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Longitudinal Speed Tracking Control of Intelligent Vehicle Based on Adaptive Adjustment Incremental PID of the BP Neural Network Intelligent Algorithm

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Abstract – **At present, Many longitudinal speed tracking controllers of smart cars adopt the PID control algorithm. The PID controller's advantages of simple structure and easy reality are widely applied in industry. With the advantages of simple structure and easy reality, the controller is widely used in industry. But like most traditional controls, PID controllers do not apply to nonlinear-and time-varying systems, and can only be used for a fixed control object. The parameters of PID controllers need to be readjusted when the control objects are changed. In order to solve the problem, the paper uses a multi-layer feed forward neural network to adjust the PID parameters according to the different control objects, and makes it adaptive for a time-varying nonlinear longitudinal speed control system. The designed controller is verified by the matlab and carsim soft. It shows that the controller keeps the vehicle tracking error only within 0.05-0.06m/s, and the control system can respond quickly and achieve stability within 2 seconds when a signal mutation occurs. Thus, the effectiveness of the designed algorithm is demonstrated.**

Keywords – **BP Neural Network, Longitudinal Speed, Tracking, Incremental PID, Intelligent Vehicle.**

I. Introduction

Unmanned driving technology covers environment perception, positioning, decision-making and planning, and control. The control part is divided into horizontal and vertical control. The mutual influence of the two control parts determines the final running posture of the vehicle. It is one of the key technologies in unmanned driving technology. At present, many scholars and research institutions have carried out a series of researches on the longitudinal tracking control of unmanned vehicles. Jingjing Zhou [1] et al proposed an improved calculation of IPSO-MPC that combines particle swarm and model prediction. This algorithm is due to the introduction of inertia factors. So that the particles will not oscillate near the global optimal solution and the algorithm can converge due to the introduction of the shrinkage factor. It is verified by simulation that this algorithm effectively reduces the number of iterations and the calculation cost, and the tracking deviation of the speed is also small and meets the requirements. Zenghui Zhu [2] et al. used fuzzy control algorithms to design the controllers of the throttle and braking system separately according to the large lag, time-varying and nonlinear characteristics of traditional fuel vehicles, and the simulation verified that they can meet the tracking control of different accelerations. Wai-lok [3] uses a fuzzy radial basis algorithm to control the speed of the vehicle so that the vehicle keeps a certain distance from the drag. The advantage of this algorithm is that it does not require data training. Experiments have verified the effectiveness of this algorithm. Speed has better tracking effect. In addition, some scholars use model predictive control [4-5], particle swarm [6-8], synovial membrane control [7], fuzzy control [10-13], generalized predictive control algorithm, genetic algorithm [14-16], and other algorithms for tracking control of longitudinal speed. STANLEY, who participated in the DARPA Ground Challenge in 2005, used simple PI control. PID controller has always been the most widely used and most mature controller in the industry because of its simple structure, easy implementation and strong robustness. Although there are many new controllers emerging in the control field, PID still occupies a dominant position. In fact, the PID control law is a linear control law, and it also has the weakness that the traditional control theory is not suitable for uncertain systems, nonlinear systems, time-varying systems, and multivariable systems. It has more advantages in simple single-variable control systems. Good control effect, but poor effect in the control of complex systems. With the development of intelligent algorithm theory, many experts and scholars have begun to combine intelligent algorithm with PID algorithm to make it have the function of automatic diagnosis and improve the function of the control system. As we all know, the intelligent vehicle longitudinal control system is a time-varying, non-linear system. The PID algorithm is applied to the longitudinal control. It is necessary to adjust the PID parameters in real time to ensure the requirements of system control accuracy and ensure the safety of driving.

II. The Design of BP Network Adaptive Adjustment Incremental PID Controller

BP neural network is a kind of multi-layer feed forward neural network. Its main feature is the forward transmission of signals and the backward propagation of errors. The essence of BP neural network is a non-linear system, which has the ability to approximate arbitrary functions, and has strong information synthesis capabilities. It can process system information that is difficult to describe with models or rules. BP neural network is processing automatic systems that require high real-time performance. Control problems have great advantages. In recent years, with the continuous development and maturity of neural networks, intelligent control systems based on neural networks have received special attention in system identification, modeling, and adaptive control, especially its better it solves the modeling and control problems of complex systems with uncertainty, severe nonlinearity, time-varying and hysteresis [17]. Neural network has the advantages of high parallelism, high nonlinearity, good fault tolerance, self-learning, self-adaptive, and associative memory function. Therefore, the combination of BP neural network and PID is adopted. Through the self-learning adjustment of the weight coefficients of the network, the parameters of the PID controller are automatically adjusted to adapt to the nonlinear longitudinal speed tracking model and accurately track the time-varying desired speed.

PID control is based on the deviation e(t) between the given value and the actual output value to perform the proportional integral derivative operation and add the results to obtain the control output u(t). The expression of the PID algorithm in the continuous time domain is:

$$u(t) = k_p[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d \frac{de(t)}{dt} \qquad (1)$$

Where: k_p is the proportional coefficient, T_i is the integral time constant, and T_d is the derivative time constant.

Discretize formula 1.1, use a series of sampling moments to represent the continuous time t, replace the integral with the sum, and replace the differential with the increment.

$$t \approx kT(k = 0,1,2,....) \tag{2}$$

$$\int_0^t e(t)dt \approx T\sum_{j=0}^{K} e(jT) = T\sum_{j=0}^{K} e(j) \tag{3}$$

$$\frac{de(t)}{dt} \approx \frac{e(kT) - e(k-1)T}{T} = \frac{e(k) - e(k-1)}{T} \tag{4}$$

$$u(k) = k_p e(k) + k_i \sum_{j=0}^{K} e(j)T + k_d \frac{e(k) - e(k-1)}{T} \tag{5}$$

Where: k_p is the proportional coefficient, k_i is the integral coefficient, $k_i = k_p / T_i$; $k_d = k_p T_d$; $u(k)$ is the output value of the controller at the kth sampling time; $e(k)$ is the kth sampling time Enter the deviation of the control system; $e(k-1)$ is the deviation value of the control system at the (k-1) th sampling time; T is the sampling period.

The incremental PID control algorithm is introduced from formula 1.5, according to the recursive principle:

$$u(k-1) = k_p e(k-1) + k_i \sum_{j=0}^{K-1} e(j-1)T + k_d \frac{e(k-1) - e(k-2)}{T} \tag{6}$$

Subtract 1.6 from 1.5 to get the expression of the incremental PID control algorithm:

$$\Delta u(k) = k_p[e(k) - e(k-1)] + k_i e(k) + k_d[e(k) - 2e(k-1) + e(k-2)] = (k_p + k_i + k_d)e(k) - (k_p + 2k_d)e(k-1) + k_d e(k-2) \tag{7}$$

$$u(k) = u(k-1) + \Delta u(k) \tag{8}$$

In the incremental control, there is no need for accumulation, and the determination of the control increment is only related to the last three sampling values, so it is easier to obtain a better control effect through weighting.

The structure of PID control system based on BP neural network is shown in Figure 1. It is mainly composed of incremental PID, bp neural network and controlled system. The incremental PID controller directly performs closed-loop feedback control on the controlled system, and the neural network adjusts the three parameters of PID in real time according to the operating status of the system.

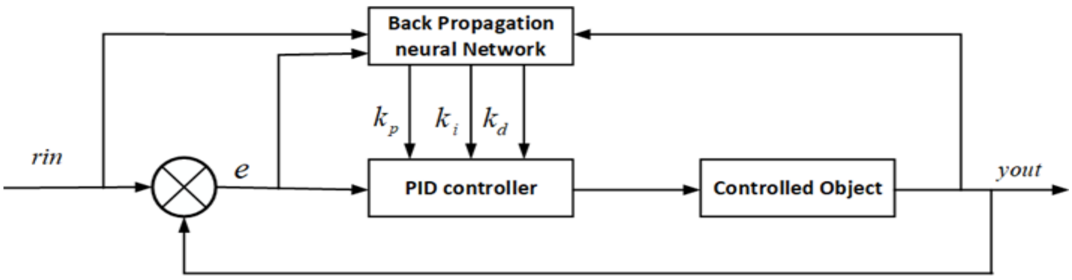

Fig. 1. The structure diagram of the BP neural network PID control system.

Figure 2 is the structure diagram of the bp neural network, where x_1, $x_2 \ldots x_n$, are the input values of the bp neural network, in this article are the expected input and the actual output of the control system, Y_1, $Y_2 \ldots Y_m$ are the output values of the neural network, in the article the three parameters k_p k_i k_d for pid, w_{ij} and w_{ji} are the weights of the BP neural network. In this way, the bp neural network can express the function mapping relationship from the expected input of 2 independent variables and the actual output to the 4 dependent variables k_p, k_i, k_d, u.

$$u(k) = f(u(k-1), k_p, k_i, k_d, e(k), e(k-1), e(k-2)) \tag{9}$$

The f relationship is a non-linear function mapping relationship, and BP neural network can be used to find an optimal control law.

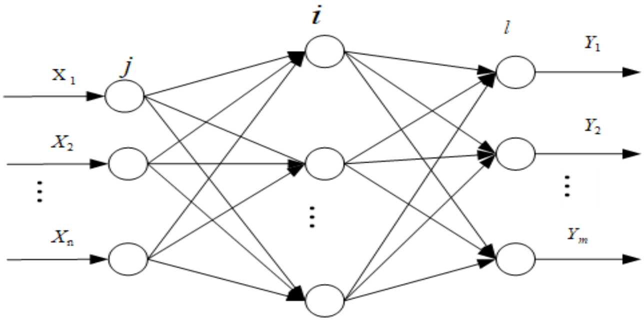

Fig. 2. BP neural network structure diagram.

This article uses a three-layer neural network, the input layer is

$$O_J^{(1)} = X(j)(j = 1, 2, ..., n) \tag{10}$$

Where n depends on the number of inputs

Input to the hidden layer of the network:

$$net_i^{(2)}(k) = \sum_{J=0}^{M} w_{ij}^{(2)} O_j^{(1)} \tag{11}$$

The output of the hidden layer is:

$$O_i^{(2)}(k) = f(net_i^2(k))(i = 1, 2, 3, ..., w) \tag{12}$$

Among them: $w_{ij}^{(2)}$ is the weighting coefficient of the hidden layer, and the superscripts (1), (2), (3) are the output layer, hidden layer and output layer.

The input of the output layer of the neural network is:

$$net_l^{(3)}(k) = \sum_{i=0}^{Q} w_{ij}^{(3)} O_i^{(2)}(k) \tag{13}$$

Output of the output layer:

$$O_l^{(3)}(k) = g(net_l^3(k))(l = 1, 2, 3) \tag{14}$$

$$O_1^{(3)}(k) = k_p \tag{15}$$

$$O_2^{(3)}(k) = k_i \tag{16}$$

$$O_3^{(3)}(k) = k_d \tag{17}$$

The activation function of the hidden layer neuron is the Signoid function.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{18}$$

The activation function of the hidden layer neuron is a non-negative Signoid function.

$$g(x)=\frac{e^{x}}{e^{x}+e^{-x}} \tag{19}$$

The performance index is:

$$E(k)=\frac{1}{2}(rink(k)-yout(k))^{2} \tag{20}$$

Adjust the weight coefficient of the network according to the gradient descent method, that is, search and adjust the negative direction of the weight coefficient according to E(k), and add a very small inertia term that makes the search quickly converge to the global.

$$\Delta w_{li}^{(3)}(k)=-\eta\frac{\partial E(k)}{\partial w_{li}^{(3)}}+\alpha\Delta w_{li}^{(3)}(k)(k-1) \tag{21}$$

In the formula: η is the learning rate; αis the inertia coefficient

$$\frac{\partial E(\mathrm{k})}{\partial\omega_{ij}^{(3)}}=\frac{\partial E(\mathrm{k})}{\partial y(k)}\cdot\frac{\partial y(k)}{\partial\Delta u(k)}\cdot\frac{\partial\Delta u(k)}{\partial O_{l}^{(3)}(k)}\cdot\frac{\partial O_{l}^{(3)}(k)}{\partial net_{l}^{(3)}(k)}\cdot\frac{\partial net_{l}^{(3)}(k)}{\partial\omega_{ij}^{(3)}} \tag{22}$$

$$\frac{\partial net_{l}^{(3)}(k)}{\partial\omega_{li}^{(3)}(k)}=O_{i}^{(2)}(k) \tag{23}$$

From the above formula, the following relationship can be obtained:

$$\frac{\partial\Delta u(k)}{\partial O_{1}^{(3)}(k)}=e(k)-e(k-1) \tag{24}$$

$$\frac{\partial\Delta u(k)}{\partial O_{2}^{(3)}(k)}=e(k) \tag{25}$$

$$\frac{\partial u(k)}{\partial O_{3}^{(3)}(k)}=e(k)-2e(k-1)+e(k-2) \tag{26}$$

The weight learning algorithm of the output layer of the neural network is as follows:

$$\Delta\omega_{li}^{(3)}(k)=a\Delta\omega_{li}^{(3)}(k-1)+\eta\delta_{l}^{(3)}O_{l}^{(2)}(k) \tag{27}$$

$$\delta_{l}^{(3)}=e(k)\,\mathrm{sgn}[\frac{\partial y(k)}{\partial\Delta u(k)}]\cdot\frac{\partial\Delta u(k)}{\partial O_{l}^{(3)}(k)}g^{'}(net_{l}^{(3)}(k))(i=1,2,3) \tag{28}$$

among them

$$g^{'}(\cdot)=g(x)(1-g(x)) \tag{29}$$

$$f^{'}(\cdot)=(1-f^{2}(x))/2 \tag{30}$$

The learning algorithm of the hidden layer weight coefficient is as follows:

$$\Delta\omega_{ij}^{(2)}(k)=a\Delta\omega_{ij}^{(2)}(k-1)+\eta\delta_{l}^{(2)}O_{j}^{(1)}(k) \tag{31}$$

$$\delta_i^{(2)} = f'(net_i^{(2)}(k))\sum_{l=1}^{3}\delta_l^{(3)}\omega_{li}^{(3)}(k) \quad (i=1,2,3,...,Q) \tag{32}$$

Where η is the learning rate and α is the inertia coefficient.

The main steps based on this algorithm are as follows:

(1) Determine the structure of the neural network, given the weighted initial value of each layer, as well as the learning rate η and the inertia coefficient α, , the value is 1 at this time.

(2) Sampling to get rink(k) and yout(k), calculate e(k);

(3) Calculate the input and output of each layer, and get the output output k_p, k_i, k_d

(4) Calculate the output of the incremental PID controller:

$$u(k)=u(k-1)+\Delta u(k)\ \Delta u(k)=k_p(e(k)-e(k-1)+k_i e(k)+k_d(e(k)-2e(k-1)+e(k-2))$$

(5) Perform neural network learning and adjust the weighting coefficient online $\omega_{ij}^{(1)}(k)$ and $\omega_{li}^{(2)}(k)$.

(6) Order k = k+1

(7) Return to step (1)

The above is the algorithm of BP neural network for adaptive adjustment of PID parameters. If this algorithm is programmed as a .m file in matlab, the controlled object will be relatively fixed, which is not suitable for generalized modeling and simulation. According to the literature [18], the program is rewritten into an s-function file. The s-function file makes this algorithm highly portable, and its use is not limited to fixed objects. Then put it into the simulink model for the simulation verification of the longitudinal speed.

III. Longitudinal Speed Tracking

The essence of longitudinal speed tracking control is that smart cars use cameras, lidars, millimeter-wave radars, etc. to perceive external environmental information, and then the planning decision-making layer makes a reasonable trajectory and speed plan, and the lower executive layer gives the decision-making layer according to the planning decision-making layer. The tracking control is carried out with a predetermined signal to ensure the accuracy of tracking and meet the requirements of normal driving of the vehicle. The focus of this paper is the effect of the BP neural network self-adjusting PID parameter control algorithm used in the longitudinal speed tracking control of the smart car. Therefore, this article no longer conducts longitudinal dynamics analysis for modeling, but uses the vehicle dynamics model that comes with carsim to conduct joint simulation experiments with simulink. The longitudinal control of unmanned driving is to control the vehicle to drive at a desired speed to achieve a safe driving distance between vehicles or to complete actions such as changing lanes and overtaking. According to the structure of the transmission system, it is actually achieved by controlling the torque, speed and pressure of the brake master cylinder of the vehicle's engine.

According to the requirements of a human driver when driving, the throttle and brake cannot work at the same time, and the throttle control amount and the brake master cylinder pressure cannot be changed arbitrarily in order to meet the speed accuracy due to the limitation of the executive structure. Therefore, this paper designs the switching logic rules for driving and braking. The acceleration is used as the control variable for whether the vehicle adopts the driving or braking mode. When the acceleration is greater than zero, drive is used, and when the acceleration is less than zero, the brake mode is used. Taking into account the limitations of the mechanism, the maximum threshold of throttle opening is set to 1, and the maximum threshold of master cylinder pressure is set to 9.

Before carrying out the simulation experiment of longitudinal speed tracking control, first use a nonlinear model to test the control effect of the set PID controller based on bp neural network with adaptive adjustment parameters. The controlled object is: $y(t)=\frac{1.2(1-0.8e^{\frac{-0.1t}{T}})y(t-1)}{1+y(t-1)^2}+u(t)$ among them, T is the sampling period, and this article takes T = 0.001s. The input signal is shown in Figure 3 below. The tracking result after BP neural network PID control algorithm control is shown in Figure 4. It can be seen from the figure that the target signal and the output signal basically coincide. The part of Figure 4 is enlarged as shown in Figure 5, and it can be seen that in 1s when the target signal has a sudden change from 0 to 6, the output signal tracks the target signal in a very short time and there is no overshoot. The process of adaptive adjustment of PID parameters is shown in Figure 6. It shows that the PID controller based on BP neural network's adaptive adjustment parameters has better control effect for this nonlinear control object.

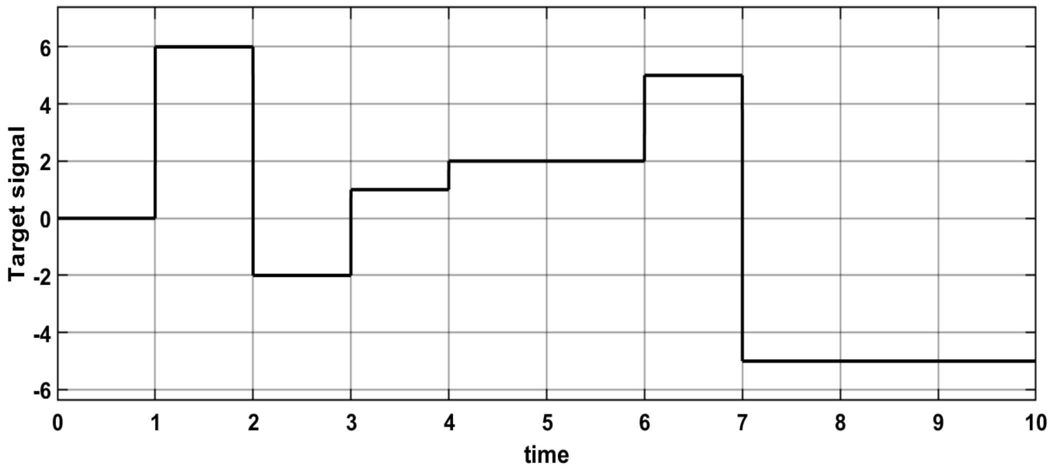

Fig. 3. Input signal.

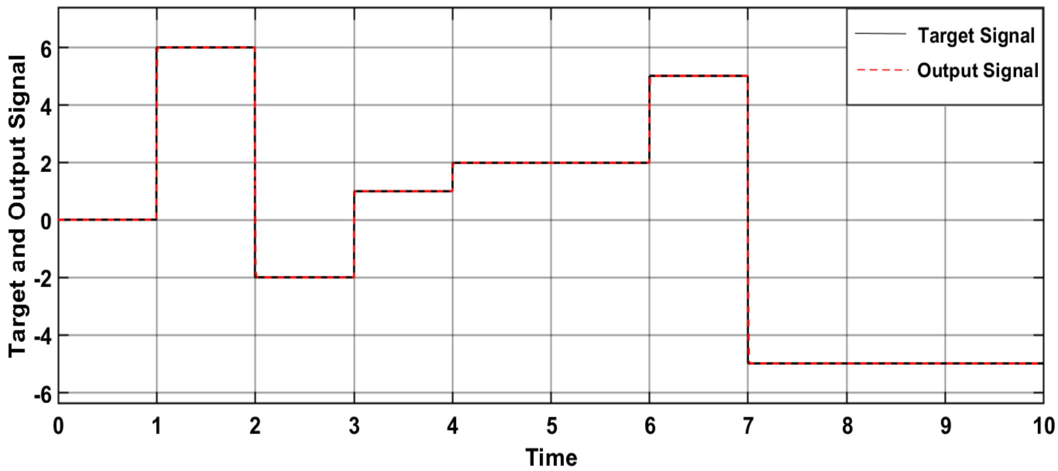

Fig. 4. Tracking effect diagram.

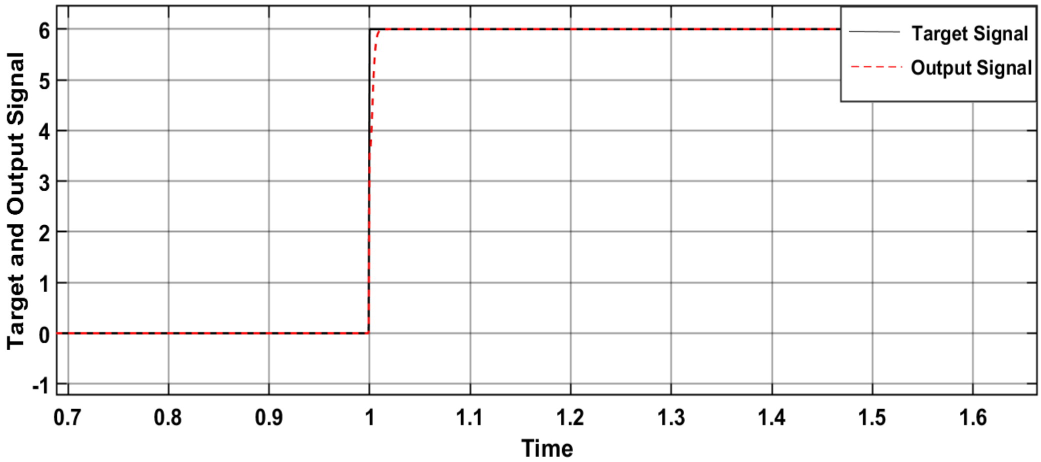

Fig. 5. Enlarged view of tracking effect.

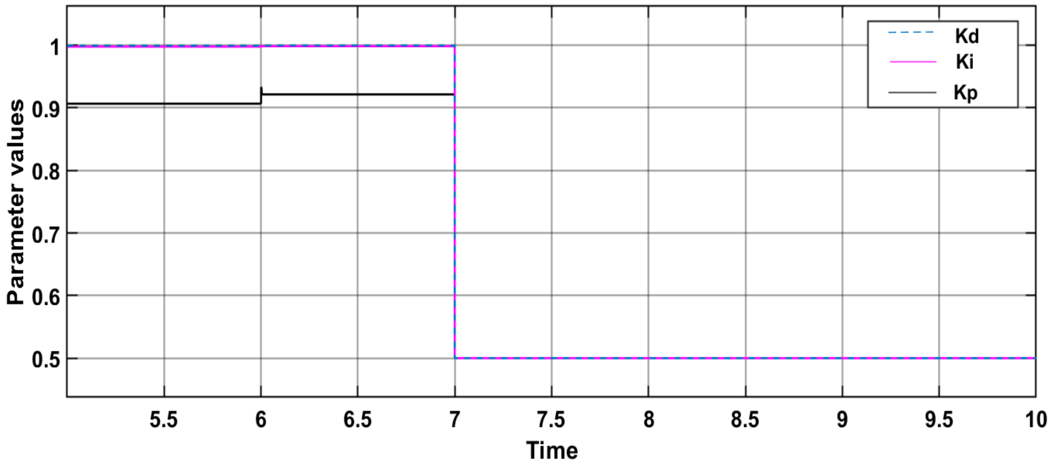

Fig. 6. PID parameter adjustment diagram.

The BP-PID controller is transplanted to the speed tracking control system for simulation verification. The block diagram of the speed tracking control system is shown in Figure 7. This longitudinal speed tracking system is composed of a desired speed composed of multi-step step signals, a BP neural network PID controller, a brake throttle logic switching module and a carsim vehicle dynamics model. Among them, the selected model is a Type C car with rear-wheel drive and front-wheel steering, which is used to realize the joint simulation of matlab and carsim to verify the effectiveness of this algorithm in longitudinal speed tracking.

Set the desired speed as shown in Figure 8 as a continuously changing step signal. The BP neural network PID transmits the desired acceleration of the control variable to the throttle brake switching logic to obtain the corresponding input throttle opening and brake master cylinder in Carsim pressure. The corresponding tracking results are shown in Figure 9, where the black solid line represents the desired speed, and the red dashed line represents the actual tracking speed. It can be seen from the figure that the actual speed and the expected speed basically coincide. In order to further observe the difference between the two, the error diagram between the actual speed and the expected speed in Figure 10 is obtained. As shown in the figure, the error value is basically at the zero line. Above, it shows that the tracking effect is better, but in the figure you will find that the error will suddenly change to zero value at a certain moment. This is because there is a sudden change in the speed at a certain moment, and the controller changes the original control amount, and it takes a certain time for the control system to respond. The shorter the sudden change, the faster the system responds and the better the real-time performance. In the partial enlarged view of Fig. 11, it can be clearly seen that the speed changes from 0 to 3. Basically, the system can accurately track in place within 2 seconds without overshooting.

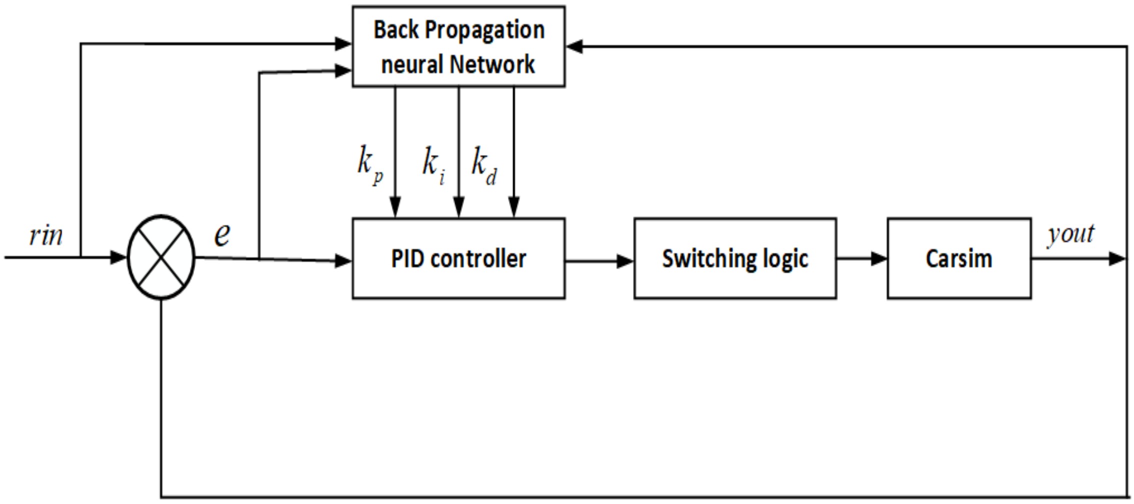

Fig. 7. Block diagram of Longitudinal Speed Tracking Control System.

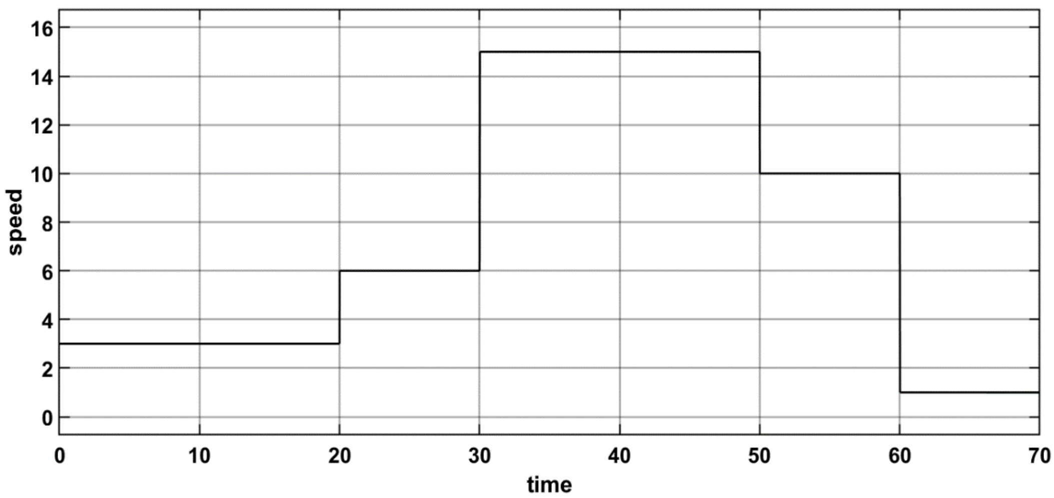

Fig. 8. The speed of the target.

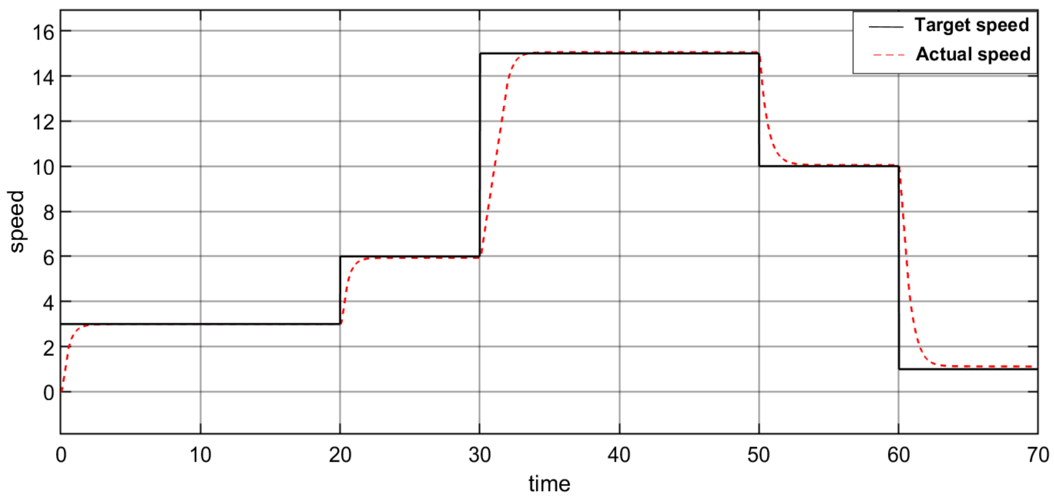

Fig. 9. Longitudinal velocity tracking results.

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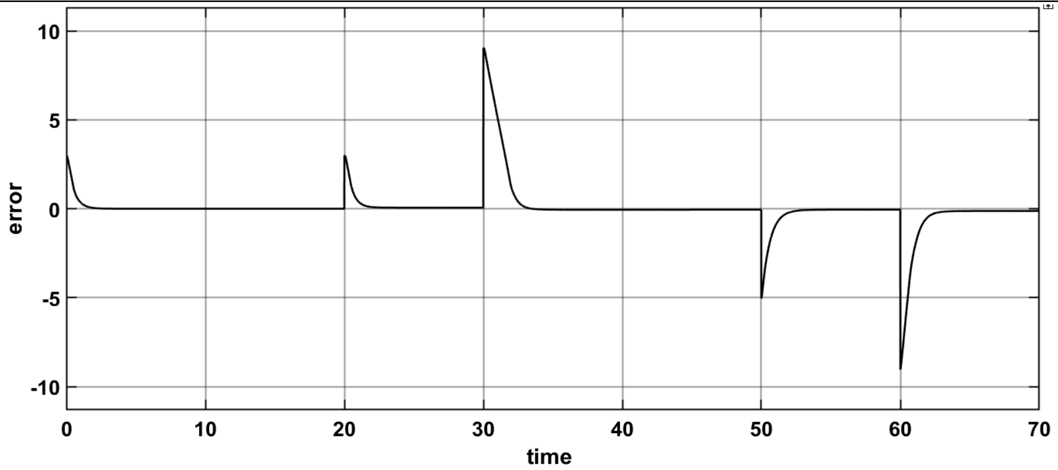

Fig. 10. Error graph.

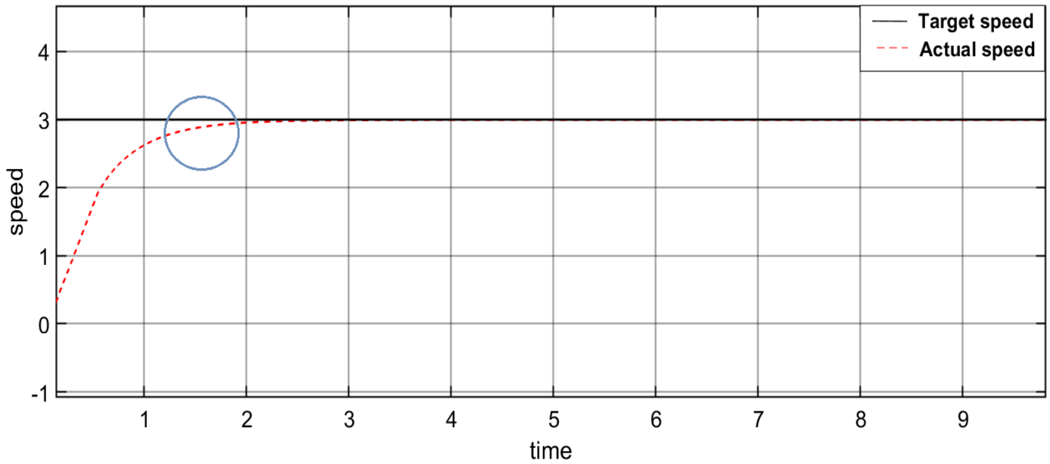

Fig. 11. Partially enlarged view.

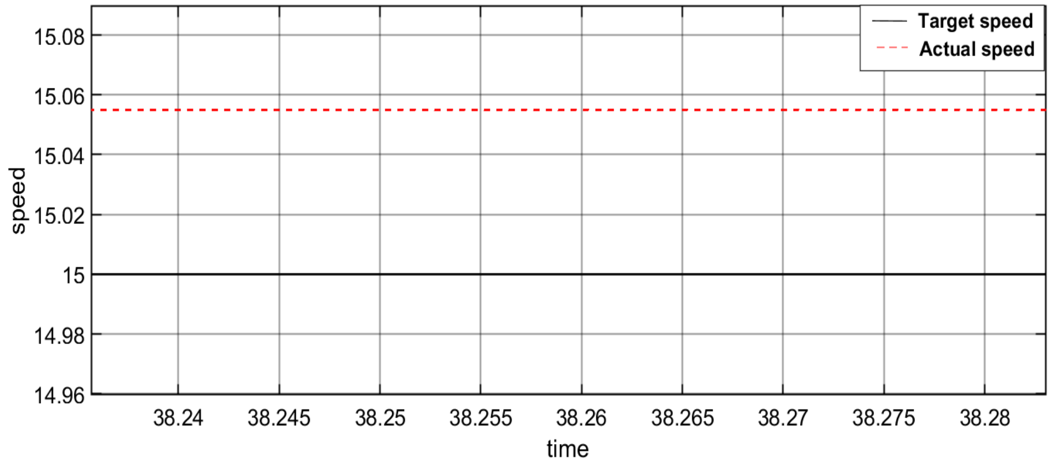

Fig. 12. Maximum error.

In order to better verify whether this algorithm can meet the requirements of actual driving conditions, the speed data of the first 500 seconds of the FTP75 cycle is used as the expected input of the simulation. Figure 13 shows the FTP75 cycle working condition, and the simulation results are shown in Figure 14. It can be seen that the tracking results basically coincide with the expectations, and the tracking effect is good. This algorithm can basically meet the needs of the actual scene.

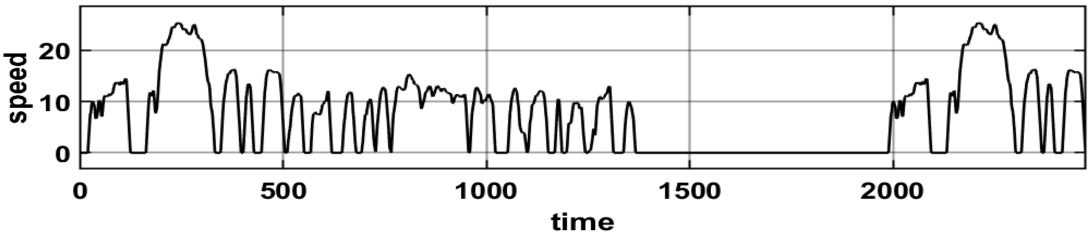

Fig. 13. FTP75 cycle conditions.

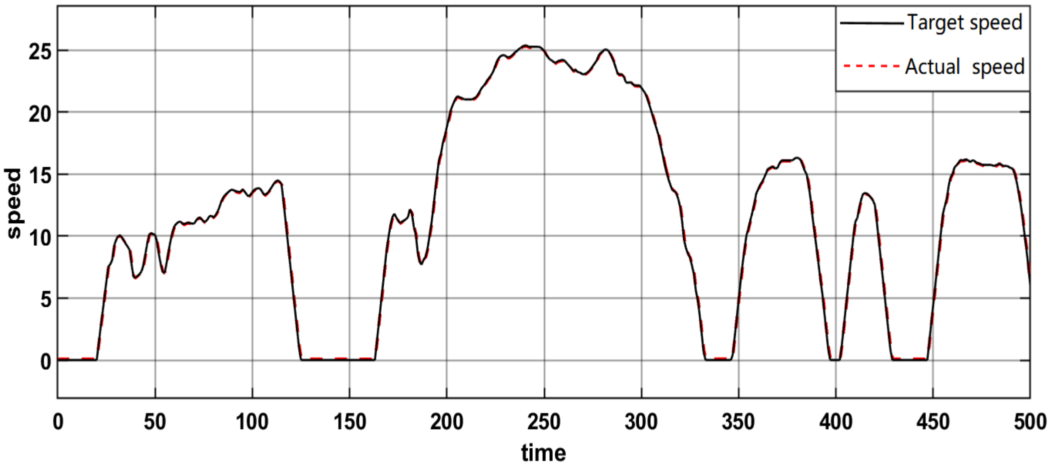

Fig. 14. Tracking result graph.

IV. Conclusion

The paper analyzes the control rules of the BP neural network and incremental PID, designs the PID control algorithm of BP neural network for longitudinal speed control, and uses a non-linear system of fixed control objects to verify the control effect of this controller. Simulation results show that the three Kp Ki Kd parameters of PID controller can be adjusted in real time according to the state of the system, the actual speed basically coincides with the desired speed, and the control effect is good. This controller is transplanted to the longitudinal speed tracking system and simulated by the matlab and carsim soft. Results show that the controller of this algorithm allows the longitudinal speed tracking control system to respond quickly and can track the desired speed within 2 seconds. If the tracking error is ignored during speed mutation, the maximum tracking error of the longitudinal speed tracking control system is between 0.05-0.06m/s, and the control accuracy is higher. Finally, the FTP75 cycle working condition is used for the simulation verification of the actual application working condition. Results show that based on adaptive adjustment of BP neural network, the control algorithm is well and can be applied to the longitudinal speed tracking control system.

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