Trajectory Reconstruction and Sensor Fusion for Underwater Robots

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TL;DR: In this project you will develop and evaluate offline state-estimation methods for underwater robots using logged GNSS, IMU, and DVL data from Eelume S. The main objective is to reconstruct more accurate trajectories than those obtained from causal filtering alone, and to compare smoothing-based and optimization-based sensor-fusion methods with the commercial Delph INS solution.

Figure 1: Eelume S

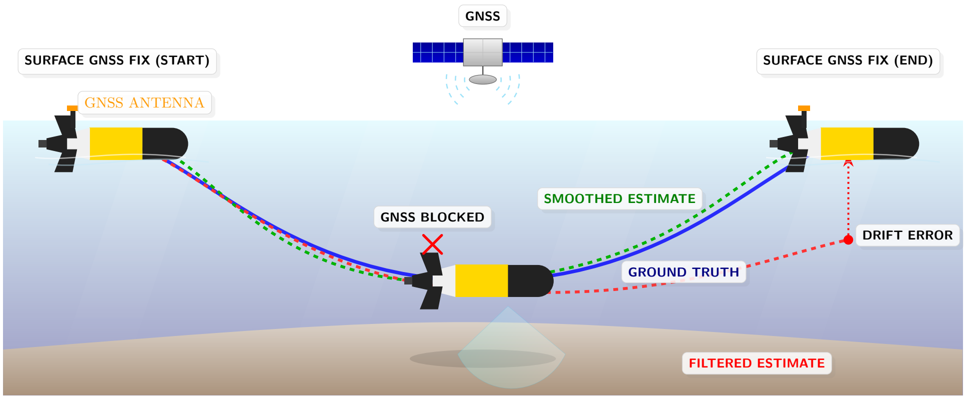

Figure 2: Without GNSS underwater, real-time navigation relies on internal sensors (IMU/DVL), causing the filtered estimate to slowly drift. However, offline post-processing utilizes the entire mission log – including the final GNSS fix upon resurfacing. By applying smoothing algorithms backward through the data, we can correct this accumulated drift to reconstruct a more accurate smoothed estimate.

Description

When an underwater vehicle is submerged, GNSS is unavailable, so navigation must rely on onboard sensors and will gradually drift over time. In this project, you will use logged GNSS, IMU, and DVL data from Eelume S to reconstruct trajectories offline and compare different estimation methods. The project gives hands-on experience with sensor fusion and state estimation on real data from an autonomous underwater vehicle.

The goal of this project is to develop and evaluate post-processing methods for state estimation on Eelume S data. INS/DVL integration is the most common navigation solution for autonomous underwater vehicles, and the work should investigate how smoothing-based methods can improve trajectory accuracy relative to causal filtering alone, and how robust the resulting estimates are to modeling errors, outliers, and sensor degradations. Relevant candidates include the extended iterated Rauch–Tung–Striebel (RTS) smoother [5] (including invariant smoothing and filtering variants [6, 7, 4]) and factor-graph-based optimization [3]. A central part of the assignment is to compare self-implemented methods with estimates produced by the commercial software Delph INS.

The assignment consists of the following steps:

1. Familiarize yourself with Eelume S, the available sensor logs, and the theory behind aided inertial navigation [2, 8], GNSS/IMU/DVL fusion [1], and smoothing-based state estimation [5].
2. Establish a reproducible offline processing pipeline for synchronized sensor data, Delph INS reference handling, and performance evaluation.
3. Design and implement at least two post-processing estimators, for example an RTS-based smoother and a factor-graph-based method.
4. Investigate robustification techniques such as outlier rejection (e.g. innovation gating [8]) and robust loss functions (also called M-estimators) [6].
5. Evaluate the methods on recorded data sets and compare the resulting trajectories, velocity estimates, and consistency properties with the output from Delph INS.
6. Discuss strengths and weaknesses of the different approaches, including computational cost, tuning sensitivity, and practical suitability for Eelume S operations.

The scope can be adapted to either a project thesis or a master's thesis. A project thesis may focus on implementation and benchmarking of a limited set of smoothers on selected data sets. A master's thesis may additionally include estimator design for sensor biases and calibration parameters, a deeper consistency analysis, and a more systematic comparison across operating conditions.

Administrative Information

The report should be written in English and edited as a typical research report. Source code should be delivered together with the report, and key implementation details should be documented in an appendix.

Prerequisites: A background in estimation, navigation, or control is helpful. Experience with probability, optimization, and scientific programming is an advantage, but students with a strong interest in robotics and sensor fusion are also encouraged to apply. Relevant courses from the Cybernetics and Robotics study program include

- TTK4190 Guidance, Navigation and Control of Marine Craft, Aircraft and Drones
- TTK4250 Sensor Fusion
- TTK5 Satellite and Inertial Navigation Systems

Guide to References

The following references cover different aspects of estimation and navigation. For a comprehensive and practical introduction to state estimation in robotics, see [6]. For a more theoretical treatment of Bayesian filtering methods, [5] is recommended. The fundamentals of tracking and classical estimation are well covered in [2].

For Lie group methods and their application to estimation, [7] provides an accessible introduction, while [4] discusses the invariant EKF.

For applications in navigation systems, especially GNSS and inertial integration, see [8]. Finally, [3] gives a modern perspective on factor graphs and optimization-based estimation.

References

[1] T. I. Fossen, *Handbook of Marine Craft Hydrodynamics and Motion Control*, 2nd ed. Wiley, 2021.

[2] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation*. Wiley, 2001.

[3] F. Dellaert and M. Kaess, “Factor graphs for robot perception,” *Foundations and Trends in Robotics*, vol. 6, no. 1–2, pp. 1–139, 2017.

[4] A. Barrau and S. Bonnabel, “The invariant extended Kalman filter as a stable observer,” *IEEE Transactions on Automatic Control*, vol. 62, no. 4, pp. 1797–1812, 2017.

[5] S. Särkkä and L. Svensson, *Bayesian Filtering and Smoothing*, vol. 17 of *IMS Textbook*. Cambridge University Press, 2023.

[6] T. D. Barfoot, *State Estimation for Robotics*, 1st ed., Cambridge University Press, 2017.

[7] J. Solà, J. Deray, and D. Atchuthan, *A Micro Lie Theory for State Estimation in Robotics*, arXiv preprint arXiv:1812.01537, 2021.

[8] P. D. Groves, *Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems*, 2nd ed., EBSCO Publishing, 2013.