Brain-Inspired Modeling and Decision-Making for Human-Like Autonomous Driving in Mixed Traffic Environment

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Abstract—In this paper, a human-like driving system is designed for autonomous vehicles (AVs), which aims to make AVs better integrate into the human transportation systems and mitigate misunderstanding and conflicts when interacting with human-driven vehicles. Based on the analysis of the real world INTERACTION dataset, a driving aggressiveness estimation model is established with the fuzzy inference approach. In the human-like lane-change decision-making algorithm, the cost function is designed comprehensively considering driving safety and travel efficiency. Based on the cost function with multi-constraint, a dynamic game algorithm is developed to model the interactions and decision making between AV and human-driven vehicles. Additionally, to guarantee the safety during lane-change of AVs, an artificial potential field model is built for collision risk assessment. Further, a human-like driving model is designed, which integrates the brain emotional learning circuit model (BELCM) with a two-point preview model. Finally, the proposed algorithm is evaluated through human-in-the-loop experiments, and the results demonstrated the feasibility and effectiveness of the proposed method.

Index Terms—Autonomous vehicles, human-like driving, decision making, driving aggressiveness, brain emotional learning circuit model.

I. INTRODUCTION

Although autonomous driving has made a great progress in recent years, it can be believed that autonomous vehicles (AVs) and human-driven vehicles will coexist for a long time [1]. It is a critical issue for AVs that human drivers feel safe and trustworthy in the interaction process with AVs, which requires AVs can merge into the transportation ecology of human driving and eliminate the misunderstanding and incompatibility of human drivers to autonomous driving [2]. Therefore, human-like driving becomes a research hotspot for AVs.

Various approaches and algorithms have been proposed for human-like driving [3], [4], [5]. In [6], a personalized computational model is designed for human-like decision making under risk, which comprehensively considers regret effects, probability weighting effects and range effects. By analyzing the driving habits of different human drivers, a personalized human-like driver model is built, which includes a longitudinal driving behavior model and a lateral lane-change trajectory planning model [7]. In [8], a concept of “staying within the safety zone” is proposed, and based on the concept, a universal control framework of human-like steering is designed, which can deal with multiple driving scenarios. In [9], a multi-point decision making strategy is proposed for human-like driving. To address the interaction and decision making between AV and human-driven vehicle at mixed-flow intersections, a logic model is combined with Bayes’ theorem to realize human-like interaction and autonomous driving [10]. In [11], an adaptive tactical behavior planner (ATBP) is designed for AVs, which can plan human-like motion behaviors at a unsignalized roundabout.

Additionally, Markov Decision Process (MDP) is a common approach to simulate the human-like decision making process [12]. Based on MDP, a human-like longitudinal decision model is designed for AV to address the velocity planning at signalized intersections [13]. However, only longitudinal decision making is considered in this model. In [14], the lane-change intention of AV is described by a Hidden Markov Model (HMM) based intention recognizer. Based on HMM, a human-like lane-change intention understanding model is proposed for autonomous driving. In [15], the partially observable Markov decision process (POMDP) is applied to the decision making for AVs at unsignalized intersections, which can conduct human-like driving behaviors. Based on MDP, a human-like driving model is constructed for AVs, which has three driving modes, i.e., leisure mode, normal mode and efficiency mode, to provide personalized driving demands for passengers [16].

Learning-based approaches have been widely applied to the human-like driving [17], [18], [19]. Based on reinforcement learning (RL), a human-like longitudinal driver model is established for AVs [20]. Besides, deep RL is used to design the human-like car-following model for AVs [21]. In [22], double Q-learning is adopted to realize human-like speed control. However, the above three models cannot deal with lateral decision making, e.g., lane-change. In [23], general regression neural network (GRNN) is applied to the human-like...
lane-change trajectory generation. Based on the deep autoencoder (DAE) network and the XGBoost algorithm, a human-like lane-change decision making model is built [24]. In [25], Long Short Term Memory (LSTM) neural network and Conditional Random Field (CRF) model are combined together to construct the human-like maneuver decision model for AVs. Based on convolutional neural network, cognitive map and recurrent neural network, a brain-inspired cognitive model is established for human-like autonomous driving [26]. Although the leaning-based approaches can realize human-like decision making, it requires a large amount of data for model training, and the model accuracy would be greatly affected by the quality of the dataset.

Although aforementioned approaches are in favor of human-like driving behaviours for AVs, few of them study the interactions between human-driven vehicles and AVs when dealing with driving conflicts. Game theory is capable of modelling the interactive decision-making process between human drivers and AVs [27]. To address the lane-change problem of AVs, MDP is combined with game theory to realize human-like driving [28]. In [29], a game theory-based decision-making algorithm is proposed for AVs to realize human-like lane-change in congested urban intersections. The above algorithms mainly consider the safety during decision making. Other performances, e.g., travel efficiency and ride comfort, are neglected. Besides, the driving aggressiveness of the surrounding human-driven vehicles is not considered, leading to a conservative design of the decision-making algorithms. In [30], a game theory-based lane-change model is built for AVs to mimic human behaviors. With the comprehensive considerations of safety and travel efficiency, a human-like decision making framework is proposed for AVs with the game theoretic approach and a single-point preview model [31]. In [32], the cooperative game theoretic approach is applied for cooperative lane-change decision making of AVs. However, without considering driving aggressiveness of human drivers, the proposed algorithms can only deal with the interactions between AVs, rather than the interactions between AVs and human driven vehicles in the mixed traffic environment.

To resolve the driving conflicts in the mixed traffic environment, based on the proposed human-like decision-making framework in previous study [31], the driving aggressiveness estimation module and the brain emotional learning circuit model (BELCM) are proposed to realize better human-like interaction and driving for AVs. The contributions of this paper are summarized as follows: (1) Based on the driving behavior analysis of the INTERACTION dataset, the fuzzy inference approach is applied to the aggressiveness estimation of surrounding vehicles, which is suitable for both AVs and human-driven vehicles; (2) To realize human-like driving of AVs, BELCM is combined with the two-point preview model to construct the human-like driving model; (3) The human-like driving model is verified through the interaction experiments with various human drivers in different driving environments, evaluating human-likeness via multiple indexes.

The remainder of this paper is organized as follows. The problem statement and the decision-making framework are presented in Section II. Section III introduces system modelling, which includes the vehicle model and the aggressiveness estimation model. Then, the dynamic game theoretic approach is used to deal with the decision-making issue of AVs in Section IV. In Section V, the BELCM-based driving model is developed for human-like driving of AVs. In Section VI, the proposed algorithm is verified via human-in-the-loop experiments. Finally, Section VII presents the conclusion and future work.

II. PROBLEM DESCRIPTION

Although AVs can realize accurate control and decision making based on high-precision sensors and super computing platform, several avoidable accidents may happen between AVs and the human driven vehicles. The major cause is the misunderstanding between the autonomous-driving system and human drivers. Human drivers usually follow some driving conventions, e.g., turning vehicles giving way to straight vehicles at unsignalized intersections. However, AVs will pass the intersection if the autonomous-driving system thinks it is safe. The unconventional behaviors of AVs do not obey the driving logic of human drivers, which may lead to wrong decisions of human drivers and bring a collision risk. Therefore, it is necessary to consider the factors of human-like driving in the autonomous-driving system, which can make AVs better integrate into the transportation ecology of human driving and eliminate the misunderstanding and incompatibility of human drivers to autonomous driving [31].

Since lane change is a common driving behavior and one of the most common causes of traffic accidents, especially in the highway condition, this paper mainly focuses on the study of human-like lane-change decision making for AVs. Fig. 1 shows a typical lane-change driving scenario. Due to the slow speed of the black tractor, the red car must make decisions, i.e., slowing down and keeping the lane, or changing lanes. If choosing lane-change, the red car must fight with the blue truck. The blue truck can yield or fight. There exists an interaction and game between the two vehicles. To study the interaction and decision making between AVs and human driven vehicles. One of the two vehicles can be regarded as AV and another is human-driven vehicle. To describe the decision-making process, some roles are defined for vehicles. Host vehicle (HV) is the vehicle that wants to make the lane-change decision, i.e., the red car in Fig. 1. Neighbor conflict vehicle (NV) is the opponent for HV in the lane-change process. Leading vehicle (LV) is the vehicle in front of HV. For instance, the black tractor is the LV for the red car if choosing lane-keeping. After finishing the lane-change, the black bus is the LV for the red car. With the difference of HV’s position, the roles of NV and LV will change accordingly.

![Fig. 1. Lane-change driving scenario.](image-url)
To deal with the above issue, a human-like driving framework is illustrated in Fig. 2. It mainly consists of three modules. Firstly, an aggressiveness estimation module is constructed based on the fuzzy inference approach. According to the motion states of NVs, the aggressiveness estimation results of NVs will be provided to the decision-making module of HV. In the human-like decision-making module, the cost function is designed comprehensively considering driving safety and travel efficiency. Based on the cost function and multi-constraint, the game theoretic approach is applied to the interaction and decision making between HV and NVs. Besides, a collision risk assessment algorithm is proposed to ensure the safety during the lane-change process. Then, the lane-change decision is provided to the human-like driving module, which is an integration of the two-point preview model and the brain emotional learning circuit model (BELCM). Finally, the ideal steering angle $\delta^*_i$ from the human-like driving module and the ideal acceleration $a^*_i$ from the human-like decision-making module are outputted to the vehicle control module to realize the motion control of AV.

### III. MODELLING

A simplified vehicle kinematic model is built for AVs. Then, according to the driving behavior analysis of human drivers, an aggressiveness estimation model is constructed for AVs using the fuzzy inference approach.

#### A. Vehicle Model

To simplify the computational model of decision making, the single-track model is adopted replacing the four-wheel vehicle model. The kinematic description of the single-track model is shown as follows [33].

$$\dot{x}(t) = F(x(t), u(t))$$

$$F(x(t), u(t)) = \begin{bmatrix} \alpha_x \\ v_x \tan \beta / b_r \\ v_x \cos \phi / \cos \beta \\ v_x \sin \phi / \cos \beta \end{bmatrix}$$

$$\beta = \arctan[b_f/(b_f + b_r) \tan \delta_f]$$

where $x = [v_x, \phi, X, Y]^T$ and $u = [\alpha_x, \delta_f]^T$ are the state vector and control vector. $v_x$, $\phi$, and $\beta$ are the longitudinal velocity, yaw angle and heading angle. $X$ and $Y$ are the position coordinates of the center of gravity. $\alpha_x$ and $\delta_f$ denote the longitudinal acceleration and the steering angle of the front wheel. $b_f$ denotes the distance from the front and rear axles to the center of mass of the vehicle.

#### B. Aggressiveness Estimation Model

To make AVs have different driving preferences like human drivers, the driving behaviors of human drivers are studied based on the INTERACTION dataset [34]. The INTERACTION dataset contains naturalistic motions of various traffic participants under highly interactive driving scenarios. In this paper, the motion data of human-driven vehicles at three urban merging and lane-change scenarios are analyzed. The aggressiveness of human drivers is usually reflected by the motion states and actions of vehicles, in which two main states, i.e., the vehicle velocity and yaw rate, are selected. As a result, the velocities and yaw rates of human-driven vehicles at three scenarios are illustrated in Fig. 3.

According to the distributions of velocity and yaw rate, the fuzzy inference approach is used to estimate the aggressiveness of vehicles [35]. The inputs of the fuzzy inference system are velocity and yaw rate, and finally, it outputs the aggressiveness. Three components make up the fuzzy inference system including fuzzification, the rule evaluation and the defuzzification [36]. The first step is fuzzification, which converts the continuous values of vehicle motion states into fuzzy values according to the membership functions. As Fig. 4 shows, S-shaped and triangular membership functions are used. Velocity and yaw rate are blurred into very small (VS), small (S), middle (M), large (L), and very large (VL). Additionally, the fuzzy values of aggressiveness are conservative (C), normal (N) and aggressive (A). After finishing the fuzzification process of velocity and yaw rate, the fuzzy value of aggressiveness can be inferred based on the fuzzy logic rule in Table I. Once the fuzzy inference process is finished, the defuzzification will be conducted to obtain the real value of aggressiveness $\kappa$, $\kappa \in [0, 1]$. Finally, the estimation of aggressiveness is done. Fig. 5 shows the map of aggressiveness with respect to velocity and yaw rate. It can be found that the larger

$$\phi = \phi + \beta$$

Fig. 3. Driving behavior analysis of human drivers based on INTERACTION dataset: (a) Velocity; (b) Yaw rate.
where \( \sigma \) is associated with the vehicle length and driving aggressiveness, i.e., \( \sigma_x = b_x e^\kappa L_NV \), in which \( b_x \) is the proportional coefficient and \( L_NV \) is the length of NV. \( \sigma_y \) is related to the vehicle width, i.e., \( \sigma_y = b_y W_NV \), in which \( b_y \) is the proportional coefficient and \( W_NV \) is the width of NV. \( \lambda \) is a function of time to collision (TTC) and driving aggressiveness. Fig. 6 shows an instance of APF distribution for NV.

\[
\lambda = \frac{\lambda_0 e^\kappa}{(TTC + \epsilon)^2}
\]  

where \( \lambda_0 \) is a constant value and \( \epsilon \) is a small value set to avoid zero denominator.

To realize safe lane change of HV, it is necessary to assess the collision risk between NV and HV during the lane-change process. An event-triggered mechanism (ETM) is defined according to the APF model.

\[
i_{k+1} \overset{\text{def}}{=} \inf\{t > t_k| \Upsilon > \Upsilon_{sf}\}
\]  

where \( \Upsilon_{sf} \) denotes the safe APF value for HV to conduct safe lane change. Eq. 7 means that when \( \Upsilon > \Upsilon_{sf} \), the trigger condition is satisfied. As a result, HV cannot execute lane-change order or continue the lane-change behavior. HV must choose lane-keeping, or returning back to the original lane if lane-change is in progress.

**B. Construction of Cost Function**

In the decision-making cost function, both the driving safety and the travel efficiency are taken into account. Defining \( V_i \) as HV, the decision-making cost function \( \Gamma_i \) for \( V_i \) is expressed as

\[
\Gamma_i = (1 - \kappa') \Gamma_{i,L} + \kappa' \vartheta^i \Gamma_{i,e}
\]  

where \( \Gamma_{i,L} \) and \( \Gamma_{i,e} \) denote the costs of driving safety and travel efficiency. The weights of the two driving performance indexes are associated with the aggressiveness \( \kappa' \), i.e., a negative correlation between \( \kappa' \) and \( \Gamma_{i,L} \), and a positive correlation for \( \kappa' \) and \( \Gamma_{i,e} \). \( \vartheta^i \) is a normalization parameter.

The cost function of driving safety \( \Gamma_{i,L} \) consists of the longitudinal safety cost and the lateral safety cost.

\[
\Gamma_{i,L} = k_{L} \log (1 - (\alpha^i)^2) \Gamma_{i,L}^{s-L} + k_{L}^{\text{lat}} \alpha^i \Gamma_{i,L}^{s-L}
\]
where $\Gamma_{s-log}^i$ and $\Gamma_{s-lat}^i$ denote the costs of the longitudinal and lateral safety, respectively. $k_{s-log}^i$, $k_{s-lat}^i$ are the weights of the two safety indexes. $\alpha^i \in \{-1, 0, 1\}$ denotes the lane-change decision making of $V_i$, i.e., left lane change ($\alpha^i = -1$), lane keeping ($\alpha^i = 0$), and right lane change ($\alpha^i = 1$).

The detailed design of $\Gamma_{s-log}^i$, $\Gamma_{s-lat}^i$ and $\Gamma_s$ is shown in the previous studies [31], [32], which will not be repeated in this paper.

C. Decision Making With Dynamic Game

If $V_i$ (AV) and $V_j$ (human driver) are regarded as two players, the lane-change decision making issue can be transformed into a dynamic game. Both $V_i$ and $V_j$ aim to minimize its own decision-making cost function. The decision-making cost functions of $V_i$ and $V_j$ are denoted by $\Gamma^i$ and $\Gamma^j$. The decision-making vectors of $V_i$ and $V_j$ are denoted by $u^i$ and $u^j$, $u^i = [\alpha^i, \alpha^j]^T \in U^i$, $u^j = [\alpha^j]^T \in U^j$. $U^i$ and $U^j$ are the strategy set of $V_i$ and $V_j$, respectively.

If the following conditions hold, $[u^{i*}, u^{j*}]$ can be regarded as a Nash equilibrium for the dynamic game [27].

$$\Gamma^i(u^i, u^{j*}) \geq \Gamma^i(u^{i*}, u^{j*})$$

$$\Gamma^j(u^{i*}, u^j) \geq \Gamma^j(u^{i*}, u^{j*})$$

(10)

which indicates that no player can decrease its cost function by single-mindedly changing its strategy, as long as the other player sticks to the equilibrium strategy.

Furthermore, $[u^{i*}, u^{j*}]$ can be derived by

$$u^{i*} = \arg \min_{u^i} \Gamma^i(u^i, u^{j*})$$

$$u^{j*} = \arg \min_{u^j} \Gamma^j(u^{i*}, u^j)$$

(11)

subject to

$$x(t) = f(t, x, u^i, u^{j*})$$

$$\dot{x}(t) = f(t, x, u^{i*}, u^j)$$

$$x(0) = x_0, \quad u^i \in U^i, \quad u^j \in U^j$$

(12)

The existence of Nash equilibrium can be guaranteed by fixed point theorem, and the heuristic dynamic programming (HDP) is used to solve the Nash equilibrium [38].

V. BRAIN-INSPIRED MODELLING FOR HUMAN-LIKE DRIVING

In this section, the working principle of BELCM is introduced. Then, a human-like driving model is built based on BELCM.

A. Brain Emotional Learning Circuit Model

Brain-inspired computing has been widely studied in the field of artificial intelligence, which can simulate the operating mechanism of the human brain to establish a calculation model [39]. As a result, the proposed model can realize human-like decision making and control in some intelligent applications. BELCM is a typical brain-inspired computational model proposed by Balkenius and Moren [40], which is able to reflect human-like control mechanism. Due to the simple structure and model-free characteristics, it can be used in complex nonlinear control, featuring good performance in real-time implementation, e.g., motor control [41], unmanned aerial vehicle (UAV) control [42], and robotic control [43]. In this section, the BELCM is used to simulate the driving control of human drivers.

The brain structure is illustrated in Fig. 7 (a), in which amygdala, prefrontal cortex, sensory cortex and thalamus are the key elements for brain emotional learning. Fig. 7 (b) shows the schematic diagram of the BELCM structure. In the BELCM, the main learning process occurs within the amygdala and prefrontal cortex sections. The role of amygdala mainly focuses on assigning an emotional value to each stimulus that is paired with a primary reinforcement signal. The prefrontal cortex is another section interacting with the amygdala reciprocally, which performs as an inhibitory controller. It monitors the emotional learning process in the amygdala to avoid the effects of under-learning and over-learning. The task of thalamus is usually simulated by passing the maximum signal, over all stimulus signals, to the amygdala. The main task of sensory cortex is to distribute the incoming sensory signal through the amygdala and prefrontal cortex.

Firstly, the stimulus inputs (SIs) are processed by the thalamus, and the maximum SI is outputted to the amygdala, i.e.,

$$A_{ih} = \max(SI_i), \quad i = 1, 2, \cdots, n$$

(13)

Then, other SIs are provided to the sensory cortex. After processing, the sensory signals are outputted to the prefrontal cortex and amygdala. Under the reference hint of the emotion...
signal (ES), the sensory signals in the amygdala start memory learning and finally output the learning signal $A$. Additionally, the sensory signals in the prefrontal cortex will correct the emotional learning loop under the supervision of ES, and output the correction signal $P$. Finally, the output of BELCM is expressed as

$$K = A - P$$  \hspace{1cm} (14)$$

It can be found that the output $K$ is determined by both the amygdala and prefrontal cortex. Therefore, it is necessary to study the learning process of amygdala and prefrontal cortex. There exists a corresponding node in the amygdala to each $SI_i$, and each amygdala node has a variable weighting coefficient $W_{A_i}$. Then, the output of the amygdala can be written as

$$A = A_{th} + \sum_{i=1}^{n} A_i$$  \hspace{1cm} (15)$$

$$A_i = SI_i \cdot W_{A_i}$$  \hspace{1cm} (16)$$

The change of $A$ reflects the tracking process of the amygdala with respect to ES. The amygdala will adjust the weighting coefficient $W_{A_i}$ to decrease the tracking error of $A$ and ES, which is a self-suggestion ability formed by the individual in long-term learning practice. From the analysis of biological characteristics, the adjustment rate of the weighting coefficient $W_{A_i}$ is defined by

$$\Delta W_{A_i} = \alpha_A \cdot SI_i \cdot \max(0, ES - A_{th} - \sum_{i=1}^{n} A_i)$$  \hspace{1cm} (17)$$

where $\alpha_A$ denotes the learning rate of the amygdala weighting coefficient, $\alpha_A \in (0, 1)$.

Similarly, there also exists a corresponding node in the prefrontal cortex to each $SI_i$, and each prefrontal cortex node has a variable weighting coefficient $W_{P_i}$. Then, the output of the prefrontal cortex can be written as

$$P = \sum_{i=1}^{n} P_i$$  \hspace{1cm} (18)$$

$$P_i = SI_i \cdot W_{P_i}$$  \hspace{1cm} (19)$$

The change of $P$ reflects the output correction of $A$, which can be regarded as a counter-inhibition mechanism. The adjustment rate of the weighting coefficient $W_{P_i}$ is defined by

$$\Delta W_{P_i} = \alpha_P \cdot SI_i \cdot \left(\sum_{i=1}^{n} A_i - \sum_{i=1}^{n} P_i - ES\right)$$  \hspace{1cm} (20)$$

where $\alpha_P$ denotes the learning rate of the prefrontal cortex weighting coefficient, $\alpha_P \in (0, 1)$.

In general, after receiving SIs, the amygdala will conduct fast predictive learning under the reference hint of ES. Besides, the prefrontal cortex will correct the output of the amygdala under the supervision of ES. With the dynamic coordination of the two loops, i.e., memory learning and correction, the BELCM can realize accurate tracking control.

**B. BELCM-Based Human-Like Driving Model**

It has been studied that human drivers usually make decisions according to two preview points, i.e., the near point and the far point [45]. The two-point preview driver model is illustrated in Fig. 8. The near point $N$ is located on the middle line of the lane. For a straight road, the far point $F$ is the vanishing point of sight. For a curve road, the far point $F$ is the tangent point 10-20 m in front of the vehicle on the inner edge of the road. The far point is used to estimate the road curvature and provide advance compensation control for smooth steering. The near point is previewed to compensate the position error and make the vehicle move in the middle of the lane. In Fig. 8, three key performance indexes for driver preview control are displayed, i.e., $\theta_N$, $e_N$, and $\theta_F$. $\eta_N$ and $e_N$ denote the preview angle and lateral error at the near point $N$, $\theta_F$ denotes the preview angle at the far point $F$. The three performance indexes can be perceived by human drivers and regarded as the feedback signals for vehicle decision making and control.

According to Fig. 8, $e_N$ can be derived as

$$e_N = Y_N - Y - \tau_N v_x \phi$$  \hspace{1cm} (21)$$

where $Y_N$ and $Y$ are the coordinates of points $N$ and $D$ at Y-axis. The point $D$ is the driver position. $\tau_N$ is the preview time of the point $N$. Additionally, $\theta_N$ and $\theta_F$ are expressed as

$$\theta_N = \arctan \left(\frac{Y_N - Y}{\tau_N v_x} - \phi\right)$$  \hspace{1cm} (22)$$

$$\theta_F = \arccos \left(\frac{R_F}{R_D}\right)$$  \hspace{1cm} (23)$$

where $R_F$ and $R_D$ denote the curvature radius at the points $F$ and $D$, respectively.

In the cognitive process, human drivers adjust their steering strategies according to the external information. The most effective information is the trajectory tracking error. Three physical quantities $e_N$, $\theta_N$ and $\theta_F$ are selected in this paper, i.e., SIs for the BELCM-based driver model. As long as the error is not zero, it will always stimulate the brain emotional learning circuit for memory learning and correction.

$$SI = [\eta_1 e_N, \eta_2 \theta_N, \eta_3 \theta_F]^T$$  \hspace{1cm} (24)$$
where $\eta_1$, $\eta_2$ and $\eta_3$ are the weighting coefficients of the three control performance indexes.

ES is an important part of the entire brain emotional learning circuit, which is a self-suggestion ability of individuals formed in long-term learning practice and experience. Human drivers will obtain a lot of information from the driving environment. By long-term learning and analysis of these external information, a self-suggestion ability is formed, achieving the control target with less energy. The control energy of the BELCM-based driver model in this paper is the ideal front control target with less energy. The control energy of the BELCM-based driver model in this paper is the ideal front control target with less energy. Therefore, ES is equivalent to a target function, which is the ultimate goal of decision-making. Therefore, ES is finally defined as

$$ES = \sigma_1 e_N + \sigma_2 \theta_N + \sigma_3 \dot{\theta} + \sigma_4 \delta_f$$  \hspace{1cm} (25)

where $\sigma_1$, $\sigma_2$, $\sigma_3$ and $\sigma_4$ are the weighting coefficients.

Based on the above analysis, inputting the stimulus inputs SI and the emotion signal ES into BELCM, it yields the ideal front steering angle $\delta^*_f$. Therefore, ES is finally defined as

$$\delta^*_f = \mathbf{K} = \mathbf{A} - \mathbf{P}$$

$$= W_A \left[ SI \right] - W_P SI \left[ A_{ih} \right]$$

$$= \xi_1 e_N + \xi_2 \theta_N + \xi_3 \dot{\theta} + W_{A_{ih}} A_{ih}$$  \hspace{1cm} (26)

where

$$W_A = [W_{A_1}, W_{A_2}, W_{A_3}, W_{A_{ih}}]$$  \hspace{1cm} (27)

$$W_P = [W_{P_1}, W_{P_2}, W_{P_{ih}}]$$  \hspace{1cm} (28)

$$\xi_i = \eta_i (W_{A_i} - W_{P_i}), \quad (i = 1, 2, 3)$$  \hspace{1cm} (29)

Since steering control is not the focus of this paper, the actual front steering angle $\delta_f$ is obtained with a simplified steering delay model considering driver’s physical delay from mental signal processing and muscular activation.

$$\delta_f = \frac{\delta^*_f}{1 + \tau_d}$$  \hspace{1cm} (30)

where $\tau_d$ denotes the physical delay time.

Finally, the detailed workflow of the BELCM-based human-like driving model is displayed in Algorithm 1.

**Algorithm 1 Workflow of the BELCM-Based Human-Like Driving Model**

1. Parameter initialization: Define $\eta_1$, $\eta_2$, $\eta_3$, $\sigma_1$, $\sigma_2$, $\sigma_3$, $\sigma_4$, $W_A$, $W_P$, $\tau_N$, $\alpha_A$ and $\alpha_P$;
2. Calculate SI and ES;
3. Calculate $\Delta W_A$ and $\Delta W_P$ to update $W_A$, $W_P$;
4. Calculate $\delta_f$ and output;
5. Go back to Step 2.

Fig. 10. Lane-change decision making scenario.

approved by the Nanyang Technological University Institutional Review Board (protocol number IRB-2018-11-025).

A. Human-in-the-Loop Experimental Platform

The human-in-the-loop experimental platform is shown in Fig. 9, in which the driving simulator mainly consists of a computer equipped with a 11th Gen Intel Core i9 CUP and an NVIDIA GTX 3080 Super GPU, three joint head-up monitors, and the Logitech G29 steering wheel suit. Besides, the driving scenario is constructed based on the Unreal Engine and Simulink. Fig. 9 (a) and (b) show the single-player simulator and the multi-player interaction platform, respectively.

B. Driving Behavior Analysis of Human Driver and Human-Like Model Identification for AV

This test case aims to study the driving behaviors of human drivers in favor of the human-like model identification for AVs. As Fig. 10 shows, V1 is controlled by human driver to conduct the lane-change behavior, V2 and V3 are set to be driven with constant speeds. The initial position coordinates of V1 and V3 are set as (-100, -3) and (-65, -3), respectively. The initial velocities of V1 and V3 are set as 12 m/s and 5 m/s, respectively. The Y coordinate position of V2 is 1.

By controlling the relative distance and velocity between

Fig. 9. The human-in-the-loop experimental platform: (a) the single-player simulator; (b) the multi-player interaction platform.
Fig. 11. Lane-change trajectories of human drivers: (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4; (e) Case 5; (f) Case 6; (g) Case 7; (h) Case 8; (i) Case 9.

V1 and V2, it yields 9 cases in Table II. Tow human drivers, i.e., human driver A (HD-A with 3-year driving experience) and human driver B (HD-B with 10-year driving experience), are considered in this case. In each case, ten repeated tests are conducted.

![Lane-change trajectories of human drivers](image1)

![Lane-change velocities of human drivers](image2)

The detailed analysis of human driving behaviors is displayed in Table III. Three evaluation indexes of the lane-change behavior are proposed, i.e., time to lane line (TTL), lane-change time (LCT), and steady Y (SY) after lane-change. For TTL, the lane line is the crossed lane line during the lane-change process. TTL and LCT reflect the lane-change speed, and SY reflects the lane-keeping performance in the steady state, which are all related to the lateral driving and decision-making behaviors of human drivers. Besides, $v_x$ is used to evaluate the longitudinal driving and decision-making behaviors of human drivers during the lane-change process. Some findings are concluded as follows.

Two human drivers show different driving styles to conduct the lane-change maneuver. From the test results of TTL and LCT, we can find that HD-B has faster lane-change speed than HD-A, especially in the extreme case. From the test result of SY, it can be found that both HD-A and HD-B have small lane-keeping error (The target path is the lane centerline, i.e., $Y = 1$) in most cases. Besides, HD-B shows larger $v_x$ than HD-A in the lane-change process, which also reflects the stronger driving aggressiveness of HD-B.

Moreover, different initial states and positions of vehicles lead to different driving behaviors and lane-change decisions. With the reduction of the initial relative distance between V1 and V2, both TTL and LCT decrease, and $v_x$ increases, which indicates human drivers want to change lanes as quickly as possible to guarantee a safe distance from the obstacle vehicle. Besides, with the rise of V2’s initial velocity, the similar conclusion can be drawn. The analysis of variance (ANOVA) is shown in Table IV. The initial velocity and position of V2 are independent variables, and the mean values of V1’s longitudinal velocity and LCT are dependent variables. From the analysis result of P-value, it can be found that the longitudinal velocity of V1 and the two independent variables are significantly correlated. However, the correlation between the LCT of V1 and the two independent variables is not significant. Based on (14), it can be explained that the relative velocity and distance between two vehicles have direct effects on the decision-making result of V1’s longitudinal velocity. Besides the relative velocity and distance of two vehicles, the LCT of V1 is largely affected by the lateral velocity of V1. Therefore, the P-value between the LCT of V1 and the two independent variables is not small.

Based on the test results of the two human drivers, the parameter identification for the human-like driving model is conducted using the Particle Swarm Optimization (PSO) algorithm and an empirical method. Firstly, the insensitive parameters are found and determined based on the experience with fine-tuning. Then, the PSO algorithm is used to identify the sensitive parameters by minimizing the defined
TABLE III
LATE-CCHANGE BEHAVIOR ANALYSIS OF HUMAN DRIVERS

| Test results | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 | Case 7 | Case 8 | Case 9 |
|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| TTL Avg (s)  | 3.33   | 3.06   | 3.18   | 3.11   | 3.26   | 2.97   | 3.32   | 3.02   |
| LCT Avg (s)  | 7.17   | 5.18   | 6.82   | 4.96   | 6.08   | 4.88   | 7.07   | 4.92   |
| SY Avg (/m)  | 1.11   | 0.96   | 1.22   | 1.07   | 1.08   | 0.94   | 1.07   | 0.86   |
| vx Max (/m/s) | 12.45  | 16.73  | 14.16  | 16.70  | 14.38  | 16.81  | 12.67  | 16.76  |
| vx Avg (/m/s) | 12.15  | 14.81  | 12.90  | 15.08  | 12.94  | 15.52  | 12.18  | 15.28  |

TABLE IV
ANALYSIS OF VARIANCE

| Parameter | HD-A | HD-B |
|-----------|------|------|
| F | P-value | F | P-value |
| $X^{\text{V}}$ | 59.57 | 0.0010 | 2.08 | 0.24 |
| $\nu_{\text{V}}^{\text{V}}$ | 25.59 | 0.0052 | 5.96 | 0.06 |

TABLE V
PARAMETERS FOR HUMAN-LIKE DRIVING MODELS

| Parameter | HLM-A | HLM-B |
|-----------|-------|-------|
| $\eta_1$ | 2.12 x 10^{-6} | 1.09 x 10^{-4} |
| $\eta_2$ | 5.37 x 10^{-5} | 1.85 x 10^{-4} |
| $\eta_3$ | 0.34 | 0.11 |
| $\alpha$ | 0.24 | 0.10 |
| $\beta$ | 0.21 | 0.12 |
| $\gamma$ | 9.87 | 6.23 |
| $\delta$ | 2.4 x 10^{3} | 2.1 x 10^{3} |

C. Interaction and Decision Making Experiments Between Human Driver and AV

In this experiment, V1 is controlled by human driver and human-like model to conduct the lane-change behavior. V2 is controlled by three human drivers, i.e., Competitor-1 (6-year driving experience), Competitor-2 (3-year driving experience), and Competitor-3 (1-year driving experience). V3 is driven with a constant speed. The initial position coordinates of V1 and V3 are set as (-100, -3) and (-65, -3), respectively. The initial velocities of V1 and V3 are set as 12 m/s and 5 m/s, respectively. The Y coordinate position of V2 is 1. Two cases are designed by setting different relative distances and velocities between V1 and V2. The initial X coordinate of V2 is set as -125 and -110 in Case 1 and 2, respectively. Besides, the initial velocity of V2 is set as 9 m/s and 12 m/s in Case 1 and 2, respectively. Two human drivers (HD-A and HD-B), and two human-like models (HLM-A and HLM-B) are considered in the test. In each case, five repeated tests are conducted. HLM-A and HLM-B are generated from the model identification results of Table V without further parameter modifications during tests. The interaction between the human driver and the human-like model is realized using the single-driver simulator shown in Fig. 9(a). Besides, the interactive test of the two human drivers is carried out using the multi-driver interaction platform shown in Fig. 9(b), in which the two human drivers control their vehicles under same driving scenario, realizing the real-time interaction.

Considering the interaction between HD-A/HLM-A and Competitor-1/Competitor-2/Competitor-3, the lane-change trajectories of V1 are illustrated in Fig. 13. It can be found that the lane-change trajectories generated by HLM-A and HD-A are highly coincident in most cases, which verifies the human-likeness of the proposed algorithm. In most conditions, both HD-A and HLM-A can change lanes easily. However, there exist some exceptions in the interaction between HD-A/HLM-A and Competitor-1/Competitor-2/Competitor-3, i.e., Fig. 13 (d) and (e). Due to the small relative distance and velocity between V1 and V2, particularly the strong driving aggressiveness of Competitor-1 and Competitor-2, both HD-A and HLM-A give ways for Competitor-1 and Competitor-2 in Case 2. Besides, the results of lane-change velocities are illustrated in Fig. 14. In the interaction between HD-A/HLM-A and Competitor-1/Competitor-2 in Case 2, i.e., Fig. 14 (d) and (e), both HD-A and HLM-A chose decelerating firstly to guarantee the safe gap between V1 and V3. After V2 moved ahead, HD-A and HLM-A conducted the lane-change behaviors. Moreover, the velocity changes of HLM-A and HD-A are highly similar in most cases. Compared with HLM-A, HD-A has some speed drops at the beginning and some overshoots before reaching the steady state. The driving aggressiveness is estimated and displayed in Fig. 15. The
aggressiveness distribution results of HD-A and HLM-A are highly similar in most cases, which means HLM-A has similar driving behavior to HD-A, verifying the human-likeness of the proposed algorithm.

The experimental results of the interaction and decision-making between HD-B/HLM-B and Competitor-1/Competitor-2/Competitor-3 are illustrated in Figs. 16, 17 and 18. The similar analysis results can be concluded, which will not be introduced repeatedly. It is worth mentioning that HD-B and HLM-B conducted the lane-change behaviors in all cases, which is different from HD-A and HLM-A in some extreme cases. The reason can be found from Fig. 18 that HD-B and HLM-B are more aggressive than HD-A and HLM-A.

The detailed test results are analyzed in Table VI. Besides, the Longest Common Sub-Sequence (LCSS) approach is used to evaluate the similarity of the lane-change trajectories. The LCSS of the two trajectories $A = \{a_1, \cdots, a_m\}$ and $B = \{b_1, \cdots, b_n\}$ is calculated as:

$$
LCSS(A, B) = \max \left\{ k \mid \exists a_i, b_j, i \leq k \leq n, a_i = b_j \right\}
$$

| vs | Case 1 | Case 2 |
|----|--------|--------|
|    | HD-A   | HLM-A  | HD-B   | HLM-B  |
|    |        |        |        |        |
| Competitor-1 | TTL Avg (s) | 4.33   | 4.20   | 3.42   | 3.45   |
|    | SY Avg (m) | 0.61   | 1.00   | 0.78   | 1.00   |
|    | $v_c$ Max (m/s) | 16.98  | 16.66  | 16.82  | 16.66  |
|    | $v_c$ Avg (m/s) | 15.06  | 15.30  | 15.55  | 15.62  |
| Competitor-2 | TTL Avg (s) | 4.21   | 4.00   | 3.19   | 3.22   |
|    | SY Avg (m) | 1.39   | 1.00   | 0.79   | 1.00   |
|    | $v_c$ Max (m/s) | 17.19  | 16.66  | 16.72  | 16.66  |
|    | $v_c$ Avg (m/s) | 15.72  | 15.81  | 15.93  | 15.84  |
| Competitor-3 | TTL Avg (s) | 3.56   | 3.85   | 3.22   | 3.21   |
|    | SY Avg (m) | 0.98   | 1.00   | 0.96   | 1.00   |
|    | $v_c$ Max (m/s) | 16.89  | 16.66  | 16.99  | 16.67  |
|    | $v_c$ Avg (m/s) | 15.70  | 15.69  | 15.99  | 15.90  |

Table VI: Test Result Analysis in the Interaction and Decision-Making Experiments Between Human Driver and AV.
Fig. 18. Aggressiveness of vehicles: (a) Competitor-1 vs HD-B/HLM-B in Case 1; (b) Competitor-2 vs HD-B/HLM-B in Case 1; (c) Competitor-3 vs HD-B/HLM-B in Case 1; (d) Competitor-1 vs HD-B/HLM-B in Case 2; (e) Competitor-2 vs HD-B/HLM-B in Case 2; (f) Competitor-3 vs HD-B/HLM-B in Case 2.

**TABLE VII**

|        | Case 1 |        |        |        |
|--------|--------|--------|--------|--------|
|        | HD-A & HLM-A | HD-B & HLM-B | HD-A & HLM-B | HD-B & HLM-B |
| Competitor-1 | 0.76 | 0.84 | 0.90 | 0.87 |
| Competitor-2 | 1.00 | 0.80 | 0.68 | 0.84 |
| Competitor-3 | 1.00 | 1.00 | 0.78 | 0.82 |

$B = \{b_1, \ldots, b_n\}$ is defined by [46]

$$LCSS(A, B) = \begin{cases} 
0, & \text{if } m = 0 \text{ or } n = 0 \\
1 + LCSS(Rest(A), Rest(B)), & \text{if } d(Head(A), Head(B)) \leq \epsilon \\
\max \{ LCSS(Rest(A), B), \ LCSS(A, Rest(B)) \}, & \text{Other} 
\end{cases}$$

(31)

where $Head(A) = a_1$, $Head(B) = b_1$, $Rest(A) = \{a_2, \ldots, a_m\}$, and $Rest(B) = \{b_2, \ldots, b_n\}$. Besides, $d(Head(A), Head(B))$ denotes the distance between $Head(A)$ and $Head(B)$, $\epsilon$ is the matching threshold.

Furthermore, the trajectory similarity ($TS$) is constructed as follows [47].

$$TS(A, B) = \frac{LCSS(A, B)}{\min(m, n)} \in [0, 1]$$

(32)

Based on Eq. 40, the analysis results of the lane-change trajectory similarity are displayed in Table VII. In most cases, the $TS$ is larger than 80%. The average $TS$ between HLM-A and HD-A is 87%, and the average $TS$ between HLM-B and HD-B is 86%, which indicates that both HLM-A and HLM-B are capable of conducting human-like lane-change behaviors.

According to the analysis results in Tables VI and VII, some findings and conclusions are summarized as follows. Firstly, the TTL of V1 decreases with the reduction of the relative distance and velocity between V1 and V2, which means for guaranteeing driving safety, drivers usually tend to accelerate to finish the lane-change process. However, there exists an interaction and game process between the two drivers, and the decision-making results are affected by the driving aggressiveness. Based on the analysis results of the key driving and decision-making indexes, i.e., TTL, SY, $v_s$, and $TS$, it can be found that the designed human-like driving models (HLM-A and HLM-B) have similar driving and decision-making behaviors to human drivers (HD-A and HD-B). The human-likeness of the proposed algorithm is verified.

**D. Comparative Study of Different Human-Like Driving Models**

In this experiment, the comparative study between different human-like driving models are carried out. V1 is controlled by human driver (HD-A) and two human-like driving models (HLM-A and SGAPF-A). The SGAPF-A model is designed based on the Stackelberg game (SG) and the artificial potential field (APF) approach [31], [48]. V2 is controlled by a human driver with 6 year driving experience. The initial position coordinates of V1, V2 and V3 are set as (-100, -3), (-118, 1) and (-65, -3), respectively. The initial velocities of V1 and V2 are set as 12 m/s, and 10.5 m/s, respectively. V3 is driven with a constant speed 5 m/s.

The lane-change trajectories of V1 under different models are illustrated in Fig. 19. Compared with SGAPF-A, the proposed human-like driving model, i.e., HLM-A, shows more similarities on lane-change trajectory, compared to the human driver HD-A. Besides, the test results of the lane-change velocity and driving aggressiveness are presented in Fig. 20 and Fig. 21, respectively. Since the application of the game theoretic approaches, SGAPF-A and HLM-A show similar decision-making results on the longitudinal velocity of V1. Compared with HLM-A, SGAPF-A can only realize
human-like decision making but not human-like control. The detailed results are illustrated in Table VIII. The results of TTL, $v_y$, and TS indicate that HLM-A shows more human-likeness than SGAPF-A. However, SGAPF-A generates smaller $J_{erk}$ value than HD-A and HLM-A, indicating a better ride comfort performance. This will be considered in the improved HLM-A.

### VII. Conclusion

To deal with the complex interactions between AVs and human-driven vehicles, a brain-inspired human-like driving framework is proposed in this paper. Based on the driving behavior analysis of human drivers from the INTERACTION dataset, an aggressiveness estimation model is built with the fuzzy inference approach. Besides, the BELCM-based driving model is designed for AVs’ human-like driving. In the human-like lane-change decision-making algorithm, the collision risk assessment is realized with the APF approach, which is used to guarantee the lane-change safety of AVs. Both the driving safety and travel efficiency are considered in the decision-making cost function. Furthermore, the dynamic game approach is applied to the interaction and decision making between AV and human driver. Finally, human-in-the-loop experiments are conducted to verify the performance of the proposed algorithm. Experiment results indicate that the proposed algorithm is capable of realizing human-like driving for AVs.

In the future, the proposed human-like driving framework will be further improved and applied to more complex scenarios.

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