Proposal and comparison of an eXogenous Kalman Filter and a Particle Filter for use with ROV thruster models

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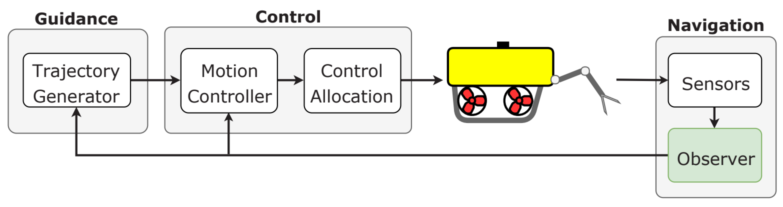
Introduction

The focus on automation and autonomy in underwater applications are increasing. This imposes strict requirements to the systems implemented on the ROV in terms of safety, robustness and accuracy. Every decision and movement made by an autonomous vehicle are based on the systems own perception of its surroundings. Hence, it is crucial that the autonomous vehicle is able to determine its current state with high accuracy. The state of the vehicle is typically described through its position, attitude and velocity. These states are observable either directly or indirectly through various sensor data. For this reason an *observer* is implemented to evaluate the sensor data and make reliable state estimates.

Objective

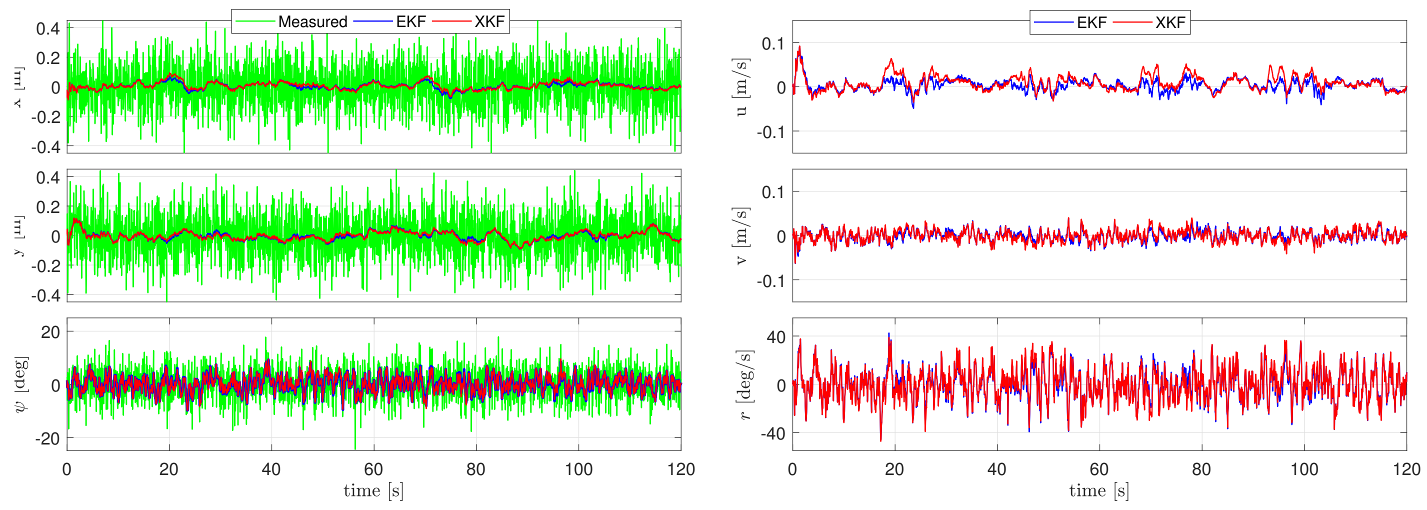
The main objective of this thesis is to explore and investigate different observer designs for underwater vehicles. The industry standard today is the Extended Kalman Filter (EKF). This observer comes without guarantees on stability and it is only able to approximate nonlinear systems to the accuracy of a first order Taylor expansion. The focus in this thesis is thus to investigate and derive observers that have both better stability properties and are more accurate.

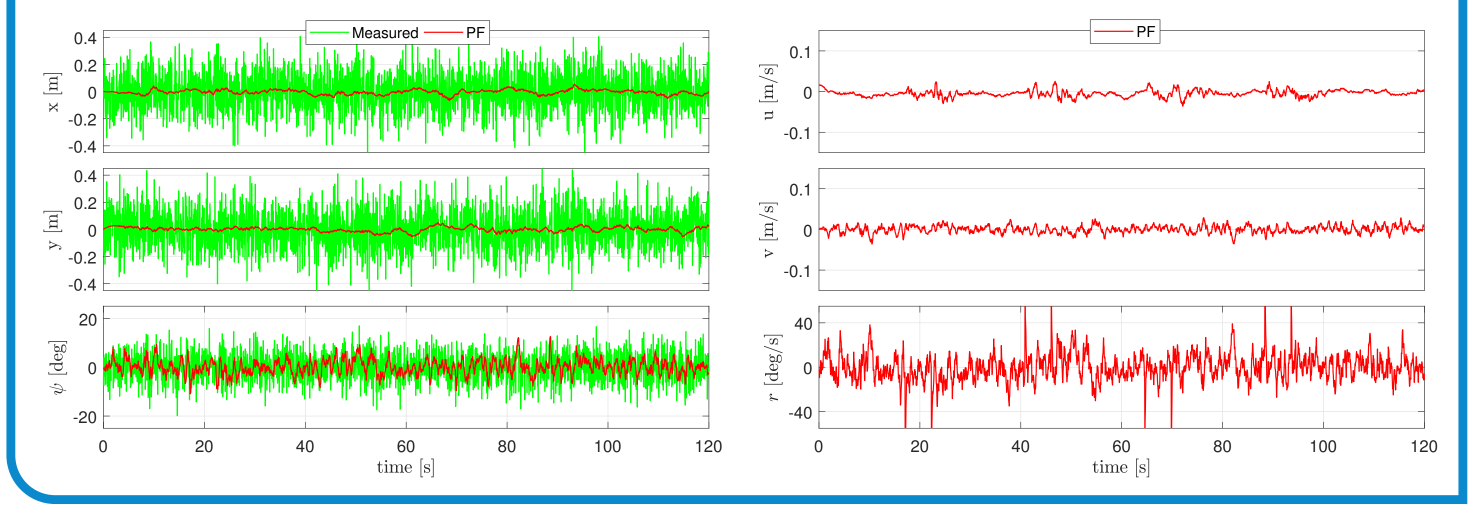


The illustration above shows the three main blocks implemented in autonomous vehicles. The observer is one of two components in the *navigation* block. In this thesis less attention is put on sensors.

Simulation results

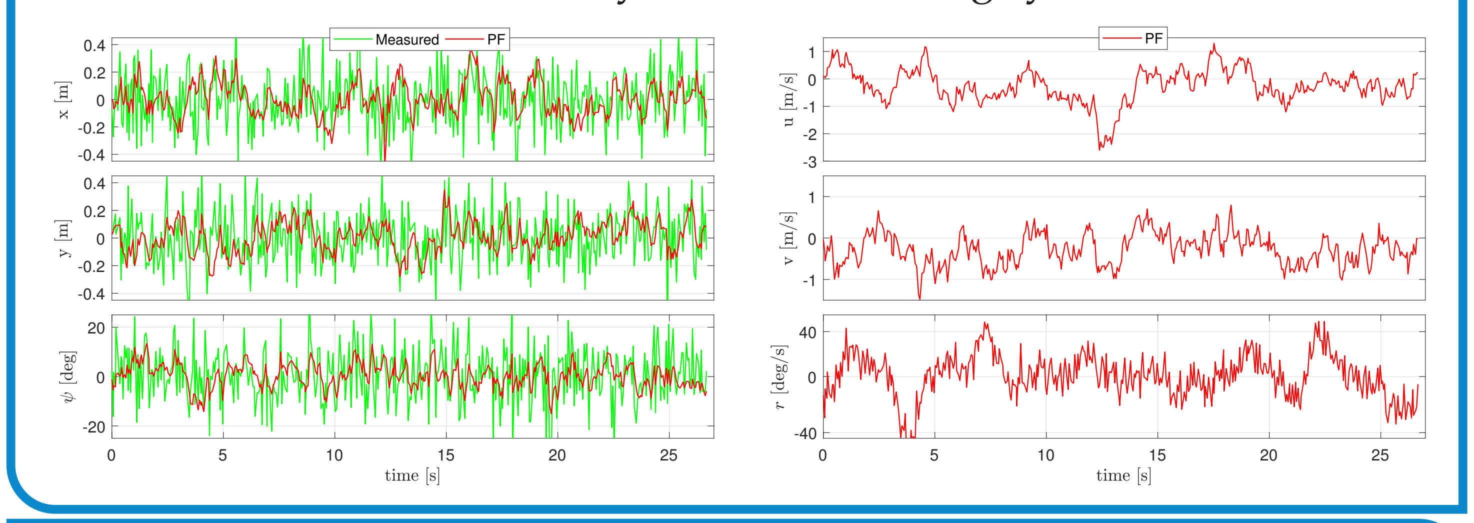
The filters were compared in different scenarios using a simulator developed in Matlab/Simulink. The figures below shows the errors in estimated pose and velocity from a steady state scenario.





Experimental results

The PF was tested using experimental data gathered in the MC-lab at NTNU. Measurements of thrust were not available in the MC-lab. Hence, the state estimates from the experimental data are based on IMU-measurements and the Qualisys Motion Tracking system.



References

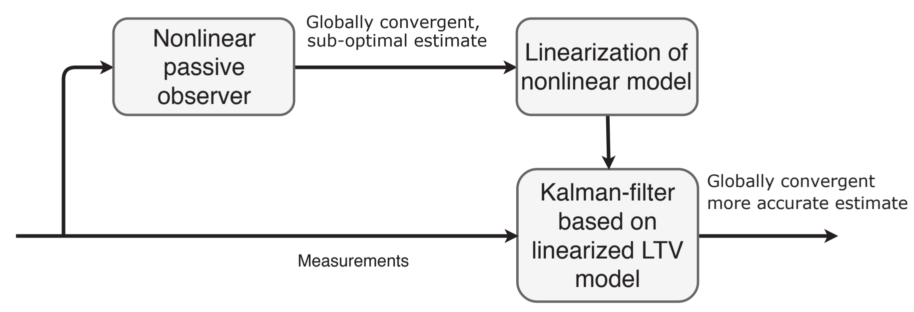
[1] Johansen, Tor A. and Fossen, Thor I. , The eXogenous Kalman Filter (XKF) , International Journal of Control (2016)

[2] Gustafsson, F. , Particle Filter Theory and Practice with Positioning Applications , IEEE AE Systems Magazine (2010)

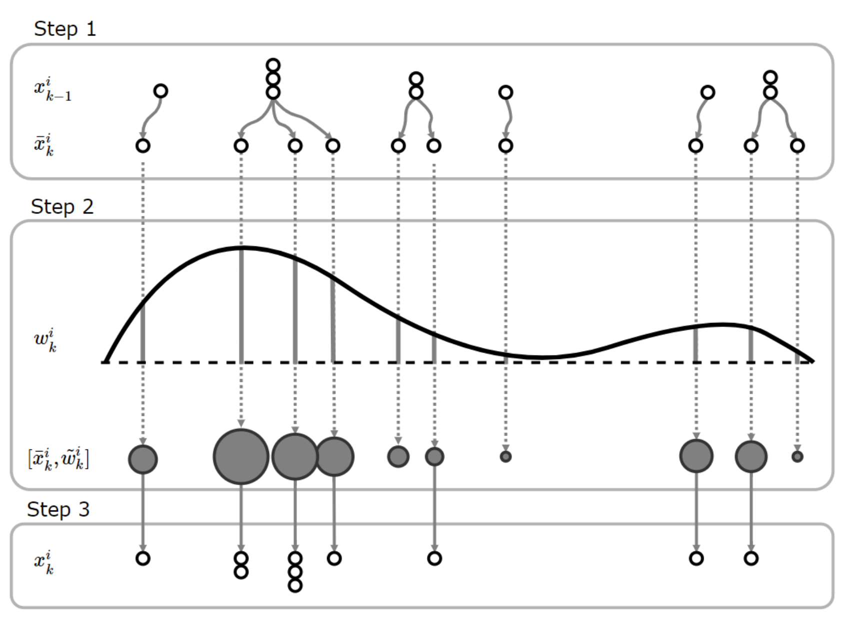
Method

Two different observer designs have been derived in the thesis. In both cases a mathematical model of an ROV is used to relate the thruster force $\boldsymbol{\tau}$ and the velocities in BODY-frame $\boldsymbol{\nu} = [u\ v\ w\ r]^T$. This is done using the the relation $\boldsymbol{M}\dot{\boldsymbol{\nu}} + \boldsymbol{C}(\boldsymbol{\nu})\boldsymbol{\nu} + \boldsymbol{D}(\boldsymbol{\nu})\boldsymbol{\nu} = \boldsymbol{\tau}$. Where $\boldsymbol{M}$ is the mass matrix, $\boldsymbol{C}$ is the Coriolis matrix, and $\boldsymbol{D}$ is the damping matrix. It is further assumed that measurements of position and heading, i.e. $\boldsymbol{\eta} = [x\ y\ z\ \psi]^T$ are available from measurements in the NED-frame. The velocities in BODY-frame and the pose in NED-frame can then be related through $\dot{\boldsymbol{\eta}} = \boldsymbol{R}_b^n(\psi)\boldsymbol{\nu}$, where $\boldsymbol{R}_b^n(\psi)$ is a rotation matrix.

The first observer derived is an eXogenous Kalman Filter (XKF). It has a structure very similar to the EKF, but it is cascaded with a globally stable Nonlinear passive Observer (NLO). From the theory of XKF, it is then shown that the cascaded structure inherits the stability properties of the NLO [1]. Hence, this filter solves the stability issues of the EKF. The structure of the XKF is seen in the illustration below.



The second observer derived is a Particle Filter (PF). As the name suggests this observer works by evaluating a huge number of particles, where each particle is a hypothesis of what the true state may be [2]. The huge amount of particles makes the PF able to approximate mathematical models more accurately than the linearization used in the EKF and the XKF. Another benefit is that the PF does not require the noise to be Gaussian distributed. The figure below shows how the PF works.



In step 1 every particle is evaluated using the mathematical ROV-model, in step 2 the particles are given a weight based on the measurements, and in step 3 the particles are resampled. Particles with high weights are likely to be resampled more often.

Conclusion

Simulations shows that the EKF and the XKF performs relatively similar in steady state. In the transient case however, the XKF converges faster and it does not diverge even with large initial errors. The XKF is thus preferable compared to the EKF. The PF is the most accurate filter in simulations and it has the fastest convergence rates in the transient case. Using the PF with experimental data verifies that the implementation suggested in the thesis works as intended, even if the errors in the velocitiy estimates are rather large. The drawback of the PF is however that the computational cost is way larger than for the EKF and the XKF. In addition, if it is not tuned correctly the PF is at risk of diverging. Hence, even if the XKF is slightly more inaccurate in simulations compared to the PF, its global stability properties and relatively low computational cost makes it a better filter for autonomous vehicles.