

Received May 15, 2020, accepted June 7, 2020, date of publication June 10, 2020, date of current version June 19, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3001208

A New Single Point Preview-Based Human-Like Driver Model on Urban Curved Roads

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This work was supported in part by the National Natural Science Foundation of China under Grant 51675235, and in part by the Innovation Plan for Postgraduate Research of Jiangsu Province in 2014 under Grant KYLX1057.

ABSTRACT To make intelligent vehicles obtain human drivers' steering characteristic, a new single point preview-based human-like driver model is proposed, which contains a preview decision module and a steering wheel angle calculation module. Enlightened by the visual gaze mechanism of human drivers when passing a curved road, the preview decision module is established using Takagi-Sugeno fuzzy inference system (T-S FIS) to adaptively adjust the preview point position in both longitudinal and lateral direction, and the steering angle calculation module would use the adjusted preview point to generate steering command based on pure pursuit algorithm. Ant colony optimization (ACO) method is used to optimize the fuzzy rules in the preview decision module according to the similarity of trajectories between the proposed driver model and human drivers. The proposed human-like driver model is verified on a two-lane urban curved road. Five experienced human drivers' driving trajectories under different speeds are collected for the verification. After the preview decision module optimization done in the PreScan/Simulink simulation platform, the proposed human-like driver model shows higher similarity with experienced human drivers than the driver model with fixed preview distance or the driver model only with changeable longitudinal preview distance.

INDEX TERMS Single point preview control, driver model, human-like, fuzzy inference system, ant colony optimization.

I. INTRODUCTION

With the developments in both artificial intelligence and sensor technology, vehicles with high-level driver assistance system or even automated vehicles (AVs) would become available in the near future, and there is no doubt that the vehicles manipulated by human drivers and AVs would share the road together [1]. To make the traffic flow more harmonious, it is good to let AVs obtain human drivers' steering characteristic, which could release the mental pressure of human drivers dealing with surrounding AVs. In addition, driver models developed for AVs are mostly concentrate on tracking accuracy and controlling stability, however human-like driver model, especially human-like steering control driver model is rarely researched [2].

Establishing a steering control driver model mainly consists of two parts. The first one is the selection of tracking reference, and the second one is the way to derive the steering wheel angle. The tracking reference refers to the target

points or direction which the vehicle need to pursuit, and it can be divided into look-down reference and look-ahead reference [3]. For the look-down reference, the vehicle would track a point that is close to the vehicle body, which can be seen in the path tracking tasks where additional magnetic markers or wires are installed on the desired vehicle path [4], [5]. For the look-ahead reference or so called preview reference, target points are set far from the vehicle body, and the distance between target point and the vehicle is typically called look-ahead distance or preview distance. Seeking for the tracking performance, the tracking target could vary from one point [6](single-point preview) to two points [7](two-point preview) or even multi-points [8](multi-point preview). Although two different references could be both used to design driver model, Peng *et al.* [9] proposed that preview reference is necessary when vehicle reaching a relative high speed, which explains the trend where preview reference is more popular in building a driver model.

For the second part of a steering control driver model design, steering wheel angle can be obtained based on geometry method, vehicle dynamic or intelligent algorithm.

The associate editor coordinating the review of this manuscript and approving it for publication was Shun-Feng Su¹.

The Ackerman relationship is used in the geometry method to derive the steering wheel angle, and one of the most popular algorithm is the pure pursuit algorithm, which have already applied in the real path tracking task due to its simplicity and high efficiency [10], [11]. To avoid slipping and tire deformation to lower the tracking performance, linear or nonlinear vehicle model are applied to derive the steering angle [12], [13], which do improve the tracking ability under the situations of facing high vehicle speed or complex road surface but increase the calculation amount of the driver model. The third method is using intelligent algorithm (IA) such as Fuzzy control [14], Genetic Algorithm (GA) [15], Particle Swarm Optimization (PSO) [16] or neural networks (NNs) [17], [18] for modeling, and the applied strategy can be divided into two different ways. The first option is to combine IA with the traditional driver model to dynamically adjust or optimize the preview distance or gain for the angle calculation so that the tracking performance of these driver models can be improved. The second option is called “end-to-end” driving control, which trains a NNs using naturalistic driving data to directly derive steering wheel angle according to the front image. The “end-to-end” method looks more similar with a human driver’s driving process, but it would encounter potential failure when the vehicle facing different scenarios from the training data set.

Though steering angle calculation method is crucial for the tracking accuracy and stability of a drive model, the overall steering characteristic is mainly depend on the tracking reference setting [19]. Researchers tend to use preview reference in their driver models, which do replicate the preview mechanism of a human driver, however the specific implementation of the preview reference still exists controversy [20]. The assumptions of preview-based tracking reference can be divided into two types: the first type was raised by Land and Lee in 1994, which assumed that the driver would gaze at the tangent point of inner road edge when passing a curve road [21]; the second type was raised by land in 1998, which assumed that the driver would gaze at the point on a future path of vehicle [22], and the path is typically the road center. Two assumptions have been both widely applied in driver models, and there is no specific evidence that shows which assumption is better in path tracking performance [23]. Some researchers use eye tracker device to directly analyze the preview mechanism of human driver. Lehtonen *et al.* pointed out that drivers would focus at near points with temporally switching to far points during driving process [24]. Based on drivers’ eye motion data, Robertshaw *et al.* claimed that drivers would not focus on the tangent point all the time when they passing a curve, and the gaze point would be changeable in the lateral direction of the road [25]. Though longitudinal visual gaze mechanism has already been applied in some driver model research [26], [27], the lateral preview point position adjustment characteristic is rarely saw in the preview reference establishment.

In this paper, enlightened by the human drivers’ visual gaze mechanism researches, we firstly build a new preview

decision module which can adaptively adjust the preview point position in in both longitudinal and lateral direction, using Takagi-Sugeno fuzzy inference system (T-S FIS). Combined the new preview decision module with a steering angle calculation module based on pure pursuit algorithm, a new single point preview-based human-like driver model is proposed. An ant colony optimization (ACO) method is used to optimize the fuzzy rules in the proposed human-like driver model according to the similarity of trajectories between the driver model and human drivers. To verify the human-like steering characteristic of driver models, five experienced drivers’ driving trajectories under different speeds are collected on a two-lane urban curve road. After the optimization done in the PreScan/Simulink platform, the proposed human-like driver model shows higher similarity with experienced human drivers than the driver model with fixed preview distance or the driver model only with changeable longitudinal preview distance, which shows the advantage of the proposed driver model in performing a human-like steering control characteristic compared with two other driver models. The novelty of the paper is expanding the adjustment mechanism of the preview point from only longitudinal direction to both longitudinal and lateral direction, which is proved to be able to let the driver model have a similar steering characteristic with human drivers. The main contributions include the following:

- 1) A new single point preview-based human-like driver model is proposed, which can adaptively adjust preview point position in both longitudinal and lateral direction.
- 2) An ACO method is applied in the fuzzy rules optimization of the proposed human-like driver model, which is able to improve its steering characteristic similarity with experienced human drivers’.
- 3) The simulation results of different driver models prove that the lateral adjustment of preview point position can greatly change the steering characteristic of a driver model, and it is necessary for a driver model obtaining human-like steering characteristic.

The reminder of the paper is organized as follows. Section II proposes the method of establishing the new single point preview-based human-like driver model. Optimization method based on ACO for tuning the fuzzy rules in the proposed human-like driver model is given in Section III. For the model verification, Section IV firstly shows the experiment process and results for collecting experienced drivers’ driving trajectories, then the simulation results of optimized human-like driver model with two other driver model are compared based on PreScan/Simulink platform. Finally, conclusions are made in Section V.

II. SINGLE POINT PREVIEW-BASED HUMAN-LIKE DRIVER MODEL

Different settings of preview reference can greatly influence a driver model’s steering control characteristic and tracking performance. To build a human-like driver model, the model should obtain similar preview mechanism with

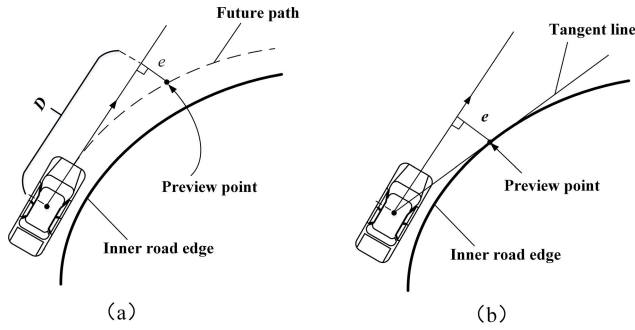


FIGURE 1. Traditional preview references: (a) Future path reference; (b) Tangent point reference.

human drivers'. Learning from the researches of human drivers' visual gaze mechanism, a new single point preview based human-like driver model is proposed in this Section, which contains a preview decision module based on T-S FIS and a steering angle calculation module based on pure pursuit algorithm.

A. PREVIEW REFERENCE

For most driver models, their preview references are set as the point on future path (FP) or tangent point (TP) with front inner road edge, as shown in Figure 1. For FP preview reference, the preview point can be adjust in the longitudinal direction by setting different preview distance, which is D in Figure 1(a). The tracking performance of the driver model can be improved by adaptively adjust preview distance according to the vehicle current tracking error and road curvature [26], which simulates the near-far scanning behavior of human drivers [28]. For TP preview reference, it can be combined with FP preview reference, which allow the driver model preview the far TP and near FP point [29]. However, none of them fully represents human drivers' preview mechanism, since drivers would also adjust their visual gaze point in the lateral direction on the road during driving process [25].

To realize human-like preview mechanism, the preview reference used in this paper is shown in Figure 2. The preview point is determined by the preview distance D and lateral adjustment distance LD . D represents the longitudinal distance between the preview point and vehicle in the direction of vehicle heading, which is the same with FP reference. LD refers to the adjustment distance of the preview point position in the vertical direction of vehicle heading, which represent the preview point's lateral adjustment of human drivers. When LD equals to 0, the preview point would fall on the lane center, which is the same with FD reference. When LD smaller than 0, the preview point would move close to the inner edge road, and it would switch to opposite direction when LD larger than 0.

Steering characteristic is the main research object in this paper. Therefore, to neglect speed control effect, the vehicle is assumed driving under a constant speed. Giving an overall consideration of current longitudinal adjustment of preview point position mechanism [26], [27] and visual

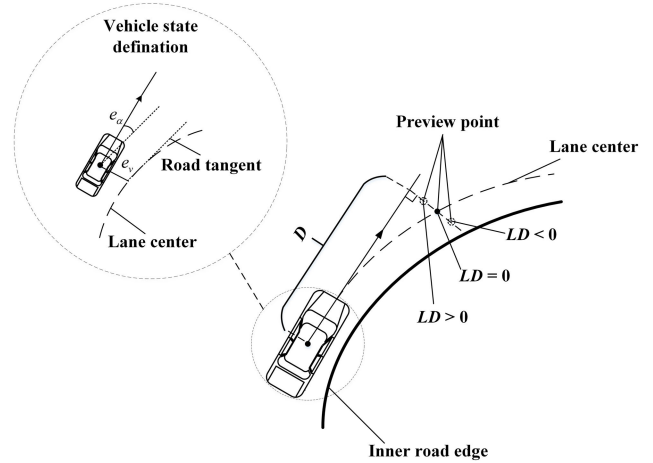


FIGURE 2. The proposed preview reference.

gaze mechanism researches of human drivers [24], [25], [28], we have made following assumptions of preview point position adjustment mechanism under constant vehicle speed:

- 1) Preview distance (D) should be adjusted according to current vehicle state (current tracking error e_v and current heading error e_α , the definition has been given in Figure 2), which represent the longitudinal direction adjustment of the preview point.
- 2) D and lateral adjustment distance LD should be adjusted according to current road curvature ρ .
- 3) LD should be adjusted according to D , when the vehicle passing a curve road.

B. PREVIEW DECISION MODULE

To realize the adaptive preview point position adjustment mentioned above, a preview decision module based on zero-order T-S fuzzy inference system (FIS) is proposed in this part.

T-S fuzzy inference system was firstly raised by Takagi and Sugeno in 1985 [30], and zero-order T-S FIS has been widely used due to its simplicity [31], [32].

A rule used in zero-order TS FIS for n inputs has the form:

$$R_l : \text{IF } x_1 \text{ is } A_1^l \text{ and } \dots \text{ and } x_n \text{ is } A_n^l \text{ THEN } f_l = K_l \quad (1)$$

where x_i is the input variable in FIS, A_i^l is the fuzzy set of x_i under rule l , K_l is the consequent parameter of the FIS output f_l under rule l . A typical T-S FIS fuzzy network structure is shown in Figure 3.

As shown in Figure 3, the network structure has 5 layers. In Layer 1, the fuzzification would be done on all input variables, using membership function to derive fuzzy membership for all input variables. The membership functions used in this paper are shown in Figure 5. In Layer 2, the firing strength ω_l of each rule l , is calculated using Equation 2:

$$\omega_l = \prod_{i=1}^n \mu^{A_i^l}(x_i) \quad (2)$$

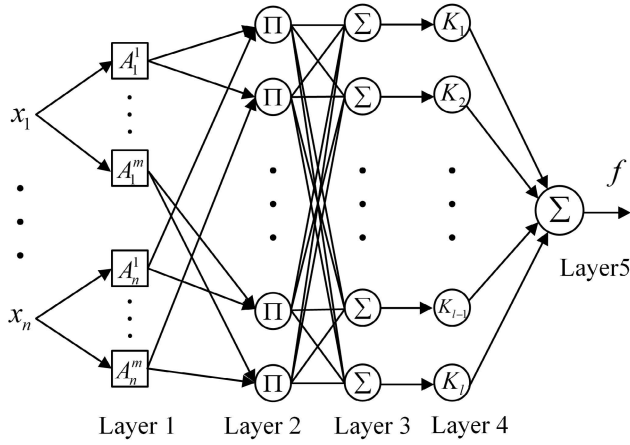


FIGURE 3. Zero-order T-S FIS network structure.

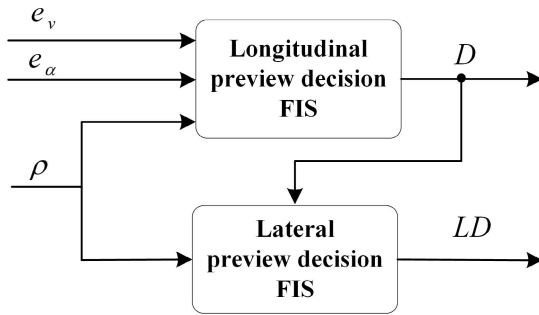


FIGURE 4. Preview decision module.

where $\mu^{A_l^i}$ represents the fuzzy membership of impute x_i under rule l calculated in layer 1. The normalized firing strength $\bar{\omega}$ is calculated in layer 3 using Equation 3:

$$\bar{\omega}_l = \frac{\omega_l}{\sum_l \omega_l} \quad (3)$$

The defuzzification process is completed in layer 4 and layer 5, and final output f of FIS can be calculated by following Equation:

$$f = \sum_l \bar{\omega}_l K_l \quad (4)$$

Based on the T-S FIS above, the preview decision module is built as the structure in Figure 4, which contains two independent FISs to respectively generate D and LD . A fuzzy rule in the longitudinal preview decision FIS has the form:

$$R_l : \text{IF } e_v \text{ is } A_1^l \text{ and } e_\alpha \text{ is } A_2^l \text{ and } \rho \text{ is } A_3^l \text{ THEN } D = K_D^l \quad (5)$$

where $A_1^l, A_2^l, \text{ and } A_3^l$ are the fuzzy sets of e_v, e_α, ρ respectively under rule $l(l=1,2,3..L)$. K_D^l is the consequent parameter for preview distance D under rule l . Based on Equation 2 to 4, the preview distance D can be derived as:

$$D = \frac{\sum_{l=1}^L \mu^{A_1^l}(e_v) \mu^{A_2^l}(e_\alpha) \mu^{A_3^l}(\rho) K_D^l}{\sum_{l=1}^L \mu^{A_1^l}(e_v) \mu^{A_2^l}(e_\alpha) \mu^{A_3^l}(\rho)} \quad (6)$$

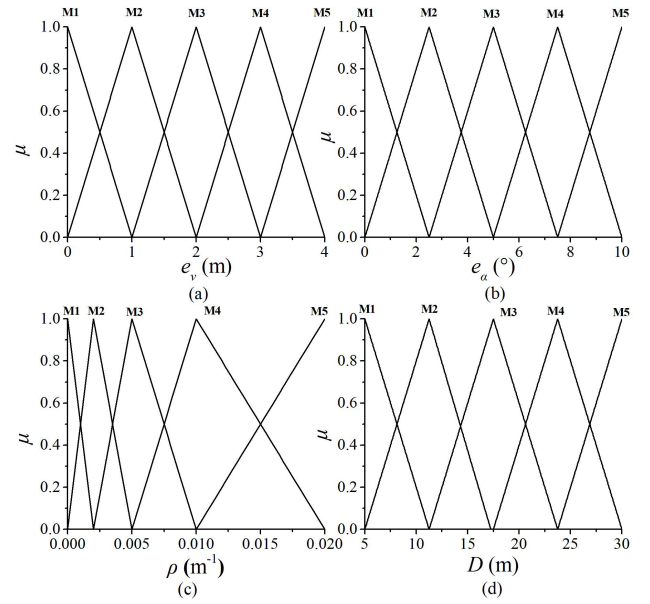


FIGURE 5. Fuzzy membership functions: (a) vehicle tracking error; (b) vehicle heading error; (c) road curvature; (d) preview distance.

Similarly, A fuzzy rule in the lateral preview decision FIS has the form:

$$R_l : \text{IF } \rho \text{ is } A_3^l \text{ and } D \text{ is } A_4^l \text{ THEN } LD = K_{LD}^l \quad (7)$$

where A_4^l is the fuzzy set of current preview distance D , K_{LD}^l is the consequent parameter for lateral adjustment distance LD under rule l , and the LD can be derived as:

$$LD = \frac{\sum_{l=1}^L \mu^{A_3^l}(\rho) \mu^{A_4^l}(D) K_{LD}^l}{\sum_{l=1}^L \mu^{A_3^l}(\rho) \mu^{A_4^l}(D)} \quad (8)$$

The fuzzy membership function for each input variable are showed in Figure 5. In this paper, we use trigonometric membership function to realize the fuzzification. The value ranges for the input variables of current vehicle tracking error e_v , current vehicle heading error e_α , current vehicle preview distance D , are $e_v \in (0, 4)\text{m}$, $e_\alpha \in (0, 10)^\circ$, $D \in (5, 30)\text{m}$. As shown in Figure 5(a), (b), and (d), each variable is divided into 5 fuzzy sets averagely. For the road curvature ρ , the fuzzy sets are divided into 5 parts by the principle of its coordinate radius, which is the reciprocal of ρ , larger than 500 m, between 500 m and 200 m, between 200 m and 100m, between 100 m and 50 m, smaller than 50 m, as shown in Figure 5 (c).

C. STEERING CALCULATION MODULE

Pure pursuit algorithm is widely used in the path tracking of autonomous vehicles, especially in the practical applications. The basic idea of pure pursuit is making the vehicle drive though a constant curvature trace to reach the preview point. To cooperate with the proposed preview decision module, we have modified the original pure pursuit algorithm in following two aspects:

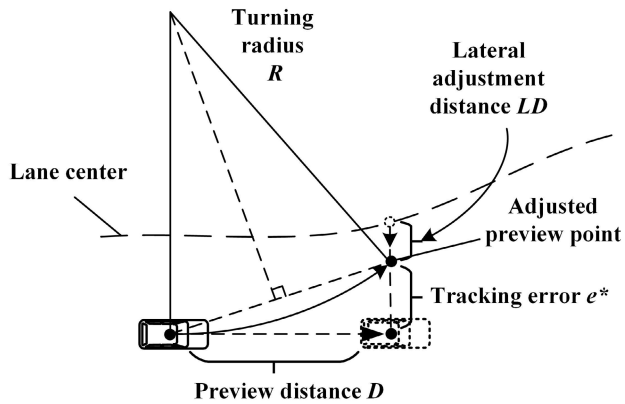


FIGURE 6. Steering angle calculation based on pure pursuit algorithm.

- 1) The preview point is not always on the lane center, and it would be adjusted in both longitudinal and lateral direction according to D and LD .
- 2) Typically, the preview distance D refers to the distance between the preview point and vehicle. In this paper, for the convenience of the preview point adjustment in longitudinal direction, D refers to the distance between preview point and vehicle in the heading direction.

According to the geometry relationship showed in Figure 6, the vehicle turning radius R can be calculated by the following equation:

$$R = \frac{(e^*)^2 + D^2}{2e^*} \quad (9)$$

where e^* is the tracking error, which is the vehicle lateral deviation at the adjusted preview point. When vehicle driving at a low speed, the relation between the driving radius and steering wheel angle satisfies the Ackerman principle, which is:

$$\frac{1}{R} = \frac{\delta_{sw}}{iL} \quad (10)$$

where δ_{sw} is steering wheel angle, i is steering ratio, and L is wheel base. According to Equation 9 and Equation 10, δ_{sw} can be derived:

$$\delta_{sw} = \frac{2iLe^*}{(e^*)^2 + D_i^2} \quad (11)$$

D. SINGLE POINT PREVIEW-BASED HUMAN-LIKE DRIVER MODEL

As shown in Figure 7, combining the preview decision module with steering angle calculation module based on pure pursuit algorithm, the single point preview-based human-like driver model can be obtained.

During driving process, the preview decision module would receive the vehicle state information (e_v , e_a), road curvature ρ , then calculate the preview distance D , and preview point lateral adjustment distance DL , which are transferred to steering angle calculation module. During steering calculation process, the module would first modify the original

tracking error e to the tracking error at the adjusted preview point e^* as shown in Figure 6, then Equation 11 can be used to derive the steering wheel angle δ_{sw} . Before δ_{sw} sent to control the vehicle, it need to be processed by a time-delay link $e^{-t_d s}$ and inertia link $\frac{1}{1+t_h s}$ which simulate the neural delay and operation delay of a human driver, where t_d and t_h are typically set as 0.2 and 0.1. In the end, the vehicle would receive steering control command δ_{sw}^* and complete the close-loop steering control process.

With the ability to adaptively adjust the preview point in both longitudinal and lateral direction, the proposed human-like driver model have the potential to show a same steering characteristic with human drivers when passing a curve road. However, for the proposed driver model obtaining human-like steering characteristic, it important to make proper fuzzy rules in the preview decision module. Since the rule number is huge ($5 \times 5 \times 5 + 5 \times 5 = 150$), it is unrealistic to set each fuzzy rule manually. Therefore, a fuzzy rule optimization method is needed.

III. MODEL OPTIMIZATION BASED ON ACO

In this paper, the optimization target is to make the proposed human-like driver model obtain similar steering control characteristic with human drivers'. Therefore, before the optimization, it is important to clarify the evaluation criterion of human-like steering characteristic. In this Section, a human-like steering characteristic evaluation method is introduced by comparing the similarity between the trajectories of the driver model and the human driver, then the human-like driver model optimization method based on ACO is proposed.

A. HUMAN-LIKE STEERING CHARACTERISTIC EVALUATION

The control results of a driver's steering maneuver is the driving trajectory of vehicle. If the vehicle drives at a constant speed, its trajectory can fully represent the steering characteristic of the driver. Therefore, human-like steering characteristic evaluation can be realized by comparing the similarity of the trajectories between a driver model and a human driver.

However, it is difficult to directly compare the similarity of two trajectories, since it is hard to find the coordinate points on them. To solve this problem, a trajectory processing method is raised in Figure 8. Virtual landmarks with equal interval are set on the lane center. By capturing the point when the trajectory pass through the normal direction of the road at each virtual point (blue and red points in Figure 8), the original trajectories in coordinates form can be transferred into the tracking error sequence updated by virtual landmarks. Using this method, it is clearer to observe the lateral position of the vehicle during driving process and compare the similarity between different trajectories.

Root mean square error (RMSE) and person correlation coefficient (PCC) are the common proximity evaluation indicators for two sequences. In this paper, RMSE is used to evaluate the position similarity and PCC is used to evaluate

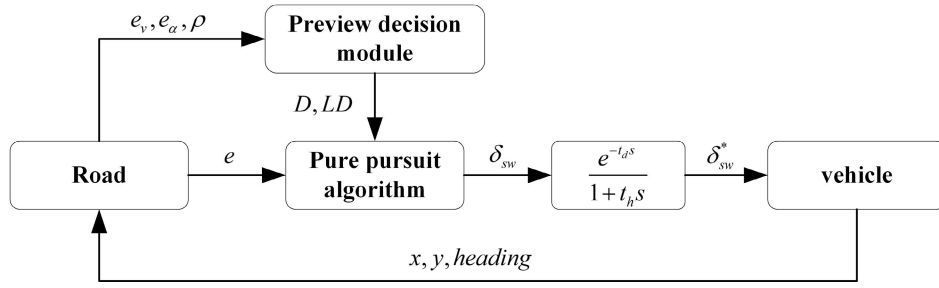


FIGURE 7. Single point preview-based human-like driver model.

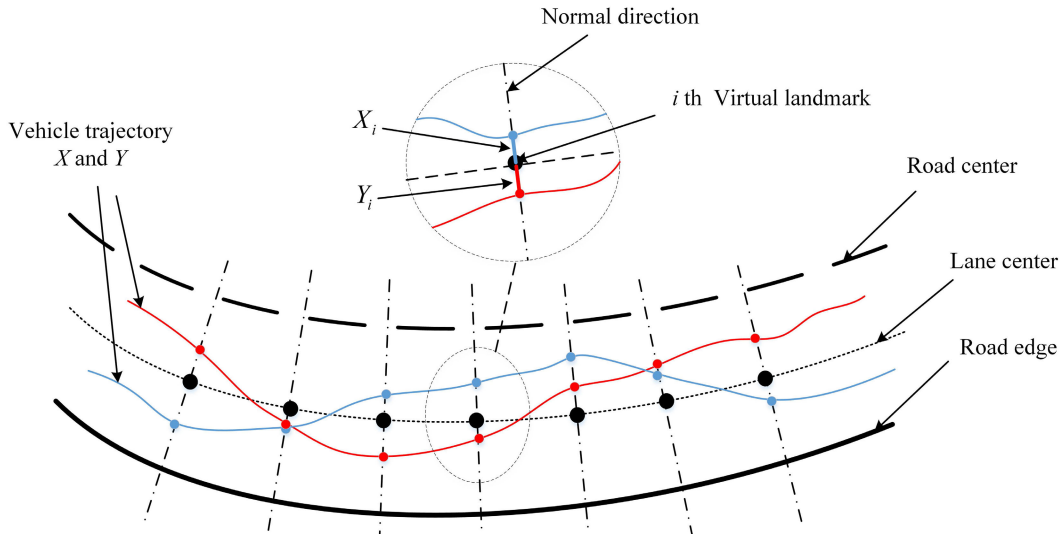


FIGURE 8. Trajectory processing method based on virtual landmarks.

the variation trend similarity between the trajectories from the driver model and human driver. Therefore, RMSE and PCC are used as a combination to evaluate the position similarity and variation trend similarity between trajectories, which is better than using Dynamic Time Wrapping (DTW) method that can only reflect trajectory position similarity. RMSE and PCC can be calculated by the following equations:

$$r_{X,Y} = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}} \quad (12)$$

$$P_{X,Y} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (13)$$

where r represents RMSE, P represents PCC, X and Y respectively represent the tracking error sequence at each virtual landmark from the driver model and human driver, i represents the serial number of virtual landmark and the total landmark number is n .

Using the comprehensive evaluation method mentioned in [33], the final evaluation score for human-like steering characteristic can be obtained according to the RMSE and PCC between the driver model and human driver. The evaluation steps are as follows:

1) Normalization

Since the RMSE and PCC are respectively min type (costs, smaller is better) and max type (benefit, larger is better), the normalization methods are different, which are:

$$r' = \frac{r_{max} - r}{r_{max} - r_{min}} \quad (14)$$

$$P' = \frac{P - P_{min}}{P_{max} - P_{min}} \quad (15)$$

The maximum and minimum of RMSE and PCC can be determined by the data distribution among different human drivers. In the paper, r_{max} and r_{min} is set as 0.8 and 0, P_{max} and P_{min} is set as 1 and 0.5.

2) Score calculation

The human-like steering characteristic evaluation score s can be obtained by the sum of weighted RMSE and PCC, the equation is:

$$s = w_r r' + w_p P' \quad (16)$$

where w_r and w_p are the weight of normalized r and P .

To figure out w_r and w_p , the entropy weight method is applied, which is a common objective weighting method using data information entropy to determine the metrics

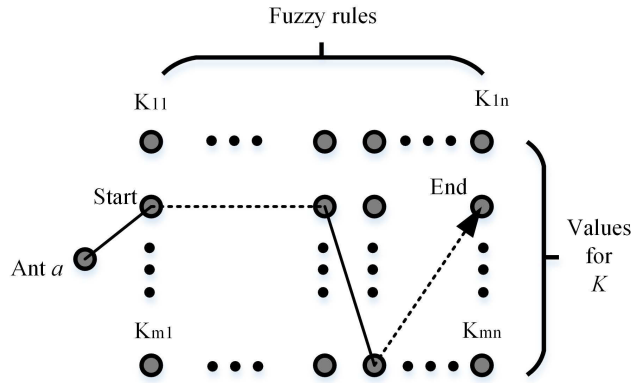


FIGURE 9. Path search process of ACO for fuzzy rule optimization.

weight. The detailed calculation process is also given in [33]. Based on the data distribution in our test field experiment in Section IV, the w_r and w_p are set as 0.6 and 0.4.

B. OPTIMIZATION METHOD FOR HUMAN-LIKE DRIVER MODEL

The optimization essence of the proposed human-like driver model is to find a proper fuzzy rules combination to make the model drive a similar trajectories with human drivers, which can prove that the model obtains human-like steering control characteristic. Ant colony optimization (ACO) takes inspiration from the foraging behavior of some ant species, which offer a good solution for combinatorial optimization problems. Considering its good search ability, some researchers have used ACO to solve FIS optimization problem [34], [35].

Different from the traditional ACO search process, where an ant would typically go back to the start point in the end, the search process of ACO for fuzzy rules optimization is in one direction, as shown in Figure 9. In the $m \times n$ node space, node K_{ij} represents the i th possible value for the consequent value K^j in the j th fuzzy rule. The value inside the node is the pheromone τ_{ij} , which represent the possibility of selecting i th consequent value when the ant at j th rule. For the node space of the preview decision module in the proposed human-like driver model, n is 150 where the first 125 columns are the fuzzy rules for the longitudinal preview decision part, other 25 columns are the fuzzy rules for the lateral preview decision part. For the longitudinal preview decision part, the selectable consequent value are {5 m, 11.75 m, 18.5 m, 25.25 m, 30 m}. For lateral preview decision part, the selectable consequent value are {-1 m, -0.5 m, 0 m, 0.5 m, 1 m}. The ant would search from the first column to the last column in sequence. When search completed, a fuzzy rules combination for the preview decision module can be obtained based on the trace of an ant.

When an ant is at column j , the possibility for selecting i th consequence value is $p_{ij} = \frac{\tau_{ij}}{\sum_{i=1}^5 \tau_{ij}}$. Using roulette wheel selection method, it is easy to obtain the consequence value for rule j . The fuzzy rules generated by the ant a would be applied on the proposed human-like driver model. Using the

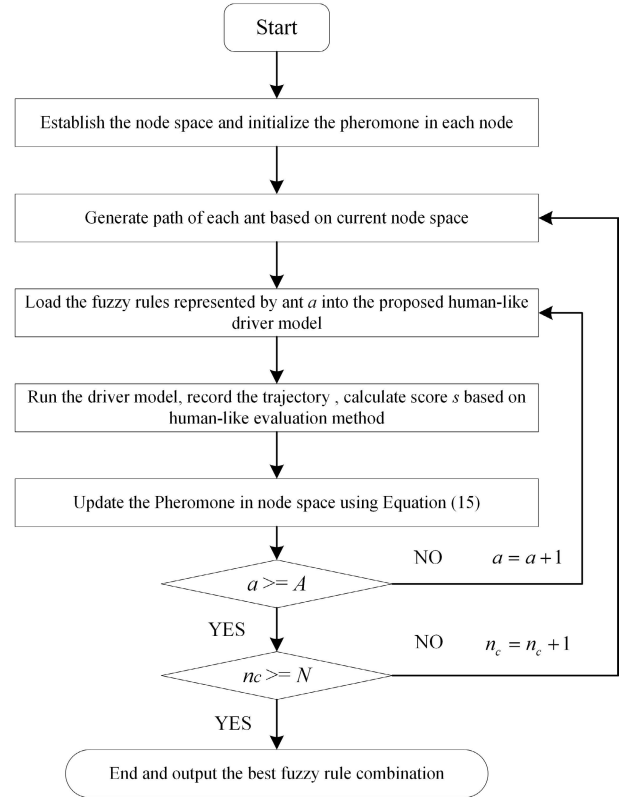


FIGURE 10. Flow chart of human-like driver model optimization.

human-like steering characteristic evaluation method mentioned above, the human-like score can be obtained for ant a , which would be used to update the pheromone of the node space.

When all the ants have finished the path search process, the pheromone at each point would be updated according to the following equation:

$$\tau_{ij} = k\tau_{ij} + \Delta\tau_{ij} \quad (17)$$

where k is the volatility coefficient of pheromone. $\Delta\tau = \sum_{a=1}^A \Delta\tau_{ij}^a$, where a is the number of ant and A represent the number of ants in colony. The score of ant a would be used to update the pheromone of the nodes on its trace.

$$\Delta\tau_{ij}^a = \begin{cases} s & \text{Ant } a \text{ pass} \\ 0 & \text{Ant } a \text{ not pass} \end{cases} \quad (18)$$

In this paper, the generation of the colony N is set as 200, A is 50, and k is 0.7. The initial value of the pheromone in all the nodes is set as 200. The flow chart of ACO optimization process is showed in Figure 10, where n_c represents the current ant colony generation number during the optimization process.

IV. MODEL VERIFICATION

To verify the human-like steering characteristic of the proposed single point preview-based human-like driver model, driving trajectories from five experienced human drivers on a

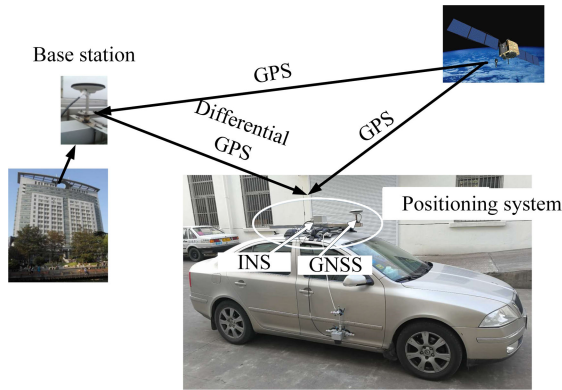


FIGURE 11. Experimental vehicle and positioning system.

two-lane urban curve are collected. Target trajectories under four different speed are selected based on all experimental trajectories, which are used for ACO optimization for the proposed human-like driver model. Then, a simulation environment is built using PreScan/Simulink platform. After the optimization done in the platform, the simulation results verify that the proposed human-like driver model obtains human-like steering characteristic.

A. TRAJECTORIES COLLECTION OF EXPERIENCED HUMAN DRIVERS

As shown in Figure 11, the model of experimental vehicle is SKODA Octavia, and the vehicle trajectory during experiments is recorded by a positioning system (SDI-600GI model) which combines Global Navigation Satellite System (GNSS) with Inertial Navigation System (INS) and returns highly accurate vehicle position information. The GNSS would also receive differential GPS signal from surrounding positioning base station, and the whole positioning system can reach the accuracy of ± 0.01 m.

To promise the accuracy of the collected trajectory data, experiments are carried out on a two-lane urban road nearby the positioning base station. Within one experiment, a driver would experience five different road segments, which are a start straight segment, the first constant curvature segment, a transition curve, the second constant curvature segment, and an end straight segment. The total length of the test road is over 400 m. The deflection angle (denoted as α) and radius of curvature (denoted as R) of two constant curvature parts are shown in Figure 12.

To implement the trajectory processing method mentioned in Section III-A, 76 virtual landmarks are set along the lane center of the test road with equal intervals (4.24 m), and the trajectories data can be transferred into the tracking error sequence updated by virtual landmarks, which make it possible to compare the similarity between different trajectories.

In order to reduce the noise among experiments coming from the maloperations of novices, five experienced drivers who are driving instructors are invited as the experiment participants to generate driving trajectories on the test field. The detailed information are shown in Table 1.

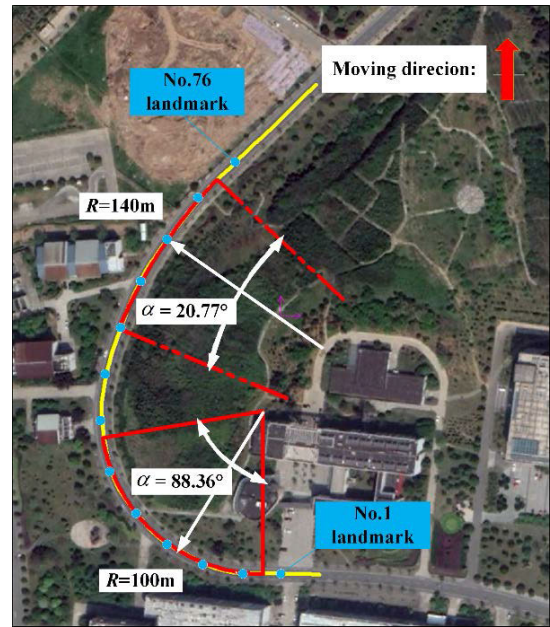


FIGURE 12. Test field.

TABLE 1. Detailed information of experienced drivers.

Participant	Gender	Age (Years)	Driving age (Years)
Diver 1	Female	55	33
Diver 2	Male	28	10
Diver 3	Male	53	31
Diver 4	Male	46	22
Diver 5	Male	53	21

To focus on analyzing the steering control characteristic, each driver is required to drive at a constant speed, which make it possible to neglect the effect of speed control. For each experiment, drivers would drive the vehicle from a sufficient distance ahead the first landmark to make sure the vehicle reach the required speed. Under each required speed, each driver would have one extra chance to adapt to the test field (driving data would not be recorded). After that, drivers would drive five times with four specified vehicle speed, 20 km/h, 30 km/h, 40 km/h, and 50 km/h, respectively.

In our study, a total of 100 trajectories of experienced drivers are collected. Using the method explained above, all the trajectory data are transformed into the tracking error sequence, and partial of them are shown in Figure 13, where J represent the experienced driver. We found that the tracking error sequence among experienced drivers are very similar, and the average PCC among those trajectories under different target speeds are 0.86, 0.88, 0.90, and 0.89, which reveals the experienced drivers have a similar steering control characteristic with each other.

To show the overall distribution of the tracking error sequence among all the experiments, a box-plot sequence shown in Figure 14 is generated. The whisker end of each box-plot represents the maximum/minimum tracking error value at each landmark. The upper edge of the box represents the 75th percentile (the third quartiles- Q_3) and the lower edge represents the 25th percentile (the first quartiles- Q_1).

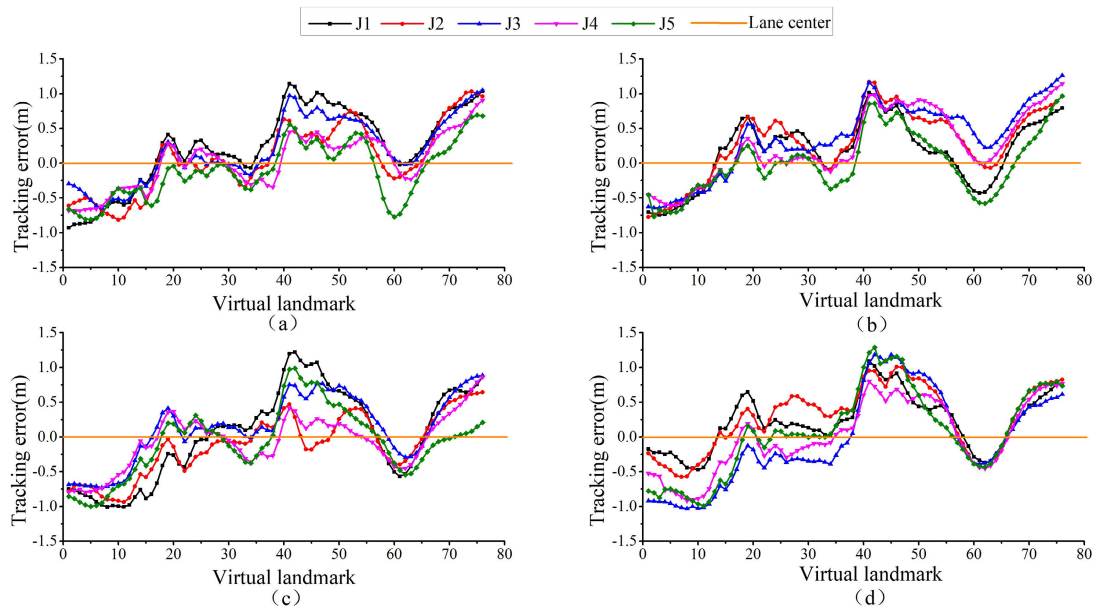


FIGURE 13. Partial trajectory data of experienced drivers under different speed: (a) vehicle trajectories under 20km/h; (b) vehicle trajectories under 30km/h; (c) vehicle trajectories under 40km/h; (d) vehicle trajectories under 50km/h.

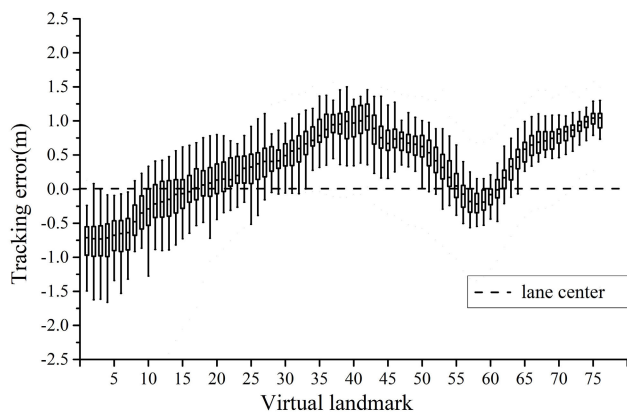


FIGURE 14. Trajectories distribution of all experiments under 40km/h.

The short horizontal line inside the box represents the 50th percentile (the second quartiles- Q_2). Therefore, the box sequence shows an area where the experienced human drivers would pass among 50 percent of the experiments, which could help offer a clear optimization reference for the human-like driver model in our paper.

B. TARGET TRAJECTORIES FOR DRIVER MODEL OPTIMIZATION

The optimization method proposed in Section III-B request one specific target trajectory under each target speeds for the human-like driver model optimization. In this paper, 50th percentile of the tracking error value at each landmark (short horizontal line inside the box in Figure 14) is selected as the target trajectory, which has two merits. Firstly, since the target trajectories is in the middle zone among all experienced

drivers' trajectories, if the driver model could driver close to this target, the model trajectory would have high possibility fall in the whole area of experienced drivers', which fulfills the need of the position similarity in the human-like steering characteristic evaluation. Secondly, since all the experienced drivers' trajectories obtain a high PCC level, the target trajectory which is the 50th percentile among all trajectories would also have a high PCC with other experienced drivers' trajectories, which is eligible to represent the variation trend characteristic of trajectories among experienced drivers. To sum up, under one constant target speed, if a driver model can generate a driving trajectory which has a low RMSE and a high PCC with the target trajectory, it will means the model's trajectory can pass through the area where most experienced drivers would drive and have a similar variation trend with all experienced drivers' trajectories, which is eligible to prove the driver model obtain the human-like steering characteristic. The selected target trajectories under each speed are shown in Figure 15.

C. SIMULATION SETUP AND RESULTS

PreScan provides plenty of tools for users to reproduce the road and environment in real world. Additionally, it can connect with Matlab/Simulink to let users test control algorithm in the environment built in PreScan. Therefore, as shown in Figure16, by importing road GPS and satellite, we build a same road test field in PreScan to run our driver model. The vehicle model is a 2-DOF dynamic model which is provided by PreScan, and essential parameters are shown in Table 2.

The proposed human-like driver model in Section II is built in Simulink, and the model is optimized under each target speed using the optimization method proposed in Section III.

TABLE 2. Essential parameters of vehicle model.

Parameter	Value	Unit
Vehicle mass	1480	kg
Length/width/height	4425/1860/1314	mm
Wheelbase	2700	mm
Front/rear wheel distance	1585/1580	mm
The distance from the vehicle centroid to the front and rear axles	1080/1620	mm
Moment of inertia of the vehicle around the X,Y,Z axis	124/2242/2562	kg.m ²
Front/rear tires stiffness	62191/98727	N/rad

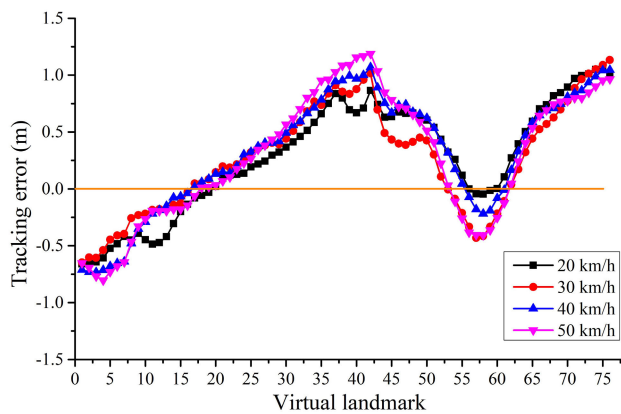
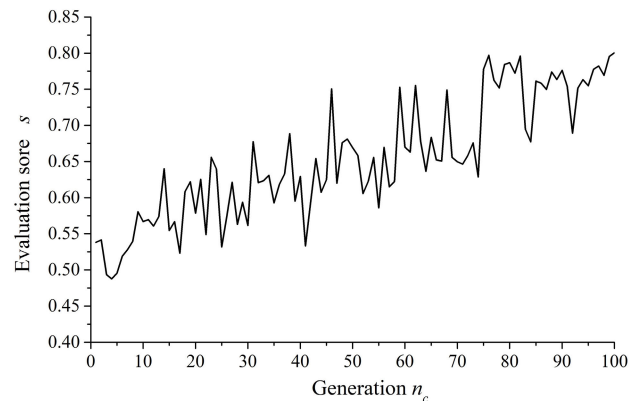
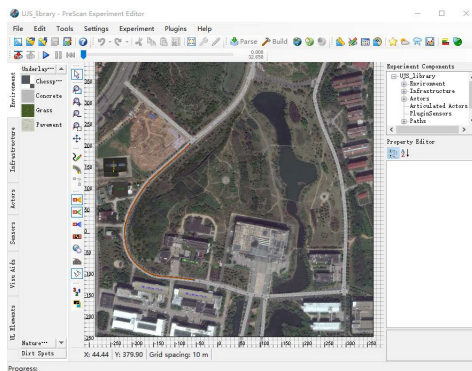
**FIGURE 15.** Optimization targets under different speeds.**FIGURE 17.** Optimization process under 40 km/h.**FIGURE 16.** Simulation environment built in PreScan.

Figure 17 shows the best human-like evaluation score s of the proposed human-like driver model under 40 km/h in each generation n_c during the optimization process, which shows that with the ACO optimization method, the fuzzy rules in the human-like driver model have been effectively optimized, and the driver model have a great improvement in the human-like steering characteristic evaluation.

The trajectories of the proposed human-like driver model after optimization under different speeds are shown in Figure 18. The target trajectories from experienced human drivers, the driver model with fixed preview distance D , and the driver model only with changeable longitudinal preview distance are also put in Figure 18 for comparison. For the driver model with fixed D , its D is set as the value which could let the model achieve the highest s . For the driver model

only with changeable D , it uses the same longitudinal preview decision module with the proposed human-like driver model (but without lateral preview decision module) and also optimized by the method proposed in Section III. The human-like steering characteristic evaluation results of three different driver model are shown in Table 3.

The simulation results in Figure 18 show that compared with the driver model with fixed D or the driver model only with variable D , the proposed human-like driver model is able to generate a similar driving trajectory with the experienced human driver under each target speed after the optimization by ACO. The human-like steering characteristic evaluation results in Table 3 show that, with the ability of adaptive adjusting the preview point position in both longitudinal and lateral direction, the proposed human-like driver model can reach a low RMSE and a high PCC in each target speed, which lead a high human-like steering evaluation score. It should be pointed out that the RMSE and PCC in Table 3 are calculated by Equation 12 and Equation 13, which represent the trajectory position similarity and variation trend similarity between the driver model and experienced human driver. The evaluation results prove that the proposed single point preview-based driver model has the ability to obtain human-like steering characteristic after using the proposed optimization method based on ACO. In addition, the evaluation results reveal that the proposed human-like driver model also obtain a much higher score than the optimized driver model only with variable D , which reveals that the adaptive preview point position adjustment in both longitudinal and lateral direction is necessary for the human-like steering control modeling.

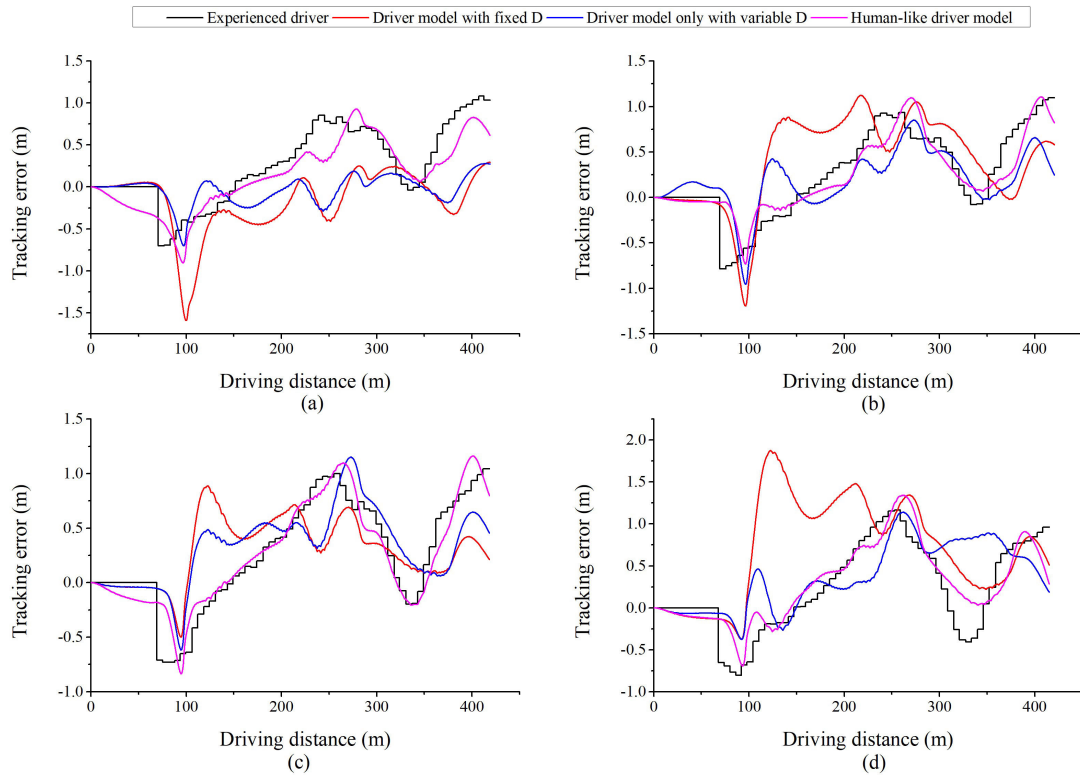


FIGURE 18. Trajectories of driver models under different speed: (a) model trajectories under 20km/h; (b) model trajectories under 30km/h; (c) model trajectories under 40km/h; (d) model trajectories under 50km/h.

TABLE 3. Human-like steering characteristic evaluation of driver models.

Speed (km/h)	Driver model with fixed D			Driver model only with variable D			Human-like driver model (with variable D and LD)		
	RMSE	PCC	s	RMSE	PCC	s	RMSE	PCC	s
20	0.61	0.57	0.20	0.51	0.60	0.42	0.22	0.85	0.72
30	0.49	0.53	0.26	0.35	0.70	0.50	0.24	0.89	0.74
40	0.51	0.49	0.21	0.38	0.68	0.47	0.19	0.92	0.80
50	0.69	0.31	-0.07	0.43	0.71	0.44	0.25	0.91	0.75

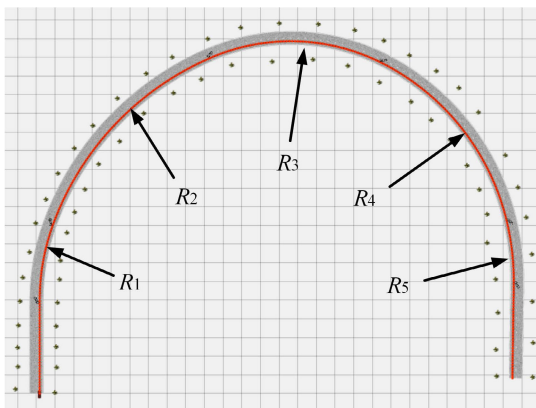


FIGURE 19. Multi-curvature test road.

To prove the validity of the proposed human-like driver model on multi-curvature curved roads, a supplementary simulation is carried out based on the PreScan/Simulink platform and a driving simulator. As shown in Figure 19, a multi-curvature test road is built in PreScan, which contains



FIGURE 20. Driving simulator.

five different curved road segments with the radius of 120 m, 160 m, 110 m, 130 m and 140m. The deflection angles of each segment are respectively 20°, 45°, 50°, 50° and 15°. The total length of the test road is 500 m. The target trajectory used for the driver model optimization is collected by an experienced human driver driving on a driving simulator

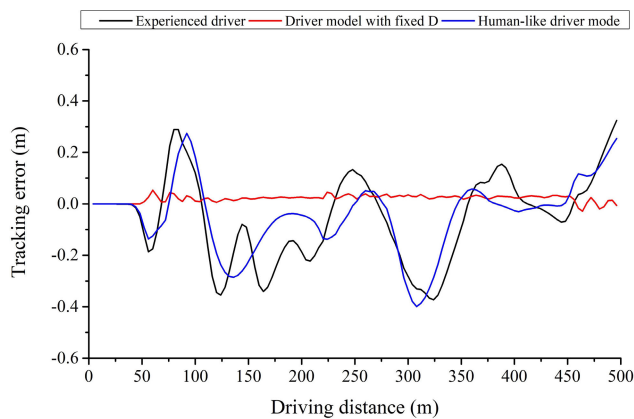


FIGURE 21. Simulation results on the multi-curvature test road.

shown in Figure 20, and the vehicle speed is set as 40 km/h. After the optimization based on the method mentioned in Section III, the trajectories of the experienced human driver, the driver model with fixed D and the optimized proposed human-like driver model are showed in Figure 21.

As shown in Figure 21, due to the lack of longitudinal and lateral adjustment of preview point, the driver mode with fixed D shows a low similarity with the experienced human driver. Even set as the best D , the RMSE, PCC and human-like steering evaluation score of the driver model with fixed D are 0.15, -1.38 and -0.06 . However, the proposed human-like driver model shows a high level trajectory similarity with the experienced human driver after the ACO optimization, and the RMSE, PCC and human-like steering evaluation score are 0.06, 0.81 and 0.81 respectively. The supplementary simulation results prove that the proposed driver model is able to obtain human-like steering control characteristic on multi-curvature curved road.

V. CONCLUSIONS

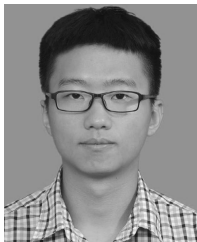
In this paper, in order to build a driver model with human-like steering control characteristic, a preview decision module is proposed based on T-S fuzzy inference system, which is able to adaptively adjust the preview point position in both longitudinal and lateral direction. Combined with a steering angle calculation module based on pure pursuit algorithm, a single point preview-based human-like driver model is proposed. For tuning the fuzzy rules in the proposed human-like driver model, an optimization method based on ACO is raised. The model verification has been done on an urban curved road. Based on the target trajectories derived from five experienced human drivers' driving data under four different speeds, the model optimization is completed in the PreScan/Simulink platform. The simulation results show the effectiveness of the proposed driver model optimization method and the high level steering control characteristic similarity between the proposed human-like driver model and experienced drivers, which is much better than the driver model with fixed preview distance or the driver model only with variable preview distance.

In current research stage, the human-like steering control modeling is only done under constant speeds. The human-like steering control under adaptive speed control would be studied in the future. Also the proposed driver model can only be applied in urban curve roads, more complex traffic and road situations should be considered in modeling in further study.

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