Design of Autonomous Vehicle Controller Based on BP-PID

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Abstract. An autonomous vehicle controller based on BP-PID (Back-Propagation - Proportion Integration Differentiation) is designed. Autonomous control is one of the most significant parts for self-driving. Traditional PID control is supposed to take conducive effects on the longitudinal control; nevertheless, it fails to ensure the lateral control stability due to the inflexible parameters setting. To cover the limitation of in-system parameters adjustment issue, the BP (Back-Propagation) neural network is adhibited in traditional PID lateral control. The BP-PID control module updates the incremental PID parameters through self-learning and makes the vehicle operates more smoothly. The learning algorithm flowchart and calculation method of parameters are provided. Moreover, dual mode (manual mode and autonomous mode) control will continue for a comparatively long period. Consequently, the dual mode switch algorithm is presented. A typical measurement is conducted which were then compared with the ordinary PID control results that verified the potential of the proposed method.

1. Introduction

In the last few years, with growing accidents of intelligent and autonomous agents, especially the frequent drone crash accidents everywhere, the system performance of autonomous vehicles received more and more attentions. In most cases, the vehicle’s system performance is affected by the controller designed and tuned by an engineer. Tuning the system to obtain a good performance is a tedious and time-consuming work, requiring years of experience and a high degree of expertise. Typically, such a design procedure relies on a prior knowledge of the vehicles behavior and the environment, which is usually based on many model assumptions [1, 2].

BP neural network, as one of the most applied neural network models, is a multilayer feed-forward network trained by error back propagation algorithm. BP networks can learn and store a host of input-to-output mapping relationships without revealing the mathematical equations that describe the mapping relationship in advance. Its learning rule is to employ the steepest descent method, by back-propagation network to continuously adjust the weights and thresholds, so the network and the minimum sum of squared errors.

The PID controller, as the earliest practical controller, possesses a history of nearly one hundred years, and it is still the most widely used industrial controller regardless of its defective performance in the procedure of controlling complex system with the features of nonlinear, time-varying, coupling, and uncertainty of parameters and structures. Adjusting PID parameters at any time by exploiting the self-learning characteristics of BP neural network, BP-PID control module can solve the problem that the parameters incapable of being corrected in-system. The autonomous vehicle safety and comfort will be exalted predictably.
Speaking at The Wall Street Journal's WSJ Tech D.Live conference on November 13, 2018, John Krafcik, head of the self-driving car unit of Google parent company Alphabet, said that though driverless cars are "truly here," they aren't ubiquitous yet. And he doesn't think the industry will ever be able to drive at any time of year in any weather and any condition, the highest driving rating [3]. It is possible to assess that dual mode (manual mode and autonomous mode) control will be required for autonomous vehicle for a considerable period. Consequently dual mode switch algorithm is discussed in detail. An emblematical test taking an autonomous field vehicle as verification platform explains that the method ensures the control safety comfort.

2. System Design

2.1 System Architecture

Compared with the centralized control, the distributed control only uses local measurement and information communicated from neighbors, which has less communication requirements and higher system performance [4–6]. In light of this, the distributed control for autonomous vehicle has been a significant research topic.

It is generally established that the autonomous vehicle control involves lateral control, longitudinal control and auxiliary control. Neglecting the auxiliary control due to its mature technology and friendly CAN (Controller Area Network) bus interface character, the system design mainly focuses on the lateral control and longitudinal control with distributed structure as shown in Fig. 1.

![Figure 1: System structure diagram.](image)

Lateral control refers to the steering control while longitudinal control deals with the accelerograph and gears signals which are sent to original vehicle driving controller and brake signal which is transmitted to a sole electromechanical brake controller. Host computer who operates the autonomous algorithm sends related commands to MECU (Main Electronic Control Unit) through CAN bus.

2.2 Hardware Design

MECU that undertakes the task of analyzing instructions from the host computer and controlling the operation of the actuators is the control core for the autonomous vehicle. It receives the vehicle feedback information including real brake position and speed and generates the autonomous control signals consisting of gears, brake, accelerograph and mode switch. The embedded processing system ordinarily fail to transfer analog signals that tally with external driving controller or electromechanical brake controller. Analog signal regulating circuits will be consequently essential. High-speed electronic switch serves as the key part of dual mode (Manual Mode and Autonomous Mode) shift. Fig. 2 displays the MECU structure [7]. Moreover, MECU circuit design schematic block diagram and MECU practical picture are illustrated in Fig. 3 and Fig. 4 separately.
Figure 2: Main Electronic Control Unit (MECU) structure diagram.

Figure 3: MECU circuit design schematic block diagram.

Figure 4: MECU practicality picture.
2.3 Software Design

In a control software sense, the challenging point is not longitudinal control but lateral control and dual mode switch. The lateral control will be explained in detail in Part 3. Accordingly, this part primarily expresses concern about dual mode switch.

Through the analysis of driver behavior model, vehicles should be equipped with 3 dual-mode shift manners, which are master mechanical switch, steering wheel intervention and brake pedal intervention. As for the master switch approach, it is not discussed any more due to its remarkable simplicity.

The basic dual-mode switch technique is as below:

2.3.1 Initialization. Start vehicle and recognize dual-mode switch state, which is set to manual mode default;

2.3.2 Autonomous Driving. Turn on the autonomous mode switch, vehicle self-drives on the set routes and can be converted to manual mode through turning off the autonomous mode switch at any time;

2.3.3 Steering Wheel Intervention. Vehicle will be altered to manual mode in the event of steering wheel intervention depends on the recognition of torque variation. It will be in a position to back to autonomous mode in case of releasing steering wheel and brake pedal. In order to ensure the safety, master switch is required to be changed from manual mode to autonomous mode at each time of returning to autonomous mode.

2.3.4 Brake Pedal Intervention. Vehicle will be altered to manual mode in the event of brake pedal intervention attributed to the artificial trigger signal. The conditions and channel back to autonomous mode behave like part 2.4.3.

The flowchart of dual mode switch algorithm is presented in Fig. 5.

2.4 Bus Protocol

MECU communicates with host computer and steering controller through CAN bus whose protocol will pose significant effects on the system performance. The bus protocols critical points between MECU and the host computer dot Table 1 and 2, respectively.

Figure 5: Dual mode (Manual Mode and Autonomous Mode) switch algorithm flowchart.
Table 1: Bus protocol between MECU and the host*

| Data bytes | Definition            | Description                                                                 |
|------------|-----------------------|------------------------------------------------------------------------------|
| D0         | Permission mode bits  | Handshake, mode switch, user ID – administrator, general user, developer    |
| D1         | Steering torque       | 0.1N•m/bit, range from -12.8 to 12.7 N•m                                      |
| D2         | Steering speed        | 1                                                                            |
| D3         | Steering angle        | The 8 MSBs of steering angle                                                 |
| D4         | Steering angle        | The 8 LSBs of steering angle                                                 |
| D5         | Gears and accelerometer | The high 4-bit: Gears The low 4-bit: the 4 MSBs of accelerograph              |
| D6         | Accelerograph         | The 8 LSBs of accelerograph                                                  |
| D7         | Brake level           | Monotone increasing, 0x00: No brake, 0xff: maximum brake                    |

* Sender frame – Data transmit from the host computer to MECU.

Table 2: Bus protocol between MECU and the host*

| Data bytes | Definition            | Description                                                                 |
|------------|-----------------------|------------------------------------------------------------------------------|
| D0         | Handshake, mode, gears and error code | Handshake, the practical feedback mode, gears and error class code |
| D1         | Vehicle velocity      | The 8 MSBs of real velocity                                                  |
| D2         | Vehicle velocity      | The 8 LSBs of real velocity                                                  |
| D3         | Brake level           | The real feedback brake level                                                |
| D4         | Accelerator pedal position | The real accelerator pedal position in manual mode or the corresponding quantities in autonomous mode |
| D5         | Steering angle        | The 8 MSBs of real steering angle                                            |
| D6         | Steering angle        | The 8 LSBs of real steering angle                                            |
| D7         | Steering torque       | The real feedback steering torque                                           |

* Receiver frame – Data transmit from MECU to the host computer.

3. BP-PID Lateral control

Exploiting the calculation of the expected steering angle, the autonomous vehicle lateral control fulfills the role in guarantee for steering safety and riding comfort coupled with the implement of perception and decision algorithm. PID lateral control is one of the classical control methods in unmanned control system. Nevertheless, it fails to adjust the PID parameters in-system and will debase the control accuracy. Consequently PID control in conjunction with BP neural network is introduced to tackle the puzzle of parameter learning in the vehicle operation procedure.

3.1 Incremental PID Controller

The lateral PID control is geared to discrete system, and the incremental PID expressions are as below:

\[
\Delta u(k) = u(k) - u(k-1)
\]

\[
\Delta u(k) = K_p[e(k) - e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)]
\]

\[
\Delta u(k) = A e(k) + B e(k-1) + C e(k-2)
\]

\[
A = K_p \left(1 + \frac{T_G}{K_i} + \frac{K_i}{T_G}\right)
\]
\[
B = -K_p(1 + 2 \frac{K_d}{T_G})
\]  \hspace{1cm} (5)

\[
C = K_p \frac{K_d}{T_G}
\]  \hspace{1cm} (6)

\[
u(k) = \Delta u(k) + u(k - 1)
\]  \hspace{1cm} (7)

Where \(e(k)\) is indicative of the difference between expected steering angle and real steering angle, and \(\Delta u(k)\) is PID increment.

### 3.2 BP-PID Controller

Zurada (1994) described back propagation networks as multilayered, feed forward and neural network that apply the error back propagation procedure for learning. The back propagation procedure employs the gradient descent optimization procedures method, which adjusts the weights in its original and simplest form by an amount proportional to the partial derivative of the error function with respect to the given weight. [8-10]

Sketch of the BP-PID controller is shown in Fig. 6, where \(x_i\) presents the input signal which is the expected steering angle \(\beta(k)\) while \(y_o\) reflects the output signal which is from steering mechanism sensors response. PID parameters \(K_p, K_i\) and \(K_d\) are updated from BP-NN self-learning. Fig. 7 demonstrates a 3 layers BP-NN instance with 4 neurons in input layer, 5 elements in hidden layer and 3 factors in output layer. The BP-NN input neurons design mainly explores that the system response \(y_o\) should be approximate to the input information \(x_i\). Accordingly, the lateral control error \(e(k)\) will be accessible to obtain the minimum. The fourth neuron constant 1 is to ensure the convergence of the BP neural network.

![Figure 6: Sketch of the BP-PID controller.](image)

![Figure 7: 3 layers BP-NN instance.](image)

All data that entered BP-PID controller must be normalized, equation (8) provides the approach in that the data are in scope of [-90, 90].

\[
X_{\text{norm}} = \frac{x_{\text{in}}}{90}
\]  \hspace{1cm} (8)

### 3.3 Parameters Setup

While learning samples are small, the algorithm employs batch-learning-mode with flowchart given in figure 7.

BP neural network input matrix is as follow:

\[
\text{Inp}_{1 \times 4} = \left[ \frac{x_i}{90}, \frac{y_o}{90}, \frac{x-y}{90}, 1 \right]
\]  \hspace{1cm} (9)

The initial conversion matrix from input layer neurons to hidden vector elements can be obtained through artificial data acquisition in human control mode such as expression (10). In contrast to parameters random settings in traditional BP-PID, it will avoid the tremor at the start of the system.
\[
\begin{bmatrix}
-0.7853 & -0.5672 & -0.6912 & -0.8301 \\
-0.2325 & -0.2628 & -0.5846 & -0.7322 \\
-1.0029 & -0.5889 & -1.3688 & -0.3357 \\
-0.3852 & -0.6574 & -0.4752 & -0.9231 \\
0.2814 & 0.1879 & -0.6584 & -0.3576
\end{bmatrix}
\]

The inactivated and activated states of the neurons in the hidden layer are described in equation (11) and (12) individually.

\[
net_{1 \times 5} = ln{p_{1 \times 4}} \times w_{5 \times 4}^T
\]  \hspace{1cm} (11)

\[
f_{w_{1 \times 5}} = \tanh(net_{1 \times j}) = \frac{e^{net_{1 \times j}} - e^{-net_{1 \times j}}}{e^{net_{1 \times j}} + e^{-net_{1 \times j}}}
\]  \hspace{1cm} (12)

\[j = 1, 2, 3, 4, 5\]

**Figure 8:** The BPNN algorithm flowchart.

In the same way, the initial conversion matrix from hidden layer neurons to output vector elements, and the inactivated and activated neurons states for output layer are shown in equation (13), (14) and (15).
\[ w_{03x5} = \begin{bmatrix} 1.0389 & 0.7458 & 0.6522 & 0.8516 & 0.6985 \\ 0.2578 & 0.6235 & 1.3584 & 0.3856 & 0.9231 \\ 1.1896 & 0.8541 & 1.2257 & 0.6574 & 0.2583 \end{bmatrix} \] (13)

\[ K_{o1x3} = f_{w1x5} \times w_{03x5}^T \] (14)

\[ f_{o1x3} = \frac{1}{2} (1 + \tanh(K_{o1xj})) = \frac{e^{K_{o1xj}}}{e^{K_{o1xj}} + e^{-K_{o1xj}}} \] (15)

\[ j = 1,2,3 \]

As a consequence, the required PID parameters are obtained.

\[ [Kp, Ki, Kd] = f_{o1x3} \] (16)

The current time system error is

\[ e(k) = x_i(k) - y_o(k) \] (17)

The BP-PID processing result is

\[ u(k) = [Kp(1 + T_G/Ki + Ki/T_G), -Kp(1 + 2 Kd/T_G), Kp Kd/T_G, 1] \times \left[ [e(k), e(k - 1), e(k - 2), u(k - 1)] \right]^T \] (18)

4. Experiment And Results

A representative experiment is designed and carried out in Olympic Rowing-Canoeing Park Shunyi District Beijing City to verify the approach, which indicates the trajectory with blue line in Fig. 9. The experimental carrier employs the autonomous field vehicle with the maximum velocity of 40km/h. The expired turning angle is capable of being obtained from reference [11], which is plotted in Fig. 10. The practical turning angle applying BP-PID control gets a better effect contrast to those of traditional PID control as shown in Fig. 11 and 12.

Figure 9: Experiment map and trajectory in Olympic Rowing-Canoeing Park Shunyi District Beijing City.

Figure 10: Expired angle from theory calculation.
5. Conclusions
In summary, we have performed both an experimental and theoretical study of the autonomous vehicle controller which highlights the important role that affects the system safety, reliability, stability, comfort and high-efficiency. Start with top-level design, dual mode (manual mode and autonomous mode) control and BP-PID lateral control have been discussed in detail. The hardware and software design as well as CAN bus protocol are presented to describe the autonomous vehicle controller completely. The experimental results have been successfully interpreted by the BP-PID method which permits to updates the incremental PID parameters through self-learning. Although the result explains that the method is valid and practicable, the higher speed issue omit to be surveyed. Furthermore, the experiment site is not adequate yet and some new experiments will be conducted in future research.

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