A particle filter SLAM approach to online iceberg drift estimation from an AUV

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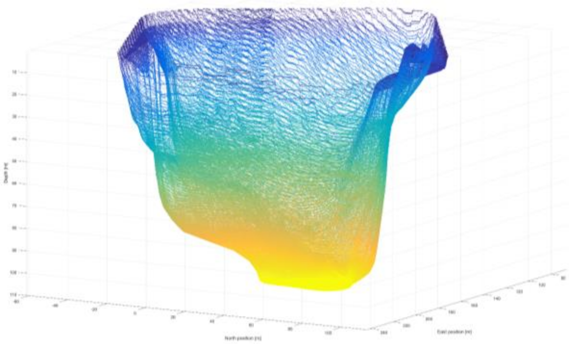
Outline

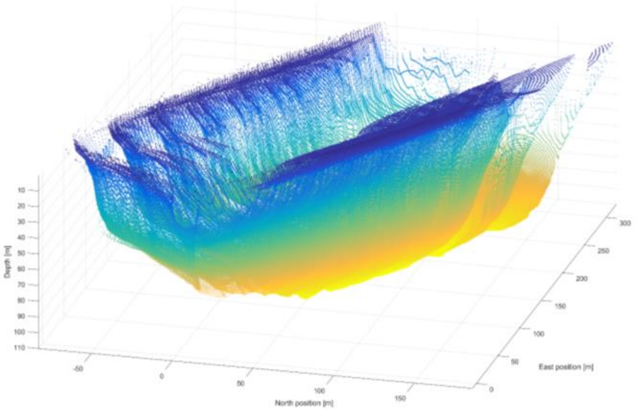
- Motivation
- Simultaneous Localization and Mapping (SLAM)
- Preliminary results
- Summary and way forward

Iceberg mapping using AUVs

Motivation

- Detailed keel geometry needed to develop iceberg drift models.
- Accurate navigation may be a problem.
  - Deep waters make down-looking DVL useless for bottom-tracking.
- Mission planning in moving reference frame.
  - Unknown translational velocity (measurable using DVL when directly below).
  - Unknown rotational velocity (not possible to measure with DVL).
- Warping of measured data due to motion of ice.

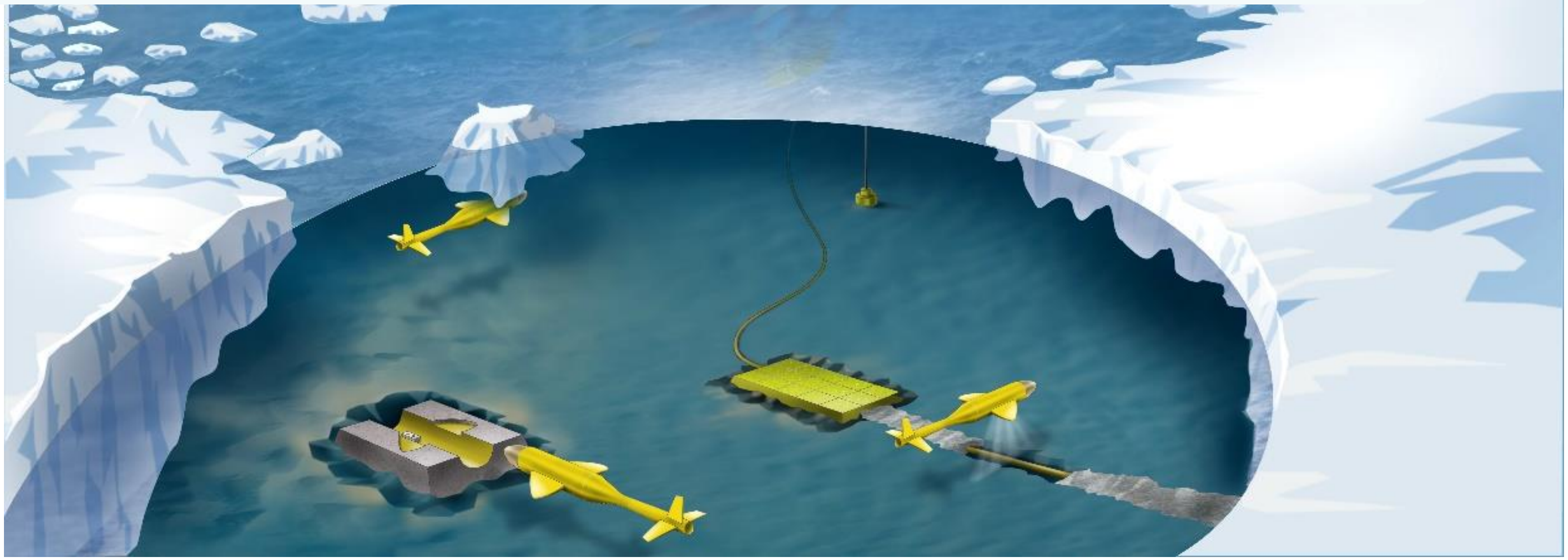




The AUV ice mapping problem

Problem statement

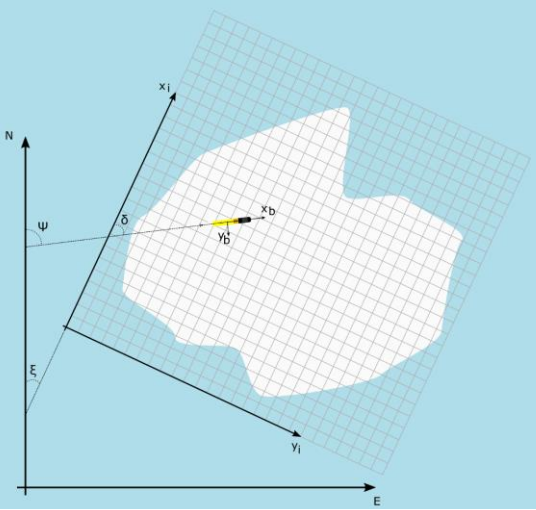
- Estimate AUV position relative to ice.
  - Reference measurements to a ice-fixed coordinate system to avoid warping.
  - Use relative position for guidance of vehicle to generate optimal path for mapping.
- Estimate translational and rotational velocities of the ice.
- Obtain 3D geometries of the underside of the ice.



The AUV ice mapping problem

Chosen strategy

- Bathymetric distributed particle filter SLAM [1].
  - Rao-blackwellized particle filter.
  - One 1D EIF for each cell in map.
  - Ancestry tree to avoid costly copy operations.
- Grid-map of predefined size and resolution.
- Static iceberg in moving reference frame.
- Upward-looking multibeam sonar.



[1] S. Barkby, S. B. Williams, O. Pizarro, and M. V. Jakuba, “A featureless approach to efficient bathymetric SLAM using distributed particle mapping”, Journal of Field Robotics, vol. 28, no. 1, pp. 19–39, 2011.

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Simultaneous Localization And Mapping

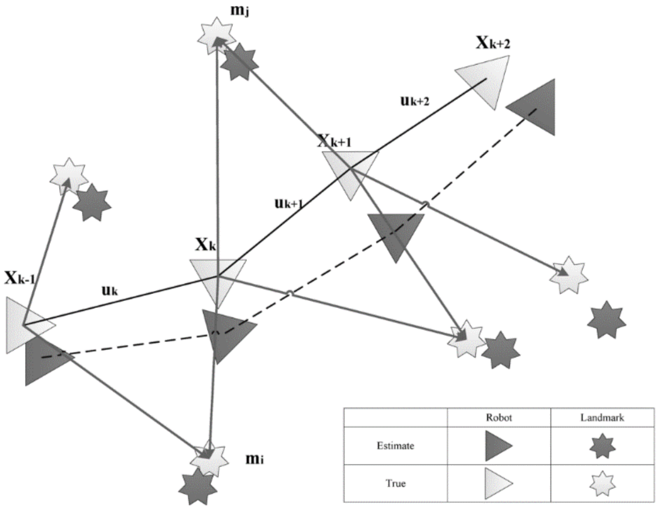
- The robot is exploring an unknown, static environment.

Given

- A set of inputs (i.e. robot controls, $\mathbf{U}_{0:k}$).
- Observations of nearby features from some sensor ($\mathbf{Z}_{0:k}$).

Estimate

- Map of features (**m**).
- Pose/path of the robot ($\mathbf{x}_k$).



Ice mapping SLAM algorithm

Particle filter algorithm

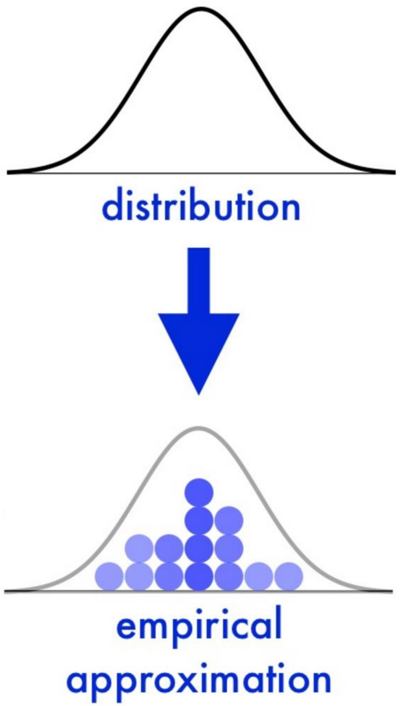
0. **Initialize** particles with initial ice pose. Initialize empty map (and insert prior information, if any).
1. **for** k=1 to **end**
   2. **for** i = 1 to $N_{particles}$
      3. **Propagate** each particle to next timestep.
      4. **Weight** particle based on agreement with map.
   5. **end for**
   6. **Resample** particle set based on weights.
   7. **Update** the maps of the surviving particles.
8. **end for**

Propagate

Iceberg model

$$\dot{\boldsymbol{\eta}}_{io}^{n} = R_i^n(\psi_{io})\boldsymbol{v}_{io}^{i}$$

$$\dot{\boldsymbol{v}}_{io}^{i} = -T^{-1}\boldsymbol{v}_{io}^{i} + \boldsymbol{\omega}_{io}$$



Courtesy: NOAA

Weighting

Multibeam observation model

Multibeam measurements:

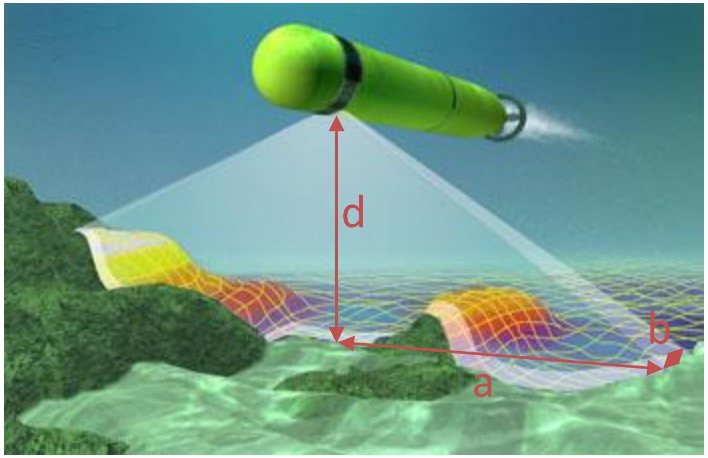
$$\boldsymbol{z} = [\boldsymbol{r} \quad \boldsymbol{\alpha} \quad \boldsymbol{\beta}]^T$$

Measurement function:

$$\hat{\boldsymbol{z}} = h\left(\boldsymbol{p}_{ra}^{i}, E_z\right) + \boldsymbol{\omega}$$

$$h = \left[\sqrt{b^2 + a^2 + d^2} \quad \operatorname{atan}\left(\frac{a}{d}\right) \quad \operatorname{atan}\left(\frac{b}{d}\right)\right]^T$$

Weighting of each beam is performed using the likelihood function for the normal distribution.



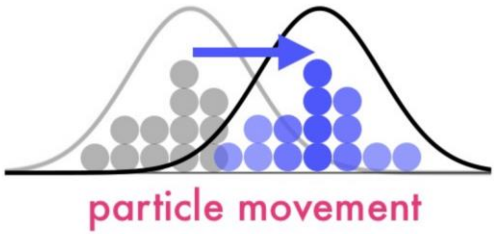
Courtesy: MBARI

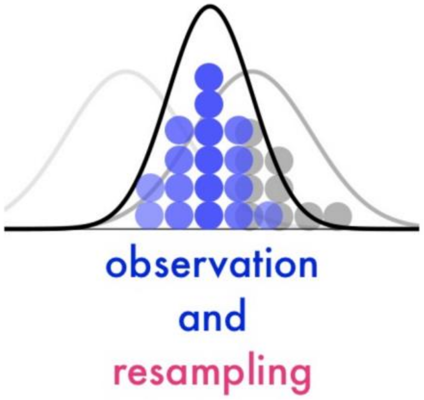
Resampling

Sampling importance resampling (SIR)

1. Calculate importance weights w_i for each particle (joint likelihood of each beam weight).
2. Normalize weights $q_i = \frac{w_i}{\sum w}$.
3. Resample particles with probability q_i.

I.e. particles that have good correspondence with map have higher probability for surviving (getting resampled).





Update

Observation map

- All observations are keyed with particle id and put in a grid-map.
- Ancestry tree keeps track on particle ancestry to avoid using one grid map per particle.
- If an update exist in grid square from a particular particle, estimate is updated using the extended information filter (EIF).
- Why EIF instead of EKF?
  - EKF has efficient prediction, but slow correction.
  - EIF has slow prediction, but efficient correction.
- One square in the grid contains one EIF per particle that has updated that square.

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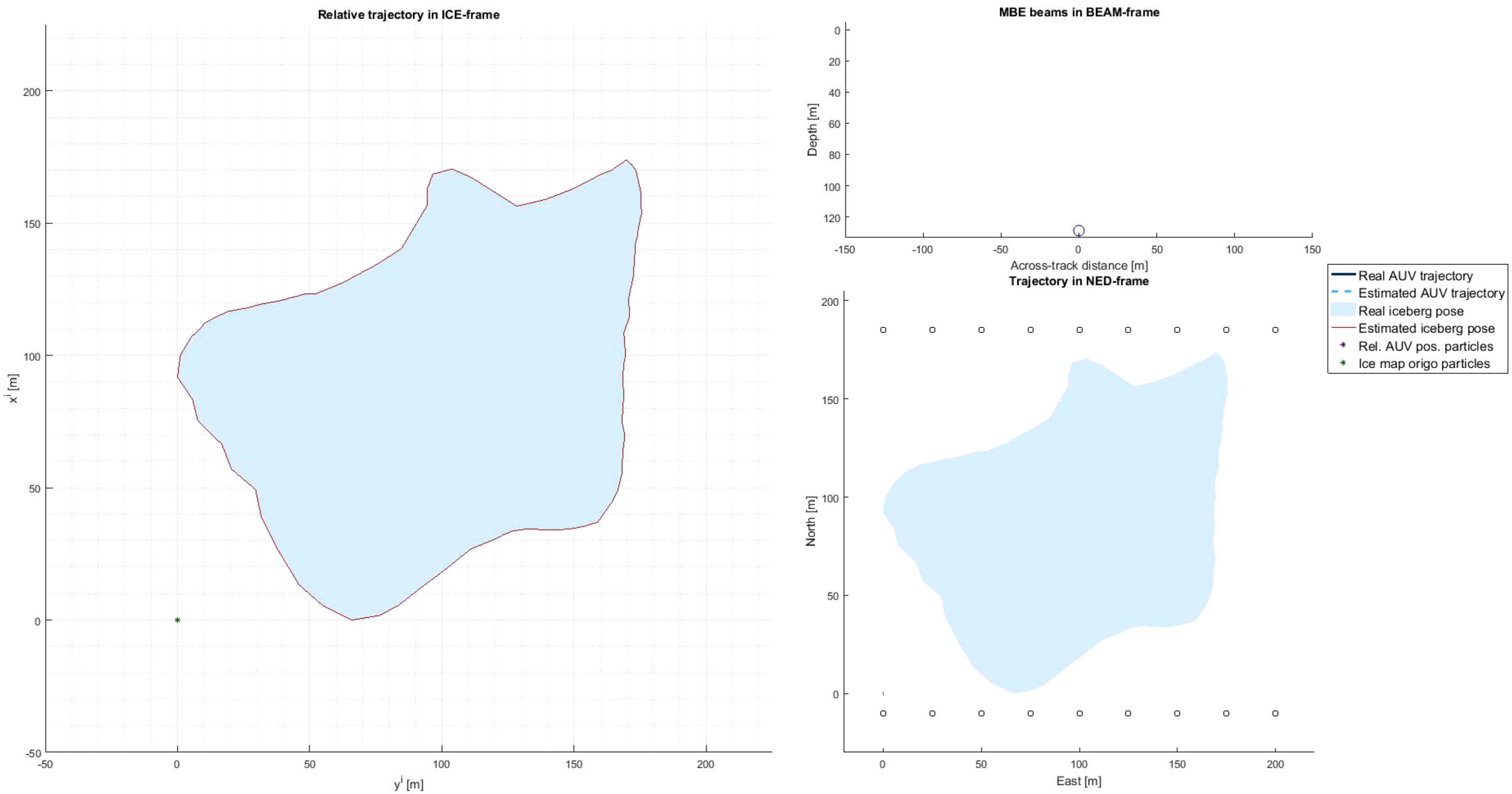
Preliminary results



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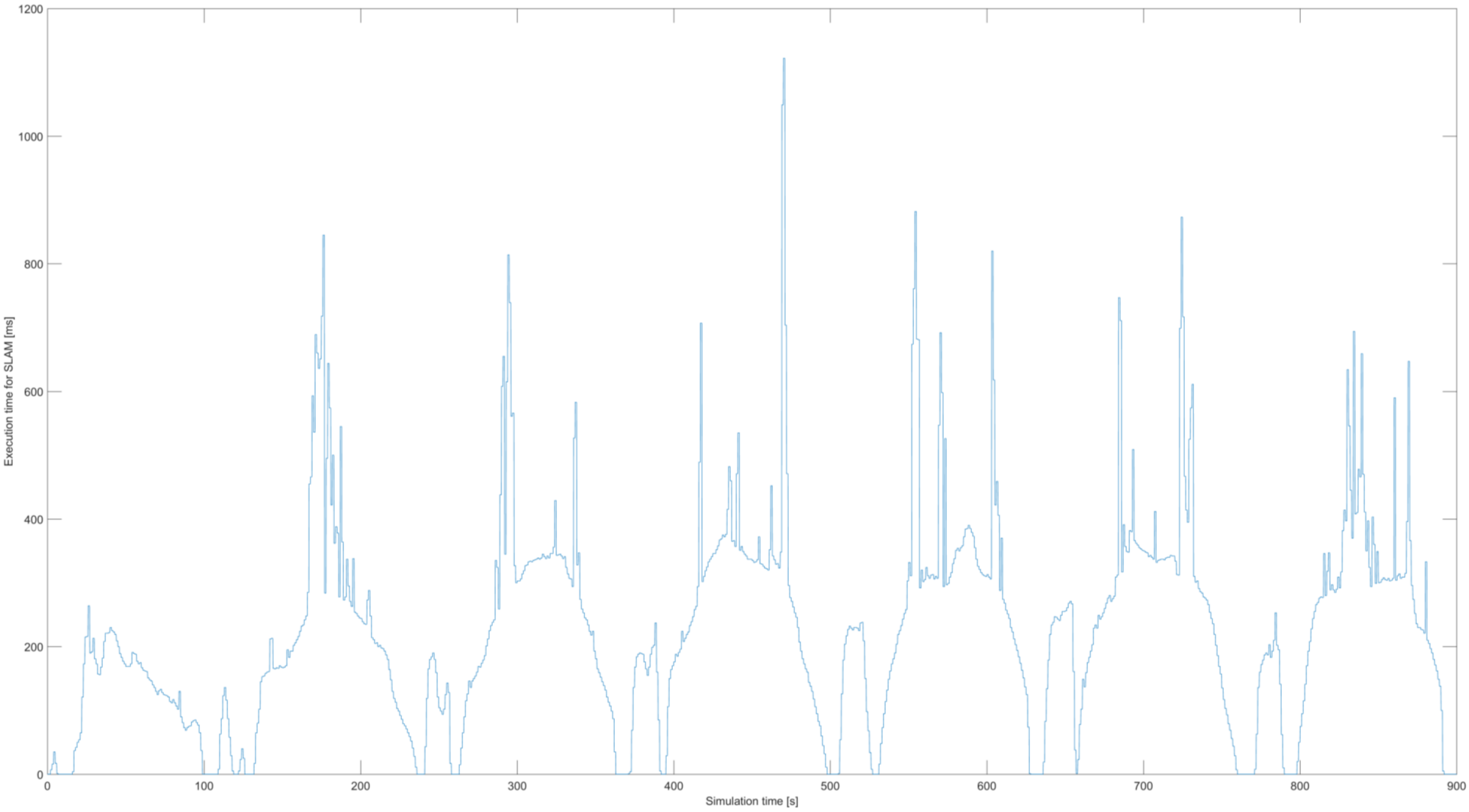
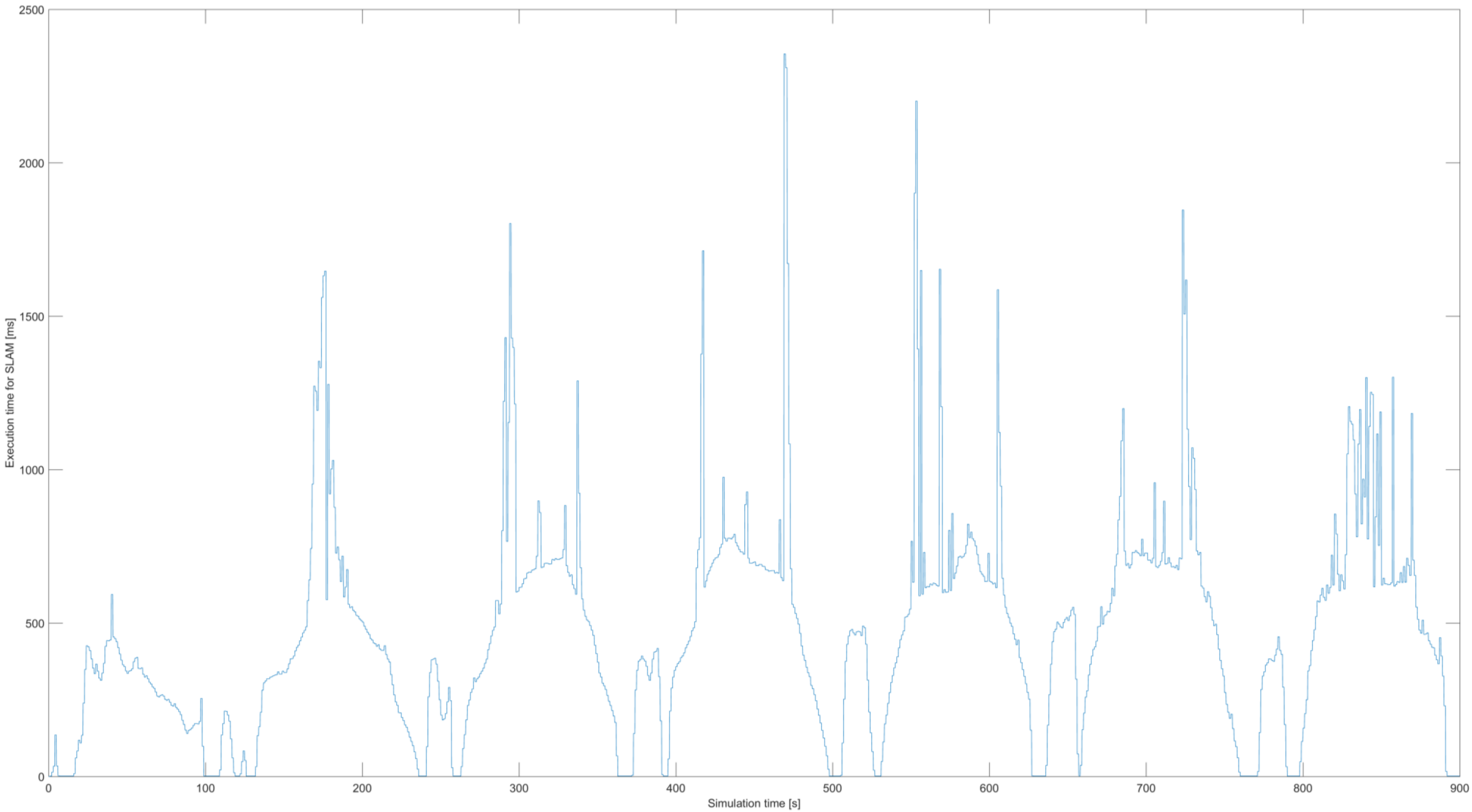
Execution time (100 particles)



Execution time (200 particles)



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Summary and way forward

- Iceberg SLAM is implemented and working for stationary iceberg.
  - Implement guidance system for following trajectory in ice-frame.
  - Test on drifting and rotating iceberg.

- Optimize algorithm for real-time execution.
  - Parallelize algorithm.
  - Look into more efficient data structures for maintaining data.

- Implement a more memory efficient map structure.

Thank you for your attention!