Longitudinal Control for *Mengshi Autonomous Vehicle* via Cloud Model

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**Abstract.** Dynamic robustness and stability control is a requirement for self-driving of autonomous vehicle. Longitudinal control method of autonomous is a key technique which has drawn the attention of industry and academe. In this 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. An experiments is applied to test the implementation of the longitudinal control algorithm. Empirical results show that if the longitudinal control algorithm based Gauss cloud model are applied to calculate the acceleration, and the vehicles drive at different speeds, a stable longitudinal control effect is achieved.

1. Introduction

The basic functions of automated longitudinal vehicle control are keeping the vehicle a safe distance behind another vehicle, maintaining a relatively constant speed with the least brake use and applying the brake as fast as possible in emergency situations. The challenges handled in the design of the longitudinal control system include nonlinear vehicle dynamics, string-stable operation with very small inter-vehicle spacing, operation at all speeds from a complete stop to high-speed cruising, and the execution of longitudinal split and join maneuvers in the presence of communication constraints. Lijuan Wu and his colleagues present a platoon control algorithm based on fuzzy logic to achieve the longitudinal control of a platoon of automotive vehicles [1]. S. Sheikholeslam and Charles A. Desoer propose control laws in the event of loss of communication between the lead vehicle and the other vehicles in the platoon, which solves the problem of longitudinal control of a platoon of automotive vehicles on a straight lane of a highway [2]. P. Zheng, M. McDonald and W. Lang et al, by use of fuzzy logic, act to control of vehicle in car following [3][4]. G. Qiang, H. Shuliang and D. Chao describe a car following controller based on fuzzy inference [5]. S. Kumarawadu and T. Lee survey a longitudinal controller based on neural network [6]. A. Ghaffari and his colleagues by use of Emotional Learning Fuzzy Inference System (ELFIS) approach, design a longitudinal controller for car following [7]. H. M. Kim et.al designs a combined brake/throttle fuzzy controller that uses a neural system to learn the fuzzy rules to control the velocity and the distance between cars in single-lane platoons [8]. L. Cai, AB. Rad and W.Lok Chan present a neuro-fuzzy controller for intelligent cruise control of semiautonomous vehicles. This approach aims at regulating the speed of the controlled vehicle in order to maintain constant time headway with respect to the vehicle in front [9]. H.I Lee and M. Tomizuka, with the method of adaptive vehicle traction force control, achieve the robust longitudinal control of vehicles in intelligent vehicle highway systems [10]. Ya-Fu Peng et. al
proposes a robust intelligent backstepping control (RIBC) scheme for the car-following control of a platoon of automated vehicles using a recurrent cerebellar model articulation controller (RCMAC) via the $H_{\infty}$ control technique [11]. AFerrara, P. Pisu, L. Nouveliere and S. Mammar propose longitudinal controllers that rely on the generation of “second order” sliding regimes [12][13]. X.Yun Lu and Karl J. Hedrick consider the theoretical part for longitudinal control of merging maneuver for Automated Highway System [14]. L.Daxue, S. Zhenping, Z. Hanqing, Li Zheng and H. Hangen design a feedforward controller for longitudinal control of autonomous ground vehicle based on the analysis of the vehicle force in off-road Environment [15]. M. Tai and M. Tomizuka use traction control and brake control solving the robust longitudinal velocity tracking of vehicles [16].

The current study aims to improve the accuracy, robustness, and adaptability to various road conditions of the vehicle control algorithm. First, the convergence of vehicles toward trajectory tracking errors is investigated from the perspective of nonlinear system stability, which is the premise of vehicle tracking trajectory. Subsequently, the robustness and control algorithm that can adapt to the environment is also considered. Finally, the function of vehicle motion control is expanded, which enables vehicles to complete automatic overtaking task, adaptive cruise task, automatic parking task, flowing into traffic task and so on.

Research on vehicle control cited above, some researches only focused on lateral tracking control, some researches only focused on longitudinal tracking control, without considering learning from people driving. When autonomous driving tasks increase in complexity, the control systems cited earlier are unable to adapt to complex tasks. In addition, the control system should be able to guarantee stability. The main contributions of our study are as follows. (1) A new uncertainty control system according to the Gauss cloud model (GCM) and cloud reasoning is illustrated. (2) The new model learning from human driving, dealing with complex tasks. (3) The longitudinal control algorithm for autonomous driving vehicles are constructed, with reference to human driving experience.

This paper is organized as follows. Section 1 presents the longitudinal control of autonomous vehicle. Section 2 presents the GCM, the GCM algorithm, and cloud reasoning, including a preconditioned Gauss cloud generator (PGCG), a post-conditioned Gauss cloud generator (PCGCG). Section 3 describes the longitudinal control rule and algorithm for autonomous vehicle. Section 4 provides the results of the experiment and analysis performed using the longitudinal control algorithm based on cloud model. Finally, the results of experiment are illustrated in Section 5.

2. Model and problem formulation

2.1. Gauss Cloud Model

The Gauss distribution (GD) is one of the most important distributions in probability theory, in which the general characteristics of random variables are represented as means of the mean and variance of two numbers. As a fuzzy membership function, the bell-shaped membership function is mostly used in sets, which is typically expressed through the analytical expressions of $m(x) = \exp(-(x - a)^2/2b^2$.

This study presents a cloud model based on the GD, called the Gauss cloud model (GCM), which is defined as follows [17][18].

**DEFINITION 1:** $U$ is expressed in a precise numerical quantitative domain. $C(Ex, En, He)$ is a qualitative concept on $U$. If the value of $x (x \in U)$ is a random realization of the qualitative concepts of $C$, then the “Expectation” of the GD $x \sim N(Ex, En^2)$ is denoted as $Ex$, and its “Variance” is denoted as $En^2$. Meanwhile, the “Expectation” of the GD $En^1 \sim N(En, He^2)$ is denoted as $En$, and its “Variance” is denoted as $He^2$. $En^1$ is the full form of the GD $En^1 \sim N(En, He^2)$ and is a random realization[19]. The certainty degree of $x$ in $C$ is satisfied via $m(x) = \exp(-(x - Ex)^2/2(En^1)^2}$. The distribution of $x$ in the domain of $U$ is called a Gauss cloud (GC) [20]. The GC algorithm is presented in table 1 [20].

| Input: Three figures $(Ex, En, He)$ and the number of cloud drops $n$. |
| Output: A sample set that represents concept extension and its certainty $(x_i, m_i)$, $i$ |
(1) To generate a Gauss random \( E_n \sim N(E_n, H_e^2) \)
(2) To generate a Gauss random \( x \sim N(E_x, E_n^2) \)
(3) To calculate the certainty: \( m(x) = \exp\left(-\frac{(x - E_x)^2}{2(E_n)^2}\right) \)
(4) Repeat (1)-(4) until the number of cloud drops is n.

![Figure 1. The GCG.](image)

The algorithm causes distribution drops, called cloud distribution (CD). The algorithm of GCM can be obtained through a cloud generator (CG), which forms a forward Gauss cloud generator (GCG), as shown in figure 1. The Gauss random number generation method is the foundation of the whole algorithm. It generates uniform random numbers in \([0, 1]\) and uses them to calculate the Gauss random number. Random number sequences are determined through the uniform random function of a seed. The method of using uniform random numbers to generate a Gauss random number is described in detail in Ref. [21]. GC distribution (GCD) is different from the GD because the GCD algorithm uses the Gauss random number twice, in which one random number is the basis of another random number. Among these,

1. When \( H_e = 0 \), the algorithm generates a precise value of \( E_n \) and the value of \( x \) is transformed into a GD.
2. When \( H_e = 0, E_n = 0 \), the value of \( x \) of the algorithm generation is an exact value of \( E_x \), and \( m \equiv 1 \).

From (1) and (2), certainty can be concluded as a special case of uncertainty, and the GD is a special case of the GCD.

For a qualitative concept of a steering angle of positive and negative 40°, given that \( E_x = 80°, E_n = 1 \), and \( H_e = 0.1 \), 1000 cloud drops are generated. The distribution of drops and its certainty degree of \( C(x, m) \) are shown in figure 2.

![Figure 2. The distribution of 1000 drops.](image)

2.2. Cloud Reasoning

2.2.1. Preconditioned Gauss cloud generators. Knowledge forms a concept and its relationship with communicating and abstracting. The relationship among concepts form certain rules, from which rules library and rules generator can be established through knowledge reasoning based on GC. Rules
include preconditioned and post-conditioned rules. Preconditioned rules include one or several rules, whereas post-conditioned rules express the results and specific control actions generated by the preconditioned rules. In the control field, “perception–action” can establish the rule library based on the relationship among concepts, thereby realizing control of uncertainty. A preconditioned Gauss cloud generators (PGCG) and a post-conditioned Gauss cloud generators (PCGCG) are composed of the GCG, which is defined as follows.

**DEFINITION 2:** Assume the following rule:

If \( A \), then \( B \),
where \( A \) corresponds to concepts \( C_1 \) in universal sets \( U_1 \), and \( B \) corresponds to concepts \( C_2 \) in universal sets \( U_2 \). \( a \) is a specific value in universal sets \( U_1 \), where the GCG generates a specific value of \( a \) based on the concept \( C_1 \) of the certainty degree of \( m \) distribution, and \( m \in [0, 1] \), which is called a PGCG [22].

### 2.2.2 Post-conditioned Gauss cloud generators.

**DEFINITION 3:** Assume the following rule:

If \( A \), then \( B \),
where \( A \) corresponds to concepts \( C_1 \) in universal sets \( U_1 \), and \( B \) corresponds to concepts \( C_2 \) in universal sets \( U_2 \). The certainty degree of \( m \) belongs to \([0, 1]\). The GCG generates the certainty degree of \( m \) drop distribution, which is satisfied by applying concepts \( C_2 \) in universal sets \( U_2 \), called PCGCG [23] [24].

### 3. Longitudinal control based on cloud model

#### 3.1 Data Analysis

As shown in figure 3, the longitudinal velocity control model is established according to the cloud model and cloud reasoning. The input of the longitudinal velocity control model is the pedal opening, the velocity of the vehicle, the acceleration of the vehicle and the expected velocity of the vehicle. The output is the acceleration required for the vehicle to reach the expected velocity [25].

**Figure 3.** Longitudinal control data model based on cloud model.

**Table 2.** The Numerical characteristics of cloud model of \( a \).

| \( v \)           | \( v (E_v, E_n, H_k) \) |
|-------------------|-------------------------|
| Positive greater  | (9.8,1.1,0.18)          |
| Positive less     | (4.9,1.0,1.9)           |
| Zero              | (0.1,0.01)              |
| Negative less     | (−4.7,1.0,0.03)         |
| Negative greater  | (−9.8,1.2,0.03)         |

**Table 3.** The Numerical characteristics of cloud model of \( a \).

| \( a \)           | \( a (E_v, E_n, H_k) \) |
|-------------------|-------------------------|
| Positive greater  | (19,2.6,0.045)          |
The real car test in the city of Beijing lasted a month, test 4 hours per day, the data recorded frequency of 1Hz. The detection data including the pedal opening, the velocity of the vehicle, the acceleration of the vehicle and the expected velocity of the vehicle. The data volume of 400,000 above. The domain of the quantitative attribute is divided into the concept of the cloud model. Table 2 and table 3 show the three digital characteristics (Ex, En, He) of vehicle velocity, vehicle acceleration [26].

3.2. Longitudinal Control Rules and Algorithm
The longitudinal control of the autonomous vehicle is single input and single output controller, the input of the cloud controller is the difference between expected velocity and actual velocity of autonomous vehicle $\Delta v$. 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: If $E$, then $F$, where $E$ is the PGCG that generates the drop distribution $(a, m)$ with a specific value of $a$ and a certainty degree of $m$. $E$ is replaced by the cloud model digital feature of the velocity obtained by the experiment, then $a$ represents the velocity of the autonomous driving 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 PCGCG 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 cloud model, which is shown in figure 4 [25].

![Figure 4. The longitudinal control algorithm chart. The longitudinal control algorithm is presented in.](figure)

The longitudinal control algorithm implies an uncertainty transfer in the conceptual reasoning process. In the universal sets $U_1$ of the PGCG, the distribution of the certainty degree of $m$ belongs to the specific value of $v_{\text{vehicle}}$, whereas the certainty degree of $m$ is the input of the PCGCG that generates the drop distribution $(a_{\text{vehicle}}, m)$ of the cloud specific value of $a_{\text{vehicle}}$ and the certainty degree of $m$. The processing of the certainty value of $v_{\text{vehicle}}$ to the certainty value of $a_{\text{vehicle}}$ is uncertain [23][25][26].

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 single laser radar, a forward four lines laser radar, and a backward millimeter wave radar. 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 5. 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 5. Experiment sensor configuration.](image)

4.1.2. Software architecture of an autonomous vehicle system. The software architecture of autonomous vehicle systems is shown in figure 6. 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.
- **Sensor and sensing layer**: This layer consists of a radar sensor, a vision sensor, a GPS sensor, and an IMU sensor. The sensor focuses on completing the collection of sensor data. The sensing layer focuses on sensor data analysis, road edge identification, obstacle detection, traffic sign detection, and body state estimation, which complete data fusion.
- **Decision and planning layer**: This layer focuses on path planning and decision, which determine the driving pattern of an autonomous vehicle by analyzing environment data and vehicle data from the

![Figure 6. Software architecture of an autonomous vehicle system.](image)
sensory module. The outputs is Acceleration and the increment of steering angle. Those commands output to control layer.

Control layer: This layer directly outputs the control order to the accelerator, as well as the braking and steering controller, of the vehicle. It also receives human instructions and performs acceleration/deceleration and steering operations.

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.

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 analysis. As shown in figure 7, the speed curve of Tianjin to Taihu Toll. As show in figure 8, the speed curve of Taihu Toll to Tianjin, the x axis represents the time of data, and the data recording interval is 200ms; The y axis indicates the speed, unit: km/s, Tianjin to Taihu station, the mileage is 86km, the average speed is 87.26km/h and program set speed is 90 km/h; Taihu to Tianjin station, the mileage is 86km, the average speed is 94.1km/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 kilometers, it used 90km 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 90km/h. Due to road construction, implement the artificial intervention, the speed is set to 50km/h, and driving with cars, the speed affected by the front car is kept at 60-100km/h. The figure shows a data speed exceeding 150km/h, which is an invalid speed value.

4.2.2. Acceleration analysis. As shown in figure 9, the acceleration curve of Tianjin to Taihu Toll. As shown in figure 10, the acceleration curve of Taihu Toll to Tianjin, the x axis represents the time of data, and the data recording interval is 200ms; The y axis indicates the acceleration, unit: km/s². In the experiment, the acceleration value of the autonomous vehicle during acceleration and deceleration is maintained at -2m/s²~1m/s². 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 \(-2m/s^2\)\text{~}1m/s^2\) range. In rare cases, the acceleration occurs more than \(1m/s^2\), causing a rapid acceleration and the passenger's subjective feeling is better.

The experimental results show that the longitudinal control based on cloud model 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 cloud model compared with other control methods, such as PID control and fuzzy logic control, 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 9. Acceleration curve of Tianjin to Taihu Toll.](image1)

![Figure 10. Acceleration curve of Taihu to Toll Tianjin.](image2)

### 5. Conclusion

This paper proposes the application of cloud model and cloud reasoning to the longitudinal control of autonomous vehicles. Because the cloud model use expected value, 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.

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