DEVELOPMENT OF A SMALL CRUISING-TYPE AUV "MANTA-CERESIA" AND GUIDANCE SYSTEM CONSTRUCTED WITH NEURAL NETWORK

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Abstract

A small cruising-type testbed vehicle named "Manta-Ceresia" is developed to validate performance of various control and guidance architectures for cruising-type Autonomous Underwater Vehicles (AUVs). It is so compact (13.8 kg in air) that one researcher can carry and handle the vehicle. Despite of smallness it is equipped with fundamental sensors and actuators required for prototype AUVs. Pairs of thrusters and elevators make it possible to swim in 3 dimensional space. The vehicle can swim along a wall of a square pool keeping constant distance automatically making use of 6 channels of range finder. Thus, the vehicle can continue swimming in a test tank as far as its energy remains. Taking advantage of these capabilities, adaptive controllers which require comparatively long swimming for adjustment can be examined in a small pool.

Performance of a constant-altitude-controller system utilizing neural-network, which can accumulate experience by adaptation, is examined with the developed vehicle. Switching structure of the neural networks is introduced to keep experience which is apt to be forgotten through additional learning and to represents mappings more precisely with same amount of learning calculation. Results of experiments with the developed testbed vehicle show that the introduced switching structure represents underwater terrain more precisely. Consequently, the controller is automatically adjusted to be applied for more complicated topography.

Introduction

It is desirable for the research of AUVs to examine validity of software architectures , guidance systems and control methods not only in simulations but also with real robots. Generally, however, real robots are so large and heavy to treat that carrying out experiments many times is difficult in respect of cost, time and place. In this paper a handy cruising-type testbed robot "manta-ceresia" is developed to enable frequent experiments with a real robot in a small pool.

Data acquisition while bottom following is regarded as one of main mission for cruising-type AUVs. A guidance system is necessary for bottom following swimming over various sedbed shapes. But considering all cases in advance is difficult because there are spectrum of topographies of seabed. Therefore adaptability is advantageous characteristics for such AUVs. In the previous papers [1, 2] a constant altitude guidance system utilizing neural network was introduced and adaptability was shown in simulations. Here a switching structure of the neural networks is introduced and the effectiveness of this guidance system is examined with the developed robot.

Development of a small cruising-type testbed vehicle

For a testbed vehicle, short verification cycle which includes modification of the software, experiment and verification of the result is required. Therefore, not only compactness of hardware but also intuitive and easy-to-modify architecture of software is important.

Hardware

The robot was designed along following guidelines.

1) The vehicle can be handled by one man's strength for convenient experiments
2) Longitudinal cross section is wing shape of NACA0030 which is same as PTEROA150 [3]. This type of vehicles has good pull-up maneuverability and suit for collision avoidance keeping speed.
3) Wide body makes distance between elevators and thrusters wider which brings good roll and yaw maneuverability.
4) The vehicle can cruise long range by swimming around a small square pool. Adaptive controller which requires comparatively long range can be examined in a small pool.
5) The vehicle can be controlled also by radio for the check of sensors and actuators. This is also used for dynamics identification.

The specification and general arrangement of the robot is shown in table 1 and fig. 1, respectively. This robot is named as "manta-ceresia" from its shape. The frame is made of ABS resin. This is sandwiched between aluminum plates and upside is covered by transparent vinyl chloride sheet. The vehicle consists of main pressure hull, battery cell unit, range finder unit, thruster unit and elevator unit. The vehicle has 4 sets of 23.5 Wh Ni-MH battery (94 Wh in total). As it consumes 38 W at maximum velocity of 1.0 m/sec, duration and range of a cruise are about 2.5 hours and about 8 km, respectively. Although this vehicle is designed as a fully autonomous vehicle, it can be remotely controlled using a commercially available proportional radio control system by selecting a switch in it. When it dives by wireless control in shallow fresh water, cruising data can also be logged in 8 Mbytes DRAM.

Table 1 Specification of the robot

Length	489 mm
Width	634 mm
Height	196 mm
Dry Weight	13.8 kg (including battery)
Maximum Depth	1.5 m (safety factor = 3)
Maximum Speed	1.0 m/sec
Duration	2.5 hours
Cruising Range	8km
CPU	INMOS T805(4MByte DRAM) x 2 / NEC V50
Sensors	6 channel range finder (0~510cm, resolution 2cm)
	Inclinometer x 2 / Compass / Inside thermometer
	Depth meter (resolution 1.2cm)
	Velocity meter (0~100cm/sec, reslution 1.2cm/sec)
	Thruster tachometer x 2
	Power supply voltage meter
Actuators	Pairs of elevators (independently)
	Pairs of thrusters (independently, fore, reverse)
Energy	Ni-MH Battery (Total 94Wh)
	16.8V 2.8Ah (For CPU)
	8.4V 2.8Ah x 2 (For thrusters)
Communication	6 channel proportional radio control system

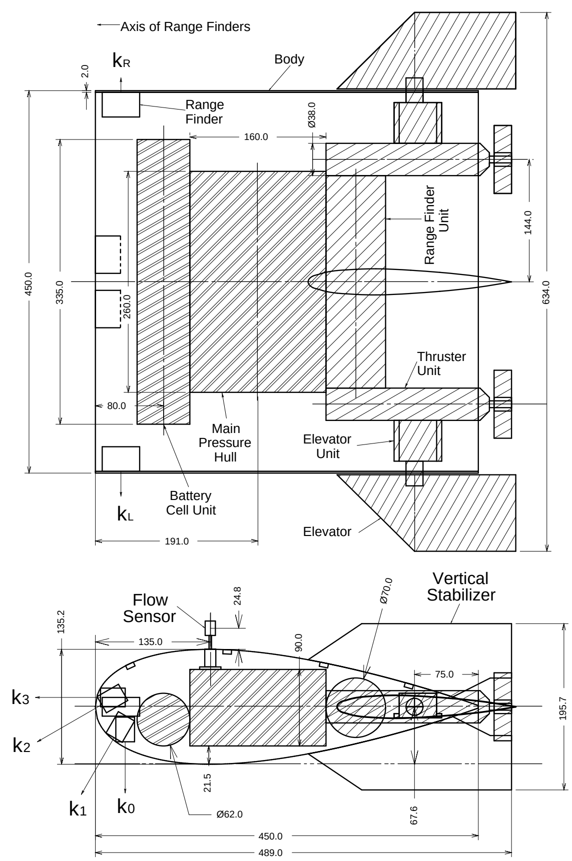

Fig. 1 General Arrangement of the robot

Computer System and Software

Two INMOS T805 transputer modules and one NEC V50 microprocessor are implemented as computer system. Structure of the computer and I/O system is shown in fig. 2. V50 processor is used for I/O system. On TRAMs (Transputer Modules) many processes (execution unit) which can be assigned to arbitrary TRAM can run simultaneously. These assigned processes are shown in fig. 3. Based on the parallel distributing software, a user has only to modify the control process which generates actuation values for control from sensory data.

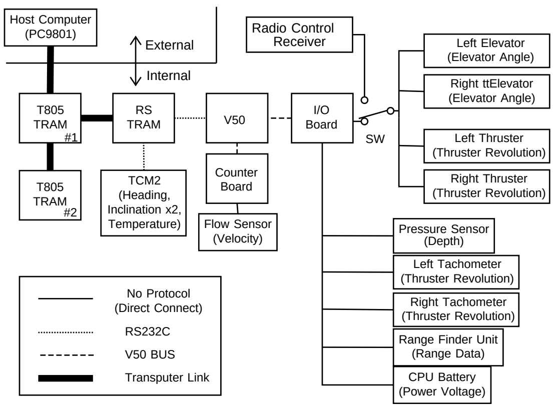

Fig. 2 Structure of the computer and I/O system

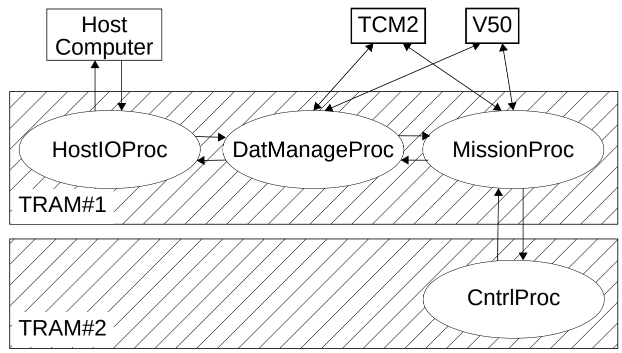

Fig. 3 Assignment of processes

Improvements of constant altitude controller constructed with neural network

Neural network is known by its nonlinear mapping representation ability, learning ability etc. It was shown in previous papers [1, 2] that adaptive constant altitude controller system making use of neural network adjusted well in computer simulations where equations of motion [4] derived from a real PTEROA type vehicle is used. This system uses two neural networks: a controller network and a forward model network. Hereafter these networks are abbreviated as CtlNN and FwdNN, respectively. The FwdNN represents dynamics of a vehicle and external environments. The CtlNN is adjusted by the output of the FwdNN by back-propagation. For appropriate adjustment of the CtlNN precise forward model network is required. In the previous papers some methods which make the FwdNN more precise are introduced. Here switching mechanism of neural networks is introduced to keep experience which is apt to be forgotten through additional learning and to represents mappings more precisely with same amount of calculation.

Neural network for constant altitude swimming

Coordinate system and values for control is shown in fig. 4 and the neural network used is shown in fig. 5. $k_0 \sim k_3$ are distances to the seabed. A is altitude defined by distance from the robot to the line defined by reflect point of k_0 and k_1. θ and δ_e are pitch angle and elevator trim angle, respectively. The vehicle is controlled only by controlling this δ_e. In fig. 5 the left network is CtlNN and right one is FwdNN which is modularized for precision consists of right 3 networks - dynamics network, geometric network and altitude network. The evaluation function for the adjustment of the CtlNN is:

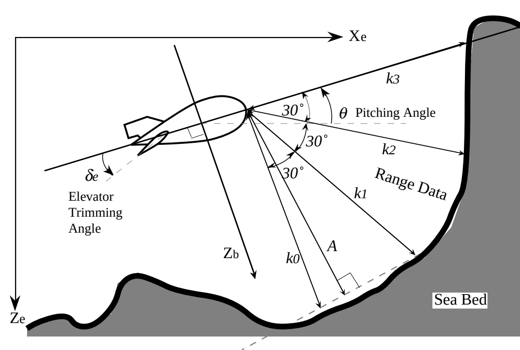

Fig. 4 Coordinate system and values for control

$$E = \frac{1}{2}\sum_{m}\left(A - A_0\right)^2 \qquad (1)$$

A_0 is a target altitude. Learning of the CtlNN is progressed to reduce this function.

Switching mechanism

When the experience accumulated in a FwdNN is forgotten by additional learning, 2 reason are stated. Firstly the system which the FwdNN represents altered. Secondly input range is changed and there is no mapping relation in the network. In both cases if additional learning is performed only by new data, the FwdNN might not represent the former mapping precisely. Here switching mechanism of neural networks, which is shown in fig. 6, is introduced to keep experience. This mechanism uses the error between the value which the FwdNN is estimated and the value which real vehicle produced to switch pairs of a CtlNN and a FwdNN. The procedure is explained as follows:

1) Continue learning of the FwdNN#1 till the error becomes smaller than a constant determined in advance. The robot is controlled by an appropriate controller CtlNN#1 which keeps the robot safe and continue learning of CtlNN#1. If learning progresses the CtlNN#1 can control the vehicle more precisely as long as the error of FwdNN#1 is small.
2) Here assuming that learning of FwdNN#1 ~ FwdNN#n is progressed and CtlNN#1 ~ CtlNN#n is adjusted properly. Forward calculation is executed in each FwdNN. The control of the vehicle is performed by the corresponding FwdNN of which error is smallest if the error is smaller than the constant determined in advance.
3) If the error is not smaller than the constant, introduce a new pair of a CtlNN#n+1 and FwdNN#n+1 and progress the learning of FwdNN#n+1. While the error of FwdNN#n+1 is not small, control of the vehicle is performed by the corresponding FwdNN of which error is smallest.

Introduction of this switching mechanism can cope with both the change of system and the change of input range. Another advantage of this mechanism is that if error of the FwdNN is small and corresponding CtlNN is adjusted properly, the vehicle is appropriately controlled at the moment the pair of networks is switched.

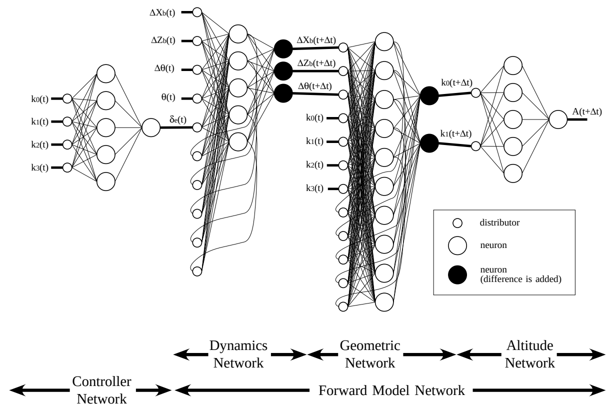

Fig. 5 Neural network for constant altitude swimming

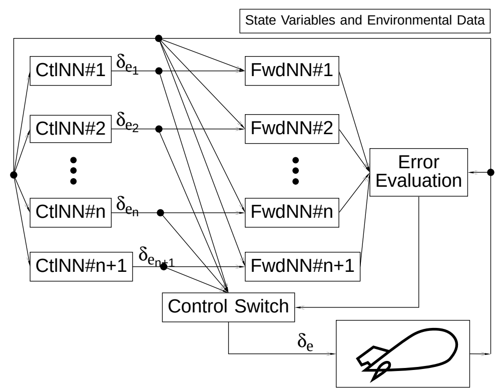

Fig. 6 Switching mechanism

Training

Verification of precision with switching mechanism

First whether introduction of switching mechanism make neural network representation more precise or not is verified. Here two geometric networks are used for simplicity. Teaching data for these networks are acquired by the developed robot which is controlled by initialized CtlNN. Underwater structure set up at

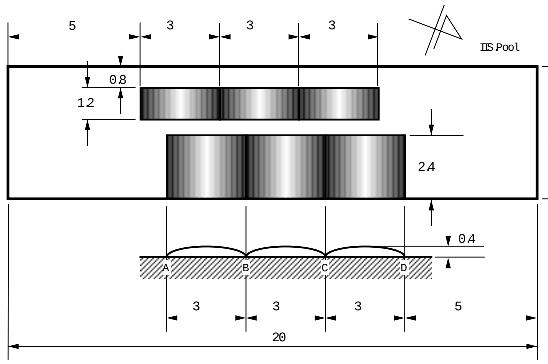

Fig. 7 Underwater Structure

bottom of a square pool is shown in fig. 7. The depth of the pool is 1.5 m. Convergence curves of geometric networks are shown in fig. 8. Teaching data of the top figure (case A) consist of data above both flat terrain and undulating terrain. Data of middle one (case B) and bottom one (case C) consist of data above flat terrain and undulating terrain, respectively. The reason why one graph has many lines is that learning of a neural network is effected by its initial weights, so 10 sets of initial weights and used. Amount of calculation of case A equals that of case B and C. But best converged error is 0.0196 about case A and 0.0149 about average of case B and C. The error reduces 25%. This means that the network with switching structure represents mapping more precisely.

Training with developed robot with switching mechanism

After giving the robot an ability of automatic swimming around the square pool, overall system which is composed of hardware and software are examined. The neural network controller controls only longitudinal motion. When the FwdNN is modularized, only the module which might change is switched. Therefore the switching structure used for the developed robot is shown as fig. 9. For simplicity two network are switched and learning of each

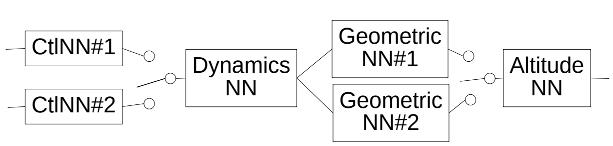

Fig. 9 Switching mechanism for modularized network

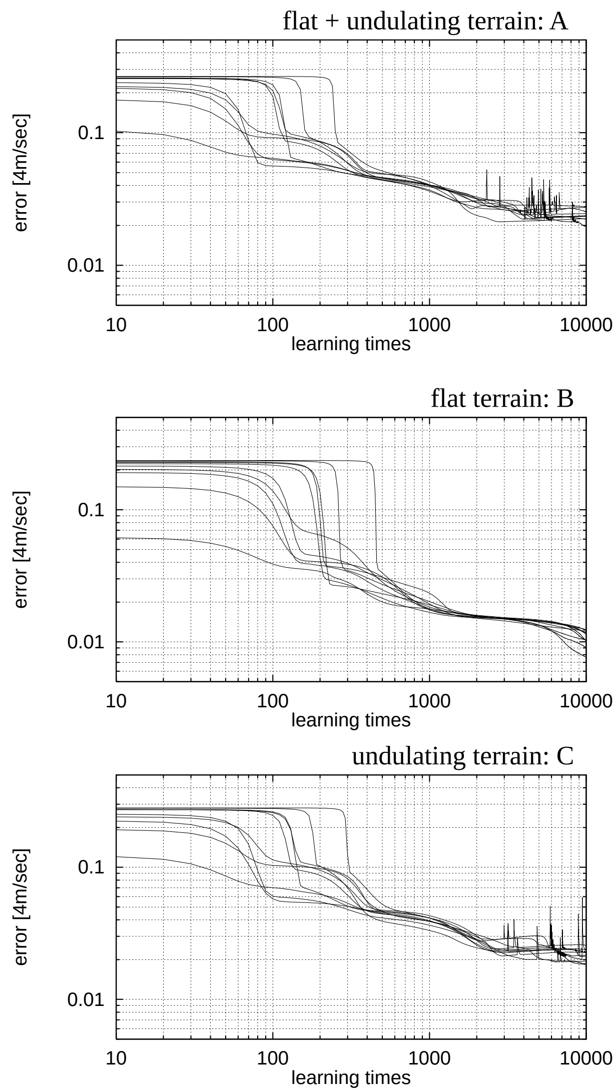

Fig. 8 Convergence of learning

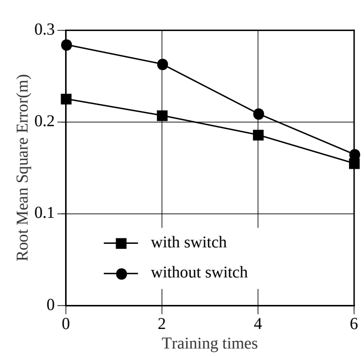

Fig. 10 Transition of error of altitude

module are done based on swimming data in advance.

A set of certain duration of swimming and adjustment of the CtlNN is called training here. The adjustment is done after swimming long sides of the pool. Fig. 10 shows training process for the constant altitude swimming. The target altitude is 0.5 m. In this figure a training process without switching mechanism is also shown. Although error accumulation times is about half with switching mechanism for each the CtlNN, the error of control is smaller. This is considered that suitable controller is switched and used at every step.

Conclusion

For verification of control system of PTEROA type AUVs in real environments a small robot with short verification cycle is developed. Although this robot is small, minimum sensors and actuators which are required for cruising-type AUVs are equipped. It's so small that experiments can be performed by one person's strength. But it can swim around a small pool automatically and continues swimming till power of battery is exhausted. So validity of adaptive controller which requires comparatively long swimming can be examined in a small pool. An adaptive constant altitude controller system using neural network which is examined only in computer simulations is also examined by real the developed real robot. It is shown that introduction of switching mechanism improves the adjustment of the neural-net controller.

References

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