Neural Network Adaptive Control for Underwater Robotic Systems

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Abstract: Neural networks are currently finding practical applications, ranging from 'soft' regulatory control in consumer products to accurate modelling of non-linear systems. This paper describes the application of neural networks to the control of a remotely operated underwater vehicle, as an example of a system containing severe non-linearities. Neural networks are been used in a closed-loop to approximate the nonlinear vehicle dynamics. No prior off-line training phase and no explicit knowledge of the structure of the vehicle are required, and the proposed scheme exploits the advantages of both neural network control and adaptive control. A control law and a stable on-line adaptive law are derived using the Lyapunov theory, and the convergence of the tracking error to zero and the bounded-ness of signals are guaranteed. In this paper, a neural network architecture based on radial basis functions has been used to evaluate the performance of the adaptive controller via computer simulation.

Keywords: neural networks, underwater vehicles, stability theory, adaptive control.

1 Introduction

The Ocean covers over sixty percent of the earth's surface, yet humans have hardly been able to fully explore their depths. Undoubtedly with the recent images captured by the Hubble Space Telescope, the Russian Mir Space Station and NASA's Galileo atmosphere probe mankind knows more about space or the outer solar system than about the Oceans. However, in the past decade, Oceanographic exploration has emerged as one of the fastest growing areas of research attracting huge grants. The main reason is the vast amount of mineral resources that satellites have mapped across the Oceans, not forgetting the oil and natural gas reserves.

The design of controllers for unmanned underwater vehicles (UUV) is challenging because of difficulties in accurately modelling the inherently non-linear dynamics of UUVs in a hazardous environment with persistent unmodelled disturbances. In general, real-time control of non-linear systems with unknown structure and parameter uncertainty remains an open area of research. Dynamic models of UUVs are required to design advanced control systems, and models of underwater vehicles have been studied in the past [1]. The nonlinear dynamics of UUVs result in parametric and structural uncertainties in the dynamic model, and this necessitates the need for advanced robust control techniques. Control strategies that address some of "modelling characteristics" have been reported in the literature, including linear control, robust control, fuzzy control, neural networks, sliding mode control, etc. Among various control techniques, sliding mode control has been successfully implemented and tested for underwater vehicles [2]. Fossen *et al*. [3] developed an adaptive controller for underwater vehicles in 6-DOF by assuming that its dynamics can be linearly parameterised. The emergence of neural networks (NNs) as effective learning systems for a wide variety of applications has resulted in the use of these networks as learning models for dynamical systems. NN controllers have important features that overcome the typical difficulties in designing control systems for underwater vehicles. For instance, the dynamics of the vehicle need not be completely known as a prior condition for controller design. This is very desirable for underwater vehicle controller to have since the dynamic characteristics of underwater vehicles change with configuration and it is impossible to consider all the effects from disturbances. Also, the ability of these networks for adaptation and disturbance rejection and their highly parallel nature of computation make this approach suitable for real-time applications. A NN based control scheme for UUV is described by Venugopal et al. [4] using direct control scheme, where the input to dynamics is implicitly used for both identification and control simultaneously. A similar idea to the above is used by Yuh [5] in his studies on the NN-based control scheme for an UUV. Fujii *et al.* [6] proposed a self-organizing neural network based control system to the development of the motion control for autonomous UUV. Kodogiannis *et al.* used several different neural network architectures to evaluate a long-range model predictive control scheme both for simulation and on-line control of vehicle depth [7]. An alternative approach to "soft-computing" techniques is the implementation of approximate controllers based on fuzzy logic theory. A new framework in sliding mode fuzzy control was presented by Trebi-Ollenu *et al.* for selecting free control parameters of an input-output linearising controller with sliding mode control for the depth control of a remotely operated underwater vehicle (ROV) [8]. In their approach, the concept of multi-objective fuzzy genetic algorithm optimisation was adopted and a new membership weighting strategy was suggested. In this paper, the development of a direct adaptive neural network controller for underwater vehicles is proposed, with a parallel investigation of the performance and robustness issues of the adopted controller. Radial basis functions networks (RBF) are used to approximate the nonlinear dynamics of underwater vehicles without explicit knowledge of the plant's dynamic structure. The on-line weight adaptation law of the neural network is derived in the context of Lyapunov stability concept. Bounded-ness of all signals as well as the convergence of the tracking errors to zero are guaranteed. The contribution of this paper is to combine adaptive control with neural network architectures to approximate the nonlinear and time-varying underwater vehicle dynamics. Tracking performances and robustness of the proposed controller is demonstrated through computer simulation.

2 Vehicle Modelling

The dynamic equations of motion of underwater vehicles have been analytically presented in the literature [9]. In this paper a nonlinear six-degree-of-freedom model based on Fossen *et al.* [10] has been considered. The rigid body underwater vehicle model in the body-fixed reference frame can be represented as

$$M\dot{n} + C(n)n + D(n)n + g(h) = t \quad (1)$$

$$\dot{h} = J(h)n \quad (2)$$

where

$n = [u,u,w,p,q,r]^T$, $h = [X,Y,Z,f,q,y]^T$. In this notation, í denotes the linear and angular velocity vector with coordinates in the body-fixed reference frame, ç denotes the position and attitude vector with coordinates in the earth-fixed reference frame, and ô is used to describe the control input forces and moments acting on the vehicle in the body-fixed reference frame. The body-fixed velocity vector can be transformed into the earth-fixed reference frame through the Euler angle transformation denoted by $J(h)$. M is the inertia matrix including added mass M_A, $C(n)$ is the matrix of Coriolis and centrifugal terms, $D(n)$ is the damping matrix, and $g(h)$ is the vector of gravitational forces and moments. The equation of motion of underwater vehicle can be represented in the earth-fixed reference frame in terms of position and attitude through the kinematic transformations (assuming that $J(h)$ is non-singular)

$$\dot{h} = J(h)n \quad \Leftrightarrow n = J^{-1}(h)\dot{h} \quad (3)$$

$$\ddot{h} = J(h)\dot{n} + \dot{J}(h)n \quad \Leftrightarrow \dot{n} = J^{-1}(h)[\ddot{h} - \dot{J}(h)J^{-1}(h)\dot{h}] \quad (4)$$

to eliminate $\dot{n}$ and n from Eq.1. Defining

$$M_h(h) = J^{-T}(h)MJ^{-1}(h) \quad (5)$$

$$C_h(n,h) = J^{-T}(h)[C(n) - MJ^{-1}(h)\dot{J}(h)]J^{-1}(h) \quad (6)$$

$$D_h(n,h) = J^{-T}(h)DJ^{-1}(h) \quad (7)$$

$$g_h(h) = J^{-T}(h)g(h) \quad (8)$$

$$t_h(h) = J^{-T}(h)t \quad (9)$$

yields the earth-fixed vector representation

$$M_h(h)\ddot{h} + C_h(n,h)\dot{h} + D_h(n,h)\dot{h} + g_h(h) = t_h \quad (10)$$

The inertia matrix $M_h(h)$, including hydrodynamic added inertia, is symmetric and positive definite. The Coriolis and centrifugal matrix, also including added inertia effect, $C_h(n,h)$, satisfies the skew symmetric relationship $x^T[\dot{M}_h(h) - 2C_h(n,h)]x = 0$. The damping matrix $D_h(n,h)$ is positive definite. A more detailed discussion on mathematical models of underwater vehicles can be found in [3].

3 Neural Network Controller Design

Due to the difficulty obtaining the exact values of hydrodynamic coefficients, but also due to the fact the coefficients change with the configuration of underwater vehicles, the robustness and adaptiveness are important requirements for the underwater vehicle controllers. The disturbances from currents and waves are also very difficult to model. Fossen *et al.* [10] derived an adaptive control law for underwater vehicles in 6 DOF assuming that M, $C(n)$, $D(n)$, and $g(h)$ are linear in their parameters and that the dynamics can be linearly parameterised, which is a common assumption in the adaptive control. The linear parameterisation in the adaptive control is usually valid and can consider the changes and uncertainties in parameters. However, it should be noted that this assumption considers the change only in parameters; the unstructured or un-modelled dynamics such as disturbances from currents and waves cannot be linearly parameterised. In this paper, an adaptive control law is derived that does not require off-line training. An RBF network is used in the approximation of a nonlinear function, assuming that the nonlinear model of the underwater vehicles is unknown.

3.1 Controller Specifications

A certain measure of error is defined as

$$s = \dot{\tilde{h}} + l\tilde{h} \quad (11)$$

where ë is any positive constant and $\tilde{h} = h - h_d$. The desired position and attitude of the vehicle denoted by h_d, and the time derivative $\dot{h}_d, \ddot{h}_d$ can be obtained from a trajectory planner. The reference model is chosen considering the vehicle kinematics as in [3]. The desired parameters n_d and h_d are computed from

$$\dot{n}_d + \Lambda n_d + J^T(h_d)\Omega h_d = J^T(h_d)\Omega r_h \quad (12)$$

$$\dot{h}_d = J^T(h_d) n_d \quad (13)$$

where r_h is a constant (or slowly varying) commanded input. The design parameters in the reference model are the matrices Ë > 0 and Ù = $Ù^T$ > 0 describing the preferred damping and stiffness of the system. Ë and Ù are usually chosen as diagonal matrices with positive entries on the diagonal. For notational simplicity, it is convenient to rewrite Eq. 11 in terms of the virtual reference trajectory h_r defined as

$$s = \dot{h} - \dot{h}_r \Rightarrow \dot{h}_r = \dot{h}_d - l\tilde{h} \quad (14)$$

The reference trajectory in the body-fixed frame can be derived

$$\dot{h}_r = J(h) n_r \quad (15)$$

$$\dot{n}_r = J^{-1}(h)[\ddot{h}_r - \dot{J}(h)J^{-1}(h)\dot{h}_r] \quad (16)$$

Now, the Eq. 10 describing the nonlinear equation of motion of an underwater vehicle in 6 DOF in the earth-fixed reference coordinate is considered. Taking the derivative of s with respect to time, the vehicle dynamics can be written in terms of s as

$$M_h \dot{s} = M_h \ddot{h} - M_h \ddot{h}_r = -(D_h + C_h)s +$$
$$J^{-T}[t - (M\dot{n}_r + C(n)n_r + D(n)n_r + g(h))] \quad (17)$$

Çere, the relationship

$$M_h \ddot{h}_r + C_h \dot{h}_r + D_h \dot{h}_r + g_h =$$
$$J^{-T}(M\dot{n}_r + Cn_r + Dn_r + g) \quad (18)$$

is used. Denoting the dynamics of vehicle in the body-fixed reference coordinate as

$$M\dot{n}_r + C(n)n_r + D(n)n_r + g(h) = f(\dot{n}_r, n_r, n, h) \quad (19)$$

and taking a control input as $t = \hat{f}(\dot{n}_r, n_r, n, h) - J^T K_d s$, the closed-loop system becomes

$$M_h \dot{s} = -(D_h + K_d)s - C_h s + J^{-T}[\hat{f}(\dot{n}_r, n_r, n, h) + e] \quad (20)$$

where $\hat{f}(\dot{n}_r, n_r, n, h)$ is the estimate of the vehicle dynamics $f(\dot{n}_r, n_r, n, h)$, K_d is a symmetric positive regulator gain matrix of appropriate dimension and å is used to denote the approximation error. Eq. 20 is an error dynamics where the filtered tracking error is driven by the functional estimation error. Following the approach in [11], the tracking problem can thus be solved by finding a adaptation law for adjusting $\hat{f}(\dot{n}_r, n_r, n, h)$ that ensures the bounded-ness of the parameter estimates and that $s(t) \to 0$ as $t \to \infty$.

3.2 Linear Parameterisation

Considering the Eq. (18), Eq. (19) can be parameterised as

$$M\dot{n}_r + C(n)n_r + D(n)n_r + g(h) = \Phi(\dot{n}_r, n_r, n, h)q \quad (21)$$

assuming that M, $C(n)$, $D(n)$, and $g(h)$ are linear in their parameters. Here, è is an unknown parameter vector and $\Phi(\dot{n}_r, n_r, n, h)$ is a known matrix function of measured signals usually referred to as regressor matrix. Consider a Lyapunov function as

$$V = \frac{1}{2}s^T M_h s + \frac{1}{2}\tilde{q}^T \Gamma^{-1}\tilde{q} \quad (22)$$

where Γ^{-1} is a positive definite weighting matrix of appropriate dimension and $\tilde{q} = \hat{q} - q$ is the parameter estimation error. Differentiating V with respect to time yields

$$\dot{V} = \frac{1}{2}(s^T M_h \dot{s} + \dot{s}^T M_h s + s^T \dot{M}_h s) + \dot{\tilde{q}}^T \Gamma^{-1}\tilde{q} \quad (23)$$

Using the symmetry of inertia matrix $s^T M_h \dot{s} = \dot{s}^T M_h s$ and the skew-symmetric property $s^T(M_h - 2C_h(n,h))s = 0$, Eq. (23) becomes

$$\dot{V} = s^T(M_h \dot{s} + C_h s) + \dot{\tilde{q}}^T \Gamma^{-1}\tilde{q} \quad (24)$$

Considering Eq. (17), Eq. (24) becomes

$$\dot{V} = -s^T D_h s + [J^{-1}(h)s]^T[t - \Phi(\dot{n}_r, n_r, n, h)q] + \dot{\tilde{q}}^T \Gamma^{-1}\tilde{q} \quad (25)$$

Let the control input be chosen as

$$t = \Phi(\dot{n}_r, n_r, n, h)\hat{q} - J^T(h)K_d s \quad (26)$$

where $\hat{q}$ is the estimated parameter vector and K_d is a symmetric positive regulator gain matrix of appropriate dimension. Hence,

$$\dot{V} = -s^T(K_d + D_h)s + \tilde{q}^T[\Phi^T(\dot{n}_r, n_r, n, h)J^{-1}(h)s + \Gamma^{-1}\dot{\tilde{q}}] \quad (27)$$

Then the parameter update law with the assumption of constant parameters $(\dot{q} = 0)$

$$\dot{\tilde{q}} = -\Gamma\Phi^T(\dot{n}_r, n_r, n, h)J^{-1}(h)s \quad (28)$$

cancels out the last term in the expression for $\dot{V}$ and yields

$$\dot{V} = -s^T(K_d + D_h)s \le 0 \quad (29)$$

Then, the convergence of s to zero and the bounded-ness of the parameters can be shown by applying Barbalat's lemma [12] as follows. Since $\dot{V}$ is negative or zero and V is positive definite, V tends to a constant as $t \to \infty$. Considering that the inertia matrix M is positive definite and s is bounded, the estimation errors $\tilde{q}$ can be shown to be bounded, consequently $\hat{q}$ is bounded. This makes $\dot{s}$ is bounded showing that s is uniformly continuous. Therefore, applying Barbalat's lemma [12], it can be shown that $\dot{V} \to 0$ and $s \to 0$ as $t \to \infty$. The convergence of s to zero implies the convergence of the tracking error $\dot{\tilde{h}}$ and $\tilde{h}$ to zero since the tracking error is driven by s through a stable dynamics as shown in Eq. (11).

4 Neural Network Modelling

The derivation of the control law and the adaptation law of the weights of the RBF network are considered in this section. This neural network shown in Fig. 1 consists of one layer of series of neurons multiplied by output weights. Such system is employed since it is known that a linear superposition of radial basis functions is the optimal solution to a class of function approximations given a finite set of data in $\Re^n$ [13]. Also, the relatively simple network structure enables the easy derivation of an adaptive network update law. The mathematical representation of the neural network is

$$f_i(x) = \sum_{j=1}^{N} w_{ij} g_j(x, x_j) \qquad \mathrm{i = 1,\ldots,n} \tag{30}$$

where $g_j = \exp[-\|x - x_j\|^2 / 2s_j^2]$ is the nonlinear function at node *j*, taken as a Gaussian function of the inner product of its arguments.

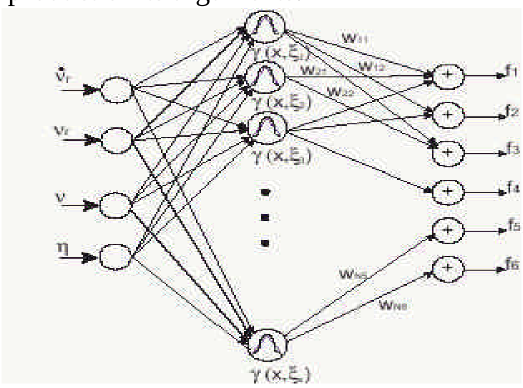

Fig. 1: Structure of RBF network

The coefficients x_j represent the centre of radial Gaussian, s_j^2 is a measure of its width at node *j*, and w_{ij} represents the output weight for that node. The number of degree-of-freedom is denoted by *n*, and *N* is the number of employed neurons. It is assumed that there exists a certain combination of optimal weights of the network that provides the satisfactory approximation of the nonlinear mapping applying enough number of neurons.

The Lyapunov function candidate is chosen as

$$V = \frac{1}{2} s^T M_h s + \frac{1}{2} tr\{\tilde{w} \Gamma_w^{-1} \tilde{w}^T\} \tag{31}$$

where Γ_w is a positive definite weighting matrix of appropriate dimension, and $\tilde{w} = \hat{w} - w$ is the estimation error of the network output weights. Here, $\hat{w}$ is the output weight estimate and w is the optimal weight. Differentiating V with respect to time yields

$$\dot{V} = \frac{1}{2}(\dot{s}^T M_h s + s^T M_h \dot{s} + s^T \dot{M}_h s) + tr\{\tilde{w} \Gamma_w^{-1} \dot{\tilde{w}}^T\} \tag{32}$$

Using the facts that $\dot{s}^T M_h s = s^T M_h \dot{s}$, the skew symmetry of $s^T(\dot{M}_h - 2C_h)s = 0$, and the closed loop system Eq. (20), Eq. (32) can be rewritten as

$$\begin{aligned}\dot{V} &= s^T(M_h \dot{s} + C_h s) + tr\{\tilde{w} \Gamma_w^{-1} \dot{\tilde{w}}^T\} \\ &= -s^T D_h s + (J^{-1}s)^T [t - f(\dot{n}_r, n_r, n, h)] + tr\{\tilde{w} \Gamma_w^{-1} \dot{\tilde{w}}^T\}\end{aligned} \tag{33}$$

The radial basis neural network is used as an approximation of the dynamics of the plant as

$$f(\dot{n}_r, n_r, n, h) = \hat{w} g(x, x) + e(x) \tag{34}$$

where $e(x)$ denotes the approximation error and it is assumed to be bounded as $|e(x)| \le e_0$ for $x \in \Omega$ where is the domain of approximation. The bound e_0 on the approximation error can be made smaller by selecting a large number of neurons in the hidden layer, and it is assumed that it can be neglected as long as enough number of neurons is adopted. Choosing the control input as

$$t = \hat{w} g(x, x) - J^T(h) K_d s \tag{35}$$

and assuming that the output of radial basis neural network approximates the function with sufficient precision as long as th domain of approximation is completely covered, Eq. (33) becomes

$$\begin{aligned}\dot{V} &= -s^T(D_h + K_d)s + (J^{-1}s)^T[\tilde{w} g(x, x)] + tr\{\tilde{w} \Gamma_w^{-1} \dot{\tilde{w}}^T\} \\ &\le -s^T(D_h + K_d)s + tr\{\tilde{w}[g(x, x)(J^{-1}s)^T + \Gamma_w^{-1} \dot{\tilde{w}}^T]\}\end{aligned} \tag{36}$$

Also, choosing the adaptive law of the network weight as

$$\dot{\hat{w}}^T = -\Gamma_w g(x, x)(J^{-1}s)^T \tag{37}$$

the Eq.(33) can be shown to be negative semi-definite, which implies the convergence of s to zero and the bounded-ness of $\tilde{w}$ applying Barbalat's lemma [12]. In summary, the control law is given by Eq. (35) and the adaptation law is given by Eq. (37). It should be noted that the approximation of the nonlinear function Eq. (34) can also be expressed as the product of regressor matrix and unknown parameters under the assumption that the nonlinear function is linear in their parameters and the dynamic structure of vehicles is completely known. The neural network approximation does not require such assumption since no explicit knowledge of the dynamic structure is required. The architecture of controller is shown in Fig. 2.

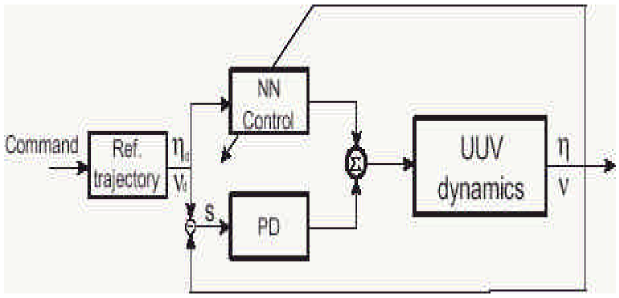

Fig. 2: Proposed controller architecture

5 ROV Case Study

The computational study in this paper was based on the model structure of the Norwegian Experimental Remotely Operated Vehicle (NEROV) [14]. The vehicle is controlled in all 6 DOF by six dc-motor driven thrusters. The fluid velocity was chosen to be zero in all computations. The desired velocities and positions were generated by a reference trajectory generator. The simulation, using the developed controller, were performed at 5Hz, which implies all the measurements and the control action occurred at a time step of 0.2 seconds. The tracking performance of the X and Y positions, the depth and the heading angle was considered in this study. The centre of gravity was assumed to be located at the origin of the vehicle coordinate system. The inertia matrix was assumed to be diagonal:

$$M = diag\{m - X_{\dot u}, m - Y_{\dot u}, m - Z_{\dot w}, I_x - K_{\dot p}, I_y - M_{\dot q}, I_z - N_{\dot r}\} \quad (38)$$

The mass is $m = 185\,Kg$. The moments of inertia around the *x*-, *y*- and *z*-axes are $I_x = 25\,\text{kgm}^2$, $I_y = 50\,\text{kgm}^2$ and $I_x = 50\,\text{kgm}^2$. The hydrodynamic added inertias are $X_{\dot u} = -30\,\text{kg}$, $Y_{\dot u} = -80\,\text{kg}$, $Z_{\dot w} = -80\,\text{kg}$, $K_{\dot p} = -15\,\text{kgm}^2$, $M_{\dot q} = -30\,\text{kgm}^2$, $N_{\dot r} = -30\,\text{kgm}^2$. The C matrix is assumed to be as

$$C = \begin{pmatrix} 0 & -mr & mq & 0 & -Z_{\dot w}w & Y_{\dot u}\mu \\ mr & 0 & -mp & Z_{\dot w}w & 0 & -X_{\dot u}\mu \\ -mq & mp & 0 & -Y_{\dot u}\mu & X_{\dot u}\mu & 0 \\ 0 & -Z_{\dot w}w & Y_{\dot u}\mu & 0 & (I_z - N_{\dot r})r & -(I_y - M_{\dot q})q \\ Z_{\dot w}w & 0 & -X_{\dot u}\mu & -(I_z - N_{\dot r})r & 0 & (I_x - K_{\dot p})p \\ -Y_{\dot u}\mu & X_{\dot u}\mu & 0 & (I_y - M_{\dot q})q & -(I_x - K_{\dot p})p & 0 \end{pmatrix} \quad (39)$$

The drag matrix is assumed to be diagonal

$$D(n) = diag\{70 + 100|u|, 100 + 200|u|, 100 + 200|w|, 30 + 50|p|, 50 + 100|q|, 50 + 100|r|\} \quad (40)$$

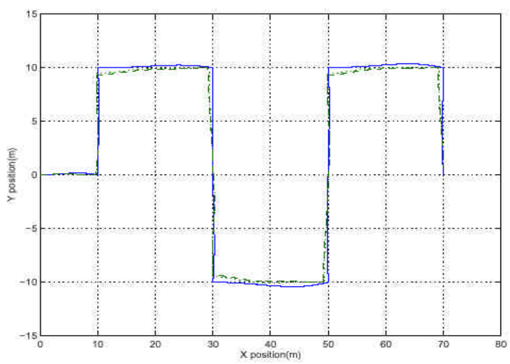

Fig. 3: X and Y trajectory (solid: desired; dashed: proposed controller)

The centre of buoyancy was assumed to be located at (x_B, y_B, z_B), where $x_B = y_B = 0$ and $z_B = 0.02$m is the *x*-, *y*- and *z*-coordinates in the vehicle coordinate system. The system was assumed to be neutrally buoyant *g=(0,0,0, z*$_B$*Bcèsö, z*$_B$*Bsè,0)*^{T}, where B=1800N is the buoyancy. One RBF network was used to approximate the nonlinear dynamics of NEROV. In this particular case, the centres of Gaussian functions $g_i(x, x_i)$ were uniformly spaced in the state space. The width of the Gaussian function $g_i(x, x_i)$ was set to 30, and the overall weights of a neural network were initially set to zero. Only a single MIMO neural network was employed with 24 input and 6 output units. The adaptive gain matrix was set to 0.3I, where I was the identity matrix of appropriate dimension. The choice of the width of the Gaussian function $g_i(x, x_i)$ was the most critical factor for overall stability of the system and related to the choice of the number of Gaussian functions over the state space. In other words, the optimal width of the Gaussian function should be found considering the width of an area in the input space to each neuron responds. The value of $g_i(x, x_i)$ should be large enough that neurons respond to enough overlapping regions of the input space. The tracking performance of the X and Y positions of the vehicle following the specified position is shown in Fig. 3. It can be seen that the proposed neural-network controller gives fairly good tracking performance. In this simulation study, only the neural network controller was used to determine the feasibility of using the proposed neural network architecture. Of course, improved and more robust tracking performance could be achieved when the PD and the adaptive control inputs are combined together. Better performance may be obtained by further tuning the update gain and increasing the number of RBF centres. Higher update gain gave better tracking performance, but when the gain was too high, oscillatory behaviour was observed. By combining with the PD part of the controller, the unwanted oscillatory motion could be removed at the price of slight increase in the control effort. Control inputs are shown in Fig. 4.

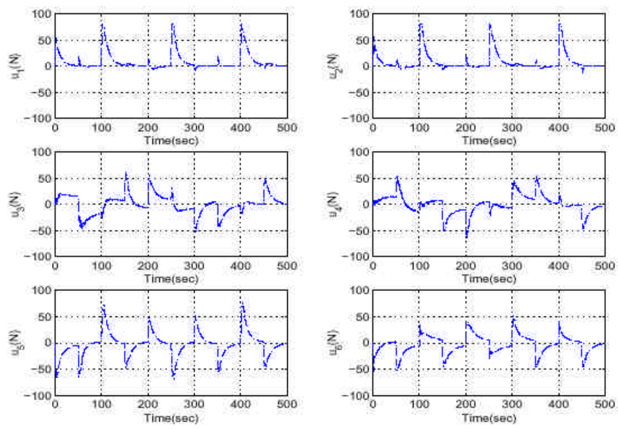

Fig. 4: Control inputs to thrusters

Robustness of the proposed controller to the unmodelled disturbance is shown in the Fig. 5. A sinusoidal disturbance is added in the yaw channel. The performance of adaptive neural network controller with radial basis neural network is compared to the adaptive controller with linear parameterisation. A robust tracking performance has been achieved using adaptive neural network, whereas the adaptive controller with linear parameterisation gives degradation in the performance.

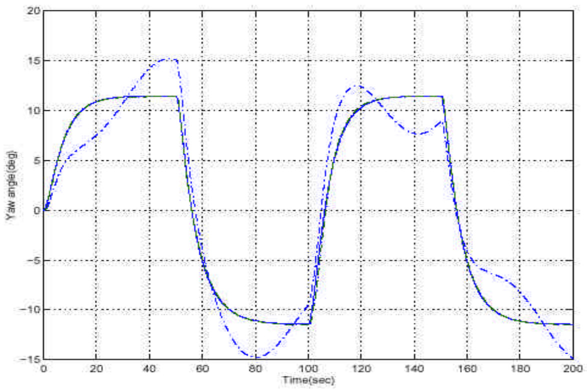

Fig. 5: Robustness test to the unmodelled disturbances in the yaw channel (solid: desired, dashed: proposed, dashdot: linearly parameterised)

6 Conclusions

An adaptive neural network controller has been developed for an underwater vehicle in 6 DOF. One RBF network was used to approximate the nonlinear dynamics of underwater vehicle. Without explicit prior knowledge of the vehicle dynamics, the proposed control technique could achieve improved tracking performance. Results have showed that the dynamics of the vehicle need not be known explicitly for the design of the controller and no linearisation is required to deal with nonlinear vehicle dynamics. The proposed controller architecture is robust and adaptive, while it does not need any prior training phase and can be applied on-line. The next stage of this study is to apply the proposed adaptive controller in the under development UUV funded from the FREESUB 5th framework EU project.

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