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System Identification of Nonlinear Vessel Steering

In this paper, the stochastic parameters describing a nonlinear ocean vessel steering model are identified, resorting to an extended Kalman filter (EKF). The proposed method is applied to a second-order modified Nomoto model for vessel steering and that is derived from first physics principles. Furthermore, the results obtained resorting to a realistic numerical simulator of nonlinear vessel steering are also illustrated in this study. [DOI: 10.1115/1.4029826]

Introduction

Ocean navigation is a process of planning, recording, and controlling the movement of a craft or a vehicle from one place to another [1]. However, the mathematical formulation of ocean navigation is complicated when compared with land and aerial navigation systems due to the existence of nonlinear hydrodynamic forces and moments that are associated with vessel dynamics.

Vessel Dynamics. The study of vessel dynamics can be divided into two components: (1) steering and maneuverability, where the vessel motion is studied in absence of wave excitations, generally denominated as maneuvering, thus corresponding to a situation where the vessel motion is under calm water conditions and (2) seakeeping that is the study of the vessel motion under the presence of wave disturbances. In both cases, a proper mathematical model of an ocean going vessel is an important part of the navigation due to its influence on the vessel maneuverability and controllability conditions.

Furthermore, in the development of these mathematical models deterministic or stochastic disturbances can be considered, with the corresponding presence of a number of model parameters. As the stochastic ocean behavior influences the vessel dynamics and these environmental effects cannot be isolated, the vessel steering and maneuverability model parameters are assumed as stochastic in this study. Therefore, this study is focused on the identification of steering parameters of an ocean going vessel that are assumed to describe their stochastic behavior. One should note that the vessel steering properties directly influence the maneuverability characteristics. Furthermore, the maneuverability conditions in an ocean going vessel can be further divided into two sections: course keeping and course changing maneuvers.

Recent Studies in System Identification. There are several recent studies of system identification (i.e., state and parameter estimation) of ocean going vessels are documented in the literature. A parameter estimation approach of ship steering dynamics based on a linear continuous-time model that influences the discrete time measurements was proposed by Astrom and Kalstrom [2]. Ma and Tong [3] proposed the EKF and second-order filter approaches for the parameter identification of ship dynamics. However, these studies are limited to speed control maneuvers that are associated only with the propulsion control system.

A parameter identification approach of ship steering dynamics based on the nonlinear Norrbin model is presented in Casado et al. [4]. The experimental data collected in course changing maneuvers are used in that analysis (i.e., an adaptive procedure and back-stepping theory). The identification of ship steering dynamics based on the support vector regression is proposed in Ref. [5]. A simplified mathematical model for the short-term path prediction, based on the vessel kinematics is presented in Ref. [6]. Similarly, the system identification approach of vessel navigation, along a desired path, based on a nonlinear ship maneuvering model is proposed by Skjetne et al. [7], where several experimental results are also presented. Sutulo and Guedes Soares [8] presented a new offline system identification algorithm using a genetic algorithm driver to minimize a metric of the difference between the reference response and the response obtained with the identified parameters.

The Nomoto model [9] is one of the most popular models to describe vessel steering and that has been extensively used in the recent literature. The fundamental observability and controllability properties, for the first- and second-order Nomoto models, are studied in Tzeng and Chen [10]. The parameter identification approach of ship steering dynamics, based on the Nomoto's first-order model, is presented in Journee [11]. Furthermore, the calculations of maneuvering indices are based on the vessel zig-zag maneuvers in the same study. However, the static behavior in vessel steering parameters can only be approximated in this model under the constant rudder angle, yaw rate, and surge velocity conditions. Therefore, the stochastic behavior of the Nomoto model parameters should be considered under course changing

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maneuvers (i.e., zig-zag maneuvers). This concept is supported by the experimental data that are reported in Ref. [12], where the estimated hydrodynamic force and moment variations are observed under rudder angle changing conditions. The Nomoto model was also adopted by Sutulo and Guedes Soares, [13], showing its applicability to practical situations.

There are several experimental platforms developed to study the hydrodynamic forces and moments of ocean going vessel under maneuvering conditions. In general, two types of experiments are conducted in this area: free steering tests and captive tests. In free steering tests, the vessel motions are observed with respect to the rudder angle variations in full-scale vessels. In the captive tests, a scaled model of the vessel is used and the experimental platform is forced into scaled environmental conditions [2,14–16]. However, the captive tests can be further divided into two sections: static and dynamic tests. The static tests consist of rotating arm tests, circular motion tests, oblique towing tests, etc. The dynamic test mainly consists of a planar motion mechanism [17,18]. However, these model tests for estimating the maneuvering parameters of ocean going vessels may suffer from the scale effects when applied to full-scale vessels [19,20]. Nevertheless, large-scale models are proposed to be used also in these situations, to overcome the model scale difficulties.

A mathematical model for vessel maneuvering based on a recursive neural network approach is proposed in Moreira and Guedes Soares [21]. Similar approaches, also resorting to neural networks, are proposed and experimentally evaluated by several studies of Refs. [22] and [23]. However, the neural network approaches can have various system identification challenges with respect to highly nonlinear steering conditions. The identification of the hydrodynamic coefficients of an ocean going vessel from the data acquired during a sea trial is presented in Ref. [12]. The accumulated hydrodynamic forces and moments for surge, sway, and yaw are estimated resorting to an EKF and a smoother, where the individual hydrodynamic coefficients are calculated by a regression method. However, considerable variations between the true and estimated hydrodynamic coefficients are reported in the same study. The identification of vessel hydrodynamic characteristics based on ship maneuvering trails is presented in Ref. [19]. The EKF based approach is considered and several zig-zag trajectories of mild, moderate and violent maneuvers are conducted to capture the nonlinear hydrodynamic behavior of the parameters in this study.

The above proposed linear and nonlinear models and their parameters of vessel steering are assumed to be deterministic in the process of system identification. In this study, the stochastic vessel steering parameter behavior describing the nonlinear ocean vessel steering model is assumed and that can be considered the first contribution in this study. Furthermore, the proposed method consists of a second-order modified Nomoto model for the vessel navigation that is derived from first physics principles.

Furthermore, the proposed stochastic parameters describing the nonlinear ocean vessel steering model are identified, resorting to an EKF and that is the second contribution in this study. The results obtained considering a realistic numerical simulator for the nonlinear vessel steering model are illustrated in this study. The work presented in this study is part of an on-going effort to formulate an autonomous navigation system for ocean going vessels [24] that is extended with collision avoidance, as further described in Refs. [25–27].

The organization of this paper is as follows: The second section contains an overview of the mathematical model of vessel steering. The third section formulates the dynamic estimation process for the nonlinear vessel steering model parameters. The discussion about the computational simulations of the proposed EKF algorithm is presented in the fourth section. Finally, the conclusions are presented in the fifth section.

Mathematical Model for Ship Steering

The proposed mathematical models of ocean vessel maneuvering can be divided into two categories: point mass models and rigid body models. Note that both types of dynamic models are subjected to external forces (i.e., environmental forces of wave, wind, and currents) and internal forces (propeller and rudder force) during their navigation. Furthermore, for both cases kinematic and dynamic relations should be considered.

Sway and Yaw Subsystem. The reference systems used in the mathematical model of vessel maneuvering is presented in Fig. 1. However, several ocean vessel kinematic and dynamic models can be found in the recent literature: surge model (u), maneuvering model (u, v), horizontal motion model (u, v, r), longitudinal motion model (u, w, q), and lateral motion model (v, p, r) that are based on the respective vessel states.

Assuming that the vessel forward speed is a constant (u_0), the coupled sway and yaw subsystem for the vessel linear steering system, as introduced by Davidson and Schiff in Ref. [28], can be written as

$$\begin{aligned} m(\dot{v} + u_0 r + x_G \dot{r}) &= Y(v, r, \delta_R, \dot{v}, \dot{r}) \\ I_Z \dot{r} + m x_G(\dot{v} + u_0 r) &= N(v, r, \delta_R, \dot{v}, \dot{r}) \end{aligned} \tag{1}$$

where the respective hydrodynamic forces and moments can be written as

$$\begin{aligned} Y(v, r, \delta_R, \dot{v}, \dot{r}) &= Y_v v + Y_r r + Y_\delta \delta_R + Y_{\dot{v}} \dot{v} + Y_{\dot{r}} \dot{r} \\ N(v, r, \delta_R, \dot{v}, \dot{r}) &= N_v v + N_r r + N_\delta \delta_R + N_{\dot{v}} \dot{v} + N_{\dot{r}} \dot{r} \end{aligned} \tag{2}$$

The state space describing the vessel linear steering system, introduced in Eq. (1) can be written as

$$M_R \dot{\upsilon} + N_R(u_0)\upsilon = B_R \delta_R \tag{3}$$

where $\upsilon = [v \quad r]^T$ and the matrices M_R, $N_R(u_0)$, and B_R can be written as

$$\begin{aligned} M_R &= \begin{bmatrix} m - Y_{\dot{v}} & m x_G - Y_{\dot{r}} \\ m x_G - N_{\dot{v}} & I_Z - N_{\dot{r}} \end{bmatrix} \\ N_R(u_0) &= \begin{bmatrix} -Y_v & m u_0 - Y_r \\ -N_v & m x_G u_0 - N_r \end{bmatrix} \\ B_R &= \begin{bmatrix} Y_\delta \\ N_\delta \end{bmatrix} \end{aligned} \tag{4}$$

Due to the positive definiteness of M_R, the vessel linear steering system presented in Eq. (3) can be rewritten as

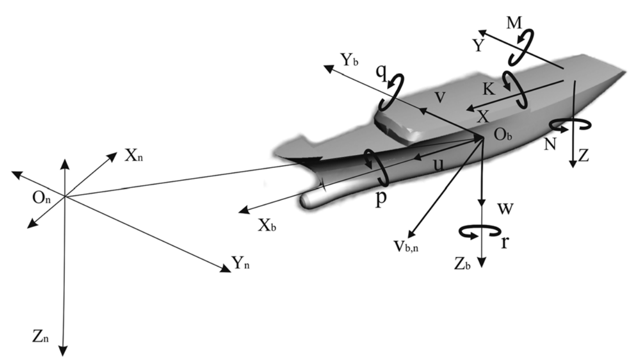

Fig. 1 Reference systems for the mathematical model of vessel maneuvering

$$\dot{v} = \underbrace{-M_R^{-1} N_R(u_0)}_{A} v + \underbrace{M_R^{-1} B_R}_{B} \delta_R \tag{5}$$

The matrices A and B of Eq. (5) can be presented as

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad B = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \tag{6}$$

where the respective coefficients are given by

$$a_{11} = \frac{(I_Z - N_{\dot{r}})Y_v + (Y_{\dot{r}} - mx_G)N_v}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})}$$

$$a_{12} = \frac{(I_Z - N_{\dot{r}})(Y_r - mu_0) + (Y_{\dot{r}} - mx_G)(N_r - mx_G u_0)}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})}$$

$$a_{21} = \frac{(m - Y_{\dot{v}})N_v + (N_{\dot{v}} - mx_G)Y_v}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})}$$

$$a_{22} = \frac{(m - Y_{\dot{v}})(N_r - mx_G u_0) + (N_{\dot{v}} - mx_G)(Y_r - mu_0)}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})}$$

$$b_1 = \frac{(I_Z - N_{\dot{r}})Y_\delta + (Y_{\dot{r}} - mx_G)N_\delta}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})}$$

$$b_2 = \frac{(m - Y_{\dot{v}})N_\delta + (N_{\dot{v}} - mx_G)Y_\delta}{(m - Y_{\dot{v}})(I_Z - N_{\dot{r}}) - (mx_G - Y_{\dot{v}})(mx_G - N_{\dot{r}})} \tag{7}$$

Second-Order Linear Nomoto Model. The second-order linear Nomoto model [9] can be derived by eliminating the sway velocity, v, in Eqs. (5)–(7), resulting in

$$T_1 T_2 \ddot{r} + (T_1 + T_2)\dot{r} + r = K_R\left(T_3 \dot{\delta}_R + \delta_R\right) \tag{8}$$

where the respective coefficients are

$$T_1 T_2 = \frac{1}{a_{11}a_{22} - a_{12}a_{21}} \quad T_1 + T_2 = \frac{a_{11} + a_{22}}{a_{12}a_{21} - a_{11}a_{22}} \quad T_3 = \frac{b_2}{a_{21}b_1 - a_{11}b_2} \quad K_R = \frac{a_{21}b_1 - a_{11}b_2}{a_{11}a_{22} - a_{12}a_{21}} \tag{9}$$

The second-order linear Nomoto model, in Eq. (8), can be rewritten considering the heading angle of the vessel

$$\psi^{(3)} + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot{\psi} + \frac{1}{T_1 T_2}\dot{\psi} = \frac{K_R}{T_1 T_2}\left(T_3 \dot{\delta}_R + \delta_R\right) \tag{10}$$

Modified Nonlinear Nomoto Model. The second-order linear Nomoto model can be used for the course keeping maneuvers but this model is not adequate for the course changing maneuvers. Therefore, the model presented in Eq. (10) must be modified to capture the course changing maneuvers as proposed in Ref. [29], where $\dot{\psi} \approx K_R H\left(\dot{\psi}\right)$ is assumed, resorting to a nonlinear function $H(\dot{\psi})$. Thus, Eq. (10) can be written as

$$\psi^{(3)} + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot{\psi} + \frac{K_R}{T_1 T_2}H\left(\dot{\psi}\right) = \frac{K_R}{T_1 T_2}\left(T_3 \dot{\delta}_R + \delta_R\right) \tag{11}$$

Assuming the nonlinear function, $H\left(\dot{\psi}\right) = a_1\dot{\psi} + a_2\dot{\psi}^3$, Eq. (11) can be written as

$$\psi^{(3)} = -d_1\ddot{\psi} - d_2\left(a_2\dot{\psi}^3 + a_1\dot{\psi}\right) + d_2\left(d_3\dot{\delta}_R + \delta_R\right) \tag{12}$$

where the parameters $d_1 = 1/T_1 + 1/T_2$, $d_2 = K_R/T_1T_2$, and $d_3 = T_3$, are straightforward to be defined. Hence, Eq. (12) can be rewritten as

$$\psi^{(3)} = \alpha_1\dot{\psi}^3 + \alpha_2\dot{\psi} + \alpha_3\ddot{\psi} + \beta_1\delta_R + \beta_2\dot{\delta}_R \tag{13}$$

where the final parameters to be identified can be defined $\alpha_1 = -a_2 d_2$, $\alpha_2 = -a_1 d_2$, $\alpha_3 = -d_1$, $\beta_1 = d_2$, and $\beta_2 = d_2 d_3$.

Dynamic Parameter Estimation

Algorithm Structure. The dynamic parameter estimation approach is described in this section and consists of three subsections: (1) vessel motion model (VMM), (2) measurement model and associated techniques (MMATs), and (3) parameter estimation technique (PET). The VMM consists of a mathematical model that is considered for parameter estimation in this study. The MMAT consists of the mathematical model of observed states of the VMM. Finally, the PET consists of the estimation algorithm, the EKF that is implemented for VMM states and parameter estimation.

Second-Order Linear Nomoto Model. The vessel nonlinear steering model derived in Eq. (13) is considered in this section and can be written as

$$\dot{x}(t) = f(x(t)) + w_w(t) \tag{14}$$

where the vessel system state vector can be presented as

$$x^T(t) = \left[\psi(t)\ \dot{\psi}(t)\ \ddot{\psi}(t)\ \alpha_1(t)\ \alpha_2(t)\ \alpha_3(t)\ \beta_1(t)\ \beta_2(t)\ \delta_R(t)\ \dot{\delta}_R(t)\right] \tag{15}$$

The function $f(x(t))$ that is presented in Eq. (14) can be written as

$$f(x(t)) = \begin{bmatrix} \dot{\psi}(t) \\ \ddot{\psi}(t) \\ \alpha_1(t)\dot{\psi}^3(t) + \alpha_2(t)\dot{\psi}(t) + \alpha_3(t)\ddot{\psi}(t) \\ + \beta_1(t)\delta_R(t) + \beta_2(t)\dot{\delta}_R(t) \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{16}$$

The Jacobian of function $f(x(t))$ is given by

$$\frac{\partial}{\partial x(t)} f(x(t)) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \begin{matrix} 3\alpha_1(t)\dot{\psi}^2(t) \\ +\alpha_2(t) \end{matrix} & \alpha_3(t) & \dot{\psi}^3(t) & \dot{\psi}(t) & \ddot{\psi}(t) & \delta_R(t) & \dot{\delta}_R(t) & \beta_1(t) & \beta_2(t) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (17)$$

MMAT. The measurement model is formulated in discrete-time due to the fact that the sensors available to provide indirect information on the vessel states at discrete time instants. The discrete time measurement model can then be written as

$$z(k) = h(x(k)) + w_v(k) \quad (18)$$

The set of measurements can be represented as the column vector

$$z^{\mathrm{T}}(k) = \begin{bmatrix} z_{\psi}(k) & z_{\dot{\psi}}(k) & z_{\delta}(k) & z_{\dot{\delta}}(k) \end{bmatrix} \quad (19)$$

The function, $h(x(k))$, can be written as

$$h^{\mathrm{T}}(x(k)) = \begin{bmatrix} \psi(t) & \dot{\psi}(t) & \delta_{\mathrm{R}}(t) & \dot{\delta}_{\mathrm{R}}(t) \end{bmatrix} \quad (20)$$

The Jacobian of function $h(x(k))$ can be computed as

$$\frac{\partial}{\partial x(k)} h(x(k)) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (21)$$

Estimation Algorithm. The EKF algorithm is proposed in this study as the PET, due to the EKF capabilities of capturing the nonlinear behavior of ocean vessel navigation. Even though the EKF is a computationally effective and powerful algorithm, it is a suboptimal recursive filter and can fail to converge in some situations. However, in many engineering applications nonlinear system parameters are estimated by the EKF algorithm and successful results are also reported [30] and in the references therein. The summarized EKF algorithm can be formulated as described in Ref. [31]

- System model

$$\begin{aligned} \dot{x}(t) &= f(x(t)) + w_w(t), \quad w_w(t) \sim \mathrm{N}(0, Q(t)) \\ E[w_w(t)] &= 0, \quad E[w_w(t); w_w(t)] = [Q(t)] \end{aligned} \quad (22)$$

- Measurement model

$$\begin{aligned} z(k) &= h(x(k)) + w_v(k), w_v(k) \sim N(0, R(k)), \quad k = 1, 2, \ldots \\ E[w_v(k)] &= 0, \quad E[w_v(k); w_v(k)] = [R(k)] \end{aligned} \quad (23)$$

- Error conditions

$$\tilde{x}(k) = \hat{x}(k) - x(k) \quad (24)$$

- State initial conditions

$$x(0) \sim N(\hat{x}(0), P(0)) \quad (25)$$

where $\hat{x}(0)$ is the state initial estimate and $P(0)$ is the state initial covariance values, describing the uncertainty present on the initial estimates. All stochastic disturbances are assumed as Gaussian distributions with zero mean values.

- Uncorrelated process and measurements noises

$$E[v(t); w(k)] = 0 \quad \text{for all } k, t \quad (26)$$

- State estimation propagation

$$\dot{\hat{x}}(k) = f(\hat{x}(k)) \quad (27)$$

- Error covariance extrapolation

$$\begin{aligned} \dot{P}(t) &= F(\hat{x}(t))P(t) + P(t)F^{\mathrm{T}}(\hat{x}(t)) + Q(t) \\ F(\hat{x}(t)) &= \frac{\partial}{\partial x(t)} f(x(t)) \Big|_{x(t)=\hat{x}(t)} \end{aligned} \quad (28)$$

- Estimate state update
  At each step, after measurement data is available from the sensors, the state estimates can be updated according to

$$\hat{x}(k^+) = \hat{x}(k^-) + K(k)[z(k) - h_k(\hat{x}(k^-))] \quad (29)$$

- Error covariance update

$$\begin{aligned} P(k^+) &= [1 - K(k)H_k(\hat{x}(k^-))]P(k^-) \\ H(\hat{x}(k^-)) &= \frac{\partial}{\partial x(k)} h(x(k)) \Big|_{x(k)=\hat{x}(k^-)} \end{aligned} \quad (30)$$

- Kalman gain computation

$$K(k) = P(k^-)H(\hat{x}(k^-))\left[H(\hat{x}(k^-))P(k^-)H(\hat{x}(k^-))^{\mathrm{T}} + R(k)\right]^{-1} \quad (31)$$

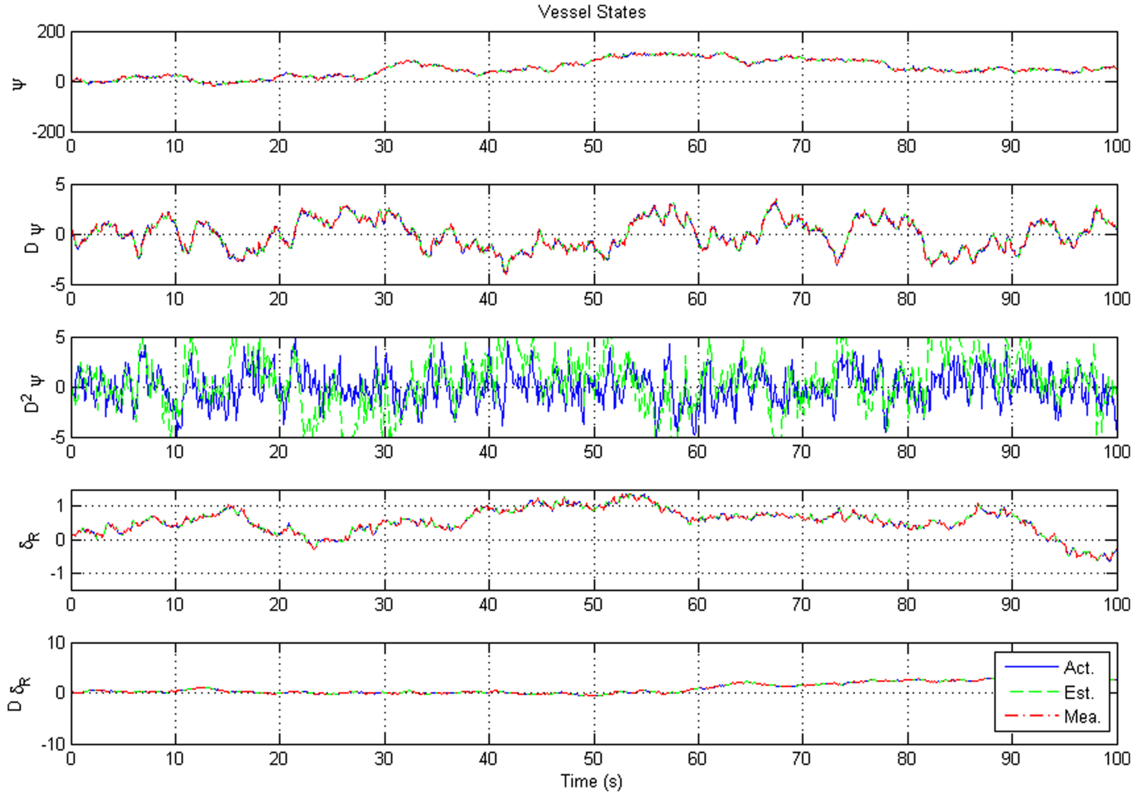

Fig. 2 Actual, measured, and estimated vessel states

Parameter Estimation. The mean values of vessel parameters in the steering model associated with stochastic behaviors are assumed as $\alpha_1 = -0.3710$ (1/rad^2), $\alpha_2 = -0.4340$ (1/s^2), $\alpha_3 = -3.4000$ (1/s), $\beta_1 = 0.3500$ (1/s^3), and $\beta_2 = 0.1225$ (1/s^2). Some of these parameter values are extracted from the study of [29] and others are generated by trial and error calculations considering the vessel response under stable steering conditions. The above vessel parameter values are implemented on

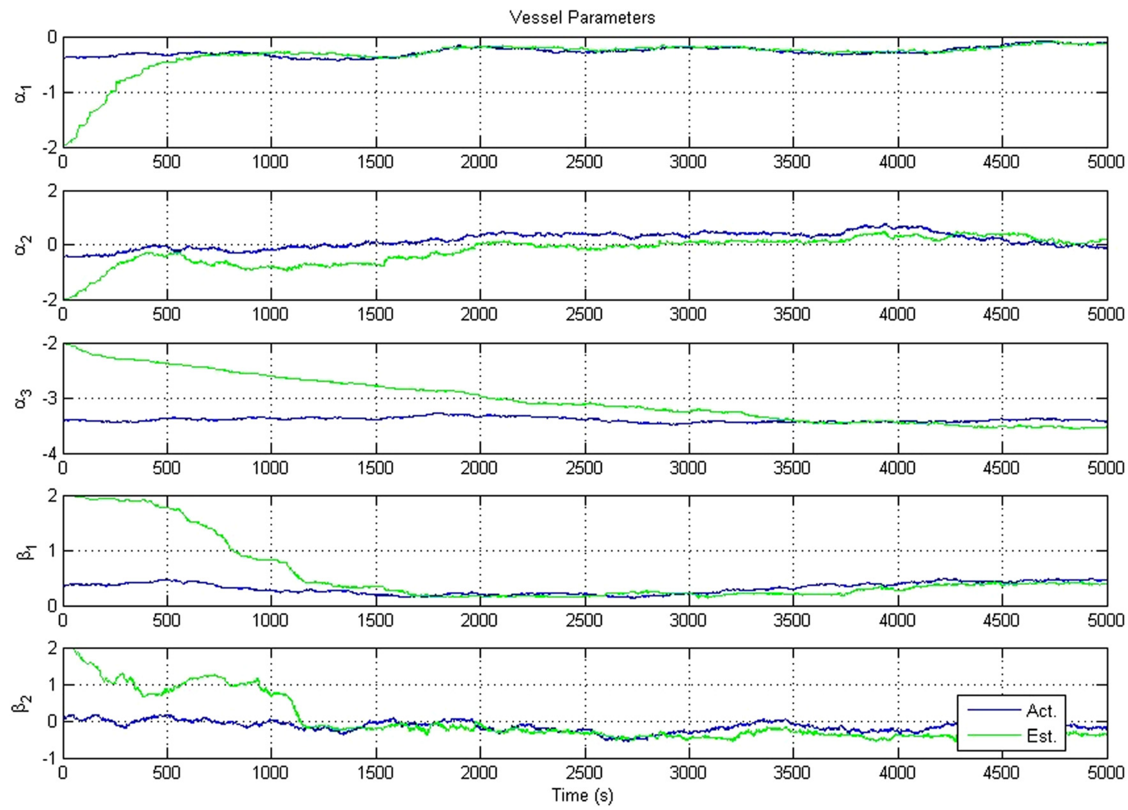

Fig. 3 Actual and estimated vessel parameters

the computational simulations that are further discussed in the following paragraph.

The computational simulations of the actual (Act.), estimated (Est.), and measured (Mea.) vessel states of heading angle, heading rate, and derivative of heading rate are presented in top three plots of Fig. 2 under the violent maneuvering conditions. The inputs of the system, the rudder angle and rate under violent maneuvering conditions are also presented in bottom two plots of Fig. 2. Furthermore, the actual (Act.) and estimated (Est.) stochastic vessel parameters of α_1, α_2, α_3, β_1, and β_2 are also presented in Fig. 3.

The EKF algorithm is implemented on the MATLAB software platform. Violent maneuvers with varying rudder angle and rudder rate values as the inputs are assumed in this study, for better EKF convergence of the vessel parameters. Note that persistent excitation of the input signal, leading to violent maneuvers, is required for unbiased identification of the system parameters, as observed also in Ref. [32].

As presented in Fig. 2, the actual (Act.), estimated (Est.), and measured (Mea.) vessel states of heading angle, heading rate are similar due to an assumption of the accurate measurements. However, the small variations of the vessel states can also be observed due to an assumption of violent maneuvering conditions of the vessel. These maneuvering conditions are generated by the rudder angle and the rudder rate under white Gaussian noise type motions. Furthermore, the actual and estimated derivatives of heading rate have some variations due to the estimation conditions.

As presented in Fig. 3, the parameters estimation of the proposed nonlinear vessel maneuvering model, α_1, α_2, α_3, β_1, and β_2 is successfully achieved, where the estimated values successfully converged into the actual values. Initially, all parameter values have been assigned with constant values and due the EKF estimation capabilities, these values have been converged into the actual parameter values that have stochastic behavior as proposed in this study.

Conclusion

The EKF performance on nonlinear parameter estimation under dynamic data handling conditions is evaluated in this study, where the estimated stochastic vessel parameter values converged into the actual values. Therefore, the evaluation of vessel nonlinear parameters under the dynamic conditions can be used to feed the nonlinear vessel autopilot models, which is a considerable contribution and a potential future development in this study.

It is observed that the estimation of the parameters of nonlinear vessel steering model can only be achieved when violent maneuvers are performed, where the rudder angle and rudder rate were excited by white Gaussian noise motion. Furthermore, it is observed that smooth maneuvers (i.e., zig-zag and circular maneuvers) that have been extensively used for systems identification of vessel kinematic and dynamic models do not excite the nonlinear parameters, in which can degrade the system identification process.

In the former cases, the estimated vessel parameter values did not converge into the actual values by smooth maneuvers as observed in the simulations and that is another contribution in this study. Therefore, this study concludes that the violent maneuvering conditions of vessel navigation should be implemented to estimate the nonlinear parameters of ocean going vessels under varying (dynamic) conditions. Furthermore, the vessel steering model and the state measurements are associated with white Gaussian noise is assumed in this study. Hence, this assumption is also contributed for successful parameters convergence as observed in the simulations.

However, one should note that the parameters, α_1, β_1, and β_2, have converged in less than 1500 (s) (approximately 25 (min)) and the parameters, α_2, and α_3, have converged around 3500 (s) (approximately 1 (hr)). Therefore, the vessel operational conditions (i.e., draft, trim, etc.) should be stationary during a longer time period for capturing the actual steering parameter values under the similar navigation conditions [33,34]. However, this requirement can only be noticed during the transient phase of the estimation algorithm, where the parameter values are iterating to converge. Therefore, the transient phase of the estimation algorithm can face some challenges in more dynamics situations, such as maneuvering in ports and restricted waterways. However, the steady state phase of the algorithm can be used under any dynamic conditions (i.e., maneuvering in ports and restricted waterways), where the algorithm has the capabilities to follow large dynamic variations. Therefore, the state and parameter reduction in the vessel steering model in Eq. (13) is considered in this study to minimize the convergence time for the proposed algorithm and that is proposed for the future work of this study.

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Nomenclature

d_1, d_2, d_3 = initial nonlinear vessel parameters
$f(x(t))$ = nonlinear vessel state function
$h(x(k))$ = measurement function
I_Z = inertia of the vessel about the z-axis
$K(k)$ = Kalman filter gain
K, M, N = roll, pitch, and yaw moments
K_R = rudder constant
m = mass of the vessel
$M_R, N_R(u_0), B_R$ = vessel linear steering system matrices
$N_v, N_r, N_\delta, N_{\dot{v}}, N_{\dot{r}}$ = respective hydrodynamic coefficients of yaw motion
O_b = origin of $X_bY_bZ_b$
O_n = origin of $X_nY_nZ_n$
p, q, r = roll, pitch, and yaw angular velocities
$P(t)$ = estimated error covariance
$P(k^-)$ = estimated prior error covariance of vessel state vector
$P(k^+)$ = estimated posterior error covariance of vessel state vector
$Q(t)$ = vessel state noise covariance
$R(k)$ = measurement noise covariance
T_1, T_2, T_3 = linear vessel parameters
u, v, w = surge, sway, and heave linear velocities
$V_{b,n}$ = vessel course-speed vector
$w_V(k)$ = measurement noise vector
$w_w(t)$ = vessel state noise vector
$x(t)$ = nonlinear vessel state vector
X, Y, Z = surge, sway, and heave forces
$\tilde{x}(t)$ = vessel state error vector
$\hat{x}(t)$ = estimated vessel state vector
$\hat{x}(k^-)$ = estimated prior vessel state vector
$\hat{x}(k^+)$ = estimated posterior vessel state vector
x_G = distance to the center of gravity
$X_bY_bZ_b$ = vessel body fixed coordinate system
$X_nY_nZ_n$ = Earth fixed coordinate system
$Y_v, Y_r, Y_\delta, Y_{\dot{v}}, Y_{\dot{r}}$ = respective hydrodynamic coefficients of sway motion
$z(t)$ = measurement vector
$z_\delta(k)$ = rudder angle measurements
$z_{\dot{\delta}}(k)$ = rudder rate measurements
$z_\psi(k)$ = heading angle measurements
$z_{\dot{\psi}}(k)$ = heading rate measurements
$\alpha_1, \alpha_2, \alpha_3, \beta_1, \beta_2$ = final nonlinear vessel parameters
δ_R = rudder angle

$\dot{\delta}_R$ = rudder rate

υ = linear vessel state vector

$\psi(k)$ = heading angle

$\dot{\psi}(k)$ = yaw rate

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