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Adaptive Fuzzy Optimal Control of Multiple Autonomous Surface Vehicles with Uncertain Dynamics

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In this paper, we present an adaptive optimal control algorithm for solving the tracking control problem of multiple autonomous surface vehicles under uncertain dynamics and unknown external disturbances. The proposed control algorithm uses an adaptive dynamic programming technique with optimal compensation terms. A disturbance observer is designed to handle the problem of unknown time-varying external disturbances. It is proven that all the signals in the closed-loop system are bounded. Simulation results are provided to illustrate the effectiveness of the proposed control algorithm.

1. Introduction

In recent years, autonomous surface vehicle (ASV) research has attracted ever-increasing attention in exploring natural resources in the ocean space. An ASV has unique advantages, such as low energy cost and high intelligence, compared with traditional surface vehicles.[(1)] A solitary ASV may not suffice to deal with complex tasks in some situations.[(2)] Thus, the coordinated control of multiple ASVs has become a burgeoning research topic.[(3–6)] Zhang *et al.* investigated the event-triggered controller for maneuver control problems of multiple ASVs.[(4)] Considering environmental disturbances, limited communication resources, and input saturation, an adaptive controller is designed on the basis of a radial basis function neural network (NN). An event-triggered mechanism is adopted to decrease the frequency of information transmission and conserve communication resources. Wu *et al.* investigated the path-tracking control of an underactuated unmanned surface vehicle, considering model uncertainties and unknown disturbances by adopting a wireless network.[(6)] The research mentioned above is effective; however, these control algorithms do not consider the issue of optimal control.

Optimal control is a foundational design principle that can improve the control performance

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by minimizing the cost function.[7] In the control area of ASVs, optimal control has been widely applied to achieve the control target with less energy consumption. Given the inherent nonlinear characteristics of ASV systems, achieving optimal control for ASVs is a complex problem.[8] To handle this problem, adaptive dynamic programming (ADP) techniques are adopted.[8,9] This framework employs a reinforcement learning (RL) system to dynamically approximate the Hamilton–Jacobi–Bellman (HJB) equation.[10,11] Gao *et al.* investigated ASVs' optimal dynamic positioning problem.[12] The observer based on a fuzzy logic system (FLS) was given to handle the problem of unmeasured states of vessels. Wang *et al.* presented a data-driven RL-based controller for addressing the optimal control problem of a single ASV.[13] A model-free control method was formulated using a data-driven approach to achieve control optimality and prescribed tracking accuracy concurrently. Wang *et al.* presented an optimal control scheme for the RL-based optimal tracking control of a single ASV.[14] Unknown dead-zone input nonlinearities and unknown disturbances are considered and handled by using an NN-based identifier. These researchers can handle the optimal control problem of a single ASV; however, the optimal tracking control problem of multiple ASVs cannot be handled directly using these methods.

When an ASV operates in a sea environment, the control effectiveness of an ASV can be affected by external disturbances such as wind and waves, potentially leading to a failure to achieve the control target.[15,16] Furthermore, the issue of disturbance from external environments is a crucial factor that requires attention, and it is important to adopt disturbance rejection techniques. Thus, adaptive controllers with disturbance observers (DOs) are designed to estimate and counteract external disturbances. In recent years, some DO-based controllers have been reported.[16–20] Hu *et al.* investigated the problem of robust leader-follower synchronization navigation for ASVs.[16] The problem of unknown external disturbances is solved by adopting DOs. Using the dynamic surface control technique, Von Ellenrieder investigated the trajectory tracking control problem of ASVs.[20] Time-varying disturbances were considered and estimated by a proposed DO. These results are powerful and inspire the authors.

Motivated by the abovementioned studies, we addressed the optimal formation tracking control problem of multiple ASVs in this study. We adopted an ADP algorithm based on shipborne sensors' feedback signal. First, an adaptive controller was designed using the backstepping technique, transforming the optimal tracking control problem into an equivalent optimal regulation problem. Subsequently, an optimal compensation term was formulated using the policy iteration method. The final controller is the sum of the adaptive controller and the optimal compensation term. It was proven that the proposed controller can guarantee that all signals in the closed-loop system remain bounded. Simulation results were provided to demonstrate the effectiveness of the proposed control algorithm.

The main contribution of this work can be summarized as follows.

(1) Unlike Refs. 4–6, 21, and 22 that focused on the tracking control problem of multiple ASVs without considering optimality, we considered optimality when designing the tracking controller. Since the tracking control problem of ASVs often needs to face the tasks related to ocean transportation or deep-sea exploration, it is necessary to consider the energy-saving

issue. The control method proposed in this paper exhibits an advantage regarding energy consumption.

(2) Unlike Refs. 13 and 14, an advantage of this study is that we investigated the optimal tracking control problem of multiple ASVs. In contrast, in Refs. 13 and 14, only a single ASV's optimal tracking control problem was explored. Therefore, the control task in this paper is more challenging than in the previous studies.

The rest of this paper is organized as follows. The control problem is formulated in Sect. 2. The adaptive controller and optimal compensation term are introduced in Sects. 3.1 and 3.2, respectively. Stability analysis is provided in Sect. 3.3. Simulation results are presented in Sect. 4. Finally, conclusions are given in Sect. 5.

2. Problem Formulation

To achieve the tracking control problem of multiple ASVs, a body-fixed frame B and an earth-fixed frame E are adopted,(23,24) as shown in Fig. 1.

Considering the optimal leader-follower formation control problem of multiple ASVs, the 3 degrees of freedom (3-DOF) system with uncertain dynamics can be described as(22,23)

$$\begin{aligned} \dot{\eta}_i &= R_i(\psi_i)\nu_i \\ M_i\dot{\nu}_i &= -C_i(\nu_i)\nu_i - D_i(\nu_i)\nu_i + \Delta(\eta_i,\nu_i) + \tau_i + d_i\,, \\ i &= 1,2,\ldots,m \end{aligned} \tag{1}$$

where $\eta_i = [x_i, y_i, \psi_i]^\top$, with x_i and y_i indicating the position of an ASV in the earth-fixed frame,

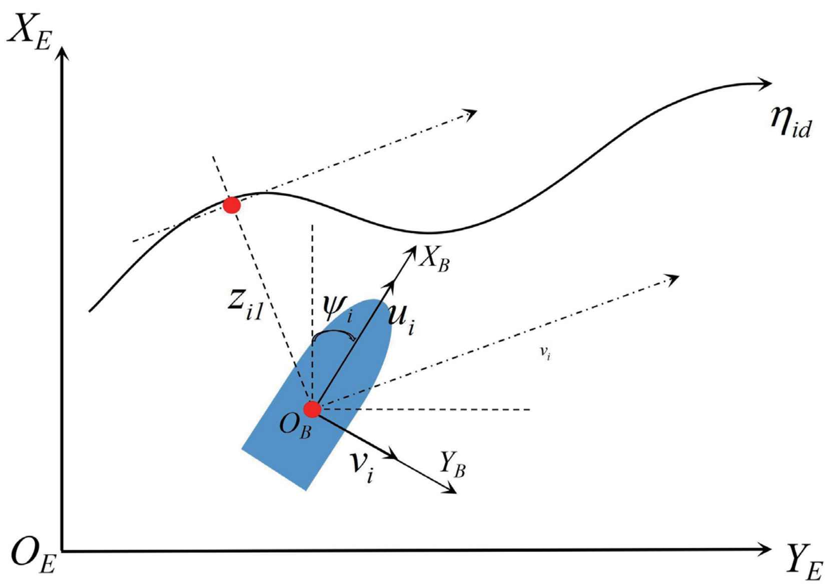


Fig. 1. (Color online) Reference frames.

ψ_i is the heading angle in the earth-fixed frame, $\nu_i = [u_i, v_i, r_i]^\top$ denotes the velocity of an ASV in the body-fixed frame, $\tau_i = [\tau_{i1}, \tau_{i2}, \tau_{i3}]^\top$ denotes the control input, and $d_i = [d_{i1}, d_{i2}, d_{i3}]^\top$ denotes the unknown time-varying external disturbance. Assume that the time derivative of unknown external disturbance d_i is bounded, i.e., $\dot{d}_i \le d_{im}$, where d_{im} is bounded. $\ddot{A}(\eta_i, \nu_i) \in \mathbb{R}^{3\times1}$ denotes the uncertain dynamics. $R_i(\psi_i) \in \mathbb{R}^{3\times3}$ is the rotation matrix from the earth-fixed frame to the body-fixed frame, which is given as

$$R_i(\psi_i) = \begin{bmatrix} \cos(\psi_i) & -\sin(\psi_i) & 0 \\ \sin(\psi_i) & \cos(\psi_i) & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

$M_i \in \mathbb{R}^{3\times3}$ is the inertia matrix, including the hydrodynamially added inertia, $D_i(\nu_i) \in \mathbb{R}^{3\times3}$ is the damping matrix, and $C_i(\nu_i) \in \mathbb{R}^{3\times3}$ is a matrix of the centripetal and Coriolis terms. Readers can check related references to find the details of these three matrices and the parameters inside.[12]

From Eq. (1), we can obtain the following equation:

$$\begin{aligned} &\dot{\eta}_i = \upsilon_i \\ &\dot{\upsilon}_i = f_i(\eta_i, \upsilon_i) + R_i(\psi_i) M_i^{-1}(\tau_i + d_i), \\ &i = 1, 2, \ldots, m \end{aligned} \tag{3}$$

where

$$\upsilon_i = R_i(\psi_i)\nu_i \tag{4}$$

and

$$f_i(\eta_i, \upsilon_i) = R_i(\psi_i) M_i^{-1}\left(-C_i(\nu_i)\nu_i - D_i(\nu_i)\nu_i + \Delta(\eta_i, \upsilon_i)\right) + \dot{R}_i(\psi_i)\nu_i . \tag{5}$$

Since $\Delta(\eta_i, \upsilon_i)$ is unknown, we cannot directly obtain $f_i(\eta_i, \upsilon_i)$. Therefore, an FLS is adopted to obtain $\hat{f}_i(\eta_i, \upsilon_i)$, an approximation of $f_i(\eta_i, \upsilon_i)$.

3. Controller Design

3.1 Design process for the adaptive controller

The proposed adaptive controller is designed on the basis of the backstepping technique. First, the change of coordinates is given as

$$z_{i1} = \eta_i - \eta_{id} , \tag{6}$$

$$z_{i2} = \upsilon_i - \alpha_i \, , \tag{7}$$

where $\eta_{id} = \eta_d + R_i(\psi_i)p_i$; $\eta_d = \left[x_d, y_d, \psi_d\right]^\top$ is the reference signal of the leader. α_i is the virtual controller for design purpose. $p_i = \left[p_{ix}, p_{iy}, 0\right]^\top$; p_{ix} and p_{iy} denote the relative position between the ith ASV and the leader in the X_E and Y_E directions, respectively. We define α_i^a as the adaptive virtual control and α_i^* as the optimal compensation term, where the actual control is composed of these two terms, i.e., $\alpha_i = \alpha_i^a + \alpha_i^*$.

From Eq. (16), we can obtain the time derivative of z_{i1} as

$$\begin{aligned} \dot{z}_{i1} &= \dot{\eta}_i - \dot{\eta}_{id} \\ &= z_{i2} + \alpha_i^a + \alpha_i^* - \dot{\eta}_{id} \, . \end{aligned} \tag{8}$$

To obtain the control objective, consider the following Lyapunov candidate:

$$V_{i1} = \frac{1}{2} z_{i1}^\top z_{i1} \, . \tag{9}$$

We can obtain the time derivative of V_{i1} as

$$\dot{V}_{i1} = z_{i1}^\top \left(z_{i2} + \alpha_i^a + \alpha_i^* - \dot{\eta}_{id} \right) . \tag{10}$$

The adaptive controller α_i^a can be designed as

$$\alpha_i^a = -r_{i1} z_{i1} + \dot{\eta}_{id} \, , \tag{11}$$

where $r_{i1} = \mathrm{diag}(r_{i11}, r_{i12}, r_{i13})$ is the positive design parameter vector. Thus, we can obtain

$$\dot{V}_{i1} = -r_{i1} z_{i1}^\top z_{i1} + z_{i1}^\top z_{i2} + z_{i1}^\top \alpha_i^* \, . \tag{12}$$

The time derivative of z_{i2} can be expressed as

$$\dot{z}_{i2} = f_i\left(\eta_i, \upsilon_i\right) + R_i\left(\psi_i\right) M_i^{-1}\left(\tau_i + d_i\right) - \dot{\alpha}_i \, . \tag{13}$$

To handle the unknown dynamic of $f_i(\eta_i, \upsilon_i)$, an FLS is adopted; one has

$$f_i\left(\eta_i, \upsilon_i\right) = \theta_i^* \varphi_i\left(\eta_i, \upsilon_i\right) + \varepsilon_i \, . \tag{14}$$

ε_i denotes the minimum approximation error, i.e., $\|\varepsilon_i\| \le \varepsilon_{dm}$, where $\varepsilon_{im} \in \mathbb{R}^{3\times 3}$ is a constant matrix. We can obtain the approximation of $f_i(\eta_i, \upsilon_i)$ as

$$\hat{f}_i(\eta_i, \upsilon_i) = \hat{\theta}_i \varphi_i(\eta_i, \upsilon_i). \tag{15}$$

To handle the problem of external unknown disturbance, a DO is given; we define the auxiliary vector q_i as

$$q_i = d_i - K_i \upsilon_i, \tag{16}$$

where $q_i = [q_{i1}, q_{i2}, q_{i3},]^\top$, and $K_i \in \mathbb{R}^{3\times 3}$ is a positive definite design matrix. The time derivative of q_i can be described as

$$\dot{q}_i = \dot{d}_i - K_i\left(f_i(\eta_i, \upsilon_i) + R_i(\psi_i) M_i^{-1}(\tau_i + q_i + K_i \nu_i)\right). \tag{17}$$

Since d_i is unknown, q_i is also unknown. We can obtain the approximation of q_i using the following equation:

$$\dot{\hat{q}}_i = -K_i\left(\hat{f}_i(\eta_i, \upsilon_i) + R_i(\psi_i) M_i^{-1}(\tau_i + q_i + K_i \upsilon_i)\right). \tag{18}$$

Thus, we can obtain the estimation of d_i as

$$\hat{d}_i = \hat{q}_i + K_i \upsilon_i. \tag{19}$$

We can obtain $\tilde{d}_i = d_i - \hat{d}_i = \tilde{q}_i$; the time derivative of $\tilde{q}_i$ can be described as

$$\dot{\tilde{q}}_i = \dot{d}_i - K_i \tilde{\theta}_i \varphi_i(\eta_i, \upsilon_i) - K_i R_i(\psi_i) M_i^{-1}(\psi_i) \tilde{q}_i. \tag{20}$$

We design the following Lyapunov function as

$$V_{i2} = V_{i1} + \frac{1}{2} z_{i2}^\top z_{i2} + \frac{1}{2} \tilde{\theta}_i^\top \tilde{\theta}_i + \frac{1}{2} \tilde{q}_i^\top \tilde{q}_i. \tag{21}$$

Using the fact $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$, we can obtain the following equation:

$$\begin{aligned} \dot{V}_{i2} &= \dot{V}_{i1} + z_{i2}^\top \dot{z}_{i2} + \tilde{\theta}_i^\top \dot{\tilde{\theta}}_i + \tilde{q}_i^\top \dot{\tilde{q}}_{\boldsymbol{i}} \\ &= \dot{V}_{i1} + z_{i2}^\top \left(f_i(\eta_i, \upsilon_i) + R_i(\psi_i) M_i^{-1}(\tau_i + d_i) - \dot{\alpha}_i\right) - \tilde{\theta}_i^\top \dot{\hat{\theta}}_i \\ &\quad + \tilde{q}_i^\top \left(\dot{d}_i - K_i \tilde{\theta}_i \varphi_i(\eta_i, \upsilon_i) - K_i R_i(\psi_i) M_i^{-1} \tilde{q}_i\right). \end{aligned} \tag{22}$$

According to Young's inequality, we can obtain

$$\tilde{q}_i \dot{d}_i \leq \frac{1}{2} \| \widetilde{q_i} \|^2 + \frac{1}{2} d_{im}^2 \tag{23}$$

and

$$\tilde{q}_i^\top K_i \tilde{\theta}_i \varphi_i \left(\eta_i, \upsilon_i\right) \leq \frac{1}{2} \| \widetilde{q_i} \|^2 + \frac{1}{2} K_i^2 \varphi_{im}^2 \| \tilde{\theta}_i \|^2 . \tag{24}$$

We define $h_i\left(Z_{i2}\right) \triangleq f_i\left(\eta_i, \upsilon_i\right) - f_i\left(\alpha_i\right)$, where $Z_{i2} = \left[\eta_i, \alpha_i\right]^\top$; one has

$$\begin{aligned} \dot{V}_{i2} \leq \dot{V}_{i1} &+ z_{i2}^\top \Big(h_i\left(Z_{i2}\right) + \hat{\theta}_i \varphi_i\left(\alpha_i\right) + \tilde{\theta}_i \varphi_i\left(\alpha_i\right) + \varepsilon_i + R_i\left(\psi_i\right) M_i^{-1} \left(\tau_i^a + \tau_i^* + d_i\right) - \dot{\alpha}_i \Big) \\ &- \tilde{\theta}_i^\top \dot{\hat{\theta}}_i - \Big(K_i R_i M_i^{-1} \left(\psi_i\right) - 1 \Big) \| \widetilde{q_i} \|^2 + \frac{1}{2} d_{im}^2 + \frac{1}{2} K_i^2 \varphi_{im}^2 \| \tilde{\theta}_i \|^2 . \end{aligned} \tag{25}$$

We can design the adaptive controller and adaptive law as

$$\tau_i^a = M_i R_i^\top \left(\psi_i\right) \Big(-z_{i1} - z_{i2} - r_{i2} z_{i2} - \hat{\theta}_i \varphi_i\left(\alpha_i\right) + \dot{\alpha}_i \Big) - \hat{q}_i - K_i \upsilon_i \tag{26}$$

and

$$\dot{\hat{\theta}}_i = z_{i2}^\top \varphi_i\left(\alpha_i\right) - \theta_i - \theta_i \| \theta_i \|^2 , \tag{27}$$

where r_{i2} = diag(r_{i21}, r_{i22}, r_{i23}) is the positive design parameter vector. According to Young's inequality, we can obtain the following equations:

$$z_{i2}^\top \varepsilon_i \leq \frac{1}{2} z_{i2}^\top z_{i2} + \frac{1}{2} \varepsilon_{im}^2 , \tag{28}$$

$$\tilde{\theta}_i^\top \hat{\theta}_i \leq -\frac{1}{2} \| \tilde{\theta}_i \|^2 + \frac{1}{2} \| \theta_i^* \|^2 , \tag{29}$$

and

$$\tilde{\theta}_i^\top \hat{\theta}_i \| \theta_i \|^2 \leq -\frac{1}{10} \| \tilde{\theta}_i \|^4 + \frac{1}{2} \| \theta_i^* \|^4 . \tag{30}$$

Thus, we can obtain

$$\begin{aligned}\dot{V}_{i2} \le& -\gamma_i \| Z_i\|^2 - \frac{1}{10}\| \tilde{\theta}_i\|^4 - (\frac{1}{2} - \frac{1}{2}K_i^2\varphi_{im}^2)\| \tilde{\theta}_i\|^2 \\ &-(K_i R_i(\psi_i)M_i^{-1} - \frac{1}{2}R_i(\psi_i)M_i^{-1}M_i R_i^{\top}(\psi_i) - 1)\|\widetilde{q_i}\|^2 \\ &+\frac{1}{2}\| \theta_i^*\|^2 + \frac{1}{2}\| \theta_i^*\|^4 + \frac{1}{2}\varepsilon_{im}^2 + \frac{1}{2}d_{im}^2 \\ &+Z_i^{\top}\left(F_i(Z_i) + \begin{bmatrix} I_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & R_i(\psi_i)M_i^{-1}\end{bmatrix}\begin{bmatrix}\alpha^{*\top} \\ \tau^{*\top}\end{bmatrix}\right),\end{aligned} \tag{31}$$

where $F_i\left(Z_i\right) = \left[0_{3\times3}, h_i\left(z_{i2}\right)\right]^{\top}$, $\gamma_i = \left[r_{i1}^{\top}, r_{i2}^{\top}\right]^{\top}$, $Z_i = \left[z_{i1}^{\top}, z_{i2}^{\top}\right]^{\top}$.

$$\dot{Z}_i = Z_i^{\top}\left(F_i\left(Z_i\right) + \begin{bmatrix} I_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & R_i\left(\psi_i\right)M_i^{-1}\end{bmatrix}U_i^*\right), \tag{32}$$

where $U_i^* = \left[\alpha_i^{*\top}, \tau_i^{*\top}\right]^{\top}$. From Eqs. (31) and (32), it can be seen that when the controller U_i^* stabilizes the system [Eq. (32)], $\dot{Z}_i$ (and $\dot{z}_{i1}$) becomes negative.(25–27) Therefore, $\dot{V}_{i2}$ becomes less than zero, which shows that all the error signals in the closed-loop system are uniformly ultimately bounded (UUB). In the following section, τ_i^* will be designed to stabilize the system [Eq. (32)] optimally.

3.2 Design process for optimal compensation term

Consider the following system

$$\dot{Z}_i = F_i\left(Z_i\right) + G_i U_i^*, \tag{33}$$

where $F_i\left(Z_i\right) = \left[0_{3\times3}, h_i\left(Z_{i2}\right)\right]^{\top}$ and $G_i = \mathrm{diag}\left(I_{3\times3}, R_i M_i^{-1}\left(\psi_i\right)\right)$. The cost function is described as

$$J_i = \int_{t0}^{\infty} r_i\left(Z_i\left(t\right)U_i^*\left(t\right)\right)dt, \tag{34}$$

where $r_i\left(Z_i, U_i^*\right) = Q_i\left(Z_i\right) + U_i^{*\top}R_i U_i^*$, $Q_i\left(Z_i\right) \in \mathbb{R}$ is a positive semidefinite penalty function and $R_i = R_i^{\top} \ge 0$ penalizes and controls input. We define a Hamiltonian function as

$$H_i\left(Z_i, U_i^{'}\right) = r_i\left(Z_i, U_i^{'}\right) + \left(\nabla J_i\left(Z_i\right)\right)^{\top}\left(F_i\left(Z_i\right) + G_i U_i^{'}\right), \tag{35}$$

where $U_i^{'}$ is associated admissible control and $\nabla J_i\left(Z_i\right)$ is the gradient of $J_i\left(Z_i\right)$ about Z_i. The optimal controller $U_i^*\left(Z_i\right)$ can be obtained by applying the condition $\partial H_i\left(Z_i, U_i^{'}\right) / \partial U_i^{'} = 0$; one has

$$U_i^*(Z_i) = -\frac{1}{2} R_i^{-1} G_i^\top \nabla J_i^*(Z_i), \tag{36}$$

where $\nabla J_i^*(Z_i)$ denotes the gradient of $J_i^*(Z_i)$ about Z_i. The HJB equation can be described as

$$Q_i(Z_i) + \left(\nabla J_i^*(Z_i)\right)^\top F(Z_i) - \frac{1}{4}\left(\nabla J_i^*(Z_i)\right)^\top G_i R_i^{-1} \left(\nabla J_i^*(Z_i)\right) = 0 \tag{37}$$

with $J_i^*(0) = 0$.

To obtain the approximation of the optimal cost function, an FLS is designed as

$$J_i^*(Z_i) = \theta_{ib}^{*\top} \varphi_{ib}(Z_i) + \varepsilon_{ib}, \tag{38}$$

where θ_{ib}^* is the ideal parameter, $\varphi_{ib}(Z_i)$ is the fuzzy basis function, and ε_{ib} is the fuzzy minimum approximation error. The gradient of the optimal cost function is

$$\partial J_i^*(Z_i) / \partial_i Z_i = \nabla \varphi_{ib}^\top (Z_i) \theta_{ib}^* + \nabla \varepsilon_{ib}, \tag{39}$$

where $\nabla \varphi_i^\top (Z_i)$ and $\nabla \varepsilon_{ib}$ are the gradients of $\varphi_{ib}^\top (Z_i)$ and ε_{ib}, respectively. The optimal controller and the Hamiltonian function can be expressed as

$$U_i^*(Z_i) = -\frac{1}{2} R_i^{-1} \left(\nabla \varphi_{ib}^\top (Z_i) \theta_{ib}^* + \nabla \varepsilon_{ib}\right), \tag{40}$$

$$\begin{aligned} H_i\left(Z_i, \theta_{ib}^*\right) = Q_i(Z_i) + \theta_{ib}^{*\top} \left(\nabla \varphi_{ib}^\top (Z_i)\right)^\top H_i(Z_i) + \varepsilon_{iHJB} \\ - \frac{1}{4} \theta_{ib}^{*\top} \left(\nabla \varphi_{ib}^\top (Z_i)\right)^\top G_i R_i^{-1} G_i^\top \nabla \varphi_{ib}^\top (Z_i) \theta_{ib}^*. \end{aligned} \tag{41}$$

We can obtain the following equation:

$$\varepsilon_{i\mathrm{HJB}} = \left(\nabla \varepsilon_{ib}\right)^\top \left(F_i(Z_i) + G_i U_i^*\right) + \frac{1}{4} \left(\nabla \varepsilon_{ib}\right)^\top G_i R_i^{-1} G_i^\top \nabla \varepsilon_{ib}. \tag{42}$$

We can obtain the approximation of the cost function by an FLS, which is described as

$$\hat{J}_i(Z_i) = \hat{\theta}_{ib}^\top \varphi_{ib}(Z_i), \tag{43}$$

where $\hat{\theta}_{ib}$ is the approximation of θ_{ib}^*. The estimation of the optimal controller can be rewritten as

$$\widehat{U_i}^{*}(Z_i) = -\frac{1}{2} R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \hat{\theta}_{ib}. \tag{44}$$

We can obtain the approximate Hamiltonian function as

$$\begin{aligned} \hat{H}_i\left(Z_i, \hat{\theta}_{ib}\right) = {} & Q_i(Z_i) + \theta_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \widehat{F}_i\left(Z_i \mid \Theta_i\right) \\ & -\frac{1}{4} \hat{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_i^{\top}(Z_i) \theta_{ib}, \end{aligned} \tag{45}$$

where $\widehat{F}_i\left(Z_i \mid \hat{\theta}_i\right) = \left[\hat{f}_{i1}\left(z_{i1} \mid \theta_{i1}\right), f_{i2}\left(z_{i2} \mid \theta_{i2}\right), \ldots, f_{in}\left(z_{in} \mid \hat{\theta}_{in}\right)\right]^{\top}$,
$\hat{f}_{i1}\left(z_{i1} \mid \hat{\theta}_{i1}\right) = \hat{f}_{i1}\left(x_{i1} \mid \theta_{i1}\right) - f_{i1}\left(x_{i1d} \mid \theta_{i1}\right)$, $\hat{f}_{ij}\left(z_{ij} \mid \hat{\theta}_{ij}\right) = f_{ij}\left(x_{ij} \mid \hat{\theta}_{ij}\right) - f_{ij}\left(x_{ijd} \mid \theta_{ij}\right)$,
$j = 2, 3, \ldots, n$. We choose the parameter updating law of $\hat{\theta}_{ib}$ as

$$\begin{aligned} \dot{\hat{\theta}}_{ib} = {} & -\left[\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \widehat{F}_i\left(Z_i \hat{\theta}_i\right) - \frac{1}{2}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \theta_{ib}\right] \\ & \times\left[Q_i(Z_i) + \hat{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \widehat{F}_i\left(Z_i \mid \Theta_i\right)\right. \\ & \left. -\frac{1}{4} \hat{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \theta_{ib}\right]. \end{aligned} \tag{46}$$

We define $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$ as the estimation error of the optimal cost function parameter. We can obtain

$$\begin{aligned} \hat{H}_i\left(Z_i, \hat{\theta}_{ib}\right) = {} & \frac{1}{2} \tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \theta_{ib}^{*} - \tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \tilde{F}_i(Z_i) \\ & -\frac{1}{4} \tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \tilde{\theta}_{ib} - \varepsilon_{i\mathrm{HJB}}. \end{aligned} \tag{47}$$

The error dynamics of Eq. (45) can be written as

$$\begin{aligned} \dot{\tilde{\theta}}_{ib} = {} & -\left[\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \dot{Z}_i - \left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \widetilde{F}_i(Z_i) + \left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \tilde{\theta}_{ib}\right. \\ & \left. + \frac{1}{2}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varepsilon_{ib}(Z_i)\right] \\ & \times\left[\tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \dot{Z}_i + \hat{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} \widetilde{F}_i(Z_i)\right. \\ & + \frac{1}{4} \tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varphi_{ib}^{\top}(Z_i) \tilde{\theta}_{ib} \\ & \left. + \frac{1}{2} \tilde{\theta}_{ib}^{\top}\left(\nabla \varphi_{ib}^{\top}(Z_i)\right)^{\top} G_i R_i^{-1} G_i^{\top} \nabla \varepsilon_{ib}(Z_i) + \varepsilon_{i\mathrm{HJB}}\right], \end{aligned} \tag{48}$$

where $\tilde{F}_i(Z_i) = F_i(Z_i) - \hat{F}_i(Z_i \mid \hat{\theta}_i)$.

3.3 Stability analysis

Theorem 1: For multiple marine vessel systems [Eq. (1)], the adaptive parameter is determined by Eq. (27), the adaptive controller is defined by Eq. (26), the optimal compensation term is provided by Eq. (44), and the updated law for the cost function is specified by Eq. (46). By selecting the design parameters appropriately, the entire control scheme ensures the boundedness of all signals in the closed-loop system, and the system outputs can optimally track the reference signal.

Proof: Consider the following Lyapunov function:

$$V_i = \frac{1}{2} z_{i1}^\top z_{i1} + \frac{1}{2} z_{i2}^\top z_{i2} + \frac{1}{2} \tilde{\theta}_i^\top \tilde{\theta}_i + \frac{1}{2} \tilde{\theta}_{ib}^\top \tilde{\theta}_{ib} + \frac{1}{2} \tilde{q}_i^\top \tilde{q}_i \,. \tag{49}$$

We can obtain

$$\dot{V}_i = z_{i1}^\top \dot{z}_{i1} + z_{i2}^\top \dot{z}_{i2} + \tilde{\theta}_i^\top \dot{\tilde{\theta}}_i + \tilde{\theta}_{ib}^\top \dot{\tilde{\theta}}_{ib} + \frac{1}{2} \tilde{q}_i^\top \dot{\tilde{q}}_i \,. \tag{50}$$

From Eqs. (46) and (48), we can obtain

$$\begin{aligned}
\tilde{\theta}_{ib}^\top \dot{\tilde{\theta}}_{ib} = \Bigg[& -\tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top \dot{Z}_i \\
& + \tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top \tilde{F}_i(Z_i) - \tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top G_i R_i^{-1} G_i^\top \nabla \varphi_{ib}^\top (Z_i) \tilde{\theta}_{ib} \\
& - \frac{1}{2} \tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top G_i R_i^{-1} G_i^\top \nabla \varepsilon_{ib}(Z_i) \Bigg] \\
& \times \Bigg[\tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top \dot{Z}_i + \hat{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top \tilde{F}_i(Z_i) \\
& + \frac{1}{4} \tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top G_i R_i^{-1} G_i^\top \nabla \varphi_{ib}^\top (Z_i) \tilde{\theta}_{ib} \\
& + \frac{1}{2} \tilde{\theta}_{ib}^\top \left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top G_i R_i^{-1} G_i^\top \nabla \varepsilon_{ib}(Z_i) + \left(\nabla \varepsilon_{ib}(Z_i) \right)^\top \left(F_i(Z_i) + G_i U_i^* \right) \\
& + \frac{1}{4} \left(\nabla \varepsilon_{ib}(Z_i) \right)^\top G_i R_i^{-1} G_i^\top \nabla \varepsilon_{ib}(Z_i) \Bigg].
\end{aligned} \tag{51}$$

Assume that $\left(\nabla \varphi_{ib}^\top (Z_i) \right)^\top R_i^{-1} \nabla \varphi_{ib}^\top (Z_i) \le \pi_{i5}$, $F_i(Z_i) + U_i^* \le c_i \sqrt{Z_i}$, $\nabla \varepsilon_i(Z_i) \le \varepsilon_{ibm}$, $\nabla \varphi_{ib}^\top (Z_i) \le \varphi_{im}$, where ℓ_{i2}, c_i, ε_{ibm}, and φ_{im} are positive constants. We can obtain

$$\dot{V}_i \le -\ell_{i1} Z_i^2 + \ell_{i2} Z_i - \ell_{i3} \tilde{\theta}_i^4 + \ell_{i4} \tilde{\theta}_i^2 - \ell_{i5} \tilde{\theta}_{ib}^4 + \ell_{i6} \tilde{\theta}_{ib}^2 - \ell_{i7} \tilde{q}_i^2 + \ell_{i8} \,, \tag{52}$$

where

$$\ell_{i1} = \gamma_i - \frac{11}{4}c_i^4 - \frac{1}{2}c_i^4 \varepsilon_{ibm}^4 , \tag{53}$$

$$\ell_{i2} = 2c_i^2 \varepsilon_{ibm}^2 , \tag{54}$$

$$\ell_{i3} = \frac{1}{10} - \frac{7}{2}\varepsilon_{im}^4 , \tag{55}$$

$$\ell_{i4} = \frac{1}{4}S_{im}^2 + 2\theta_{ib}^* \varepsilon_{im}^4 - \frac{1}{2}, \tag{56}$$

$$\ell_{i5} = \frac{1}{4}\pi_{i5}^2 - \frac{99}{32}\varphi_{im}^4 G_i^4 R_i^{-12} - \frac{77}{16}\varphi_{im}^4 , \tag{57}$$

$$\ell_{i6} = \frac{3}{8}\varphi_{im}^2 G_i^4 R_i^{-12} \varepsilon_{ibm}^2 + \frac{1}{8}\varphi_{im}^2 G_i^4 R_i^{-12} , \tag{58}$$

$$\ell_{i7} = K_i R_i(\psi_i) M_i^{-1}(\psi_i) - \frac{1}{2} - 2K_i^2 \varphi_{im}^2 - \frac{1}{2}A_i , \tag{59}$$

$$\begin{aligned} \ell_{i8} = \; & \frac{3}{32}G_i^8 R_i^{-14} \varepsilon_{ibm}^4 + \frac{3}{32}G_i^4 R_i^{-12} \varepsilon_{ibm}^4 + \frac{1}{2}\varepsilon_{im} \\ & + \frac{1}{2}d_{im}^2 + \frac{1}{2}\| \theta_i^* \|^2 + \frac{1}{2}\| \theta_i^* \|^4 . \end{aligned} \tag{60}$$

If the following equations hold:

$$Z_i > \frac{-\ell_{i2} + \sqrt{\ell_{i2}^2 + 4\ell_{i1}\ell_{i8}}}{2\ell_{i1}} \tag{61}$$

or

$$\tilde{\theta}_i > \sqrt{\frac{-\ell_{i4} + \sqrt{\ell_{i4}^2 + 4\ell_{i3}\ell_{i8}}}{2\ell_{i3}}} \tag{62}$$

or

$$\tilde{W}_i > \sqrt{\frac{-\ell_{i6} + \sqrt{\ell_{i6}^2 + 4\ell_{i5}\ell_{i8}}}{2\ell_{i5}}} \tag{63}$$

or

$$\tilde{q}_i > \sqrt{\frac{\ell_{i8}}{\ell_{i7}}}. \tag{64}$$

We can get $\dot{V}_{i3} < 0$. Thus, it can be concluded that all the signals in the closed-loop system are bounded.

4. Simulation

In the simulation part, a multiple-ASV system consisting of three ASVs is adopted, named ASV_1, ASV_2, and ASV_3. The details of the simulation model can be found in Ref. 28. The initial positions of the three ASVs are $x_1(0) = 0$, $y_1(0) = 0.7$, $\psi_1(0) = 0$, $x_2(0) = -0.5$, $y_2(0) = -0.5$, $\psi_2(0) = 0$, and $x_3(0) = 0.5$, $y_3(0) = -0.5$, $\psi_3(0) = 0$, respectively. The desired tracking signal of the leader is chosen as $\eta_0 = \left[10\sin\left(0.02t\right), 10(1-\cos\left(0.02t\right), 0.02t\right]^{\top}$. The relative position parameters are chosen as $p_{1x} = \sqrt{2}/2$, $p_{1y} = 0$, $p_{2x} = -0.5$, $p_{2y} = -0.5$, $p_{3x} = -0.5$, and $p_{3y} = 0.5$. The design parameters are chosen as $r_{i1} = diag(10, 10, 10)$, $r_{i2} = diag(10, 10, 10)$, and $K_i = diag(5, 5, 5)$. The time-varying external disturbance is adopted as $d_{i1} = 5(0.5\cos(0.25t) + 0.5\sin(0.15t))$, $d_{i2} = 5(-0.5\cos(0.15t) - 0.5\sin(0.25t))$, $d_{i3} = 5(0.5\cos(0.25t) + 0.5\sin(0.15t))$. The fuzzy parameters in the FLSs are settled randomly in (0, 1), and the fuzzy membership functions of the FLSs are designed as

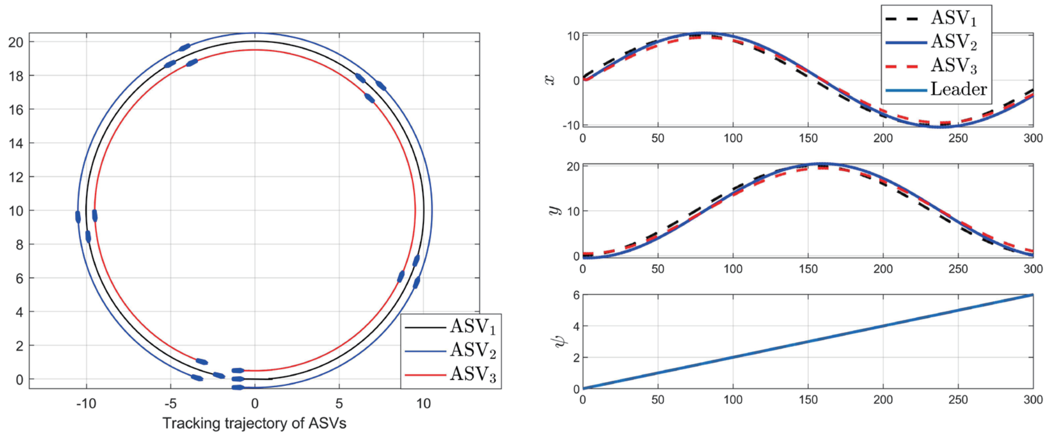
$$\mu_{F^l}(x_1) = \exp\left[-\frac{(x_1 + l)^2}{2}\right], \tag{65}$$

and

$$\mu_{F^l}(x_1, x_2) = \exp\left[-\frac{(x_1 + l)^2}{2}\right] \times \exp\left[-\frac{(x_2 + l)^2}{2}\right], \tag{66}$$

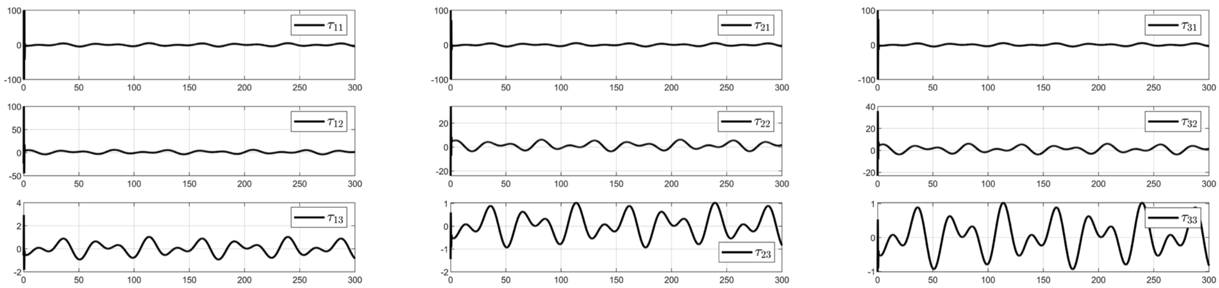
where $l = -2, -1, 0, 1, 2$. x_1 and x_2 denote the inputs of FLSs.

The simulation results are given in Figs. 2–4. The tracking trajectory and system states of ASVs are given in Figs. 2(a) and 2(b), respectively. Control inputs of the ASVs are shown in Fig. 3. The estimation of the disturbances of the ASVs is shown in Fig. 4. From the simulation results, it can be concluded that the proposed optimal algorithm can handle the control task and that the proposed DO can handle the estimation task of an unknown external disturbance.



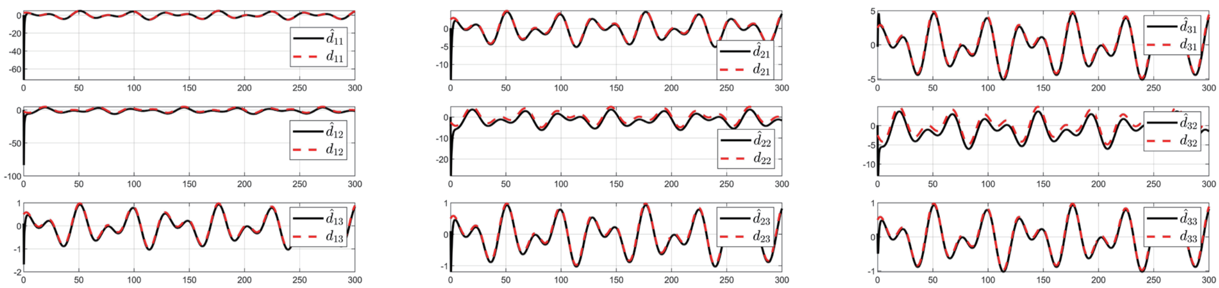
(a) (b)

Fig. 2. (Color online) (a) Tracking trajectory and (b) system states of ASVs.



(a) (b) (c)

Fig. 3. Control outputs of (a) ASV_1 , (b) ASV_2, and (c) ASV_3.



(a) (b) (c)

Fig. 4. External disturbances and their estimations of (a) ASV_1, (b) ASV_2, and (c) ASV_3.

5. Conclusions

In this paper, we provided an adaptive fuzzy optimal controller for the tracking control problem of multiple ASVs with uncertain dynamics. FLSs have been employed to handle the uncertain dynamics of the ASVs. We utilized the ADP algorithm, incorporating a technique based on optimal compensation terms, to ensure the optimal achievement of the control objective. Additionally, a DO has been proposed to address unknown disturbances. The proposed controller has been proven to guarantee that all signals in the closed-loop system are bounded. Simulation results have been provided to illustrate the effectiveness of the proposed algorithm. The future work of this paper is to solve the control problem of multiple ASVs with unmeasured states and investigate the output-feedback control algorithm by adopting the state observer technique.

Acknowledgments

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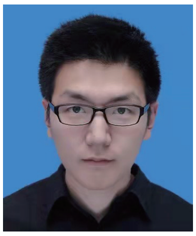

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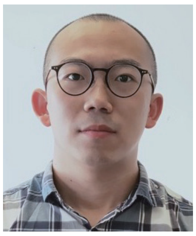

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