Command filter based globally stable adaptive neural control for cooperative path following of multiple underactuated autonomous underwater vehicles with partial knowledge of the reference speed

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A B S T R A C T

This paper investigates the problem of cooperative path following for a fleet of underactuated autonomous underwater vehicles (AUVs) with uncertain nonlinear dynamics. Path following controllers for individual AUVs are developed to ensure that each AUV converges to the desired position. The coordination mission is completed by reaching synchronization on a suitably defined path variable, even in the presence of partial knowledge of the reference speed. The key features of the proposed cooperative path following design scheme can be summarized as follows. First, the command filter design technique based cooperative path following control strategy is derived by introducing compensating error signals to remove the requirement of the higher derivative of reference signal, and a simplified cooperative path following controller is proposed. Second, a smoothly switching function is designed to yield neural network (NN) based energy-efficient controller. Third, by designing the distributed speed estimator, the global knowledge of the reference speed is relaxed. Finally, all the signals in the closed-loop system are guaranteed to be globally uniformly ultimately bounded (GUUB) under the proposed algorithm, and the path following error is proven to converge to a small neighborhood of the origin. Simulation example is provided to validate the performance of the control strategy.

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1. Introduction

In the past decade, research on networked cooperative systems control of multiple autonomous vehicles has attracted much attention due to its broad application in such areas as coordinated control of satellite flying [1], formation control of ground vehicles [2], and cooperative control of a fleet of surface and underwater vehicles [3–5]. One of the basic issue in formation control is the problem of cooperative path following where multiple vehicles are required to follow pre-specified spatial paths while keeping a desired formation pattern [6,7].

The problem of cooperative path following for multiple underactuated AUVs has drawn great attention from control communities. Many approaches to this problem have been reported in early works. In [8], a leader–follower based cooperative path following controller is proposed with arbitrary parallel paths. At the same time, with the absence of leader’s velocity, the follower tracks a reference path based on the leader’s position. In [9], a combination of Lyapunov theory and backstepping technique is employed to yield a cooperative path following control strategy for a fleet of homogenous AUVs. In [10], with the consideration of controllability constraints arising due to underactuation, a nonlinear cooperative path following controller is developed, and that is suitable for both unidirectional and bidirectional communication links. However, a key feature of the aforementioned results [3,8–10] is that the cooperative path following controllers are designed based on a backstepping technique [11–13]. The backstepping based cooperative path following controller has an obvious drawback. That is, the controllers are complicated for the sake of repeating differentiations of virtual controls. In order to overcome this problem, an NN based DSC technique is proposed for the
adaptive tracking control of strict-feedback systems with arbitrary nonlinearities in [14]. This method is later applied to solve the formation control problem of autonomous surface vehicles in the presence of dynamic uncertainty and environmental disturbances in [15]. It should be noted that although the simplified formation controllers have been derived for many kinds of cooperative control of multi-agent/robot system [15–21,47], the higher derivative of the reference signal is required to be known due to the NN based DSC technique, which is quite impractical in applications.

Dealing with nonlinear uncertainties is an important issue in motion control for mobile robots [22–24]. This is even more prominent for the underwater vehicles [25]. The function of the adaptive controller is confronted with greatness challenge since marine control applications are characterized by widely changing sea conditions and unmodeled dynamics [26]. Universal function approximators such as NNS have been widely applied on approximating uncertain nonlinear functions owing to the fact that they have a good approximation ability over a compact domain [30]. In [27], by combining NN approximation capabilities and adaptive techniques, the unknown AUV model parameters and environmental disturbances can be compensated and thus contribute to a robust tracing controller. In [28], the uncertain dynamics of the AUV are approximated through a one-layer NN inner loop, and an NN adaptive controller is developed to control the AUV to track a desired trajectory. It is shown that, in the absence of unknown disturbances and modeling errors, the NN controller guarantees semi-globally uniformly ultimately bounded (SGUUB). In [29], a semi-on-line NN Q-learning algorithm is proposed to learn the behavior state/action mapping. Besides, the effectiveness of the presented control algorithm for AUV is shown by experimental results.

A common feature of all the aforementioned NN-based strategies is that, they can only guarantee the SGUUB stability of closed-loop system with an assumption that the NN approximation is valid throughout the control process. However, such condition is difficult to verify beforehand. As a result, under the influence of external disturbances or an improper initialization, the tracking performance will be destroyed or even cause the instability of the system. [31] proposed a method that each virtual and actual controller switches between a robust controller and an NN controller for a class of strict-feedback systems and the overall controllers ensure GUUB. Despite that, [31] requires both robust controller and NN controller must work together all the time in the NN active region. The consequence is that the control commands will be inevitably repeatedly imposed on the system and cause the problem of the waste of control energy [32]. This problem is of great importance in AUV system since AUV works in the harsh underwater environment and energy supply is very hard and little work of GUUB controller has been developed until now. From a practical perspective, it is meaningful to design an energy-efficient control strategy for the problem of cooperative path following of multiple AUVs.

On the other hand, a major assumption in cooperative path following design of [3,6,9,10,19–21] is the global knowledge of the reference speed. In spite of leading to decentralized control laws that only exchange of path variables among the vehicles, the common reference speed must assume to be known to all vehicles. This may bring more information exchanges even more communication constrains under the harsh ocean environment for AUVs. Besides, cooperative control of multiple AUVs with less communication is of special interest in practical implementations. In order to eliminate the need of global knowledge of the reference speed, one option is to employ the distributed control strategy [33,34] proposed a distributed observer that enables the leader to be followed in the presence of unknown reference speed. Then, a leader–follower problem for a multi-agent system under a switching topology is solved. In [35], a neighbor local controller is derived based on the neighbor state-estimation rule. Then, a distributed cooperative control algorithm for estimation of the active leaders unmeasurable state is presented.

Motivated by the previous discussions, we present in this paper a cooperative path following control algorithm for multiple underactuated AUVs in the presence of uncertain dynamics and partial knowledge of the reference speed. The proposed control design use a combination of command filter design technique, NN adaptive technology, switching control strategy and a distributed estimator. First, by incorporating the command filter design technique, a smoothly switching function based NN adaptive path following controller is designed to steer each AUV to track a predefined path, where only NN controllers work in the NN active region. Second, under the cooperative design tool of graph theory, the speed and path variables are synchronized to each AUV owing to the proposed synchronization control law where the distributed speed estimate strategy is incorporated. Rigorous theoretical analysis shows that all signals in the closed-loop system are guaranteed to be GUUB. Compared with the previous results for the problem of cooperative path following of AUVs, the main contributions of this paper are summarized as follows.

- For the first time, the cooperative path following controller is derived based on the command filter technology that generates certain command signals and their derivatives, which leads to a much simpler path following controller than traditional backstepping-based design. In this way, analytic computation of the higher derivatives of the reference signal is no longer necessary, i.e., only the first derivative of reference path is required in our design while standard DSC design needs the knowledge of second derivative [5,14,20,21].

- By using smoothly switching function based NN adaptive technique to compensate for system uncertainties, an energy-efficient cooperative path following controller is developed. This is the first trial to address the switching function based cooperative path following controllers of multiple underactuated AUVs, which include a conventional NN adaptive controller works in the NN active region and a robust controller works outside the NN active region. The whole design ensures the GUUB stability of the closed-loop system and therefore is appealing to practical applications for AUVs.

- Each AUV is able to learn the speed information of virtual leader and neighboring vehicles by the distributed speed estimator (66). Under this control strategy, the communication burden to convey the reference speed to each AUV is decreased.

This rest of this paper is organized as follows: Section 2 introduces some preliminaries and gives the problem illustration. Section 3 presents the main designs including individual path following, cooperative design and stability analysis. Section 4 provides the simulation results to illustrate the proposed control algorithm. Section 5 concludes this paper.

2. Preliminaries and problem formulation

2.1. Stability results

In this subsection, we review the following stability results here for ease of reference. Consider a general nonlinear system [32],

\[ \dot{x} = f(x, t), \]  

with state \( x(t) \in \mathbb{R}^n \). We say that the solution of (1) is UUB if there exits a compact set \( \Omega \in \mathbb{R}^n \) such that for all \( x(t_0) = x_0 \in \Omega \), there exits a \( \epsilon_0 > 0 \) and a number \( T(\epsilon_0, x_0) \) such that \( ||x(t)|| < \epsilon_0 \) for all \( t \geq T(\epsilon_0, x_0) + t_0 \). Especially, if the compact set \( \Omega = \mathbb{R}^n \), then the solution of system (1) is GUUB.
2.2. Graph theory

An undirected graph $\mathcal{G} = (\mathcal{V}, E)$ consists of a finite set $\mathcal{V} = \{1, 2, \ldots, n\}$ of $n$ vertices and a finite set $E$ of $m$ pairs of vertices $(i, j) \in E$ named edges. If $(i, j)$ belongs to $E$ then $i$ and $j$ are said to be adjacent. If there is a path in $\mathcal{G}$ between any two vertices, then the graph $\mathcal{G}$ is said to be connected [18]. The adjacency matrix of the graph $\mathcal{G}$, denoted by $A = [a_{ij}] \in \mathbb{R}^{n \times n}$, is a square matrix with rows and columns indexed by the vertices, such that $a_{ij}$ equals one if $(i, j) \in E$ and zero otherwise. The Laplacian associated with the graph $\mathcal{G}$ is defined as $L = D - A$, where $D \in \mathbb{R}^{n \times n}$ is degree matrix. In this paper, each AUV will be represented by a vertex, then the communication link between two AUVs can be described by an edge between the corresponding vertices.

2.3. Neural networks

In this paper, Linear-in-parameter NN is used to approximate the uncertainties in the system. Before introducing our control design method, let us first recall the approximation property of the NNs [11–14, 36–45]. The NNs take the form of $\mathbb{W}^T \sigma (\xi)$ where $W \in \mathbb{R}^{p \times n}$ is a called weight matrix, with $p$ being the number of NN nodes; and $\sigma (\xi) \in \mathbb{R}^l$ is a vector valued function defined in $\mathbb{R}^l$, with $\xi \in \mathbb{R}^n$ being the NN input vector. Denote the components of $\sigma (\xi)$ by $\rho_i (\xi), i = 1, \ldots, \ell$, and $\rho_i (\xi)$ is a basis function. In this work, $\rho_i (\xi)$ is chosen as the commonly used hyper tangent function, which have the following form:

$$\rho_i (\xi) = \frac{1 - \exp(-p \xi)}{1 + \exp(-p \xi)},$$

where $p \in \mathbb{R}$ is a positive constant. According to the approximation property of the NNs, given a continuous real-valued function $f (\xi) : \Omega \rightarrow \mathbb{R}^m$, with $\Omega \subset \mathbb{R}^n$ a compact set, and any $\varepsilon > 0$, for some sufficiently large integer $\ell$, there exists $\|W\|_{\ell} \leq \varepsilon_M$, such that the NN $\mathbb{W}^T \sigma (\xi)$ can approximate the given function $f (\xi)$ as

$$f (\xi) = \mathbb{W}^T \sigma (\xi) + \varepsilon,$$

where $\|\varepsilon\| \leq \varepsilon_M$ represents the network reconstruction error.

2.4. Key definition

In this subsection, a switching function is introduced below, and then a property of this function is given by Lemma 1 which is crucial to the cooperative path following design.

**Definition 1.** For all $\sigma \in \mathbb{R}^n$, and given constants $0 < c_1 < c_2$, function $f (\sigma)$ is called an $n$-order smoothly switching function, if it satisfies the following conditions:

(a) $\|\sigma\| \leq c_1, f (\sigma) = 0$;

(b) $\|\sigma\| \geq c_2 > c_1, f (\sigma) = 1$;

(c) $f (\sigma)$ is the $n$-order continuous differentiable.

In particular, for all $\xi_i \in \mathbb{R}^p$, the following switching function is incorporated into the design:

$$m(\xi_i) = \begin{cases} 0, & \|\xi_i\| \leq c_{1i} \\ \frac{1 - \cos \left( \frac{\|\xi_i\|^2 - c_{1i}^2}{c_{2i}^2 - c_{1i}^2} \right)}{\frac{c_{2i}^2 - c_{1i}^2}{2}}, & \text{otherwise} \\ 1, & \|\xi_i\| \geq c_{2i} \end{cases}$$

**Lemma 1.** The function $m(\xi_i)$ is an $n$-order smoothly switching function for all $\xi_i \in \mathbb{R}^p$.

**Proof.** The proof can be found in [32], and thus omitted here for brevity. □

2.5. Problem formulation

The 6-degree-of-freedom model of underactuated AUV to be studied in this paper is described by the following equations [46]:

$$\dot{\eta}_i = R_i \nu_i,$$

$$\dot{R}_i = R_i S (\alpha_i),$$

$$M_i \dot{v}_i = -S (\alpha_i) M_i v_i + f_{iv_i} (\cdot) + b_1 u_i,$$

$$J \dot{\omega}_i = -S (v_i) M_i v_i - S (\alpha_i) J \omega_i + f_{i\omega_i} (\cdot) + b_2 u_i,$$

where

$$f_{iv_i} (\cdot) = \left[ \begin{array}{c} c \psi_i c \theta_i \\ -s \psi_i s \theta_i - c \psi_i s \theta_i \\ s \psi_i c \theta_i + c \psi_i s \theta_i \\ -s \theta_i \\ c \theta_i s \theta_i \\ -s \theta_i s \theta_i \\ -s \theta_i c \psi_i \\ s \theta_i c \psi_i \end{array} \right],$$

$$f_{i\omega_i} (\cdot) = \left[ \begin{array}{c} c \psi_i c \theta_i \\ -s \psi_i s \theta_i - c \psi_i s \theta_i \\ s \psi_i c \theta_i + c \psi_i s \theta_i \\ -s \theta_i \\ c \theta_i s \theta_i \\ -s \theta_i s \theta_i \\ -s \theta_i c \psi_i \\ s \theta_i c \psi_i \end{array} \right].$$

$\eta_i = [x_i, y_i, z_i]^T \in \mathbb{R}^3$ represents the position vector in the earth-fixed reference frame, $v_i = [u_i, v_i, w_i]^T \in \mathbb{R}^3$ and $\omega_i = [p_i, q_i, r_i]^T \in \mathbb{R}^3$ denote the linear and angular velocities in the body-fixed reference frame, respectively. $M_i = M_i^T \in \mathbb{R}^{3 \times 3}$ and $J_i = J_i^T \in \mathbb{R}^{3 \times 3}$ denote constant symmetric positive definite mass and inertia matrices, respectively. $f_{iv_i} (\cdot) = f_{iv_i} (v_i, \eta_i, R_i)$ and $f_{i\omega_i} (\cdot) = f_{i\omega_i} (v_i, \eta_i, \omega_i, R_i)$ represent all the remaining forces and torques acting on the vehicle including physical parameters and unmodeled dynamics. $u_i \in \mathbb{R}$ and $u_i \in \mathbb{R}^3$ denote the control inputs, which act upon the system through $b_1 = [1.0, 0]^T \in \mathbb{R}^3$ and $b_2 = \text{diag}[1] \in \mathbb{R}^{3 \times 3}$, respectively. $R_i \in \mathbb{R}^{3 \times 3}$ is a rotation matrix that describes the orientation (i.e. Euler angles $\psi_i, \theta_i, \phi_i$), denoted by $\dot{\eta}_i = [\psi_i, \theta_i, \phi_i]^T$ of the vehicle by mapping body coordinates into inertial coordinates. $S (\cdot) \in \mathbb{R}^{3 \times 3}$ is a skew-symmetric matrix defined by

$$S (\chi) = \left[ \begin{array}{ccc} 0 & -x_i & x_i \\ x_i & 0 & -x_i \\ -x_i & x_i & 0 \end{array} \right], \forall \chi = [x_i, y_i, z_i]^T \in \mathbb{R}^3.$$

The inertial and body-fixed coordinate frames are shown in Fig. 1.

**Assumption 1** [3,32]. For $i = 1, \ldots, n$, suppose there exist known positive smooth functions $F (\xi_i)$ such that

$$|f (\xi_i)| \leq F (\xi_i) f_{IM},$$

where $f_{IM}$ is a unknown constant.

The control objective of this paper is stated as follows. Cooperative path following problem. Let $\eta_{id} (\theta_i) = [x_{id} (\theta_i), y_{id} (\theta_i), z_{id} (\theta_i)]^T \in \mathbb{R}^3, i = 1, \ldots, n$, be a series of desired paths parameterized by continuous variables $\theta_i \in \mathbb{R}$. Suppose that each $\eta_{id} (\theta_i)$ is sufficiently smooth and its derivative is bounded, i.e., given any positive number $\delta_{ii}$, the set...
\[ \Omega_{11} = \{ \eta_{id}^T \eta_{id}^0 : \| \eta_{id} \|^2 + \| \eta_{id}^0 \|^2 \leq \delta_{11} \} \] is compact, where \( \eta_{id}^0 = (\partial(\cdot)/\partial \eta_i) \), \( \| \eta_{id} \| \leq \delta_{11} \) with \( \eta_{id}^0 \) being a positive constant. Design the feedback control laws for \( u_{id} \) and \( u_{id}^0 \), such that all signals in the closed-loop control network system are GUUB, and the path following error \( \eta_i - \eta_{id} \), along-path speed tracking error \( \dot{\eta}_i - \dot{\eta}_{id} \), and path variable coordination error \( \dot{\theta}_i - \dot{\theta}_{id} \) satisfy

\[
\lim_{t \to \infty} \| \eta_i - \eta_{id} \| \leq \epsilon_{1i},
\]

\[
\lim_{t \to \infty} \| \dot{\eta}_i - \dot{\eta}_{id} \| \leq \epsilon_{2i},
\]

\[
\lim_{t \to \infty} \| \dot{\theta}_i - \dot{\theta}_{id} \| \leq \epsilon_{3i},
\]

where \( \dot{\eta}_{id} \in \mathbb{R} \) is the estimate of \( v_0 \) and \( v_0 \) is a constant reference speed which assigned by the virtual leader; \( \epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i} \in \mathbb{R} \) are some small constants. The control architecture is shown in Fig. 2.

3. Globally stable adaptive cooperative path following controller design

3.1. Individual path following design

In this subsection, path following control strategy for single AUV will be derived by incorporating command filter based NN adaptive control technique. The synchronization control law for cooperative path following control design will be derived in the next subsection.

**Step 1.** Define the following error variables:

\[
z_{1i} = R_i^T (\eta_i - \eta_{id}),
\]

\[
p_{id} = \dot{p}_{id} - v_0,
\]

\[
\gamma_i = \dot{\theta}_i - \dot{\theta}_{id},
\]

where \( z_{1i} \) is the path following error, \( \gamma_i \) denotes the along-path tracking error. Taking the time derivative of \( z_{1i} \) and using (5) and (15) yields

\[
z_{1i} = -S(\omega_i)z_{1i} + v_i - R_i^T \eta_{id}^0 (\dot{\theta}_{id} + \gamma_i). \tag{16}
\]

In order to stabilize (16), design the virtual control law \( \alpha_i \) as

\[
\alpha_i = -K_i z_{1i} + R_i^T \eta_{id}^0 p_{id} + S(\omega) z_{1i}, \tag{17}
\]

where \( K_i \in \mathbb{R}^{3 \times 3} \) is a diagonal matrix and its diagonal elements are positive constants. The update law for \( \dot{p}_{id} \) will be specified in the next subsection, since it is supported by the information exchanges between its neighbors.

Introduce a new state variable \( \dot{\eta}_{id} \in \mathbb{R}^3 \) and let virtual control \( \alpha_i \) pass through a first-order filter with a time constant \( \chi_i \in \mathbb{R} \)

\[
\chi_i \dot{p}_{id} + \dot{p}_{id} = \alpha_i. \tag{18}
\]

Define \( z_{12} = v_i - \dot{p}_{id} \). Invoking (17), then (16) can be rewritten as

\[
z_{1i} = -K_i z_{1i} + z_{12} - R_i^T \eta_{id}^0 \gamma_i + (\dot{p}_{id} - \alpha_i). \tag{19}
\]

To remove the known error \( \dot{p}_{id} - \alpha_i \), the compensating signal \( \delta_{1i} \) is designed as

\[
\delta_{1i} = -K_i e_{1i} + e_{2i} + (\dot{p}_{id} - \alpha_i). \tag{20}
\]

where \( e_{2i} \) will be defined in the next step.

Then we obtain the compensated tracking error \( \tilde{z}_{1i} \)

\[
\tilde{z}_{1i} = z_{1i} - e_{1i}. \tag{21}
\]

The time derivative of \( \tilde{z}_{1i} \) is given by

\[
\dot{\tilde{z}}_{1i} = -K_i \tilde{z}_{1i} + K_i e_{1i} - e_{2i} + z_{12} - R_i^T \eta_{id}^0 \gamma_i. \tag{22}
\]

Consider a scalar function

\[
V_{1i} = \frac{1}{2} \tilde{z}_{1i}^T \dot{\tilde{z}}_{1i}. \tag{23}
\]
Its time derivative along (22) is
\[
\dot{V}_{i1} = -z_i^T K_{ii} z_i + z_i^T z_i - z_i^T \eta_{id} - \mu_i \dot{y}_i.
\]  
(24)
where \( \mu_i = \frac{z_i^T R_i^- \eta_{id}}{\rho_i} \).

**Step 2.** The time derivative of \( z_i \) is
\[
M_i \ddot{z}_i = 2M_i z_i \omega_i + f_i(\cdot) + b_i \dot{u}_i - S(\omega_i) M_i \dot{v}_i - M_i \dot{v}_{id}.
\]  
(25)

Owing to the lack of actuation, (25) cannot be stabilized by designing \( u_{id} \) directly. As a result, define \( \Phi_i = z_i - \beta_i \) with \( \beta_i \in \mathbb{R}^3 \) being a design parameter. Then, we obtain
\[
M_i \dot{\Phi}_i = B_i \tau_i - \dot{S}(\omega_i) M_i \dot{\Phi}_i + f_i(\xi_i),
\]  
(26)
where \( B_i = [b_1, S(\omega_i) M_i] \), \( \tau_i = [u_{id}, \omega_i \alpha_i]_T \). \( f_i(\xi_i) = -f_0(\cdot) + S(\omega_i) M_i \dot{v}_i + M_i \dot{v}_{id} \) and satisfies \( |f_i(\xi_i)| \leq F(\xi_i) \| \xi \|_{1M} \) with \( F(\xi_i) \) being a known positive smooth function and \( \dot{f}_{iM} \) being an unknown positive constant. Note that the matrix \( B_i \) can always be made full-rank by choosing a suitable \( \beta_i \).

The control command \( u_{id} \) will be designed next. Note that \( \tau_i \) can be regarded as the control law (actually its second component can be treated as a virtual control) to stabilize (26). To this effect, choose the following desired indirect law:
\[
\Lambda_i = B_i^T (B_i B_i^T)^{-1} \left[ -z_i - (K_{ii} - S(\omega_i) M_i) \Phi_i + f_i(\xi_i) \right],
\]  
(27)
where \( K_{ii} \in \mathbb{R}^{3 \times 3} \) is a diagonal matrix and its diagonal elements are positive constants. Consider a desired control \( u_{id} \) to be equal to the first entry of \( \Lambda_i \), and the second virtual control to be equal to the last three entries of \( \Lambda_i \),
\[
\begin{align*}
\dot{u}_{id} &= b_3 \Lambda_i, \\
\alpha_{id} &= b_{4} \Lambda_i,
\end{align*}
\]  
(28)
where \( b_3 = [b_1^T, 0], b_4 = [0_{3 	imes 1}, b_2] \).

In practice, \( f_i(\xi_i) \) in (28) is very hard to obtain accurately. Hence, the controller (28) can not be implemented. To overcome this problem, an NN is employed to approximate \( f_i(\xi_i) \). According to the approximation property of the NNs, we have
\[
f_i(\xi_i) = W_{i1}^T \sigma(\xi_i) + \dot{\varepsilon}_{i1},
\]  
(30)
where \( \dot{\varepsilon}_{i1} = [1, \omega_i, \dot{\omega}_i, \dot{\theta}_i, \dot{\eta}_i, \dot{\phi}_i, \dot{\phi}_i]_T \in \mathbb{R}^{10} \) is the NN input, \( W_{i1} \) is the NN weight, \( \dot{\varepsilon}_{i1} \) is the approximation error satisfying \( \| \dot{\varepsilon}_{i1} \| \leq \varepsilon_{i1M} \) with \( \varepsilon_{i1M} \) being a positive constant. Then, (27) can be rewritten as
\[
\Lambda_i = B_i^T (B_i B_i^T)^{-1} \left[ -z_i - (K_{ii} - S(\omega_i) M_i) \Phi_i + W_{i1}^T \sigma(\xi_i) + \dot{\varepsilon}_{i1} \right],
\]  
(31)
where \( \Lambda_i^m \) and \( \Lambda_i^r \) denote the adaptive neural controller dominating in the neural active region and the robust controller works outside the neural active region, respectively. They are designed as follows:
\[
\begin{align*}
\Lambda_i^m &= -W_{i1}^T \sigma(\xi_i) - \tanh \left( \frac{z_i^T}{\rho_i} \right) \dot{\varepsilon}_{i1M}, \\
\Lambda_i^r &= -F(\xi_i) \tanh \left( \frac{z_i^T F(\xi_i)}{\rho_i} \right) \dot{f}_{i1M}
\end{align*}
\]  
(32)
(33)
where \( \rho_i \in \mathbb{R} \) is a positive constant, \( \dot{W}_{i1} \), \( \dot{\varepsilon}_{i1M} \) and \( \dot{f}_{i1M} \) are the estimates of \( W_{i1}, \varepsilon_{i1M} \) and \( f_{i1M} \), respectively. Their update laws will be specified later. \( \dot{z}_i \) is an error variable which will be further illustrated in the following design.

Substituting (28) and (29) with (31) into (26) yields
\[
M_i \dot{\Phi}_i = -z_i - K_{ii} \Phi_i + \left( 1 - m(\xi_i) \right) \left[ -W_{i1}^T \sigma(\xi_i) - \tanh \left( \frac{z_i^T}{\rho_i} \right) \dot{\varepsilon}_{i1M} \right]
\]  
(34)
\[
\begin{align*}
+ &\left( 1 - m(\xi_i) \right) \left( \left[ -W_{i1}^T \sigma(\xi_i) - \tanh \left( \frac{z_i^T}{\rho_i} \right) \dot{\varepsilon}_{i1M} \right] \right) + m(\xi_i) \left[ -F(\xi_i) \tanh \left( \frac{z_i^T F(\xi_i)}{\rho_i} \right) \dot{f}_{i1M} \right]
\end{align*}
\]  
(40)
Consider the second scalar function
\[
V_{i2} = V_{i1} + \frac{1}{2} z_i^2 \dot{z}_i.
\]  
(41)
whose time derivative along (24) and (40) is given by
\[ V_{i2} \leq -\tilde{z}_1^T F_{i1} \tilde{z}_1 + \tilde{z}_1^T (M_1^{-1} - I) \tilde{z}_1 + z_1^T \beta_i - \mu_i \gamma_i \\
+ \tilde{z}_2^T \left\{-K_2 M_1^{-1} \tilde{z}_2 + (1 - m(\xi_i)) \right\} \\
+ \tilde{z}_2^T \left\{-W_i \sigma(\xi_i) - \tanh \left( \frac{\tilde{z}_2^T}{\rho_3} \right) \tilde{e}_{i1M} \right\} \\
+ m(\xi_i) \left\{-F(\xi_i) \tanh \left( \frac{\tilde{z}_2^T F(\xi_i)}{\rho_3} \right) \tilde{f}_{i1M} + F(\xi_i) \tilde{f}_{i1M} \right\} \\
+ S(M, \beta_i)(z_3 - e_3) \right\}. \tag{42}
\]

Further, we have
\[ V_{i2} \leq -\tilde{z}_1^T F_{i1} \tilde{z}_1 + \tilde{z}_1^T (M_1^{-1} - I) \tilde{z}_1 + z_1^T \beta_i - \mu_i \gamma_i - \tilde{z}_2^T K_2 M_1^{-1} \tilde{z}_2 \\
- (1 - m(\xi_i)) \tilde{z}_2^T W_i \sigma(\xi_i) - \tilde{e}_{i1M} \right\} \\
+ (1 - m(\xi_i)) \left\{ -\tilde{z}_2^T \tilde{z}_2^T \tanh \left( \frac{\tilde{z}_2^T}{\rho_3} \right) \tilde{e}_{i1M} \right\} \\
+ m(\xi_i) \left\{ -\tilde{z}_2^T F(\xi_i) - \tilde{z}_2^T F(\xi_i) \tanh \left( \frac{\tilde{z}_2^T F(\xi_i)}{\rho_3} \right) \tilde{f}_{i1M} \right\} \\
+ S(M, \beta_i)(z_3 - e_3). \tag{43}
\]

where
\[ \tilde{e}_{i1M} = \left(1 - m(\xi_i)) \right) \tilde{e}_{i1} \]

with
\[ \tilde{e}_{i1M} = \left[ \tilde{e}_{i1} \tilde{f}_{i1M} \right]. \tag{44}
\]

The adaptation laws are chosen as
\[ \hat{W}_i = \Gamma_i \left(1 - m(\xi_i)) \sigma(\xi_i) \tilde{z}_2 - k_{11W} \tilde{W}_i \right). \tag{45}
\]

Define the third scalar function as
\[ V_3 = V_2 + \frac{1}{2} \text{tr}(W_i \Gamma_i^{-1} \tilde{W}_i) + \frac{1}{2} \tilde{e}_{i1} \Gamma_i^{-1} \tilde{e}_{i1}, \tag{46}
\]

whose time derivative along (43)-(45) is given by
\[ V_3 \leq -\tilde{z}_1^T F_{i1} \tilde{z}_1 + \tilde{z}_1^T (M_1^{-1} - I) \tilde{z}_1 + z_1^T \beta_i - \mu_i \gamma_i - \tilde{z}_2^T K_2 M_1^{-1} \tilde{z}_2 \\
- k_{11W} \text{tr}(W_i \Gamma_i^{-1} \tilde{W}_i) - k_{11W} \tilde{W}_i \tilde{W}_i \\
+ (1 - m(\xi_i)) \left\{ -\tilde{z}_2^T \tilde{z}_2^T \tanh \left( \frac{\tilde{z}_2^T}{\rho_3} \right) \tilde{e}_{i1M} \right\} \\
+ m(\xi_i) \left\{ -\tilde{z}_2^T F(\xi_i) - \tilde{z}_2^T F(\xi_i) \tanh \left( \frac{\tilde{z}_2^T F(\xi_i)}{\rho_3} \right) \tilde{f}_{i1M} \right\} \\
+ S(M, \beta_i)(z_3 - e_3). \tag{47}
\]

Step 3. Taking the time derivative of \( z_3 \) along (8) gives
\[ J_3 \tilde{z}_3 = b_2 u_{am} - f(\tilde{z}_3). \tag{48}
\]
\[
+ m(\xi_1) \left[ \frac{\partial^2 F(\xi_1)}{\partial \hat{\Theta}_1^2} - \frac{\partial^2 F(\xi_1)}{\partial \hat{\Theta}_1^2} \right] \epsilon_{13M} \\
+ \tanh \left( \frac{\partial^2 F(\xi_1)}{\partial \epsilon_{13}^2} \right) f_{13M} + \frac{\partial^2 F(\xi_1)}{\partial \hat{\Theta}_1^2} \right] \epsilon_{23M} \\
+ (1 - m(\xi_2)) \left[ \frac{\partial^2 F(\xi_2)}{\partial \hat{\Theta}_2^2} - \frac{\partial^2 F(\xi_2)}{\partial \hat{\Theta}_2^2} \right] \epsilon_{23M} \\
+ \tanh \left( \frac{\partial^2 F(\xi_2)}{\partial \epsilon_{23}^2} \right) f_{23M} + \frac{\partial^2 F(\xi_2)}{\partial \hat{\Theta}_2^2} \right] \epsilon_{32M} \\
+ \frac{\partial^2 F(\xi_1)}{\partial \epsilon_{13}^2} \mathbf{m} \subseteq \mathbf{z}_2. \\
\right]
\]

Remark 1. In fact, using the traditional backstepping based method, the derivative of virtual control laws \( \alpha_{11} \) and \( \alpha_{22} \) would have to appear in the control algorithm.

\[
\hat{\alpha}_{11} = \frac{K_1}{k_{12}}(rS\mathbf{z}_1 - v_i - R_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1)) - R_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1) - \mathbf{k}_{21}(v_i - \mathbf{k}_1(\mathbf{rS}\mathbf{z}_1 - v_i - R_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1)) - \mathbf{R}_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1) - \mathbf{S}(\sigma_i)\mathbf{M}_i\Phi_1 + \mathbf{S}(\sigma_i)\mathbf{M}_i - \mathbf{k}_1(rS\mathbf{z}_1 - v_i - \mathbf{R}_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1)) - \mathbf{R}_i^2 \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1) + [1 - \bar{m}(\xi_1)] \mathbf{A}^m_i \\
+ [1 - m(\xi_1)] \mathbf{A}^m_i + \mathbf{m}(\xi_1) \mathbf{A}_i + m(\xi_1) \mathbf{A}_i.
\]

The consequence is that the expression of \( \mathbf{u}_d \) and \( \mathbf{u}_d \) would be much more complicated. Our design leads to a much simpler cooperative path following controller.

Remark 2. Since the compensating error signals are designed to remove the errors of \( \mathbf{u}_d - \mathbf{a}_1 \) and \( \mathbf{a}_2 - \mathbf{a}_2 \), there is no need to analyze the boundedness of them. In this way, only \( \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1) \) is required in this design while standard DSC design needs the knowledge of \( \eta \mathbf{u}_d(\hat{\Theta}_1 + \gamma_1) \). It is important to note that in some practical applications for AUVs, the desired path may be generated by a planner or a user input device that does not provide higher order derivatives. Besides, this is the first trial in designing cooperative path following controllers for multiple underactuated AUVs. Removing the need of the higher derivative of reference signal is helpful to practical applications.

3.2. Cooperative path following design

Cooperative control strategies for multiple AUVs are supported by the communications network over which the AUVs exchange information. Since more than one AUV is involved, the path variables and speed should be synchronized to each AUV, in order to maintain the desired formation. We assume that the AUVs can exchange relative path variables information by using the network infrastructure. To satisfy the constraints imposed by the communication network, the cooperative control law for the AUV \( i \) can only depends on its own local states and on the information exchanged with its neighbors. Furthermore, since not all the AUVs can obtain the value of common reference speed, some of them have to be estimated throughout the process. Let \( \mathbf{L}_i \) be the set of labels of those AUVs that are neighbors of AUV \( i \), \( \mathbf{N}_i \) be the set of labels of those AUVs that are neighbors of the virtual leader. In such a way, the common reference speed assigned by a virtual leader is available to only one or one subset of AUVs, so the speed estimate strategy is distributed. To this end, choose the following cooperative control law with an auxiliary state \( \mathbf{z}_i \) as

\[
\gamma_i = -k_{14} \left[ \sum_{j \in \mathbf{L}_i} \gamma_j(\theta_i - \theta_j) + \mu_i \right] - \mathbf{z}_i, \\
\mathbf{z}_i = -(k_{45} + k_{55}) \zeta_i - \sum_{j \in \mathbf{N}_i} \gamma_j(\theta_i - \theta_j) - \mu_i,
\]

where \( k_{14} \in \mathbb{R} \) and \( k_{45} \in \mathbb{R} \) are positive constants; \( \gamma_j \) has been defined in Section 2.3. The distributed speed update law is designed as

\[
\mathbf{v}_d = -k_{16} \sum_{j \in \mathbf{L}_i} \gamma_j(\mathbf{v}_d - \mathbf{v}_d) - k_{27} \sum_{i \in \mathbf{N}_i} \mathbf{b}_i(\mathbf{v}_d - \mathbf{v}_d).
\]
where $k_b \in \mathbb{R}$ and $k_\gamma \in \mathbb{R}$ are positive constants, $b_{iw}$ is the connection weight between vehicle $i$ and the virtual leader, $b_{iw} = 1$ if the virtual leader is available to ith vehicle and $b_{iw} = 0$ otherwise. Let $\zeta = [\zeta_1, \ldots, \zeta_n]^T \in \mathbb{R}^n$, $\mu = [\mu_1, \ldots, \mu_n]^T \in \mathbb{R}^n$, $y = [y_1, \ldots, y_n]^T \in \mathbb{R}^n$, $K_i = \text{diag}[k_i] \in \mathbb{R}^{n \times n}$, $K_f = \text{diag}[k_f] \in \mathbb{R}^{n \times n}$, $K_S = \text{diag}[k_S] \in \mathbb{R}^{n \times n}$, $\dot{v}_d = [\dot{v}_{i1}, \ldots, \dot{v}_{in}]^T \in \mathbb{R}^n$. Then, (63) can be written as
\[
\dot{\theta} = \dot{v}_d - K_i^T(\theta - \mu) - \zeta,
\]
(65)
\[
\dot{\zeta} = -(K_f + K_S)\zeta - \theta - \mu,
\]
(64) can be written as
\[
\dot{v}_d = -L\dot{v}_d + K_f\theta + f_n,
\]
(66)
where $\mathcal{L} = K_iL + K_fB$, $B = \text{diag}[b_{1w}, \ldots, b_{nw}] \in \mathbb{R}^{n \times n}$. Because the fixed undirected graph is connected and at least one $b_{iw}$ is nonzero, $\mathcal{L}$ is symmetric positive definite. Noting that $\dot{v}_d = \dot{v}_d - v_01_n$, then we have
\[
\dot{v}_d = -L\dot{v}_d.
\]
Consider the sixth scalar function as
\[
\nu_6 = \frac{1}{2}\dot{\theta}^T\theta + \frac{1}{2}r^T\xi + \frac{1}{2}n^T\dot{v}_d + \sum_{i=1}^n \nu_5,
\]
and its time derivative along (62), (65) and (67) is
\[
\nu_6 \leq -y^T K_4 y - r^T K_5 r - \dot{v}_d^T C \dot{v}_d + \sum_{i=1}^n \left[-z_{iT}^T K_i \dot{z}_i - z_{iT}^T K_2 z_{i2} \right] + \left[ -z_{iT}^T K_3 z_{i1} - z_{iT}^T K_5 z_{i1} \right] + \left[ -z_{iT}^T K_4 z_{i1} - z_{iT}^T K_6 z_{i1} \right] + \left[ -z_{iT}^T K_5 z_{i1} - z_{iT}^T K_7 z_{i1} \right]
\]
(68)
Remark 3. The distributed speed estimator (66) is first designed for the problem of cooperative path following of AUVs. The common speed information is available only to one or partial fleet of AUVs and all the other AUVs reconstruct this speed by estimators. The amount of communications is reduced effectively due to the distributed speed estimate strategy. This is crucial for AUVs since they work in the underwater environment and the bandwidth of underwater acoustic communication is severely constrained.

3.3. Stability analysis

Theorem 1. Consider a network of underactuated AUVs with the vehicle dynamics given in (5)-(8). Suppose the communication network is undirected and connected. Design the first-order filters (18) and (36), control laws (28) with (31) and (49), adaptive laws (44), (45), (59) and (60), cooperative control law (65) and distributed speed estimator (66). Then, given any positive number $\delta_d$, for all initial conditions satisfying $\Omega_2 = \{z_{12}^T, z_{13}^T, z_{14}^T, \ldots, \}, \nu_6 \leq \delta_d$, there exist $K_1, K_2, K_3, K_4, K_5, K_6, K_7, \Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4, k_{i1w}, k_{i2w}, k_{i1b}$ and $k_{i2b}$ such that all the closed-loop signals remain bounded all the time, and the path following error $\eta_1 - \eta_{id}$, along-path speed tracking error $\dot{\theta}_i - \dot{\theta}_{id}$ and path variable coordination error $\theta_i - \theta_j$ satisfy (10), (11), (12), respectively.

Proof. Using Young’s inequality, we obtain
\[
\begin{align*}
&\left\|z_{i1}^T (M_i + I)^{-1} \hat{z}_{i2}\right\| \leq \frac{\lambda_{\min}(M_i + I)^{-1}}{2d_{i1}} \left\|\hat{z}_{i1}\right\|^2 + \frac{d_{i2}}{2} \left\|\hat{z}_{i2}\right\|^2, \\
&\left\|z_{i2}^T S(M_i) \hat{z}_{i3}\right\| \leq \frac{\sigma(S(M_i))}{2d_{i2}} \left\|\hat{z}_{i2}\right\|^2 + \frac{d_{i3}}{2} \left\|\hat{z}_{i3}\right\|^2, \\
&\left\|z_{i3}^T M_i \hat{z}_{i4}\right\| \leq \frac{\lambda_{\min}(M_i + I)^{-1}}{2d_{i3}} \left\|\hat{z}_{i3}\right\|^2 + \frac{d_{i4}}{2} \left\|\hat{z}_{i4}\right\|^2, \\
&\left\|z_{i4}^T \hat{z}_{i1}\right\| \leq \frac{1}{2d_{i4}} \left\|\hat{z}_{i1}\right\|^2 + \frac{d_{i5}}{2} \left\|\hat{z}_{i2}\right\|^2 + \frac{d_{i6}}{2} \left\|\hat{z}_{i3}\right\|^2 + \frac{d_{i7}}{2} \left\|\hat{z}_{i4}\right\|^2.
\end{align*}
\]
Remark 4. Many general adaptive neural controllers ensure the SGUUB tracking stability for marine vehicles [113–15,27–29], provided that the trajectory stays within the neural active region throughout the control process. However, under the influence of external disturbances or an improper initialization, the tracking performance will be destroyed or even cause the instability of the system. In this paper, we proposed a GUUB cooperative path following controller and enables the performance of energy-efficient. The energy-efficient control strategy is mainly rely on switching function (m(ξ₁) and m(ξ₂)) based NN adaptive laws [44, 59] and controllers [28, 49]. Besides, it is necessary to point out that the NN approximation domains can be set by the designers under the proposed design, and ε₁₁, ε₁₂ can be determined according to the experience and the practical requirements before the controllers are designed.

4. Simulation example

To illustrate the control performance of the proposed NN based DSC design for the problem of cooperative path following, a network system consisting of three AUVs is considered. An example along given circle paths in 3D space is implemented with the proposed controllers. The communication links between AUVs can be expressed by the following Laplacian matrix \( L \) and connection weight \( B \):

\[
L = \begin{bmatrix}
1 & -1 & -1 \\
-1 & 2 & -1 \\
-1 & -1 & 1
\end{bmatrix},
\]

\( B = \text{diag}(1, 0, 0) \).

The initial linear and angular velocities are \( u_i = 0, v_i = 0, \omega_i = 0, p_i = 0, q_i = 0, r_i = 0 \). Select the control parameters as follows. \( K_1 = \text{diag}(0.34, 0.02, 0.02) \), \( K_2 = \text{diag}(300, 600, 300) \), \( k_3 = \text{diag}(50, 50, 50) \), \( K_4 = \text{diag}(1, 1, 1) \), \( K_5 = \text{diag}(1, 1, 1) \), \( K_6 = \text{diag}(1, 1, 1) \), \( K_7 = \text{diag}(1, 1, 1) \), \( k_{12W} = k_{22W} = 0.1 \), \( \Gamma_1 = \Gamma_2 = 100 \). The filter time constants are chosen as \( \zeta_1 = 0.5, \zeta_2 = 0.2 \). The uncertainty of AUV 1 is given as \( f_{1w}(\cdot) = [0.2u_1^2 + 0.13p_1^2]u_1 + 0.15p_1 + 0.09p_1\theta_1 + 0.1w_1^2 \). For AUV 1, \( i_1 = 21.79, r_{12} = 21.83 \) and the initial states are chosen as \( \eta_1(0) = [18.8\cos(-3\pi/4); 18.8\sin(-3\pi/4); -13]^T \), which is outside the neural active region.

Fig. 3 shows the tracking performance of three AUVs. We can observe that each AUV converges to its desired path even without explicit knowledge of the model.

In order to illustrate the learning ability of NN, a test of approximation performance for AUV 1 is shown in Fig. 4, where \( f_{1w1}(\cdot) \) denotes the vehicle 1’s uncertainties in the three directions, and \( NN_{w1} \) is the corresponding
NN outputs. We can see that the unknown nonlinear functions are efficiently compensated by the proposed NN adaptive strategy.

The effect of switching between the NN adaptive controllers (32), (50) and robust controllers (33), (51) is mainly rely on the the switching signal depicted in Fig. 5. The boundedness of $\hat{W}_{11}$, $\varepsilon_{11M}$ and $f_{11M}$ are shown in Figs. 6 and 7, respectively. From Fig. 5 we can see that the switching function equals to one when

the time range is about 0–8 s or 91–138 s, which means the NN controllers are not working. The NN controllers will work as soon as they are leaving the stages of 0–8 s or 91–138 s, and this can be observed from Fig. 6.

The path variables coordination errors is given in Fig. 8. Fig. 9 shows that the speed information is well estimated by the proposed distributed speed estimate strategy while AUV 2 and AUV 3 can not obtain the common reference speed $v_0 = 0.2 \text{ m/s}$. From Figs. 3, 8 and 9 we can observe that with the analytic tool of graph theory and the proposed distributed speed estimate strategy, the desired coordination behavior is achieved.

Furthermore, to demonstrate the effectiveness of the proposed method, the proposed switching function based NN adaptive control law is compared with the traditional NN adaptive control scheme which is given by the following form:

$$u_{ic} = b_3 \Lambda_1,$$

(76)

with

$$\Lambda_1 = B_i^T (B_i B_i^T)^{-1} [-z_{i1} - (K_2 - S(\omega_i)M) \Phi_i + \hat{W}_{i1} \sigma (\xi_{i1})].$$

$$\hat{W}_{i1} = \Gamma_{W} \{ -\sigma (\xi_{i1}) \Phi_i \} - k_W \hat{W}_{i1},$$

$$u_{ic} = b_3 \Lambda_1 = -K_{i2} z_{i2} + b_4 \Phi_i + \hat{W}_{i2} \sigma (\xi_{i2}).$$

(77)

$$\hat{W}_{i2} = \Gamma_{W} \{ -\sigma (\xi_{i2}) z_{i2} \} - k_W \hat{W}_{i2}.$$
we can verify that the proposed switching function based NN adaptive control achieves a better tracking accuracy since control law (76) and (77) only can guarantee the SGUUB stability of the closed-loop system, but the controller proposed in this paper can obtain the GUUB stability result of the closed-loop system, i.e., the proposed design achieves more efficient usage of control energy.

5. Conclusions

The cooperative path following problem of multiple AUVs with unknown nonlinear uncertainty and partial knowledge of the reference speed is addressed in this paper. For the individual design, the command filter design technique based path following control strategy is developed by introducing compensating error to eliminate the higher derivative of reference signal, and a simplified cooperative path following controller is proposed. Besides, an energy-efficient path following control scheme is developed by designing smoothly switching function. For the cooperative design, the proposed distributed speed estimator will decrease the communication burden to convey the reference speed to each AUV, which means the global knowledge of the reference speed is relaxed. Finally, through rigorous theoretical analysis, the stability result of GUUB is obtained. Simulation results illustrate the performance of the proposed design method.

References


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