Autonomous Navigation of an ROV using tightly coupled integration of inertial and pseudo-range measurements

NTNU
Norwegian University of Science and Technology

Katrine Seel

Supervisor: Ingrid Schjølberg, Co-supervisor(s): Brede Thorkildsen (TechnipFMC), Stian Sandøy

Introduction

A remotely operated vehicle (ROV) is a tethered, unmanned vehicle, used for various subsea operations. Currently, the majority of all ROV operations are manually controlled by a human operator using joysticks. Making ROV operations more autonomous will help reduce the workload on the operators, minimize human errors and increase efficiency in operation. In order to achieve safe autonomous motion control of ROVs, accurate underwater navigation will be a precondition.

Underwater navigation using range and inertial measurements is a popular research topic and is treated in this thesis. For underwater applications acoustic range measurements are typically provided by long baseline (LBL) systems. If the wave speed for which the acoustic signals propagate with is unknown, the measurements are corrupted by an uncertainty modelled as a slowly-varying bias and are referred to as *pseudo-range measurements*. *Acceleration measurements* are provided by an inertial measurement unit (IMU) that is mounted directly on the vehicles. These measurements can be combined in integration filters, in order to estimate the position and linear velocities. The filters that are considered use raw measurements directly, and have a *tightly coupled integration*, making it a nonlinear estimation problem.

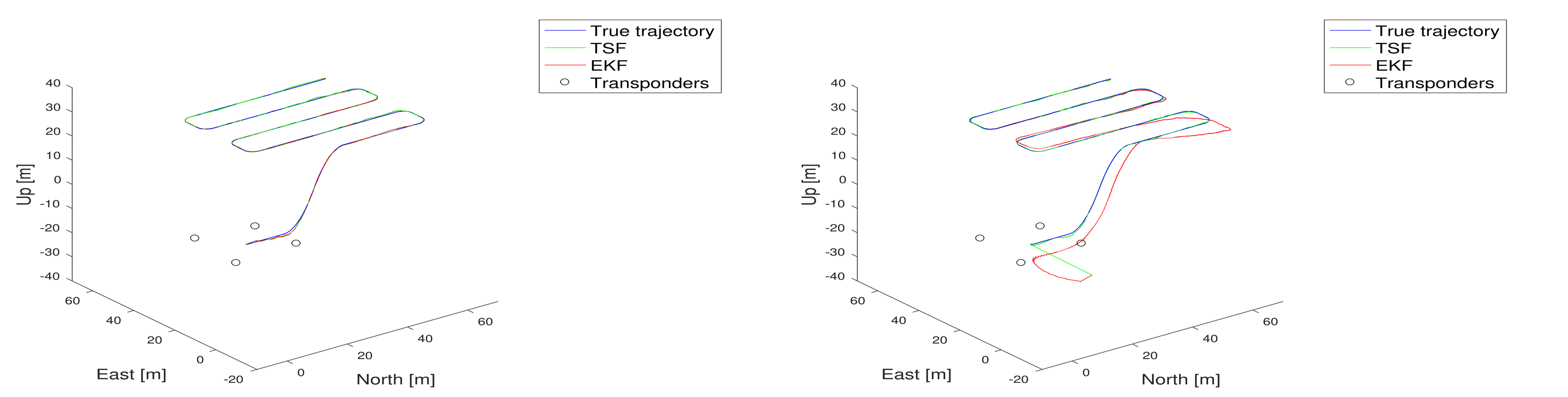
Objectives

The main objective of this thesis is to investigate two different filters for integration of inertial and pseudo-range measurements suited for underwater navigation of an ROV. This is done by verifying and comparing two different implementations of integration filters in simulations. In addition the integration filters are tested in offline runs using experimental data to test their robustness in more realistic conditions. All experimental work is done in the MC-laboratory at Tyholt, NTNU.

Courtesy of TechnipFMC.

Simulation results

A simulator was built in MATLAB. This generated necessary measurements and a trajectory for an ROV. Measurements were modelled with realistic noise and error characteristics, and were updated at reasonable frequencies. The integration filters were tested in steady-state behaviour, by using the correct initial conditions to initialize the filters, and in transient behaviour, when the filters are initialized with inaccurate initial conditions. Below the true and estimated 3D trajectories are plotted.



Conclusion

Simulation and experimental results indicate good performance of the TSF when benchmarked against the EKF. The two filters show similar performance in steady-state, and the TSF converges faster in transient behaviour. Compared to the EKF, the performance of the TSF is less dependent on tuning. Based on the investigation done in this thesis, the TSF is recommended for the estimation problem considered.

References

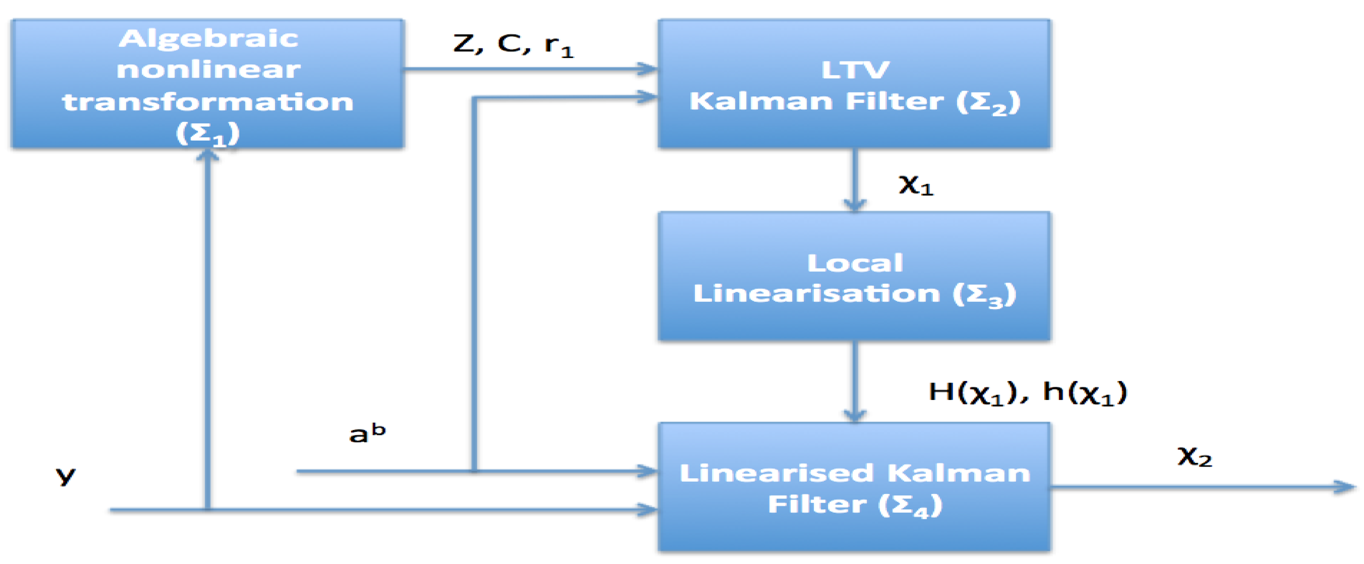
[1] Johansen, Tor A. and Fossen, Thor I, *The eXogenous Kalman Filter (XKF)*, International Journal of Control (2016)

[2] B. Stovner, Bård and A. Johansen, Tor and I. Fossen, Thor and Schjølberg, Ingrid, *Three-stage Filter for Position and Velocity Estimation from Long Baseline Measurements with Unknown Wave Speed*, American Control Conference (2016)

Method

The typical integration filter used for nonlinear estimation problems is the extended Kalman filter (EKF). This is motivated by its wide applicability, but comes with the drawback that global stability cannot be guaranteed. This is traced back to the EKF using its own state estimate to linearize the nonlinear measurement matrix.

The main contribution made in this thesis is the implementation of a three-stage filter (TSF) for the same estimation problem. The TSF is based on a novel approach of using an *exogenous state estimator*. The idea is that an external estimate is used for linearizing the nonlinear estimation problem, in order to avoid a feedback loop in the filter that can potentially destabilize it [1]. For the TSF it can be proved that the error dynamics are globally exponentially stable (GES).



The figure shows the overall structure of the TSF and is based on the work done in [2]. Above $\boldsymbol{y}$ are the range measurements, $\boldsymbol{a}^b_{imu}$ are the acceleration measurements fed into the filter and χ_2 is the final state estimate provided by the TSF. All filters are designed using the system model

$$
\begin{aligned}
\dot{\boldsymbol{p}}^n &= \boldsymbol{v}^n \\
\dot{\boldsymbol{\beta}} &= \boldsymbol{\varepsilon}_\beta \\
\dot{\boldsymbol{v}}^n &= \boldsymbol{R}^n_b(\boldsymbol{q})[\boldsymbol{a}^b_{imu} - \boldsymbol{\varepsilon}^b_{acc} - \boldsymbol{b}^b_{acc}] + \boldsymbol{g}^n \\
\dot{\boldsymbol{b}}^b_{acc} &= \boldsymbol{\varepsilon}^b_{bacc}
\end{aligned}
$$

Where $\boldsymbol{p}^n$ is the position in NED, $\boldsymbol{v}^n$ the linear velocities and $\boldsymbol{\beta}$ the wave speed bias. $\boldsymbol{R}^n_b(\boldsymbol{q})$ is the rotation matrix, $\boldsymbol{\varepsilon}^b_{acc}$ is the noise contained in the acceleration measurements and $\boldsymbol{b}^b_{acc}$ are the acceleration biases. $\boldsymbol{\varepsilon}_\beta$ and $\boldsymbol{\varepsilon}^b_{bacc}$ define the random walk processes for the wave speed and acceleration biases respectively.

Experimental results

The 2D trajectories were estimated using logged measurement data, and the filters were initialized with accurate and inaccurate initial conditions. Position estimates obtained from an external positioning system (Qualisys) were used as ground truth during the experiments.