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Modeling and Intelligent Control System Design for Overtaking Maneuver in Autonomous Vehicles

The purpose of this study is to design an intelligent control system to guide the overtaking maneuver with a higher performance than the existing systems. Unlike the existing models which consider constant values for some of the effective variables of this behavior, in this paper, a neural network model is designed based on the real overtaking data using instantaneous values for variables. A fuzzy controller is then designed to present trajectory of the overtaking vehicle. Validation of the proposed controller is done by comparing the responses of the controller with the behavior of human drivers. Results show that the controller system intelligently performs like a human driver and also eliminates their mistakes and sudden moves.

1 Introduction

Driver's error contributes to over 75 percent of road crashes especially in overtaking maneuvers. Intelligent transport systems (ITS) are under active development worldwide as a means of reducing loss of life. Since overtaking maneuver is a complex 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.

Extremely nonlinear nature of Overtaking behavior asks for the development of intelligent algorithms to describe, model and control this phenomenon. Uncertainties and inaccuracies, intervention of judgments and human logic in controlling the vehicle, necessitates use of intelligent control methods based on soft computing techniques like neural network and fuzzy logic systems. Integration of human expert knowledge, and learning based on data, are powerful tools enabling fuzzy systems to deal with nonlinear nature of driving behaviors. Usually, classic control methods are not proper to control nonlinear time dependent behaviors. Driving behaviors are certainly among these behaviors [1, 2].
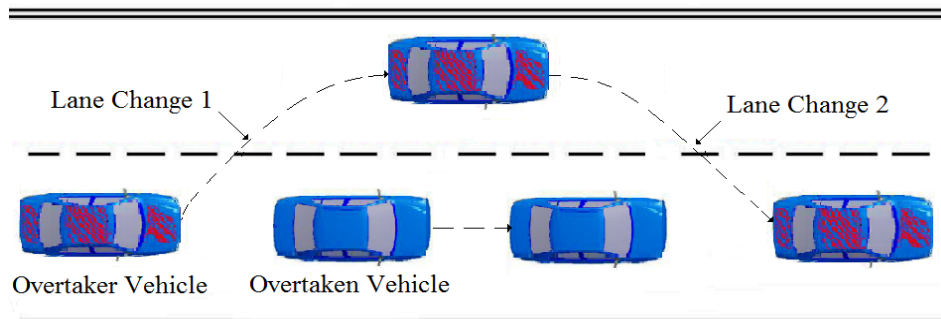
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Driver behavior is an issue that contributes directly or indirectly to the traffic congestion and safety on the road. These behaviors can be categorized into three main behaviors; car following [3, 4], lane changing [5, 6] and overtaking [1, 2, 7]. Here, the concentration is on the overtaking behavior as the most challenging behavior on highways. In a microscopic perspective; overtaking can keep the velocity of the high-speed vehicle, in a macroscopic perspective; overtaking can improve the traffic flow rate by reducing the negative impact generated by low-speed vehicle. Overtaking is the most complex driving behavior including observing, information processing, decision making, planning and maneuvering. 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 figure 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 [8].

Figure 1 The overtaking maneuver and its two lane changes [1]

The objective of the study presented in this paper is to design an intelligent control system to lead the overtaking maneuver in a smooth and safe trajectory. The following sections of this study are categorized as follows: Section 2 deals with an overview of related works on modeling and control of this behavior. Section 3 brings in the design of the model presented for this maneuver. In section 4, intelligent control design of the overtaking maneuver is described, and the conclusion is given in Section 5.

2   Brief Review of Related Works on Overtaking Studies

Overtaking maneuver is a complicated maneuver. Therefore, few researchers and scientists choose this behavior to work on. So, studies on the overtaking behavior are not widespread as the studies on other driving behaviors such as car following or lane changing. In this section, a brief review of the most important studies on this behavior is introduced.

Mahdi stated that the overtaking maneuver commence when the overtaking vehicle first crossed the centerline and completes when the vehicle is clear of the opposing traffic lane [9]. Matson and Forbes used photographic techniques to measure the distances between the overtaking and the overtaken vehicle at the start and the end of the overtaking maneuver. So they were able to calculate the overtaking distance [10]. Roozenburg suggested that there are a number of input variables to develop a mathematical model of the overtaking behavior. The variables can be the impeder vehicle speed, oncoming vehicle speed, decision time of passer, headway between passer and impeder at start of the maneuver, safety margin between passer

and oncoming vehicles at completion of maneuver and vehicle acceleration [11]. Mota believed that one of the reasons that the overtaking maneuver is a risky one is due to the lack of the driver's attention. The driver's focus is usually on his way forwards or sometimes he does not use the rear-view mirror [12]. Crawford has concluded that the drivers should not hesitate to commence the overtaking maneuver as it has a negative impact on road safety and they will take a longer time to act [13]. Gordon and Mart claimed that drivers are unable to estimate the overtaking distances and safety margins correctly because these calculations depend on the speed of the involved vehicles especially the overtaken vehicle [14]. Jenkins et. al. studied overtaking maneuver on a two-way two-lane roadway. They classified this behavior on the basis of a quantitative description of overtaking behavior by analyzing data collected during a overtaking experiment conducted in a driving simulator [15]. Jamson et al. investigated how mandatory and voluntary intelligent speed adaptation might affect a driver's overtaking decisions on rural roads, by presenting drivers with a variety of overtaking scenarios designed to evaluate both the frequency and safety of the maneuvers [16]. Bar-Gera et al. assessed the speed differential threshold-if there is one-at which drivers decide to overtake a lead vehicle [17]. Hegeman et al. studied a microscopic traffic simulation of the potential effects of an overtaking assistant for two-lane rural roads. The overtaking assistant was developed to support drivers in judging whether or not an overtaking opportunity can be accepted based on the distance to the next oncoming vehicle [18]. Clarke et. al studied overtaking road accidents involving overtaking maneuvers. They distinguished ten types of overtaking accident, and discussed three in detail: collision with a right-turning vehicle, which tends to occur either because a young driver makes a faulty overtaking decision, or an older driver makes a faulty right turn; head-on collision, and the 'return-and-lose-control' accident, which is associated particularly with young drivers [19]. Farah et al. tested the hypothesis that the frequency of overtaking maneuvers on a driving simulator is associated with a faulty decision making style in the Iowa Gambling Task (IGT), a popular decision task employed for assessing cognitive impulsivity [20].

One category of studies on overtaking present a model for different parameters of this behavior. Due to the variety of the factors that affect this maneuver, the presented models consider different factors. Besides, the approaches to study this behavior are different. Cellular automata modeling and differential equation modeling are examples of the main approaches to study overtaking maneuver. In addition, the system theoretic approach and the neural network method are applied to study the human operating behavior in overtaking procedure. Recently, the overtaking distance-based approach has also attracted attention. A brief review on some of the previously proposed overtaking models is presented [7].

In 2000, Polus et al. developed a model to estimate passing sight distance of the overtaking process [21]. In 2003, Naranjo et al. offered a rule to calculate the overtaking distance. The inputs of this model were the velocity of the two involved vehicles. This formula was calculated based on the least square method [22]. In 2004, Shamir designed a smooth and ergonomic optimal trajectory for the overtaking maneuver. To determine the trajectory of vehicle P, Shamir fitted a general fifth-degree polynomial expression for coordinates $x(t)$ and $y(t)$, satisfying appropriate boundary conditions. [23]. In 2005, Hassan developed a mathematical model based on the overtaking parameters which affect the behavior. Overtaking vehicle speed (*OGS*), was chosen as a dependent variable since it describes the behavior of the overtaking drivers and it depends on the other variables. The best subset regression method was chosen to select the independent variables which entered the relationships. [24]. In 2007, Tang et al. proposed three rules for the overtaking maneuver. These rules presented the time required for completing an overtaking maneuver (*T*), the time which the overtaking vehicle loses during overtaking maneuver ($\Delta t^{(A)}$), and the overtaking distance of vehicle (S_A). These rules were based on the maximum and minimum velocity of

the overtaking vehicle and the safe distances for car following the involved vehicles. Basic dynamic rules were the base of the rules presented in this study [25]. In 2008, Naranjo et al. offered a rule to estimate the distance of an overtaking maneuver [26]. 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 times on traffic flow were investigated [27].

As mentioned above, the study of overtaking models has been widespread. But neither of the presented models is able to present a model which is completely accordant to the real behavior. It is important to notice that most of the presented models are designed based on mathematical equations. But, input-output models which are based on real data of a behavior are more accurate than the models which are designed based on mathematical equations. Also, due to the variety of the factors that affect this maneuver, each model considers different factors and offer distinctive rules. Besides, these rules are calculated according to various methods. So, complexity of this maneuver makes it difficult to present a model which is close to the real behavior to an acceptable extent. These models could be more reliable if they had considered most of the major factors that affect this behavior. In the meanwhile, it seems more beneficiary if they had taken into account the instantaneous value of the factors instead of a constant value [1, 2].

Therefore, in this study, an input-output model is presented which considers the major factors that affect this behavior. Also, in the design of this model, instantaneous values of the parameters are used which improve the performance of the model. The model presented here is able to estimate the trajectory of the overtaking vehicle during an overtaking maneuver. In the next section, the design procedure of this model is described.

Another category of studies are those who offer a control system for overtaking maneuver. As mentioned before, classic methods are not appropriate for dealing with these kinds of behaviors. On the other hand, intelligent techniques such as fuzzy control have shown powerful capabilities dealing with these kinds of nonlinear behaviors. Among the past studies, only a few studies have presented fuzzy technique to control this behavior. So, in this study we have concentrated only on studies which have applied fuzzy logic to control overtaking behavior.

In (2008), Naranjo et al. presented an overtaking system for autonomous vehicles equipped with path-tracking and lane-change capabilities. The system used fuzzy controllers that mimicked human behavior and reactions during overtaking maneuvers. The system was based on the information that was supplied by a high-precision Global Positioning System and a wireless network environment. It was able to drive an automated vehicle and overtake a second vehicle that is driving in the same lane of the road. [26]

Also, in (2008), another study concentrated on controlling the overtaking behavior by fuzzy logic. Jin-ying et al. designed and simulated a controller for overtaking process based on the fuzzy control theory. They stated that for the control strategy of intelligent vehicles, most research institutions construct the model according to the given moving trajectory, which has the disadvantages of low anti-jamming capability, great costs and lower response speed. But, the fuzzy control strategy for intelligent vehicles in this paper was a new dynamical fuzzy controller with three-input and three-output, and its control rule base was composed of 135 pieces of fuzzy reasoning rule. The simulation result proved that the control system of this dynamical fuzzy controller was obviously superior to the traditional system of non-fuzzy controller. [28]

In (2011), Perez et al. implemented a fuzzy decision system based on fuzzy logic able to execute an autonomous overtaking in two-way roads. The experiments were focused on the longitudinal control when an autonomous vehicle is overtaking to other. Moreover, different cases had been considered using an oncoming vehicle from the other direction on a two-way

road. They carried out several trials with three real vehicles communicated via a wireless network. The results showed a good behavior. [29]

Since these controllers had different control objectives, they had structural and parametric differences with each other. Consequently, they had different inputs and outputs and consistent with each system, different types and numbers of membership functions were used. But it is important to notice that none of the presented controllers considered the trajectory of the overtaking vehicle as the objective of their controller. If the overtaking vehicle travels in a safe and smooth trajectory, it will be considered that the maneuver is accomplished correctly and safety issues of vehicles and passengers are guaranteed. So in this study, after designing a neural network model, a fuzzy controller will be designed to define the trajectory of the overtaking vehicle.

3   Neural Network Overtaking Behavior Model Design

In this study, a neural network (NN) model is proposed to offer trajectory of an overtaking vehicle during an overtaking behavior. The neural network theory is frequently used to model human driver's behaviors. The proposed neural network architecture, datasets, implementation and evaluation of the proposed model are discussed in the following sections.
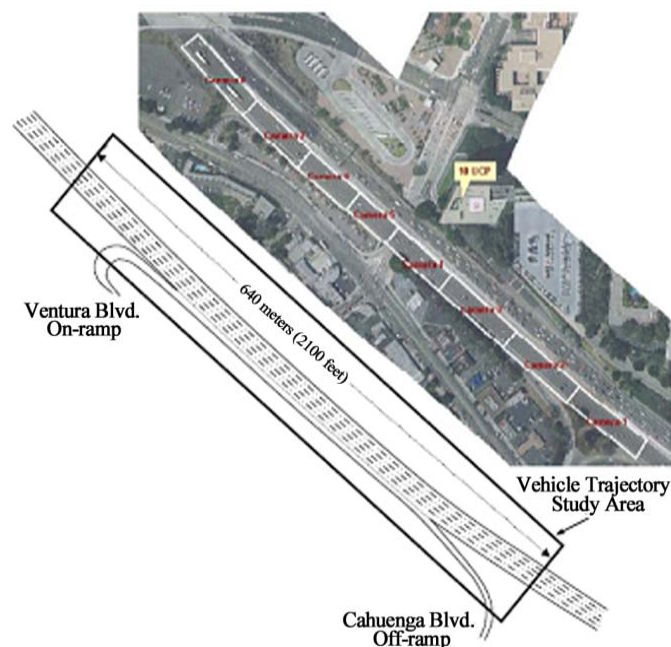
3.1 Neural Networks

The neural network models are able to model complex behaviors. Several studies explored the neural network approach to model different driving behaviors. One contribution of this study is development of neural network architecture to model the complex driving behavior during an overtaking behavior. Neural network resembles the biological network of the human brain. In a neural network, nodes or neurons are arranged in layers, beginning with an input layer, and ending with the final output layer with a hidden layer in between. Each hidden layer will be having more than one node passing information from the input layer to the output layer. The nodes in one layer are connected to nodes in the next layer and strength of these connections is measured by connection weights. Each node in a layer receives the weighted inputs from the previous layer, converts the weighted sum of the inputs to a single output using an activation function. The connection weights between nodes are optimized through training to produce outputs closest to the measured values. The most commonly used network is a feed-forward network. A multi-layer feed-forward network with back propagation is used in the present study. A feed-forward back propagation neural network is the most commonly used network and the working principle of this network is as follows. First, the effect of the input is passed forward through the network, then the error between targets and predicted output is estimated at output layers, and then propagated back towards the input layer through each hidden node to adjust the connection weight. One complete forward and backward process is known as an iteration (or epoch). This process is repeated until the error between the predicted and measured values falls below a pre-specified error goal or until the number of epochs reaches a pre-determined maximum value. A multi-layer feed-forward network will have one or more hidden layers between the input and output layers. Each hidden layer consists of number of nodes passing information from the input layer to the output layer, and vice-versa in the case of a back propagation network [30]. To design the neural network presented in this study, real overtaking data is needed.
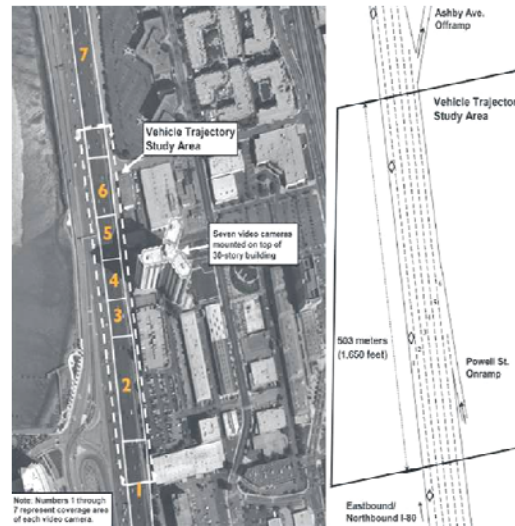
3.2 Datasets

Real overtaking data from US Federal Highway Administration's NGSIM dataset is used to train the neural network model [31]. The NGSIM datasets represent the most detailed and accurate field data collected to date for traffic micro simulation research and development. 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, 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 figure 2. 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 [31].
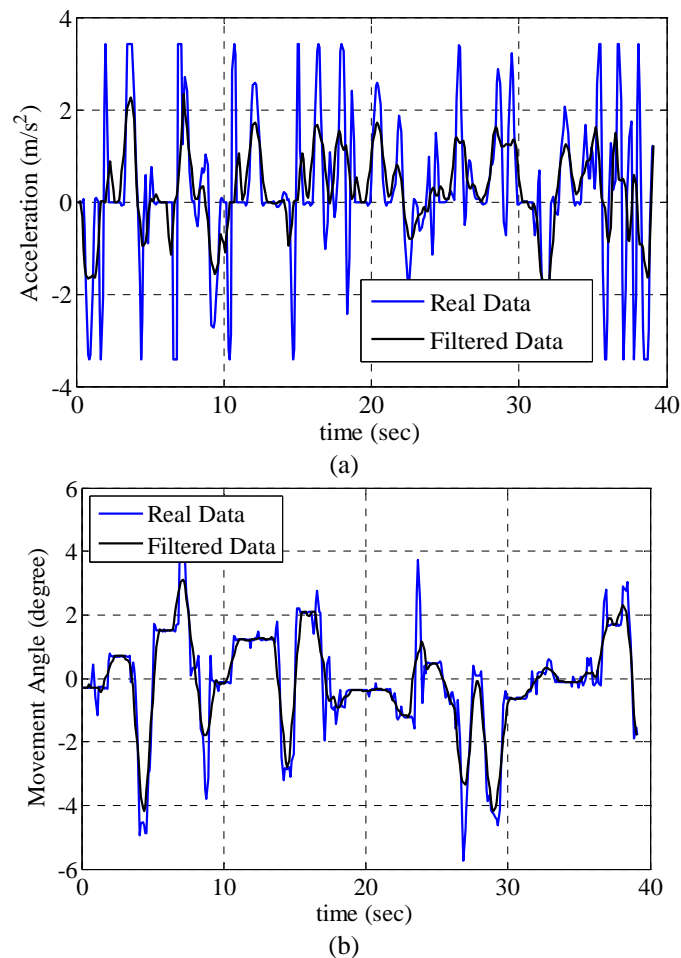

Figure 2 A segment of Interstate 101 highway in Emeryville, San Francisco, California [31]

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 figure 3, 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. An onramp also was located within the study area. Seven synchronized digital video cameras, mounted from the top of a 30-story building adjacent to the freeway, recorded vehicles passing through the study area. 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. A total of 45 minutes of data are available in the full dataset, segmented into three 15-minute periods. These periods represent the buildup of congestion, or the transition between uncongested and congested conditions, and full congestion during the peak period [31].

Figure 3 A segment of eastbound I-80 in the San Francisco Bay area in Emeryville, California [31]

The data extracted from the datasets, seem to be unfiltered and exhibit some noise artifacts, so these data must be filtered like [7, 32]. 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, the acceleration and the movement angle of the overtaking vehicle is predicted. So, at first, comparison of the unfiltered and filtered data of the acceleration and movement angle of the overtaking vehicle are shown in figure 4.
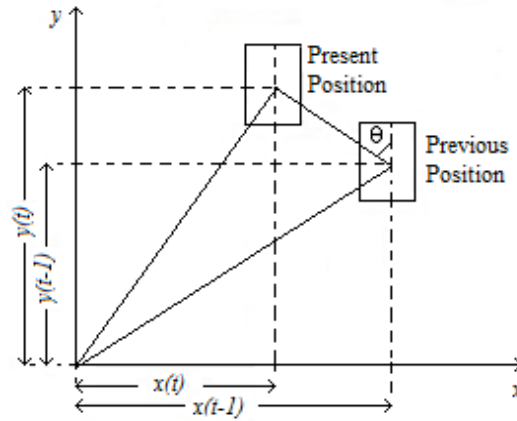

(a)

(b)

Figure 4 Comparison of unfiltered and filtered data, (a) Acceleration, (b) Movement Angle

3.3 Movement Angle of the Overtaking Vehicle

The vehicle's movement angle, as shown in figure 5, 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. 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 Eq. (1) [1, 2, 7].

Figure 5 The movement angle of the overtaking vehicle [1]

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

3.4 Neural Network Model Implementation

In the development of Neural Network model, the first step is to define the inputs and outputs of the model. This model offers the trajectory of the overtaking vehicle. Therefore, the displacement in the lateral and longitudinal coordinate is chosen as the outputs of the model. 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 and brake pedals, the acceleration of the vehicle changes. So, in this model, the movement angle and the acceleration of the vehicle is chosen as the inputs of the model. Table 1 shows these parameters.
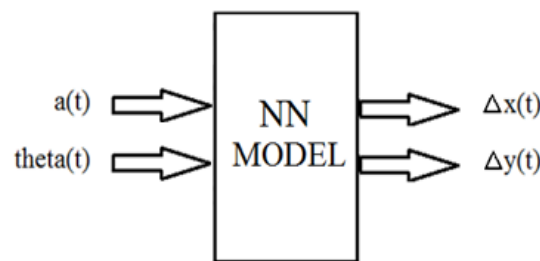
Table 1 Inputs and outputs of the NN model

Type	Parameter Name	Symbol
input	acceleration	$a_A(t)$
input	movement angle	$\theta_A(t)$
output	Displacement in the lateral coordinate	$\Delta x(t+1) = x(t+1) - x(t)$
output	Displacement in the longitudinal coordinate	$\Delta y(t+1) = y(t+1) - y(t)$

The available datasets are 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 [1-4].
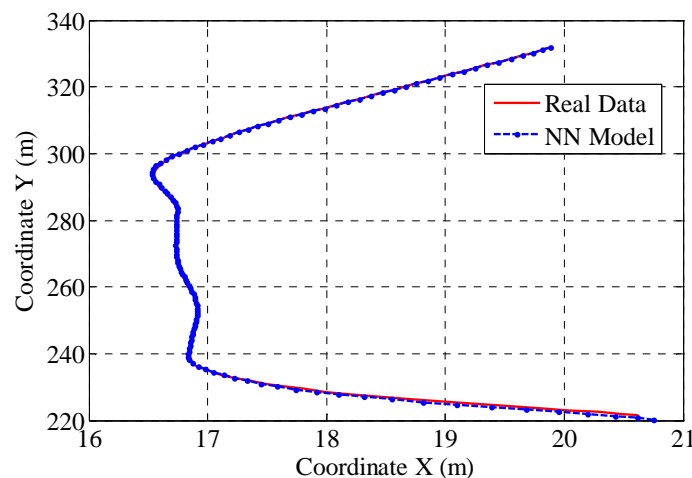
This model is based on Feed-Forward Back propagation network. Levenberg marquardt and descent gradient are chosen as the training and learning function, respectively and the network has three hidden layers. The schematic of the neural network is shown in figure 6. MATLAB software is used in this study.

Figure 6 Schematic of the neural network [7]

3.5 Evaluating model's performance

To assess the performance of the neural network model, the designed model is simulated in simulink, MATLAB, and 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 model is compared to the real output, which are the output columns of the validation data. The comparisons of the output of the neural network model with real data are shown below. Figure 7 shows the trajectory of one vehicle during an overtaking maneuver. Notice that the validation datasets are composed of the data of several overtaking maneuvers. Here, the output of only one overtaking maneuver is shown.

Figure 7 Comparison of the NN model and real data [7]

To examine the performance of the developed model and, various criteria are used to calculate errors. The absolute horizontal transport deviation (AHTD), according to Eq. (2), shows the mean deviation between a modeled trajectory and the corresponding true trajectory. The trajectory based on field data is considered as true trajectory. Another useful statistical concept is the mean relative horizontal deviation (RHTD), according to Eq. (3). This is defined as the ratio between the absolute transport deviation and the mean total travel distance of the true trajectory ($L_H(t)$), according to Eq. (4). In these equations, $X_n(t)$ and $x_n(t)$, respectively, show the real and model value of the coordinate x. In addition, $Y_n(t)$ and $y_n(t)$ show the real and model value of the coordinate y. N is the number of test observations at travel time t [7].

$$AHTD(t) = \frac{1}{N}\sum_{n=1}^{N}\{[X_n(t) - x_n(t)]^2 + [Y_n(t) - y_n(t)]^2\}^{1/2} \tag{2}$$

$$RHTD(t) = \frac{AHTD}{L_H(t)} \times 100 \tag{3}$$

$$L_H(t) = \frac{1}{2}\sum_{t_i=1}^{t}\{[X_n(t_i) - X_n(t_{i-1})]^2 + [Y_n(t_i) - Y_n(t_{i-1})]^2\}^{1/2} + \{[x_n(t_i) - x_n(t_{i-1})]^2$$
$$+ [y_n(t_i) - y_n(t_{i-1})]^2\}^{1/2} \tag{4}$$

Errors in modeling the trajectory of the overtake maneuver of four test vehicles, considering these criteria are summarized in table 2. The last column of tables shows the mean value of each error criteria.

Table 2 Errors for NN Overtaking Model

Criteria	Test 1	Test 2	Test 3	Test 4	Mean
AHTD (m)	0.0422	0.0345	0.0673	0.0046	0.0372
RHTD (%)	0.2754	0.1032	0.1298	0.0275	0.1340

3.6 Comparing model's performance with another existing model

As mentioned in section 2, in (2004), there was a study presented by Shamir, which proposed trajectory for overtaking maneuver. It was stated that the proposed trajectory is an optimal trajectory. Shamir believed that an overtaking maneuver consists of three phases: 1) diverting from the original lane, 2) driving straight in the adjacent lane, and 3) returning to the lane. So his model offered three different trajectories for the three different phases of an overtaking maneuver. The trajectory for the third phase of the maneuver is stated by equations mentioned in Eq. (5) and (6).

$$x(t) = Vt + (VT - D)(-10(\frac{t}{T})^3 + 15(\frac{t}{T})^4 - 6(\frac{t}{T})^5) \tag{5}$$

$$y(t) = W + W(-10(\frac{t}{T})^3 + 15(\frac{t}{T})^4 - 6(\frac{t}{T})^5) \tag{6}$$
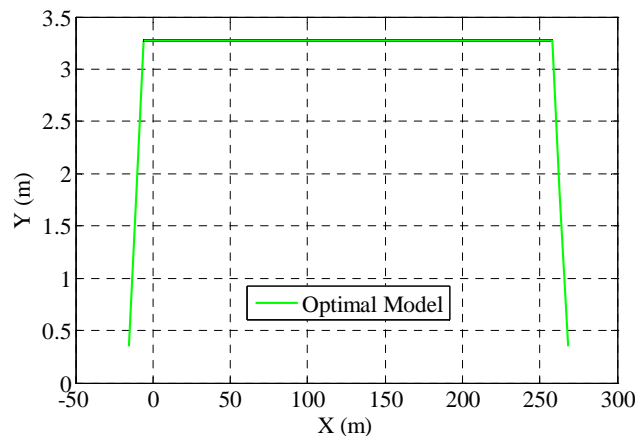
For the trajectory of the first lane change, the equations were the same, and only symmetry and time reversal was used. For the second phase, which is the passing phase and the overtaking vehicle only travels in a straight path, the optimal time and distance which must be traveled were calculated according to Eq. (7) and (8). Also, it was assumed that in the second phase the lateral displacement is the width of the lane (W), and the longitudinal distance is equal to the optimal distance (D(b)), according to Eq. (9).

$$D^* \approx 2.4V\sqrt{\frac{W}{A}} \tag{7}$$

$$T^* \approx \sqrt{3}\frac{W^{3/2}\sqrt{A}}{V^2} + 2.4\frac{\sqrt{W}}{\sqrt{A}} \tag{8}$$

$$D_{(b)} = ((L + L_1)/(V + V_1)) * V \tag{9}$$

For the test vehicle that its trajectory from NN model was shown in figure 7, the optimal model offers the trajectory shown in figure 8. Notice that the NN model and the optimal model present the lateral and longitudinal coordinates with unlike parameters. In the NN model, lateral coordinate is shown by x and the longitudinal coordinate is shown by y. But in the optimal model, the names of the parameters are vice versa. Another point that must be noted is that in the optimal model, the horizontal axis shows the longitudinal coordinate of the trajectory, and the vertical axis shows the lateral coordinate of the trajectory. In order to compare the performance of the two models numerically, some parameters of the trajectories shown in figure 7 and figure 8 are compared with the real overtaking trajectory in table 3.
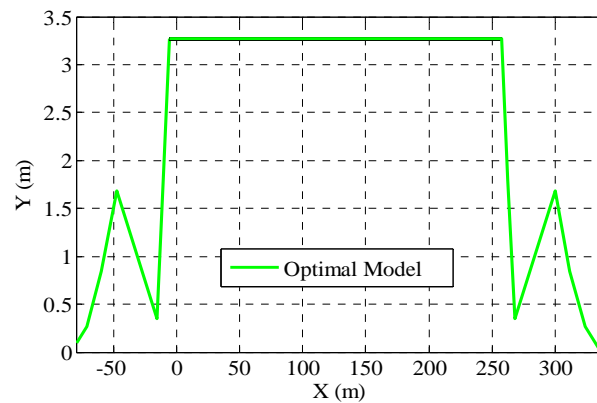

Figure 8 The trajectory of the optimal model for the same vehicle used in figure 7

Table 3 Comparison of the parameters of the two models with real data

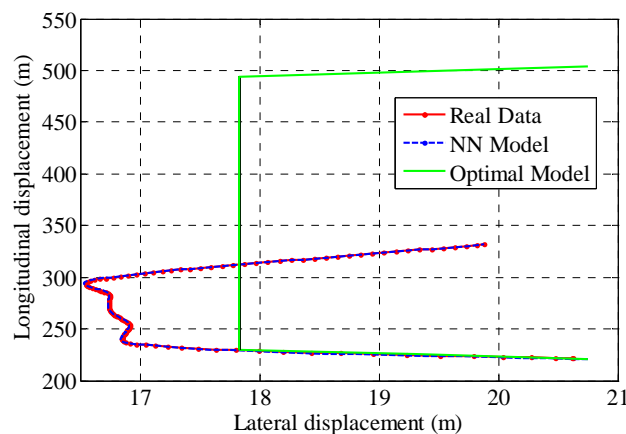| Parameters of the trajectories of test vehicle 1	Real data	NN model	Optimal model
Time (s)	34	34	46.5
Mean lateral distance (m)	4.35	4.3	3.6
Mean longitudinal distance (m)	112	111	284
Coordinate x of the start point (m)	20.75	20.63	-20
Coordinate y of the start point (m)	220.3	220.1	0.2
Coordinate x of the end point (m)	19.88	19.88	270
Coordinate y of the end point (m)	332	331.2	0.2

As it is apparent from table 3, major differences exist between the real and optimal trajectory. One disadvantage of the optimal model is that the lateral distance traveled is always equal to the width of the road (W). But in reality, it does not happen as ideal as the optimal model shows. Due to this characteristic, the second phase always starts from a point with lateral coordinate equal to W. Therefore, the trajectory of the first phase always starts from a point with negative coordinate x. All the trajectories resulted by this model have this property. Because of this property, the start and final points of the trajectory are not even close to reality. Having three distinct trajectories instead of a continuous one, similar to the real trajectory, is another disadvantage of the optimal model. In addition, the optimal model

isn't able to predict the trajectory for test vehicles with negative or zero acceleration, but the NN model is completely capable of predicting the trajectory for different values of the acceleration. Also, for cases with positive acceleration, the model does not have a proper result when the value of the acceleration increases. In these situations, the trajectory for the lane change phases of the maneuver will not be a smooth trajectory anymore (See figure 9). Another problem is that in the optimal model, the total time of the maneuver is not equal to the time spent in reality. One more disadvantage is about the total distance traveled during the maneuver. The optimal model isn't able to predict the total distance correctly. So, in some cases the distance is more than the real distance, and sometimes it is less.

Figure 9 Example of a case where optimal model isn't able to offer a smooth trajectory

Here, in order to have a better comparison between the trajectories of the two models, the trajectory of the optimal model is rotated, and then shifted to the start point of the real trajectory. After rotation, in both trajectories, the horizontal axis shows the lateral displacement, and the vertical axis shows the longitudinal displacement. The comparison of the output of the two models with real data for the test vehicle used in figure 7 and figure 8, is shown in figure 10.

Figure 10 Comparison of the results of the two models with real data for the test vehicle used in figure 7 and figure 8

4 An Intelligent Control System Design for Overtaking Behavior Based on fuzzy
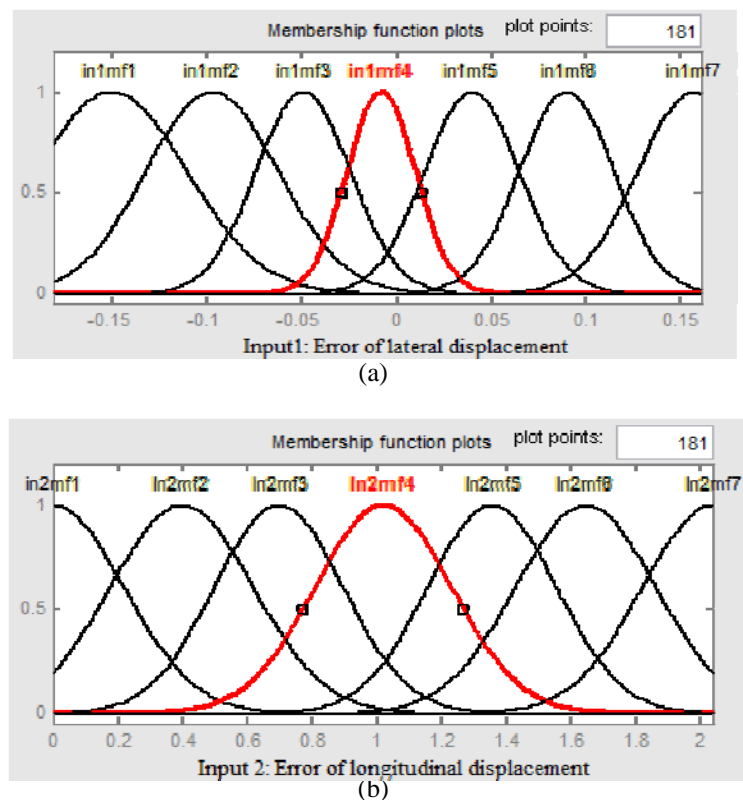
In this section, a fuzzy controller will be designed to lead the overtaking vehicle in a safe and smooth trajectory during the maneuver. Then, the designed controller will be evaluated by

comparing the result with real behavior of human drivers. Also, different error criteria are used to investigate the performance of the designed controller numerically.

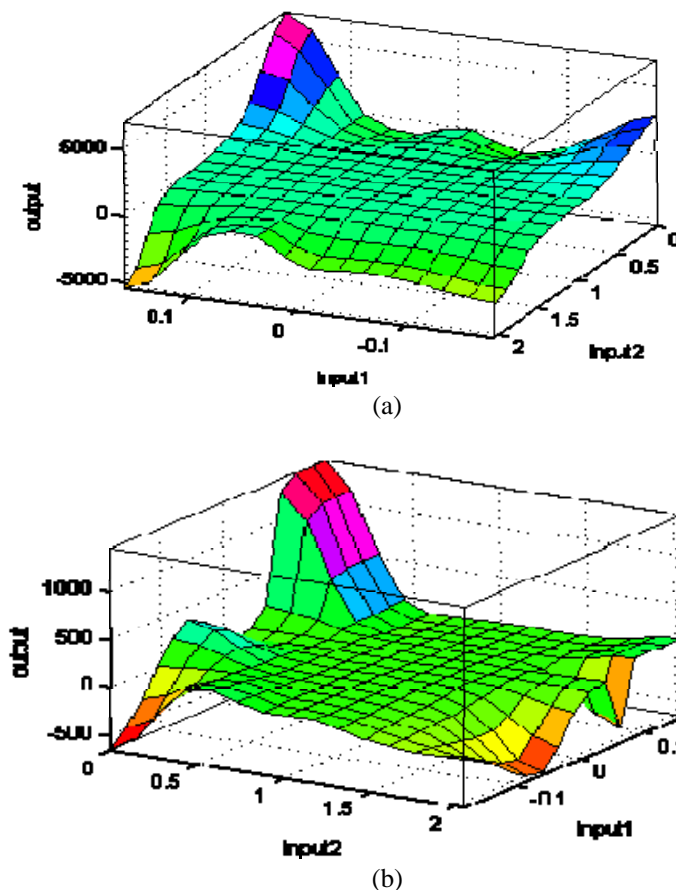### 4.1 Fuzzy Controller Design

In this section, a fuzzy controller will be designed to lead the overtaking vehicle in a safe and smooth trajectory during the maneuver. Fuzzy-logic based control methods provide an alternative tool for dealing with vehicle and subsystem complexity. Fuzzy control is capable of handling nonlinear control problems to maneuver a model car using oral instructions. By applying fuzzy logic to control a vehicle in desired trajectory, in fact, we are modeling the driver's, and not the vehicle's behavior and responses. Autonomous driving is an interesting field to apply fuzzy logic using human driver experience as expert knowledge [7].

   To design a fuzzy controller, the first step is to decide about the inputs and outputs of the controller. Since in this study, the objective of the control system is to offer the trajectory, therefore the displacement in the lateral and longitudinal coordinate will be chosen as the target of the system to control. As mentioned before, in real driving situations, the driver only has the chance to control the steering wheel and the pedals of the vehicle. By turning the steering wheel, the movement angle of the vehicle varies and by pushing one of the pedals; throttles or brake, the acceleration of the vehicle changes. As a result, the movement angle and the acceleration of the vehicle are chosen as the outputs of the fuzzy controller, because the controller system can lead the vehicle by affecting these two parameters. After deciding about the inputs and outputs of the controller, the next step is determining the type and number of the membership function of the parameters and fuzzy if-then rules of the controller. After considering different types of the membership functions to choose the best type, the gaussmf membership was selected for the input variables. Figure 11 shows the membership functions for the inputs of the fuzzy controller [7].

(a)

(b)

Figure 11 Type and number of the membership function of the input variables. First input: acceleration, (b) Second input: movement angle [7]

This controller uses the Takagi-Sugeno inference system. Fuzzy rules are chosen in a way to satisfy two criteria. The first one is that the controller system must intelligently perform like a human driver. The second criterion is the safety issues. It means that if a driver, intentionally or unintentionally, had an unsafe behavior, the controller must be able to detect it and wisely perform a safer behavior. By considering these two criteria, the fuzzy rule base is established. For the defuzzification step, center of area method is used. The control surfaces for two Sugeno parameters of the outputs are shown in figure 12. As it is apparent in these figures, the surfaces are smooth which show that the outputs have been designed properly.
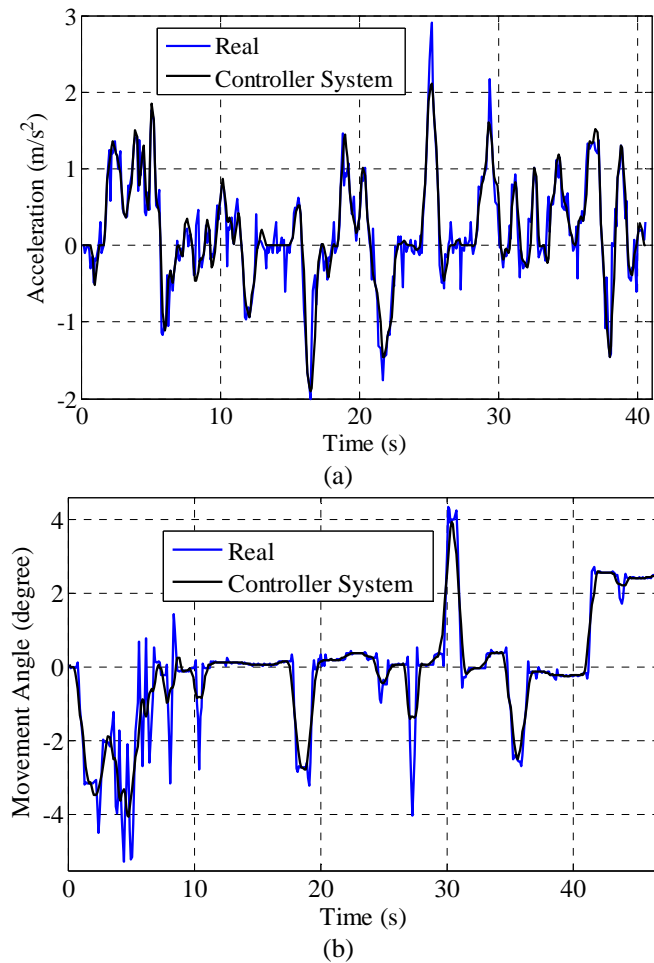

(a)

(b)

Figure 12 Control surfaces for one Sugino parameters of each output. One of the parameters of 1st output, (b) One of the parameters of 1st output [7]

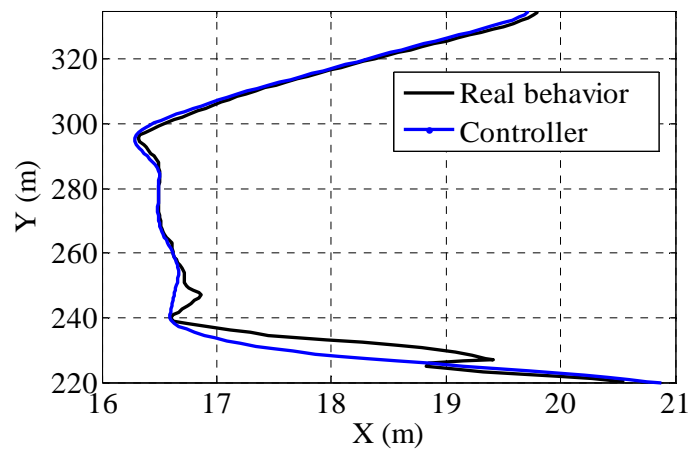## 4.2 Fuzzy Controller Evaluation

To evaluate the performance of the controller, it is necessary to investigate the performance of the controller on a model of the overtaking behavior to see how the controller actually behaves. So, a model is needed which its inputs and outputs match with the ones of the designed controller. The NN model designed in the previous section perfectly matches with the designed controller. Therefore, the control system consisted of the NN model and the fuzzy controller can be built in simulink, MATLAB.

One objectives of this control system is that the acceleration and the movement angle of the system be similar to those of the behavior of a human driver. In the meanwhile, they should have smooth and soft changes to compensate the mistakes and sudden actions of real drivers to provide a pleasant trip for the driver and others abroad. Since the if-then rules of the controller are chosen in a way to provide these requirements, the system shows satisfying results for these to parameters. Comparisons between the acceleration and the movement angle of the controller and the behavior of a real driver are shown in figure 13 (a) and (b) [7].

Figure 13 Comparisons between the acceleration and the movement angle of the controller and the behavior of a real driver. (a) acceleration, (b) movement angle [7]

The main objective of this control system is to offer a trajectory similar to those of the behavior of a human driver. Just like the acceleration and the movement angle, the trajectory should have smooth and soft changes too. The results show that the system is totally able to satisfy these needs. Comparison between the trajectory of the controller and the behavior of a real driver for the same driver is shown in figure 14.

Figure 14 Comparison between the trajectory of the controller and the behavior of a real driver [7]

To have a better understanding of the function of the controller, it is feasible to calculate the two mentioned error criteria in Eq. (2) and Eq. (3) and investigate the performance of controller for the trajectory it offers. For four test vehicles, the trajectory of the controller is compared with the trajectory the human driver took during an overtaking maneuver. Table 4 shows the results of these criteria for the four test vehicles used [7].

Table 4 Errors for the Fuzzy Controller

Criteria	Test 1	Test 2	Test 3	Test 4	Mean
AHTD (m)	0.0437	0.0135	0.0632	0.0530	0.0434
RHTD (%)	3.3046	1.3213	4.0830	2.5900	2.8247

5 Conclusion

The focus of this study was on the overtaking maneuver as the most dangerous and common driving behavior. The main goal was to design an intelligent control system to guide the overtaking maneuver in a safe and smooth trajectory. To accomplish this goal, first a neural network model was presented. Real overtaking data was extracted from real traffic datasets and instantaneous values of the variables were used to design this model. The performance of the model was evaluated by comparing the results with real behavior and by using different error criteria. The results showed that the presented model was enhanced in compare to other models from different aspects, since in this model instantaneous values of the variables were used and the approach of modeling was input-output approach which is superior to models based on mathematical equations. Also, the result of the trajectory model is compared with the result of another trajectory model called the optimal model. This comparison provided a better chance to analyze the performance of the presented model. The simulation results showed that the presented model has a very close compatibility with the field data and reflect the situation of the traffic flow in a more realistic way. After modeling the overtaking behavior, a fuzzy controller was designed to offer trajectory of the overtaking vehicle. Validation of the proposed controller was completely done by comparing the response of the control system with real behavior of human drivers and by using different error criteria. The results showed that the proposed controller was able to provide smooth and soft trajectories which were highly accordant with real trajectories of human drivers. Also, the controller was able to compensate the mistakes and sudden actions of real drivers to provide a pleasant trip for the driver and other passengers.

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Nomenclature

A	: Magnitude of the maximal resultant acceleration of overtaking vehicle in optimal model
$AHTD$	: Absolute horizontal transport deviation
D^*	: Optimal x-direction distance traveled during the second phase in optimal model
$D_{(b)}$	: Absolute distance that overtaking vehicle must travel in optimal model
L	: Length of overtaking vehicle in optimal model
L_1	: Length of slow vehicle in optimal model
$L_H(t)$	: Mean total travel distance of the true trajectory
N	: Number of test observations
$RHTD$	: Mean relative horizontal deviation
t	: Time in optimal model
T	: Total time duration of an overtaking maneuver in optimal model
V	: The initial and final Velocity of overtaking vehicle in optimal model
V_1	: Velocity of slow vehicle in optimal model
W	: Width of the lane or of the diversion in optimal model
x	: Lateral displacement in optimal model
x_n	: Model value of the coordinate x
X_n	: Real value of the coordinate x
y	: Longitudinal displacement in optimal model
y_n	: Model value of the coordinate y
$Y_n(t)$	: Real value of the coordinate y

Greek symbols

θ	: Movement angle of the overtaking vehicles

چکیده

هدف اصلی از انجام این پژوهش طراحی یک سیستم کنترلی هوشمند برای فرآیند سبقت‌گیری با در نظر گرفتن رفتار ریزساختار رانندگان است. در این پژوهش، مدل‌سازی، شبیه‌سازی و کنترل رفتار سبقت‌گیری مورد توجه قرار گرفته است. مدل‌سازی این رفتار بر مبنای داده‌های واقعی خواهد بود و بر خلاف مدل‌های موجود، از مقدار لحظه‌ای تمامی پارامترها استفاده می‌شود. سپس با استفاده از این داده‌های واقعی، به جای طراحی مدلی بر مبنای معادلات ریاضی، مدلی بر مبنای ورودی- خروجی طراحی می‌کنیم که با توجه به غیرخطی بودن رفتار سبقت‌گیری رویکرد مناسب‌تری برای مدل کردن این رفتار می‌باشد. برای مدل‌سازی این رفتار، با استخراج پارامترهای مورد نیاز از مجموعه‌ی داده‌های واقعی، یک مدل شبکه عصبی برای مسیرحرکت رفتار سبقت‌گیری طراحی می‌شود. بعد از طراحی مدل، با مقایسه‌ی خروجی آن با رفتار واقعی، استفاده از معیارهای خطای مختلف و مقایسه با خروجی مدل‌های دیگران، عملکرد مدل سنجیده می‌شود. نتایج نشان می‌دهند که مدل ارائه شده از لحاظ مختلف نسبت به مدل‌های موجود برتری دارند. بعد از مدل‌سازی دینامیک سیستم، یک کنترل‌کننده فازی برای هدایت مسیرحرکت خودروی سبقت‌گیرنده در بزرگراه‌های شهری با جریان ترافیک یک طرفه ارائه می‌شود. اعتبارسنجی و صحه‌گذاری کنترل‌کننده ارائه شده به صورت کامل با مقایسه با رفتار واقعی راننده انسانی و استفاده از معیارهای خطای مختلف صورت می‌پذیرد. نتایج حاصل نشان می‌دهند که کنترل‌کننده ارائه شده قادر است به خوبی مسیرحرکتی مشابه مسیرحرکت مطلوب ارائه دهد. هم‌چنین، کنترل‌کننده طراحی شده قادر است با اصلاح اشتباهات رفتار یک راننده انسانی، نکات لازم را ایمنی سرنشینان و خودروها رعایت کند.