Hindawi
Journal of Control Science and Engineering
Volume 2018, Article ID 2316957, 8 pages
https://doi.org/10.1155/2018/2316957

Research Article

Neural Network Predictive Control for Autonomous Underwater Vehicle with Input Delay

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Received 6 January 2018; Accepted 24 April 2018; Published 29 May 2018

Academic Editor: Jongrae Kim

A path tracking controller is designed for an autonomous underwater vehicle (AUV) with input delay based on neural network (NN) predictive control algorithm. To compensate for the time-delay in control system and realize the purpose of path tracking, a predictive control algorithm is proposed. An NN is used to estimate the nonlinear uncertainty of AUV induced by hydrodynamic coefficients and the coupling of the surge, sway, and yaw angular velocity. By Lyapunov theorem, stability analysis is also given. Simulation results show the effectiveness of the proposed control strategy.

1. Introduction

With the rapid development of demands for the resources, countries around the world have attached importance to the exploration and application of the marine resources. Autonomous underwater vehicle (AUV) is a mobile carrier which is small in size and convenient in controllability as the special equipment for resource exploration, environmental monitoring, and ocean investigation. It has the ability for long-time navigating and great-weight carrying and satisfies the different demands of the fields of military science and economics (see [1–3] and references therein).

In recent years, control problems of AUV such as setpoint stabilization, trajectory tracking control, and path tracking control have been actively considered by many researchers. Based on nonlinear control theory, several control methods have been proposed, such as sliding mode control [4–6], adaptive control [7–11], and predictive control [12–15]. However, a common problem of the above literatures is that the time-delays are not taken into account. In practical systems, time-delays are unavoidable in information acquisition and transmission. Time-delay phenomenon is often a source of instability and poor performance [16–18]. From this point of view, considerable amount of attention has been paid to the problem of stabilization and control of time-delay systems. Predictive control is a good method with the ability to handle constraints and time-delays [19–23]. Now, it has become one of the most popular control methodologies no matter in theory or the reality (see [24–27]). The NN predictive control for nonlinear dynamic systems with input delay was studied in [24], but the considered predictive model is required for linear ones and this condition is removed in this paper. The predictor-based control algorithm for an uncertain input delay Euler-Lagrange system was studied in [26], but the controller is an iteration form. To overcome the problem of input delay in Euler-Lagrange dynamical systems directly, a predictor with uncertain system dynamics was proposed in [27]. Recently, predictive control has been applied in many kinds of practical systems [28–31]. Up to now, only a few papers have considered this problem because of its complexity. Paper [32] addressed the control problem with input delay and synthesized a robust controller for underwater vehicles which requires only knowledge of mass matrix. The region tracking problem for AUV with input delay based on predictive control was studied in [33], but it assumes that all the states are known in advance. Therefore, it is a very challenging and significant work to investigate the path tracking control of AUV with input delay.

In this paper, a novel controller is investigated for path tracking control of AUV with input delay. Because of the hydrodynamic coefficients and the surge, sway, and yaw angular velocity coupling, an NN is used to identify the nonlinear part of AUV at first. Then predictive control algorithm is employed to compensate for the delay produced in input channel. The proposed predictive model is a nonlinear model. Stability of the closed-loop system is guaranteed based on Lyapunov stability theory. Finally, a simulation example is presented to show the effectiveness of the proposed control strategy.

The remainder of this paper is organized as follows. The problem of path tracking for AUV is formulated in Section 2. Section 3 is devoted to identification of AUV system by NN. Stability analysis for the boundness of error state and NN weight estimation error are also performed. The predictor and the corresponding control are derived in Section 4. The problems of dealing with the time-delay and stability analysis are illustrated in Section 5. Section 6 validates the feasibility and performance of the proposed control law by simulation experiment. Some conclusions are given in Section 7.

2. Problem Formulation

In the horizontal plane, a 3-DOF AUV with input delay can be modeled as

$$\begin{aligned} \dot{\eta} &= J(\eta)\nu, \\ M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) &= \overline{\tau}(t-d), \\ h &= \eta, \end{aligned} \tag{1}$$

where $\eta = [x \ \ y \ \ \psi]^T$ denotes the vehicle location and orientation in the earth-fixed frame. The vector $\nu = [u \ \ v \ \ r]^T$ is the velocities expressed in the body-fixed frame. $M = M_{RB} + M_A$ is the inertia matrix of rigid body M_{RB} with added mass M_A. The matrix $C(\nu)$ is skew symmetrical and it denoted the Coriolis and centripetal forces. Linear and quadratic damping forces are considered in the total hydrodynamic damping matrix $D(\nu)$. The vector $g(\eta)$ is the combined gravitational and buoyancy forces in the body-fixed frame. $\overline{\tau}$ is the input of the system and the vector of the forces and moments on AUV induced by the input and fins. d is a known constant time-delay. h is the output of the system. The kinematic transformation matrix transformation from the body-fixed frame to earth-fixed frame is denoted by $J(\eta)$, and

$$J(\eta) = R(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

Let

$$\begin{aligned} \xi_1 &= \eta, \\ \xi_2 &= J(\eta)\nu. \end{aligned} \tag{3}$$

Then system (1) changed to

$$\begin{aligned} \dot{\xi}_1 &= \xi_2, \\ \dot{\xi}_2 &= f(\xi_1, \xi_2) + J(\xi_1) M^{-1} \overline{\tau}(t-d), \\ y &= \xi_1, \end{aligned} \tag{4}$$

where nonlinear uncertain function

$$\begin{aligned} f(\xi_1, \xi_2) &= \dot{J}(\xi_1) J^{-1}(\xi_1)\xi_2 + J(\xi_1) \\ &\quad \cdot M^{-1}\left[-C\left(J^{-1}(\xi_1)\xi_2\right)\right. \\ &\quad \left. - D\left(J^{-1}(\xi_1)\xi_2\right) J^{-1}(\xi_1)\xi_2 - g(\xi_1)\right]. \end{aligned} \tag{5}$$

The objective of this paper is that the output y of system (4) tracks a desired trajectory η_d, with all internal signals and control commands remaining bounded. For this purpose, we make the following assumption.

Assumption 1. The desired trajectory vector $\zeta_d = [\eta_d \ \ \dot{\eta}_d \ \ \ddot{\eta}_d]^T$ is available for measurement, and η_d and $\dot{\eta}_d$ are bounded.

3. Identification of AUV System

There are two steps to design the output feedback controller for AUV with input delay. First, an NN is designed to identify system (4). Then we will use predictive control algorithm to compensate for the delay that presents in communication channel of AUV.

Let

$$\begin{aligned} A &= \begin{bmatrix} 0 & I_3 \\ A_1 & A_2 \end{bmatrix}, \\ B &= \begin{bmatrix} 0 \\ I_3 \end{bmatrix}, \\ C &= [I_3 \ \ 0]^T, \end{aligned} \tag{6}$$

where I_3 denotes the identity matrix; matrices A_1 and A_2 are parameters that can be chosen such that matrix A is stable. Then there exist symmetric positive definite matrices P and Q such that Lyapunov matrix equations $A^T P + PA = -Q$ hold.

Hence, system (4) can be expressed as

$$\begin{aligned} \dot{\xi} &= A\xi + B\left[f_0(\xi) + \tau(t-d)\right], \\ y &= C^T\xi, \end{aligned} \tag{7}$$

where $\xi = \left[\xi_1^T \ \ \xi_2^T\right]^T$, $\tau(t-d) = J(\xi_1)M^{-1}\overline{\tau}(t-d)$, and $f_0(\xi) = f(\xi) - A_1\xi_1 - A_2\xi_2$.

According to the approximation of NN, there exists a bounded reconstruction error $\varepsilon(\|\varepsilon\| \le \overline{\varepsilon})$ and an ideal weight W such that system (4) is described by

$$\begin{aligned} \dot{\xi} &= A\xi + B\left[W^T\Phi(\xi) + \tau(t-d) + \varepsilon\right], \\ y &= C^T\xi, \end{aligned} \tag{8}$$

where W is the ideal NN weight and $\|W\| \le \overline{W}$ ($\overline{W}$ is a positive constant). The sigmoid function $\Phi(Z) = [\Phi_1(Z), \Phi_2(Z), \cdots, \Phi_n(Z)]^T \in R^n$ is differentiable with respect to x and $\|\Phi(\cdot)\| \le \overline{\Phi}$ holds with a positive constant $\overline{\Phi}$.

Then the NN of system (8) can be written as

$$\begin{aligned}\dot{\hat{\xi}} &= A\hat{\xi} + B\left[\widehat{W}^T\Phi\left(\hat{\xi}\right) + \tau\left(t-d\right)\right],\\ \hat{y} &= C^T\hat{\xi},\end{aligned} \tag{9}$$

where $\hat{\xi}$ is a state vector of NN and $\widehat{W}$ is a synaptic weight matrix. The sigmoid function $\Phi(x) = a/(1+e^{-bx})+c, \forall a, b \in R^+, c \in R$, where a, b, and the real number c are the bound, the slope, and the bias of sigmoidal curvature, respectively.

Let estimation error $\tilde{\xi} = \xi - \hat{\xi}$, output error $\tilde{y} = y - \hat{y}$, and NN weight error $\widetilde{W} = W - \widehat{W}$. Using (8) and (9), we have

$$\begin{aligned}\dot{\tilde{\xi}} &= A\tilde{\xi} + B\left[W^T\Phi\left(\xi\right) - \widehat{W}^T\Phi\left(\hat{\xi}\right) + \varepsilon\right],\\ \tilde{y} &= C^T\tilde{\xi}.\end{aligned} \tag{10}$$

Next, a main result will be given. In the following, $\lambda_{\mathrm{m}}(P)$ and $\lambda_{\mathrm{M}}(P)$ denote the minimum and maximum eigenvalue of corresponding matrix P.

Theorem 2. *Consider system (1) with the identification model (9) and conditions (19). Let the NN weight update law be provided by*

$$\dot{\widehat{W}} = \Gamma\left(\tilde{y}^T\Phi\left(\hat{\xi}\right) - \mu\widehat{W}\right), \tag{11}$$

in which $\Gamma = \Gamma^T > 0$ is the learning parameter and μ is a constant. Then the estimation error $\tilde{\xi}$ and neural network weight error $\widetilde{W}$ are uniformly ultimately bounded (UUB).

Proof. Consider a Lyapunov function defined by

$$V = \frac{1}{2}\tilde{\xi}^T P\tilde{\xi} + \frac{1}{2}\operatorname{tr}\left(\widetilde{W}^T\Gamma^{-1}\widetilde{W}\right). \tag{12}$$

Calculate the derivative (12) along (10) and (11); we have

$$\begin{aligned}\dot{V} = &-\frac{1}{2}\tilde{\xi}^T Q\tilde{\xi} + \tilde{\xi}^T PB\left[W^T\Phi\left(\xi\right) - \widehat{W}^T\Phi\left(\hat{\xi}\right) + \varepsilon\right]\\ &+ \operatorname{tr}\left(\widetilde{W}^T\Gamma^{-1}\dot{\widetilde{W}}\right).\end{aligned} \tag{13}$$

From (11), it follows that

$$\begin{aligned}\dot{V} = &-\frac{1}{2}\tilde{\xi}^T Q\tilde{\xi} + \tilde{\xi}^T PB\left[W^T\Phi\left(\xi\right) - \widehat{W}^T\Phi\left(\hat{\xi}\right) + \varepsilon\right]\\ &- \tilde{y}\widetilde{W}^T\Phi\left(\hat{\xi}\right) + \mu\operatorname{tr}\left(\widetilde{W}^T\widehat{W}\right).\end{aligned} \tag{14}$$

From the definition of $\widetilde{W}$, we obtain the following equation:

$$\operatorname{tr}\left(\widetilde{W}^T\widehat{W}\right) = \operatorname{tr}\left(\widetilde{W}^T\left(W - \widetilde{W}\right)\right) = W^T\left\|\widetilde{W}\right\| - \left\|\widetilde{W}\right\|^2. \tag{15}$$

Moreover, there exist three positive constants α_1, α_2, and α_3 such that

$$\left\|W^T\Phi\left(\xi\right) - \widehat{W}^T\Phi\left(\hat{\xi}\right) + \varepsilon\right\| \le \alpha_1\left\|\tilde{\xi}\right\| + \alpha_2\left\|\widetilde{W}\right\| + \alpha_3. \tag{16}$$

So

$$\begin{aligned}\dot{V} \le &-\left(\frac{1}{2}\lambda_{\mathrm{m}}\left(Q\right) - \alpha_1\left\|PB\right\|\right)\left\|\tilde{\xi}\right\|^2\\ &+ \left(\alpha_2\left\|PB\right\| + \overline{\Phi}\right)\left\|\widetilde{W}\right\|\left\|\tilde{\xi}\right\| + \alpha_3\left\|PB\right\|\left\|\tilde{\xi}\right\|\\ &+ \mu\overline{W}\left\|\widetilde{W}\right\| - \mu\left\|\widetilde{W}\right\|^2.\end{aligned} \tag{17}$$

According to Young's inequality $ab \le (a^2 + \kappa^2 b^2)/2\kappa$ with $\kappa > 0$; then there are $\kappa_0 > 0$, $\kappa_1 > 0$ and $\kappa_2 > 0$ such that

$$\begin{aligned}\left\|\widetilde{W}\right\|\left\|\tilde{\xi}\right\| &\le \frac{\left\|\tilde{\xi}\right\|}{2\kappa_0} + \frac{\kappa_0}{2}\left\|\widetilde{W}\right\|^2,\\ \alpha_3\left\|PB\right\|\left\|\tilde{\xi}\right\| &\le \frac{\left(\alpha_3\left\|PB\right\|\right)^2}{2\kappa_1} + \frac{\kappa_1}{2}\left\|\tilde{\xi}\right\|^2,\\ \left\|W\right\|\left\|\widetilde{W}\right\| &\le \frac{\left\|W\right\|^2}{2\kappa_2} + \frac{\kappa_2}{2}\left\|\widetilde{W}\right\|^2.\end{aligned} \tag{18}$$

Assume that

$$\begin{aligned}R_1 &= \frac{1}{2}\lambda_{\mathrm{m}}\left(Q\right) - \alpha_1\left\|PB\right\| - \frac{1}{2\kappa_0} - \frac{1}{2}\kappa_1 > 0,\\ R_2 &= \mu - \frac{1}{2}\mu\kappa_2 - \frac{1}{2}\kappa_0 > 0.\end{aligned} \tag{19}$$

Then

$$\dot{V} \le -R_1\left\|\tilde{\xi}\right\|^2 - R_2\left\|\widetilde{W}\right\|^2 + R_3 \le -\eta V + R_3, \tag{20}$$

where

$$\begin{aligned}\eta &= \min\left\{\frac{R_1}{\lambda_{\mathrm{M}}\left(P\right)}, R_2\right\},\\ R_3 &= \frac{\alpha_3^2\left\|PB\right\|^2}{2\kappa_1} + \frac{\left\|W\right\|^2}{2\kappa_2}.\end{aligned} \tag{21}$$

Thus, estimator error $\tilde{\xi}$ and NN weight error $\widetilde{W}$ are UUB. □

4. Predictive Control

Input delay (measurement delay and computational delay can be represented by input delay) is a source of instability, which is frequently encountered in the practical systems. For achieving tracking performance, a predictive controller is proposed to compensate for the time-delay present in AUV. Figure 1 is the control structure diagram of AUV system (1).

In fact, the NN weight $\widehat{W}$ stores the dynamical system information. Based on the structure of NN in (9), an online predictor is proposed. For improving the accuracy of path tracking effectively, the nonlinear prediction model is employed here. Now, let the predictor of system (8) be

$$\begin{aligned}\dot{\xi}_p\left(t+d \mid t\right) = &A\xi_p\left(t+d \mid t\right)\\ &+ B\left[\widehat{W}^T\Phi\left(\xi_p\left(t+d \mid t\right)\right) + \tau\left(t\right)\right],\\ y_p\left(t+d \mid t\right) = &C^T\xi_p\left(t+d \mid t\right),\end{aligned} \tag{22}$$

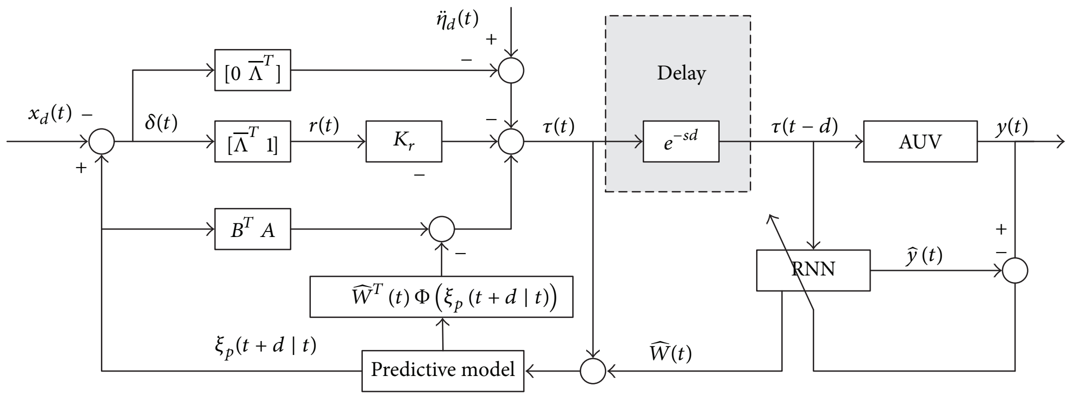

Figure 1: Control structure of AUV system (1).

where $\xi_p(t+d \mid t)$ and $y_p(t+d \mid t)$ are the prediction state and output of system (8) with the initial condition $\xi_p(d \mid 0) = \xi(0)$.

If prediction model (22) is precise, then $\xi_p(t+d \mid t) = \xi(t+d)$. This mean that ξ ahead of time d can be predicted via $\xi_p(t+d \mid t)$ in prediction model. Therefore, the difficulty in controlling time-delay plant can be overcome. However, due to the modeling errors, in prediction model (22) errors exist inevitably. Now, define a predictor error as $e(t) = \xi(t+d) - \xi_p(t+d \mid t)$. It follows from (8) and (22) that

$$\begin{aligned}\dot{e}(t) &= Ae(t) + B\left[W^T\Phi(\xi(t+d)) - \widehat{W}^T(t)\Phi\left(\xi_p(t+d \mid t)\right) + \varepsilon(t+d)\right], \\ y_e(t) &= C^T e(t).\end{aligned} \tag{23}$$

Next, we will prove that the predictor error (23) is bounded. Define an error vector as

$$\delta(t) = \xi_p(t+d \mid t) - \eta_d(t). \tag{24}$$

Define a filtered error as

$$r(t) = \Lambda^T\delta(t) = \left[\overline{\Lambda}^T \quad 1\right]\delta(t), \tag{25}$$

where $\overline{\Lambda} = [\lambda_1 \quad \lambda_2]^T$ is an appropriately chosen coefficient vector such that $\delta(t) \to 0$ exponentially as $r(t) \to 0$. Then, using (22), the filtered error can be written as

$$\begin{aligned}\dot{r}(t) &= \Lambda^T\dot{\delta}(t) = \Lambda^T\left[A\xi_p(t+d \mid t) + B\left(\widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) + \tau(t)\right)\right] \\ &= \left[0 \quad \overline{\Lambda}^T\right]\delta(t) - \ddot{\eta}_d + B^T A\xi_p(t+d \mid t) + \widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) + \tau(t).\end{aligned} \tag{26}$$

Now choose $K_r > 0$ and let

$$\begin{aligned}\tau(t) &= -\left[0 \quad \overline{\Lambda}^T\right]\delta(t) + \ddot{\eta}_d - B^T A\xi_p(t+d \mid t) - \widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) - K_r r(t) \\ &= -\left[0 \quad \overline{\Lambda}^T\right]\delta(t) + \ddot{\eta}_d - B^T A\delta(t) - B^T A\eta_d(t) - \widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) - K_r r(t).\end{aligned} \tag{27}$$

That is, a control input of AUV is

$$\begin{aligned}\overline{\tau}(t) &= MJ^{-1}(\xi_1)\left(-\left[0 \quad \overline{\Lambda}^T\right]\delta(t) + \ddot{\eta}_d - B^T A\xi_p(t+d \mid t) - \widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) - K_r r(t)\right) \\ &= MJ^{-1}(\xi_1)\left(-\left[0 \quad \overline{\Lambda}^T\right]\delta(t) + \ddot{\eta}_d - B^T A\delta(t) - B^T Ax_d(t) - \widehat{W}^T\Phi\left(\xi_p(t+d \mid t)\right) - K_r r(t)\right).\end{aligned} \tag{28}$$

Note that the predictor state $\xi_p(t+d \mid t)$ and the associated error $r(t)$ are used in AUV controller (28); the NN approximation term $\widehat{W}^T(t)\Phi(\xi_p(t+d \mid t))$ from (22) is employed to accommodate the unknown nonlinearity. Therefore, the stability of the closed-loop system can be guaranteed.

From (28), (26) becomes

$$\dot{r}(t) = -K_r r(t). \tag{29}$$

5. Stability Analysis

Assume that the parameters are chosen such that

$$\begin{aligned}R_4 &= R_2 + \frac{1}{2}\kappa_3 > 0, \\ R_5 &= \frac{1}{2}\lambda_m(Q)\frac{1}{2\kappa_3} - \frac{1}{2}\kappa_4 - \beta_2 > 0, \\ R_6 &= -K_r > 0,\end{aligned} \tag{30}$$

where R_2 is defined as in Theorem 2 and κ_3, κ_4 are positive constants that can be chosen.

Theorem 3 (let Assumption 1 hold). *Consider the input delay AUV system (1) under condition (30), the NN weight update law (11), and controller (28). Then*

(1) *all the closed-loop signals are UUB;*

(2) *the path tracking error $\omega(t) = y(t+d) - \eta_d(t)$ converges to a neighborhood of the origin, whose size can be adjusted by control parameters.*

Proof. Consider a Lyapunov function defined by

$$\begin{aligned}\overline{V} &= \frac{1}{2}\tilde{\xi}^T P\tilde{\xi} + \frac{1}{2}\widetilde{W}^T\Gamma^{-1}\widetilde{W} + \frac{1}{2}e^T Pe + \frac{1}{2}r^2 \\ &\coloneqq V_1 + V_2 + V_3 + V_4.\end{aligned} \tag{31}$$

The derivative of V_1 and V_2 can be deduced following the proof of Theorem 2. Thus we have

$$\begin{aligned}\dot{V}_3 = \frac{1}{2}e^T\left(A^T P + PA\right)e + e^T PB\left[W^T\Phi\left(\xi\left(t+d\right)\right)\right. \\ \left. - \widehat{W}^T\Phi\left(\xi_p\left(t+d \mid t\right)\right) + \varepsilon\left(t+d\right)\right].\end{aligned} \tag{32}$$

In fact, via Taylor series expansion, there exist positive constants β_1, β_2, and β_3 such that

$$\begin{aligned}&\left\|W^T\Phi\left(\xi\left(t+d\right)\right) - \widehat{W}^T\Phi\left(\xi_p\left(t+d \mid t\right)\right)\right\| \\ &\quad = \left\|\widetilde{W}\Phi\left(\xi_p\left(t+d \mid t\right)\right)\right. \\ &\quad\quad \left. + W^T\left[\Phi\left(\xi\left(t+d\right)\right) - \Phi\left(\xi_p\left(t+d \mid t\right)\right)\right]\right\| \\ &\quad \le \beta_1\left\|\widetilde{W}\right\| + \beta_2\left\|e\right\| + \beta_3.\end{aligned} \tag{33}$$

So

$$\dot{V}_3 \le -\frac{1}{2}Q_{\mathrm{m}}\left\|e\right\|^2 + \left\|e\right\|\left(\beta_1\left\|\widetilde{W}\right\| + \beta_2\left\|e\right\| + \beta_3 + \bar{\varepsilon}\right). \tag{34}$$

By using Young's inequality, there exist positive numbers κ_3 and κ_4 such that

$$\begin{aligned}\left\|e\right\|\left\|\widetilde{W}\right\| &\le \frac{\left\|e\right\|^2}{2\kappa_3} + \frac{\kappa_3}{2}\left\|\widetilde{W}\right\|^2, \\ \left(\beta_3 + \bar{\varepsilon}\right)\left\|e\right\| &\le \frac{\left(\beta_3 + \bar{\varepsilon}\right)^2}{2\kappa_4} + \frac{\kappa_4}{2}\left\|e\right\|^2,\end{aligned} \tag{35}$$

$$\begin{aligned}\dot{V}_3 \le -\left(\frac{1}{2}Q_{\mathrm{m}} - \frac{1}{2\kappa_3} - \frac{1}{2}\kappa_4 - \beta_2\right)\left\|e\right\|^2 \\ + \frac{1}{2}\kappa_3\left\|\widetilde{W}\right\| + \frac{\left(\beta_4 + \bar{d} + \bar{\varepsilon}\right)^2}{2\kappa_4},\end{aligned} \tag{36}$$

$$\dot{V}_4 = r\dot{r} = -K_r\left\|r\right\|^2. \tag{37}$$

Therefore,

$$\begin{aligned}\dot{\overline{V}} &\le -R_1\left\|\tilde{\xi}\right\|^2 - R_4\left\|\widetilde{W}\right\|^2 - R_5\left\|e\right\|^2 - R_6\left\|r\right\|^2 + R_7 \\ &\le -\bar{\eta}\overline{V} + R_7,\end{aligned} \tag{38}$$

where R_1 is defined as in (19), and $\bar{\eta}$ is positive constant defined by

$$\begin{aligned}\bar{\eta} &= \min\left\{\frac{R_1}{\lambda_{\max}\left(P\right)}, R_4, \frac{R_5}{\lambda_{\max}\left(P\right)}, R_6\right\}, \\ R_7 &= R_3 + \frac{\left(\beta_4 + \bar{d} + \bar{\varepsilon}\right)^2}{2\kappa_4}.\end{aligned} \tag{39}$$

Then according to Lyapunov theorem, error $\tilde{\xi}$, NN weight error $\widetilde{W}$, predictor error e, and filtered error r are all UUB. The control error δ is thus bounded based on (24) and Assumption 1. Therefore, the NN weights $\widehat{W}$ and $\xi_p(t+d \mid t)$ are bounded.

Finally, the boundedness of path tracking error $\omega(t)$ will be proved. Since

$$\begin{aligned}\omega\left(t\right) &= y\left(t+d\right) - \eta_d\left(t\right) \\ &= \xi_1\left(t+d\right) - \xi_{p1}\left(t+d \mid t\right) + \xi_{p1}\left(t+d \mid t\right) \\ &\quad - y_d = e_1\left(t\right) + \delta_1\left(t\right),\end{aligned} \tag{40}$$

then

$$\begin{aligned}\lim_{t\to\infty}\left\|\omega\left(t\right)\right\| &= \lim_{t\to\infty}\left\|e_1\left(t\right)\right\| + \lim_{t\to\infty}\left\|\delta_1\left(t\right)\right\| \\ &\le \lim_{t\to\infty}\left\|e\left(t\right)\right\| + \lim_{t\to\infty}\left\|\delta\left(t\right)\right\|.\end{aligned} \tag{41}$$

Therefore, the tracking error $\omega(t)$ is bounded because $e(t)$, $\delta(t)$, and $\xi(t)$ are bounded. □

Remark 4. Compared with [20–33], there are three advantages. Firstly, output feedback is considered in this paper. Secondly, the nonlinear prediction model is employed to improve the accuracy of predictive control. Finally, time-delay is considered in path tracking control of AUV which has more real significance.

6. Simulation Analysis

Example 5. The simplified dynamics model of INFANTE AUV [2] in the horizontal plane with input delay is adopted as follows in this paper:

$$\begin{aligned}\dot{x} &= u\cos\left(\psi\right) - v\sin\left(\psi\right), \\ \dot{y} &= u\sin\left(\psi\right) + v\cos\left(\psi\right), \\ \dot{\psi} &= r, \\ 0 &= m_v\dot{v} + m_{ur}ur + d_v, \\ \Gamma &= m_r\dot{r} + d_r,\end{aligned} \tag{42}$$

where x, y, and ψ are the surge position, sway position, and yaw angle in the body-fixed frame, and u, v, and r denote surge, sway, and yaw velocities, respectively. Γ is the yaw moment. The symbol I_z denotes the moment of inertia of the AUV, $N_{\{\cdot\}}$ is nonlinear hydrodynamic damping, and

$$
\begin{aligned}
m_v &= m - Y_{\dot{v}}, \\
m_{ur} &= m - Y_r, \\
d_v &= -Y_v uv - Y_{v|v|} v\,|v|\,, \\
m_r &= I_z - N_{\dot{r}}, \\
d_r &= -N_v uv - N_{v|v|} v\,|v| - N_r ur.
\end{aligned}
\tag{43}
$$

Since the considered model (42) is in the horizontal plane and has no disturbance, we can assume that $u = 1m/s$ in principle. In the following, the desired path is $x_d(t) = 20\sin 2\pi t/200$, $y_d(t) = 20 - 20\cos 2\pi t/200$, and $\psi_d(t) = 2\pi t/200$.

The model parameters of INFANTE AUV are as follows:

$$
\begin{aligned}
m &= 2234.5kg, \\
I_z &= 2000Nm^2, \\
X_{\dot{u}} &= -142kg, \\
N_{\dot{r}} &= -1350Nm^2, \\
Y_{\dot{v}} &= -1715kg, \\
Y_v &= -346kg/m, \\
Y_r &= 435kg, \\
N_v &= -686kg, \\
N_r &= -1427kgm, \\
Y_{v|v|} &= -667kg/m, \\
N_{v|v|} &= 443kg.
\end{aligned}
\tag{44}
$$

NN parameters are selected as follows: $\Phi(x) = 1/(1 + e^{-ax})$, where $a = 0.5$, $\mu = 0.3$, $\Gamma = 6$.

The delay constant $d = 2$. Other parameters in controller are $A_1 = -3I_3$, $A_2 = -2I_3$, $\lambda_1 = 2$, $\lambda_2 = 2$, and $K_r = 8$.

The initial position and the surge speed of the AUV are $(0, 20)$ and $0m/s$, respectively. The simulation results are shown in Figures 2–4. The path tracking errors in x, y, and ψ are given in Figure 2. The control forces in x and y and the control torque of yaw ψ are given in Figure 3. From these simulation figures, we can see that the tracking performance is unsatisfying at the beginning of simulation; this is because the controller performs mainly depending on the adaptive control. The good tracking of position is obtained by the proposed adaptive NN predictive controller by and by. Figure 4 is the path tracking in horizontal plane. From Figure 4 we can see that AUV can realize tracking control smoothly and converge to the desired trajectory.

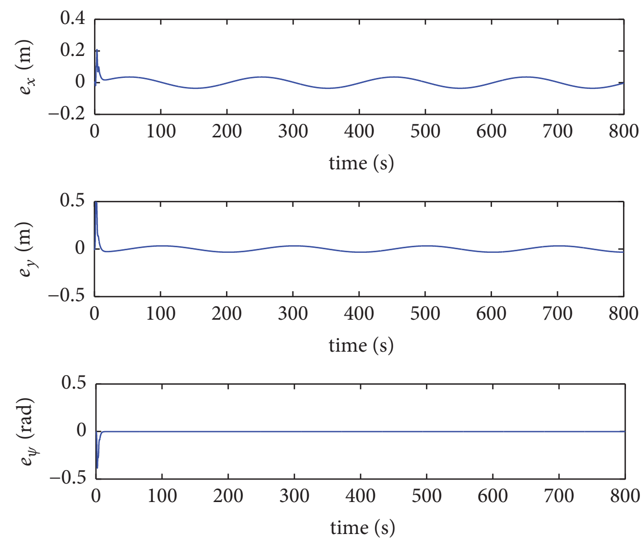

Figure 2: Path tracking errors.

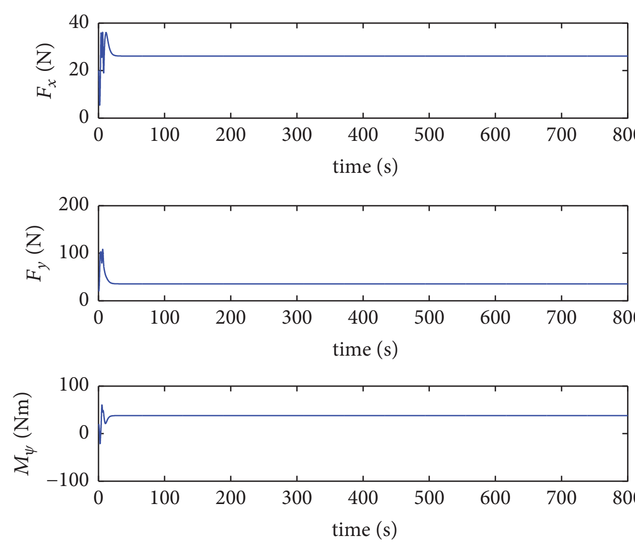

Figure 3: Control forces in x and y and control torque of yaw.

7. Conclusion

This paper investigates the path tracking problem for an AUV with input delay. Based on predictive and adaptive NN control theory, a predictive controller is given. The output feedback control algorithm is employed here. The NN is used to estimate the dynamic uncertain nonlinear function induced by hydrodynamic coefficients and coupling of the surge, sway, and yaw angular velocity. The predictive control is introduced to compensate the input delay present in AUV. The stability of the controller was analyzed by Lyapunov theorem. Simulation results showed that the proposed controller performs well with stability.

Data Availability

We are sorry that we cannot share the data in our article now because future works are based on its results. The methods in this paper are effective methods for investigation of path following for autonomous underwater vehicles with input

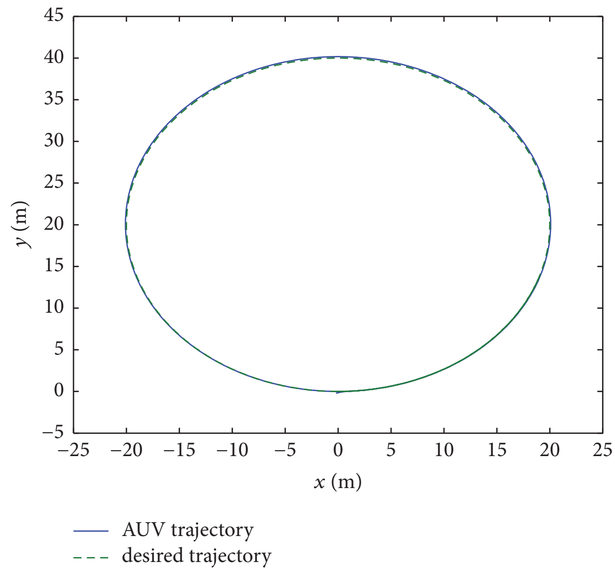

Figure 4: Path tracking response in xy plane.

delay. We will apply a patent on the relevant studies. So, we cannot share the data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work is supported by the Hubei Provincial Natural Science Foundation of China (2016CFB273) and the Research and Innovation Initiatives of WHPU (2018Y20).

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