Abstract—We compare dead-reckoning of underwater vehicles based on inertial sensors and kinematic models on one hand, and control inputs and hydrodynamic model on the other hand. Both can be used in an inertial navigation system to provide relative motion and absolute orientation of the vehicle. The combination of them is particularly useful for robust navigation in the case of missing data from the crucial doppler log speedometer. As a concrete result, we demonstrate that the performance critical doppler log can be replaced with longitudinal dynamics in the case of missing data, based on field test data of a remotely operated vehicle.

I. INTRODUCTION

Unmanned Underwater Vehicles (UUV) are widely used around the world, both in military applications such as mine hunting and mine disposal, and in civilian applications such as surveillance of divers and tunnel or hull inspections. There are different kinds of UUV which are mainly divided into Remotely Operated Vehicles (ROV) and Autonomous Underwater Vehicles (AUV). The main difference between these two is that the ROV is tethered either to a submarine, a surface vessel or a used in a harbour and is thereby controlled by an operator. AUVs often just move forward and steer the heading and depth with rudders like a torpedo, contrary, ROVs can be steered in many directions since they usually have several thrusters. The ROV used in the experiments is the Saab Seaeye Falcon which is depicted in Fig. 1.

Inertial navigation is the key component in most advanced navigation systems, and the only approach that does not rely on external infrastructure of information. The key idea is that angular speeds measured by gyroscopes can be integrated to provide the orientation of the vehicle, while accelerations from accelerometers are after rotation with the current orientation integrated twice to provide the position relative the starting point. Inertial navigation suffers from drift, more severe to the consumer grade than tactical grade sensors. A magnetometer and the indirect information from the gravity can be used to stabilize the orientation. Nevertheless, gravity leakage into the acceleration will occur, that causes a drift in position that is cubic in time. Integration of position information from global navigation satellite systems (GNSS) eliminates this drift, but satellite signals are not available in underwater environments. An additional velocity sensor, as the doppler log studied here, reduces this drift considerably to linear in time. Thus, velocity information is crucial for low-cost navigation systems. The doppler log is subject to outliers and missing data during certain operating conditions, so a backup system for speed information is highly desirable.

We here investigate whether a dynamic model of the vehicle can be used for navigation, together with the control signals (engine reference speed and rudder for general AUV’s, input voltage to five thrusters for our ROV). The model potentially provides an independent observation of vehicle speed and angular rate. We will demonstrate that in particular the speed can be accurately predicted by the model. That is, fusion of kinematic and hydrodynamic models allows for robust navigation. Further, the dynamic model gives the speed in water, while the doppler log gives the speed over seabed. The difference corresponds to water stream, which is an important parameter for the control system, that can be estimated by fusion of the two models. Our experimental conditions did not have a significant stream and this potential benefit is not further investigated here.

Having two separate sources of speed and angular rate can also be used for fault detection and monitoring. For instance, a change in hydrodynamics caused by a foreign object stuck to the vehicle, or malfunctioning thrusters, can be detected and isolated. This might be a subject for future studies.

This paper is organised as follows. Section II discuss related literature. Section III gives a brief system overview and introduce the kinematics. The hydrodynamic models are presented in Section IV while the sensor models are described in Section V. The sensor fusion in combination with the hydrodynamic model is described in Section VI and the results are presented in Section VII on data from actual sea trials conducted in Lake Vättern, Sweden. Finally, Section VIII contains concluding remarks and gives some suggestions for future directions.

II. RELATED WORK

Navigation of underwater vehicles are in general based on the onboard inertial navigation system (INS) but due its inherent drift, these systems are often aided. Support systems can for instance include doppler speedometers [1], GNSS fixes at the surface and acoustic baseline positioning using transponders [2, 3]. The INS can also be supplemented with
map-aided bathymetric navigation [4–6] where the bottom profile is measured using echo sounders. Other, interesting, approaches are using stereo camera systems which estimates terrain information and navigation states on the fly [7, 8]. Another way of improving navigation is considering physically motivated dynamic models, which in naval terminology is known as hydrodynamics. Hydrodynamic models can be seen as aiding sensors [9] which are independent of the INS, making them particularly useful for robust navigation and model based fault-detection. Estimation of hydrodynamic parameters has a long tradition, see [10, 11], usually involving lengthy and costly experiments. Due to the complexity of the often largely over-parametrized models, specialized experiments have to be conducted isolating only a single or a few degrees of freedom. Motions like these will however rarely occur under normal operation conditions. Recently, methods for identification has emerged which do not rely on expensive reference systems as in [12, 13]. ROVs are often configured differently, depending on the mission, and hence online estimation techniques are of great interest. Identification of underwater vehicles using an observer based method is done in [12]. Caccia et al. [14] is a further development of the work in [15] where they identified a ROV from the inexpensive onboard sensor using an EKF with augmented state which inspired the work of Millert et al. [16].

III. SYSTEM OVERVIEW

The Falcon is an Open-Frame ROV similar to the JHUROV in [17] and the ROMEO in [14]. A variable configuration makes the ROV highly attractive as it can be equipped differently depending on the mission. However, this may also alter previously estimated hydrodynamic parameters. The ROV has a cascade control structure where the outer loop consists of the operator which demands a reference speed and a reference heading and the inner loop consists of thruster PID-controllers striving to minimize the speed and heading errors by means of the INS. The dimensions are $0.7 \times 0.6 \times 1.0 \text{m}$ and is symmetrical along its axes. The dry mass of the Falcon is approximately 73kg with the standard sensor payload. The propulsion system consists of five brushless thrusters of which four are horizontal vectored thrusters for motions in surge, sway and yaw and a thruster for motion in heave. Thus, the Falcon is under-actuated as it is only controllable in four degrees of freedom. The thruster configuration can be seen in Fig. 2. The Falcon is equipped with five sensors, these are vector magnetometer, vector gyroscope, vector specific force, doppler velocity log (measuring linear speed) and a depth sensor.

A. Kinematics

The kinematics is expressed in the commonly used SNAME notation [18]. The ROV is a rigid body and its position and orientation can be described using seven coordinates

$$\eta = [x \ y \ z \ q]^T, \quad (1)$$

where $x$, $y$ and $z$ denote the position decomposed a local North-East-Down (NED) frame called the $e$-frame which is a plane tangential to the earth’s surface at the current location. This frame is considered to be inertial. Furthermore, $\eta$ is a unit quaternion

$$q = [q_0 \ q_1 \ q_2 \ q_3]^T. \quad (2)$$

parametrising the orientation of the vehicle w.r.t. the inertial frame, see e.g., [10, 19] for details. The velocities

$$\nu = [u \ v \ w \ p \ q \ r]^T, \quad (3)$$

decomposed in the body fixed frame $b$. Here, $u$, $v$ and $w$ denote the velocity in surge, sway and heave and $p$, $q$ and $r$ denote the angular velocities in roll, pitch and yaw, respectively. The $b$ frame is fixed in the vehicle with the $u$-axis pointing forewords in the vehicle’s direction, $v$-axis to the port and the $w$-axis upwards. The origin of the frame will be the approximate centre of mass. The kinematic equations are then

$$\dot{\eta} = J(\eta)\nu, \quad (4)$$
where $J(\eta)$ is the transformation from the body fixed frame to the $e$ frame.

IV. ROV MODELING

Hydrodynamics is the terminology of submerged or partially submerged bodies subject to forces and torques. Hydrodynamic model structures can be derived using first principles of physics and some unknown parameters may be identified with e.g., bollard pull or towing tank experiments. The parameters in the models are in general time varying, however an alternative is to estimate constant models for different regions of the ROV movement, such as uniform acceleration, uniform translation and hover, as suggested by [20]. This approach was considered in [16] in which several model structures for the Falcon were identified of which some will be described and utilized in the following sections. The six degrees of freedom (DOF) hydrodynamics of the ROV, using notation from [10], is

$$\dot{\eta} = J(\eta)\nu, \quad (5a)$$

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau + \vec{w}. \quad (5b)$$

where $M$ is the inertia matrix, $C(\nu)$ is the Coriolis and centripetal matrix, $D(\nu)$ is the hydrodynamic damping matrix, $g(\eta)$ is the hydrostatic restoring force vector, $\vec{w}$ is the vector of environment disturbances, such as currents, and

$$\tau = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}, \quad (6)$$

where

$$\tau_1 = [X \ Y \ Z]^T, \quad (7a)$$

$$\tau_2 = [K \ M \ N]^T. \quad (7b)$$

is the vector of forces and torques related to the propulsion. In previous work [16, 21] model structures for (5) was identified using free decay experiments and least squares.

The inertia matrix is invertible and therefore the hydrodynamics (5) can be put into the form

$$\dot{\eta} = J(\eta)\nu, \quad (8a)$$

$$\dot{\nu} = M^{-1}\left(\tau - C(\nu)\nu - D(\nu)\nu - g(\eta) + \vec{w}\right). \quad (8b)$$

Let the state vector be defined as $\mathbf{x} = [\eta^T \ \nu^T]^T$ and the input as $\mathbf{u} = \tau$ and write (8) in compact form as

$$\dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}) + \mathbf{w}. \quad (9)$$

This notation will be useful later when estimation is concerned in Section VI.

A. Hydrodynamic Models

This section presents the hydrodynamic modeling approach that have been used for the different types of forces and torques.

1) Added Mass and Inertia: The loss of acceleration in water can be modeled as an added mass [10, 21]. This applies both for the translation and rotation of the vehicle. The vehicle has three planes of symmetry and it is therefore fair to neglect the coupling terms in the added mass matrix

$$M_A = -\text{diag}\{X_b, Y_b, Z_b, K_p, M_q, N_r\}, \quad (10)$$

which gives the total inertia matrix, $M = M_{RB} + M_A$, where $M_{RB}$ is the rigid body inertia matrix. This approximation is applicable at the low speeds in which the Falcon operates and furthermore, off-diagonal parameters are difficult to estimate. The Coriolis and centripetal matrix $C(\nu) = C_{RB}(\nu) + C_A(\nu)$, where $C_{RB}(\nu)$ can be calculated from the mass matrix

$$C(\nu) = \begin{bmatrix} \begin{bmatrix} 0 & -S(M_{11}\nu_1 + M_{12}\nu_2) \\ -S(M_{21}\nu_1 + M_{22}\nu_2) \end{bmatrix} \end{bmatrix}, \quad (11)$$

where

$$M = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}, \quad S(\alpha) = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix}. \quad (12)$$

This is an off-diagonal structure that introduces desired coupling between the states.

2) Gravity: The gravity is called a restoring force and it can be modeled as

$$g_{1,G} = R^{be} \begin{bmatrix} 0 \\ mg \end{bmatrix}, \quad (13)$$

$$g_{2,G} = 0$$

where $R^{be} = R(g)$ denotes a rotation from the $e$ frame to the $b$ frame and $g \approx 9.81m/s^2$ in Sweden. The force of gravity is affecting the vehicle in the centre of mass and therefore the moment from the gravity force is zero.

3) Buoyancy: Another restoring force is buoyancy which acts on the vehicle and prevents it from sinking. Buoyancy arises when a body moves the fluid surrounding itself and take its place. Buoyancy forces and torques can be modeled as

$$g_{1,B} = R^{be} \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad (14a)$$

$$g_{2,B} = r^{cb} \times g_{1,B}, \quad (14b)$$

where the vector $r^{cb}$ is pointing from the centre of mass to the centre of buoyancy, $\rho$ is the water density and $V$ is the displaced water volume. In most underwater vehicles the centre of buoyancy is above the centre of gravity since this will give a restoring torque on the vehicle which helps stabilizing the vehicle in roll and pitch. In most underwater applications the vehicle has almost the same buoyancy and gravity magnitude since it otherwise would sink to the bottom or reach the surface. Therefore, the buoyancy force is set to
$g_{1,B} = -g_{1,G}$, since the vehicle then is neutral in the water. In summary, the restoring force and moments vector is

$$g(\eta) = \begin{bmatrix} g_{1,G} + g_{1,B} \\ g_{2,B} + g_{2,B} \end{bmatrix} = \begin{bmatrix} 0 \\ g_{2,B} \end{bmatrix}. \quad (15)$$

4) Drag: The damping forces acting on a marine vessel is described as a sum of potential damping, skin friction, wave drift damping and vortex shedding, these are generally non-linear and difficult to model. At moderate speed it is custom to assume uncoupled motion, hence, the damping matrix $D(\nu)$ is diagonal. The drag force model matrix is then

$$D_{1,D} = -\text{diag}\{X_u, Y_U, Z_w\}$$

$$-\text{diag}\{X_u|u|, Y_U|v|, Z_w|w|\}, \quad (16)$$

assuming both linear and quadratic damping as in e.g., [22]. As seen in (16) the drag force is assumed to affect the system independently in the three axes. The drag force is assumed to affect the vehicle in the centre of mass and therefore the drag force will not produce any moment. However, the rotational drag will produce a moment according to

$$D_{2,D} = -\text{diag}\{K_p, M_q, N_r\}$$

$$-\text{diag}\{K_p|p|, M_q|q|, N_r|r|\}. \quad (17)$$

The complete damping model is then

$$D(\nu) = \begin{bmatrix} D_{1,D} & 0 \\ 0 & D_{2,D} \end{bmatrix}. \quad (18)$$

5) Thrusters: Thruster modeling is a thoroughly studied area with many alternatives proposed in the literature and one of the most common and simplest models describe the output force as quadratic function of the input voltage (or propeller revolution rate) as

$$\tau = Cu|u| \quad (19)$$

where $C$ is a constant and the absolute value accounts for the propeller direction. Previous work [16] has suggested a slightly different model for the thrusters on this vehicle. This is a dynamic model with a rise time of approximately $120\text{ms}$ which was estimated in bollard pull tests using a load cell measuring the produced force. This dynamics is fast compared to the rest of the system and is therefore neglected. The actual force produced when the vehicle is moving may however differ from stationary experiments to a large extent [11]. The force from the thrusters as function of the input signals can be described by

$$\tau_{1,i} = (2.98 \cdot 10^{-4} u_i^3 - 0.16 u_i |u_i| + 0.32 u_i), \quad (20)$$

where $\tau_{1,i}$ is the force from thruster $i = 1, 2, \ldots, 5$ and $u_i$ is the measured input signal for thruster $i$. It was noted that the thrusters saturate at $90\%$ of its maximum input producing $127N$. The force expressed in the ROV coordinate frame is

$$\tau_{1,i} = \tau_{1,i} v_i \quad (21)$$

$v_i$ is a unit vector pointing in the direction as the thruster exerts its force. This force also create a moment on the vehicle which can be calculated by

$$\tau_{2,i} = r_i^T \times \tau_{1,i} \quad (22)$$

where $r_i^T$ is the vector pointing from the origin to the location of the $i^{th}$ thruster. All forces and moments generated by the thrusters may be collected as

$$\tau_1 = \sum_{i=1}^{5} \tau_{1,i}, \quad (23a)$$

$$\tau_2 = \sum_{i=1}^{5} \tau_{2,i}. \quad (23b)$$

B. Discretization

The hydrodynamic model (8) is discretized with Eulers’s method which gives

$$\eta_{t+1} = \eta_t + T J(\eta_t) u_t, \quad (24a)$$

$$u_{t+1} = u_t + T M^{-1} (\tau_t - C(\nu_t) u_t - D(\nu_t) u_t - g(\eta_t)) + w_t, \quad (24b)$$

and it is assumed that the control input $\tau$ is constant over the sampling interval $T$. A simplified notation for (24) is

$$x_{t+1} = f(x_t, u) + w_t, \quad (25)$$

where $u = \tau$ and $T$ is implicit. The process noise is $w_t \sim N(0, Q_t)$ and a simple discretization is $Q_D = T Q_t$. The quaternion should also be normalized in each time step whereas otherwise it will not represent an orientation.

C. Kinematic model

As a comparison the sensor data will also be processed in an Extended Kalman Filter (EKF) using a kinematic model with inertial measurement signals rather than control inputs. The state vector composed in the $e$ and $b$ frame is

$$x = [(p^e)^T (v^b)^T (a^b)^T (q^c)^T (\omega)^T]^T, \quad (26)$$

denoting the position, velocity, acceleration, the rotation (parametrized with a unit quaternion) and the angular velocity, respectively. As in the hydrodynamic model the velocities and accelerations are expressed in the body frame introducing a few extra non-linearities. On the other hand when using this setup then the same sensor models, see Section V, can be used. The continuous-time non-linear dynamic model for the states is

$$\dot{p}^e = R^{eb} v^b, \quad (27a)$$

$$\dot{v}^b = a^b - \omega \times v^b, \quad (27b)$$

$$\dot{a}^b = -\omega \times a^b + w_{ai}, \quad (27c)$$

$$\dot{q}^{be} = \frac{1}{2} S(\omega) q, \quad (27d)$$

$$\dot{\omega} = w_{\omega i}, \quad (27e)$$

where $S$ is the skew-symmetric matrix of $\omega$.
where, $w_{\alpha t}$ and $w_{\omega t}$ is noise accounting for the unknown jerk and the unknown angular acceleration, respectively. This acceleration state is also used in the hydrodynamic model since it is needed for the accelerometers. Furthermore, $S(\omega) q_{t}^{ae}$ is the quaternion product of the angular velocity and the unit quaternion in matrix vector notation where $S(\omega)$ is defined as

$$
S(\omega) = \begin{bmatrix}
0 & -\omega_z & \omega_y \\
\omega_z & 0 & -\omega_x \\
-\omega_y & \omega_x & 0
\end{bmatrix}.
$$

Again using Euler’s method on (27) with sampling interval $T$ gives

$$
p_{t+1}^b = p_t^b + T R_t^b v_t^b,
$$

$$
v_{t+1}^b = v_t^b + T (a_t^b - \omega_t \times v_t^b)
$$

$$
a_{t+1}^b = a_t^b - T (\omega_t \times a_t^b) + T w_{\alpha t},
$$

$$
q_{t+1}^{ae} = q_t^{ae} + \frac{T}{2} S(\omega_t) q_t^{ae}
$$

$$
\omega_{t+1} = \omega_t + T w_{\omega t}.
$$

This kinematic model can be expressed as

$$
x_{t+1} = f(x_t) + w_t,
$$

where $f(\cdot)$ is a nonlinear function of the state and $w_t$ is noise.

V. SENSOR MODELS

The Falcon ROV sensor suite consists of a vector magnetometer, a vector gyroscope, a vector specific force sensor, a Doppler velocity log (DVL) and a hydrostatic pressure sensor (HPS). The typical equations for sensors are

$$
y = h(x_t) + e_t,
$$

where $h(\cdot)$ is a nonlinear function of the state $x_t$ and $e_t$ is noise where subscript $t$ denotes time dependency. Selection of such sensors can be crucial since size, weight, price, energy consumption and other physical limitations need to be considered. Moreover, cheaper sensors do not offer the same accuracy as in the higher range. Models of strapdown inertial sensors can be found in most books on navigation, see e.g., [23].

A. Inertial Measurement Unit and Magnetometer

The inertial measurement unit (IMU) provides measurements of the specific force and angular velocity.

1) Specific Force: The measured specific force is the sum of the linear acceleration and the force from the gravitational field which is independent of reference frame. The orientation of the sensor plays an important role since the gravitational field will affect the measurements and an error in the estimated sensor orientation is manifested as an acceleration error. Also, the measured force due to the rotational velocity depends on the mounting of the sensor relative to the body rotational centre. This offset is modeled by the vector $r^{IMUb}$ which is pointing to the sensor with the origin at the vehicle’s centre of mass. A measurement model for the acceleration is

$$
y_a = R^{IMUb} (a_t^b - R_t^{be} g^f + \omega_t \times (\omega_t \times r^{IMUb})) + e_{\alpha t},
$$

where $g^f$ is the gravity vector and $r^{IMUb}$ is the vector from the body origin to the IMU centre and $e_{\alpha t}$ is measurement noise which also includes the unknown angular acceleration.  

2) Gyroscope: The triad of gyroscopes measures the sensor unit’s angular velocity and a measurement model for this sensor is

$$
y_{\omega} = R^{IMUb} \omega_t + e_{\omega_t},
$$

where $R^{IMUb}$ is the rotation matrix from the body frame to the IMU frame and $e_{\omega_t}$ is measurement noise. This model is very simple and a common extension is to add a slowly time varying bias to capture sensor drift which may be due to e.g., temperature changes.

3) Magnetometer: The vector magnetometer is also contained in the IMUs’ housing and therefore the origin and rotation w.r.t. the body frame is considered to be the same. The measurement model for the magnetometer is

$$
y_m = R^{IMUb} R_t^{be} n_{np}^e + e_{m_t},
$$

where $R^{IMUb}$ is the rotation matrix from the body frame to the IMU frame, $n_{np}^e$ is the normalised local earth magnetic field vector and $e_{m_t}$ is the measurement noise. At the location where the measurements were acquired, the magnetic field was $[15661, 1103, 47978]nT$ denoting north, east and vertical components (NED), respectively.

B. Doppler Velocity Log

The Doppler Velocity Log (DVL) measure the linear velocity of the vehicle relative to the seabed. The sensor is an acoustic device that sends sound pings through the water and measures the reflections at the seabed [24] using a multi-beam echo-sounder. In these reflections there will be a doppler shift where the measurements were acquired, the magnetic field was $[15661, 1103, 47978]nT$ denoting north, east and vertical components (NED), respectively.

$$
y_v = R^{DV Lb} (v_t^b + \omega_t \times r^{DV Lb}) + e_{v_t},
$$

where $R^{DV Lb}$ is the rotation matrix from the body frame to the DVL frame, $r^{DV Lb}$ is the vector from the vehicle body origin to the DVL origin and $e_{v_t}$ is measurement noise. The measurement error in the DVL is mainly due to a scale error and this error is due to the uncertainty of the speed of sound in the water which depend on the water’s salinity.

VI. ESTIMATION

In this section the estimation process using the onboard sensors and the hydrodynamic model is described.
A. Filtering

A standard method for non-linear filtering is to apply the Extended Kalman Filter (EKF) to the dynamic equations and the measurements, see e.g., [25], and this is often the preferred solution when dealing with attitude estimation using integrated inertial systems [26]. The EKF is summarized in Algorithm 1 below.

Algorithm 1 Extended Kalman Filter

Require an initial state, \( x_{0|0} \), and an initial state covariance, \( P_{0|0} \).

1) Time Update

\[
\hat{x}_{t|t-1} = f(\hat{x}_{t-1|t-1}, u_t), \quad (36a)
\]

\[
P_{t|t-1} = F_tP_{t-1|t-1}F_T + Q_t, \quad (36b)
\]

2) Measurement Update

\[
K_t = P_{t|t-1}H_T(H_tP_{t|t-1}H_T^T + R_t)^{-1}, \quad (37a)
\]

\[
\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(y_t - h(\hat{x}_{t|t-1})), \quad (37b)
\]

\[
P_{t|t} = P_{t|t-1} - K_tH_tP_{t|t-1}. \quad (37c)
\]

In Algorithm 1 the Jacobian matrices are defined according to

\[
F_t \triangleq \frac{\partial f(x_t, u_t)}{\partial x_t} \bigg|_{(x_t, u_t) = (x_{t-1|t-1}, u_t)}, \quad (38)
\]

\[
H_t \triangleq \frac{\partial h(x_t)}{\partial x_t} \bigg|_{(x_t) = (x_{t|t-1})}, \quad (39)
\]

Furthermore, \( Q_t \) and \( R_t \) are the covariance matrices of \( w_t \) and \( e_t \), respectively.

B. Synchronization

The sensors and control inputs are sampled at different rates and at different time instants. It is crucial that these signals are synchronized since otherwise the performance of the filter is degraded. The synchronization is handled in a post-processing step using the time-stamps from each sensor and the control inputs. To handle the different sampling rates in the EKF the following is done:

At a time instant \( t_k \)

1) Find the next signal (sensor(s) and/or control input) at time \( t_{k+1} \).
2) If it is a control input, perform a time update according to (36) over the interval \( T = t_{k+1} - t_k \) using the control input \( u_{t_k} \).
3) If it is a sensor signal return to the step 2) and then perform a measurement update according to (37).
4) Return to 1).

VII. RESULTS

Data was collected in Lake Vättern, Sweden, under rather good weather conditions. A path, which is marked by a cable, was followed each run where a lattice marks one end of the cable and a crayfish cage marks the other end, see Fig. 3. Note that the ROV was only steered such that it finished at the other end of the cable. The DVL is fairly accurate and can hence serve as a reliable reference. The model explains both the dynamic behaviour and constant motion very well. Also note the consistency with the measured surge speed when the ROV was moving slightly backwards at about 200s.

B. Angular Velocity Model

The simulated yaw rate compared to the gyroscope can be seen Fig. 5 where it is obvious that the hydrodynamic model does not capture the true rate particularly well. An
The ROV was not controlled such that it ran along the cable and it was measured using another DVL, where a nearly constant velocity model is used for describing the motion. On the positive side, the longitudinal dynamics turned out to be comparable to the inertial system in accuracy. This is particularly useful in situations when the doppler log is not reliable. In future work it would be interesting to find better models for the angular rates and possibly different ones for different modes as the results indicates. Also, a more accurate model for the lateral dynamics is desirable.

Fig. 5. Left: The yaw rate from the hydrodynamic model in red compared to the sensor reading from the gyroscope in blue shows that the model do not capture the rate dynamics satisfactorily. Right: The yaw rate from a data set with a slowly creeping surge speed is a lot closer to the likely yaw rate.

Fig. 6. The trajectory using the hydrodynamic model without the DVL in red, the kinematic model (27) using all sensors in green and the blue curve is the reference trajectory.

C. Position Estimates

The angular velocity models were simply too poor to be used for estimation of the position, instead the hydrodynamics were aided with the onboard consumer grade inertial and magnetometer sensor MTI from XSens. A view of the trajectory estimated trajectory using the aided hydrodynamic model (8), the kinematic model (27) with DVL and the reference trajectory can be seen in Fig. 6. The reference trajectory marks the coordinates of the cable and it was measured using another ROV equipped with a more sophisticated navigation system. The ROV was not controlled such that it ran along the cable the whole track. The position estimate with the hydrodynamic model is comparable to the kinematic model meaning that the DVL can be aided using the hydrodynamics.

VIII. CONCLUSION

We have compared two different Extended Kalman filters for navigation of a ROV. The first one is based on inertial navigation principles supported with a DVL, where a nearly constant velocity model is used for describing the motion. The second one is based on a hydrodynamical model with the five thruster controls as inputs, and where the inertial sensors can be used as feedback. It was shown that the available models for this ROV for the lateral dynamics were not good enough to compete with inertial navigation. On the positive side, the longitudinal dynamics turned out to be comparable to the inertial system in accuracy. This is particularly useful in situations when the doppler log is not reliable. In future work it would be interesting to find better models for the angular rates and possibly different ones for different modes as the results indicates. Also, a more accurate model for the lateral dynamics is desirable.

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