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Towards more autonomous ROV operations: Scalable and modular localization with experiment data. ⋆

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Abstract: Remotely Operated Vehicles (ROVs) are pivotal for subsea inspection, maintenance and repair (IMR) operations. Increased autonomy in such IMR operations may constitute significant improvements in HSE (Health- Safety, Environment) and cost-effectiveness of operations. Localization is an enabling technology for autonomy. In this paper, we extend a localization framework called Vind (developed by SINTEF) from 2D mobile robot localization to 3D ROV localization. Vind framework keywords include modularity, scalability and reconfigurability. This includes that the framework facilitates easy change of, e.g., system modules, integration filters and sensors. We experimentally validate the system with real sensor data from an ROV mission. The localization systems performs even after we add additional drop-outs and varying noise characteristics to the sensor data. In the paper, we also discuss aspects concerning autonomy in IMR operations with unmanned underwater vehicles.

Keywords: Localization, Autonomous vehicles, Inspection and maintenance.

1. INTRODUCTION

Inspection, maintenance and repair (IMR) operations with Remotely Operated Vehicles (ROVs) on subsea oil and gas facilities are crucial to maintain reliable subsea production. Operations with ROVs are to a large degree manually controlled by an operator located on a support vessel (Schjølberg and Utne, 2015). IMR operations are costly and may be interrupted/delayed by, e.g., weather conditions. This can in many cases be due to the need for presence of a topside support vessel during ROV operations. Increased autonomy in IMR operations with ROVs and the potential to replace ROVs with Autonomous Underwater Vehicles (AUVs) for some operations may constitute a significant improvement in HSE (Health, Safety, Environment) and cost-effectiveness of operations due to, e.g., the potential reduced need for topside support vessels.

We emphasize that a high degree of autonomy is in itself not a target (Grøtli et al., 2015a,b). The target should rather be to find the best degree of autonomy and human-machine interaction which optimizes, e.g., HSE- and cost-related aspects. Localization [1] is a key enabling technology for increasing the level of autonomy (SPARC, 2015).

Behind basically any new autonomy related functionality in subsea IMR operations for ROVs is the need for an accurate and robust self-localization system. The interest for more advanced functionalities, has resulted in a large number of publications on ROV localization, Skoglund et al. (2012), Zhao et al. (2014), Dukan (2014), Lekkas et al. (2015). The trend has been amplified by the introduction of cheaper and smaller sensors. In Skoglund et al. (2012) it is shown that the longitudinal dynamics of a hydrodynamic model can be used when the Doppler Velocity Log (DVL) measurements are not reliable. A particle filter

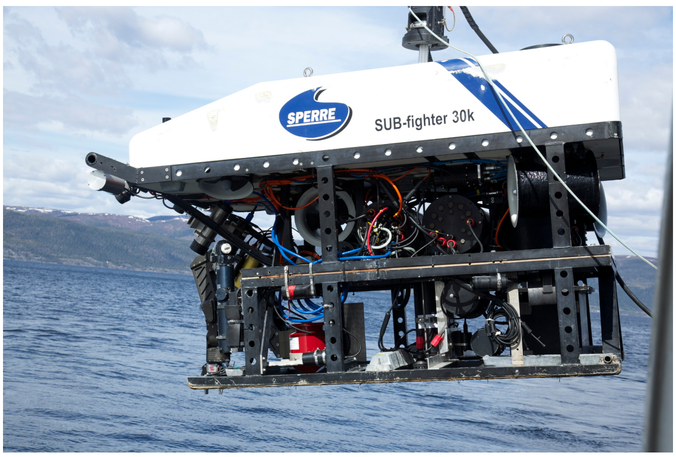

Fig. 1. The ROV SF 30k at the NTNU Autonomous Underwater Robotics lab. Photo credit: Geir Johnsen, NTNU AUR-Lab.

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[1] In this paper we will adapt the robotics communities terminology and use *localization* about the process of a system to estimate its own position, orientation, translational and rotational velocities and accelerations, i.e. its state variables.

is used in Zhao et al. (2014) for fault diagnosis and localization. In particular, the fault diagnostic system focuses on detection of outliers and dropouts from the Hydro-acoustic Positioning System (HPS), dropouts and bias in the DVL measurements and thruster faults. In Lekkas et al. (2015) variance based statistics is used for outlier detection and -rejection of HPS measurements before they enter the Extended Kalman Filter (EKF) localization algorithm. While the above literature is dedicated to robust localization, often with respect to a particular sensor suite, and/or degradation due to particular sensor dropouts or faults, there has been little focus on how to design a system with easily interchangeable modules (e.g. integration filters, models or sensors), and which scales well with a large number of sensors. Some exceptions exist, for instance the toolbox accompanying Gustafsson (2012) where in fact a number of integration filters, vehicle models and sensor models are available, and can be interchanged. There is however little or no emphasis made on communication and sensor interface.

SINTEF has developed a localization system framework called Vind. Vind decouples the state estimation implementation from other system integration related problem, such as interfacing with sensors and communication. The first implementation of this framework targeted 2D mobile robot operations (Azpiazu et al., 2016). While there are other middleware alternatives such as ROS, Orocos, Micro and Yarp Elkady and Sobh (2012), the Vind framework is designed explicitly for sensor fusion for localization. The Vind framework was developed with Research, Development and Innovation (R&D&I) in mind, where new sensors are tested and integrated on a regular basis, or where new filters or models are developed and need to be experimentally validated. This also includes robots in industrial settings as they do not always carry the same sensors at any given time. For instance, different ROV IMR operations may require different sensors, and all sensor may not be permanently integrated on the vehicle due to for instance costs of rental or space limitations. Furthermore, as new sensors or models are continuously developed, the performance of a vehicle can be enhanced by including the latest technology.

In this paper we extend the Vind framework from 2D mobile robot localization to 3D ROV localization. We focus on the state estimation implementation in detail, but also provide a description of the main components in the Vind framework. We show that the implementation offers modularity, in the sense that filters, models and sensors are easily interchangeable, and we show that the framework offers scalability, in the sense that the implementation include support for a large number of new sensors. We provide experiment data where we test the localization system with real sensor data from an ROV operation with the NTNU SF ROV 30k depicted in Fig. 1. Moreover, we add drops-outs and varying noise characteristics to this sensor data to stress-test our system, and we show that the system performs even for such degraded input data. We also present and discuss advantages of an increased level of autonomy in ROV IMR operations. The modularity and scalability that Vind offers is highly relevant for localization in commercial ROV IMR operations. The ease of integration of new sensors, both from a communication perspective, a integration filter perspective, and calibration perspective, means that Vind is suited in maintenance and repair operations where fast integration may be important.

The reminder of this paper is organized as follows: In Section 2 we present and discuss advantages of increased level of autonomy in ROV IMR operations. Section 3 contains a general description of the Vind framework, and its advantages and disadvantages. Section 4 gives a short background on integration filters based on Bayesian filtering. These filters are similar in structure, and we show that inheritance can be used to have general interface, while minor code is required to specify a particular filter. Section 5 and Section 6 describe respectively the specific model and sensors used for ROV localization in this paper, and in Section 7 we use experiment data from the SF ROV 30k to demonstrate the performance of the localization framework and discuss the results. Conclusions are given in Section 8.

2. AUTONOMY IN INSPECTION AND MAINTENANCE WITH UNMANNED UNDERWATER VEHICLES

ROVs are utilized for a large range of inspection and maintenance operations subsea, and technologies for autonomy and localization are highly relevant for the corresponding set of use cases for such operations. ROV operations are typically carried out as remote manually controlled operations today. The ROV operators are located on offshore support vessel and are controlling and monitoring ROV operations in real-time. An umbilical between the support vessel and the ROV supports high-bandwidth communication of data for control and monitoring. Some ROVs are equipped with semi-autonomous/automatic functionalities. Such functionalities include, e.g., automatic pipeline following, automatic station keeping, and automatic displacement. While ROVs are commonly used for IMR tasks, AUVs on the other hand are more commonly used for seabed surveying. AUVs are also to some degree used for pipeline inspection.

An increased level of autonomy in ROV operations can provide advantages and new possibilities within subsea inspection and maintenance. Some of these are briefly outlined in the following.

Shared control: An operator and an autonomous system can share control of an underwater vehicle, e.g., an ROV, in order to cooperate on producing optimal results. Autonomous support functions can relieve the operator of high-strain/tedious tasks and allow him/her to focus on overall planning and execution of the tasks to be carried out with the ROV. I.e., ROV pilots should be relieved of low-level decisions such as, e.g., path planning, and rather think of operations in terms of “macro” steps, Cohan (2008) which for instance could be *go to selected location*, *insert hot-stab*, etc. Moreover, the competence and skills of ROV operators vary as with most other professions. Some operators are highly skilled and can handle challenging operations efficiently and safely, while others have more difficulties in achieving this. More and more subsea installations are coming. Hence, if the current use of ROVs is continued then there will be continued growth in the need for qualified ROV operators. Increased autonomy and shared control in operations represent one way of addressing this challenge. To this end, autonomous functionalities can provide increased efficiency and precision for, e.g., high-precision intervention operations. Moreover, we could have, e.g., that an operator can select from a live video feed from an ROV-mounted camera which valve to operate, and an autonomous system then guides an ROV manipulator arm in order to carry out the commanded operation.

"Underwater residents" and "one-to-many" control: ROVs/AUVs could possibly be (semi-)permanently stationed in the vicinity of subsea infrastructure. The vehicles could, e.g., perform routine operations autonomously and report back to an operator onshore if anomalies are detected. Then, the operator can resume control of a vehicle to investigate the anomaly more closely while the other vehicles continue on their routine operations. Hence, several underwater vehicles can be monitored and operated by an operator at the same time – i.e., one-to-many control. Underwater residents could significantly cut cost due to a reduced need for surface support vessels. Moreover, they can be part of the key enabling technologies for supporting and maintaining subsea infrastructure at locations which can be difficult/impossible to access from surface vessel at certain times due to, e.g., weather conditions, ice, etc. In addition, resident ROVs/AUVs can significantly reduce response time in case of emergencies. A key element in integrity management is regular in-service inspections (Mcleod et al., 2012). Such regular inspections could be more easily available with residents ROVs/AUVs.

An increase in autonomy leads to higher demands on quality, robustness and availability of ROV localization data – as localization is a key enabling technology for autonomy (SPARC, 2015). The reader is also referred to Sørensen and Ludvigsen (2015) for more on autonomy of underwater vehicles and future trends within this area.

3. FRAMEWORK REQUIREMENTS

The design of Vind is guided by four main requirements: modularity, scalability, reconfigurability and performance.

- *Modularity*: It shall be possible to transparently divide the different components of the framework among a distributed system. Each component should be encapsulated with clearly defined messages and interfaces.
- *Scalability*: It shall be possible to extend the system to include support for new sensors as well as implementation of new filters, supporting inheritance within a Bayesian filtering framework.
- *Reconfigurability*: It shall be easy to adapt the system to different types of robots and different kinds of environments without re-engineering an entire solution. Adaptation to changes in the sensor configuration is dealt with by modifying parameters in a human-readable text configuration file.
- *Performance*: The communication traffic generated by the framework and the number of dependencies where the framework is able to run should be kept at a minimum.

The Vind framework is illustrated in Fig. 2. The focus on

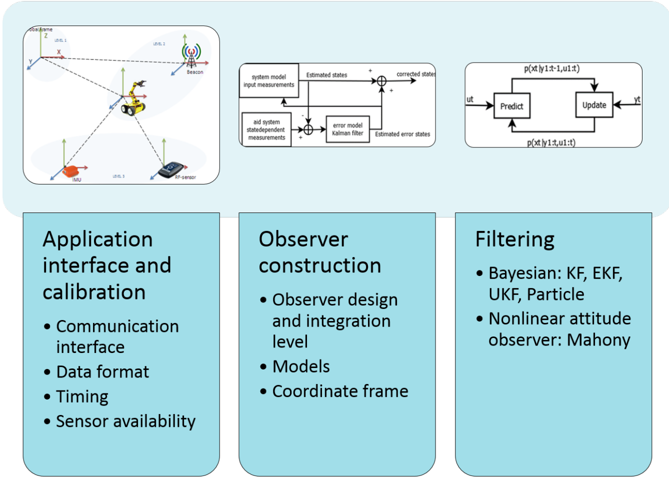

Fig. 2. Illustration of the localization framework.

a modular and flexible framework means that accuracy of the state estimates to some degree is sacrificed. For instance, Vind only supports loose integration of HPS in its current form where as thight integration typically give better accuracy. Reconfigurability and performance are closely tied to the developed communication framework and autocalibration module. These parts of the Vind framework have already been thoroughly treated for the 2D implementation in Azpiazu et al. (2016). To this end, we only briefly discuss the communication framework in this paper.

3.1 Communication framework

Vind generates very little communication traffic and is able to run with a low number of dependencies. Each message sent throughout the software framework is specified in simple text ".proto" files following a specific proto language. For example this is the definition for the 3D pose messages in the Vind framework:

```
message Pose3D { double timestamp = [s]; double x = [m];
 double x_variance = [m^2]; double psi = [rad];
 double psi_variance = [rad^2]; double y = [m]; ... }
```

Passing messages with accurate time and measurement properties (value and "belief") information is central and required for good performance of the localization time update (prediction) and measurement update (estimation) steps. The proto files define the message structure. This lets us define clear interfaces, and it is also used by the communication layer to serialize and deserialize the messages. The framework currently supports three kinds of sensor data types:

- *Pose sensors* which provide position and orientation data.
- *Twist sensors* which provide linear and angular velocities.
- *Acceleration sensors* which provide linear and angular acceleration data.

A treatment of typical sensors for underwater localization that fall into these categories will be given in Section 6. Some examples of sensors that do not fall into these categories are magnetometers, electro optical cameras and sonars. How to incorporate measurements from such sensors within the current framework is also discussed in Section 6. The twist and acceleration data is sent "raw" to the integration filter, as it is not straightforward to do the transformation from within the sensors "driver". Pose data is transformed into the global frame of reference, as this transformation is static. The transformation will be given in the sensor's configuration file, and Vind applies the transformation to the sensor data before relaying the data to the integration filter. The configuration file contains information about the type of sensor, the sensor ID, sensor data uncertainty, and the location and orientation of the sensor frame and the corresponding uncertainties (which for instance can be found by autocalibration).

4. INTEGRATION FILTER FOR LOCALIZATION

4.1 Inheritance from Bayesian filtering

The Kalman Filter (KF), originally published in the early 60s, and its modern variants such as the Unscented Kalman Filter (UKF) and the Extended Kalman Filter (EKF), are still very popular for localization due to their general applicability and typical good performance. KF based variants were for instance used in Skoglund et al. (2012), Dukan (2014) and Lekkas et al. (2015). The Information Filter (IF) is a variant which is computationally equivalent to the KF, but instead of maintaining a covariance matrix, the IF maintains an inverse of the covariance matrix, known as the information matrix, Thrun et al. (2004). The IF has for instance been applied for cooperative localization and tracking, see for instance Cristofaro et al. (2013), Capitán et al. (2009). Deterministic nonlinear observers have also been used to some extent, mainly because of their strong stability properties. In particular the attitude observers of Mahony et al. (2008), and variants of these have been popular in the literature, often in combination with linear filters. In Johansen and Fossen (2016) the eXogenous Kalman filter was introduced, where it was shown that the stability properties of a nonlinear observers are maintained when used in cascade with a linearized KF if the linearization is about the estimated state trajectory from the nonlinear observer. The combination was shown to give global stability properties and low variance. In Vind we have chosen to implement integration filters which are based on the recursive Bayesian solution, (Thrun et al., 2006, Chapter 2.4), (Gustafsson, 2012, Chapter 6.3).

The traditional KF and non-linear variants such as EKF and UKF, can all be thought of as special cases of the Bayesian recursive filter, each containing a time update and a measurement update. The realization that the KF could be divided into two distinct parts is credited the National Aeronautics and Space Administration (NASA) Ames Research Center, possible the first group to implement the KF on a digital computer, (Grewal and Andrews, 2010). In Vind a bank of filters is implemented inheriting the same structure, but with specific implementations where necessary, and in particular for the time- and measurement updates. The fact that Bayesian filters can be separated in a time update and a measurement update means that asynchronous measurements can be handled easily. It is important to keep in mind that sensor measurements both can be considered both as inputs and outputs of the filter, which will be explained in more detail in Section 4.3. In Vind we deal with asynchronous measurements the following way: The filter maintains information about when the last time update was carried out. Each time a new measurement arrives (input or output) a new time update is carried out to integrate the system states up to the time stamp of the new measurement. If the measurement was an output a measurement update is carried out.

4.2 Numerical accuracy

The accuracy of the localization algorithm will depend on many different factors. As already mentioned, being able to pass messages with accurate timing and measurement information is required for good performance. The numerical accuracy is also depending on the specific implementation of the integration filter, as round-off errors and other numerical inaccuracies may propagate and lead to divergence. As an example we have used a square-root implementation of the Kalman filters, (Simon, 2006, Chapter 9.5), (Gustafsson et al., 2010, Chapter 8.6). The square-root implementation resolves a number of problems that may occur in practice, e.g. that the error covariance matrix is not symmetric or not positive definite, or that representing the error covariance matrix is difficult due to large differences in scaling of the states. The use of square-root filters, and other precautions against divergence can be found in any textbook regarding a practical implementation of the Kalman filter (Gustafsson, 2012).

The accuracy will also depend on the type of model used to propagate the state vector. Typically, as we show in Section 5, the model of the vehicle is given as an ordinary differential equation. In our current implementation a discrete time model is obtained by forward Euler discretization. In order to ensure numerical stability, we enforce an upper bound on the length of time between two consecutive time updates. We emphasize that better accuracy could be achieved using more sophisticated numerical integration methods. An interesting comparison of the differences between the continuous Kalman filter, and the discrete counterpart obtained by sampling can be found in Salgado et al. (1988).

4.3 ROV integration filter

For ROV localization we have chosen to use the EKF, as this is probably the most popular integration filter for underwater localization, see e.g. Gade (2005). When using a filter based on some kind of linearization, several variations in how the linearisation is performed exists. An *error state* Kalman filter will estimate the state error with respect to some nominal trajectory, and corrects the nominal trajectory by adding the estimate of the error state. One of the main advantages of the error-state Kalman filter is that the measurement update can run on a much slower sampling rate, while the estimates are provided by IMU dead-reckoning. There are two versions of the error-state Kalman filter; the feedforward and the feedback error state Kalman filter, which are algebraically equivalent to the linearised Kalman filter and the EKF, respectively (Gustafsson, 2012, Chapter 8.1). The basic difference is that in the feedforward form the updated state error will not affect the reference trajectory, while in the

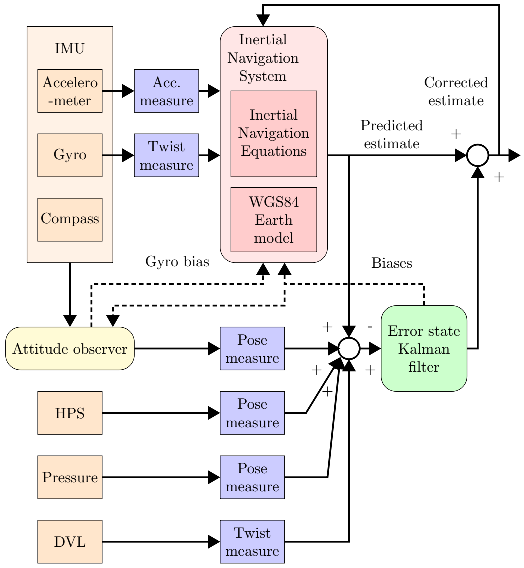

Fig. 3. Illustration of the integration filter and sensors used in this paper.

feedback form the reference trajectory will be corrected. In this paper we have chosen the latter, which means that the Inertial Navigation System (INS) is corrected to a new starting point from which the integration of the time update will start from, (Roumeliotis et al., 1999). Fig. 3 gives a schematic overview of error-state Kalman filter used for ROV localization in this paper. As mentioned in the introduction of this section, nonlinear deterministic observers are often used in combination with linear filters. As seen in Fig. 3 we have chosen to use a Mahony observer (Mahony et al., 2008) to calculate the orientation of the vehicle based on measurements from the IMU. As a general rule in the Vind framework, we have made a choice to use the measurements furthest down the integration chain as inputs to our models. For the ROV localization system this means that measurements from the accelerometer and rate gyro will be used to drive the inertial navigation equations, to be presented in the next section.

5. MODEL FOR STATE PREDICTION

Several models for state prediction are implemented in the Vind framework. In Roumeliotis et al. (1999) kinematic models, rather than dynamic models are favoured. One of the arguments is that dynamic models have to be redone every time modifications are made to the vehicle. For a framework like Vind where reconfigurability is important, we favour simple models because they can be re-used for many applications. The specific model used for ROV localization in this paper is a simple 3D model ignoring the effects of Earth's rotation, but with additional states for bias estimation. It is given by:

$$\begin{aligned} \dot{p}^n &= v^n \\ \dot{v}^n &= R_b^n(\theta)a^b + g^n + R_b^n(\theta)b_{\mathrm{acc}}^b \\ \dot{\theta} &= T(\theta)\omega + T(\theta)b_{\mathrm{gyr}}^b \\ \dot{b}_{\mathrm{acc}} &= 0 \\ \dot{b}_{\mathrm{gyr}} &= 0 \end{aligned} \tag{1}$$

where $p^n \in \mathbb{R}^3$ is the position in the NED-frame (North-East-Down), $v^n \in \mathbb{R}^3$ is the velocity in NED-frame, $a^b \in \mathbb{R}^3$ is the acceleration in body-frame, $g^n \in \mathbb{R}^3$ is the gravitational vector in the NED-frame, $\theta \in \mathcal{S}^3$ is the Euler angles relating the object body-frame to the NED-frame, $R_b^n \in SO(3)$ is the rotation matrix from the body-frame to the NED-frame and $T \in \mathbb{R}^{3\times 3}$ is the angular velocity transformation matrix.

6. SENSORS FOR ROV LOCALIZATION

Typical sensors used for underwater localization include:

Pressure gauge: The depth of the sensor is calculated based on the measured pressure, and is given by

$$y_{\mathrm{pg}} = z^n + [0\ 0\ 1]\, R_b^n(\theta)r_{\mathrm{pg}}^b, \tag{2}$$

where $r_{\mathrm{pg}}^b \in \mathbb{R}^3$ is the position of the pressure gauge with respect to the body frame. The above sensor model equation is solved for the depth of the vehicle in NED-frame, z^n, which is an element of the state vector in our integration filter.

DVL: A Doppler Velocity Log (DVL) has typically four beam transducers facing downwards. The relative velocity between the sensor and the sea bottom (or water column) along the axis of the sensor system is calculated based on the Doppler shift in the echoes of the acoustic signals sent from the transducers (Kinsey and Whitcomb, 2007). The velocity measured by the DVL, y_{dvl}, is given by

$$y_{\mathrm{dvl}} = R_b^{\mathrm{dvl}}(R_n^b(\theta)v^n + \omega^b \times r_{\mathrm{dvl}}^b), \tag{3}$$

where $R_b^{\mathrm{dvl}} \in SO(3)$ is the rotation matrix from the DVL sensor-frame to the body reference frame, and $r_{\mathrm{dvl}}^b \in \mathbb{R}^3$ is the position of the DVL sensor with respect to the body frame. The translational velocities of the vehicle decomposed in the NED-frame, $v^n \in \mathbb{R}^3$, are elements of state vector of the integration filter.

HPS: In a Hydro-acoustic Positioning System (HPS) the position a transponder attached to the ROV is calculated based on range and phase measurements from an external system of known position. The HPS used in our case study in Section 7 uses a single multi element transducer placed on supply ship to calculate the relative transponder position. A commercial navigation package typically fuses the measurements with DVL velocity measurements and position measurements from a Global Navigation Satellite System (GNSS), to output the transponder position in the NED-frame. The measurement equation for the transponder position, is

$$y_{\mathrm{hps}} = p^n + R_b^n(\theta)r_{\mathrm{hps}}^b, \tag{4}$$

where $r_{\mathrm{hps}}^b \in \mathbb{R}^3$ is the position of the transponder relative to the body frame. The above equation is solved for the position of ROV body frame centre, p^n, containing elements of the state vector of the integration filter.

IMU: A typical Inertial Measurement Unit (IMU) consists of three rate gyros and three accelerometers that measure angular velocity and linear acceleration, respectively. Commonly, IMUs also include a three-axis flux-gate magnetometers, which measure the strength and direction of the magnetic field. The equation for the measured acceleration in the IMU sensor-frame, y_{acc} is given by

$$y_{\mathrm{acc}} = R_b^{\mathrm{imu}}(a^b - R_n^b(\theta)g^n + \omega^b \times (\omega^b \times r_{\mathrm{imu}}^b) + b_{\mathrm{acc}}^b), \tag{5}$$

Sensor	Vind data type	Make
Pressure sensor	Pose (Position)	Valeport Mini IPS
HPS	Pose (Position)	HiPAP 500 USBL system and ROV mounted MST 319 transponder
DVL	Twist (Velocity)	RDI Teledyne Navigator 1200 kHz
Accelerometer	Acc. (Lin. acc.)	
Rate gyro	Twist (Ang. vel.)	Xsens MTi-100 MEMS
Magnetometer	n/a	

Table 1. Some sensors and the sensor data type they represent in the Vind framework. The table also include the specific make of the sensors used in Section 7.

The equation for the measured angular velocity in the IMU sensor-frame, $y_{\text{gyr}} \in \mathbb{R}^3$, is given by

$$y_{\text{gyr}} = R_b^{\text{imu}}(\omega^b + b_{\text{gyr}}^b), \tag{6}$$

The equations for acceleration and rate gyro measurements are similar to the ones found in Skoglund et al. (2012), but extended with additional terms for biases. As mentioned in Section 3, measurements from magnetometers are not simple functions of the state variable of the integration filter, and therefore not on the format of supported sensors for the Vind framework. Magnetometer measurements can however be indirectly incorporated in the current Vind framework in two ways: 1) Either through the orientation estimate typically provided by modern IMUs, or through some orientation measurement calculated by the use of a filter or an observer on a dedicated processing unit at the sensor side, such as the Mahony observer (Mahony et al., 2008).

The above list is not complete and the reader is referred to, for instance, Kinsey et al. (2006) and Kinsey et al. (2014) for more sensors, and a more in-depth treatment of each sensor. Electro optical cameras or sonars are other examples of sensors that do not fall into the supported categories of sensor data types. These are sensor that can provide information about the motion of the ROV relative to the environment, and by using dedicated processing units, twist measurments can be calculated (e.g by optical flow). In Table 6 the sensor type each sensor represent to the Vind framework is summarized, together with specific make of the sensors used in the case-study in Section 7.

7. CASE-STUDY

In this section we present a case study where the localization framework presented in this paper is extended from 2D mobile robot operations to 3D ROV operations, and applied to a possible scenario for an ROV inspection operation. Sensor data from an actual ROV has been used as basis for the results.

7.1 Case-study description

In this section we outline a possible scenario where an ROV is used for inspection operations in the vicinity of a subsea installation. The scenario serves as an illustrative example of a possible real ROV usage where the localization framework presented in this paper may be beneficial. The motivation for the scenario is to investigate

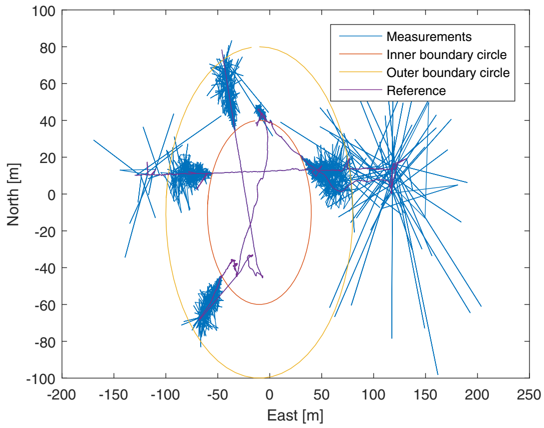

Fig. 4. Illustration of HPS degradation around template. The purple and blue lines illustrate respectively the real HPS measurements ("Reference"), and the degraded measurements ("Measurements") used in this case-study.

the performance of the localization framework in the case of where the main localization sensor for a ROV degrades and eventually fails for some regions of ROV operation. The scenario is as follows: An ROV performs an inspection operation in an area with one or several different subsea installations. The ROV has a "main" localization sensor (HPS) which provides 3D position measurements of the ROV's whereabouts. In the scenario, the North-East position output from this sensor degrades and sometimes even fails completely in certain regions around the subsea installations. Degradation/failure may have been caused by e.g. limited coverage or multi-path signals. There are three such regions – See Fig. 4. The inner region is enclosed by the "Inner boundary circle" (in red). In this region, the aforementioned localization sensor remains unaffected. In the mid region (between the red "inner boundary circle" and the yellow "outer boundary circle"), North-East position data from the localization sensor is subject to an increasing amount of sensor data noise as well as sensor data drop-outs. Outside the yellow "Outer boundary circle", the North-East data can be regarding as data from a failed sensor.

Sensor data for the case-study was realized as follows: We employed real data from a ROV mission carried out by NTNU AUR-lab with their ROV SF 30K (See Fig. 1) on 19 May 2015 in the Trondheim fjord. The ROV SF 30k is a small electric work class ROV custom built for research in general, and specifically for the Ormen Lange archaeology project Søreide (2011). The vehicle carries a seven-function force feedback manipulator from Kraft Telerobotics and is hence suitable for light intervention tasks. For manoeuvring manual control can be applied, or a Dynamic Positioning (DP) system can be engaged supporting the ROV pilot with waypoint and path following functionality (Dukan, 2014), (Sørensen et al., 2012). For surface navigation the vessel was equipped with a Kongberg Seatex DPS232 utilising a Fugro HP/XP differential signal allowing sub meter accuracy. For vessel heading a Seapath GPS gyro from the same vendor was applied. The mission included that the ROV was moved around beneath the ocean surface. In order to simulate degradation/failure

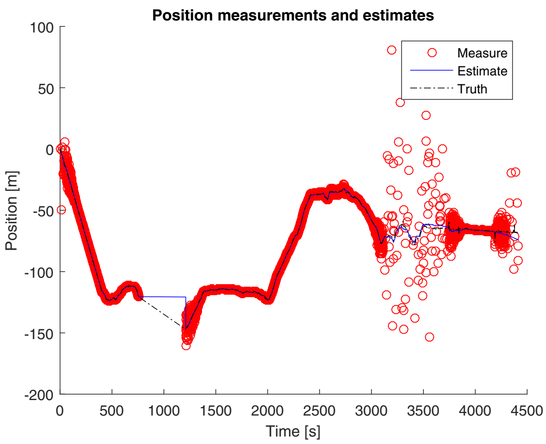

Fig. 5. The figure shows the estimated position of the vehicle in the North direction (solid blue line), HPS measurements corrupted with artificial noise and fed to the integration filter (red circles), and finally the uncorrupted measurements from the HPS (dashed black line). Notice that HPS measurements are missing around 1000 s.

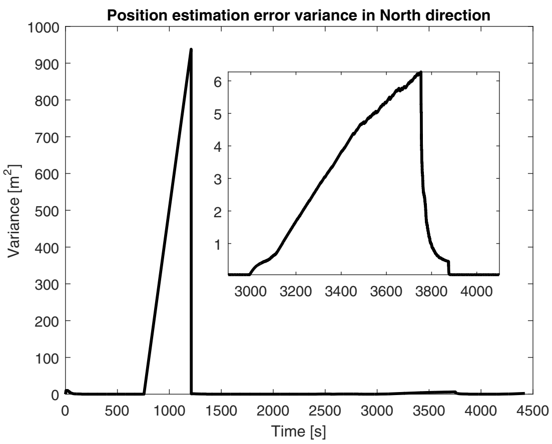

Fig. 6. The figure shows the estimation error variance of the position in the North direction. A complete loss of HPS measurements cause the variance to increase rapidly around 1000 s. The magnified portion also shows an increase in variance around 3500 s, which is due to the heavily disturbed HPS signal, see Fig. 5.

of North-East position data, we added white noise with increasing co-variance outwards from the "inner boundary circle" to the "outer boundary circle". Moreover, we also similarly increased the number of sensor data drop-outs in this region.

7.2 Experiment results and discussion

In this section we present the experiment results from tests of the localization framework on sensor data that simulates the case-study description outlined in Sec. 7.1. Fig. 5 shows the estimated position of the vehicle in the North direction (solid blue), the HPS measurements corrupted with artificial noise as described in Section 7.1 (red circles) and finally the uncorrupted measurements from the HPS (dashed black line). HPS measurements are completely missing around 1000 s. During the loss of measurements the ROV has moved, which is not captured by localization system. This may perhaps suggest too little trust in other sensors in the system, e.g. DVL. The localization system seems on the other hand to perform well even when measurements are highly corrupted with noise, as for instance around 3500 s. Fig. 6 shows the position estimation error variance in the north direction. The variance increases abruptly when there is loss of HPS measurements. The magnified portion of the figure also shows a clear increase in the variance when the ROV gets into an area where the HPS measurements have higher variance. Future work will consists of detecting large variations in real-time and adapt the integration filter in order to improve its performance.

As pointed out in Grøtli et al. (2015a) industrial autonomous systems will in many cases need a human supervising operator. This will also be the case for ROV IMR operations in the foreseeable future. It is necessary that the operator has the proper level of understanding of limitations and capabilities of the system, including trust in its performance. The fact that the state covariance matrix of Kalman filter can be used as a measure of the performance of the localization algorithm was realized already in the early years of its use, (Grewal and Andrews, 2010). Such a performance measure is an important piece of information for the operator, and provide decision support for whether an operation can be carried out or must be aborted. As mentioned in the introduction, basically any new introduction of autonomous functionality will rely on accurate ROV localization, and the KF error covariance matrix (Fig. 6) can be used for identifying situations jeopardizing safety. Future work will focus on incorporating means for fault detection into the Vind framework.

8. CONCLUSION

In this paper, we have extended the Vind framework for localization originally implemented for 2D mobile robot operations to 3D ROV operations. We have experimentally validated the system with real sensor data from an ROV mission, and further stress-tested it with simulating additional drop-outs and varying noise characteristics. The experiment data shows that the localization system performs well for the tests carried out in this paper.

Remotely Operated Vehicles (ROVs) represent an essential tool in subsea inspection, maintenance and repair (IMR) operations. Increased autonomy in such IMR operations may constitute significant improvements in HSE (Health-Safety, Environment) and cost-effectiveness of operations, and localization constitutes an enabling technology for such operations. The modularity and scalability that Vind offers is highly relevant for localization in both R & D and commercial ROV IMR operations. The ease of integration of new sensors, both from a communication perspective, a integration filter perspective, and calibration perspective, means that Vind is suited in maintenance and repair operations where fast integration may be important.

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