Adaptive Control of an Autonomous Underwater Vehicle Testbed Using Neural Networks

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Abstract - The control of autonomous underwater vehicles has been a challenge to control engineers due to combined non-linear nature of both the vehicle itself and the environment in which they operate. This paper presents an implementation research on the adaptive controller of an autonomous underwater vehicle testbed in which the controller architecture is made using multi-layered neural networks. The problem considered is that of designing a controller for an autonomous underwater vehicle to provide directional control. A flux gate compass is used to measure the yaw angle and yaw rate. Directional control is performed by two thrusters in the horizontal plane. Weight adaptation of the neural network is achieved by minimizing an objective function that is weighted sum of tracking errors and control input rates. According to the experimental tests on various command trajectories, we show that when the learning process is kept active through the control operation, the neural network adapts to time-varying plant dynamics as well as disturbance upsets.

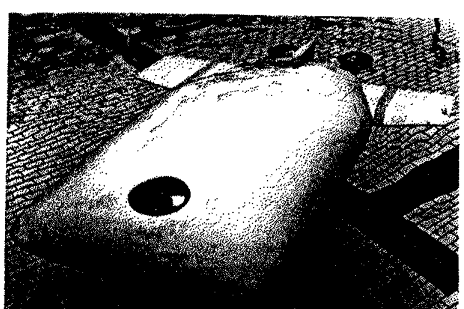

Figure 1 : The AUV testbed developed at NTU

1. INTRODUCTION

In past years, an increasing attention has been devoted to the exploration of oceans and the utilization of oceanic resources located around the Taiwan Island. This fact has promoted the development of unmanned underwater vehicles for inspection and monitoring of submarine environment and underwater structures.

Research is currently underway to develop autonomous underwater vehicles (AUVs) in the Department of Naval Architecture and Ocean Engineering of National Taiwan University. This research represents the first step in the design and simulation efforts of the AUV system. As an initial step to develop design capabilities, a testbed vehicle is constructed for investigation of various AUV related technologies, such as guidance, navigation, control, underwater imaging and communications. The AUV testbed and the internal arrangement of the testbed is shown in Figure 1 and Figure 2. Table 1 shows its principal particulars.

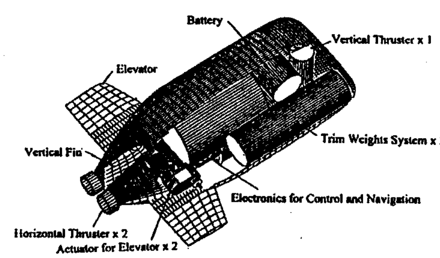

Figure 2: Internal arrangement of the AUV testbed

Table 1
Principal particulars of the AUV testbed

Items	Particulars
Dimensions	$2.0m(L) \times 1.0m(W) \times 0.6m(H)$
Weights	about 500kg in air ,neutral in water
Operating depth	50m
Max. Speed	4.0 kt
CPU	MVME 187 RISC Processor
Memory Capacity	16 MB
Thrusters	Horizontal $2 \times 200W$
	Vertical $1 \times 100W$
	Control Surface $2 \times 10W$
	Trim Weights $2 \times 20W$
Battery	Lead-acid battery $10 \times 12V \times 26AH$
Sensors	Obstacle avoidance sonars
	Altimeter
	Depthometer
	Accelerometers
	Rate gyros

A design/simulation package is also under developing concurrently as part of our AUV research. The optimal size and position of stabilizing fins and control surfaces for the underwater vehicle testbed can be determined using this computer program. This computer program predicts performance characteristics from calculated vehicle hydrodynamic coefficients, and merges with motion simulation that utilizes the characteristic coefficients of the design vehicle configuration. The overall system is described in detail in reference [1].

For missions such as underwater survey or pipe line inspection, directional control is a basic feature for the AUV motion control system. Control problems related to AUVs are very complex, due to their non-linear dynamics, the presence of disturbance, and the observation noises.

Neural networks as effective learning controller for a variety application has been recognized. For an introduction to the basic concept of neural network controllers, the reader is referred to [2]. One of the advantages in using neural networks for the control applications is that the dynamics of the controlled system need not be completely known for the design of the controller. Also the ability of these networks for adaptation and disturbance rejection as well as their highly parallel nature of computation makes them good candidates for many control applications.

In recent years, several control strategies based upon neural networks have been discussed for the application in underwater vehicles. Fuji and Ura [3] presented a self-organizing neural network controller for the pitch control of AUVs. The controller consists of a controller network and a forward model network. A fuzzy controller, called premature controller, is used as a start-up controller until the controller network learns the plant dynamics. The adaptation is achieved according to backward-propagated signals, which in turn is derived by the evaluation of the resultant motion estimated by the forward model network. The control system had been demonstrated through free-swimming tank tests. Yuh[4] presented an on-line neural network control architecture using a three-layered network. Unlike the approach taken by Fuji an Ura, the error at the output of the network is estimated from the tracking error of the vehicle. Simulation results of Yuh's showed that good trajectory tracking can be achieved for the vehicle. Also, some results dealing with issues such as robustness of the controller toward parameter and environmental disturbances were presented. Venugopal *et al.* [5] described a modified control scheme of Yuh's network controller. A gain layer is introduced between the neural network and the plant that aid the stability of the control system. They have also shown that the dynamic response and the tracking performance could be controlled by adjusting the network learning rate. Results of simulation studies on the robustness to disturbances in AUV dynamics were also presented.

In this paper, we describe an implementation work using the on-line learning neural network controller for AUV motion control in the horizontal plane. Using the back-propagation [6] as the learning algorithm, the neural network weight adaptation is achieved by minimizing an objective function that is weighted sum of tracking errors and control input rates. In section 2, we present the control scheme. Results of simulation and experimental studies on the AUV testbed vehicle are described in section 3. In section 4, we discuss implementation issues regarding neural network based adaptive controllers.

2. CONTROL SYSTEM DESIGN

The dynamics of an AUV is highly non-linear, the number of parameters that affects the nonlinearities is large. For example, hydrodynamic coefficients, thruster dynamics, etc. are usually poorly known. Besides, due to highly uncertain working

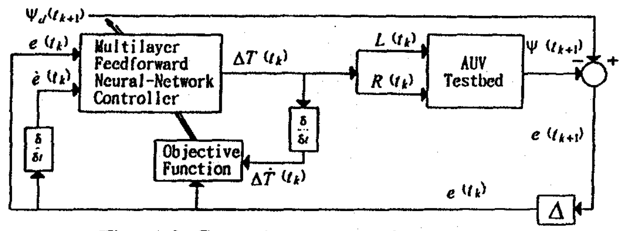

Figure 3: Control system architecture

environment in the ocean, and the requirement of control action over large operating range, traditional model-based design approaches demands enormous efforts on system modeling and controller design. As mentioned above, neural networks can be the suitable controller architecture for AUVs. In this paper, we use a multi-layered feedforward neural network as the AUV motion controller. The network represents a dynamic system with ability to adapt itself according to a performance index. The interconnection strength of the network is updated using the back- propagation algorithm . Figure 3 shows the control system architecture, where ψ represents the heading angle in the horizontal plane. The tracking error at time t_k is the error between the vehicle output and its desired value at the time t_k, Because of the time discretization of the vehicle dynamics, a control command generated at time t_k by the network controller will affect the output of the vehicle at time t_{k+1}. Consequently, the interconnection weight of the neural network was updated at time t_k based upon information becoming available at one time step later. The closed-loop performance of this control system is demonstrated in the next section through simulations and experiments.

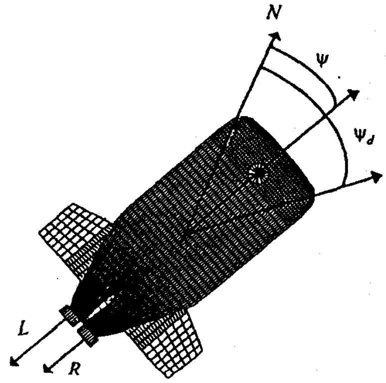

Figure 4: Heading control of the AUV testbed

The heading control of the AUV testbed is achieved through the thrust force difference between the right and left thrusters as shown in Figure 4. In this figure, T_O represents a constant thrust force in Newtons , and $L = T_O + \Delta T$, is the command thrust force to the left thruster, while $R = T_O - \Delta T$, is the command thrust force to the right thruster. A three-layer network with two input nodes, five hidden layer nodes, and one output node (2x5x1) is chosen for the controller. The size of the network is determined based on results of closed-loop control simulation of the AUV testbed. Inputs to the network correspond to e and $\dot{e}$, where e denotes the tracking error between the desired heading ψ_d and the actual signals of heading, that is $e = \psi_d - \psi$. Noted that the differentiation of the tracking error $\dot{e}$ is filtered before sending to the network controller. The network then outputs a thrust force difference command ΔT to the thrusters.

The training of network was performed in two stages:

Stage 1: The neural network control architecture is first trained with an automated teacher that implements a linear control law. The simulation package was used as the controller plant at this stage. For training, we used back-propagation algorithm. The three-layer network was able to learn the linear mapping. For example, in Figure 5, an arbitrarily chosen PD controller was used as a teacher. Training was terminated after 20,000 iterations. The average squared error at the termination was less than 0.012. After training, the network controlled the process and the teacher was removed. The objective of this stage is to provide the neural network controller with initial weightings, and to verify the feasibility of the control algorithm.

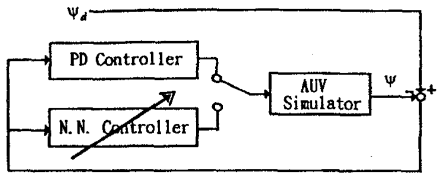

Figure 5: Network training and control simulation architecture

Stage 2: The interconnection weights adjusted in stage 1 using the simulation program were adopted as initial weighting values. Experimental tests of the neural network control algorithm were then conducted with AUV testbed operating in the swimming pool. In this stage, in order to maximize the heading tracking performance while minimizing the costs associated with high control efforts, the neural network is trained to minimize an objective function that includes tracking errors, and control rate requirement:

$$J(t_k)=\frac{1}{2}[\alpha\left(\psi_d(t_{k+1})-\psi(t_{k+1})\right)^2 + \beta\left(\Delta j(t_k)\right)^2] \quad (1)$$

where α, and β are constants whose values can be adapted so that they can be used to modify the characteristic of the neural network controller to achieve a practical performance/control effort tradeoff. As will be shown in the next section, satisfactory tradeoff between tracking performance and control effort can be achieved with finite values of α and β, since the bandwidth effect of the actuators is explicitly considered in the training loop.

3. SIMULATION AND EXPERIMENTAL RESULTS

The feasibility of the controller architecture is studied through computer simulations and experiments. In the simulation tests, the response of the vehicle is measured by numerical integrating the differential equation of motion. The neural network used is 2x5x1, with 21 interconnections. On-line learning of the controller network is performormed with 10 updates within each sampling period. The sampling time used in both simulation and experiments is 0.05 second, and the learning rate used in the back-propagation algorithm is 0.001. Figure 6 shows the heading response and commanded ΔT when the vehicle is subjected to a step input. The result of the simulation is close to the one obtained from the experimental test, indicating that the AUV model utilized for simulation is adequate.

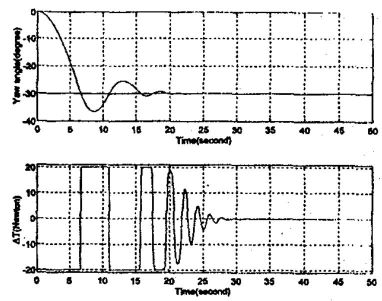

Figure 6: Simulated response of the vehicle to a step heading command

Figure 7 shows the step response under the thruster parameter variation. In this case, the thrust force coefficient of the right thruster is increased such that under the same command, it provides 5 newtons thrust force more than the left thruster does. As is observed in the simulation result, a 5 newtons command bias is generated at the steady state, indicating the adaptivity of the neural network controller.

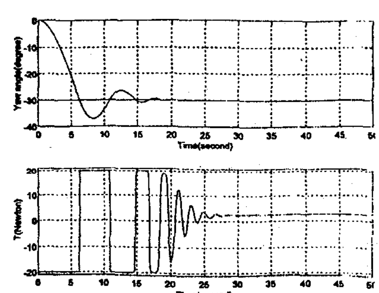

Figure 7: Simulated response of the vehicle under thruster parameter variation

Figure 8 shows the results that when training the neural network to minimize only tracking error led to high control rate requirements.

Pool tests were performed with the AUV testbed. Figure 9 and Figure 10 show the vehicle tracking responses for step and sinosoidal heading commands respectively. As pointed out earlier, the step response of the vehicle is very close to the one obtained in Figure 6. Also in these figures, the commanded ΔT and actual thrust force signals measured directly by the force sensors are shown. The robustness of the control system towards constant and sudden disturbances is investigated, and the results are shown in Figure 11 and Figure 12. It is observed in the thrust force measurements, that under external disturbances, the control system is learning the change of the environment. By adjusting the controller weights to provide proper control signals, the desired trajectory is followed satisfactorily. We investigated the robustness of the neural network controller to slowly varying changes in the AUV parameters by experimenting at different forward speeds. Figure 13 shows the vehicle performance when constant forward thrust force To = 20 newtons(and then 12 newtons) was applied to the vehicle. In all cases, with different initial headings, the controller adapted to changes in dynamics. The results of this case study show that the neural network control architecture can be used for the robust control of underwater vehicles.

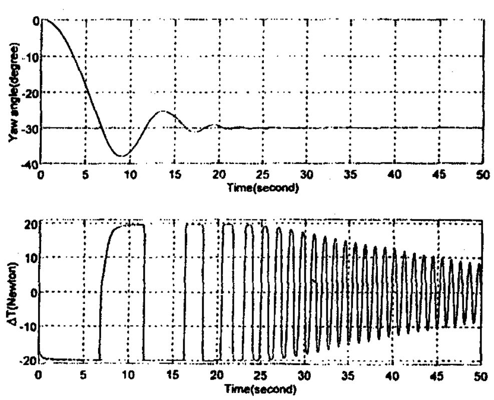

Figure 8: Network trained to minimize only tracking error

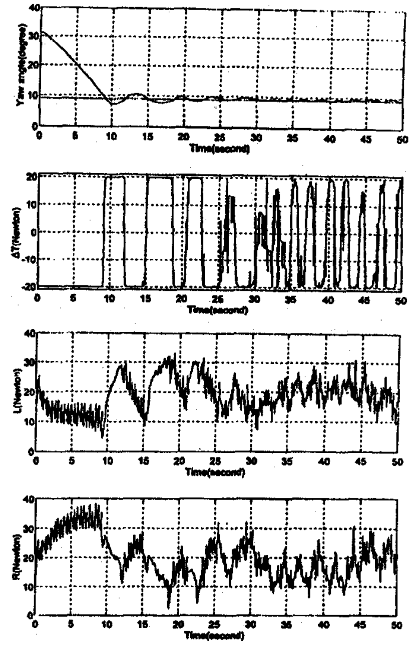

Figure 9: Experimental response of the vehicle to step heading command

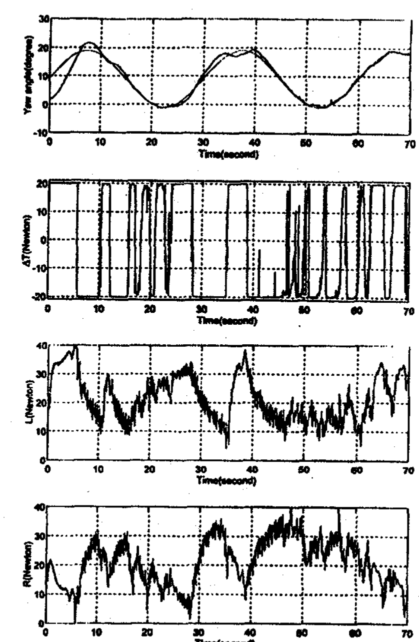

Figure 10: Experimental tracking response to a sinusoidal trajectory

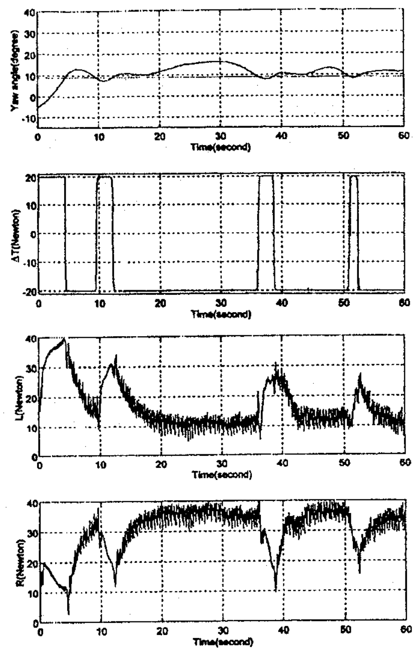

Figure 11: Experimental response when the vehicle is subjected to a constant external disturbance

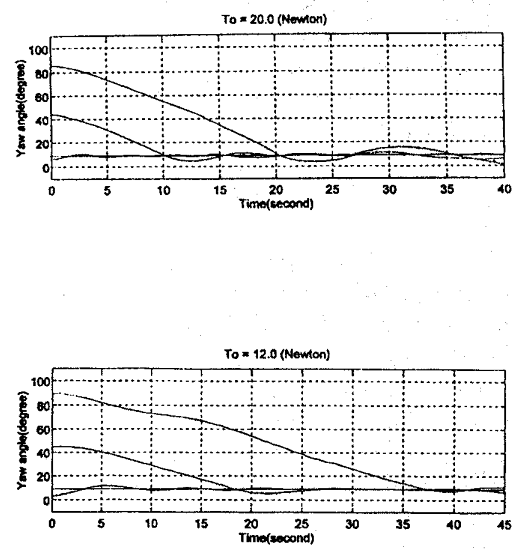

Figure 13: Robustness tests to show that the controller adapts to slow varying AUV dynamics

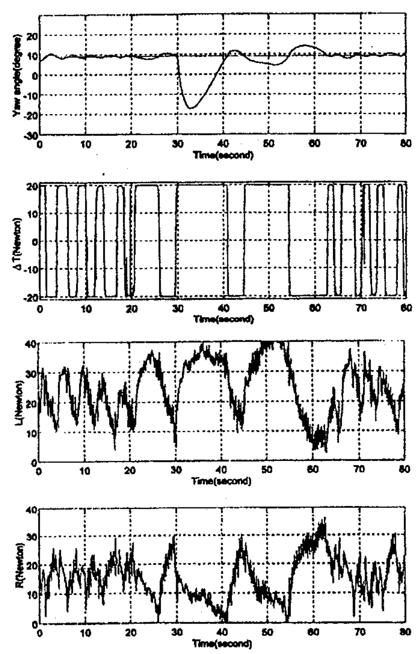

Figure 12: Experimental response when the vehicle is subjected a sudden external disturbance

4. DISCUSSION

Direct control and indirect control are two different main strategies generally used in the case of neural network based adaptive controllers [2]. In the indirect control strategy, the inverse dynamics of the plant is identified using a forward model network at one instant, and based on the identified plant dynamics, predicted error on the output of the controller is then used to train the controller network in the next instant. Along the course of our study, we found that the network architecture of forward model for plant dynamics is very problem specific. It usually requires large network with recurrent connections. The training of the network dynamics requires many learning cycles. Therefore, it is not suitable for implementation on the control of time-varying systems, or systems operating in the uncertain environment. On the other hand, in the direct control strategy, the controller generates the proper control signal to achieve the desired performance of the plant. It requires a smaller network and less computing time. In general, AUV systems are limited in their computing power and memory space. It is obvious that for a low level operation such as the heading control, a simple and effective control strategy is more suitable for the practical implementation.

5. CONCLUSIONS

The direct control scheme using a neural network adaptive controller is shown to be applicable for the heading control of AUVs. This conclusion is based on simulation and experimental tests with an AUV testbed operating in a swimming pool. In this work, we have demonstrated the following:

(1) the neural network based on-line control scheme can cope with unknown vehicle dynamics and can adapt to slow or fast varying disturbances.

(2) the design of the controller is relatively simple, the requirement on memory size and computing speed is low.

Future research is now being directed towards the depth control of the AUV testbed using a neural network based controller.

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