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Lateral control of autonomous vehicles based on learning driver behavior via cloud model

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Abstract

In order to achieve the lateral control of the intelligent vehicle, use the bi-cognitive model based on cloud model and cloud reasoning, solve the decision problem of the qualitative and quantitative of the lateral control of the intelligent vehicle. Obtaining a number of experiment data by driving a vehicle, classify the data according to the concept of data and fix the input and output variables of the cloud controller, design the control rules of the cloud controller of intelligent vehicle, and clouded and fix the parameter of cloud controller: expectation, entropy and hyper entropy. In order to verify the effectiveness of the cloud controller, joint simulation platform based on Matlab/Simulink/CarSim is established. Experimental analysis shows that: driver's lateral controller based on cloud model is able to achieve tracking of the desired angle, and achieve good control effect, it also verifies that a series of mental activities such as feeling, cognition, calculation, decision and so on are fuzzy and uncertain.

Keywords cloud model, driver behavior, autonomous vehicles, lateral control

1 Introduction

In academic and industrial circles, studies on intelligent vehicles have drawn considerable attention. Such studies play an important role in the research on vehicles and intelligent transportation. Control methods are the key to the study of intelligent vehicles. Vehicle model parameters are extremely complex. The system model equation is nonlinear, and its system parameters constantly change over time.

The lateral control of vehicle includes tradition methods and intelligent methods, the tradition methods include support vector method (SVM) [1], step control method [2], proportion-integral-derivative (PID) method [3]. Intelligent methods include fuzzy control method [4–5], and neural network control method [6–7], and so on.

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, thereby ensuring control performance when the running conditions of a vehicle are drastically changed. Finally, the function of vehicle motion control is expanded, which enables vehicles to complete the automatic overtaking task, adaptive cruise task, automatic parking task, flowing into traffic task and so on.

Research on vehicle control cited above, some researchers only focused on lateral tracking control, some researchers only focused on longitudinal tracking control, without considering driving speed and driving direction as input values. When intelligent 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

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contributions of our study are as follows.

1) A new uncertainty control system according to the Gaussian cloud model (GCM) and cloud reasoning is illustrated.

2) The new model considers both speed and direction, whereas velocity and direction are mutually constrained.

3) The speed control rules for intelligent driving vehicles are constructed, with reference to human driving experience.

The results of each simulation experiment of tradition control method and intelligent control method are the same. The driver's lateral control operation is different in the actual driving process, therefore, the simulation results of these control methods cannot represent the driver's operations results. In this paper, the model of the driver's lateral control based on cloud model is proposed.

In the driving processing, the driver operate the steering wheel by driving experience according to the road environment, to make the vehicle drive with the expected target. Driver lateral control model is to build the vehicle steering control model, to make the vehicle's driving direction track the desired direction self-adaptive, and satisfy the conditions of satisfying, smooth, speed and smart.

Based on the fuzzy and uncertainty of a series of driver's psychological activities, such as driver's feeling, cognition, calculation and decision, the cloud model is introduced into the driver's direction control model. The algorithm of cloud control has no special requirements for the mathematical model of the controlled object, and use intuitive control rules. The cloud model is founded on the traditional fuzzy set theory and probability statistics theory, it makes the precision of membership function extend to the uncertainty of statistical distribution, it realized uncertainty transformation between the qualitative and quantitative. The cloud controller of the driver lateral control use uncertainty in a statistical distribution, use cloud reasoning to enrich the driver's lateral control model based on fuzzy reasoning, in order to express driver's lateral control randomness that brings certainty in diversity.

This paper is organized as follows. Sect. 1 presents the lateral control of the intelligent vehicle. Sect. 2 presents the GCM, the GCM algorithm, and cloud reasoning, including a preconditioned Gaussian cloud generator (PGCG), a post-conditioned Gaussian cloud generator (PCGCG), and a rule generator. Sect. 3 describes model of driver lateral control and cloud controller rules. Sect. 4 provides the results of the simulation experiment and analysis. Finally, the conclusion of this paper is illustrated in Sect. 5.

2 Model and problem formulation

2.1 GCM

The Gaussian distribution (GD) is one of the most important distributions in probability theory, in which the general characteristics of random variables are represented by 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 $m(x) = \exp\left\{-(x-a)^2/(2b^2)\right\}$. This study presents a cloud model based on the GD, called the GCM, which is defined as follows [8–9]

Definition 1 U is expressed in a precise numerical quantitative domain. $C(E_\mathrm{x}, E_\mathrm{n}, H_\mathrm{e})$ 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 $x \sim N\left(E_\mathrm{x}, E_\mathrm{n}'^2\right)$ is denoted as E_x, and its variance is denoted as $E_\mathrm{n}'^2$. Meanwhile, the expectation of the GD $E_\mathrm{n}' \sim N\left(E_\mathrm{n}, H_\mathrm{e}^2\right)$ is denoted as E_n, and its variance is denoted as H_e^2. E_n' is the full form of the GD $E_\mathrm{n}' \sim N\left(E_\mathrm{n}, H_\mathrm{e}^2\right)$ and is a random realization [10]. The certainty degree of x in C is satisfied via $m(x) = \exp\left\{-(x-E_\mathrm{x})^2/\left(2(E_\mathrm{n}')^2\right)\right\}$. The distribution of x in the domain of U is called a Gaussian cloud (GC) [11]. The GC is given in Algorithm 1 [8,12].

Algorithm 1 The GC algorithm

Input: three figures $(E_\mathrm{x}, E_\mathrm{n}, H_\mathrm{e})$ and the number of cloud drops n.

Output: a sample set that represents concept extension and its certainty (x_i, m_i), i=1,2,…,n.

Step 1 To generate a Gaussian random $E_\mathrm{n}' \sim N\left(E_\mathrm{n}, H_\mathrm{e}^2\right)$

Step 2 To generate a Gaussian random $x \sim N(E_\mathrm{x}, E_\mathrm{n}'^2)$

Step 3 To calculate the certainty: $m(x) = \exp\left\{-(x-E_\mathrm{x})^2/\left(2(E_\mathrm{n}')^2\right)\right\}$

Step 4 Repeat Steps 1–3 until the number of cloud drops is n.

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 Gaussian cloud generator (GCG), as shown in Fig. 1. The Gaussian 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 Gaussian 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 Gaussian random number is described in detail in Ref. [13]. GC distribution (GCD) is different from the GD because the GCD algorithm uses the Gaussian random number twice, in which one random number is the basis of another random number. Among these:

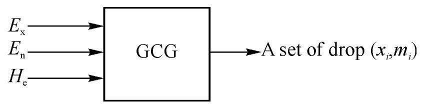

Fig. 1 The GCG

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

2.2 Cloud reasoning

2.2.1 PGCG and PCGCG

Knowledge forms a concept and its relationship with communicating and abstracting. The relationship among concepts forms 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 PGCG and a 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 PGCG [14], as shown in Fig. 2.

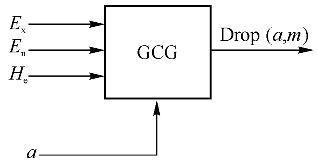

Fig. 2 The PGCG

The PGCG is given in Algorithm 2 [14].

Algorithm 2 The PGCG

Input: three figures (E_x, E_n, H_e) and a specific value a.

Output: the distribution of drops (a, m)

1) To generate a Gaussian random $E_n' \sim N(E_n, H_e^2)$

2) To calculate the certainty: $m(x) = \exp\{-(x-E_x)^2 / (2(E_n')^2)\}$

3) To generate the distribution of drops (a, m)

The distribution of drop (a, m) of the specific value of a and the certainty degree of m is shown in Fig. 3.

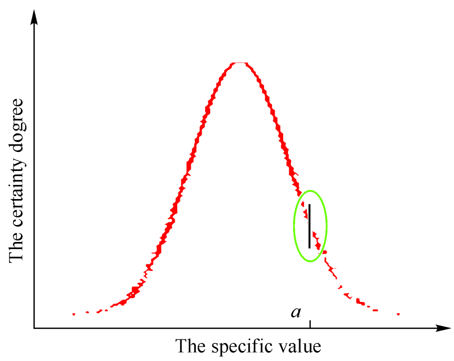

Fig. 3 Cloud drop distribution of the PGCG

Defintion 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 [15], as shown in Fig. 4.

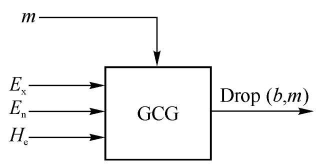

Fig. 4 The PCGCG

The PCGCG is given in Algorithm 3.

Algorithm 3 The PCGCG

Input: three figures (E_x, E_n, H_e) and certainty degree m.

Output: the drop distribution (b, m)

1) To generate a Gaussian random $E_n' \sim N(E_n, H_e^2)$

2) To calculate the certainty: $b = E_x \pm E_n'\sqrt{-2\ln m}$

3) To generate the distribution of drops (b, m)

The drop distribution (b,m) of the cloud drop the specific value of b and the certainty degree of m is shown in Fig. 5.

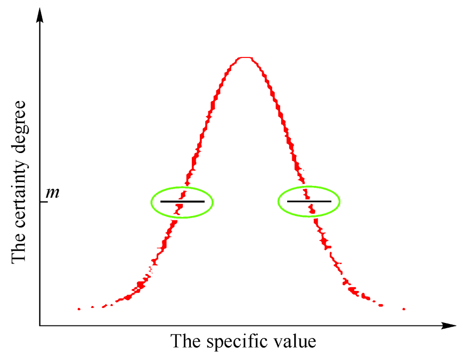

Fig. 5 Cloud drop distribution of the PCGCG

2.2.2 Rule generator

Definition 4 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. 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, which is called the single-condition single-rule GCG (SCSRGCG) [16–18]. The composition diagrams of PGCG and PCGCG are shown in Fig. 6.

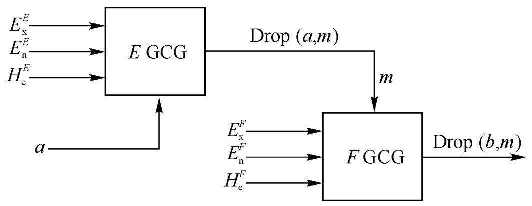

Fig. 6 The SCSRGCG

The SCSRGCG is given in algorithm 4.

Algorithm 4 The SCSRGCG

Input: three figures (E_x^E, E_n^E, H_e^E), three figures (E_x^F, E_n^F, H_e^F), and a specific value a.

Output: the drop distribution (b, m)

1) To generate a Gauss random $E_n^{E'} \sim N(E_n^E, H_e^{E2})$

2) To calculate the certainty: $m = \exp\left\{-\left(x - E_x^E\right)^2 / \left(2\left(E_n^{E'}\right)^2\right)\right\}$

3) To generate a Gauss random $E_n^{F'} \sim N(E_n^F, H_e^{F2})$

4) If $a < E_x$, then to calculate the certainty: $b = E_x^F - E_n^{F'}\sqrt{-2\ln m}$

5) If $a > E_x$, then to calculate the certainty: $b = E_x^F + E_n^{F'}\sqrt{-2\ln m}$

6) To generate the distribution of drops (b, m)

The SCSRGCG 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 a, whereas the certainty degree of m is the input of the PCGCG that generates the drop distribution (b, m) of the cloud specific value of b and the certainty degree of m. The processing of the certainty value of a to the certainty value of b is uncertain [19–20].

3 Model of driver lateral control

3.1 Driver data analysis

The lateral control of intelligent vehicle uses the cloud control and cloud reasoning on the vehicle steering of intelligent control. The purpose of vehicle steering control is to adjust the steering wheel so that the angle θ between the preview point and the heading direction of intelligent vehicle become zero, it is shown in Fig. 7.

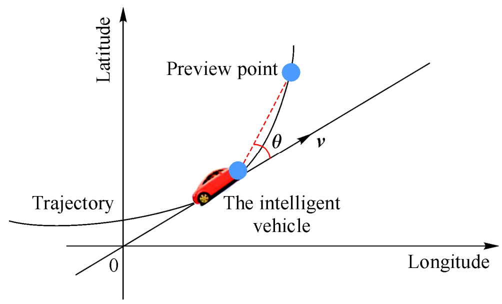

Fig. 7 The angle θ

The model of driver lateral control includes input data and output data. The driver controls the operation of the steering wheel and obtains angular velocity of steering wheel ω. The input data of driver lateral control model is the angle θ that is between the preview point and the heading direction of intelligent vehicle and acceleration of intelligent vehicle a_v. The output data of driver lateral control model is angular velocity of steering wheel, the angle of the steering wheel is obtained by the integral of the angular velocity. The preview distance is obtained by the speed of vehicle, then the preview point is calculated out, then angle θ is calculated out. The acceleration of the intelligent vehicle a_V is obtained by inertial navigation on the intelligent vehicle, the angular velocity of steering wheel ω is obtained by controller area network (CAN) bus of intelligent vehicle.

The input and output of driver lateral control model are shown in Fig. 8.

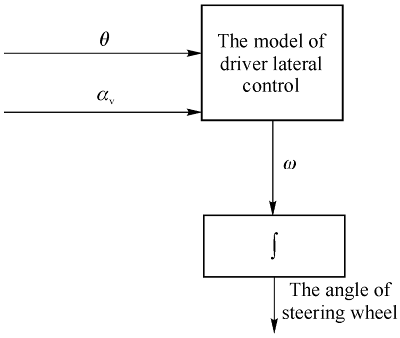

Fig. 8 The input and output of driver lateral control model

The driver lateral control model is based on the theory of cloud model and cloud reasoning, the data of driver lateral control model is obtained by experiment, carries on the statistical analysis, and builds the driver lateral control model: cloud controller. The experiment is adopted on Park Avenue, Beijing, which lasted 180 h of artificial driving, and record data once per 50 ms, the data record is more than 1.2 million. The probability density of input and output variable of driver lateral control model are shown in Figs. 9–11.

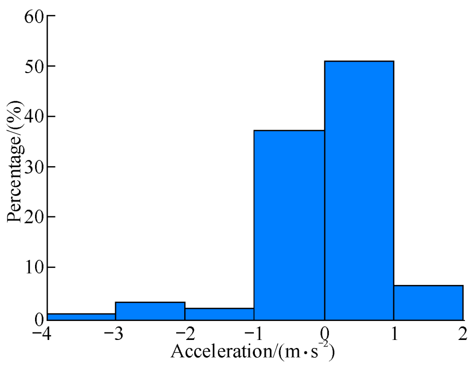

Fig. 9 The probability density of a_V

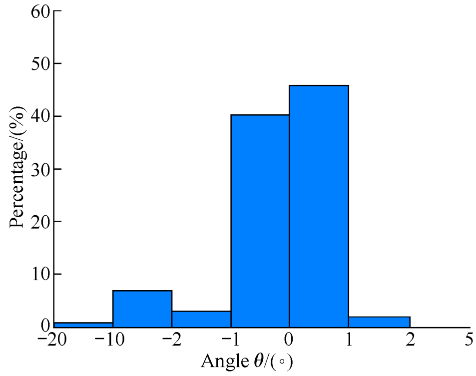

Fig. 10 The probability density of θ

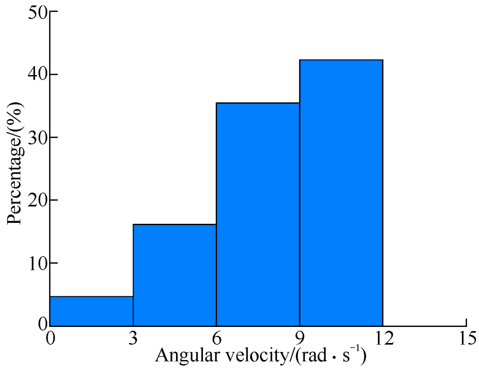

Fig. 11 The probability density of the angular velocity ω

3.2 Cloud controller rules

The lateral control of the intelligent vehicle is single input and single output controller, the input of the cloud controller is the accelerator of intelligent vehicle a_V, the angle θ between the heading directions of the intelligent vehicle and preview point. The output is the angular velocity ω. The variables a_V, θ and ω 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.

The detailed the lateral control rules for intelligent vehicles are given in Algorithms 5 and 6.

Algorithm 5 Rule sets $R_S(a_V)$ of a_V

1) If accelerator a_V is positive greater
2) Angular velocity ω is less
3) If accelerator a_V is positive less
4) Angular velocity ω is greater
5) If accelerator a_V is negative less
6) Angular velocity ω is more
7) If accelerator a_V is negative more

8) Angular velocity ω is less

Algorithm 6 Rule sets $R_S(\theta)$ of angle θ

1) If preview point θ is positive greater
2) Angular velocity ω is negative greater
3) If preview point θ is positive less
4) Angular velocity ω is negative less
5) If preview point θ is zero
6) Angular velocity ω is zero
7) If preview point θ is negative less
8) Angular velocity ω is positive less
9) If preview point θ is negative greater
10) Angular velocity ω is positive greater

The parameter E_x, E_n and H_e settings of the qualitative concepts are shown in Tables 1–3.

Table 1 Numerical characteristics of cloud model of α_V

α_V	$\alpha_V(E_x, E_n, H_e)$
Positive greater	(1.5,0.20,0.004)
Positive less	(0.5,0.15,0.003)
Zero	-
Negative less	(− 0.5,0.15,0.003)
Negative greater	(− 1.5,0.20,0.004)

Table 2 Numerical characteristics of cloud model of θ

θ	$\theta(E_x, E_n, H_e)$
Positive greater	(10,1.2,0.02)
Positive less	(5,1,0.02)
Zero	(0,1,0.01)
Negative less	(− 5,1,0.02)
Negative greater	(− 10,1.2,0.02)

Table 3 Numerical characteristics of cloud model of ω

ω	$\omega(E_x, E_n, H_e)$
Positive greater	(20,3,0.005)
Positive less	(10,2,0.020)
Zero	(0,2,0.008)
Negative less	(− 10,2,0.020)
Negative greater	(20,3,0.050)

According to numerical characteristics of cloud model of input variables and output variables, establish to control rules of cloud controller for an intelligent vehicle, they are shown in Table 4.

Table 4 Steering wheel angular velocity control rules

α_V	ω				
	θ is 1	θ is 2	θ is 3	θ is 4	θ is 5
1	5	6	6	7	7
2	3	5	5	8	8
3	2	3	4	6	6
4	1	2	2	4	4

The data in Table 4 represent the concept level of each variable. The ability of nonlinear mapping from input to output based on cloud model, complete the reasoning process of intelligent driving vehicles from the known input conditions to the quantitative output control, based on reasoning rules in Table 4.

4 Simulation experiment of lateral control based on cloud model

In order to verify tracking control ability of the cloud controller, the joint Simulink platform is established, the designed controller is simulated and verified, and the simulation platform is shown in Fig. 12.

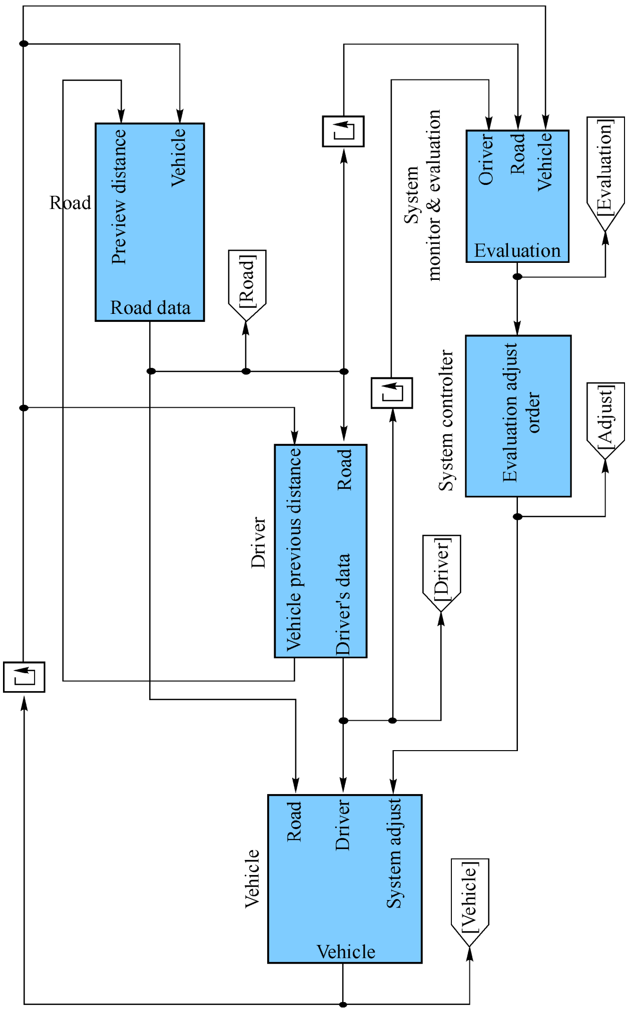

Fig. 12 Joint Simulink platform of cloud controller

Target tracking angles and acceleration are experiment data of the vehicle in simulation platform. The acceleration tracking curve of cloud controller is shown in Fig. 13, the angle tracking curve of cloud controller is shown in Fig. 14.

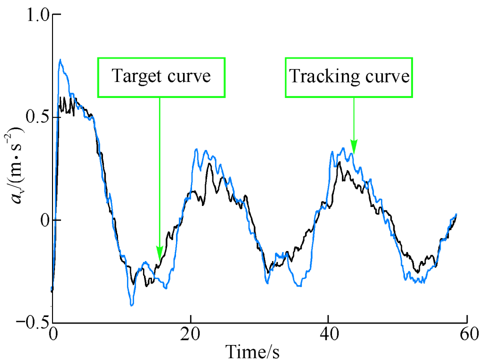

Fig. 13 α tracking curve

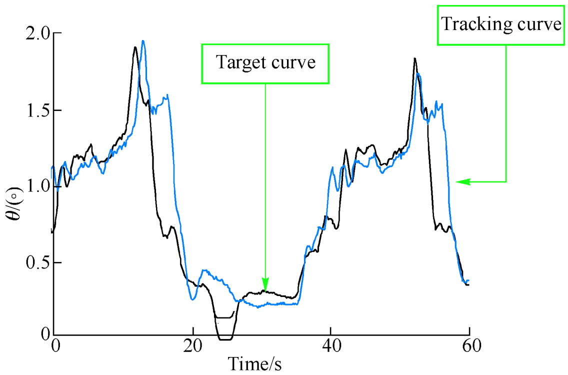

Fig. 14 θ tracking curve

From the simulation results, it can be shown that the lateral controller based on cloud model learning driver behavior can realize the desired angle tracking, and verify the uncertain of the desired angle tracking according to simulation experiments, the tracking curve of cloud controller is different for the same angle tracking curve, as is shown in Figs. 13 and 14. In the driving process, the driver's steering operation is different, and it also verifies that a series of mental activities such as feeling, cognition, calculation, decision and so on are fuzzy and uncertain, and show that the randomness of the driver in the lateral control generates the diversity.

5 Conclusions

In this paper, cloud model and cloud reasoning are applied to the lateral control of the intelligent vehicle. Under the same environmental conditions, there is uncertainty about the control behavior of the driver, but the control behavior of the driver has a statistical certainty. In the driving process, the control of the vehicle by the driver does not require specific accurate numerical values, the driver can achieve control well according to the qualitative operation. In intelligent driving, the intelligent vehicle satisfies the constraints of safety, speed, smart and smooth, and is a need for accurate numerical control. Cloud model and cloud reasoning are both qualitative and quantitative expressions, the qualitative concept is expressed quantitatively by the cloud model's expectation, entropy, and hyper entropy, it can simulate the driver operation uncertainty in the driving process , but the cloud model's expectation, entropy, and hyper entropy reflects the basic certainty of driving behavior uncertainty with statistical regularity. The simulation experiment results of driver lateral controller based on cloud model achieve control effect well.

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References

1. Gao F, Li K Q, Lian X M. Hierarchical switching control of multiple models based on robust control theory. Acta Automatica Sinica, 2006, 32(3): 411–416
2. Zhuang D J, Yu F, Lin Y. The vehicle directional control based on fractional order PD~μ controller. Journal of Shanghai Jiaotong, 2007, 41(2): 278–283
3. Li Y, Ang K H, Chong G C Y. PID control system analysis and design. IEEE Control Systems, 2006, 26(1): 32–41
4. Hessburg T, Tomizuka M. Fuzzy logic control for lateral vehicle guidance. Proceedings of the 1993 IEEE International Conference on Control and Applications: Vol 2, Sept 13–16, 1993, Vancouver, Canada. Piscataway, NJ, USA: IEEE, 1993: 581–586
5. Choomuang R, Afzulpurkar N. Hybrid Kalman filter/fuzzy logic based Position control of autonomous mobile robot. International Journal of Advanced Robotic Systems, 2005, 2(3):197–208
6. Scott G M, Shavlik J W, Ray W H. Refining PID controller using neural networks. Neural Computation, 1992, 4(5): 746–757
7. Wai R J. Tracking control based on neural network strategy for robot manipulator. Neurocomputing, 2003, 51: 425–445
8. Wang S L, Li D R, Shi W Z, et al. Cloud model-based spatial data mining. Geographic Information Sciences, 2003, 9(1/2): 60–70
9. Li D Y, Liu Y C, Du Y, et al. Artificial intelligence with uncertainty. Journal of Software, 2004, 15(11): 1538–1594 (in Chinese)
10. Cao B H, Li D Y, Qin K, et al. An uncertain control framework of cloud

model. Proceedings of the 5th International Conference on Rough Set and Knowledge Technology (RSKT'10), Oct 15–17, 2010, Beijing, China. Berlin, Germany: Springer, 2010: 618–625
11. Li D Y, Liu Y C, Gan W Y. A new cognitive model: cloud model. International Journal of Intelligent Systems, 2009, 24(3): 357–375
12. Gao H X. Statistical calculation. Beijing, China: Peking University Press, 1995: 33–120
13. Li D Y, Du Y. Artificial intelligence with uncertainay. Beijing, China: National Defence Industry Press, 2005: 137–185
14. Gao H B, Jiang J, Zhang L, et al. Cloud model: detect unsupervised communities in social tagging network. Proceedings of the 2013 International Conference on Information Science and Cloud Computing Companion (ISCC-C'13), Dec 7–8, 2013, Guangzhou, China. Piscataway, NJ, USA: IEEE, 2013: 317–323
15. Gao H B, Zhang X Y, Zhang T L, et al. Research of intelligent vehicle variable granularity evaluation based on cloud model. Acta Electronica Sinica, 2016, 44(2): 365–373 (in Chinese)
16. Li D R, Wang S L, Li D Y, et al. Theories and technologies of spatial data mining and knowledge discovery. Geomatics and Information Science of Wuhan University, 2002, 27(3): 221–233 (in Chinese)
17. Du Y. Research and applications of association rules in data mining. Nanjing, China: PLA University of Science and Technology, 2000: 34-45 (in Chinese)
18. Deng W H, Wang G Y, Xu J. Piecewise two-dimensional normal cloud representation for time-series data mining. Information Sciences, 2016, 374: 32–50
19. Wang G Y, Xu C L, Li D Y. Generic normal cloud model. Information Sciences, 2014, 280:1–15
20. Xu C L, Wang G Y, Zhang Q H. A new multi-step backward cloud transformation algorithm based on normal cloud model. Fundamenta Informaticae, 2014, 133(1): 55–85

(Editor: Wang Xuying)

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6. Donoho D L. Compressed sensing. IEEE Transactions on Information Theory, 2006, 52(4): 1289–1306
7. Candès E J. The restricted isometry property and its implications for compressed sensing. Comptes Rendus Mathematique, 2008, 346(9/10): 589–592
8. Zhao X M, Zhang S Q, Lei B C. Robust emotion recognition in noisy speech via sparse representation. Neural Computing and Applications, 2014, 24(7): 1539–1553
9. Haupt J, Nowak R. Signal reconstruction from noisy random projections. IEEE Transactions on Information Theory, 2006, 52(9): 4036–4048
10. Lanckriet G R G, Cristianini N, Bartlett P, et al. Learning the kernel matrix with semidefinite programming. Journal of Machine Learning Research, 2004, 5(1): 27–72
11. Jin Y, Song P, Zheng W M, et al. Novel feature fusion method for speech emotion recognition based on multiple kernel learning. Journal of Southeast University, 2013, 29(2): 129–133
12. Baraniuk R G. Compressive sensing. IEEE Signal Processing Magazine, 2007, 24(4): 118–120
13. Needell D, Vershynin R. Signal recovery from inaccurate and incomplete measurements via regularized orthogonal matching pursuit. IEEE Journal of Selected Topics in Signal Processing, 2010, 4(2): 310–316
14. Needell D, Tropp J A. CoSaMP: iterative signal recovery from incomplete and inaccurate samples. Applied and Computational Harmonic Analysis, 2008, 26(3): 301–321
15. Dai W, Milenkovic O. Subspace pursuit for compressive sensing signal reconstruction. IEEE Transactions on Information Theory, 2009, 55(5): 2230–2249
16. Tropp J A, Gilbert A C. Signal recovery from random measurements via orthogonal matching pursuit. IEEE Transactions on Information Theory, 2007, 53(12): 4655–4666
17. Saligrama V, Zhao M Q. Thresholded basis pursuit: LP algorithm for oder-wise optimal support recovery for sparse and approximately sparse signals from noisy random measurements. IEEE Transactions on Information Theory, 2011, 57(3): 1567–1586
18. Chen S S, Donoho D L, Saunders M A. Atomic decomposition by basis pursuit. SIAM Review, 2001, 43(1): 129–159
19. Figueiredo M A, Nowak R D, Wright S J. Gradient projection for sparse reconstruction: application to compress sensing and other inverse problems. IEEE Journal of Selected Topics in Signal Processing, 2007, 1(4): 586–597
20. Blumensath T, Davies M. Iterative hard thresholding for compressed sensing. Applied and Computational Harmonic Analysis, 2009, 27(3): 265–274
21. Plumbley M D. Recovery of sparse representations by polytope faces pursuit. Proceedings of the 2006 International Conference on Independent Component Analysis and Blind Source Separation, Mar 5–8, 2006, Charleston, SC, USA. LNCS3889. Berlin, Germany: Springer, 2006: 206–213
22. Yeh C Y, Su W P, Lee S J. An efficient multiple-kernel learning for pattern classification. Expert Systems with Applications, 2013, 40(9): 3491–3499
23. Chen L J, Mao X, Xue Y L, et al. Speech emotion recognition: features and classification models. Digital Signal Processing, 2012, 22(6): 1154–1160
24. Chandaka S, Chatterjee A, Munshi S. Support vector machines employing cross-correlation for emotional speech recognition. Measurement, 2009, 42(4): 611–618
25. Lee C C, Mower E, Busso C, et al. Emotion recognition using a hierarchical binary decision tree approach. Speech Communication, 2011, 53(9/10): 1162–1171
26. Burkhardt F, Paeschke A, Rolfes M, et al. A database of German emotional speech. Proceedings of the 9th European Conference on Speech Communication and Technology (INTERSPEECH'05), Sept 4–8, 2005, Lisbon, Portugal. 2005: 1517–1520
27. Jiang X Q, Xia K W, Xia X Y, et al. Speech emotion recognition using semi-definite programming multiple-kernel SVM. Journal of Beijing University of Posts and Telecommunications, 2015, 38(S1): 67–71 (in Chinese)
28. Yang B, Lugger M. Emotion recognition from speech signals using new harmony features. Signal Processing, 2010, 90(5): 1415–1423
29. Meyer P E, Schretter C, Bontempi G. Information-theoretic feature selection in microarray dada using variable complementarity. IEEE Journal of Selected Topics in Signal Processing, 2008, 2(3): 261–274
30. Löfberg J. YALMIP: A toolbox for modeling and optimization in MATLAB. Proceedings of the 2004 International Symposium on Computer Aided Control Systems Design, Sept 2–4, 2004, Taipei, China. Piscataway, NJ, USA: IEEE, 2004: 284–289
31. Henríquez P, Alonso J B, Ferrer M A, et al. Nonlinear dynamics characterization of emotional speech. Neurocomputing, 2014, 132: 126–135

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