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Longitudinal Control for Mengshi Autonomous Vehicle via Gauss Cloud Model

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Abstract: Dynamic robustness and stability control is a requirement for self-driving of autonomous vehicle. Longitudinal control technique of autonomous vehicle is basic theory and one key complex technique which must have the reliability and precision of vehicle controller. The longitudinal control technique is one of the foundations of the safety and stability of autonomous vehicle control. In our paper, we present a longitudinal control algorithm based on cloud model for Mengshi autonomous vehicle to ensure the dynamic stability and tracking performance of Mengshi autonomous vehicle. The longitudinal control algorithm mainly uses cloud model generator to control the acceleration of the autonomous vehicle to achieve the goal that controls the speed of Mengshi autonomous vehicle. The proposed longitudinal control algorithm based on cloud model is verified by real experiments on Highway driving scene. The experiments results of the acceleration and speed show that the algorithm is validity and stability.

Keywords: Gauss cloud model; longitudinal control; autonomous vehicle

1. Introduction

The autonomous vehicle controller includes longitudinal controller and lateral controller. The lateral controller control the steering of the autonomous vehicle, and the longitudinal controller controls the acceleration of the autonomous vehicle to achieve the goal that control the speed of autonomous vehicle according to the distance between vehicles. The function of longitudinal controller of autonomous vehicle includes that are maintaining safety distance between vehicle, controlling the amount of acceleration or deceleration each time, and the operation of braking is as fast as possible in case of emergency situations. The challenges handled by the algorithm and technique of longitudinal controller include the solution of real time performance of nonlinear complex vehicle dynamics, keeping the safe distance of vehicles driving at high speed on Highway scene, the stability of accelerating and decelerating operation at high speed, and the stability and accuracy of the controller.

At present, the researches of longitudinal control algorithm for intelligent vehicle can be divided into three research ways: The first way: the longitudinal control algorithm based on rule model. L. Wu et al. introduces the fuzzy control algorithm into a longitudinal control system of the platoon. It can stably complete the following tasks of a platoon, without requiring for the accurate vehicle information [1]. S. Sheikholeslam et al. presents control laws to achieve the longitudinal control of a self-acting vehicle platoon driving in a straight line on the highway, in the context of losing communication of the lead vehicle with the other vehicles [2]. By observing and recording the vehicle following behavior of driver, P. Zheng et al. establishes a database and use neuro-fuzzy to realize the data analysis. In order to deep understand of car-following behavior of manually-driven vehicles, the parameters of the neuro-fuzzy analysis system are assigned to quantify driver behavior [3]. G. Qiang et al. applies fuzzy inference to create and simulate an algorithm of the car-following model. Based on simulation results, the uncertainty and behaviors of drivers can be theoretically described by using this fuzzy controller [4]. S. Kumarawadu and and C. Lv provide a neural network control method for IVHN (Intelligent Vehicle Highway Systems), and commit to solve the collision avoidance problem for car-following systems [5,6]. H. M. Kim et al. designs an additive fuzzy system, which is comprise of throttle and brake controllers, to implement the vehicle to vehicle distance control and speed control [7]. In order to perform the intelligent cruise control for semi-automatic vehicles, L. Cai et al. presents a neuro-fuzzy control system [8]. H. I. Lee and C. Lv use adaptive vehicle traction force control (ATFC) to accomplish robust longitudinal control of vehicles in intelligent vehicle highway system (IVHS) [9,10]. Y. F. Peng et al. uses a recurrent cerebellar model articulation controller (RCMAC) to accomplish a robust intelligent back-stepping control (RIBC) scheme for the car-following control of a platoon of automated vehicles. This method can achieve robust tracking performance [11]. A. Ferrara et al. describes a minimum sensor variable structure control strategy for cruise and tracking longitudinal control of vehicles which relies on the generation of "second-order" sliding modes control in the sense that the control signals act on the second derivative of the sliding variable but only the sliding variable is measurable [12]. L. Nouveliere et al. performs an experiment, which regards to the longitudinal control of vehicle on the basis of second-order sliding model, to increase capacity while ensuring safety [13]. In order to solve the longitudinal control problem of vehicle merging, X. Y. Lu designs a general adaptive algorithm [14]. In this paper, a longitudinal controller with feedforward and feedback structure is designed based on the vehicle's force analysis [15].

The second way: the longitudinal control algorithm based on nonlinear theory and algorithm. M. Tai and M. Tomizuka devise a vehicle longitudinal control system that includes traction and brake control. For each mode, the author designed different nonlinear controllers based on backstepping [16]. A. Raffin et al. design an adaptive longitudinal controller by improving Model Reference Adaptive Control (MRAC) technology, without the requirement of vehicle identification parameters [17]. H. M. Y. Naeem et al. establishes the vehicle longitudinal control model. Use H infinity control strategies to reduce the impact of uncertainty and interference [18]. B. Boulkroune and C. Lv propose an observer-based controller with integral action (OBCI) for linear parameter-varying (LPV) system to solve the problem of longitudinal control [19,20]. S. E. Li et al. proposes a new longitudinal dynamics acceleration tracking control technology to achieve automatic control of platoon [21]. In order to realize approximate optimal longitudinal control of Autonomous Land Vehicle (ALV), Z. Huang et al. proposes the parameterized batch actor-critic (PBAC) algorithm [22]. Considering the problem that the longitudinal control of an autonomous vehicle is usually affected by lateral interruption, K. Liu et al. proposes a method based on model prediction considering lateral interruption to longitudinal control the autonomous driving [23]. L. Menhour et al. proposes a new method of vehicle control that does not use the vehicle evolutionary model, and use Matlab and Peugeot 406 (with 10 DoF) dynamic model for simulation verification [24]. S. E. Li et al. proposes a distributed $H \infty$ control method for the distribution of multi-car units [25].

The third way: the longitudinal control algorithm based on artificial intelligence algorithm. A. Garg et al. proposes a kind of artificial intelligent method based on automated neural networks search (ANS) and is proved to be effective [26]. A. Rajan et al. proposes a Framework based on the combination of artificial network and uncertainty evaluation technology [27]. V. Vijayaraghavan et al. proposes a holistic method and analyze its impact on the potential failure problem [28]. X. S. Hu et al. propose a kind of framework for control to maximally optimize the performance of fuel economy in the situation of car-following. The experiment results verify the proposed scheme and prove that the proposed method is more precise and thereby induces higher car-following energy efficiency. Inspired by this work, it will be play an important role in energy saving control by applying this framework to autonomous driving control [29].

Based on the researches of longitudinal control algorithm for intelligent vehicle mentioned above, A few researches only based on rule model, a few researches only based on nonlinear theory and algorithm, a few researches only based on artificial intelligence algorithm. Few researches consider the method that learns from experienced drivers, obtaining the driving data and establishing the longitudinal control algorithm. Based on the idea, the main contributions of this paper are as follows. (1) According to Gauss cloud model (GCM) algorithm and cloud reasoning (CR) algorithm, a new control algorithm is designed to solve the uncertainty in the control process; (2) Propose a new way to deal with complex driving tasks by learning human driving behavior; (3) According to the human driving experience data, the parameters of the longitudinal speed control algorithm for autonomous driving vehicles are established.

This paper is organized as follows. Section 1 describes the algorithms and methods of longitudinal controller of autonomous vehicle briefly. Section 2 describes the Gauss cloud model (GCM), Cloud reasoning (CR), and the algorithm of GCM and CR is presented, the CR includes preconditioned Gauss cloud generator (Pre-GCG) and post-conditioned Gauss cloud generator (Post-GCG). Section 3 presents the rules and algorithm of longitudinal controller based on the GCM that we proposed. Section 4 describes the experiment that includes experiment's setup and the result and analysis of the experiment based on our proposed algorithm. Finally, we draw some conclusion and comment about future work in Section 5.

2. Model and Problem Formulation

2.1. Gauss Cloud Model

The uncertainty of human intelligence is the manifestation of human ability that is cope with uncertain complex environments. The uncertainty is reflected by fuzziness and randomness. Gauss distribution is one of the most important distributions in Probability Theory. The two characteristics of mean and variance are used to represent the overall characteristics of random variables. The fuzziness is expressed by membership, and membership is the object which is quantized by fuzzy mathematics. Where a fuzzy subset of A is in the domain U , it cannot simply express that elements belong to U and other elements do not belong to U. Each element u in the domain U belongs to U in certain probability. The $u_A(u)$ represents membership of u to A. The $u_A(u)$ is called membership function of A. In this paper, we combine fuzzy with randomness, and propose Gauss cloud model (GCM) based on Gauss distribution (GD) and bell-ship membership function of $m(x) = \exp\{(-(x-a)^2)/(2b^2)\}$ [30,31].

Definition 1. *Where U is a quantitative domain that is represented by precise numerical and the range of U is between 0 and 1. C is a set of qualitative concepts corresponding to U and be represented by Ex, En and He, Ex represents Expect, En represents Entropy, He represents Hyper Entropy. Where the value of x belongs to U, and is a random value of qualitative concepts on Set C. The value of x obeys Gauss distribution (GD)* $x \sim N(Ex, En'^2)$*, and En′ obeys Gauss distribution (GD)* $En' \sim N(En, He^2)$ *[32]. The certainty degree of x to C is defined as follows:*

$$m(x) = \exp\{(-(x-Ex)^2)/(2(En')^2)\}$$

where the distribution of x on the domain of U is called a Gauss cloud (GC), and each the value of x is called cloud drop [33]. The Gauss cloud (GC) algorithm is presented in Table 1 [30,32].

Table 1. The Gauss cloud model (GCM) algorithm.

Input: ***(Ex, En, He)*** **and *N*. (Three numerical features *(Ex, En, He)* of qualitative concept *C* represent the quantification of a concept, the value of *N* represents the number of cloud drops)**
Output: $drop(x_i, m_i), i = 1 \cdots N$. **(The drop of x_i and the certainty degree of x_i.)**
(1) to generate a Gauss random number: $En' \sim N(En, He^2)$
(2) to generate a Gauss random number: $x \sim N(Ex, En'^2)$
(3) to calculate the certainty degree of x_i: $m(x) = \exp\{(-(x - Ex)^2)/(2(En')^2)\}$
(4) to add the drop of x_i to a set of drop
(5) Repeat (1)–(4) until the number of cloud drops equals to N.

The distribution of drops generated by Gauss model (GM) algorithm and called the Gauss cloud distribution (GCD). The Gauss cloud (GC) algorithm cloud be implemented by the Gauss cloud generator (GCG), as shown in Figure 1. The Gauss model (GM) algorithm based on Gauss random number generation method, Gauss model (GM) algorithm uses Gauss random number twice, the first random number is the basis of the second random number, as shows in the table of the Gauss cloud model (GCM) algorithm of the first step and the second step. When random number is generated, the variance is not allowed to equal to zero, so the algorithm requires En and He are greater than zero [33]. (1) Where He equals to zero, the first step of the Gauss Cloud Model algorithm generate a certainty En, the distribution of drops $drop(x_i, m_i)$ is Gauss distribution; (2) Where En equals to zero and He equals to zero, the Gauss random number is a certainty Ex, and m equals to one. According to (1) and (2), we draw the conclusion that Gauss cloud distribution (GCD) is different from the Gauss distribution (GD), Gauss distribution (GD) is a special case of Gauss cloud distribution (GCD). With respect to the qualitative concept of the velocity of 80 km/h, we assume that $Ex = 80$, $En = 1$, and $He = 0.1$. Then we use the Gauss cloud (GC) algorithm mentioned above to generate 1000 cloud drops. The distribution of cloud drops of the velocity of 80 km/h and its certainty degree $C(x, m)$ are shown in Figure 2.

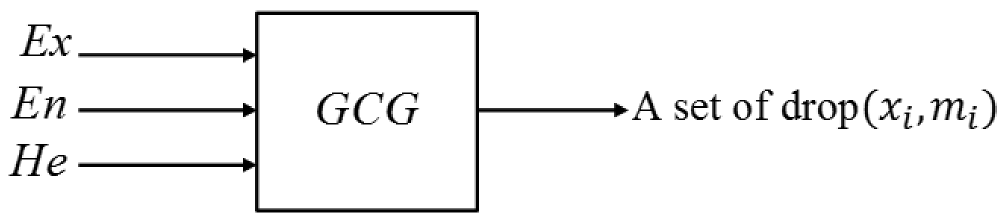

Figure 1. A Gauss cloud generator (GCG).

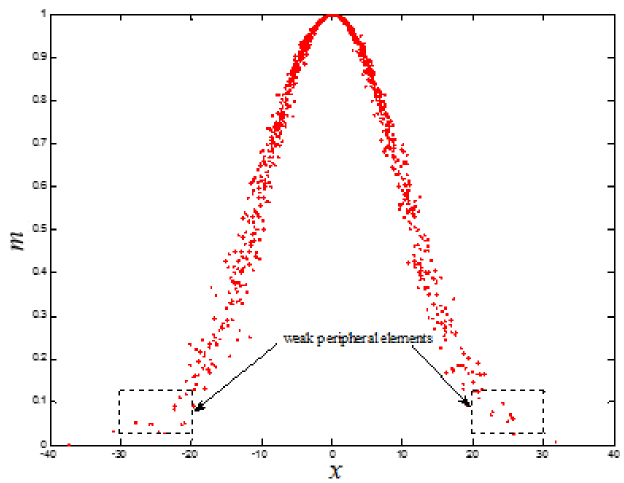

Figure 2. The distribution of 1000 drops.

2.2. Cloud Reasoning

Knowledge is expressed by the concepts and the relationship of concepts. It is the result of human abstracting, communicating and summarizing. In a control system, the program of the "perception-action" control the system, perception results create knowledge, knowledge is expressed by the concept, The control system takes corresponding control actions according to the concept of perception results, and establish the control relationship between concept and object, control relations constitute a rule database, according to the relationship between concepts and objects, mining the causal relationship between knowledge from the rule database, it is implemented by Gauss cloud model (GCM) algorithm, and is constructed a control rule generator. When a particular condition is inputting, many rules are activated, a rule is selected to execute according to the inference engine, achieve reasoning and control of uncertainty. Rule generator is composed of Preconditioned and post-conditioned. The preconditioned and post-conditioned are expressed by concept. The preconditioned is a prerequisite for being triggered. The preconditioned is consisted of single condition or multiple conditions. The post-conditioned represents the specific control action.

2.2.1. Preconditioned Gauss Cloud Generators

A preconditioned Gauss cloud generators (Pre-GCG) is defined as follow.

Definition 2. *The following definition is shown:*

$$If\ A,\ then\ B,$$

where A corresponds to the concept in quantitative domain that is U_1. corresponds to the concept in quantitative domain that is U_2. Given a specific value that equals to a which belongs to U_1. Gauss Cloud Generator generate the certainty degree distribution of the specific value that equals to a that belongs to concept A. This Cloud Generator is called preconditioned Gauss cloud generator [34]. As shown in Figure 3.

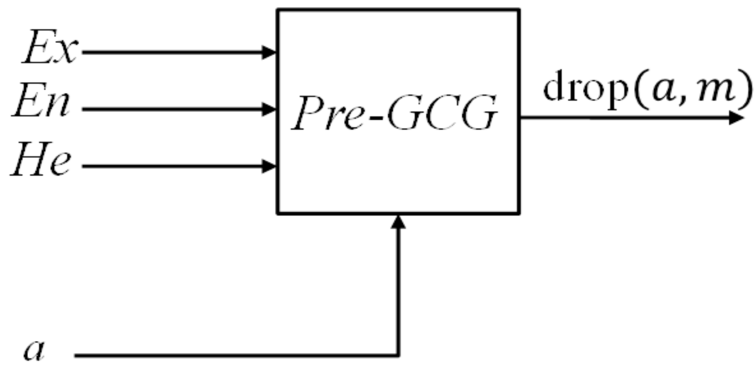

Figure 3. A preconditioned Gauss cloud generator (Pre-GCG).

2.2.2. Post-Conditioned Gauss Cloud Generators

A post-conditioned Gauss cloud generators (Post-GCG) is defined as follow.

Definition 3. *The following definition is shown:*

$$If\ A,\ then\ B,$$

where A corresponds to the concept in quantitative domain that is U_1. B corresponds to the concept in quantitative domain that is U_2. Given a certainty degree that equals to m. Gauss Cloud Generator generate the distribution which satisfies certainty degree which belongs to concept B in quantitative domain that is U_2. This Cloud Generator is called post-conditioned Gauss cloud generator [35,36]. As shown in Figure 4.

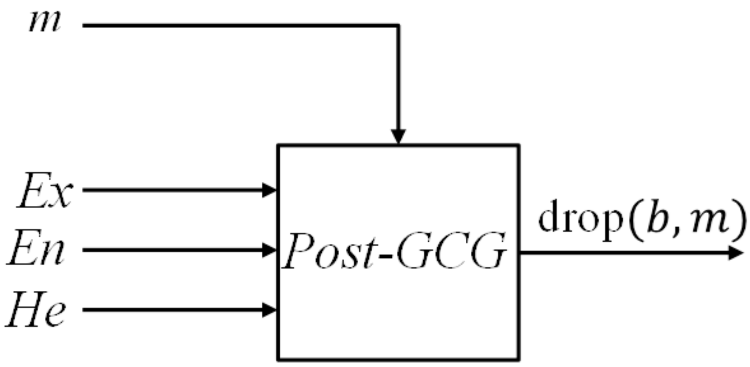

Figure 4. A post-conditioned Gauss cloud generator (Post-GCG).

3. Longitudinal Control Based on Gauss Cloud Model

3.1. Data Analysis

The longitudinal velocity control algorithm for Mengshi autonomous vehicle is established according to the Gauss cloud model (GCM) and cloud reasoning (CR) [37]. The input of the longitudinal velocity control model is the pedal opening angle, the velocity of the Mengshi autonomous vehicle, the acceleration of the Mengshi autonomous vehicle and the expected velocity of the Mengshi autonomous vehicle. The output is the acceleration required for the Mengshi autonomous vehicle to achieve the expected velocity. The longitudinal velocity control algorithm for Mengshi autonomous vehicle is shown in Figure 5.

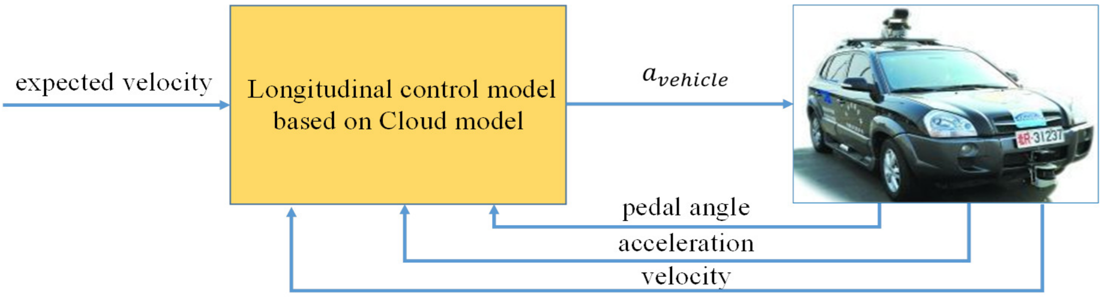

Figure 5. Longitudinal control algorithm based on Gauss cloud model.

The real vehicle test in the city of Beijing lasted a month, test 4 h per day, the data recorded frequency of 1 Hz. The detection data including the pedal opening angle value, velocity, acceleration and expected velocity. The data volume is above 400,000. The domain of the quantitative attribute is divided into the concept of the Gauss cloud model (GCM). Tables 2 and 3 respectively show the three digital characteristics (Ex, En, He) of vehicle velocity and vehicle acceleration [35,37,38].

Table 2. Numerical characteristics of Gauss cloud model of v.

v	$v(Ex, En, He)$
Positive greater	(9.8, 1.1, 0.18)
Positive less	(4.9, 1, 0.19)
Zero	(0, 1, 0.01)
Negative less	(−4.7, 1, 0.03)
Negative greater	(−9.8, 1.2, 0.03)

Table 3. Numerical characteristics of Gauss cloud model of a.

a	$a(Ex, En, He)$
Positive greater	(19, 2.5, 0.045)
Positive less	(9, 2.1, 0.02)
Zero	(0, 2, 0.007)
Negative less	(−9, 2, 0.02))
Negative greater	(19, 2.8, 0.05)

3.2. Longitudinal Control Rules and Algorithm

The input of longitudinal velocity controller of the Mengshi autonomous vehicle is single value, and The output of longitudinal velocity controller of the Mengshi autonomous vehicle is also single value, the input value of the longitudinal velocity controller of the Mengshi autonomous vehicle is the difference between expected velocity and actual velocity of autonomous vehicle $\triangle v$. The output is the acceleration a. The variable a can be described using five qualitative concepts, namely, 'positive greater', 'positive less', 'near-zero', 'negative less', and 'negative greater'. The input and output variables define the five qualitative concepts and construct a corresponding cloud regulation generator.

Assume the following rule:

$$\text{If } E\text{, then } F,$$

where E is the Pre-GCG that generates the drop distribution (a, m) with a specific value of a and a certainty degree of m. E is replaced by the Gauss cloud model (GCM) digital feature of the velocity obtained by the experiment, then a represents the velocity $V_{vehicle}$ of the Mengshi autonomous vehicle, m represents the degree of determination of the velocity, the degree of determination of the velocity is related to the acceleration. F is the Post-GCG that generates the drop distribution (b, m) of the cloud with a specific value of b and a certainty degree of m. F is replaced by the numerical model of the cloud model of the acceleration obtained by the experiment, then m is the degree of determination of this acceleration, b is the acceleration required for the autonomous driving vehicle to reach the expected velocity, which is called longitudinal control model based on Gauss cloud model (GCM) [39], as is shown in Figure 6.

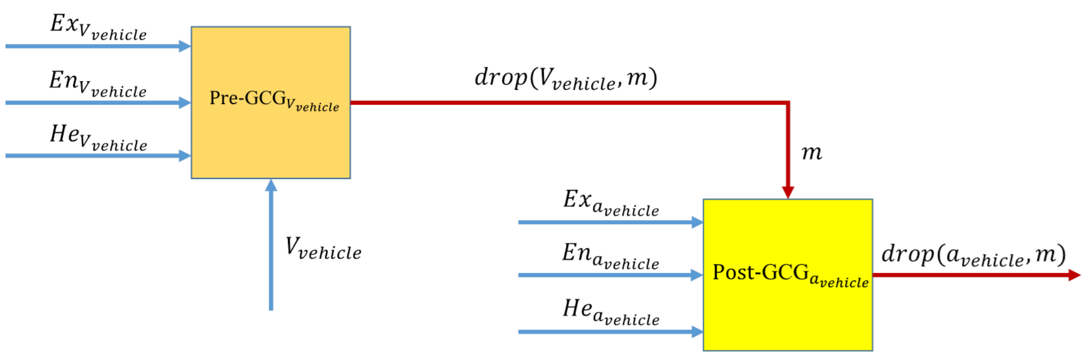

Figure 6. The longitudinal control algorithm chart.

The longitudinal control algorithm is presented in Table 4.

The longitudinal control algorithm implies an uncertainty transfer in the conceptual reasoning process. In the universal sets U_1 of the Pre-GCG, the distribution of the certainty degree of m belongs to the specific value of $v_{vehicle}$, whereas the certainty degree of m is the input of the Post-GCG that generates the drop distribution $(a_{vehicle}, m)$ of the Gauss cloud specific value of $v_{vehicle}$ and the certainty degree of m. The processing of the certainty value of $v_{vehicle}$ to the certainty value of $v_{vehicle}$ is uncertain [35,37–39].

Table 4. The longitudinal control algorithm.

Input: Three figures (Ex_v, En_v, He_v), three figures (Ex_a, En_a, He_a), and a specific value $v_{vehicle}$.   **Output: The drop distribution $(a_{vehicle}, m)$.**
(1) To generate a Gauss random $En_v' \sim N(En_v, He_v^2)$ (2) To calculate the certainty: $m(x) = \exp\{(-(x - Ex_v)^2)/(2((En_v')^2)\}$ (3) To generate a Gauss random $En_a' \sim N(En_a, He_a^2)$ (4) If $v_{vehicle} < Ex$, then to calculate the certainty:$a_{vehicle} = Ex_a - En_a'\sqrt{-2lnm}$ (5) If $v_{vehicle} > Ex$, then to calculate the certainty:$a_{vehicle} = Ex_a + En_a'\sqrt{-2lnm}$ (6) To generate the distribution of drops $(a_{vehicle}, m)$

4. Experiment Result and Analysis

4.1. Experiment Setup

4.1.1. Hardware Architecture of an Autonomous Vehicle System

The on-board sensor configuration of an autonomous vehicle comprises a radar sensor, a vision sensor, and a positioning sensor. The radar sensor consists of a 32 lines laser radar on the vehicle, a forward SICK radar, a forward four lines laser radar, and a backward millimeter wave radar (MMW). The vision sensor comprises three front-facing cameras, two rear-facing cameras, and two lateral cameras set in both rear-view mirrors. The positioning sensor consists of the Global Positioning System (GPS) and an Inertial Measurement Unit (IMU), as is shown in Figure 7. This study is based on a MengShi autonomous vehicle, as is shown in Figure 8. All types of sensors are mainly applied to sense the surroundings of the vehicle for real-time acquisition of its location, posture, velocity, and time.

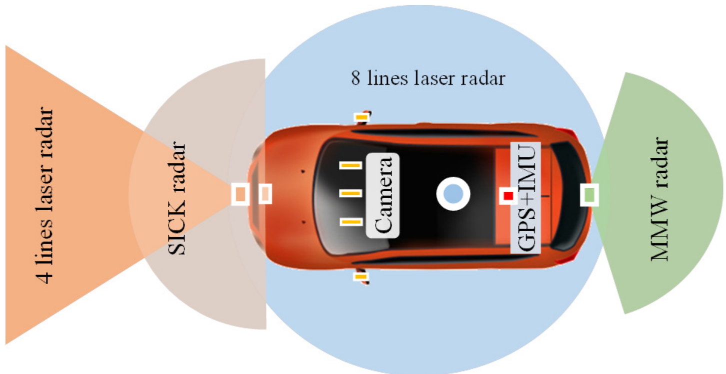

Figure 7. Experiment sensor configuration.

Figure 8. MengShi autonomous vehicle.

4.1.2. Software Architecture of an Autonomous Vehicle System

The design and development of autonomous vehicles aims to study the key techniques of multi -interaction and collaborative driving based on visual and auditory information. The software architecture of autonomous vehicle systems is shown in Figure 9. This architecture comprises a human computer interaction (HCI) layer, a sensor and sensing layer, a planning and decision layer, and a control layer.

HCI layer: This layer receives the touch commands and emergency braking instructions of the driver and relays them to the control layer. It simultaneously provides the driver with feedback information from the surroundings and other vehicles through sounds and images.

Sensor and sensing layer: This layer consists of a radar sensor, a vision sensor, a GPS sensor, and an IMU sensor. It focuses on completing the collection of sensor data. To realize the "plug and play" feature of the sensor, the standard data format of various sensors should be normative, which requires transforming the specific data format of the sensor to the standard format understood by an autonomous vehicle. The sensor data collected in this layer is delivered to the sensory module. The sensing layer focuses on sensor data analysis, road edge identification, obstacle detection, traffic sign detection, and body state estimation, which can facilitate the planning and decision of an autonomous vehicle.

Decision and planning layer: This layer focuses on path planning and navigation, which determine the driving pattern of an autonomous vehicle by analyzing environment data and vehicle data from the sensory module. This layer also determines the position of the vehicle in a detailed electronic map and generates the traveling track according to the coordinates of the target point. Human intervention and obstacles also influence on the track.

Control layer: This layer controls vehicles to enable them to proceed based on track data and current vehicle state. It also receives human instructions and performs acceleration/deceleration and steering operations. This layer directly outputs the control order to the accelerator, as well as the braking and steering controller, of the vehicle.

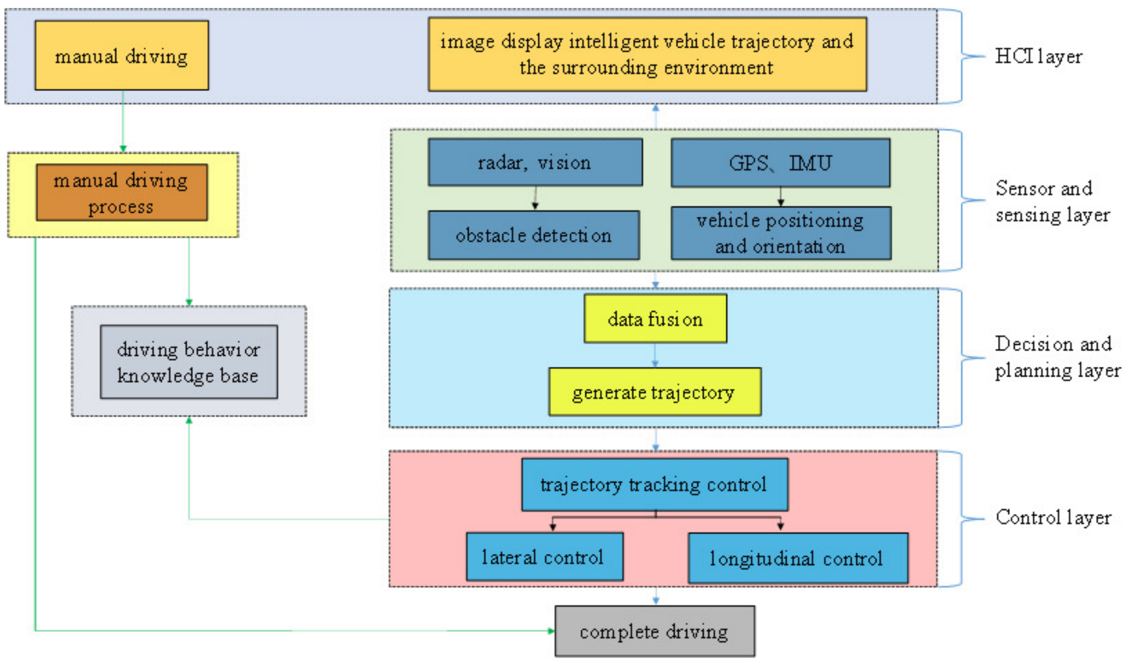

Figure 9. Software architecture of an autonomous vehicle system.

4.1.3. Experimental Environment

The Beijing-Tianjin Expressway, which spans the Taihu Toll Station and the Dongli Toll Station, covers 121 km of shuttle distance. Rain is moderate rain in Tianjin, with a small amount of water on the ground. The weather is rainy in the Tianjin section of the Beijing-Tianjin Expressway. When the sun occasionally shines, the weather remains sunny until reaching Beijing, where it is cloudy. The temperature outside the vehicle is 32 °C , and that on the road is 40 °C. Visibility is over 200 m. The experiment path is designated by the blue line in Figure 10.

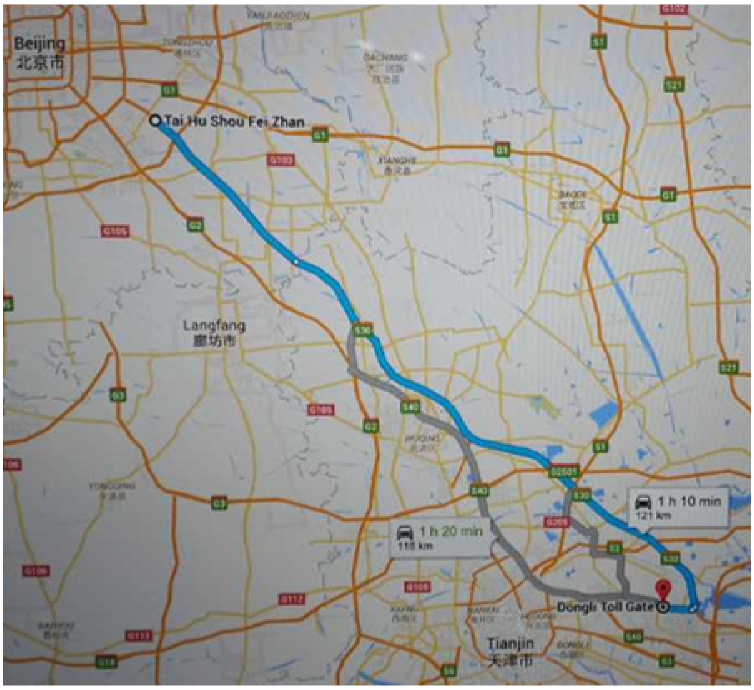

Figure 10. Experiments paths.

4.2. Experiment Result and Analysis

When the autonomous vehicle proceeds, the instant velocity is obtained using GPS, and the acceleration is obtained using inertial measurement unit (IMU).

4.2.1. Speed and Acceleration Analysis Based on Mileage

As shown in Figure 11, Speed curve of Dongli Toll Station to Taihu Toll Station based on mileage. As show in Figure 12, Acceleration curve of Dongli Toll Station to Taihu Toll Station based on mileage, the x axis represents the mileage of data, unit: km. The y axis in Figure 11 indicates the speed, unit: km/s. The y axis in Figure 12 indicates the acceleration, unit: km/s^2.

Automatic driving mileage is 105 km, the average speed is 87.32 km/h, the target speed set by the program is 100 km/h. In the real test, the Mengshi autonomous vehicle follows the other cars at part of the road (9–15 km, 55–60 km, 76–81 km). As shown in Figure 11, during to road traffic accidents, the speed is reduced to 0 at 21.5 km, the driver drives the Mengshi autonomous vehicle through the road. As shown in Figure 12, in the whole process of the real test, because of the large traffic flow, the acceleration value of the autonomous vehicle is within -5 km/s^2$\sim$$+5$ km/s^2, and the ride comfort is decreased, which needs to be improved in further.

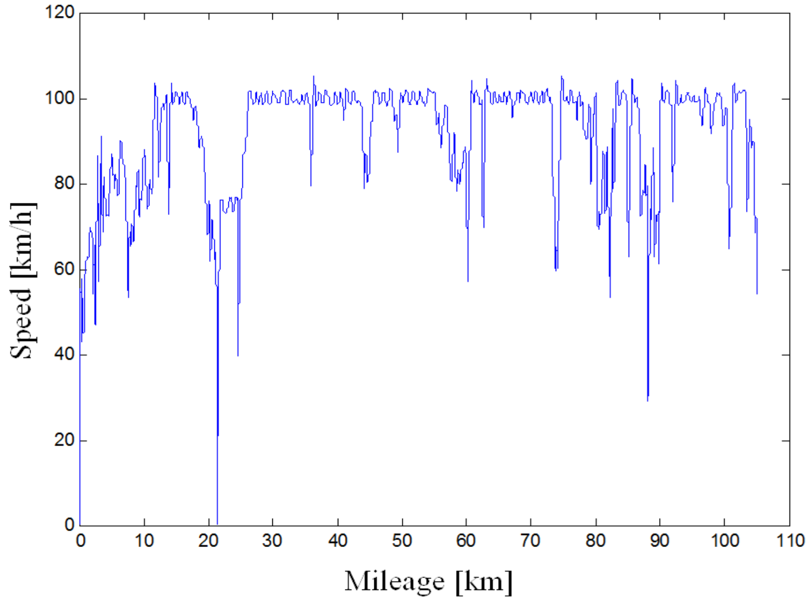

Figure 11. Speed curve of Dongli Toll Station to Taihu Toll Station based on mileage.

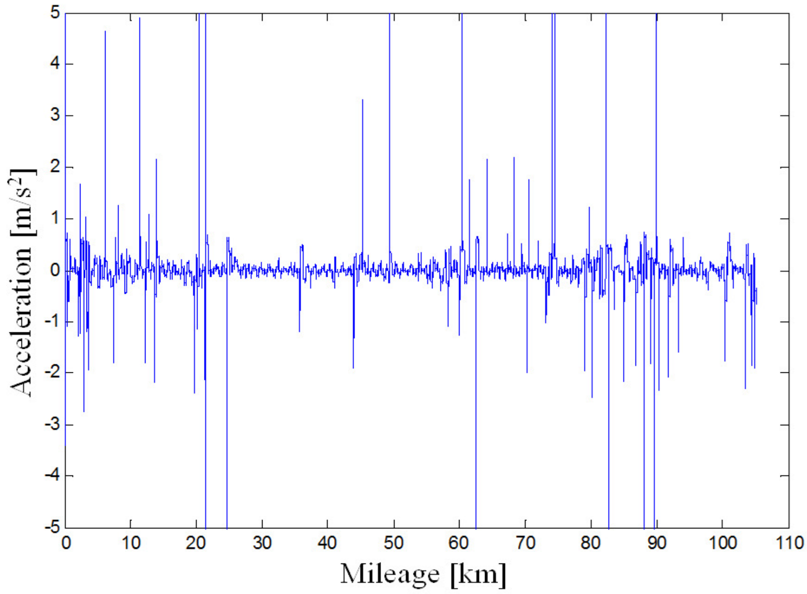

Figure 12. Acceleration curve of Dongli Toll Station to Taihu Toll Station based on mileage.

4.2.2. Speed Analysis Based on Time

As shown in Figure 13, the 15 s speed curve of Dongli Toll Station to Taihu Toll Station which is described. As show in Figure 14, the 15 s speed curve of Taihu Toll Station to Dongli Toll Station which is described, the x axis represents the time of data, and the data recording interval is 200 ms; The y axis indicates the speed, unit: km/s, Dongli Toll Station to Taihu Toll Station, the mileage is 86 km, the average speed is 87.26 km/h and program set speed is 90 km/h; Taihu Toll Station to Dongli Toll Station, the mileage is 86 km, the average speed is 94.1 km/h and program set speed is 100 km/h; The situation of speed changing reflects the driving pattern. In the experiment, within the first 30 km, it used 90 km of the vehicle search driving model. During the experiment, the speed of the Beijing-Tianjin high-speed on his car speed fast, the autonomous driving vehicle without Slow speed vehicles and speed maintained in 90 km/h. Due to road construction, implement the artificial intervention, the speed is set to 50 km/h, and driving with cars, the speed affected by the front car is kept at 60–100 km/h. The figure shows a data speed exceeding 150 km/h, which is an invalid speed value.

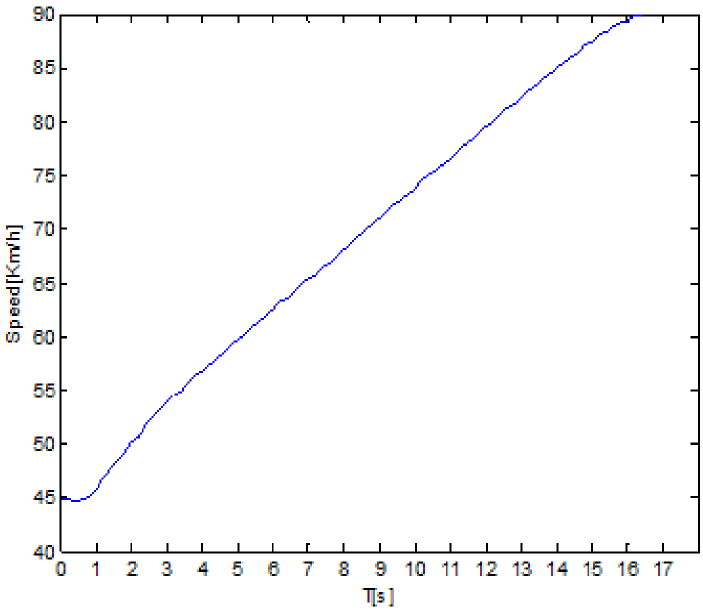

Figure 13. 15 s speed curve of Dongli Toll Station to Taihu Toll Station.

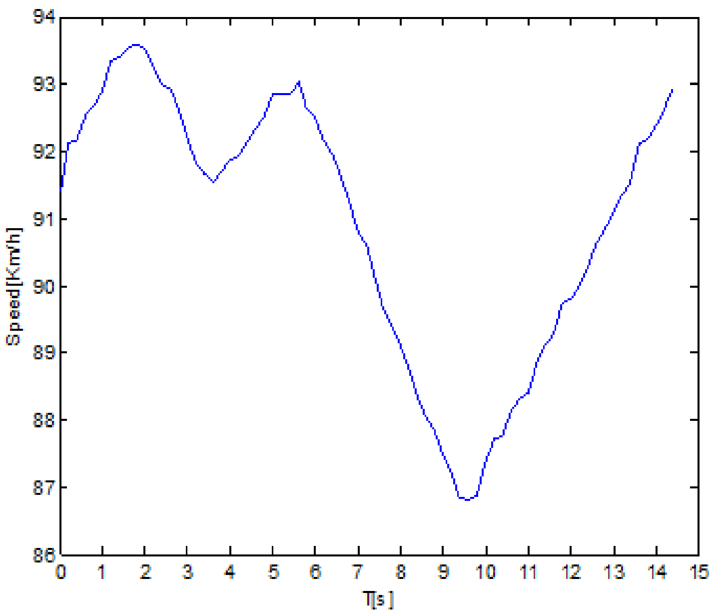

Figure 14. 15 s speed curve of Taihu Toll Station to Dongli Toll Station.

4.2.3. Acceleration Analysis Based on Time

As shown in Figure 15, the 15 s acceleration curve of Dongli Toll Station to Taihu Toll Station which is described. As shown in Figure 16, the 15 s acceleration curve of Taihu Toll Station to Dongli Toll Station which is described, the x axis represents the time of data, and the data recording interval is 200 ms; The y axis indicates the acceleration, unit: km/s^2. In the experiment, the acceleration value of the autonomous vehicle during acceleration and deceleration is maintained at $-2\,\mathrm{m/s^2} \sim 1\,\mathrm{m/s^2}$. Korea k. Yi use the linear optimal control theory to design the upper control, considering the need of vehicle ride comfort, the output of the upper controller is saturation limited, the vehicle longitudinal acceleration is limited to $-2\,\text{m/s}^2 \sim 1\,\text{m/s}^2$ range. In rare cases, the acceleration occurs more than $1\ \text{m/s}^2$, causing a rapid acceleration and the passenger's subjective feeling is better. The result of the real experimental test shows that the longitudinal control based on Gauss cloud model (GCM) can achieve good control effect on speed and acceleration, the speed and acceleration have strong stability and small fluctuation. The phase plane of velocity and acceleration shows a certain diversity, reflecting the phenomenon of real experiment. The longitudinal control based on Gauss cloud model (GCM) compared with other controller, such as PID controller, fuzzy logic controller, and so on, the results of the longitudinal velocity control based on cloud model is not the only constant, it can reflect the uncertainty of longitudinal velocity control.

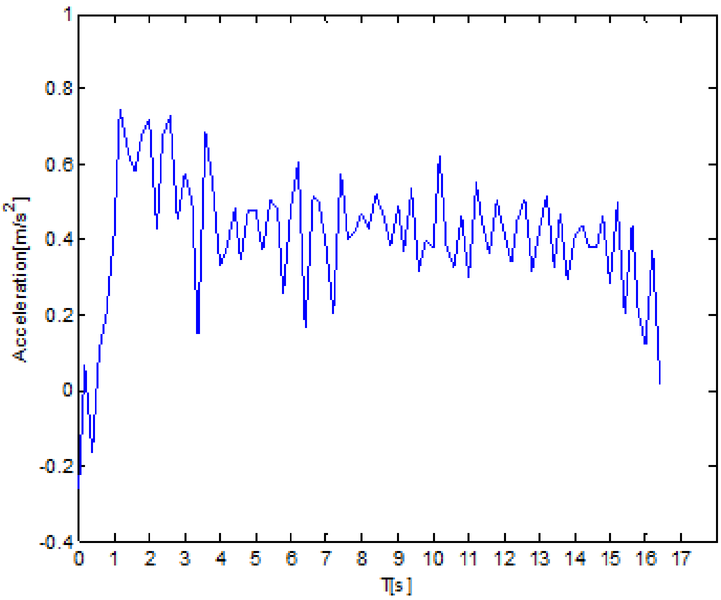

Figure 15. 15 s acceleration curve of Dongli Toll Station to Taihu Toll Station.

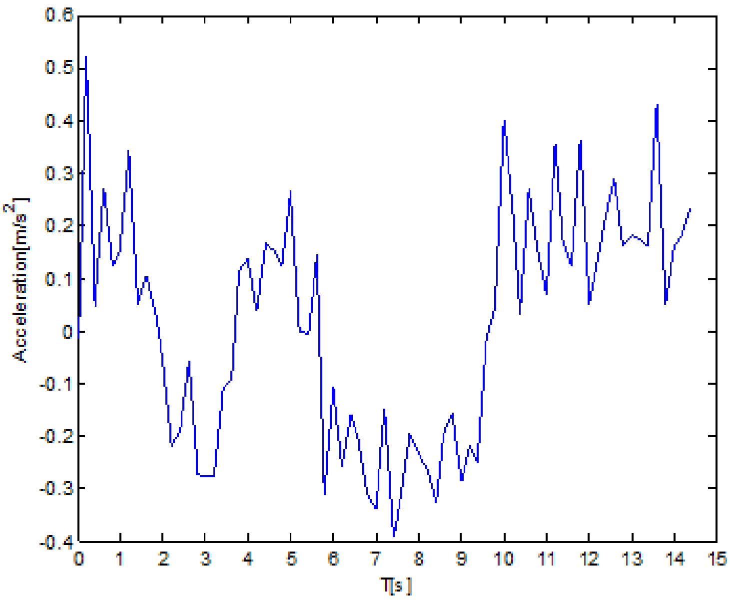

Figure 16. 15 s acceleration curve of Taihu Toll Station to Dongli Toll Station.

5. Conclusions

This paper proposes the application of cloud model and cloud reasoning to the longitudinal control of autonomous vehicles. Because the cloud model use the value of expected, entropy and hyper entropy to characterize the qualitative concept, so it can integrate the fuzziness and randomness together in qualitative and quantitative conversion to overcome the inherent defects of the membership function in fuzzy set theory. The uncertainty of the control of autonomous driving vehicle has the fuzziness and randomness, cannot be expressed by the precise mathematical model, and the control of the driver pedal operation is realized by using the cloud inference, expressed the randomness of the speed control. In this paper, we classify the speed and acceleration of the cloud model, classify it according to experience, no certification, therefore, this will be the follow-up research work, by the introduction of cloud transformation, the data in the same concept cluster together, the data between different concepts are classified, fully reflect the actual distribution characteristics of the data.

This research presents the longitudinal speed control algorithm for autonomous vehicle, the presented longitudinal speed control algorithm has been tested on High-speed road. The limitation of the proposed algorithm is dependent on a large number of driver's driving data. Based on the existing research, a direction to extend this work is to consider lateral control for Mengshi autonomous vehicle and to build new algorithm based on a small amount of driver's driving data. Additionally, the future work is to carry out research on fuel consumption for autonomous vehicles and to maximally optimize the performance of fuel economy based on Xiaosong Hu et al. propose a predictive fuel-optimal control scheme, experiment result prove that the proposed method is more precise and thereby induces higher car-following energy efficiency [29].

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References

1. Wu, L.; Chen, X.; Ling, Y. The Application of Fuzzy Control Algorithm in the Longitudinal Control System for a Platoon of Vehicles. In Proceedings of the 6th World Congress on Intelligent Control and Automation, Dalian, China, 21–23 June 2006; pp. 1242–1245.
2. Sheikholeslam, S.; Charles, A. Longitudinal Control of a Platoon of Vehicles with no Communication of Lead Vehicle Information: A System Level Study. *IEEE Trans. Veh. Technol.* **1993**, *42*, 546–554.
3. Zheng, P.; McDonald, M. Application of Fuzzy Systems in the Car-Following Behavior Analysis. In *Fuzzy Systems and Knowledge Discovery*; Springer: Berlin/Heidelberg, Germany, 2005; Volume 3613, pp. 782–791.
4. Qiang, G.; liang, H.; Chao, D. The Modeling and Simulation of the Car-following Behavior Based on Fuzzy Inference. In Proceedings of the 2008 International Workshop on Modelling, Simulation and Optimization, Hong Kong, China, 27–28 December 2008; pp. 322–325.
5. Kumarawadu, S.; Lee, T. A Model Based Neuro Control Approach for Car Following Collision Prevention. In Proceedings of the IEEE International Conference on Networking, Sensing and Control, Taipei, Taiwan, 21–23 March 2004; pp. 152–157.
6. Lv, C.; Zhang, J.; Li, Y.; Yuan, Y. Mechanism analysis and evaluation methodology of regenerative braking contribution to energy efficiency improvement of electrified vehicles. *Energy Convers. Manag.* **2015**, *92*, 469–482.

7. Kim, H.; Dickerson, J.; Kosko, B. Fuzzy throttle and brake control for platoons of smart cars. *Fuzzy Sets Syst.* **1996**, *84*, 209–234.
8. Cai, L.; Rad, A.; Chan, W. An Intelligent Longitudinal Controller for Application in Semiautonomous Vehicles. *IEEE Trans. Ind. Electron.* **2010**, *57*, 1487–1497.
9. Lee, H.; Tomizuka, M. Adaptive Vehicle Traction Force Control for Intelligent Vehicle Highway Systems (IVHSs). *IEEE Trans. Ind. Electron.* **2003**, *50*, 37–47.
10. Lv, C.; Wang, H.; Cao, D. High-Precision Hydraulic Pressure Control Based on Linear Pressure-Drop Modulation in Valve Critical Equilibrium State. *IEEE Trans. Ind. Electron.* **2017**, *64*, 7984–7993.
11. Peng, Y.; Hsu, C.; Lin, C.; Lee, T. Robust Intelligent Backstepping Longitudinal Control of Vehicle Platoons with H Tracking Performance. In Proceedings of the 2006 IEEE International Conference on Systems, Man, and Cybernetics, Taipei, Taiwan, 8–11 October 2006; pp. 4648–4653.
12. Ferrara, A.; Pisu, P. Minimum Sensor Second-Order Sliding Mode Longitudinal Control of Passenger Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2004**, *5*, 20–32.
13. Nouveliere, L.; Mammar, S. Experimental Vehicle Longitudinal Control. Using Second Order Sliding Modes. In Proceedings of the American Control Conference, Denver, CO, USA, 4–6 June 2003; pp. 4705–4710.
14. Lu, X.; Hedrick, J. Longitudinal Control Algorithm for Automated Vehicle Merging. In Proceedings of the 39th IEEE Conference on Decision and Control, Sydney, Australia, 12–15 December 2000; pp. 450–455.
15. Liu, D.; Sun, Z.; Zhao, H.; Li, Z. Longitudinal Controller Design For Autonomous Ground Vehicle in Off-road Environment. In Proceedings of the 27th Chinese Control Conference, Kunming, China, 16–18 July 2008; pp. 687–690.
16. Tai, M.; Tomizuka, M. Robust Longitudinal Velocity Tracking of Vehicles Using Traction and Brake Control. In Proceedings of the International Workshop on Advanced Motion Control, Nagoya, Japan, 30 March–1 April 2000; pp. 305–310.
17. Raffin, A.; Taragna, M.; Giorelli, M. Adaptive longitudinal control of an autonomous vehicle with an approximate knowledge of its parameters. In Proceedings of the 11th International Workshop on Robot Motion and Control, Wasowo, Poland, 3–5 July 2017; pp. 1–6.
18. Naeem, H.M.Y.; Mahmood, A. Robust and optimal control of longitudinal dynamics of automotive vehicle. In Proceedings of the International Conference on Electrical Engineering, Lahore, Pakistan, 2–4 March 2017; pp. 1–6.
19. Boulkroune, B.; Aalst, S.V.; Lehaen, K.; Smet, J.D. Observer-based Controller with Integral Action for Longitudinal Vehicle Speed Control. In Proceedings of the 2017 IEEE Intellient Vehicles Symposium (IV), Los Angeles, CA, USA, 11–14 June 2017; pp. 322–327.
20. Lv, C.; Zhang, J.; Li, Y. Extended-Kalman-filter-based regenerative and friction blended braking control for electric vehicle equipped with axle motor considering damping and elastic properties of electric powertrain. *Veh. Syst. Dyn.* **2014**, *52*, 1372–1388.
21. Li, S.E.; Gao, F.; Gao, D. Multiple-Model Switching Control of Vehicle Longitudinal Dynamics for Platoon-Level Automation. *IEEE Trans. Veh. Technol.* **2016**, *65*, 4480–4492.
22. Huang, Z.; Xu, X.; He, H.; Tan, J.; Sun, Z. Parameterized Batch Reinforcement Learning for Longitudinal Control of Autonomous Land Vehicles. *IEEE Trans. Syst. Man Cybern. Syst.* **2017**, 1–12, doi:10.1109/TSMC.2017.2712561.
23. Liu, K.; Gong, J.; Kurt, A.; Chen, H.; Ozguner, U. A Model Predictive-based Approach for Longitudinal Control in Autonomous Driving with Lateral Interruptions. In Proceedings of the 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, USA, 11–14 June 2017; pp. 359–364.
24. Menhour, L.; D'Andréa-Novel, B.; Fliess, M.; Gruyer, D.; Mounier, H. An Efficient Model-Free Setting for Longitudinal and Lateral Vehicle Control: Validation through the Interconnected Pro-SiVIC/RTMaps Prototyping Platform. *IEEE Trans. Intell. Transp. Syst.* **2017**, 1–15, doi:10.1109/TITS.2017.2699283.
25. Li, S.; Gao, F.; Li, K.; Wang, L.-Y.; You, K.; Cao, D. Robust Longitudinal Control of Multi-Vehicle Systems—A Distributed H-Infinity Method. *IEEE Trans. Intell. Transp. Syst.* **2017**, 1–10, doi:10.1109/TITS.2017.2760910.
26. Garg, A.; Vijayaraghavan, V.; Zhang, J.; Liang, X. Design of robust battery capacity model for electric vehicle by incorporation of uncertainties. *Int. J. Energy Res.* **2017**, doi:10.1002/er.3723.
27. Rajan, A.; Vijayaraghavan, V.; Ooi, M.P.; Kuang, Y.C. A Simulation-based Probabilistic Framework for Lithium-ion Battery Modelling. *Measurement* **2018**, *115*, 87–94.

28. Vijayaraghavan, V.; Garg, A.; Liang, G. Fracture Mechanics Modelling of Lithium-ion Batteries under pinch torsion test. *Measurement* **2017**, *114*, 382–389.
29. Hu, X.; Wang, H.; Tang, X. Cyber-Physical Control for Energy-Saving Vehicle Following with Connectivity. *IEEE Trans. Ind. Electron.* **2017**, *64*, 8578–8587.
30. Li, D.; Wang, S.; Li, D. *Spatial Data Mining: Theory and Application*; Springer: Berlin/Heidelberg, Germany, 2016; ISBN 978-3-662-58536-1.
31. Li, D.; Liu, Y.; Du,Y. Artificial Intelligence with Uncertainty. *J. Softw.* **2004**, *15*, 1538–1594.
32. Cao, B.; Li, D.; Qin, K.; Chen, G.; Liu, Y.; Han, P. An Uncertain Control Framework of Cloud Model. In Proceedings of the International Conference on Rough Set and Knowledge Technology (RSK), Beijing, China, 15–17 October 2010; pp. 618–625.
33. Li, D.; Liu, Y.; Gan. W. A new cognitive model-Cloud model. *Int. J. Intell. Syst.* **2009**, *24*, 357–375.
34. Gao, H. *Statistical Calculation*; Peking University Press: Beijing, China, 1995.
35. Li, D.; Du, Y. *Artificial Intelligence with Uncertainay*; National Defence Industry Press: Beijing, China, 2005; pp. 137–185.
36. Gao, H.; Jiang, J.; Zhang, L.; Liu, Y.; Li, D. Cloud Model-Detect Unsupervised Communities in Social tagging Network. In Proceedings of the International Conference on Information Science and Cloud Computing, Guangzhou, China, 7–8 December 2013; pp. 317–323.
37. Li, X. Research and Application of Association Rules in Data Mining. *Comput. Study* **2010**, *3*, 049.
38. Li, D.; Du, Y.; Yin, G. Commonsense Knowledge Modeling. In Proceedings of the 16th World Computer Congress, Beijing, China, 1 August 2000; pp. 34–45.
39. Gao, H.; Zhang, X.; Zhang, T.; Liu, Y.; Li, D. Research of intelligent vehicle variable granularity evaluation based on cloud model. *Acta Electron. Sin.* **2016**, *44*, 365–373.

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