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Lane-changes prediction based on adaptive fuzzy neural network

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ABSTRACT

Lane changing maneuver is one of the most important driving behaviors. Unreasonable lane changes can cause serious collisions and consequent traffic delays. High precision prediction of lane changing intent is helpful for improving driving safety. In this study, by fusing information from vehicle sensors, a lane changing predictor based on Adaptive Fuzzy Neural Network (AFFN) is proposed to predict steering angles. The prediction model includes two parts: fuzzy neural network based on Takagi–Sugeno fuzzy inference, in which an improved Least Squares Estimator (LSE) is adopt to optimize parameters; adaptive learning algorithm to update membership functions and rule base. Experiments are conducted in the driving simulator under scenarios with different speed levels of lead vehicle: 60 km/h, 80 km/h and 100 km/h. Prediction results show that the proposed method is able to accurately follow steering angle patterns. Furthermore, comparison of prediction performance with several machine learning methods further verifies the learning ability of the AFNN. Finally, a sensibility analysis indicates heading angles and acceleration of vehicle are also important factors for predicting lane changing behavior.

1. Introduction

Automatic vehicles, relying on the collaboration of artificial intelligence, visual computing, radar monitoring device, and global positioning system, can automatically and safely operate motor vehicles in the absence of any human activities. As a key part of Advanced Driver Assistance System (ADAS), this technology can largely improve the driving safety and avoid traffic accidents. Furthermore, it can also help to rationalize driving behavior, improve travel efficiency and further relive traffic pressures. The whole driving process generally contains several maneuvers, such as, lane changing, overtaking, car following and so on. In fact, due to the impact of many external factors, the behavior of a driver is complicated and mainly depends on human's physiological status and psychological activity. In addition, modeling driving behavior is a complex problem which involves control theory, robotics, and psychology. As one of most common and challenging behavior, drivers should not only consider the safety distance from the front vehicle on the current lane but also the safety space between the front and latter vehicles on target lane during lane changing process. Traffic accidents caused by unreasonable lane-changing behavior will result in personal injury and deterioration of traffic condition. Therefore, exploring the intent recognition and analyzing the route patterns are definitely conducive to improving the safety of lane changing behavior (Hou, Edara, & Sun, 2015; You et al., 2015).

1.1. Related works

Currently, one practical solution is sole turn signal. It is an apparent indicator to reflect lane-changing intention of drivers. However, this signal can be also used for other behavior, such as specific direction turning. Furthermore, many researchers (Deutscher, 2007; Lee, Olsen, & Wierwille, 2004; Ponziani, 2012; Schmidt, Beggiato, Hoffmann, & Krems, 2014) have conducted experiments to estimate the sensitivity of the turn signal as indicator for lane change. They found that this method lacked sensitivity and specificity to predict lane changing behavior. Another method is considered as using data from multi-sensor installed on the vehicle to predict the behavior of lane changing. Morris, Doshi, and Trivedi (2011) introduced several data source to be implemented for route or path prediction, which include driver behavior observation (e.g., eye-tracking, electrocardiogram), sensor information about the environment (e.g., safe distance detection, GPS data) and vehicle parameters (e.g., vehicle speed, acceleration, steering wheel angle). By integrating these data source, various methods are pro-

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posed to predict lane changing behaviors. They can be classified into following five categories: (1) Hidden Markov Model (HMM) (Kuge, Yamamura, & Shimoyama, 2000; Liu & Pentland, 1997; Pentland & Liu, 1999; Sathyanarayana, Boyraz, & Hansen, 2008); (2) Neural Networks (NN) (Cheng, Xiao, & LeQuoc, 1992; Ding, Wang, Wang, & Baumann, 2013; Macadam & Johnson, 1996; Tomar, Verma, & Tomar, 2010); (3) Regression Model (RM) (Henning, Georgeon, & Krems, 2007; Olsen, 2003); (4) Cognitive Model (CM) (Baumann & Krems, 2007; Pickering, 2001; Salvucci, 2006; Salvucci, Mandalia, Kuge, & Yamamura, 2007); (5) Fuzzy Logic System (FLS) (Errampalli, Okushima, & Akiyama, 2008; Hessburg & Tomizuka, 1995; Kim, 2002; Okushima & Akiyama, 2005; Shi & Zhang, 2013);

(1) For the Hidden Markov Model (HMM), HMM can infer unobservable (hidden) states from observable actions, and studies in this part mainly focus on constructing probabilistic model to predict driving routes. Kuge et al. (2000) introduced a driver behavior recognition model based on HMM considering driver characteristics by using driving simulation data. Sathyanarayana et al. (2008) proposed a hierarchical framework to modeled driver behavior signals, in which the first layer considered isolated maneuver recognition and second layer models the entire route based on HMM. (2) For the Neural Networks (NN), due to its strong generalization and learning ability as well as adaptability, NN is also a popular approach selected by scholars to finish lane-changing prediction. To overcome the disadvantage that existing lane change models do not consider the uncertainties and perceptions in the human behavior, Tomar et al. (2010) constructed a neural network with multilayer perceptron to predict the lane changing trajectory in future steps based on field data from the Next Generation Simulation (NGSIM). Ding et al. (2013) developed a Back-Propagation (BP) neural network to predict lane-changing trajectory, and they also compared prediction results between BP neural network and Elman Network using the data collected from driving simulator data and NGSIM. (3) For the Regression Model (RM), because of its simple structure and fast calculation speed, researches used this approach to fit the relationship between input variables (vehicle speed, acceleration, safe distance and so on) and output variables (steering wheel angle or lane changing routes). In order to model lane changing process with slow lead vehicle, Olsen (2003) applied a logistic regression model considering the distance to the front and rear adjacent vehicle, forward time-to-collision (TTC), and turn signal activation. Henning et al. (2007) used regression model to predict the intention of lane changes considering some environmental and behavioral indicators: glance to the left outside mirror, turn signal, and lane crossing. (4) For the Cognitive Model (CM), it can be used to approximate human cognitive processes for the purposes of comprehension and prediction. Salvucci (2006) introduced an Adaptive Control of Thought-Rational cognitive architecture and proposed an integrated driver model to accomplish processes of control, monitoring and decision making in a multilane highway environment. Baumann and Krems (2007) introduced some major preconditions of safe driving in drivers' cognitive process. (5) For the Fuzzy Logic System (FLS), it is built on a probabilistic reasoning process that uses fuzzy input parameters. Through optimizing parameters in fuzzy membership functions, FLS can be used to accurately predict driving trajectories in lane changing process. Errampalli et al. (2008) introduced fuzzy reasoning in lane changing model to realistically indicate uncertainties and perceptions in driving behavior, and they compared simulation results with traditional multinomial logit model to validate its effectiveness. Shi and Zhang (2013) adopted fuzzy logic to analyze multi lane change behavior, in which several indicators are considered as input variables and steering wheel angle is set as output variable to evaluate the efficiency of lane change process.

1.2. Aims of study

Abundant works focused on lane changing behavior prediction have been obtained in previous researches, however, there still exists some issues need to be solved in emulating the complex and multi-ruled behavior of the driver and incorporating the uncertainties of driver's perception and decisions. Fuzzy logic is a kind of method that can deal with the transformation between qualitative and quantitative information. By implementing fuzzy comprehensive judgment, it deals with some problems with fuzzy information that are difficult to be solved by traditional methods. Fuzzy logic is good at expressing the qualitative knowledge and experience with uncertainty. In the process of lane changing, the decision-making behavior of the driver obviously contains fuzzy or uncertain process. So, it is effective and feasible to use fuzzy logic theory to analyze the behavior of the lane changing. However, according to current studies, there are several disadvantages: (1) the rules used in fuzzy inference are not comprehensive; (2) lacking adaptive learning mechanism will result in unsatisfactory prediction performance; (3) indicators or factors considered in fuzzy input variables are limited.

Aim to aforementioned three deficiencies, this study proposes a fuzzy neural network with adaptive learning ability to predict lane changing behavior. The main work includes following three parts. (1) Establish FNN model, determine the input and output variables, and construct the rule base and inference mechanism. (2) Introduce an adaptive learning process, in which the prediction errors are used to adjust structure of fuzzy membership function, and then improve fuzzy reasoning process by enriching the rule base. (3) Consider the effects of various information in input variables for driving behavior, which includes vehicle parameters: vehicle speed, acceleration, heading angles, and distance from the front vehicle in the horizontal axis and vertical axis, the output variables is determined as driving steering angle. Finally, using the data collected from driving simulator, the effectiveness of this study is validated based on statistical analysis of prediction results.

The remainder of the paper is organized as follows. Section 2 briefly introduces the models used in study. The car-steer modeling based on FNN is provided in Section 3. Section 4 discusses the experiment results and compares prediction accuracy between different models. Section 5 provides the conclusion of the paper.

2. Lane-changing driving behavior

For the vehicle model, we consider a simplified movement model of a four wheeled vehicle as following:

$$\left.\begin{aligned} x(k+1) &= x(k) + v(k)\cdot\Delta s\cdot\cos[\theta(k)] \\ y(k+1) &= y(k) + v(k)\cdot\Delta s\cdot\sin[\theta(k)] \\ \theta(k+1) &= \theta(k) + v(k)\cdot\Delta s\cdot\tan\alpha(k)/l \end{aligned}\right\} \tag{1}$$

where θ is the heading of the vehicle, x and y represent the position of vehicle, x_0 and y_0 represent the centroids of vehicle, which are determined on the basis of vehicle rear wheel, α is the steering angle, v indicates the instantaneous velocity, l means the wheelbase, Δs is the computation sampling time, and k is the simulation step, see Fig. 1a. Define t_0 as the starting time, T as the ending time when subject vehicle finishes the lane changing maneuver, the $k\in[t_0, T]$. Therefore, according to the values of x, y and θ, we can determine vehicle attitude. Fig. 1b shows lane changing maneuver. Lag vehicle 2 is the subject vehicle, lead vehicle 2 is the lead vehicle in the current lane, and the lag vehicle 1 and lead vehicle 1 represent the following vehicle and lead vehicle in the target lane, respectively. The acceleration (acc) can be calculated as: