ANFIS Based Modeling and Prediction Lane Change Behavior in Real Traffic Flow

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***Abstract*—In recent years, because of importance of intelligent transportation systems in increasing safety and decreasing traffic flow, various researches have been done on these systems. The lane change system is among the most important components of these systems for a vehicle. This paper proposes a novel adaptive neuro fuzzy inference systems approach to simulate and predict the future behavior of a Driver-Vehicle-Unit in lane change maneuver. Integration of the driver's reaction time delay and omission of the necessity of regime classification are considered while developing the model. The proposed model's satisfactory performance is demonstrated through comparisons with real traffic data. The results showed that new model based on adaptive neuro fuzzy inference systems outperformed the other lane change models. The proposed method can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other intelligent transportation systems applications.**

Keywords- ANFIS, lane change, modeling, Intelligent Transportation System

I. INTRODUCTION

Nowadays, intelligent transportation system (ITS) has a significant assistance to decrease the traffic flow and increase the safety in transportation systems [1-2]. Researches show that human error is the most important factor in occurrence of the accident [3]. ITS can be used as one option to decrease the accidents, by decrease the human error. These systems could be used as an efficient tool in transportation industry by applying and using computers, telecommunications, and advanced control systems [2]. Many ITS sub-systems are strongly 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 to meet the information requirements of these sub-systems and to aid in the evaluation of ITS traffic management and information strategies [1].

A section of the ITS sub-systems are various microscopic models of traffic flow, such as car following models and lane keeping models. Lane change models are among the most important microscopic traffic flow modeling, that aim of these models is obtain desired behavior of Driver-Vehicle-Unit (DVU) in the lane change process. Fig. 1 shows the lane change process. At first, vehicle moves in the straight line. For starting the lane change, the distances between the main vehicle and around vehicles should be checked. If these distances are enough to preventing accidents, the lane change process can be started, using changing of the steering angle. Therefore the heading angle of the vehicle be changed, and the vehicle moves to the adjacent line. The changing of the heading angle be increased from the starting of the process, to about the middle of the lane change path, and then be decreased to the end of the process. When the vehicle reached to the mid of the target line, moves in the straight line again, and the lane change process be completed.

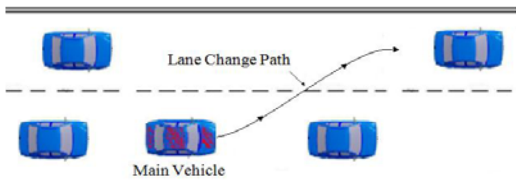

Figure 1. Lane change behavior.

In a general classification, lane-changing behavior microscopic models can be divided into two groups: equation-based and input-output-based. In the equation-based model, the lane-changing behavior is presented by a set of mathematical equations. Results of these models are only matched to the test cases and are not reliable. In the input-output-based model, the lane-changing behavior is presented based on the real measured values and using signal-based modeling approaches. In these models, the inputs and outputs are modeled to design and train based on the experimental or real data [4]. Few studies on lane-change behavior modeling are discussed here [5-6]. Hsu and Liu presented a lane change model for platoon maneuvers in highways. In this study, first the required relations for modeling of vehicle lane change maneuver was obtained using two robots, and then the model was generalized for the vehicle. In the next section of this study, a method to vehicle lane change and then car following simultaneously which is

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done using a new maneuver, that called lane change and following (LCF) maneuver. And finally, the model is generalized for platoon lane change maneuvers using LCF [7]. Ahle and Soffker presented a lane change model based on the relationships governing the parameters and situation of operator. In this paper, first, define various situations of vehicle and actions of operators (mean braking, driving and lane changing). Then by using these, presented a lane change algorithm base on situation-operator mode1 (SOM) [8]. Seimenis and Fotiades presented a completely mathematical lane change model based on Clothoidal Theory and Bezier Points. In this model, the points of the lane change trajectory be approximated using a polynomial, that called s-series. This model used to fast lane change in highway [9]. Wakasugi presented a model to alarm the appropriate time for lane change, based on the relationship between lane-change tasks and closing vehicles in the passing lane. In this paper, simulation is done by a linear prediction model, using data related to real experiments [10]. Dogan et al presented a neural network model for lane change maneuver. In this model, back propagation algorithm is used, and data related to real experiments use for training. This model is presenting a representation of driver's lane change behavior in order to predict driver's intentions as a first step towards a realistic driver model [11]. Toledo-Moreo and Zamora-Izquierdo presented a lane change prediction model, for collision avoidance in highways, based on interactive multiple models (IMM) method. This model predicts the position and heading of the vehicle in during the lane change path. In this model, for the sensor unit, are used GPS and INS systems. This model is useful for predicting lane changes with very short latency times [12]. Alonso *et al* presented a lane change model using image processing method. Basis of this model are motion-driven vehicle tracking, and monitoring the rear view of vehicle. For modeling, first, optical flow in real time is computed, using a digital signal processor (DSP), then, by tracking the vehicle path, the position of the lane change trajectory points are computed, using a standard processor [13]. Liu et al presented a lane change model based on parallel bayesian networks (PBN). Basis the operation of this model, is analysis and estimation of steering angles and their difference, and determine the final status of driver behavior, using the largest probability of the each status during lane change maneuver [14]. These models are applied for lane change in direct paths, but some of them like [6] and [12] can be applied for curve paths as well as direct paths.

Highly nonlinear nature of lane changing 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 lane changing 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. Integration of human expert knowledge expressed by linguistic variables, and learning based on the data are powerful tools enabling neuro-fuzzy models to deal with uncertainties and inaccuracies [1, 15]. In this paper, a new ANFIS model is provided to predict the lane change maneuver in real traffic flow.

II. ANFIS LANE CHANGE MODEL DESIGN

In this section, first, the ANFIS network architecture is defined and then a brief description is expressed about the database. In next stage, noises of the data are decreased as much as possible using a filter. Then the data separation conditions are described. In the end of this section, the model structure is described.

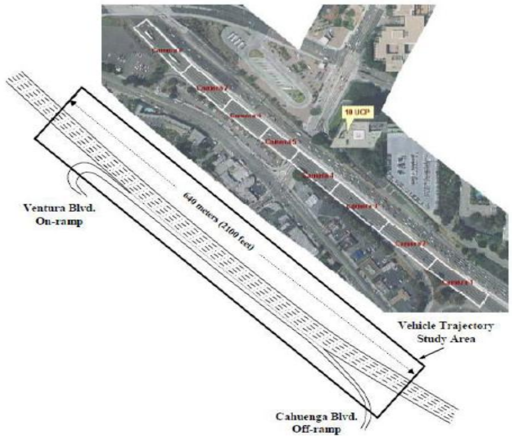

Figure 2. A segment of Interstate 101 highway in Emeryville, San Francisco, California.

Now introduces the basics of the ANFIS network architecture applied for the lane change prediction system. A detailed coverage of ANFIS can be found in [16, 17]. ANFIS enhances fuzzy controllers with self-learning capability for achieving optimal control objectives. An adaptive network is a multilayer feed-forward network where each node performs a particular node function on incoming signals. It is characterized with a set of parameters pertaining that node. To reflect different adaptive capabilities, both square and circle node symbols are used. A square node (adaptive node) has parameters, while a circle node (fixed node) has none. The parameter set of an adaptive network is the union of the parameter sets associated to each adaptive node. To achieve a desired input-output mapping, these parameters are updated according to given training data and a recursive least square (RLS) based learning procedure.

In order to design an ANFIS prediction system, a dataset of lane change behavior is needed. So, real lane change data from US Federal Highway Administration's NGSIM dataset is used to train the ANFIS prediction model [18]. 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 dataset consists of detailed vehicle trajectory data on a merge section of eastbound US-101. The data is collected in 0.1 second intervals. Any measured sample in this dataset has 18 features of each driver-vehicle unit in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle and etc.

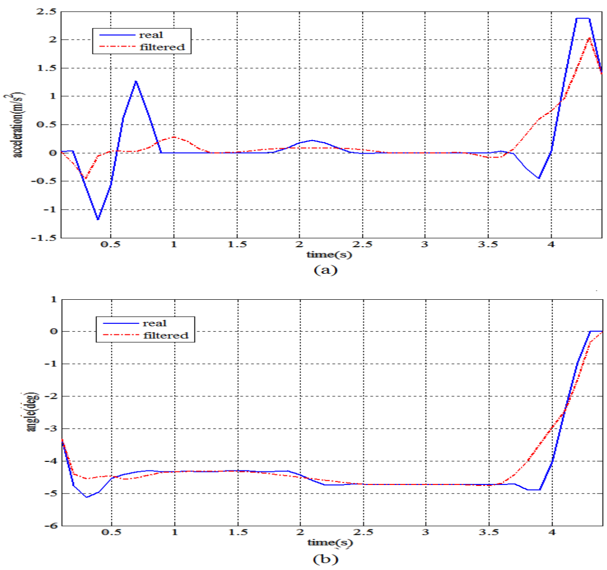

Figure 3. Comparison of filtered and unfiltered data: (a) acceleration, (b)heading angle.

It seems that, lane changes data are unfiltered. Therefore, before starting the modeling all data are filtered using a moving average filter. Fig. 3 shows the comparison of filtered and unfiltered data related to acceleration and heading angle of one of the lane changes.

Generally there is no general rule to determine appropriate and normal lane changes. Our novel idea for determining the conditions can be obtained by analyzing the data related to DVU behavior in lane change maneuver. These conditions must be gained so that, generally they provide safety and convenience of the vehicle's passengers and the vehicle should have a soft and uniform maneuver.

- The vehicle must have passed half of the width and half of the length of the lane change path in half of the time.
- However there is no special rule to determine a maximum for heading angle of vehicle's movement, but in order to uniform the data for modeling, it is better to determine a value for the maximum heading angle limit while lane changing.
- Another necessary condition for balanced maneuver is that, sign of heading angle changes only in one point of the path.
- Next stage is determining a limit for heading angle changes in each stage. By investigating the data related to lane changes, maximum angle changes at each stage can be determined using equation (1). In this equation φ_{MAX} is maximum authorized heading angle.

$$\Delta\varphi_{MAX} = \pm\frac{\varphi_{MAX}}{5} \qquad (1)$$

- Next stage, is investigating the lack of vehicle's slip while lane changing. To do this, at first free diagram of the vehicle is drawn simply in Fig. 4, then this condition be surveyed using Newton equations. Where M is the mass of vehicle, I is the inertia moment, c and b are the distances from the center of mass to the front and rear tires, a and v are vehicle's acceleration and velocity, F_1 and F_2 are the lateral forces of front and rear tires, and R is the radius of path curve. In this stage, if F_1 and F_2 are less than their maximums, velocity and acceleration of vehicle's maneuver are acceptable for non-slipping of the vehicle. And if each of them is more than its maximum authorized amount, this condition cannot be satisfied.

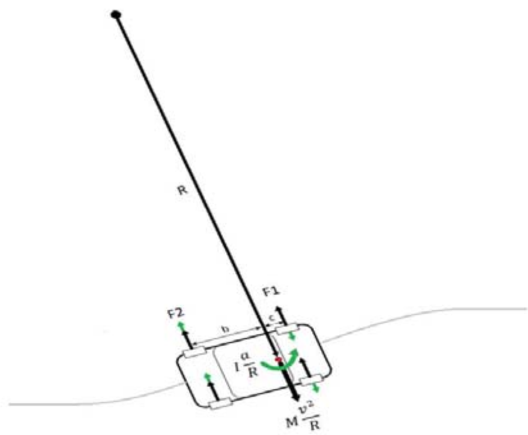

Figure 4. Free diagram of the vehicle in the lane change path.

- The last condition is determination a limitation for rhythm of acceleration changes for smooth movement.

Now that appropriate data for modeling lane change of vehicle's maneuver have been separated from all the data related to lane changes, in this section we intend to model this maneuver using fuzzy-neural networks. To do this we will use ANFIS. For modeling, data related to 75% of the lane changes are randomly selected. The remaining 25% was set aside for model validation. Generally, this model has five inputs and two outputs. Inputs of the system include: velocity, acceleration, jerk, heading angle and heading angle race, and outputs of the system include: acceleration and heading angle (means the acceleration and heading angle predicted by the model, related to the next stage of maneuver). In Fig. 5 is demonstrated the structure of ANFIS model designed for predicting the acceleration and heading angle. This model has 162 fuzzy if–then rules of Takagi-Sugeno's type [19], and for every input 3 membership functions have been used which are trimf type. Hybrid algorithm was used for training of the system.

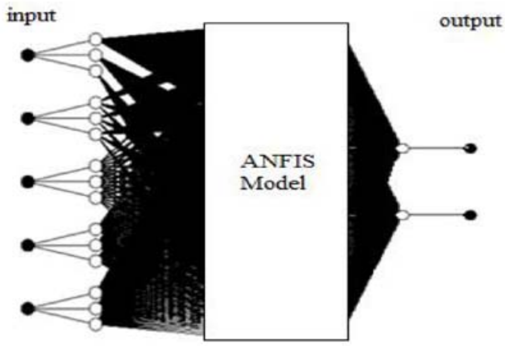

Figure 5. Structure of ANFIS model to predict acceleration and heading angle.

III. Discussion and Results

In order to validate the ANFIS lane change model, this model must be evaluated and tested using behavior of several other vehicles. Less difference between the outputs of the model and real values causes less model error and makes the model more desired.

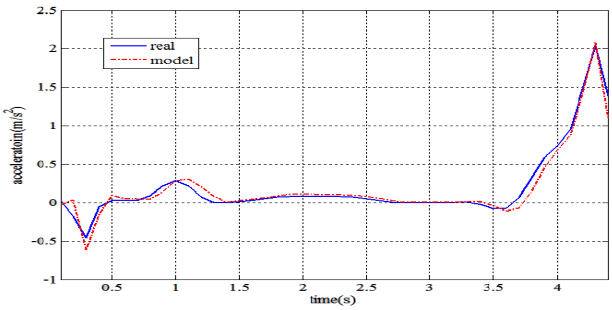

Figure 6. Results of the ANFIS model performance to predict acceleration for first test sample (LC_1).

Fig. 6 and Fig. 7 Show the obtained graph of the model performance results for predicting the acceleration and heading angle for the first test sample (LC_1), respectively. As it can be seen in these figures, outputs resulted from this model and DVU performance results are much close to each other. This means a desired performance for the model to predict acceleration and heading angle for the first test sample (LC_1).

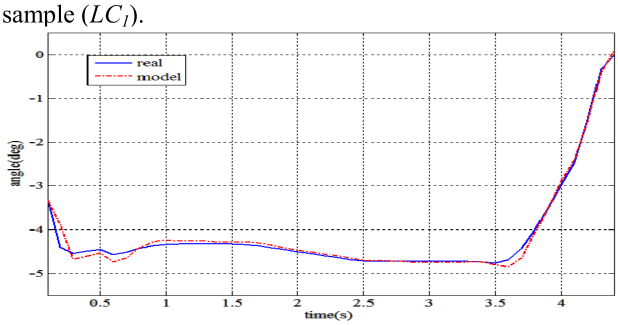

Figure 7. Results of the ANFIS model performance to predict heading angle for first test sample (LC_1).

Finally in Fig .8 trajectory of the real data and trajectory of results obtained from the model are drawn. As it is evident in this figure, these two trajectories are almost in conformity with each other and they can be recognized difficultly, it means that the model error is little and it has a high preciseness in predicting for the first test sample (LC_1).

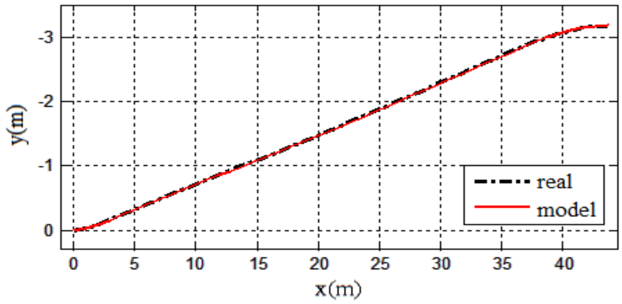

Figure 8. Trajectory of real data and results obtained of the ANFIS model, for the first test sample (LC_1).

In order to investigate performances of different systems, various criteria are used to evaluate the amount of error. Root mean square error (RMSE) criterion which is according to equation (2) is one of the well-known standard errors, and is used as a criterion to compare error aspects in various models [20]. Second Exponent of the Correlation Coefficient (R^2) is according to equation (3). This value denotes the amount of conformity between the predicted data and real data. This value is a figure between zero and one. One means complete conformity between real data and predicted data. Mean Absolute Error (MAE) criterion is according to equation (4). In statistics this method shows that, how much the predicted results conform to reality. As it is clear from its name, this value is a mean absolute error. And finally, Mean Bias Error (MBE) criterion is according to equation (5). This criterion represents the mean bias error of the predicted value from the real value, and in fact, shows the amount deviation of predicted values from real values.

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

$$R^2 = 1 - \{[\sum_{i=1}^{N}(x_i - \hat{x}_i)^2] / [\sum_{i=1}^{N}(x_i - \bar{x})^2]\} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{x}_i - x_i| \tag{4}$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - x_i) \tag{5}$$

In these equations, N is the number of test observation, 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 average of the x_i s.

According to the above-mentioned criteria, the errors obtained for acceleration (m/s^2) and heading angle (degree) of five test samples, along with maximum errors are provided in Table I and Table II, respectively.

TABLE I. RESULTS OF ACCELERATION ERROR, FOR FIVE EXAMINED SAMPLES

	LC_1	LC_2	LC_3	LC_4	LC_5
MAX(e)	0.3022	0.5328	1.2569	0.8918	0.3299
RMSE	0.0842	0.1686	0.2635	0.2120	0.1131
R^2	0.9656	0.8761	0.8813	0.9430	0.9327
MAE	0.0565	0.1126	0.1296	0.1250	0.0773
MBE	-0.0072	-0.0424	0.0875	-0.0817	-0.0144

The results obtained from testing model, show that this model has a small rate of error and compared to other lane change models has relatively less error. Therefore, it is considered as good model for lane change.

TABLE II. RESULTS OF HEADING ANGLE ERROR, FOR FIVE EXAMINED SAMPLES

	LC_1	LC_2	LC_3	LC_4	LC_5
MAX(e)	0.5224	0.6865	1.1156	0.4739	1.2804
RMSE	0.1091	0.1782	0.2882	0.1289	0.2597
R^2	0.9897	0.9877	0.9839	0.9890	0.9478
MAE	0.0701	0.1080	0.1863	0.0788	0.1288
MBE	0.0085	-0.0030	0.0285	-0.0118	-0.0489

IV. CONCLUSION

In this study, an ANFIS model has been provided for lane change of vehicle, whose inputs were velocity, acceleration, jerk, heading angle, and heading angle race, and its outputs are acceleration and healing angle. Since DVU behavior data have been used in the presented ANFIS model, the obtained results are so close to reality. A wide range of data are used in this model, and it has been tried to use the most appropriate data for modeling so that, while providing passengers' safety and convenience, lane change maneuver is done soft and uniformly. Also, before modeling by applying a filter, noise of data was reduced as much as possible to achieve the most desired model. Tests performed on the obtained model show that, the provided model has a very low error, and predictions made by this model are very near to real data.

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