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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 $m(x) = \exp\{-(x-a)^2/(2b^2)\}$. 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. $C(E_x, E_n, H_e)$ 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 $x \sim N(E_x, E_n'^2)$ is denoted as E_x, and its variance is denoted as $E_n'^2$. Meanwhile, the expectation of the GD $E_n' \sim N(E_n, H_e^2)$ is denoted as E_n, and its variance is denoted as H_e^2. E_n' is the full form of the GD $E_n' \sim N(E_n, H_e^2)$ and is a random realization [10]. The certainty degree of x in C is satisfied via $m(x) = \exp\{-(x-E_x)^2/(2(E_n')^2)\}$. 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_x, E_n, H_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 $E_n' \sim N(E_n, H_e^2)$

Step 2 To generate a Gaussian random $x \sim N(E_x, E_n'^2)$

Step 3 To calculate the certainty: $m(x) = \exp\{-(x-E_x)^2 / (2(E_n')^2)\}$

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