A Neural Network Adaptive Controller for Autonomous Diving Control of an Autonomous Underwater Vehicle

Ji-Hong Li, Pan-Mook Lee, and Bong-Huan Jun

Abstract: This paper presents a neural network adaptive controller for autonomous diving control of an autonomous underwater vehicle (AUV) using adaptive backstepping method. In general, the dynamics of underwater robotics vehicles (URVs) are highly nonlinear and the hydrodynamic coefficients of vehicles are difficult to be accurately determined *a priori* because of variations of these coefficients with different operating conditions. In this paper, the smooth unknown dynamics of a vehicle is approximated by a neural network, and the remaining unstructured uncertainties, such as disturbances and unmodeled dynamics, are assumed to be unbounded, although they still satisfy certain growth conditions characterized by 'bounding functions' composed of known functions multiplied by unknown constants. Under certain relaxed assumptions pertaining to the control gain functions, the proposed control scheme can guarantee that all the signals in the closed-loop system satisfy to be uniformly ultimately bounded (UUB). Simulation studies are included to illustrate the effectiveness of the proposed control scheme, and some practical features of the control laws are also discussed.

Keywords: Adaptive backstepping method, AUV, neural networks, nonlinear uncertain systems, URVs.

1. INTRODUCTION

Because of the highly nonlinear dynamics and the unpredictable operating environments of URVs, conventional control schemes such as the PID controller may not be able to provide satisfactory outcomes in relation to the control problems experienced by underwater vehicles. Therefore, high performance control systems of URVs need to have the capacities of learning and adapting to the variations of dynamics and hydrodynamic coefficients of vehicles in order to provide desired performance [1].

So far, various control strategies have been presented for the motion control of URVs. Goheen and Jefferys [2] proposed an adaptive control scheme for autopilots of autonomous and remotely operated underwater vehicles, where the uncertainties composed of certain unknown constant parameters multiplied by known functions. To deal with the unstructured uncertainties, such as disturbances and unmodeled dynamics, many researchers concentrated their interests on the applications of sliding mode control methodology [3-6]. In these literatures, the bounds of uncertainties were often assumed to be known *a priori*, and this was a somewhat strong restricting condition in the practice, because of the high nonlinearities and unpredictable operating environments of target plants. This kind of restriction was relaxed so that the uncertainties were bounded by unknown constants, and certain adaptation schemes for these constants were introduced in [1,7]. However, according to the features of the adaptation laws introduced in the above two literatures, nonzero tracking errors could cause divergence of estimations of unknown constants, and further cause the closed-loop systems to be unstable. In practice, the tracking errors will always be nonzero due to some neglected factors.

Almost independently from above nonlinear control researches, due to the approximation capacities of neural networks for nonlinear mappings [8,9] and their learning characteristics, considerable interests have been taken in the applications of neural networks to the control problems associated with URVs [10-14]. The common feature of these neural network control schemes was just to approximate the smooth uncertainties of URVs' dynamics using general multi-layer neural networks, and the networks' weights values were updated by back propagation algorithms. The back propagation algorithm, which is one of the gradient descent methods, is a widely used weights' adjustment method for neural networks and has been proven to be quite effective in practice. However, it is difficult to obtain analytical results

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concerning the stability of the networks [15]. In practice, while we can construct a neural network to approximate a given unknown function, we could not exactly determine the number of hidden neurons or the basis of a given unknown function *a priori*. Therefore, there always remains certain mismatching resulting in network's reconstruction error. For this reason, robustness has become one of the most important issues related to neural network control problems.

Recently, several neural network adaptive control schemes [16-19] have been presented for general nonlinear uncertain systems with various relaxed assumptions concerning the uncertainties. Known bound disturbances have been considered in [17]. Polycarpou [16] proposed a neural network adaptive control scheme for a class of strict-feedback nonlinear systems where the control gain functions were exactly known. Zhang *et al.* [18] expanded the above result to the general strict-feedback nonlinear systems where the control gain functions were assumed to be unknown. In [19], unstructured uncertainties that satisfy certain growth conditions characterized by 'bounding functions' were considered and certain projection algorithms were used for the adaptation laws of networks' weights values. However, there was no adaptation scheme for unknown bounds of networks' weights values being introduced. Therefore, if the initial estimation values (certain design parameters) of these unknown bounds were chosen unsuitably (smaller than the exact values), then the proposed control scheme could somewhat lose the functional approximation capacities of the neural networks, even if the basis function vectors (or hidden layers) satisfy the persistency excitation conditions.

In this paper, we present a semi-globally stable neural network adaptive control scheme for autonomous diving control of an AUV, where the unstructured uncertainties are assumed to be unbounded, although they still satisfy certain growth conditions characterized by 'bounding functions'. All adaptation laws for the unknown bounds of the uncertainties are derived from the Lypunov-based method as well as the update laws of the networks' weights values. Furthermore, we do not approximate the unknown control gain functions directly using neural networks and therefore avoid the possible controller singularity problem. Under certain relaxed assumptions on the control gain functions, the presented control scheme can guarantee that all the signals in the closed-loop system are UUB. Simulation studies are included to illustrate the effectiveness of the presented control scheme and some practical features of the control law are also discussed.

2. PROBLEM STATEMENTS

Dynamical behavior of an AUV can be described in a common way through 6 degree-of-freedom (DOF) nonlinear equations in the two coordinate frames as indicated in Fig. 1 [20]

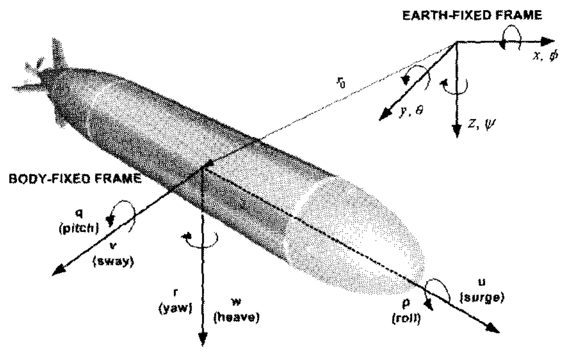

Fig. 1. Inertia, Earth-fixed frame and body-fixed frame for AUV.

$$\begin{aligned} &M(\nu)\dot{\nu} + C_D(\nu)\nu + g(\eta) + d = \tau, \\ &\dot{\eta} = J(\eta)\nu, \end{aligned} \tag{1}$$

where $\eta = [x, y, z, \phi, \theta, \psi]^T$ is the position and orientation vector in the earth-fixed frame, $\nu = [u, v, w, p, q, r]^T$ is the velocity and the angular rate vector in the body-fixed frame, $J(\eta)$ is the transformation matrix, $M(\nu) \in \Re^{6\times 6}$ is the inertia matrix (including added mass), $C_D(\nu) \in \Re^{6\times 6}$ is the matrix of Coriolis, a centripetal and damping term, $g(\eta) \in \Re^6$ is the gravitational forces and moments vector, d denotes the unstructured uncertainty vector, such as exogenous input terms and unmodeled dynamics, and τ is the input torque vector.

The diving equations of AUVs should include the heave velocity w, the angular velocity q in pitch motion, the pitch angle θ, the depth z and the stern plane deflection and/or thrust force of the propellers. Restrictions are placed on the vehicle in the constant forward motion and, for simplicity; it is assumed that the heave velocity during diving is small and negligible. This is quite realistic since most small underwater vehicles are designed to have neutral buoyancies and move slowly in the vertical direction. Further, in general, underwater vehicles are designed to have symmetric structures, so, it is reasonable to assume that the body fixed coordinate is located at the center of gravity with the gravity force equal to the buoyancy force of the vehicle. Consequently, the pitch and depth motion of the vehicle during diving can be expressed as the following, which is a certain modified expression from [20]

$$\begin{aligned} &\dot{z} = -u_0\theta + \Delta_z, \\ &\dot{\theta} = q, \\ &\dot{q} = f_q + b\tau_q + \Delta_q, \end{aligned} \tag{2}$$

where u_0 is a known constant forward speed, Δ_z, which could be expressed as $\Delta_z = f_{\Delta z}(u,v,w,\phi,\theta,t)$, denotes the unmodeled dynamics and disturbance term, f_q and b could be defined as $f_q := \zeta_1(M, C_D, g)$, $b := \zeta_2(M)$ with $\zeta_1(\cdot)$ and $\zeta_2(\cdot)$ smooth functions.

Due to the highly nonlinear characteristic of AUVs' dynamics and the unpredictable operating environments of the vehicles, in most applications of AUVs, it is hard to determine the exact values of M and C_D in the (1) *a priori*. For this reason, we make the following assumptions on (2).

Assumption 1: f_q and b are smooth unknown functions, and b is nonzero with known sign. Without any loss of generality, we assume that $b \geq b_0 > 0$ with b_0 being an unknown constant. Furthermore, we assume that $|d(b^{-1})/dt| \leq c_b \varphi_b$, where φ_b is a known function and c_b is the smallest among the unknown positive constants that satisfy the above inequality.

Remark 1: In general, most AUVs are designed to move slowly in the deep-sea environment. Furthermore, the vehicles are desired to maintain constant forward speeds while in diving motions. In this case, the control gain function b varies slowly, and this causes Assumption 1 to be reasonable.

Assumption 2: $|\Delta_z| \leq c_z \varphi_{\Delta z}$, where $\varphi_{\Delta z}$ is a known function and c_z is the smallest among the unknown positive constants that satisfy the above inequality.

For a given desired trajectory $z_d(t)$, the control objective is to design a neural network adaptive controller for the system described by (2) such that all the signals in the closed-loop system are guaranteed to be UUB.

Here we define the following new error variables as $x_1 = z - \alpha_0$, $x_2 = \theta - \alpha_1(z_d, z)$, $x_3 = q - \alpha_2(z_d, z, \theta)$, where $\alpha_0 = z_d(t)$ and $\alpha_1(z_d, z)$, $\alpha_2(z_d, z, \theta)$ are *stabilizing functions* [21]. Then, in combination with Assumption 1, (2) can be expressed as

$$\begin{aligned} \dot{x}_1 &= -\dot{\alpha}_0 - u_0\theta + \Delta_z, \\ \dot{x}_2 &= -\dot{\alpha}_1 + q, \\ b^{-1}\dot{x}_3 &= b^{-1}(f_q - \dot{\alpha}_2) + \tau_q + b^{-1}\Delta_q. \end{aligned} \tag{3}$$

In (3), $\dot{\alpha}_0 = \dot{z}_d$ is known and α_1, α_2 are also known design functions. However, because of the unknown uncertainty of term Δ_z, $\dot{\alpha}_1, \dot{\alpha}_2$ include certain unknown uncertainties, too. For this reason, (3) can be expanded as follows

$$\begin{aligned} \dot{x}_1 &= -\dot{\alpha}_0 - u_0\theta + \Delta_z, \\ \dot{x}_2 &= -[(\partial\alpha_1/\partial z_d)\dot{z}_d - (\partial\alpha_1/\partial z)u_0\theta] + q - (\partial\alpha_1/\partial z)\Delta_z, \\ b^{-1}\dot{x}_3 &= b^{-1}\{f_q - [(\partial\alpha_2/\partial z_d)\dot{z}_d - (\partial\alpha_2/\partial z)u_0\theta \\ &\quad + (\partial\alpha_2/\partial\theta)q]\} + \tau_q + b^{-1}[\Delta_q - (\partial\alpha_2/\partial z)\Delta_z]. \end{aligned} \tag{4}$$

According to Assumption 1, the first term of the right side of the third equation in (4), denoted by F, is an unknown smooth function. Here we want to approximate this unknown smooth function F using a neural network. A given unknown function F can always be written in the following parametric form [9]

$$F = W^{*T}\Phi^*, \tag{5}$$

where $W^* \in \Re^{N^*}$ is an unknown constant vector, and $\Phi^*(v, \dot{v}, b_3) \in \Re^{N^*}$ with $b_3 = (\partial\alpha_2/\partial z_d)\dot{z}_d - (\partial\alpha_2/\partial z)u_0\theta + (\partial\alpha_2/\partial\theta)q$ is the basis function vector of F. If the basis of a function is exactly known, then the functional approximation problem can be converted to the well-known parameter estimation problem. However, in practice, we could not exactly know the basis of an unknown function *a priori*. Therefore, there always remains certain mismatching resulting in network's reconstruction error. Consequently, (5) can be expressed as

$$F = W^T\Phi + \varepsilon, \tag{6}$$

where $W \in \Re^N$ is the optimal weight vector of the constructed network, $\Phi(v, \dot{v}, b_3) \in \Re^N$ is the constructed basis function vector, and $\varepsilon(v, v, b_3)$ is the network's reconstruction error.

The optimal weight vector W in (6) is an "artificial" quantity required only for analytical purposes. Typically, W is chosen as the value of W' that minimizes ε for all $v, \dot{v}, b_3 \in \Omega$, where $\Omega \subset \Re^6$ is a compact region, i.e.,

$$W := \arg\min_{W' \in \Re^N} \left\{ \sup_{v, \dot{v}, b_3 \in \Omega} |F - W'^T\Phi| \right\}. \tag{7}$$

Substituting (6) into (4), we have

$$\begin{aligned} \dot{x}_1 &= -\dot{\alpha}_0 - u_0\theta + \Delta_z, \\ \dot{x}_2 &= -[(\partial\alpha_1/\partial z_d)\dot{z}_d - (\partial\alpha_1/\partial z)u_0\theta] + q - (\partial\alpha_1/\partial z)\Delta_z, \\ b^{-1}\dot{x}_3 &= W^T\Phi + \tau_q + \varepsilon + b^{-1}[\Delta_q - (\partial\alpha_2/\partial z)\Delta_z]. \end{aligned} \tag{8}$$

Now, the previous tracking control problem for (2) is converted to the regulation problem of (8). Here we make the following assumption on the network's reconstruction error and the unstructured uncertainties.

Assumption 3: $|\varepsilon + b^{-1}[\Delta_q - (\partial\alpha_2/\partial z)\Delta_z]| \le c_q\varphi_{\Delta q}$, with $\varphi_{\Delta q}$ a known function and c_q the smallest among the unknown positive constants that satisfy the above inequality.

3. NEURAL NETWORK ADAPTIVE CONTROL DESIGN

In this section, we develop a neural network adaptive control scheme for autonomous diving control of an AUV, whose dynamics can be expressed as (2), or the equivalent as (8), using adaptive backstepping method [21].

Step 1:

Consider the first equation in (8)

$$\dot{x}_1 = -\dot{\alpha}_0 - u_0\theta + \Delta_z. \quad (9)$$

By substituting $\alpha_0 = z_d$, $\theta = x_2 + \alpha_1$ into (9), we have

$$\dot{x}_1 = -\dot{z}_d - u_0x_2 - u_0\alpha_1 + \Delta_z. \quad (10)$$

The first stabilizing function α_1 is chosen as follows

$$\alpha_1 = -u_0^{-1}[(\dot{z}_d - k_1x_1) - \hat{c}_z\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z)], (11)$$

where $k_1 > 0$ is a design parameter, $\hat{c}_z$ is the estimation of c_z, $\sigma_z > 0$ is a design parameter, and $\tanh(\cdot)$ denotes hyperbolic function. Substituting (11) into (10) yields

$$\dot{x}_1 = -u_0x_2 - k_1x_1 + \Delta_z - \hat{c}_z\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z). (12)$$

Consider the following Lyapunov function candidate

$$V_1 = 1/2(x_1^2 + \gamma_z^{-1}\tilde{c}_z^2), \quad (13)$$

where $\gamma_z > 0$ is a weighting factor and $\tilde{c}_z = c_z - \hat{c}_z$ is the estimation error for c_z. Differentiating (13) and substituting (12) into it, we have

$$\begin{aligned}\dot{V}_1 &= x_1\dot{x}_1 + \gamma_z^{-1}\tilde{c}_z\dot{\tilde{c}}_z \\ &= -u_0x_1x_2 - k_1x_1^2 + x_1\Delta_z - \hat{c}_zx_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z) \\ &\quad + \gamma_z^{-1}\tilde{c}_z\dot{\tilde{c}}_z \\ &\le -u_0x_1x_2 - k_1x_1^2 + c_z|x_1\varphi_{\Delta z}| \\ &\quad - \hat{c}_zx_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z) + \gamma_z^{-1}\tilde{c}_z\dot{\tilde{c}}_z. \end{aligned} \quad (14)$$

Here we use the following Lemma.

Lemma 1: The following inequality holds for any $\sigma > 0$ and $\forall x \in \Re$

$$0 \le |x| - x\tanh(x/\sigma) \le \kappa\sigma, \quad (15)$$

where κ is a constant that satisfies $\kappa = e^{-(\kappa+1)}$.

Proof: Refer to Polycarpou (1996). □

Using Lemma 1, (14) can be rewritten as

$$\begin{aligned}\dot{V}_1 &\le -u_0x_1x_2 - k_1x_1^2 + c_z|x_1\varphi_{\Delta z}| - c_zx_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z} \\ &\quad /\sigma_z) + \tilde{c}_zx_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z) + \gamma_z^{-1}\tilde{c}_z\dot{\tilde{c}}_z \\ &\le -u_0x_1x_2 - k_1x_1^2 + \kappa c_z\sigma_z + \tilde{c}_zx_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z) \\ &\quad + \gamma_z^{-1}\tilde{c}_z\dot{\tilde{c}}_z. \end{aligned} \quad (16)$$

Choose the parameter update laws as follows

$$\dot{\hat{c}}_z = \gamma_z[x_1\varphi_{\Delta z}\tanh(x_1\varphi_{\Delta z}/\sigma_z) - a_z(\hat{c}_z - c_{z0})], (17)$$

where $a_z \ge 0$ is a certain weighting factor, and c_{z0} is a certain design parameter. Substituting (17) into (16), we have

$$\dot{V}_1 \le -u_0x_1x_2 - k_1x_1^2 + \kappa c_z\sigma_z + a_z\tilde{c}_z(\hat{c}_z - c_{z0}). (18)$$

Step 2:

Consider the equation

$$\begin{aligned}\dot{x}_2 &= -[(\partial\alpha_1/\partial z_d)\dot{z}_d - (\partial\alpha_1/\partial z)u_0\theta] \\ &\quad + q - (\partial\alpha_1/\partial z)\Delta_z.\end{aligned} \quad (19)$$

Similar to *Step 1*, here we choose the second stabilizing function α_2 as

$$\begin{aligned}\alpha_2 &= [(\partial\alpha_1/\partial z_d)\dot{z}_d - (\partial\alpha_1/\partial z)u_0\theta] - k_2x_2 + u_0x_1 \\ &\quad - \hat{c}_{z2}(\partial\alpha_1/\partial z)\varphi_{\Delta z}\tanh[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}/\sigma_{z2}]. \end{aligned} (20)$$

where $k_2 > 0$ is a design parameter and $\hat{c}_{z2}$ is another estimation of c_z, and $\sigma_{z2} > 0$ is a design parameter. Substituting (20) into (19) yields

$$\dot{x}_2 = -k_2 x_2 + x_3 + u_0 x_1 - \hat{c}_{z2}(\partial\alpha_1/\partial z)\varphi_{\Delta z} \times \tanh[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}/\sigma_{z2}] - (\partial\alpha_1/\partial z)\Delta_z . \quad (21)$$

Consider the following Lyapunov function candidate

$$V_2 = V_1 + 1/2(x_2^2 + \gamma_{z2}^{-1}\tilde{c}_{z2}^2), \quad (22)$$

where $\gamma_{z2} > 0$ is a certain weighting factor and $\tilde{c}_{z2} = c_z - \hat{c}_{z2}$.

Differentiating (22) and substituting (21) into it, we have

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + x_2\dot{x}_2 + \gamma_{z2}^{-1}\tilde{c}_{z2}\dot{\tilde{c}}_{z2} \\ &= \dot{V}_1 + u_0 x_1 x_2 - k_2 x_2^2 + x_2 x_3 - x_2(\partial\alpha_1/\partial z)\Delta_z \\ &\quad - \hat{c}_{z2}x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}\tanh[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}/\sigma_{z2}] \\ &\quad + \gamma_{z2}^{-1}\tilde{c}_{z2}\dot{\tilde{c}}_{z2} . \end{aligned} \quad (23)$$

According to Assumption 2 and (15) and (18), the above (23) can be rewritten as

$$\begin{aligned}\dot{V}_2 &\le -k_1 x_1^2 - k_2 x_2^2 + \kappa c_z\sigma_z + a_z\tilde{c}_z(\hat{c}_z - c_{z0}) + x_2 x_3 \\ &\quad + c_z\left|x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}\right| - \hat{c}_{z2}x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z} \\ &\quad \times \tanh[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}/\sigma_{z2}] + \gamma_{z2}^{-1}\tilde{c}_{z2}\dot{\tilde{c}}_{z2} \\ &= -k_1 x_1^2 - k_2 x_2^2 + \kappa c_z(\sigma_z + \sigma_{z2}) + a_z\tilde{c}_z(\hat{c}_z - c_{z0}) \\ &\quad + x_2 x_3 + \tilde{c}_{z2}x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}\tanh[x_2(\partial\alpha_1/\partial z) \\ &\quad \cdot \varphi_{\Delta z}/\sigma_{z2}] + \gamma_{z2}^{-1}\tilde{c}_{z2}\dot{\tilde{c}}_{z2} . \end{aligned} \quad (24)$$

Choose the parameter update laws as follows

$$\dot{\hat{c}}_{z2} = \gamma_{z2}[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}\tanh[x_2(\partial\alpha_1/\partial z)\varphi_{\Delta z}/\sigma_{z2}] - a_{z2}(\hat{c}_{z2} - c_{z0})], \quad (25)$$

where $a_{z2} \ge 0$ is a certain weighting factor. Substituting (25) into (24), we have

$$\begin{aligned}\dot{V}_2 &\le -k_1 x_1^2 - k_2 x_2^2 + \kappa c_z(\sigma_z + \sigma_{z2}) + a_z\tilde{c}_z(\hat{c}_z - c_{z0}) \\ &\quad + a_{z2}\tilde{c}_{z2}(\hat{c}_{z2} - c_{z0}) + x_2 x_3 . \end{aligned} \quad (26)$$

Step 3:

This is the final step and the actual control input would be derived in this step. Consider the final equation in (8)

$$b^{-1}\dot{x}_3 = W^T\Phi + \tau_q + \varepsilon + b^{-1}[\Delta_q - (\partial\alpha_2/\partial z)\Delta_z] . \quad (27)$$

Similar to the previous step, the actual control input τ_q is selected as

$$\tau_q = -k_3 x_3 - x_2 - \hat{W}^T\Phi - 1/2\hat{c}_b x_3\varphi_b\tanh(x_3^2\varphi_b/\sigma_b) - \hat{c}_q\varphi_{\Delta q}\tanh(x_3\varphi_{\Delta q}/\sigma_q), \quad (28)$$

where $k_3 > 0$ is a design parameter, $\hat{c}_b$ and $\hat{c}_q$ are the estimation of c_b, c_q defined in Assumptions 1 and 3, and $\sigma_b > 0$ and $\sigma_q > 0$ are certain design parameters. Substituting (28) into (27) yields

$$\begin{aligned}b^{-1}\dot{x}_3 &= -k_3 x_3 - x_2 + \tilde{W}^T\Phi + \varepsilon + b^{-1}[\Delta_q - (\partial\alpha_1/\partial z)\Delta_z] \\ &\quad - 1/2\hat{c}_b x_3\varphi_b\tanh(x_3^2\varphi_b/\sigma_b) \\ &\quad - \hat{c}_q\varphi_{\Delta q}\tanh(x_3\varphi_{\Delta q}/\sigma_q), \end{aligned} \quad (29)$$

where $\tilde{W} = W - \hat{W}$ is the network's weight estimation error vector.

Theorem: Consider the autonomous diving equation of an AUV expressed as (2) with Assumptions 1~3. Choose the control laws as (11), (20), and (28), and the parameters update laws are selected as (17) and (25) as follows

$$\begin{aligned}\dot{\hat{W}} &= \Gamma[\Phi x_3 - a_W(\hat{W} - W_0)], \\ \dot{\hat{c}}_b &= \gamma_b[1/2x_3^2\varphi_b\tanh(x_3^2\varphi_b/\sigma_b) - a_b(\hat{c}_b - c_{b0})], \\ \dot{\hat{c}}_q &= \gamma_q[x_3\varphi_q\tanh(x_3\varphi_q/\sigma_q) - a_q(\hat{c}_q - c_{q0})], \end{aligned} \quad (30)$$

where Γ is a strictly positive definite matrix, $\gamma_b, \gamma_q > 0$ are weighting factors, $a_W, a_b, a_q \ge 0$ and W_0, c_{b0}, c_{q0} are certain design parameters. Then, all the signals in the closed-loop system are guaranteed to be UUB.

Proof: Consider the following Lyapunov function candidate

$$V_3 = V_2 + 1/2[b^{-1}x_3^2 + \tilde{W}^T\Gamma^{-1}\tilde{W} + \gamma_b^{-1}\tilde{c}_b^2 + \gamma_q^{-1}\tilde{c}_q^2], \quad (31)$$

where $\tilde{c}_b = c_b - \hat{c}_b$ and $\tilde{c}_q = c_q - \hat{c}_q$ are corresponding parameter estimation errors.

Differentiating (31) and substituting (29) into it, and combining this with Assumptions 1 and 3, we have

$$\begin{aligned}\dot{V}_3 &\le \dot{V}_2 - k_3 x_3^2 - x_2 x_3 + x_3\tilde{W}^T\Phi + \tilde{W}^T\Gamma^{-1}\dot{\tilde{W}} + 1/2c_b \\ &\quad \cdot \varphi_b x_3^2 - 1/2\hat{c}_b x_3^2\varphi_b\tanh(x_3^2\varphi_b/\sigma_b) + c_q|x_3|\varphi_q \\ &\quad - \hat{c}_q \cdot x_3\varphi_q\tanh\left(x_3\varphi_q/\sigma_q\right) + \gamma_b^{-1}\tilde{c}_b\dot{\tilde{c}}_b + \gamma_q^{-1}\tilde{c}_q\dot{\tilde{c}}_q . \end{aligned} \quad (32)$$

Substituting (30) into (32), we get

$$\begin{aligned}\dot{V}_3 &\le -k_1 x_1^2 - k_2 x_2^2 - k_3 x_3^2 + \kappa c_z(\sigma_z + \sigma_{z2}) + 1/2\kappa c_b \sigma_b \\ &\quad + \kappa c_q \sigma_q + a_z \tilde{c}_z(\hat{c}_z - c_{z0}) + a_{z2}\tilde{c}_{z2}(\hat{c}_{z2} - c_{z0}) \\ &\quad + a_W \tilde{W}^T(\hat{W} - W_0) \\ &\le -k_1 x_1^2 - k_2 x_2^2 - k_3 x_3^2 - 1/2(a_W \tilde{W}^T \tilde{W} + a_z \tilde{c}_z^2 \\ &\quad + a_{z2}\tilde{c}_{z2}^2 + a_b \tilde{c}_b^2 + a_q \tilde{c}_q^2) + \kappa c_z(\sigma_z + \sigma_{z2}) \\ &\quad + 1/2\kappa c_b \sigma_b + \kappa c_q \sigma_q + 1/2[a_W \| W - W_0 \|_2^2 \\ &\quad + a_z(c_z - c_{z0})^2 + a_{z2}(c_{z2} - c_{z0})^2 + a_b(c_b - c_{b0})^2 \\ &\quad + a_q(c_q - c_{q0})^2] + a_W \tilde{W}^T(\hat{W} - W_0) \\ &\le -\lambda V_3 + \rho, \end{aligned} \tag{33}$$

where λ and ρ are positive constants defined by

$$\lambda := \min\left\{2k_1, 2k_2, 2bk_3, a_W / \lambda_{\min}(\Gamma^{-1}), a_z\gamma_z, a_{z2}\gamma_{z2}, a_b\gamma_b, a_q\gamma_q\right\}, \tag{34}$$

$$\begin{aligned}\rho &:= \kappa c_z(\sigma_z + \sigma_{z2}) + 1/2\kappa c_b\sigma_b + \kappa c_q\sigma_q + 1/2[a_W \\ &\quad \cdot \| W - W_0 \|_2^2 + a_z(c_z - c_{z0})^2 + a_{z2}(c_{z2} - c_{z0})^2 \\ &\quad + a_b(c_b - c_{b0})^2 + a_q(c_q - c_{q0})^2].\end{aligned} \tag{35}$$

Let $\mu := \rho / \lambda$, then (33) satisfies

$$0 \le V_3 \le \mu + [V_3(0) - \mu]e^{-\lambda t}. \tag{36}$$

Therefore, $x_1, x_2, x_3, \hat{W}, \hat{c}_z, \hat{c}_{z2}, \hat{c}_b, \hat{c}_q$ are all UUB. Furthermore, since z_d, α_1, α_2 are bounded, it is obvious that z, θ and q are also bounded. Consequently, all the signals in the closed-loop are guaranteed to be UUB.

Rewrite (33) as the following form

$$\begin{aligned}\dot{V}_3 &\le -k_1 x_1^2 + \kappa c_z(\sigma_z + \sigma_{z2}) + 1/2\kappa c_b\sigma_b + \kappa c_q\sigma_q - a_z \\ &\quad \cdot[\tilde{c}_z^2 - \tilde{c}_z(c_z - c_{z0})] - a_{z2}[\tilde{c}_{z2}^2 - \tilde{c}_{z2}(c_{z2} - c_{z0})] \\ &\quad - a_W[\tilde{W}^T\tilde{W} - \tilde{W}^T(W - W_0)] - a_b[\tilde{c}_b^2 - \tilde{c}_b \\ &\quad \cdot (c_b - c_{b0})] - a_q[\tilde{c}_q^2 - \tilde{c}_q(c_q - c_{q0})] \\ &\le -k_1 x_1^2 + \kappa c_z(\sigma_z + \sigma_{z2}) + 1/2\kappa c_b\sigma_b + \kappa c_q\sigma_q \\ &\quad + 1/4[a_W \| W - W_0 \|_2^2 + a_z(c_z - c_{z0})^2 + a_{z2} \\ &\quad \cdot (c_{z2} - c_{z0})^2 + a_b(c_b - c_{b0})^2 + a_q(c_q - c_{q0})^2].\end{aligned} \tag{37}$$

Since $k_1 > 0$, if

$$|x_1| \ge \sqrt{\zeta / k_1}, \tag{38}$$

then, $\dot{V}_3 \le 0$ regardless of the values taken by other signals, where the strictly positive definite constant ζ is defined by

$$\begin{aligned}\zeta &:= \kappa c_z(\sigma_z + \sigma_{z2}) + 1/2\kappa c_b\sigma_b + \kappa c_q\sigma_q \\ &\quad + 1/4[a_W \| W - W_0 \|_2^2 + a_z(c_z - c_{z0})^2 + a_{z2} \\ &\quad \cdot (c_{z2} - c_{z0})^2 + a_b(c_b - c_{b0})^2 + a_q(c_q - c_{q0})^2].\end{aligned} \tag{39}$$

From (38) and (39), it is easily seen that depth tracking error $x_1 = z - z_d$ could be made as small as desired through the suitable selection of design parameters.

Remark 2: In many practical applications, given a control plant, the constructed neural network's optimal weight vector W and the bounding parameter c_z, c_b, c_q may not be completely unknown. Instead, we may have rough estimations of them through off-line identification or other useful schemes. In this case, the design parameters W_0, c_{z0}, c_{b0} and c_{q0} are considered as the initial estimation values of W, c_z, c_b and c_q. From (38) and (39), we can see that the accurate initial estimations of these parameters may result in smaller tracking errors.

Remark 3: From (33), we can see that large k_1, k_2, k_3 or small $\sigma_z, \sigma_{z2}, \sigma_b$ and σ_q may result in smaller tracking errors. However, increasing k_1, k_2, k_3 may cause certain high-gain control problems and the small values of $\sigma_z, \sigma_{z2}, \sigma_b$ and σ_q could result in certain infinite frequency efforts. Therefore, these design parameters should be chosen carefully in practice.

Remark 4: Design parameters a_W, a_z, a_{z2}, a_b and a_q present a certain trade-off between the tracking performance and the robustness of the proposed control scheme. In particular, if the basis function vectors $\Phi(\nu, \dot{\nu}, b_3)$ satisfy the persistency excitation conditions, then $a_W = a_z = a_{z2} = a_b = a_q = 0$ could result in the exact estimation of W. However, the persistency excitation conditions are difficult to satisfy in many practical applications. In this case, $a_W, a_z, a_{z2}, a_b, a_q > 0$ could keep the parameter estimations from being divergent.

4. SIMULATION STUDIES

The 6 degree-of-freedom dynamical model of

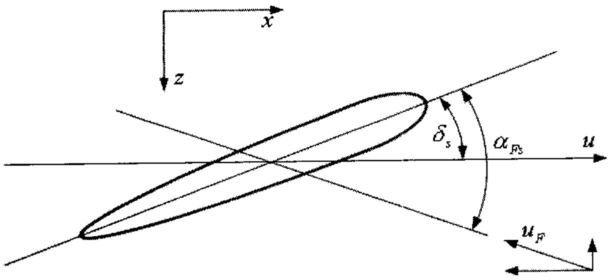

Fig. 2. Effective stern plane angle of attack.

ASUM AUV, which is under development in KRISO [22], is employed in this simulation. The auto-diving equation of ASUM AUV can be expressed as follows

$$\begin{aligned} \dot{z} &= -u_0\theta + \Delta_z, \\ \dot{\theta} &= q, \\ \dot{q} &= f_q + b_q\delta_s + \Delta_q, \end{aligned} \tag{40}$$

where

$$\begin{aligned} f_q &= (I_{yy} - M_{\dot{q}})^{-1}\{-mz_g\dot{u} + (mx_g + M_{\dot{w}})\dot{w} + M_{w|w|}w \\ &\cdot |w| + M_{q|q|}q|q| + (M_{uq} - mx_g)uq + (M_{vp} + mx_g) \\ &\cdot vp + [M_{rp} - (I_{xx} - I_{zz})]rp + mz_g(vr - wq) \\ &+ M_{uw}uw - (z_gW - z_bB)\sin\theta - (x_gW - x_bB) \\ &\cdot \cos\theta\cos\phi\}, \\ b_q &= (I_{yy} - M_{\dot{q}})^{-1}M_{uu\delta_s}u^2, \end{aligned}$$

with δ_s stern plane angle depicted in Fig. 2.

4.1. Construction of neural network

In general, there are two types of neural networks usually applied in the control practice. One of them is the general multi-layer neural network, where the network's weights values are updated by using back propagation algorithms, and has been proved to be the quite effective in practice. However, it is hard to obtain analytical results concerning the stability of the control system using this method. The other one is the linearly parameterized neural network (LPNN) where the basis function vector could be derived according to the physical properties of the target plants [17].

In this simulation, we will construct a LPNN to approximate the nonlinear smooth function F described by (4). According to the physical properties of AUVs [20], we construct the basis function vector of the neural network as follows

$$\Phi(v, \dot{v}, b_3) = [\dot{v}^T, v^T, (v\otimes v)^T, G^T, (G\otimes G)^T, b_3]^T, \tag{41}$$

where $G = [\sin\phi\sin\theta\cos\phi\cos\theta]^T$ and $\otimes$ denotes Kronecker product. For more details, refer to [23].

So far, literatures focused on the applications of underwater vehicles only consider up to second order velocity terms of vehicles' dynamics, because the higher order components are negligible, and furthermore, their coefficients are hard to determine exactly in practice. The structure of the basis function vector, expressed in (41), may need to be modified in practice to satisfy suitable performance for various applications.

4.2 Simulation results

According to (28), the actual control input δ_s is taken as

$$\begin{aligned} \delta_s = (M_{uu\delta_s}u^2)^{-1}[-k_3x_3 - x_2 - \hat{W}^T\Phi - 1/2\hat{c}_bx_3\varphi_b \\ \times\tanh(x_3{}^2\varphi_b/\sigma_b) - \hat{c}_q\varphi_{\Delta q}\tanh(x_3\varphi_{\Delta q}/\sigma_q)], \end{aligned} \tag{42}$$

where $x_1 = z - z_d$, $x_2 = \theta - \alpha_1$, $x_3 = q - \alpha_2$, with α_1 and α_2 are taken as (11) and (20). In the process of simulation, according to the physical properties of underwater vehicles [20], unstructured uncertainties in (3) are taken as $\Delta_z = u_0\theta - u\sin\theta$, $\Delta_q = q\cdot\cos(10t)$ and the corresponding bounding functions are chosen as $\varphi_{\Delta z} = u_0\theta - u\sin\theta$, $\varphi_b = 1$, $\varphi_q = (\partial\alpha_2/\partial z)\varphi_{\Delta z}$. Desired trajectory is taken as $z_d = 5 + \sin(0.3t) + 2\cos(0.1t)$, and other design parameters are taken as

$$\begin{aligned} &k_1 = 0.3,\ k_2 = 0.5,\ k_3 = 0.5, \\ &\gamma_z = \gamma_{z2} = \gamma_b = \gamma_q = 1.0, \\ &\Gamma^{34\times 34} = diag\{20,\cdots,20\}, \\ &a_z = a_{z2} = a_b = a_q = 0.3,\ a_W = 0.005, \\ &\sigma_z = \sigma_{z2} = \sigma_b = \sigma_q = 5.0. \end{aligned} \tag{43}$$

Simulation results are depicted in Figs. 3~6. Fig. 3 shows the comparison between the true value of nonlinear function F expressed in (4) and its approximation by a constructed neural network. From Fig. 3, we can see that the constructed neural network has satisfactory approximation capacities under the above simulation conditions and clearly results in a superior tracking performance (Fig. 4). Fig. 5 presents the corresponding control input and some networks' weights estimation values are shown in Fig. 6. All these simulation results confirm the effecttiveness of the proposed neural network adaptive control scheme.

In the simulation procedure, we find that various

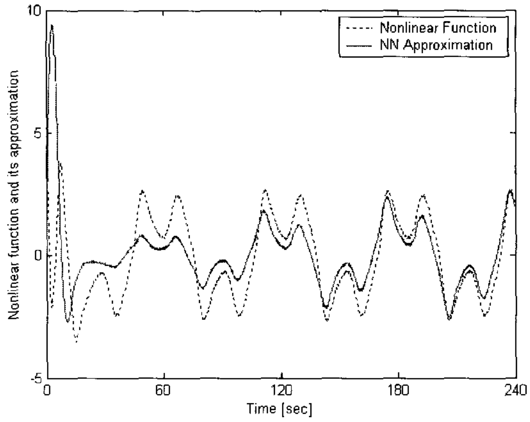

Fig. 3. Functional approximation capacity of the constructed neural network.

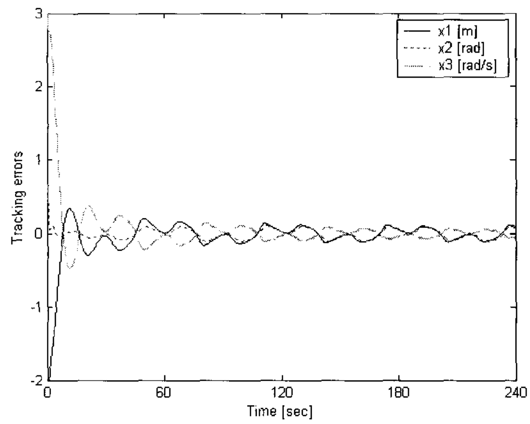

Fig. 4. Vehicle's tracking errors, $x_1 = z - z_d$, $x_2 = \theta - \alpha_1$, $x_3 = q - \alpha_2$.

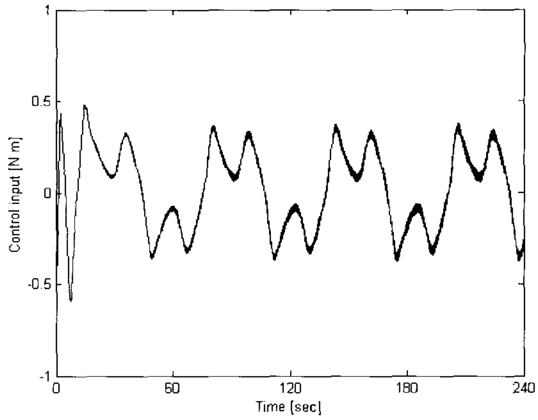

Fig. 5. Actual control input.

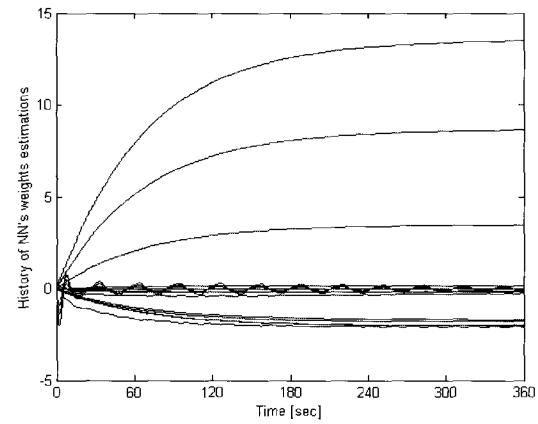

Fig. 6. History of network's weights estimation values.

desired trajectories could result in different tracking performances, even in the divergence of the closed-loop system, under the same simulation conditions. The reason for this phenomenon can be explained as in this case, $\nu, \dot{\nu}$ and b_3 may slip out of the compact set Ω defined in (7) for the constructed basis function vector $\Phi(\nu, \dot{\nu}, b_3)$ expressed in (6), and therefore, Assumption 3 may not be satisfied. How to construct the neural network (typically the basis function vectors or hidden layers) for different situations and for different plants still remains open.

5. CONCLUSIONS

The dynamics of underwater vehicles are highly nonlinear and their operating environments are hard to predict accurately *a priori*. For this reason, the autonomous diving equation of an AUV, which is a certain simplification of 6 DOF nonlinear equations of URVs, may include various unbound uncertainties. In order to deal with these unbound uncertainties, in this paper, we propose a robust neural network adaptive control scheme for autonomous diving control of an AUV. Unstructured uncertainties are assumed to be unbounded, although they still satisfy certain growth conditions characterized by 'bounding functions'. All adaptation laws for unknown bounds of uncertainties are derived from the Lypunov-based method as well as the update laws of the networks' weights values. Furthermore, we do not approximate the unknown control gain functions directly using neural networks and therefore can avoid the possible controller singularity problem. Simulation studies are included to illustrate the effectiveness of the presented control scheme and some practical features of the control law are also discussed. Further investigations on how to construct the basis function vectors and somewhat simply the structure of the stabilizing functions may be needed in the future practical applications.

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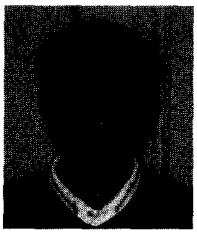

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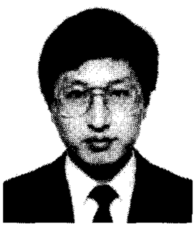

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