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Outlier Rejection in Underwater Acoustic Position Measurements Based on Prediction Errors

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Abstract: Outlier detection and rejection is an important step toward more robust underwater navigation systems. More specifically, acoustic positioning measurements can be notoriously intractable by introducing spikes, or freezing for periods of time, hence driving the navigation filter state estimates to wrong values. In this paper, a simple approach for detecting and rejecting outliers for underwater operations is presented. Acoustic positioning measurements are combined with absolute velocity measurements from a DVL (Doppler Velocity Log) sensor in order to robustify the filter when the vehicle navigates in the operative range of the DVL. Simple χ^2 statistic tests are employed in order to evaluate every new measurement and result in discarding those measurements which give large residuals compared to the predicted value from the Extended Kalman Filter. Moreover, the sum of the prediction errors is computed over a fixed number of valid acoustic measurements for filter divergence monitoring purposes. The efficacy of the approach is demonstrated using experimental data acquired during ROV operations.

Keywords: underwater navigation, outlier detection, acoustic positioning, filter monitoring, ROV

1. INTRODUCTION

Over the last years significant effort has been made by the research community towards the development of underwater operations with increased level of autonomy. The ability to perform underwater tasks autonomously is invaluable not only to researchers, such as marine biologists and archaeologists, but also to the oil industry. It is indicative that, currently, a vast amount of money is spent daily on surface vessels which support time-consuming ROV (Remotely Operated Vehicle) operations for the offshore industry, many of which would require only a fraction of that time if they were performed onshore, see also Nichols (2013).

However, underwater autonomy does not come without high demands for robustness almost at all levels. This is a reasonable consequence since large deviations from the desired behavior in any of the important building blocks of the system will inevitably affect the remaining blocks. The navigation system, for instance, is responsible for fusing all available measurements in order to provide estimations of the vehicle's position, velocity and attitude. Inaccurate state estimations can lure the guidance system into generating wrong reference trajectories, which in turn leads to the control system calculating moments and forces inappropriate for the task in hand. It can be easily concluded that a low performance navigation system will most likely put both the vehicle and the operation in danger.

Underwater navigation poses great challenges, mostly due to the lack of a reliable positioning system, such as the GNSS (Global Navigation Satellite System) in the case of aerial and terrain applications. For more information on underwater vehicle navigation and relevant practical considerations the reader is referred to (Kinsey et al., 2006; Partan et al., 2007). As a result, in addition to onboard sensors such as accelerometers, gyroscopes, magnetometers, DVL (Doppler Velocity Logger), underwater vehicles rely mostly on acoustic measurements for positioning purposes. A thorough overview of acoustic positioning systems was given by Vickery (1998). One major problem with acoustic positioning systems, though, is that the measurements are affected by noise, dropouts and outliers, a phenomenon which is attributed to the presence of multiple acoustic propagation paths between the source and the receiver (Vaganay et al., 1996).

According to Hawkins (1980), an outlier is defined as "an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism", and is considered to be one of the oldest problems in statistics. In addition to the book by Hawkins, other standard references targeting the statistics community are the works of Rousseeuw and Leroy (2005); Barnett and Lewis (1994), whereas the more recent book by Aggarwal (2013) is targeted to a wider audience, including the data mining and machine learning communities. A considerable amount of research work has been done in the past on outlier rejection for underwater applications.

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One of the first papers on the subject was by Vaganay et al. (1996), where the authors considered Long Base Line (LBL) navigation and presented two techniques (one in the time domain and one in the spatial domain) for performing outlier rejection. The same authors presented a comparison between fix computation and filtering for autonomous acoustic navigation in Vaganay et al. (1998). A nonlinear measurement feedback, instead of the conventional linear position observer gain, and a diffusion-based observer was employed by Vike and Jouffroy (2005). An offline hypothesis grid representation concept consisting of three steps was devised in (Bingham and Seering, 2006). A comparison of three outlier detection algorithms (maximum speed thresholding, a parallel Kalman filter approach, and sigma filter) for hydro-acoustic positioning was presented in (Fauske and Hallingstad, 2006). A three-dimensional underwater acoustic network time synchronization scheme with outlier detection was proposed in (Hu et al., 2008). An observer, which is robust with respect to outliers, for estimating the states of a nonlinear system was developed by Jaulin (2009) and a test case related to an underwater robot was presented. The method assumes that both the measurement errors and the number of outliers within a given time window are bounded. Morgado et al. (2013) presented a data classification algorithm based on causal median filters and provided the theoretical tools for the design of the filter parameters. In Indiveri (2013) the author presented a methodology based on the Least Entropy-Like parameter estimation technique, hence resulting in a robust and simple approach.

In this paper the goal is to investigate the efficacy of fusing acoustic positioning and DVL measurements, which are typically available onboard ROVs, for outlier detection and rejection purposes. An *Extended Kalman Filter (EKF)* is employed as the navigation filter which gives full state estimates and the main task is to detect and reject outliers *before* they enter the EKF. In order to achieve this, a number of χ^2 statistical tests are implemented every time a new measurement is available. These tests aim at evaluating the significance of the residuals which are the outcome of the predicted and measured values. The χ^2 tests are not performed on the total position prediction error but on each degree of freedom (i.e. North, East) separately. As mentioned in (Fauske and Hallingstad, 2006), such an approach could perform poorly if the estimates are inaccurate and good measurements are discarded, hence leading to *filter divergence*. Moreover, measurements from noisy sensors, such as Inertial Measurement Units (IMUs), can be deceiving since they are affected by thruster-induced vibrations that can alter the magnetic field in the neighborhood of the instrument. However we show that fusing acoustic positioning measurements with DVL absolute velocities (with respect to the sea bottom) measurements results in a satisfactory and reliable performance capable of rejecting outliers with very low computational cost. In order to avoid filter divergence, we implement a simple filter monitoring technique which calculates the sum of the prediction errors for a sliding window over a fixed sample horizon. Depending on the values of the error sum it is possible to take actions, such as commanding the ROV to enter Dynamic Positioning (DP) mode, until the values return within a certain threshold. The suggested methodology is tested using real data acquired during a recent mission in the Trondheim fjord.

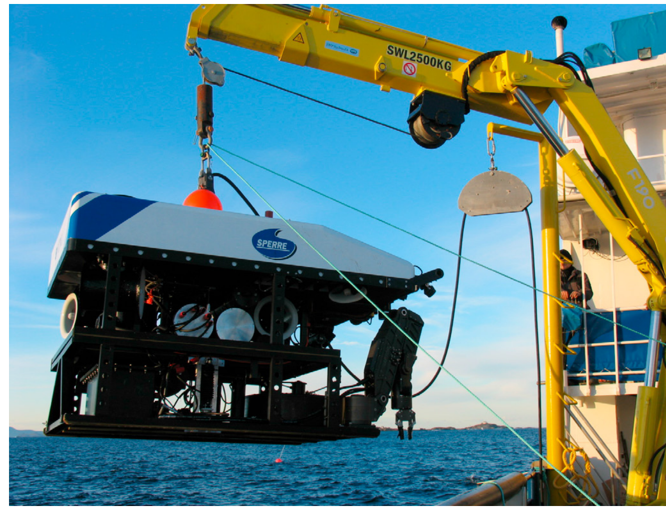

Fig. 1. ROV 30k during deployment. Courtesy of AUR-Lab, NTNU.

2. ROV CONTROL MODEL

The efficacy of the approach presented in this work will be based on experimental data acquired during a mission of the NTNU-owned ROV 30K, which is depicted in Fig. 1. When not in dynamic positioning mode, the ROV moves at a low speed, typically around 0.2 m/sec. As a consequence, for *control purposes*, the following 4DOF model is considered (more details are given by Candeloro et al. (2012), Dukan (2014) and Fossen (2011)):

$$\dot{\boldsymbol{\eta}} = \mathbf{J}(\boldsymbol{\eta})\boldsymbol{\nu}, \tag{1}$$

$$\mathbf{M}\dot{\boldsymbol{\nu}} + \mathbf{C}(\boldsymbol{\nu})\boldsymbol{\nu} + \mathbf{D}(\boldsymbol{\nu})\boldsymbol{\nu} + \mathbf{g}(\boldsymbol{\eta}) = \boldsymbol{\tau} + \mathbf{J}(\boldsymbol{\eta})^T\boldsymbol{b} + \boldsymbol{w}_m, \tag{2}$$

$$\dot{\boldsymbol{b}} = -\boldsymbol{T}_b^{-1}\boldsymbol{b} + \boldsymbol{w}_b, \tag{3}$$

where $\mathbf{M}$ is the mass and inertia matrix, $\mathbf{C}(\boldsymbol{\nu})$ the Coriolis and centripetal matrix, $\mathbf{D}(\boldsymbol{\nu})$ is the damping matrix, $\mathbf{g}(\boldsymbol{\eta})$ describes the gravitational and buoyancy forces, $\boldsymbol{\tau}$ includes the control forces and moments, and $\mathbf{b}$ is the bias vector. Moreover $\mathbf{M}, \mathbf{T}_b \in \mathbb{R}^{4\times4}$, $\boldsymbol{\tau} \in \mathbb{R}^4$, and it should be noted that the Coriolis force has a destabilizing effect on the vehicle that normally is canceled by dissipative effect due to lift effect or transom stern effects that can be included in the damping matrix.

Accordingly, the generalized position and velocity are recognized as:

$$\boldsymbol{\eta} = [x,\ y,\ z,\ \psi]^{\mathrm{T}},\ \ \boldsymbol{\nu} = [u,\ v,\ w,\ r]^{\mathrm{T}}, \tag{4}$$

where (x, y, z) is the vehicle's inertial position in Cartesian coordinates and ψ is the yaw angle. In addition, u is the surge velocity, v is the sway velocity, w is the heave velocity, and r is the yaw rate.

3. SENSORS AND NAVIGATION FILTER

3.1 Available Sensors

The vehicle is equipped with a number of sensors including: