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DYNAMIC PARAMETER ESTIMATION OF A NONLINEAR VESSEL STEERING MODEL FOR OCEAN NAVIGATION

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ABSTRACT

In this paper the stochastic parameters describing the nonlinear ocean vessel steering model are identified, resorting to an Extended Kalman Filter. The proposed method is applied to a second order modified Nomoto model for the vessel navigation that is derived from first physics principles. The results obtained resorting to a realistic numerical simulator for the nonlinear vessel steering model considered are illustrated in this study.

NOMENCLATURE

$X_nY_nZ_n$	Earth fixed coordinate system
$X_bY_bZ_b$	Vessel body fixed coordinate system
u,v,w	Surge, sway, and heave linear velocities
p,q,r	Roll, pitch and yaw angular velocities
X,Y,Z	Surge, sway, and heave forces
$Y_v, Y_r, Y_\delta, Y_{\dot{v}}, Y_{\dot{r}}$	Respective hydrodynamic coefficients of sway motion
$N_v, N_r, N_\delta, N_{\dot{v}}, N_{\dot{r}}$	Respective hydrodynamic coefficients of yaw motion
K, M, N	Roll, pitch, and yaw moments
M_R, $N_R(u_0)$, B_R	Vessel linear steering system matrices
Ψ	Heading angle
$\dot{\psi}(k)$	Heading rate
δ_R	Rudder angle
$\dot{\delta}(k)$	Rudder rate
x_G	Distance to the center of gravity
m	Mass of the vessel
I_z	Inertia of the vessel along the z-axis
T_1, T_2, T_3	Linear Vessel parameters
K_R	Rudder constant
d_1, d_3, d_3	Initial nonlinear Vessel parameters
α_1, α_2, α_3, β_1, β_2	Final nonlinear Vessel parameters
x(t)	Nonlinear vessel state vector
$\tilde{x}(t)$	Vessel state error vector
$\hat{x}(t)$.	Estimated vessel state vector
$x(k^-)$	Estimated prior vessel state vector
$x(k^+)$	Estimated posterior vessel state vector
f (x(t))	Nonlinear vessel state function
w(t)	Vessel state noise vector
z(t)	Measurement vector
$z_\psi(k)$	Heading angle measurements
$z_{\dot{\psi}}(k)$	Heading rate measurements
$z_\delta(k)$	Rudder angle measurements
$z_{\dot{\delta}}(k)$	Rudder rate measurements
h(x(k))	Measurement function
v(k)	Measurement noise vector
Q(t)	Vessel state noise covariance
R(k)	Measurement noise covariance
ν	Linear vessel state vector
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
$K(k)$	Kalman filter gain

INTRODUCTION

Ocean navigation is the 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 the land and aerial navigation systems due to the existence of hydrodynamic nonlinearities associated with the vessel dynamics.

The study of vessel dynamics can be divided into two components: i) 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 ii) 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 vessel is an important part of the navigation due to its influence on the vessel maneuverability as well as on the vessel controllability.

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 the ocean dynamics can not 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 ocean vessels that are assumed to describe its stochastic behavior. However, the vessel steering properties directly influences the maneuverability characteristics. Therefore, the maneuverability conditions can be further divided into two sections: course keeping and course changing maneuvers.

There are several recent studies of system identification of ocean vessel navigation documented in the literature. The parameter estimation of ship steering dynamics based on a linear continuous-time model that influences the discrete time measurements was proposed by Astrom et al. [2]. Ma and Tong [3] proposed the Extended Kalman Filter (EKF) and the second order filter approaches for the parameter identification of ship dynamics. However, this study is limited to speed control maneuvers that are associated with the propulsion control system.

The parameter identification of ship steering dynamics based on the non-linear Norrbin model was presented by Casado [4]. The experimental data collected in course changing maneuvers was used in that analysis work (i.e. an adaptive procedure and back-stepping theory). The identification of ship steering dynamics based on the Support Vector Regression (SVR) was proposed in [5]. A simplified mathematical model for the short-term path prediction, based on the vessel kinematic was presented in [6]. Similarly, the system identification of vessel navigation, along a desired path, based on a nonlinear ship maneuvering model was proposed by Skjetne [7], where several experimental results were also presented.

Nomoto model [8] is one of the most popular models to describe vessel steering. The fundamental properties, observability and controllability, of the first and second order Nomoto models were studied by Tzeng [9]. The parameter identification of ship steering dynamics based on the Nomoto's first order model was presented by Journee [10]. Furthermore, the calculations of maneuvering indices are based on the vessel zig-zag maneuvers. However, the constant vessel parameter behavior can only be approximated in the Nomoto model under constant rudder angle, constant yaw rate, and constant surge velocity conditions. Therefore, the stochastic behavior of the Nomoto model parameters should be assumed under the course-changing maneuvers (ie. zig-zag maneuvers). This concept is supported on the experimental data that were reported in [11], where the estimated hydrodynamic forces and moment variations were observed under rudder angle changing conditions.

There are several experimental platforms developed to study the hydrodynamic forces and moments of ocean vessel navigation due to its maneuverability effects. 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, the scaled model of a vessel is used and the experimental platform is forced into scaled environmental conditions ([12] and [13]). However, the captive tests can be further divided into two sections: Static test and Dynamic tests. The static tests consist of Rotating arm test (RAT), Circular motion test (CMT), Oblique towing tests (OTT), etc. The dynamic test mainly consists of Planar Motion Mechanism (PMM) [14]. However, these model tests of the maneuvering parameter estimations of ocean vessel may suffer from the scale effects when applied to full scale vessels [15]. Nevertheless, large scale models were proposed to be used in these tests to overcome the model scale sufferings.

A model of free steering maneuverability of an ocean vessel using a recursive neural network was proposed by Moreira and Guedes Soares [16]. Similar approaches, also resorting to neural networks, were proposed and experimentally evaluated by several studies of Chiu et al. [17] and Rajesh and Bhattacharyya [18]. The identification of hydrodynamic coefficients of an ocean vessel from data acquired during a sea trial was presented in [11]. The accumulated hydrodynamic forces and moment for surge, sway and yaw are calculated by the EKF and the smoother, where the individual hydrodynamic coefficients are calculated by a regression method. However, considerable variations between true and estimated hydrodynamic coefficients are reported in the same study.

The identification of vessel hydrodynamic characteristics based on ship trial maneuvers is presented in [15]. The EKF based approach is considered and several zig-zag trajectories of

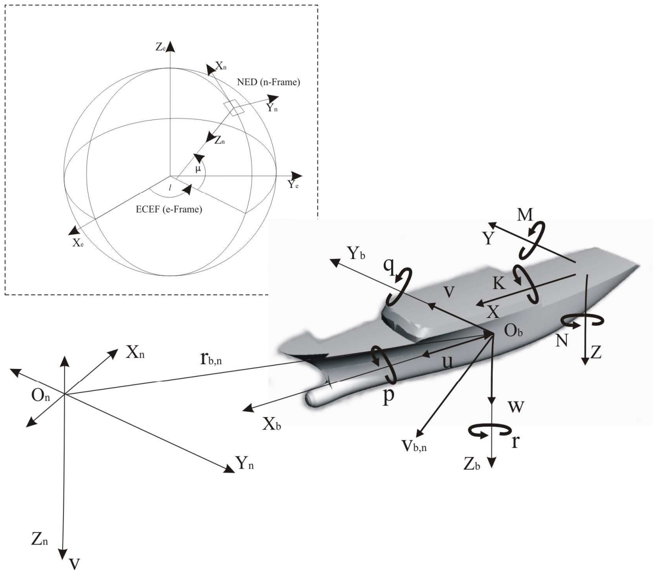

Figure 1. Reference systems for the mathematical model of vessel maoneuvring

mild, moderate and violent maneuvers are conducted to capture the nonlinear hydrodynamic behavior of the parameters in this study.

The proposed linear and nonlinear models in the system identification of vessel steering parameters in the literature are assumed to be deterministic. In this study, the stochastic vessel steering parameter behavior describing the nonlinear ocean vessel steering model is assumed and that is the first contribution in this study. 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 Extended Kalman Filter and that is the second contribution in this study. The results obtained considering a realistic numerical simulator for the nonlinear vessel steering model is 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 [19] that is extended with collision avoidance, as further described in [20].

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

MATHEMATICAL MODEL OF VESSEL MANEUVERING

The 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 its navigation. Furthermore, for both cases kinematic and dynamic relations should be considered. The reference systems adopted in the mathematical model of ocean vessel navigation is presented in Figure 1.

Sway and Yaw Sub-system

Several ocean vessel kinematic and dynamic models can be found in the recent literature: surge model (u), maneuvering model (v, r), horizontal motion model (u, v, r), longitudinal motion model (u, w, q) and lateral motion model (v, p, r) that are based on respective vessel states.

Assuming that the vessel forward speed is a constant (u_0), the coupled sway and yaw sub-systems for the vessel linear steering system, as introduced by Davidson & Schiff in [21], can be written as:

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

where the respective hydrodynamic forces can be written as:

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

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

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

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

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

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

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

The matrices A and B of Equation (5) can be presented as:

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

where the respective coefficients are given by:

$$\begin{aligned}
a_{11} &= \frac{(I_Z - N_{\dot r})Y_v + (Y_{\dot r} - mx_G)N_v}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})} \\
a_{12} &= \frac{(I_Z - N_{\dot r})(Y_r - mu_0) + (Y_{\dot r} - mx_G)(N_{\dot r} - mx_G u_0)}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})} \\
a_{21} &= \frac{(m - Y_{\dot v})N_v + (N_{\dot v} - mx_G)Y_v}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})} \\
a_{22} &= \frac{(m - Y_{\dot v})(N_r - mx_G u_0) + (N_{\dot v} - mx_G)(Y_r - mu_0)}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})} \\
b_1 &= \frac{(I_Z - N_{\dot r})Y_\delta + (Y_{\dot r} - mx_G)N_\delta}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})} \\
b_2 &= \frac{(m - Y_{\dot v})N_\delta + (N_{\dot v} - mx_G)Y_\delta}{(m - Y_{\dot v})(I_Z - N_{\dot r}) - (mx_G - Y_{\dot v})(mx_G - N_{\dot r})}
\end{aligned} \quad . \tag{7}$$

The Second-order Linear Nomoto Model

The second-order linear Nomoto model [8] can be derived by eliminating the sway velocity, v, in Equations (5), (6) and (7), resulting in:

$$T_1T_2\ddot r + (T_1 + T_2)\dot r + r = K_R\left(T_3\dot\delta_R + \delta_R\right) \tag{8}$$

where the respective coefficients are:

$$\begin{aligned}
T_1T_2 &= \frac{1}{a_{11}a_{22} - a_{12}a_{21}} \\
T_1 + T_2 &= \frac{a_{11} + a_{22}}{a_{12}a_{21} - a_{11}a_{22}} \\
T_3 &= \frac{b_2}{a_{12}a_{21} - a_{11}a_{22}} \\
K_R &= \frac{a_{21}b_1 - a_{12}b_2}{a_{11}a_{22} - a_{12}a_{21}}
\end{aligned} \tag{9}$$

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

$$\psi^{(3)} + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot\psi + \frac{1}{T_1T_2}\dot\psi = \frac{K_R}{T_1T_2}\left(T_3\dot\delta_R + \delta_R\right) \tag{10}$$

The Modified Non-linear Nomoto Model

The second-order linear Nomoto model can be used for the course keeping maneuvering but this model is not adequate for the course changing maneuvers. Therefore, the model presented in Equation (10) must be modified to allow the vessel modeling course changing maneuvers, as proposed in [22], where $\dot\psi \approx K_R H(\dot\psi)$ is assumed, resorting to a nonlinear function $H(\dot\psi)$. Thus, equation (10) can be written as:

$$\psi^{(3)} + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot\psi + \frac{K_R}{T_1T_2}H(\dot\psi) = \frac{K_R}{T_1T_2}\left(T_3\dot\delta_R + \delta_R\right) \tag{11}$$

Assuming the nonlinear function, $H(\dot\psi) = a_1\dot\psi + a_2\dot\psi^3$, Equation (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 straight forward to be defined. Hence, Equation (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 $\alpha_1=-a_2d_2$, $\alpha_2=-a_1d_2$, $\alpha_3=-d_1$, $\beta_1=d_2$, and $\beta_2=d_2d_3$.

DYNAMIC ESTIMATION OF NONLINEAR PARAMETERS

This section consists of three subsections: Vessel Motion Model (VMM), Measurement Model and Associated Techniques (MMAT) and Parameter Estimation Technique (PET).

The VMM consists of the 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 extended Kalman filter that is implemented for VMM states and parameter estimation.

Vessel Motion Model

The vessel nonlinear steering model derived in Equation (13) is considered in this section and can be written as:

$$\dot x(t) = f\left(x(t)\right) + w(t) \tag{14}$$

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 Equation (14) can be written as:

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

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

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

Measurement Model and Associated Technique

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

$$
z(k) = h\left(x(k)\right) + v(k) \tag{18}
$$

The set of measurements can be represented as the column vector:

$$
z^T(k)=\left[z_{\psi}(k)\ z_{\dot{\psi}}(k)\ z_{\delta}(k)\ z_{\dot{\delta}}(k)\right]. \tag{19}
$$

The function h(x(k)) can be written as:

$$
h^T\left(x(k)\right)=\left[\psi(t)\ \dot{\psi}(t)\ \delta_R(t)\ \dot{\delta}_R(t)\right] \tag{20}
$$

The Jacobian of function h(x(k)) can be written as:

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

Parameter Estimation Technique

The Extended Kalman Filter (EKF) algorithm is proposed in this study as the Parameter Estimation Technique, 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 sub-optimal 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 were reported in [23] and in the references therein. The summarized EKF algorithm can be formulated as described in [24]:

- System Model

$$
\begin{gathered} \dot{x}(t) = f(x(t)) + w(t), \quad w(t) \sim N(0,Q(t)) \\ E\left[w(t)\right] = 0, \ E\left[w(t);\ w(t)\right] = \left[Q(t)\right] \end{gathered} \tag{22}
$$

- Measurement Model

$$
\begin{gathered} z(k) = h(x(k)) + v(k), \quad v(k) \sim N\left(0, R(k)\right), \ k = 1,2,... \\ E\left[v(k)\right] = 0, \ E\left[v(k);v(k)\right] = \left[R(k)\right] \end{gathered} \tag{23}
$$

- Error Conditions

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

- State Initial Conditions

$$
x(0) \sim N\left(\hat{x}(0), P(0)\right) \tag{25}
$$

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 zero mean and Gaussian.

- Uncorrelated process and measurements noises

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

- State Estimation Propagation

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

- Error Covariance Extrapolation

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

- Estimate State Update

At each step, after measurement data is available from the sensors, the state estimates can be updated

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

- Error Covariance Update

$$P(k^+) = \left[1 - K(k)H_k\left(\hat{x}\left(k^-\right)\right)\right] P(k^-)$$
$$H\left(\hat{x}\left(k^-\right)\right) = \frac{\partial}{\partial x(k)} h\left(x(k)\right)\Big|_{x(k)=\hat{x}\left(k^-\right)} \tag{30}$$

- Kalman Gain Computation

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

DISCUSSION ON COMPUTATIONAL SIMULATIONS

The mean values of vessel parameters in the steering model associated with stochastic behaviors are assumed as α_1 = -0.3710 (1/rad^2), α_2 = -0.4340 (1/s^2), α_3 = -3.4000 (1/s), β_1 = 0.3500 (1/s^3), and β_2 = 0.1225 (1/s^2). Some of these parameter values are extracted from the study of [22] and others are generated by trial and error calculations considering the vessel response under stability conditions. The above vessel parameter values are implemented on computational simulations that are further discussed in following section.

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 3 plots of Figure 2 under the violent maneuvering conditions. The inputs of the system, the rudder angle and rudder rate under violent maneuvering conditions are also presented in bottom 2 plots of Figure 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 Figure 3.

The EKF algorithm that was discussed in this study is implemented on the MATLAB software platform. Violent variations in the rudder angle and rudder rate as 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 [25].

As presented in Figure 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 vessel states are also observed due 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 derivative of heading rate has some variation due to the estimation conditions.

As presented in Figure 3, the parameters estimation of nonlinear vessel maneuvering model, α_1, α_2, α_3, β_1 and β_2, is successfully achieved, where all the estimated values successfully converged into the actual values. Initially all parameters 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 Extended Kalman Filter (EKF) performance on nonlinear parameter estimation under dynamic 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 could be used to feed the nonlinear vessel autopilot models, which is a considerable contribution and future development in this study.

It is observed that the actual estimation of 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 vessel and do not allow for the nonlinear vessel parameters identification.

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 state measurements are associated with white Gaussian noise is assumed in this study. However, this assumption is also contributed for successful parameters convergence as observed in the simulations.

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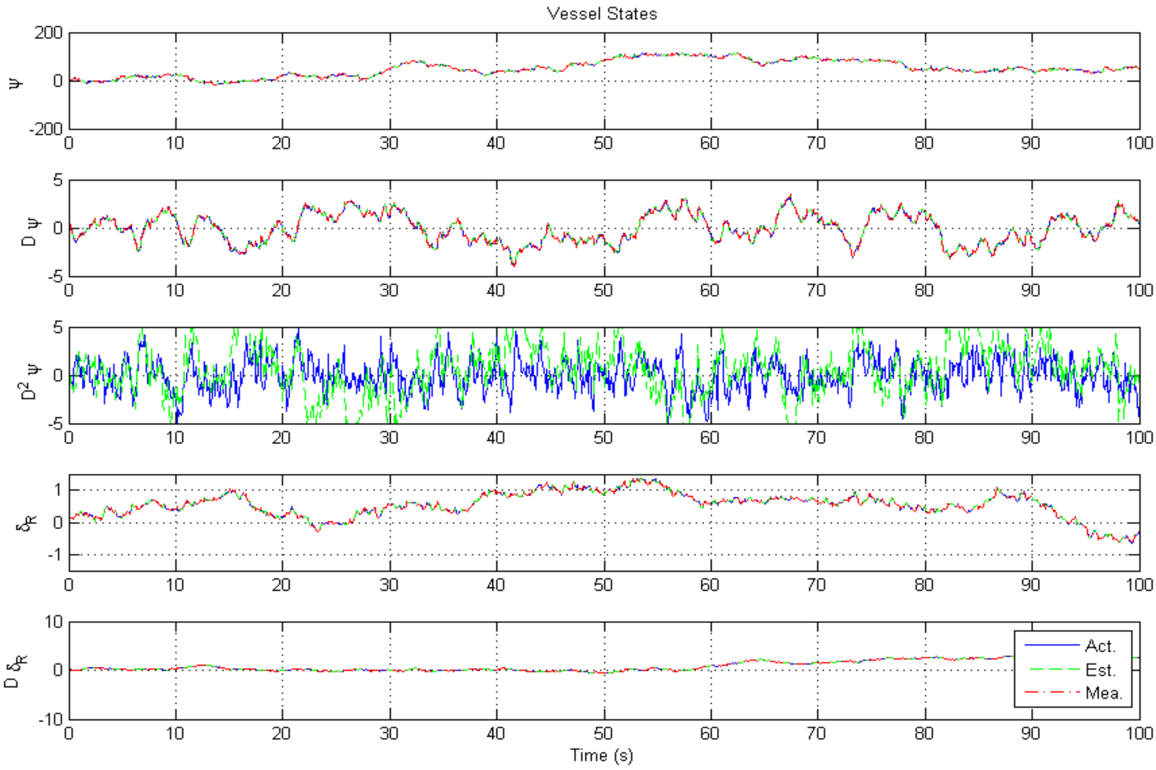

Figure 2. Actual, Measured and Estimated vessel states

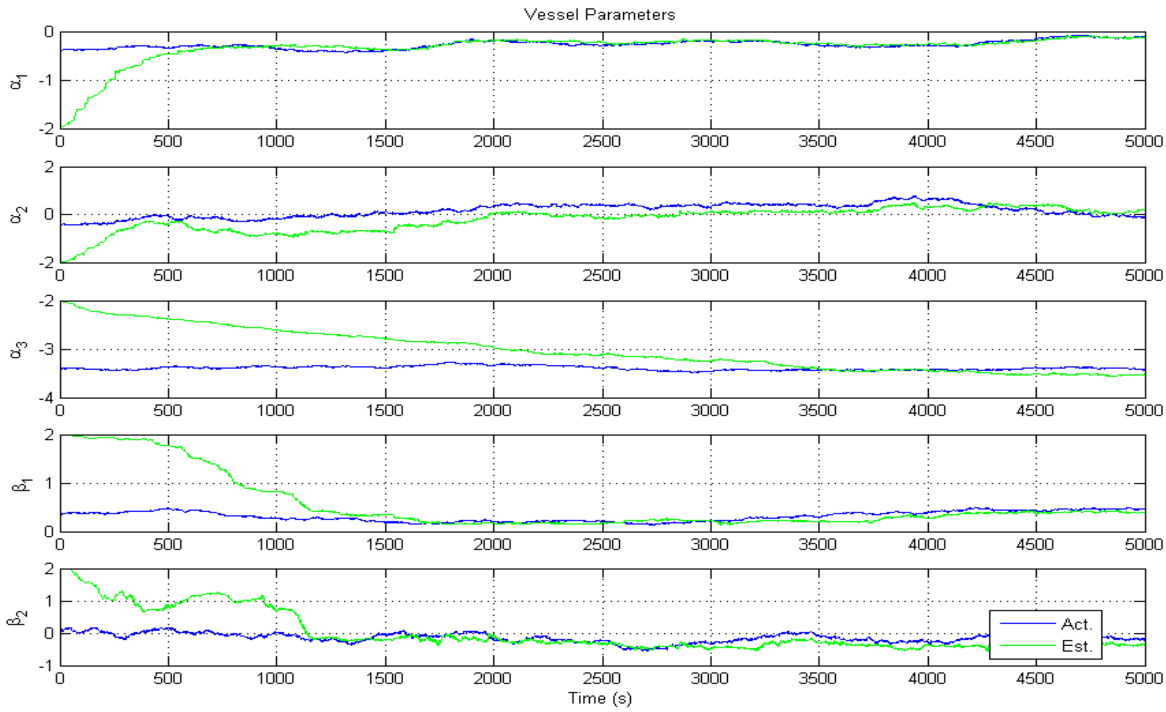

Figure 3. Actual and Estimated vessel parameters