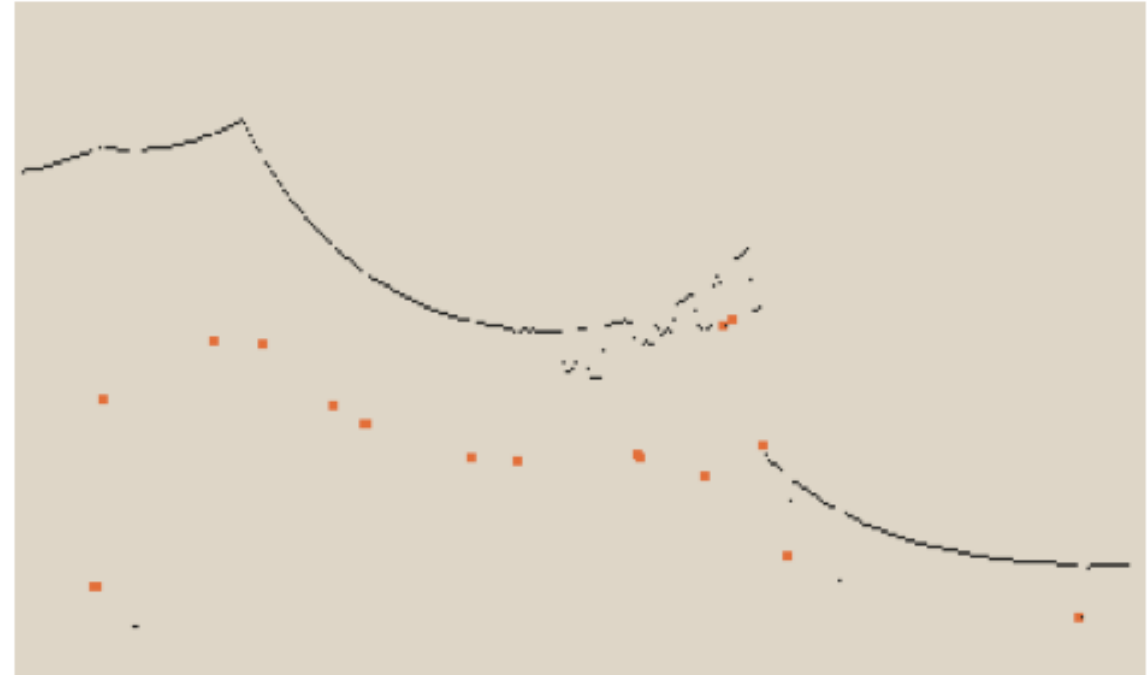


SLAM | Landmark Extraction

- Depends on type of landmarks
- Two landmark extraction algorithms
 - Spikes
 - RANSAC

SLAM | Landmark Extraction | Spikes

-
- Uses **extrema** to find landmarks
 - **two values differ > certain amount** [e.g. 0.5]
 - Detects big changes
 - Some beams reflect from walls, others don't



SLAM | Landmark Extraction | RANSAC

- RANdom SAMpling Consensus
- Extract lines from a laser scan
 - (e.g. straight lines from walls)
- Lines used as landmarks

SLAM | RANSAC | High-Level

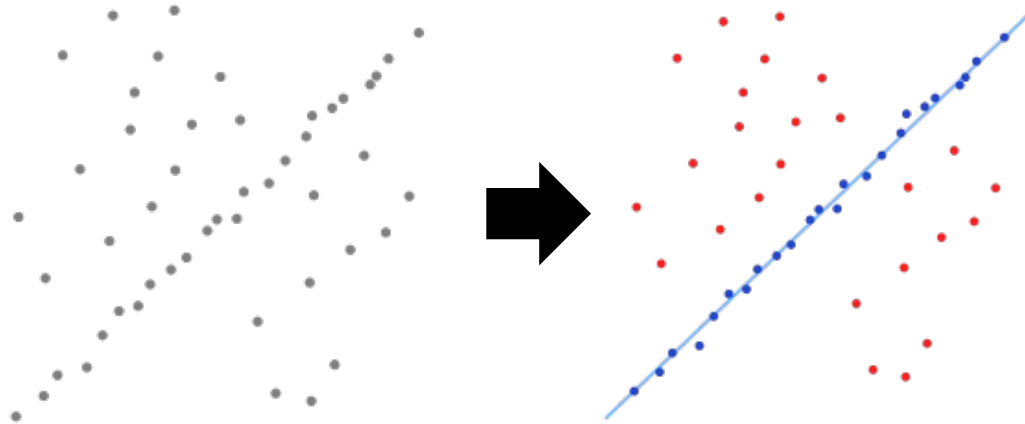
Random sampling of laser reading

Least square approximation → best line through readings

SLAM | RANSAC | High-Level

Random sampling of laser reading

Least square approximation → best line through readings

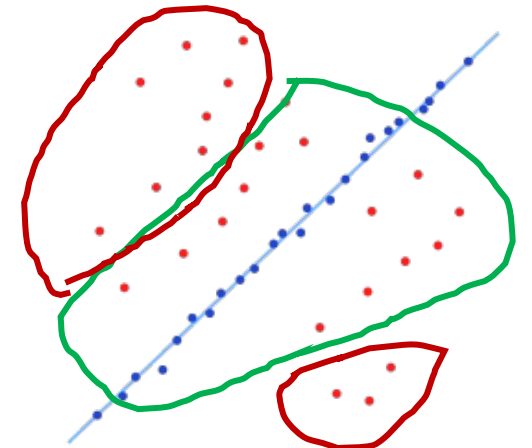


SLAM | RANSAC | High-Level

Random sampling of laser reading

Least square approximation → best line through readings

How many laser readings lie close to best fit line?



SLAM | RANSAC | High-Level

Random sampling of laser reading

Least square approximation → best line through readings

How many laser readings lie close to best fit line?

If number > threshold → line is seen

Consensus

SLAM | RANSAC | Algorithm

While

- there are still unassociated laser readings
- # of readings > consensus **C**
- completed < **N** trials

N → max number of attempts
S → number of samples to compute initial line
D → degrees from initial reading to sample from
X → max distance reading may be from line
C → number of points that must line on line

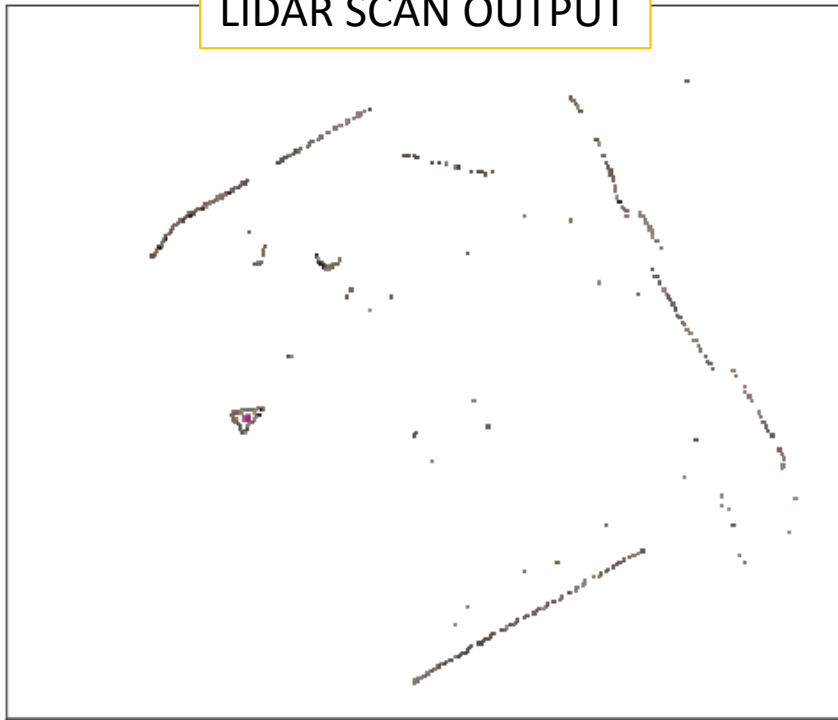
Do

- select *random laser data reading*, **R**
- randomly sample **S** data readings within **D** degrees of **R**
- calculate *least squares best fit line* using **S** and **R**
- determine how many laser data readings lie within **X** cm of best fit line
- if number of laser data readings on best fit line > *consensus C*
 - calculate *new least squares best fit line* → based on all readings that lie on old line
 - add new best fit line to lines extracted so far
 - remove number of readings lying on this line from total set of unassociated readings

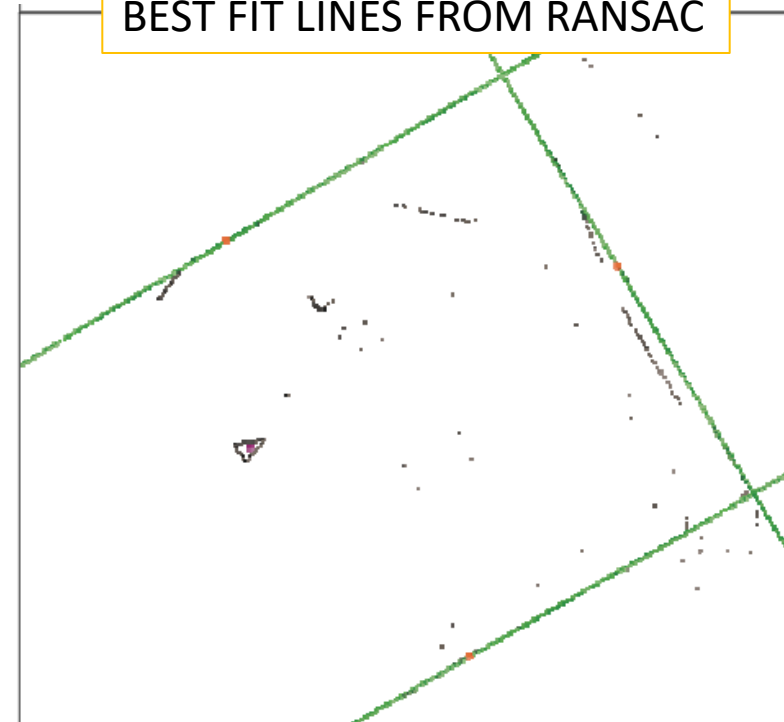
SLAM | RANSAC | Example

- Can extrapolate lines as dots as well → easier calculations
- RANSAC is **robust against people**

LIDAR SCAN OUTPUT



BEST FIT LINES FROM RANSAC



SLAM | Spikes vs RANSAC

Spikes

Simple algorithm

Not robust against people

RANSAC

More involved calculations

Robust against people

SLAM | Data Association

- **Matching** observed landmarks from different scans with each other
- **Re-observing** landmarks





SLAM | Data Association | Challenges

- May not re-observe landmarks at every step
- May wrongly observe something as landmark
 - never seen again!
- Wrong associate a landmark to a previously seen one

SLAM Data Association Policy

- Assume a **database** of previously seen landmarks
 - Initially empty
- Don't consider a landmark unless seen **N** times

Nearest Neighbor Approach

- use landmark extraction to extract all visible landmarks
- associate each extracted landmark → closest landmark seen > **N** times in database
- pass each pair of associations (extracted, seen in database) through validation gate
 - If pair passes validation gate, it must be same landmark → increment number in database
 - if pair fails validation gate → add as new landmark in database

Validation Gate → check if landmark lies within area of uncertainty from EKF



SLAM Challenges

- Localization errors accumulate over time
 - E.g. in a loop, robot's start/end positions don't match
 - Localization fails and map position is lost
 - Discontinuities in position estimates
 - High computational costs
 - image processing/point clouds/etc.
- pose graphs
- EKF+landmarks
- Parallelism

References

- SLAM for Dummies:

[https://dspace.mit.edu/bitstream/handle/1721.1/36832/16-412JSpring2004/NR/rdonlyres/Aeronautics-and-Astronautics/16-412JSpring2004/A3C5517F-C092-4554-AA43-232DC74609B3/0/1Aslam blas report.pdf](https://dspace.mit.edu/bitstream/handle/1721.1/36832/16-412JSpring2004/NR/rdonlyres/Aeronautics-and-Astronautics/16-412JSpring2004/A3C5517F-C092-4554-AA43-232DC74609B3/0/1Aslam%20blas%20report.pdf)

- SLAM Overview [Matlab article]

<https://www.mathworks.com/discovery/slam.html>

- SLAM examples and Matlab code/API form

<https://www.mathworks.com/help/nav/slam.html>

- SLAM using pose graph estimation:

<https://www.youtube.com/watch?v=saVZtgPyyJQ&list=PLn8PRpmsu08rLRGrnF-S6TyGrmcA2X7kg&index=3>