Overtaking Maneuver Behaviour Modeling Based on Adaptive Neuro-Fuzzy Inference System

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Abstract— **Overtaking is a complex and hazardous driving maneuver. The automation of this maneuver is considered to be one of the toughest challenges in the development of autonomous vehicles. Here, a novel overtaking model based on adaptive neuro-fuzzy inference system is proposed. This model is able to simulate and predict the future behaviour of the overtaker vehicle in real traffic flow. In this model, important factors such as relative longitudinal and lateral distance, relative velocity, and also the acceleration and the movement angle of the overtaker vehicle are considered. Using the field data, the performance of the model is validated and compared with the real traffic dataset. The results show very close agreement between field data and model outputs.**

Keywords- Overtaking Maneuver Behaviour, ANFIS, Modelling, Intelligent Automation.

I. INTRODUCTION

Overtaking is one of the most dangerous driving maneuvers and thus a clear candidate for driving assistance systems improved by Intelligent Transportation Systems (ITS). The development of intelligent vehicles promises to improve the safety of vehicle's operations, including overtaking. 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 performed by an intelligent vehicle is related to a variety of decision-making and control technologies [1]. A considerable number of research projects relative to the cooperative driving and control of automated vehicles have been carried out in the past decades, such as the PATH project in USA [2], Demo 2000 in Japan [3], and the ARCOS project in France [4]. Most of these research projects emphasize the operation of the platoon, such as Stop & Go, platooning, splitting, merging, lane changing, and obstacle avoidance. Vehicle control technologies, such as adaptive cruise control, automated lane following, and automated lane changing, have extensively been investigated. However, the control algorithm for overtaking and the relative security issues have somewhat been neglected [5].

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 [6], lane changing [7] and overtaking. Here, the concentration is on the overtaking behavior as the most challenging behavior on highways.

Overtaking is the most complex driving subtask including observing, information processing, decision making, planning, manoeuvring, and other traffic. 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 [8]. These phases are shown in Fig. 1.

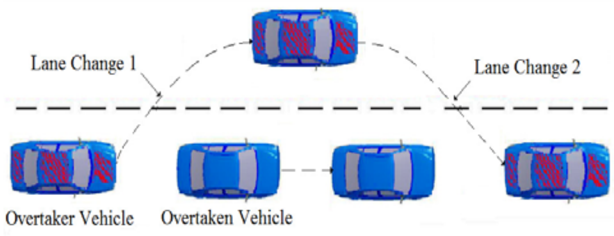

Fig. 1. Two lane changes during the overtaking maneuver.

Highly nonlinear nature of the overtaking 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 overtaking behavior. 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 [9].

In this paper, an innovative ANFIS model for modeling and prediction of the driver-vehicle unit (DVU) behavior in overtaking scenarios is presented. 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 model designed. In Sections IV, the proposed model is evaluated through different error criteria, and the conclusion is given in Section V.

II. BRIEF REVIEW OF OVERTAKING MODELS

The major methods to analyse overtaking behaviour are cellular automata modelling [10-15] and differential equation modelling [16, 17]. Also the system theoretic approach and the neural network method are applied to study the human operating behavior in overtaking procedure [18-20]. Newly, the overtaking distance-based approach has attracted attention [21-24]. In this section, a brief review on the previously presented overtaking models is presented.

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. This formula was calculated according to the least square method. The driving controllers were based on fuzzy logic. S is the necessary distance to perform a change of lane, as in

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equation (1). A is S minus the distance the overtaken car travels in the same time and is related to the velocity v_1 and v_2 of both by formula (2) [25].

$$S = 0.019v_1^3 - 0.450v_1^2 + 3.868v_1 + 12.36 \quad (1)$$

$$A = \left(1 - \frac{v_2}{v_1}\right).S \quad (2)$$

In 2004, Shamir deals with the three-phase overtaking maneuver and with designing a smooth and ergonomic optimal lane-change trajectory to be used under normal conditions. 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. It is convenient to consider the maneuver for phase 3. To determine the trajectory of vehicle P, Shamir fitted a polynomial expression for $x(t)$ and $y(t)$, satisfying appropriate boundary conditions. The boundary conditions are shown as equation (3).

$$\begin{cases} x(0) = 0, x(T) = D, \\ \dot{x}(0) = \dot{x}(T) = V, \ddot{x}(0) = \ddot{x}(T) = 0 \\ y(0) = W, y(T) = 0, \\ \dot{y}(0) = \dot{y}(T) = 0, \ddot{y}(0) = \ddot{y}(T) = 0 \end{cases} \quad (3)$$

By writing down a general fifth-degree polynomial and applying the boundary conditions (3), Shamir obtained the following equations [26]:

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

$$y(t) = W + W(-10(\frac{t}{T})^3 + 15(\frac{t}{T})^4 - 6(\frac{t}{T})^5) \quad (5)$$

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.

It could be concluded that there were only five factors that affected the overtaking maneuver. The factors were speed of overtaken vehicle (*OGS*), decision time (*DT*), start headway (*SH*), overtaking distance (*OD*) and acceleration of overtaking (*OA*). A mathematical model, as stated in equation (6), was developed using these factors [27].

$$\begin{aligned} OGS &= 21.2 + 0.402\,ONS - 5.56\,DT \\ &\quad + 0.431\,SH + 0.220\,OD + 0.916\,OA \end{aligned} \quad (6)$$

In 2007, Tang et al. presented three rules for the overtaking maneuver. These rules which are mentioned in equation (7)-(9), give the time required for completing an overtaking maneuver (T), the time which the overtaker vehicle loses during overtaking ($\Delta t^{(A)}$), and the overtaking distance of vehicle (S_A). Assume A is the overtaker vehicle and Vehicle B is the slow vehicle.

$$T = \frac{2h_A + 2h_B + 2t_0(v_{\max}^{(A)} + v^{(B)})}{v_{\max}^{(A)} - v^{(B)}} \quad (7)$$

$$\Delta t^{(A)} = \frac{h_A + h_B + t_0(v_{\max}^{(A)} + v^{(B)})}{v_{\max}^{(A)}} \quad (8)$$

$$S_A = h_A + h_B + \frac{2h_A + 2h_B + 2t_0\left(v_{\max}^{(A)} + v^{(B)}\right)}{v_{\max}^{(A)} - v^{(B)}} v^{(B)} \quad (9)$$

Where $v^{(A)}$ and $v^{(B)}$ are respectively the velocities of vehicles A and B, h_A and h_B are the safe distances for car following of vehicles A and B, t_0 is the reactive delay time for deceleration, acceleration and lane-changing which is assumed to be constant and equal to 3s, $v_{max}^{(A)}$ is the initial speed of vehicle A and $v^{(B)}$ is the speed of vehicle B which is assumed to be constant and clearly, $v_{max}^{(A)} > v^{(B)}$ [28].

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 was considered. The traffic flow on a one-way two-lane road was controlled by a series of synchronized signals. The interval between signals is constant, denoted by M. The green signal period is $S_p t_s$ and the red signal period is $(1-S_p)t_s$, in which time t_s is the cycle time and S_p is the ratio of green signal time to cycle time. The location of vehicle a at time t is defined as $[i,j]_{a,t}$, for which $i_{a,t}$ denotes the lattice of vehicle a in a certain lane while $j_{a,t}$ denotes the lane of vehicle a in a certain lattice. Besides, $[i,j]_{a+1,t}$ denotes the location of vehicle $a+1$ at time t, which is the preceding vehicle of vehicle a in the same lane. The rule of overtaking is mentioned in equation (10):

$$\begin{aligned} F(a) &= cell\left[(i+1)_{a,t} - j_{a,t}\right] \| \, cell\left[i_{a,t} - j_{a,t}\right] \\ &\quad \| \, cell\left[(i-1)_{a,t} - j_{a,t}\right] \end{aligned} \quad (10)$$

If and only if $F(a)=0$, $C=1$, vehicle a can overtake. The location of vehicle a at time $t+1$ is shown in equation (11) [29]:

$$\begin{cases} i_{a,t+1} = \varphi(a)\left\{1 - \upsilon\left(\sin(2\pi t/t_s)\right\}\right. \\ \quad + \min\left\{\varphi(a), \left(X_{a,t} - 1\right)\right\}\upsilon\left(\sin(2\pi t/t_s)\right) \\ j_{a,t+1} = \left(-1^C\right) j_{a,t} \\ \varphi(a) \equiv H(a)\left(i_a + V_{\max}\right) + \\ \quad \left(1 - H(a)\right) \times \left\{G(a)\left(i_a + V_{\max} - C\right) + F(a)\left(i_{a+1,t} - 1\right)\right\} \end{cases} \quad (11)$$

As mentioned above, the study of overtaking models has been extensive. Due to the variety of the factors that affect it, the presented models consider different factors and offer different rules. Moreover, these rules are calculated according to various methods. However, neither of the presented models is able to present a model which is completely accordant to the real behavior. It is due to the complexity of this maneuver. These models could be more reliable if they had considered all the main 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 the constant value. In this paper, an input-output model is presented to estimate the acceleration and movement angle of the overtaker vehicle. This model considers the instantaneous value of the parameters to predict the future value of them.

III. New ANFIS Overtaking Model Design

The basics of the adaptive neuro-fuzzy inference system network architecture applied for the overtaking prediction system is introduced here. A detailed coverage of ANFIS can be found in [6, 30]. ANFIS enhances fuzzy inference system with self-learning capability for achieving optimal control objectives. An adaptive network is a multilayer feed-forward network where each node performs a particular node function on incoming signals. It is characterized with a set of parameters related to that node. To reflect different adaptive capabilities, both square and circle node symbols are used. A square node (adaptive node) has parameters, while a circle node (fixed node) doesn't have. The parameter set of an adaptive network is the union of the parameter sets associated to each adaptive node. To achieve a desired input-output mapping, these parameters are updated according to given training data and a recursive least square (RLS) based learning procedure [9].

In order to design an ANFIS prediction system, a dataset of overtaking behavior is needed. So, real overtaking data from US Federal Highway Administration's NGSIM dataset is used to train the ANFIS prediction model [31]. In June 2005, a dataset of trajectory data of vehicles travelling during the morning peak period on a segment of Interstate 101 highway in Emeryville (San Francisco), California has been made using eight cameras on top of the 154m tall 10 Universal City Plaza next to the Hollywood Freeway US-101. On a road section of 640m, as shown in Fig. 2, 6101 vehicle trajectories have been recorded in three consecutive 15-minute intervals. This dataset has been published as the US-101 Dataset. 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 [32].

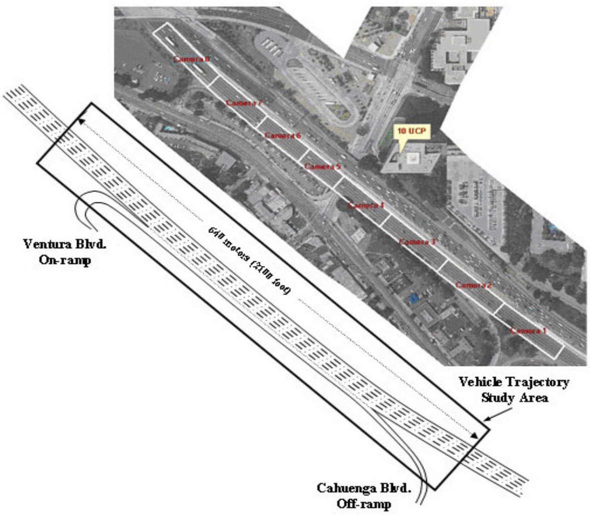

Fig. 2. A segment of Interstate 101 highway in Emeryville, San Francisco, California [32].

The other dataset was published as the I-80 Dataset. Researchers collected detailed vehicle trajectory data on eastbound I-80 in the San Francisco Bay area in Emeryville, CA, 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. 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. A total of 45 minutes of data are available in the full dataset, segmented into three 15-minute periods [33].

The trajectory data seem to be unfiltered and exhibit some noise artifacts, so these data must be filtered like [34, 35]. A moving average filter have been designed and applied to all trajectories before any further data analysis. Comparison of the unfiltered and filtered data of the acceleration and movement angle of the overtaking vehicle are shown in Fig. 3 and Fig. 4.

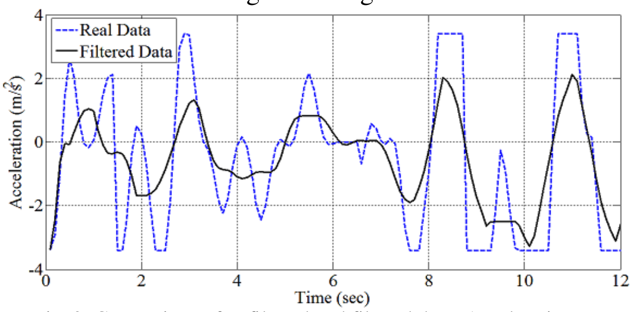

Fig. 3. Comparison of unfiltered and filtered data: Acceleration.

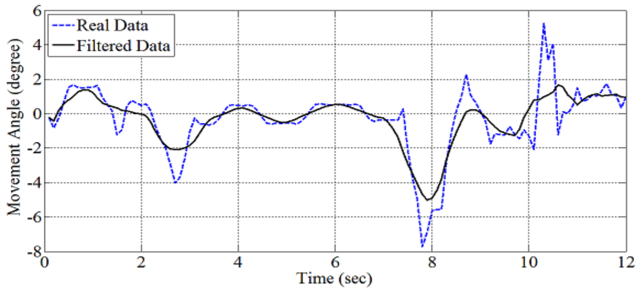

Fig. 4. Comparison of unfiltered and filtered data: Movement Angle.

In this study, an ANFIS model is designed. This model predicts the acceleration and the movement angle of the overtaker vehicle. The fuzzy inference system applied for prediction model has five inputs. These inputs are relative lateral and longitudinal distance, relative velocity, and finally the acceleration and the movement angle of the overtaker vehicle. There are three gaussmf membership functions for each input. The rule base contains 243 fuzzy if-then rules of Takagi-Sugeno's type [36] and hybrid algorithm is used to train this model.

The presented model is able to predict the future value of the movement angle. The vehicle's movement angle, as shown in Fig. 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 and only shows the angle of the vehicle with the imaginary line of the road during the movement of the vehicle. This angle helps to find the trajectory of the overtaking maneuver.

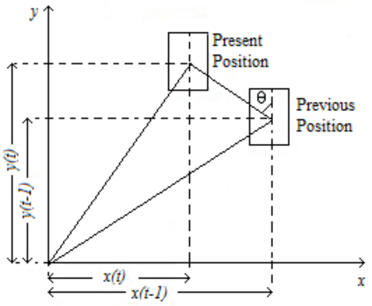

Fig. 5. The movement angle of the overtaker vehicle.

In the development of ANFIS prediction model, 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.

IV. Discussion and Results

To evaluate the competence of ANFIS estimator system, the validation dataset is used. 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 comparison of the output of the acceleration ANFIS model with real data and the movement angle ANFIS model with real data is shown in Fig. 6 and Fig. 7.

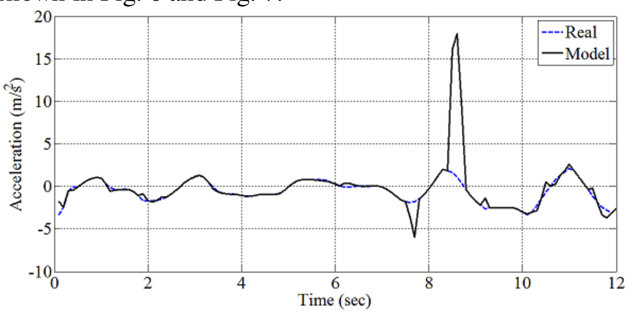

Fig. 6. Comparison of the ANFIS model and real data: Acceleration.

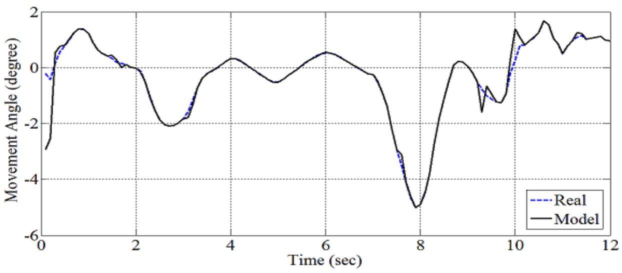

Fig. 7. Comparison of the ANFIS model and real data: Movement Angle.

To examine the performance of the developed model, various criteria are used to calculate errors. The mean square error (MSE) of an estimator, according to equation (12), is one of the many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. Root mean squares error (RMSE), according to equation (13), is a criterion for comparing error dimension in various models. The normalized mean square error (NMSE), according to equation (14), is an estimator of the overall deviations between predicted and measured values. The mean absolute error (MAE), according to equation (15), is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The Symmetric mean absolute percentage error (SMAPE), according to equation (16), is an accuracy measure based on percentage (or relative) errors. In these equations, x_i shows the real value of the variable being modeled (observed data), $\hat{x}_i$ shows the real value of variable modeled by the model and $\bar{x}$ is the real mean value of the variable and N is the number of test observations [37].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \qquad (12)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \qquad (13)$$

$$NMSE = \frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (14)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{x}_i - x_i\right| \qquad (15)$$

$$SMAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|x_i - \hat{x}_i\right|}{\left|x_i + \hat{x}_i\right|} \qquad (16)$$

Errors in modeling the acceleration output and the movement angle output considering these criteria are summarized in Table I and II. The last column of tables shows the mean value of each error criteria.

TABLE I.
RESULT OF ERROR FOR ANFIS OVERTAKING MODEL: ACCELERATION

Criteria	Test 1	Test 2	Test 3	Test 4	Test 5	Mean
MSE	0.0034	0.0580	0.0447	0.0351	0.0300	0.034
RMSE	0.0581	0.2409	0.2114	0.1873	0.1731	0.174
NMSE	0.0020	0.1663	0.0387	0.0372	0.0216	0.053
MAE	0.0303	0.2457	0.0610	0.1455	0.1270	0.122
SMAPE	0.1170	0.0977	0.0515	0.2464	0.3258	0.168

TABLE II.
RESULT OF ERROR FOR ANFIS OVERTAKING MODEL: MOVEMENT ANGLE

Criteria	Test 1	Test 2	Test 3	Test 4	Test 5	Mean
MSE	6.724e-005	0.0405	0.0028	0.0095	0.0115	0.013
RMSE	0.0082	0.2012	0.0530	0.0973	0.1072	0.093
NMSE	4.878e-004	0.0456	0.0062	0.0216	0.0144	0.018
MAE	0.0061	0.1003	0.0221	0.0677	0.0823	0.056
SMAPE	0.0110	0.1002	0.0912	0.1005	0.5661	0.174

V. Conclusion

In this paper, a novel overtaking model was studied. This model considers important factors such as relative longitudinal and lateral distance, relative velocity, and the acceleration and movement angle of the overtaker vehicle. Satisfactory performance of the proposed model was demonstrated through comparisons with real traffic data. The simulation tests for different experimental configurations have shown the effectiveness of the proposed overtaking model. This effectiveness was in prediction of the future value of the acceleration and movement angle of the overtaker vehicle. Using the instantaneous value of the parameters to predict the future value of them is the prominent aspect of the proposed overtaking model. By using the results of the suggested model, an autonomous vehicle, equipped with appropriate sensors, can estimate the acceleration and movement angle for its future movement. The proposed method can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

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