DIRECT FUZZY NEURAL CONTROL FOR TRAIN TRAVELING PROCESS①

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ABSTRACT A novel methodology to realize the automatic train operation is proposed based on a direct fuzzy neural control scheme that is functionally equivalent to the conventional fuzzy controller. Firstly, the structure, train pattern coding method and inference criteria of the proposed fuzzy neural controller were described in details. Then, based on the idea of process partition of complex process, the mathematics description of train traveling process was provided. Finally, a group of simulation results for train traveling process was compared with the human driver's control. The results have demonstrated the effectiveness of the proposed approach.

Key words ATO(automatic train operation) fuzzy controller train traveling process process partition

1 INTRODUCTION

In recent years, the automatic train operation (ATO) system has been one of research focuses in the field of railway automation over the world with the development of micro-computer technology. However, these ATO systems are usually inferior to skilled human operator due to the complexity of controlled process. It is well known that the train traveling process is affected by many uncertain factors and belongs to a complex dynamic process that is hard to be modeled by using conventional identification method. Under different working conditions, the control objectives and control strategies are so different with the varying process characteristics[1, 2] that those ATO systems based on conventional control theory are hard to meet the requirements of the process. Therefore, based on experienced driver's knowledge, the intelligent control systems for the train traveling process have been proposed during the past ten years, including Yasumobu's fuzzy ATO[3, 4] and Jia's FMOC (Fuzzy Multiobjective Optimal Control) ATO[1, 2]. Although these systems have approached encouraging results with the computer simulations and practical applications, including field-test, the existing common drawbacks are the following two aspects:

(1) The partition of fuzzy linguistic variables and the shapes of membership function, which are excessively dependant on the expert's experience, are usually hard to on-line adjusting.

(2) Fuzzy inference methods are not adaptive enough.

In one word, it is difficult to further improve the ATO system performance just using fuzzy control method.

In this paper, we incorporate the learning ability of neural network into the fuzzy system to form a direct fuzzy neural control for train traveling process. This integrated controller which comprises the complementary characteristics of fuzzy system and neural network improves the adaptability of the conventional fuzzy system for the changing system parameters[5, 6].

① Supported by the National Natural Science Foundation of China Received Apr. 17, 1996; accepted Oct. 4, 1996

2 FUZZY NEURAL CONTROLLER

Fuzzy control and neural network are two promising and fruitful branches of intelligent control[7, 8]. In recent years, the fusion research of fuzzy control and neural network has been an active area because that they are complementary and ideal tools to achieve linguistic knowledge representation and the adaptive knowledge evolution, the two essential features in human controls[2, 9, 10]. Currently, the integrating methods can be mainly divided into two aspects: one is to realize the fuzzy control system directly through structurally equivalenting to fuzzifier, fuzzy rule base and defuzzifier by using corresponding neural network, respectively[11, 12]. In this method, the knowledge structures of the original fuzzy system are contained with the burden of slowly learning speed. Another approach is functional equivalent to fuzzy system by neural network[2, 6]. In our fuzzy neural controller, the second integrating method is considered.

2.1 Architecture

The basic fuzzy system which performs a mapping from crisp $U \subset R^n$ to crisp $V \subset R^m$ comprises four components[14]:

(1) Fuzzy rule base consisted of fuzzy rules describes how the fuzzy system performs.

(2) Fuzzy inference engine determines a mapping from the fuzzy sets in the input space $U \subset R^n$ to the fuzzy sets in the output space $V \subset R^m$.

(3) Fuzzifier maps the crisp value in the input space into fuzzy sets.

(4) Defuzzifier maps the fuzzy sets in the output space into crisp values.

The core of the whole fuzzy system is the fuzzy rules which are in the form of "IF A is A_k and B is B_k THEN C is C_k". Each fuzzy rule defines a fuzzy relationship between the input space and the output space corresponding to a fuzzy implication "A_k, $B_k \rightarrow C_k$". The input fuzzy sets A and B active one or more fuzzy rules and can get corresponding output fuzzy set C by implementing fuzzy inference. This can be described as follows: "$F: A \times B \rightarrow C$" which approximates a nonlinear mapping between variables. On the other hand, neural network which is also an ideal tool for performing a nonlinear mapping, has been proved that a continuous function can be approximated arbitrarily well by multilayer neural network[2]. The similar nonlinear mapping, approximation ability of fuzzy system and neural networks provide a chance for integrating the learning ability of neural network into fuzzy system. Therefore, we adopt a multilayered forward neural network to implement the mapping in the fuzzy system. Without losing generality, the fuzzy system is considered, which has two input variables, one output variable and a total of five layers. Nodes at layer one are input nodes (linguistic nodes) which represent input linguistic variables and no weights relating to layer two. Layer five is the output layer which performs the defuzzification process. In this situation, the COA (center of area) method is used . The layer two consists of membership function nodes which represent the all fuzzy sets of input linguistic variables and complete the mapping from the crisp input values to fuzzy values. Layer three is the middle layer whose nodes has no clear meaning. Nodes at layer four represent the points in the discrete universe of discourse of output variable which range from -6 to 6. It is obvious that the links $[W_{ij}]$ at layer two and $[W_{jk}]$ at layer three are trained to store the fuzzy control rules. The active functions of nodes at layer three and layer four are sigmoid function as follow:

$$\Phi(x) = 1/(1+e^{-x})$$

With this five-layered structure of the proposed connectionist model, the whole process of fuzzy system from fuzzification, fuzzy inference to defuzzification can be performed through the forward calculation of the neural network. In the following, the building of fuzzy relations, i. e., the memory of fuzzy rules by connectionist model is discussed.

2.2 Building fuzzy relationships

The fuzzy relationships of the fuzzy system, i. e., the fuzzy rule base can be parallel stored in the weights of the neural network by the learning procedure. For convenience of discussion, suppose we have a fuzzy controller with two input (A and B) and one output C. The fuzzy sets of A, B and C are defined as { NB, NM, NS, ZE, PS, PM, PB } whose membership functions are triangular shape(see Fig. 1) .

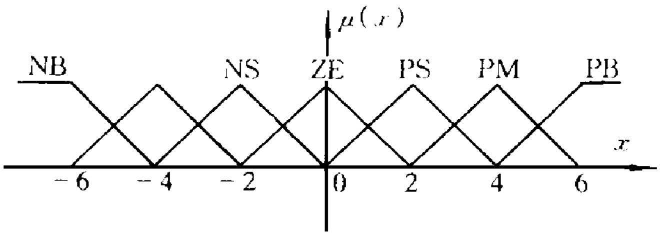

Fig. 1 Membership function

The fuzzy rule base comprises the following 6 rules:

R_1: IF(A is PB and B is PB) THEN C is PB.
R_2: IF(A is PM and B is PB) THEN C is PM.
R_3: IF(A is PS and B is PS) THEN C is ZE.
R_4: IF(A is PM and B is NB) THEN C is NM.
R_5: IF(A is PS and B is NM) THEN C is NS.
R_6: IF(A is PS and B is NS) THEN C is ZE.

Thus, the outputs of layer two corresponding to the degree of membership of input fuzzy sets can be represented as Formula (1) .

$$[\mu_{NB}(a),\ \mu_{NM}(a),\ \dots,\ \mu_{PM}(a),\ \mu_{PB}(a),\ \mu_{NB}(b),\ \mu_{NM}(b),\ \dots,\ \mu_{PM}(b),\ \mu_{PB}(b)] \tag{1}$$

The outputs of layer four are the degree of membership of output fuzzy set which can be represented as Formula (2) .

$$[\mu_c(-6),\ \mu_c(-5),\ \dots,\ \mu_c(-1),\ \mu_c(0),\ \mu_c(1),\ \dots,\ \mu_c(5),\ \mu_c(6)] \tag{2}$$

The corresponding training samples can expressed as follows, e. g. , for rule R_1, there are

input sample:

[0, 0, 0, 0, 0, 0, 1; 0, 0, 0, 0, 0, 0, 1]

output sample:

$$[0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0.5,\ 1,\ 0.5,\ 0] \tag{3}$$

For other rules, the training samples are similar to Formula (3) .

Based on the learning samples, the error back propagation learning algorithm is adopted to train the neural network. After learning, the whole fuzzy rules can be kept in the weights of network. The increase and/ or updating of the rules can be completed by increasing and/ or updating the train data sets. Moreover, the calculation burden are relatively small.

2.3 Fuzzy inference

The fuzzy inference of the original fuzzy system can be implemented by the parallel calculation of the fuzzy neural network based on the following two principles:

(1) When the input fuzzy sets A and B are similar to A_k and B_k, the fuzzy implication (A_k, $B_k \rightarrow C_k$) is active, then the output fuzzy set C is similar to C_k.

(2) When the input fuzzy sets are different from the sample fuzzy sets, several fuzzy implications (sample fuzzy rules) will be active with different degree, then the output is the nonlinear interpolation of the corresponding activated rules. The influence of a given rule on the output depends on how closely an input pattern matches the input training pattern for that rule. In other words, the influence of a rule is inversely proportional to the distance between the presented input pattern and the pattern used for training.

3 MATHEMATICS DESCRIPTION OF TRAIN TRAVELING PROCESS

Train traveling process is very complex and affected by many uncertain factors, such as railway conditions (curve and gradient), traveling speed, environment (weather) and working conditions. It is hard to give the accurate mathematical model of train traveling process. Therefore, from the engineering practice point of view, we use the following model:

$$\frac{\mathrm{d}v}{\mathrm{d}t} = \zeta \cdot f(n,\ v) = \zeta \cdot \frac{F(n,\ v)}{G + P} \tag{4}$$

where ζ —acceleration coefficient, usually equals to 120 for electric train; $f(n, v)$ —unitary joint effort; n —control notch; v —traveling speed; P —weight of locomotive; G —total weight of wagons; $F(n, v)$ —joint effort.

$$F(n,\ v) = F_q(n,\ v) - B_d(n,\ v) -$$

$$B_p(r, v) - (P + G) \cdot [W_0(v) + W_1(v)] \quad (5)$$

where $F_q(n, v)$ —the tractive force of locomotive; $B_d(n, v)$ —the power-braking force of locomotive; $B_p(n, v)$ —the pneumatic braking force; r —the pressure decrement on pneumatic pipe; $W_0(v)$ —the basic resistance of the train; $W_1(v)$ — the additional resistance due to the curve, gradient and tunnels etc.

According to the features of the train traveling process under different working conditions, it is partitioned into five characteristically distinguishable subprocesses with different control objectives which are SUP1(speed-up-from-still subprocess), SUP (speed-up subprocess), CSP (constant speed subprocess), SAP(speed-adjusting subprocess) and TSP (train stopping process). In different subprocesses, the force $F(n, v)$ is different. Therefore, we have five different models of process corresponding to different subprocesses and need five fuzzy neural controllers which comprise five groups of different control rules. In the next section, we give out the close-loop control system diagram based on the fuzzy neural controller and simulation results.

4 SIMULATIONS

The close-loop control system of train traveling process based on the proposed fuzzy neural controller is shown in Fig. 2.

We choosed an 8 k electrical locomotive as a typical simulation model which drives the train of 1 000 t traveling on a typical line including several sections with different environment conditions. We have five fuzzy neural controller corresponding to different subprocess. For instance, for SUP subprocess, we adopt $V_p = V_0 - V$ (the difference of given speed and traveling speed) and $V_s = V_0 - V_d$ (the difference of given speed and control degree designing speed) as the input variable of the network, while the change of traction notch DPN as output variable. Layer three has 8 nodes and initialized weights of neural network are random values in [- 0. 5, 0. 5]. BP learning algorithm is adopted to train the controller and the learning rate is 0. 15 while the error tolerance is 0. 01.

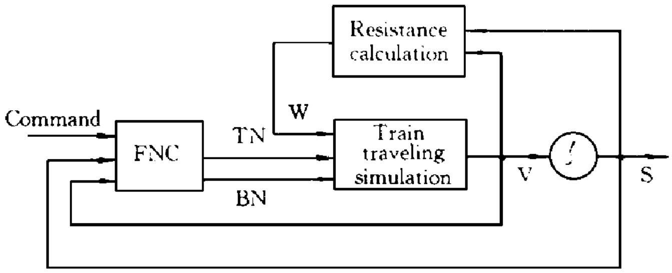

Fig. 2 The diagram of close-loop control system

A group of simulation results for five subprocesses compared with a human driver's control results are shown in Fig. 3. From the curves, we can find that the control results of proposed fuzzy neural controller is satisfying with the decrease of the change time of notch compared with a skilled driver's control, thus the riding comfort, energy saving and traceability performance indices can be met simultaneously.

5 CONCLUSIONS

A novel scheme for implementing automatic train traveling operation based on fuzzy neural controller was proposed and the simulation results was satisfying. As a part of project "Intelligent control of high-speed train", the proposed approach provided a meaningful attempt to achieving the adaptive fuzzy system by incorporating neural network into fuzzy system. Future research will focus on the following aspects:

(1) Modeling of complex dynamic system based on fuzzy neural networks.

(2) Research on more efficient learning algorithm superiority over the traditional back-propagation learning algorithm adopted in this paper.

(3) Conversion from the control rules extracted from expert's experiences to training data sets, for example, one fuzzy control rules may correspond to a group of training samples.

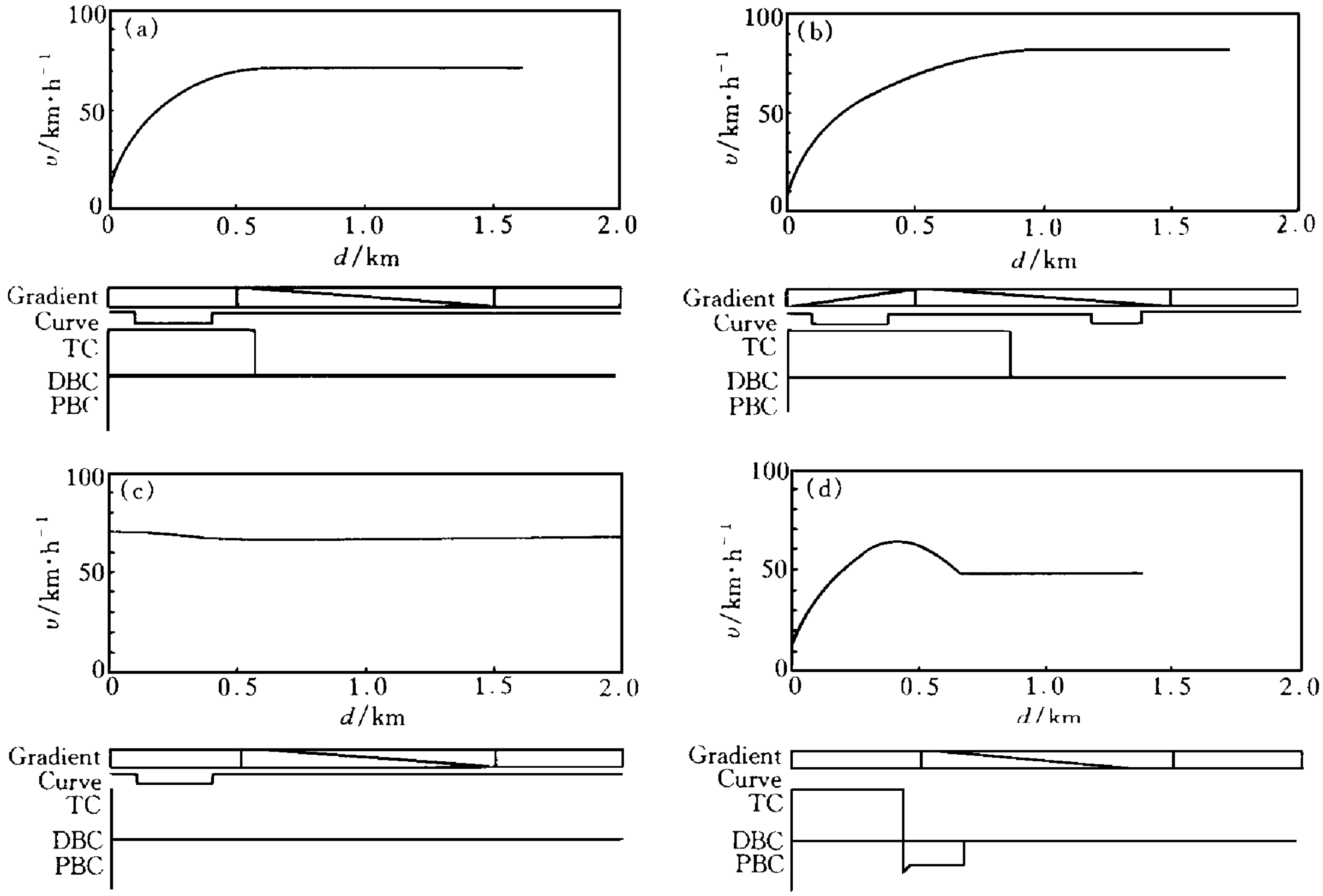

Fig. 3 Simulation results

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(Edited by He Xuefeng)