Intelligent Control System Design for Car Following Maneuver Based on the Driver's Instantaneous Behavior

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Abstract

Due to the increasing demand for traveling in public transportation systems and increasing traffic of vehicles, nowadays vehicles are getting to be intelligent to increase safety, reduce the probability of accident and also financial costs. Therefore, today, most vehicles are equipped with multiple safety control and vehicle navigation systems. In the process of developing such systems, simulation has become a cost-effective chance for the fast evolution of computational modeling techniques. The most popular microscopic traffic flow model is car following models which are increasingly being used by transportation experts to evaluate new Intelligent Transportation System (ITS) applications. The control of car following is essential to its safety and its operational efficiency. This paper presents a car-following control system that was developed using a fuzzy model predictive control (FMPC). This system was used to simulate and predict the future behavior of a Driver-Vehicle-Unit (DVU) and was developed based on a new idea to calculate and estimate the instantaneous reaction of a DVU. At the end, for experimental evaluation, the FMPC system was used along with a human driver in a driving simulator. The results showed that the FMPC has better performance in keeping the safe distance in comparison with real data of human drivers behaviors. The proposed model can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

Keywords: *Intelligent transportation systems, car following maneuver, modeling and control, fuzzy system, model predictive system.*

1. Introduction

Despite wide planning in the route management, adequate infrastructure and traffic rules for safe driving, still developed countries are faced with the problem of traffic congestion and therefore a waste of time, fuel and financial resources due to increased travel demands. A solution could be to create new roads, but this solution with respect to environmental and political reasons are less capable of being implemented. For this reason, a good alternative, as a basic infrastructure is needed.

Intelligent transportation Systems (ITS) are being developed and deployed to improve the efficiency, productivity, and safety of existing transportation facilities and to alleviate the impact of transportation on the environment. These systems exploit currently available and emerging computer, communication, and vehicle-sensing technologies to monitor, manage, and control the highway transportation system. The success of ITS deployment depends on the availability of advanced traffic analysis tools to predict network conditions and to analyze network performance in the planning and operational stages. Many ITS sub-systems are heavily dependent on the availability of timely and accurate wide-area estimates of prevailing and emerging traffic conditions. Therefore, there is a strong need for a Traffic Estimation and Prediction System (TrEPS) to meet the information requirements of these subsystems and to aid in the evaluation of ITS traffic management and information strategies [1].

Intelligent vehicles are the future generation vehicle that has the ability to achieve the most efficient performance of a DVU. An intelligent vehicle system senses the vehicle environment to reach the efficient operation of a vehicle. That is to assist the driver by an advice or warning, or fully control the vehicle as in autonomous vehicles. Intelligent vehicles will perform longitudinal and lateral movement of the vehicle with increasing its safety, performance efficiency and driving comfort and all these performances are done by their integrated sub control system. These actions, when combined with autonomous controlling, can reduce the reaction time of the DVU and also to help achieve the minimum safe distance between vehicles; and thus lead to an improved traffic performance.

Microscopic models are increasingly being used by transportation experts to evaluate the applications of new ITS [2]. A variety of applications including vehicle navigation systems, adaptive cruise control systems, lanes keeping assistance systems and collision prevention systems directly use the microscopic traffic flow models [3 and 4]. Car following models are among the most popular microscopic traffic flow modeling approaches aiming to describe the process of following a leader vehicle by a vehicle. As shown in Fig.1, car following describes the longitudinal action of a driver when he follows another vehicle and tries to maintain a safe distance to the leading car. The majority of available car-following models assume that the driver of the follower vehicle (FV) responds to a set of variables like relative velocity and relative distance between the leader vehicle (LV) and the FV, velocity of the FV, and/or desired distance and/or velocity of the target driver. The response is typically considered to be as acceleration or velocity changes of the following vehicle [1].

Highly nonlinear nature of car following behavior necessitates the development of intelligent algorithms to describe, model and predict this phenomenon. Fuzzy logic can be a potential method dealing with structural and parametric uncertainties in the car following behavior. Model predictive control system by using proper information from the car following behavior can predict the future behavior of the DVU [5]. With fuzzy inference systems (FIS), it cans simultaneously using the advantages of both methods. Integration of human expert knowledge expressed by linguistic variables, and learning based on the data are powerful tools enabling FIS to deal with uncertainties and inaccuracies [6].

Humans play an essential role in the operation and control of human-machine systems such as driving a car. With advances in emerging vehicle-based ITS technologies, it becomes even more important to understand the normative behavior response of drivers and changes under new systems [7]. Based on Rasmussen's human-machine model, driver behavior can also be separated into a hierarchical structure with three levels: the strategic, tactical, and operational level [8]. At the highest or strategic level, goals of each driver are determined, and a route is planned based on these goals. The lowest operational level reflects the real actions of drivers, e.g., steering, pressing pedal, and gearing. In the middle tactical level, certain maneuvers are selected to achieve short-term objectives, e.g., interactions with other road users and road infrastructures. The behavior at this level is dominated by the most recent situations but is also influenced by driver's goals at the higher level.

To develop microscopic traffic simulation of high fidelity, researchers are often interested in imitating human's real driving behavior at a tactical level. That is, without describing the detailed driver actions, DVUs in the simulation are modeled to replicate their states in reality, i.e., the profiles of vehicle position, velocity, acceleration, and steering angle.

Car following behavior, which describes how a pair of vehicles interacts with each other, is an important consideration in traffic simulation models. A number of factors have been found to influence car-following behavior, and these include individual differences of age, gender, and risk-taking behavior [3]. Regarding literatures, car-following models can be classified into 14 groups [9].

In a general classification, car following behavior microscopic models can be divided into 2 groups: mathematical equation-based and input-output based. The most important point in mathematical models is calculation and obtaining model parameters. Therefore, these parameters can be always obtained by average of values or regarding them as a fix value of DVU. Because these parameters are as a function of time, results of these models are proper for test cases and are not reliable. In input-output models, by considering the fixed DVU reaction time, output values are applied to input. Since the DVU reaction time is not actually fixed, other parameters vary with time. So an error in modeling is appeared because of the difference between real data and data used for modeling [10].

In this paper, a FMPC system is presented to predict the car following behavior in real traffic flow considering the effects of driver's behaviors. The instantaneous reaction delay of DVU is used as a human effect and applied as an input of the car-following model. Then the presented control system is evaluated with simulation on the car following simulator. This paper is organized as follows: In Section 2.1, a brief review on model predictive control (MPC) is presented and at enjambment, at Section 2.2 the ANFIS car following behavior model which will be used in the design of the controller is explained. In Section 2.3, the FMPC based on the instantaneous reaction delay as an input is proposed to predict the DVU behavior in car following scenarios and to maintain the safe distance with the

LV. In Section 3, the proposed FMPC model is linked with a driving simulator and the results of simulation are presented. Finally, conclusion is presented in Section 4.

2. Designing Fuzzy Model Predictive Control System for Car-Following Behavior

In this section the design process of our FMPC is explained. But before that, a brief review on MPC, the advantages of this method and the theory of calculation of the instantaneous reaction delay of a DVU is presented.

2.1 Model Predictive Control Basics

Model predictive control is a form of control in which the current control action is obtained by solving, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state; the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant. An important advantage of this type of control is its ability to cope with hard constraints on controls and states [11].

MPC is probably the most applied advanced control technique in the industry due to several reasons:

It handles multivariable control problems naturally.

It can take account of actuator limitation.

It can handle constraints on the inputs and the outputs of the process in a systematic way during the design and the implementation of the controller.

It can handle changes in system parameters or system structure (including sensor or actuator failures) by regularly updating the parameters and the structure of the prediction model [12].

However, the use of MPC is not limited to the industry. The many advantages that MPC offers are also relevant for traffic control. In fact, MPC has already been extended to conventional roadside-based non-IV traffic management, traffic management and intelligent vehicles control [13, 14 and 15]. It has also been used as driver assistant for ecological driving [16], path tracking of autonomous vehicle [17] and safe distance control in car following behavior [5].

The general design objective of model predictive control is to compute a trajectory of a future manipulated variable u to optimize the future behavior of the plant output y. The optimization is performed within a limited time window by giving plant information at the start of the time window [18]. Fig. 2 shows a schematic representation of MPC [13].

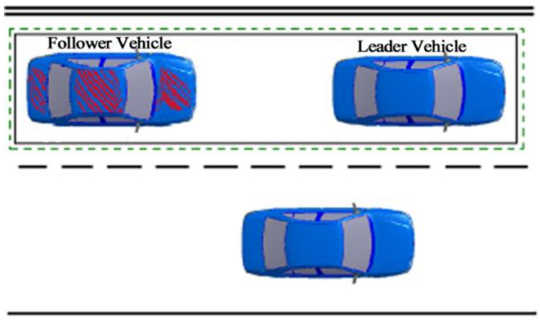

Fig1. Car-following behavior (LV and FV) [2].

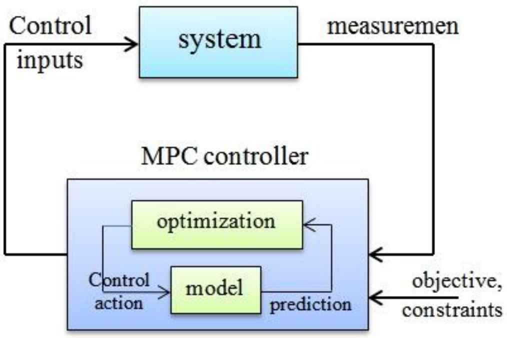

Fig2. Schematic representation of MPC [13].

In the next section, a new input-output model will be presented which estimates the FV's acceleration. Using this model, the DVU's instantaneous reaction time is calculated as an input for the system and then other inputs and outputs are chosen according to this reaction delay. The DVU's reaction delays are not the same in subsequent moments, so inputs and outputs must be chosen properly as a function of the correct reaction delay.

2.2 ANFIS Car Following Behavior Model Considering the Human Effects

Artificial Neural Network (ANN) is a proper method to solve the complex and ill-defined problems. This method has the following advantages: they can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with nonlinear problems, and once trained they can perform predictions and generalizations at high speed. They are particularly useful in system modeling, such as in implementing complex mapping and system identification [7].

ANN models may be used as alternative methods in engineering analyses and predictions. These models mimic the learning process of a human brain. They operate like a black box model, and require no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying the previously recorded data, in a way similar to how a nonlinear regression might be performed [7].

Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance, and instead, concentrate on the more important inputs [7].

Fuzzy logic can be a potential method dealing with structural and parametric uncertainties in the car following behavior. Integration of human expert knowledge expressed by linguistic variables is a powerful tool enabling fuzzy models to deal with uncertainties and inaccuracies [19]. Additionally, artificial neural networks can be favorable tools providing the possibility of exploiting real observed data while developing the models. Neuro-fuzzy models, such as ANFIS, are combinations of artificial neural networks and fuzzy inference systems, simultaneously using the advantages of both methods [20].

In [10], a new input-output model based on ANFIS was presented which estimates the FV's acceleration. The most important point in that model is that DVU's instantaneous reaction time is used as an input for the model. This variable is calculated considering the proposed idea. Proper outputs are chosen according to the DVU's reaction delay based on Stimulus-Reaction idea. This means that the accurate and appropriate output, for each step of inputs, must be chosen from further step in the real dataset (which will be explained in Section 3). The difference between the occurrence time of inputs and output in the real data is equal to the DVU's reaction delay. This delay is not the same in subsequent moments, and hence, the input and output must be chosen as a function of the proper and correct reaction times. In fact, the stimulus and reaction should be considered as an input and output with respect to the accurate instantaneous reaction time. Therefore, the idea in which the DVU's reaction time was considered as a constant value can be modified by introducing this new idea.

To design the FIS model shown in Fig. 3, it is assumed that the ANFIS model for the prediction has four inputs and one output. The four inputs are the estimated instantaneous reaction delay (τ), the relative speed (ΔV), the relative distance (ΔX), and the velocity of FV (v_{FV}). The output is the acceleration of FV (a_{FV}). The training of the ANFIS model was performed based on choosing suitable inputs and output with respect to the instantaneous reaction delay. There was one hidden layer with nine nods, and back-propagation algorithm was used to train this model. Back-propagation is a general purpose network paradigm, and calculates the errors between the desired and actual output and also propagates the error back to each node in the network. The back-propagated error drives the learning at each node [20].

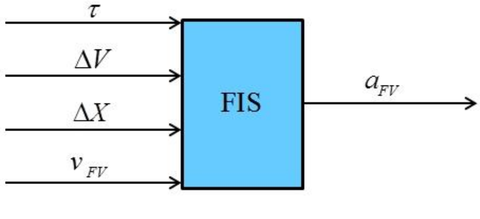

Fig3. Designed ANFIS model for car-following behavior.

In this paper, similar structure and approach (similar to ANFIS) is used, but with addition to MPC's advantages. So a modified FMPC has been designed for car following behavior to predict the behavior of the LV and to maintain safe distance with it. This issue is discussed in the next chapter.

2.2 Designing of the FMPC system

An accurate representation of car following behavior should take into account the nonlinearity of human response and limitations of a human perception system, i.e. drivers may not be able to perceive relative speed and headway accurately, and the decision process (acceleration control) could be highly nonlinear. The FMPC can map between variables that the driver can perceive and those that the driver can directly control. This mapping can be done with arbitrary accuracy based on fuzzy reasoning and MPC algorithm. This makes the system perform naturally and appropriate to model a human in the system loop [21].

To design FMPC, the main problem was defining the proper inputs and outputs and membership function. The optimal membership function values are usually found by trial and error which is laborious. But, in this paper, prior works experience in this filed [10, 22 and 23] were used to find the proper inputs and outputs. The controller works in such a way that the acceleration is predicted as an output variable for future moments. That is completed by considering the effects of the driver behavior and calculating instantaneous delay of the DVU. In the designing process of this controller which is based on fuzzy, four inputs has been selected. They are; the acceleration of the leader vehicle (a_{LV}), driver's instantaneous delay (τ), the relative distance between the two vehicles (Δx) and the safe distance between the two vehicles (S). These inputs are applied to the controller which makes it comparable with the reference input of the controller. The safe distance between the two vehicles (S) is applied to the controller as the reference input to keep the safe distance. This safe distance is calculated by Pipe's rule [24]:

$$S = L(1+\frac{V_{FV}}{4.47}) \tag{1}$$

Note that this distance is a function of the follower vehicle's velocity (V_{FV}) which is calculated in each time step by integration of the acceleration of FV (a_{FV}). In fact the controller receives a new value as a reference at each time step that has no information about it. Hence the controller must predict it in a way to keep the safe distance between the two vehicles. Fig. 4 shows the FMPC controller structure.

For each input, 3 Gaussian membership functions are defined and in the first phase the rules are fully defined. For this controller, 81 fuzzy Sugeno rules are used. Then these rules are modified and optimized and reduced to 53 fuzzy Sugeno rules.

3. Discussion and results

When talking about driving behaviors, uncertainty, inaccuracies and involvement of human reasoning and logic are involved. These are part of the driving nonlinear nature, traffic flow and related phenomena and existence of DVU time delay. So these parameters create a lot of complexity in the control commands and problem solving. Therefore simultaneous use of methods that have the ability to deal with inaccuracy and uncertainty are beneficent solutions. This solution must have the ability to model nonlinear systems and the ability to express mathematical arguments and human decision. Also it must have a high potential to be used in simulation, modeling and traffic control. These methods must be able to perform online calculation and prediction optimization at estimating and applying the commands. So it could calculate and predict driver behavior and DVU time delay.

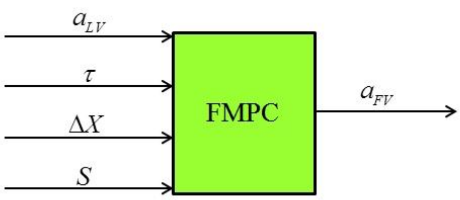

Fig4.. Designed FMPC controller for car-following behavior.

The FMPC, given the instantaneous delay of the DVU and driver behavior at the moment, will predict the driver behavior in the future. The FMPC will apply the control inputs for predicted behavior and navigation of the vehicle at each moment. These inputs are chosen with the aim for adjusting the velocity and safe region for vehicle and also regulating and improving vehicles platoon. Fig. 5 shows the schematic of the closed-loop control system and dynamic behavior of the pair of vehicles with main components of the loop.

In the next step, car-following simulation experiment of the suggested control system was implemented on the K.N.T.U driving simulator (ASARAN). The vehicle model used in this simulator has been validated by real automobile model. By receiving dynamic inputs from virtual environment, this simulator applies the outputs as slope, roll and height to the driver and passengers in order to induce the feeling of being in real vehicle. Fig. 6 shows the general form of the driving simulator (ASARAN).

Next, the performance of the designed FMPC system for car following behavior control is evaluated. For this issue, a scenario for LV, regarding the actual behavior of the DVU in the real traffic flow has been designed. Until the driver in the simulator follow the scenario and perform a car following behavior.

To design a car following scenario, a dataset of car following behavior was needed. Therefore, real car following data from the US Federal Highway Administration's NGSIM dataset have been used [25]. 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, was made using eight cameras on top of the 154-m-tall 10 Universal City Plaza, next to the Hollywood Freeway US-101. On a road section of 640 m, as shown in Fig. 7, 6101 vehicle trajectories were recorded in three consecutive 15-min 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 were collected in 0.1-sec intervals. Any measured sample in this dataset has 18 features of each DVU in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle, etc.

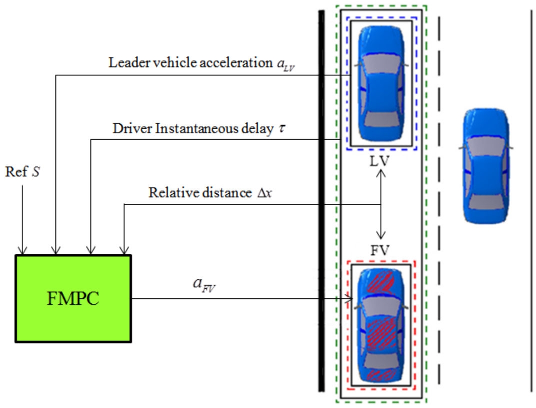

Fig5. Schematic of the ANFIS control system closed-loop

Fig6. General form of the K.N.T.U driving simulator

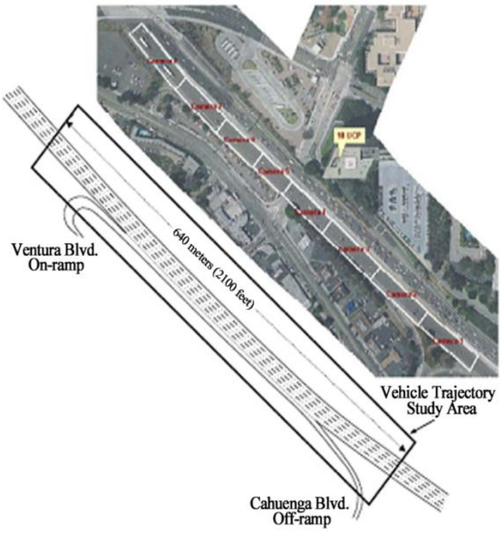

Fig7. A segment of Interstate 101 highway in Emeryville, San Francisco, California [25].

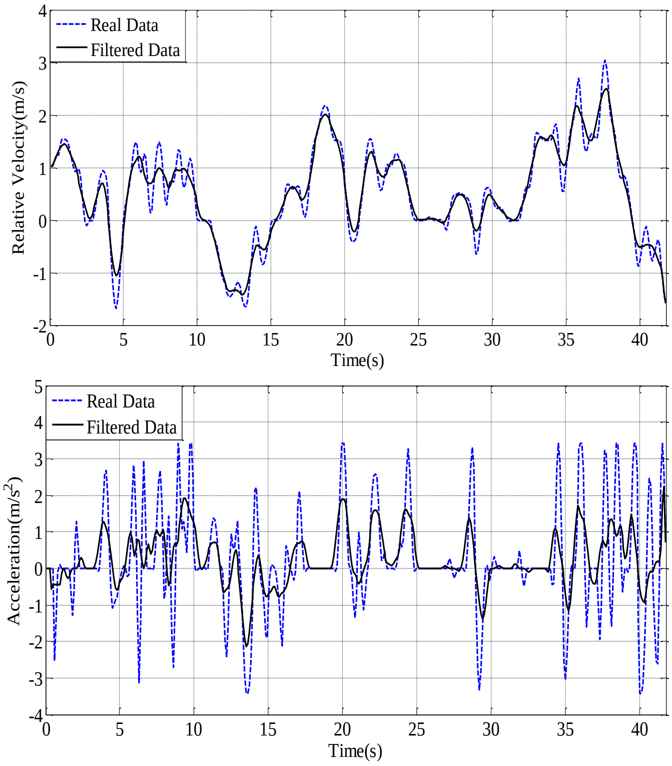

Fig8. Comparison of unfiltered and filtered data; (a) relative velocity, (b) acceleration.

However, the trajectory data appeared unfiltered and exhibited some noise artifacts; hence, they were filtered as done earlier in [26 and 27]. A moving average filter was designed and applied for duration of about 1 sec to all trajectories before any further data analysis. An example of the comparison of unfiltered and filtered data is shown in Fig. 8.

The necessary data for designing LV scenario was extracted from the NGSIM dataset. Then by repeating and adjusting these data, a scenario for the LV movement has been created. In this scenario, a specified behavior from LV is repeated 5 times. The reason of performing this repeated behavior is to evaluate and analyze the different reaction of the FV towards that specific behavior of the LV. Fig. 3 shows the variations of the leader vehicle's velocity.

As it can be seen from the Fig. 9, the scenario has 5 repeated behaviors. All behaviors are same and each one start when velocity is at 5(m/s) and ends at 27(m/s). In the simulator, navigation of the FV is done by human driver and he/she tries to follow the LV and keep the safe distance with it. To evaluate the performance of the controller, the simulation has been done for two cases. In the first case, the controller has been turned on from the second repetitive behavior. In this case, the output from human driver behavior and controller system doesn't influence on each other. This means that the FMPC system is working off-line and its control inputs don't interfere with that of the human driver. Therefore, the human driver's behavior with the one of the FMPC system can be compared side by side (well). In the second case, the controller has been turned on from the fourth repetitive behavior. That means the FV will be navigated by the FMPC system. And as the result, the FMPC system will keep the FV in the safe condition by maintain safe distance with the LV.

The sample time for car following behavior simulation has been selected as 0.1 second and for the prediction horizon (N_p) and the control horizon (N_c), 20 sec and 4 sec were selected respectively.

Car following behavior in general is a calm and steady process. A large part of this uniformity is due to the vehicle's limitation such as increase and decrease limitation of velocity and braking. Therefore in the design of the FMPC, constrains has been applied on the acceleration by fuzzy definition. These constraints will get the behavior of the model closer to reality. Also by adjusting them, smoother vehicle motion can be delivered and hence enjoyable trip provided.

Fig. 10 shows the relative distance between the follower and the LV as the result of the first case simulation. For better illustration of the result, each two repetitive behavior has been separated and then plotted in different diagrams.

As it can be seen from the Fig. 10, the FMPC system has been turned on from the second repetitive behavior and the results of the first case simulation shows that the human driver followed the LV and traversed each repetitive behavior differently. On the other hand, the FMPC system navigated each repetitive behavior according to the safe distance definition and alike the real scenario. This result shows that the human driving judgment for maintaining safe distance is dependent on the personal characteristics much more than the behavior of the LV. Also, it can be seen that the FMPC system maintains the safe distance by the rules and the safe distance definitions and its performance doesn't get influenced by the driver's personal characteristics. Thus it will navigate each repetitive behavior by maintaining the safe distance definition.

Fig. 15 shows the simulation result of the second case scenario. In this case, The FV has been navigated by human driver from the beginning to the third repetitive behavior. After that, the FMPC has been turned one, and the FV has been navigated by the controller. The result shows the relative distance and the relative distance dynamic error regarding the pipe's rule for keeping the safe distance with the LV.

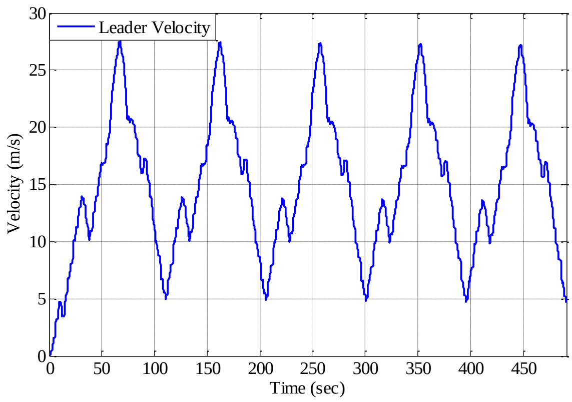

Fig9.. Leader vehicle movement scenario

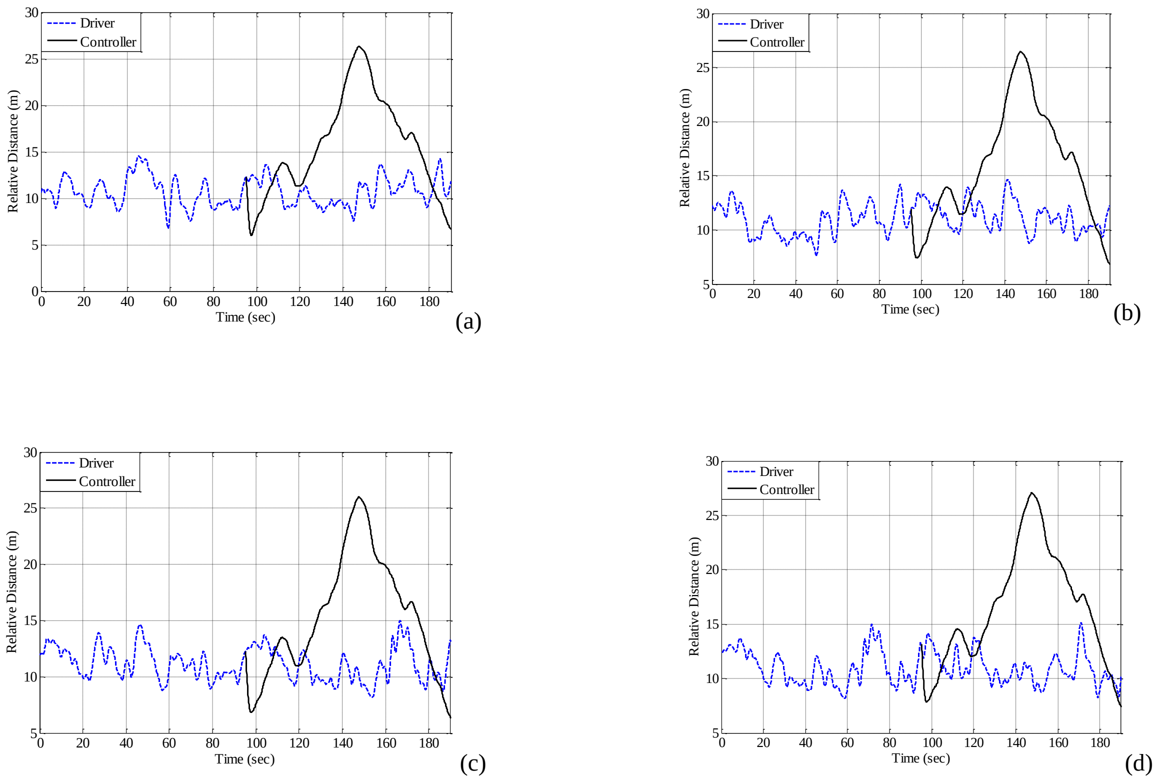

Fig10. Result of the first case simulation: (a) 1-2 repetitive behavior, (b) 2-3 repetitive behavior, (c) 3-4 repetitive behavior, (d) 4-5 repetitive behavior

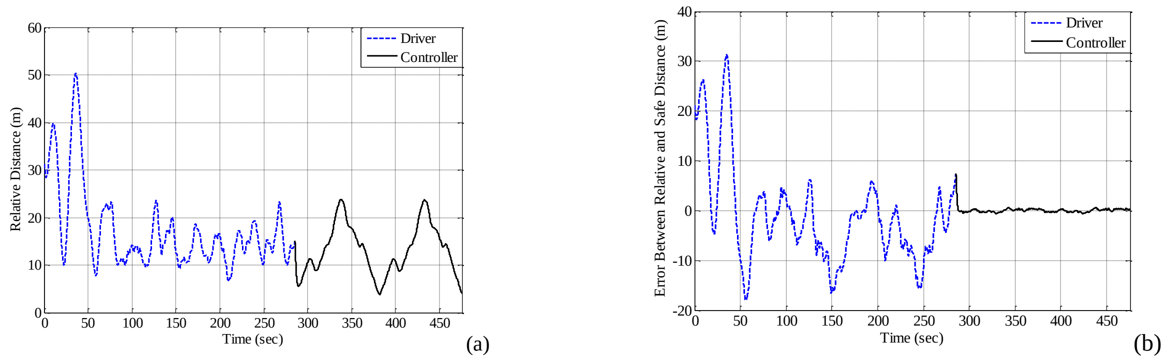

Fig11. performance of the FMPC system for car following behavior in comparison to the human driver, (a) relative distance between LV and FV, (b) relative distance error based on pipe rule

As it can be seen in the above, from the beginning of this experiment, the human driver have been followed the LV for three repetitive behavior, and none of them are alike. This means the human driver behaves differently even if the condition that he/she is encountered is repeated three times. As the result shows, the human driver has high error in keeping the safe distance. After that, when the FMPC system has been turned one, the FV has been navigated by the controller. It can be seen from the above result, that the controller navigated all the remaining behaviors alike each other. Also the error of the FMPC system for keeping the safe distance is very low and around zero. This means that the FMPC system was able to maintain the safe distance and keep the FV in the safe region for car following behavior.

4. Conclusion

In this paper, a control system based on fuzzy predictive system for car following behavior has been presented. In the design of this control system, an innovation idea for calculating DVU's instantaneous reaction delay has been used. Then, other proper inputs and membership functions have been defined with respect to the instantaneous reaction delay. This control system, based on input information, predict the LV driver behavior. The control command (acceleration) which is compatible with the safe distance reference will be applied. Since the control system is associated with human behaviors, the presented FMPC system has been simulated with a driver in the loop. K.N.T.U driving simulator (ASARAN) has been used for the car following simulation. Also the behavior of the LV for simulator has been extracted from real car following dataset. This data is modified to consist five repetitive alike behavior. For evaluation of the FMPC system, two case scenarios for simulation have been designed. The results of the two case scenarios show that the behavior of the human driver at following the LV in each similar (repetitive) behavior is not like each other. That means, the human driving judgment for following the LV and maintaining the safe distance is dependent on the personal characteristics much more than the behavior of the LV. Also, the human error in keeping the safe distance is high. On the other hand, the FMPC system has followed the LV observing the safe distance definition. The result is that, each repetitive behavior that is navigated by FMPC is alike. Also the control system error in keeping the safe distance is around zero. That means that the FMPC system doesn't get influenced by human driver personal characteristics. The FMPC system can perform car following behavior maneuver by keeping the FV in safe condition. The presented control system can be used in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications. Also this control system can be used to improve the current control systems performance and also for evaluation of the driver behavior at maintaining the safe distance.

References

[1]. Ma, X., Andréasson, I., (2007), Behavior Measurement, Analysis, and Regime Classification in Car Following, IEEE Transactions on Intelligent Transportation Systems, 8(1), 144-156.

[2]. Ge, Q., Menendez, M., (2013), An improved approach for the sensitivity analysis of computationally expensive microscopic traffic models: a case study of the Zurich network in VISSIM, Transportation Research Board 92nd Annual Meeting Compendium of Papers, Washington, D.C., January 13-17.

[3]. Panwai, S., Dia, H. , (2007), Neural Agent Car Following Models, IEEE Transactions on Intelligent Transportation Systems, vol. 8, no. 1, 60–70.

[4]. Zarringhalam, R., Ghaffari, A., (2013), Collision Prevention While Driving in Real Traffic Flow Using Emotional Learning Fuzzy Inference Systems, SAE International Journal of Transportation Safety, 1, 58-63.

[5]. Ghaffari, A., Khodayari, A., Nouri, M., Salehinia, S., and Alimardani, F., (2012), Model Predictive Control System Design for Car-Following Behavior in Real Traffic flow, IEEE International Conference on Vehicular Electronics and Safety (ICVES'12), Istanbul, Turkey, 87–92.

[6]. Petrov, M., Ahmed, S., Ichtev, A., Taneva, A., (2011), Fuzzy–neural Model Predictive Control of Multivariable Processes, Advanced Model Predictive Control, Publisher: InTech, www.intechopen.com.

[7]. Khodayari, A., Ghaffari, A., Kazemi, R., and Braunstingl, R., (2012), A Modified Car-Following Model Based On a Neural Network Model of the Human Driver Effects, IEEE Transactions on Systems, Man and Cybernetics, Part A -Systems and Humans, 42(6), 1440-1449.

[8]. Rasmussen, J., (1986), Information Processing and Human-Machine Interaction: An Approach to Cognitive Engineering, New York: Elsevier.

[9]. Khodayari, A., Ghaffari, Ameli, S., Falahatger, J., (2010), A Historical Review on Lateral and Longitudinal Control of Autonomous Vehicle Motions, the 2010 IEEE International Conference on Mechanical and Electrical Technology (ICMET 2010), Singapore, 421-429.

[10]. Khodayari, A., Ghaffari, A., Kazemi, R., Manavizadeh, N., (2010) ANFIS Based Modeling and Prediction Car Following

Behavior in Real Traffic Flow Based on Instantaneous Reaction Delay, 13th International IEEE Conference on Intelligent Transportation Systems (ITSC 2010), Portugal, 599-604.

[11]. Limon, D., Alvarado, I., Alamo, T., Camacho, E.F., (2008), MPC for tracking piecewise constant references for constrained linear systems, Automatica, 44, 2382–2387.

[12]. Maciejowski, J. M., (2002), Predictive Control with Constraints. Prentice Hall, Harlow, England.

[13]. Baskar, L. D., Schutter, B. D., and Hellendoorn, H., (2008), Model-Based Predictive Traffic Control for Intelligent Vehicles: Dynamic Velocity Limits and Dynamic Lane Allocation, IEEE Intelligent Vehicles Symposium.

[14]. Zegeye, S. K., DeSchutter, B., Hellendoorn, H., and Breunesse, E., (2009), Reduction of Travel Times and Traffic Emissions Using Model Predictive Control, American Control Conference, Hyatt Regency Riverfront, St. Louis, MO, USA, June 10-12.

[15]. Bellemans, T., De Schutter, B., and De Moor, B., (2006), Model predictive control for ramp metering of motorway traffic: A case study, Control Engineering Practice, 14(7), 757–767.

[16]. Kamal, M. A. S., Mukai, M., Murata, J. and Kawabe, T., (2009), Driving Assist System for Ecological Driving Using Model Predictive Control, SICE -TA13.

[17]. Lei, L., Zhurong, J., Tingting, C., Xinchun, J., (2011), Optimal Model Predictive Control for Path Tracking of Autonomous Vehicle, IEEE Third International Conference on Measuring Technology and Mechatronics Automation, Shangshai, Vol. 2, pp. 791-794.

[18]. Wang, L., (2009), Model Predictive Control System Design and Implementation Using MATLAB, Springer, Australia.

[19]. Khodayari, A., Ghaffari, A., Kazemi, R., Manavizadeh, N., (2010), Modeling and Intelligent Control Design of Car Following Behavior in Real Traffic Flow, IEEE International Conference on Cybernetics and Intelligent Systems (CIS2010), Singapore, 261-266.

[20]. Kosko, B., (1991), Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence, Prentice-Hall.

[21]. Zheng, P., McDonald, M., (2005), Application of Fuzzy Systems in the Car-Following Behavior Analysis, Lecture Notes in Computer Science, Springer, book: Fuzzy Systems and Knowledge Discovery, 3613, 782-791.

[22]. Khodayari, A., Ghaffari, A., Kazemi, R., and Braunstingl, R., (2011), Design of an Improved Fuzzy Logic Based Model for Prediction of Car Following Behavior, 2011 IEEE International Conference on Mechatronics (ICM2011), Turkey, 200-205.

[23]. Khodayari, A., Ghaffari, A., Kazemi, R., and Braunstingl, R., (2011), Modify Car Following Model by Human Effects Based on Locally Linear Neuro Fuzzy, 2011 IEEE Intelligent Vehicles Symposium (IV 2011), Germany, 661-666.

[24]. Pipes, L. A., (1953), An Operational Analysis of Traffic Dynamics, Journal of Applied Physics, 24(3), 274-281.

[25]. US Department of Transportation, (2009), NGSIM – Next Generation Simulation, http://www.ngsim.fhwa.dot.gov.

[26]. Thiemann, C., Treiber, M., Kesting, A., (2008), Estimating Acceleration and Lane-Changing Dynamics Based on NGSIM Trajectory Data, Transportation Research Record: Journal of the Transportation Research Board, 2088, 90-101.

[27]. Lu, X. Y., Skabardonis, A., (2007), Freeway Traffic Shockwave Analysis: Exploring the NGSIM Trajectory Data, 86th Annual Meeting Transportation Research Board, Washington, D.C.