GAPSLAM: Blending **G**aussian **A**pproximation and **P**article Filters for Real-Time Non-Gaussian **SLAM**

MRG — Marine Robotics Group

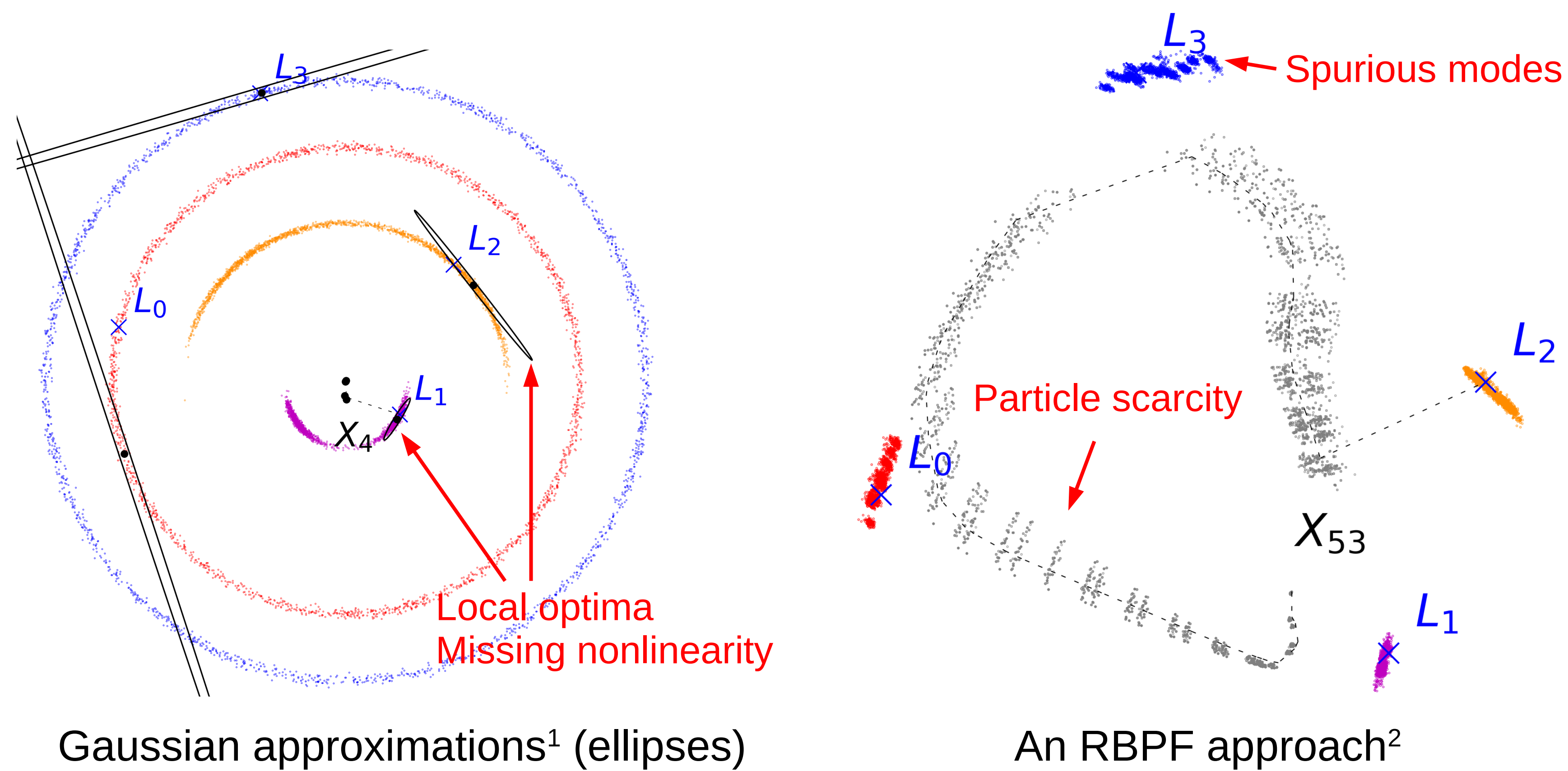Ph.D. student: Qiangqiang Chad Huang (hqq@mit.edu)   Advisor: John Leonard

1. Introduction: Inferring posterior distributions of robot poses and landmarks
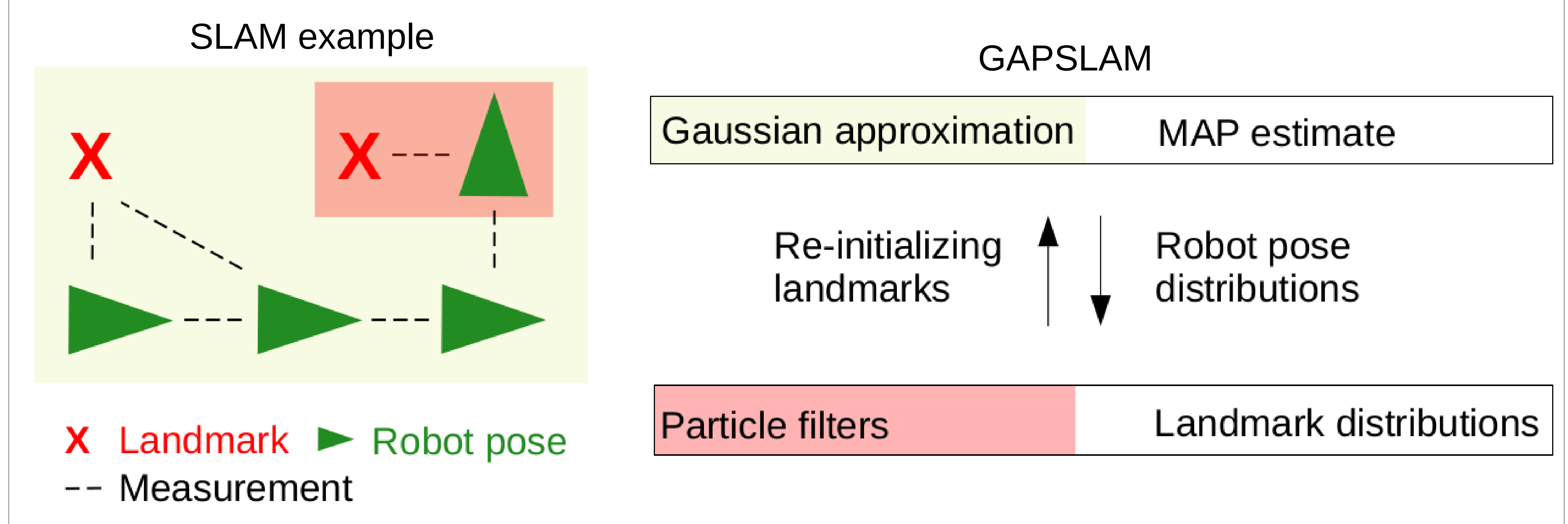
- Motivation:
    1) Evaluating uncertainty of localization and mapping
    2) Planning how to reduce uncertainty for safe navigation
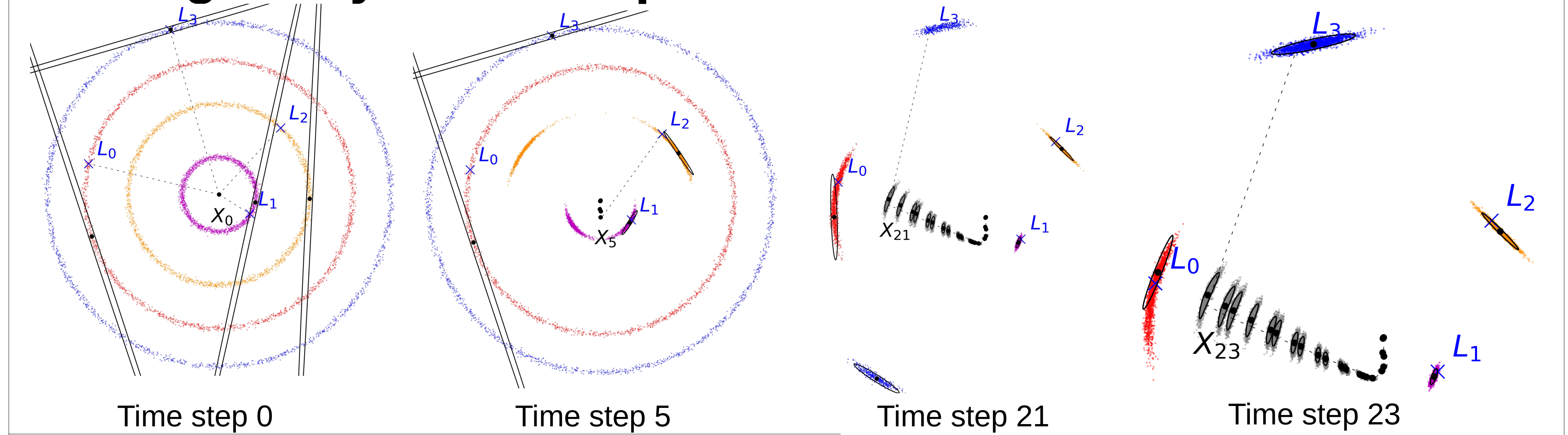- Standard real-time methods:
    1) Gaussian approximation[1]:
        Good scalability but poor expressiveness
    2) Rao-Blackwellized particle filters[2] (RBPF):
        Good expressiveness but poor scalability
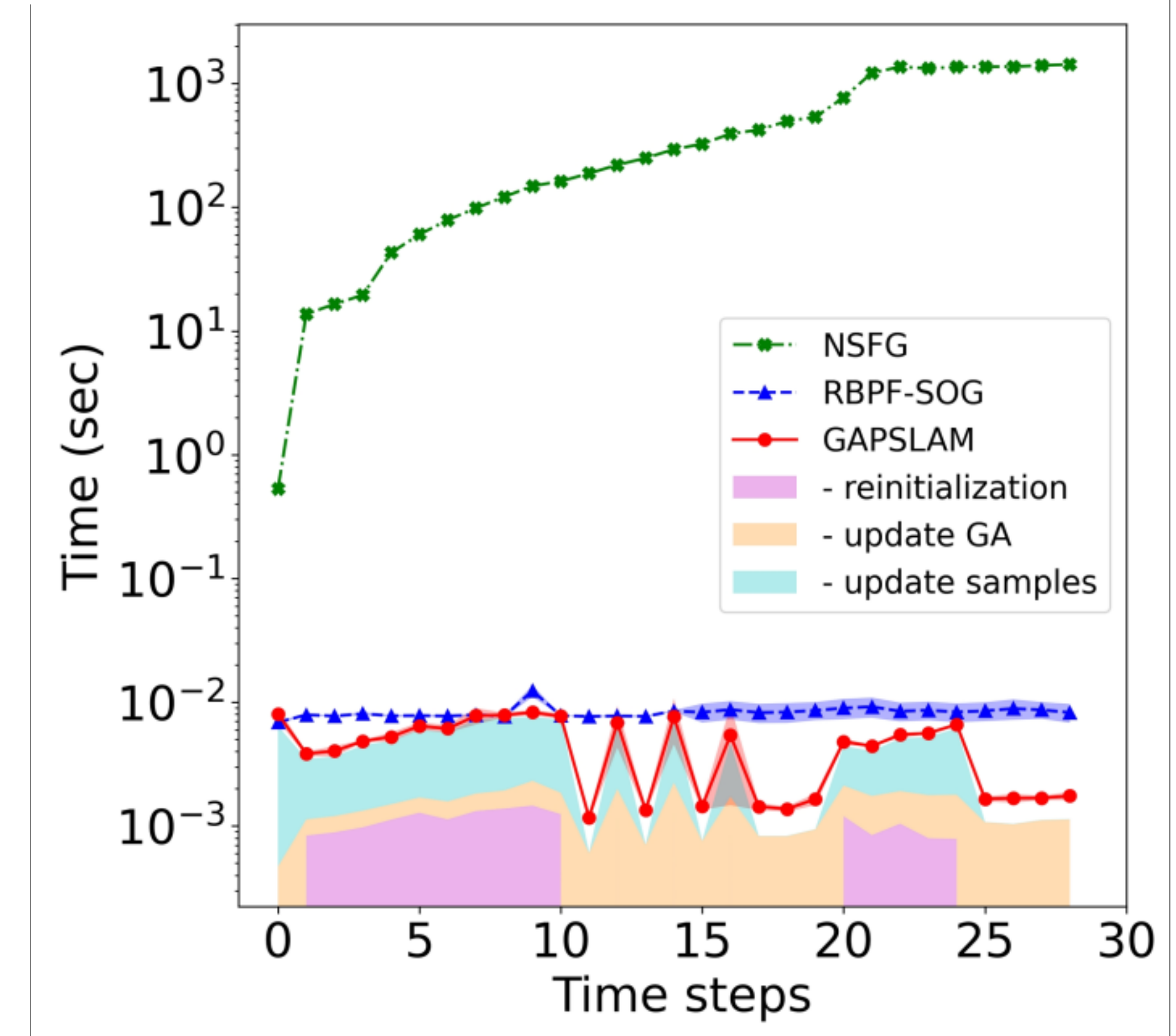

L_3 L_2 L_0 L_1 X_4
Local optima
Missing nonlinearity

Gaussian approximations[1] (ellipses)

L_3 — Spurious modes
Particle scarcity
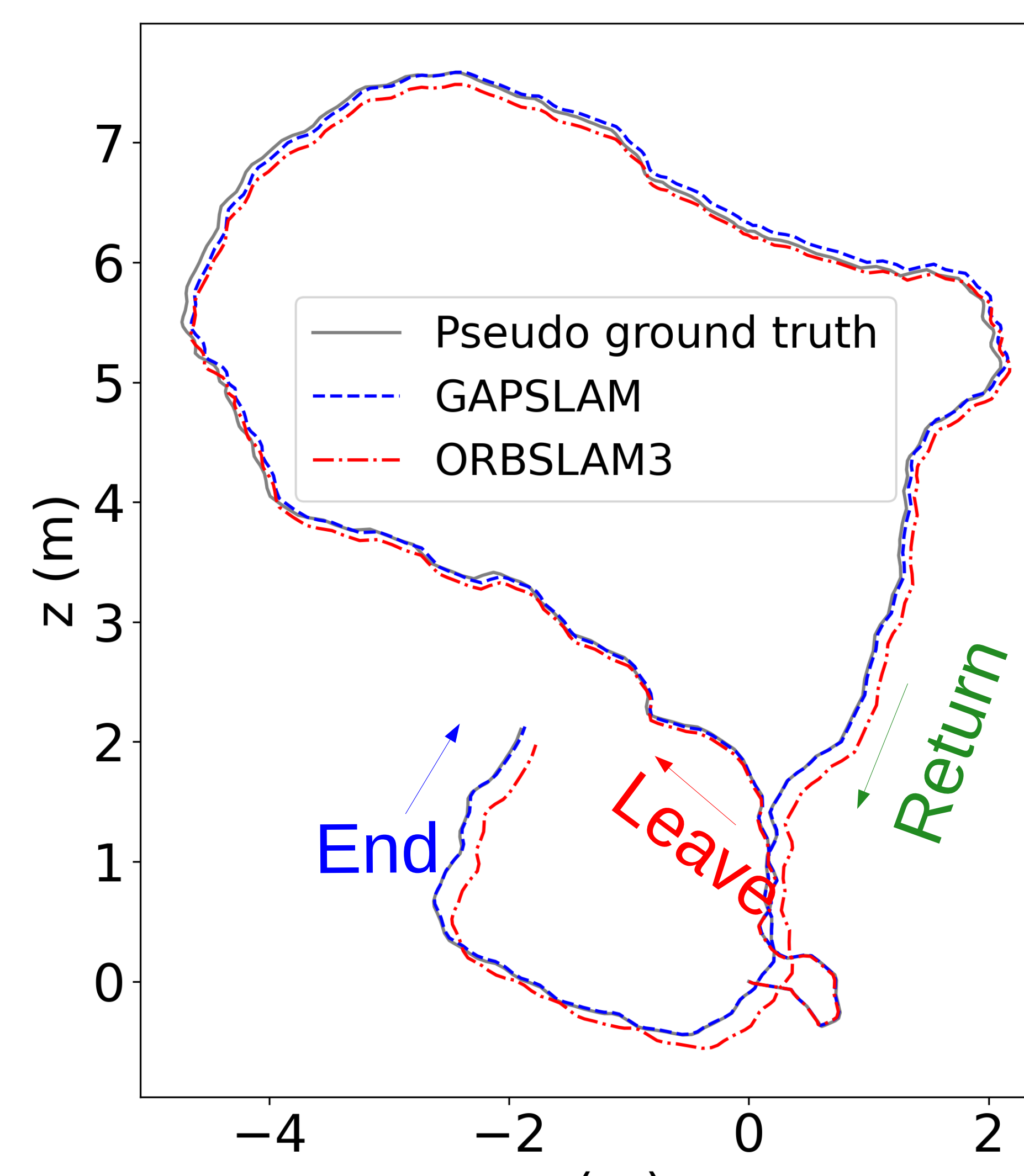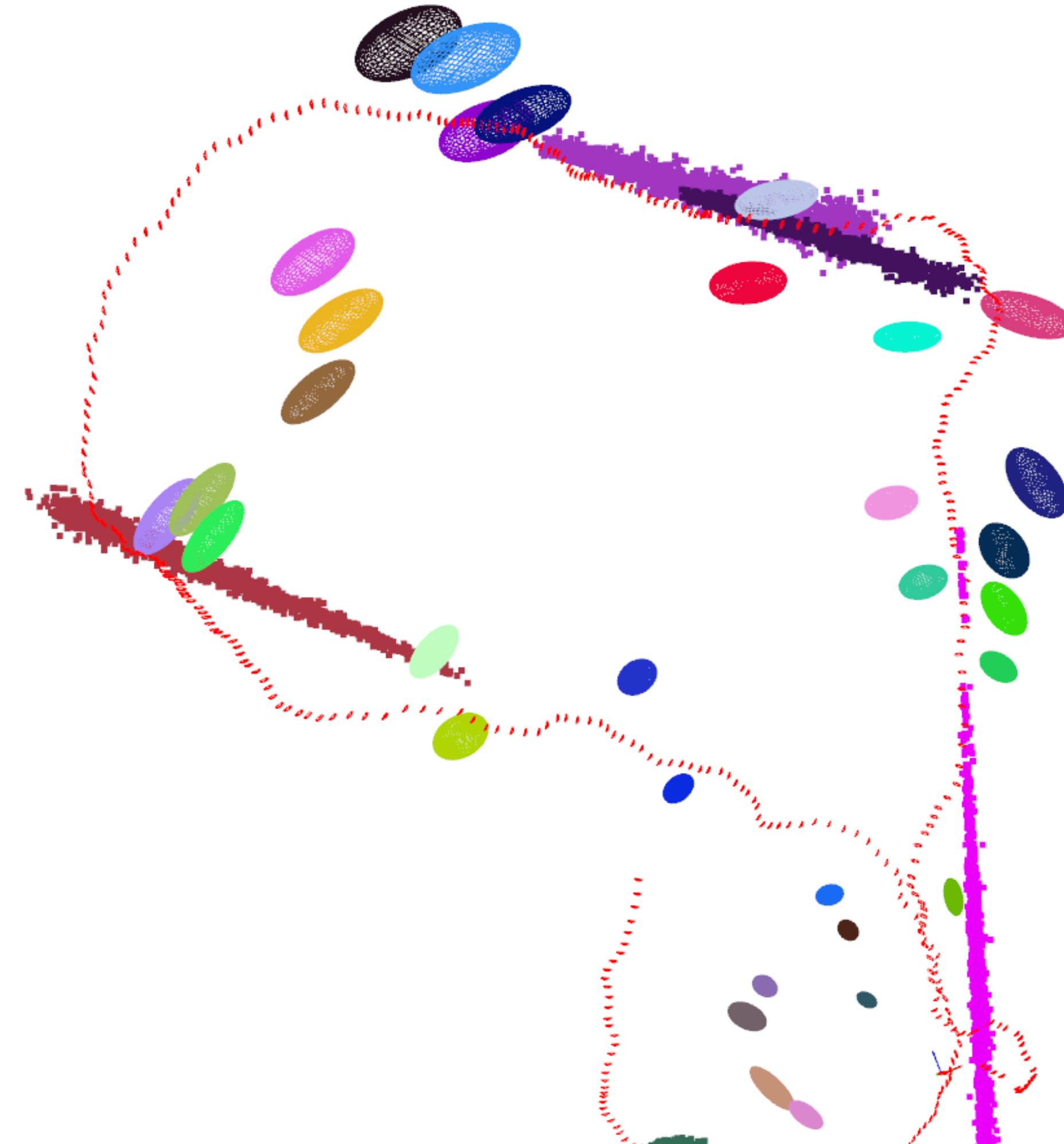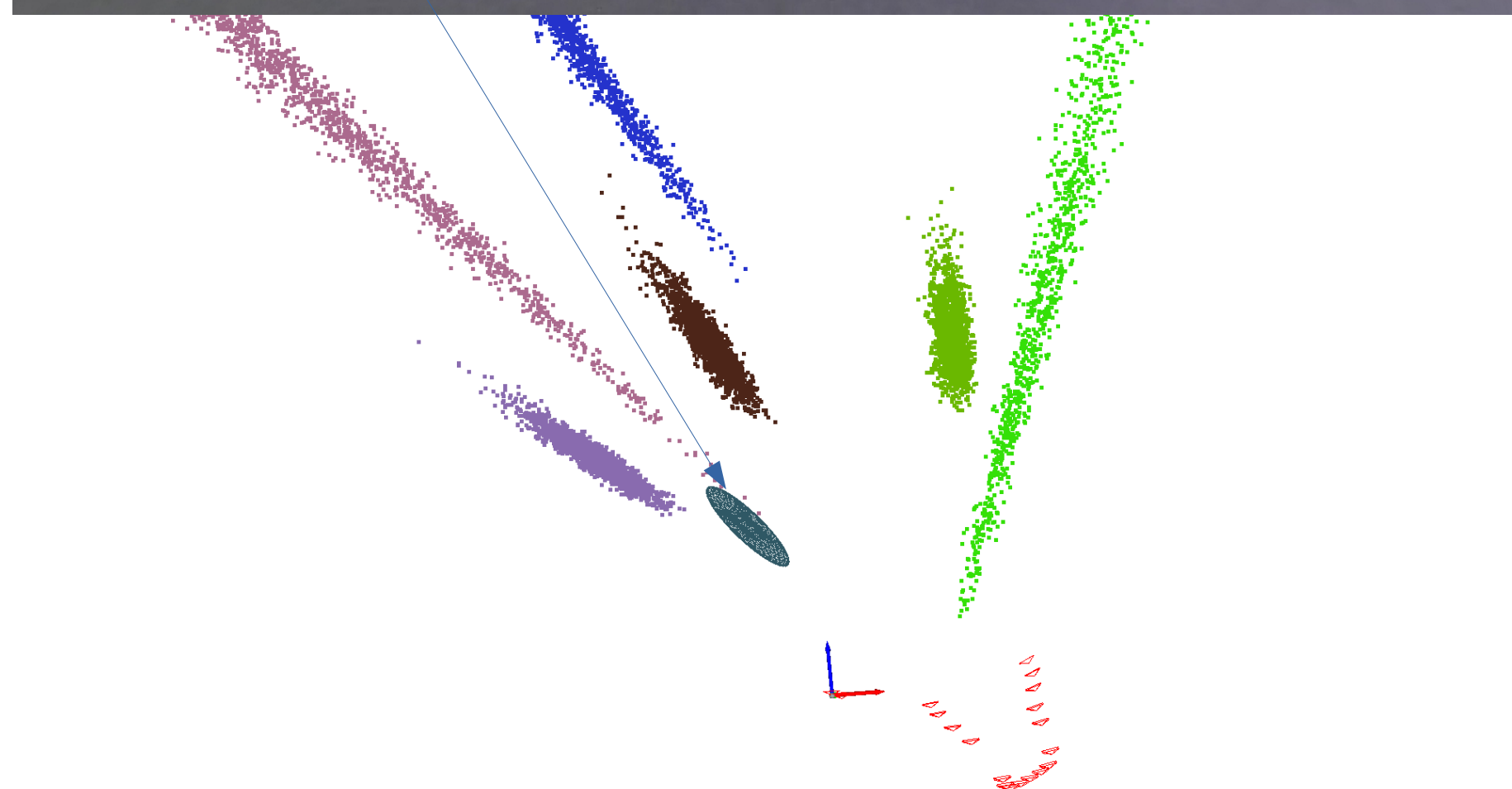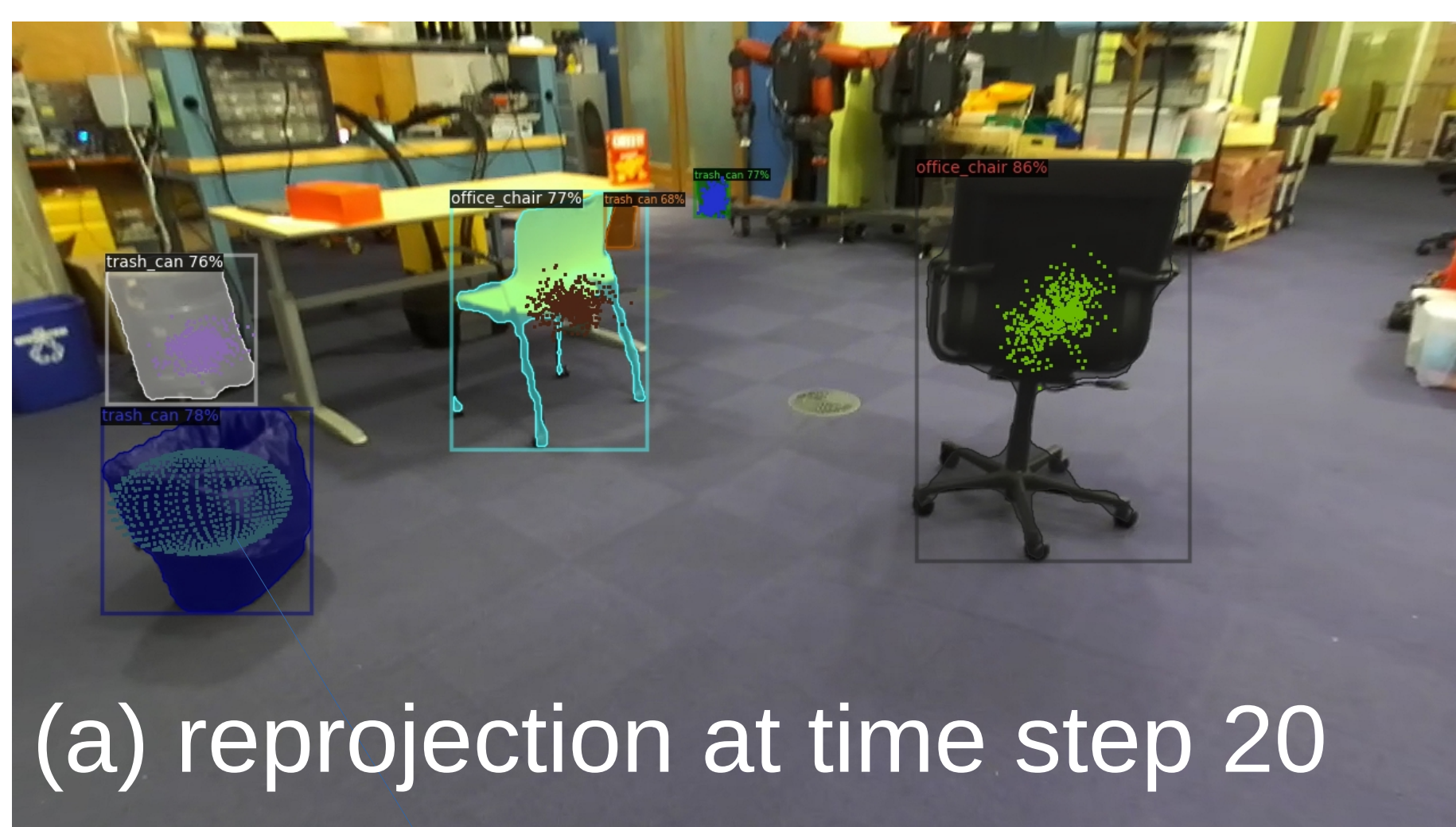L_0 L_2 L_1 X_{53}

An RBPF approach[2]

2. Our algorithm: Blending Gaussian approximation and particle filters for their complementary strengths.

SLAM example

GAPSLAM

| Gaussian approximation | MAP estimate |

Re-initializing landmarks ↑   ↓ Robot pose distributions

| Particle filters | Landmark distributions |

X Landmark   ► Robot pose   -- Measurement

3. Range-only SLAM Experiment

L_3 L_2 L_0 L_1 X_0 Time step 0

L_3 L_2 L_0 L_1 X_5 Time step 5

L_3 L_2 L_0 L_1 X_{21} Time step 21

L_3 L_2 L_0 L_1 X_{23} Time step 23

Time (sec) vs Time steps

- NSFG
- RBPF-SOG
- GAPSLAM
- reinitialization
- update GA
- update samples

4. Object-based bearing-only SLAM Experiment

(a) reprojection at time step 20

(b) 3D map at time step 20

(c) final 3D map

- Pseudo ground truth
- GAPSLAM
- ORBSLAM3

End   Leave   Return

z (m) vs x (m)

(d) comparison

References

[1] J. Blanco, J.-A. Fernández-Madrigal, and J. González, "Efficient probabilistic range-only SLAM," IEEE/RSJ IROS, 2008, pp. 1017–1022.

[2] F. Dellaert, "Factor graphs and GTSAM: A hands-on introduction," Georgia Institute of Technology, Tech. Rep., 2012.