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Published in:
IEEE Transactions on Vehicular Technology

DOI:
[10.1109/TVT.2021.3099736](https://doi.org/10.1109/TVT.2021.3099736)

Published: 01/09/2021

Document Version
Publisher's PDF, also known as Version of record

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Please cite the original version:
Tajdari, F., Golgouneh, A., Ghaffari, A., Khodayari, A., Kmali, A., & Hosseinkhani, N. (2021). Simultaneous intelligent anticipation and control of follower vehicle observing exiting lane changer. *IEEE Transactions on Vehicular Technology*, 70(9), 8567-8577. <https://doi.org/10.1109/TVT.2021.3099736>

Simultaneous Intelligent Anticipation and Control of Follower Vehicle Observing Exiting Lane Changer

Farzam Tajdari , Alireza Golgouneh, Ali Ghaffari, Alireza Khodayari, Ali Kamali, and Niloofar Hosseinkhani

Abstract—Despite the advances related to car-following and lane-changing behaviors, the influence of lane-changing on the car-following models, which results in a complex transient merging behavior, has not comprehensively been investigated. This paper presents a novel fuzzy controller based on a human factor to optimize the Follower Vehicle (FV) behavior subject to safety, comfort, and convenient traveled time in the complex behavior where the Lane Changer (LC) vehicle exits the temporary lane. The factor enables the controller to mimic the current driver behavior in terms of maximum pleasantness of drive. Accordingly, the data of real-life experiments were used to design the human-like fuzzy controller, to build a predictive model to suggest the appropriate acceleration, velocity, and travel distance. At best, the correlation coefficient of 0.93 and the Root Mean Square Error (RMSE) of 0.71 were achieved for modeling using the adaptive Neuro-Fuzzy Inference System (ANFIS) utilizing Gaussian function as a membership function. Furthermore, to evaluate the robustness of the controller to uncertainties and unknown disturbances for real-time driving experiments, a test-bed was fabricated to mount the feedback sensors, including vision, accelerometer, and distance measurement sensors. The results of running the controller in various driving scenarios showed 70% and 38% improvements in safety and ride comfort, respectively. The proposed intelligent controller is intended to be used for vehicle route guidance and on urban highways.

Index Terms—Human-like fuzzy controller, safety, comfort, car-following behavior, lane-changing behavior.

I. INTRODUCTION

AMONG the microscopic traffic flow modeling, the car-following models are increasingly being used to evaluate new Intelligent Transport System (ITS) applications. These models have been derived by modeling the feedbacks of a Follower Vehicle (FV) to its Leader Vehicle (LV), which aim

to describe the longitudinal movement of a driver following other vehicles. Two consequential examples are the Optimal Velocity Model (OVM) [1], and the Intelligent Driving Model (IDM) [2]. Meanwhile, the car-following control strategy plays a fundamental role in the field of automated and connected vehicles in different forms of Advance Driving Assistant Systems (ADAS) [3]. The car-following behavior in the practical scenario may witness some special situations affected by the vehicles in the adjacent lane that divert the behavior from the conventional car-following conditions [4], [5], e.g., a FV behavior witnesses a lane-changing. As a result, a fast change in relative lateral distance and velocity affected by the adjacent vehicle is expected, which mainly leads the traffic flow to the traffic conflicts [6]. Addressing the complex condition, human drivers practically may anticipate the surrounding vehicles before lane-changing to make safe control decisions for the behavior [7]. Thus, the approach of detecting, anticipating and controlling the behavior subject to comfort and safety [8] is very challenging. The approach will improve the conventional car-following ADAS, towards a fully automated car-following strategy during a lane-changing. The challenge contains two scenarios: A. Always detecting and reacting to the surrounding vehicles, which is computationally and effort-wise expensive, B. Detecting and reacting to the neighboring drivers only when they deviate from the conventional car-following behavior, which is highly complex. However, recent studies have investigated the complex behavior of the follower vehicle solely in the two scenarios; the anticipation models consider the neighboring vehicles are relatively rare [9]. In addition to the fewer studies of modeling the complex behavior, controlling the merging phenomenon has not been comprehensively discussed, though one of the substantial restitution of temporary car-following models should be anticipating and evaluating the complex behavior, as the probability of car accident is considerably high, during lane-changing [10]. Thus, in this paper, we design the architecture for fuzzy control of the FV in the complex behavior based on the anticipation and evaluation states in the case that the Lane Changer (LC) is exiting the target lane. Our scientific contributions are:

- 1) Introducing the architecture of predicting the behavior via soft computing methods and by exploring the behavior of several real drivers behavior, including a novel human factor;
- 2) Integrating the human factor in the metric for establishing a robust fuzzy controller mimics the current driver behavior subject to safety and comfort;

Manuscript received July 26, 2020; revised January 30, 2021 and June 2, 2021; accepted July 5, 2021. Date of publication July 26, 2021; date of current version September 17, 2021. The review of this article was coordinated by Dr. M. Shahgir Ahmed. (Corresponding author: Farzam Tajdari.)

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Digital Object Identifier 10.1109/TVT.2021.3099736

- 3) Extensively investigating sensitivity and robustness of the controller inputs and parameters, safety and ride comfort criteria, and explore the feasibility study of the approach by implementing the controllers on a test-bed in a realistic driving scenario.

A preliminary version of this work is included in [11], which is extended here with a more rigorous formulation; a thorough discussion on controller stability properties for the proposed control law; a set of numerical investigations on robustness to parameter choices; and additional experiments, including a scenario considering a state-of-the-art conventional control strategy and a scenario considering additional disturbances through a practical test-bed in real traffic condition.

II. RELATED WORK

Regarding the first scenario, a car-following model, proposed in [12], is developed based on inverse correlation of longitudinal distance between FV and the front vehicle and the lateral distance from FV to the vehicles driving in the adjacent lanes. The speed-space-based model is introduced firstly by Ponnuru *et al.* [13]. The model demonstrates a considerable large following distance kept by the FV as a result of the large relative speed between the FV and the vehicle in the adjacent lane. Moreover, a hybrid model is proposed in [14] able to consider the effects of the vehicle behavior in the adjacent lane. The aforementioned studies reveal a substantial connection between the FV and the vehicles in adjacent lanes, which confirms an undeniable anticipation behavior by the FV before a lane change happens [15], [16].

Regarding the second scenario, models of the complex behavior anticipation have been studied. A model capable of capturing the relaxation state for LCs through the macroscopic theory of lane change maneuver was derived by Laval and Leclercq (LL) [17]. The model was proposed based on the Newell theory in [18] validated experimentally. Duret *et al.* [19] recruited passing rate to investigate both the anticipation and the relaxation behavior of the follower driving in the target lane. Zuduo *et al.* [20] determined the start of the anticipation and the endpoint of the relaxation through the simplified Newell car-following theory. The theory claims the time-space trajectory of FV is linearly similar to the preceding trajectory vehicle but for shifts in time and space [18]. A few years later, Ghaffari *et al.* [4], [5], [21] comprehensively assessed the hypothesis of linearity between spacing and speed of FV in real traffic flow and showed the behavior is highly nonlinear by comparing the space-speed trajectories through standard experimental datasets. Thus, detecting and anticipating the complex behavior require a higher level of human logic perceptions based on soft computing.

Regarding the non-linearity, a Long-Short-Term Memory (LSTM) model, developed in [22], could anticipate the motion of the adjacent vehicles on a motorway. Moon *et al.* [23] employed an intelligent controller based on fuzzy logic to anticipate the complex behavior of neighboring vehicles. A fuzzy support vector machine (FSVM) method was used in [24] by Vogel, to anticipate and model the complex behavior parameters. As more

examples of soft computing methods, a deep neural-network-Semantic-based Intention and Motion Prediction (SIMP) strategy were proposed in [25] to anticipate the inception of the complex behavior. Comparing SIMP with the previous method of Support Vector Machine (SVM), SIMP improved the anticipation accuracy and the start of the anticipation for about 2 seconds.

In terms of comfort and safety during a car-following behavior, a wide range of researches presented different strategies, namely the adaptive cruise control (ACC) systems employing cut-in-sense [8]. A robust ACC practical approach presented in [26] used a model predictive control (MPC) for designing an optimal controller to investigate the lane change behavior of surrounding vehicles. In addition, Li *et al.* [27] presented an ACC strategy based on dynamical car-following parameters, capable of tackling with tracking quality, economical fuel consumption, and acceptable human-like response. Recent studies [28], [29] investigated the possible strategies to sensibly adjust the stabilised car-following behavior among the safety and comfort in terms of journey arrival time. Although the studies integrated safety and comfort to the car-following behavior, the significance of comfort and safety subject to pleasant of drive and the impact of lane-changing are missed.

Thus in this paper, we formulate a fuzzy personalised human-like controller for the FV observing the LC for the merging behavior, which guarantees comfort and safety.

III. CONTROLLER

For the car-following behavior involves in a lane change, two main scenarios exist [4], [5], [21]. One is that a LC is exiting the FV's lane, and the other is that a LC is entering the FV's lane. The latter scenario is modeled in [5] through a fuzzy-based model as the behavior predictor, employing a discrete human factor to consider the influence of human logic in the model. While controlling the behavior has never been comprehensively investigated. Regarding the prior scenario, a methodology in [21] is presented based on a continuous human factor estimator capable of distinguishing the driver's driving characteristics and simultaneously predict and the complex behavior while exiting the LC. In the study, it is assumed that the behavior consists of two main behaviors of anticipation and evaluation and several hierarchical sub-behaviors as follows.

A. Anticipation and Evaluation Behavior

Anticipation and evaluation behavior are transient states between the two conventional car-following maneuvers [21]. Amongst, lane-changing behavior affects any involved FVs and leads them to deviate from the conventional car-following behavior. In the situation, 2 FVs (one before and one after lane-changing) are affected and involved in the transient states; consequently, which their behavior is supposed to deviate from the conventional car-following behavior. The anticipation behavior is a prediction to the future lane-changing, which is instigated based on hidden evidence, and thus it is complex. In contrast, the evaluation behavior is detected based on visible signals regarding the FV responses to the lane-changing. The

Fig. 1. The complex merging scenarios.

evaluation behavior is a part of the complex merging behavior throughout at the time of which FV does not follow common car-following models. Therefore, this state should be studied individually. Besides the significant effects of the temporary state on the behavior of the FV, the anticipation and evaluation control has not been comprehensively characterized yet. Thus, according to Fig. 1, this paper studies the behavior of FV1 in case LC2 exits the target lane. Based on this figure, the FV1 immediately faces a considerably large space with LV3 when the LC2 leaves the target lane. Generally, this is time-consuming for the driver to adjust desired distance regarding the vehicle speed [30]. Please note that for the rest of this paper, the proposed FV is the behavior of the FV1, the LC denotes the behavior of the LC2, and the LV explains the behavior of LV3 in Fig. 1. Logically, the inherent non-linearity in the behavior of human drivers makes it exceedingly difficult to determine the precise time at which drivers decide to execute a maneuver. Considering the behavior of drivers in real traffic flow, Ghaffari, *et al.* [21] presented an innovative method to determine the inception of anticipation and endpoint of evaluation behavior. Determination of the beginning and ending point of anticipation and evaluation behavior for a test vehicle, based on the mentioned criteria, is summarized in Fig. 2, where the negative value of time indicates before the complete lane change maneuver. According to Fig. 2(a), the “attack” [21] signal from the LC as a stimulation for the start point of anticipation of the FV is specified. The attack is defined as a fast movement of the LC that aims to have a lane change and happens when the lateral velocity of any vehicle exceeds 0.05 m/s [21]. Therefore, the FV responds to this stimulation signal by not following the front vehicle (the LC). Thus, the time at which the total acceleration of the FV becomes zero (the values less than 0.08 m/s^2 are considered as zero according to [21]) for the first time after the attack is assumed as the inception of anticipation, shown in Fig. 2(b). Fig. 2(c) shows the start point of the evaluation state during which the relative lateral distance of the two vehicles (FV and LC) exceeds a safe lateral distance after the inception of the anticipation state. In real driving maneuvers and during lane-changing, the FV keeps the safe lateral distance with the LC to observe the behavior of both the LV and the LC at the same time to ensure accuracy of anticipation and prevent collision with the LC. This safe lateral distance, investigated in [21], is named as y_{safe} and described as following.

$$y_{safe} = -0.2716 \exp(\text{Distance}) + 0.0116 \sin(V_{ave}) + 0.1585 \sin(a_{LC} - a_{FV}), \quad (1)$$

where, *Distance* is the relative longitudinal spacing between FV and LC, and V_{ave} , a_{LC} , and a_{FV} denote the average velocity of FV and LC, the longitudinal acceleration of LC, and longitudinal acceleration of FV, respectively. The ending point of evaluation, as depicted in Fig. 2(d), is the time at which the longitudinal distance between the FV and the LV decreases to the value of the modified Pipe’s law (S_{MP}) [21] denoted as

$$S_P = L \left(1 + \frac{V_{FV}}{4.47} \right), \quad (2)$$

$$S_{MP} = f S_P. \quad (3)$$

Where S_P is a distance suggested by the Pip’s law and S_{MP} is suggested by modified Pipe’s law, respectively. L is the length of FV, and V_{FV} is the velocity of FV. As shown in Fig. 3, f is a correction coefficient introduced in [21] proposed to define the end-point of evaluation behavior due to the human factor (t_{sc}), where $f = t_{sc}^{0.3026}$. In fact, Pipe’s law or modified Pipe’s law proposes an online safe longitudinal distance depending on the drivers’ velocity and length of their vehicles. In the end, the comparison of acceleration between the LC and the FV is shown in Fig. 2(e). Thus, in this paper, we aim to design an intelligent human-like controller based on the anticipation and evaluation behavior of the FV in [21].

B. Controller Design

As stated in Sections I and II, there are several types of controllers used in the previous studies. However, addressing the non-linearity of the behavior affected by the uncertainty (e.g., unknown disturbances and unknown dynamic parameters) and complexity of human logic as a controller, utilizing intelligent methods is necessary. In addition to the conventional control design strategies [31]–[34], nowadays, fuzzy logic and Artificial Neural Network (ANN) have drawn much attention in recent years in various domains such as [15], [16] owing to their ability to handle any forms of non-linearity perfectly. Compared to the conventional ANNs, ANFIS has some advantages over the classical back-propagation methods. ANFIS can generate an input-output mapping based on human knowledge and predetermined input-output data pairs using the hybrid algorithm [35]. The main advantage of this hybrid approach is the fast convergence due to the reduction of the search space dimensions used in common neural networks [35]. Additionally, the structure of the ANFIS is fixed, and it requires less justification than those are required in other ANNs. Also, the ANFIS structure allows for parallel computation to ease the use for real-time applications [36]. Therefore, due to the complexity of movement that we study in this paper, the ANFIS controller was employed:

1) *NGSim Dataset*: To train and test the ANFIS controller, the dataset proposed in [21], which includes 44 data subsets consisting the complex behavior, was used which was built on the U.S. Federal Highway Administrations Next Generation SIMulation (NGSIM) [37]. This dataset consists of 18 parameters, including longitudinal and lateral position, velocity, acceleration, time, lane number, vehicle class, etc., which were collected at 10 Hz frequency from the drivers. Before building the model, all the data related to trucks and motorcycles were excluded from

Fig. 2. The procedure of determining anticipation and evaluation states.

Fig. 3. Correction coefficient f as a function of t_{sc} [21].

Fig. 4. Inputs-output of fuzzy controller for anticipation and evaluation behaviors.

the dataset to secure a homogeneous model. Moreover, multiple successive lane changes are extracted to prohibit the effects of unfavorable lane-changing on the other vehicles of the network. Also, a moving average filter with a window size of 9 was applied to reduce the noise. A subset of the dataset including 33 sample data (75% of the entire dataset length) was randomly chosen to train the model, and the rest of the data, 11 sample data, was used to test the constructed ANFIS model [38].

2) *ANFIS Controller Design According to Anticipation and Evaluation Behavior*: One of the objectives of the fuzzy controller was to mimic the driver's behavior, while considering the efficient safety and maneuver duration. Therefore, before designing the controller, determining appropriate independent inputs and output is necessary. As the car-following behavior includes only longitudinal movements, the acceleration of FV, adjustable with the gas or brake pedal, is the only available parameter that describes the total movements of the FV (e.g., velocity and traveled distance). Thus, the fuzzy controller is able to satisfy the desire goals by adjusting the acceleration values, which is selected as the only output of the controller. The fuzzy system inputs that explain the anticipation and evaluation behavior in Section III-A are chosen based on the real human driving behavior and among the variable introduced in [21]. These inputs are shown in Fig. 4 and listed as follows: 1. The relative lateral distance between the FV and its front vehicle (which is LC before lane-changing and LV after lane-changing);

TABLE I
THE AVERAGE RMSE AND ACCURACY OF RUNNING ANFIS
ON THE TEST DATA (NGSIM DATASET)

MF type	trimf	trapmf	gbellmf	gaussmf
RMSE	0.852	2.3841	0.7491	0.7138
Accuracy	0.88	0.729	0.862	0.93
MF type	gaussm2f	pimf	dsigmf	psigmf
RMSE	0.7541	2.3812	0.7258	0.7258
Accuracy	0.854	0.740	0.876	0.871

2. the relative velocity of FV concerning its front vehicle; 3. the actual velocity of FV; and 4. the duration of the uncertainty state (t_{sc}), which is specific to each driver and it is regulated based on the level of awareness and of the driver. The larger the t_{sc} values belong to more careful drivers, i.e., the vehicles anticipate earlier the exiting vehicle and respond faster accordingly, and gradually relax to more spacing. Therefore, t_{sc} is an input to the fuzzy controller to take care of the influence of human driving behavior on the complex transient states. The inputs and the output of the designed intelligent controller are shown in Fig. 4. Obviously, the first three inputs are measurable through the sensors, and the last input, t_{sc} , is not measurable. As stated earlier, in this study, the ANFIS network was adopted to predict and control the behavior of the FV during anticipation and evaluation states. To do so, eight different membership functions (MF), including, Triangular (trimf) [39], Trapezoidal (trapmf), Generalized bell-shaped (gbellmf) [40], Gaussian (gaussmf), Gaussian combination (gauss2mf) [41], Pi-shaped (pimf) [42], Difference between two sigmoidal membership functions (dsigmf) [43], and Product of two sigmoidal membership (dsigmf) [44] were used in the ANFIS network. The Root Mean Square Error (RMSE) and the correlation coefficient (R^2) between the predicted values (controller output) and the actual training values were used to evaluate the performance of each MF, leading to the lowest modeling RMSE and highest correlation coefficient. The results of averaging the RMSE and accuracy for ten runs over 500 training epochs are summarized in Table I. According to the modeling results mentioned in Table I, among the tested membership functions, gaussmf leads to the highest accuracy and the least RMSE. Gaussmf utilizes the general form of a gaussian function, $f(x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}}$, where σ and c are the Standard Deviation (SD) and mean parameters, respectively. The

TABLE II
THE PARAMETERS OF THE ANFIS MODEL

Method/Parameter	Magnitude/Explanation
Training Method	Back-propagation
Clustering Method	Grid Partitioning (num of MFs: 3)
Input membership function	Gaussian (gaussmf)
Output membership function	Linear mapping
Loss function	RMSE (Root-mean-square error)
Number of training epochs	500
Least training error	10^{-5}
Input data pre-processing	1. Removing constant input 2. Input data normalization [0, 1]

final ANFIS network parameters, used in the further controller design, are listed in Table II. Moreover, the parameters corresponding to the membership functions of the four ANFIS inputs are listed in Table III. To assess the effectiveness of the parameter t_{sc} on performance of the controller, two controllers were built with the same structure and membership functions; however, the controller was firstly built without inputting t_{sc} and then t_{sc} was fed to the controller. The ANFIS rules were chosen to mimic an efficient, safe, convenient, and satisfying real driving behavior that resulted in 81 fuzzy rules. Fig. 5 shows four of these rules (1, 28, 55, and 81) in which the center of the largest area is used for defuzzification. To study the sensitivity of the controller inputs changes to its output changes, the level of control is shown in Fig. 6. Regarding the figure, the control level attained through the FV acceleration depicts a flat area around the employed range of output, and inputs of the controller reached steady, which explains the acceptable level of design relationships, sensitivity, and robustness of the controller output to its inputs.

IV. EXPERIMENT SET-UP

In order to collect real data and evaluate the designed controller, a real-life experiment was conducted in Daneshgah Boulevard, Tehran, Iran. The aerial map of the test location is shown in Fig. 7(a) with white rectangular and Fig. 7(b) with red rectangular. The reported speed limit in this boulevard was $60 \frac{km}{hr}$ and there was no on-ramp, off-ramp, and lane-drops in this street. All the vehicles were at 12 pm o'clock relative to the FV at the beginning of the test. The vehicles contributed to the experiment were a 206-series Peugeot (FV), a Pars-series Peugeot (LV), and a Samand (LC). As will be explained later, to detect the LV and LC better, they were marked by a piece of green and red fabric, respectively, which were attached to the trunk of these vehicles. The sensing device attached to the front side of the FV to measure the dynamics parameters (including the acceleration of the FV and relative position and relative velocity of the LV and LC) using the vision, distance meter, and IMU sensors and transfer the data through a microcontroller to a laptop, running MATLAB 2018a for analyzing and storing the data. The scenario is measuring the position and velocity of the front vehicle and the FV, and acceleration of the FV, and then comparing the real driver behavior of the FV with the controller.

Thus, the controller output is just for comparison and is not implemented on the vehicle.

A. Sensors

To install the required sensors on the FV, a CAD model was first designed in Solidworks software and then fabricated using laser-cut thick 15 mm Plexiglass sheets to hold the sensors and a metallic bracket to be attached to the vehicle (Fig. 8 and Fig. 9(a)). Then the sensors and a microcontroller were mounted on the fabricated frame. An analog ADXL335 accelerometer was used to measure the FV acceleration. Also, an A4Tech PK-710 G camera (30 f/s) and a UT390B distance-meter which was placed on a Dynamixel mx-64 DC motor, were installed to measure the relative position and velocity of the LC and LV. In addition, as shown in Fig. 9(b), an incremental rotary encoder with the resolution of 200 pulses/rev were placed on the rear wheel of the vehicle to measure the actual position, and velocity of FV, similar to the setup in [45]. An Arduino Mega 2560 was used to take the samples from the analog sensors and transfer the FV acceleration data to a laptop running MATLAB 2018a. Once the setup was ready, from the FV view, the relative position of the other two vehicles was expressed in the polar coordinate. Therefore, the distance and the relative angle of LV and LC were required.

To do so, an image processing algorithm was written in MATLAB, which was capable of finding the LC and LV based on the shape and the color of the fabric pieces placed on their trunk. Once the targeted vehicles were found in the image, the Dynamixel DC motor was commanded to rotate the UT390B distance-meter toward the targeted vehicle to measure the distance and the velocity of LC and LV relative to the FV. The final frequency of running the script in a *while* loop in MATLAB, was obtained as 8 Hz. The details about the fabricated sensing device components (numbered in Fig. 8(b)) are described in Table IV.

B. Sensing Hardware-Software Integration

In this section, the integration of the system's components is discussed. As extracting the vehicles' movement information was not a simple task due to natural disturbances, this requires the accomplishment of three steps, shown in Fig. 10: 1. Image objects calibration; 2. Lane change detection; and 3. Measurement of the front-vehicle dynamics states. These three steps are highlighted by blue, gray, and orange color, respectively, in Fig. 10.

In summary, in the first stage, the actual thresholds for red (thr_{d_G}) and green (thr_{d_R}) color were calibrated, and the shape boundaries of r_R , and r_G for the rectangular fabric pieces attached to the LC and LV vehicles were calculated using the first 80 frames acquired by the camera at the beginning of the experiment, and before the vehicles start to move. Since the designed sensing system is able to track one vehicle at a time, in the second step, the areas of the red and green objects are compared to determine which vehicle is targeted by FV (via R_{LC} ratio) to be tracked through the laser distance meter. After the position of the target vehicle (either LC or LV) was found in the image, the distance sensor was rotated towards the target

TABLE III
RANGE ([MIN, MAX]), CENTER (c), AN STANDARD DEVIATION (σ) OF THE ANFIS INPUTS MEMBERSHIP FUNCTIONS

	Relative velocity		Relative lateral distance		Velocity of FV		t_{sc}	
	Range	$[\sigma, c]$	Range	$[\sigma, c]$	Range	$[\sigma, c]$	Range	$[\sigma, c]$
MF 1	[-4.3, 3.7]	[1.9, -4.2]	[0.0, 3.7]	[0.2, -0.2]	[4.6, 10.0]	[0.9, 4.6]	[0.1, 2.3]	[2.3, 1.9]
MF 2	[-4.3, 3.7]	[1.6, -0.3]	[0.0, 3.7]	[0.3, 1.8]	[4.6, 10.0]	[0.7, 7.1]	[0.1, 2.3]	[0.1, 0.2]
MF 3	[-4.3, 3.7]	[1.8, 3.6]	[0.0, 3.7]	[0.9, 3.6]	[4.6, 10.0]	[1.2, 9.9]	[0.1, 2.3]	[0.8, 1.8]

Fig. 5. Rule viewer of the final controller with t_{sc} .

Fig. 6. Fuzzy surfaces for the intelligent controller. (a) Acceleration of controller, based on relative lateral distance and velocity of FV. (b) Acceleration of controller, based on velocity of FV and relative velocity.

Fig. 7. A segment of Daneshgah Boulevard in Tehran, Iran. (a) Satellite view. (b) Schematic view.

Fig. 8. Sensing device. (a) Designed in SolidWorks. (b) Manufactured.

vehicle to extract the required information. The details of these steps are explained as follows:

1) *Image Objects Calibration*: Detecting the red and green rectangular shape objects in the image is the most crucial step to be done. Without finding the objects, the other two steps could not be completed, and extracting the LC and LV's movement information was not possible. Therefore, in this step, we proposed a robust algorithm which was based on finding the threshold

Fig. 9. The test-bed. (a) Final sensing device installed on Peugeot 206 series. (b) Encoder used to measure current velocity and position of FV [45].

TABLE IV
COMPONENTS OF THE FINAL PRODUCT IN FIG. 8

Part Number	Description	Application
1	UT390B digital distance meter	Measuring distance
2	A4TECH camera	Identifying desired vehicle
3	ADXL335 accelerometer	Measuring acceleration
4	Arduino Mega2560	Computing unit
5	Dynamixel mx64 motor	Twisting laser to desired direction
6	Holders of laser	Maintaining the laser and adjusting around X axis
7	Laser base	Motor and laser connector
8	Camera base	Motor and camera connector
9 and 10	Accelerometer and Arduino retainer plates	The site of the sensors, motor and camera
11	Holder of accelerometer	Retaining accelerometer with ability of twisting that around X and Z axis
12	LW-125 base	Main base with ability of twisting all parts around X and Y axis

for converting the red and green layers of the camera RGB frames e.g., Fig. 11(a), to binary images such that the desired objects were visible and detectable in the images. To do so, 80 frames were acquired from the camera at the beginning of the experiment prior to the movement of the vehicles. Then, the red and green layers of the images were taken and processed separately to find the threshold for converting the grayscale images to binary. To find the appropriate threshold ($thr(k)$, where k is the frame index) for each layer, the intensity level was incrementally increased from 0 to 1 at a rate of $\frac{1}{80}$. For each increment, the

Fig. 10. The proposed method to measure the front vehicle dynamic states process.

Fig. 11. The effect of threshold variation of red color on the processing of finding the desired object. (a) Original image. (b) Binary image with a low threshold. (c) Binary image with suitable threshold. (d) Binary image with a high threshold.

number of the detected objects in the image was found. Finally, the median value for intensity level was calculated for all the binary images in which there was only one object found. For instance, the threshold of 0.128 was not favorable in Fig. 11(b) as there are four objects found according to Fig. 12(a). Also, the area of the object found in Fig. 11(d) is relatively small and could easily be identified as noise. Therefore, the suitable threshold of 0.204 in Fig. 11(c) was chosen, which is the median value for

Fig. 12. (a) Count of detected red object by variation of threshold. (b) Distribution box plot for red and green color threshold. (c) Processing of computing r limitation using recorded frames in the first 80 frames. (d) Variation of R_{LC} with respect to the frame number with the presence of both red and blue.

the intensity level of the red color reported in Fig. 12(b). The optimum threshold for the green color was found to be 0.248 with the same approach.

Furthermore, since it was likely that other red and green objects appeared in the image throughout the experiment, another criterion was found to increase the robustness of the object detection algorithm, which was based on the ratio of the area and perimeter of the objects in the acceptable frames (where only one object was found in the images). Accordingly, the shape ratio, $r = \frac{A}{P^2}$ was calculated for the objects where A was the object area, and P was the object perimeter measured in pixel. As demonstrated in Fig. 12(c), the maximum and minimum values of r for red and green colors, was computed as $r_r \in [1.1081 \times 10^{-6}, 1.6186 \times 10^{-6}]$ and $r_g \in [1.0112 \times 10^{-6}, 1.7038 \times 10^{-6}]$, respectively.

2) *Lane Change Detection*: The sensing system was able to track only one vehicle at a time. Therefore, it was necessary that the sensing system quickly switched between the LC to LV to track the LC before completion of the lane-changing task and track the LV after that. Therefore, R_{LC} parameter was introduced as $R_{LC} = \frac{A_R}{A_G}$, where A_R was the area of the red object and A_G was the area of the green object, both measured in pixel. This parameter can be representative of the current position of the LV and LC, i.e., when the red object is far from the green object, R_{LC} is supposed to be a small value, as the A_R is less than A_G . At the time that the lane change task was completed, it was expected that A_R and A_G were approximately equal because the size of the red and green fabrics was roughly equal in reality. Based on the experimental data, R_{LC} was calculated as 0.9 for this moment. Fig. 12(d) shows the variation of R_{LC} for 80 frames of a real maneuver.

3) *Measurement of the Front-Vehicle Dynamics States*: In this step, after detecting the target vehicle, its relative angular position from FV was estimated using the image processing algorithm proposed and discussed earlier. Then the serial commands were sent through the UART protocol to the Dynamixel motor to rotate the laser distance meter towards the target vehicle.

Fig. 13. Closed-loop control diagram regarding anticipation and evaluation behavior. (a) Including the plant of FV. (b) Schematic structure of the process.

V. RESULTS AND DISCUSSION

We compared performances of the proposed final controller including t_{sc} with the controller excluding t_{sc} , the Controller based on the model in [4], the Controller in [46], the test data subset extracted from NGSim dataset [37] and the sensing device, as the real driver. Briefly, the model in [4] introduces the relative longitudinal acceleration between the FV and its front vehicle as a novel input for their ANFIS model. However, this input is susceptible to noise in practical applications, and thus the method has solid restrictions. Likewise, the controller proposed in [46] employs the relative longitudinal distance instead of the relative longitudinal acceleration. Although the input is supposed to be less sensitive to the noise comparing to [4], this models also lack considering the human safety and convenience, which we know that as t_{sc} as a human factor in our study.

A. Results Via NGSim Data

To examine the controller built with the NGSim data, it was placed in a closed-loop system, shown in Fig. 13(a). As shown in Fig. 13(a) and (b), the NGSim dataset did not only contribute to design the fuzzy controller but also to estimate the t_{sc} which was also inputted to the controller. In the proposed system of Fig. 13(b), t_{sc} is estimated online based on an estimator which explains t_{sc} through the velocity and the position of FV and LC, which is one of the inputs of the intelligent controller. Accordingly, the lateral distance and longitudinal traveled distance of the front vehicle and the lateral distance of FV were taken from the NGSim data at each time instant. The longitudinal traveled distance (X_{FV}) and the actual velocity of the FV (V_{FV}) were directly obtained from the controller output, FV acceleration (a_{FV}). It is worth mentioning that the plant used in the closed-loop system of Fig. 13(a) is a linear system previously used in [21] and works based on estimation of V_{FV} and X_{FV} from the integration of the nonlinear controller output, the FV acceleration, using the adaptive Kalman filter [47].

Addressing the objective goal of this study, the designed controller should generate the FV acceleration and velocity that mimics the real driver behavior subject to the passengers' comfort and safety. In this regard, the quality of the replicating real driver performance is studied by comparing the similarities level of the traveled distance trajectory for the controller with the driver. The comfort is explained as the smoothness level of the generated acceleration and velocity of the controllers and

Fig. 14. Simulation results. (a) Longitudinal traveled distance. (b) Current position. (c) Velocity. (d) Acceleration. (e) Relative longitudinal distance. (f) Error with modified safe distance.

the driver during the maneuvers. Finally, the safety is defined by comparing the followed longitudinal distance of the controllers or the driver with the safe longitudinal distance known as modified Pipe's law in [21].

Aiming to the similar behavior, the trajectories of traveled distance by the controllers and the driver according to time and lateral coordinate are depicted in Fig. 14(a) and (b) respectively. The trajectories are comparable, as they have the same initial conditions, show that the controller with t_{sc} follows a similar path with the lowest deviation from the real driver's path.

To study comfort criterion, smoothness of the velocity and the acceleration generated by the controllers and the driver is investigated. Looking at Fig. 14(c) and (d), the trajectories reveal less fluctuation for the velocity and acceleration of the controller with t_{sc} than the real driver and other controllers, which determines smoother velocity and acceleration generation of the FV for controlled-case than the human logic decision and the proposed controllers. In addition, the quantitative results of the velocity variance of the controllers with the driver using the NGSim dataset are summarized in Table V. Regarding the table, the FV velocity trajectories that were generated by the controller with t_{sc} was 55% smoother than the controller without t_{sc} , 37% smoother than the controller generated based on the model in [4], 27% smoother than the controller in [46], and finally 79% smoother than the real driver. Similarly, the acceleration variances listed in this table also states that the controller with t_{sc} performs relatively better than the other controllers such that it is 20% smoother than the controller designed based on the model in [4], 6% smoother than the controller in [46], and 37% smoother than the real driver in terms of the acceleration variance. However, the acceleration variance for the controller

TABLE V
REPORTED RESULTS FOR THE TESTS USING THE NGSIM DATA AND THE EXPERIMENT TESTS

	NGSim data						Sensing device					
	variance						variance					
	Velocity $\frac{m}{s}$		Acceleration $\frac{m}{s^2}$		Error with S_{MP} (m)		Velocity $\frac{m}{s}$		Acceleration $\frac{m}{s^2}$		Error with S_{MP} (m)	
	The test	All tests	The test	All tests	The test	All tests	The test	All tests	The test	All tests	The test	All tests
Controller with t_{sc}	0.3049	0.3233	0.3099	0.4051	1.059	2.341	0.5885	0.5442	0.6134	0.6893	5.953	5.014
Controller without t_{sc}	0.6705	0.7143	0.0621	0.074	9.084	10.591	0.6101	0.6733	0.9851	1.0023	14.96	16.274
Controller based on the model in [4]	0.4835	0.5101	0.4943	0.5002	14.32	12.93	0.7132	0.7309	1.2271	1.2803	29.32	31.77
Controller in [46]	0.4234	0.4441	0.3933	0.4289	8.295	9.591	0.6842	0.7011	1.1025	1.1322	33.91	31.42
Real driver	1.6262	1.5381	0.6705	0.6387	3.529	5.182	1.8424	1.8991	1.3267	1.4108	0.2195	3.998

without t_{sc} is considerably lower than the other cases, which might seem to be good to some extent, but it may also lead to slow reaction and the conservative movement and consequently large relative longitudinal distance and traffic queue. To assess the safety of the drive followed by the controllers, the Pipe's law (2) and the modified Pipe's law [21], were used. Therefore the error between the modified Pipe's law and the longitudinal distance between the FV and the LV that is produced by the controllers throughout the experiments were calculated and reported as a measure for driving safety. The longitudinal distance of the controllers, the real driver, the Pipe's law, and the modified Pipe's law are demonstrated in Fig. 14(e). Also, the absolute error between these longitudinal distances and the values computed from the modified Pipe's law equation over time is shown in Fig. 14(f). The average for these errors are mentioned in Table V. It should be noted that these plots, correspond to an aggressive driving with $f = 0.7$ derived from (3) ($S_P = 14$ m, and $S_{MP} = 10$ m). According to Table V the human-like fuzzy controller accounts for the lowest average error of 2.341 m overall tests, which is 79% lower than that of the controller without t_{sc} , 81% lower than the controller designed based on the model in [4], 75% lower than the controller of [46], and 55% lower than the real driver.

The obtained simulation results emphasize that the designed human-like controller accounting for t_{sc} can make safe and comfortable decisions such that the followed safe distance, the variance of the velocity, and acceleration over all the tests were minimized, led to fewer traffic queues.

B. Results Via Experimental Data

To evaluate the designed controllers in practice, the real data were collected using the sensing device developed in Section IV. In total, 15 experiments were conducted. However, 5 experiments were eliminated from the dataset as no lane-changing happened due to safety or the road was terminated. Therefore, the data of 10 experiments were contributed to assess the controllers' performance. In this section, the results of just one experiment are detailed, and the results of the rest of the experiments are mentioned in Table V. Unlike the previous section, the inputs of the fuzzy controller in Fig. 13 were measured or estimated i.e., t_{sc} , directly from the sensors installed on the FV. According to Fig. 15(a) and (b), visually, the real driver movement was

Fig. 15. Experiment results. (a) Longitudinal traveled distance. (b) Current position. (c) Velocity. (d) Acceleration. (e) Relative longitudinal distance. (f) Error with modified safe distance.

very close to the estimated values by the developed intelligent controller. Also, as depicted in Fig. 15(c) and (d), the estimated acceleration and velocity of the FV were smoother than those of the real driver. The quantitative results of comparison between the real driver data and the data resulted from the controllers with and without t_{sc} and the ones proposed in [4] and [46] are mentioned in the sensing device section of Table V. Regarding the table, it can be seen that the variance of acceleration and velocity of the controller with t_{sc} was relatively lower than the other controllers and even the real driver. In this regard, the acceleration variances over all the experiments, were 20%, 25%, 22%, 71% lower than the controller without t_{sc} , the controller based on [4] and [46], and that of the real driver, respectively. Similarly, the velocity variances were respectively 31%, 46%, 39%, 52% lower than the aforementioned controllers. These low variances lead to more comfortable travel for the passengers and less fuel consumption. Furthermore, to investigate the maneuver

safety, the followed longitudinal distances were estimated and compared with the real driver data and the other mentioned controllers. Fig. 15(e) belongs to a conservative driver with $f = 1.3$ from (2) and (3) where $L = 3.8$ m, $V_{FV} = 7$ m/s, and $S_{MP} = 12.5$ m. The error between the modified Pipe's law and the controllers' output is shown in Fig. 15(f). Also, the average value for these absolute errors is reported in Table V. Accordingly, this error value for the controller with t_{sc} was 70%, 84%, and 84% lower than for the controller without t_{sc} and the controller extracted from [4] and [46]. Although the real driver keeps the same level of distance to the modified Pipe's law as the human-like controller (same level of safety), the human-like controller maintains about averagely of 60% more comfort than the real drive, which is a considerable improvement comparing to the other assessed control methods.

VI. CONCLUSION

Anticipation and control before and during the complex merging behavior subject to neighboring vehicles are substantially necessary to enhance the safety, ride comfort, and acceptability of the intelligent car-following strategy. In this study, a human-like fuzzy car-following controller for the anticipation and evaluation behavior is proposed while exiting the LC. The human factor is determined as the duration of the introduced uncertainty state, employed as one of the controller's inputs. The controller is designed based on the results of real on-road datasets and assessed through naturalistic experiments. In terms of validation, the fuzzy controller performance is compared with three other controllers designed with NGSim data, and the driver behavior of the NGSim data, and the driver behavior data collected experimentally online via a novel sensing device. Results show that the intelligent controller recommends averagely 70% shorter longitudinal safe distance and 38% more comfortable drive than the real drivers and other compared controllers, aims to homogeneous traffic flow with shorter traffic queues, safer and more pleasant drive. Future developments could be developing an intelligent model and control strategy to anticipate the behavior of LC, which will be a complementary achievement to this study.

ACKNOWLEDGMENT

The authors would like to thank Prof. Claudio Roncoli (Aalto University) for the useful discussions.

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