IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 8, 2018, accepted September 9, 2018, date of publication September 28, 2018, date of current version October 25, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2872779

Data-Driven Adaptive Tracking Control of Unknown Autonomous Marine Vehicles

YONGPENG WENG[1], NING WANG[1], (Senior Member, IEEE), HONGDE QIN[2], HAMID REZA KARIMI[3], (Senior Member, IEEE), AND WENHAI QI[4]

[1]College of Marine Electrical Engineering, Dalian Maritime University, Dalian 116026, China
[2]College of Shipbuilding Engineering, Harbin Engineering University, Harbin 150001, China
[3]Department of Mechanical Engineering, Politecnico di Milano, 20133 Milan, Italy
[4]School of Engineering, Qufu Normal University at Rizhao, Rizhao 276826, China

Corresponding author: Ning Wang (n.wang.dmu.cn@gmail.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 51009017, Grant 51379002, Grant 61703231, and Grant 61803063, in part by the Fund for Dalian Distinguished Young Scholars under Grant 2016RJ10, in part by the Innovation Support Plan for Dalian High-level Talents under Grant 2015R065, in part by the Stable Supporting Fund of Science and Technology on Underwater Vehicle Laboratory under Grant SXJQR2018WDKT03, and in part by the Fundamental Research Funds for the Central Universities under Grant 3132016314, Grant 3132018132, and Grant 3132018126.

ABSTRACT This paper is concerned with data-driven adaptive tracking control for unknown autonomous marine vehicles (AMVs) with uncertainties and disturbances. By deploying the data-driven technique and observer design, an equivalent data model of the AMV is firstly established. Based on the proposed data model, a novel data-driven adaptive tracking controller is designed, and the corresponding stability analysis for the closed-loop AMV system is presented theoretically. Finally, simulation studies are given to demonstrate the validity of the main results.

INDEX TERMS Autonomous marine vehicles, data-driven control, tracking control, adaptive control.

I. INTRODUCTION

In the past decades, autonomous marine vehicles (AMVs), owing to their independent planning and autonomous navigation capability, have been playing a vital role in ocean engineering, e.g., missions search, rescue, sea investigation and so on. Thus, achieving stable tracking control [1]–[4] of AMVs is an important issue in both theory and practice [5]. Unfortunately, as the AMV inevitably suffers from uncertainties and disturbances due to the harsh marine environment such as winds, waves, and ocean currents, it is not an easy task to design an efficient and reliable controller.

To deal with this complex problem, all kinds of advanced control strategies have been developed, including model-based control schemes [6]–[11] and model-free control schemes [12]–[18]. Specifically, in [19], by applying the Lyapunov's direct method, the global exponential tracking of AMVs is achieved. In [10], to deal with uncertainties and disturbances in the AMV, the sliding mode control scheme has been successfully applied into the controller design. To make the control schemes more applicable, the neural network control approaches have also been proposed to deal with the tracking control problem of the AMV in [12]–[18]. In this context, the requirement of nominal model of the AMV is omitted, but it is still an intractable problem when the system order is also unavailable. Then, the PID and fuzzy control approaches have also been utilized to deal with the tracking control problem of the AMV [20]. Unfortunately, the PID controllers cannot cope with the nonlinearity in the AMV. In addition, there exist too many parameters to be determined in the Fuzzy controllers, which is not an easy task for the control engineers.

Although much progress has been made for controller design of the AMV, there still remain certain open problems in this field that are of great theoretical and practical interest. First, a digital controller is desirable since these achievements [2], [11], [15] are mainly focus on continuous controller design, which cannot apply the widely applied digital technique in modern control engineering. Second, a controller with fewer parameters and less model information will be desirable; otherwise, it may bring considerable trouble to the controller design and its application [20]. Third, to enhance the controller's applicability, an adaptive mechanism for tracking control of positions of AMVs will also be desirable.

It is worth mentioning that the data-driven control approaches, owing to its strong robustness and model-independent property, have been applied to a variety of systems, including freeway traffic system [21], three-tank system [22], gas collector pressure system [23], [24] and so on. In light of the process data, this technique could realize adaptive control while without the requirement of model information [25]–[28]. Thus, the data-driven approach can provide a more effective strategy in dealing with the unknown AMV. However, there still exist some issues to be resolved. First, it is difficult to handle the uncertainties and disturbances with the available nonparametric dynamic linearization technique (NDLT). Second, the stability analysis will become more complicated and intractable.

Motivated by the above observations, a novel data-driven adaptive tracking control approach is proposed in this study. Unlike the available data-driven control scheme [27], the uncertainties and disturbances are considered in the established data-model. The main contributions of this paper are threefold: (i) By utilizing the NDLT and extended state observer (ESO), an equivalent data-model of the AMV is proposed; (ii) Based on the obtained data model, a tracking controller is designed such that the closed-loop AMV system is asymptotical stable; (iii) Theoretical analysis and simulation studies are presented to illustrate the effectiveness of the proposed approach.

The remainder of this study is organized as follows. In section 2, a description of the AMV system and the corresponding control objective are presented. In section 3, a novel data-driven adaptive tracking controller is developed to deal with the tracking control problem of the AMV, and the corresponding stability analysis is also given in section 3. Afterwards, simulation studies regarding the proposed controllers is conducted in section 4. Finally, in section 5, some concluding remarks are drawn to summarize this study.

II. PROBLEM STATEMENT

Consider the following AMV system [12]:

$$\dot{\boldsymbol{\eta}} = \boldsymbol{R}(\varphi)\boldsymbol{\omega} \tag{1a}$$

$$\boldsymbol{M}\dot{\boldsymbol{\omega}} = \boldsymbol{\tau} - \boldsymbol{C}(\boldsymbol{\omega})\boldsymbol{\omega} - \boldsymbol{D}(\boldsymbol{\omega})\boldsymbol{\omega} - \boldsymbol{g}(\boldsymbol{\eta}) + \boldsymbol{\tau}_d(t) \tag{1b}$$

where $\boldsymbol{\eta} = [x, y, \varphi]^T$ denotes the 3-DOF position (x, y) and heading angle φ of the vehicle in the earth-fixed frame $\{E\}$, and $\boldsymbol{\omega} = [u, v, r]^T$ denotes the surge velocity (u), sway velocity (v) and angular rate (r) of the vehicle in the body-fixed frame $\{B\}$. $\boldsymbol{\tau} = [\tau_u, \tau_v, \tau_r]^T$ denotes the control input, $\boldsymbol{g} = [g_u, g_v, g_r]^T$ denotes the vector of gravitational/buoyancy forces and moments, $\boldsymbol{\tau}_d = [\tau_{ud}, \tau_{vd}, \tau_{rd}]^T$ denotes the total disturbances induced by model uncertainties and external environmental disturbances, and $\boldsymbol{R}(\varphi)$ denotes the rotation matrix with

$$\boldsymbol{R}(\varphi) = \begin{bmatrix} \cos\varphi & -\sin\varphi & 0 \\ \sin\varphi & \cos\varphi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

Also, $\boldsymbol{M}$, $\boldsymbol{C}$, and $\boldsymbol{D}$ denote respectively the inertia matrix, the coriolis/centripetal matrix, and the damping matrix, which are totally treated as unknown in this study.

Then, applying the first-order Euler method on (1), we have

$$\boldsymbol{\eta}(k+1) = \boldsymbol{\eta}(k) + T_s\boldsymbol{R}(\varphi(k))\boldsymbol{\omega}(k) \tag{3a}$$

$$\boldsymbol{\omega}(k+1) = \boldsymbol{\omega}(k) + \boldsymbol{G}(\boldsymbol{\eta}(k), \boldsymbol{\omega}(k), \boldsymbol{\tau}(k), \boldsymbol{\tau}_d(k)) \tag{3b}$$

where T_s is the sampling time, $\boldsymbol{\eta}(k)$, $\boldsymbol{\omega}(k)$, $\boldsymbol{\tau}(k)$, and $\boldsymbol{\tau}_d(k)$ denote the measurement values at instant k, $\boldsymbol{G}(\boldsymbol{\eta}(k), \boldsymbol{\omega}(k), \boldsymbol{\tau}(k), k) = T_s\boldsymbol{M}^{-1}\{-\boldsymbol{C}(\boldsymbol{\omega}(k))\boldsymbol{\omega}(k) - \boldsymbol{D}(\boldsymbol{\omega}(k))\boldsymbol{\omega}(k) - \boldsymbol{g}(\boldsymbol{\eta}(k)) + \boldsymbol{\tau}_d(k)\boldsymbol{\tau}(k)\}$ denotes the unknown dynamics of the AMV with both uncertainties and disturbances.

Throughout this study, the AMV system (3) satisfies the following assumptions.

Assumption 1: The function $\boldsymbol{G}(\cdot)$ is smooth and nonlinear, and the partial derivative of $\boldsymbol{G}(\cdot)$ with respect to $\boldsymbol{\tau}(k)$ is continuous.

Assumption 2: The AMV system (3) is generalized Lipschitz for $\Delta\boldsymbol{\tau}(k)$, i.e., satisfying $\|\Delta\boldsymbol{\omega}(k+1) - \Delta\boldsymbol{\omega}(k)\| \leq \rho\,\|\Delta\boldsymbol{\tau}(k)\|$, where $\Delta\boldsymbol{\omega}(k+1) = \boldsymbol{\omega}(k+1) - \boldsymbol{\omega}(k)$, $\Delta\boldsymbol{\tau}(k) = \boldsymbol{\tau}(k) - \boldsymbol{\tau}(k-1)$, and ρ is a positive constant.

Remark 1: These assumptions imposed on AMV system (3) are necessary and reasonable from the practical viewpoint. Assumption 1 is a typical condition for controller design, which could be satisfied by many nonlinear systems, including AMV system. For facilitating the controller design, Assumption 2 poses a limitation on the AMV system (3), i.e., the rates of change of $\Delta\boldsymbol{\omega}(k)$ cannot go to infinity if the changes of $\Delta\boldsymbol{\tau}(k)$ is in a limited altitude. Note that Assumption 2 is also reasonable from the 'energy' viewpoint.

In this context, our objective is to develop a novel model-free adaptive decoupling controller for the unknown AMV system (3) such that the output of the AMV system (3) can asymptotically track the desired trajectory $\boldsymbol{\eta}_d(k)$.

III. MAIN RESULTS

This section will focus on the problem of data-driven adaptive tracking controller design and its corresponding stability analysis.

A. DESIGN OF THE DATA-DRIVEN ADAPTIVE TRACKING CONTROLLER

To obtain the DATC law, an equivalent data model of subsystem (3b) is firstly established.

Lemma 1: For AMV system (3) satisfying Assumptions 1 and 2, there must exist a matrix $\boldsymbol{\Pi}(k)$ such that when $\|\Delta\boldsymbol{\tau}(k)\| \neq 0$, the AMV system (3) can be transformed as

$$\Delta\boldsymbol{\omega}(k+1) = \Delta\boldsymbol{\omega}(k) + \boldsymbol{\Pi}(k)\Delta\boldsymbol{\tau}(k) \tag{4}$$

where

$$\boldsymbol{\Pi}(k) = \begin{bmatrix} \phi_{11}(k) & \phi_{12}(k) & \phi_{13}(k) \\ \phi_{21}(k) & \phi_{22}(k) & \phi_{23}(k) \\ \phi_{31}(k) & \phi_{32}(k) & \phi_{33}(k) \end{bmatrix},$$

and $\boldsymbol{\Pi}(k)$ satisfies $\|\boldsymbol{\Pi}(k)\| \leq \rho$.

Proof: From (3b), we have

$$\begin{aligned}\Delta\boldsymbol{\omega}(k+1) = \Delta\boldsymbol{\omega}(k) &+ \boldsymbol{G}(\boldsymbol{\eta}(k), \boldsymbol{\omega}(k), \boldsymbol{\tau}(k), \boldsymbol{\tau}_d(k)) \\ &- \boldsymbol{G}(\boldsymbol{\eta}(k), \boldsymbol{\omega}(k), \boldsymbol{\tau}(k-1), \boldsymbol{\tau}_d(k)) + \boldsymbol{\delta}(k)\end{aligned} \tag{5}$$

with $\boldsymbol{\delta}(k) = \boldsymbol{G}(\boldsymbol{\eta}(k), \boldsymbol{\omega}(k), \boldsymbol{\tau}(k-1), \boldsymbol{\tau}_d(k)) - \boldsymbol{G}(\boldsymbol{\eta}(k-1), \boldsymbol{\omega}(k-1), \boldsymbol{\tau}(k-1), \boldsymbol{\tau}_d(k-1))$.

Utilizing Assumptions 1-2 and mean value theorem [29], we can further have

$$\Delta\boldsymbol{\omega}(k+1) = \Delta\boldsymbol{\omega}(k) + \frac{\partial \boldsymbol{G}^*}{\partial \boldsymbol{\tau}_\lambda(k)}\Delta\boldsymbol{\tau}(k) + \boldsymbol{\delta}(k) \tag{6}$$

where

$$\frac{\partial \boldsymbol{G}^*}{\partial \boldsymbol{\tau}_\lambda(k)} = \begin{bmatrix} \frac{\partial G_1{}^*}{\partial \boldsymbol{\tau}_{\lambda 1}(k)} & \frac{\partial G_1{}^*}{\partial \boldsymbol{\tau}_{\lambda 2}(k)} & \frac{\partial G_1{}^*}{\partial \boldsymbol{\tau}_{\lambda 3}(k)} \\ \frac{\partial G_2{}^*}{\partial \boldsymbol{\tau}_{\lambda 1}(k)} & \frac{\partial G_2{}^*}{\partial \boldsymbol{\tau}_{\lambda 2}(k)} & \frac{\partial G_2{}^*}{\partial \boldsymbol{\tau}_{\lambda 3}(k)} \\ \frac{\partial G_3{}^*}{\partial \boldsymbol{\tau}_{\lambda 1}(k)} & \frac{\partial G_3{}^*}{\partial \boldsymbol{\tau}_{\lambda 2}(k)} & \frac{\partial G_3{}^*}{\partial \boldsymbol{\tau}_{\lambda 3}(k)} \end{bmatrix},$$

$\lambda \in [0, 1]$, $\boldsymbol{\tau}_\lambda(k) = [\boldsymbol{\tau}_{\lambda 1}(k), \boldsymbol{\tau}_{\lambda 2}(k), \boldsymbol{\tau}_{\lambda 3}(k)]^T$, $\boldsymbol{\tau}_{\lambda i}(k) = \lambda\boldsymbol{\tau}_i(k) + (1-\lambda)\boldsymbol{\tau}_i(k-1)$, $i = 1, 2, 3$. $\frac{\partial \boldsymbol{G}^*}{\partial \boldsymbol{\tau}_\lambda(k)}$ denotes the value of gradient vector of $\boldsymbol{G}(\cdot)$ with respect to $\boldsymbol{\tau}(k)$ at $\boldsymbol{\tau}_\lambda(k)$.

Consider an equation with numerical matrix $\boldsymbol{\chi}(k) \in R^{3\times 3}$ as

$$\boldsymbol{\delta}(k) = \boldsymbol{\chi}(k)\Delta\boldsymbol{\tau}(k) \tag{7}$$

Since $\|\Delta\boldsymbol{\tau}(k)\| \neq 0$, there must exist at least one solution $\boldsymbol{\chi}(k)$, e.g., $\boldsymbol{\chi}(k) = \boldsymbol{\delta}(k)\Delta\boldsymbol{\tau}^T(k)/(\Delta\boldsymbol{\tau}^T(k)\Delta\boldsymbol{\tau}(k))$ satisfies equation (7).

Then, by selecting $\boldsymbol{\Pi}(k) = \frac{\partial \boldsymbol{G}^*}{\partial \boldsymbol{\tau}_\lambda(k)}$ and in light of (6) and (7), equation (4) is obtained. Moreover, the inequality $\|\boldsymbol{\Pi}(k)\| \leq \rho$ can also be derived from Assumption 2.

The proof is completed. ■

In view of (4), we have

$$\boldsymbol{\omega}(k+1) = \boldsymbol{\Lambda}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{d}_{NL}(k) \tag{8}$$

where $\boldsymbol{d}_{NL}(k) = [d_{NL1}(k), d_{NL2}(k), d_{NL3}(k)]^T$ with $d_{NLi}(k) = 2\omega_i(k) - \omega_i(k-1) + \sum_{j=1}^{3}\phi_{ij}\Delta\tau_j(k) - \phi_{ii}\Delta\tau_i(k)$, $i = 1, 2, 3$, and $\boldsymbol{\Lambda}(k) = diag\{\phi_{11}(k), \phi_{22}(k), \phi_{33}(k)\}$.

To estimate $\boldsymbol{\Lambda}(k)$, a performance index function is given as

$$J(\hat{\boldsymbol{\Lambda}}(k)) = \left\|\boldsymbol{\omega}(k) - \hat{\boldsymbol{\Lambda}}(k)\Delta\boldsymbol{\tau}(k-1) - \Delta\boldsymbol{d}_{NL}(k-1)\right\|^2 + \mu\left\|\hat{\boldsymbol{\Lambda}}(k) - \hat{\boldsymbol{\Lambda}}(k-1)\right\|^2 \tag{9}$$

where $\hat{\boldsymbol{\Lambda}}(k)$ is the estimation value of $\boldsymbol{\Lambda}(k)$, μ is a positive weight coefficient.

Solving $\frac{\partial J(\hat{\boldsymbol{\Lambda}}(k))}{\partial \hat{\boldsymbol{\Lambda}}(k)} = 0$ yields

$$\hat{\boldsymbol{\Lambda}}(k) = \hat{\boldsymbol{\Lambda}}(k-1) + \frac{\kappa\Delta\boldsymbol{\tau}(k-1)}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2}[\boldsymbol{\omega}^T(k) - \hat{\boldsymbol{\Lambda}}(k-1)\Delta\boldsymbol{\tau}^T(k-1) - \boldsymbol{d}_{NL}{}^T(k-1)] \tag{10}$$

$$\hat{\phi}_{ii}(k) = \hat{\phi}_{ii}(1),\ if\ \left|\hat{\phi}_{ii}(k)\right| < \varepsilon \tag{11}$$

where $\kappa \in (0, 1)$ is a step-size constant, and ε is a small positive constants.

Let $\tilde{\boldsymbol{\Lambda}}(k) = \hat{\boldsymbol{\Lambda}}(k) - \boldsymbol{\Lambda}(k)$, then it follows from (8) that

$$\boldsymbol{\omega}(k+1) = \hat{\boldsymbol{\Lambda}}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{d}'_{NL}(k) \tag{12}$$

where $\boldsymbol{d}'_{NL}(k) = \boldsymbol{d}_{NL}(k) - \tilde{\boldsymbol{\Lambda}}(k)\boldsymbol{\tau}(k)$, which indicates the unmodeled dynamics are also regarded as disturbances.

Then, in light of the ESO strategy [30], the unknown term $\Delta\boldsymbol{d}'_{NL}(k)$ can be compensated by

$$\begin{cases} z(k+1) = \hat{\boldsymbol{\Lambda}}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{\xi}(k) \\ \boldsymbol{\xi}(k) = \boldsymbol{\xi}(k-1) + \boldsymbol{L}(\boldsymbol{\omega}(k) - z(k)) \end{cases} \tag{13}$$

where $z(k)$ denotes the estimation value of $\boldsymbol{\omega}(k)$, $\boldsymbol{\xi}(k)$ denotes the estimation value of $\boldsymbol{d}'_{NL}(k)$, and $\boldsymbol{L} = diag\{L_1, L_2, L_3\}$, $L_i \in (0, 1)$, $i = 1, 2, 3$ are positive constants.

Consequently, an equivalent data model of subsystem (3b) can be established as follows:

$$\boldsymbol{\omega}(k+1) = \hat{\boldsymbol{\Lambda}}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{\xi}(k) \tag{14}$$

with the following updating laws

$$\hat{\boldsymbol{\Lambda}}(k) = \hat{\boldsymbol{\Lambda}}(k-1) + \frac{\kappa\Delta\boldsymbol{\tau}(k-1)}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2}[\boldsymbol{\omega}^T(k) - \hat{\boldsymbol{\Lambda}}(k-1)\Delta\boldsymbol{\tau}^T(k-1) - \boldsymbol{\xi}^T(k-1)] \tag{15}$$

$$\hat{\phi}_{ii}(k) = \hat{\phi}_{ii}(1),\ if\ \left|\hat{\phi}_{ii}(k)\right| < \varepsilon \tag{16}$$

$$\boldsymbol{\xi}(k) = \boldsymbol{\xi}(k-1) + L(\omega(k) - z(k)) \tag{17}$$

where $z(k) = \hat{\boldsymbol{\Lambda}}(k-1)\Delta\boldsymbol{\tau}(k-1) + \boldsymbol{\xi}(k-1)$.

Remark 2: To obtain an appropriate and feasible adaptive law for $\hat{\boldsymbol{\Lambda}}(k)$, μ should be chosen no larger than $\|\Delta\boldsymbol{\tau}(k-1)\|$.

Then, combining with (3), we have

$$\boldsymbol{\eta}(k+2) = \boldsymbol{\eta}(k+1) + T_s\boldsymbol{R}(\varphi(k+1))\left(\hat{\boldsymbol{\Lambda}}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{\xi}(k)\right) \tag{18}$$

To obtain the model-free adaptive decoupling control law, a performance index function is selected as follows:

$$J(\boldsymbol{\tau}(k)) = \left|\boldsymbol{\eta}_d(k+2) - \boldsymbol{\eta}(k+2)\right|^2 + \lambda|\boldsymbol{\tau}(k) - \boldsymbol{\tau}(k-1)|^2 \tag{19}$$

where λ is a positive weight coefficient.

In light of (14) and solving $\frac{\partial J(\boldsymbol{\tau}(k))}{\partial \boldsymbol{\tau}(k)} = 0$, we can finally obtain the DATC law as

$$\Delta\boldsymbol{\tau}(k) = \frac{\boldsymbol{\rho}_0 T_s\hat{\boldsymbol{\Lambda}}(k)\boldsymbol{R}^T(\varphi(k+1))}{\lambda + \left\|T_s\boldsymbol{R}(\varphi(k+1))\hat{\boldsymbol{\Lambda}}(k)\right\|^2}[\boldsymbol{\eta}_r(k+2) - \boldsymbol{\eta}(k+1) - T_s\boldsymbol{R}(\varphi(k+1))\boldsymbol{\xi}(k)] \tag{20}$$

where $\boldsymbol{\rho}_0 = diag\{\rho_{01}, \rho_{02}, \rho_{03}\}$, $\rho_{0i} \in (0, 1)$, $i = 1, 2, 3$ are step-size constants.

B. STABILITY ANALYSIS

In this section, the analysis of the boundedness of the estimation error of $\boldsymbol{\Lambda}(k)$ and $\boldsymbol{\xi}(k)$, and the convergence of the tracking error are provided to demonstrate the whole stability of AMV system (3).

Theorem 1: Consider AMV system (3) under Assumptions 1 and 2. Let the AMV system (3) be written as the data model form as in (14) with $\hat{\mathbf{\Lambda}}(k)$ and $\boldsymbol{\xi}(k)$ updated by (15)–(17), then $\hat{\mathbf{\Lambda}}(k)$ and $\boldsymbol{\xi}(k)$ are bounded, provided that L_i, $i = 1, 2, 3$ are selected as $L_i \in (0, 1)$.

Proof: First, it is noticed that the initial value satisfies the conclusion.

Second, define $\tilde{\mathbf{\Lambda}}(k) = \hat{\mathbf{\Lambda}}(k) - \mathbf{\Lambda}(k)$, and suppose $\tilde{\mathbf{\Lambda}}(j)$, $\boldsymbol{\xi}(j)$ and $\boldsymbol{d}'_{NL}(j)$ are bounded with $i = 1, 2, 3$ and $j = 1, 2, \cdots, k-1$, then the following conclusions can be obtained at instant k:

For $\left|\hat{\phi}_{ii}(k)\right| \leq \varepsilon$, equation (16) indicates $\hat{\phi}_{ii}(k)$ is bounded.

Outside the bound ε, subtracting $\mathbf{\Lambda}(k)$ on both sides of (15) gives

$$\tilde{\mathbf{\Lambda}}(k) = \left(I - \frac{\boldsymbol{\eta}\Delta\boldsymbol{\tau}(k-1)\Delta\boldsymbol{\tau}^T(k-1)}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2}\right)\tilde{\mathbf{\Lambda}}(k-1) + \frac{\boldsymbol{\eta}\Delta\boldsymbol{\tau}(k-1)}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2}\tilde{\boldsymbol{\varsigma}}^T(k-1) - \Delta\mathbf{\Lambda}(k) \tag{21}$$

where $\tilde{\boldsymbol{\varsigma}}(k-1) = \boldsymbol{d}'_{NL}(k-1) - \boldsymbol{\xi}(k-1)$.

From Lemma 1, it can be concluded that $\|\Delta\mathbf{\Lambda}(k)\| \leq 2\rho$. Furthermore, according to [27], there exists a constant $d_1 \in (0, 1)$ for (21) such that

$$\left\|\tilde{\mathbf{\Lambda}}(k)\right\| < d_1\left\|\tilde{\mathbf{\Lambda}}(k-1)\right\| + \frac{\boldsymbol{\eta}\,\|\Delta\boldsymbol{\tau}(k-1)\|}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2}\|\tilde{\boldsymbol{\varsigma}}(k-1)\| + 2\rho \tag{22}$$

From [31], we have

$$\frac{\boldsymbol{\eta}\,\|\Delta\boldsymbol{\tau}(k-1)\|}{\mu + \|\Delta\boldsymbol{\tau}(k-1)\|^2} \leq \frac{\boldsymbol{\eta}}{2\sqrt{\mu}} \tag{23}$$

On the other hand, it is noticed that there exist a constant δ_1 such that

$$\|\tilde{\boldsymbol{\varsigma}}(k-1)\| \leq \delta_1 \tag{24}$$

with $j \in \{1, 2, \cdots, k-1\}$.

Therefore, it follows from (21)–(24) that

$$\begin{aligned}\left\|\tilde{\mathbf{\Lambda}}(k)\right\| &< d_1\left\|\tilde{\mathbf{\Lambda}}(k-1)\right\| + \frac{\boldsymbol{\eta}}{2\sqrt{\mu}}\delta_1 + 2\rho \\ &< \cdots < {d_1}^{k-1}\left\|\tilde{\mathbf{\Lambda}}(1)\right\| + \frac{c_1}{1-d_1}\end{aligned} \tag{25}$$

where $c_1 = \frac{\eta}{2\sqrt{\mu}}\delta_1 + 2\rho$, $i = 1, 2, 3$.

Thus, $\tilde{\mathbf{\Lambda}}(k)$ is bounded, which further indicates the boundedness of $\hat{\mathbf{\Lambda}}(k)$.

Let $\tilde{\boldsymbol{\omega}}(k) = \boldsymbol{\omega}(k) - z(k)$, $\tilde{\boldsymbol{\xi}}(k) = \boldsymbol{\xi}(k) - \boldsymbol{d}'_{NL}(k)$, then from (12) and (13), we have

$$\tilde{\boldsymbol{\omega}}(k+1) = (\boldsymbol{I} - \boldsymbol{L})\,\tilde{\boldsymbol{\omega}}(k) + \boldsymbol{d}'_{NL}(k-1) - \boldsymbol{d}'_{NL}(k) \tag{26}$$

where $\boldsymbol{I} \in R^{3\times 3}$ is the unit matrix.

Note that the boundedness of $\hat{\mathbf{\Lambda}}(k)$ could ensure the boundedness of $\boldsymbol{d}_{NL}(k)$ and $\boldsymbol{d}'_{NL}(k)$ according to (12). Thus, it is noticed that there exists a positive constant γ_0 such that

$$\max\left\|\boldsymbol{d}'_{NL}(i-1) - \boldsymbol{d}'_{NL}(i)\right\| < \gamma_0 \tag{27}$$

where $i \in \{1, 2, \cdots, k\}$.

Let $\Xi(k) = \boldsymbol{d}'_{NL}(k) - \boldsymbol{d}'_{NL}(k-1)$, then it follows from (26) and (27) that

$$\begin{aligned}\|\tilde{\boldsymbol{\omega}}(k+1)\| &\leq \left\|\boldsymbol{A}^k\tilde{\boldsymbol{\omega}}(1)\right\| + \left\|\boldsymbol{A}^{k-1}\Xi(2)\right\| + \left\|\boldsymbol{A}^{k-2}\Xi(3)\right\| \\ &\quad + \cdots + \|\boldsymbol{A}\,\Xi(k-1)\| + \|\Xi(k)\| \\ &\leq \left\|\boldsymbol{A}^k\tilde{\boldsymbol{\omega}}(1)\right\| \\ &\quad + \left(\left\|\boldsymbol{A}^{k-1}\right\| + \cdots + \|\boldsymbol{A}\| + \|\boldsymbol{I}\|\right)\gamma_0\end{aligned}$$

where $\boldsymbol{A} = \boldsymbol{I} - \boldsymbol{L}$.

Since the eigenvalues' modules of matrix $\boldsymbol{A}$ are smaller than 1, $\tilde{\boldsymbol{\omega}}(k+1)$ is bounded. Therefore, according to $\tilde{\boldsymbol{\omega}}(k+1) = \tilde{\boldsymbol{\xi}}(k)$, it can be concluded that $\boldsymbol{\xi}(k)$ is bounded.

Consequently, according to the mathematical induction method [32], the estimation value of $\mathbf{\Lambda}(k)$, and $\boldsymbol{d}'_{NL}(k)$ are bounded.

The proof is completed. ■

Before proceeding, the following proposition is given.

Proposition 1: Consider the AMV system (3) and its equivalent data model (18), and define $\bar{\boldsymbol{d}}(k) = \Delta\boldsymbol{d}_{NL}(k) - \boldsymbol{\xi}(k)$. Let $\boldsymbol{L}$ be chosen as $\boldsymbol{L} \in (0, 1)$, then the adaptive laws (15)–(17) could ensure $\bar{\boldsymbol{d}}(k)$ is bounded such that

$$\left\|\bar{\boldsymbol{d}}(k)\right\| \leq \upsilon_0 \tag{28}$$

where υ_0 is a small positive constant.

Let $\boldsymbol{e}(k) = \boldsymbol{\eta}(k) - \boldsymbol{\eta}_d(k)$ denote the tracking error of AMV system (3), then the stability analysis under the proposed DATC law are finally given as follows.

Theorem 2: Consider AMV system (3) and its equivalent data model (18). Suppose that Assumptions 1–2 and Proposition 1 hold and $\boldsymbol{\eta}_d(k)$ is bounded. Take the control input for AMV system (3) as in (20) with $\hat{\mathbf{\Lambda}}(k)$ and $\boldsymbol{\xi}(k)$ updated by (15)–(17). Then the proposed DATC law could ensure the tracking error is bounded such that

$$\lim_{k\to\infty}|e_i(k)| \leq \frac{\upsilon_1}{d_{1i}} \tag{29}$$

where υ_1 and d_{1i}, $i = 1, 2, 3$ are small positive constants.

Proof: From (3) and (8), we have

$$\boldsymbol{\eta}(k+2) = \boldsymbol{\eta}(k+1) + T_s\boldsymbol{R}(\varphi(k+1))\left(\mathbf{\Lambda}(k)\Delta\boldsymbol{\tau}(k) + \boldsymbol{d}_{NL}(k)\right) \tag{30}$$

Then, substituting (20) into (30) yields

$$\begin{aligned}\boldsymbol{\eta}(k+2) &= \boldsymbol{\eta}(k+1) + \frac{\rho_0{T_s}^2\mathbf{\Lambda}(k)\hat{\mathbf{\Lambda}}(k)}{\lambda + \left\|T_s\hat{\mathbf{\Lambda}}(k)\right\|^2} \\ &\quad\times\left(\boldsymbol{\eta}_d(k+2) - \boldsymbol{\eta}(k+1)\right) + T_s\boldsymbol{R}(\varphi(k+1))\boldsymbol{d}_{NL}(k) \\ &\quad - \frac{\rho{T_s}^2\mathbf{\Lambda}(k)\hat{\mathbf{\Lambda}}(k)}{\lambda + \left\|T_s\hat{\mathbf{\Lambda}}(k)\right\|^2}\boldsymbol{\xi}(k)\end{aligned} \tag{31}$$

Let $\boldsymbol{\varpi}(k) = \dfrac{\rho {T_s}^2 \boldsymbol{\Lambda}(k)\hat{\boldsymbol{\Lambda}}(k)}{\lambda + \left\| T_s \hat{\boldsymbol{\Lambda}}(k) \right\|^2}$, then it is noticed that

$$0 < \varpi_i(k) < \frac{\rho_i {T_s}^2 \phi_{ii}(k)\hat{\phi}_{ii}(k)}{\lambda + \left\| T_s \hat{\phi}_{ii}(k) \right\|^2} \tag{32}$$

Thus, if ρ_i and λ satisfy $\lambda > (\rho_i \rho T_s)^2/4$, then according to [23], it can be concluded that there must exist two constants d_{1i} and d_{2i} such that

$$0 < d_{1i} \leq \varpi_i(k) \leq d_{2i} < 1 \tag{33}$$

Furthermore, from Proposition 1, we can conclude that there must exists a small constant υ_1 such that

$$\left\| T_s \boldsymbol{R}(\varphi(k+1))\boldsymbol{d}_{NL}(k) - \frac{\rho {T_s}^2 \boldsymbol{\Lambda}(k)\hat{\boldsymbol{\Lambda}}(k)}{\lambda + \left\| T_s \hat{\boldsymbol{\Lambda}}(k) \right\|^2} \boldsymbol{\xi}(k) \right\| \leq \upsilon_1 \tag{34}$$

Therefore, subtracting $\boldsymbol{\eta}_d(k+2)$ on both sides of (31), we have

$$|e_i(k+2)| \leq |1 - \varpi_i(k)|\, |e_i(k+1)| + \upsilon_1 \tag{35}$$

Then, it follows from (33) that

$$|e_i(k+2)| \leq (1 - d_{1i})^{k+1} |e_i(1)| + \frac{1 - (1 - d_{1i})^{k+2}}{d_{1i}} \upsilon_1 \tag{36}$$

which further gives

$$\lim_{k \to \infty} |e_i(k)| \leq \frac{\upsilon_1}{d_{1i}} \tag{37}$$

The proof is completed. ■

IV. SIMULATION STUDIES

In this section, to further testify the effectiveness of the proposed DATC controller, the CyberShip II [33] is selected to perform the simulation. Moreover, the conventional PID controller is also selected to perform comparison analysis. The concrete parameters of the AMV system (3) are as follows:

$$\boldsymbol{M} = \begin{bmatrix} 25.8 & 0 & 0 \\ 0 & 24.6612 & 1.0948 \\ 0 & 1.0948 & 2.76 \end{bmatrix},$$
$$\boldsymbol{g}(\boldsymbol{\eta}) = 0,$$
$$\boldsymbol{\tau}_d = \begin{bmatrix} 5 + 0.1|u|^3 \\ 2 + 0.1|u|^2 \\ -0.1r^3 + \sin(v) \end{bmatrix},$$

$C_{13}(\boldsymbol{\omega}) = C_{31}(\boldsymbol{\omega}) = -24.6612v - 1.0948r$, $C_{23}(\boldsymbol{\omega}) = C_{32}(\boldsymbol{\omega}) = 25.8u$, $D_{11}(\boldsymbol{\omega}) = 0.7225 + 1.3274\,|u| + 5.8664|u|^2$, $D_{22}(\boldsymbol{\omega}) = 0.8612 + 36.2823\,|v| + 8.05\,|r|$, $D_{23}(\boldsymbol{\omega}) = -0.1079 + 0.845\,|v| + 3.45\,|r|$, $D_{32}(\boldsymbol{\omega}) = -0.1052 - 5.0437\,|v| - 0.13\,|r|$, and $D_{33}(\boldsymbol{\omega}) = 1.9 - 0.08\,|v| + 0.75\,|r|$.

In the simulation, the sampling time is 0.03s, and the simulation time is 18s. The initial conditions of the AMV system (3) are $\boldsymbol{\eta}(1) = [-0.5, 0.5, 0.5]^T$, $\boldsymbol{\omega}(1) = [0.2, 0, 0]^T$, and the desired trajectory is $\boldsymbol{\eta}_d(k) = [sin(k), cos(k), sin(k)]^T$.

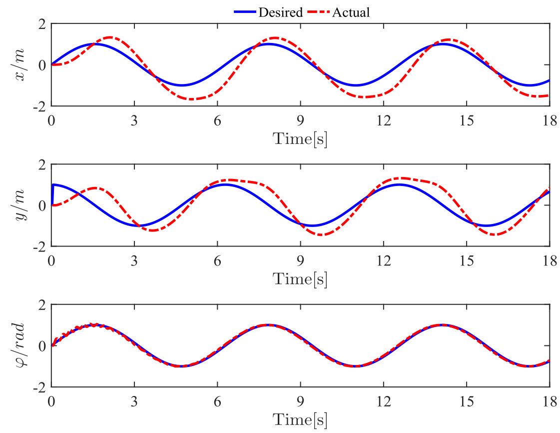

FIGURE 1. Simulation curves of position tracking under the PID control scheme.

In DATC control algorithm, κ is selected as $\kappa \in (0, 1)$, μ is selected as a positive constant according to Remark 2. L_i, $i = 1, 2, 3$ are selected as $L_i \in (0, 1)$, the initial value of $\hat{\boldsymbol{\Lambda}}(k)$ is selected according to the I/O data of the AMV system (3), ε is selected as a small positive constant, and then $\hat{\boldsymbol{\Lambda}}(k)$ will be updated by the adaptive laws (15)-(17). In light of Remark 2, it is noticed that κ and μ will greatly affect the updating speed of $\hat{\boldsymbol{\Lambda}}(k)$. The step-size constants ρ_{0i}, $i = 1, 2, 3$ in $\boldsymbol{\rho}_0$ are selected as $\rho_{0i} \in (0, 1)$, and the weight coefficient λ is selected as a positive constant. In addition, if a small $\boldsymbol{\rho}_0$ or large λ is chosen, the control force $\boldsymbol{\tau}(k)$ may not be sufficient to ensure the tracking convergence of the controlled AMV system (3). Conversely, if a large $\boldsymbol{\rho}_0$ or small λ is chosen, the control force $\boldsymbol{\tau}(k)$ will turn to be very large, and it may even cause undesirable chattering. Finally, based on the above tuning guidelines and by trail and error, the controller parameters of DATC is chosen as $\hat{\boldsymbol{\Lambda}}(1) = \hat{\boldsymbol{\Lambda}}(2) = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{bmatrix}$, $\mu = 0.1$, $\kappa = 0.8$, $\lambda = 2$, $\boldsymbol{\rho}_0 = diag\{0.8, 0.8, 0.8\}$, $\boldsymbol{L} = diag\{0.75, 0.75, 0.75\}$, $\varepsilon = 1$.

In PID control algorithm, the particle swarm optimization (PSO) algorithm to optimize the controller parameters. Specifically, all the controller parameters are firstly normalized in the range of [0.1,1], and then return to original values via anti-normalized approach. The population size is 20, and the fitness function is chosen as $Q = \sum_{k=0}^{N} \{[y_r(k+1) - y(k+1)]^2 + 0.3[u(k) - u(k-1)]^2\}$. The maximum position and the minimum position are chosen as 1 and 0.1, respectively. The initial velocities of the particles are generated randomly in the range $[-0.2, 0.2]$, the maximum velocity and minimum velocity are 0.2 and -0.2, respectively. The maximum iteration is 120, and the final optimal parameters are $K_{p1} = 0.0821$, $K_{i1} = 0.0002$, $K_{d1} = 0.1875$, $K_{p2} = 0.07989$, $K_{i2} = 0.0002$, $K_{d2} = 0.2109$, $K_{p3} = 0.0809$, $K_{i1} = 0.002$, $K_{d1} = 0.1955$. Figs. 1, 2 and 3 show the simulation results of AMV

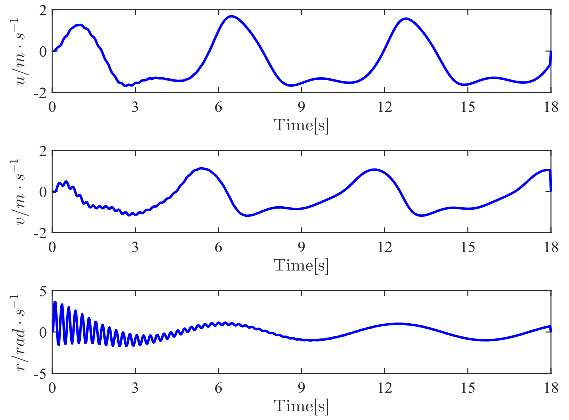

FIGURE 2. **Simulation curves of surge velocity, sway velocity and angular rate under the PID control scheme.**

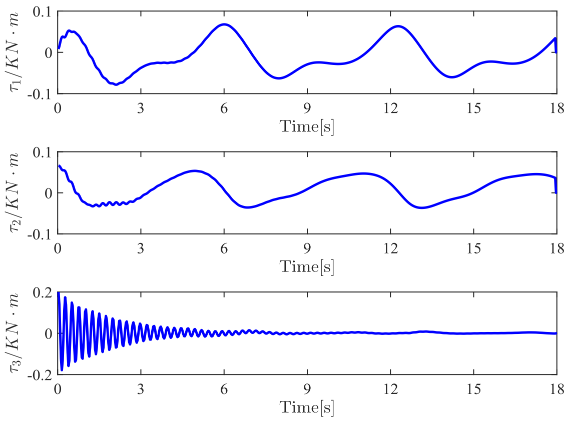

FIGURE 3. **Simulation curves of control inputs under the PID control scheme.**

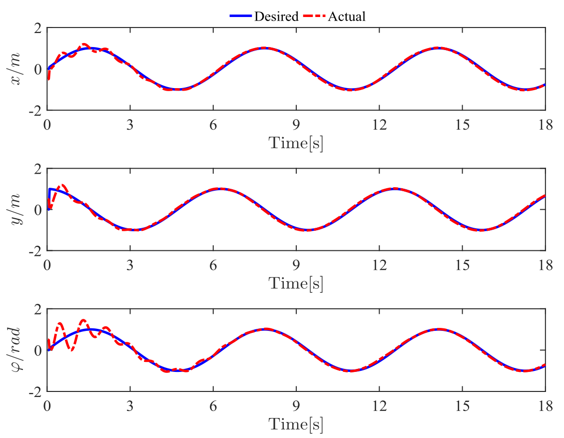

FIGURE 4. **Simulation curves of position tracking under the DATC control scheme.**

system (3) under the PID controller, and Figs. 4, 5 and 6 show the simulation results of AMV system (3) under the DATC scheme.

From the simulation results, it is noticed that the proposed DATC scheme could exhibits a better control performance than that of the PID controller. Although there are disturbances in the AMV system, the DATC approach shows

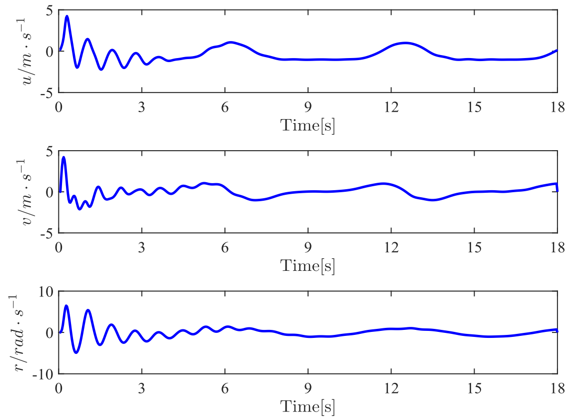

FIGURE 5. **Simulation curves of surge velocity, sway velocity and angular rate under the DATC control scheme.**

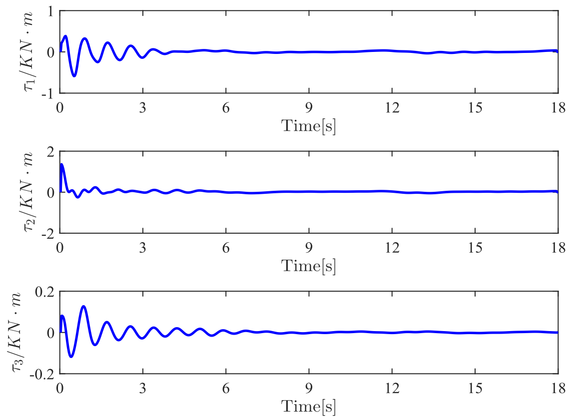

FIGURE 6. **Simulation curves of control inputs under the DATC control scheme.**

strong adaptability, where the outputs of the surface vehicle has only a small fluctuation, and it goes back to the reference trajectory quickly. For the conventional PID algorithm, the same disturbances in AMV system cause obvious changes in the outputs of the surface vehicle.

V. CONCLUSIONS

In this paper, we deal with the problem of data-driven adaptive tracking control for AMVs with uncertainties and disturbances. By applying the NDLT and ESO, the unknown nonlinear AMV system has been transformed into the data model form. Based on the obtained data model, a novel data-driven adaptive tracking controller and its corresponding stability analysis has been proposed for the closed-loop AMV system. Finally, the efficacy of the proposed approach has been demonstrated via simulation analysis.

REFERENCES

[1] N. Wang, S.-F. Su, M. Han, and W.-H. Chen, "Backpropagating constraints-based trajectory tracking control of a quadrotor with constrained actuator dynamics and complex unknowns," *IEEE Trans. Syst., Man, Cybern. Syst.*, to be published, doi: 10.1109/TSMC.2018.2834515.

[2] N. Wang, J.-C. Sun, and M. J. Er, "Tracking-error-based universal adaptive fuzzy control for output tracking of nonlinear systems with completely unknown dynamics," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 869–883, Apr. 2018.

[3] N. Wang, J.-C. Sun, M. Han, Z. Zheng, and M. J. Er, "Adaptive approximation-based regulation control for a class of uncertain nonlinear systems without feedback linearizability," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 8, pp. 3747–3760, Aug. 2018.
[4] N. Wang, C. Qian, and Z.-Y. Sun, "Global asymptotic output tracking of nonlinear second-order systems with power integrators," *Automatica*, vol. 80, pp. 156–161, Jun. 2017.
[5] N. Wang, C. Qian, J.-C. Sun, and Y.-C. Liu, "Adaptive robust finite-time trajectory tracking control of fully actuated marine surface vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 4, pp. 1454–1462, Jul. 2016.
[6] P. Ioannou and J. Sun, *Robust Adaptive Control* (Dover Books on Electrical Engineering). Upper Saddle River, NJ, USA: Prentice-Hall, 1996.
[7] Y. Gao, N. Wang, and Z. Zheng, "Disturbance observer-based trajectory tracking control of unmanned surface vehicles with unknown disturbances and input saturation," in *Proc. IEEE 36th Chin. Control Conf.*, Dalian, China, Jul. 2017, pp. 4859–4863.
[8] M. Wondergem, E. Lefeber, K. Y. Pettersen, and H. Nijmeijer, "Output feedback tracking of ships," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 2, pp. 442–448, Mar. 2011.
[9] R. Zhang, Y. Chen, Z. Sun, F. Sun, and H. Xu, "Path control of a surface ship in restricted waters using sliding mode," *IEEE Trans. Control Syst. Technol.*, vol. 8, no. 4, pp. 722–732, Jul. 2000.
[10] H. Ashrafiuon, K. R. Muske, L. C. McNinch, and R. A. Soltan, "Sliding-mode tracking control of surface vessels," *IEEE Trans. Ind. Electron.*, vol. 55, no. 11, pp. 4004–4012, Nov. 2008.
[11] N. Wang, S.-F. Su, J. Yin, Z. Zheng, and M. J. Er, "Global asymptotic model-free trajectory-independent tracking control of an uncertain marine vehicle: An adaptive universe-based fuzzy control approach," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 3, pp. 1613–1625, Jun. 2018.
[12] N. Wang and M. J. Er, "Direct adaptive fuzzy tracking control of marine vehicles with fully unknown parametric dynamics and uncertainties," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 5, pp. 1845–1852, Sep. 2016.
[13] N. Wang and M. J. Er, "Self-constructing adaptive robust fuzzy neural tracking control of surface vehicles with uncertainties and unknown disturbances," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 3, pp. 991–1002, May 2015.
[14] F. G. Harmon, A. A. Frank, and S. S. Joshi, "The control of a parallel hybrid-electric propulsion system for a small unmanned aerial vehicle using a CMAC neural network," *Neural Netw.*, vol. 18, nos. 5–6, pp. 772–780, Jul./Aug. 2005.
[15] N. Wang, S. Lv, W. Zhang, Z. Liu, and M. J. Er, "Finite-time observer based accurate tracking control of a marine vehicle with complex unknowns," *Ocean Eng.*, vol. 145, pp. 406–415, Nov. 2017.
[16] K. P. Venugopal, R. Sudhakar, and A. S. Pandya, "On-line learning control of autonomous underwater vehicles using feedforward neural networks," *IEEE J. Ocean. Eng.*, vol. 17, no. 4, pp. 308–319, Oct. 1992.
[17] S.-L. Dai, C. Wang, and F. Luo, "Identification and learning control of ocean surface ship using neural networks," *IEEE Trans. Ind. Informat.*, vol. 8, no. 4, pp. 801–810, Nov. 2012.
[18] Y. Yang and J. Ren, "Adaptive fuzzy robust tracking controller design via small gain approach and its application," *IEEE Trans. Fuzzy Syst.*, vol. 11, no. 6, pp. 783–795, Dec. 2003.
[19] Z.-P. Jiang, "Global tracking control of underactuated ships by Lyapunov's direct method," *Automatica*, vol. 38, no. 2, pp. 301–309, 2002.
[20] A. Mei, L. Baoan, and F. Zhang, "Trajectory tracking control of unmanned surface vehicle based on fuzzy control," *Metrol. Meas. Technol.*, vol. 38, no. 1, pp. 48–52, Jan. 2018.
[21] R.-H. Chi and Z.-S. Hou, "A model-free periodic adaptive control for freeway traffic density via ramp metering," *Acta Autom. Sinica*, vol. 36, no. 7, pp. 1029–1033, Jul. 2010.
[22] Z. Hou and S. Jin, "A novel data-driven control approach for a class of discrete-time nonlinear systems," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 6, pp. 1549–1558, Nov. 2011.
[23] Y. Weng and X. Gao, "Data-driven robust output tracking control for gas collector pressure system of coke ovens," *IEEE Trans. Ind. Electron.*, vol. 64, no. 5, pp. 4187–4198, May 2017.
[24] Y. P. Weng and X. W. Gao, "Data-driven sliding mode control of unknown MIMO nonlinear discrete-time systems with moving PID sliding surface," *J. Franklin Inst.*, vol. 354, no. 15, pp. 6463–6502, Oct. 2017.
[25] Z. Hou, R. Chi, and H. Gao, "An overview of dynamic-linearization-based data-driven control and applications," *IEEE Trans. Ind. Electron.*, vol. 64, no. 5, pp. 4076–4090, May 2017.
[26] Z.-S. Hou and Z. Wang, "From model-based control to data-driven control: Survey, classification and perspective," *Inf. Sci.*, vol. 235, pp. 3–35, Jun. 2013.
[27] Z. Hou and S. Jin, "Data-driven model-free adaptive control for a class of MIMO nonlinear discrete-time systems," *IEEE Trans. Neural Netw.*, vol. 22, no. 12, pp. 2173–2188, Dec. 2011.
[28] Z. Hou and Y. Zhu, "Controller-dynamic-linearization-based model free adaptive control for discrete-time nonlinear systems," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2301–2309, Nov. 2013.
[29] Q. Shen and T. Zhang, "Novel design of adaptive neural network controller for a class of non-affine nonlinear systems," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 3, pp. 1107–1116, Mar. 2012.
[30] Y. Weng and X. Gao, "Adaptive sliding mode decoupling control with data-driven sliding surface for unknown MIMO nonlinear discrete systems," *Circuits Syst. Signal Process.*, vol. 36, no. 3, pp. 969–997, Mar. 2017.
[31] B. Xuhui, H. Zhongsheng, Y. Fashan, and F. Ziyi, "Model free adaptive control with disturbance observer," *J. Control Eng. Appl. Inform.*, vol. 14, no. 4, pp. 42–49, Apr. 2012.
[32] W. Zhang, Y. Tang, Q. Miao, and J.-A. Fang, "Synchronization of stochastic dynamical networks under impulsive control with time delays," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 10, pp. 1758–1768, Oct. 2014.
[33] R. Skjetne, T. I. Fossen, and P. V. Kokotović, "Adaptive maneuvering, with experiments, for a model ship in a marine control laboratory," *Automatica*, vol. 41, no. 2, pp. 289–298, Feb. 2005.

YONGPENG WENG was born in Yingkou, Liaoning, China, in 1986. He received the B.S. degree in electrical engineering and automation from Liaoning University in 2010, and the M.S. and Ph.D. degrees in control theory and control engineering from the School of Information Science and Engineering, Northeastern University. He is currently with the School of Marine Electrical Engineering, Dalian Maritime University, Dalian, China. His research interests include data-driven adaptive control, sliding mode control, modeling of complex industry process and intelligent control, unmanned vehicles, and autonomous control.

NING WANG (S'08–M'12–SM'15) received the B.Eng. degree in marine engineering and the Ph.D. degree in control theory and engineering from Dalian Maritime University (DMU), Dalian, China, in 2004 and 2009, respectively. He is currently a Full Professor with the School of Marine Electrical Engineering, DMU. His research interests include fuzzy neural systems, machine learning, nonlinear control, self-organizing fuzzy neural modeling and control, unmanned vehicles, and autonomous control.

HONGDE QIN was born in 1976. He received the Ph.D. degree in design and construction of naval architecture and ocean structure from Harbin Engineering University. He is the Director of science and technology with the Underwater Vehicle Laboratory, Harbin Engineering University. His research interests include autonomous underwater vehicle technique, off-shore structure hydrodynamics, and ship strength analysis.

HAMID REZA KARIMI (M'06–SM'09) was born in 1976. He received the B.Sc. degree (Hons.) in power systems from the Sharif University of Technology, Tehran, Iran, in 1998, and the M.Sc. and Ph.D. (Hons.) degrees in control systems engineering from the University of Tehran, Tehran, in 2001 and 2005, respectively. He is currently a Professor of applied mechanics with the Department of Mechanical Engineering, Politecnico di Milano, Milan, Italy. His current research interests include control systems and mechatronics with applications to automotive control systems and wind energy.

WENHAI QI was born in Tai'an, Shandong, China, in 1986. He received the B.S. degree in automation and the M.S. degree from Qufu Normal University in 2008 and 2013, respectively, and the Ph.D. degree in control theory and control engineering from Northeastern University. He is currently with the School of Engineering, Qufu Normal University, Rizhao, China. His research interests include Markovian jump systems, switched systems, positive systems, and networked control systems.