Dynamic Parameter Estimation of Nonlinear Vessel Maneuvering Model in Ocean Navigation

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July 7, 2010

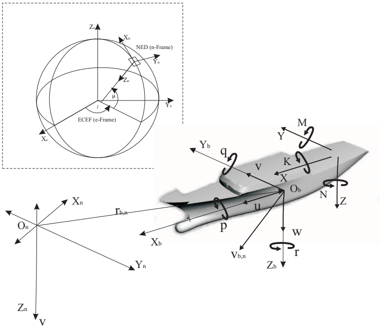
Introduction

- Ocean navigation: The process of planning, recording, and controlling the movement of a craft/vehicle from one place to another.
- The hydrodynamic behavior of a vessel sailing under different sea conditions are associated with higher order non-linearity in the vessel model as well as the sea conditions.
- The study of vessel dynamics is divided into two sections: Steering & maneuverability (absence of wave excitations), and Seakeeping (presence of wave excitations).
- A proper systems identification of the vessel steering system is ultimately influences on the vessel maneuverability as well as the controllability.

Objectives

- Identification of the steering & maneuverability parameters of ocean vessels that assumed to be associated with the stochastic behavior.
- The maneuverability conditions can further divide into two section: Course keeping and Course changing conditions.
- The linearized model of vessel steering can use for the course keeping maneuvering not adequate for the course changing maneuvers.
- Therefore for a nonlinear model of vessel steering is proposed to facilitate course changing maneuvers.
- Extended Kalman Filter is proposed as the tool for estimating nonlinear model parameters of vessel steering system.

Vessel Maneuvering Model



- $X_n Y_n Z_n$ earth fixed coordinate system.
- $X_b Y_b Z_b$ vessel body fixed coordinate system.
- u surge linear velocity , v sway linear velocity , and w heave linear velocity.
- p roll angular velocity , q pitch angular velocity, and r yaw angular velocity.
- X surge force, Y sway force, and Z heave force.
- K roll moment, M pitch moment, and N yaw moment.

Linear Vessel Maneuvering Model

$$m\left(\dot{v} + u_0 r + x_G \dot{r}\right) = Y(v, r, \delta_R, \dot{v}, \dot{r}) \tag{1}$$

$$I_z \dot{r} + m x_G \left(\dot{v} + u_0 r\right) = N(v, r, \delta_R, \dot{v}, \dot{r}) \tag{2}$$

where

$$Y(v, r, \delta_R, \dot{v}, \dot{r}) = Y_{\dot{v}} \dot{v} + Y_{\dot{r}} \dot{r} + Y_v v + Y_r r + Y_\delta \delta_R \tag{3}$$

$$N(v, r, \delta_R, \dot{v}, \dot{r}) = N_{\dot{v}} \dot{v} + N_{\dot{r}} \dot{r} + N_v v + N_r r + N_\delta \delta_R \tag{4}$$

Further $Y_{\dot{v}}, Y_{\dot{r}}, Y_v, Y_r, Y_\delta, N_{\dot{v}}, N_{\dot{r}}, N_v, N_r$ and N_δ, are respective hydrodynamic coefficients and the rudder angle is presented by δ_R.

Linear Nomoto Model

The Nomoto model derived by eliminating the sway velocity v from Equations 1 and 2.

$$T_1 T_2 \ddot{r} + (T_1 + T_2)\,\dot{r} + r = K_R \left(T_3 \dot{\delta}_R + \delta_R \right) \tag{5}$$

The Nomoto model could be presented in transfer function format with $r = \dot{\psi}$:

$$T_1 T_2 \dddot{\psi} + (T_1 + T_2)\,\ddot{\psi} + \dot{\psi} = K_R \left(T_3 \dot{\delta}_R + \delta_R \right) \tag{6}$$

The Equation 6 could be written as

$$\dddot{\psi} + \left(\frac{1}{T_1} + \frac{1}{T_2} \right) \ddot{\psi} + \frac{1}{T_1 T_2} \dot{\psi} = \frac{K_R}{T_1 T_2} \left(T_3 \dot{\delta}_R + \delta_R \right) \tag{7}$$

Modified Nomoto Model

The linearized model could be used for the course keeping maneuvering but this model not adequate for the course changing maneuvers. Therefore for Nomoto is modified into facilitate course changing maneuvers as proposed with the formulation of $(1/K_R)\dot{\psi} \approx H(\dot{\psi})$:

$$\psi^{(3)} + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot{\psi} + \frac{K_R}{T_1 T_2} H(\dot{\psi}) = \frac{K_R}{T_1 T_2}\left(T_3\dot{\delta}_R + \delta_R\right) \quad (8)$$

where $H(\dot{\psi}) = a_1\dot{\psi} + a_2\dot{\psi}^3$ is a non-linear function represents the steady-state relation between δ_R and r.

Modified Nomoto Model (cont.)

The Non-linear model could be written as

$$\psi^{(3)} = -a_1'\ddot{\psi} - K_R'\left(a_2\dot{\psi}^3 + a_1\dot{\psi}\right) + K_R'\left(a_2'\dot{\delta}_R + \delta_R\right) \qquad (9)$$

where $a_1' = \frac{1}{T_1} + \frac{1}{T_2}$, $K_R' = \frac{K_R}{T_1 T_2}$ and $a_2' = T_3$. The Equation 9 could be rewritten as

$$\psi^{(3)} = -a_2 K_R'\dot{\psi}^3 - a_1 K_R'\dot{\psi} - a_1'\ddot{\psi} + a_2' K_R'\dot{\delta}_R + K_R'\delta_R \qquad (10)$$

could be written as

$$\psi^{(3)} = \alpha_1\dot{\psi}^3 + \alpha_2\dot{\psi} + \alpha_4\ddot{\psi} + \beta_1\delta_R + \beta_2\dot{\delta}_R \qquad (11)$$

where the system parameters are defined as $\alpha_1 = -a_3 K_R'$, $\alpha_2 = -a_2 K_R'$, $\alpha_3 = -a_1 K_R'$, $\alpha_4 = -a_1'$, $\beta_1 = K_R'$ and $\beta_2 = a_2' K_R'$

Nonlinear Dynamic System Model

The dynamic system model is formulated in continuous-time:

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), t) + w(t) \tag{12}$$

where $w(t) \sim N(0, Q(t))$ process noise is Gaussian distribution with the mean value of 0 and covariance of $Q(t)$.

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

The Jakobian Matrix $f(\mathbf{x}(t), \mathbf{u}(t), t)$

$$\frac{\partial}{\partial \mathbf{x}} f(.) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3\alpha_1\dot{\psi}^2 + \alpha_2 & \alpha_3 & \dot{\psi}^3 & \dot{\psi} & \ddot{\psi} & \delta_R & \dot{\delta}_R & \beta_1 & \beta_2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (13)$$

Measurement Model

The measurement model has been considered in discrete-time:

$$\mathbf{z}(k) = h_k(\mathbf{x}(k), \mathbf{u}(k), k) + \mathbf{v}_k \tag{14}$$

where $z_k = \begin{bmatrix} z_{\psi}(k) \\ z_{\dot{\psi}}(k) \\ z_{\delta_R}(k) \\ z_{\dot{\delta}_R}(k) \end{bmatrix}$, $h_k = \begin{bmatrix} \psi(k) \\ \dot{\psi}(k) \\ \delta_R(k) \\ \dot{\delta}_R(k) \end{bmatrix}$ and $v_k \sim N(0, R_k)$ is measurement noise with Gaussian distribution with mean value of 0 and covariance of R_k.

The Jakobian Matrix $h(\mathbf{x}(t), \mathbf{u}(t), t)$

$$\frac{\partial}{\partial \mathbf{x}} h(.) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (15)$$

where system states are:

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

Extended Kalman Filter

System Model	$\dot{x}(t) = f(x(t), u(t), t) + w(t)$ $w(t) \sim N(0, Q(t))$
Measurement Model	$z_k = h_k(x(k), u(k), k) + v_k$ $v_k \sim N(0, R_k)$
Initial Conditions **Other Conditions**	$x(0) \sim N(\hat{x}_0, P_0)$ $E(w(t)v_k^T) = 0$ for all k, t
State Estimation Propagation **Error Covariance** **Extrapolation**	$\dot{\hat{x}}(t) = f(\hat{x}(t), t)$ $\dot{P}(t) = F(\hat{x}(t), t)P(t)$ $+P(t)F^T(\hat{x}(t), t) + Q(t)$

Table: Summary of Continuous Discreet Extended Kalman Filter Equations

Extended Kalman Filter (cont.)

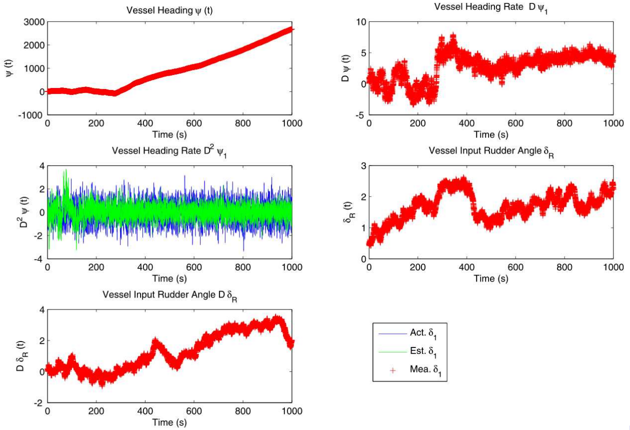
State Estimate Update **Error Covariance Update**	$\hat{x}_{k+} = \hat{x}_{k-} + K_k[z_k - h_k(\hat{x}_{k-})]$ $P_{k+} = [1 - K_k H_k(\hat{x}_{k-})]P_{k-}$
Kalman Gain Matrix	$K_k = P_{k-} H_k^T(\hat{x}_{k-})[H_k(\hat{x}_{k-})P_{k-} H_k^T(\hat{x}_{k-}) + R_k]^{-1}$
Definitions	$F(\hat{x}(t), t) = \left.\frac{\partial f(x(t),t)}{\partial x(t)}\right\|_{x(t)=\hat{x}(t)}$ $H_k(\hat{x}_{k-}) = \left.\frac{\partial h_k(x(t_k))}{\partial x(t_k)}\right\|_{x(t_k)=\hat{x}_{k-}}$

Table: Summary of Continuous Discreet Extended Kalman Filter Equations

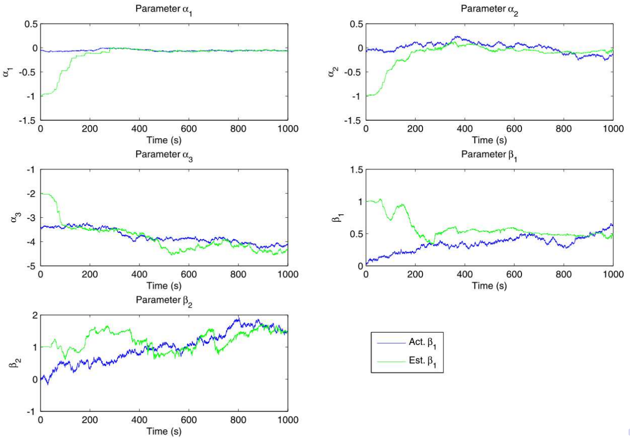
Nonlinear Parameter Estimation Estimation

- Implemented on MATLAB software platform.
- Nonlinear system model approximated by Taylor series expansion.
- Sampling time of 0.1 (s) is used for the simulations.
- Violent maneuvers of the vessel navigation is considered for the simulations.
- Rudder angle and rudder rate are considered as independent states.

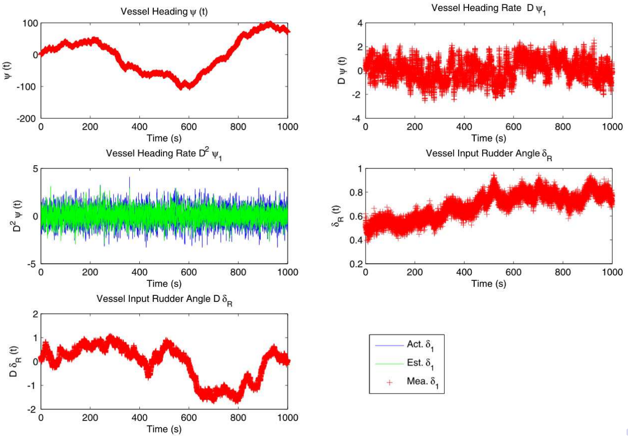
Computational Simulations (Wide Rudder Angle)



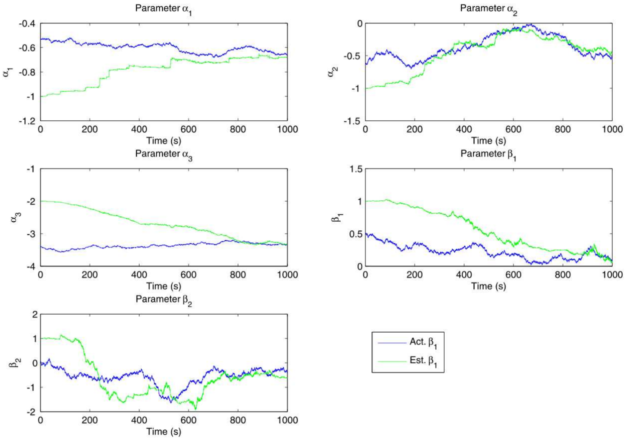
Computational Simulations (WRA (cont.))



Computational Simulations (Narrow Rudder Angle)



Computational Simulations (NRA (cont.))



Conclusion

- The EKF Performance on Dynamic Parameter Estimations is evaluated.
- The accurate estimation of nonlinear parameters can be archived by
  - violent variation in associated state variable if the parameter value is small.
  - moderate variation in associated state variable if the parameter value is large.
- However some state variables could not in-cooperated with violent variations.

References

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