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Enhanced Hydroacoustic Range Robustness of Three-Stage Position Filter based on Long Baseline Measurements with Unknown Wave Speed ⋆

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Abstract: This paper considers the problem of constructing a globally convergent position- and velocity estimator with close-to-optimal noise properties using hydroacoustic long baseline measurements. Three ways of improving the range robustness of the three stage filter for long baseline measurements with unknown wave speed are suggested. One addition is employing depth measurements in addition to pseudo-range measurements, thus increasing range noise robustness and relaxing requirements for transponder placement from not co-planar to not co-linear. Furthermore, a Kalman Filter with a linear measurement model is used, instead of a pseudo-linear time-varying measurement model and a step solving an optimization problem is also added. The proposed scheme is validated through simulation and compared to a standard Extended Kalman Filter and a perfect (non-implementable) Linearized Kalman Filter using real states as linearization point. Simulations suggest that the improved three stage filter will have similar stationary performance as the EKF while having significantly better transient performance and stability subjected to inaccurate initial estimates.

Keywords: Positioning systems, Asymptotic stability, Kalman filtering, XKF, LBL

1. INTRODUCTION

Range-based positioning is used in many areas today such as for indoor positioning of sensors and vehicles, and global positioning of marine vessels. Many different methods are applied for acquiring range data. Examples include the Global Navigation Satellite System (GNSS), underwater acoustic long baseline (LBL) systems, and short-range systems such as measuring signal strength of radio signals or laser-based ranging. These methods are based on measuring the range from a unit to a known base position, and determining the position based on these measurements. However, it is often not the range itself that is measured, but other parameters relating directly to the range. This paper considers the time- of-arrival (TOA) measurement in range based positioning of underwater units. The measured TOA is modeled as a pseudo-range; a range affected by an unknown parameter. As a result the measurement equation has four unknowns (Cartesian position and the unknown parameter), thus requiring at least four measured pseudo-ranges to estimate the variables.

Relating the position and unknown parameter to the pseudo-ranges is a highly nonlinear estimation problem, and a review of range-based positioning can be found in Yan et al. (2013). A globally exponentially stable (GES) filter for underwater navigation using LBL measurements is suggested in Batista (2015), and a globally asymptotically stable (GAS) filter is suggested in Batista et al. (2010). Some classical approaches for underwater navigation using LBL measurements can be found in Vaganay et al. (1998), Bell et al. (1991), Alcocer et al. (2007), Kinsey and Whitcomb (2004) and Whitcomb et al. (1999). Furthermore, a growing topic is single-range underwater navigation, investigated in for example Batista et al. (2011) and Webster et al. (2012).

Traditionally the unknown parameter is modeled as an additive bias to take into account system clock offset between the sender and receiver, and two main types of solutions have been suggested in this case. The first is employing the pseudo-ranges as measurement equations, and using an estimator for nonlinear systems such as the Extended Kalman Filter (EKF) where a local approximate linearization of the measurement model is applied (Alcocer et al. (2007)) or a particle filter (Ko et al. (2012)). The second type of solution is employing a globally valid non-linear transform or an optimization problem to express the measurements in a linear form with respect to the states in the filter. This is called a quasi-linear time-varying measurement model, as the equations are reformulated to fit a linear measurement model either by introducing extra states or eliminating non-linear terms. When the quasi-linear measurement model has been obtained, an estimator for linear systems can be applied, such as the Kalman Filter (KF).

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However, both of these approaches have weaknesses. The estimators for the nonlinear system with pseudo-range measurements do not have proven convergence, and are often based on linearizing the nonlinear equations about the current estimate, as is done in the EKF. This makes the filter dependent on sufficiently accurate initial state estimates to achieve convergence, and can also lead to slow convergence if the initial state estimates are inaccurate. It is possible to use linear filters with proven convergence by transforming pseudo-ranges into a quasi-linear measurement model. However, the nonlinear transform is not robust towards noise in each measured pseudo-range. This can lead to amplification of noise and a bias in measurements which can decrease performance. In addition, if a KF is used it is assumed that the probability distribution of the measurements is Gaussian. Even if the noise in the pseudo-ranges is approximately Gaussian, the probability distribution of the measurements after the nonlinear transform can be far from Gaussian, which can also decrease performance.

The Three-Stage Filter (TSF) suggested by Johansen et al. (2016) is seeking to combine the best properties of the two approaches; the close-to-optimal noise properties of the first approach with the globally convergent nature of the second approach. This is done in three stages; first the measurements are run through an algebraic transform. This is then used as input for a KF with a quasi-linear measurement model. The output from this filter is used as the linearization point for a Linearized Kalman Filter (LKF) using the non-linear pseudo-range measurement equations. The third stage is similar to using an EKF, but an important difference is that the linearization points are not the state estimates of the filter itself, thus eliminating the feedback in the EKF, which can otherwise cause instability. From cascade theory the system is uniformly globally asymptotically stable (UGAS) seeing as both filters in the feed-forward structure are UGAS (Loría and Panteley (2005), Johansen and Fossen (2016b)). Simulations suggest that even though the linearization points are somewhat noisy, the stationary performance of the TSF is similar to the EKF, and has quicker convergence when initial estimates are inaccurate. Furthermore, the TSF is UGAS which is a very important property guaranteeing stability of the filter.

The general approach of using a globally convergent auxiliary state estimator for providing linearization points for a LKF is called the eXogenous Kalman Filter (XKF) and is described in detail in Johansen and Fossen (2016b). Furthermore, the relation between the TSF and the XKF is discussed in Johansen and Fossen (2016a).

In the case of underwater TOA measurements, it is valuable to take into account the fact that the acoustic wave propagation speed in water can be varying, and as a result the unknown parameter can be modeled as multiplicative instead of additive. This has been done in Stovner et al. (2016), where a TSF is formulated using a pseudo-range measurement model with a multiplicative parameter. This leads to a slightly different quasi-linear measurement model, which involves a quadratic nonlinear transformation of the pseudo-range measurement. Consequently, the measurement noise of the pseudo-ranges is amplified linearly with increased pseudo-range, which can reduce performance.

The main contribution of this paper is three ways of making the TSF presented in Stovner et al. (2016) more robust towards pseudo-range measurement noise. This is essential in for example acoustic underwater positioning where temperature layers, and salinity may introduce transmission errors. Firstly, as almost all underwater vehicles have a pressure-sensor that relates directly to depth, the depth measurement can be used in the algebraic transformation. This significantly increases robustness towards pseudo-range measurement noise, and also increases robustness regarding transponder placement in the z-direction. Secondly, as the noise in the quasi-linear measurement model increases linearly with pseudo-range due to the nonlinear transformation of the pseudo-range measurement in the $\boldsymbol{C}$-matrix, it is suggested to use a calculated algebraic solution for the position and unknown parameter as the measurement instead. This solution is available in Stovner et al. (2016) as a part of calculating the quasi-linear measurement, and leads to a linear measurement model with a covariance matrix that is more complicated, but smaller in magnitude. Thirdly, a suggested improvement is adding an extra step before the first KF by solving an optimization problem resulting in a decrease in measurement bias. The paper also contains discussion regarding measurement variance and bias for the suggested scheme. The proof of concept is presented and the results are verified through simulations.

The paper is organized as follows. Section 2 describes how the computed measurements are found from the original measurements. Section 3 gives the overall structure of the position and velocity filters. Section 4 shows simulation and results, Section 5 provides a short discussion of the problem and results and Section 6 holds the conclusion.

2. COMPUTED MEASUREMENTS

2.1 Measurement Equation

The pseudo-range measurement model is based on TOA measurements for an acoustic signal in an underwater LBL system consisting of several transponders placed in fixed, known positions on the sea-bottom. Following the notation in Stovner et al. (2016), the range measurement y_i is described as $y_i = c_0 t_i$ where c_0 is the assumed wave propagation speed, and t_i is the TOA for the signal. However, as the wave propagation speed can vary, the real wave propagation speed, c, is modeled as c_0 multiplied with a parameter giving $c = \sqrt{\beta} c_0$. The position of the vehicle is defined as $p^n = [x, y, z]^T$ and the position of transponder i is defined as $\breve{p}_i^n = [\breve{x}_i, \breve{y}_i, \breve{z}_i]^T$, both in the NED frame. The geometric range is defined as $\rho_i = ct_i = \|p^n - \breve{p}_i^n\|$ where $\|\cdot\|$ is the 2-norm. Also considering that the TOA measurement is subject to measurement noise it is now possible to write the pseudo-range measurement equation as

$$y_i = \frac{1}{\sqrt{\beta}}(\rho_i + \epsilon_{y,i}) \tag{1}$$

where $\epsilon_{y,i}$ is assumed to be zero-mean Gaussian white noise with variance $\sigma_{y,i}^2$.

Furthermore, in most underwater vehicles a depth measurement is available. The depth measurement is modeled as

$$z_m = z + \epsilon_z \tag{2}$$