Direct Fuzzy Neural Control with Application to Automatic Train Operation*

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Abstract: This paper proposes a novel methodology to perform the automatic train operation based on direct fuzzy neural control scheme which is functionally equivalent to the conventional fuzzy controller. Firstly, based on the idea of the partition of the complex process, the mathematic description of train traveling process is provided. Then, the structure, training sample coding method, learning algorithm and inference criteria of the proposed fuzzy neural controller are described in details. Finally, a group of simulation results for the train traveling process are compared with the human driver's control. The results have demonstrated the effectiveness of the proposed approach.

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

1 Introduction

In recent years, the automatic train operation (ATO) system has been one of the research focuses in the field of railway automation all over the world with the developments of microcomputer technologies. However, these ATO systems are usually inferior to skilled human operators due to the complex of the controlled process. It is well known that the train traveling process is affected by many uncertain factors and belongs to a kind of complex dynamic process whose accurate mathematic model is hard to be obtained by using the conventional identification methods. Under different working conditions, the control objectives and control strategies are so different with the varying process characteristics[1,2] that conventional control theories based ATO systems are hard to meet the requirements of the varying processes. Therefore, the experienced driver's knowledge based 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]. These intelligent ATO systems aim to form controllers directly with the control rules extracted from the skilled drivers' experiences based on the fuzzy sets theory by Zadeh[5] which is an effective method dealing with the uncertainty and vagueness of the

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process without considering the accurate mathematic model of the process. Although these ATO systems have got some encouraging results with the computer simulations and practical applications, their common existing drawbacks include the following two aspects: 1) The partitions of the fuzzy linguistic variables and the shapes of the membership functions which excessively depend on the experts' experiences are usually hard to be on-line adjusted; 2) The fuzzy inference methods are not adaptive enough. In one word, it is difficult to further improve the performances of the ATO systems by merely using the conventional fuzzy control methods.

In this paper, we incorporate the learning ability of the neural network into the fuzzy system to form a direct fuzzy neural controller for the train traveling process. This integrated controller which comprises the complementary characteristics of fuzzy system and neural network can improve the adaptive ability of the conventional fuzzy system with the changing system parameters. Moreover, this implementation has the potentialities of high-speed processing of rules if the network is realized in hardware.

2 Mathematic Description of the Train Traveling Process

2.1 Problem Statement

The train traveling control is a process where the operator (human or machine) drives the train based on the railway signals which include railway conditions (such as gradients, curves), train current speed, traveling commands, disturbances and so on. The major objective of train traveling control system is to operate the train safely, punctually and economically. And the system realizes the train speed control according to the distance from the preceding train, the conditon of the section to be entered and the allowable velocity assigned by either signaling system or traffic control system.

Generally, the problem can be stated as follows[1,2]:

Given: 1) Description of train operation process: $\frac{dv}{dt} = f(C,E,V,N,L,\cdots)$;

2) Safety, time and other physical constraints: $C_s, C_t, C_p, \cdots$;

3) Target speed: V_0(or speed pattern: $V_0(t,s)$).

Find control sequence: $N_1, N_2, \cdots, N_n$, such that $V \to V_0(V_0(t,s))$.

Where V,C,E,N,L denote the variables of functions characterizing the train speed, marshaling status of the trains, track condition, control notch and tracking and braking characteristics of the locomotive, respectively.

2.2 Train Traveling Process modeling

From the engineering practice point of view, the complex dynamics of the train traveling process can be represented by the following approximate kinetic equations:

$$\frac{dv}{dt} = c \cdot f(n,r,v) = c \cdot \frac{F(n,r,v)}{P+G}, \tag{1}$$

$$F(n,r,v) = F_q(n,v) - B_d(n,v) - B_p(r,v) - (P+G)[W_0(v) + W_i(j,R)], \tag{2}$$

where c: acceleration coefficient of the train (km/h^2), usually equal to 120 for electric train; n: control notch; r: air pressure decrement in the pneumatic pipe (KPA); v: train traveling speed (km/h); P: weight of the locomotive (kN); G: total weight of all vehicles (kN); $f(n, r, v)$: unitary composite force (N/kN); $F(n,r,v)$: composite force (kN); $F_q(n,v)$: traction force of the locomotive (kN); $B_d(n,v)$: powerbraking force of the locomotive (kN); $B_p(r,v)$: air braking force (kN); $W_0(v)$: basic unitary running resistance of the train (N/kN); $W_i(j,R)$: unitary additional resistance due to the slope, curve and tunnels (N/KN). j: the grade of slope; R: the radius of the curve.

According to the features of the train traveling process under different working conditions and the idea of "Partitioning complex process and Hierarchical intelligent control"[2,6,8], the whole train traveling process from start to stop can be partitioned into five subprocesses whose characteristics are relatively stable.

1) The speed-up-from-still subprocess (SUP1)

$$\frac{\mathrm{d}v}{\mathrm{d}t} = \frac{c \cdot [F_q(n,v) - W_q(v)]}{P+G}, \quad v \leqslant 10 \text{ km/h}, \tag{3}$$

$$\frac{\mathrm{d}v}{\mathrm{d}t} = \frac{c \cdot [F_q(n,v) - W(v)]}{P+G}, \quad v > 10 \text{ km/h}, \tag{4}$$

where $W_q(v)$ and $W(v)$ denote the running resistance under the starting and traction operational modes respectively.

$$W_q(v) = W'_q(v) \cdot P + W''_q(v) \cdot G + i_q(P+G), \tag{5}$$

where $W'_q(v) = 5\text{N/kN}, \quad W''_q(v) = 3 + 0.4 i_q \text{ N/kN}.$

$$W(v) = W'_0(v) \cdot P + W''_0(v) \cdot G + i_j(P+G), \tag{6}$$

where $W'_0(v), W''_0(v)$ are the unitary basic resistance on the locomotive and wagons in powering mode.

2) The smoothly speedup subprocess (SUP)

$$\frac{\mathrm{d}v}{\mathrm{d}t} = c \cdot \frac{F_q(n,v) - W(v)}{P+G}. \tag{7}$$

3) The constant-speed-subprocess (CSP)

$$\frac{\mathrm{d}v}{\mathrm{d}t} = c \cdot \frac{F_q(n,v) - B_d(n,v) - W(v)}{P+G}. \tag{8}$$

4) The speed-adjusting subprocess (SAP)

$$\frac{\mathrm{d}v}{\mathrm{d}t} = c \cdot \frac{-B_d(n,v) - W(v)}{P+G}. \tag{9}$$

5) The train-stop braking subprocess (TSP)

$$\frac{\mathrm{d}v}{\mathrm{d}t} = c \cdot \frac{-B_p(r,v) - W(v)}{P+G}. \tag{10}$$

From the preceding statements, it is noticed that the key problem to solve the equations is the force calculations (traction power, resistance and braking power). Based upon the engineering experiments, the traction characteristics and braking characteristics of the locomotive have been derived and a series of force curves can be obtained. Thus, the approximate force calculation formula can be obtained by decentralizing the notch characteristics into multi-level[6,7].

3 Fuzzy Neural Controller

3.1 Architecture

The basic fuzzy system performs a mapping from crisp $U \subset \mathbb{R}^n$ to crisp $V \subset \mathbb{R}^m$[9] and 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 relation between the input space and the output space corresponding to a fuzzy implication "$A_k, B_k \to C_k$". The input fuzzy sets A and B active one or more fuzzy rules and can get corresponding output fuzzy set C by implementing fuzzy inferences. This can be described as "$F: A \times B \to C$" which approximates a nonlinear mapping between variables. Neural network is also ideal tool to perform a nonlinear mapping. It has been proved that a continuous function can be approximated arbitrarily well by a multilayered neural network[8]. The similar nonlinear mapping and approximation ability of fuzzy system and neural network 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. The architecture diagram is shown in Fig. 1. Without losing generality, we consider the fuzzy system which has two input variables and one output variable.

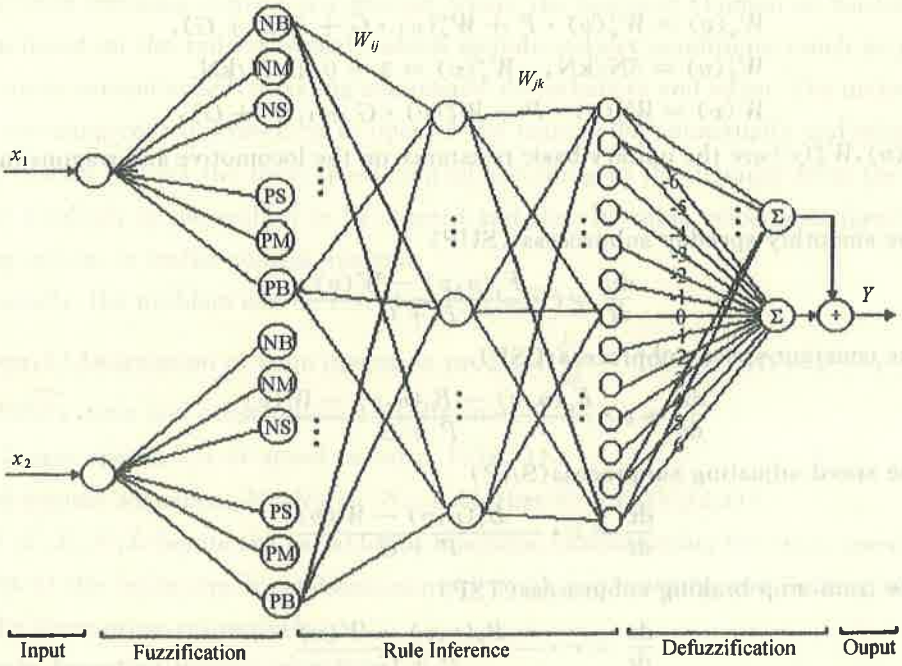


Fig. 1 The architecture of fuzzy neural controller

As Fig. 1. shown, the fuzzy system has a total of five layers. Nodes at the layer one are input nodes (linguistic nodes) which represent input linguistic variables and no weights relating to the layer two. The layer five is the output layer which performs the defuzzification process. In this situation, the COA[9] (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 the fuzzy values. The layer three is the middle layer whose nodes have no clear meaning. Nodes at layer four represent the points in the discrete universe of discourse of the output variable which are $[-6,-5,-4,-3,-2,-1,0,1,2,3,4,5,6]$. It is obvious that the links $[W_{ij}]$ at the layer three and $[W_{jk}]$ at the layer four are trained to store the fuzzy control rules. The active functions of nodes at the layer three and the layer four are sigmoid function $\phi(x)=1/(1+e^{-x})$. The input and output mapping relations between layers can be represented as follows:

Layer 1 $\quad I_i^1 = x_i,\quad O_i^1 = I_i^1,\quad i=1,2,$ (11)

Layer 2 $\quad I_{1j}^2 = O_1^1,\quad I_{2j}^2 = O_2^1,$ (12)

$$O_{1j}^2 = \mu_{x1(j)}(I_{1j}^2),\quad O_{2j}^2 = \mu_{x2(j)}(I_{2j}^2),\quad j=1,2,\cdots,6, \tag{13}$$

Layer 3 $$I_j^3 = \sum_{i=1}^{6} O_{1i}^2 \cdot W_{ij} + \sum_{i=1}^{6} O_{2i}^2 \cdot W_{i+6,j}, \tag{14}$$

$$O_j^3 = 1/(1+e^{(-I_j^3)}),\quad j=1,\cdots,8, \tag{15}$$

Layer 4 $$I_k^4 = \sum_{j=1}^{8} W_{jk} \cdot O_j^3, \tag{16}$$

$$O_k^4 = 1/(1+e^{(-I_k^4)}),\quad k=1,\cdots,13, \tag{17}$$

Layer 5 $$I^5 = \sum_{i=-6}^{6} i \cdot O_{i+7}^4, \tag{18}$$

$$O^5 = I^5. \tag{19}$$

The final output of the fuzzy neural network is:

$$Y = O^5 / \sum_{i=-6}^{6} O_{i+7}^4. \tag{20}$$

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.

3.2 A Simple Coding Scheme for Training Samples

The fuzzy relations 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, supposed we have a fuzzy controller with two inputs (x_1 and x_2) and one output Y. The fuzzy sets of x_1, x_2 and Y are defined as shown in Fig. 2(a) and Fig. 2(b).

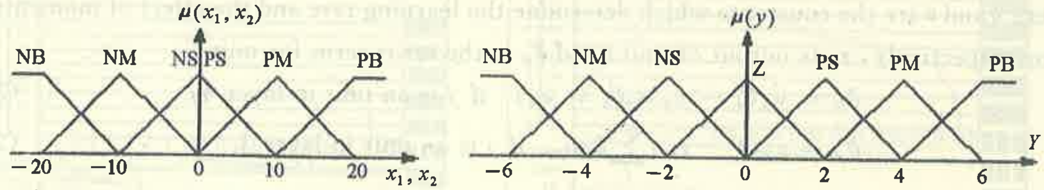


Fig. 2 (a) The fuzzy sets of input variables   Fig. 2(b) The fuzzy sets of output variables

In order to train the fuzzy neural controller, a simple coding scheme for training samples is introduced firstly.

The outputs of the layer two corresponding to the degree of membership of input fuzzy sets can be represented as (21).

$$[\mu_{NB}(x_1), \mu_{NM}(x_1), \mu_{NS}(x_1), \mu_{PS}(x_1); \mu_{PM}(x_1), \mu_{PB}(x_1), \mu_{NB}(x_2), \mu_{NM}(x_2), \mu_{NS}(x_2), \mu_{PS}(x_2), \mu_{PM}(x_2), \mu_{PB}(x_2)]. \tag{21}$$

The outputs of the layer four are the degree of membership of output fuzzy set which can be represented as (22).

$$[\mu_Y(-6),\mu_Y(-5),\mu_Y(-4),\mu_Y(-3),\mu_Y(-2),\mu_Y(-1),\mu_Y(0), \\ \mu_Y(1),\mu_Y(2),\mu_Y(3),\mu_Y(4),\mu_Y(5),\mu_Y(6)]. \tag{22}$$

Thus, corresponding to formulae (21) and (22), the training samples can be derived. For example, for control rule IF x_1 is PB and x_2 is PB THEN Y is PB, there are

Input sample: $$[\underbrace{0,\ 0,\ 0,\ 0,\ 0,\ 1}_{x_1};\ \underbrace{0,\ 0,\ 0,\ 0,\ 0,\ 1}_{x_2}]; \tag{23}$$

Output sample: $$[\underset{-6}{0},\ \underset{-5}{0},\ \underset{-4}{0},\ \underset{-3}{0},\ \underset{-2}{0},\ \underset{-1}{0},\ \underset{0}{0},\ \underset{1}{0},\ \underset{2}{0},\ \underset{3}{0},\ \underset{4}{0},\ \underset{5}{0.5},\ \underset{6}{1}]. \tag{24}$$

For other rules, the training samples are similar to (23) and (24).

Based on the learning samples, the error backpropagation (BP) learning algorithm is adopted to train the neural network. After learning, the whole fuzzy rules can be kept in the weights of the 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.

3.3 Learning Algorithm

As shown in Fig. 1, only the weights between the layer 2 and the layer 3, and the weights between the layer 3 and the layer 4 need to be adjusted by off-line training of the neural network. Based on the proposed coding scheme for training samples, we adopt the gradient descent based error backpropagation algorithm which minimizes the sum-squared error E between the target output and the actual output of the network to train the neural network.

$$E = \sum_k \sum_{i=1}^{m} (d_{ik} - y_{ik})^2, \tag{25}$$

where d_{ik} and y_{ik} are components of target output pattern and actual ouput pattern. To minimize E, the weights of the network are adjusted at each pattern presentation by the equation:

$$\Delta w_{ij}(k) = \eta\delta_{jk}z_{ik} + \alpha\Delta w_{ij}(k-1), \tag{26}$$

where η and α are the constants which determine the learning rate and the effect of momentum term, respectively, z_{ik} is output of unit i and δ_{jk} is the error term for unit j.

$$\delta_{jk} = y_{jk}(1-y_{jk})(d_{jk}-y_{jk}) \quad \text{if } j \text{ is an unit in layer 4;} \tag{27}$$

$$\delta_{jk} = z_{jk}(1-z_{jk})\sum_l \delta_l w_{jl} \quad \text{if } j \text{ is an unit in layer 3.} \tag{28}$$

3.4 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:

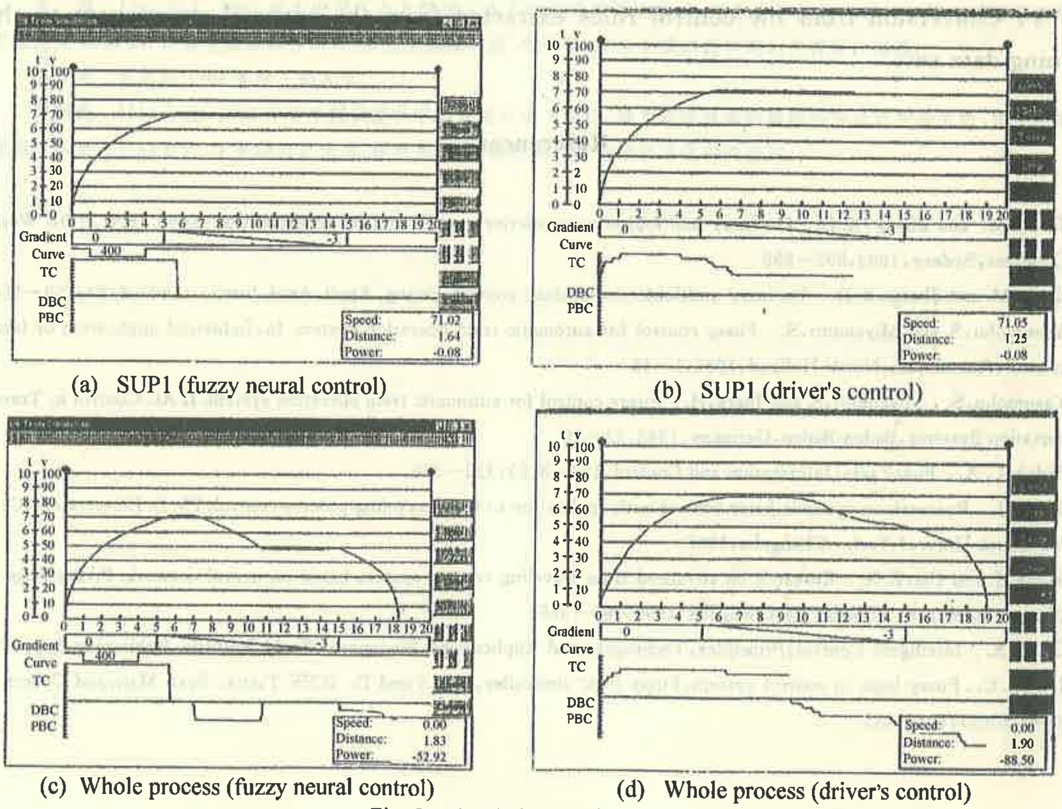
1) When the input fuzzy sets A and B are similar to A_k and B_k, the fuzzy implication $(A_k, B_k \to C_k)$ is activated, then the output fuzzy set C is similar to C_k.

2) When the input fuzzy sets are different from the sample fuzzy sets, several fuzzy implications (sample fuzzy rules) will be activated with different degrees, 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.

4 Simulations

We choose the 8k electrical locomotive as a typical simulation model which drive the train of 1000 tons traveling on a typical line including several sections with different environment conditions. We have five fuzzy neural controllers corresponding to different subprocesses. In general, the architectures of all fuzzy neural networks are similar to Fig. 1, except the adjusting of input variables and the universe of discourse of output variable. For instance, in the SUP subprocess, we adopt $V_p = V_0 - V$ (the difference between the given speed and the traveling speed) and $V_s = V_0 - V_d$ (the difference between the given speed and the control degree designing speed) as the input variables of the network, while the change of traction notch DPN as the output variable. The training samples are shown in formulae (23) and (24). The layer three has 8 nodes and the initialized weights of neural network are random values in [−0.5, 0.5]. The BP learning algorithm is adopted to train the controller and the learning rate is 0.75, momentum factor is 0.2 while the error tolerance is 0.01.



(a) SUP1 (fuzzy neural control)

(b) SUP1 (driver's control)

(c) Whole process (fuzzy neural control)

(d) Whole process (driver's control)

Fig. 3 Simulation results

(TC: Traction grade; PBC: air braking grade; DBC: power braking grade)

A group of simulation results are shown in Fig. 3 compared with a human driver's control results. The chosen railway for simulation includes one slope: gradient −3 from 500m to

1500m; one curve: radius 400m from 100m to 400m. Fig. 3(a) represents SUP1 subprocess of the train from still to 70km/h by fuzzy neural controller; Fig. 3(b) SUP1 subprocess by driver's operation; Fig 3(c) the whole train traveling proess (SUP1—SUP—CSP—SAP—TSP) by fuzzy neural controller; Fig. 3(d) the whole train traveling process by driver's control. From the curves, we can find that the control results of the proposed fuzzy neural controller are satisfying with the decrease of the change times of notch compared with a skilled driver's control results, thus the riding comfort, energy saving and traceability performance index can be met simultaneously.

5 Conclusions

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

1) Modeling of the complex dynamic system based on fuzzy neural networks;

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

3) Conversion from the control rules extracted from the experts' experiences to the training data sets.

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直接模糊神经控制及其在列车自动操纵中的应用

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摘要：本文基于模糊神经控制方法提出一种新的列车自动操纵策略. 首先基于复杂动态过程划分的思想,建立列车运行过程的五个子过程近似工程数学模型;接着对所提的模糊神经控制器的结构、训练样本编码方法、学习算法和推理准则作了详细的描述;文末利用所提控制方法对列车在一段特定的线路上作了仿真研究,结果表明了所提方法的有效性.

关键词：列车自动操纵; 模糊神经控制器; 列车运行过程; 过程划分

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