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Experimental validation of attitude and rate-sensor bias filter using range-difference measurements

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A R T I C L E I N F O

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A B S T R A C T

This paper considers the problem of constructing a filter for estimating attitude and rate-sensor bias, that has both proven stability and close-to-optimal performance with respect to noise. The filter is based on measuring the difference in time of arrival for signals sent from three or more known, fixed positions to two or more receivers on the vehicle. An inertial measurement unit is also used, both rate-sensor and accelerometer measurements, and a position estimate is needed, generated from depth and time of arrival measurements. The vectors between receivers on the vehicle are assumed to be known in the body frame, and are calculated in the inertial frame through an algebraic transformation. These vectors are used as input for a non-linear observer along with rate-sensor and accelerometer data, estimating Euler angles and rate-sensor bias. These estimates are used as a linearization point for a Linearized Kalman Filter, taking the full non-linear system into account. Two experiments are run, and the filter is compared to an Extended Kalman Filter, and a non-implementable Linearized Kalman Filter using the true state as linearization point.

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1. Introduction

Robust and accurate position and attitude estimation is an important part in reaching the goal of autonomy for underwater vehicles. A common approach for positioning is to use an underwater long baseline (LBL) network, measuring the time of arrival (TOA) of acoustic signals from several fixed, known positions. These measurements relate directly to the range, and from these ranges position can be calculated. This paper builds on the work presented in Jørgensen and Schjølberg (2016), where the LBL network is used to determine the yaw angle of the vehicle. This is done by placing several receivers on the vehicle, and measuring the difference in TOA between the receivers. If the LBL system is already in place, this means adding one or more extra receivers on the vehicle, yielding only a small increase in infrastructure. Similar approaches can be found for surface vehicles, in which several GPS antennas are placed on the vehicle, and the measurements are used to determine attitude (Cohen, Parkinson, & McNally, 1994; Vik, 2009).

It is possible to measure angular velocities with rate-sensors, usually a part of an inertial measurement unit (IMU), but these measurements are often corrupted by biases and noise. Consequently, simply integrating the rate-sensor output will not give accurate attitude estimates, and some extra measurements relating directly to the attitude is necessary. A common approach is to use two or more non-parallel reference vectors known in either the body- or the global frame, and measured in the other. These can be used to determine attitude (Shuster & Oh, 2012). For constant reference vectors, a non-linear observer (NLO) for estimating attitude and rate-sensor bias with global stability properties was suggested by Hamel and Mahony (2006), and extended to time-varying reference vectors by Grip, Fossen, Johansen, and Saberi (2012). Traditionally these methods have been applied using the measured acceleration from the accelerometer combined with either magnetometer- or gyrocompass measurements. Other approaches for non-linear attitude determination are suggested for example in Sabatini (2006) and Salcudean (1991), and a survey can be found in Crassidis, Markley, and Cheng (2007).

It is common to use two reference vectors to determine attitude for underwater vehicles: accelerometer measurements combined with either magnetometer- or gyrocompass measurements. These are used as input to the NLO for estimating attitude. The acceleration vector in the global frame is assumed to be the gravity vector, and the magnetic field in the global frame is assumed to be known beforehand. For

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small accelerations (which is usually the case for underwater vehicles, especially autonomous vehicles), the gravity vector will be dominating, and the acceleration measurement will therefore give good results. However, the second reference vector measurement, provided by either magnetometer or gyrocompass has some drawbacks. The magnetometer is prone to disturbances; the magnetic field can be varying over time and position, as well as local disturbances from thrusters and electronics. The gyrocompass is very accurate, but is heavy, large, expensive and requires recalibration. As a result of this, it is suggested and demonstrated in this paper how to use the acoustic LBL system for providing extra reference vector measurements in addition to the acceleration measurement.

By using the difference-in-time-of-arrival (DTOA), it is possible to calculate the reference vectors in the global frame, while it is assumed the reference vectors are known in the body frame. The length of the vectors are naturally dependent on the size of the underwater vehicle, but in general the demand for accurate calibration and DTOA measurements increases with smaller distance between receivers. However, these measurements are assumed to be unbiased, and not distorted over time or with changing vehicle position. A similar approach can be found in Batista, Silvestre, and Oliveira (2012), in which a NLO is suggested, based on a combination of LBL, Ultra Short BaseLine (USBL) and rate-sensor measurements.

The goal of the work is to develop a filter with proven stability and close-to-optimal performance wrt. bounded noise, for determining attitude and rate-sensor bias without employing magnetometer or gyrocompass measurements. This can increase robustness and redundancy for underwater vehicle attitude estimation. Filter design, stability analysis and simulations have been carried out in Jørgensen and Schjølberg (2016), and consequently experimental validation is the next step. The main contribution of this paper is a full experimental validation of the filter suggested in Jørgensen and Schjølberg (2016). Furthermore, the filter is compared to an Extended Kalman Filter (EKF) and a non-implementable optimal Linearized Kalman Filter (LKF) to validate the claim that the filter has close-to-optimal stationary performance, and similar stationary performance as the EKF. The experiments were performed in LabOceano, a lab testing facility at the Federal University of Rio de Janeiro. The filter is also modified slightly from Jørgensen and Schjølberg (2016) to relax one of the assumptions stated, in which one of the receivers has to be in the origin of the body frame. Furthermore, implementation aspects and practical issues are discussed and solutions to these issues are proposed.

1.1. The eXogenous Kalman Filter

The presented filter is based on the eXogenous Kalman Filter (XKF) principle, in which an exogenous state estimate provided by a globally stable auxiliary estimator is used as a linearization point for a LKF. As is shown in Johansen and Fossen (2017), under certain assumptions and if the system has certain properties, this results in a filter with proven stability and with close-to-optimal noise properties. In this paper the term "optimal" is used in the sense that the linear Kalman Filter is proven to be optimal; for the given stochastic uncertainties in the system, assuming that these are modeled correctly, the state estimate is as accurate as theoretically possible. However, we use the term "close-to-optimal" as this is a nonlinear system, in which linearization errors and uncertainty in the linearization point are apparent. The globally stable auxiliary estimator has proven stability properties, but does not have close-to-optimal noise properties. This is in contrast to the EKF, which has close-to-optimal noise properties, but no proven stability for the given model, resulting in potentially unpredictable and unstable behavior. The computational complexity of the XKF is larger than the EKF, as an auxiliary estimator needs to be run in addition to the LKF. However, the computational load is small compared to other, more robust alternatives to the EKF such as the particle filter or Monte-Carlo filter. For more examples of the XKF, see Johansen and Fossen (2016) and Jørgensen, Johansen, and Schjølberg (2016).

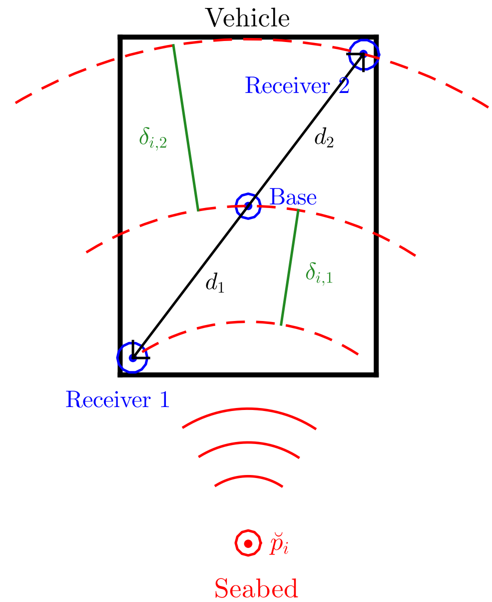

Fig. 1. Illustration of system with range difference measurements. Variables are defined and explained in Section 2.3 (Jørgensen & Schjølberg, 2016).

The paper is organized as follows. Section 2 describes how to transform the original measurements into the computed measurements. Section 3 shows the overall structure of the filter, and presents details about each step. Section 4 discusses the practical aspects, regarding system setup, calibration of equipment and implementation of the filters. Section 5 provides the results, Section 6 gives a short discussion regarding the results and possible improvement of the system, and Section 7 holds the conclusion.

2. Computed measurements

2.1. Acoustic system description

The acoustic system consists of N senders with fixed, known positions located on the seafloor, and $M + 1$ receivers with fixed, known positions located on the vehicle. Acoustic signals are sent simultaneously from each sender, and the TOA is measured from each sender at each receiver. One receiver is chosen as the "base receiver" and the vectors from this receiver to the other receivers in the body frame are denoted $\mathbf{d}_{1,\ldots,M}$. The DTOA between the base receiver and the other receivers are calculated, converted to ranges, and from these measurements the vectors can be calculated in the global frame, and used to determine attitude. An illustration of the system is shown in Fig. 1.

2.2. Attitude representation

In the suggested filter, the attitude is described by Euler angles, $\boldsymbol{\Theta} = [\phi, \theta, \psi]^T$. This is an intuitive way of representing attitude, and fits well with the acceleration measurement, in which two out of three Euler angles can be determined. A well known drawback of the Euler angles are singularities, resulting in only a locally stable filter. However, these singularities are well defined, and as mentioned in Fossen (2011), it is possible to change representation if the filter is approaching one of the singularities. Alternatively, unit quaternions can be used (Kuipers et al., 1999). The representation chosen is the same as in Fossen (2011), the roll–pitch–yaw sequence, in which the singularities will be at $\theta = \pm\frac{\pi}{2}$, as having a pitch angle of $\pm\frac{\pi}{2}$ is a rare state for the type of Remotely Operated Vehicles (ROVs) used in underwater operations today.

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