Observer Design for GNSS-aided Position Estimation of Autonomous Surface Vessels

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***Abstract*—State estimation is one of the crucial technologies in the navigation system of unmanned surface vehicles (USVs). However, many previous works on Kalman Filter design ignores the accuracy loss due to the velocity change. In this paper, a Time-varying Extended Kalman Filter (TEFK) is designed for ASV north-east position estimation in the presence of time-variant noise and unknown external disturbances to address the challenge. The observer is verified through the simulation with Cybership II. The simulation results have shown its robustness and effectiveness in estimating the states compared to the non-linear observer. The simulation results have provided strong evidence that the proposed method can be considered as a practical approach for state estimation.**

Keywords—extended kalman filter, unmanned surface vehicles, observer, state estimation

I. Introduction

With the development of artificial intelligence and robotics, the field of unmanned systems have attracted many researchers. Particularly, huge attention is given to unmanned surface vehicles [1]. Wave filtering is one of the crucial issues in designing ASV navigation system. Modern ASVs are equipped with multiple sensors including Global Navigation Satellite Systems (GNSS), Inertial Measurement Unit (IMU), Radar, etc. However, It is known that receivers for Global Navigation Satellite Systems (GNSS) are sensitive to ionospheric disturbances, loss of signals, the number of available satellites, and other factors; hence, the reliability might occasionally be inadequate due to these factors [2]. Therefore, the technique of wave filtering is required to enhance the performance of the sensors.

Early wave filters are mainly based on PID control and notch filter [3]. Starting from the 1970s, the development of Kalman Filter (KF) [4] promoted the evolution of observer design to a new level. The use of KF has proven to be a reliable approach in providing optimal state estimates, both for linear and nonlinear systems. The modified and extended versions have been widely applied in ship navigation systems. After then, a passive nonlinear observer (NO) is designed by Fossen [5]. The nonlinear observer offers a way to cope with the lack of global stability, which is a major problem that exists in KF.

In the last two decades, observer techniques to improve the accuracy and reliability of the ship's navigation system have been developed rigorously. Davari and Gholami [6] designed a variational Bayesian adaptive Kalman Filter for a multi-sensor integrated navigation system. Experiments data have shown that the relative root means square error of the position was largely decreased compared to that of the multi-rate error state Kalman Filter. Sajedi and Bozorg [7] proposed a Kalman and H-infinity filter to estimate the dynamics of Autonomous Underwater Vehicles (AUVs). Simulation through real AUV experiment data has shown it is more robust and accurate compared to standard EKF. Another hybrid observer combining EKF and Particle Filtering (PF) was proposed by Rigatos [8]. It was successfully applied to the dynamic positioning system through simulation experiments. Hansen et al [9] developed a nonlinear observer for time-delayed GNSS measurements. The simulator combines the inertial measurements from the delayed state estimation to provide a state estimation at current time. Moreover, a nonlinear disturbance observer is designed by [10] for model predictive control of dynamic positioning ships. Simulation results have demonstrated its effectiveness in estimating the unknown disturbances and uncertainties. However, many previous works on Kalman Filter design ignores the accuracy loss due to the velocity change. For instance, the measurements are more accurate than the estimation when the ship is in slow motion movements. Conversely if the velocity is large, the measurements will not be reliable anymore. Therefore, a time-varying covariance matrix should be design to coordinate with the velocity change.

In this paper, a Time-varying Extended Kalman Filter is designed for ship position and velocity estimation considering time-varying noise due to the velocity change. Section II introduces the observer design and the establishment of the simulation model. Section III presents the simulation results in Cybership II. The conclusion is shown in section IV.

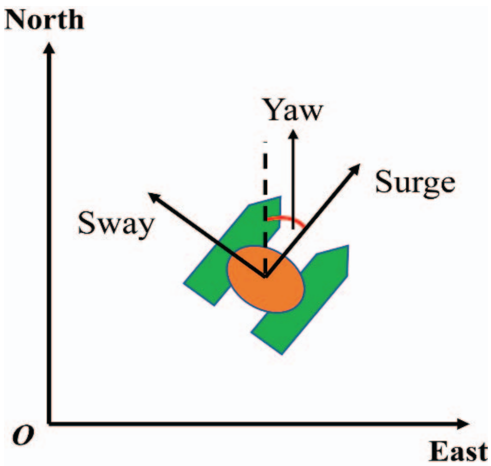

Fig. 1. Reference frame

II. Methodology

A. Observer Design

We assume that the USV can move in the two-dimensional reference frame shown in Fig. 1 in order to estimate the motion states of a surface vehicle heading north and east. The surface vessel model consists of two parts: kinematics, which only considers geometrical motion, and kinetics, which treats the forces causing the motion. A frequently used simplification of the ship model is the 3 DOF representation

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for marine craft. This is based on the assumption that roll and pitch are small, which is a good approximation for most conventional ships. The vessel model is constructed in three reference frames, i.e. the North-East reference frame denoted the position as $\eta = [x^n,\ y^n, \psi]^T$, the body-fixed frame denoted the velocity vector as $\upsilon = [u, v, r]^T$, where x^n and y^n are position states in north and east directions respectively, and ψ is the yaw angle, u and v are the surge and sway velocity, and r denotes the yaw rate. The motion equation is presented as follows [13]:

$$\dot{\eta} = R(\psi)\upsilon \tag{1}$$

$$M\dot{\upsilon} + D\upsilon = \tau + \tau_{en} \tag{2}$$

In (1), $R(\psi) \in \mathbb{R}^{3\times 3}$ is the transfer matrix between North-east frame and body-fixed frame, see (3). In (2), $M \in \mathbb{R}^{3\times 3}$ and $D \in \mathbb{R}^{3\times 3}$ are the inertia matrix that denotes the body rigidity factor and damping matrix which is due to the wave drift damping. $\tau \in \mathbb{R}^3$ and $\tau_{en} \in \mathbb{R}^3$ are the input vectors presented by the propellers and the environment, respectively.

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

From (2), one obtains $\upsilon = \dot{\eta} R(\psi)^{-1}$. Similarly one obtains $\dot{\upsilon} = \dot{R}(\psi)^T\dot{\eta} + R(\psi)^T\ddot{\eta}$. Therefore, this gives

$$J(\eta)\ddot{\eta} + C(\eta,\dot{\eta})\dot{\eta} + F(\eta)\dot{\eta} = \tau^* \tag{4}$$

Where

$$J(\eta) = R(\psi)MR(\psi)^T \tag{5}$$

$$C(\eta,\dot{\eta}) = R(\psi)M\dot{R}(\psi)^T \tag{6}$$

$$F(\eta) = R(\psi)DR(\psi)^T \tag{7}$$

$$\tau^* = R(\psi)\tau \tag{8}$$

The generalized state vector is $x = [x^n,\ y^n, \psi, u, v, r]^T$. Therefore, it obtains the general ship state-space model:

$$\dot{x} = A(x)x + B(x)u + \omega \tag{9}$$

$$y = Cx + \upsilon \tag{10}$$

where $\omega \in \mathbb{R}^3$ denotes the process noise, and $\upsilon \in \mathbb{R}^3$ is the measurement noise of GNSS. The matrices are presented as follows:

$$A(x) = \begin{bmatrix} 0_{3\times 3} & I_{3\times 3} \\ 0_{3\times 3} & -J^{-1}(x)[C(x,\dot{x}) + F(x)] \end{bmatrix} \tag{11}$$

$$B = [0_{3\times 3} \quad -J^{-1}(x)]^T \tag{12}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{13}$$

The discrete-time representation of the state-space model is obtained by being expanded into the Taylor series around the point $\hat{x}$, which is given by:

$$f[x(t), u(t)] = f[\hat{x}(t), u(t)] + \left.\frac{\partial f[x(t), u(t)]}{x(t)}\right|_{x=\hat{x}} + [x(t) - \hat{x}(t)] \tag{14}$$

The discrete model of the ship in the vector form is presented as follows:

$$\dot{x}(k+1) = Ax(k) + Bu(k) + \omega(k) \tag{15}$$

$$y(k) = Cx(k) + \upsilon(k) \tag{16}$$

Using the above state-space representation, state vector x can be estimated by processing GNSS measurements of north and east position using EKF.

B. Time-varying Noise EKF

The Extended Kalman Filter design is based on the model presented by:

$$\dot{x}(k+1) = Ax(k) + Bu(k) + \omega(k) \tag{17}$$

$$y(k) = Cx(k) + \upsilon(k) \tag{18}$$

Where $x = [\eta^T, \dot{\eta}^T]^T$, and the A matrix represents the kinematic and dynamic relationship of the model. The first three rows indicate the kinematic motion in surge, sway, and yaw. The rest represent the vessel dynamics. B matrix denotes the input configuration and $u(k)$ is the propeller forces. C matrix indicates that only position $(x^n,\ y^n)$ measurements are available. The GNSS provides the measurement signal at the sampling frequency of 1 Hz.

$\omega(k)$ and $\upsilon(k)$ are process noise with the covariance matrix $Q \in \mathbb{R}^{3\times 3}$ and $R \in \mathbb{R}^{2\times 2}$ respectively. $\omega(k)$ present the velocity variance between each sample time. To enhance the performance of the estimator, the variance of the process noise $\omega(k)$, the Q matrix, is chosen to be time-varying to keep pace with the velocity change, see equations below:

$$Q = \begin{bmatrix} 1 + \frac{2.5}{f_{sat}(\hat{u})} & 0 & 0 \\ 0 & 1 + \frac{2.5}{f_{sat}(\hat{v})} & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{19}$$

$$f_{sat}(x) = \min\ (\max(x, 0.5), 0.25) \tag{20}$$

Since the Q matrix denotes the reliability of the estimates, large values in Q mean the measurements are more reliable than the estimation. It means that the typical values of $\omega(k)$ are larger when the velocity is relatively lower. For example, the measurements are more accurate when the ship is in slow motion and therefore, $\omega(k)$ is larger. We introduce a saturation function to construct Q, see (20). The variance of w is represented by the diagonals of Q, and it grows inversely with the squares of $\hat{u}$ and $\hat{v}$. The saturation function capped the range of allowable Q values. Using a least-squares fit on 0-0.5 m/s acceleration time data for a dynamic positioning ship, the coefficient 2.5 is computed. And the coefficient can be modified according to different vessel.

Therefore, the discrete-time EKF are given in the following procedure:

- Initial values

$$\overline{x}_{k=0} = x_0 \tag{21}$$

$$\overline{P}_{k=0} = P_0 \tag{22}$$

- Kalman filter gain matrix

$$K_k = \overline{P}_k C^T [C\overline{P}_k C^T + R]^{-1} \tag{23}$$

- State vector and covariance matrix corrector

$$\hat{P}_k = (I - K_k C)\overline{P}_k (I - K_k C)^T + K_k R K_k^T \tag{24}$$

$$\hat{x}_k = \overline{x}_k + K_k(y_k - H\overline{x}_k) \tag{25}$$

- State vector and covariance matrix predictor

$$\bar{x}_{k+1} = A\hat{x}_k + Bu_k \tag{26}$$

$$\bar{P}_{k+1} = A\hat{P}_k A^T + Q \tag{27}$$

C. Control Design

In this paper, we use a dynamic positioning (DP) model to test the proposed algorithm. According to [3], the linear 3 DOF DP model takes the form as (1) and (2). The M and D matrices are expressed as follows:

$$M = \begin{bmatrix} m - X_{\dot{u}} & 0 & 0 \\ 0 & m - Y_{\dot{v}} & mx_g - Y_{\dot{r}} \\ 0 & mx_g - Y_{\dot{r}} & I_z - N_{\dot{r}} \end{bmatrix} \tag{28}$$

$$D = \begin{bmatrix} -X_u & 0 & 0 \\ 0 & -Y_v & -Y_r \\ 0 & -Y_r & -N_r \end{bmatrix} \tag{29}$$

where m is the mass value of the vessel, $X_{\dot{u}}$, $Y_{\dot{v}}$, $Y_{\dot{r}}$ and $N_{\dot{r}}$ are coefficients of added mass caused by hydrodynamics, X_u, Y_v, Y_r, and N_r are terms denoting the damping coefficients. I_z is the moment inertia of z axis.

A PID controller is designed to accomplish the control objective. The control law is presented as follows:

$$\tau = K_p\tilde{x} + K_d\dot{x} + K_i\int_0^t \tilde{x}(t)\,dt \tag{30}$$

with gains $K_p > 0$, $K_d > 0$, and $K_i > 0$ and tracking error $\tilde{x} = x - x_d$.

The tuning law is designed according to [11], see the following equations:

$$K_p = m\omega_n^2 \tag{31}$$

$$K_d = 2\zeta\omega_n m \tag{32}$$

$$K_i = \frac{\omega_n}{10}K_p \tag{33}$$

where $m = I_z - N_{\dot{r}}$, ω_n is the natural frequency which is determined by control bandwidth ω_b (typically 0.01 rad/s for large tankers), and ζ denotes the relative damping ratio which is usually be chosen in the range 0.8-1.0.

III. SIMULATION

This section presents a case study with the proposed method to illustrate how it can yield excellent performance in estimating north-east position using GNSS data.

TABLE I. MASS RELATED PARAMETERS

Parameter	*Value*	*Parameter*	*Value*
m	23.800	$Y_{\dot{v}}$	-10.0
I_z	1.760	$Y_{\dot{r}}$	-0.0
x_g	0.046	$N_{\dot{v}}$	-0.0
$X_{\dot{u}}$	-2.0	$N_{\dot{r}}$	-1.0

The DP vessel model in the simulation is selected to be the Cybership II (CS2) which is designed by Norwegian University of Science and Technology, see Fig. 2. Cybership II is a model of a supply vessel in 1:70 scale. The main parameters are: $m = 23.8\ kg$, the length of the model is $L = 1.255\ m$, and the width is $B = 0.29\ m$. Cybership II is powered by two propellers, rudders, and one bow thruster. Experimental studies have been carried out by [12] to identify the parameters of CS2, the results are presented in Table I and II.

Fig. 2. Cybership II

TABLE II. DAMPING RELATED PARAMETERS

Parameter	*Value*
X_u	-2.0
Y_v	-7.0
Y_r	-0.1
N_r	-0.5

The PID parameters are presented in the following matrices:

$$K_p = \begin{bmatrix} 0.5160 & 0 & 0 \\ 0 & 0.6760 & 0.0202 \\ 0 & 0.0202 & 0.0552 \end{bmatrix} \tag{36}$$

$$K_d = \begin{bmatrix} 4.1280 & 0 & 0 \\ 0 & 5.4080 & 0.1618 \\ 0 & 0.1618 & 0.4416 \end{bmatrix} \tag{37}$$

$$K_i = \begin{bmatrix} 0.0026 & 0 & 0 \\ 0 & 0.0034 & 0.0001 \\ 0 & 0.0001 & 0.0003 \end{bmatrix} \tag{38}$$

The simulation environment is set as MATLAB R2022a environment with a PC equipped with Intel (R) Core (TM) i7-8700 CPU and 8-GB RAM. The setpoint objective is illustrated as follows:

$$P = \begin{cases} (0\,m, 0\,m, 0\,°), & t = 0 - 10s \\ (10\,m, 10\,m, 45\,°), & t = 10 - 100s \end{cases}$$

Fig. 3-5 presents the comparison of the estimated positions between the proposed method and the nonlinear observer (NO). In Fig 3, the red curve is the estimation from the proposed observer, the blue curve is obtained by NO, and the black dashed line is the true position. In Fig 4 and Fig 5, the red curves denote the estimated states while the blue curves are the true states. As can be seen from the figures, the deviation from true states presented by EKF is smaller than NO in both directions, which means it can efficiently estimate the true states of the motion. Moreover, the average estimation error is shown in Table III. As is shown in the table, the estimation error of the proposed observer (0.0783 m and 0.0782 m for north and east) is much less than the nonlinear observer (0.1603 m and 0.1611 m for north and east), which yields the results with higher accuracy.

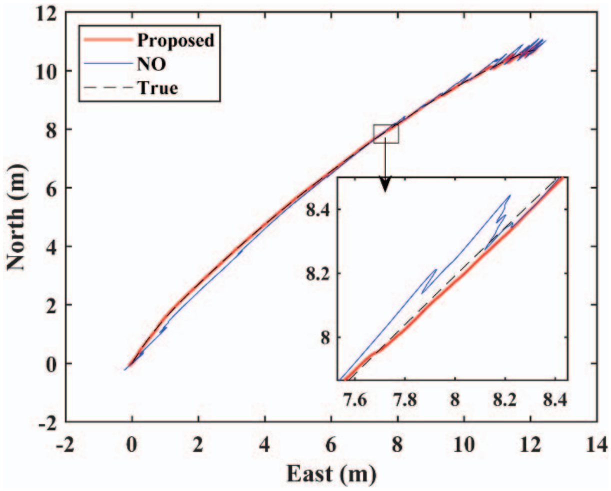

Fig. 3. Estimated position of proposed observer and NO

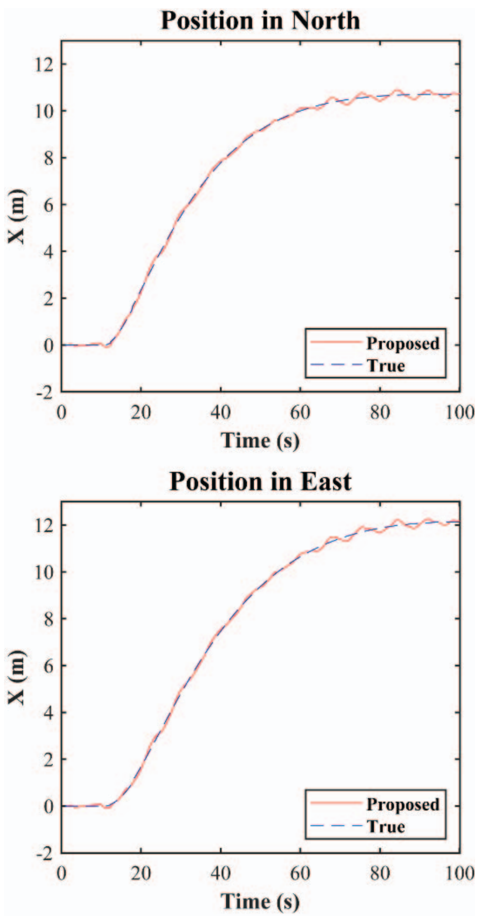

Fig. 4. Position estimation using proposed observer

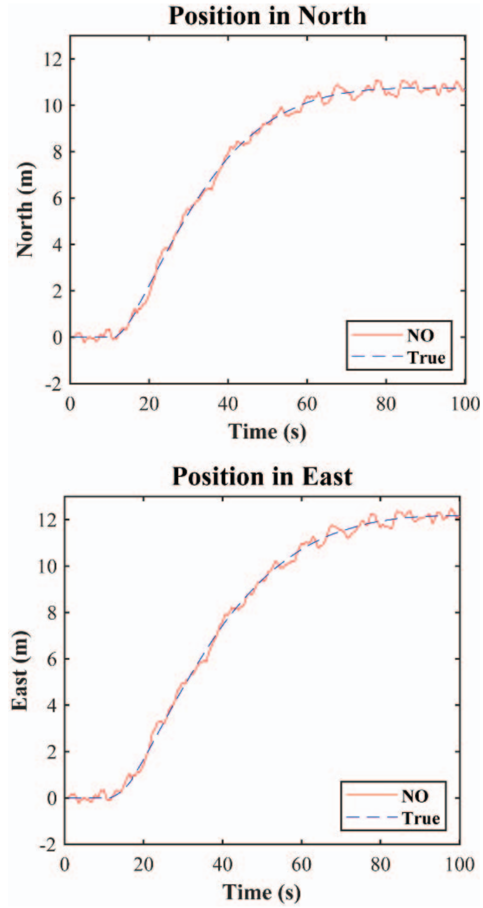

Fig. 5. Position estimation using nonlinear observer

TABLE III. QUANTITATIVE RESULTS

Directions	*Average Estimation Error (m)*	
	Proposed	*Nonlinear Observer*
North	0.0783	0.1603
East	0.0782	0.1611

IV. CONCLUSION

In this paper, a Time-varying Extended Kalman Filter (TEFK) is designed for ASV north-east position estimation in the presence of time-variant noise and unknown external disturbances. The observer is verified through the simulation with Cybership II. The simulation results have shown it was more robust and effective in estimating the states compared to the non-linear observer. The simulation results have provided strong evidence that the proposed method can be considered as a practical approach for state estimation.

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