Research on Adaptive Control Method of Autonomous Vehicle Lateral Motion

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***Abstract*—This paper studies the application of the adaptive control method in lateral control of the autonomous vehicle. Based on the classical PID control, the design scheme accomplishes online parameter self-tuning of PID controller through the single neuron. It designs a non-model and non-parametric adaptive control method. On the basis of the preview follow theory and two degrees of freedom linear model, we establish the vehicle control model and verify the control method of the lateral control with the MATLAB simulation. The simulation results show that the control method can more effectively control the longitudinal stability of a vehicle and have better real-time performance than methods which need a precise mathematical model or need to define a model and its parameters.**

Keywords-adaptive; lateral control; preview model; PID; autonomous vehicle

I. Introduction

The lateral control of the autonomous vehicle is one of the core technologies to realize the autonomous driving. The lateral control, which means on the condition of different speed and road, can meet the basic performance requirements of the vehicle, including the accuracy of the tracking and the adaptability of the environmental change on vehicle parameters. The autonomous vehicle tracks the trajectory automatically and maintains certain comfort and stability. However, due to the inherent nonlinear characteristic on the lateral movement of vehicles and the changes of vehicle and road parameters, they make the controller design has become a complex issue.

People have done a lot of research on the lateral control of the vehicle. Many methods have been used to design the lateral controller, such as the standard linear quadratic control[1], the sliding mode method[2], the Nonlinear-Gain-Optimized method[3], the prediction technology[4], H_∞ methods[5][6][7] and the fuzzy logic control methods[8][9]. The above methods solve the problem of the lateral control on vehicles effectively, but there is a common flaw that they all need a precise mathematical model or need to define a model and its parameters. Therefore, the real-time performance of algorithms in the changing curvature of the tracking control is not so good.

For these problems, this paper designs an adaptive lateral PID controller by which three controlling parameters through the single neural network of PID are tuned online to improve the real-time performance of controlling and the algorithm's adaptability of the road curvature changing. It's based on the classic PID control algorithm.

II. The Design Of Self-Adaptive Pid Controller For Lateral Control

A. Adaptive Single Neuron

The concept of the artificial neural and the network model appeared in the late 50s and early 60s first, and it is subsequently used to solve the difficult optimization problem and the associated memory and other issues. Because artificial neural networks have the parallel mechanism, the ability of learning and the memory function, they have been widely used in the control area.

By the neuron model we can achieve the binary logic operations such as AND, OR, AND-NOT, OR-NOT and so on, moreover this model describes the artificial neural network can generate rather complicated behavior by the simple calculation. However, it is a static neuron, that is, the fixed structure, and the metric can not be adjusted because of a lack of a critical element — the ability to learn.

In this paper, we choose the adaptive neuron model (Fig. 1), its environment adaptation and its role as shown in Fig. 2:

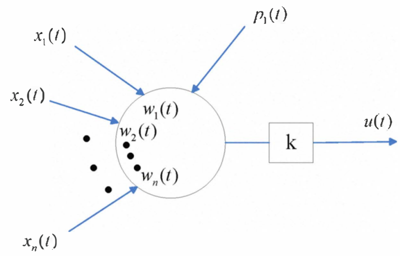

Figure 1. Adaptive Neuron Model

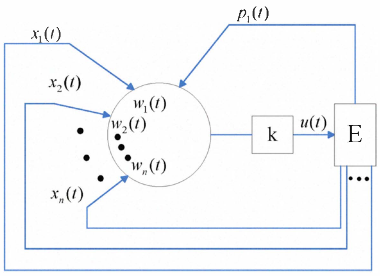

Figure 2. The adaptation and effect of the neuron to environment

Fig. 2 shows a adaptive neuron model which has numbers of n inputs $x_i(t)$ (i=1, 2, …, n), $p_i(t)$ is progressive signal or performance indicator, E is the environment, $w_i(t)$ is the weighted value corresponding to $x_i(t)$, k>0 is the coefficient of proportionality of the neuron, the output of the adaptive neuron $u(t)$ can be expressed as:

$$u(t) = k\sum_{i=1}^{n} w_i(t)x_i(t) \tag{1}$$

Suppose that the associated weighted value $w_i(t)$ in learning time is proportional to the progressive signal $p_i(t)$, at the same time it attenuates slowly, so the update of the neuron weighted value can be indicated as:

$$w_i(t+1) = w_i(t) + \eta p_i(t) \tag{2}$$

Where . is the learning efficiency and greater than zero.

For the progressive signal $p_i(t)$, there are some kinds of typical learning rules as follows:

1) *Non-supervised Hebb learning rule.* It means the adaptive neuron by learning a dynamic unknown environment to adapt their ability and make reflection and effect for the outside world that is:

$$p_i(t) = u(t)x_i(t)$$

2) *Supervised Delta learning rule.* In the learning rule of the Hebb, we introduce the teacher signal which will change the actual output into the difference of the desired output and the actual output.The actual output shows that:

$$p_i(t) = z(t)x_i(t)$$

3) *Supervised Hebb learning rule.* It combines the non-supervised Hebb learning rule and the supervised Delta learning rule :

$$p_i(t) = z(t)u(t)x_i(t)$$

According to the mentioned adaptive neuron model and learning rules, by the (1), (2), we take c = 0 and can obtain the following learning control algorithm:

$$\begin{cases} u(t) = k\sum_{i=1}^{n} w_i(t)x_i(t) \\ w_i(t+1) = w_i(t) + \eta(r(t) - y(t))x_i(t) \end{cases} \tag{3}$$

Where k and η are undetermined constants, the weighted value can be confirmed by $w_i(t+1) = w_i(t) + \eta(r(t) - y(t))u(t)x_i(t)$, if n=3, the status $x_i(t)$ (i=1, 2, …, n) can be indicated to:

$$x_1(t) = r(t)$$

$$x_2(t) = r(t) - y(t)$$

$$x_3(t) = \Delta x_2(t)$$

Generally speaking, η is the speed of learning, we hope it is bigger; the value of k can use k=1 or a smaller value on the basis of the learning condition.

B. *The improved adaptive PID control through single neuron*

The adaptive single neuron has the ability of learning and adjusts the weighted value by learning. Therefore we introduce the adaptive single neuron to the PID controlling for tuning PID parameters, where the proportion unit(P), the integral unit(I) and the differential unit(D) are the input of the adaptive neuron x_P, x_I and x_D. There are three parameters of PID k_P, k_I and k_D which are the inputs weighted value. We employ the supervised Hebb learning rule to achieve the adjustment of the weighting coefficient and to realize the function of self-adaption and self-organization. The structure of the adaptive single neuron PID control is shown in Fig. 3:

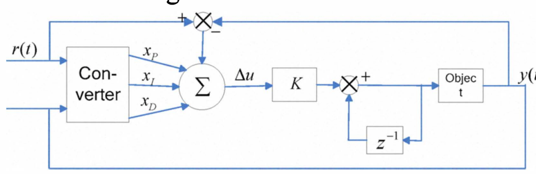

Figure 3. Structure of the adaptive single neuron PID control

The specific controlling algorithms and learning methods are:

$$\begin{cases} u(t) = u(t-1) + K(k_P x_P + k_I x_I + k_D x_D) \\ k_P(t+1) = k_P(t) + \eta_P(r(t) - y(t))x_P(t) \\ k_I(t+1) = k_I(t) + \eta_I(r(t) - y(t))x_I(t) \\ k_D(t+1) = k_D(t) + \eta_D(r(t) - y(t))x_D(t) \end{cases} \tag{4}$$

Here: $x_P = e(t)$,

$$x_I = \sum_{t=0}^{n} e(t)T,$$

$$x_D = \frac{e(t) - e(t-1)}{T},$$

η_P、η_I、η_D are the learning speed of proportion, integral and differential, k is the neuron proportional coefficient. The larger k is; the better quickness is. If the overshoot is large that may even make the system not steady. When the controlled object's delay increases, the value of k must be reduced to stabilize the system. But the value of k is very small and will make the quickness of the system become worse.

Therefore we use (4) to improve the PID control and design the adaptive PID lateral controller.

III. MODELING OF CONTROL OBJECT

We should establish a model of autonomous vehicle if we want to research the control which would effect the lateral movement of an autonomous vehicle. According to the requirements of structuring road environment and travelling at a low speed, the mathematics model of the autonomous vehicle could be simplified as a linear model which has two degrees of freedom, and the process of modeling is as follows:

Firstly: according to fixing the coordinate system on the centre of gravity of the autonomous vehicle, neglecting the influence on the steering system, directly inputting the front wheel steering angle and neglecting influences come from barrel rolling, pitching, vibrating and braking, we could consider that the carriage of vehicle only moving parallel to the ground, that is, the displacement of the vehicle which along *z*-axis, the pitching angle which rounds *y*-axis and the side-drifting angle which rounds *x*-axis are all for zero.

Secondly: assuming that the forward speed of the autonomous vehicle is a constant value, thus the vehicle only have two degrees of freedom when it moves along *y*-axis lateral and transverse-swinging around *z*-axis.

Thirdly: assuming that steering angle is small, and the model of tires is linear, in this situation, the pre and post vehicle wheels would be exerted the same steering force when they rotate at the same angle separately. Furthermore, the model of autonomous vehicle should be simplified in complicating the pre and post vehicle wheels.

Fourthly: based on the knowledge about vehicle kinetics of automobile theory, we could get a model of vehicle kinetics about linear two degrees of freedom (Fig. 4), because the features of kinetics are similar to bicycle, which move in the plane, in this situation, the model of vehicle kinetics would be recognized as the model of bicycle. In the Fig. 4, *oxy* is a coordinate system of vehicle, *o* is the centroid of the vehicle, *ox*-axis is in the plane, in which the vehicle is transverse movement. The vehicle movement is a panel movement which consists of latitudinal motion on the *x*-axis, transverse motion on the *y*-axis and transverse swinging around vertical axis which stick the *o*-point.

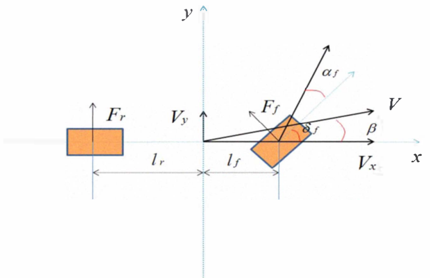

Figure 4. Two degrees of freedom linear vehicle model

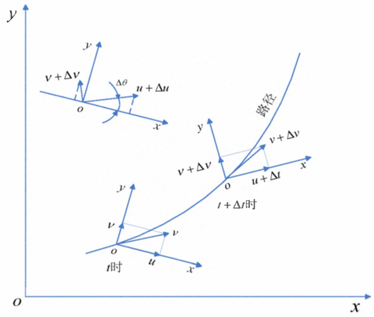

Figure 5. Analysis of vehicle movement by selecting body coordinates

Fifthly: according to the Newtonian mechanics, provided that the absolute acceleration, angular acceleration of the vehicle, external force and external torque are decomposed along the vehicle body coordinate system, then we could get a vehicle model which travels on an ordinary road. In Fig. 5, by using the vehicle body coordinate system to analyze the vehicle's movement and the vehicle motion differential equation which would be deduced is:

$$\begin{cases} -(c_f+c_r)\beta+\dfrac{1}{V_x}(l_r c_r-l_f c_f)\dot{\psi}+c_f\delta_f=m(\dot{V}_y+V_x\dot{\psi}) \\ (l_r c_r-l_f c_f)\beta-\dfrac{1}{V_x}(l_f^2 c_f+l_r^2 c_r)\dot{\psi}+l_f c_f\delta_f=I_\psi\ddot{\psi} \end{cases} \tag{5}$$

Among them:

V - the velocity vector;

V_x, V_y - represent velocity decomposition along x-axis and y-axis;

α_f, α_r - represent the pre and post vehicle wheels' side-slip angle;

β - is the side-slip angle of the centroid of vehicle;

δ_f - represents the revolve angle of the front wheel;

m - represents the mass of a vehicle;

$\dot{\psi}$ - is the speed of the vehicle's transverse-swinging angle;

I_ψ - the rotational inertia when the vehicle move around the center of gravity;

l_f - the distance from the front-axle to the center of gravity;

l_r - the distance from the rear-axle to the center of gravity;

l - the distance from the front-axle to the rear-axle;

c_f, c_r - represent the cornering stiffness of the pre and post vehicle wheels;

Sixthly: choosing V_y and $\dot{\psi}$ as state variables, and then the equation of kinetics status would be deduced is:

$$\begin{bmatrix} \dot{V}_y \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} -\dfrac{a_1}{mV_x} & \dfrac{-mV_x^2+a_2}{mV_x} \\ \dfrac{a_3}{I_\psi V_x} & -\dfrac{a_4}{I_\psi V_x} \end{bmatrix} \begin{bmatrix} V_y \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \delta_f \tag{6}$$

Here:

$$a_1 = c_f + c_r \qquad a_2 = c_r l_r - c_f l_f$$

$$a_3 = -l_f c_f + l_r c_r \qquad a_4 = l_f^2 c_f + l_r^2 c_r$$

$$b_1 = \frac{c_f}{m} \qquad b_2 = \frac{l_f c_f}{I_\psi}$$

Seventhly: the kinematic equation about vehicle could be deduced by geometric relation in Fig. 6,

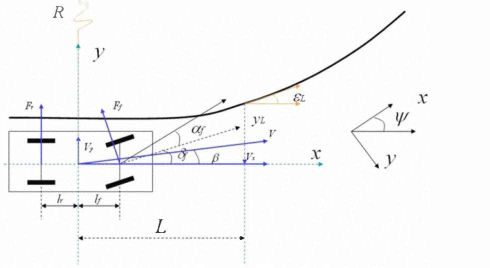

Figure 6. Relationship of vehicle and road when the preview distance is L

$$\begin{cases} y_L = V_x(\varepsilon_L - V_y) - \dot{\psi} L \\ \varepsilon_L = V_x \rho - \dot{\psi} \end{cases} \tag{7}$$

Finally: according to (6) (7), the model equation of vehicle linear two degrees of freedom (8) would be established to pre-tracking, as the mathematics model of the controlled object (the autonomous vehicle).

$$\begin{bmatrix} \dot{V}_y \\ \ddot{\psi} \\ \dot{y}_L \\ \dot{\varepsilon}_L \end{bmatrix} = \begin{bmatrix} -\frac{a_1}{mV_x} & \frac{-mV_x^2 + a_2}{mV_x} & 0 & 0 \\ \frac{a_3}{I_\psi V_x} & -\frac{a_4}{I_\psi V_x} & 0 & 0 \\ -1 & -L & 0 & V_x \\ 0 & -1 & 0 & 0 \end{bmatrix} \begin{bmatrix} V_y \\ \dot{\psi} \\ y_L \\ \varepsilon_L \end{bmatrix} + \begin{bmatrix} b_1 & 0 \\ b_2 & 0 \\ 0 & 0 \\ 0 & V_x \end{bmatrix} \begin{bmatrix} \delta_f \\ \rho \end{bmatrix} \tag{8}$$

IV. SIMULATION EXPERIMENT AND RESULT ANALYSIS

In the MATLAB simulation about lateral controlling, we use improved algorithm to design the lateral controlling instrument and employ the vehicle parameters in Table 1 to initialize the mathematics model of the controlled object.

In this situation, the curvature radius would be set at zero to simulate the conditions of a linear road. The initial state of the vehicle $[\varepsilon_L, 2\text{-}y_L]$ is parallel to the reference road. The distance from the setting point to the reference road is 2-meter condition that the vehicle is travelling on the linear road, the controlling instrument is designed based on the single neuron self-adaptive control algorithm, and its performance under the lateral controlling is displayed as Fig. 7 and Fig. 8.

TABLE I. THE PARAMETERS OF THE VEHICLE [10][11]

Parameters	Implication	Unit	Nominal Value
m	Mass of a Vehicle	Kg	1480
I_ψ	the rotational inertia	$Kg \cdot m^2$	2350
l_f	the distance from the front-axle to the center of gravity	M	1.05
l_r	the distance from the rear-axle to the center of gravity	M	1.63
c_f	the cornering stiffness of the pre vehicle wheel	N/rad	67500
c_r	the cornering stiffness of the post vehicle wheel	N/rad	47500

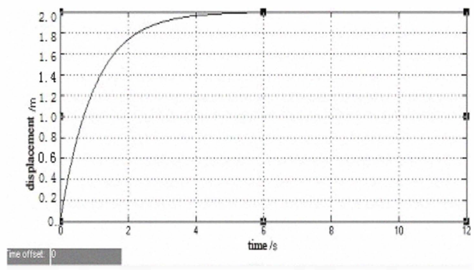

Figure 7. Lateral Displacement of Vehicle

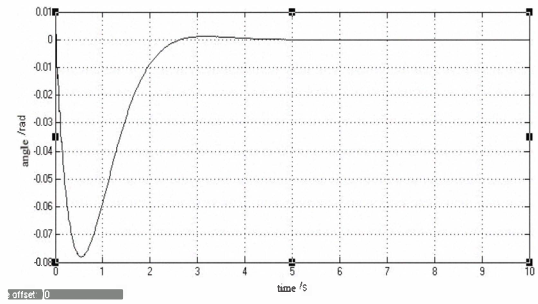

Figure 8. the Side-slip Angle of Vehicle

From above figures, under the controlling of instrument, the vehicle's lateral position would reach the setting point after 5 seconds and reach a stable status. The angle would reach the max 0.08rad after 0.5 seconds, and then reach 0rad after 5 seconds.

By analyzing this simulation experiment we can get the result that: the single neuron self-adaptive controlling instrument could rapidly eliminate the generated lateral deviation. It has no overshoot. The slip single of the vehicle has a little overshoot at the balance position. Conclusively, this controlling instrument has a steady performance at the lateral controlling process, and it could respond to the controlling signal rapidly, so it displays fairly strong practicality.

V. CONCLUSION

On the ground of the classic PID control, this paper presents an improved method to carry out online parameter self-tuning of PID controller through single neuron and it realizes the adaptive lateral control. We design an adaptive lateral PID controller by which three controlling parameters of PID k_P, k_I and k_D through the single neural network of PID. They are tuned online to improve the real-time performance of controlling and the algorithm's adaptability of the road curvature changing. The method achieves the control of the lateral movement on nonlinear characteristics autonomous vehicles by simple treatment. It provides an effective way for the lateral control on vehicles and has some practical value.

REFERENCES

[1] Steven E. Shladover, etal. Automatic Vehicle Control Developments in the PARTH Program [J]. Vehicular Technology, 1991, 40(1): 114-130.

[2] J R Zhang, etal. Sliding Mode Controller for Automatic Steering of Vehicle [A]. The 27th Annual Conference of the IEEE Industrial Electronics Society [C]. 2001, 2149-2153.

[3] Dirk E Smith, John M Starkey, Robert E Benton. Nonlinear- Gain-Optimized Controller Development and Evaluation for Automated Emergency Vehicle Steering [A]. Proceedings of the American Control Conference [C]. 1995, 3586-3591.

[4] Ching-Yao Chan, Han-Shue Tan. Lane Tracking in Vehicle-Following Collision Situation [A]. Proceedings of the American Control Conference [C]. 1999, 3697-3701.

[5] R T O'Brien, P A Iglesias, T J Urban. Vehicle Lateral Control for Automated Highway Systems [J]. Control Systems Technology,1996, 4(3): 266-273.

[6] Kai-Ten Feng, Han-Shue Tan, Masayashi Tomizuka. Automatic Steering Control of Vehicle Lateral Motion with the Effect of Roll Dynamics [A]. Proceedings of the American Control Conference [C]. 1998, 2248-2252.

[7] Jeng-Yu Wang, Masayoshi Tomizuka. Robust H∞ Lateral Control of Heavy-Duty Vehicles in Automated Highway System [A]. Proceedings of the American Conference [C]. 1999, 3671-3675.

[8] Thomas Hessburg, Masayoshi Tomizuka. Fuzzy Logic Control for Lateral Vehicle Guidance [J]. IEEE Control Systems, 1994, 55-63.

[9] Ecole Centrale de Lille, LAIL. Fuzzy Controller For Lateral. Guidance of Busses [A]. Proceedings of the 2002 IEEE. International Symposium on Intelligent Control [C]. 2002, 110-115.

[10] J R Zhang, etal. Sliding Mode Controller for Automatic Steering of Vehicle [A]. The 27th Annual Conference of the IEEE Industrial Electronics Society [C]. 2001, 2149-2153.

[11] Jeng-Yu Wang, Masayoshi Tomizuka. Robust H∞ Lateral Control of Heavy-Duty Vehicles in Automated Highway System [A].Proceedings of the American Conference [C]. 1999, 3671-3675.