Modeling and Intelligent Control Design of Car Following Behavior in Real Traffic Flow

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***Abstract*— The control of car following is essential to its safety and its operational efficiency. For this purpose, this paper builds a linear, continuous and time-delay model of car following. And then, presents a controller based on an adaptive network fuzzy inference system (ANFIS) for the car-following collision avoidance system to adaptively control the speed of the vehicle. The relative distance and relative speed to the in front car are measured and are applied to the controller. The output acceleration or deceleration rate of the controller is based on the characteristics of the vehicles. The presented ANFIS controller can solve the problems of the oscillations for final distance between the leader vehicle (LV) and the follower vehicle (FV) and their relative speed. The designed ANFIS controller is linked to the car following model. The simulation results show that the ANFIS control design is more effective and can provide a safe, reasonable, and comfortable drive than real driver.**

***Keywords*—car following, modelling, intelligent control, ANFIS.**

I. INTRODUCTION

Car following is quite common in many traffic fields such as railway, highway and etc. Car following is a crucial tactical-level model for a microscopic simulation system. Car following describes the longitudinal action of a driver when it follows another car and tries to maintain a safe distance to the leading car, as shown in Fig. 1. One of the major achievements is the control laws for collision avoidance while the front car brakes suddenly in emergency in the course of their following operation [1~3]. However, due to the complexity of the car following problem, the current control of car following operation mainly dependents on the drivers' subjective judgment and their corresponding behavior. Its complexity could be summarized as follow [3]. The control of car following is a problem with more constraints and multi-objective optimization; The control of car following is similar to the pursuit and escape problem in differential game, but somehow different from, which study the bilateral dynamic optimal control laws between the pursuer and the escapee; The control of car following belongs to the problems of time-delay systems. Because of the complexity of this problem and the technological needs of current high-speed and intelligent traffic, it is necessary to explore it consistently, and has its practical significance.

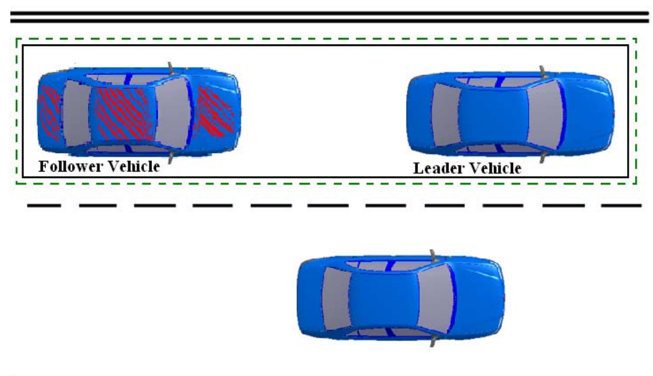

Figure 1. Driver-vehicle unites (LV and FV) in car following behavior.

Intelligent Vehicles (IV) enables the next generation approach for obtaining a more efficient driver-vehicle operation [4]. An IV system senses the environment around the vehicle and strives to achieve more efficient vehicle operation by assisting the driver or by taking complete control of the vehicle. IV application areas can be divided into three categories depending on the level of support provided to the driver. Advisory systems use optic or acoustic systems to provide an advisory/warning to the drivers; Semi-autonomous systems use haptic (meaning "based on the sense of touch") measures to assist/take partial control of the vehicle; Fully autonomous systems take complete control of vehicle operation. IV-based control measures offer lateral, longitudinal, or integrated control systems for improving safety, operational efficiency, and driving comfort [5]. These measures, when combined with autonomous control, could help to reduce the reaction time of the driver and vehicle, and allow achieving a decreased minimum safe distance between vehicles which in turn leads to an improved traffic throughput.

In this paper, we are going to focus on modeling an intelligent control system design for car following behavior in real traffic flow, considering the effects of driver's behaviors. It can make adjustment with traffic subcontractors to develop the operations of controlling system in a car and on a road.

II. CAR FOLLOWING BEHAVIOR MODELING

To examine the operations of intelligent control system, we need to model the car following behavior. However, first, we build the ideal linear continuous system model without time-delay, then add time-delay factor, and construct the discrete model for computer control of car following behavior for drivers-vehicles system, LV and FV, as shown in Fig.2. Finally, this model is verified by using real data and used to simulate the above car following states.

A liner continuous model of car following is shown in Fig. 2.

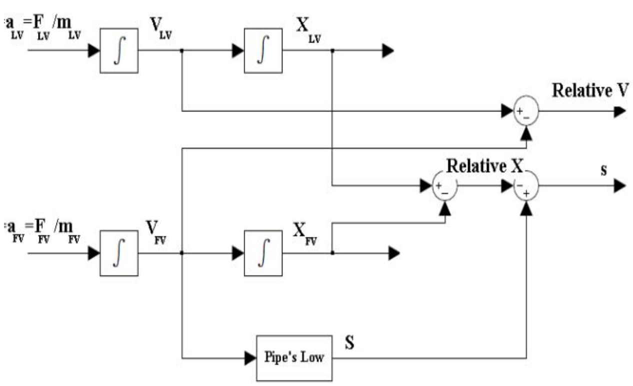

Figure 2. Block diagram of car following behavior.

In this model, m_{LV} and m_{FV} represent the mass of the LV and FV respectively, a_{LV} and a_{FV} represent the acceleration respectively, V_{LV} and V_{FV} represent their speed respectively, X_{LV} and X_{FV} represent their running distance respectively. s represents the dynamic safe distance between two cars. S is the standard safety interval distance between two cars under the certain speed of car following in the steady-state which is obtained by Pipe's Low. as equ. 1:

$$S = L(1+\frac{V_{FV}}{16.1}) \tag{1}$$

where L and V_{FV} are length and speed of FV, respectively.

The state space equations of system can be expressed as follows.

$$\begin{cases} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ y = \begin{bmatrix} 0 & -1 & 0 & +1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + S \end{cases} \tag{2}$$

Where u_1 and u_2 are inputs representing LV and FV accelerations, x_1 and x_3 also represented LV and FV speed and x_2 and x_4 are LV and FV running distance and $S = L + (L/16.1)x_3$.

Based on the minimum and maximum speed and length of vehicles, this value can be approximated as a linear relation as $S = ax_3$, where a is constant.

Driver in FV tries to keep relative distance from LV by increasing or decreasing acceleration and by being close or far from LV. There are two factors which prevent the reaction of FV against LV; the delaying reaction of driver and the mechanisms in the car that transfer acceleration and deceleration. So FV delays about τ in reaction. So, we can write the inputs of system as follow:

$$\begin{cases} u_1 = u_1(t) \\ u_2 = u_2(t-\tau) \end{cases} \tag{3}$$

Based on equation (3), state space equations of system can be stated as follow:

$$\begin{cases} \dot{\bar{x}} = A\bar{x} + B\begin{bmatrix} u_1(t) \\ u_2(t-\tau) \end{bmatrix} \\ \bar{y} = C\bar{x} \end{cases} \tag{4}$$

To realize the control systems by high-precision computer, the quantization effects can be ignored. Generally continuous control object is quantified together with its front zero-holder, thereby the computer control system can be simplified into purely discrete systems to analyze and design [6].

Suppose T is sampling period and $\lambda \in I$, we might as well assume $\tau = \lambda T$ to simplify its calculations. Further define

$$u(t) = u(kT) = u(k) \quad , \quad kT \le t < (k+1)T \tag{5}$$

By this, we have

$$\begin{cases} \bar{x}(t) = e^{A(t-t_0)}\bar{x}(t_0) + \int_0^t e^{A(t-\eta)} B \begin{bmatrix} u_1(\eta) \\ u_2(\eta-\tau) \end{bmatrix} d\eta \\ \bar{y}(t) = C\bar{x}(t) \end{cases} \tag{6}$$

In the above equations, we assume $t_0 = kT$ and $t = (k+1)T$ in the state equation and $t = kT$ in the output equation, thus

$$\begin{cases} \bar{x}(k+1) = e^{AT}\bar{x}(k) + \int_0^T e^{A\eta} B\, d\eta \begin{bmatrix} u_1(k) \\ u_2(k-\lambda) \end{bmatrix} \\ \bar{y}(k) = C\bar{x}(k) \end{cases} \qquad (7)$$

This car following behavior model is simulated and verified using actual measured values. Real car following data from US Federal Highway Administration's Next Generation Simulation (NGSIM) dataset [7] is used to validate the model and to assess its performance. The dataset presents trajectory data of vehicles travelling during the morning peak period on a segment of Highway 101 (Hollywood Freeway) in the Universal City neighborhood of Los Angeles, California. The dataset consists of detailed vehicle trajectory data on a merge section of eastbound US-101. The data is collected in 0.1 second intervals. Velocity of a couple of vehicles (one following the other) and their relative distance are used to build up the models. The model is simulated in its best available performance to make a proper comparison feasible. Fig. 3 shows the comparison of real data and results of simulation for the same inputs for car following behavior. There is a small difference between the simulation results and real data because of the existence of noise in the measurement datasets.

III. Intelligent Control Design for Car Following Behavior

In reasonable car-following behavior of the real world, the reactions of a driver to the actions of other drivers may differ with different drivers or different conditions. Therefore, the reactions of a driver to the actions of other drivers are not based on a deterministic one-to-one relationship but on a set of vague driving rules developed through experience from different drivers and conditions. It assumes that a decision made by a driver is the result of a fuzzy reasoning process and then predicts the possibilities of the reaction of the FV. Kikuchi and Chakroborty used a fuzzy inference system (FIS) to control the car speed [8]. In their model, regardless of the different initial distance between the LV and FV and the relative speed, the final safe distance approaches a constant value. Lang et al. proposed an FIS car-following model with a proper membership function and rule base, which can solve both problems of the different final relative safe distances and oscillations [9]. Jang has used ANFIS to formalize a systematic approach to generating a fuzzy rule and membership function [10].

This section introduces the basics of the ANFIS network architecture applied for the car-following control system. A detailed coverage of ANFIS can be found in [11~13]. ANFIS enhances fuzzy controllers with self-learning capability for achieving optimal control objectives. An adaptive network is a multilayer feed-forward network where each node performs a particular node function on incoming signals. It is characterized with a set of parameters pertaining that node. To reflect different adaptive capabilities, both square and circle node symbols are used. A square node (adaptive node) has parameters, while a circle node (fixed node) has none. The parameter set of an adaptive network is the union of the parameter sets associated to each adaptive node. To achieve a desired input–output mapping, these parameters are updated according to given training data and a recursive least square (RLS) based learning procedure.

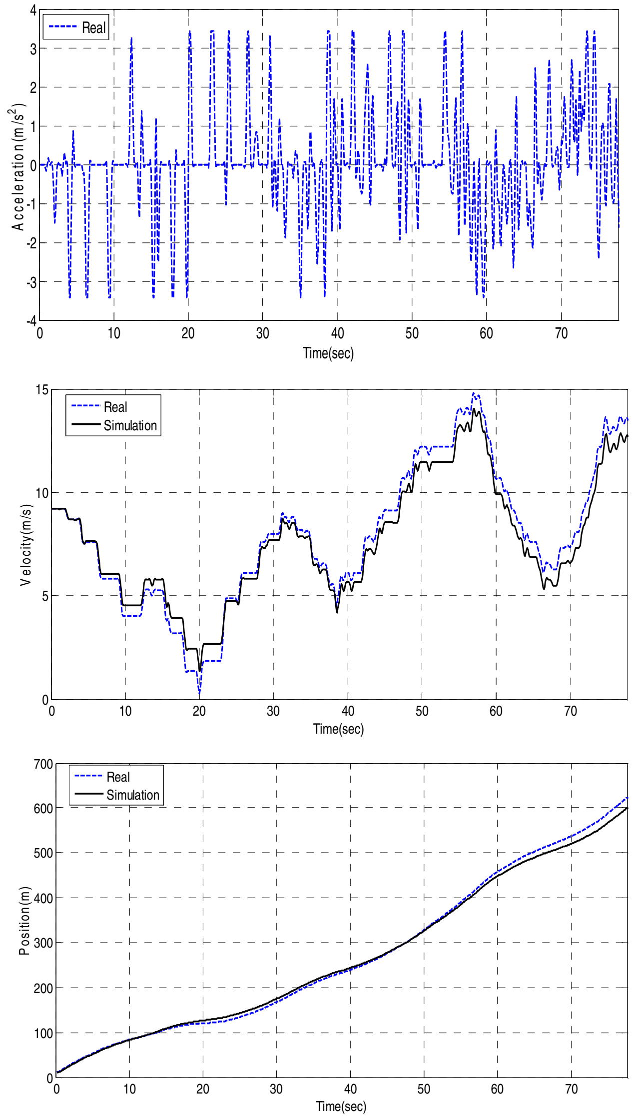

Figure 3. Comparison between real data and results of simulation for the same inputs for FV.

In order to design an ANFIS control system, a dataset of car following behavior is needed. So, real car following data from US Federal Highway Administration's NGSIM dataset is used to train the ANFIS controller. In June 2005, a dataset of trajectory data of vehicles travelling during the morning peak period on a segment of Interstate 101 highway in Emeryville (San Francisco), California has been made using eight cameras on top of the 154m tall 10 Universal City Plaza next to the Hollywood Freeway US-101. On a road section of 640m, as shown in Fig. 4, 6101 vehicle trajectories have been recorded in three consecutive 15-minute intervals. This dataset has been published as the "US-101 Dataset". The dataset consists of detailed vehicle trajectory data on a merge section of eastbound US-101. The data is collected in 0.1 second intervals. Any measured sample in this dataset has 18 features of each driver-vehicle unit in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle and etc.

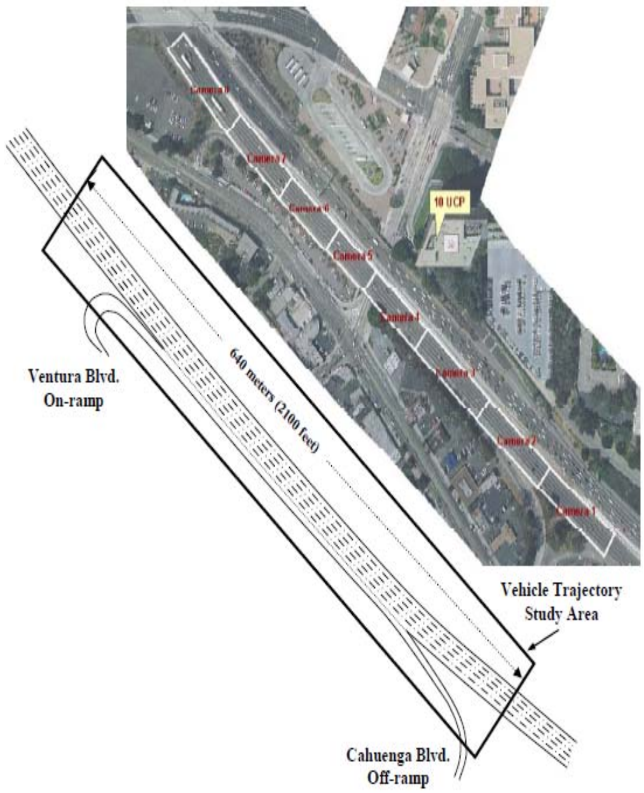

Figure 4. A segment of Interstate 101 highway in Emeryville, San Francisco, California.

The trajectory data seems to be unfiltered and exhibits some noise artefacts, so we have applied a moving average filter to all trajectories before any further data analysis. Comparison of unfiltered and filtered data is shown in Fig. 5.

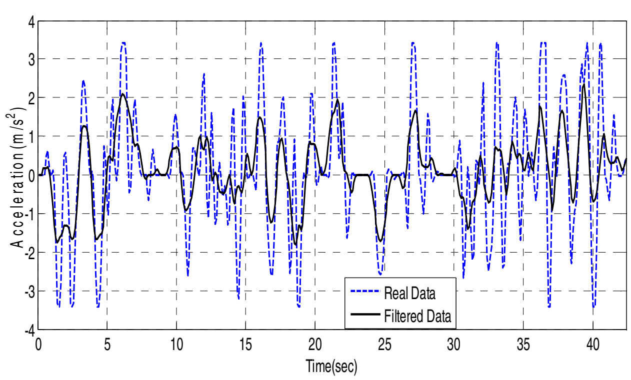

Figure 5. Comparison of unfiltered and filtered data.

To design ANFIS controller shown in Fig. 6, it is assumed that the fuzzy inference system applied for controller has three inputs and one output, which inputs are relative speed, relative distance and acceleration of LV, and output is acceleration of FV. There are three dsigmf membership functions for each input. The rule base contains 27 fuzzy if-then rules of Takagi and Sugeno's type [10] and hybrid algorithm is used to train this controller.

In the development of ANFIS controller, the available data are usually divided into two randomly selected subsets. The first subset is known as the training and testing data set. This data set is used to develop and calibrate the controller. The second data subset (known as the validation data set), which was not used in the development of the controller, is utilized to validate the performance of the trained controller. For this paper, 70% of the master data set was used for training and testing purposes. The remaining 30% was set aside for model validation.

Figure 6. Designed ANFIS controller for car following behavior.

Figure 7.

IV. Discussion and Results

In order to evaluate the designed intelligent control system, the performance of this controller which has been linked to the presented car following model in this paper is compared to the real behavior of drivers based on NGSIM dataset.

Fig. 7 reveals that suitable input acceleration signals are applied to FV in comparison to real driver by ANFIS controller. That is, these signals have better effects on acceleration or deceleration, obtaining safe conditions, vehicle stability and also proper performance of vehicle mechanisms and systems. There is also smoother trajectory which makes better and safer vehicle motion in the produced signals by controller than driver.

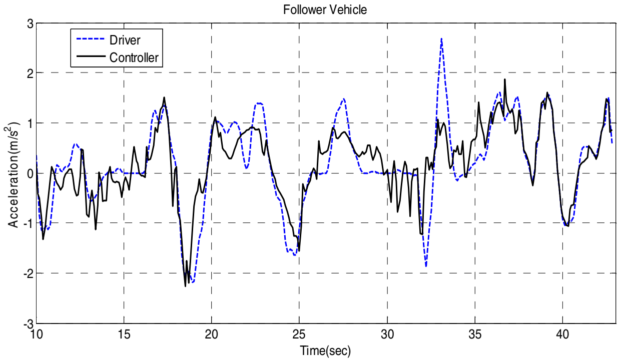

Figure 8. Controller acceleration input signal in comparison to real driver for FV.

As shown in Fig. 8 and Fig. 9, ANFIS controller systems have better effects on obtaining position and velocity outputs of FV. It means, resulted outputs especially in control of velocity regulation reveal suitable conditions and safety comparing to a real driver while driving. The results of using intelligent controller related to driver are smoother trajectory of velocity and preventing of extreme variation of speed which can be calculated by the sum square of velocities.

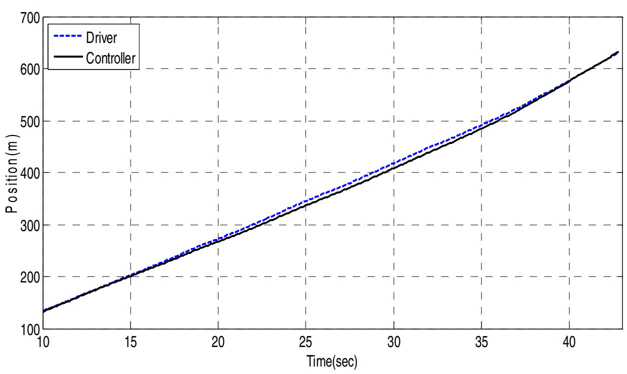

Figure 9. Comparison of ANFIS controller and real driver on obtaining position of FV.

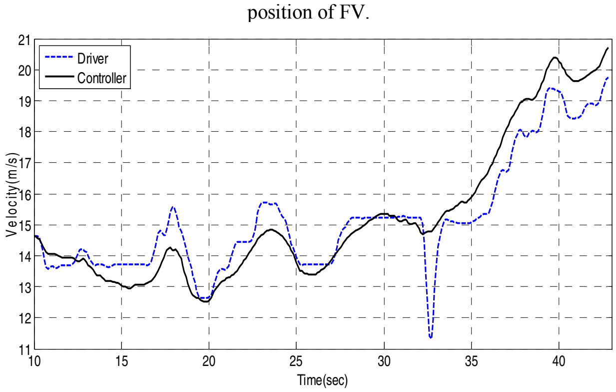

Figure 10. Comparison of ANFIS controller and real driver on obtaining velocity of FV.

Fig. 10 shows the better effects of ANFIS controller on dynamic safe distance of vehicles comparing to real driver. Less error average in regulation of safe distance has been shown in the results of controller related to driver. That is, resulted outputs reveal suitable conditions with less unsafety and also co-operation of traffic management and roadside infrastructure. These results cab be properly obtained by using the sum square of errors according to Fig. 10.

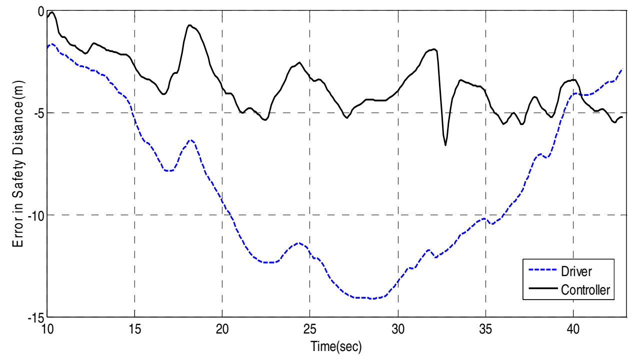

Figure 11. Comparison of ANFIS controller and real on obtaining dynamic safe distance of FV.

V. Conclusion

This article focuses on modeling and intelligent control of car following behavior. The car following behavior has been modeled by nonlinear equations, and this model has been validated by measured data of different drivers and cars and has been simulated in MATLAB software. An ANFIS controller for car following behavior has been designed and simulated in this paper. The simulated relative distance between the LV and the FV and relative speed measured by the radar sensor are sent into the ANFIS controller to simulate the car following performance. The simulation results show that the ANFIS controller has better effect than the real drivers to obtain objective of setting the least relative speed and safe distance. The presented controller can be used in analyzing and correcting driver's behaviors, developing cooperative systems and safety systems of driving, intelligent car and traffic flow.

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