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# Identification of an Underactuated Unmanned Surface Vehicle

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**Abstract:** Hydrodynamic coefficients strongly affect the dynamic performance of underactuated unmanned surface vehicle ( USV) . Towing tank test is the traditional approach to identify these coefficients, however, the obtained values are not completely reliable since experimental difficulties and errors are involved. In this paper, an extended Kalman filter ( EKF) method and a least squares ( LS) method are proposed, only using onboard sensor data for identification of a small underactuated USV. The vehicle prototype as well as the system integration is delineated. Performance of the identification is evaluated by comparing the estimated coefficients, and the feasibility and accuracy of the proposed approach is demonstrated by simulation.

**Key words:** Computer simulation, Computer software, Errors, Estimation, Experiments, Hydrodynamics, Identification ( control systems) , Kalman filters, Least squares approximations, Mathematical models, Measurement errors, Sensors; Extended Kalman filter, Underactuated unmanned surface vehicle

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## 1 Introduction

Technology of unmanned surface vehicle ( USV) is rather new in contrast to other unmanned marine vehicles ( UMVs) , such as autonomous underwater vehicle ( AUV) which was first developed in the early 1960s and remotely operated vehicle ( ROV) which began to be mature in the early 1980s[1] . However, experts and organizations have realized the potential of USVs due to their capacity of carrying out various missions as follows:

- **Scientific uses** Oceanographic surveys, seafloor mapping, environmental monitoring, platform to predict natural disasters;
- **Civil uses** Target searching and rescue, marine resources discovery, network notes for fisheries management, group of meteorological stations;
- **Military uses** Harbor defense, mine countermeasures, maritime security, weapon delivery;
- **Other uses** Educational use, cooperative missions with other autonomous vehicles such as AUVs and ROVs, educational use, etc.

Path following and tracking missions of underactuated vehicles with enhanced maneuverability and controllability usually require an accurate mathematical model. Recently, work has been reported on practical approach for USV modeling[2,3] , identification of hydrodynamic coefficients using estimation-before-modeling technique[4] , identification and adaptive control for a model ship[5] , etc. Traditional approach to obtain hydrodynamic coefficients depends on the towing tank tests which fit the scope of small vehicles or scaled model vehicles. By towing the vehicle at many different

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velocities with zero acceleration and zero input forces, and then repeating the same processes with the thrusters activated, a succession of towing tests are usually complex and expensive for identification of USVs.

Northwest Polytechnical University (NWPU) has developed an USV for the purpose of path following control and cooperative missions. This paper addresses problem of estimating the hydrodynamic coefficients and thruster model using only onboard sensor data. The contributions of this paper can be summarized as follows:

- An extended Kalman filter (EKF) method and a least squares (LS) method to identify the USV model are presented, only using the data acquired by the mechatronic system.
- The system integration of NWPU USV is enhanced by increasing the capacity of autonomous navigation and real-time operation.
- Identified results by simulations are compared to obtain an assessment of the feasibility and accuracy for the proposed approaches.

The remainder of the paper is organized as follows. In Section 2, the problem formulation for nonlinear model of the underactuated vehicle to be identified is presented. In Section 3, an EKF method and a LS method to estimate hydrodynamic coefficients is presented. Next, a mechatronic system is introduced to obtain the needed data, and simulation results are illustrated in Section 4. Finally, conclusions are outlined in Section 5.

## 2 Problem formulation

This section describes the vehicle and thruster model of USV, and provides the formulation of system identification problem.

### 2.1 Vehicle modeling

For the motion description of the USV, we define a body-fixed frame $\{B\}$ and a global coordinate frame $\{E\}$ as shown in Fig. 1. In the body-fixed frame, the dynamic equation of USV can be described as[6]:

$$\boldsymbol{M}\dot{\boldsymbol{\nu}} + \boldsymbol{C}(\boldsymbol{\nu})\boldsymbol{\nu} + \boldsymbol{D}(\boldsymbol{\nu})\boldsymbol{\nu} = \boldsymbol{\tau} + \boldsymbol{\omega} \tag{1}$$

where $\boldsymbol{M}$, $\boldsymbol{C}((\boldsymbol{\nu})$ and $\boldsymbol{D}(\boldsymbol{\nu})$ are the inertia matrix, the Coriolis and Centripetal matrix, and the damping matrix, respectively, and $\boldsymbol{\nu}$ is the velocity of the USV, $\boldsymbol{\tau}$ is the vector of the input signals, and $\boldsymbol{\omega}$ is the vector of external disturbances.

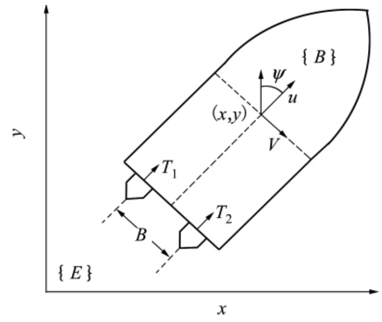


Fig. 1 USV model

Without loss of generality, we assume that the USV motion is restricted to the horizontal plane, namely, neglecting pitch, roll and heave. Then, with nomenclature indicated in Table 1,

$$\boldsymbol{\nu} = [u, v, r]^{\mathrm{T}} \qquad \boldsymbol{\tau} = [\tau_1, 0, \tau_2]^{\mathrm{T}}$$

$$\boldsymbol{M} = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix} \quad \boldsymbol{D}(\nu) = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & d_{23} \\ 0 & d_{32} & d_{33} \end{bmatrix}$$

$$\boldsymbol{C}(\nu) = \begin{bmatrix} 0 & 0 & -m_{22}v - m_{23}r \\ 0 & 0 & m_{11}u \\ m_{22}v + m_{23}r & -m_{11}u & 0 \end{bmatrix}$$

where $m_{11} = m - X_{\dot{u}}$, $m_{22} = m - Y_{\dot{v}}$, $m_{23} = mx_G - Y_{\dot{r}}$, $m_{32} = mx_G - N_{\dot{v}}$, $m_{33} = I_z - N_{\dot{r}}$, $d_{11} = -X_u - X_{|u|u}|u|$, $d_{22} = -Y_v - Y_{|v|v}|v|$, $d_{23} = -Y_r - Y_{|r|r}|r|$, $d_{32} = -N_v - N_{|v|v}|v|$, $d_{33} = -N_r - N_{|r|r}|r|r$. The notation of SNAME[7] is used in this expression.

**Table 1 Nomenclature**

| Symbol | Description | Unit |
|---|---|---|
| $u$ | Linear velocity in surge | $\mathrm{m \cdot s^{-1}}$ |
| $v$ | Linear velocity in sway | $\mathrm{m \cdot s^{-1}}$ |
| $r$ | Yaw velocity | $\mathrm{rads^{-1}}$ |
| $\tau_1$ | Force in surge | N |
| $\tau_2$ | Moment in yaw | Nm |
| $x$ | Position in surge | m |
| $y$ | Position in sway | m |
| $\psi$ | Yaw | rad |
| $m$ | Weight of the USV | kg |

It is obvious that there is no control input in the sway direction, so this USV is an underactuated vehicle, namely, with more degrees of freedom to be controlled than the number of control actuators. Position of the USV in global coordinate frame $\{E\}$ can be described as:

$$\dot{\eta} = \boldsymbol{J}(\eta)\nu \tag{2}$$

where $\eta = [x, y, \psi]^{\mathrm{T}}$ is the generalized position of the USV, and the transformation matrix $\boldsymbol{J}$ related through the functions of Euler angles can be described as

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

### 2.2 Thruster modeling

In recent years, the modeling and control of thruster systems in marine vehicles have received wide attention in the literature [8-10].

As thruster dynamics can be neglected with respect to the vehicle dynamics[11], the thruster model might be described as a function of the angular speed of the propeller and the linear velocity of the vehicle in the thruster direction[6]:

$$\boldsymbol{T} = \boldsymbol{C}_n n|n| - \boldsymbol{C}_v v_a |n| \tag{4}$$

where $\boldsymbol{T}$ is the actuator force produced by a single propeller, $n$ and $v_a$ are the propeller revolution rate and the velocity of the fluid through the propeller, respectively, and $\boldsymbol{C}_n$ and $\boldsymbol{C}_v$ are unknown positive constants. In low-speed applications, the bilinear model can be approximated as:

$$\boldsymbol{T} = \boldsymbol{C}_\tau n|n| \tag{5}$$

where $\boldsymbol{C}_\tau$ is an unknown positive constant.

Assuming that the actuator forces of the USV are generated by two same thrusters with revolutions per second and respectively. The yaw moment is determined by differential propeller revolution rates. This relationship can be described as:

$$\boldsymbol{T}_1 = \boldsymbol{C}_\tau n_1|n_1| \qquad \boldsymbol{T}_2 = \boldsymbol{C}_\tau n_2|n_2| \tag{6}$$

$$\tau_1 = \boldsymbol{T}_2 + \boldsymbol{T}_2 \qquad \tau_2 = \boldsymbol{B}(\boldsymbol{T}_1 - \boldsymbol{T}_2)/2 \tag{7}$$

where $\boldsymbol{T}_1$ and $\boldsymbol{T}_2$ are actuator forces produced by the two propellers, respectively, and $B$ is the distance between the propellers.

### 2.3 Group of coefficients

The basic functions of the underactuated vehicle such as to keep its position at a fixed point and to follow predefined way-points require to obtain the unknown coefficients in the presented model above. In detail, the following coefficients in Table 2 are expected to be estimated.

**Table 2　Coefficients to be estimated**

| Type | Coefficients terms |
|---|---|
| Linear damping | $\boldsymbol{X}_u, \boldsymbol{Y}_v, \boldsymbol{Y}_r, \boldsymbol{N}_v, \boldsymbol{N}_r$ |
| Added mass | $\boldsymbol{X}_{\dot{u}}, \boldsymbol{Y}_{\dot{v}}, \boldsymbol{Y}_{\dot{r}}, \boldsymbol{N}_{\dot{v}}, \boldsymbol{N}_{\dot{r}}$ |
| Quadratic damping | $\boldsymbol{X}_{\lvert u \rvert u}, \boldsymbol{Y}_{\lvert v \rvert v}, \boldsymbol{Y}_{\lvert r \rvert r}, \boldsymbol{N}_{\lvert v \rvert v}, \boldsymbol{N}_{\lvert r \rvert r}$ |
| Thruster coefficients | $\boldsymbol{C}_\tau, \boldsymbol{C}_n, \boldsymbol{C}_v$ |

## 3 Identification method

Identification methods based on continuous-time model and discrete-time model have been both extensively used in nonlinear model estimation. An advantage of using the discrete-time model consists in the facility to implement related algorithms on computers, while continuous-time model described by a set of differential equations is more direct and much easier to be used into an identification algorithm.

In this section, the hydrodynamic coefficients are estimated by two methods, EKF and LS. The first method is based on the augmented state-space equations while the second is based on nonlinear dynamics differential equations.

### 3.1 EKF method

The Kalman filter can perfectly estimate the state variables in nonlinear stochastic cases, and particularly, unknown parameters can be estimated by converting them to state variables in format.

The nonlinear dynamics equation (1) is rewritten as follows

$$\dot{v} = f(v, \theta) + \omega_1 \tag{8}$$

$$\dot{\theta} = \omega_2 \tag{9}$$

and this state equation can be described in discrete-time model:

$$\nu_{k+1} = f(\nu_k, \theta_k) + \omega_{1k} \tag{10}$$

$$\theta_{k+1} = \theta_k + \omega_{2k} \tag{11}$$

where $v_k \in R^n$ and $\theta_k \in R^p$ are the generalized velocity and the unknown coefficients to be estimated, respectively, $\omega_{1k} \in R^n$ and $\omega_{2k} \in R^p$ are zero-mean process noise sequences.

Together with the measurement equation, the augmented state-space model can be expressed in form as:

$$\boldsymbol{x}_{k+1} = \begin{bmatrix} \nu_{k+1} \\ \theta_{k+1} \end{bmatrix} + \begin{bmatrix} f(\nu_k, \theta_k) \\ \theta_k \end{bmatrix} + \begin{bmatrix} \omega_{1k} \\ \omega_{2k} \end{bmatrix} \tag{12}$$

$$\boldsymbol{y}_k = h(x_k) + \omega_{3k} \tag{13}$$

where $\boldsymbol{x}_k \in R^{n+p}$ and $\boldsymbol{y}_k \in R^m$ are the state vector and the measurement vector, respectively, $\omega_{3k}$ is a zero-mean measurement noise sequence.

Using the above system, the discrete-time EKF technique can be applied to estimate the vector of unknowns $\theta$. The Kalman filter for equations (5) ~ (12) is summarized as follows:

Time update:

$$\hat{\boldsymbol{x}}_{k+1/k} = f(\hat{\boldsymbol{x}}_k) \tag{14}$$

$$\boldsymbol{P}_{k+1/k} = \boldsymbol{F}_k \boldsymbol{P}_k \boldsymbol{F}_k^{\mathrm{T}} + \boldsymbol{Q}_k \tag{15}$$

Measurement update:

$$\boldsymbol{K}_{k+1} = \boldsymbol{P}_{k+1/k} \boldsymbol{H}_{k+1}^{\mathrm{T}} (\boldsymbol{H}_{k+1} \boldsymbol{P}_{k+1/k} \boldsymbol{H}_{k+1}^{\mathrm{T}} + \boldsymbol{R}_{k+1})^{-1} \tag{16}$$

$$\hat{\boldsymbol{x}}_{k+1} = \hat{\boldsymbol{x}}_{k+1/k} + \boldsymbol{K}_{k+1} [\boldsymbol{y}_{k+1} - h(\hat{\boldsymbol{x}}_{k+1/k})] \tag{17}$$

$$\boldsymbol{P}_{k+1} = (\boldsymbol{I} - \boldsymbol{K}_{k+1} \boldsymbol{H}_{k+1}) \boldsymbol{P}_{k+1/k} \tag{18}$$

where $\boldsymbol{P}$ and $\boldsymbol{K}$ are the error covariance and the gain matrix, respectively, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are the process noise covariance and the measurement noise covariance, respectively.

On condition that the system is observable at any $t_k > 0$, and $\boldsymbol{Q}$ and $\boldsymbol{R}$ in the equations (14) ~ (15) are both positive definite, the parameters vector $\theta$ can be estimated by extended Kalman filter equations (13) ~ (17). The state variable can yield to $\boldsymbol{x} = [u, v, r, X_u, Y_v, Y_r, N_v, N_r, \cdots, N_{|v|v}, N_{|r|r}]^{\mathrm{T}}$. The output variables are chosen as velocity measurements such as $\boldsymbol{y} = [u, v, r]^{\mathrm{T}}$, while acceleration measurements also can be used.

### 3.2 LS method

Another description of dynamics equation (1) is as follows[6]:

$$m(\dot{u} - vr - x_G r^2) = \boldsymbol{X} \tag{19}$$

$$m(\dot{v} + uv + x_G \dot{r} = \boldsymbol{Y} \tag{20}$$

$$\boldsymbol{I}_z \dot{r} + m x_G (\dot{v} + ur) = \boldsymbol{N} \tag{21}$$

where $\boldsymbol{X}$, $\boldsymbol{Y}$, and $\boldsymbol{N}$ represent the total surge force, sway force, and yaw moment, respectively, which takes into account the forces exerted on the USV by the propulsion system, and the hydrodynamic effects from hull movements.

The uncoupled model structure for the force terms can be described as[5]:

$$\boldsymbol{X} = \boldsymbol{X}_{\dot{u}} \dot{u} + \boldsymbol{X}_u u + \boldsymbol{X}_{|u|u} |u| u + \tau_1 \tag{22}$$

$$\boldsymbol{Y} = \boldsymbol{Y}_{\dot{v}} \dot{v} + \boldsymbol{Y}_{\dot{r}} \dot{r} + \boldsymbol{Y}_v v + \boldsymbol{Y}_r r + \boldsymbol{Y}_{|v|v} |v| v + \boldsymbol{Y}_{|r|r} |r| r \tag{23}$$

$$\boldsymbol{N} = \boldsymbol{N}_{\dot{v}} \dot{v} + \boldsymbol{N}_{\dot{r}} \dot{r} + \boldsymbol{N}_v v + \boldsymbol{N}_r r + \boldsymbol{N}_{|v|v} |v| v + N_{|r|r} |r| r + \tau_2 \tag{24}$$

and if an experiment takes samples, replacing $\tau_1$ by equation (7) and marking $n_1 |n_1| + n_2 |n_2|$ as $n_0$, equation (21) will expand to rows as:

$$\underbrace{\begin{bmatrix} \boldsymbol{X}_1 \\ \boldsymbol{X}_2 \\ \cdots \\ \boldsymbol{X}_i \end{bmatrix}}_{y} \underbrace{\begin{bmatrix} \dot{u}_1 & u_1 & |u_1| u_1 & n_{0,1} \\ \dot{u}_2 & u_2 & |u_2| u_2 & n_{0,2} \\ \cdots & \cdots & \cdots & \cdots \\ \dot{u}_i & u_i & |u_i| u_i & n_{0,i} \end{bmatrix}}_{H} \cdot \underbrace{\begin{bmatrix} \boldsymbol{X}_{\dot{u}} \\ \boldsymbol{X}_u \\ \boldsymbol{X}_{|u|u} \\ \boldsymbol{G}_\tau \end{bmatrix}}_{\theta} + \underbrace{\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_i \end{bmatrix}}_{\varepsilon} \tag{25}$$

where the output $y$ is determined via equations (18), $\varepsilon$ is a measurement noise term. Hence, an equation linear in the vector of unknowns is obtained. Using equations (24), the LS method can be applied to estimate the coefficients vector $\boldsymbol{\theta} = [X_{\dot{u}}, X_u, X_{|u|u}, C_\tau]^{\mathrm{T}}$ in the surge model through the equations as follows:

$$\hat{\boldsymbol{\theta}}_{LS} = (\boldsymbol{H}^{\mathrm{T}} \boldsymbol{H})^{-1} \boldsymbol{H}^{\mathrm{T}} \boldsymbol{y} \tag{26}$$

and the similar structures can be obtained in the sway and yaw model.

## 4 System integration and simulation

This section is devoted to the description of the system integration and simulation results which are prepared for field experiments. To support the theory development and algorithm validation, an USV prototype has been developed by NWPU in 2010, as shown in Fig 2.

### 4.1 Mechatronic system

The USV system is designed with the following requirements in mind:

- The generalized position, velocity, accelera-

Fig. 2　NWPU USV prototype in testing

tion, and propeller revolution measurements should be all obtained at one experiment to complete identification.

• Sufficient control ability to support basic way-points following and seakeeping is required. Therefore, autonomous and accurate navigation must be ensured.

• Communication between the onboard computer and ground control station should be available to allow real-time monitoring and deploying missions.

To meet the requirements above, a mechatronic system is developed for NWPU USV. Fig. 3 describes the system integration structure that runs the USV both in remote control and autonomous mode.

The Photonic Integrated Navigation System is installed at the vehicle to measure its 3D orientations, velocities, and accelerations. These data are collected by the onboard computer via serial ports. A global position system (GPS) is also connected to PHINS to perform high accuracy inertial navigation.

A PC104 computer, running VxWorks operating system is selected as the onboard processor. This compact size computer is typically used for data acquisition and real-time control missions, capable of communicating with ground station by a full-duplex wireless modem. The monitoring computer can send control instructions and the predefined way-points to onboard system, and the status of the vehicle can be also transmitted back to the ground in time.

The main propulsion mechanism is composed of two dc servomotors that drive thrusters. Each of them is fitted with an encoder to measure the speed of pro-

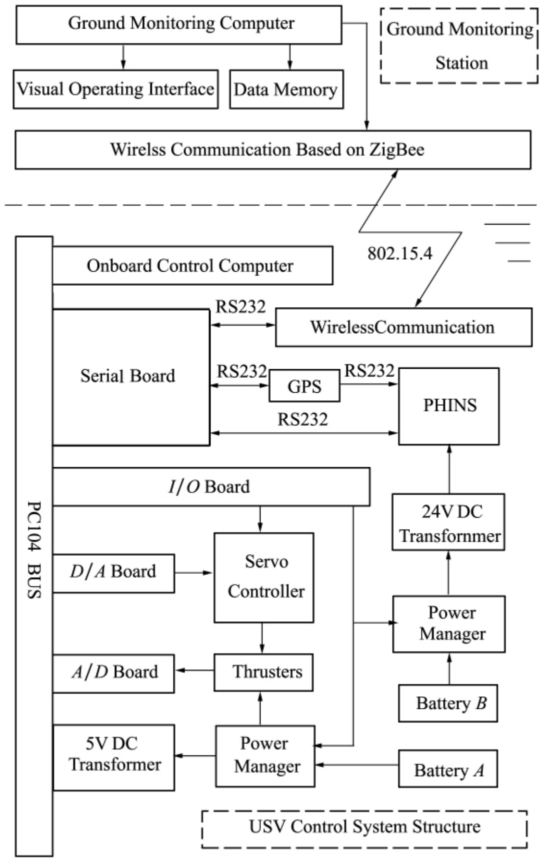


Fig. 3　System integration of NWPU USV

peller revolution. Two 24V battery packs with power managers are selected to power for the thrusters, and other equipments such as onboard computer, PHINS, GPS, modem, etc.

### 4.2　Simulation

To validate the reliability and efficiency of the identification algorithms, and estimate the errors, sufficient simulations are required before experiments. The coefficients adopted from [12] are used as true values and compared with the estimated results by EKF and LS.

The EKF and the LS are designed in two different types according to the measurement. EKF method uses velocity measurement $\boldsymbol{y} = [u, v, r]^{\mathrm{T}}$ as output vector, while LS method uses velocity and acceleration measurements $\boldsymbol{y}$ (refer equation (25)) as output vector. Without loss of generality, the circular motion is selected for the estimation. Two types of motion scenarios are reviewed for accuracy as follows:

·For EKF1, the initial state is set to be 20 for all the velocities and unknown coefficients. The same velocity and acceleration measurements are used in LS1.

·For EKF2, the initial state is set to be −20 for all the velocities and unknown coefficients. The same velocity and acceleration measurements are used in LS2.

·Fig. 4 ~ Fig. 6 compare the estimation results of the coefficients in surge equation by EKF1 and EKF2, the solid and dashed lines corresponding to the EKF1 and EKF2, respectively.

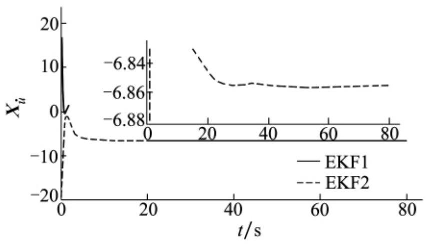


Fig. 4　Estimation results of surge coefficient $\boldsymbol{X}_{\dot u}$

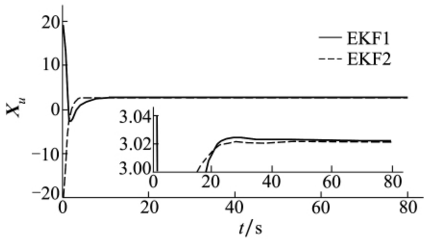


Fig. 5　Estimation results of surge coefficient $\boldsymbol{X}_u$

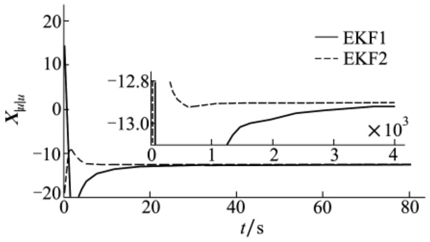


Fig. 6　Estimation results of surge coefficient $\boldsymbol{X}_{|u|u}$

As shown above, both EKF1 and EKF2 estimate the coefficients with sufficient accuracy. However, the initial state with a larger offset to true values of the coefficients leads to a slower convergence. For instance, EKF2 performs a faster convergence than EKF1 in estimating $X_{\dot u}$ and $X_{|u|u}$, since the initial state of the unknowns and its true values are both negative.

**Table 3　The steady-state errors of estimated coefficients(%)**

| Symbol | EKF1 | EKF2 | LS1 | LS2 | Average |
|---|---|---|---|---|---|
| $\boldsymbol{X}_{\dot u}$ | 0.38 | 0.32 | 4.52 | 4.72 | 2.49 |
| $\boldsymbol{X}_u$ | 0.06 | 0.07 | 2.28 | 2.49 | 1.23 |
| $\boldsymbol{X}_{\lvert u\rvert u}$ | 0.79 | 0.39 | 4.10 | 4.85 | 2.53 |
| $\boldsymbol{Y}_{\dot v}$ | 7.84 | 5.12 | 16.33 | 16.84 | 11.53 |
| $\boldsymbol{Y}_{\dot r}$ | – | – | – | – | – |
| $\boldsymbol{Y}_v$ | 5.07 | 4.38 | 8.94 | 9.41 | 6.95 |
| $\boldsymbol{Y}_r$ | 3.98 | 4.87 | 9.02 | 9.37 | 6.81 |
| $\boldsymbol{Y}_{\lvert v\rvert v}$ | 9.44 | 6.91 | 19.30 | 18.55 | 13.55 |
| $\boldsymbol{Y}_{\lvert r\rvert r}$ | 8.17 | 9.02 | 14.25 | 14.04 | 11.37 |
| $\boldsymbol{N}_{\dot v}$ | – | – | – | – | – |
| $\boldsymbol{N}_{\dot r}$ | 2.73 | 3.25 | 6.68 | 6.40 | 4.77 |
| $\boldsymbol{N}_v$ | 0.31 | 1.47 | 3.27 | 3.79 | 2.21 |
| $\boldsymbol{N}_r$ | 1.94 | 1.90 | 4.62 | 4.40 | 3.22 |
| $\boldsymbol{N}_{\lvert v\rvert v}$ | 11.72 | 9.58 | 6.88 | 6.63 | 8.70 |
| $\boldsymbol{N}_{\lvert r\rvert r}$ | 1.26 | 2.55 | 2.89 | 2.44 | 2.29 |
| Average | 4.13 | 3.83 | 7.92 | 7.99 | |

The steady-state errors of all the estimated coefficients are given in Table 3. In general, the estimated results by EKF show better performance than LS, as demonstrated in terms of the average values of estimation errors. It is mainly a result of ignorance of the interaction between different degrees caused by LS method which is based on the uncoupled model structure. A series of simulations seem to indicate that the estimated results in sway direction, by both EKF and LS, contain larger steady-state errors than other degrees, probably owing to the lack of control input in the sway direction. It has also shown that linear damping coefficients predicted by both methods have better accuracy than added mass and quadratic damping coefficients.

## 5　Conclusion

To obtain an accurate model and analyze the maneuverability and controllability of an USV, the hydrodynamic coefficients are estimated based on EKF and LS without any towing tank tests. We have addressed the detailed identification methods as well as the system integration of the NWPU USV for the task of path following control and cooperative missions. Extensive simulations have been carried out and the results clearly demonstrate that proposed schemes provide sufficient accuracy for identification of USVmodel. More precisely, it is found that in a coupled model EKF performs better than LS for identification of hydrodynamic coefficients, using only onboard sensor data. Future work will focus on the field experiments to obtain the true model parameters and to validate the feasibility of the methods further.

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