Application of Sensor Fusion to Drive Vessel Performance

Ikonomakis, Angelos; Galeazzi, Roberto; Dietz, Jesper; Kähler Holst, Klaus; Nielsen, Ulrik Dam

Publication date: 2019

Document Version
Publisher's PDF, also known as Version of record

Link back to DTU Orbit

Citation (APA):
Application of Sensor Fusion to Drive Vessel Performance

Angelos Ikonomakis, Maersk Line Fleet Performance, Copenhagen/Denmark, angelos.ikonomakis@maersk.com

Roberto Galeazzi, DTU Electrical Engineering, Copenhagen/Denmark, rg@elektro.dtu.dk

Jesper Dietz, Maersk Line Fleet Performance, Copenhagen/Denmark, jesper.dietz@maersk.com

Klaus Kähler Holst, Maersk Digital Research, Copenhagen/Denmark, klaus.holst@maersk.com

Ulrik Dam Nielsen, DTU Mechanical Engineering, Copenhagen/Denmark, udn@mek.dtu.dk

Abstract

Typically, slow steaming is adopted to lower ship’s resistance, which in turn reduces exhaust gas emissions due to lower propulsion power demands. Fine tuning of the underlying hydrodynamic models is key to the reliable forecasting of fuel consumption. Accurate knowledge of the vessel’s speed-through-water (STW) is paramount to estimate the actual resistance of the vessel. The paper presents a feasibility study about the use of sensor fusion methods for real-time estimation of STW based on inertial measurements of ship motions and measurement of sea current. By combining a purely kinematic model together with linear Kalman filtering, the paper addresses the challenge of designing an optimal STW estimator by detailing the fundamental design choices. The proposed STW estimator is verified on simulated data and tested with measured data from an in-service container vessel.

1. Introduction

1.1. Background and motivation

At sea the speed of a moving craft is measured either relative to the seabed (speed over ground - SOG) or relative to the water flowing past the hull (speed through water - STW). Both of these speed types apply in modern navigation systems. The STW is a crucial source of data for the performance monitoring of a container vessel. Hull and propeller fouling estimation derive from the knowledge of the STW, hence its accurate observation is a key element towards energy efficiency. Traditionally, maritime speed logging devices use either of the following measurement principles to obtain the STW: water pressure, electromagnetic induction, or the transmission of low frequency radio waves Tetley and Calcutt (2007). The latter refers to as the Doppler velocity log (DVL), which is the speed log used by the vessels dealt with in this paper. A range of environmental factors can sometimes influence the accuracy of the measured speed log, Litton (1998). In addition to that, speed log manufacturers always provide distinct information concerning the possible accuracy.

The speed log measurements cannot be categorically trusted, Griffiths and Bradley (1998). Occasionally, offsets occur when measured STW is compared with computed STW, obtained through post-processing of hindcast and propulsion data. This observation, along with other influences, such as trim, aeration, sensor fouling and water clarity, are factors that diminish the confidence of the measured STW. Therefore, the availability of tools for reliably estimating the STW based on either already available measurements or measurements deriving from potentially installed sensors, is of interest to fleet managers for the optimization of fleet performance. The scope of this work is to estimate STW with an accuracy significantly higher than that of the signal measured by the Doppler velocity log. This is achieved by fusing both onboard inertial measurements and external data into a kinematic model of vessel motions. The virtual sensor can be used as input for associated applications such as data-driven fuel tables, trim optimization and accurate hull cleaning predictions.

1.2 State-of-the-art

The analysis of the data provided by onboard sensors is a complex and necessary task, in order to get a clear picture of the ship’s behavior and condition. When data derives from sensors, there is always some uncertainty on the measurements, hence it is necessary to analyze each sensor with respect to its
type. Besides the manufacturer information on the sensor uncertainty, several uncertainty analyses have been published. With regard to the ITTC Powering Prediction Method, ITTC (2002), an analysis has been conducted on the uncertainty assessment of the performance parameters during sea trials, ITTC (2005). The results of the trials include errors due to measurements, hull form production and corrections of environmental conditions.

It is noted in the literature, ITTC (2005), that, as speed increases, both bias and precision errors decrease. Bias errors are 5% for all speed range and 3% at the design speed, while the precision errors are 9% at lower speeds and 7% at the design speed. Concerning STW, there is a claim from Boom et al. (2013) which states that the speed log is one of the most inaccurate onboard measurement devices. Bos (2016) identifies situations where STW data can result in misleading performance trends. These statements have to be investigated and different values of uncertainty should be tested for STW before reaching conclusions.

Numerous researchers have pinpointed the various difficulties in STW estimation including Pyörre (2012) and Antola et al. (2017). Antola et al. (2017) proposed a Bayesian approach to the STW estimation combining an extended Kalman filter with a mixed kinematic-kinetic model of the vessel. Despite the very promising results showed through validation on almost 200 vessels, three main elements are pointed out that could impact negatively the STW estimate: (i) the model assumes knowledge of the vessel’s calm water resistance; (ii) to exploit measurements of shaft torque it is assumed that the vessel STW equals the propeller speed of advance, thereby neglecting wake effects that for ships with a single propeller may account for reductions in the range of 20% to 45% for the speed of advance; (iii) the vessel accelerations due to wave motion are neglected. Power-resistance curves are available for each operating vessel; however this data, usually obtained through model tests, reflects the characteristics of the vessel as new and does not necessarily account for changes in the hull due to retrofits or simply aging. For a given shaft rotational speed switching the speed of advance of the propeller with the vessel STW gives rise to a larger advance ratio, which may determine a systematic mismatch between measured and modelled shaft torque. For a vessel sailing in waves a thrust-resistance balance to achieve zero surge acceleration is rather unrealistic since it demands the thrust/torque/ shaft speed control systems to completely compensate for wave-induced speed variations. Therefore, a vessel in seaway can experience substantial accelerations that, at least locally, influence the vessel’s STW. These elements can potentially introduce systematic errors in the estimate of the vessel’s STW.

1.3 Novelty and contribution

This paper addresses the reliable estimation of the STW within the linear Kalman filtering framework by combining a purely kinematic model of vessel dynamics with inertial measurements of the vessel’s position, velocity and acceleration as well as velocity of the sea current. The vessel kinematic model is favored because it does not require partial or full knowledge of vessel hydrodynamics or propulsion characteristics. The available STW measurement is not considered in the estimation, while it is used for the evaluation of the estimated STW. Although the adopted model may be used to estimate the speed through water for a vessel sailing in an arbitrary sea state, this feasibility study focuses on calm water condition to determine the potential estimation performance in absence of major disturbances affecting the vessel dynamic behavior.

The paper details the modeling procedure towards the design of an optimal estimator of STW and illustrates a systematic approach for the evaluation of the obtained estimate. The STW estimator is evaluated both on simulated and full-scale data from an in-service container ship. Preliminary results confirm the possibility to improve the knowledge of the STW with respect to the DVL measurement.

2. Problem Formulation

For a correct formulation of the problem the following assumptions are made:
**Assumption 1:** The motion of the vessel in the horizontal plane is described by three degrees-of-freedom (DOF), namely surge, sway and yaw.

**Assumption 2:** Two reference frames are used to represent the motion of the vessel: the North-East-Down (NED) coordinate frame \( [n] \) is the inertial frame used to describe the pose of the vessel; the body-fixed coordinate frame \( [b] \) is the non-inertial frame fixed to the vessel used to describe linear and angular velocities.

**Assumption 3:** The ocean current in the inertial frame \( [n] \) \( \mathbf{V}_c^n = [V_x, V_y, 0]^T \) is constant and irrotational, i.e. \( \mathbf{V}_c^n = 0 \).

**Assumption 4:** The vessel is equipped with a GNSS (global navigation satellite system) receiver providing synchronous measurements of vessel position \( (N, E) \) and speed over ground \( U_o \) at the rate \( 0 < f_p < 1 \) Hz. The position measurement in the North and East directions is affected by zero mean white Gaussian noise with variance \( \sigma^2_p \), i.e. \( w_N \sim \mathcal{N}(0, \sigma^2_p) \) and \( w_E \sim \mathcal{N}(0, \sigma^2_p) \). The SOG measurement is affected by zero mean white Gaussian noise with variance \( \sigma^2_o \), i.e. \( w_{U_o} \sim \mathcal{N}(0, \sigma^2_o) \). It is further assumed that the noise sources \( w_N, w_E \) and \( w_{U_o} \) are uncorrelated among each other.

**Assumption 5:** The vessel is equipped with a tri-axis accelerometer providing measurements of linear accelerations \( \mathbf{a}^b = [a_u, a_v, a_w]^T \) along directions parallel to the axes of the body-fixed frame at the rate \( f_a \geq f_p \) Hz. Each measured acceleration is affected by zero mean white Gaussian noise with variance \( \sigma^2_a \), i.e. \( w_{a_i} \sim \mathcal{N}(0, \sigma^2_a) \) with \( i = \{u, v, w\} \). The three noise sources are uncorrelated among each other.

**Assumption 6:** The vessel is equipped with a compass providing a measurement of heading at the rate \( f_{\theta} \geq f_p \) Hz. The heading measurement is affected by zero mean white Gaussian noise with variance \( \sigma^2_{\theta} \), i.e. \( w_{\theta} \sim \mathcal{N}(0, \sigma^2_{\theta}) \).

**Assumption 7:** A prediction of the sea current velocity vector \( \mathbf{V}_c^n \) is available through an external provider at a rate \( 0 < f_c \ll 1 \). Each predicted component of the velocity vector is subject to zero mean white Gaussian noise with variance \( \sigma^2_c \), i.e. \( w_{c_j} \sim \mathcal{N}(0, \sigma^2_c) \) with \( j = \{x, y\} \). The two noise sources are uncorrelated between each other.

**Remark 1.** The noise sources impacting the GNSS measurements of position and SOG are strongly correlated when the SOG is computed by differencing two consecutive position measurements. This is the case in low-end receivers that are usually not adopted in motion control applications of marine crafts. Medium to high-end receivers provide the SOG measurement based on either the Doppler frequency shift of the received signal due to vessel-satellite relative motion or the time differenced carrier phase, Freda et al. (2015), Gaglione (2015). Here the uncertainty of the SOG depends on the quality of the phase measurements (affected by measurement noise and multipath) as well as on the accuracy of the computed position, although to a minor degree. Hence in this case the noise source \( w_{U_o} \) can be assumed uncorrelated with the noise affecting the position measurement.

Let \( \eta^n = [N, E, \psi]^T \in \mathbb{R}^3 \) be the pose vector in the \( [n] \) frame and \( \mathbf{v}^b = [u, v, r]^T \in \mathbb{R}^3 \) be the velocity vector in the \( [b] \) frame. Then the 3-DOF maneuvering model reads, Caharija et al. (2012), Moe et al. (2014).\(^{1}\)

\[
\dot{\eta}^n = R_n^b(\psi) \mathbf{v}_r^b + \mathbf{v}_c^n \\
M \ddot{\mathbf{v}}_r^b + N(\mathbf{v}_r^b) \mathbf{v}_r^b = \tau
\]
where $M = M_{RB} + M_A$ is the total mass given by the sum of the rigid body contribution and the added mass/inertia; $N(v^b) = \sum v^b$ is the sum of centripetal and frictional forces; $v = [x, v_x, 0] \in \mathbb{R}^3$ is the vector of generalized forces and moments; $v^b = v^b - v^c = [u_r, v_r, r] \in \mathbb{R}^3$ is the relative ship speed, i.e. the speed though water. $v^c = (R^b_b(\psi))Tv^c$ is the velocity vector of the current in the $\{b\}$ frame. The transformation of coordinates between the reference frames $\{b\}$ and $\{n\}$ is achieved through the rotational matrix

$$R^b_b(\psi) = \begin{bmatrix}
\cos \psi & -\sin \psi & 0 \\
\sin \psi & \cos \psi & 0 \\
0 & 0 & 1
\end{bmatrix}$$ (3)

Based on the Assumptions 4 – 7, the output model is given as

$$
y_1 = N_m = N + w_N \\
y_2 = E_m = E + w_E \\
y_3 = \psi_m = \psi + w_\psi \\
y_4 = U_{z,m} = U_z + w_u \\
y_5 = V_{x,p} = V_x + w_{v_x} \\
y_6 = V_{y,p} = V_y + w_{v_y} \\
y_7 = a_{u,m} = a_u + w_{a_u} \\
y_8 = a_{v,m} = a_v + w_{a_v}$$

where the subscripts $m$ and $p$ indicate “measured” and “predicted”, respectively.

**Problem statement:** Consider a ship sailing in calm water along a piecewise continuous path with SOG $U_s(t) = \sqrt{u^2 + v^2}$ and heading $\psi(t)$. The vessel is subject to an ocean current with speed $U_c = \sqrt{v_x^2 + v_y^2}$. Exploiting asynchronous inertial measurements of vessel motion and predictions of the ocean current velocity, generate an estimate of the vessel’s STW $U_r(t) = \sqrt{u^2 + v^2}$.

3. **STW Estimator Design**

Sensor measurements are noisy and their accuracy proportionally relates to cost. To overcome the limitations introduced by each individual measurement system, in multi-sensor applications the overall quality of the information is improved by using sensor fusion methods. In Elmenreich (2002), sensor fusion is defined as “the combining of sensory data or data derived from sensory data such that the resulting information is in some sense better than would be possible when these sources were used individually”. Some of the most common sensor fusion methods are the Weighted Least Squares, the Maximum Likelihood, the Maximum Posterior, the Particle Filter, and the Kalman Filter, Castanedo (2013). In this paper the Kalman filter is adopted because in the presence of uncertainty it provides the optimal estimate of the quantities of interest in the sense of minimum variance.

Designing an estimator of STW based on the maneuvering model (1)-(2) requires detailed knowledge of the vessel hydrodynamic characteristics, which in general might be unavailable or simply outdated due to aging of the hull or hull modifications. Therefore, robustness of the estimation could be achieved only through the parallel estimation of $U_r(t)$ and model parameters. This will obviously increase complexity of the estimation scheme.

An alternative approach, which conjugates both simplicity and robustness, based on only the vessel kinematics (1) and exploiting the available measurements of ship motion and predictions of current velocity. Since an estimate of STW is sought, rather than its projection onto the body axes, $u_r$ and $v_r$, then the estimation problem can be formulated in terms of traveled distance and cruising speeds, $U_s(t)$ and $U_r(t)$.
Let $\hat{x} = [\hat{d}, \hat{U}_s, \hat{U}_r, \hat{U}_c]^T \in \mathbb{R}^4$ be the state estimation vector, where $\hat{d}$ is the estimate of the traveled distance $d = \sqrt{N^2 + E^2}$ and $\hat{U}_c$ is the estimate of the speed of the current $U_c = \sqrt{V_s^2 + V_y^2}$. Then the discrete time state space model at the core of the estimator is given by

$$
\begin{align*}
\hat{d}(k+1) &= \hat{d}(k) + \hat{U}_s(k)T_s + \frac{1}{2}A_s(k)T_s^2 \\
\hat{U}_s(k+1) &= \hat{U}_s(k) + A_s(k)T_s \\
\hat{U}_r(k+1) &= \hat{U}_r(k) - \hat{U}_c(k) + A_s(k)T_s \\
\hat{U}_c(k+1) &= \hat{U}_c(k) + V_c 
\end{align*}
$$

where $T_s = 1/\max\{f_p, f_a, f_c\}$ is the sampling time, $A_s$ is the total ship acceleration, i.e. $A_s = \sqrt{a_u^2 + a_v^2}$, and $V_c$ is a zero mean white Gaussian noise source with variance $\sigma_v^2$.

**Remark 2:** Eqs. (14)-(15) are valid only when the vessel sails with constant heading, i.e. $r \approx 0$. During heading alterations the equations should also account for fictitious accelerations due to centripetal forces, Fossen (2011), [Section 8.3].

**Remark 3:** Based on the direct measurements (10)-(11) the indirect measurement of total ship acceleration is given by $u_A = \sqrt{y_s^2 + y_0^2}$, which is a stochastic process whose characteristics are in general non-Gaussian. When the acceleration components $a_u$ and $a_v$ are both zero, then $u_A$ will be a Rayleigh distributed random process. However, when the acceleration along the surge and/or sway directions is different from zero then the random component of $u_A$ is still well approximated by a Gaussian distribution. For the sake of simplicity and in order to apply standard results in Kalman filtering, it is assumed that the measured total ship acceleration can be approximated as $u_A \approx A_s + v_A$, where $v_A$ is zero mean white Gaussian noise with variance $\sigma_v^2$. Hence the total ship acceleration $A_s$ in Eqs. (12)-(14) is given by $A_s = u_A - v_A$.

Based on the output model (4)-(11) and considering asynchronous measurements the following measurement models are defined

$$
\begin{align*}
\mathbf{z}(k) &= [y_d, y_4, y_c]^T + \mathbf{w}_1(k) & k = LT_c/T_s \\
\mathbf{z}(k) &= [y_d, y_4]^T + \mathbf{w}_2(k) & k \neq LT_c/T_s
\end{align*}
$$

where $y_d = d$ is the measured traveled distance, $y_c = \sqrt{y_s^2 + y_0^2}$ is the predicted sea current speed, $T_c = 1/f_c$ and $L \in \mathbb{N}$ is a counter.

The measurement noise vectors $\mathbf{w}_1 = [w_d, w_{U_s}, w_{U_c}]^T$ and $\mathbf{w}_2 = [w_d, w_{U_s}]^T$ are described by independent and uncorrelated Gaussian distributed stochastic processes, i.e. $\mathbf{w}_1 \sim \mathcal{N}(0, \mathbf{R}_1)$ with $\mathbf{R}_1 = \text{diag}[[\sigma_d^2, \sigma_s^2, \sigma_v^2]]$ and $\mathbf{w}_2 \sim \mathcal{N}(0, \mathbf{R}_2)$ with $\mathbf{R}_2 = \text{diag}[[\sigma_d^2, \sigma_s^2]]$.

**Remark 4:** The measurement $y_d$ of the travelled distance $d$ is indirect since it is computed from the direct GNSS measurements $y_1$ and $y_2$. Similarly, the measurement $y_c$ of the speed of the current is indirectly computed based on the predicted $V_c^2$. Both $y_d$ and $y_c$ are in general non-Gaussian stochastic process due to the nonlinear processing of the white Gaussian noise affecting the direct measurements. Applying the same line of reasoning of Remark 3, the measurement models (16)-(17) are adopted.

**Remark 5:** Deviations of the true measurements from the proposed approximations in Remarks 3 and 4 will determine a poorer performance of the Kalman filter with respect to the theoretical expectation.
In particular, the estimation error covariance will be larger than the theoretical expected value and correlation may appear in the estimation error.

Based on the estimator model (12)-(15) and measurement model (16)-(17) the discrete time state transition matrix $F$, the input matrix $G$, the process noise input matrix $G_p$, and the output matrices $H_1$ and $H_2$ can be set up:

$$F = \begin{bmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad G = \begin{bmatrix} \frac{1}{2}T_s^2 \\ T_s^2 \\ T_s \\ 0 \end{bmatrix}, \quad G_p = \begin{bmatrix} \frac{1}{2}T_s^2 & 0 \\ -T_s & 0 \\ -T_s & 0 \\ 0 & 1 \end{bmatrix}$$

(18)

$$H_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad H_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

(19)

The last step towards the implementation of the STW estimator based on linear Kalman filtering is to define the process noise covariance matrix $Q$. Given the estimator model (12)-(15) two process noise sources are identified, namely $v_A$ and $v_p$, which are assumed to be uncorrelated between each other. Therefore, the process noise covariance matrix is given by $Q = \text{diag}\{\sigma^2_A, \sigma^2_p\}$. Whilst the variance of the process noise component $v_A$ as well as the variances of the measurement noise $w_1$ are given by the noise characteristics of the individual sensors, the variance $\sigma^2_p$ is a tuning parameter for the Kalman filter that can be used to determine the trade-off between smoothness of the estimation and promptness to changes in the operational conditions of the system to perform estimation on. The linear optimal STW estimator in its predictor-corrector formulation reads Lewis et al. (2017) [Section 2.3]

**Time update**

$$\tilde{x}^-(k+1) = F\tilde{x}(k) + G\tilde{u}_A$$

(20)

$$P^-(k+1) = FP(k)F^T + G_pQG_p^T$$

(21)

**Measurement update**

$$\cdot k = LT_c/T_s$$

$$\tilde{x}(k+1) = \tilde{x}^-(k+1) + K_1(k+1)[z(k+1) - H_1\tilde{x}^-(k+1)]$$

(22)

$$P(k+1) = [(P^-(k+1))^{-1} + H_1^T R_1^{-1} H_1]^{-1}$$

(23)

$$\cdot k \neq LT_c/T_s$$

$$\tilde{x}(k+1) = \tilde{x}^-(k+1) + K_2(k+1)[z(k+1) - H_2\tilde{x}^-(k+1)]$$

(24)

$$P(k+1) = [(P^-(k+1))^{-1} + H_2^T R_2^{-1} H_2]^{-1}$$

(25)

where $K_i(k) = P(k)H_iR_i^{-1}, i = \{1,2\}$, is the Kalman gain. During the time update the state prediction $\tilde{x}^-$ and the a-priori estimation error covariance $P^-$ are computed based on the linear time invariant discrete time model $(F, G, G_p)$ and the process noise covariance $Q$. When a new measurement becomes available, the state estimate $\tilde{x}$ and the a-posteriori estimation error covariance $P$ are updated based on the measurement model $H_i$, the Kalman gain $K_i$, and the measurement noise covariance $R_i$.

4. Implementation on Simulated Data

The simulations are carried out using the Marine Systems Simulator (MSS), Fossen (2011). The simulator is a Matlab/Simulink library for marine systems that includes models for ships, underwater vehicles, and floating structures, https://github.com/cybergalactic/MSS. The library also contains guidance, navigation, and control functionalities for real-time simulation. The library has been translated
to Python and then focused on the model for coupled motion of steering and rolling of a high-speed container ship, introduced in Son and Nomoto (1981). The simulation study case represents a \( L = 175 \) m vessel, which travels with variable SOG \( U_x \), subject to a sea current coming from astern with constant speed \( U_c = 1 \) m/s.

The simulation environment has been configured to run with an integration time step of 0.01 seconds, in order to mimic the continuous time nature of the vessel motion and enable further resampling of the data due to simulated measurement processes. To verify the ability of the designed estimator to converge in mean value towards the true value as well as to track time-varying behaviors, the vessel has been initialized with \( U_x(0) = 10 \) m/s and the shaft angular velocity \( n(0) = 70 \) rpm, which gives rise to a non-stationary condition when \( n \) is increasing or decreasing over time.

The measurement process has been set up by simulating sensors with sampling rates and noise characteristics as stated in Table 1.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Frequency [Hz]</th>
<th>Noise [std]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_m )</td>
<td>0.033 [30s]</td>
<td>2.5 [m]</td>
</tr>
<tr>
<td>( E_m )</td>
<td>0.033 [30s]</td>
<td>2.5 [m]</td>
</tr>
<tr>
<td>( U_{OG} )</td>
<td>0.033 [30s]</td>
<td>0.065 [m/s]</td>
</tr>
<tr>
<td>( U_{curr} )</td>
<td>0.008 [20min]</td>
<td>0.2 [m/s]</td>
</tr>
<tr>
<td>( a_x )</td>
<td>0.033 [30s]</td>
<td>0.05 [m/s²]</td>
</tr>
<tr>
<td>( a_y )</td>
<td>0.033 [30s]</td>
<td>0.05 [m/s²]</td>
</tr>
</tbody>
</table>

Table 1: Sampling frequency and noise intensity (1\( \sigma \)) of each sensor used by the estimator.

Fig.1 shows the estimate of the speed through water \( \hat{U}_r \) (virtual STW). The true STW obtained from the simulation is indicated by the dashed-blue line. It is evident by checking the log lines that the data is asynchronous meaning that it resembles a real-world scenario where the measurement of the current speed \( U_c \) is acquired with a different frequency than the SOG measurement from the GPS sensor.

Simulated results show that the designed estimator performs well in reconstructing the STW: although there is a noticeable phase lag, in only a few iterations it is visible that despite the noise and the asynchronicity of the sensor rates, the STW estimator converges in mean value to the true value of the relative ship speed \( U_r \).
Fig. 3: Virtual STW residual within $1\sigma$, $2\sigma$ and $3\sigma$ confidence bounds

To qualify and quantify the performance of STW estimator an analysis of the estimation error $U_v = U_r - \hat{U}_r$ is carried out. Fig. 2 illustrates the estimation error $\hat{U}_b$ with the $1\sigma$, $2\sigma$ and $3\sigma$ confidence bounds. Fig. 3 shows the autocorrelation function of the estimation error.

Under ideal conditions, if the STW estimator correctly reconstructs the vessel’s STW then $\hat{U}_b$ should be a white noise process with zero mean and bounded small variance. Figs. 2 and 3 show that the residual is well within the $3\sigma$ confidence bound and that the autocorrelation falls within its confidence bound as soon as the stationary condition is achieved. Therefore, the estimation error $\hat{U}_b$ can be considered a white sequence, meaning that the designed estimator reconstructs the dynamics of interest.

5. Implementation on full-scale data

The data originates from a 10,500 TEU container vessel owned and operated by Maersk Line. Only relevant vessel information and values are included. Fig. 4 illustrates the vessel route and speed profile for a 1-month sample data of the vessel. It can be noticed that along the route there are periods when the speed is switching from high to low values and vice versa. Sea currents affect the STW either positively or negatively according to their angle of attack. When $U_c < 0$, it refers to head currents.
When measuring and analyzing data, it is desirable that the underlying measured process is wide sense stationary, i.e. its statistical properties are time invariant. In practice, the measured process and, thereby, the collected data will often display non-stationary features over certain periods of time. Changes in environmental or operational conditions over time, such as variations in current speed magnitude and direction or ship’s heading alterations, result to changes in vessel’s speed leading to non-stationary data. It is possible, though, to find cases where the ship can be assumed to operate in a stationary condition.

An inspection on the whole 1-month-dataset has been conducted to ascertain how stationary the STW sensor is overtime; always keeping in mind to maintain the mean draught in the same level and the trim close to zero (even keel). Additionally, the sea state was loosely inferred by checking both roll and pitch angles so as to focus on calm water conditions. Moreover, when visualizing the sea current speed $U_c$ and the speed over ground $U_s$, it is clear that their patterns do not always match, which is probably due to the fact that sea currents are not accurately predicted, especially in open waters. By checking Fig.5 one can see that the two signals have a strong match only in days 18-19.
Thus, the estimator is applied to data collected while the vessel passed through the English Channel, which refers to day 19 of the dataset. Fig. 6 shows location and direction of the vessel when operating on this specific trip. Based on the small amplitude of the roll and pitch angles it is assumed that the vessel sailed in calm weather conditions. The ship’s heading angle is considered constant for most of the time (the variance of heading angle is \( \text{var}\{\psi\} \approx 3 \text{ deg}^2 \) in between indicated turns in Fig. 6). Note-worthy that for the selected vessel the only measurement of acceleration is not provided by an inertial measurement unit, but it is given by processing the GNSS outputs. This introduces correlation between the measurements used in the Kalman filter, which as stated in Remark 5 potentially determines a poorer performance of the estimator.

![Fig. 6: On top the trip of interest drawn on a map. On the bottom, map is connected with the sea state characteristics (roll, pitch on the left y-axis and true heading on the right y-axis).](image)

Fig. 7 shows the speed profiles of the "trip of interest". It is evident from the measurements that the STW is not stationary and there are strong and changing sea currents.
The STW estimator has been applied to a synchronous sensor rate implementation and then to an asynchronous one, similar to the simulation implementation where the predictions of the sea current speed were invoked at a lower frequency than the rest of the signals. The synchronous implementation outcome is shown in Fig. 8. The estimated STW $\hat{U}_r$ (virtual STW in the plot) shows some significant deviations from the measured STW, up to approximately 0.5 m/s, and in general seems to better account for variations in current speed.

In Fig. 9 the asynchronous implementation of the filter is depicted, when current speed is provided every 20 minutes, which is standard for most of the hindcast data providers. This time the estimated STW $\hat{U}_r$ (virtual STW in the plot) shows a more fluctuating behavior induced by the more sporadic knowledge of the current speed. The jerky variations are related to each measurement update performed by the estimator whenever a new prediction of the current speed is available. Despite the reduced smoothness, the estimated STW is in line with the results obtained through the synchronous implementation both in terms of maximum deviations from the measured STW and the overall trend of the estimate.
6. Discussion

Throughout the paper, the methodology, the model design, the application as well as the results, have all been described and meticulously assessed. The outcome of the implemented filter is highly dependent on the input parameters, i.e. the auto-logged vessel data. On a literature basis study, the indicated total of errors can be expected up to 9% for the auto-logged data, ITTC (2005). However, it is believed that precision errors are limited, due to the extended data processing.

The Kalman filter is a mathematical tool that conjugates the knowledge about physical phenomena formalized in a model with measurements of quantities directly or indirectly related to that phenomena in order to provide estimates of unmeasured states as well as to improve the signal-to-noise ratio of the measured quantities. Hence its performance is tightly coupled with the accuracy of the model and the quality of the available measurements.

In order to provide a simple solution that could be used as reference for future studies, some assumptions have been made concerning linearity of models, Gaussianity and uncorrelation of noise sources. However, these assumptions are not always satisfied in reality giving rise to performance deterioration of the estimation process. Accounting for correlation among the available measurements can potentially improve the estimation in terms of lower estimation error covariance, however this will come at the cost of a somewhat more complex implementation.

The STW estimator was tested on simulated data, before being applied to full-scale data. The availability of high-fidelity simulators able to produce numerical data capturing the phenomena of interest facilitates the design and tuning of the Kalman filter, especially when the true value of the variables to be estimated is in reality unknown. In the addressed study case a measurement of the STW was actually available but considered untrustworthy, thereby it was not included in the estimator design. Despite the simplifying assumptions, the evaluation of the designed STW estimator on the full-scale data is positive and it shows the feasibility of using a pure kinematic model to estimate a STW signal, which appears more aligned with the other inertial measurements than that one provided by the DVL.

7. Conclusion

A kinematic-based linear Kalman filter was designed to compute an estimate of the STW based on onboard inertial measurements and external hindcast sea current measurements of a large container vessel sailing in calm water. The analysis of the results obtained by processing full-scale measurements indicates an improvement of estimated STW with respect to the measurement provided by the onboard DVL, that is the estimate explains better changes in vessel’s SOG and sea current’s speed.
However, these results are preliminary and an extended investigation should be conducted by e.g. broadening the analysis to various container vessels of different characteristics, including more comprehensive and extended analyses made during sailing in seaway.

References

ANTOLA, M.; SOLONEN, A.; PYÖRRE, J. (2017), Notorious speed through water, 2\textsuperscript{nd} HullPIC Conf., Ulrichshusen, pp.156-165

BOOM, H.V.D.; HUISMAN, H.; MENNEN, F. (2013), New guidelines for speed/power trials: Level playing field established for IMO EEDI, SWZ Maritime, Schip en Werf de Zee Foundation, Rotterdam

BOS, M. (2016), How MetOcean data can improve accuracy and reliability of vessel performance Estimates, 1\textsuperscript{st} HullPIC Conf., Pavone, pp.106-114


FOSSEN, T.I. (2011), Handbook of Marine Craft Hydrodynamics and Motion Control, John Wiley & Sons


GAGLIONE, S. (2015), How does a GNSS receiver estimate velocity?, Inside GNSS, pp.38-41


ITTC (2005), Final Report and Recommendations to the 24\textsuperscript{th} ITTC, Manoeuvring Committee et al., 24\textsuperscript{th} ITTC, pp.137-198

ITTC (2002), Final report and recommendations to the 23rd ITTC, Propulsion Committee et al., 23\textsuperscript{rd} ITTC


PYÖRRE, J. (2012), Overcoming the challenges in vessel speed optimisation, HANSA 149, pp.130-135
