

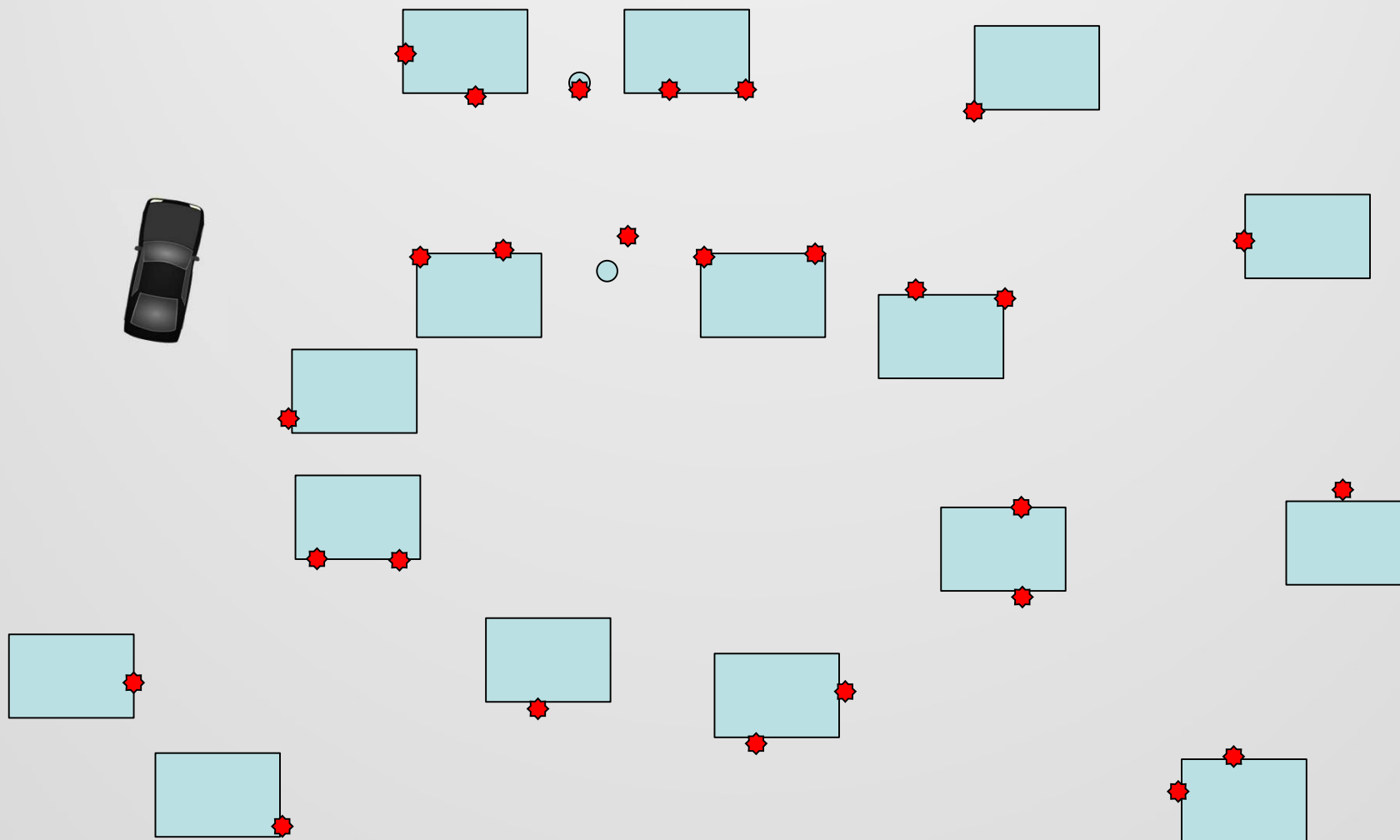
COMP0130: Robotic Vision and Navigation

Lecture 05B: Notation and the Big SLAM Equation

Goals

- Introduce the mathematical description and notation used to model the system
- Present the joint probabilistic model which is the cornerstone for SLAM

SLAM



Mathematical Description

- Platform state
- Platform process model
- Landmark state
- Platform / landmark observation model

Platform State

- This is the state that the robot is in on a timestep-by-timestep basis
- For example, for a driven car with position and heading, the state might be

$$\mathbf{X}_k = \begin{bmatrix} \underbrace{x_k \quad y_k} & \underbrace{\psi_k} \end{bmatrix}^T$$

Platform Process Model

- The platform state evolves according to the familiar Kalman filter-type of process model

$$\dot{\mathbf{x}}_k = \mathbf{f}[\mathbf{x}_{k-1}, \mathbf{u}_k, \mathbf{v}_k]$$

Handwritten annotations: A horizontal wavy line is drawn below the equation. An arrow labeled Q points from below the line to the \mathbf{v}_k term. To the right, an arrow labeled R points upwards to a handwritten ω symbol.

Map State

- The map is a set of N landmarks or features

$$\mathbf{m} = \{ \mathbf{m}^{\textcircled{1}}, \mathbf{m}^2, \dots, \mathbf{m}^N \}$$

- Each landmark maintains its own state, such as its position

$$\mathbf{m}^i = \begin{bmatrix} u^i & v^i \end{bmatrix}^\top$$

\nearrow \uparrow

Map State

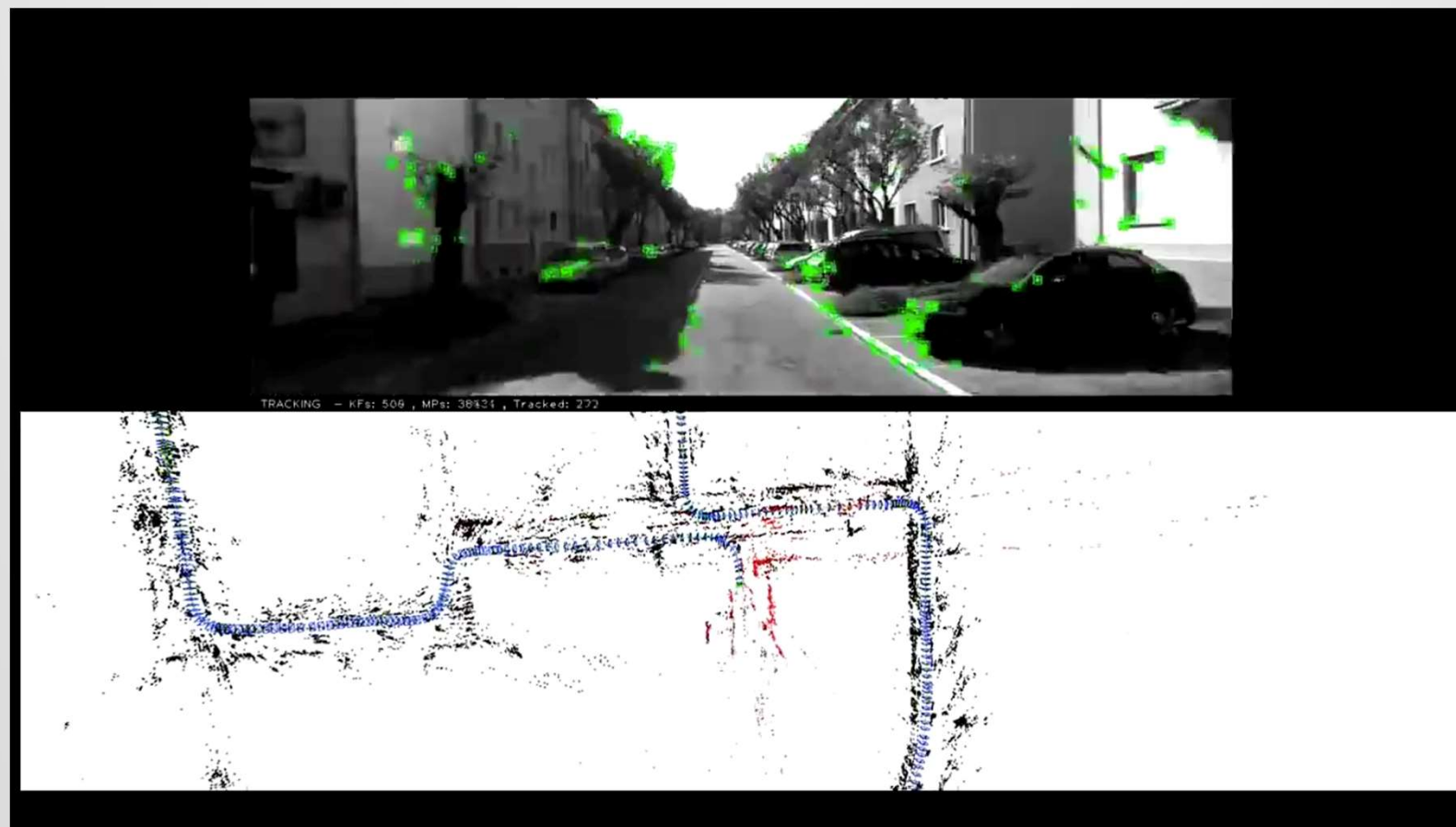
- We made two innocent-looking assumptions
 1. All the landmarks have a unique label associated with them
 2. All landmarks are static and don't change over time

Labelling Landmarks

$$M = \{m^1, m^2, \dots, m^N\}$$

- Each landmark has some label associated with it
- This can become very complicated when you don't know how many landmarks are out there, there are multiple robots, etc.
- We are going to use a simple integer counter which increases by 1 each time

Landmarks Are Static?



From <https://www.youtube.com/watch?v=8DISRmsO2YQ>
(00:57.5-00:62.5 seconds)

Landmarks Are Static



*Fixed
Real
World*

*Varying
Estimate*

Describing Sensor Observations

- At time k , the robot observes a set of M_k landmarks,

$$\mathbf{Z}_k = \left\{ \mathbf{z}_k^1, \mathbf{z}_k^2, \dots, \mathbf{z}_k^{M_k} \right\}$$

- Each observation comes from a landmark
- The mapping index is

$$I_k = \left\{ i_k^1, i_k^2, \dots, i_k^{M_k} \right\}$$

Sensor Observations

$$\mathbf{Z}_k = \{ \mathbf{z}_k^1, \mathbf{z}_k^2, \dots, \mathbf{z}_k^{M_k} \}$$



$$\rightarrow I_k = \left\{ \begin{matrix} i_k^1 \\ 2 \end{matrix}, i_k^2, \dots, i_k^{M_k} \right\} \leftarrow \begin{matrix} 7 \\ 21 \end{matrix}$$

Process and Observation Models

- The observation model for the j th landmark is

$$z_k^j = h \left[\underset{\uparrow}{x_k}, \underset{\uparrow}{m}^{\overset{\circlearrowleft}{i_j}}, \underset{\uparrow}{w}^{\overset{\circlearrowleft}{j}} \right] \quad \checkmark \quad w$$

Handwritten notes: Above the equation, $z_k = \{ \dots \}$ is written in red. Red circles are drawn around i_j and j . Red arrows point to x_k , m , and w . A red checkmark and the letter w are to the right of the equation.

Probabilistic Equation for SLAM

- The expression for the probabilistic formulation is

$$f(\mathbf{x}_k, \mathbf{m} | \mathbf{Z}_{0:k}, \mathbf{U}_{0:k}, \mathbf{x}_0)$$

Current
pose of the
platform

Map

Set of all
observations

$$\mathbf{Z}_{0:k} = \{\mathbf{Z}_0, \dots, \mathbf{Z}_k\}$$

Set of all
control inputs

$$\mathbf{U}_{0:k} = \{\mathbf{u}_0, \dots, \mathbf{u}_k\}$$

Initial
conditions

So... How Do We Implement SLAM?

- We have the problem that we want to estimate the joint distribution of the pose of the platform and the landmarks in one go
- This is an estimation algorithm which takes in a set of observations and control inputs to estimate a state vector
- We have already seen a solution – the Kalman filter

SLAM

