

Collision Prevention While Driving in Real Traffic Flow Using Emotional Learning Fuzzy Inference Systems

Reza Zarringhalam
University Of Waterloo

Ali Ghaffari
K N Toosi Univ of Technology

ABSTRACT

This paper proposes a methodology for collision prevention in car following scenarios. For this purpose, Emotional Learning Fuzzy Inference System (ELFIS) approach is used to simulate and predict the behavior of a driver-vehicle-unit in a short time horizon ahead in the future. Velocity of the follower vehicle and relative distance between the follower and the lead vehicles are predicted in a parallel structure. Performance of the proposed algorithm is assessed using real traffic data and superior accuracy of this method is demonstrated through comparisons with another available technique (ANFIS). The predicted future driving states are then used to judge about safety of the current driving pattern. The algorithm is used to generate a warning message while a safe-distance keeping measure is violated in order to prevent a collision. Satisfactory performance of the proposed method is demonstrated through simulations using real traffic data. The proposed method can be applied, in real time, for a variety of applications including driver assistant and collision prevention systems as well as other intelligent transportation applications.

CITATION: Zarringhalam, R. and Ghaffari, A., "Collision Prevention While Driving in Real Traffic Flow Using Emotional Learning Fuzzy Inference Systems," *SAE Int. J. Trans. Safety* 1(1):2013, doi:10.4271/2013-01-0623.

INTRODUCTION

Development of efficient driving assistant and autonomous driving systems is among the main initial steps towards large-scale implementation of intelligent transportation systems (ITSs). Such systems are expected to intelligently assist the driver or control the vehicle in a safe, efficient and comfortable way. Several motivations like simplification of the driving procedure, optimization of the traffic flow and increasing the safety, justify real word implementation of the intelligent systems in transportation applications. Accordingly, this paper investigates development of an intelligent collision prevention method for assisting the driver in hazardous situations.

Rear-end collision is a common type of road accidents reported to have a major share of all road accidents [1]. Several studies have recently addressed development of collision prevention controllers or warning generation systems. Jameson et al. [2] investigated two types of collision prevention systems using a driving simulator. They studied performance of different drivers using adaptive and non-adaptive forward collision warning systems. They concluded that the drivers can benefit from both of these systems. Mar

and Lin [3] developed an ANFIS collision prevention controller to avoid rear-end collisions.

However, such systems are expected to be customized for individual drivers according to their specific driving styles. Driving models can be trained either in offline or online manners and driver assistant systems can use appropriate models for a certain driver through driver identification [4]. In order to develop an efficient rear-end collision prevention system, accurate modeling of the car-following behavior that adapts to the current driving style can play an important role. Car following models describe dynamic behavior of a driver-vehicle-unit (DVU) while following a leader vehicle [5]. A variety of applications including navigation systems, adaptive cruise control systems, lane keeping assistance systems and collision prevention systems directly use the car-following models [6][7][8]. Generally, such models assume that the driver of the follower vehicle (FV) responds to a set of input variables to control longitudinal dynamics of the vehicle. Such inputs include velocity of the follower vehicle, relative distance between the leading (LV) and the follower vehicles, etc. [9]. However, identification of the driving behavior is a

challenging problem due to nonlinearities, uncertainties and effects of human decisions.

This paper proposes a predictive collision prevention system for safety assurance in a car-following scenario. An emotional learning-based fuzzy inference system (ELFIS) method is developed to predict future states of the driving maneuver for a short term horizon in the future. The predicted states are then used to assess safety of the current driving pattern and generate a warning signal in the high-risk situations to prevent rear-end collisions. Moreover, the proposed method can adapt to the current driving style through online training using the observation data.

EMOTIONAL LEARNING FUZZY INFERENCE SYSTEMS

Neuro-fuzzy systems are compositions of fuzzy logic systems and neural networks and therefore are empowered by the benefits of both methods. The integration of trainability by real data and integration of human expert's knowledge in the form of if-then rules have introduced neuro-fuzzy systems as efficient methodologies to deal with nonlinear uncertain systems. Takagi-Sugeno (T-S) fuzzy inference system [10] is used in this paper for modeling of the driving pattern and prediction of the future driving states. In the TS model, the rules are defined as:

$$\begin{aligned} \text{Rule}_i: & \text{ if } u_1 = A_{i1} \text{ and } \dots \text{ and } u_p = A_{ip} \\ & \text{ then } \hat{y}_i = f_i(u_1, u_2, \dots, u_p) \quad i = 1, 2, \dots, M \end{aligned} \quad (1)$$

where $u_1, u_2, \dots, u_p$ are the inputs, A_{ij} denotes the fuzzy set for the input u_j , M is the number of fuzzy rules and $f_i(\cdot)$ is a linear combination of the inputs:

$$\hat{y}_i = \omega_{i0} + \omega_{i1}u_1 + \omega_{i2}u_2 + \dots + \omega_{ip}u_p \quad (2)$$

Final output of the system is therefore calculated by

$$\hat{y} = \frac{\sum_{i=1}^M f_i(u_1, u_2, \dots, u_p) \mu_i(u_1, u_2, \dots, u_p)}{\sum_{i=1}^M \mu_i(u_1, u_2, \dots, u_p)} \quad (3)$$

$$\mu_i(u_1, u_2, \dots, u_p) = \prod_{j=1}^p \mu_{ij}(u_j) \quad (4)$$

where μ_i is weight of the i -th rule, $\mu_{ij}(u_j)$ is the membership function of the j -th input in the i -th rule and $\hat{y}$ is the output.

Many nonlinear local optimization techniques can be used to update the weights (ω_{ij}). ANFIS [11] is one of the most frequently employed algorithms for this purpose and has successfully been implemented for different applications. In

this paper, the emotional learning-based fuzzy inference system (ELFIS) method is used to tune the rules for development of the required state predictors. Detailed description of the method can be found in [12]. In this method, as a summary, the cost function is defined with respect to the opinion of a critic towards performance of the system (emotional reaction of the critic):

$$J = \frac{1}{2} K \sum_{i=1}^N (es(i))^2 \quad (5)$$

where $es(i)$ is the emotional signal (emotional reaction) to the i -th sample of the training data, K is a constant gain matrix and N is the dimension of the training data set. Using such representation, the update rule can be formed as

$$\Delta \omega = -\eta \frac{\partial J}{\partial \omega} \quad (6)$$

where η is the learning rate. The differentiation can be performed using the chain rule:

$$\frac{\partial J}{\partial \omega} = \frac{\partial J}{\partial es} \cdot \frac{\partial es}{\partial y} \cdot \frac{\partial y}{\partial \omega} \quad (7)$$

where $\frac{\partial y}{\partial \omega}$ is accessible from (2), and considering (5):

$$\frac{\partial J}{\partial es} = K \cdot es \quad (8)$$

Calculation of the middle term $\frac{\partial es}{\partial y}$ is not straightforward [12]. However, using appropriate simplifications, an approximation of this term is achievable. Considering y_r as the target actual output, the prediction error is defined as

$$e = y_r - y \quad (9)$$

and therefore

$$\frac{\partial es}{\partial y} = -\frac{\partial es}{\partial e} \quad (10)$$

Consequently, the term $\frac{\partial es}{\partial y}$ in (7) can be replaced by its sign (-1) [12].

Eventually, the update rule can be presented as: