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Adaptive Depth Control for Autonomous Underwater Vehicles Based on Feedforward Neural Networks

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Abstract

This paper studies the design and application of the neural network based adaptive control scheme for autonomous underwater vehicle's (AUV's) depth control system that is an uncertain nonlinear dynamical one with unknown nonlinearities. The unknown nonlinearity is approximated by a feedforward neural network whose parameters are adaptively adjusted on-line according to a set of parameter estimation laws for the purpose of driving the AUV to cruise at the preset depth. The Lyapunov synthesis approach is used to develop the adaptive control scheme. The control law consists two parts: One is the certainty equivalent control and the other serves to compensate the neural network approximation error. The overall control system can guarantee that the tracking error converges in the small neighborhood of zero and all adjustable parameters involved are uniformly bounded. Simulation examples are given to illustrate the design procedure and the applicability of the proposed method. The results indicate that the proposed method is suitable for practical applications.

Keywords: Autonomous underwater vehicles (AUVs), adaptive nonlinear control, feedforward neural netowrks, Lyapunov stability.

1 Introduction

Autonomous underwater vehicles (AUVs) have various potential applications and great advantages in terms of operational cost and safety: When performing manipulations or inspection tasks, AUVs can help us better understand marine and other environmental issues, protect the ocean resources, and efficiently utilize them for further development. So far, there are more than 46 AUV models worldwide, and numerous worldwide research and development activities have occurred in the area of AUVs [19]. However, a number of complex issues due to the unstructured, hazardous underwater (or undersea) environment make it difficult to travel in the ocean even though today's technologies have allowed humans to land on the moon and robots to travel to Mars.

Major facts that make it difficult to control AUVs include: (1) the highly nonlinear, time-varying dynamic behavior of the AUVs; (2) uncertainties in hydrodynamic coefficients; (3) disturbances by ocean currents. It is difficult to fine-tune the control gains during cruise underwater. Therefore, it is highly desirable to have an AUV control system that has a self-adaptive ability when the control performance degrades during operation due to changes in the dynamics of the AUV and its environment.

In recent years, several advanced control techniques have been developed for autonomous under-water vehicles (AUVs), aimed at improving the capability of tracking given reference position and attitude trajectories [3]. AUVs performing manipulations or inspection tasks need to be controlled in six degrees of freedom. Even though the control problem is kinematically similar to the control of a rigid body in a six-dimensional space, which has been largely studied in the literature, the presence of hydrodynamic effects makes the problem of controlling an AUV much more challenging. Reference [13] presents the state of the art of several existing AUVs and their control architecture. Typical results include sliding control [6, 15], nonlinear control [10], adaptive control [11], neural network based control [16, 17, 18, 8], and fuzzy control [2, 9].

Since neural networks (NNs) have an inherent capability of approximating nonlinear functions, it is attractive to apply them in motion control systems, e.g., AUVs. In [16, 17], a neural network control system has been proposed using a recursive adaptation algorithm with a critic function (reinforced learning approach), and thus the system adjusts itself directly and on-line without an explicit model of vehicle dynamics. In [8], a self-organizing neural-net-controller system (SONCS) was developed for the heading keeping control of AUVs, which features with the fast adaptation method.

In this paper, the development of a feedforward neural network based adaptive control for AUV's depth control system is proposed. By employing a feedforward NN to on-line approximate the uncertain nonlinear dynamics of the AUV without explicit knowledge of its dynamic structure, the depth tracking performance is further investigated. The on-line parameter estimation law of the NN is developed in the context of the Lyapunov stability concept. Boundedness of all parameters involved as well as the convergence of the tracking errors to zero is guaranteed.

The rest of the paper is organized as follows. In Section 2 we discuss the uncertain nonlinear model of the AUV's depth control system. In Section 3 the feedforward NN is then briefly introduced and its universal approximation property is reviewed. In Section 4, by using the feedforward NN as an on-line approximator, we propose the adaptive control law and associated parameter estimation laws, and analyze the tracking performance and the stability of the whole AUV depth control system. In Section 5 we present an illustrative example to demonstrate the effectiveness of the proposed method. Finally, we offer some concluding remarks in Section 6.

2 AUV Model

Dynamics of AUVs, including hydrodynamic parameter uncertainties, are highly nonlinear, coupled, and time varying. Several modeling and system identification techniques for underwater robotic vehicles have been proposed by researchers [14, 3]. The motion of an AUV is discussed in 6 degrees of freedom (DOF) since 6 independent coordinates are necessary to determine the position and orientation of a rigid body AUV, and 6 different motion components are conveniently defined as: surge, sway, heave, roll, pitch, and yaw. When analyzing the motion of AUVs in 6 DOF it is convenient to define two coordinate frames as illustrated in Figure 1.

In this work, we focus on the depth control system of the AUV. Suppose the AUV has a rigid body, and assume that the forward speed v is constant and that the sway and yaw modes can be neglected, then the following equations of motion of the AUV's depth system include the angular velocity in pitch w_{z_1}, the pitch angle q, the attack angle a, the depth y_e, and the stern plane deflection d_e.

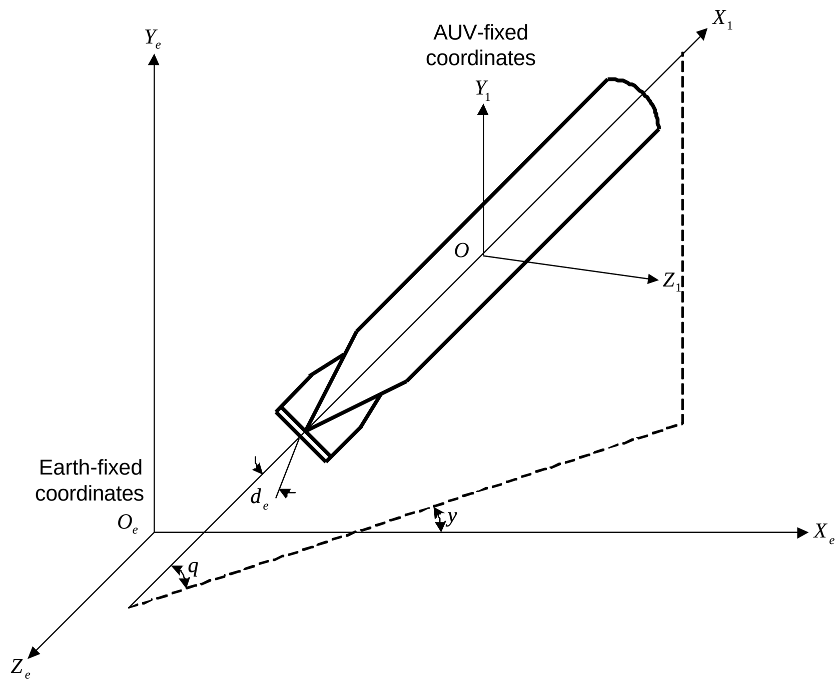

Figure 1: AUV.

$$
\begin{cases}
\dot{v} = k_{11}v^2 + k_{14}\sin\Theta + k_{18}\cos a \\
\dot{a} = \dfrac{1}{v}(k_{21}v^2 a + k_{22}vw_{z_1} + k_{231}a\cos a + k_{232}\sin a + k_{24}a\sin\Theta \\
\qquad + k_{25}\cos\Theta + k_{26}\cos q + k_{27}\sin q + k_{28} + k_{29}v^2 d_e) \\
\dot{w}_{z_1} = k_{301}\sin a + k_{302}a\cos a + k_{31}v^2 a + k_{32}vw_{z1} + k_{34}a\sin\Theta \\
\qquad + k_{35}\cos\Theta + k_{36}\cos q + k_{37}\sin q + k_{38} + k_{39}v^2 d_e \\
\dot{q} = w_{z_1} \\
\dot{y}_e = v\sin(q - a) \\
\dot{x}_e = v\cos(q - a)
\end{cases}
\tag{1}
$$

where $\Theta = q - a$, x_e is the moving distance on the X_e direction, d_e is the controller to be designed, and k_i (is the subscript appearing in the above equations) are coefficient appropriately define in [14].

From (1), we have

$$
\begin{aligned}
\ddot{y}_e &= v\cdot\cos(q - a)\cdot(\dot{q} - \dot{a}) \\
&= v\cdot\cos(q - a)\cdot(w_{z1} - \dot{a}) \\
&= v\cdot\cos(q - a)\cdot w_{z1} - \cos(q - a)\cdot[k_{21}v^2 a + k_{22}vw_{z1} + k_{231}a\cos a \\
&\quad + k_{232}\sin a + k_{24}a\sin(q - a) + k_{25}\cos(q - a) + k_{26}\cos q + k_{27}\sin q \\
&\quad + k_{28} + k_{29}v^2 d_e] \\
&:= f(x) + g(x)d_e
\end{aligned}
$$

where $x = [y_e \quad q \quad a \quad w_{z1}]^T$, and

$$f(x) := v \cdot \cos(q - a) \cdot w_{z1} - \cos(q - a) \cdot [k_{21} v^2 a + k_{22} v w_{z1} + k_{231} a \cos a + k_{232} \sin a$$
$$+ k_{24} a \sin(q - a) + k_{25} \cos(q - a) + k_{26} \cos q + k_{27} \sin q + k_{28}]$$
$$g(x) := k_{29}[-v^2 \cos(q - a)].$$

Therefore, the model of the AUV can be represented in the following compact form

$$\ddot{y}_e = f(x) + g(x) d_e. \tag{2}$$

3 Feedfoward Neural Networks

NNs are promising tools for identification and control applications because of the universal approximation property [7, 5]. A three-layer feedforward NN (shown in Figure 2) can perform as an online approximator [4].

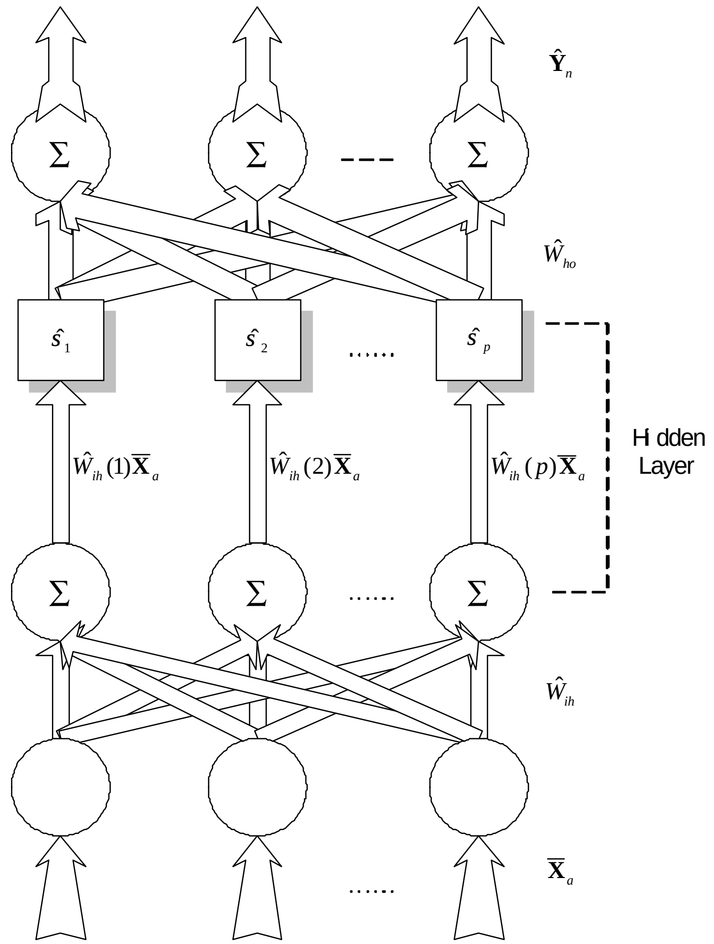

Figure 2: Neural network structure.

The NN's vector output can be represented in matrix form

$$\hat{Y}_n(x_a, \hat{W}_{ih}, \hat{W}_{ho}) = \hat{W}_{ho}\, s\,(\hat{W}_{ih}\, x_a), \tag{3}$$

where $\hat{W}_{ih} \in \mathbb{R}^{p\times(n+1)}$ and $\hat{W}_{ho} \in \mathbb{R}^{m\times p}$ are the input-hidden weight matrix and hidden-output weight matrix, respectively; $x \in \mathbb{R}^{n\times 1}$ is the input vector; $x_a = (x^T, -1)^T \in \mathbb{R}^{(n+1)\times 1}$ is the augmented neural input vector (the -1 term denotes the input bias),

$$s_j(\hat{W}_{ih}(i)x_a) = \frac{1}{1+\exp(-\hat{W}_{ih}(i)x_a)} \in \mathbb{R}, \quad i = 1,2,\cdots,p$$

is a sigmoid function, and

$$s(\hat{W}_{ih}x_a) = \begin{bmatrix} s_1(\hat{W}_{ih}(1)x_a) \\ \vdots \\ s_p(\hat{W}_{ih}(p)x_a) \end{bmatrix},$$

and

$$\hat{W}_{ih} := \begin{bmatrix} \hat{W}_{ih}(1) \\ \vdots \\ \hat{W}_{ih}(p) \end{bmatrix},$$

where $\hat{W}_{ih}$ includes the threshold.

NN's universal approximation property is stated formally in the following theorem [7, 5].

Theorem 1 *[7,5] Let* $\bar{x} \in D$ *(a compact subset of* $\mathbb{R}^n$*),* $Y(x): D \to \mathbb{R}^m$ *be a continuous function vector. For an arbitrary constant* $\varepsilon > 0$*, there exists an integer p (the number of hidden neurons) and real constant optimal weight matrices* $W_{ih}^* \in \mathbb{R}^{p\times(n+1)}$ *and* $W_{ho}^* \in \mathbb{R}^{m\times p}$ *such that*

$$Y(x) = Y_n^*(x, W_{ih}^*, W_{ho}^*) + r_n(x), \tag{4}$$

where $r_n(x)$ *is the approximation error vector satisfying* $\| r_n(x) \| \le r, \forall x \in D$*. The optimal approximator can be described as*

$$Y_n^*(x_a, W_{ih}^*, W_{ho}^*) = W_{ho}^* s(W_{ih}^* x_a). \tag{5}$$

4 Adaptive Control Design for AUV Depth System

For the AUV's depth control system modeled in (2), the control objective is to drive the AUV to track an expected depth trajectory y_{em}. The tracking performance can always be characterized by the tracking error $e := y_{em} - y_e$. In order to increase the robustness of the controller to be designed,a sliding surface is introduced as:

$$S = \dot{e} + l e,$$

where l is a small positive constant. Define

$$S_\Delta = S - \varepsilon \cdot \text{sat}\left\{\frac{S}{\varepsilon}\right\}, \quad \text{sat}(h) = \begin{cases} h & \text{if } |h| \le 1, \\ \text{sgn}(h) & \text{otherwise.} \end{cases}$$

If $\| S \| \le \varepsilon$, $S_\Delta = \dot{S}_\Delta = 0$; and if $\| S \| > \varepsilon$, $S_\Delta = S - \varepsilon$ and $\dot{S} = \dot{S}_\Delta$. Then the derivative of S is

$$\begin{aligned} \dot{S} &= \ddot{e} + l\dot{e} \\ &= \ddot{y}_e + l\dot{e} \\ &= f(x) + g(x)d_e + (-\ddot{y}_{em} + l\dot{e}) \\ &= -\Lambda S + [\Lambda S + f(x) + (-\ddot{y}_{em} + l\dot{e})] + g(x)d_e. \end{aligned} \tag{6}$$

Define

$$Y(x) := \Lambda S + f(x) + (-\ddot{y}_{em} + l\,\dot{e}), \tag{7}$$

which is uncertain, and can be on-line approximated by a feedforward NN described in Section 3.

4.1 Using NN as an online approximator

When the AUV cruises underwater, additional force and moment coefficients are added to account for the effective mass of the fluid that surrounds the vehicle and must be accelerated with the AUV. These coefficients are referred to as added (virtual) mass and include added moments of inertia and cross coupling terms such as force coefficients due to linear and angular accelerations. It would be difficult task to obtain the exact values of hydrodynamic coefficients, let alone those disturbances from currents and waves.

The main idea of NN based control schemes is to apply NNs to online approximate the unknown nonlinear functions involved in the nonlinear systems to be controlled. On the basis of Theorem 1, we can see that there exists an optimal neural network approximator $Y_n^*(x_a, W_{ih}^*, W_{ho}^*)$ over a properly defined compact set, and we design a NN approximator $\hat{Y}_n(x_a, \hat{W}_{ih}, \hat{W}_{ho})$ to model the unknown function $Y(x)$, given the estimates $\hat{W}_{ih}$ and $\hat{W}_{ho}$. The NN approximation error $\tilde{Y}_n$ and the weight matrix estimation error are defined as follows, respectively

$$\tilde{Y}_n := Y(x) - \hat{Y}_n(\bar{x}_a, \hat{W}_{ih}, \hat{W}_{ho}),$$

$$\tilde{W}_{ih} := W_{ih}^* - \hat{W}_{ih},$$

$$\tilde{W}_{ho} := W_{ho}^* - \hat{W}_{ho}.$$

According to Theorem 1, we can re-write the NN approximation error as

$$\begin{aligned}\tilde{Y}_n &= W_{ho}^* s(W_{ih}^* x_a) + r_n(x) - \hat{W}_{ho}\, s(\hat{W}_{ih}\, x_a) \\ &= \tilde{W}_{ho}\, s(W_{ih}^* x_a) + \hat{W}_{ho}\, s(W_{ih}^* x_a) + r_n(x) - \hat{W}_{ho}\, s(\hat{W}_{ih}\, x_a)\end{aligned} \tag{8}$$

Taking the Talor-series expansion on $s(W_{ih}^* x_a)$, we have

$$s(W_{ih}^* x_a) = s(\hat{W}_{ih}\, x_a) + s'(\hat{W}_{ih}\, x_a)\left[W_{ih}^* x_a - \hat{W}_{ih}\, x_a\right] + J(\tilde{W}_{ih}\, x_a), \tag{9}$$

where $s'(\hat{W}_{ih}\, x_a) = \mathrm{diag}\left(\frac{ds_1(z)}{dz}\Big|_{z=\hat{W}_{ih1} x_a}, \frac{ds_1(z)}{dz}\Big|_{z=\hat{W}_{ih2} x_a}, \cdots, \frac{ds_1(z)}{dz}\Big|_{z=\hat{W}_{ihp} x_a}\right) \in \mathbb{R}^{p\times p}$, and $J(\cdot)$ is the sum of the high-order terms of the argument in the Taylor-series expansion. Substituting (9) into (8), we can get

$$\tilde{Y}_n = \tilde{W}_{ho}\left[s(\hat{W}_{ih}\, x_a) - s'(\hat{W}_{ih}\, x_a)\hat{W}_{ih}\, x\right]_a + \hat{W}_{ho}\, s'(\hat{W}_{ih}\, x_a)\tilde{W}_{ih}\, x_a + \Psi \tag{10}$$

where $\Psi = \tilde{W}_{ho}\, s'(\hat{W}_{ih}\, x_a) W_{ih}^* x_a + \tilde{W}_{ho}\, J(\tilde{W}_{ih}\, x_a) + r_n(x)$.

Adaptive control and estimation laws to be designed will suppress the NN approximation error, and thus achieve satisfactory tracking performance. In order to facilitate the following design, we analyze the lumped term Ψ in the NN approximation error and explore its upper bound, following the approach used in [4].

Sigmoid function and its derivative are always bounded by certain constants, hence we assume c_1 and c_2 are some constants, and

$$\| s(\hat{W}_{ih}\, x_a) - s(W_{ih}^* x_a) \| \le c_1, \quad \| s'(\hat{W}_{ih}\, x_a) \| \le c_2.$$

Therefore

$$\| J(\tilde{W}_{rmih} x_a) \| = \| s(\hat{W}_{ih} x_a) - s(W_{ih}^* x_a) - s'(\hat{W}_{ih} x_a)\tilde{W}_{ih} x_a \| \le c_1 + c_2 \|\tilde{W}_{ih}\| \|x_a\|. \tag{11}$$

According to Theorem 1, the norm of the optimal weight matrices of the trained NNs should be bounded by certain constants that are assumed to be $\bar{W}_{ih}$ and $\bar{W}_{ho}$,

$$\|W_{ih}^*\|_F \le \bar{W}_{ih}, \quad \|W_{ho}^*\|_F \le \bar{W}_{ho},$$

where $\|\cdot\|_F := \operatorname{tr}\{(\cdot)^T(\cdot)\}$ with tr indicating the trace of a matrix, representing the Frobenius norm of a matrix. It is noted that the Frobenius norm of a vector is equivalent to the 2-norm of a vector.

Then the norm on the residual term Ψ of the NN approximation error is

$$\begin{aligned}
\|\Psi\| &= \|\tilde{W}_{ho} s'(\hat{W}_{ih} x_a) W_{ih}^* x_a + \tilde{W}_{ho} J(\tilde{W}_{ih} x_a) + e_n(x)\| \\
&\le \|\tilde{W}_{ho}\|_F \cdot \|s'(\hat{W}_{ih} x_a)\|_F \cdot \|W_{ih}^*\|_F \cdot \|x_a\| + \|W_{ho}^*\|_F \cdot \left[c_1 + c_2\|\tilde{W}_{ih}\|_F \|x_a\|\right] + \|e_n(x)\| \\
&\le \|\tilde{W}_{ho}\|_F \cdot c_2 \cdot \bar{W}_{ih} \cdot \|x_a\| + \bar{W}_{ho}\left[c_1 + c_2\|\tilde{W}_{ih}\|_F \|x_a\|\right] + e \\
&\le (c_1 \bar{W}_{ho} + e) + 2c_2 \bar{W}_{ih} \bar{W}_{ho} \|x_a\| + c_2 \bar{W}_{ih} \|\hat{W}_{ho}\|_F \|x_a\| + c_2 \bar{W}_{ho} \|\hat{W}_{ih}\|_F \|x_a\|, \\
&:= \mathrm{b}^T w
\end{aligned}$$

where

$$\mathrm{b} = [\, c_1 \bar{W}_{ho} + e \quad 2c_2 \bar{W}_{ih} \bar{W}_{ho} \quad c_2 \bar{W}_{ih} \quad c_2 \bar{W}_{ho} \,]^T \in \mathbb{R}^{1\times 4},$$

$$w = [\, 1 \quad \|x_a\| \quad \|\hat{W}_{ho}\|_F \|x_a\| \quad \|\hat{W}_{ih}\|_F \|x_a\| \,] \in \mathbb{R}^{4\times 1}.$$

Then we have

$$\Psi \le \mathrm{b}^T w. \tag{12}$$

It is also noticed that $g(x)$ is uncertain in that the involved coefficient k_{29} is unknown. Therefore, we need to adaptively estimate k_{29}. For the convenience of expression, define $k := k_{29}$, and the parameter estimation error $\tilde{k} = \hat{k} - k$ then the estimated $g(x)$ can be expressed as:

$$\hat{g}(x) = \hat{k}[-v^2 \cos(q - a)] \tag{13}$$

4.2 Control and arameter estimation laws

Once $\hat{Y}_n$ and $\hat{g}$ are employed as on-line approximators, we can design an adaptive AUV depth control system based on NNs:

$$d_e = \hat{g}^{-1}(-\hat{Y}_n + u_c), \tag{14}$$

where u_c is the compensation control term and has the following form

$$u_c = -\operatorname{sat}\left(\frac{S}{e}\right)\hat{\mathrm{b}}^T w, \tag{15}$$

where $\hat{\mathrm{b}} \in \mathbb{R}^{4\times 1}$ is an unknown vector to be estimated.

The parameter estimation laws for the NN and associated unknown coefficients are designed as follows

$$\dot{\hat{W}}_{ho}^T = \Gamma_{ho}\left[s(\hat{W}_{ih} x_a) - s'(\hat{W}_{ih} x_a)\hat{W}_{ih} x_a S_\Delta\right], \tag{16}$$

$$\dot{\hat{W}}_{ih}^{T} = \Gamma_{ih}\left[x_a S_\Delta \hat{W}_{ho}\, s'(\hat{W}_{ih}\, x_a) \right], \quad (17)$$

$$\dot{\hat{k}} = \Gamma_k S_\Delta [-v^2 \cos(q - a)], \quad (18)$$

$$\dot{\hat{b}} = \Gamma_w \,| S_\Delta |\, w. \quad (19)$$

Figure 3 depicts the structure of the depth control system developed herein. In the implementation of the controller, the depth y_e can be measured by a pressure meter; the pitch angle q can be measured by an inclinometer while the pitch rate w_{z1} requires a rate gyro or rate sensor.

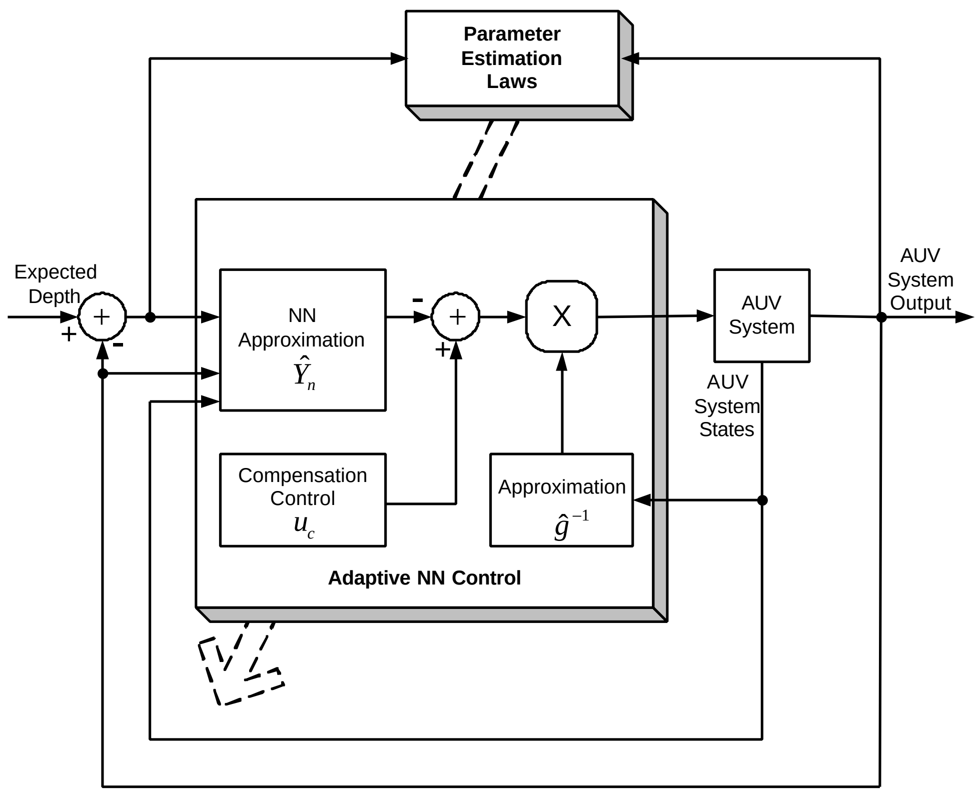

Figure 3: Block diagram for the control scheme.

4.3 Stability analysis

Theorem 2 (Stability) *Consider the AUV depth control system described by (1) or (2) with the control given by (14) and parameter estimation laws provided by (16), (17), (18), and (19). Then the AUV depth tracking error will asymptotically converge to a neighborhood of zero, and all adjustable parameters will remain bounded.*

Proof Choose a Lyapunov function $V = V_1 + V_2$, where

$$V_1 = \frac{1}{2} S_\Delta{}^2, \quad (20)$$

and

$$V_2 = \frac{1}{2}\mathrm{tr}(\tilde{W}_{ho}\Gamma_{ho}^{-1}\tilde{W}_{ho}^{T}) + \frac{1}{2}\mathrm{tr}(\tilde{W}_{ih}\Gamma_{ih}^{-1}\tilde{W}_{ih}^{T}) + \frac{1}{2}\Gamma_k \tilde{k}^2 + \frac{1}{2}\tilde{b} w \tilde{b}^{T}. \tag{21}$$

In the following, the time derivative $\dot{V}$ is to be evaluated for two cases: (1)$|S| > e$, and (2)$|S| < e$

(1) **Case 1**: If $|S| > e$, then $S_\Delta = S - e$. Hence, the time derivative of V_1 can be derived as follows: $\dot{V}_1 = S_\Delta \dot{S}_\Delta$.

Substituting (6), (14), and (15) into the above equation yields

$$\begin{aligned}\dot{V}_1 &= S_\Delta[-\Lambda S + Y(x) + g(x)d_e] \\ &= S_\Delta\left\{-\Lambda S + \left[\tilde{Y}_n(x) + \hat{Y}_n(x)\right] + [\tilde{g}(x) + \hat{g}(x)]\left[\hat{g}^{-1}(x)\left(-\hat{Y}_n(x) + u_c\right)\right]\right\} \\ &= S_\Delta\left[-\Lambda S + \tilde{Y}_n(x) + \tilde{g}(x)d_e + u_c\right].\end{aligned} \tag{22}$$

Taking the NN approximation error $\tilde{Y}_n(x)$ (10) and control law d_e (14) into (22), we have

$$\begin{aligned}\dot{V}_1 = &-S_\Delta \Lambda S_\Delta - S_\Delta e + S_\Delta u_c + S_\Delta \tilde{k}\left[-v^2\cos(q-a)\right]d_e \\ &+ S_\Delta\left\{\tilde{W}_{ho}\left[s(\hat{W}_{ih}x_a) - s'(\hat{W}_{ih}x_a)\hat{W}_{ih}x_a\right] + \hat{W}_{ho}s'(\hat{W}_{ih}x_a)\tilde{W}_{ih}x_a + \Psi\right\}\end{aligned}$$

According to (12), we can further obtain

$$\begin{aligned}\dot{V}_1 \le &-\Lambda S_\Delta^2 + \mathrm{tr}\left\{S_\Delta \tilde{W}_{ho}\left[s(\hat{W}_{ih}x_a) - s'(\hat{W}_{ih}x_a)\hat{W}_{ih}x_a\right]\right\} \\ &+ \mathrm{tr}\left\{S_\Delta \tilde{W}_{ho}s'(\hat{W}_{ih}x_a)\tilde{W}_{ih}x_a\right\} + \tilde{k}[-v^2\cos(q-a)]d_e S_\Delta + |S_\Delta|\tilde{b}^{T}w\end{aligned} \tag{23}$$

On the other hand, the time derivative of V_2 is

$$\dot{V}_2 = -\mathrm{tr}(\tilde{W}_{ho}\Gamma_{ho}^{-1}\dot{\hat{W}}_{ho}^{T}) - \mathrm{tr}(\tilde{W}_{ih}\Gamma_{ih}^{-1}\dot{\hat{W}}_{ih}^{T}) - \Gamma_k^{-1}\tilde{k}\dot{\hat{k}} - \tilde{b}^{T}w^{-1}\dot{\hat{b}}.$$

Substituting the parameter estimation laws (16), (17), (18), and (19), and the control law (14) into the above equation yields

$$\begin{aligned}\dot{V}_2 &= -\mathrm{tr}(\tilde{W}_{ho}\Gamma_{ho}^{-1}\dot{\hat{W}}_{ho}^{T}) - \mathrm{tr}(\tilde{W}_{ih}\Gamma_{ih}^{-1}\dot{\hat{W}}_{ih}^{T}) - \Gamma_k^{-1}\tilde{k}\dot{\hat{k}} - \tilde{b}^{T}w^{-1}\dot{\hat{b}} \\ &= -\mathrm{tr}\left\{S_\Delta \tilde{W}_{ho}\left[s(\hat{W}_{ih}x_a) - s'(\hat{W}_{ih}x_a)\hat{W}_{ih}x_a\right]\right\} \\ &\quad - \mathrm{tr}\left\{S_\Delta \hat{W}_{ho}s'(\hat{W}_{ih}x_a)\tilde{W}_{ih}x_a\right\} - \tilde{k}[-v^2\cos(q-a)]d_e S_\Delta - |S_\Delta|\tilde{b}^{T}w.\end{aligned} \tag{24}$$

Combining (23) and (24) leads to

$$\dot{V} \le -\Lambda S_\Delta^2. \tag{25}$$

(2) **Case 2**: If $|S| \le e$, then $S_\Delta = 0$. Hence

$$\dot{V} = 0. \tag{26}$$

Considering the above two cases, (25) and (26) obviously imply that: (1) $S_\Delta, \tilde{W}_{ho}, \tilde{W}_{ih}$, and w are all bounded; (2) $S_\Delta \in L_2$. According to the boundedness of all the adjustable parameters, we can straightforwardly see that d_e, u_c and $\dot{S}_\Delta$ are also bounded. Furthermore, $\lim_{t\to\infty}\int_0^\infty S_\Delta dt$ is bounded, and S_Δ is uniformly continuous. Applying the Barbalat Lemma [12] yields

$$\lim_{t\to\infty} S_\Delta = 0, \tag{27}$$

which implies that the depth tracking error will asymptotically converge to a neighborhood of zero.

5 AUV Case Study

The simulation study is based on the model structure of certain AUV developed in [14]. Preset the expected cruising depth $y_{em} = 50m$. Assume the following initial conditions: $v = 30m/s$, $y_e = 0; w_{z1}(0) = 0.$ Then we employ a feedforward NN with the structure - 8 inputs, 10 hidden neurons, and 1 output to approximate the uncertain nonlinearity. The adaptive update gain matrices are set to be $\Gamma_{ho} = \text{diag}5,\cdots 5 \in \mathbb{R}^{10\times 10}$, $\Gamma_{ih} = \text{diag}0.2,\cdots 0.2 \in \mathbb{R}^{8\times 8}$ and $\Gamma_k = 0.05$, and all the initial weights are set to 0. For the sliding surface, we choose $S = \dot{e} + 4e$, and $e = 0.3$. Figure 4 illustrates the depth response of the AUV (y_e), and Figure 5 shows the input (d_e) - the stern plane deflection.

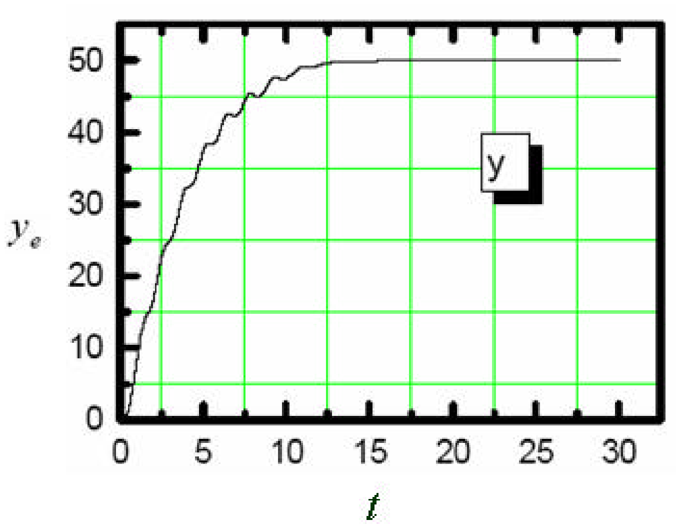

Figure 4: Depth response of the AUV (y_e).

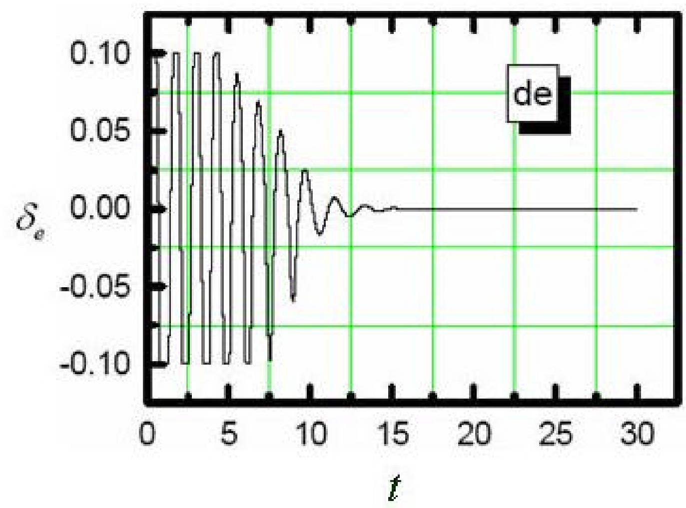

Figure 5: Control input - the stern plane deflection of the AUV (d_e).

A better performance may be obtained by further tuning the update gain and increasing the number of neurons in the hidden layer. A higher update gain gave a better tracking performance but, when the gain was too high, oscillatory behavior may happen.

6 Conclusion

An adaptive NN controller for an AUV's depth control system has been developed. The NN controller offers guaranteed tracking performance. Feedforward NN has been used to on-line approximate the uncertain nonlinear dynamics of the AUV. Without explicit prior knowledge of the vehicle dynamics, the proposed control technique could achieve satisfied tracking performance, and all the adjustable parameters involved are bounded during the course. Case studies show the effectiveness of the proposed method for AUV system. Whereas this work is only for the AUV's depth channel, the next stage of the study is to apply the proposed NN based adaptive control scheme for AUV's three-channel control system design.

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