

Leaderless and leader-follower cooperative control of multiple marine surface vehicles with unknown dynamics

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Abstract Unlike the tracking control of a single marine vehicle, this paper considers the leaderless and leader-follower cooperative control of multiple marine surface vehicles subject to unknown nonlinear dynamics and ocean disturbances, all seeking to maintain a relative formation. For both cases, a cooperative control design approach is proposed by integrating neural networks, a backstepping technique, and graph theory. It is shown that with the developed cooperative controllers, formation behavior among vehicles can be achieved for any undirected connected communication graphs without requiring the accurate model of each vehicle. Based on Lyapunov stability analysis, all signals in the closed-loop system are guaranteed to be uniformly ultimately bounded, and cooperative tracking errors converge to a small neighborhood of the origin. Simulation results are given to show the efficacy of the proposed methods.

Keywords Cooperative control · Marine surface vehicles · Neural networks · Nonlinear dynamics

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1 Introduction

Cooperative control of multivehicle (agent) systems has received significant attention due to wide applications in engineering which include cooperative rescue and search, coordinated exploration and exploitation, sensor networks, situation awareness for military missions, etc. In a typical theoretical setup, the cooperative control problem is reduced to a consensus problem, which has been extensively studied in recent years [1–7]. For cooperative control of multiagent systems, *leaderless consensus* means that the agents reach a common value via local interaction; while *leader-follower consensus* means that there exists a leader who specifies a reference trajectory for the whole group to follow. In recent years, numerous results on these two topics have been reported in literature and readers are referred to the papers [8–14] and references therein. In most existing works on consensus, the agent dynamics are assumed to be first-, second-, high-order integrators or linear systems [8–14], which may not be adequate to describe the agent dynamics as they perform maneuvers in a harsh and demanding environment.

Since most practical systems are inherently nonlinear and subject to external disturbances, and cooperative control of nonlinear systems is more challenging. In [15], a neural adaptive control approach is applied to leaderless consensus of first-order nonlinear systems on undirected graph. In [16], neural leader-follower consensus controllers are developed for first-

order nonlinear systems, and this result is extended to second-order nonlinear systems in [17] and further to high-order nonlinear systems in [18]. Robust consensus tracking control of second-order nonlinear systems is presented in [19], where *identifier*-based continuous consensus protocols are developed to enable global asymptotic tracking performance both for undirected and directed graphs. In [20], robust finite-time consensus tracking controllers are proposed for second-order nonlinear systems based on the terminal sliding-mode technique. Despite these efforts, how to develop systematic design methods for cooperative control of real-world agents is still an open problem.

During the past decade, the marine control community has focused on the cooperative control of marine surface vehicles (MSVs), and a variety of approaches have been proposed, ranging from leader-follower mechanisms [22, 23], virtual structure method [24], behavioral approach [25], to cooperative path following framework [26]. Obviously, these control approaches only result in low-level cooperative behaviors. However, to execute more challenging missions, it needs the use of multiple vehicles working together to achieve a collective objective [1–3]. For instance, a fleet of MSVs are required to track a moving target, which can be regarded as a leader, in a sensor network, where only the instantaneous motion of the target can be obtained by a portion of vehicles due to limited sensing region, and they update their knowledge by communicating with a subset of nearby vehicles, in order to track the leader. Apparently, such motion control scenario cannot be accomplished by those formation control strategies mentioned above.

Motivated by the above observations, this paper considers the *leaderless* and *leader-follower* cooperative control of MSVs subject to uncertain nonlinear dynamics and external ocean disturbances. The communication graph among the vehicles is assumed to be undirected and connected. In the leaderless case, the objective is that a group of MSVs achieve desired relative deviations on their vectors of earth-fixed positions and attitudes via local interaction. As for the leader-follower case, the objective is to drive a group of MSVs to a time-varying reference trajectory with desired deviations. This control design different from the traditional tracking control of MSV is that only a fraction of followers have access to the reference trajectory. For both cases, distributed adaptive controllers

are proposed by employing neural networks (NNs), a backstepping technique and graph theory. It is shown that, with the developed controllers, all signals in the closed-loop system are guaranteed to be uniformly ultimately bounded, and cooperative tracking errors converge to a small neighborhood of origin. The developed leaderless cooperative controller holds promise for applications in automated docking of marine vehicles through a distributed decision-making strategy; and the leader-follower cooperative controller can be regarded as an extension of the traditional tracking control of a single vehicle [27–29] to those of networked multivehicle systems.

Comparisons with the existing results are as follows: Unlike the vehicles modeled as single integrators [8, 9], double integrators [10–12], nonholonomic integrators [13], and linear systems [14], the vehicle dynamics considered in this paper are more practical. Although the vehicle model belongs to a class of second-order systems, the classical method like feedback linearization cannot be used to deal with this problem because there exist unknown nonlinear dynamics in the vehicle model. Thus, these results for linear system models cannot be directly applied to our case. In contrast to the neural cooperative control designs in [15–18] where the NN identification of system dynamics is coupled with the communication graph, the proposed backstepping-based cooperative design approach separates the NN learning of system dynamics and the communication scheme, and hence the cooperative controllers are practical to implement. Compared with the neural tracking controllers developed for single vehicles [27–30], the control problem confronted in this paper is more challenging in the sense that it does not permit a centralized tracking approach. Different from the cooperative path following controllers proposed in [26], where each vehicle must have access to a reference path, the proposed controllers can be implemented in a distributed manner that allows even only one vehicle has access to the reference trajectory.

This paper is organized as follows. Section 2 introduces some preliminaries and states the problem formulation. The leaderless and leader-follower cooperative control algorithms with stability results are presented in Sects. 3 and 4, respectively. An example is given to illustrate the theoretical results in Sect. 5. Section 6 concludes this paper.

2 Problem formulation and preliminaries

2.1 Preliminaries

Before proceeding, some notations are presented below. $\|\cdot\|$ denotes the Euclidean norm. $\|\cdot\|_F$ denotes the Frobenius norm. $\lambda_{\min}(\cdot)$ denotes the smallest eigenvalue of a square matrix (\cdot) . \otimes denotes the Kronecker product. $\text{tr}(\cdot)$ represents the trace of a given matrix (\cdot) . I_N represents the identity matrix of dimension N . $\mathbf{1}$ denotes a column vector with all entries equal to one. $\text{diag}\{A_i\}$ represents a block-diagonal matrix with matrixes $A_i, i = 1, \dots, N$, on its diagonal. If $x = [x_1, \dots, x_N]^T$, then define $\tanh(x) = [\tanh(x_1), \tanh(x_2), \dots, \tanh(x_N)]^T$.

2.1.1 Graph theory

Let us introduce some graph concepts. A graph $\mathcal{G} = \{V, \mathcal{E}\}$ consists of a node set $V = \{n_1, \dots, n_N\}$ and an edge set $\mathcal{E} = \{(n_i, n_j) \in V \times V\}$ with element (n_i, n_j) that describes the communication from node i to node j . Define an adjacency matrix $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$ given by $a_{ij} = 1$, if $(n_j, n_i) \in \mathcal{E}$; and $a_{ij} = 0$, otherwise. The Laplacian matrix $L = [l_{ij}]$ associated with the graph \mathcal{G} is defined as $l_{ij} = -a_{ij}$, if $j \neq i$, and $l_{ij} = \sum_{k=1}^N a_{ik}$, otherwise. If $a_{ij} = a_{ji}$, for $i, j = 1, \dots, N$, then the graph \mathcal{G} is *undirected*. A *path* in the graph is an ordered sequence of nodes such that any two consecutive nodes in the sequence are an edge of the graph. An undirected graph is *connected* if there is a path between every pair of nodes. For simplicity, we assume that the communication graph between MSVs is undirected and connected. Finally, define a diagonal matrix $B = \text{diag}(b_1, \dots, b_N)$ to be a leader adjacency matrix, where $b_i > 0$ if and only if the i th vehicle is a neighbor of the leader; otherwise $b_i = 0$. Denote $H = L + B$.

Lemma 1 [8] *If \mathcal{G} is a connected undirected graph and at least one vehicle has access to the leader, then the matrix H is symmetric and positive definite.*

Lemma 2 *If \mathcal{G} is a connected undirected graph, then there exist a positive definite matrix P such that $z^T Lz = s^T P s$, where $z = [z_1, \dots, z_N]^T$, $s = [s_1, \dots, s_N]^T$, $s_i = \sum_{j=1}^N a_{ij}(z_i - z_j)$.*

Proof Omitted here for brevity and the proof details can be found in [15]. □

2.1.2 Neural networks [31]

NNs are commonly used as a tool for modeling unknown nonlinear dynamics due to their approximation capabilities. A multilayer feed-forward NN with x_k as the input and y_i the output is described as follows:

$$y_i = \sum_{j=1}^{N_2} \left[w_{ij} \sigma_j \left(\sum_{k=1}^{N_1} \vartheta_{jk} x_k + \vartheta_{j0} \right) \right] + w_{i0}, \tag{1}$$

$$i = 1, \dots, N_3, j = 1, \dots, N_2, k = 1, \dots, N_1,$$

where ϑ_{jk} is the weight from the input neuron i to the hidden neuron j , ϑ_{j0} the bias term, w_{ij} the weight from the hidden neuron j to the output y_i , w_{i0} the bias term to the output y_i , N_2 the number of hidden neurons, and σ_j the activation function. For simplicity, the input-output mapping of NN is expressed by

$$f(x_1, \dots, x_{N_1}) = W^T \sigma(V^T \check{v}), \tag{2}$$

where $\check{v} = [1, x_1, \dots, x_{N_1}]^T$. W is a matrix with its i th column give by $[w_{i0}, w_{i1}, \dots, w_{iN_2}]^T$. $\sigma = [1, \sigma_1, \dots, \sigma_{N_2}]$ is a vector consisting of σ_j . V is a matrix with its j th column given by $[\vartheta_{j0}, \vartheta_{j1}, \dots, \vartheta_{jN_1}]^T$.

The universal approximation theorem claims that, given a continuous real-valued function $f(x) : \Omega \rightarrow \mathbb{R}^{N_3}$ with a compact set $\Omega \in \mathbb{R}^{N_1}$, and a constant real number $\epsilon_M > 0$, there exist ideal weights W and V such that

$$f(x) = W^T \sigma(V^T \check{v}) + \epsilon(\check{v}), \tag{3}$$

where $\|\epsilon(\check{v})\| \leq \epsilon_M$.

In general, the ideal weights W and V are unknown and require to be estimated in controller design. Let \hat{W} and \hat{V} be the estimates of the idea weights W and V , respectively, and then the weight estimation errors are described by $\tilde{W} = \hat{W} - W$, $\tilde{V} = \hat{V} - V$.

For (3), the function approximation error can be expressed as

$$\hat{W}^T \sigma(\hat{V}^T \check{v}_i) - W^T \sigma(V^T \check{v}) = \tilde{W}^T (\hat{\sigma} - \hat{\sigma}' \hat{V}^T \check{v}) + \hat{W}^T \hat{\sigma}' \tilde{V}^T \check{v} + d_{nn}, \tag{4}$$

where $\hat{\sigma} = \sigma(\hat{V}^T \check{v})$, $\sigma = \sigma(V^T \check{v})$, $\hat{\sigma}'$ denotes the Jacobian matrix.

For the sigmoid activation function, the residual term d_{nn} satisfies

$$\|d_{nn}\| \leq \varrho_1 \|\check{v} \hat{W}^T \hat{\sigma}'\|_F + \varrho_2 \|\hat{\sigma}' \hat{V}^T \check{v}\| + \varrho_3, \tag{5}$$

where $\varrho_1, \varrho_2, \varrho_3$ are positive constants.

2.2 Problem formulation

Consider a group of N MSVs governed by the three degrees-of-freedom (DOF) nonlinear model with kinematics and kinetics [32]

$$\begin{cases} \dot{\eta}_i = R(\psi_i)v_i, \\ M_i \dot{v}_i + C_i(v_i)v_i + D_i(v_i)v_i + g_i(v_i) = \tau_i + \tau_{iw}, \end{cases} \tag{6}$$

where

$$R(\psi_i) = \begin{bmatrix} \cos \psi_i & -\sin \psi_i & 0 \\ \sin \psi_i & \cos \psi_i & 0 \\ 0 & 0 & 1 \end{bmatrix}; \tag{7}$$

$\eta_i = [x_i, y_i, \psi_i]^T \in \mathbb{R}^3$ is the position vector in the earth-fixed reference frame; $v_i = [u_i, v_i, r_i]^T \in \mathbb{R}^3$ is the velocity vector in the body-fixed reference frame; $M_i = M_i^T \in \mathbb{R}^{3 \times 3}$, $C_i(v_i) \in \mathbb{R}^{3 \times 3}$, $D_i(v_i) \in \mathbb{R}^{3 \times 3}$ denote the inertia matrix, Coriolis/centripetal matrix, and damping matrix, respectively; $g_i(v_i) = [g_{iu}, g_{iv}, g_{ir}]^T \in \mathbb{R}^3$ represents the unmodeled dynamics; $\tau_i = [\tau_{iu}, \tau_{iv}, \tau_{ir}]^T \in \mathbb{R}^3$ denotes the control input with τ_{iu} the surge force and τ_{ir} the yaw moment; $\tau_{iw} = [\tau_{iwu}, \tau_{i wv}, \tau_{i wr}]^T$ denotes the disturbances from the environment.

Leaderless cooperative control Design a distributed cooperative control law τ_i for the vehicle (6) using its own states (η_i, v_i) and its neighbor's states (η_j, v_j) such that

$$\eta_i - \Delta_i \rightarrow \eta_j - \Delta_j, \quad \forall i = 1, \dots, N, \tag{8}$$

with bounded errors. $\Delta_i = [\Delta_{ix}, \Delta_{iy}, \Delta_{i\psi}]^T \in \mathbb{R}^3$ is desired relative final configuration.

Suppose there exists a virtual leader who moves along a time-varying reference trajectory $\eta_r \in \mathbb{R}^3$ with bounded derivatives, and in the network, only a fraction of the vehicles have access to the leader; then the leader-follower cooperative control problem is stated as below.

Leader-follower cooperative control Design a distributed cooperative control law τ_i for the vehicle (6) using its own states (η_i, v_i) and its neighbors' states (η_j, v_j) such that

$$\eta_i - \Delta_i \rightarrow \eta_r, \quad \forall i = 1, \dots, N, \tag{9}$$

with bounded errors.

To move on, we make use of the following assumptions.

Assumption 1 For the time-dependent disturbance τ_{iw} , there exists a positive constant $\rho_{wM} \in \mathbb{R}$ such that $\|\tau_{iw}\|_\infty \leq \rho_{wM}$.

Assumption 2 The time-varying reference trajectory $\dot{\eta}_r$ is bounded. That is, there exists a positive constant $\rho_M \in \mathbb{R}$ such that $\|\dot{\eta}_r\|_\infty \leq \rho_M$.

3 Leaderless cooperative control

In this section, we show that NNs, the backstepping technique and graph theory can be integrated to design the leaderless cooperative controllers. At first, a distributed kinematic control law is developed based on graph theory; next, NNs are employed to account for the model uncertainties.

3.1 Controller design

Following the backstepping design technique [34], we first introduce the change of coordinates

$$\begin{cases} z_{i1} = \eta_i - \Delta_i, \\ z_{i2} = v_i - \alpha_{i1}, \quad i = 1, \dots, N, \end{cases} \tag{10}$$

where α_{i1} are virtual control signals. Then the time derivative of z_{i1} and z_{i2} with (6) can be described by

$$\begin{cases} \dot{z}_{i1} = R(\psi_i)v_i, \\ M_i \dot{z}_{i2} = -C_i(v_i)v_i - D_i(v_i)v_i - g_i(v_i) + \tau_{iw} \\ \quad + \tau_i - M_i \dot{\alpha}_{i1}, \quad i = 1, \dots, N. \end{cases} \tag{11}$$

To facilitate the controller design, define

$$\begin{cases} z_1 = [z_{11}^T, \dots, z_{N1}^T]^T, \quad z_2 = [z_{12}^T, \dots, z_{N2}^T]^T, \\ \mathcal{R} = \text{diag}\{R(\psi_i)\}, \quad M = \text{diag}\{M_i\}. \end{cases} \tag{12}$$

The iterative design procedure is described as follows.

Step 1: At this step, a distributed kinematic virtual control law α_{i1} based on the local information is constructed as follows:

$$\alpha_{i1} = -k_{i1}R^T(\psi_i)s_i, \tag{13}$$

where $k_{i1} \in \mathbb{R}^{3 \times 3}$ is a diagonal matrix with its diagonal entries being positive and nondiagonal entries being zero, and

$$s_i = \sum_{j=1}^N a_{ij}[\eta_i - \Delta_i - (\eta_j - \Delta_j)], \tag{14}$$

where s_i is the cooperative tracking error. In what follows, we obtain the closed-loop subsystem:

$$\dot{z}_{i1} = -k_{i1}s_i + R(\psi_i)z_{i2}, \tag{15}$$

which can be expressed in a matrix form

$$\dot{z}_1 = -K_1(L \otimes I_3)z_1 + \mathcal{R}z_2, \tag{16}$$

where $K_1 = \text{diag}\{k_{i1}\}$.

Consider the Lyapunov function candidate

$$V_{11} = \frac{1}{2}z_1^T(L \otimes I_3)z_1, \tag{17}$$

whose time derivative along (16) is given by

$$\dot{V}_{11} = -z_1^TK_1(L^2 \otimes I_3)z_1 + z_1^T(L \otimes I_3)\mathcal{R}z_2. \tag{18}$$

Step 2: At this step, consider another Lyapunov function candidate

$$V_{12} = V_{11} + \frac{1}{2}z_2^TMz_2, \tag{19}$$

whose time derivative with (11) is

$$\begin{aligned} \dot{V}_{12} \leq & \sum_{i=1}^N \{z_{i2}^T(-C_i(v_i)v_i - D_i(v_i)v_i - g_i(v_i) + \tau_i \\ & + \tau_{iw} - M_i\dot{\alpha}_{i1} + R^T(\psi_i)s_i)\} \\ & - z_1^TK_1(L^2 \otimes I_3)z_1. \end{aligned} \tag{20}$$

The desired kinetic control law τ_i is chosen as

$$\tau_i = -k_{i2}z_{i2} - R^T(\psi_i)s_i + f_i(\cdot), \tag{21}$$

where $f_i(\cdot) = M_i\dot{\alpha}_{i1} + C_i(v_i)v_i + D_i(v_i)v_i + g_i(v_i) - \rho_{wM} \tanh(z_{i2})$; $k_{i2} \in \mathbb{R}^{3 \times 3}$ is a diagonal matrix with

its diagonal entries being positive constants and non-diagonal entries being zero. In practice, the parameters C_i , D_i , g_i , M_i , and ρ_{wM} are very hard to obtain. Hence, an NN is employed to handle the unknown dynamics as follows:

$$f_i(\cdot) = W_i^T \sigma(V_i^T \check{v}_i) + \epsilon_i(\check{v}_i), \tag{22}$$

where $\check{v}_i = [1, \dot{\alpha}_{i1}^T, v_i^T]^T \in \mathbb{R}^7$ is the input vector; W_i , V_i are the NN weights; $\epsilon_i(\check{v}_i)$ is the approximation error satisfying $\|\epsilon_i(\check{v}_i)\| \leq \epsilon_{iM}$ with ϵ_{iM} a positive constant.

Then an NN-based kinetic control law is proposed as

$$\tau_i = \hat{W}_i^T \sigma(\hat{V}_i^T \check{v}_i) - (k_{i2} + h_i)z_{i2} - R^T(\psi_i)s_i, \tag{23}$$

with an adaptive law

$$\begin{cases} \dot{\hat{W}}_i = -\Gamma_{iW}[(\hat{\sigma} - \hat{\sigma}'\hat{V}_i^T \check{v}_i)z_{i2}^T + k_W \hat{W}_i], \\ \dot{\hat{V}}_i = -\Gamma_{iV}[\check{v}_i z_{i2}^T \hat{W}_i^T \hat{\sigma}' + k_V \hat{V}_i], \end{cases} \tag{24}$$

where h_i is an auxiliary function defined as

$$h_i = k_{i3}(\|\check{v}_i \hat{W}_i^T \hat{\sigma}'\|_F^2 + \|\hat{\sigma}'\hat{V}_i^T \check{v}_i\|^2 + 1)I_3, \tag{25}$$

and $k_W \in \mathbb{R}$, $k_V \in \mathbb{R}$, $\Gamma_{iW} \in \mathbb{R}$, $\Gamma_{iV} \in \mathbb{R}$, $k_{i3} \in \mathbb{R}$ are positive constants.

Finally, substituting the control law (23) into (20) gives

$$\begin{aligned} \dot{V}_{12} \leq & \sum_{i=1}^N \{z_{i2}^T[-h_i z_{i2} + \tilde{W}_i^T(\hat{\sigma} - \hat{\sigma}'\hat{V}_i^T \check{v}_i) \\ & + \hat{W}_i^T \hat{\sigma}' \tilde{V}_i^T \check{v}_i + d_{inn} - \rho_{wM} \tanh(z_{i2}) + \tau_{iw}]\} \\ & - z_1^TK_1(L^2 \otimes I_3)z_1 - z_2^TK_2z_2, \end{aligned} \tag{26}$$

where $K_2 = \text{diag}\{k_{i2}\}$.

Remark 1 Different from the passivity-based approach for output synchronization [21], the proposed controller does not rely on the passivity property of system and is model-independent in that the controller does not require the knowledge of the inertial matrix, Coriolis and centrifugal force, and hydrodynamic damping.

3.2 Stability analysis

To analyze the stability of overall system, the following theorem is proposed.

Theorem 1 Consider a networked system consisting of N MSVs governed by the dynamics (6) with Assumption 1 satisfied. Let the network topology be undirected, fixed and connected. Select the control law (23) with the adaptive law (24). Then, for bounded initial conditions, all the signals in the closed-loop system are uniformly ultimately bounded (UUB), and (8) holds for $1 \leq i \leq N$, provided that the control parameter K_2 satisfies

$$\lambda_{\min}(K_2) > 1/2. \tag{27}$$

Proof Consider the Lyapunov function candidate

$$V_1 = V_{12} + \frac{1}{2} \sum_{i=1}^N \{ \text{tr}(\tilde{W}_i^T \Gamma_{iW}^{-1} \tilde{W}_i) + \text{tr}(\tilde{V}_i^T \Gamma_{iV}^{-1} \tilde{V}_i) \}, \tag{28}$$

where $\tilde{W}_i = \hat{W}_i - W_i$, $\tilde{V}_i = \hat{V}_i - V_i$. Taking the time derivative of (28), and using (24) and (26), we have

$$\begin{aligned} \dot{V}_1 \leq & -s^T K_1 s - z_2^T K_2 z_2 + \sum_{i=1}^N \{ z_{i2}^T (-\epsilon_i + d_{inn} \\ & - h_i z_{i2}) - \rho_{wM} z_{i2}^T \tanh(z_{i2}) + \|z_{i2}\|_1 \rho_{wM} \\ & - k_W \text{tr}(\tilde{W}_i^T \hat{W}_i) - k_V \text{tr}(\tilde{V}_i^T \hat{V}_i) \}, \end{aligned} \tag{29}$$

where $s = [s_1^T, \dots, s_N^T]^T$.

Using Young's inequality and the fact $|\gamma| - \gamma \tanh(\gamma) \leq 0.2785$ for a given variable $\gamma \in \mathbb{R}$, the following inequalities hold:

$$\begin{cases} |z_{i2}^T \epsilon_i| \leq \frac{1}{2} \|z_{i2}\|^2 + \frac{1}{2} \|\epsilon_M\|^2, \\ -k_V \text{tr}\{\tilde{V}_i^T \hat{V}_i\} \leq -\frac{k_V}{2} \|\tilde{V}_i\|_F^2 + \frac{k_V}{2} \|V_i\|_F^2, \\ -k_W \text{tr}\{\tilde{W}_i^T \hat{W}_i\} \leq -\frac{k_W}{2} \|\tilde{W}_i\|_F^2 + \frac{k_W}{2} \|W_i\|_F^2, \\ 0.8355 \geq -z_{i2}^T \tanh(z_{i2}) + \|z_{i2}\|_1, \\ z_{i2}^T d_{inn} \leq k_{i3} \|z_{i2}\|^2 (\|\tilde{v}_i \hat{W}_i^T \hat{\sigma}'\|_F^2 + \|\hat{\sigma}' \hat{V}_i^T \tilde{v}_i\|^2 + 1) \\ \quad + \frac{\varrho_{i1}^2 + \varrho_{i2}^2 + \varrho_{i3}^2}{4k_{i3}}. \end{cases} \tag{30}$$

Then we derive that

$$\begin{aligned} \dot{V}_1 \leq & -\lambda_{\min}(K_1) \|s\|^2 - \left[\lambda_{\min}(K_2) - \frac{1}{2} \right] \|z_2\|^2 \\ & - \sum_{i=1}^N \left\{ \frac{k_W}{2} \|\tilde{W}_i\|_F^2 + \frac{k_V}{2} \|\tilde{V}_i\|_F^2 \right\} \end{aligned}$$

$$\begin{aligned} & + \sum_{i=1}^N \left\{ \frac{1}{2} \|\epsilon_M\|^2 + \frac{k_W}{2} \|W_i\|_F^2 + \frac{k_V}{2} \|V_i\|_F^2 \right. \\ & \left. + 0.8355 \varrho_{wM} + \frac{\varrho_{i1}^2 + \varrho_{i2}^2 + \varrho_{i3}^2}{4k_{i3}} \right\}, \end{aligned} \tag{31}$$

which can be described as

$$\dot{V}_1(t) \leq \alpha_1 V_1(t) + \beta_1, \tag{32}$$

where

$$\begin{cases} \alpha_1 = \min\left\{ \frac{2\lambda_{\min}(K_1)}{\lambda_{\max}(P)}, \frac{2\lambda_{\min}(K_2)-1}{\lambda_{\max}(M)}, \frac{k_W}{\Gamma_{iW}^{-1}}, \frac{k_V}{\Gamma_{iV}^{-1}} \right\}, \\ \beta_1 = \sum_{i=1}^N \left\{ \frac{1}{2} \|\epsilon_M\|^2 + \frac{k_W}{2} \|W_i\|_F^2 + \frac{k_V}{2} \|V_i\|_F^2 \right. \\ \quad \left. + 0.8355 \varrho_{wM} + \frac{\varrho_{i1}^2 + \varrho_{i2}^2 + \varrho_{i3}^2}{4k_{i3}} \right\}. \end{cases} \tag{33}$$

By integration of (32), we have

$$V_1(t) \leq V_1(0)e^{-\alpha_1 t} + \frac{\beta_1}{\alpha_1} (1 - e^{-\alpha_1 t}), \tag{34}$$

It is straightforward to verify that all signal in the closed-loop system are UUB [35]. By Lemma 2, we obtain

$$\frac{1}{2} \lambda_{\min}(P) \|s\|^2 \leq V_1(t). \tag{35}$$

Therefore, the cooperative tracking error $\|s\|$ converges to a compact set $\Omega_s := \{ \|s\| \leq \sqrt{\frac{2\beta_1/\alpha_1}{\lambda_{\min}(P)}} \}$ as $t \rightarrow \infty$. Also note that $z_1^T (L \otimes I_3) z_1 \geq \lambda_2(L) \|z_1 - \mathbf{1} \otimes \text{Ave}(z_1)\|$ where $\text{Ave}(z_1) = \sum_{i=1}^N z_{1i}$ [36], we have

$$\frac{1}{2} \lambda_2(L) \|z_1 - \mathbf{1} \otimes \text{Ave}(z)\|^2 \leq V(t). \tag{36}$$

It follows that $\|z_1 - \mathbf{1} \otimes \text{Ave}(z_1)\|$ is bounded by $\sqrt{\frac{2\beta_1}{\lambda_2(L)\alpha_1}}$ as $t \rightarrow \infty$, implying $z_{i1} \rightarrow z_{j1} \rightarrow \text{Ave}(z)$. This completes the proof. \square

Remark 2 Note that by appropriately increasing the control gains $K_1, K_2, \Gamma_{iW}, \Gamma_{iV}$, the bound $\sqrt{\frac{2\beta_1}{\lambda_2(L)\alpha_1}}$ can be reduced.

4 Leader-follower cooperative control

In the preceding section, there does not exist a leader in the group which means that the final position of each vehicle is not known. In many instances, it is

desirable for the group to follow a time-varying reference trajectory, and the reference trajectory may be only available to a fraction of vehicles. To handle this case, a leader-follower cooperative control design is developed by incorporating the leader-follower synchronization strategy, the backstepping technique and NNs. In this section, we continue to use the symbols and notations defined for the leaderless case. If they need to be modified for the leader-follower case, we redefine them explicitly.

4.1 Controller design

In this case, redefine z_{i1} as

$$z_{i1} = \eta_i - \Delta_i - \eta_r, \tag{37}$$

whose time derivative is given by

$$\dot{z}_{i1} = R(\psi_i)v_i - \dot{\eta}_r. \tag{38}$$

Similar to the leaderless case, the iterative design procedure is elaborated as follows.

Step 1: Since only a portion of vehicles have access to η_r , the traditional tracking control scheme cannot be applied. Here, a distributed virtual control law α_{i1} based on the local information is proposed as follows:

$$\alpha_{i1} = -k_{i1}R^T(\psi_i)\delta_i - \kappa_i R^T(\psi_i) \tanh(\delta_i), \tag{39}$$

where $\kappa_i \in \mathbb{R}^{3 \times 3}$ is a diagonal matrix with its diagonal entries being positive constants and nondiagonal entries being zero. Here, the additional term $\kappa_i R^T(\psi_i) \tanh(\delta_i)$ is used to cancel out the unknown term $\dot{\eta}_r$ in (38), leading to a distributed kinematic controller. δ_i is defined as

$$\delta_i = \sum_{j=1}^N a_{ij} [\eta_j - \Delta_j - (\eta_j - \Delta_j)] + b_i z_{i1}. \tag{40}$$

It follows that (38) is

$$\dot{z}_{i1} = -k_{i1}\delta_i - \kappa \tanh(\delta_i) + R(\psi_i)z_{i2} - \dot{\eta}_r, \tag{41}$$

which can be expressed in a matrix form

$$\begin{aligned} \dot{z}_1 = & -K_1[(H \otimes I_3)z_1] - \kappa \tanh[(H \otimes I_3)z_1] \\ & - \mathbf{1} \otimes \dot{\eta}_r + \mathcal{R}z_2, \end{aligned} \tag{42}$$

where $\kappa = \text{diag}\{\kappa_i\}$.

Consider a Lyapunov function candidate

$$V_{21} = \frac{1}{2}z_1(H \otimes I_3)z_1, \tag{43}$$

whose time derivative along (42) is given by

$$\begin{aligned} \dot{V}_{21} \leq & -z_1^T K_1(H^2 \otimes I_3)z_1 + z_1^T (H \otimes I_3)\mathcal{R}z_2 \\ & + z_1^T (H \otimes I_3)\{-\kappa \tanh[(H \otimes I_3)z_1] \\ & + \|z_1^T (H \otimes I_3)\|_{1\varrho_M}, \end{aligned} \tag{44}$$

where the inequality

$$|z_1^T (H \otimes I_3)(\mathbf{1} \otimes \dot{\eta}_r)| \leq \|(H \otimes I_3)z_1\|_{1\varrho_M} \tag{45}$$

is applied. In addition, note that

$$\begin{aligned} \|(H \otimes I_3)z_1\|_{1\varrho_M} \leq & z_1^T (H \otimes I_3) \tanh[(H \otimes I_3)z_1] \\ & + 0.8355N, \end{aligned} \tag{46}$$

and it follows that (44) can be further put into

$$\begin{aligned} \dot{V}_{21} \leq & -z_1^T K_1(H^2 \otimes I_3)z_1 + z_1^T (H \otimes I_3)\mathcal{R}z_2 \\ & - [\lambda_{\min}(\kappa) - \varrho_M][z_1^T (H \otimes I_3)] \\ & \times \tanh[(H \otimes I_3)z_1] + 0.8355\varrho_M N. \end{aligned} \tag{47}$$

Select $\lambda_{\min}(\kappa) > \varrho_M$ such that

$$\begin{aligned} \dot{V}_{21} \leq & -z_1^T K_1(H^2 \otimes I_3)z_1 + z_1^T (H \otimes I_3)\mathcal{R}z_2 \\ & + 0.8355\varrho_M N. \end{aligned} \tag{48}$$

Step 2: Consider another Lyapunov function candidate

$$V_{22} = V_{21} + \frac{1}{2}z_2^T M z_2, \tag{49}$$

and its time derivative with (48) and (11) satisfies

$$\begin{aligned} V_{22} \leq & -z_1^T K_1(H^2 \otimes I_3)z_1 + 0.8355\varrho_M \\ & + \sum_{i=1}^N \{z_{i2}(-C_i(v_i)v_i - D_i(v_i)v_i - g_i(v_i) \\ & + \tau_i + \tau_{iw} - M_i \dot{\alpha}_{i1} + R^T(\psi_i)s_i)\}. \end{aligned} \tag{50}$$

Similar to the leaderless case, the kinetic controller is taken as

$$\tau_i = \hat{W}_i^T \sigma(\hat{V}_i^T \check{v}_i) - (k_{i2} + h_i)z_{i2} - R^T(\psi_i)s_i, \tag{51}$$

where \hat{W}_i and \hat{V}_i are updated as (24).

Finally, substituting the control law (51) into (50) gives

$$\begin{aligned} \dot{V}_{12} \leq & \sum_{i=1}^N \{z_{i2}^T [-h_i z_{i2} + \tilde{W}_i^T (\hat{\sigma} - \hat{\sigma}' \hat{V}_i^T \check{v}_i) \\ & + \hat{W}_i^T \hat{\sigma}' \tilde{V}_i^T \check{v}_i + d_{inn} - \rho_{wM} \tanh(z_{i2}) + \tau_{iw}] \} \\ & - z_1^T K_1 (L^2 \otimes I_3) z_1 - z_2^T K_2 z_2 + 0.8355 \varrho_M N. \end{aligned} \tag{52}$$

Remark 3 The NNs-based cooperative control designs are presented in [15–18]. Note that in these works, the NN identification of system dynamics is coupled with the communication graph, which may be undesirable in practice since the nonlinear vehicle dynamics is local. The backstepping-based cooperative control design proposed in this paper separates the NN learning of system dynamics and the communication scheme, and hence are practical to implement for real-world vehicles.

4.2 Stability analysis

We are ready to state the second result of this paper.

Theorem 2 Consider a networked system consisting of N MSVs governed by the dynamics (6) with Assumptions 1–2 satisfied. Let the network topology be undirected, fixed and connected and at least one MSV has access to η_r . Select the control law (51) with the adaptive law (24). Then, for bounded initial conditions, all the signals in the closed-loop system are UUB, and (9) holds for $1 \leq i \leq N$, provided the control parameters κ and K_2 satisfy

$$\lambda_{\min}(\kappa) > \varrho_M, \lambda_{\min}(K_2) > \frac{1}{2}. \tag{53}$$

Proof Consider the Lyapunov function candidate

$$V_2 = V_{22} + \frac{1}{2} \sum_{i=1}^N \{ \text{tr}(\tilde{W}_i^T \Gamma_{iW}^{-1} \tilde{W}_i) + \text{tr}(\tilde{V}_i^T \Gamma_{iV}^{-1} \tilde{V}_i) \}, \tag{54}$$

whose time derivative with the adaptive law (24) and (52) is

$$\dot{V}_2 \leq -z_1^T K_1 (H^2 \otimes I_3) z_1 - z_2^T K_2 z_2 + \sum_{i=1}^N \{ z_{i2}^T (-\epsilon_i$$

$$\begin{aligned} & + d_{inn} - h_i z_{i2}) - k_W \text{tr}(\tilde{W}_i^T \hat{W}_i) - k_V \text{tr}(\tilde{V}_i^T \hat{V}_i) \\ & - \rho_{wM} z_{i2}^T \tanh(z_{i2}) + \|z_{i2}\| \rho_{wM} + 0.8355 \varrho_M \}. \end{aligned} \tag{55}$$

By Lemma 1 and using the inequalities in (30), it leads to

$$\begin{aligned} \dot{V}_2 \leq & -\lambda_{\min}(K_1) \lambda_{\min}(H^2) \|z_1\|^2 \\ & - \left[\lambda_{\min}(K_2) - \frac{1}{2} \right] \|z_2\|^2 \\ & - \sum_{i=1}^N \left\{ \frac{k_W}{2} \|\tilde{W}_i\|_F^2 + \frac{k_V}{2} \|\tilde{V}_i\|_F^2 \right\} + \sum_{i=1}^N \left\{ \frac{1}{2} \|\epsilon_M\|^2 \right. \\ & + \frac{k_W}{2} \|W_i\|_F^2 + \frac{k_V}{2} \|V_i\|_F^2 + 0.8355(\varrho_{wM} + \varrho_M) \\ & \left. + \frac{\varrho_{i1}^2 + \varrho_{i2}^2 + \varrho_{i3}^2}{4k_{i3}} \right\}, \end{aligned} \tag{56}$$

which can be described as

$$\dot{V}_2(t) \leq \alpha_2 V_2(t) + (\beta_2), \tag{57}$$

where

$$\begin{cases} \alpha_2 = \min\{2\lambda_{\min}(K_1) \lambda_{\min}(H^2), \frac{2\lambda_{\min}(K_2)-1}{\lambda_{\max}(M)}, \\ \frac{k_W}{\Gamma_{iW}^{-1}}, \frac{k_V}{\Gamma_{iV}^{-1}}\}, \\ \beta_2 = \sum_{i=1}^N \left\{ \frac{1}{2} \|\epsilon_M\|^2 + \frac{k_W}{2} \|W_i\|_F^2 + \frac{k_V}{2} \|V_i\|_F^2 \right. \\ \left. + 0.8355(\varrho_M + \varrho_{wM}) + \frac{\varrho_{i1}^2 + \varrho_{i2}^2 + \varrho_{i3}^2}{4k_{i3}} \right\}, \\ i = 1, \dots, N. \end{cases}$$

By integration of (58), we have

$$V_2(t) \leq V_2(0) e^{-\alpha_2 t} + \frac{\beta_2}{\alpha_2} (1 - e^{-\alpha_2 t}). \tag{58}$$

We conclude that all signals in the closed-loop system are UUB.

From (54) and (58), we obtain

$$\frac{1}{2} \lambda_{\min}(H) \|z_1\|^2 \leq \frac{1}{2} z_1^T (H \otimes I_3) z_1. \tag{59}$$

Thus, the tracking error $\|z_1\|$ converges to a compact set $\Omega_z := \{\|z_1\| \leq \sqrt{\frac{2\beta_2}{\lambda_{\min}(H)\alpha_2}}\}$ as $t \rightarrow \infty$, implying (9). By increasing $K_1, K_2, \Gamma_{iW}, \Gamma_{iV}$, the compact set to which the tracking error converges can also be reduced. This completes the proof. \square

Remark 4 In contrast to the traditional tracking control of single vehicle to which one trajectory must be assigned [27–29], here, only a portion of vehicles have access to the reference trajectory, and thus the control problem confronted in this paper is more challenging. The cooperative tracking controllers designed in this paper can be regarded as an extension of traditional tracking control of single vehicle to those of the networked multivehicle systems.

Remark 5 For simplicity, the backstepping design technique is used to construct the cooperative controllers in this paper. If needed, the dynamic surface control approach proposed in [33] can be employed to estimate the derivatives of virtual control signals. Therefore, a possible future work includes an extension to the dynamic surface control-based design.

5 An example

Consider a networked system that consists of five MSVs and the model parameters can be found in Table 1 [37]. Without loss of generality, some model uncertainties and ocean disturbance are introduced into the model. Suppose that the information-exchange topology among the five vehicles is given in Fig. 1.

5.1 Leaderless cooperative control

This subsection considers the leaderless cooperative control case. At first, we discuss how to choose the number of neurons and control parameters. As in most control systems, the performance can be improved by trying a few simulation runs and adjusting the parameters to obtain good results. The number of neurons is selected as follows. The simulation was firstly performed with eight neurons when six neurons were used, and it was found that the approximation performance degraded. On the other hand, a simulation using twelve neurons did not improve the approximation performance dramatically. Therefore, eight neurons were selected. For the NN activation function, we use the sigmoid basic function of the form $1/[1 + \exp(-x)]$. The NN weights are initialized with zero. Once started, the NN weights can be adjusted online to obtain better performance. For control parameters, we know the control gains should be selected large and another consideration is

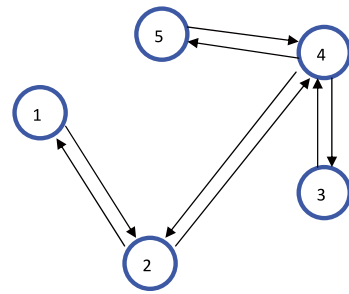


Fig. 1 Communication topology

Table 1 Model parameters

Parameters	Value
m_{11}	25.8
m_{22}	33.8
$m_{23} = m_{32}$	1.0115
$c_{13} = -m_{31}$	$-33.8v - 1.0115r$
$c_{23} = -m_{32}$	$25.8u$
d_{11}	$0.72 + 1.33 u + 5.87u^2$
d_{22}	$0.8896 + 36.5 v + 0.805 r $
d_{23}	$7.25 + 0.845 v + 3.45 r $
d_{32}	$0.0313 + 3.96 v + 0.130 r $
d_{33}	$1.90 - 0.080 v + 0.75 r $
g_u	$0.0279uv^2 + 0.0342v^2r$
g_v	$0.0912u^2v$
g_r	$0.0156ur^2 + 0.0278urv^3$
τ_{uu}	$-2 \cos(0.5t) \cos(t) + 0.3 \cos(0.5t) \sin(0.5t) - 3$
τ_{vv}	$0.01 \sin(0.1t)$
τ_{wr}	$0.6 \sin(1.1t) \cos(0.3t)$

that the adaptive terms should be faster than the proportional terms such that a good approximation can be obtained. Therefore, the adaptive gains are taken as $\Gamma_{W_i} = 100$, $\Gamma_{V_i} = 100$, $k_W = 0.1$, $k_V = 0.1$. Accordingly, the proportional gains are taken as $k_{i1} = \text{diag}\{0.2, 0.2, 0.2\}$, $k_{i2} = \text{diag}\{75, 22, 68.4\}$.

Simulation results are depicted in Figs. 2–4. Figure 2 shows the entire formation geometries of the five vehicles with information-exchange given by Fig. 1. It can be seen that they come into the desired star formation. The geometric pattern of the formation is stationary. The norms of consensus errors $\|s_{i1}\|$ are plotted in Fig. 2, and it demonstrates that the consensus errors are bounded to a small neighborhood of the origin. To verify the learning ability of NN, the approximation errors are depicted in Fig. 3 where it shows that the

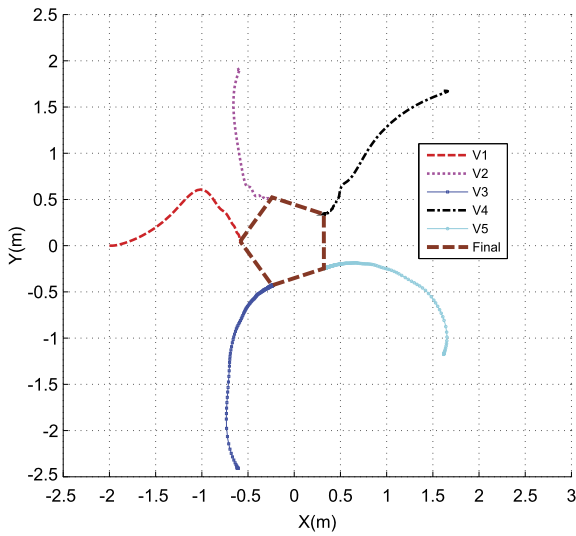


Fig. 2 Case 1: Formation trajectories in 2D plane

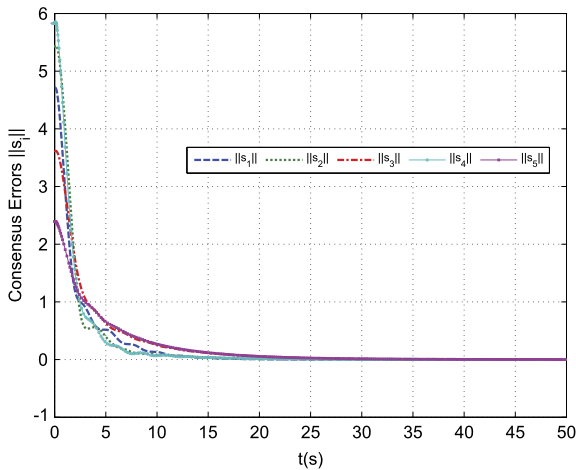


Fig. 3 Case 1: Consensus errors

uncertainties are efficiently compensated by outputs of NNs.

5.2 Leader-follower cooperative control

In this subsection, we consider the case where only the MSV 1 has access to a time-varying reference trajectory $[0.1t; 2 \sin(\pi t/150); a \tan 2(0.1t, 2 \sin(\pi t/150))]$. The control parameters $\Gamma_{W_i}, \Gamma_{V_i}, k_W, k_V, k_{i1}, k_{i2}$ are taken as the same as the above and others are selected as $b_i = 10, \kappa_i = \text{diag}\{0.2, 0.15, 0.2\}$. Simulation results are provided in Figs. 5–7. Figure 5 shows the entire formation geometries of the five vehicles with

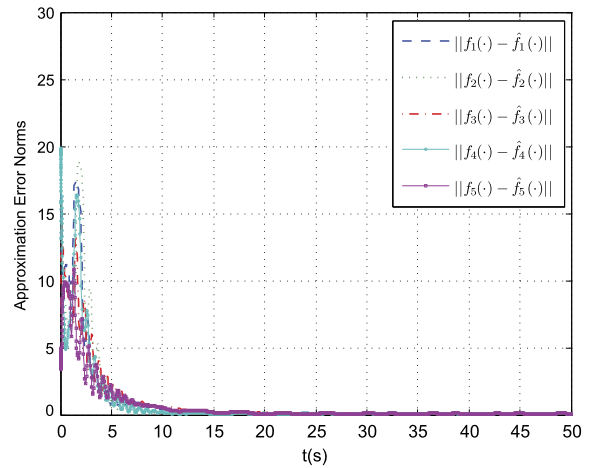


Fig. 4 Case 1: Approximation errors

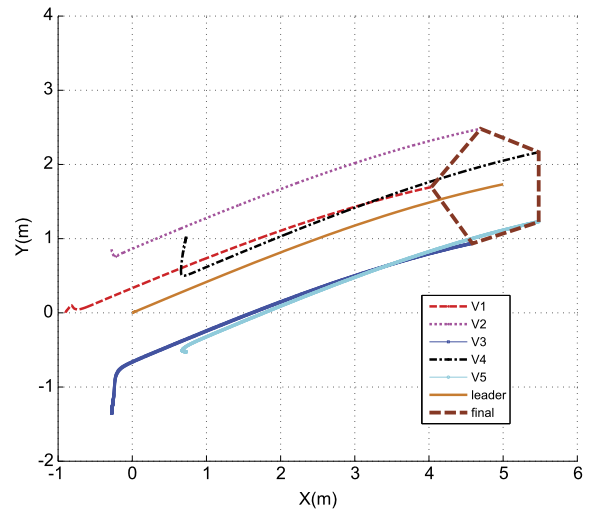


Fig. 5 Case 2: Formation trajectories in 2D plane

information-exchange given by Fig. 1. It can be observed that the star formation is also well established despite the existence of the uncertain dynamics and external disturbances. The norms of consensus errors $\|s_{i1}\|$ are plotted in Fig. 6, and it reveals that the consensus errors are bounded to a small neighborhood of the origin. To verify the learning ability of NNs, the approximation errors are depicted in Fig. 7, and it demonstrates that the uncertainties are also efficiently compensated by outputs of NNs.

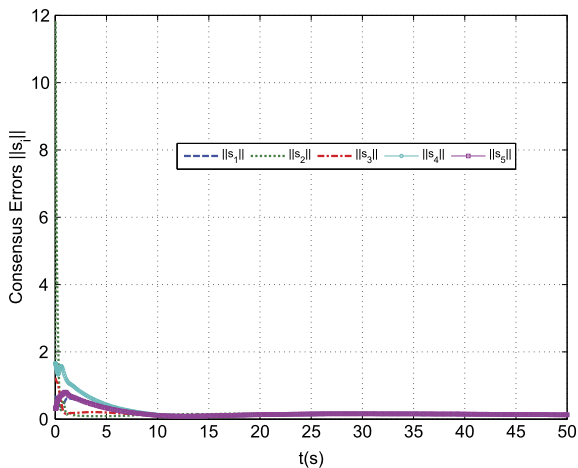


Fig. 6 Case 2: Consensus errors

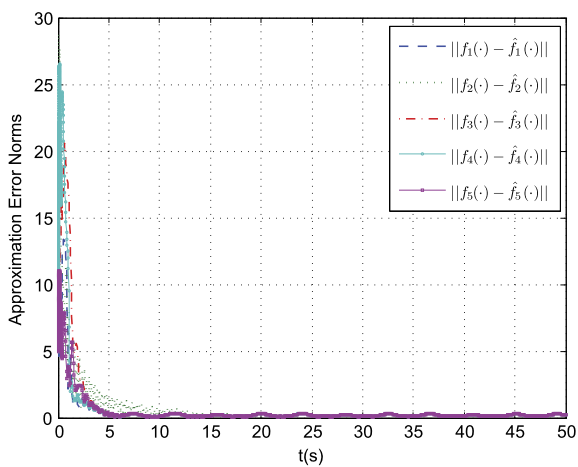


Fig. 7 Case 2: Approximations errors

6 Conclusions

This paper considered the leaderless and leader-follower cooperative tracking control of multiple marine surface vehicles with uncertain nonlinear dynamics. Two cooperative controllers have been proposed and analyzed based on neural networks, the backstepping technique and graph theory. These two neural controllers have been designed to ensure that formation behavior among vehicles can be reached for any undirected connected communication graph without requiring the accurate model of each vehicle. Based on Lyapunov stability analysis, all signals in the closed-loop systems are guaranteed to be uniformly ultimately bounded. Simulation results have demon-

strated the efficacy of the cooperative controllers and the learning ability of neural networks.

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