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Research Article

Containment control of networked autonomous underwater vehicles: A predictor-based neural DSC design

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ABSTRACT

This paper investigates the containment control problem of networked autonomous underwater vehicles in the presence of model uncertainty and unknown ocean disturbances. A predictor-based neural dynamic surface control design method is presented to develop the distributed adaptive containment controllers, under which the trajectories of follower vehicles nearly converge to the dynamic convex hull spanned by multiple reference trajectories over a directed network. Prediction errors, rather than tracking errors, are used to update the neural adaptation laws, which are independent of the tracking error dynamics, resulting in two time-scales to govern the entire system. The stability property of the closed-loop network is established via Lyapunov analysis, and transient property is quantified in terms of L_2 norms of the derivatives of neural weights, which are shown to be smaller than the classical neural dynamic surface control approach. Comparative studies are given to show the substantial improvements of the proposed new method.

1. Introduction

In recent years, coordinated control of autonomous surface vehicles (ASVs) and autonomous underwater vehicles (AUVs) has drawn great attention from control communities, due to its wide applications in marine industry, such as cooperative search and rescue, collaborative explorations, and sensor networks [1–3]. Coordinated control enables multiple vehicles working together to achieve a collective objective, offering enhanced reliability, performance, and effectiveness over a singe one [4–8].

Coordinated control of multiple AUVs was reported in [9–14]. In [9], a nonlinear path following controller was derived for two underwater vehicles along identical parallel paths, while guaranteeing that the lateral distance between them remains constant. In [10], a coordinated path following scheme was developed for networked AUVs in the presence of communication losses and time delays. The coordination between AUVs was achieved by exchanging the path variables assigned for them. In [11], a synchronized path following scheme for homogeneous AUVs was presented, and a decentralized speed adaptation mechanism was introduced to assure that the reference velocity for each vehicle converges to a constant value. In [12], a leader–follower formation control scheme was presented for multiple AUVs. By constructing a virtual vehicle that converges to a reference trajectory of the follower, robust adaptive formation control laws were designed based on backstepping and function approximation techniques. In [13], decentralized control laws were developed for multiple fully actuated AUVs both for state- and output-feedback cases. In [14], distributed coordinated tracking of multiple AUVs with unknown dynamics was discussed, and the reference trajectory does not require to be known to all vehicles. In all aforementioned studies, a key feature is that only one leader exists in the motion control setup.

In the presence of multiple leaders, the objective is to drive the followers to converge to the convex hull spanned by the leaders, which is called as the containment problem. The vehicle dynamics considered in the previous works correspond to first-order systems, second-order systems, high-order systems, and Lagrange systems [15–22]. A typical application that matches the containment in marine industry is the automatic seafloor exploration and monitoring. In this formation control scenario, a group of AUVs are guided by another group of ASVs, which are equipped with sensors to detect the hazardous obstacles and play as the communication relays between the AUVs and mother vessel. The ASVs can shape a safe area for the AUVs to follow, ensuring that the follower AUVs are contained within the moving safety area formed by the leader ASVs. Meanwhile, the data collected by the AUVs can be transmitted to the ASVs on the sea surface, which further send them to the mother vessel. Obviously, such coordinated control scheme has not been fully explored for networked marine vehicles.

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Adaptation and robustness is critical for high-performance control of AUVs. However, this is inhibited by the fact the AUV dynamics are intrinsic nonlinear and uncertain. It contains model parameters such as hydrodynamics damping, and external disturbances such as ocean currents, which are very hard to model accurately. A number of results have been reported that rely on their exact model knowledge, which is obtained from empirical studies. Obviously, the stability of the resulting controllers are difficult to guarantee. In order to preserve the stability and robustness in the presence of model uncertainty and ocean disturbances, adaptive control schemes have been widely suggested [24–28]. In [24], a direct adaptive control law was developed for way-point tracking of underactuated AUVs in the presence of ocean currents. In [25], neural networks (NNs) combined with a variable structure method were employed to derive a robust adaptive tracking control law. In [26], a dynamic recurrent fuzzy NN was used to estimate the dynamic uncertainties for AUV, and the improved tracking performance can be achieved due to their memory features. In [27], an adaptive fuzzy sliding mode control law was developed for kinematic control of AUV. In [28], a nonlinear control law was derived for a fully actuated AUV based on a robust integral of the sign of the error (RISE) structure with a feedforward NN term. In these studies, although the stability results are available, the design and applications of adaptive/neural controllers are overly challenging due to the following facts. First, oscillations will exacerbate with the increment of adaptation gains, which may exceed the available bandwidths of actuators. As such, it leads to constraints on the speed of adaptation [29,31]. Second, any nonzero tracking errors during the transient phase can result in control signals of large magnitude, which are unacceptable by actuators. This situation gets worse due to the nonzero initial conditions in the formation control setup. These challenges may limit their applications.

This paper presents a new design method, named predictor-based neural dynamic surface control (PNDSC) design approach, to develop the containment controllers for multiple AUVs in the presence of model uncertainty and unknown ocean disturbances. In order to achieve the desired performance, adaptation is indeed necessary because AUVs contain plenty of model uncertainty and ocean disturbances [24–28]. For this problem, although the classical neural dynamic surface control (NDSC) approach can be applied [23,32,33]; it may not be efficient due to the fact the speed of adaptation is limited. To overcome the limitations of the NDSC approach, by incorporating a predictor design into the classical NDSC approach, a new PNDSC architecture is proposed that allows for using the prediction errors, instead of tracking errors, to update the neural weights. The key is that the prediction error dynamics can be made to converge faster than the tracking error dynamics by choosing a particular parameter, and results in two time-scales to govern the closed-loop system dynamics. The stability property of the proposed scheme is established based on Lyapunov theory, and the transient property is quantified in terms of L_2 norms of the derivatives of neural weights. Comparative studies are given to illustrate the substantial improvement of the proposed scheme.

The contribution of this paper is three-fold:

- In contrast to the NDSC approach [32,33], a new type of PNDSC architecture for multi-input multi-output (MIMO) system is proposed. The prediction errors, rather than tracking errors, are used to update the neural adaptive laws, which are independent of the tracking error dynamics. It is rigorously proved that the transient property of the proposed PNDSC architecture performs better than the NDSC approach, with smaller L_2 norms of the derivatives of neural weights.
- In contrast to the contributions in [9–14] and [24–28] where the motion controllers are developed for AUVs in the presence of a single leader, this paper addresses the containment control problem of multiple AUVs in the presence of multiple reference trajectories over a directed graph. This is done by introducing a distributed diffeomorphic coordinate transformation, which has not been reported for AUV control.
- Distributed adaptive containment controllers for AUVs are developed based on the new PNDSC approach, with the guaranteed stability and transient performance. Besides, the model uncertainty and external disturbances can be reconstructed using the sampled input and output data.

The rest of this paper is organized as follows. Section 2 introduces some preliminaries and gives problem formulation. Section 3 presents the PNDSC method for an MIMO system. Section 4 gives the containment controller design, together with stability and transient analysis. Section 5 provides an example for illustrations. Section 6 concludes this paper.

Notations: $\mathbb{R}^n$ denotes the n-dimensional Euclidean Space. $\|\cdot\|$ denotes the Euclidean norm. $\lambda(\cdot)$, $\lambda_{min}(\cdot)$, and $\lambda_{max}(\cdot)$ denote the eigenvalue, the smallest eigenvalue, and the largest eigenvalue of a square matrix $(\cdot)$, respectively. $\underline{\sigma}(\cdot)$ denotes the smallest singular value of a given matrix. diag$\{a_1,\ldots,a_N\}$ is a block-diagonal matrix with matrixes $a_i, i=1,\ldots,N$, on its diagonal. Given $p\geq 1$ and $v\in\mathbb{R}^n$, the L_p norm and truncated L_p norm is defined by $\|v\|_{L_p}=(\int_0^\infty \|v(s)\|^p\,ds)^{1/p}$ and $\|v\|_{L_p,t^*}=(\int_0^{t^*}\|v(s)\|^p\,ds)^{1/p}$ with $t^*>0$, respectively.

2. Preliminaries and problem formulation

2.1. Preliminaries

A graph $\mathcal{G}=\{\mathcal{V},\mathcal{E}\}$ consists of a node set $\mathcal{V}=\{n_1,\ldots,n_N\}$ and an edge set $\mathcal{E}=\{(n_i,n_j)\in\mathcal{V}\times\mathcal{V}\}$ with element (n_i,n_j) that describes the communication from node i to node j. A *path* from node n_{i_1} to node n_{i_l} is a sequence of ordered edges of the form $n_{i_k},n_{i_{k+1}}$, $k=1,\ldots,l-1$. A *directed 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. A digraph has a *spanning tree* if there is a node called as the root, such that there is a directed path from the root to every other node in the graph. The adjacency matrix $\mathcal{A}=[a_{ij}]\in\mathbb{R}^{N\times N}$ associated with the directed graph $\mathcal{G}$ is defined as $a_{ij}=1$, if $(n_j,n_i)\in\mathcal{E}$; and $a_{ij}=0$, otherwise. Self-connections are not allowed, i.e., $a_{ii}=0$. The Laplacian matrix $\mathcal{L}$ associated with the graph $\mathcal{G}$ is defined as $\mathcal{L}=\mathcal{D}-\mathcal{A}$ where $\mathcal{D}=\text{diag}\{d_1,\ldots,d_N\}$ with $d_i=\sum_{j=1}^{N}a_{ij}, i=1,\ldots,N$.

Definition 1 (*Brualdi and Ryser [34]*). The set $E\subseteq\mathbb{R}^n$ is *convex* if

$$\lambda x_1+(1-\lambda)x_2\in E, \tag{1}$$

whenever $x_1\in E, x_2\in E$, and $0\leq\lambda\leq 1$. The *convex hull* $Co(X)$ for a set of points $X=\{x_1,\ldots,x_n\}$ is the minimal convex set containing all points in X and is defined as

$$Co(X)=\left\{\sum_{i=1}^{n}\lambda_i x_i \,|\, x_i\in X, \lambda_i>0, \sum_{i=1}^{n}\lambda_i=1\right\}. \tag{2}$$

Lemma 1 (*Cui et al. [12]*). *For bounded initial conditions, if there exists $\mathcal{C}^1$ continuous and positive definite Lyapunov function $V(\xi)$ satisfying $\kappa_1(\|\xi\|)\leq V(\xi)\leq\kappa_2(\|\xi\|)$, such that $\dot{V}(\xi)\leq-\mu V(\xi)+\epsilon$, where $\kappa_1,\kappa_2:\mathbb{R}^n\to\mathbb{R}$ are class $\mathcal{K}$ functions and ϵ is a positive constant, then the solution $\xi=0$ is uniformly ultimately bounded.*

2.2. Problem formulation

Consider a network of multi-vehicle system consisting of M followers, labeled as AUV 1 to M. In the horizontal plane, the