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Distributed model-free formation control of networked fully-actuated autonomous surface vehicles

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This paper presents a distributed constant bearing guidance and model-free disturbance rejection control method for formation tracking of autonomous surface vehicles subject to fully unknown kinetic model. First, a distributed constant bearing guidance law is designed at the kinematic level to achieve a consensus task. Then, by using an adaptive extended state observer (AESO) to estimate the total uncertainties and unknown input coefficients, a simplified model-free kinetic controller is designed based on a dynamic surface control (DSC) design. It is proven that the closed-loop system is input-to-state stable. The stability of the closed-loop system is established. A salient feature of the proposed method is that a cooperative behavior can be achieved without knowing any priori information. An application to formation control of autonomous surface vehicles is given to show the efficacy of the proposed integrated distributed constant bearing guidance and model-free disturbance rejection control.

KEYWORDS

dynamic surface control, adaptive extended state observer, autonomous surface vehicle, model-free control, formation tracking

1. Introduction

In recent years, there has been a surge of interest in distributed cooperative control of autonomous surface vehicles (ASVs). It can be envisioned that multiple ASVs enable vehicles to collaborate with each other to execute difficult missions, contributing to improved efficiency and effectiveness over a single one (Arrichiello et al., 2006; Cui et al., 2010; Peng et al., 2011, 2013, 2020, 2021a,b,c; Wang and Han, 2016; Li et al., 2018; Chen et al., 2020; Guo et al., 2020; Liu et al., 2020a,b, 2022; Zhang et al., 2020; Zhu et al., 2021, 2022; Gu et al., 2022a,b,c,d; Hu et al., 2022a,b; Rout et al., 2022). Recently, distributed control methods have been widely studied (see references, Cao and Ren, 2010; Wang et al., 2010; Zhang et al., 2011, 2012; Cui et al., 2012; Zhang and Lewis, 2012; Hong et al., 2013; Peng et al., 2014; Jiang et al., 2021). In Cao and Ren (2010), a distributed control method is proposed to deal with the formation control problem. In Jiang et al. (2021), a distributed model-free control method is designed using a data-driven fuzzy predictor and extended state observers for ASVs to achieve cooperative target enclosing. A distributed adaptive control method is presented to achieve the cooperative tracking

with unknown dynamics in Zhang and Lewis (2012). In Cui et al. (2012), a distributed synchronized tracking control method is designed based on an adaptive neural network for ASVs. In Wang et al. (2010), a distributed control approach is designed to deal with the asymptotic tracking under disturbances generated by the exosystem. A distributed leader-follower control method is proposed using the output regulation theory and internal model principle in Hong et al. (2013). In Peng et al. (2014), a distributed adaptive control method is presented by using the state information of neighboring ASVs only. In Zhang et al. (2011), a distributed control method is presented by using the observer to achieve cooperative tracking. In Zhang et al. (2012), an adaptive distributed control technique is designed based on neural network to deal with the cooperative tracking problems. Its key advantage is that the group objective can be achieved *via* local information exchanges. Consensus-based distributed formation control schemes are presented in Ren (2007), Ren and Sorensen (2008), and Hu (2012). In Ren (2007), a consensus-based distributed control method is proposed to deal with the formation control problem. In Ren and Sorensen (2008), a consensus-based approach is designed to achieve the distributed formation control. In Hu (2012), a distributed consensus-based control method is designed to achieve global asymptotic consensus tracking.

As for autonomous surface vehicle systems, the modeling process is time-consuming and a large number of experiments is required for identifying model parameters. On the other hand, robustness against model uncertainty and ocean disturbances is critical for high-performance control of ASVs (Fossen, 2002; Skjetne et al., 2005; Tee and Ge, 2006; Li et al., 2008; Dai et al., 2012; Chen et al., 2013; How et al., 2013). To deal with this problem, adaptive backstepping and DSC techniques has been widely suggested; see the references (Fossen, 2002; Skjetne et al., 2005; Tee and Ge, 2006; Li et al., 2008; Dai et al., 2012; Chen et al., 2013; How et al., 2013). In Tee and Ge (2006), a stable tracking control method is proposed using backstepping and Lyapunov synthesis for multiple marine vehicles under the unmeasurable states. In Chen et al. (2013), a variable control structure based on backstepping and Lyapunov synthesis is designed for the positioning of marine vessels with the parametric uncertainties and ocean disturbances. In How et al. (2013), an adaptive approximation technique is designed using the backstepping to estimate the uncertainties. In Dai et al. (2012), an adaptive neural networks control method is designed based on the backstepping and Lyapunov synthesis with uncertain environment. In Skjetne et al. (2005), an adaptive recursive control method is designed using the backstepping and Lyapunov synthesis for marine vehicles with the unknown model parameters. Although the adaptive backstepping and DSC are recursive and systematic design methods, it does not offer the freedom to choose the parameter adaptive laws (Krstić et al., 1995). Besides, the identification process depends on the tracking error dynamics, and the transient performance

cannot be guaranteed (Cao and Hovakimyan, 2007; Yucelen and Haddad, 2013).

Motivated by the above observations, this article presents a distributed constant bearing guidance and model-free disturbance rejection control method for formation tracking of ASVs subject to fully unknown kinetic model. Specifically, a distributed constant bearing guidance law is designed at the kinematic level to achieve a consensus task. Then, an AESO is constructed for estimating the model uncertainty and unknown ocean disturbances, which can achieve the uncertainty and disturbance estimation. Next, a controller module is developed by using a DSC technique. Simulation results are provided to show the efficacy of the proposed modular design integrated distributed constant bearing guidance and model-free disturbance rejection control method. The main contribution of the proposed control method are stated as follows. Firstly, the proposed design results in the decoupled estimation and control, where the estimation loop is faster than the control loop, yielding the improved transient performance. This contributes to the certainty equivalence control of multi-vehicle systems. Secondly, the security level of ASVs is enhanced by using an AESO to identify the total uncertainties. Finally, the salient feature of the proposed method is that a cooperative behavior can be achieved without knowing any priori information.

The rest of this paper is organized as follows: The problem formulation is presented in Section 2. Section 3 presents the distributed constant bearing guidance and model-free disturbance rejection control method. Section 4 provides simulation results to illustrate the designed model-free disturbance rejection control method for distributed formation tracking. Section 5 concludes this paper.

2. Problem formulation

A three degree-of-freedom (DOF) dynamical model for ASVs in a horizontal plane as shown in Figure 1 can be expressed with kinematics (Fossen, 2002; Skjetne et al., 2005).

$$\dot{\eta}_i = R(\psi_i)v_i, \quad (1)$$

$$\dot{v}_i = M_i^{-1}f_i(v_i) + M_i^{-1}\tau_i + M_i^{-1}\tau_{wi}(t), \quad (2)$$

where

$$R(\psi_i) = \begin{bmatrix} \cos \psi_i & -\sin \psi_i & 0 \\ \sin \psi_i & \cos \psi_i & 0 \\ 0 & 0 & 1 \end{bmatrix}; \quad (3)$$

$\eta_i = [x_i, y_i, \psi_i]^T \in \mathbb{R}^3$ represents the earth-fixed position and heading; $v_i = [u_i, v_i, r_i]^T \in \mathbb{R}^3$ includes the body-fixed surge and sway velocities, and the yaw rate; $M_i = M_i^T \in \mathbb{R}^{3 \times 3}$, $C_i(v_i) \in \mathbb{R}^{3 \times 3}$, $D_i(v_i) \in \mathbb{R}^{3 \times 3}$ denote the inertia matrix, coriolis/centripetal matrix, and damping matrix, respectively; $\tau_i = [\tau_{ui}, \tau_{vi}, \tau_{ri}]^T \in \mathbb{R}^3$ denotes the control input; $\tau_{wi}(t) =$

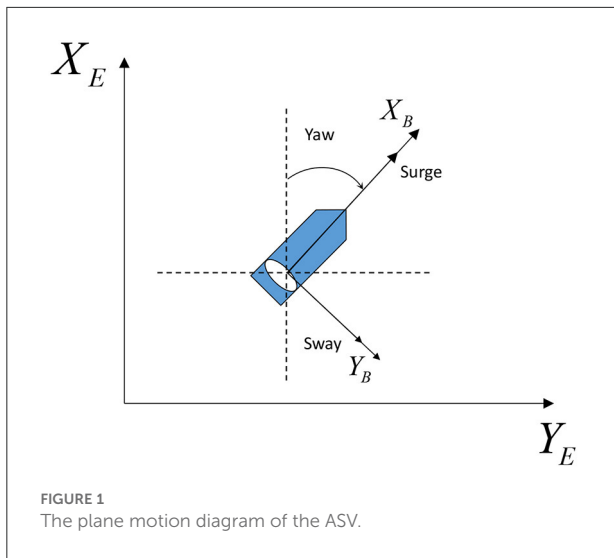


FIGURE 1
The plane motion diagram of the ASV.

$[\tau_{wui}(t), \tau_{wvi}(t), \tau_{wri}(t)]^T \in \mathbb{R}^3$ represents the disturbance vector caused by the wind, waves, and ocean currents.

Since the robot dynamics (1) contain unknown dynamics induced by model uncertainty and ocean disturbances, we rewrite the robot kinetics (1) as follows.

$$\dot{\eta}_i = R(\psi_i)v_i, \tag{4}$$

$$\dot{v}_i = \Lambda_i \tau_i + s_i, \tag{5}$$

where

$$s_i = M_i^{-1}f_i(v_i) + M_i^{-1}\tau_{wi}(t), \Lambda_i = M_i^{-1}. \tag{6}$$

The control objective is to design a cooperative control law τ_i for ASVs with dynamics (1) to track a reference trajectory $\eta_0(t)$ such that

$$\lim_{t \rightarrow \infty} \|\eta_i(t) - \eta_0(t)\| \leq \delta_i, \tag{7}$$

for some small constant δ_i .

We use the following assumption.

Assumption 1: The reference signals $\eta_0(t)$, $\dot{\eta}_0(t)$, and $\ddot{\eta}_0(t)$ are bounded.

3. Cooperative tracking

In this section, a modular design approach is presented to develop the cooperative formation controllers for ASVs. First, by using the designed AESO to estimate the total uncertainties and fully unknown input coefficients, a simplified model-free dynamic kinematic controller is designed with the aid of a dynamic surface control.

3.1. Controller design

Step 1. At first, a cooperative tracking error is defined as

$$z_{i1} = R_i^T \left\{ \sum_{j \in \mathcal{N}_i} a_{ij}(\eta_i - \eta_j) + a_{i0}(\eta_i - \eta_0) \right\}, \tag{8}$$

where $R_i^T = R^T(\psi_i)$, and a_{ij} and a_{i0} are determined by the communication graph, if the i th ASV obtains the information of the j th, $a_{ij} = 1$; otherwise, $a_{ij} = 0$. The definition of a_{i0} is similar to a_{ij} .

Assumption 2: The augmented graph contains a spanning tree with the root node being the leader node n_0 .

Then, define a global formation tracking error ϵ_i as

$$\epsilon_i = \eta_i - \eta_0. \tag{9}$$

Define \mathcal{L} as the Laplacian matrix of the graph and \mathcal{A}_0 as the leader adjacency matrix, which leads to

$$z_1 = \mathcal{R}(\mathcal{H} \otimes I_3)\epsilon. \tag{10}$$

where $\mathcal{H} = \mathcal{L} + \mathcal{A}_0$, $z_1 = [z_{11}^T, \dots, z_{iN}^T]^T$, $\epsilon = [\epsilon_1^T, \dots, \epsilon_{iN}^T]^T$, and $\mathcal{R} = \text{diag}\{R_1^T, \dots, R_N^T\}$. Define $a_{id} = d_i + a_{i0}$, then, it follows from (1) that the time derivative of z_{i1} in (8) is obtained

$$\dot{z}_{i1} = -r_i S z_{i1} + a_{id} v_i - \sum_{j \in \mathcal{N}_i} a_{ij} R_i^T R_j v_j - a_{i0} R_i^T \dot{\eta}_0, \tag{11}$$

where

$$S = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \tag{12}$$

A distributed constant-bearing guidance law α_{i1} is proposed as follows

$$\alpha_{i1} = \frac{1}{a_{id}} \left\{ -k_{i\eta} \frac{z_{i1}}{\sqrt{z_{i1}^2 + \Delta^2}} + \sum_{j \in \mathcal{N}_i} a_{ij} R_i^T R_j v_j + a_{i0} R_i^T \dot{\eta}_0 \right\}, \tag{13}$$

where Δ is positive constant, and $k_{i\eta} = \text{diag}\{k_{i\eta 1}, k_{i\eta 2}, k_{i\eta 3}\} \in \mathbb{R}^{3 \times 3}$ with $k_{i\eta 1} \in \mathbb{R}$, $k_{i\eta 2} \in \mathbb{R}$, and $k_{i\eta 3} \in \mathbb{R}$ being positive constants.

Let us suppose here that α_{i1} are unknown, and let it pass through a first-order filter as follows

$$\gamma_i \dot{v}_{id} = \alpha_{i1} - v_{id}, v_{id}(0) = \alpha_{i1}(0), \tag{14}$$

where $\gamma_i \in \mathbb{R}$.

Then, the derivative of q_i is obtained as

$$\dot{q}_i = -\frac{q_i}{\gamma_i} - \dot{\alpha}_{i1}. \tag{15}$$

where $q_i = \alpha_{i1} - v_{id}$.

Now using (15), we can conclude that

$$q_i(t) = q_i(0)e^{-\frac{t}{\gamma_i}} - \int_0^t e^{-\frac{1}{\gamma_i}(t-\tau)} \dot{\alpha}_{i1}(\tau) d\tau. \quad (16)$$

We can obtain that the bound of $\|q_i(t)\|$ satisfies the following inequality

$$\|q_i(t)\| \leq \|q_i(0)\| e^{-\frac{t}{\gamma_i}} + \alpha_{i1}^* \gamma_i,$$

where α_{i1}^* is a positive constant.

Step 2: To start with, define the velocity tracking error z_{i2} as

$$z_{i2} = v_i - v_{id}. \quad (17)$$

Take the time derivative of z_{i2} along (4) is

$$\dot{z}_{i2} = \Lambda_i \tau_i + s_i - \dot{v}_{id}. \quad (18)$$

For the robot kinetics (4), an AESO is designed as

$$\begin{cases} \dot{\hat{v}}_i = \hat{\Lambda}_i \tau_i + \hat{s}_i - k_{iv}(\hat{v}_i - v_i), \\ \dot{\hat{s}}_i = -k_{is}(\hat{v}_i - v_i), \\ \dot{\hat{\sigma}}_i = -\Gamma_{i\sigma}(\hat{s}_i - \hat{\sigma}_i), \\ \dot{\hat{\Lambda}}_i = -\Gamma_{i\Lambda} \tau(\hat{s}_i - \hat{\sigma}_i), \end{cases} \quad (19)$$

where $\sigma = s_i + \Lambda_i \tau_i - \hat{\Lambda}_i \tau_i$, $k_{iv} = \text{diag}\{k_{iv1}, k_{iv2}, k_{iv3}\} \in \mathbb{R}^{3 \times 3}$, $k_{is} = \text{diag}\{k_{is1}, k_{is2}, k_{is3}\} \in \mathbb{R}^{3 \times 3}$, and $k_{iv1} \in \mathbb{R}$, $k_{iv2} \in \mathbb{R}$, $k_{iv3} \in \mathbb{R}$, $k_{is1} \in \mathbb{R}$, $k_{is2} \in \mathbb{R}$, and $k_{is3} \in \mathbb{R}$ are positive constants. \hat{v}_i , \hat{s}_i , $\hat{\sigma}_i$, and $\hat{\Lambda}_i$ are the estimates of v_i , s_i , σ_i , and Λ_i , respectively.

Assumption 3: For unknown functions s_i and σ_i , there are $s_i^* \in \mathfrak{N}^+$ and $\sigma_i^* \in \mathfrak{N}^+$, such that $\|s_i\| \leq s_i^*$ and $\|\sigma_i\| \leq \sigma_i^*$.

Let the parameter estimation be $\tilde{\Lambda}_i = \hat{\Lambda}_i - \Lambda_i$, and the prediction error be $\tilde{v}_i = \hat{v}_i - v_i$. Define $\tilde{s}_i = \hat{s}_i - s_i$ and $\tilde{\sigma}_i = \hat{\sigma}_i - \sigma_i$. It can be obtained $\dot{\tilde{\sigma}}_i - \tilde{\Lambda}_i \tau_i = -\tilde{s}_i - \tilde{\Lambda}_i \tau_i + a_{i1}$ with a_i being the reconstruct error. Then, the error dynamics can be expressed as

$$\begin{cases} \dot{\tilde{v}}_i = -k_{iv} \tilde{v}_i + \tilde{s}_i, \\ \dot{\tilde{s}}_i = -k_{is} \tilde{v}_i - \dot{\tilde{s}}_i, \\ \dot{\tilde{\sigma}}_i = -\Gamma_{i\sigma}(\tilde{s}_i - \hat{\sigma}_i) - \dot{\tilde{\sigma}}_i, \\ \dot{\tilde{\Lambda}}_i = -\Gamma_{i\Lambda} \tau(\tilde{s}_i - \hat{\sigma}_i) - \dot{\tilde{\Lambda}}_i. \end{cases} \quad (20)$$

To stabilize z_{i2} , a model-free disturbance rejection control law is proposed as follows

$$\tau_i = \frac{-k_{i\tau} z_{i2} + \dot{v}_{id} - \hat{s}_i}{\hat{\Lambda}_i}, \quad (21)$$

where $k_{i\tau} = \text{diag}\{k_{i\tau1}, k_{i\tau2}, k_{i\tau3}\} \in \mathbb{R}^{3 \times 3}$, and $k_{i\tau1} \in \mathbb{R}^+$, $k_{i\tau2} \in \mathbb{R}^+$, and $k_{i\tau3} \in \mathbb{R}^+$.

Substituting (21) into (18) yields

$$M_i \dot{\hat{z}}_{i2} = -k_{i\tau} \hat{z}_{i2} - \varrho_i \tilde{v}_i, \quad (22)$$

where ϱ_i is a positive constant.

The following lemma presents the stability of AESO error subsystem (20).

Lemma 1: Under Assumption 2, the AESO error subsystem (20), viewed as a system with the states being \tilde{v}_i , \tilde{s}_i , $\tilde{\sigma}_i$, and $\tilde{\Lambda}_i$, the inputs being $\dot{\tilde{s}}_i$, $\dot{\tilde{\sigma}}_i$, and $\dot{\tilde{\Lambda}}_i$ is ISS.

Proof: Construct the Lyapunov function as

$$V_{\sigma i} = \frac{1}{2}(\tilde{\sigma}_i^T \Gamma_{\sigma i}^{-1} \tilde{\sigma}_i + \tilde{\Lambda}_i^T \Gamma_{\Lambda i}^{-1} \tilde{\Lambda}_i), \quad (23)$$

and the time derivatives of $V_{\sigma i}$ is

$$\begin{aligned} \dot{V}_{\sigma i} &= \tilde{\sigma}_i^T \Gamma_{\sigma i}^{-1} (-\Gamma_{\sigma i}(\tilde{s}_i - \hat{\sigma}_i) - \dot{\tilde{\sigma}}_i) + \tilde{\Lambda}_i^T \Gamma_{\Lambda i}^{-1} (-\Gamma_{\Lambda i}(\tilde{s}_i - \hat{\sigma}_i)) \\ &= \tilde{\sigma}_i^T(\tilde{s}_i - \hat{\sigma}_i) - \Gamma_{\sigma i}^{-1} \tilde{\sigma}_i \dot{\tilde{\sigma}}_i + \tilde{\Lambda}_i^T \tau_i(\tilde{s}_i - \hat{\sigma}_i) \\ &\leq -\tilde{\sigma}_i^2 - 2\tilde{\sigma}_i \tilde{\Lambda}_i \tau_i - \tilde{\Lambda}_i^2 \tau_i^2 - \tilde{\Lambda}_i \tau_i a_{i1} + \Gamma_{\sigma i}^{-1} \tilde{\sigma}_i \sigma_i^* \\ &\leq -\|\epsilon_i\|^2 + \|\iota_i\| \|\epsilon_i\|, \end{aligned} \quad (24)$$

where $\epsilon_i = \tilde{\sigma}_i + \tilde{\Lambda}_i \tau_i$ and $\iota_i = \max\{a_{i1}, \Gamma_{\sigma i}^{-1} \sigma_i^*\}$.

Since

$$\|\epsilon_i\| \geq \|\iota_i\| / \theta_i, \quad (25)$$

renders

$$\dot{V}_{\sigma i} \leq -(1 - \theta_i) \|\epsilon_i\|^2 \quad (26)$$

with $\theta_i \in (0, 1)$. Therefore, it can conclude that the error ϵ_i is bounded.

It follows from (20) that the dynamics of the \tilde{v}_i and \tilde{s}_i can be rewritten as

$$\dot{\tilde{\chi}}_i = A_{\chi i} \tilde{\chi}_i - \dot{s}_{\chi i}, \quad (27)$$

where $\tilde{\chi}_i = [\tilde{v}_i, \tilde{s}_i]^T$, $\dot{s}_{\chi i} = [0, \dot{s}_i]^T$, and

$$A_{\chi i} = \begin{bmatrix} -k_{i\tau} & 1 \\ -k_{is} & 0 \end{bmatrix}, \quad (28)$$

with $A_{\chi i}$ being Hurwitz. There exists a unique positive definite matrix $P_{\chi i}$, such that

$$A_{\chi i}^T P_{\chi i} + P_{\chi i}^T A_{\chi i} = -I. \quad (29)$$

Construct the Lyapunov function for system (27) as

$$V_{\chi i} = \frac{1}{2} \tilde{\chi}_i^T P_{\chi i} \tilde{\chi}_i. \quad (30)$$

The dynamics of the $V_{\chi i}$ is

$$\begin{aligned} \dot{V}_{\chi i} &= \tilde{\chi}_i^T (A_{\chi i}^T P_{\chi i} + P_{\chi i}^T A_{\chi i}) \tilde{\chi}_i + \tilde{\chi}_i^T P_{\chi i} (-\dot{s}_{\chi i}) \\ &\leq -\|\tilde{\chi}_i\|^2 + \|\tilde{\chi}_i\| \|P_{\chi i}\| \|\dot{s}_{\chi i}\| \end{aligned} \quad (31)$$

Since

$$\|\tilde{\chi}_i\| \geq (\|P_{\chi i}\| \|\dot{s}_{\chi i}\|) / a_{i2}, \quad (32)$$

renders

$$\dot{V}_{\chi i} \leq -(1 - a_{i2}) \|\tilde{\chi}_i\|^2 \tag{33}$$

with $a_{i2} \in (0, 1)$. It is concluded that the error subsystem (20) is ISS. There exists class \mathcal{KL} function β_{i1} such that

$$\|\chi_i(t)\| \leq \max\{\beta_{i1}(\|\chi(0)\|, t), \kappa_{i1}^{s_i}(\|\dot{s}_{\chi i}\|)\}, \tag{34}$$

with the gain function (Wang et al., 2006) given by

$$\kappa_{i1}^{s_i}(s) = \sqrt{\frac{\lambda_{\max}(P_{\chi i})}{\lambda_{\min}(P_{\chi i})} \frac{\|P_{\chi i}\|s}{a_{i2}}}.$$

Recalling (11), (17), and (22), the error dynamics is addressed as

$$\begin{cases} \dot{z}_{i1} = -r_i S z_{i1} - k_{i\eta} z_{i1} + a_{id}(-\tilde{v}_i + \hat{z}_{i2} + q_i), \\ M_i \dot{\hat{z}}_{i2} = -k_{i\tau} \hat{z}_{i2} - \rho_i \tilde{v}_i, \end{cases} \tag{35}$$

where $q_i = v_{id} - \alpha_{i1}$.

By using the coordinations of z_{i1} and \hat{z}_{i2} , the above subsystem (35) is only perturbed by \tilde{v}_i and q_i . Obviously, these two variables will vanish soon as time evolve by choosing the control parameters of predictors and filters.

Lemma 2: The error subsystem (35), viewed as a system with the states being z_{i1} and \hat{z}_{i2} and the inputs being \tilde{v}_i and q_i , is ISS.

Proof: Construct a Lyapunov function as follows

$$V_c = \frac{1}{2} \{ z_{i1}^T z_{i1} + \hat{z}_{i2}^T M_i \hat{z}_{i2} \}. \tag{36}$$

Taking the time derivative of V_c along (35), it renders

$$\begin{aligned} \dot{V}_c \leq & -\lambda_{\min}(k_{i\eta}) z_{i1}^T z_{i1} + a_{id} z_{i1}^T (-\tilde{v}_i + \hat{z}_{i2} + q_i) \\ & - \lambda_{\min}(k_{i\tau}) \hat{z}_{i2}^T \hat{z}_{i2} - \hat{z}_{i2}^T \rho_i \tilde{v}_i. \end{aligned} \tag{37}$$

Using the inequalities

$$|z_{i1}^T \hat{z}_{i2}| \leq \frac{1}{2} \|z_{i1}\|^2 + \frac{1}{2} \|\hat{z}_{i2}\|^2 \tag{38}$$

$$|z_{i1}^T q_i| \leq \frac{1}{2} \|z_{i1}\|^2 + \frac{1}{2} q_i^{*2} \tag{39}$$

$$|z_{i1}^T \tilde{v}_i| \leq \frac{1}{2} \|z_{i1}\|^2 + \frac{1}{2} \|\tilde{v}_i\|^2 \tag{40}$$

it follows that

$$\begin{aligned} \dot{V}_c \leq & -\left(\lambda_{\min}(k_{i\eta}) - \frac{3a_{id}}{2}\right) \|z_{i1}\|^2 - \left(\lambda_{\min}(k_{i\tau}) \right. \\ & \left. - \frac{\lambda_{\max}(\rho_i) + a_{id}}{2}\right) \|\hat{z}_{i2}\|^2 + \frac{\lambda_{\max}(\rho_i) + a_{id}}{2} \|\tilde{v}_i\|^2 \\ & + \frac{a_{id}}{2} \|q_i\|^2. \end{aligned} \tag{41}$$

By selecting $c_i = \min\left\{\lambda_{\min}(k_{i\eta}) - \frac{3a_{id}}{2}, \lambda_{\min}(k_{i\tau}) - \frac{\lambda_{\max}(\rho_i) + a_{id}}{2}\right\} > 0$ and $Z_i = [z_{i1}^T, \hat{z}_{i2}^T]$, one has

$$\begin{aligned} \dot{V}_c \leq & -c_i \|Z_i\|^2 + \frac{\lambda_{\max}(\rho_i) + a_{id}}{2} \|\tilde{v}_i\|^2 + \frac{a_{id}}{2} \|q_i\|^2 \\ \leq & -\frac{c_i}{2} \|Z_i\|^2 - \left\{ \frac{c_i}{2} \|Z_i\|^2 - \frac{\lambda_{\max}(\rho_i) + a_{id}}{2} \|\tilde{v}_i\|^2 \right. \\ & \left. - \frac{a_{id}}{2} \|q_i\|^2 \right\}. \end{aligned} \tag{42}$$

Since

$$\begin{aligned} \|Z_i\| \geq & \frac{\sqrt{\lambda_{\max}(\rho_i) + a_{id}}}{\sqrt{c_i}} \|\tilde{v}_i\| + \frac{\sqrt{a_{id}}}{\sqrt{c_i}} \|q_i\| \\ \geq & \frac{\sqrt{(\lambda_{\max}(\rho_i) + a_{id}) \|\tilde{v}_i\|^2 + a_{id} \|q_i\|^2}}{\sqrt{c_i}}, \end{aligned} \tag{43}$$

renders

$$\dot{V}_c \leq -\frac{c_i}{2} \|Z_i\|^2. \tag{44}$$

There exists class \mathcal{KL} function β_{i2} such that

$$\|Z_i(t)\| \leq \max\{\beta_{i2}(\|Z_i(0)\|, t), \kappa_{i1}^{\tilde{v}_i}(\|\tilde{v}_i\|) + \kappa_{i2}^{q_i}(\|q_i\|)\}, \tag{45}$$

where the gain functions are given by

$$\begin{cases} \kappa_{ic}^{\tilde{v}_i}(s) = \sqrt{\frac{\lambda_{\max}(P_{i2})}{\lambda_{\min}(P_{i2})} \frac{\lambda_{\max}(\rho_i) + a_{id}}{c_i} s} \\ \kappa_{ic}^{q_i}(s) = \sqrt{\frac{\lambda_{\max}(P_{i2})}{\lambda_{\min}(P_{i2})} \frac{a_{id}}{c_i} s} \end{cases} \tag{46}$$

with $P_{i2} = \text{diag}\{M_i, 1\}$. The proof is completed.

3.2. Cascade stability

Theorem: Consider the closed-loop network system consisting of the vessels dynamics (1) (2), the AESO (19), the distributed constant-bearing guidance law (13), and the controller (21). If Assumptions 1–3 and $c_i > 0$ are satisfied, all signals in the closed-loop system are bounded, and the global CFT error ε_i converges to a neighborhood around zero.

Proof: From Lemma 1, we have proved that subsystem (20) with states being $(\tilde{v}_i, \tilde{s}_i)$ and input being \dot{s}_i is ISS. From Lemma 2, it can be obtained that subsystem (35) with states being (z_{i1}, \hat{z}_{i2}) and inputs being \tilde{v}_i and q_i is ISS. By Krstić et al. (1995), it proves that the cascade system formed by (20) and (35) with states being $(z_{i1}, \hat{z}_{i2}, \tilde{v}_i, \tilde{s}_i)$ and the inputs being q_i and \dot{s}_i is ISS. Since q_i and \dot{s}_i is bounded by q_i^* and \dot{s}_i^* , respectively. Then, the error signals $z_{i1}, \hat{z}_{i2}, \tilde{v}_i$, and \tilde{s}_i are all bounded. Observing that $\|z_{i2}\| = \|\tilde{v}_i + \hat{z}_{i2}\| \leq \|\tilde{v}_i\| + \|\hat{z}_{i2}\|$, it follows that z_{i2} is bounded.

Note that as $t \rightarrow \infty$, $\beta_{i1}(\cdot)$ and $\beta_{i2}(\cdot) \rightarrow 0$, and it follows from (34) and (45) that z_{i1} is ultimately bounded by

$$\begin{aligned} \lim_{t \rightarrow \infty} \|z_{i1}\| &\leq \lim_{t \rightarrow \infty} \|Z_i\|, \\ &\leq \kappa_{i1}^{s_i}(\|s_{\chi_i}\|) + \kappa_{i2}^{q_i}(\|q_i\|), \\ &\leq \kappa_{i1}^{s_i}(s_i^*) + \kappa_{i2}^{q_i}(q_i^*). \end{aligned} \tag{47}$$

Then, define $\varrho(\mathcal{H})$ as the minimal singular value of \mathcal{H} , and it follows from Assumption 2 that

$$\|\varepsilon_i\| \leq \frac{\|z_{i1}\|}{\varrho(\mathcal{H})}. \tag{48}$$

From (47) and (48), ε_i is ultimately bounded as

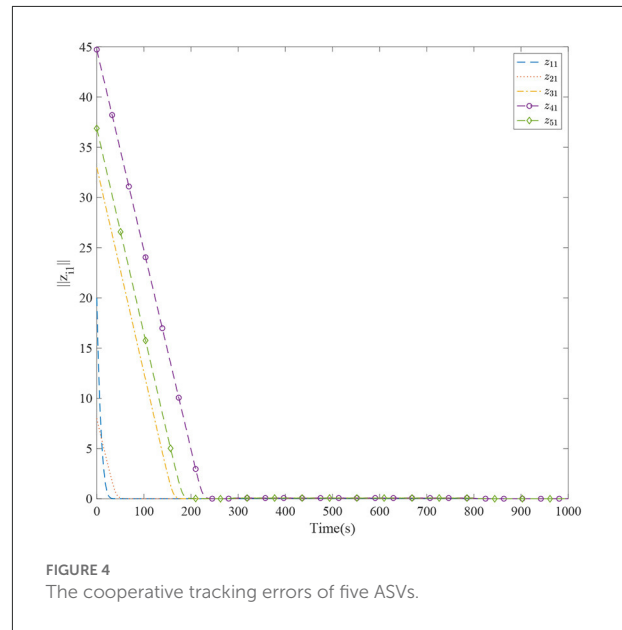
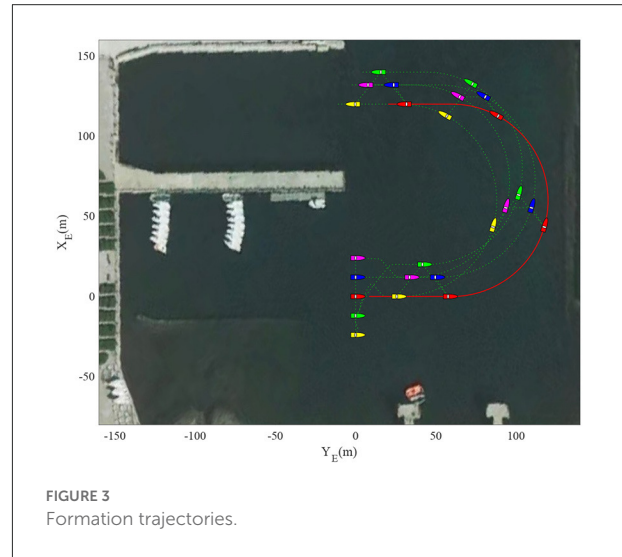
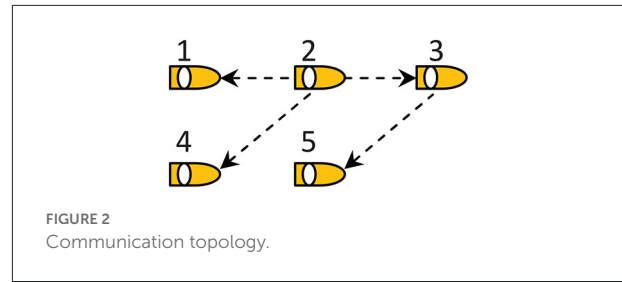
$$\lim_{t \rightarrow \infty} \|\varepsilon_i\| \leq \frac{1}{\varrho(\mathcal{H})} \sum_{i=1}^N \left\{ \kappa_{i1}^{s_i}(s_i^*) + \kappa_{i2}^{q_i}(q_i^*) \right\}.$$

4. An example

Consider a networked system consisting of five ASVs, and the communication topology is shown in Figure 2 with the ASV 2 being the leader. The parameters for each model ship are taken from Skjetne et al. (2005). The initial states of five ASVs are set to $\eta_1 = (0, 0, 0)$, $\eta_2 = (0, 12, 0)$, $\eta_3 = (0, -12, 0)$, $\eta_4 = (0, 24, 0)$, and $\eta_5 = (0, -24, 0)$. In order to better emerge the simulation effect, we add the desired deviations Δ_{ij} between the ASVs as follows $\Delta_{12} = (12, 12, 0)$, $\Delta_{15} = (36, 0, 0)$, $\Delta_{23} = (8, 8, 0)$, and $\Delta_{34} = (8, -8, 0)$. The control parameters are chosen as $k_{i\eta} = \text{diag}\{2, 2, 2\}$, $k_{iv} = \text{diag}\{20, 20, 20\}$, $k_{is} = \text{diag}\{100, 100, 100\}$, $k_{i\tau} = \text{diag}\{285, 338, 27.6\}$, and $\gamma_{i1} = 0.02$. Define the path variable as ϑ , and the information of path is given in (49)

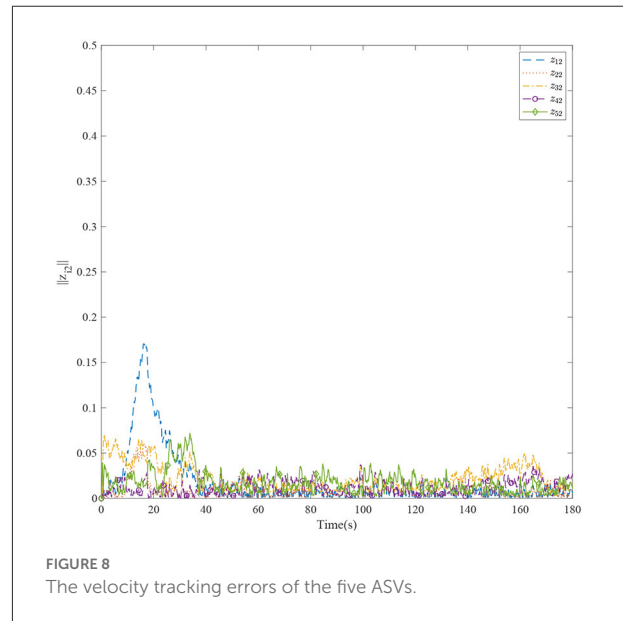
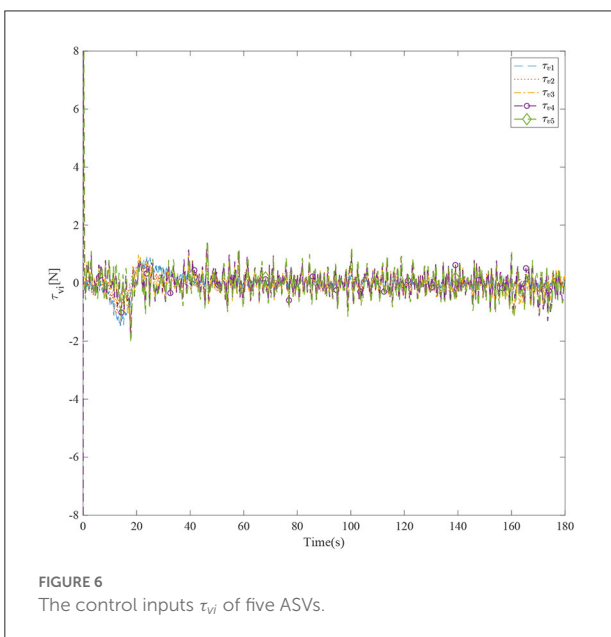
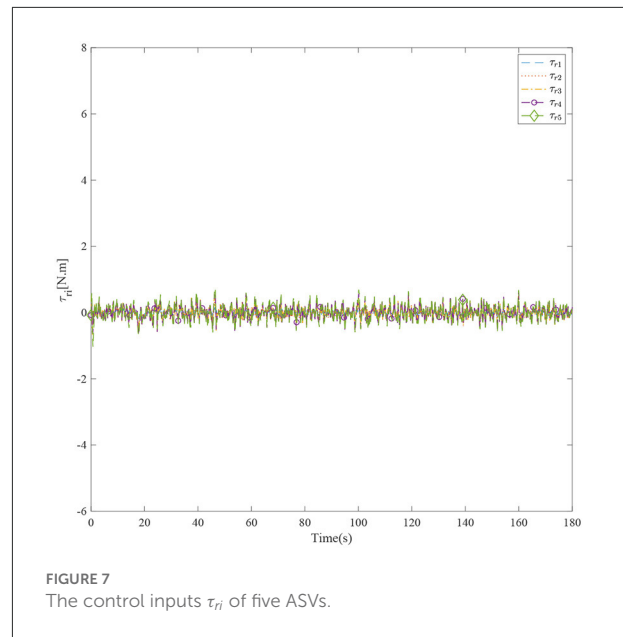
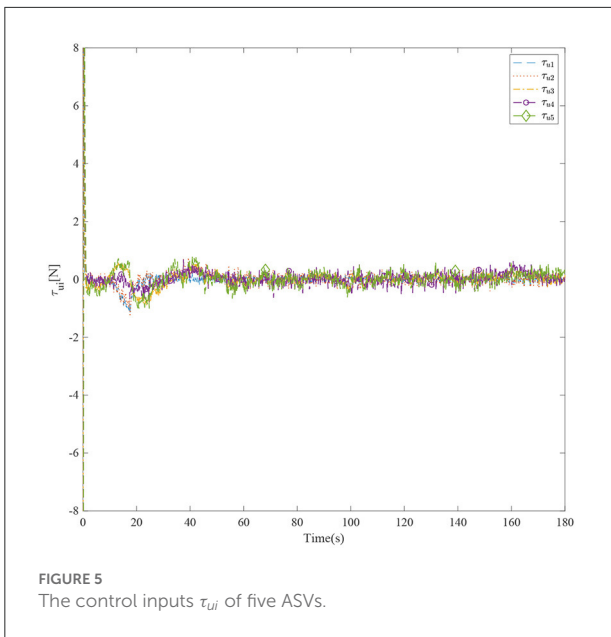
$$\begin{cases} [0.1\vartheta + 20; 0; 0], \vartheta < 400, \\ [60 + 60 \sin(0.003(\vartheta - 400)); \\ 60(1 - \cos(0.003(\vartheta - 400))); \\ 0.003(\vartheta - 400)], \\ \vartheta < (400 + \pi/0.003); \\ [-0.1(\vartheta - 400 - \pi/0.003) + 60; 120; \pi], \\ \vartheta \geq (400 + \pi/0.003). \end{cases} \tag{49}$$

Figure 3 shows the formation trajectories of the five ASVs. It reveals that the a triangle formation can be well established without knowing any priori of the model parameters. Figure 4 shows the cooperative tracking error norms of z_{i1} . It can be seen that the cooperative tracking errors $\|z_{i1}\|$ converge to a neighborhood of the origin. Figures 5–7 show the control inputs in terms of τ_{ui} , τ_{vi} , and τ_{ri} , respectively. It verifies that the control inputs are all bounded. The velocity tracking error norms of z_{i2} are shown in Figure 8. It can be seen that the velocity tracking errors $\|z_{i2}\|$ converge to a neighborhood of the origin.



5. Conclusions

In this paper, an integrated distributed constant bearing guidance and model-free disturbance rejection control method



was presented for cooperative tracking of ASVs subject to fully unknown kinetic model. At the kinematic level, a distributed constant bearing guidance law is designed to achieve a formation task. By using AESO to estimate the total uncertainties and unknown input coefficients, a simplified model-free dynamic kinematic controller is designed with the aid of a dynamic surface control. The stability of the closed-loop cooperative system is proven. The application to formation control of autonomous surface vehicles is given to show the efficacy of the proposed model-free disturbance rejection control method for distributed formation tracking.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

Conceptualization, validation, investigation, and writing—review and editing: XN, SG, and ZX. Methodology and resources: XN, SG, and SF. Software and data curation:

XN. Formal analysis and writing—original draft preparation: SG. All authors contributed to the article and approved the submitted version.

Conflict of interest

Author ZX was employed by China State Shipbuilding Corporation Limited.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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