Control Model of Watershed Water Environment System Simulating Human Neural Network Structure

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ABSTRACT

On the basis of analyzing the characteristics of watershed water environment system, the neural network control model of watershed water environment system is established according to the neural network structure of human brain, so as to correct the errors of traditional water environment system control. The simulation results show that the proposed control algorithm has higher path-tracking accuracy and strong adaptability and robustness to the dynamic uncertain factors in the watershed water environment system.

Key Words: Watershed Water Environment System, Cerebral Nervous System, Differential Correction

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Introduction

With the development of neuroscience so far, a large number of synaptic plasticity rules have been proposed. The best known among them is the hypothesis of synaptic plasticity proposed by Herb: If the neuronal activity patterns correspond to different behaviors, then strengthening and solidifying a particular neuronal activity pattern mean learning a new behavior pattern. In a system, however, the synaptic strength cannot only increase instead of decreasing, so Herb's hypothesis must have additional supplementary rules to describe the condition of the decrease in synaptic strength (Chiang *et al.*, 1996; Hu *et al.*, 1999). This is very similar to the mechanism of analyzing watershed water environment system.

At present, the overall condition of watershed water environment in China has entered a new stage of large-scale ecological degradation and complex environmental pollution, with increasing pollution load, difficult progress of pollution control, and lack of systematic, synergetic and innovative scientific researches for a long time, and the technical support of water pollution control is relatively weak. For this reason, researchers pay more and more attention to how to optimize water resources system models, mainly adopting dynamic programming, linear planning or simulation techniques (Cannistraro *et al.*, 2017; Houria *et al.*, 2017; Ngo *et al.*, 2015; Viola *et al.*, 2016). With the development of intelligent optimization algorithms, more and more intelligent optimization methods such as simulated annealing algorithms, genetic algorithms and artificial neural networks are applied to multi-objective optimization solutions (Huang *et al.*, 2016; Kadri and Mouss, 2017; Keshtkar, 2017; Lee *et al.*, 2003; Li, 2017; Wang and Xie, 2016; Yuan *et al.*, 2017; Zhang *et al.*, 2017;). However, a single optimization algorithm cannot avoid its own defects, and a better algorithm is needed to optimize, so it is necessary

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to strengthen the study of multi-objective model optimization, so as to get a more reasonable optimization scheme.

Based on the expected trajectory of water resources development and utilization in the water environment system, this paper carries out nonlinear correction to the conventional differential correction control algorithm, in combination with the motion control of the neural network model of human brain, for the limitation of the differential correction algorithm in dealing with the strong nonlinear problem of variable dynamics, so as to solve the problem of parameter identification faced by traditional differential correction control model in dealing with nonlinear problems and the inadaptability of the model to the dynamic changes of the watershed environmental system, thus improving the self-adaptability and robustness of the model to the water resources system.

Related description

The watershed system is linked by water circulation, and can be divided into three aspects: artificial lateral branch water circulation process under the influence of human social and economic activities; natural water circulation process such as land surface runoff and hydrodynamics processes in river and lake waters; process of pollutant migration transformation and energy transformation with water body movement. In order to form a comprehensive management platform for watershed water environment, a model framework of watershed water environment system covering social-economic-hydrological-water environment-water ecology is constructed with the reflection of watershed pollution load estimation and water quality response relationship of receiving waters area (Sivakumar *et al*., 2014; Gounemat *et al*., 2015).

Like the structure of the neural network of the human brain, the different functions are not caused by the different kinds of neurons, but by the different connections between neurons. Neurons connect and transmit signals through synapses. The size or efficiency of the signal transfer function of synapses is not static. When and how the synaptic efficiency changes is called synaptic plasticity, which mainly includes two kinds of abilities: one is the control ability of self-movement and the other is the control ability of external manipulation. The model structure of cerebellar model articulation controller (CMAC), which simulates the characteristics of human brain participating in motion control and the structure of neural network, is a local neural network based on table query input and output. Because of its good nonlinear approximation ability, it has been widely used in nonlinear real-time control in complex dynamic environment such as system control in recent years.

The principle of human brain nerve network structure is shown in Figure 1, where, S is an n-dimensional input vector space, A is an associative memory space, and Y is an output response vector. Each vector in the input space S is quantized and fed into the memory area A, and each input variable Si activates C consecutive memory cells in the memory area A. The network output yi is the accumulation result of the values (i.e., weights wi) of C corresponding units. For a certain input sample, the weight can always be adjusted to reach the desired output value. As can be seen from Figure 1, each input sample corresponds to C units in the memory area A. When each sample is dispersed and stored in area A, the closer samples in S will overlap in A, and their output values are close, that's, the C units follow the principle of "input adjacent and output close". This phenomenon is called the local generalization characteristic of CMAC neural network. C is the generalization parameter. The bigger C is, the greater the effect on the mapping relation of samples is, and the better the generalization ability is.

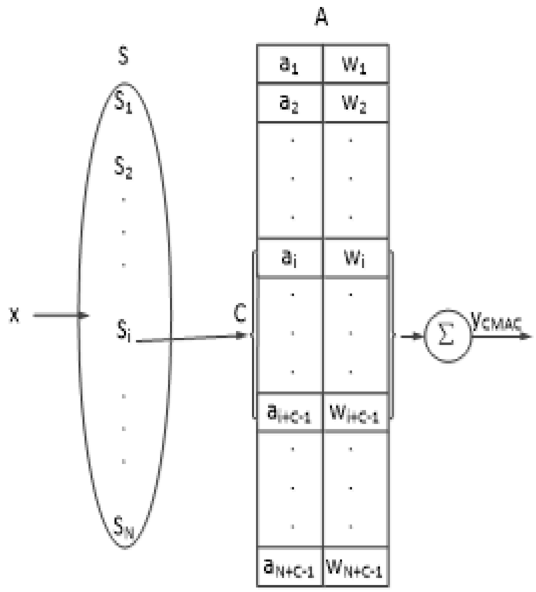

Figure 1. Principle of human brain nerve network structure

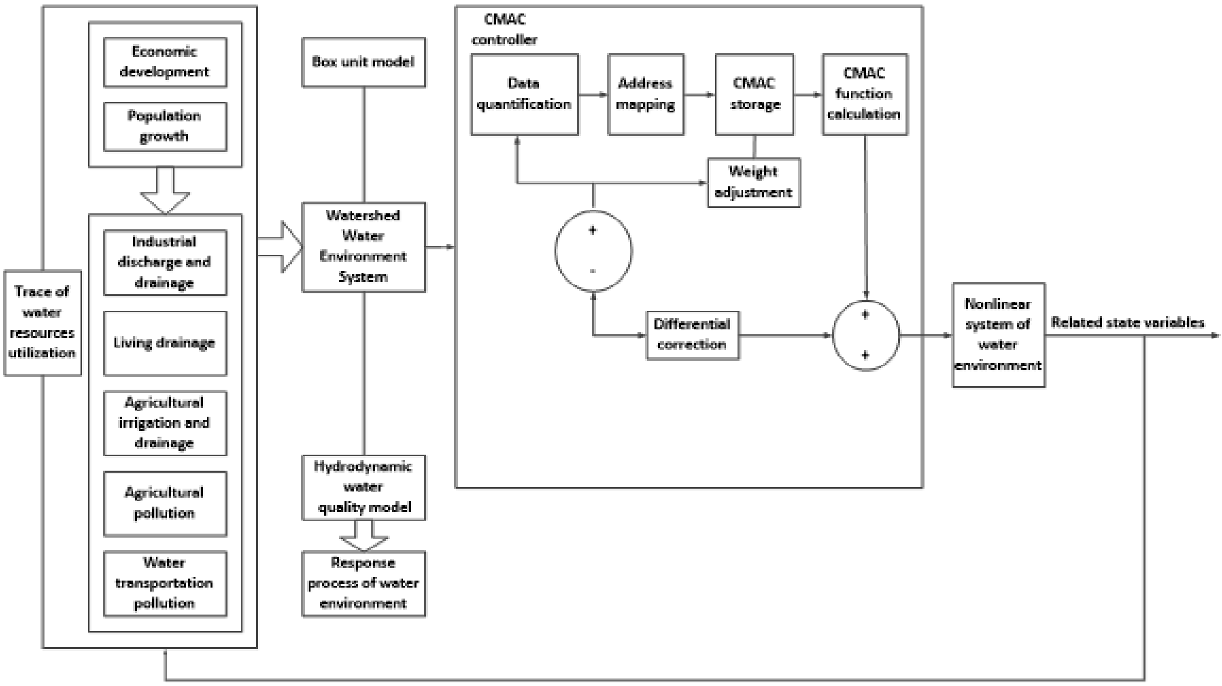

Figure 2. Neural network model of human brain neural network structure in watershed water environment system

Differential Correction of Watershed Water Environment System and Structure Fusion of Human Brain Neural Network

The watershed water environment system model simulating the structure of human brain nerve network is based on the expected track of water resources development and utilization, and extends the differential correction control idea of the model to the linear dynamic characteristics of the watershed water environment system, and uses the above CMAC model to carry out nonlinear correction to the conventional differential correction control algorithm. Furthermore, the strong nonlinear time-varying problem of watershed water environment system is solved. The control model of differential correction+CMAC for watershed water environment system is shown in Figure 2.

In the model, the ideal variable limit and the actual variable limit are the input values of the controller. The ideal variable limit is taken as the control input of differential correction, the limit error value (the difference between the ideal variable limit and the actual variable limit) is quantized and taken as the input of the CMAC, and the CMAC control output is calculated by functions through the address mapping and space storage of the CMAC controller. This is added to the differential correction control output as the water environment system response level. At the same time, the error value is passed to the CMAC control part to adjust its weight value and thus obtain the ideal control output value.

CMAC uses the control algorithm. At the end of each control period, the corresponding CMAC output is calculated and compared with the total control input to correct the weight and enter the limiting process. The purpose of the limits is to minimize the difference between the total control input and the output of the CMAC. Through the cyclic action of CMAC, the total control output of the system is generated by CMAC. Conventional control uses a conventional differential correction control algorithm:

$$u_p(k)=C_0(1+T_cS)\ddot{y}^{*} \tag{1}$$

$$u_n(k)=\sum_{i=1}^{C}w_ia_i \tag{2}$$

$$\delta_{sw}(k)=u_p(k)+u_n(k) \tag{3}$$

At the end of each control period, the CMAC output un(k) is compared with the total control amount u(k) to correct the weight wi and enter the cyclic process. The adjustment index of CMAC is

$$\Delta w(k)=\eta\frac{u(k)-u_n(k)}{C}a_i=\eta\frac{u_p(k)}{C}a_i \tag{4}$$

$$w(k)=w(k-1)+\Delta w(k)+\alpha[w(k)-w(k-1)] \tag{5}$$

Where, a_i is a binary selection vector; C is the generalization parameter of CMAC network; un (k) is the corresponding output generated for CMAC; up (k) is the output generated by the conventional differential correction control; η is the limiting rate, η∈(0,1); α is inertial quantity, α∈(0,1).

Neural Network Simulation of Human Brain in Watershed Water Environment System

In that process of development and repeated practice, human acquired movement gradually forms an optimized neural network in the central nervous system through the experience of success and failure to carry out programmed control of the movement, which includes the selection and division of the muscle participating in the movement and the setting of the muscle contraction sequence, speed, strength, etc. Programming makes the complex movement control simple with the spontaneity, and repeated practice makes the neural network or the movement control program optimize unceasingly, and form the energy-saving and the high-efficient movement pattern. In order to effectively reflect that dynamic characteristics of variable movement in watershed water environment system and carry out simulation calculation of control algorithm, a nonlinear watershed water environment system model is established, and the simulation of expected water resource exploitation trajectory-hydrodynamic water quality-water environment response under the condition of watershed water environment system is carried out.

Take Hanjiang River Basin of China as an example, Hanjiang River is one of the four major rivers in Guangdong Province, with a total length of 470 km², the average gradient of 0.40 per thousand; the drainage area of 30,112 km², including 17,851 km² in the province, average annual rainfall of 1,600 mm, the average annual runoff of 27.4 billion m³, including the average annual flow in the province of 15.73 billion m³, the measured flow at Chaoan control station of 13,300 m³/s, and the minimum of 33m³/s.

Figures 3 to 5 show trajectory simulation curves of watershed water environment system of 40%, 80% and 100% double-shift line test and snaking test of human brain nerve network structure, respectively. The simulation test is designed according to the stability test standard of watershed water environment system.

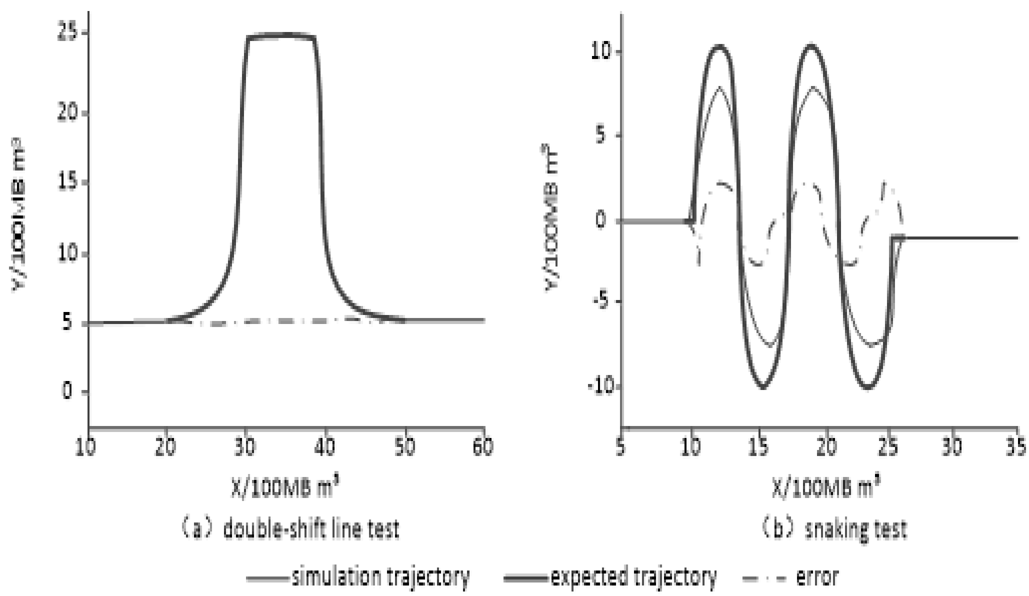

Figure 3. 40% simulation calculation curve

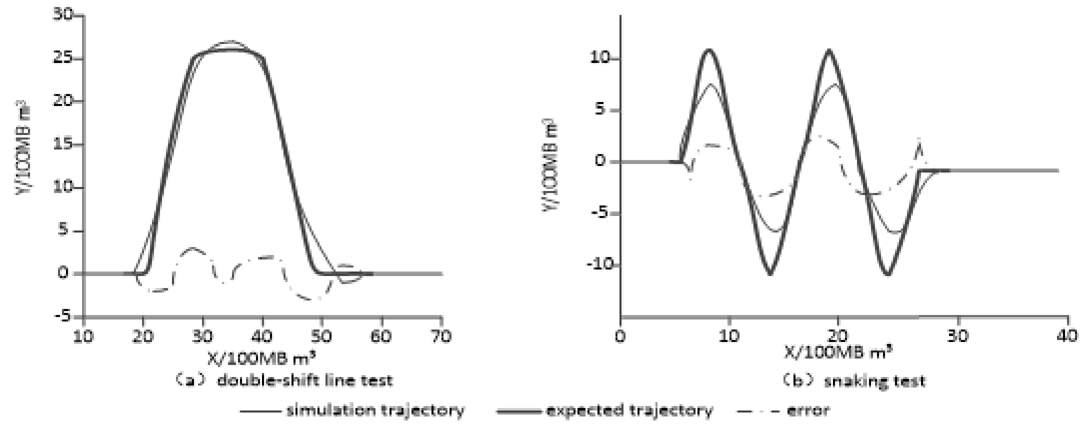

Figure 4. 80% simulation calculation curve

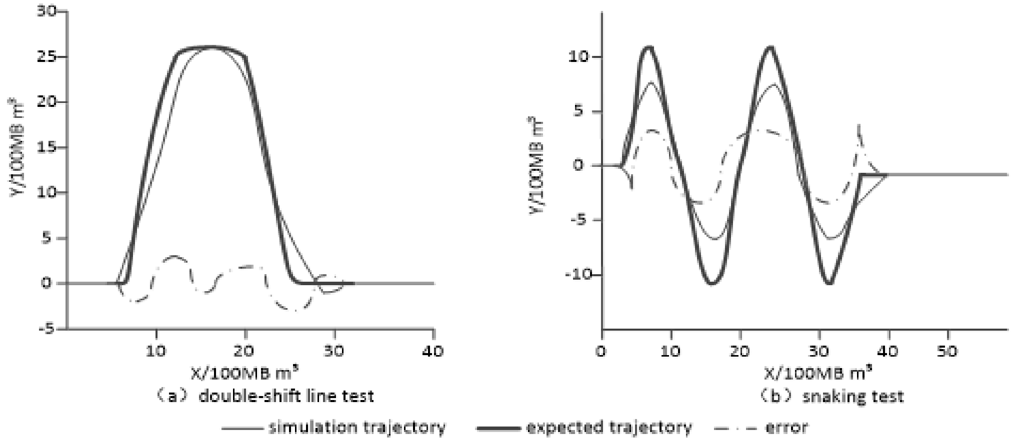

Figure 5. 100% simulation calculation curve

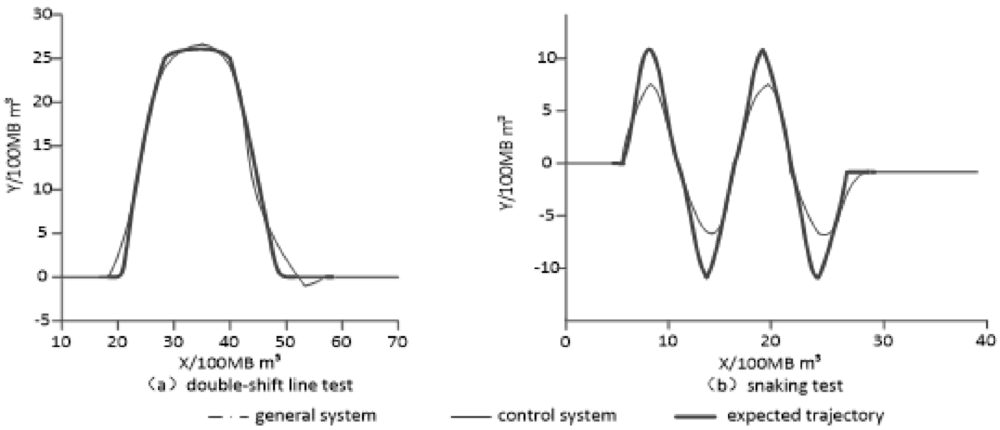

Figure 6. Comparison test of water environment with 80% different adhesion coefficients

It can be seen from Figure 3 that the CMAC control algorithm can well control the watershed water environment system to follow the expected operation, and its control effect reflects the good trajectory following performance of the watershed water environment system cycle and the adaptive ability of the algorithm.

In order to further verify the robustness of the algorithm to the watershed water environment, simulation experiments under the coefficients are carried out in this paper. The watershed water environment coefficients are set as the normal flow velocity of 1.04 and the lower limit of 0.35 respectively.

Figure 6 is a curve comparing the control results of double-shift line and snaking test with 80% coefficients of the watershed water environment circulation system simulating the structure of the neural network of the human brain. It can be seen from the figure that there is basically no difference in the control trajectory between the lower limit case and the normal case, indicating that both have good control capability and exhibit strong robustness.

To sum up, the differential correction + neural network structure controller proposed in this paper can well simulate the real situation of watershed water environment coefficients. In general, if the variable dynamics is in the linear region and the conventional differential control has small error, the watershed water environment coefficients can be well controlled, and then CMAC control is not effective. When the variable dynamics enters the non-linear region, that's, the CMAC controller is used to correct the errors caused by the conventional differential correction control, it works together with the differential correction to achieve a good following control capability.

Conclusions

In this paper, the neural network control model is used to simulate a nonlinear control model of flow correction behavior in the micro-simulation of water environment system based on the macro-simulation of control structure of water environment system. The model uses the CMAC network of the human motion control center (cerebellum) to correct the control error of the differential correction model of the watershed water environment system, and effectively solves the parameter identification faced by the traditional differential correction control model in dealing with nonlinear problems. The simulation results of normal flow velocity and lower limit flow velocity show that the model can effectively control the flow of watershed water environment system according to the expected numerical value, reflect better trajectory following ability, and has strong adaptability and robustness to the dynamic uncertain factors such as normal and lower limit flow processes.

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