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EXPLORATION AND MINING LEARNING ROBOT OF AUTONOMOUS MARINE RESOURCES BASED ON ADAPTIVE NEURAL NETWORK CONTROLLER

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ABSTRACT

To study the autonomous learning model of the learning robot for marine resource exploration, an adaptive neural network controller was applied. The motion characteristics of autonomous learning robots were identified. The mathematical model of the multilayer forward neural network and its improved learning algorithm were studied. The improved Elman regression neural network and the composite input dynamic regression neural network were further discussed. At the same time, the diagonal neural network was analysed from the structure and learning algorithms. The results showed that for the complex environment of the ocean, the structure of the composite input dynamic regression network was simple, and the convergence was fast. In summary, the identification method of underwater robot system based on neural network is effective.

Keywords: adaptive neural network, marine resources, learning robot

INTRODUCTION

Based on a study, the total area of the ocean accounts for 70.8 % of the total area of the Earth, and it is an important part of the global life support system [1]. According to research, rich marine life resources, marine mineral resources, water resources and marine energy are contained, which is a valuable asset to help achieve sustainable development. Marine resources play a vital role in the sustainable development of mankind [2–3]. Marine development requires advanced technology and equipment. Underwater robots are currently the only equipment that can work in the deep sea, which has an irreplaceable role in deep sea development. Underwater robot technology is a high-tech that has been developed with the deepening of marine research and development. It is an important part of marine high technology.

The exploration and mining learning robot of marine resources is taken as the research object, and the neural network is used as a tool to systematically identify its motion characteristics. The forward and predictive models of the robot are established separately. Taking the neural network as the starting point, the nonlinear system identification method based on neural network and the network characteristics commonly used for identification are discussed. Study showed the neural network is optimized from two aspects of network topology and learning algorithm [4]. The neural network identification model of multi-layer forward neural network and dynamic regression neural network based on improved Elman algorithm is studied. Through comparison, an effective method to improve the identification effect is proposed.

STATE OF THE ART

The research of underwater robots has been more than 20 years old. Many coastal countries, especially developed countries, are committed to underwater robot technology research and product development. Countries such as the United States, Canada, the United Kingdom, Japan, Russia, and China have established specialized institutions or established research laboratories in universities to study underwater robot technology, such as Centre for Autonomous Underwater

Vehicle Research, Marine Systems Engineering Laboratory at Maine State University, The Autonomous Undersea Systems Institute, British Maritime Technology Center, Underwater Robot Application Laboratory of the University of Tokyo, Japan, Shenyang Institute of Automation and Harbin Engineering University, National Key Laboratory of Underwater Robots [5]. Some professional associations established internationally, such as IEEE Marine Engineering Association, IEEE Robotics and Automation Association, Maritime Technology Association, etc. have contributed to the development of underwater robot technology [6].

The research of neural network can be divided into two aspects: theoretical research and applied research. Theoretical research can be divided into neurophysiological and cognitive science research human thinking and intelligent mechanism. The research results and mathematical methods of neural basic theory are more complete. The performance of the neural network model is superio [7]. Network algorithms and performance are studied in depth, such as stability, convergence, fault tolerance, and robustness. New network mathematical theory has been developed, such as neural network dynamics, nonlinear neural fields, and so on. Application research can be divided into the following two categories: software simulation of neural networks and hardware implementation research and application of neural networks in various fields. These areas include system identification, pattern recognition, signal processing, knowledge engineering, expert systems, optimization combinations, and robot control [8]. With the development of neural network theory itself and related theories and related technologies, the application of neural networks will be more in-depth and extensive.

METHODOLOGY

ONLINE IDENTIFICATION OF NONLINEAR SYSTEMS

Based on a study, the neural network is used to model the nonlinear dynamic system, which mainly reflects the nonlinear mapping ability of the neural network [9]. However, if the external environment of the system changes, the output of the system will also change, so that the dynamic response to the network has higher requirements. From the structure of the network, learning algorithms, identification structure and other aspects, the adverse effects are eliminated. In view of this, online recognition was introduced. The parameters of the online identification neural network model are determined by a certain online learning algorithm. Thus, a controlled object model that satisfies a certain precision needs to be established. The initial information of the network is obtained through offline learning. Then, by embedding the identification structure in series and parallel form into the system, the model can be modified in time by adjusting the weight and threshold of the neural network model online. The model has good robustness.

SBPTT (simplified backpropagation through time) is developed based on the BPTT algorithm combined with the requirements of online identification. The algorithm takes into account the online learning ability of the BPTT algorithm and the small amount of online learning. The learning of the model requires a condition that enables it to jump out. Because online learning has certain requirements for the learning time of the network, the logical or relationship of the precision and the number of learning is used as a condition. Once the accuracy meets the requirements or the number of learnings of the network reaches a predefined number of times, the network ends the current learning process.

A series-parallel identification structure is adopted between the controlled system and the identification network. The identification network uses a modified Elman network. The learning algorithm uses a BPTT algorithm suitable for online identification. However, online identification has strict requirements on the amount of calculation, convergence speed and consumption time of the network. The online learning method uses the SBPTT algorithm. For the nonlinear system with multiple inputs and multiple outputs, on the one hand, the mapping capability of the system is higher; on the other hand, there are certain requirements for the coupling and decoupling of the identification system.

In many practical problems, the identification may not always be performed in an open loop state, such as learning the speed experiment of the robot. If the difference in motor performance of the learning robot is not very large, it can be done by direct open-loop experiment. However, if the experiment of the robot is carried out, it is almost impossible to learn the robot based on different control amounts and to obtain the desired angle of inclination. There are many reasons, such as robot inertia, hydrodynamics, and robot energy. In some cases, if the feedback channel is disconnected, the system will be unstable, and some systems or most systems will not allow or cannot disconnect the feedback channel [10].

ESTABLISHMENT OF NONLINEAR SYSTEM PREDICTION MODEL

The plane motion output information of the learning robot includes information such as longitudinal speed and slant angle. They are chronologically ordered and have some statistical relationship [11]. The information can be statistically described by a probability distribution function or a function group. The fitted mathematical model is used to predict future possible values, which is one of the main application purposes of the time series analysis method [12]. Thus, the output prediction of the learning robot can be performed using a time series analysis method.

The representation of the nonlinear system uses the following structure:

$$y(\mathrm{k}+1) = \mathrm{f}[\mathrm{y}(\mathrm{k}), \mathrm{y}(\mathrm{k}-1), \cdots, \mathrm{y}(\mathrm{k}-\mathrm{n}+1); u(\mathrm{k}), u(\mathrm{k}-1), \cdots, u(\mathrm{k}-m+1)] \quad (1)$$

Neural network prediction of time series is usually based on existing sample data to train the network. If the past $N\ (N \geq 1)$ data is used to predict the value of the future $M\ (M \geq 1)$ moments, the M-step prediction is performed. The sequence of N adjacent samples is a sliding window and maps them to M values. These M values represent the predicted values of the samples at the M moments after the window. The training data is divided into data segments with K segments of length N+M, and the first N data of each segment is used as the input of the network, and the last M data is used as the output of the network [13].

The method of neural networks to describe nonlinear systems is maturing. Therefore, a method of constructing a multi-step predictive model with a neural network has emerged. In summary, there are two options, one is the recursive multi-step prediction model, and the other is the non-recursive multi-step prediction model [14].

The recursive multi-step prediction model is used as a one-step prediction model, which is obtained after offline or online training. According to the network structure, the input link can be increased or decreased. This requires relatively more system information when applying multiple layers of forward static networks [15]. When using dynamic regression network for modelling, the dynamic mapping of the network itself can be utilized to reduce the structure of the network. It facilitates the implementation of programs for online identification and generalized predictive control.

According to the longitudinal motion of the learning robot to simplify the model and the relationship between thrust and voltage, equation (2) is obtained:

$$5.64V_c - 3.1 - D_{Q,x}\left|v_x\right|v_x - D_{L,x}v_x = M_x v_x \tag{2}$$

Nonlinear system identification requires a computer to process, while a computer can only process discrete time models. Therefore, it is necessary to digitally discretize the above formula. The parameters obtained by longitudinal identification and the control period and sampling period are both 0.1s. Equation (4) is obtained:

$$v_x(\mathrm{k+1}) = v_x(\mathrm{k}) + \frac{5.64v_c(\mathrm{k}) - 146.8857\left|v_x(\mathrm{k})\right|v_x(\mathrm{k}) - 22.2157v_x(\mathrm{k}) - 3.1}{2365.319} \tag{3}$$

According to the actual input and output of the learning robot, the input allowable range is -5V~5V. However, the model between the thrust and voltage of the propeller here is derived from the forward data. The relationship between the voltage and the thrust when learning the robot back is different from the parameter at the time of advancement [16]. Therefore, the amount of control should be in the range of 0 to 5V when performing longitudinal experiments.

EXPERIMENTAL DESIGN

A set of sinusoidal curves of amplitude-frequency variation distributed in the range of 0~5V is designed as an excitation signal for learning the robot model. However, due to the presence of the pull-wire sensor at the rear of the learning robot and the static resistance of the robot, there is a dead zone in the starting voltage. When the starting control voltage satisfies Vc>0.55V, the learning robot can generally generate the forward thrust.

This model is a nonlinear system with a certain time lag. The learning robot model is identified by using multi-layer forward neural network, improved Elman neural network and composite input dynamic regression neural network. The recognizer uses a series-parallel structure, that is, the output of the model is used as an input to identify it. The convergence speed of the nonlinear identification system is effectively improved.

RESULT AND DISCUSSION

IDENTIFICATION OF MULTI-LAYER FORWARD NEURAL NETWORKS

There are many learning algorithms for multi-layer forward networks. The earliest algorithm was the standard back propagation (BP). The input vector u of the network is n-dimensional, the output vector y is m-dimensional, and the input/output sample length is N. The BP learning algorithm consists of two phases: forward propagation and back propagation. In forward propagation, the input signal passes from the input layer through the hidden layer to the output layer. If the output layer gets the desired output, the learning algorithm ends; otherwise, it goes to backpropagation. Backpropagation is to calculate the error signal (the difference between the sample output and the network output) in the reverse direction of the original connection path. The gradient descent method adjusts the weight and threshold of each layer of neurons to reduce the error signal.

The neural network structure of N(2,6,1) is designed, and the serial-parallel identification structure is adopted. The input of the network is Vc(k) and v(k-1), and the output of the network is v(k). The network learning algorithm uses an improved BP learning algorithm with momentum terms. After the trained network, the square wave of the input variable amplitude frequency is obtained as shown in Figure 1.

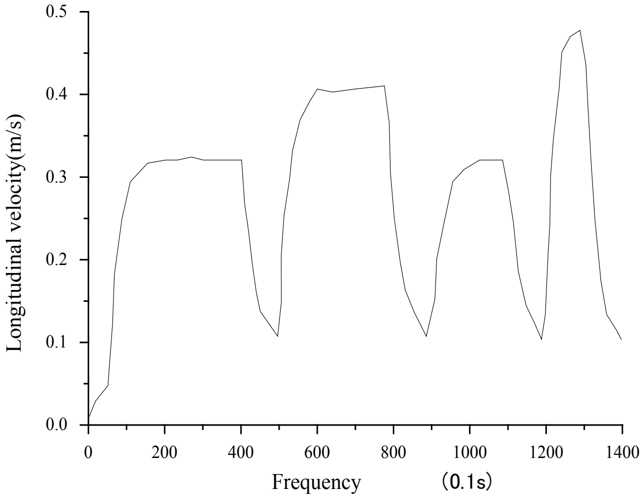

Fig. 1. Identification results of multilayer feedforward networks

IDENTIFICATION OF IMPROVED ELMAN NEURAL NETWORK

The nonlinear system has hysteresis, and the order of the nonlinear system is difficult to determine. Therefore, the Elman algorithm is improved. Based on the basic Elman structure, a self-feedback link is added to the structural elements of the network. The self-gain factor generally takes a fixed value a. The network can map higher order nonlinear systems. The structure is shown in Figure 2.

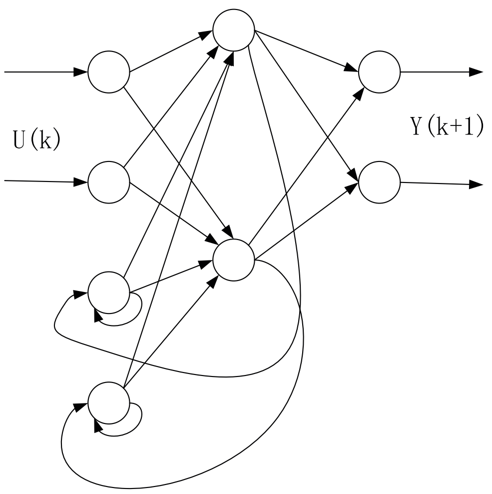

Fig. 2. Improved Elman neural network

The weight learning algorithm of Elman network can be performed by standard BP learning algorithm. However, since Xc(k) is a dynamic recursive process, and the BP algorithm only uses a step, it will lead to poor stability of the structural unit connection weight. To ensure learning convergence, for high-order systems, the learning rate must be minimal, resulting in poor approximation accuracy. Therefore, the Elman network can only identify first-order linear dynamic systems. To overcome this shortcoming, a dynamic backpropagation learning algorithm was used to train the Elman network. The improved Elman neural network uses an N(1,3,1) structure. The initial value of the state layer of the network has a large impact on the convergence of the network. Therefore, the method of simulating data is used to obtain the initial value of the state layer, that is, the neural network is used to learn the state layer value of the offline learning to initialize the initial state layer of the recognizer.

The network learning algorithm uses a variable-step error feedback learning algorithm. In the improved Elman network, the learning method can identify higher-order nonlinear systems. Using the state layer of the Elman network, only three neurons are selected in the middle layer, and the learning memory parameter is 0.1. If the memory parameters are too large, the system learning is prone to oscillation. The step size from the input layer to the hidden layer and the step size from the hidden layer to the output layer are both 0.8, which can improve the learning adjustment speed of the state layer to the hidden layer unit. The historical information of the system can be easily input into the network. The output of the network approaches the output of the actual system. The identification effect of the network is shown in Figure 3.

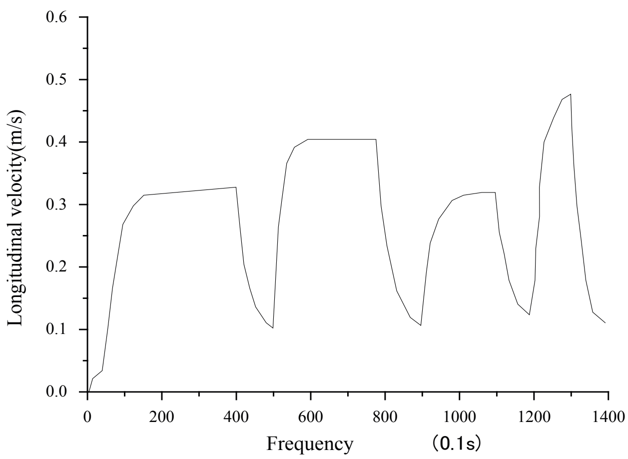

Fig. 3. Identification results of improved Elinan neural network

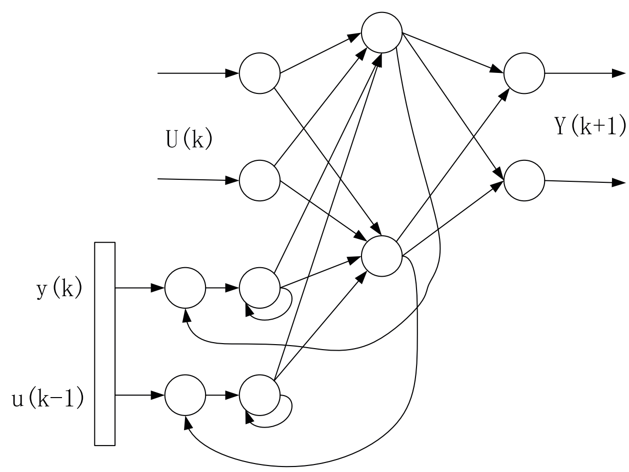

Fig. 4. Characteristics of compound input dynamic neural network

IDENTIFICATION OF COMPLEX INPUT DYNAMIC NEURAL NETWORKS

Compound input dynamical recurrent neural networks (CIDRNN) takes into account the more information of the input system of the BP network and the dynamic characteristics of the Elman network. The structure is shown in Figure 4.

Composite input neural networks can be trained using standard BP algorithms. Compared with the Elman network, CIDRNN's generalization ability and convergence speed have been improved due to the use of more system resources, but this also brings the characteristics of large structure. The composite input neural network was developed based on Elman. It inputs certain historical information of the network into the network as an augmented input to the network. The inputs of the recognizer network include Vc(k), Vc(k-1), and v(k-1). Among them, Vc(k-1) and v(k-1) are the augmented inputs of the network. The output of the network is v(k). The weight of the network is adjusted by learning the output of the robot model as an error. The network adjustment algorithm uses an improved error back propagation learning algorithm.

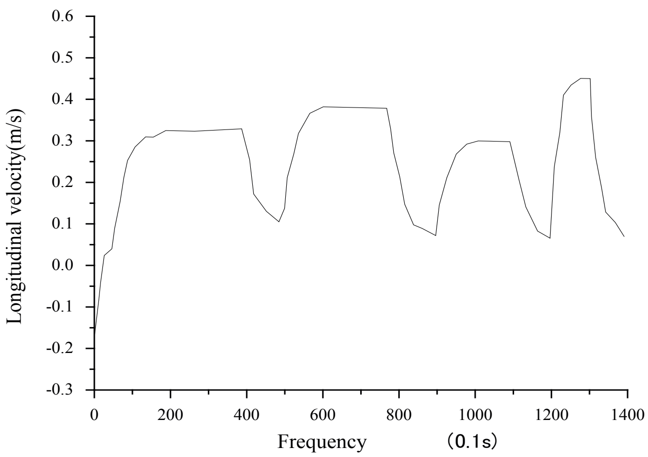

Fig. 5. Identification effect of compound input dynamic regression neural network

ANALYSIS OF SIMULATION EXPERIMENT RESULTS

The training error curves of the three networks were analyzed. It can be seen that the improved Elman network is initially oscillating because the initial value of the state layer is not optimal.

The recognition effects of the learning robot models of the above three networks are compared. It can be found that the overall accuracy of the multilayer forward neural network is relatively high. The model system has no noise. From the perspective of static network mapping, the model can be well identified. An improved Elman neural network and a composite input dynamic regression neural network were compared. It can be seen that the turning point is mainly due to the memory function of the network, which is closely related to the characteristics of the input quantity. The data analysis is shown in Table 1.

Tab. 1. Comparison of neural network identification effects

Parameter name	Multi-layer forward network	Improved Elman network	Composite input dynamic network
Structure	N(1,6,1)	N(1,3,1)	N(3,6,1)
Training error	8.968e-005	2.083e-004	8.946e-005
Number of iterations	4000	2500	1000
Mean value of test error	-7.475 e-004	-0.0213	0.0011
Variance of test error	1.1608 e-005	0.002	8.386e-005

CONCLUSION

The identification of nonlinear dynamic systems based on neural networks is introduced. The structure, algorithm, and convergence of neural network identification are analysed. At the same time, the differences between the identification of open-loop system and closed-loop system are analysed, and the methods commonly used to construct one-step prediction model and multi-step prediction model are discussed. In addition, combined with the learning robot model, the model identification experiment was designed by applying multi-layer forward network and regression network respectively. By learning robot simulation experiments, the performance between different networks is compared. The composite input dynamic regression network has a simple structure and fast convergence.

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