Toward a framework for high integrity navigation of autonomous underwater vehicles

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Abstract: A key component of an autonomous underwater vehicle (AUV) is the navigation system. It is important for navigating the vehicle but it is also vital for being able to utilize the data collected during a mission. This paper presents the main challenges faced when designing reliable underwater navigation systems, and outlines a framework for detecting and isolating sensor faults using a bank of Kalman filters and innovation testing.

Keywords: Navigation systems, Fault detection, Fault isolation, Fault accommodation, Autonomous underwater vehicles

1. INTRODUCTION

There has been an increased interest in AUVs over the last decade. One of the driving forces has been the offshore industry and the need for rapid and accurate surveying and inspection. AUVs have also become increasingly important for oceanography. The oceans are virtually unexplored and the use of AUVs is one of the few viable options for surveying large areas. Such operations require the AUVs to be submerged for extended periods of time and that they possess high degree of autonomy. Closely related to autonomy is the increasingly important requirement for AUV reliability. Faults will inevitable occur and detection and handling mechanisms must therefore be implemented onboard.

Years of experience from operations with the HUGIN AUVs have shown that the navigation system is a key component for achieving mission success. Our focus is to improve the navigation reliability and integrity.

2. PREVIOUS WORK

Research on fault detection and identification (FDI) has been an active field of research for the last couple of decades. Applications of FDI on underwater robotics has received considerable attention since the early 1990s. A recent survey of fault detection and fault tolerant schemes for underwater vehicles can be found in Antonelli (2003). A majority of published papers focuses on the control system, and how to detect and accommodate actuator faults. See for instance Omerdic and Roberts (2004); Sarkar *et al.* (2002); Beale and Kim (2002).

Much of the published literature focus on vehicles with redundant actuation, for which it is possible to reconfigure the systems to compensate for malfunctions in thrusters and fins, i.e. the control allocation problem. The HUGIN AUVs have only one propeller and limited fin redundancy, hence control reconfiguration will not be possible if a propeller malfunction occur. Nevertheless, detecting actuator faults will be useful for aborting a mission.

As stated in Alessandri *et al.* (1999), a distinction should be made between the model-free and model-based paradigms for fault detection. Models are attractive for fault detection because they can avoid introducing new and costly hardware in the system. A model-based method requires a mathematical model of the vehicle. Commonly used structures for the dynamic model of an underwater vehicle can be found in (Fossen, 2002) (See also Hegrenæs *et al.* (2007*a*)). However, finding good parameter values is a non-trivial task. This has been the topic for several papers related to fault detection and accommodation (Healey, 1992; Alekseev *et al.*, 1994; Takai and Ura, 1999; Ni and Fuller, 2003). Some results have also been reported on estimation of parameters for the HUGIN class of AUVs (Hegrenæs *et al.*, 2007*a*; Fauske *et al.*, 2007).

There are few results on design of fault-tolerant navigation systems for underwater vehicles. A notable exception is Babcock and Zinchuk (1990), where sensitivity analysis is used to optimize the design of an integrated navigation system. The analysis allows the system designer to quickly evaluate different designs based on parameters such as cost, redundancy levels and FDI processes.

Navigation systems for aerospace, land, and surface vehicles are similar to navigation systems for underwater vehicles. It is therefore natural to draw inspiration from research on high-integrity navigation systems for aircrafts and surface vessels. The methods applied in this paper are motivated by those presented in Smestad and Ørpen (1978); Brumback and Srinath (1987); McMillan *et al.* (1993); Bird *et al.* (1998); Schultze (1999).

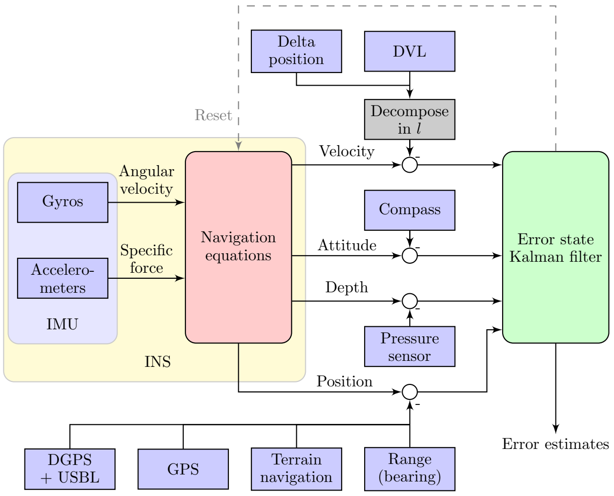

Fig. 1. Structure of an aided inertial navigation system (AINS) for underwater vehicles.

3. PROPERTIES OF UNDERWATER NAVIGATION SYSTEMS

Integrated navigation systems mechanized by inertial sensors and aided by position and velocity sensors, have been the traditional approach to high performance navigation. Such systems offer both good short term and long term performance and are used for aerospace, land, sea and underwater vehicles.

Navigation of an AUV remains a challenging problem, in particular for long submerged operations and in deep waters. With no satellite navigation systems available underwater, vehicles rely upon inertial navigation or dead reckoning for navigation. These navigation solutions are prone to position error drift over time, and external aiding is therefore necessary.

The reliance on aiding sensors makes the navigation system vulnerable to sensor faults and spurious measurements. Acoustic position measurements may for instance include outliers due to ray-bending and multi-path propagation effects on the acoustic signals. The spurious measurements must be removed before they are used for navigation purposes. Temporal sensor dropouts may also occur, or the error characteristics of the sensors can change.

3.1 Sensors

The overview of a typical aided inertial navigation system (AINS) for underwater vehicles is shown in Figure 1 (Jalving *et al.*, 2003). A wide range of sensors are fused in an suboptimal manner using an extended Kalman filter (EKF). A recent survey of sensors for underwater vehicle navigation can be found in Kinsey *et al.* (2006). A brief summary of the main sensors and typical problems related to the sensors is given below.

IMU An inertial measurement unit (IMU) consists of at least three accelerometers measuring specific force and three gyros measuring angular rate. Modern IMUs are very reliable.

DVL A Doppler velocity log (DVL) measures velocity with a high degree of accuracy. The preferred configuration is a so called bottom-track mode where the vehicle speed is measured relative to the bottom. Bottom lock can be lost over areas with very rough bathymetry, during diving and ascending, and for operations in the mid-depth zone. Navigation error will then increase quickly. To counter this effect, use of vehicle models as a complement to water referenced DVL is an ongoing research effort (Hegrenæs *et al.*, 2008, 2007*b*; Hagen *et al.*, 2007).

Depth Vehicle depth can be computed using measurements from a pressure sensor combined with a density profile estimate, measurements of tidal height and atmospheric pressure. If the pressure sensor is properly calibrated, depth can be estimated very accurately.

Baseline positioning A position estimate is typically made by either combining range measurements from the vessel to at least three different beacons, or by measuring range and direction from the vessel to a single beacon. The prior is known as long baseline positioning (LBL) positioning. The latter is known as super short baseline positioning (SSBL) navigation or ultra short baseline positioning (USBL) positioning. In an USBL scenario the beacon is typically placed on the underwater vehicle and tracked by a mother ship. Position updates are then regularly transmitted using an acoustic link down to the vehicle.

GPS The signals from GPS satellites are not available underwater. Still, an AUV can surface and get a GPS surface fix. A GPS unit offers excellent position accuracy. However, surfacing is not always possible. After ascending, the accuracy of the navigation system can be low if DVL bottom track is lost. Special care should be taken to ensure that a position fix is correct. Diving with erroneous and overconfident navigation estimates can have severe consequences.

The acoustic sensors like DVL and USBL are the most problematic of the aiding sensors. Water is a challenging transmission medium. Effects like multipath propagation and ray bending occur frequently.

4. FDI SYSTEM

4.1 Goals

When evaluating a FDI framework the following questions should be answered:

a) How are hard faults detected? A hard fault is a large fault where the effect develops quickly. Hard faults are usually straightforward to detect because of the large and abrupt deviation from normal operation. Typical hard faults for sensors are missing data and outliers.

b) How are soft faults detected? A soft fault is a small and slowly developing fault. These are usually much more challenging to detect than hard faults. Soft faults are often caused by unmodeled errors like for instance slowly varying biases.

c) How are faults and faulty sensors isolated? Detecting that a fault has occurred is only the first step. To handle a fault properly, it is necessary to know which sensor or component failed. Isolation becomes more difficult farther away from the fault source due to signal processing and dilution. A fault should therefore be detected as close as possible to the source.

d) How are faults accommodated? In many cases it is possible to reconfigure a faulty system using only healthy components. For a navigation system typical accommodation is to not use a faulty sensor. However, for systems with little functional redundancy, it is often not possible to reconfigure the system and still have sufficient performance to continue a mission.

4.2 Performance measures

The probability of false alarm (P_{FA}) and probability of detection (P_D) are fundamental to the performance of detection decision (Kerr, 1980). These measures corresponds to the well known type I and type II statistical errors. For the total system performance the required navigation performance (RNP) concept can be used. RNP is specified in terms of *accuracy, integrity, continuity* and *availability* (Kelly and Davis, 1994). Of special interest is *integrity*, which is specified by the parameters:

Alert limit Largest error which results in safe operation.

Time-to-alarm Time elapsed between the occurrence of a failure and a warning of the condition.

Integrity risk The probability that the alert limit is exceeded undetected.

The above measures are not considered in this paper. Evaluating the actual performance of an FDI framework is difficult and often not considered in the literature. However, for actual implementation this is very important.

5. ARCHITECTURE

With the above questions in mind we now outline a possible architecture for FDI.

5.1 Detection of hard faults

Typical hard faults in a navigation system are sensor dropouts and outliers. Before a measurement is incorporated in a navigation filter it should be validated to ensure that it is not an outlier. A natural approach is to use the Kalman filter innovations for testing. A common approach is to use a validation region around the *predicted* measurement. For a Kalman filter, the measurement should be within an ellipsoid region around the predicted measurement. The size of the ellipsoid determines the probability that this is the case.

The residual between the the real and predicted measurement is

$$\boldsymbol{\nu}_k = \mathbf{z}_k - \mathbf{H}\hat{\mathbf{x}}_{k|k-1}, \tag{1}$$

where $\mathbf{z}_k$ is the measurement at time k and $\hat{\mathbf{x}}_{k|k-1}$ is the predicted state vector value. If all the Kalman filter assumptions hold, the residual will be normally distributed according to

$$\boldsymbol{\nu}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{S}_k), \text{ where } \mathbf{S}_k = \mathbf{H}\mathbf{P}_k\mathbf{H}^T + \mathbf{R}_k. \tag{2}$$

For validation the normalized innovation squared can be used

$$\boldsymbol{\epsilon}_k = \boldsymbol{\nu}_k^{\mathrm{T}}\mathbf{S}_k^{-1}\boldsymbol{\nu}_k \sim \chi^2_{n_z}. \tag{3}$$

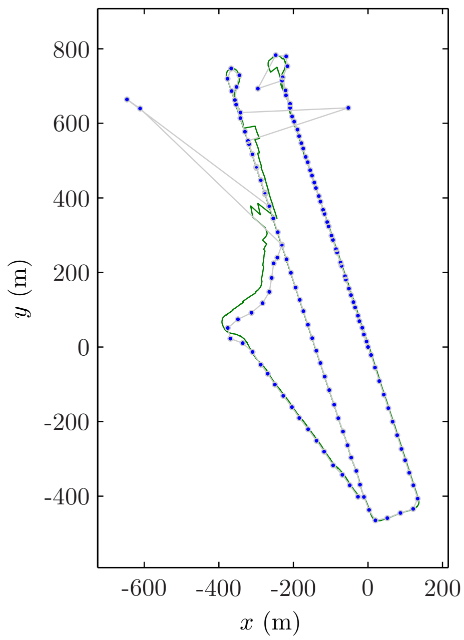

Fig. 2. Position measurements with outliers. Solid line shows the position estimate of the Kalman filter when no outlier filtering is performed.

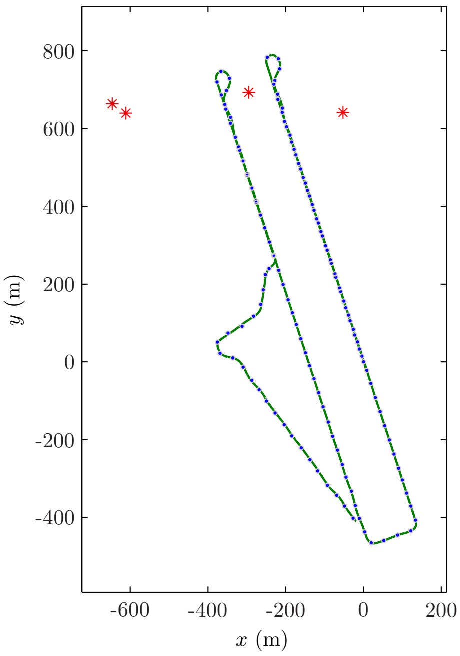

Fig. 3. Outlier filtered position measurements. Detected outliers are shown as stars. Solid line shows the position estimate of the Kalman filter when outliers are removed.

The validation region will in this case be

$$\mathcal{V}_k = \left\{\mathbf{z}_k : \boldsymbol{\nu}_k^{\mathrm{T}}\mathbf{S}^{-1}\boldsymbol{\nu}_k \leq \gamma\right\} \tag{4}$$

The gate threshold γ is a design parameter. A proper threshold value can found from tables of the χ^2 distribution.

Innovation testing is effective for detecting outliers typically found in acoustic signals. An example which shows USBL measurements collected during a sea-trial with the HUGIN 4500 vehicle is shown in Figure 2. Several large

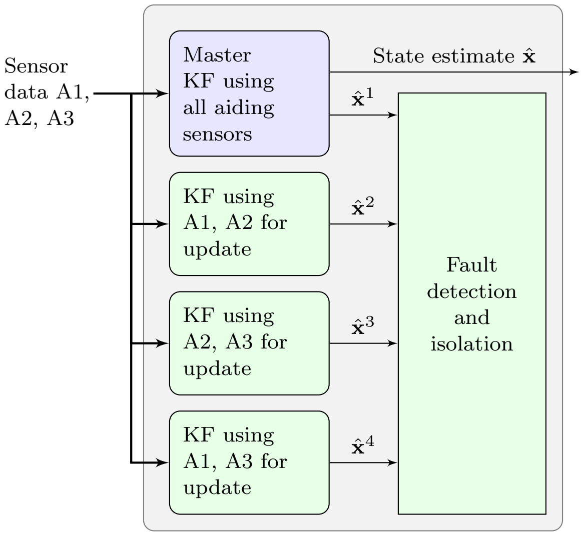

Fig. 4. A Bank of Kalman filters estimating the same state vector using different sets of aiding sensors.

outliers are present. The solid line shows the position estimate from the Kalman filter when the outliers are not removed.

Running the above test where position measurements are accepted if

$$\boldsymbol{\nu}_k^{\mathrm{T}} \mathbf{S}^{-1} \boldsymbol{\nu}_k < 25,$$

gives the result shown in Figure 3. All of the outliers are detected and the estimated trajectory is clearly improved.

Soft failures in sensors are difficult to detect due to their slowly evolving nature. Testing the filter innovations will usually not work because the residuals are too small and the Kalman filter will adapt to the faulty sensor.

5.2 Fault isolation and accommodation

An architecture that simultaneously solves the sensor fault isolation and accommodation problem is to use parallel navigation filters. The idea is that each filter uses all aiding sensors except one. If one sensor fails, there is always a filter that does not use the faulty sensor and hence will no be corrupted. By comparing the output from the different filters the faulty sensor can be isolated. This method has been successfully applied to navigation systems for surface vessels McMillan *et al.* (1993); Bird *et al.* (1998); Schultze (1999). An example is shown in Figure 4, where four Kalman filters are run in parallel with different sets of aiding sensors. The validity of this approach is demonstrated in Figure 5. The solid line is from a Kalman filter with all aiding sensors, while the dashed line is from a Kalman filter that does not use position measurements for aiding. It is clear that the filter with all aiding sensors is affected by the position outliers, while the other filter is not.

A simple check is to compare the output from the filters pairwise. Ideally the residuals should be close to zero, but due to imperfect modeling, noise and different aiding sensors this will not be the case. To account for this a gating technique similar to the outlier filtering above can be used.

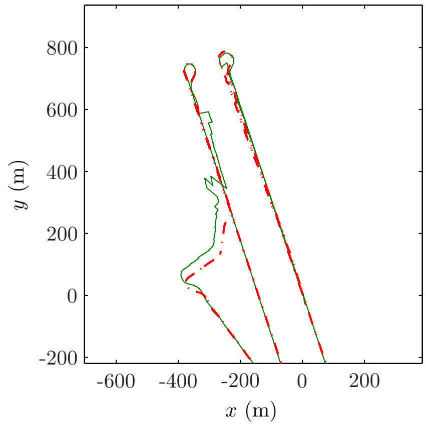

Fig. 5. Position estimates from two Kalman filters with different aiding sensors. Solid line is output from the filter with all aiding sensors. Dashed line is output from filter with no position aiding.

Consistency testing Given two estimates $\hat{\mathbf{x}}_k^i$ and $\hat{\mathbf{x}}_k^j$ of the same quantity $\mathbf{x}_k$. The covariances of the estimates are $\mathbf{P}_k^i$ and $\mathbf{P}_k^j$ respectively. The residual is

$$\mathbf{r}_k^{ij} = \hat{\mathbf{x}}_k^i - \hat{\mathbf{x}}_k^j. \tag{5}$$

Assuming that both $\hat{\mathbf{x}}_k^i$ and $\hat{\mathbf{x}}_k^j$ are normally distributed. The covariance of $\mathbf{r}_k^{ij}$ is

$$\begin{aligned} \mathbf{P}_k^r &= \mathrm{E}\left[\mathbf{r}_k^{ij}(\mathbf{r}_k^{ij})^{\mathrm{T}}\right] && (6)\\ &= \mathrm{E}\left[(\hat{\mathbf{x}}_k^i - \hat{\mathbf{x}}_k^j)(\hat{\mathbf{x}}_k^i - \hat{\mathbf{x}}_k^j)^{\mathrm{T}}\right] && (7)\\ &= \mathbf{P}_k^i + \mathbf{P}_k^j - \mathbf{P}_k^{ij} - \left(\mathbf{P}_k^{ij}\right)^{\mathrm{T}}, && (8) \end{aligned}$$

where $\mathbf{P}_k^{ij}$ is the cross correlation between $\hat{\mathbf{x}}_k^i$ and $\hat{\mathbf{x}}_k^j$. A scalar test statistic is

$$s = (\mathbf{r}_k^{ij})^{\mathrm{T}} \mathbf{P}_r^{-1} \mathbf{r}_k^{ij} \sim \chi^2_{n_r}. \tag{9}$$

This can visually be interpreted as shown in Figure 6. The covariance ellipsoids centered around the estimates should overlap if the estimates are statistically consistent. A special case is when both filter have the same system model and initial conditions, but only one of the filters receives measurements. The residual covariance is in this case simply (Brumback and Srinath, 1987):

$$\mathbf{P}_k^r = \mathbf{P}_k^j - \mathbf{P}_k^i. \tag{10}$$

This can be used to test that the Kalman filters are statistically consistent. If one of the filters fail this test, it is an indication that one of the aiding sensors or the IMU is faulty. This test can be used to detect soft faults.

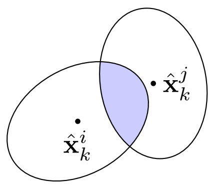

Fig. 6. Overlapping ellipsoid test. The covariance ellipsoids centered around the estimates should overlap if the estimates are statistically consistent.

6. DISCUSSION AND FUTURE WORK

In Figure 4 all the Kalman filters rely on the same IMU. A faulty IMU will corrupt all estimates. Navigation systems for aircrafts and military vehicles often use several IMUs for maximum reliability and fault tolerance (Hammett, 2002). In Bird *et al.* (1998) two IMUs are used in the filter bank. For most AUVs the extra cost of an additional IMU is not justified. However, modern IMUs are very reliable. Faults in the aiding sensors are more probable than IMU faults.

An alternative to using extra sensors is a mathematical model of the vehicle. This is an ongoing research topic, see e.g. Fauske *et al.* (2007). In Hegrenæs *et al.* (2007*b*, 2008) a model-aided inertial navigation system (INS) for underwater vehicle navigation is implemented and experimentally evaluated. The vehicle model is in this case used together with real-time sea current estimation to estimate the ground-relative velocity. The estimate is then used to aid the INS when a DVL is not available. A possible extension to this framework is to treat the vehicle model as an aiding sensor in one or several of the filters in the filter bank. This will increase the redundancy in the system and make it easier to detect and isolate faults. A vehicle model can ultimately also be used to detect faults in the IMU.

This paper has outlined a possible framework for detecting and isolating faults in a navigation system. Future work is to fully implement, evaluate and improve the framework. Of special interest is the use of vehicle models for creating a more reliable navigation system.

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