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An On-Line Adaptive Control of Underwater Vehicles Using Neural Network

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ABSTRACT: *An adaptive neural network controller has been developed for a model of an underwater vehicle. This controller combines a radial basis neural network and sliding mode control techniques. No prior off-line training phase is required, and this scheme exploits the advantages of both neural network control and sliding mode control. An on-line stable adaptive law is derived using Lyapunov theory. The number of neurons and the width of Gaussian function should be chosen carefully. Performance of the controller is demonstrated through computer simulation.*

1. Introduction

Underwater robotic vehicles are useful tools to explore the ocean environment. The dynamics of underwater vehicles are strongly nonlinear, coupled, time-varying, and uncertain within the parameters. These facts make it difficult to design a controller with good tracking performance.

Several different control approaches have been studied, including linear control (non-adaptive and adaptive), fuzzy control, neural networks and sliding mode control(Hills and Yoerger, 1994). Among them, sliding mode control has been tested and successfully implemented for use with underwater vehicles by several authors (Healey and Lienard, 1993). Sliding mode control is a model-based method that can handle nonlinear and uncertain, time-varying systems. It also can be extended to include adaptive control, in order to compensate for changes in environment and vehicle configuration. However, it requires a good dynamic model of the system, as well as knowledge of the inaccuracies and uncertainties associated with the model.

Neural network controllers have important advantages, which can overcome the typical difficulties associated with designing control systems for underwater vehicles. For example, the dynamics of the vehicle need not be completely known, as a prior condition for controller design. Also, the ability of these networks for adaptation and disturbance rejection, combined with their highly parallel nature of computation, makes this approach suitable for real-time application.

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Application of neural network control to underwater vehicles has been reported by several authors. Lee et al. (2002) and Lee and Lee (1994) developed a neural net-based, nonlinear adaptive controller for an autonomous underwater vehicle. Yuh (1990) proposed the use of an on-line approach of neural networks for underwater vehicle control, using direct learning scheme. This approach showed good heading control performance. Venugopal et al. (1992) tested several different neural network architectures to evaluate a long-range model predictive control, both in simulation and for on-line control of vehicle depth. Ishii et al. (1995) proposed the use of a neural network-based control system to improve the time-consuming adaptation process.

Sanner et al., (1992) employed a network of Gaussian radial basis functions to adaptively compensate for the plant nonlinearities. This can be used as a direct adaptive controller for a class of nonlinear dynamic systems, for which an explicit linear parameterization of the uncertainties in the dynamics is difficult.

In this paper, the use a neural network controller, in combination with an adaptive sliding mode controller, is proposed. Radial basis neural network is used to approximate the nonlinear dynamics of underwater vehicles, without any prior knowledge of the system. The simplicity of the network structure, proposed in this study, enables faster approximation of the nonlinear dynamics of underwater vehicles. The on-line weight adaptation law of the neural network is derived in the context of the Lyapunov stability concept.

2. Dynamics of underwater vehicles

The dynamic equations of the motion of underwater vehicles have been presented by several authors (Healehy and Lienard, 1993, Fossen and Sagatun, 1991). In this study, we consider a nonlinear six degrees-of-freedom mathematical model. The rigid body underwater vehicle model for the body fixed frame can be represented as follows:

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau \qquad (1)$$

$$\dot{\eta} = J(\eta)\nu \qquad (2)$$

where $\nu=[u,v,w,p,q,r]'$, $\eta=[X,Y,Z,\Phi,\theta,\Psi]'$. Here, ν denotes the linear and angular velocity vector with respect to the body-fixed coordinates, η denotes the position and attitude vector with respect to the earth-fixed coordinates, and τ is used to describe the forces and moments acting on the vehicle in the body-fixed coordinates. The body-fixed velocity vector can be transformed into the earth-fixed frame through an Euler angle transformation denoted by $J(\eta)$. M is the inertia matrix, including added mass, $C(\nu)$ is the matrix of Coriolis and centrifugal terms, $D(\nu)$ is the damping matrix, and $g(\eta)$ is the vector of gravitational forces and moments.

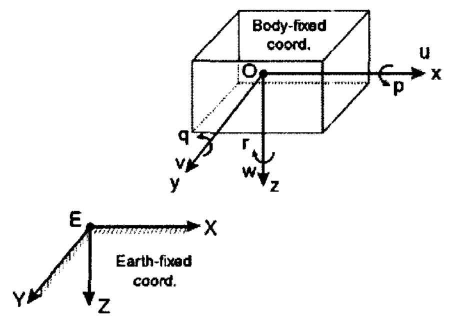

Fig. 1 Coordinate system

Also, the equation of motion for the underwater vehicle can be represented in earth-fixed frame, in terms of position and attitude, through the transformation as follows:

$$M_\eta(\eta)\ddot{\eta} + C_\eta(\nu,\eta)\dot{\eta} + D_\eta(\nu,\eta)\dot{\eta} + g_\eta(\eta) = J^{-T}(\eta)\tau \qquad (3)$$

Here, each term is defined by:

$$\begin{aligned} M_\eta(\eta) &= J^{-T}(\eta) M J^{-1}(\eta) \\ C_\eta(\nu,\eta) &= J^{-T}(\eta)[C(\nu) - MJ^{-1}(\eta)\dot{J}(\eta)]J^{-1}(\eta) \\ D_\eta(\nu,\eta) &= J^{-T}(\eta) D(\nu) J^{-1}(\eta) \\ g_\eta(\eta) &= J^{-T}(\eta) g(\eta) \end{aligned} \qquad (4)$$

The coordinate system is shown in Fig. 1. A more detailed discussion on mathematical models of underwater vehicles can be found in Fossen (1994).

3. Neural network controller design

In the following sections, a neural network control law, with on-line adaptation law in 6 DOF, is derived. A Radial basis function neural network 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 R^n (Sanner and Slotine, 1992). Moreover, the relatively simple network structure enables the derivation of an adaptive network update law.

As mentioned in the previous section, underwater vehicles are difficult to model. It is not only difficult to obtain the exact value of hydrodynamic coefficients, but the coefficients also change depending upon the configuration of underwater vehicles. Therefore, robustness and adaptability are important requirements for the underwater vehicle controller.

Recently, neural networks have shown great promise in the realm of nonlinear control, due to their universal approximation and learning capabilities. Also, a large amount of prior knowledge of the plant is not required in designing a controller. Usually, neural networks require iterative off-line training for parameter adjustment. In this study, however, no prior off-line training is necessary for the adaptation law derived here. Specifically, the intent is to design a controller having advantages of both neural network control and sliding mode control.

3.1 Radial basis neural network

Now, the derivation of the neural network is considered. The architecture of the network is shown in Fig.2. Research by Sanner and Slotine (1992) supports the assertion that one hidden layer network can uniformly approximate complex functions to a specified degree of accuracy, provided a sufficient number of nodes are employed. This kind of neural network can be represented mathematically as follows:

$$f_i(x) = \sum_{j=1}^{N} w_{ij}\gamma_j(x,\xi_j) \qquad i=1,\ldots,n \qquad (5)$$

where $\gamma=\exp[-\|x-\xi_i\|^2/2\sigma_i^2]$ is the nonlinear function at node i, taken as a Gaussian function of the inner product of its arguments, and $x=[\dot{\nu}_r, \nu_r, \nu, \eta]^T$. The coefficient ξ_i represents the center of radial Gaussian and σ_i^2 is a measure of its width at node i, while w_{ij} represents the output weight for that node.

It is assumed that there exists a certain combination of optimal weights of the network, which provides the approximation of the nonlinear mapping, with an adequate number of neurons. The radial basis neural network is chosen, because they can be designed in a fraction of time that it takes to train standard feed-forward networks, even though they may require a larger number of neurons.

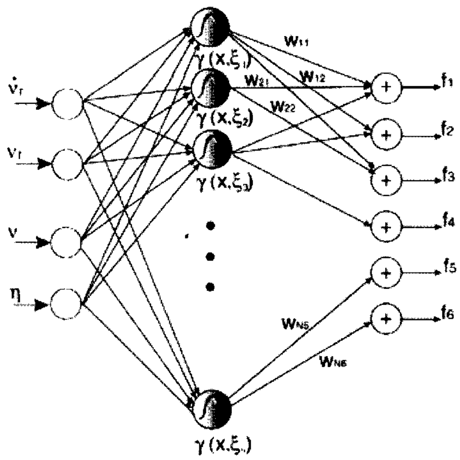

Fig. 2 Structure of neural network

3.2 Controller Structure

A certain measure of error is defined as follows:

$$s = \dot{\tilde{\eta}} + \lambda \tilde{\eta} \tag{6}$$

where λ is any positive constant and $\tilde{\eta} = \eta - \eta_d$. η_d is the desired position and attitude of the vehicle, generated by a trajectory planner.

For notational simplicity, it is convenient to rewrite the equation (6) in terms of the virtual reference trajectory η_r defined as follows:

$$s = \dot{\eta} - \dot{\eta}_r \Rightarrow \dot{\eta}_r = \dot{\eta}_d - \lambda \tilde{\eta} \tag{7}$$

The reference trajectory in body-fixed frame can be derived as follows:

$$\dot{\eta}_r = J(\eta)\nu_r \tag{8}$$

$$\nu_r = J^{-1}(\eta)\,\dot{\eta}_r \tag{9}$$

$$\dot{\nu}_r = J^{-1}(\eta)\,[\,\ddot{\eta}_r - \dot{J}(\eta)J^{-1}(\eta)\,\dot{\eta}_r] \tag{10}$$

The Lyapunov function candidate is chosen as follows:

$$V = \frac{1}{2}\, s^T M_\eta s + \frac{1}{2}\, tr\{\tilde{w}\Gamma^{-1}\tilde{w}^T\} \tag{11}$$

Γ is a positive definite weighting matrix of appropriate dimensions, and $\tilde{w} = \hat{w} - w$ is the estimation error of the network output weights.

Differentiating V with respect to time yields:

$$\begin{aligned} \dot{V} = \frac{1}{2}(\ \dot{s}^T M_\eta s\ + s^T M_\eta \dot{s} + s^T \dot{M}_\eta s) \\ + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \end{aligned} \tag{12}$$

Using the fact that $\dot{s}^T M_\eta s = s^T M_\eta \dot{s}$ and $s^T(\dot{M}_\eta - 2C_\eta)s = 0$, ∀s,v,η∈Rn (Fossen, 1994), we can rewrite the equation (11) as follows:

$$\dot{V} = s^T(M_\eta \dot{s} + C_\eta s) + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \tag{13}$$

Further, it can be shown as follows:

$$\begin{aligned} \dot{V} &= s^T(M_\eta \ddot{\eta} + C_\eta \dot{\eta} - M_\eta \ddot{\eta}_r - C_\eta \dot{\eta}_r) + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \\ &= s^T(J^{-T}(\eta)\,\tau - D_\eta \dot{\eta} - g_\eta - M_\eta \ddot{\eta}_r - C_\eta \dot{\eta}_r) \\ &\qquad + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \\ &= s^T(-D_\eta)s + s^T(J^{-T}(\eta)\,\tau - M_\eta \ddot{\eta}_r - C_\eta \dot{\eta}_r \\ &\qquad - D_\eta \dot{\eta}_r - g_\eta) + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \\ &= s^T(-D_\eta)s + s^T(J^{-T}(\eta)\,\tau - J^{-T}[M\dot{\nu}_r + C\nu_r \\ &\qquad + D\nu_r + g]) + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \end{aligned} \tag{14}$$

Here, the following relationship is used(Fossen, 1994).

$$\begin{aligned} M_\eta \ddot{\eta}_r + C_\eta \dot{\eta}_r\ + D_\eta \dot{\eta}_r + g_\eta \\ = J^{-T}(\eta)\,[M\dot{\nu}_r + C\nu_r + D\nu_r + g] \end{aligned} \tag{15}$$

The neural network is employed to approximate the nonlinear function:

$$M\dot{\nu}_r + C(\nu)\nu + D(\nu)\nu_r + g(\eta) = w\gamma(x,\xi) \tag{16}$$

Now, as we take the control input:

$$\tau = \hat{w}\gamma(x,\xi) - J^T(\eta)K_d s \tag{17}$$

the time derivative of the Lyapunov function becomes:

$$\begin{aligned} \dot{V} &= -s^T(D + K_d)s + (J^{-1}s)^T\tilde{w}\gamma(x,\xi) + tr\{\tilde{w}\Gamma^{-1}\dot{\tilde{w}}^T\} \\ &\le -s^T(D + K_d)s + tr\{\tilde{w}[\,\gamma(x,\xi)(J^{-1}s)^T + \Gamma^{-1}\dot{\tilde{w}}^T]\} \end{aligned} \tag{18}$$

The adaptive law of the network weight is chosen as:

$$\dot{\tilde{w}}^T = -\Gamma\gamma(x,\xi)(J^{-1}s)^T \tag{19}$$

Then, it can be shown that the Lyapunov function candidate becomes negative and semi-definite, which, in turn, implies the convergence of s to zero, by applying Barbalăt's lemma. Also, this means that w is bounded.

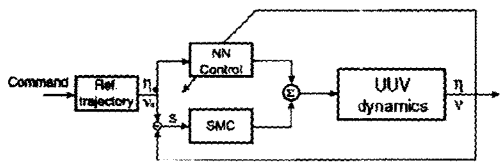

Fig. 3 Illustration of the structure of the controller

In summary, the control law is given by (17) and the adaptation law is given by (19). It should be noted that the approximation of the nonlinear function (16) 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. The neural network approximation does not require such an assumption, and it is assumed that the dynamics of the vehicles are unknown. The architecture of the controller is shown in Fig.3. Sliding mode control is used with neural network control to compensate for the modeling error.

4. Simulation

In this section, the results of the computer simulation for an underwater vehicle model (Spangelo and Egland, 1994) are presented. The equation of motion for a 6 DOF underwater vehicle is considered. All simulations are performed at 5Hz.

4.1 Reference trajectory generation

A more realistic way to produce the desired state can be shown as follows:

$$\dot{\nu}_d+\Lambda\nu_d+J^T(\eta_d)\Omega\eta_d=J^T(\eta_d)\Omega\eta_c$$
$$\dot{\eta}_d=J(\eta_d)\nu_d \tag{20}$$

Here η_c is a reference input, $\Omega=\Omega^T>0$ and $\Lambda>0$. We can specify the desired characteristics of the underwater vehicle by tuning the matrix Ω and Λ.

4.2 Controller setup

The architecture of the neural network is illustrated in Fig.2. The centers of Gaussian function $\gamma_i(x,\xi_i)$ were uniformly spaced in the state space. The width of the Gaussian function $\gamma_i(x,\xi_i)$ is set to 30. The overall weights of the neural network are initially set at zero. Only a single MIMO neural network is employed in combination with the sliding mode control. The adaptive gain matrix is set to 0.5Γ. The inputs to the network are normalized between -1 to 1.

The choice of the width of the Gaussian function $\gamma_i(x,\xi_i)$ is the most critical factor for the overall stability of the system, and is 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 determined, considering the width of an area in the input space to each neuron response. The value of $\gamma_i(x,\xi_i)$ should be large enough that the neurons respond to enough overlapping regions of the input space. Note that the Gaussian function produces the output of value 1 when the input exactly matches the weight of the function. This, in turn, can be tuned by changing the width of the Gaussian function. The weighting matrix is multiplied by the output of the Gaussian function, and is updated by the adaptive law.

A Sliding mode control technique is combined with the neural network controller, in order to compensate for the modeling error and to improve the robustness of the controller.

4.3 Results

The tracking performance of the X,Y position of the vehicle for the position command is shown in Fig.4. It can be seen that the proposed neural network controller provides fairly good tracking performance. The performance of the neural network is compared with the sliding mode controller and with the combined controller of neural network and sliding mode control. The Sliding mode controller, alone, offers almost the same tracking performance. However, when the neural network controller is combined with the sliding mode controller, improved tracking performance can be achieved.

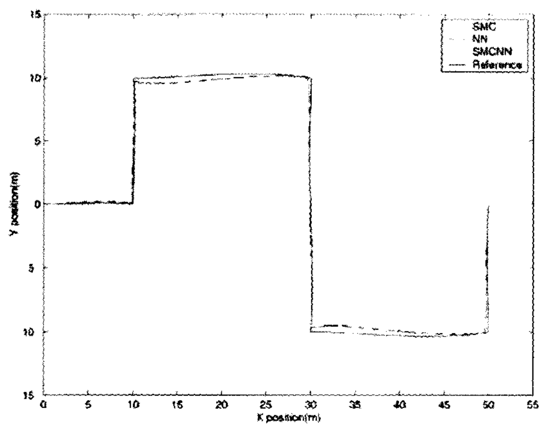

Fig. 4 X and Y trajectory

Fig.5 shows the depth control performance, and Fig.6 shows the heading angle control performance. Similar to the X, Y position control, the neural network controller provides good depth control performance. However, small oscillation is observed in the heading angle response when the neural network controller is used, due to the high gain in the adaptation. By combining it with the sliding mode controller, the unwanted oscillatory motion can be removed. Fig.7 illustrates the control efforts for the different degrees-of-freedom of the vehicle.

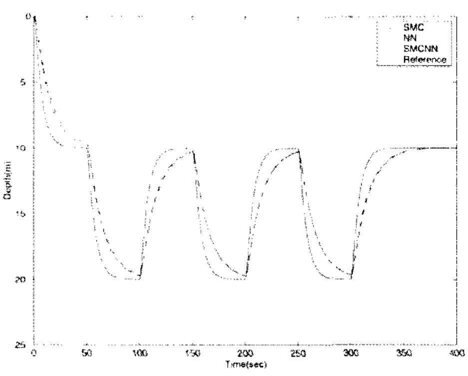

Fig. 5 Response of the vehicle depth

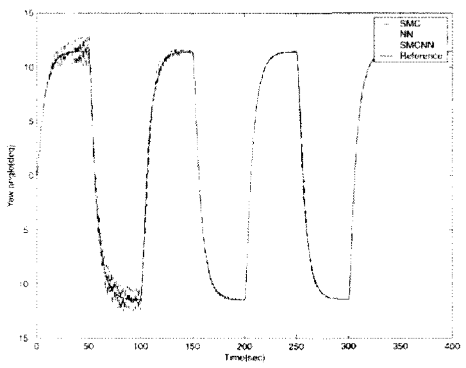

Fig. 6 Response of the vehicle yaw angle

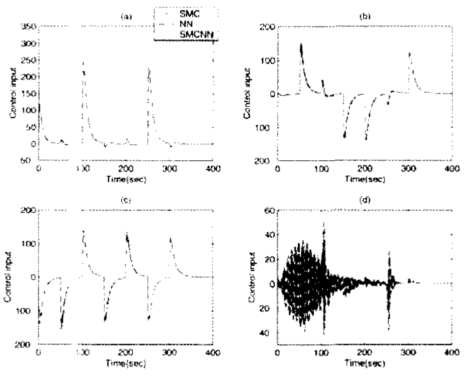

Fig. 7 Control inputs for each degree of freedom (a) X position control input (b) Y position control input (c) Depth control input (d) Yaw control input

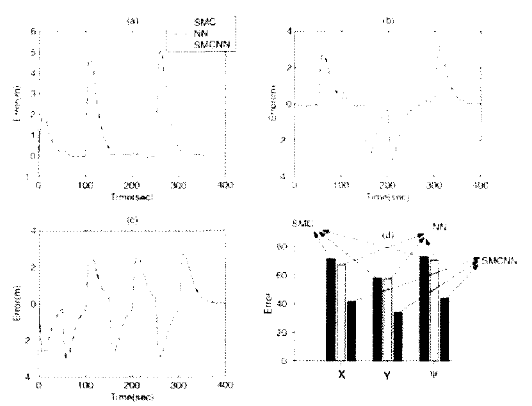

Fig. 8 Tracking errors (a) X position error (b) Y position error (c) yaw angle error (d) error norms for each

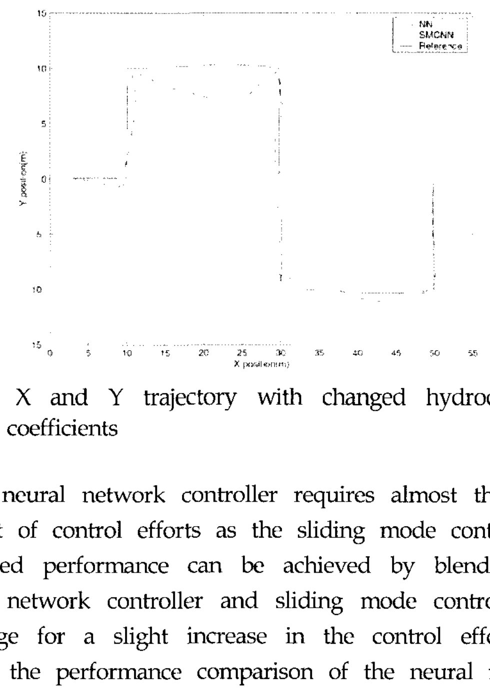

Fig. 9 X and Y trajectory with changed hydrodynamic coefficients

The neural network controller requires almost the same amount of control efforts as the sliding mode control. An improved performance can be achieved by blending the neural network controller and sliding mode controller, in exchange for a slight increase in the control effort. For clarity, the performance comparison of the neural network controller, the sliding mode controller, and the combined controller, in terms of error, are illustrated in Fig.8. Fig.8 (a),(b),(c) shows the error between the desired trajectory and the actual trajectory, using each type of controller. The metric of the error is illustrated at (d) of Fig.8.
The neural network controller produces slightly better results than the sliding mode controller. Robustness of the proposed control technique is tested by changing the hydrodynamic coefficients of the vehicle.

As shown in Fig.9, a combined controller produces a more robust performance with changed parameters, compared to using the neural network controller, alone. In the simulation, the values of the inertia matrix are reduced by 50%, the Coriolis and centrifugal matrix is reduced by 30%, and the damping matrix is reduced by 50%, respectively.

5. Conclusion

An adaptive neural network controller has been developed for an underwater vehicle in six degrees-of-freedom. This controller combines the radial basis neural network and sliding mode control techniques. With limited prior knowledge of the vehicle dynamics, the proposed control technique can achieve improved tracking performance. The number of neurons and the width of Gaussian function should be chosen carefully. The following conclusions can be drawn from this study. First, for design of the controller, the dynamics of the vehicle need not be precisely known. Second, no linearization is required to deal with nonlinear vehicle dynamics. Third, the controller is robust and adaptive. Fourth, the controller does not need any prior training phase and can be applied on-line. Future study will be performed, including actuator dynamics for the system.

Acknowledgements

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