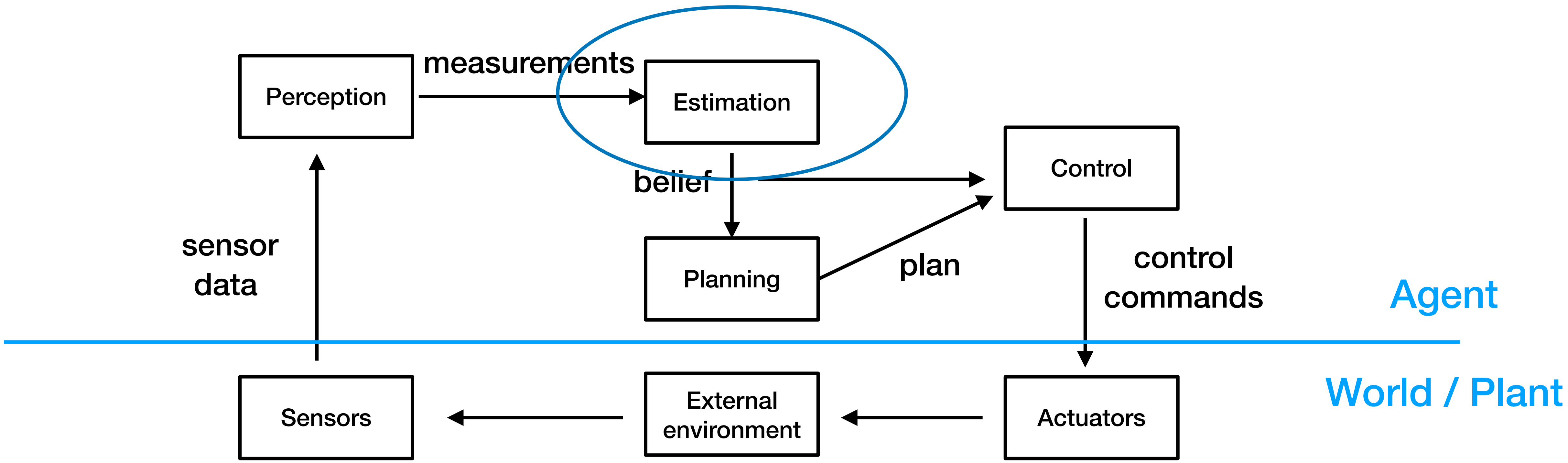
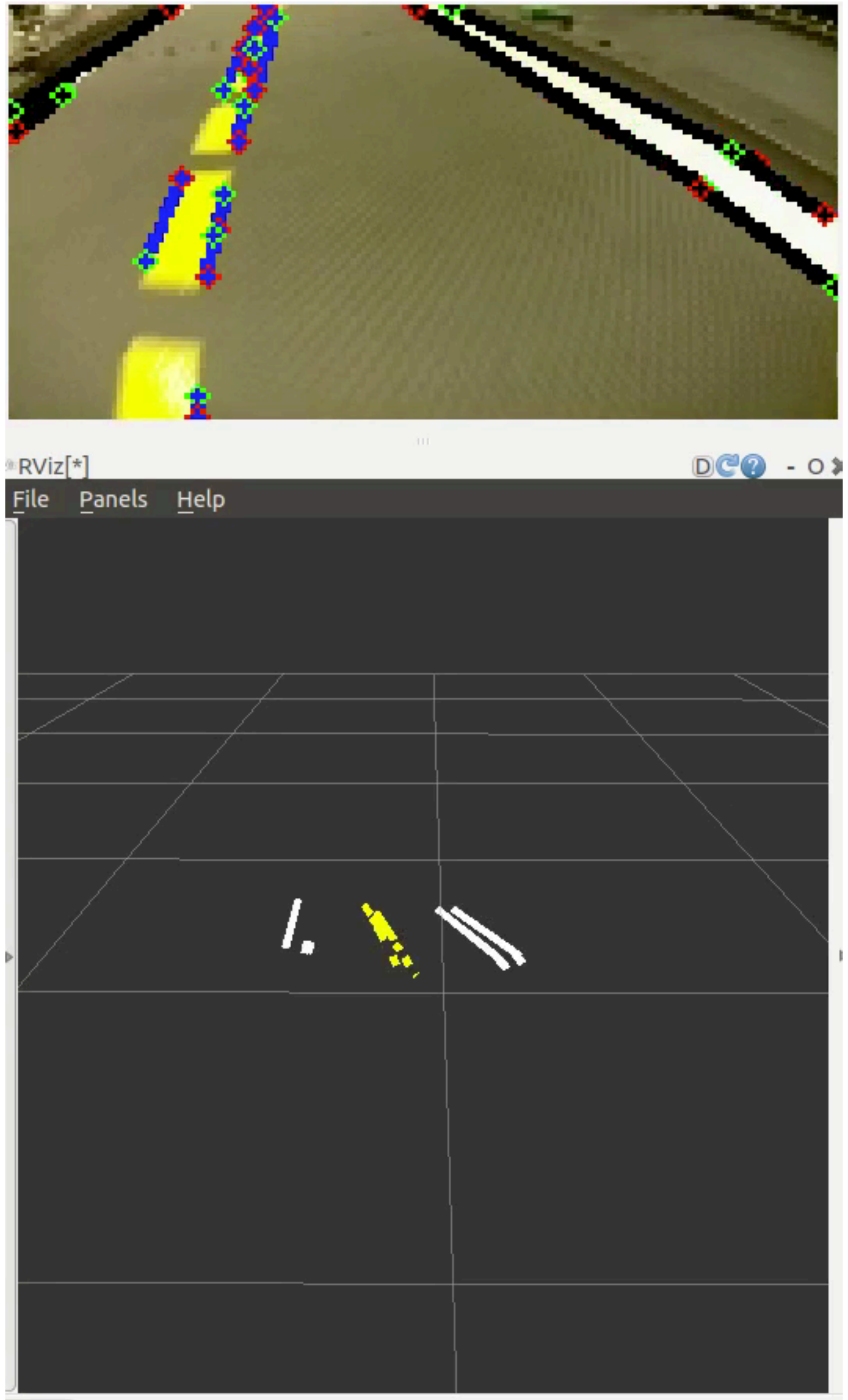
Simultaneous Localization and Mapping (SLAM)

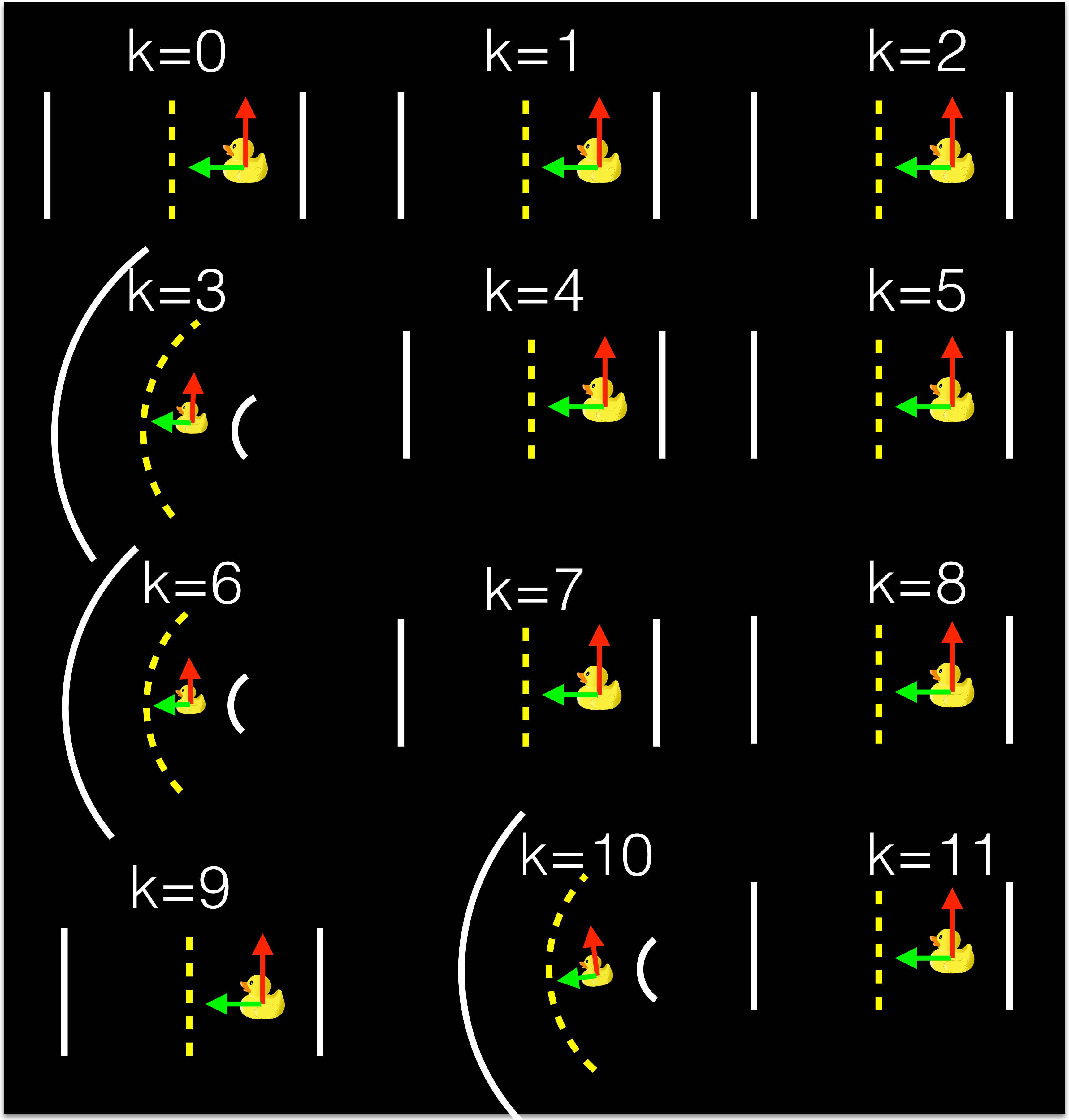
Big picture



We are going back to estimation, but now consider that we don't have a model of the environment a priori



RViz[*]
File
Panels
Help



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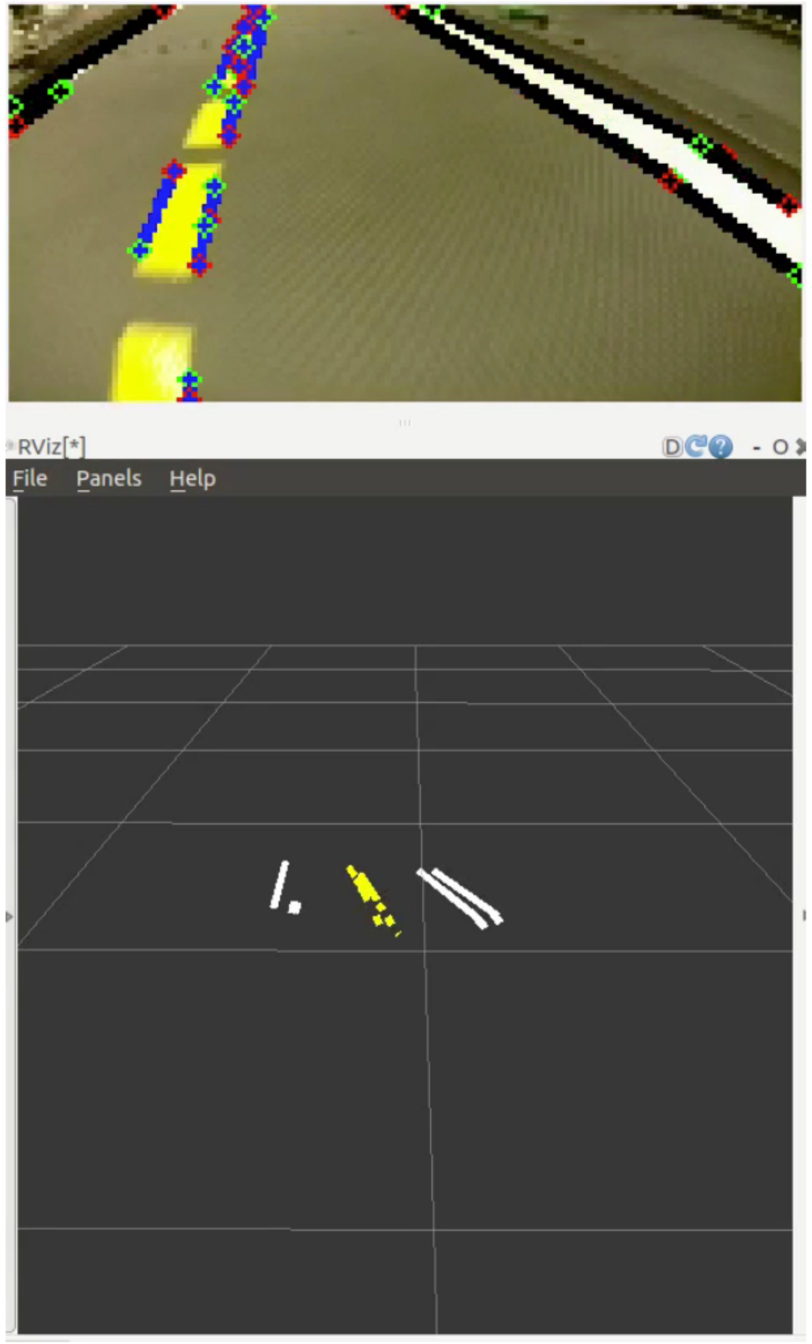
k=1
k=2
k=3
k=4
k=5
k=6
k=7
k=8
k=9
k=10
k=11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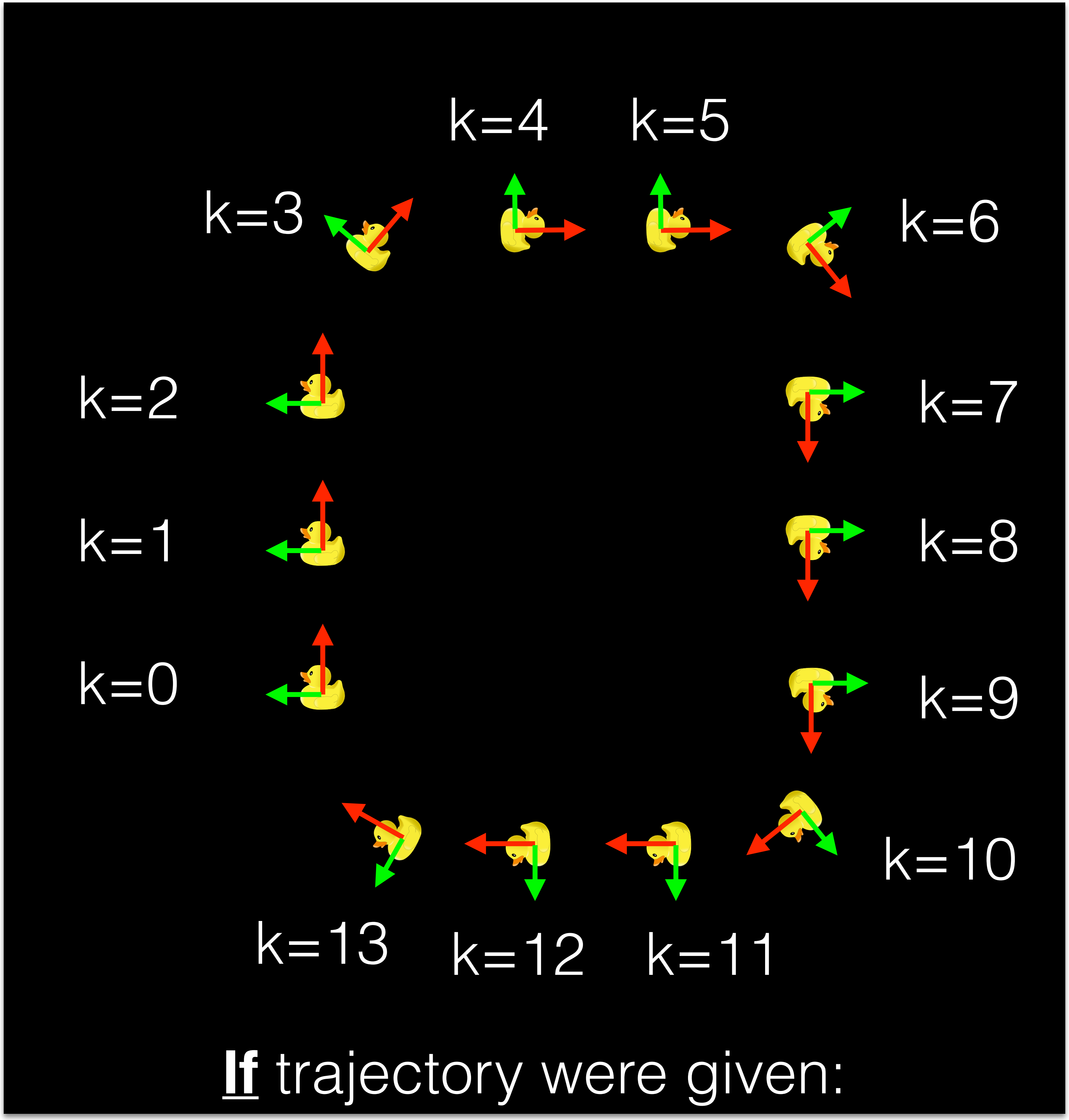
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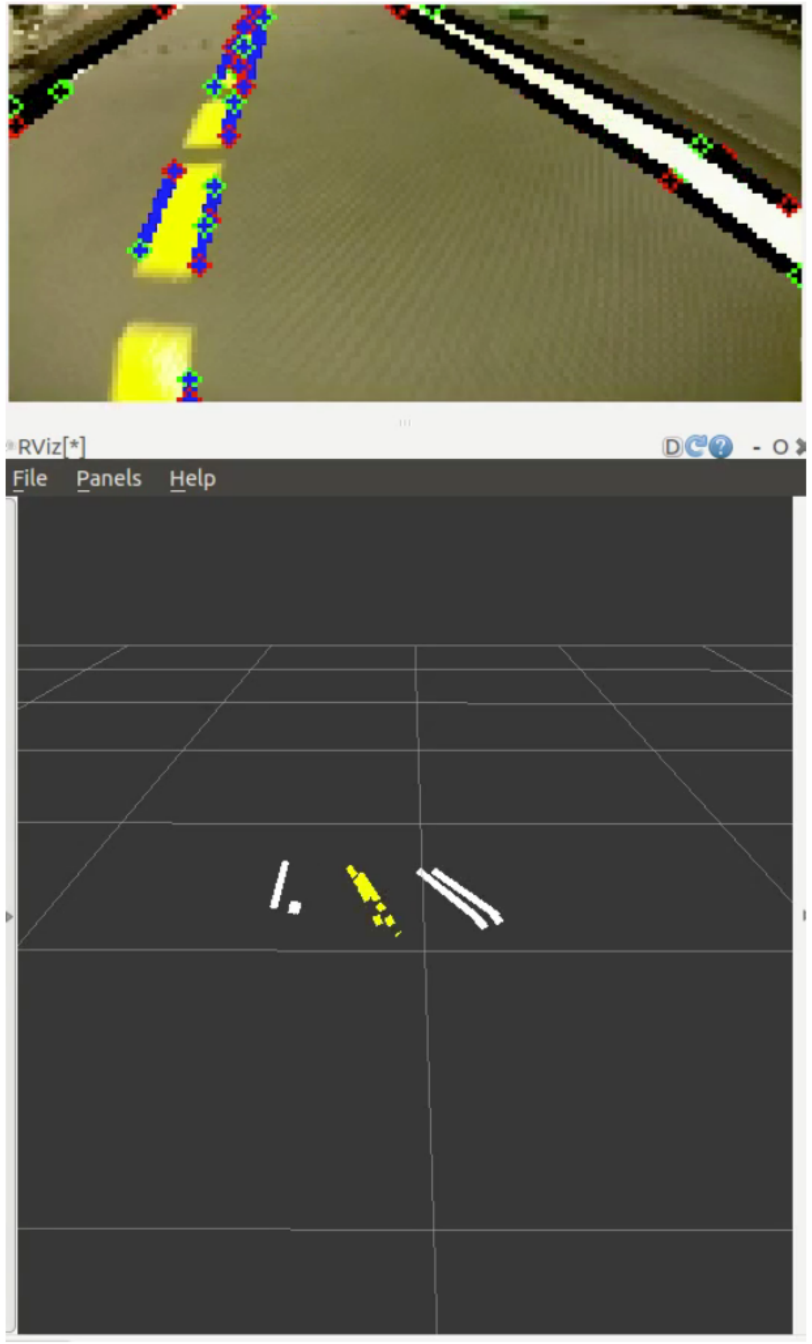
k=5
k=3
k=6
k=2
k=7
k=1
k=8
k=0
k=9
k=10
k=13
k=12
k=11
If trajectory were given:



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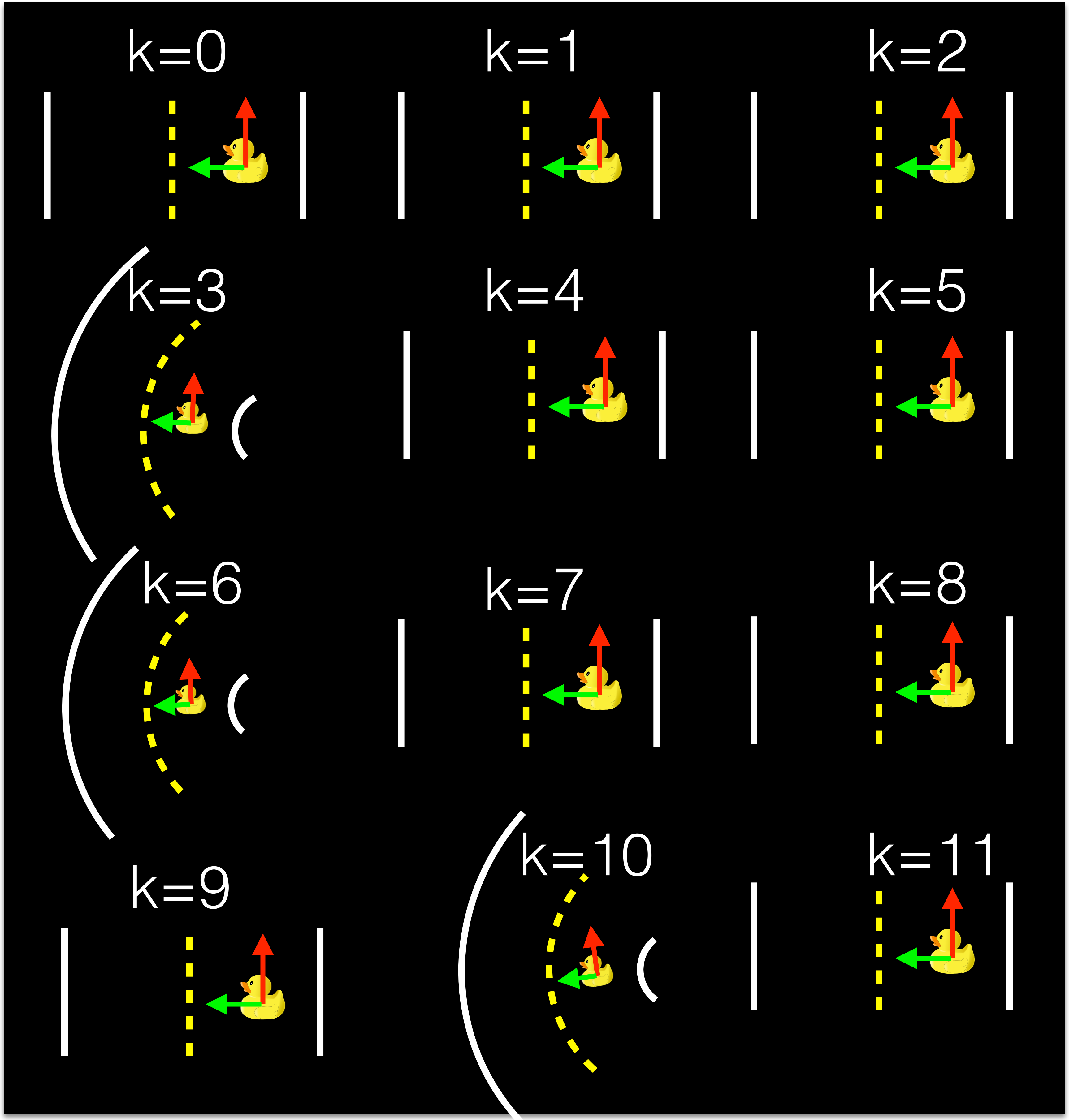

k=0
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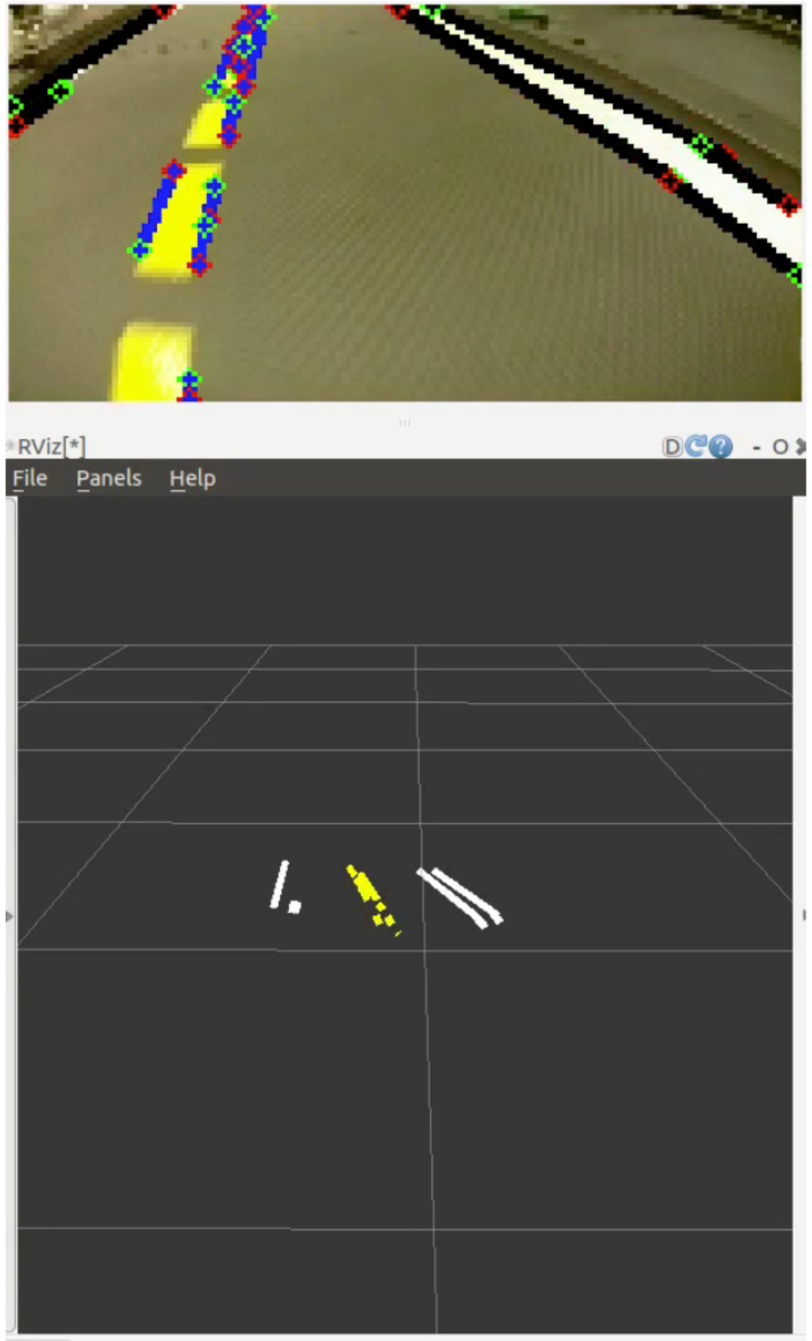
k=11


RViz[*]
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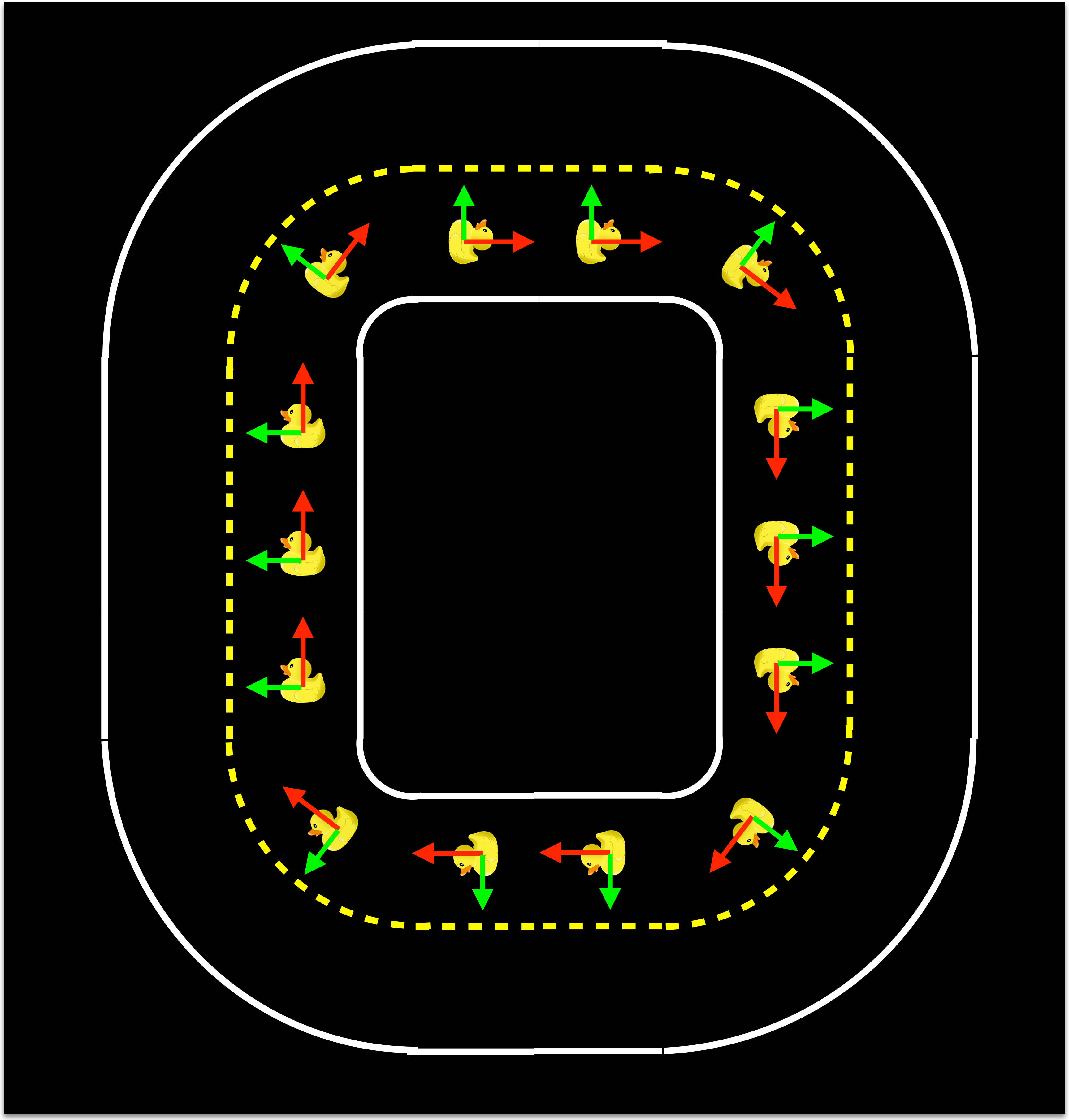
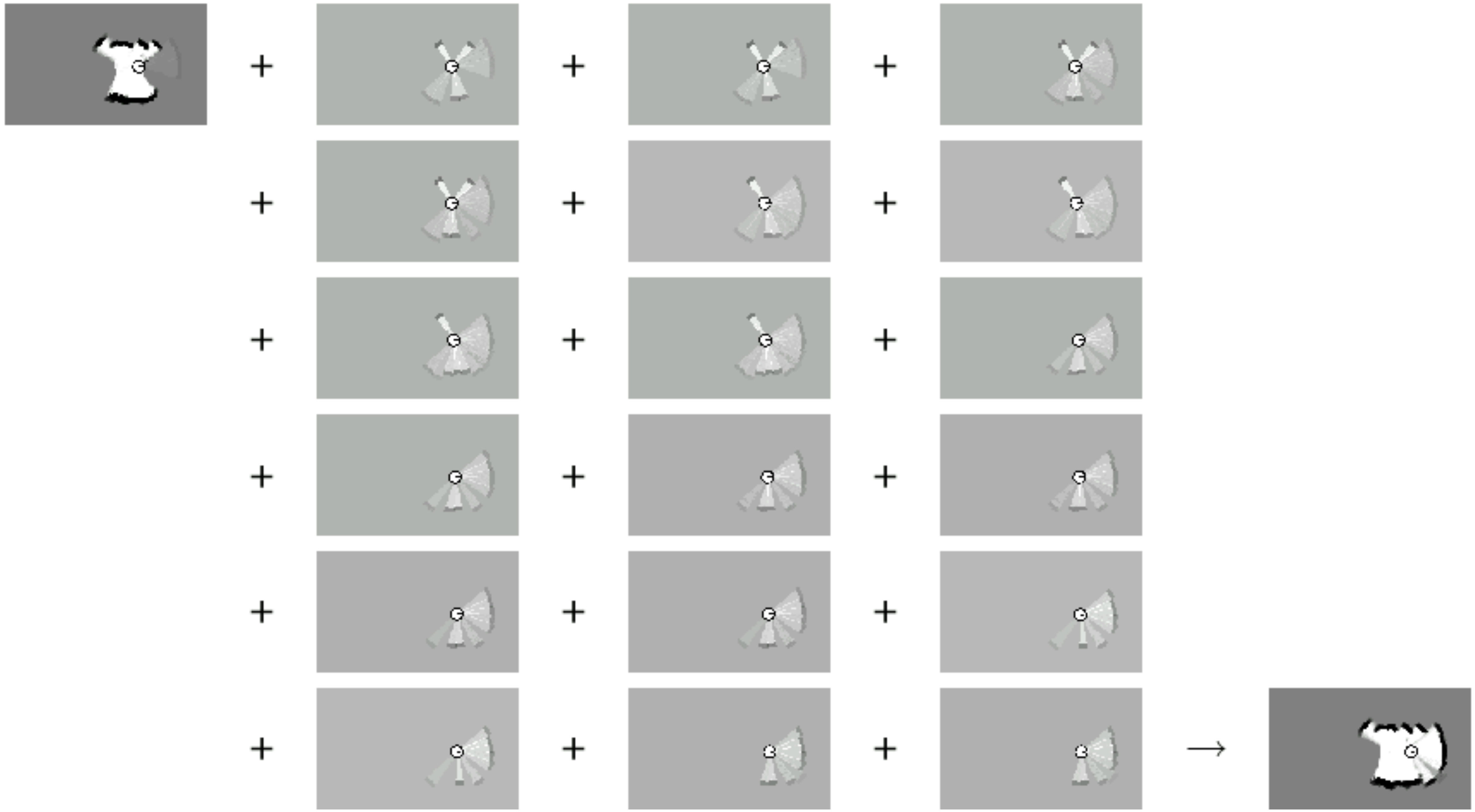
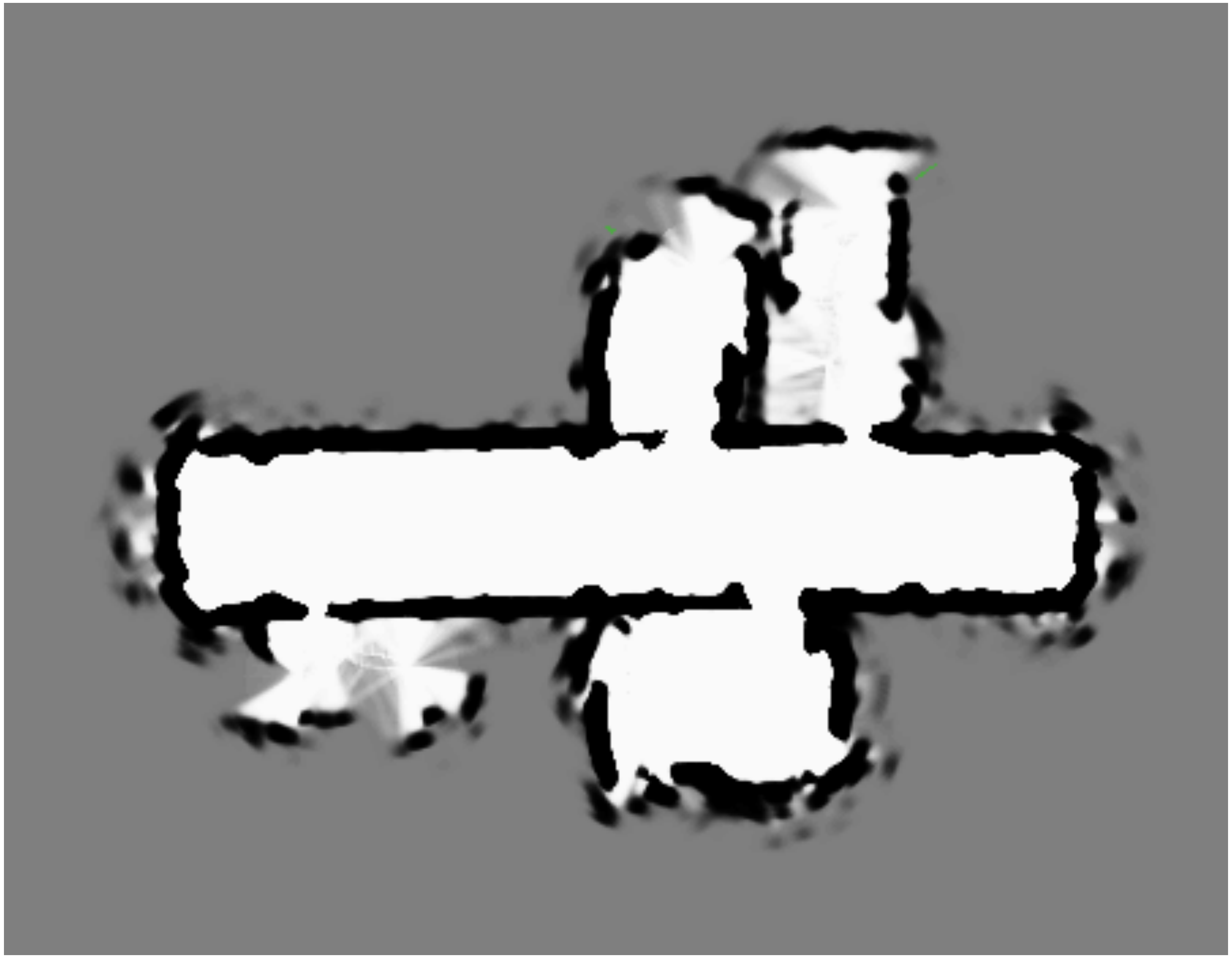


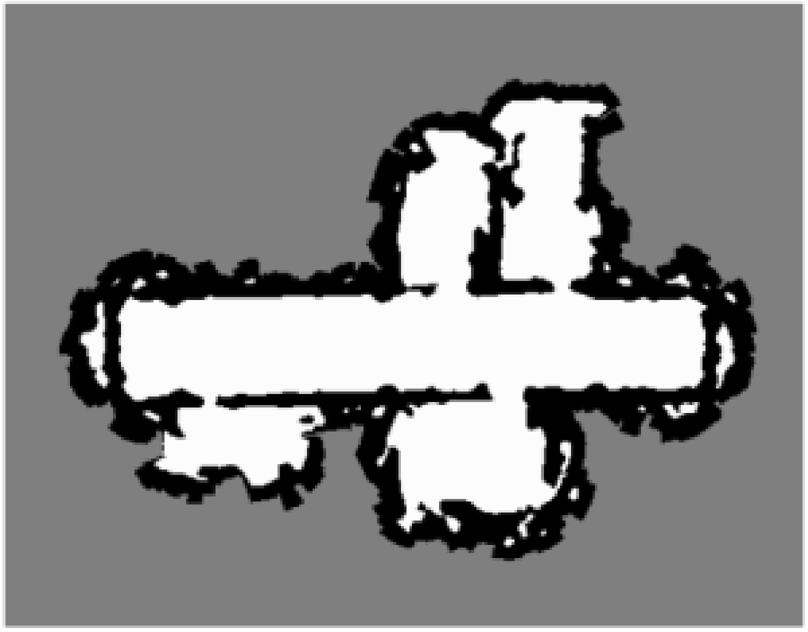
Mapping from Known Poses



Resulting Map



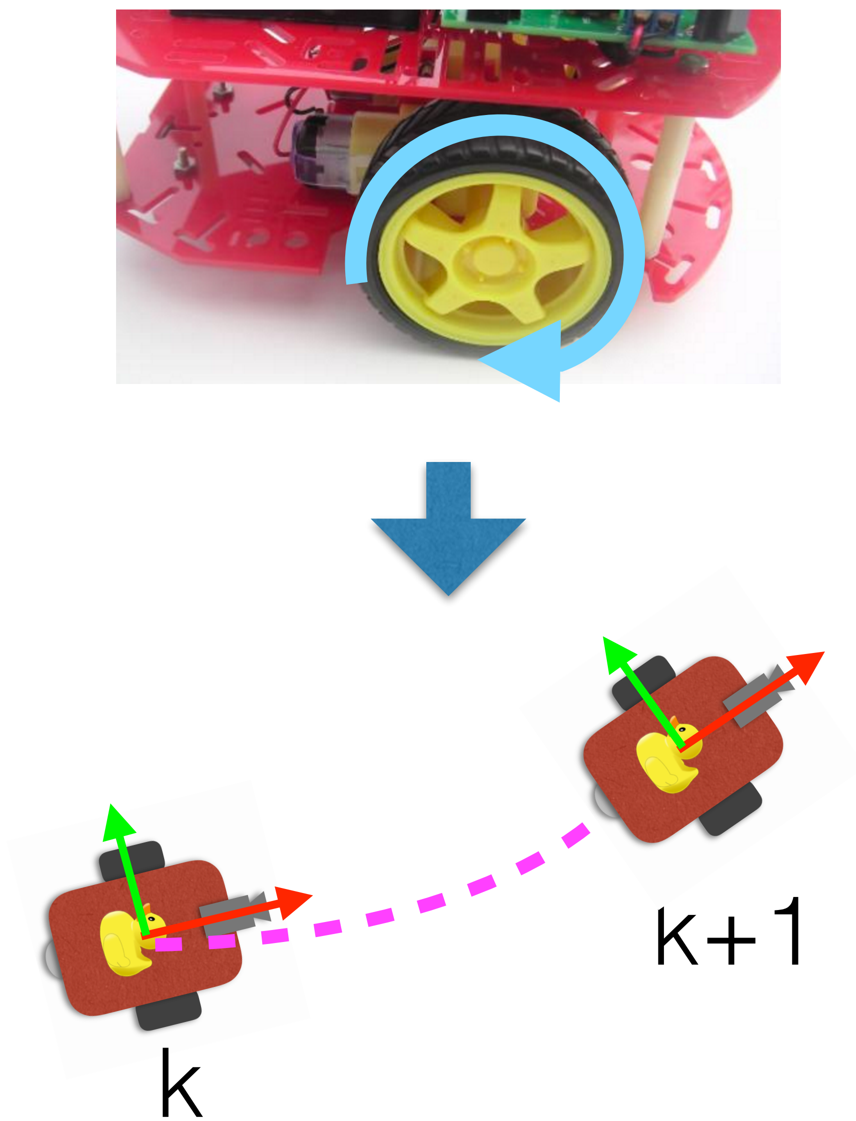
Maximum Likelihood Estimate

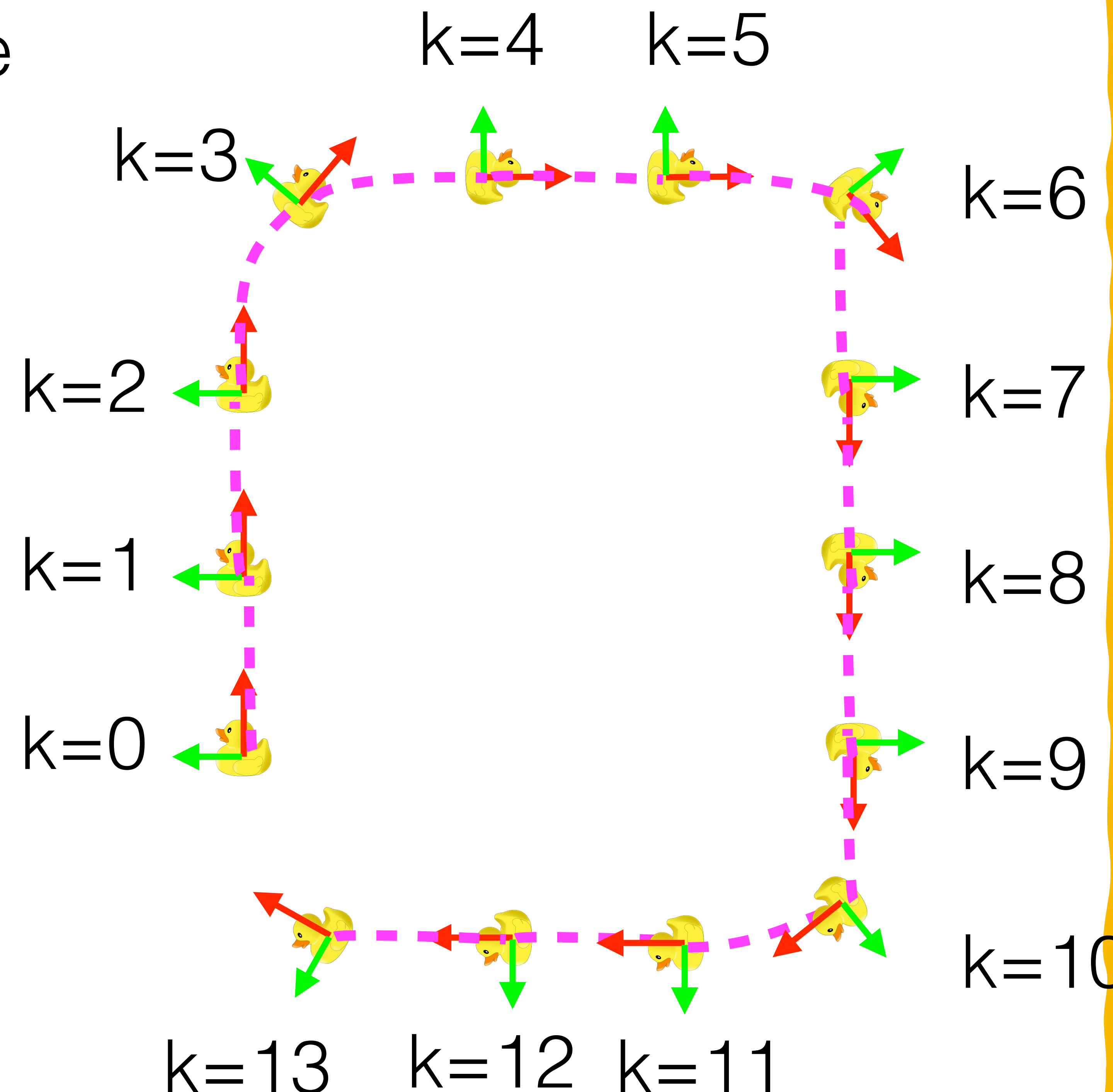
Clip the occupancy grid map at a threshold of 0.5

Motion integration (odometry)

We can estimate
motion between consecutive
poses from motion controls

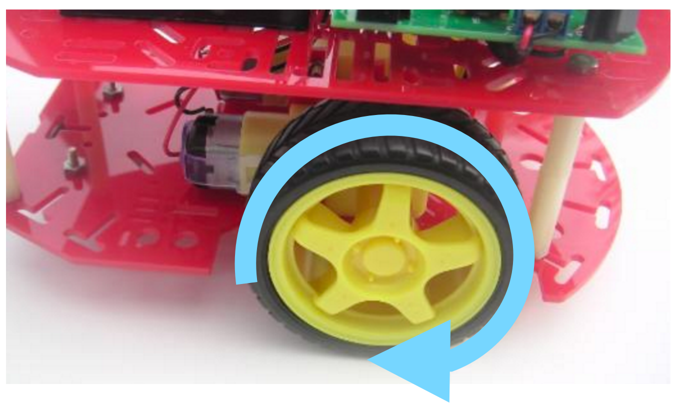


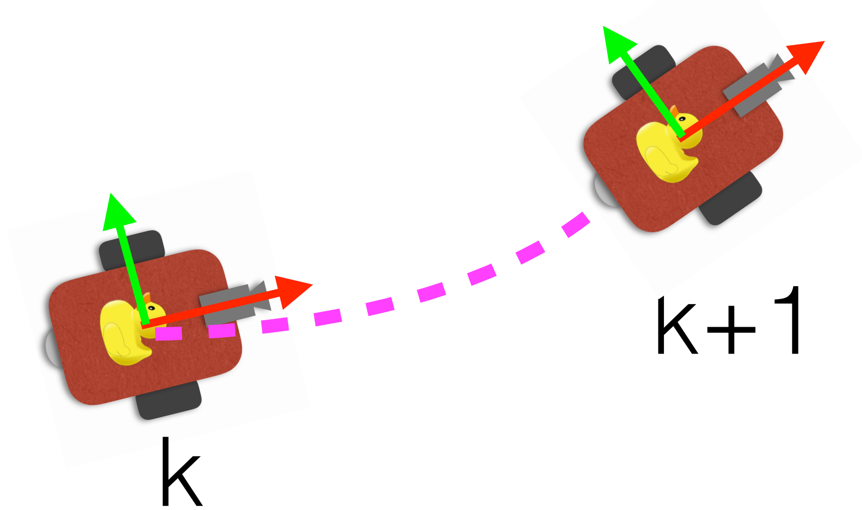
ideal (noiseless) world

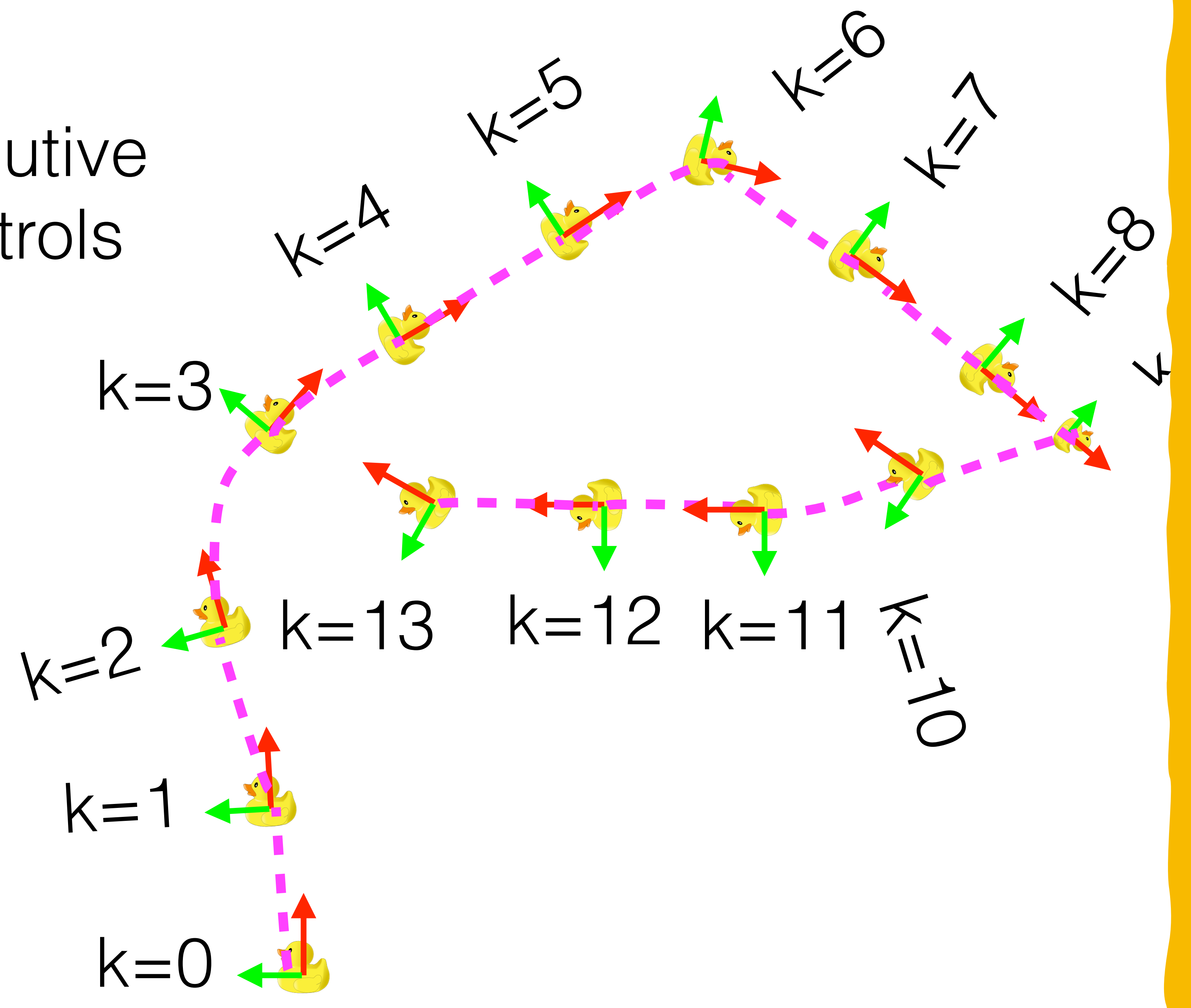


Motion integration (odometry)

We can estimate
motion between consecutive
poses from motion controls

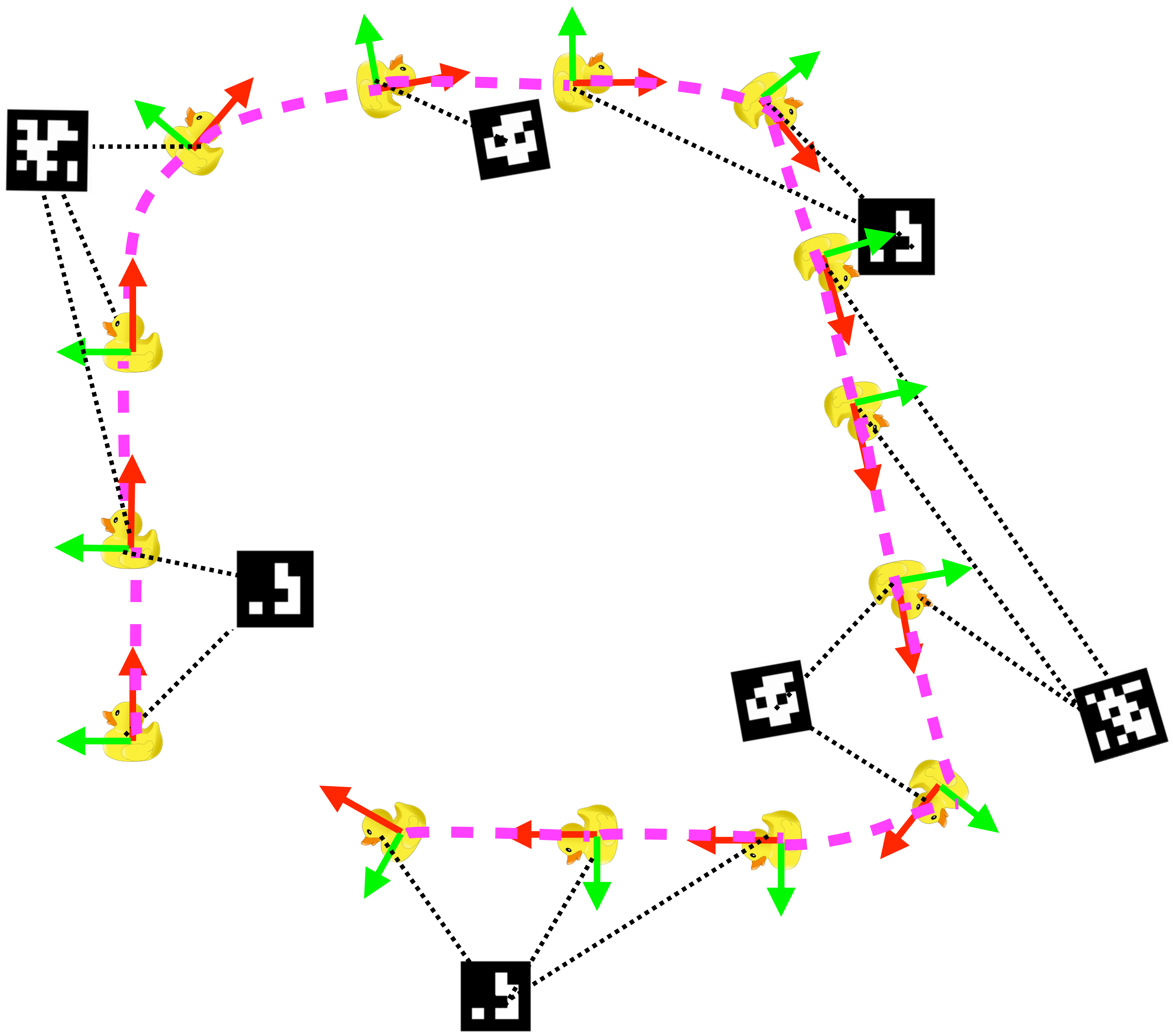




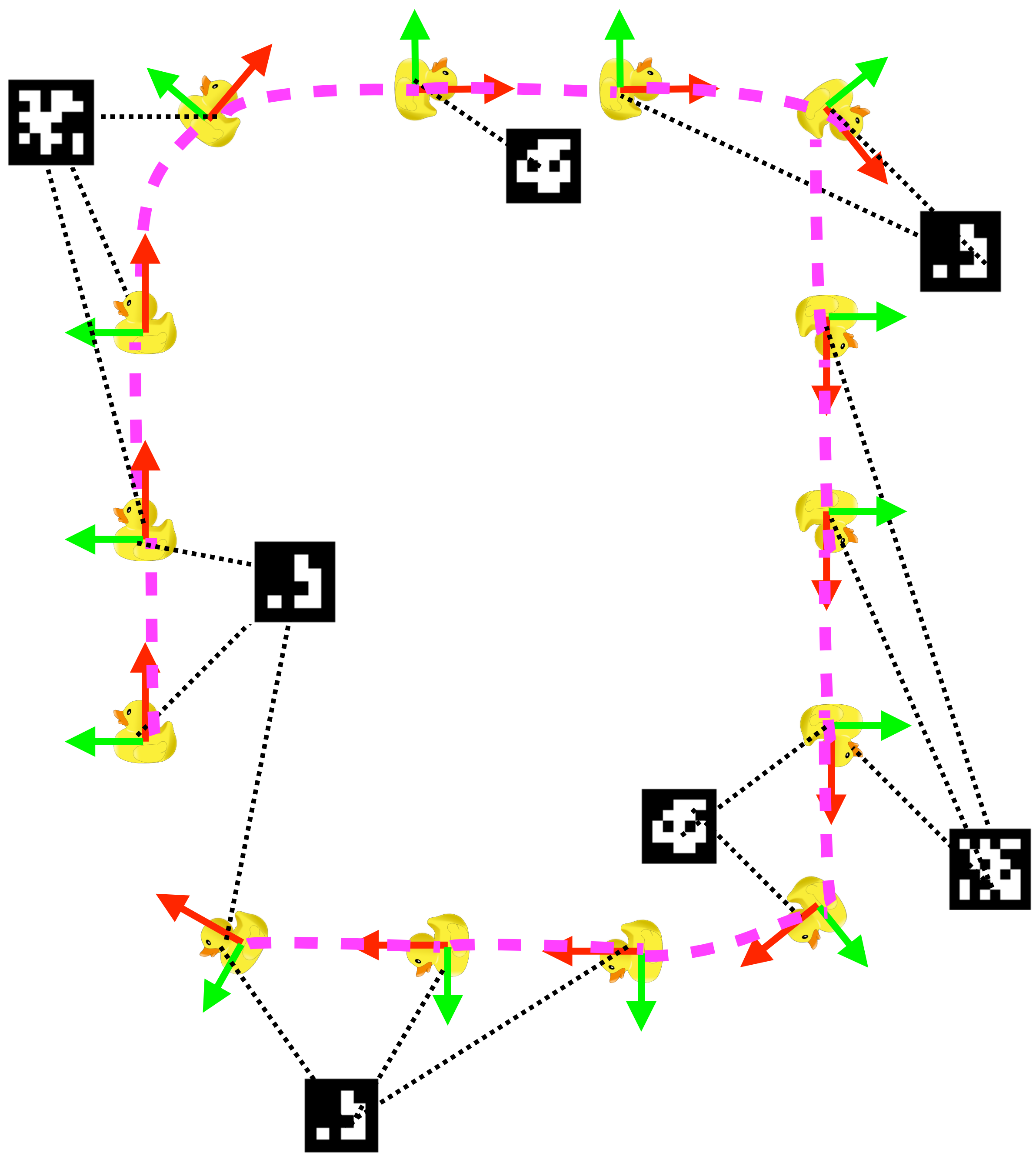


real (noisy) world

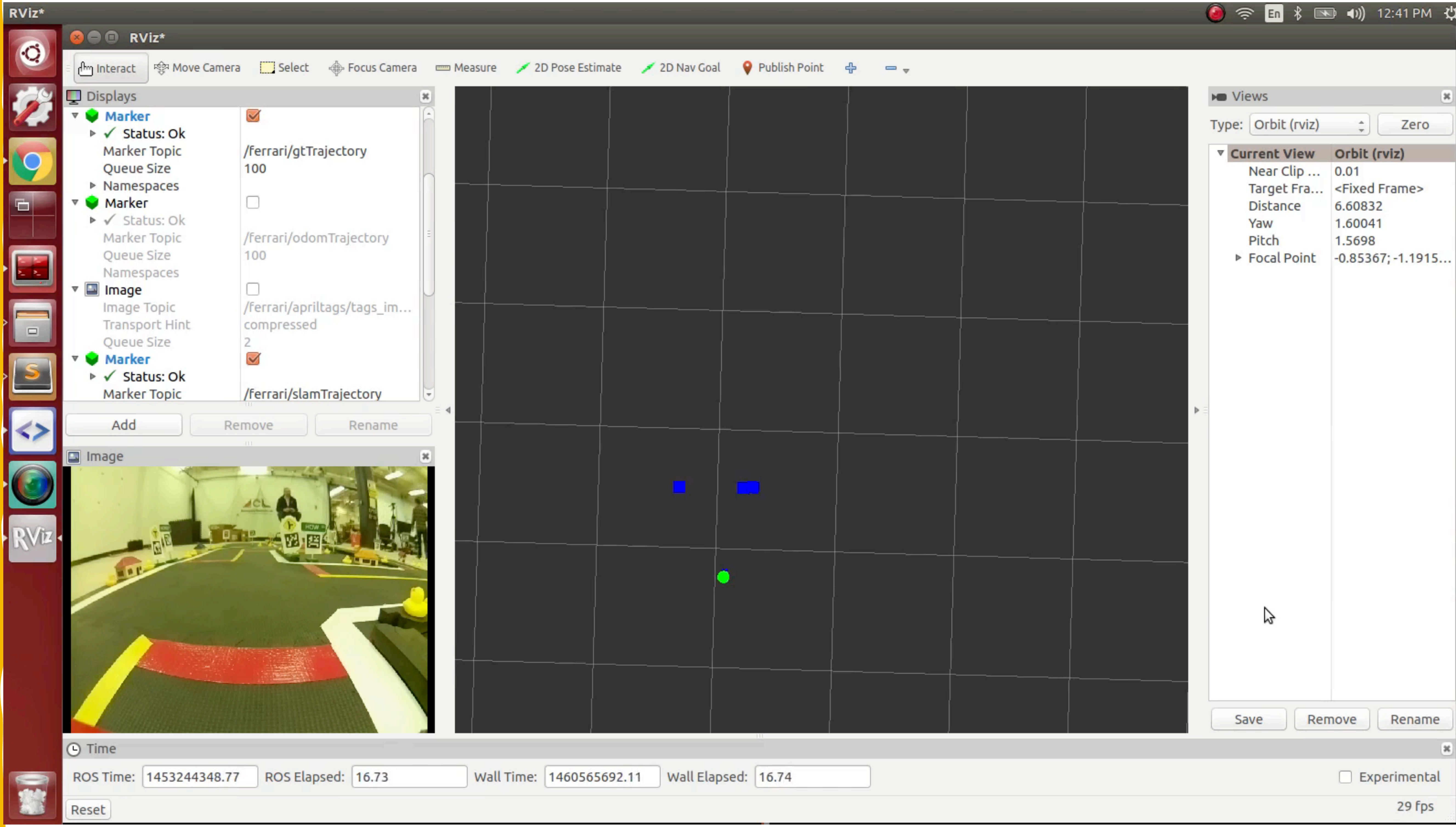
Combining odometry & landmarks: the SLAM problem



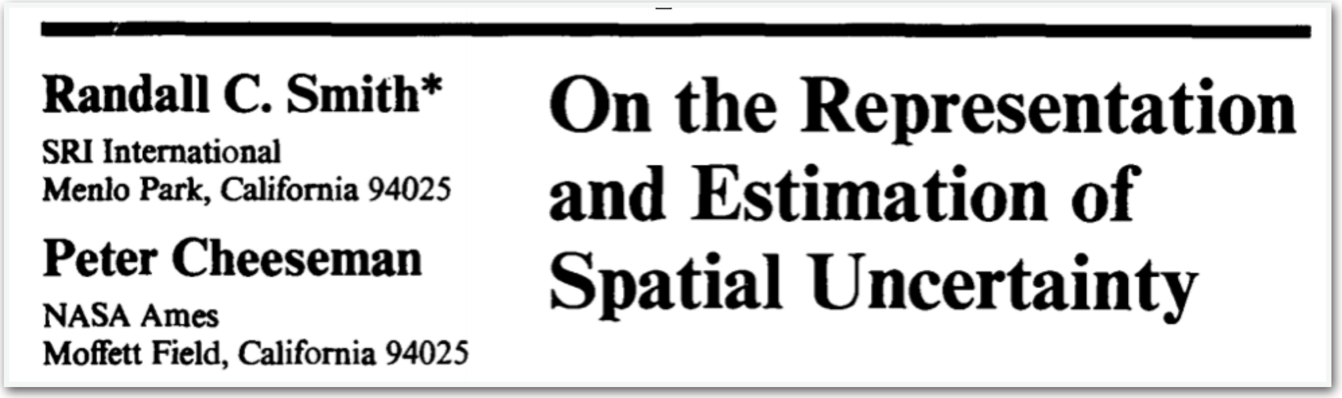
Combining odometry & landmarks: the SLAM problem



Feature-based SLAM in Duckietown



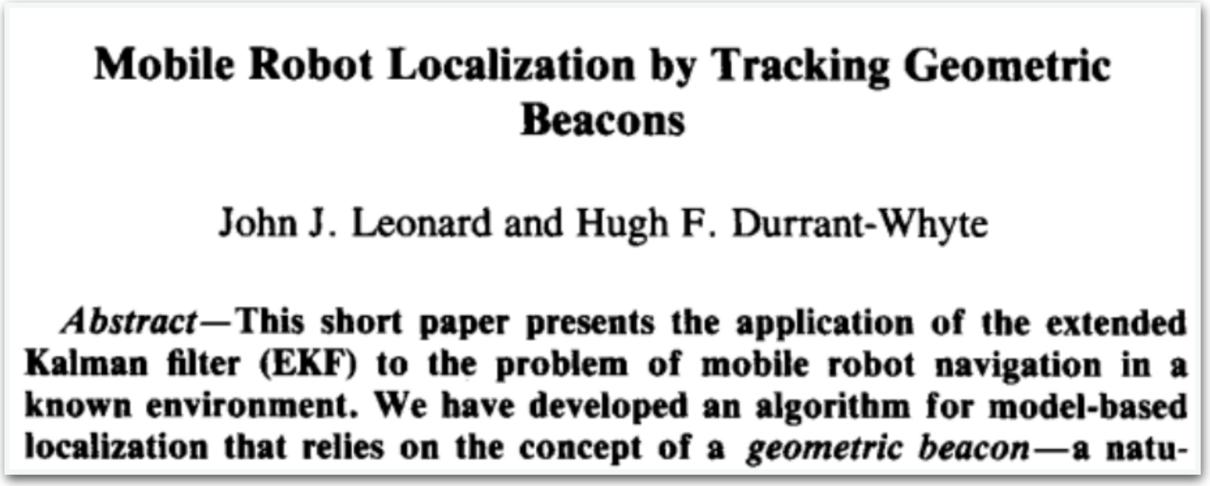
SLAM: a bit of history



Randall C. Smith*
SRI International
Menlo Park, California 94025

Peter Cheeseman
NASA Ames
Moffett Field, California 94025

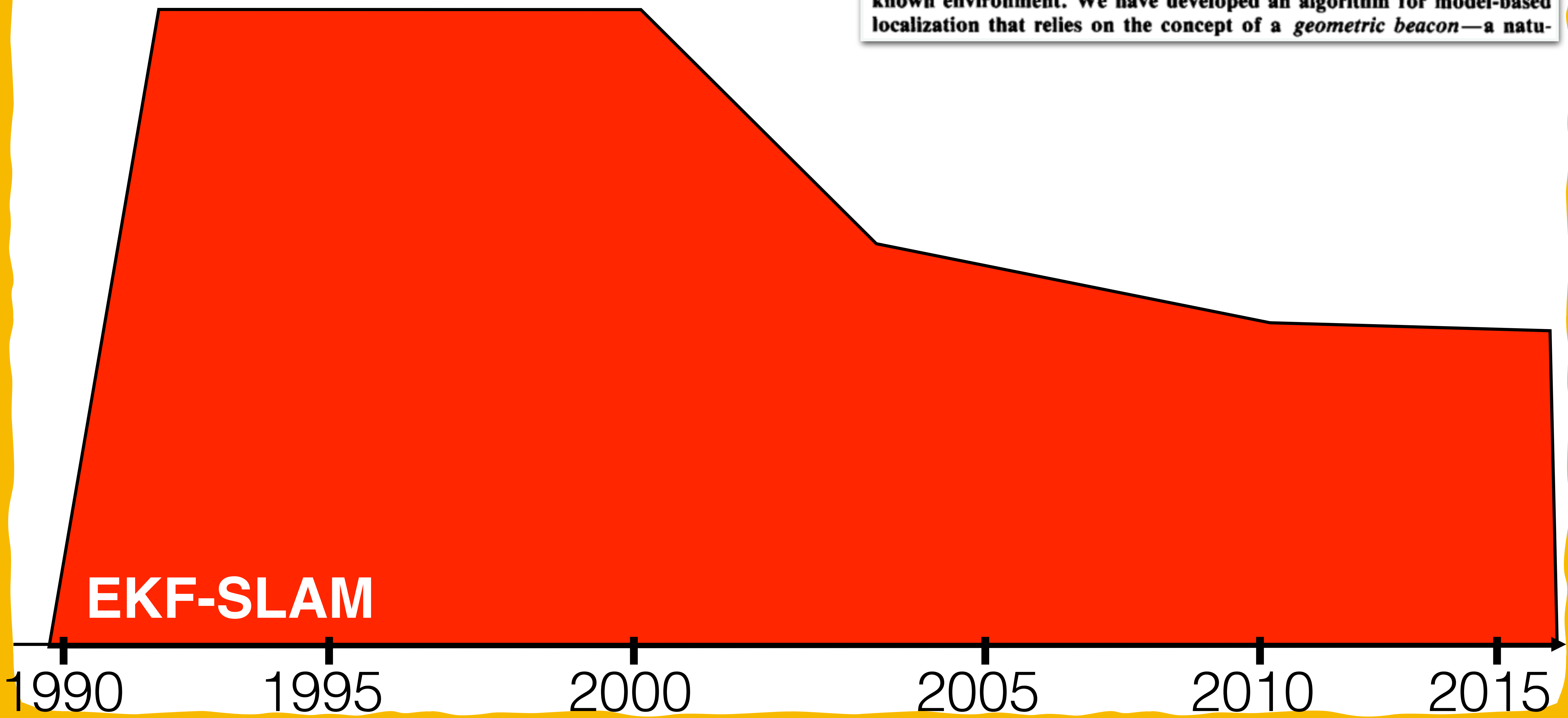
On the Representation and Estimation of Spatial Uncertainty



Mobile Robot Localization by Tracking Geometric Beacons

John J. Leonard and Hugh F. Durrant-Whyte

***Abstract*—This short paper presents the application of the extended Kalman filter (EKF) to the problem of mobile robot navigation in a known environment. We have developed an algorithm for model-based localization that relies on the concept of a *geometric beacon*—a natu-**



SLAM: a bit of history

Rao-Blackwellised Particle Filtering for Dynamic Bayesian Networks

Arnaud Doucet[‡] **Nando de Freitas**[†] **Kevin Murphy**[†] **Stuart Russell**[†]

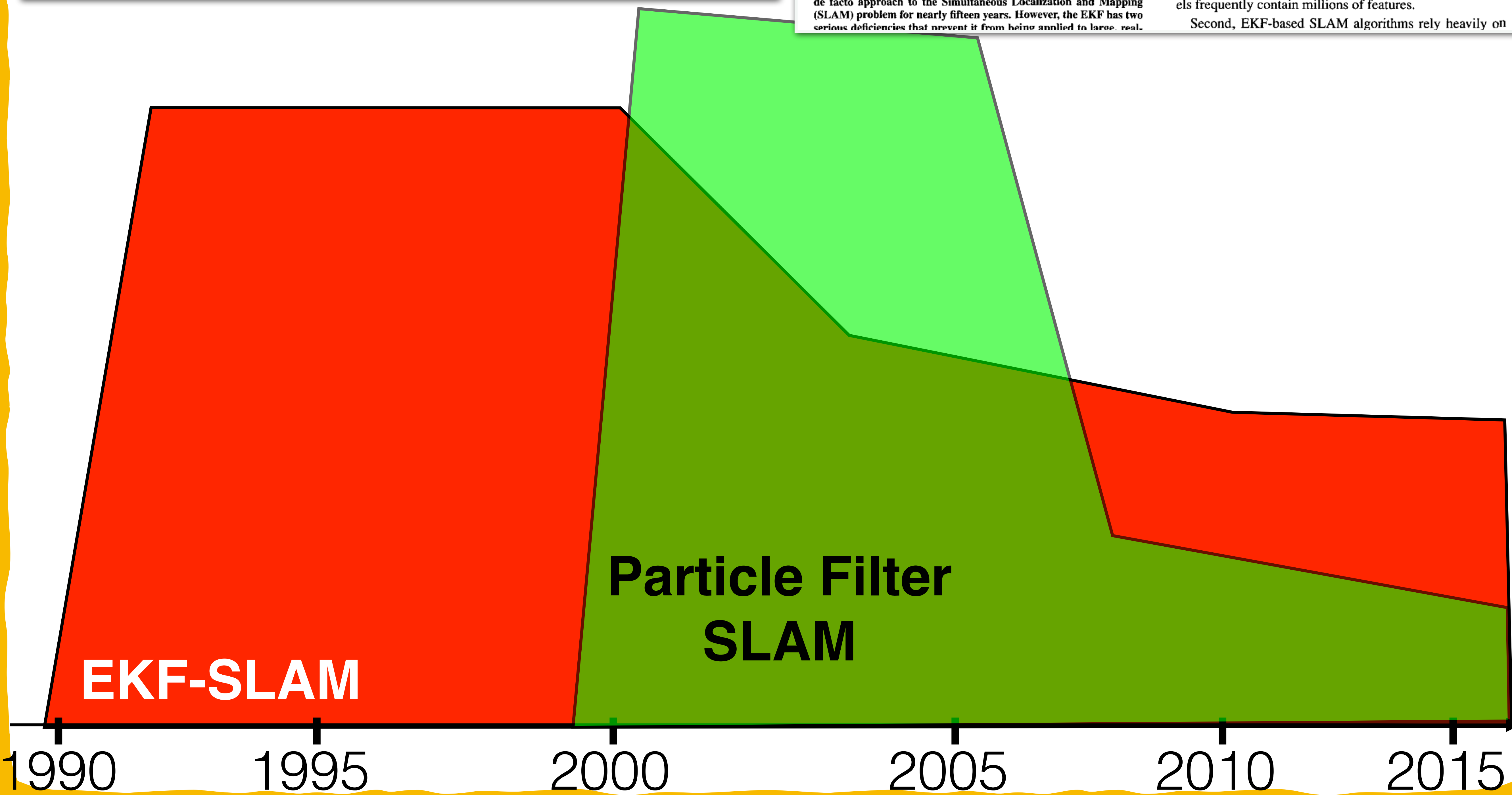
Simultaneous Localization and Mapping with Unknown Data Association Using FastSLAM

Michael Montemerlo, Sebastian Thrun

Abstract— **The Extended Kalman Filter (EKF) has been the de facto approach to the Simultaneous Localization and Mapping (SLAM) problem for nearly fifteen years. However, the EKF has two serious deficiencies that prevent it from being applied to large, real-**

to only a few hundred—whereas natural environment models frequently contain millions of features.

Second, EKF-based SLAM algorithms rely heavily on



SLAM: a bit of history

Globally Consistent Range Scan Alignment for Environment Mapping

F. Lu*, E. Milios
Department of Computer Science,
York University,
North York, Ontario, Canada
{lufeng, eem}@cs.yorku.ca

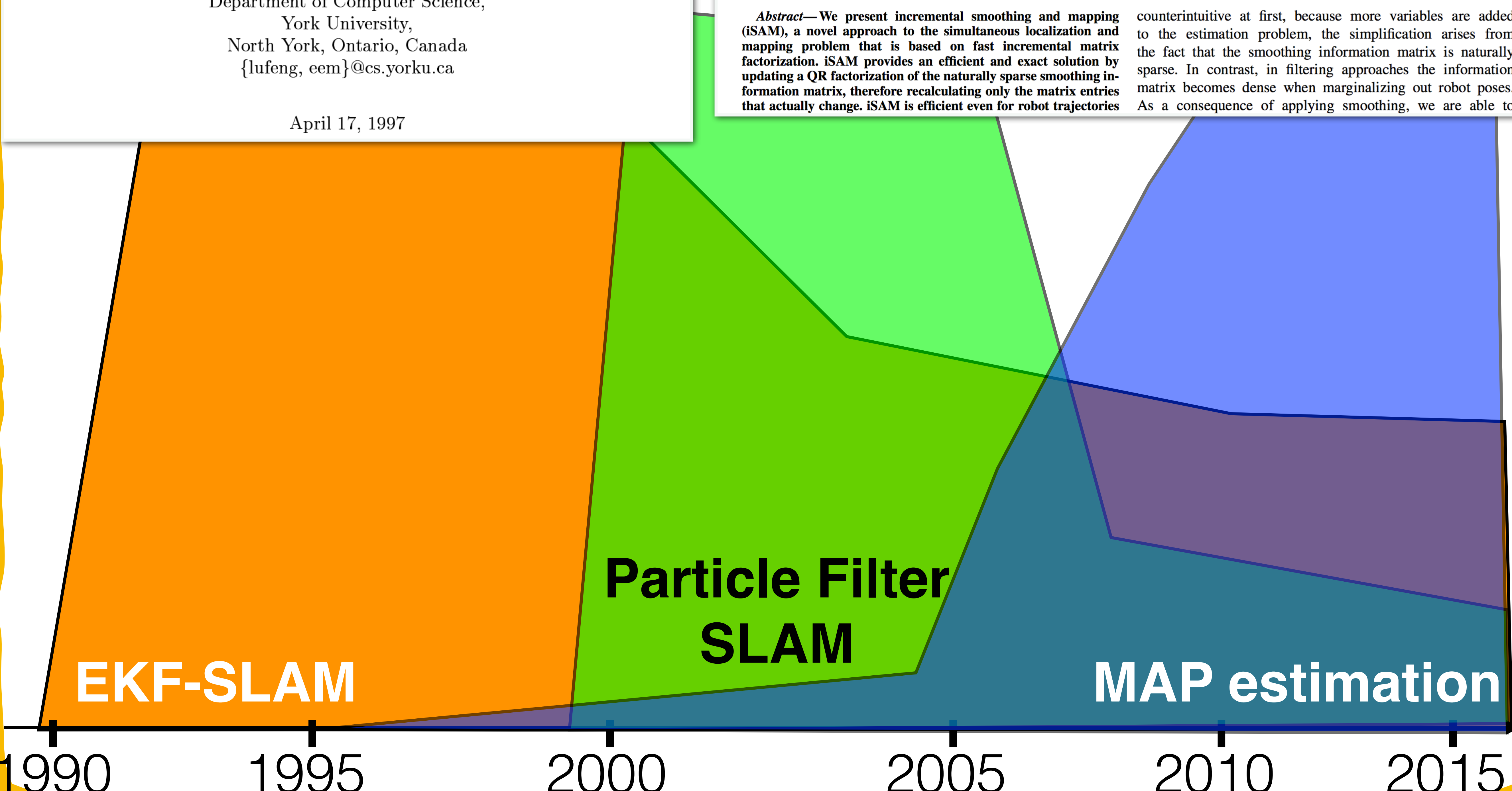
April 17, 1997

iSAM: Incremental Smoothing and Mapping

Michael Kaess, *Student Member, IEEE,* Ananth Ranganathan, *Student Member, IEEE,*
and Frank Dellaert, *Member, IEEE*

***Abstract*— We present incremental smoothing and mapping (iSAM), a novel approach to the simultaneous localization and mapping problem that is based on fast incremental matrix factorization. iSAM provides an efficient and exact solution by updating a QR factorization of the naturally sparse smoothing information matrix, therefore recalculating only the matrix entries that actually change. iSAM is efficient even for robot trajectories**

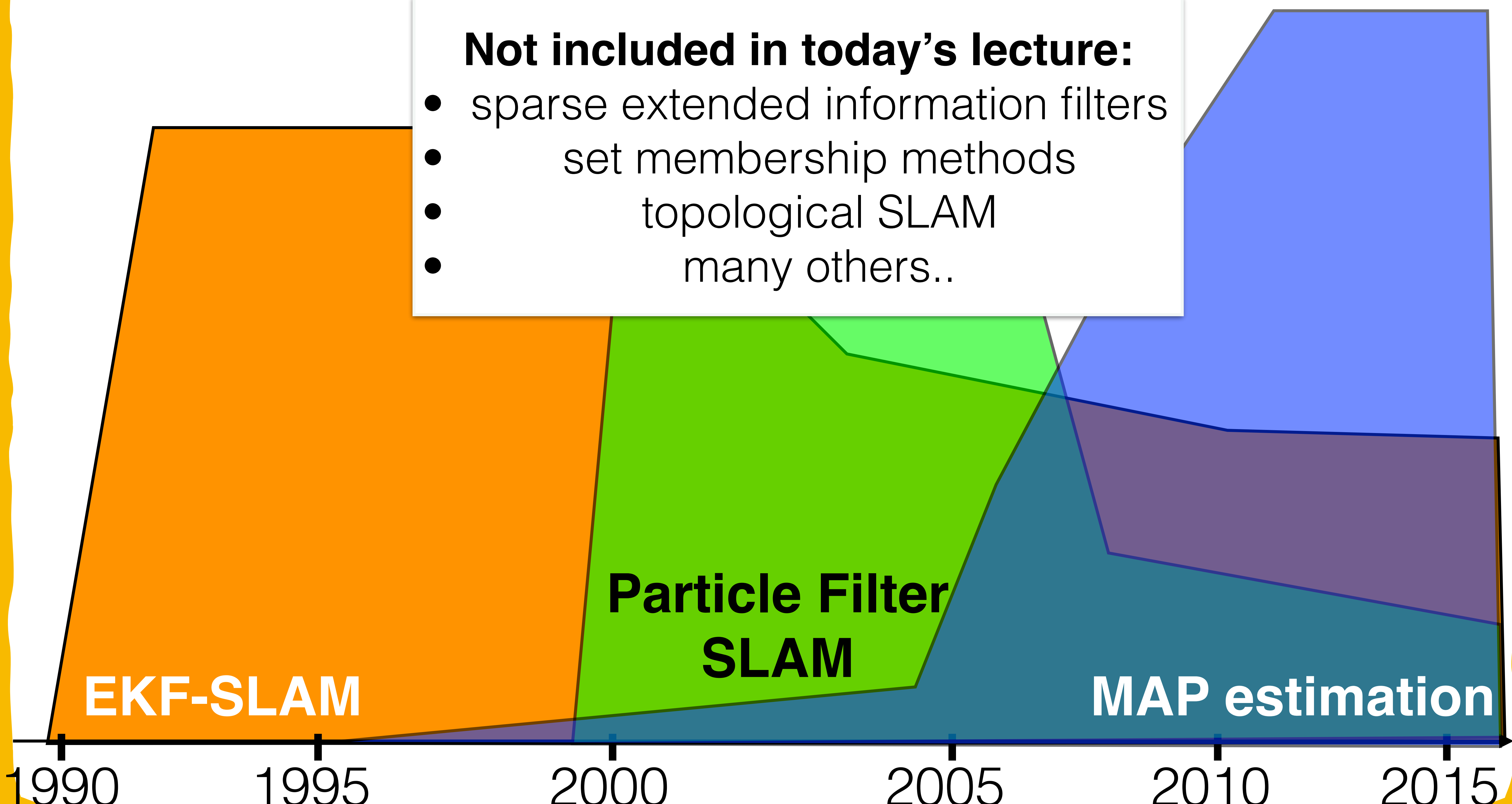
counterintuitive at first, because more variables are added to the estimation problem, the simplification arises from the fact that the smoothing information matrix is naturally sparse. In contrast, in filtering approaches the information matrix becomes dense when marginalizing out robot poses. As a consequence of applying smoothing, we are able to



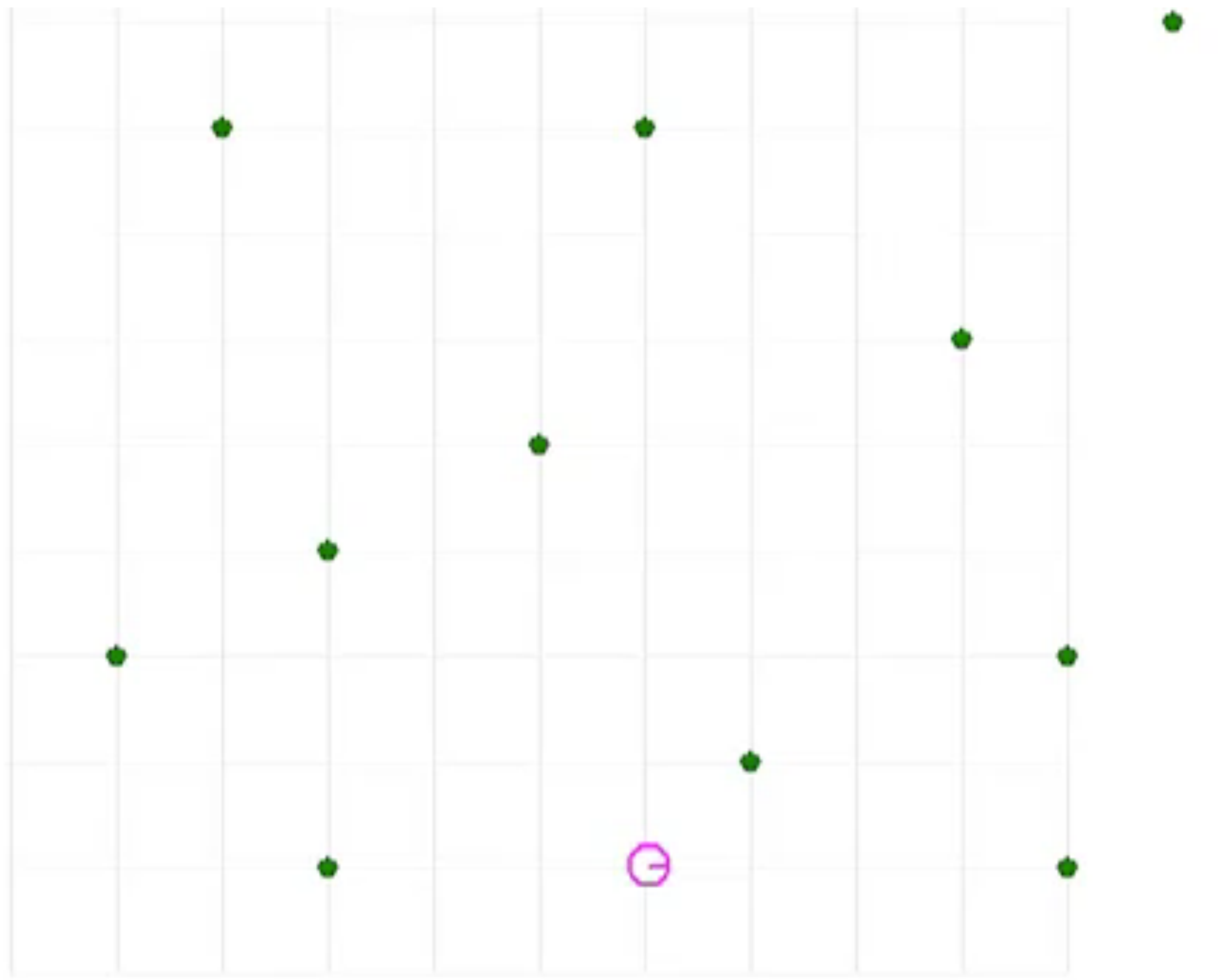
SLAM: a bit of history

Not included in today's lecture:

- sparse extended information filters
- set membership methods
- topological SLAM
- many others..



EKF-SLAM

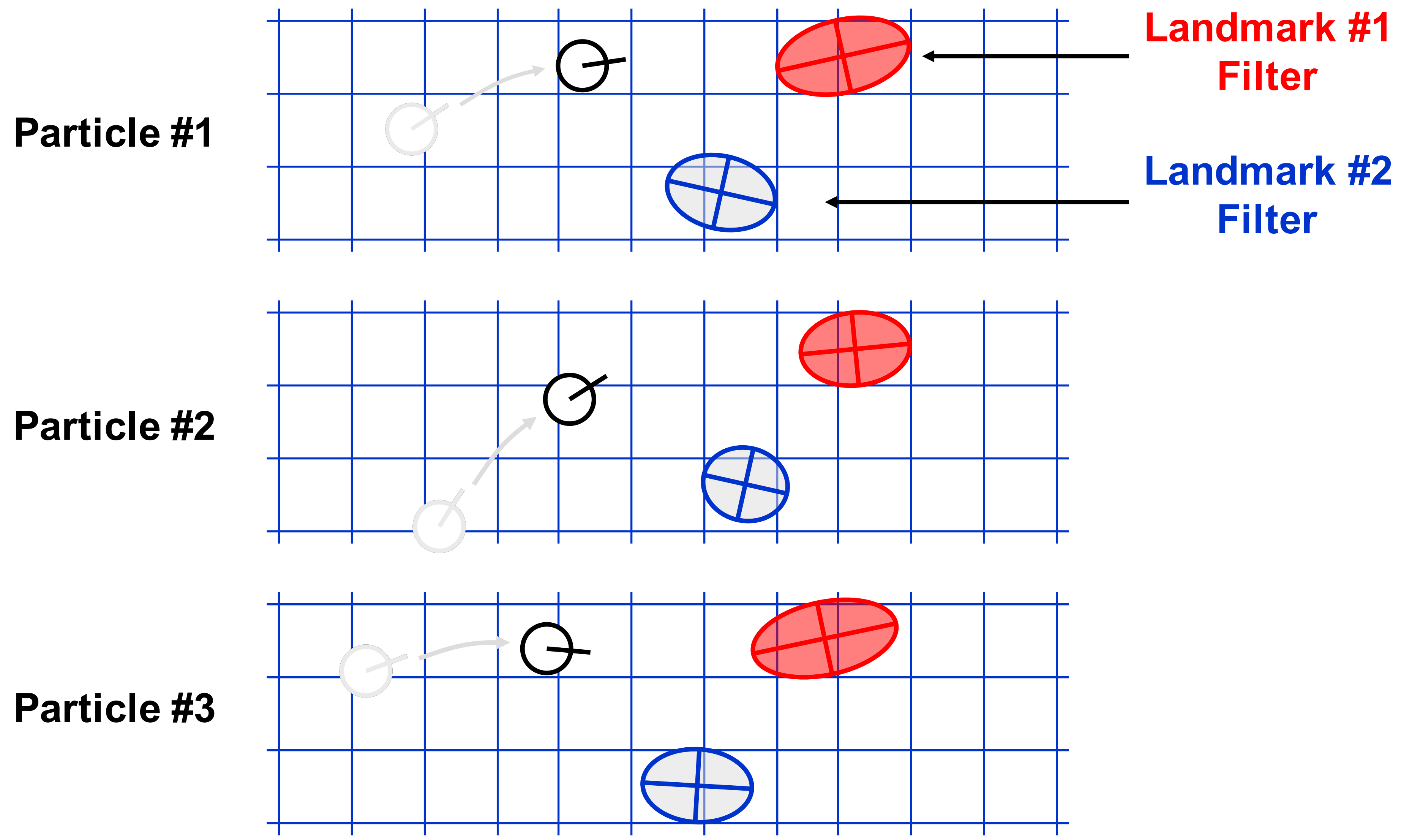


https://www.youtube.com/watch?v=vCVS9WAffi4

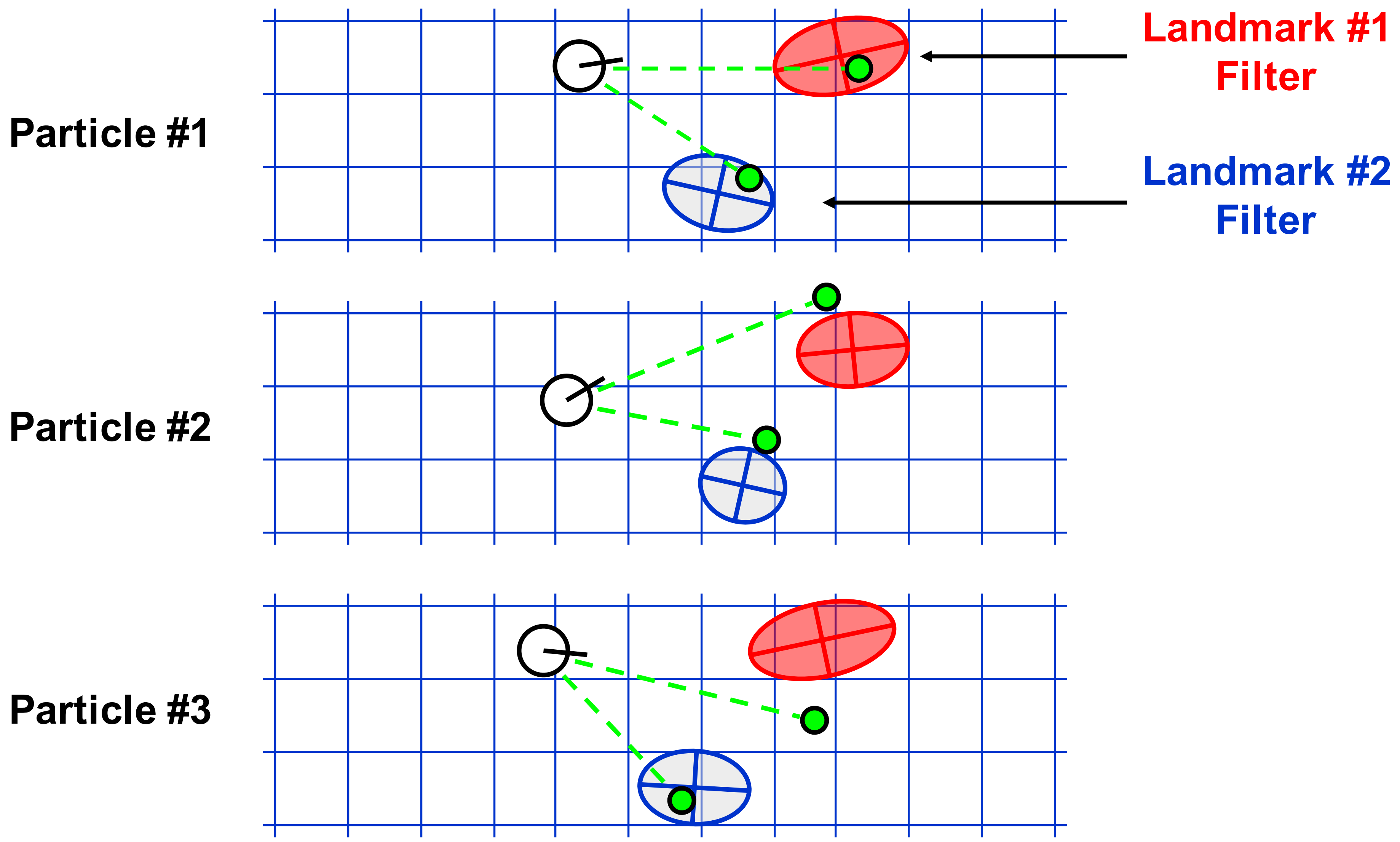
Limitations

- **Filter divergence**: linearization may be a poor approximation of original nonlinear system
- **Robustness**: noise, outliers
- **Scalability**: complexity is quadratic in the number of landmarks
- **Convergence? Consistency?** hard to provide performance guarantees

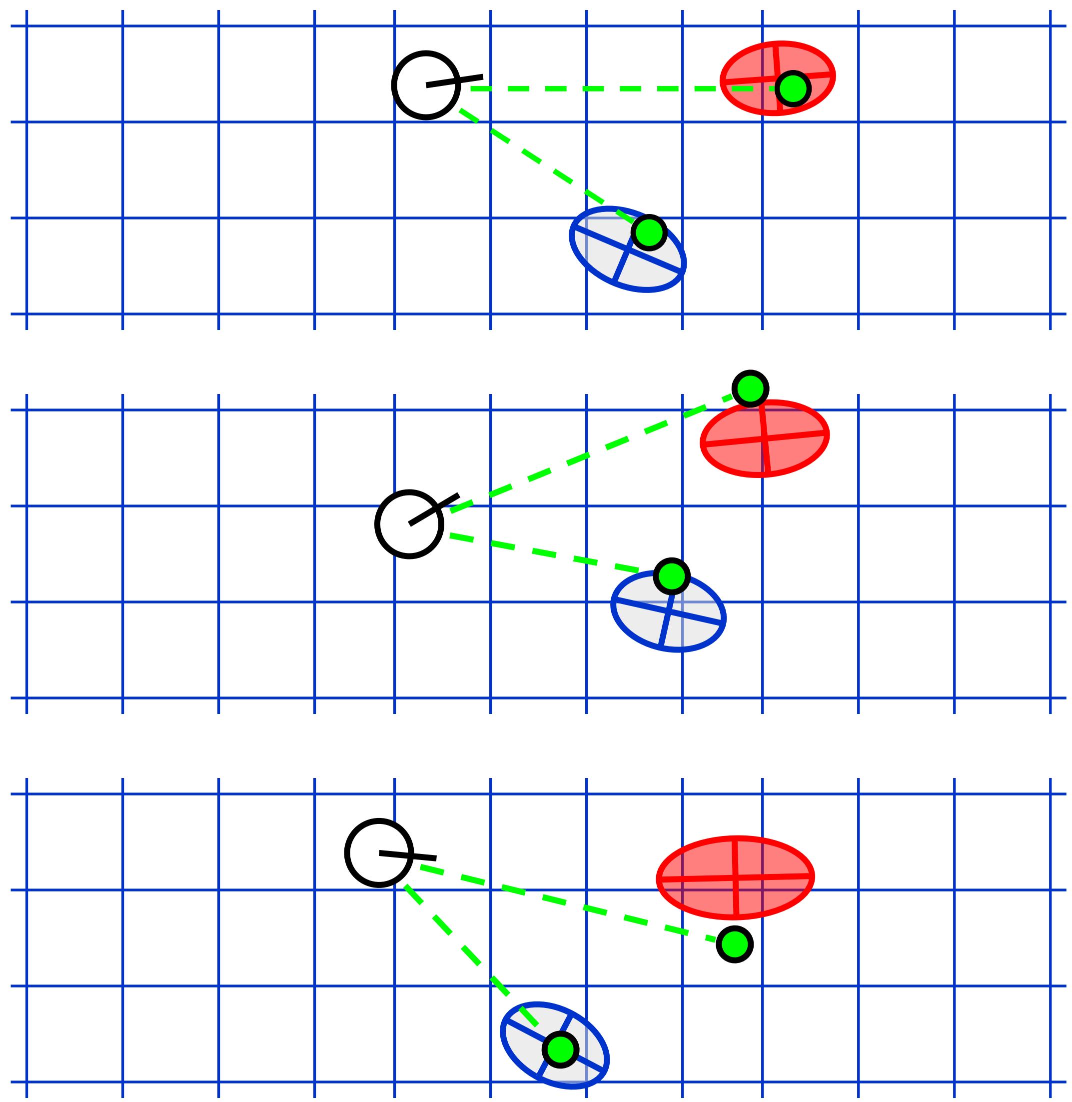
FAST-SLAM - Prediction



FAST-SLAM Update (pt. 1)



FAST-SLAM Update (pt. 2)

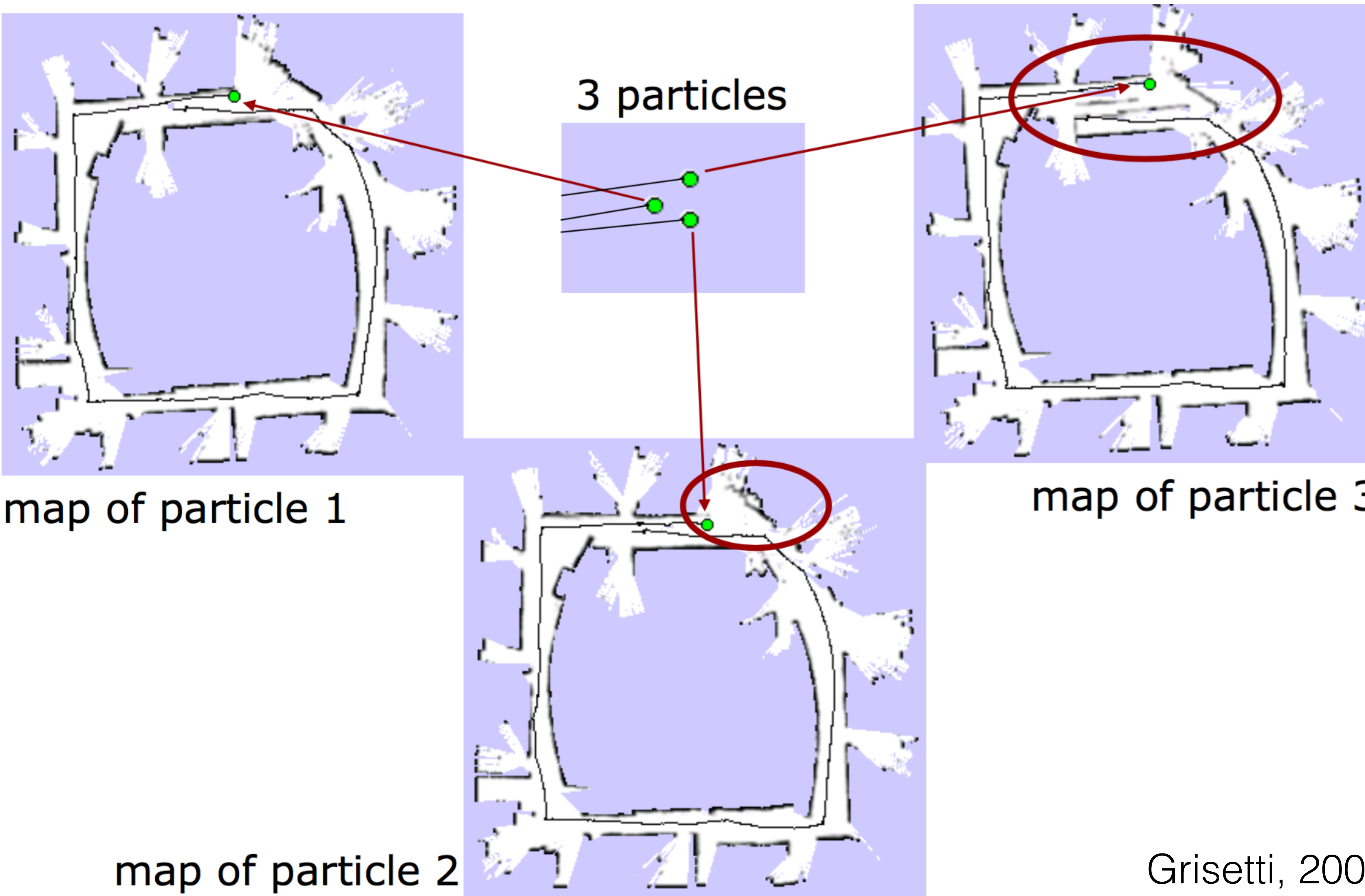


Particle #1 — **Weight = 0.8**

Particle #2 — **Weight = 0.4**

Particle #3 — **Weight = 0.1**

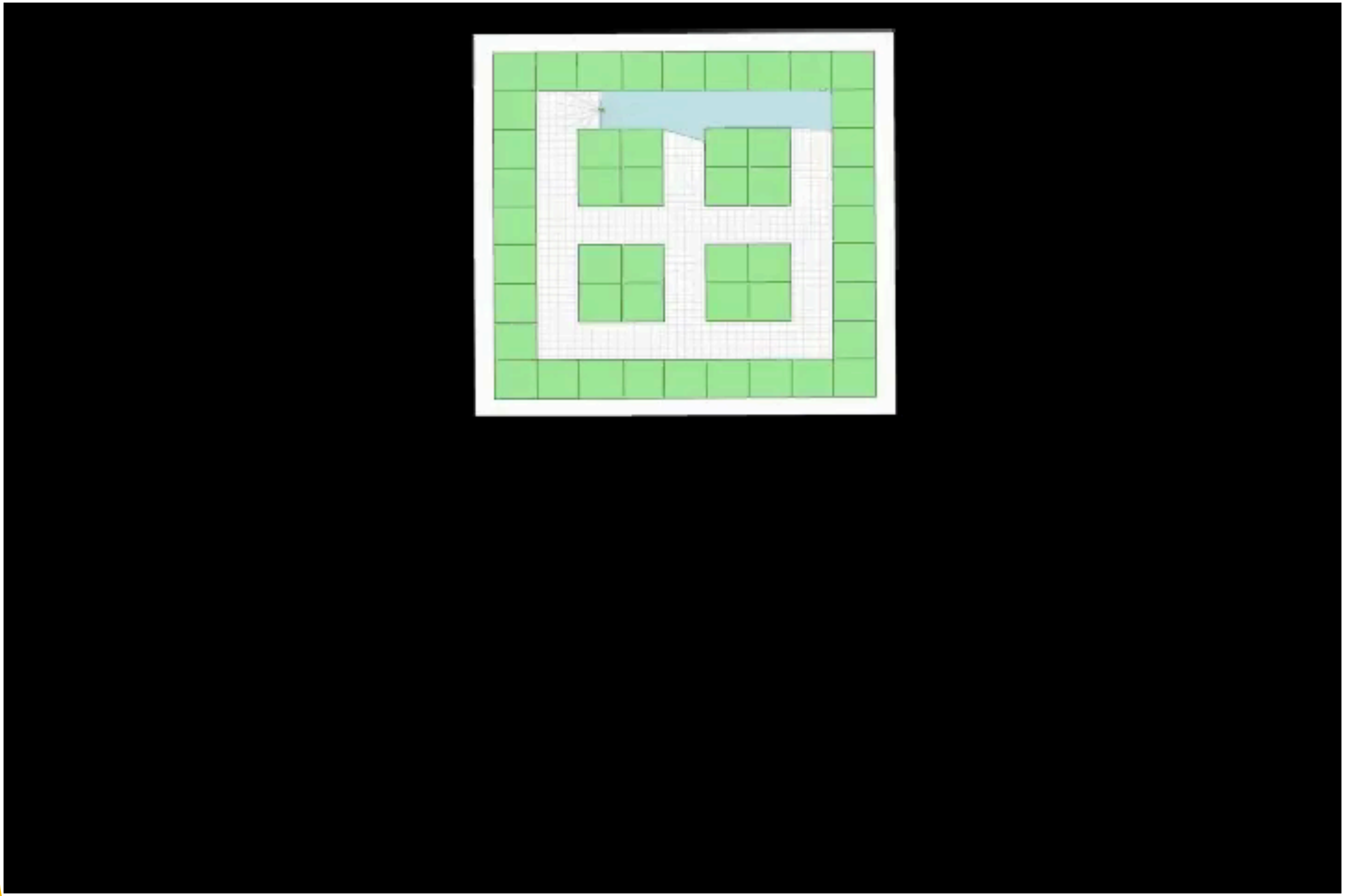
Particle Filter View-based SLAM



Grisetti, 2007

Particle Filter view-based SLAM

samples represent possible trajectories of the robot



Top:
ground truth

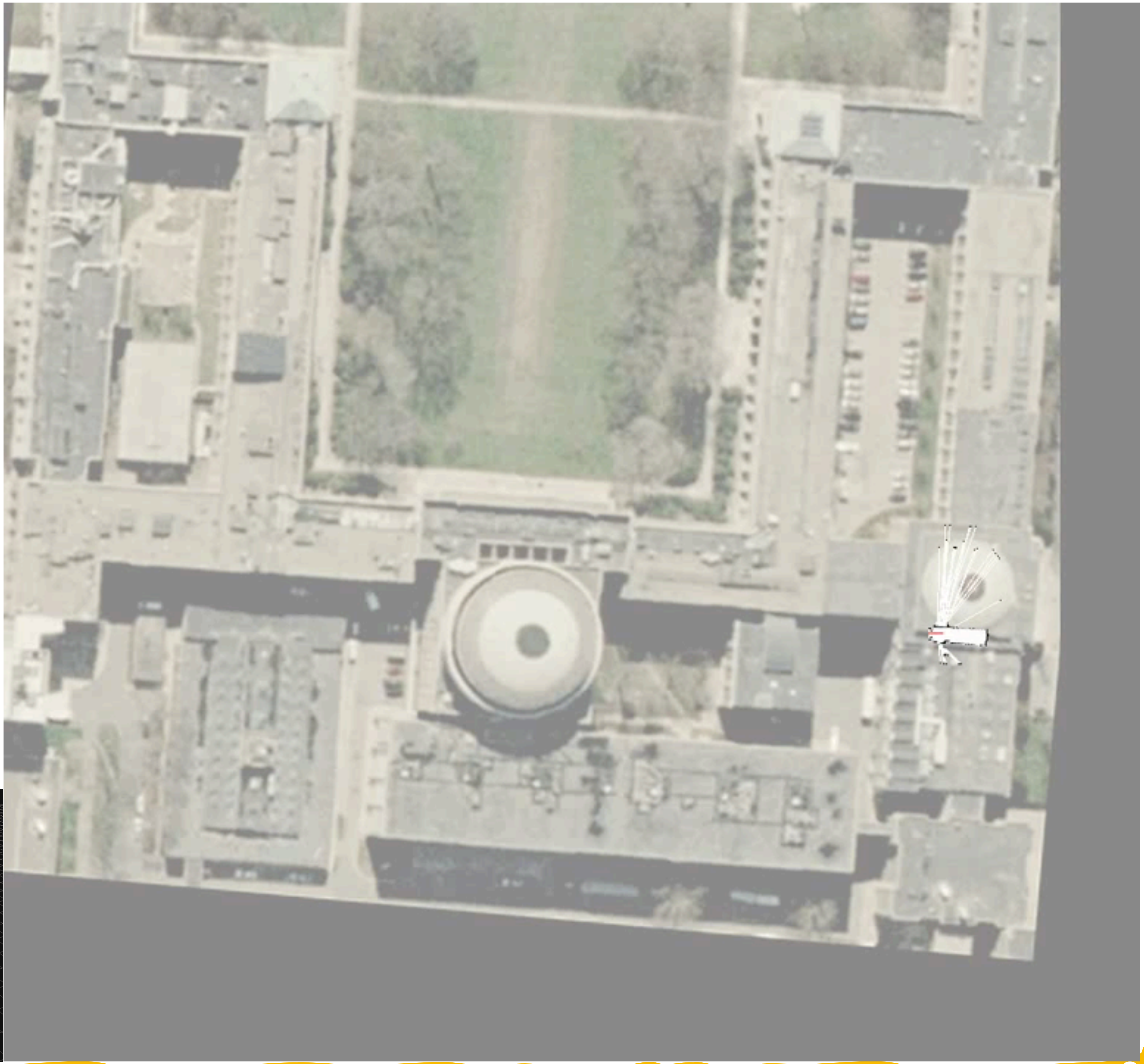
Left:
PF-SLAM

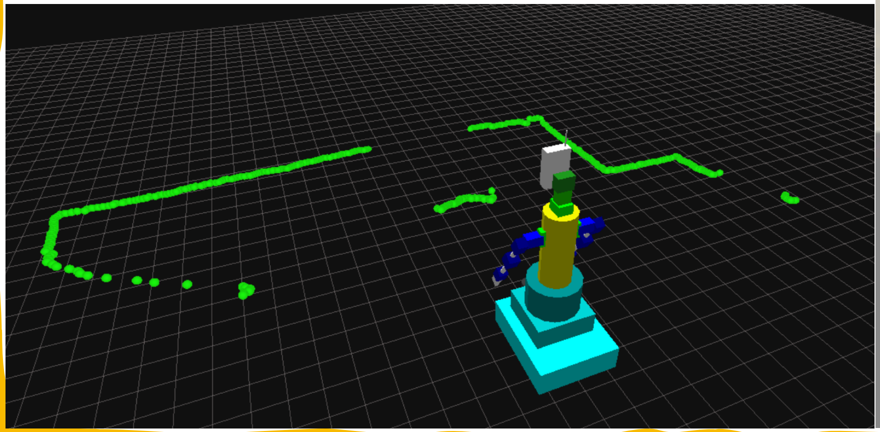
Right:
mapping from odometry

PF-SLAM in ROS

gmapping: ROS package for PF-SLAM

Plug & play, but requires a 2D laser scanner and a decent odometry





[courtesy of Cyrill Stachniss]

Advantages & Limitations

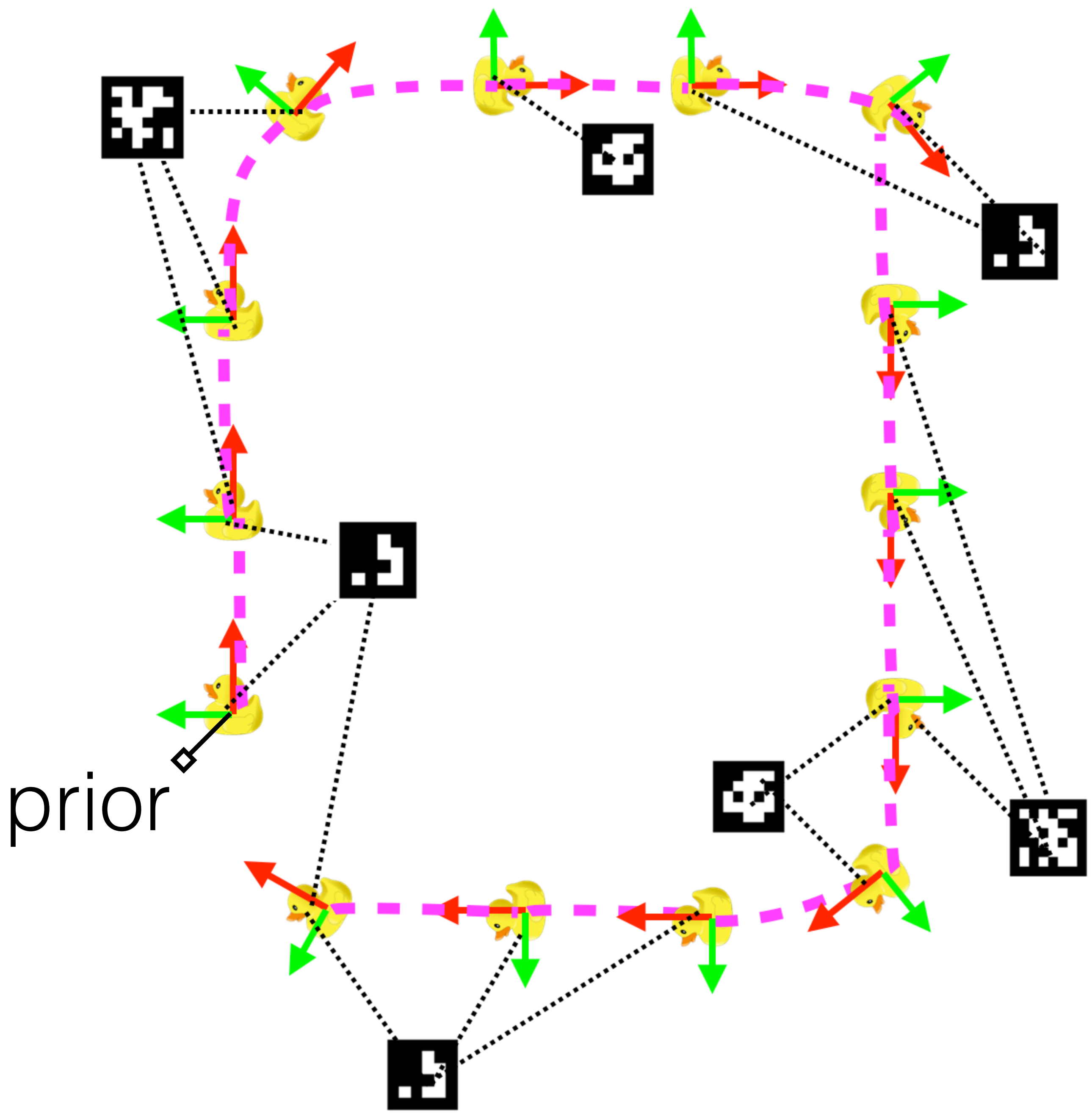
Relax EKF assumption ✓
nonlinear, non-Gaussian,
less strict requirements on measurement model

Particle depletion ✗
when uncertainty is large, a limited number of particles if a poor approximation of the posterior (poor performance in 3D)

\# **particles VS computational cost** ✗
the more particles, the better the estimate, but computationally expensive

Graph interpretation

$$x^\star = \arg\min_x \sum_k \left(\|z_k - h_k(x)\|_R^2 + \|u_k - f_k(x)\|_Q^2 \right) + \|\mu - g(x)\|_\Sigma^2$$



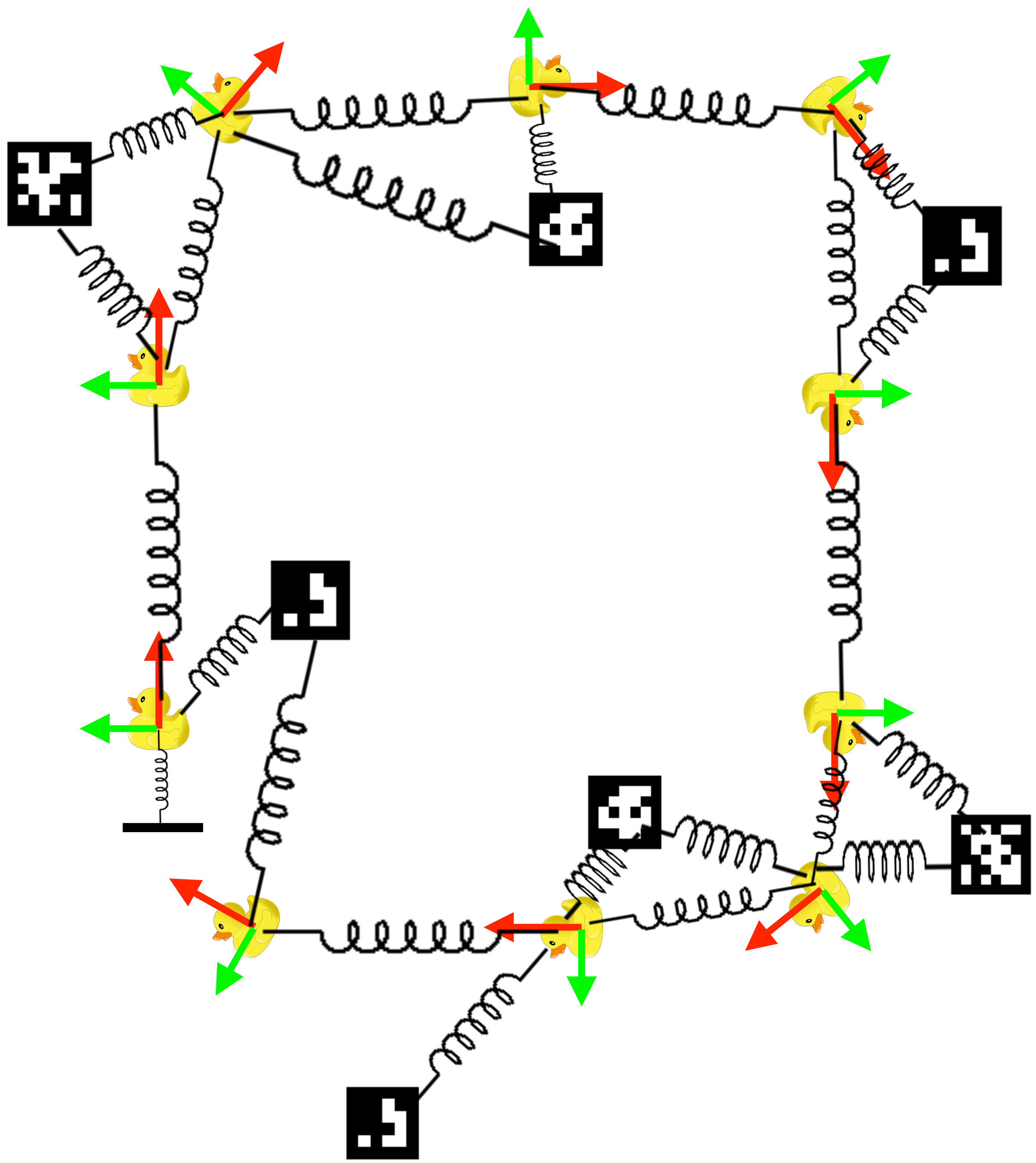
Graph:

- **vertices**: poses to be estimated
- **edges**: measurements between pair of poses

Pose Graph Optimization

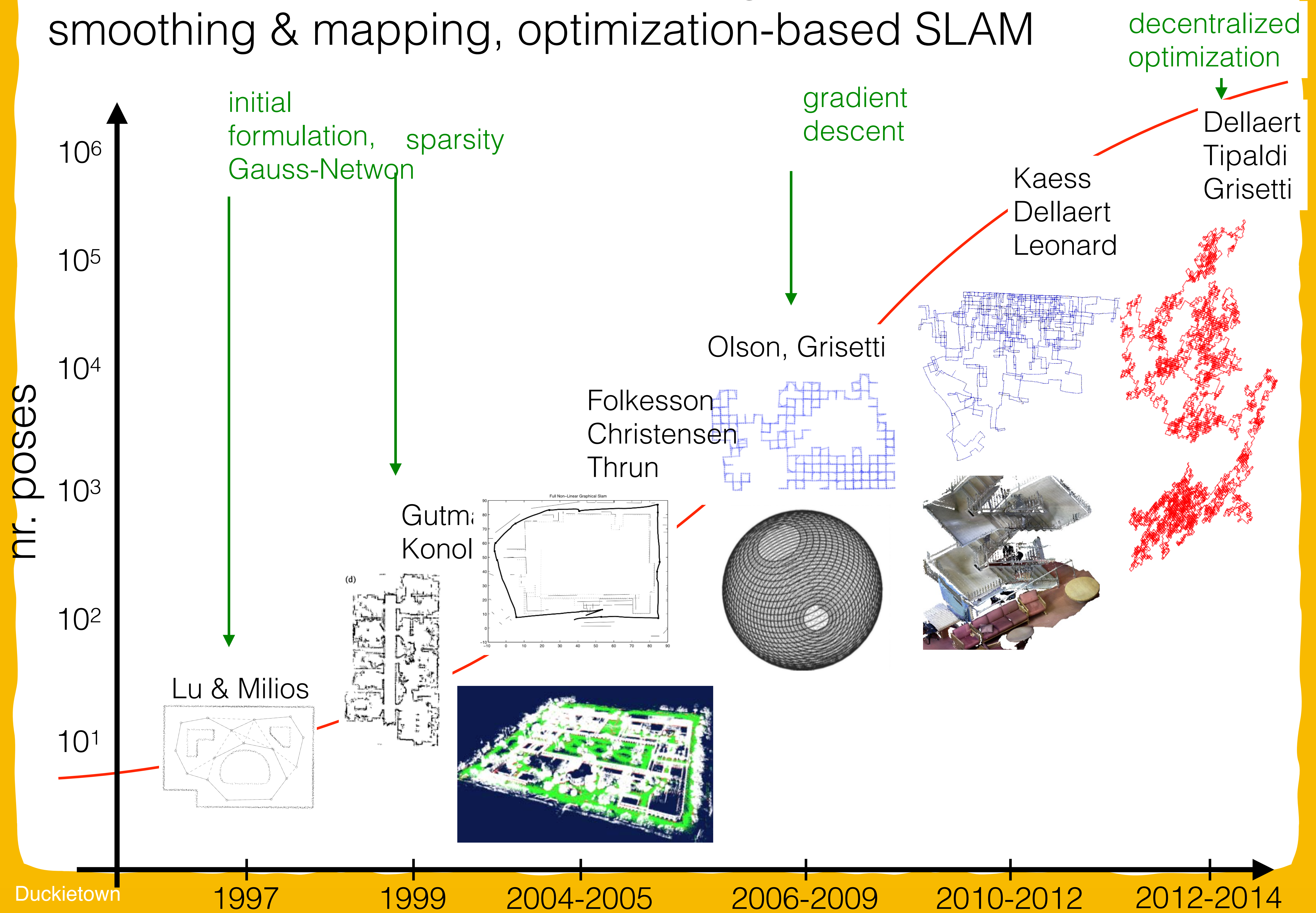
Mechanical interpretation

$$x^\star = \arg\min_x \sum_k \left(\|z_k - h_k(x)\|_R^2 + \|u_k - f_k(x)\|_Q^2 \right) + \|\mu - g(x)\|_\Sigma^2$$



- measurements as **springs** connecting pairs of masses
- MAP estimate is the position of the masses minimizing energy

MAP estimation for SLAM: pose graph optimization, smoothing & mapping, optimization-based SLAM

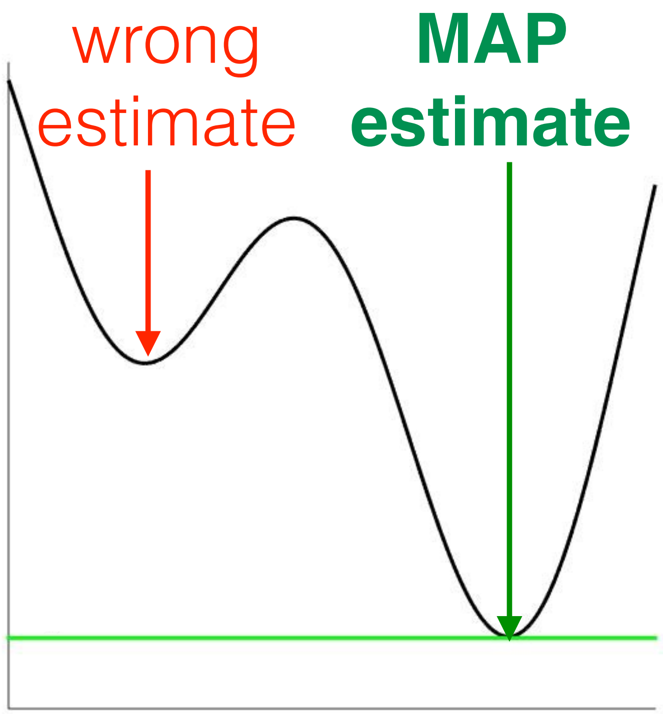


Challenges: MAP Estimation for SLAM

- **Large scale optimization:**

✓ efficient & incremental solvers exist

✗ problem keeps growing over time



- **Non-convex optimization**

✓ available initialization techniques (new!)

✓ possible to study convergence (new!)

- **Not robust to outliers**

✓ possible to improve robustness using robust cost functions

✗ need more research on performance guarantees

✗ dynamic environments