Adaptive Neural Network Control of Autonomous Underwater Vehicles

Ahmad Forouzantabar, Babak Gholami, Mohammad Azadi

Abstract—An adaptive neural network controller for autonomous underwater vehicles (AUVs) is presented in this paper. The AUV model is highly nonlinear because of many factors, such as hydrodynamic drag, damping, and lift forces, Coriolis and centripetal forces, gravity and buoyancy forces, as well as forces from thruster. In this regards, a nonlinear neural network is used to approximate the nonlinear uncertainties of AUV dynamics, thus overcoming some limitations of conventional controllers and ensure good performance. The uniform ultimate boundedness of AUV tracking errors and the stability of the proposed control system are guaranteed based on Lyapunov theory. Numerical simulation studies for motion control of an AUV are performed to demonstrate the effectiveness of the proposed controller.

Keywords—Autonomous Underwater Vehicle (AUV), Neural Network Controller, Composite Adaptation.

I. INTRODUCTION

IN the last 3 decades, autonomous underwater vehicle (AUV) has become a research topic in the field of robotics because of the commercial and military potential and the technological challenge in developing them [1], [2]. Because of the non-linearity and the unpredictable operating environment of the AUV, many design parameters must be considered during the design of AUV control system. Indeed, the high frequency oscillating movement can seriously affect on the performance of sensors, especially optical and acoustical sensors.

In brief, the main factors that make the control of AUVs difficult are: (1) the highly nonlinear, time-varying dynamic behavior of the AUVs; (2) uncertainties in hydrodynamic coefficients; (3) disturbances by ocean currents [3]. To remedy these aforementioned problems and enhance the AUV performance along with strengthen robustness, adaptability and autonomy; it is necessary that the motion control system has the ability of learning and self-adaptation.

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Several control approaches have been applied, such as sliding control [4, 5], nonlinear control [6], adaptive control [7], and fuzzy control [8, 9].

The capability of neural networks for function approximation, classification, and their ability to deal with uncertainties and parameter variations [10, 11] make them a valuable choice for use in control of the AUVs. Xiao *et al.* [12] proposed a novel motion controller based on parallel neural network for the

AUV, which can enhance the training speed of neural network. It is shown that parallel neural network can be utilized for the establishment of highly reliable and robust

control systems for the AUV. In [13], a neural network adaptive controller with a linearly parameterized neural network (LPNN) is introduced to approximate the nonlinear uncertainties of AUV dynamics. In this approach, the basis function vector of LPNN is built according to the physical properties of the AUV. Moreover, a sliding mode control structure is used to remedy the effects of network reconstruction errors and disturbances in AUV dynamics. The method in [14] developed a fuzzy neural network controller with a novel immune particle swarm optimization (IPSO) algorithm based on immune theory and nonlinear decreasing inertia weight (NDIW) strategy to adapt the controller parameters. According to the restraint factor and NDIW strategy, IPSO algorithm can effectively prevents premature convergence and keeps balance between global and local searching ability.

In this paper, a novel control structure, with composite adaptation low, for autonomous underwater vehicles (AUVs) is proposed. In this regard, a stable adaptive controller is developed to approximate unknown nonlinear functions in the AUV dynamics; hence overcoming some limitation of conventional controllers such as PID/PD controller and improve AUV tracking performance. This controller can easily reject disturbance and robust to dynamic exchange in AUV dynamics during movement in unpredictable operating environment.

The rest of this paper organized as follows. Section II describes the uncertain nonlinear model of the AUV's dynamic. In Section III we describe the structure of stable adaptive controller with composite adaptation low. In Section IV shows the simulation results. And finally, Section V draws conclusions and sum up the whole paper.

II. AUV DYNAMIC MODEL

The dynamic model of an AUV is introduced in this section. This AUV model is useful for both formulating control

algorithms and simulations. The AUV dynamic model, which presented in this section, is based on the underwater robotic models proposed by Fossen [15] and Yuh [16].

The dynamic model, which is derived from the Newton-Euler motion equation, is given by,

$$M\dot{v} + C(v)v + D(v)v + G = \tau \tag{1}$$

where M is a mass and inertia matrices, $C(v)$ is a Coriolis and centripetal terms matrices, $D(v)$ is a hydrodynamic damping matrices, G is the gravitational and buoyancy vector, τ is the external force and torque input vector, and v is the velocity state vector. Note that in equation (1), environmental forces do not take into account.

A. Mass and Inertia Matrices

$M \in \Re^{6\times 6}$ consists of both a rigid body mass and inertia, $M_{RB} \in \Re^{6\times 6}$, and a hydrodynamic added mass, $M_A \in \Re^{6\times 6}$. given by,

$$M = M_{RB} + M_A \tag{2}$$

B. Coriolis and Centripetal Matrices

$C(v) \in \Re^{6\times 6}$, like the mass matrices consists of two matrices, $C_{RB}(v) \in \Re^{6\times 6}$ and $C_A(v) \in \Re^{6\times 6}$, which can be expressed as,

$$C(v) = C_{RB}(v) + C_A(v) \tag{3}$$

$C_{RB}(v)$ is the rigid body Coriolis and centripetal matrices induced by M_{RB}, while $C_A(v)$ is a Coriolis-like matrices induced by M_A.

C. Hydrodynamic Damping Matrices

The hydrodynamic damping matrices represents the drag and lift forces acting on a moving underwater vehicle. Nevertheless, for a low-speed underwater vehicle, the lift forces are negligible when compared to the drag forces. These drag forces can be separated into two different terms composed of a linear and quadratic term [17], given by,

$$D(v) = diag\{D_L + D_Q|v|\} \tag{4}$$

where $D_L \in \Re^{6\times 6}$ is the linear damping term, while $D_Q \in \Re^{6\times 6}$ is the quadratic damping term.

D. Gravitational and Buoyancy Vector

The gravitational and buoyancy vector, $G \in \Re^{6\times 1}$, is defined as,

$$G = \begin{bmatrix} f_B + f_C \\ r_B \times f_B + r_C \times f_C \end{bmatrix} \tag{5}$$

where f_B and f_C are the buoyant force vector and the gravitational force vector, respectively. Moreover, r_B is the centre of buoyancy and r_C is the centre of gravity or mass in frame {B}.

E. Forces and Torque Vector

The external force and torque vector produced by the thrusters can be expressed as,

$$\tau = LU \tag{6}$$

where L is a mapping matrices and U is a thrust vector. U is the vector of thrusts produced by the vehicle's thrusters,

$$U = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \vdots \\ \tau_n \end{bmatrix} \tag{7}$$

The number of thrust values in U is related to the number of thrusters on the vehicle. The mapping matrices L is essentially a $6 \times n$ matrices that uses U to find the overall forces and moments acting on the vehicle.

III. NEURAL NETWORK CONTROL STRUCTURE

The AUV dynamic in (1) can be rewritten as

$$M\ddot{q} + C(\dot{q})\dot{q} + D(\dot{q})\dot{q} + G + \tau_d = \tau \tag{8}$$

where M, $C(v)$, $D(v)$ and G are introduced in pervious section. Moreover, q is the configuration and τ_d represents environmental forces and/or disturbances. To make the AUV follow a prescribed desired trajectory $q_d(t)$, we define the tracking error $e(t)$ and filtered tracking error $r(t)$ by

$$e = q_d - q, \quad r = \dot{e} + \Lambda e \tag{9}$$

with $\Lambda > 0$ a positive definite design parameter matrices. The AUV dynamics are expressed in terms of the filtered error as

$$M\dot{r} = -Cr + f(x) + \tau_d - \tau \tag{10}$$

where the unknown nonlinear function of AUV dynamic is given by

$$\begin{aligned} f(x) = M(q)(\ddot{q}_d + \Lambda\dot{e}) + \\ C(\dot{q})(\dot{q}_d + \Lambda e) + D(\dot{q})\dot{q} + G \end{aligned} \tag{11}$$

One may define $x \equiv [e^T, \dot{e}^T, q_d^T, \dot{q}_d^T, \ddot{q}_d^T]^T$. A general sort of approximation- based controller is based on

$$\tau = \hat{f} + K_v r - \upsilon(t) \tag{12}$$

with $\hat{f}$ an estimate of $f(x)$, $K_v r = K_v \dot{e} + K_v \Lambda e$ an outer PD tracking loop, and $\upsilon(t)$ an auxiliary signal to maintain robustness in the face of environmental forces, disturbances and modeling error [10]. The multi-loop control structure

implied by this structure is shown in fig. 2. Employing this controller, the closed-loop error dynamics are

$$M\dot{r} = -Cr - K_v r + \tilde{f} + \tau_d + \upsilon(t) \qquad (13)$$

where the function approximation error is defined as

$$\tilde{f} = f - \hat{f} \qquad (14)$$

According to the universal approximation property of NN, if the $\phi(.)$ provides a basis, then a smooth function $f(x)$ from $\Re^n$ to $\Re^m$ can be approximated on a compact set S of $\Re^n$, by

$$f(x) = W^T \phi(x) + \varepsilon \qquad (15)$$

for some ideal weights and thresholds W and some number of hidden layer neurons L. In fact, for any choice of a positive number ε_N, one can find a feed forward NN such that

$$\|\varepsilon\| < \varepsilon_N \qquad (16)$$

for all x in S [10].
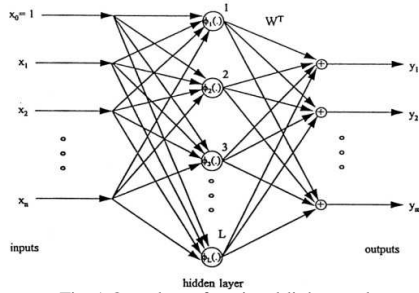The One–layer functional-link neural network (FLNN) structure is shown in fig. 1.

Fig. 1 One –layer functional-link neural net

It has been shown that the sigmoid can form a basis set. In Sanner and Slotine [18] it was shown that redial basis functions can form a basis. Determining the number of hidden layer neuron required for good approximation in an open problem for general fully connected two-layer NN. If we want a good approximation for $f(x)$, the number of hidden layer neuron should be large enough. Extracting the NN weight-tuning algorithm, some assumptions and lemmas are needed. These assumptions are true in every practical situation.

Assumption 1: The desired trajectory is bounded so that

$$\left\| \begin{matrix} q_d(t) \\ \dot{q}_d(t) \\ \ddot{q}_d(t) \end{matrix} \right\| < q_B \qquad (17)$$

with q_B a known scalar bound.

Suppose that a FLNN is used to approximate the nonlinear functions of the AUV model (11) according to (15), with W the ideal approximating weights. The ideal weights are unknown and may even be non-unique. Assume they are constant and bounded so that

$$\|W\|_F \leq W_B \qquad (18)$$

with W_B known and $\|.\|_F$ the Frobenius norm.

Then, an estimate of $f(x)$ is given by

$$\hat{f}(x) = \hat{W}^T \phi(x) \qquad (19)$$

with $\hat{W}$ the actual values of the NN weights given by the tuning algorithm to be specified. Select the control input

$$\tau = \hat{W}^T \phi(x) + K_v r - \upsilon \qquad (20)$$

The proposed NN control structure is shown in fig.2, where $q = [q^T \ \dot{q}^T]^T$, $e = [e^T \ \dot{e}^T]^T$.
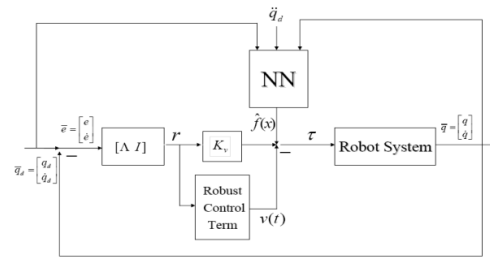

Fig. 2 NN controller structure

It is now necessary to show how to tune the NN weights $\hat{W}$ on-line to ensure stable tracking. The tuning algorithm found will presumably modify the actual weights $\hat{W}$ so that they become close to ideal weights W, which are unknown. For this purpose, define the weight deviations or weight estimation error as

$$\tilde{W} = W - \hat{W} \qquad (21)$$

Then, $f - \hat{f} = W^T \phi(x) + \varepsilon - \hat{W}^T \phi(x)$ and the close loop filtered error dynamics (13) becomes

$$M\dot{r} = -(C + K_v)r + \tilde{W}^T \phi(x) + (\varepsilon + \tau_d) + \upsilon \qquad (22)$$

Now we give a FLNN weight-tuning algorithm with composite adaptation low that guarantee the tracking stability of the closed loop system. It is required to demonstrate that the tracking error $r(t)$ is suitably small and that the FLNN weights $\hat{W}$ remain bounded, for then the control $\tau(t)$ is bounded. The resulting controller is given in below theorem. In this case, the tracking error does not go to zero with time, but is bounded by a small enough value.

Theorem

Let the desired trajectory $q_d(t)$ be bounded by q_B as in Assuption1. Assume the ideal target NN weights are bounded by W_B as in (18) and the initial tracking error $r(0)$ is bounded. Let the estimate error bound ε_N and the disturbance bound d_B be constants. Let the control input for the AUV model with $\upsilon = 0$ be given by

$$\tau = \hat{W}^T \phi(x) + K_v r \qquad (23)$$

with gain satisfying

$$\sigma_{\min}(K_v) \geq \frac{(\varepsilon_N + d_B)}{b_r} \qquad (24)$$

Let NN weight tuning be given by

$$\dot{\hat{W}} = F\phi r^T - \kappa F \phi^T \phi \tilde{W} \qquad (25)$$

with any constant matrices $F = F^T > 0$ and $\kappa > 0$ a small scalar design parameter. Then the filtered tracking error $r(t)$ and NN weight estimates $\hat{W}$ are *UUB* with practical bounds. Moreover, the tracking error may be kept as small as desired by increasing the gain K_v.

Proof

Let the NN approximation property (15) hold for the function $f(x)$ given in (11) with a given accuracy ε_N for all x in the compact set $S_x \equiv \{x \mid \|x\| < b_{x_2}\}$ with $b_x > q_B$ .Define $S_r \equiv \{r \mid \|r\| < b_r\}$ and $r(0) \in S_r$.

Select the Lyapunov function candidate

$$L = \frac{1}{2} r^T M r + \frac{1}{2} tr\{\tilde{W}^T F^{-1}\tilde{W}\} \qquad (26)$$

Differentiating yields

$$\dot{L} = r^T M \dot{r} + \frac{1}{2} r^T \dot{M} r + \frac{1}{2} tr\{\tilde{W}^T F^{-1}\dot{\tilde{W}}\} \qquad (27)$$

Substituting from (25) yields

$$\dot{L} = -r^T K_v r + \frac{1}{2} r^T (\dot{M} - 2C) r +$$
$$tr\{\tilde{W}^T (F^{-1}\dot{\tilde{W}} + \phi r^T)\} + r^T (\varepsilon + \tau_d) \qquad (28)$$

The skew symmetry property makes the second term zero. Using tuning rule (25) yields

$$\dot{L} = -r^T K_v r - \kappa tr\{\tilde{W}^T \varphi^T \varphi \tilde{W}\} + r^T (\varepsilon + \tau_d) \qquad (29)$$

Now,

$$\dot{L} \leq -\sigma_{\min}(K_v)\|r\|^2 + \|r\|(\varepsilon_N + d_B) - \kappa tr\{\tilde{W}^T \varphi^T \varphi \tilde{W}\} \qquad (30)$$

with $\sigma_{\min}(K_v)$ the minimum singular value of K_v. Since $(\varepsilon_N + d_B)$ is positive constant, $\dot{L} < 0$ if

$$\|r\| > \frac{(\varepsilon_N + d_B)}{\sigma_{\min}(K_v)} \equiv b_2 \qquad (31)$$

Thus, $\dot{L}$ is negative outside a compact set. Selecting the gain according to (24) ensure that the compact set defined by

$\|r\| \leq b_2$ is contained in S_r, so that approximation property holds throughout. This demonstrates the UUB of both $\|r\|$ and $\|\tilde{W}\|_F$. As a result, the AUV tracking error $r(t)$ is bounded and continuity of all functions shows as well the boundedness of $\dot{r}(t)$. Boundedness of $r(t)$ guarantees the boundedness of $e(t)$ and $\dot{e}(t)$, therefore boundedness of desired trajectory in AUV dynamic shows q and $\dot{q}$ are bounded. Moreover, $\tilde{W}$ is bounded and therefore $\hat{W}$ and $\hat{f}$ are bounded.

Note that NN control with composite adaptive low guarantees prediction error ($\tilde{f} = f - \hat{f}$) and tracking error ($r(t)$) are bounded, while direct adaptive or NN control only guarantees that of the tracking error. This is because the fact that NN composite adaptation low explicitly pay attention to both tracking and prediction error.

This NN controller has no preliminary off-line learning phase. The weights can simply initiated at zero. Because of the PD controllers in (23) the closed loop system remains stable until the neural networks began to learn. The weights are tuned online in real time as the system tracks the desired trajectory. As the NN learns $f(x)$, the tracking performance improves.

IV. SIMULATION

The simulation results obtained from the implementation of presented NN tracking controller on a low-speed AUV named the Mako[19], which have high symmetry, modularity and stability. The NN controller parameters chosen for the simulation were as follows,

$$F = 100 \times I_{10 \times 10}, \kappa = 0.1, K_v = 40 \times diag(8,1,15,1,1,0.8)$$
$$\Lambda = 5 \times dig(2.5,0.5,1.5,5,5,5)$$

The response of the simulated controller for linear velocities u, v and w represent the surge, sway and heave respectively; are shown in fig.3. The angular velocities roll, pitch and yaw about the x, y and z-axes respectively, are shown in fig.4.
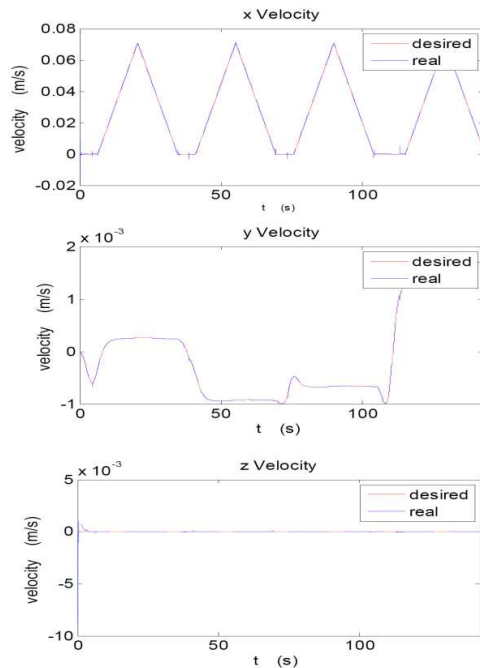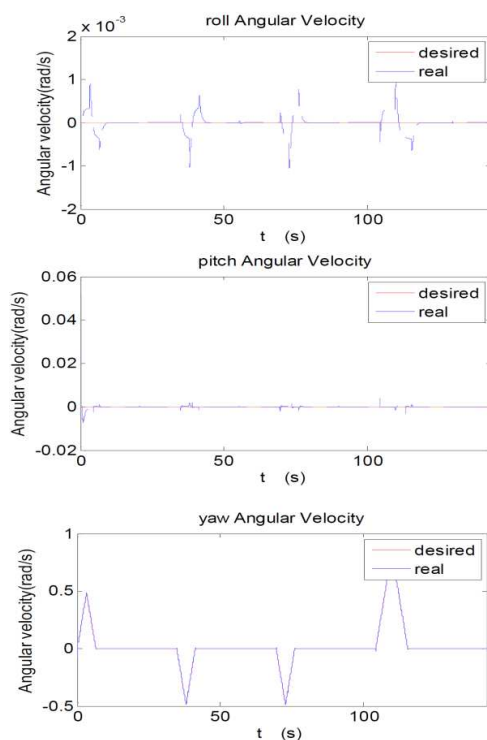
Fig. 3 Simulation results for the linear velocities

Fig. 4 Simulation results for the angular velocities

The control signals of NN controller and the NN weight estimations are shown in fig.5 and fig.6, respectively. The velocities tracking response is good and the weight estimations are bounded. No initial training or learning phase was needed. The initial unknown terms were simply initialized at zero in this simulation.
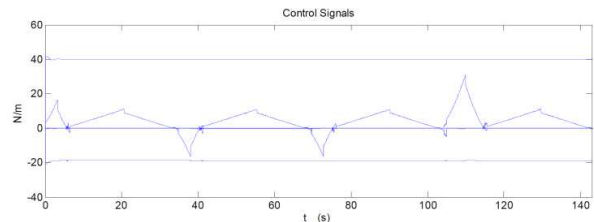

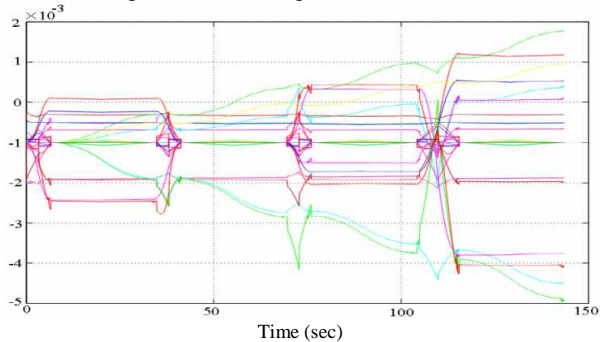Fig. 5 The Control signal of NN Controller

Fig. 6 The NN weights estimation

V. CONCLUSION

This paper introduced a novel stable neural network controller with composite adaptive low for application of an autonomous underwater vehicle (AUV). The proposed controller improved velocities tracking performance of the AUV, while guarantee boundedness of both tracking error and prediction error. In this regard, guarantee accurate and dynamic fallowing of prescribed trajectories. The proposed controller has superior tracking performance than that of conventional controllers. Numerical simulation results in MATLAB showed the validity and effectives of the proposed controller.

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