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MANFIS-Based Overtaking Maneuver Modeling and Prediction of a Driver-Vehicle-Unit in Real Traffic Flow

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Abstract— **The purpose of this study is to design multiple-input multiple-output ANFIS (MANFIS) models to simulate and predict the future state of the overtaking maneuver in real traffic flow for four different time steps ahead. These models are designed to predict the behavior for 1, 2, 4 and 6 time steps ahead. Each time step is equal to 0.1 second. In these models, important factors such as distance, velocity, acceleration and the movement angle of the overtaking vehicle are considered. In these models, for all the variables, instantaneous values are used and none of them is considered constant. The presented models predict the future value of the acceleration and the movement angle of the overtaking vehicle. These models are designed based on the real traffic data and validated at the microscopic level. The results show very close agreement between field data and models outputs. The proposed models can be employed ITS applications and the like.**

I. INTRODUCTION

Driver's error contributes to over 75 percent of road crashes. A high percent of these crashes are related to overtaking maneuvers due to its complexity. Intelligent transport systems (ITS) are under active development worldwide as a means of reducing loss of life. Since overtaking maneuver is a complicated maneuver and so many factors affect it, the automation of this maneuver has been considered to be one of the toughest challenges in the development of autonomous vehicles.

Driver behavior can be categorized into three main behaviors; car following [1, 2], lane changing [3, 4] and overtaking [5, 6]. Here, the concentration of this study is on the overtaking behavior as one of the most challenging behaviors on highways. An overtaking maneuver consists of three phases: a) diverting from the original lane, b) driving straight in the adjacent lane, and c) returning to the lane. The phases of the overtaking maneuver are shown in Fig. 1. These three phases can be called in short: lane changing, overtaking and returning. From this point, it is indicated that the relation between lane changing and overtaking is intimate, lane changing is an important part of overtaking process, and it is the base of overtaking, because it is necessary to change lane before overtaking [7].

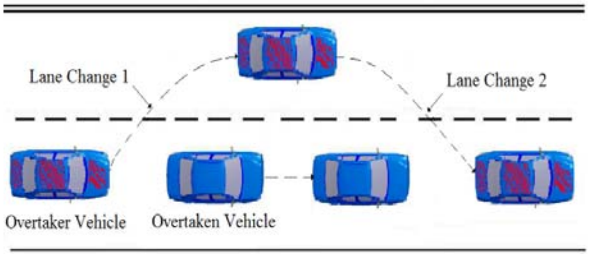

Fig. 1. Two lane changes during the overtaking maneuver.

In this paper, multiple-input multiple-output ANFIS (MANFIS) models for modeling and prediction of the Driver-Vehicle-Unit (DVU) behavior in overtaking scenarios for different time steps ahead is presented. These models predict the future value of the acceleration and the movement angle of the overtaking vehicle. In real driving situations, driver can only control the steering wheel and the pedals. By turning the steering wheel, the movement angle of the vehicle varies, and by pushing one of the pedals, throttle or brake pedals, the acceleration of the vehicle changes.

The remaining parts of this paper are organized as follows: Section II describes a brief review of the previously presented models. Section III presents the new overtaking models design. Four MANFIS models are designed based on real traffic datasets to predict the acceleration and the movement angle of the overtaking vehicle. These models predict the acceleration and the movement angle of the overtaking vehicle of 1, 2, 4 and 6 time steps ahead. Each time step is equal to 0.1 second since the data sampling time is equal to 0.1 second. In other words, these models can predict the acceleration and the movement angle of the overtaking vehicle of 0.1, 0.2, 0.4 and 0.6 seconds ahead. In Sections IV, the proposed models are evaluated and the conclusion is given in Section V.

II. RELATED WORKS ON OVERTAKING MANEUVER MODELING

The study of overtaking models has not been very extensive. In this section, a brief review on the few previously presented overtaking models is presented. In 2000, Polus et al. developed a model to estimate passing sight distance of the overtaking process [8]. In 2003, Naranjo et al. offered a rule which its inputs were the velocity of the two involved vehicles and its output was the overtaking distance [9]. In 2004, Shamir designed a smooth and ergonomic optimal trajectory for the overtaking maneuver [10]. In 2005, Hassan developed a mathematical model based

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on the overtaking parameters which affect the behavior to calculate the overtaking vehicle speed [11]. In 2007, Tang et al. proposed three rules to present the time required for completing an overtaking maneuver, the time which the overtaking vehicle loses during overtaking maneuver, and the overtaking distance of vehicle [12]. In 2008, Naranjo et al. offered a rule to estimate the distance of an overtaking maneuver [13]. In 2010, Chen et al. presented a model based on the cellular automata method (*CA* method) for two-lane traffic flow. In this model, the effect of vehicular density and signal cycle time on traffic flow were investigated [14].

Due to the variety of the factors that affect this maneuver, the presented models consider different factors and offer different rules. Moreover, these rules are calculated according to various methods. Presenting a model which has a behavior completely accordant with the real behavior is almost impossible. But, from a general point of view, input-output models have a better performance in comparison to models based on mathematical equations. In the meanwhile, it is more beneficiary if the presented models take into account the instantaneous value of the effective factors instead of the constant value of them. In this paper, four MANFIS models are presented to estimate the acceleration and movement angle of the overtaking vehicle. These models consider the instantaneous value of the variables and predict the future state of the overtaking maneuver in real traffic flow for four different time steps ahead.

III. MANFIS OVERTAKING MODELS DESIGN

In this section, first, the MANFIS structure will be introduced. Then, details on the datasets of real traffic flow used to design these models are explained. At the end, the models improved in this study are proposed.

A. *Multiple-input multiple-output Adaptive Neuro-Fuzzy Inference System (MANFIS)*

The acronym ANFIS is the abbreviation for Adaptive Neuro-Fuzzy Inference System. ANFIS enhances fuzzy inference system with self-learning capability for achieving optimal control objectives [15]. ANFIS uses the advantages of neural networks and fuzzy systems simultaneously. Some of the advantages of ANFIS in comparison with neural network and fuzzy systems are: Faster convergence than typical feed forward neural networks, smaller size training set, model compactness (smaller number of rules than using labels), automatic fuzzy logic controller parametric tuning and smoothness guaranteed by interpolation. On the other hand, ANFIS has its own disadvantages too. Surface oscillations around points (caused by high partition number) and spatial exponential complexity are some of these disadvantages.

However, the major disadvantage of ANFIS is that it can have only one output. Since multi-output systems are more frequent than single output ones, this issue influences the efficiency of ANFIS. In order to work out this problem, multi-output model can be designed by connecting several single output models [15]. In other words, putting as many ANFIS models side by side, as there are required outputs is an approach of having multiple outputs [16]. The architecture of a two-output MANFIS model is shown in Fig. 2.

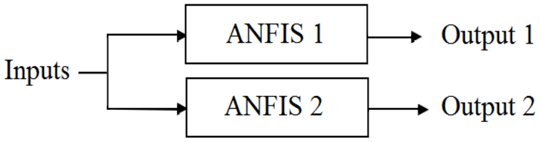


Fig. 2. A two-output MANFIS structure [16]

MANFIS has all the advantages of ANFIS. Besides, fewer numbers of training sets are required in MANFIS to achieve the same error of single ANFIS. Therefore, faster and simpler solutions can be obtained based on MANFIS. Also, a MANFIS model can improve to be a single-input-multi-output model [15]. In this study, MANFIS is used to effectively predict the future behavior of an overtaking maneuver.

B. *Datasets*

Real overtaking data from US Federal Highway Administration's NGSIM dataset [17] is used to train the MANFIS prediction models. In June 2005, a dataset of trajectory data of vehicles on a segment of Interstate 101 highway in Emeryville (San Francisco), California has been made using eight. On a road section of 640m, 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, as shown in Fig. 3. The data is collected in 0.1 second intervals [17].

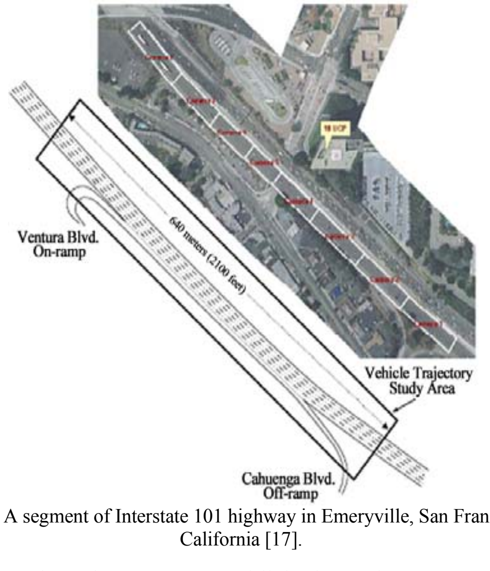


Fig. 3. A segment of Interstate 101 highway in Emeryville, San Francisco, California [17].

The other dataset was published as the I-80 Dataset. Researchers for the NGSIM program collected detailed vehicle trajectory data on eastbound I-80 in the San Francisco Bay area in Emeryville, CA, as shown in Fig. 4, on April 13, 2005. The study area was approximately 500 meters (1,640 feet) in length and consisted of six freeway lanes, including a high-occupancy vehicle (HOV) lane. This vehicle trajectory data provided the precise location of each vehicle within the study area every one-tenth of a second, resulting in detailed lane positions and locations relative to other vehicles [17].

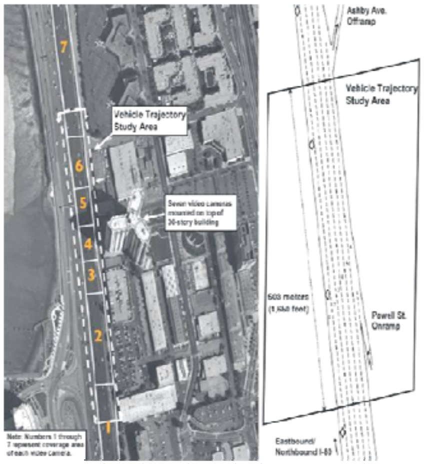
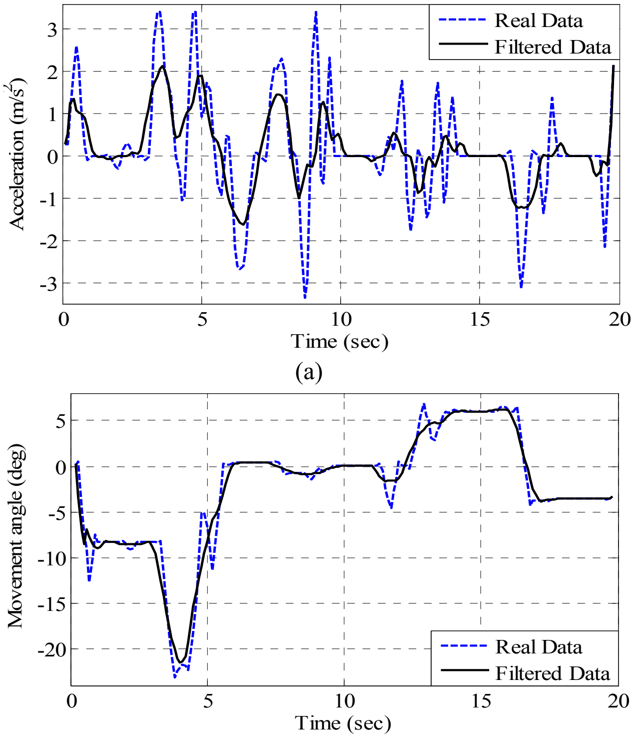


Fig. 4. A segment of eastbound I-80 in the San Francisco Bay area in Emeryville, California [17].

The data extracted from the datasets, seem to be unfiltered and exhibit some noise artifacts, so these data must be filtered like [1, 18]. A moving average filter has been designed and applied to all data before any further data analysis. In the first model improved in this study, velocity and spacing of the follower vehicle is simulated. So, at first, comparison of the unfiltered and filtered data of the velocity and spacing of the follower vehicle are shown in Fig. 5.



(a)

(b)

Fig. 5. Comparison of unfiltered and filtered data, (a) Acceleration, (b) Movement Angle.

C. *Movement Angle of the Overtaking Vehicle*

The vehicle's movement angle (θ), as shown in Fig. 6, is the angle between the vertical axis of the vehicle and the imaginary line through the direction of the road. This angle is different from the steering angle of the vehicle. When the overtaking vehicle deviates to the left from the straight direction of the road, the movement angle will have a negative value. But deviation to the right, leads to a positive value for this angle.

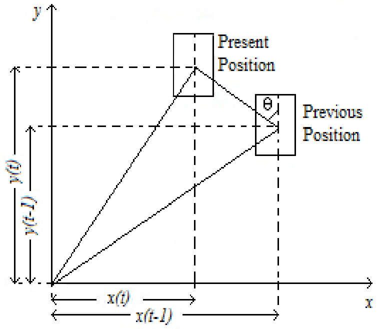


Fig. 6. The movement angle of the overtaking vehicle.

In the available datasets, there is no data available for this angle. But, it can be calculated from the coordinates of the previous and present position of the overtaking vehicle. The movement angle equation is shown in (1).

$$\theta = \arctan\left(\frac{x(t) - x(t-1)}{y(t) - y(t-1)}\right) \qquad (1)$$

D. *MANFIS Models Design*

In this study, four MANFIS model are designed. These models predict the acceleration and the movement angle of the overtaking vehicle. As stated before, each MANFIS model has several multiple-input-single-output ANFIS models, which make a multiple-input-multiple-output adaptive neuro-fuzzy inference system called MANFIS. To achieve an accurate prediction hybrid algorithm is used to train each ANFIS model. These four models are similar (i. e., similar variables for inputs and outputs, similar number of membership functions and similar structure). The only difference is that they can predict the output for different time steps due to the different arrangements of data in the training datasets. TABLE I briefly shows the difference of the MANFIS models of this study.

TABLE I. DIFFERENCE OF THE MANFIS MODELS

MANFIS model	Outputs	Prediction times (sec)
1st	$a_A(t+1), \theta_A(t+1)$	0.1
2nd	$a_A(t+2), \theta_A(t+2)$	0.2
3rd	$a_A(t+4), \theta_A(t+4)$	0.4
4th	$a_A(t+6), \theta_A(t+6)$	0.6

In the development of the MANFIS prediction models, the available data are usually divided into two randomly selected subsets. The first subset is known as the training and testing dataset. This dataset is used to develop and calibrate the model. The second data subset (known as the validation dataset), which was not used in the development of the model, is utilized to validate the performance of the trained model. For this paper, 70% of the master dataset was used for training and testing purposes. The remaining 30% was set aside for model validation. In the following parts, each of the developed models will be described in details.

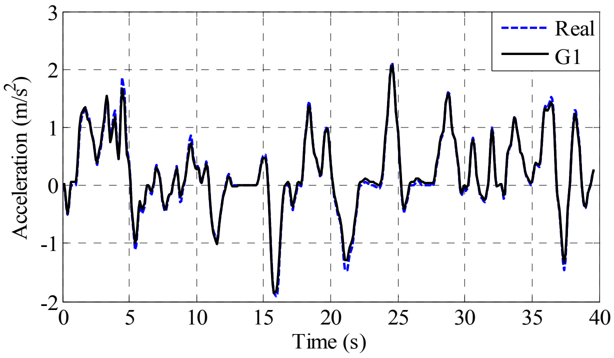
These models predict the acceleration and the movement angle of the overtaking vehicle. The inputs and outputs of this model are shown in TABLE II with their notations. The MANFIS system applied for this prediction model has five inputs and 2 outputs. These inputs are relative lateral and longitudinal distance, relative velocity, and also the acceleration and the movement angle of the overtaking vehicle. As mentioned before, these MANFIS models are made of two ANFIS models that each of them predicts one of the outputs. There are three gaussmf membership functions for each input. The rule base contains 243 fuzzy if-then rules of Takagi-Sugeno's type [19].

TABLE I. INPUTS AND OUTPUTS OF ALL MANFIS MODELS

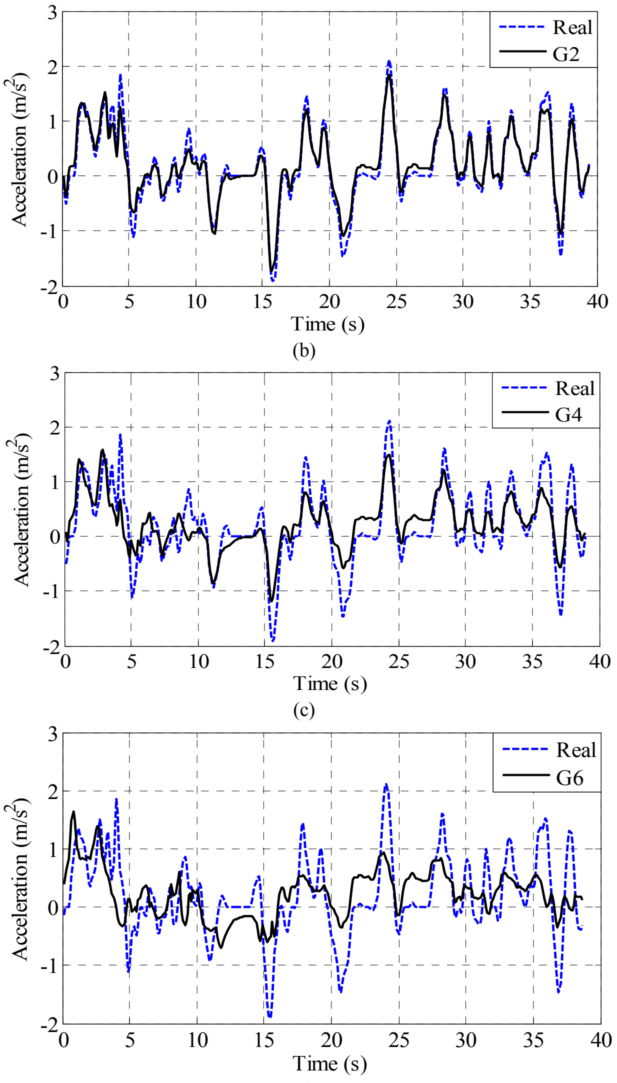
Type	Parameter Name	Symbol
input	relative lateral coordinate	$\Delta x(t) = x_A(t) - x_B(t)$
input	relative longitudinal coordinate	$\Delta y(t) = y_A(t) - y_B(t)$
input	relative velocity coordinate	$\Delta v(t) = v_A(t) - v_B(t)$
input	acceleration	$a_A(t)$
input	movement angle	$\theta_A(t)$
output	acceleration	$a_A(t+1)$
output	movement angle	$\theta_A(t+1)$

IV. DISCUSSION AND RESULTS

To assess the performance of the MANFIS models, the validation datasets are used to evaluate the proficiency of the model. The matrix of the validation data is divided to two groups, the input columns and the output columns. The input columns are fed as the inputs of the models. Then, the output of the models is compared to the real output, which are the output columns of the validation data. The comparisons of the output of the four MANFIS models with real data and are shown below. Fig. 7 show the acceleration of FV during a overtaking maneuver predicted in one, two, four and six time steps ahead. Notice that the validation datasets are composed of the data of several overtaking maneuvers. Here, the output of one overtaking maneuver for one test vehicle is shown from the four designed models.



(a)



(b)

(c)

(d)

Fig. 7. Comparison of the acceleration output of MANFIS models with real data, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.4 second ahead model, (d) 0.6 second ahead model.

In order to have a better understanding of the performance of these models, errors between the outputs of the models and real data for the same test vehicles used in Fig. 7 for each of the designed model are shown in Fig. 8.

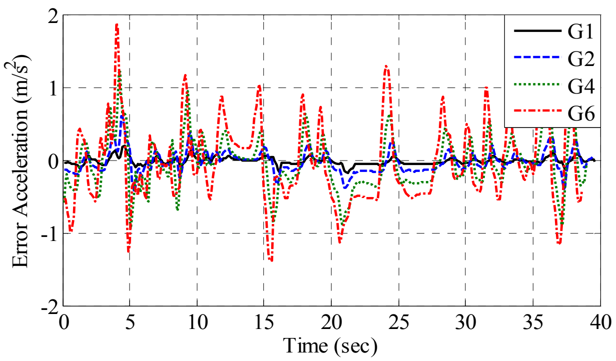
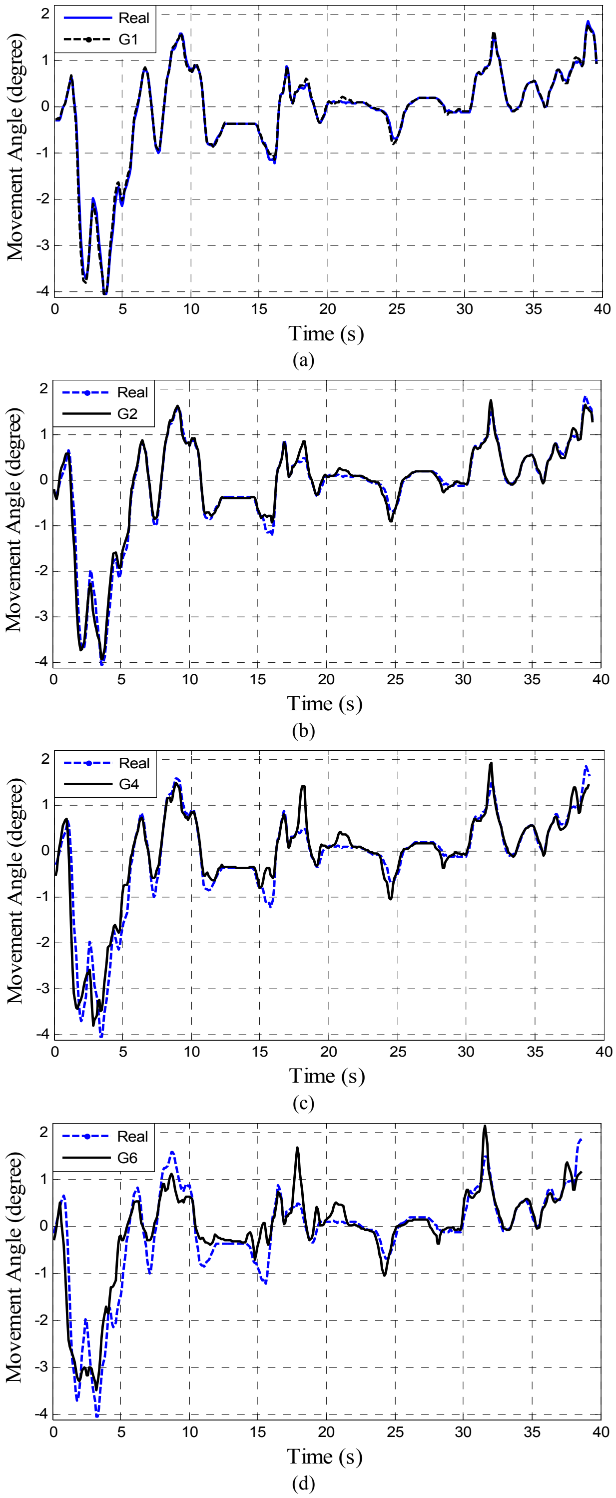


Fig. 8. Comparison of all the errors for the same test vehicles of Fig. 7

Fig. 9 shows the movement angle of FV during a overtaking maneuver predicted in one, two, four and six time steps ahead. Here, the output of one overtaking maneuver for one test vehicle is shown from the four designed models.



(a)

(b)

(c)

(d)

Fig. 9. Comparison of the movement angle output of MANFIS models and real data, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.4 second ahead model, (d) 0.6 second ahead model.

In order to have a better understanding of the performance of these models, errors between the outputs of the models and real data for the same test vehicles used in Fig. 7 for each of the designed model are shown in Fig. 10.

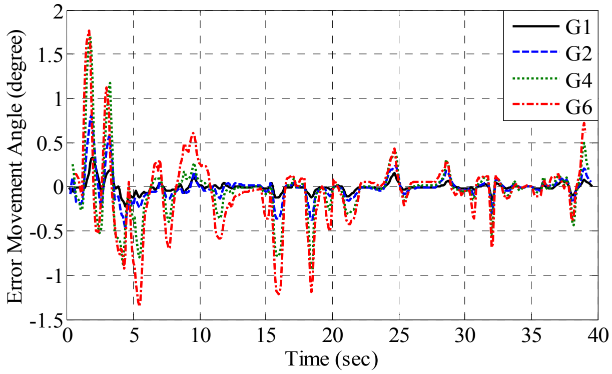


Fig. 10. Comparison of all the errors for the same test vehicles of Fig. 8.

To examine the performance of the developed models, various criteria were used to calculate errors. The criterion mean absolute percentage error (MAPE), according to (2), shows the mean absolute error that can be considered as a criterion to model risk to use it in real-world conditions. Root mean squares error (RMSE), according to (3), is a criterion to compare error dimension in various models. Closer values to zero show closer results with real data. In these equations, x_i shows the real value of the variable being modeled (observed data), $\hat{x}$ denotes the real value of variable modeled by the model, and N is the number of test observations [20].

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|x_i - \hat{x}_i\right|}{x_i} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \tag{3}$$

Errors in modeling of the four designed MANFIS overtaking models by considering MAPE and RMSE are summarized in Table II for the test vehicle that was used for Fig. 7 and Fig. 8.

TABLE III. RESULT OF THE ERRORS FOR TEST VEHICLE 1

MANFIS MODELS	Acceleration		Movement Angle	
	MAPE	RMSE	MAPE	RMSE
0.1 second prediction	0.2597	0.0535	0.1986	0.0345
0.2 second prediction	2.2577	0.1505	1.4573	0.0943
0.4 second prediction	6.3402	0.5421	4.0254	0.3865
0.6 second prediction	9.8505	0.8743	6.6536	0.6785

We could not show the error table for all the test vehicles since we had over hundreds of vehicles in the test dataset. Therefore, we provided the error table below to show the mean value of each error for the different models designed.

TABLE IV. RESULT OF THE MEAN VALUE OF THE ERRORS CRITERIA FOR ALL TEST VEHICLES IN THE TEST DATASET

MANFIS MODELS	Acceleration		Movement Angle	
	MAPE	RMSE	MAPE	RMSE
0.1 second prediction	0.3845	0.0759	0.2386	0.0455
0.2 second prediction	3.7743	0.2187	1.9365	0.1544
0.4 second prediction	7.9374	0.5257	3.1253	0.3265
0.6 second prediction	10.8743	0.9769	5.6578	0.5235

V. CONCLUSION

In this study, four MANFIS models were improved to predict the future state behavior of overtaking maneuver based on real traffic datasets. These models considered important factors such relative velocity, relative distance, acceleration and velocity of the follower vehicle in overtaking maneuver. These models can predict the future state of FV in four different time steps ahead. These steps are 1, 2, 4 and 6 time steps ahead which each time step is equal to 0.1 second. Using the instantaneous value of the variables is the prominent aspect of the proposed models. Evaluation of the designed models was investigated through simulation and comparing the outputs of the models with behaviors of human drivers from real traffic datasets. Comparison showed that the designed models were highly accordant with real behaviors. In addition, different error criteria were used to evaluate the performance of these models numerically. Low rates of errors also proved the high compatibility of the desired models with real traffic flow. The proposed models can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

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REFERENCES

[1] A. Khodayari, A. Ghaffari, R. Kazemi, and Reinhard Braunsting, “A Modified Car-Following Model Based On a Neural Network Model of the Human Driver Effects”, *Accepted for publication in IEEE Transactions on Systems, Man, and Cybernetics, Part A-Systems and Humans* (2011).

[2] A. Khodayari, A. Ghaffari, “Using the Reaction Delay as the Driver Effects in the Development of Car-Following Models”, *International Journal of Automotive Engineering*, vol. 2, no. 1, pp. 50-60, 2012.

[3] A. Ghaffari, A. Khodayari, S. Arvin, ‘ANFIS Based Modeling and Prediction Lane Change Behavior in Real Traffic Flow’, *IEEE International Conference on Intelligent Computing and Intelligent Systems* (ICIS 2011), China (2011).

[4] A. Ghaffari, A. Khodayari, S. Arvin, F. Alimardani, “An ANFIS Design for Prediction of Future State of a Vehicle in Lane Change Behavior”, *IEEE International Conference on Control System, Computing and Engineering* (ICCSCE 2011), Malaysia (2011).

[5] A. Khodayari, F. Alimardani, A. Ghaffari, H. Sadati, ‘Overtaking Maneuver Behaviour Modeling Based on Adaptive Neuro-Fuzzy Inference System’, *IEEE International Conference on Intelligent Computing and Intelligent Systems* (ICIS 2011), China (2011).

[6] A. Ghaffari, A. Khodayari, F. Alimardani, and H. Sadati, “ANFIS Based Modeling for Overtaking Maneuver Trajectory in Motorcycles and Autos”, *IEEE International Conference on Control System, Computing and Engineering* (ICCSCE 2011), Malaysia (2011).

[7] F. Wang, M. Yang, and R. Yang, “Conflict-Probability-Estimation-Based Overtaking for Intelligent Vehicles”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 10, No. 2, June (2009).

[8] A . Polus , M . Livneh and B. Frischer “Evaluation of the passing process on two-lane rural highways”. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1701, TRB, pp. 53–60. Washington, DC: National Research Council (2000).

[9] J. E. Naranjo J. Reviejo C. González R. García T. de Pedro, “Overtaking Maneuver Experiments with Autonomous Vehicles”, *The 11th International Conference on Advanced Robotics* ,Coimbra, Portugal, June 30 - July 3 (2003).

[10] T. Shamir, “How should an autonomous vehicle overtake a slower moving vehicle: Design and analysis of an optimal trajectory,” *IEEE Trans. Autom. Control*, vol. 49, no. 4, pp. 607–610 (2004).

[11] S. A. B. Hassan, “Driver’s Overtaking Behavior On Single Carriageway Road”, M.Sc. Thesis, Faculty of Civil Engineering, University Technology of Malaysia (2005).

[12] T. Q. Tang, H. J. Huang, S. C. Wong, X. Y. Xu, “A New Overtaking Model and Numerical Tests”, *Elsevier, Physica A*, vol. 376, pp. 649–657 (2007).

[13] J. E. Naranjo, C. Gonzalez, R. Garcia, and T. Pedro, “Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver,” *IEEE Transactions on Intelligent Transportation Systems*, Vol. 9, No. 3, pp. 438–450, Sep. (2008).

[14] C. Chen, J. Chen, X. Guo, “Influences of overtaking on two-lane traffic with signals”, Department of Mechanics, Huazhong University of Science and Technology, Wuhan 430074, China, Physica A, vol. 389, pp. 141-148 (2010).

[15] A. H. Suhail, N. Ismail, S. V. Wong and N. A. Abdul Jalil, “Cutting parameters identification using multi adaptive network based Fuzzy inference system: An artificial intelligence approach”, *Scientific Research and Essays*, Vol. 6 (1), pp. 187-195, 2011.

[16] T. O. S. Hanafy, “A modified Algorithm to Model Highly Nonlinear System”, *Journal of American Science*, Vol. 6 (12), 2010.

[17] US Department of Transportation, “NGSIM - Next Generation Simulation”, ngsim.fhwa.dot.gov, 2009.

[18] C. Thiemann, M. Treiber, A. Kesting, “Estimating Acceleration and Lane-Changing Dynamics Based on NGSIM Trajectory Data”, *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2088, pp. 90-101, 2008.

[19] J. S. R. Jang, C.T. Sun, and E. Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, *Prentice Hall*, 1996.

[20] J. R. Taylor, “An introduction to error analysis: the study of uncertainties in physical measurements”, *University Science Books, Mill Valley*, CA, 1982.