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A Trust-based Human-Vehicle Co-driving System with Model Free Adaptive Dynamic Programming Controller

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Abstract— **Trust is one of the crucial factors influencing the performance and safety of human-vehicle co-driving system. The evolution mechanism of human-vehicle trust is studied in this work, and a trust-based steering control model (SCM) is designed to allow the autonomous driving system to adjust its control behavior based on real-time trust level, on the purpose of improve the efficiency and trust. The contributions made in this paper are as follows: 1) a novel quantitative model of human-vehicle dynamic trust is established for the first time in shared steering control by considering the deviation of human-vehicle driving expectations; 2) a trust-based steering controller using model free adaptive dynamic programming (MFADP) is designed which can solve the optimal control policy according to the value of trust without the dependencies on parameters of dynamic model of the controlled system. The rationality of proposed trust model and trust-based steering control method are validated by high-fidelity Carsim-Simulink simulations.**

I. Introduction

As intelligent vehicles and autonomous driving technologies advance, intelligent transportation systems have significantly improved, offering convenience in specific scenarios. However, due to the limitations of high-level autonomous driving and regulatory constraints, fully autonomous vehicles are unlikely to be widely adopted in the near future. Thus, intelligent vehicle technology will remain in a state of human-vehicle co-driving [1]–[3]. In this context, trust is a crucial factor in human-vehicle interaction [4]–[6]. The level of human trust in the intelligent system fluctuates during cooperative driving, and it is essential for the autonomous system to adjust its control actions in real-time based on the estimated trust level to better align with the driver's expectations and enhance collaboration efficiency.

Human-machine trust is typically defined as an individual's confidence in an automated system's ability to help achieve specific goals [7]. Due to the importance of trust in human-machine collaboration, various trust modeling studies have been conducted. For example, an online probabilistic trust model is developed using a partially observable Markov decision process (POMDP) based on behavioral data of drivers [8]. This POMDP model is further applied to enhance human-machine collaboration in [9]. Other researchers use measurable data, such as EEG, ECG, and gaze behavior, to build quantitative trust models [10]–[12]. Most existing trust models rely on probabilistic or machine learning methods based on physiological and behavioral data, which are limited by data quality and scenario conditions. Additionally, these models do not specifically focus on the dynamics of trust in human-vehicle co-driving systems.

In human-vehicle cooperation, co-driving systems can be classified into traded control and shared control based on the mode of interaction [13], [14]. In this context, trust reflects the driver's willingness to accept the control actions of the autonomous system. The dynamic mechanism of trust in human-vehicle interaction is first explored in [15], where a quantitative trust model is developed for adaptive cruise control (ACC) in traded control mode. However, this work focuses solely on longitudinal control, ignoring steering scenarios, and the application of traded control is limited by technology and uncertainties in control takeover. Therefore, studying trust modeling in shared steering control is essential. The authors of [16] develop a predictive model of objective trust in steering control by modifying the cost function. Moreover, a human-vehicle mutual trust model is introduced for authority allocation based on the steering behavior and performance of driver and automation. However, trust dynamics in human-vehicle shared steering control are not studied in these works.

Furthermore, in human-vehicle shared steering control, the dynamics of the controlled system involve significant complexity and uncertainty. It is essential to employ data-driven methods, such as MFADP, to address optimal control problems when the system model parameters are unknown [18]. In [19], a data-driven ADP controller is designed for intelligent vehicle path tracking, with steering input compensation calculated in real-time using a radial basis function neural network (RBFNN). Additionally, a human-vehicle shared steering control framework is proposed in [20] using an ADP controller, which solves the optimal control policy through iterative learning. However, as one of the most critical human factors in human-machine collaborative driving, trust level is not considered in these studies, which may lead to human-vehicle conflicts and even nasty accidents.

Therefore, to improve the performance and stability of co-driving system while reducing the human-vehicle conflicts and operational workload, a trust dynamics modeling method and a trust-based human-vehicle shared steering control

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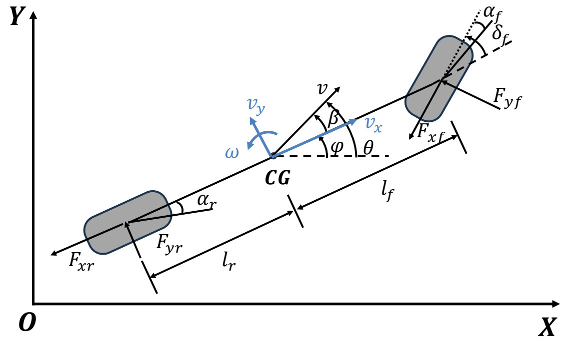

Fig. 1. Diagram of vehicle dynamics.

framework are proposed. Contributions made in this work are as follows:

1) A novel quantitative model of human-vehicle trust in shared steering control is established for the first time. The deviation between the driving expectations of human driver and automated vehicle is evaluated to describe the performance of co-driving system for establishing trust dynamics.
2) A modified trust-based model-free ADP controller is designed for trajectory tracking, which adapts its steering behavior based on the human-vehicle trust level in the real-time. Optimal control is solved by data-driven iterations without reliance on the precise knowledge of system parameters.

The rest of this paper is structured as follows. First in Section II, the vehicle dynamics and driver preview model as well as the trust dynamics in shared steering control are introduced. Then, the MFADP-based steering controller and a modified trust-based ADP steering control method are proposed in Section III. Further, the simulation studies are conducted in Section IV to validate the proposed trust-based co-driving framework. Finally, the last section summarizes this paper and discuss some future work.

II. Trust Dynamics Construction for Shared Steering Control

A novel quantitative trust model is established in this section to describe the evolution mechanism of trust level during human-vehicle co-driving process.

A. Vehicle Dynamic Model

A linear single-track model of vehicle shown in Fig. 1 is utilized for steering control in this work, and the differential equations of the controlled system can be written as [21]

$$\begin{cases} \dot{v}_y = \dfrac{C_f + C_r}{mv_x} v_y + \left(\dfrac{l_f C_f - l_r C_r}{mv_x} - v_x \right) \omega - \dfrac{C_f}{m} \delta_f, \\ \dot{\omega} = \dfrac{l_f C_f - l_r C_r}{I_z v_x} v_y + \dfrac{l_f^2 C_f + l_r^2 C_r}{I_z v_x} \omega - \dfrac{l_f C_f}{I_z} \delta_f, \end{cases} \tag{1}$$

where, v_x, v_y indicate the longitudinal and lateral velocity; ω is the yaw rate; m is the mass of the vehicle; C_f and C_r are the cornering stiffness of front and rear wheel; l_f and l_r present the distance from mass center of the vehicle to front and rear axis; I_z denotes the yaw moment of inertia; δ_f is the steering angle of front wheel.

With the assumptions that the steering angles as well as the tire sideslip angles are small [22], [23], if the vehicle is considered moving at constant longitudinal velocity, the vehicle dynamics can be linearized as

$$\begin{cases} \dot{\boldsymbol{x}} = A\boldsymbol{x} + B\delta_f, \\ \boldsymbol{y} = C\boldsymbol{x}, \end{cases} \tag{2}$$

where, $\boldsymbol{x} = [Y, \varphi, v_y, \omega]^T$ is the state variables in which Y is lateral global coordinate and φ is the yaw angle; A, B, C are constant matrices describing the system's input-output relationship and dynamic characteristics, which are given by

$$A = \begin{bmatrix} 0 & v_x & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{C_f + C_r}{mv_x} & \frac{l_f C_f - l_r C_r}{mv_x} - v_x \\ 0 & 0 & \frac{l_f C_f - l_r C_r}{I_z v_x} & \frac{l_f^2 C_f + l_r^2 C_r}{I_z V_x} \end{bmatrix}$$

$$B = [0, 0, -\frac{C_f}{m}, -\frac{l_f C_f}{I_z}]^T, \quad C = \mathbf{I}_{4\times 4}$$

B. Driver Expectation Model

A diver preview model is established to describe the driver's control expectation considering the characteristics of actual driving behavior [24]. When driving a car, the driver always looks ahead on the road and generates a preview point on his desired trajectory forward at current time t. During the preview time T_p, the vehicle is expected to move from the starting point $(x(t), y(t))$ to the preview point, which can be described as

$$y(t + T_p) = y(t) + \Delta y = f(t + T_p), \tag{3}$$

where, $y(t + T_p)$ is the predictive lateral position of vehicle; $f(t + T_p)$ is the desired lateral position of preview point. The preview time is chosen as $0.5s$ in this paper.

Suppose the vehicle conduct uniformly accelerated rectilinear motion laterally in the short preview time, thus the lateral displacement of vehicle can be present as [25]

$$\Delta y = T_p \cdot \dot{y}(t) + \frac{1}{2} T_p^2 \cdot \ddot{y}(t), \tag{4}$$

where, $\dot{y}(t)$ and $\ddot{y}(t)$ are the lateral velocity and lateral acceleration, respectively.

In every single time element, we can assume that the vehicle conducts circular motion with a radius R, then we can obtain an optimal curvature (i.e., the desired or expected moving curvature of vehicle by the human driver) as (5).

$$\rho^* = \frac{1}{R} = \frac{2 \cdot [f(t + T_p) - y(t) - T_p \cdot \dot{y}(t)]}{d^2}, \tag{5}$$

where, d denotes the preview distance with $d = v_x T_p$; ρ^* is the expected curvature of the driving trajectory by human driver. Considering the dynamic steering characteristics, the yaw rate gain during steady steering process can be given by $G_\omega = \dfrac{v_x/L}{1+Kv_x^2}$ with $K = \frac{m}{L^2}(\frac{l_f}{C_r} - \frac{l_r}{C_f})$ being the stability factor of vehicle [26], [27] and $L = l_f + l_r$ is the wheelbase.

According to Ackermann steering theory, there is a direct proportional relationship between the vehicle's trajectory curvature and the steering wheel angle. Hence, the optimal steering angle of front wheel is derived by the driver's preview model as

$$\delta_d = \frac{2 \cdot v_x[f(t+T_p) - y(t) - T_p \cdot \dot{y}(t)]}{G_\omega d^2}. \tag{6}$$

It is important to emphasize that in practical applications, data-driven methods can be used to establish human-like driving decision-making and planning models which can be utilized to generate the desired trajectories of drivers. In this paper, the steering angles calculated by (6) based on known trajectories is regarded as the driver's expected steering operation.

C. Shared Control and Trust Dynamic Model

In this part, the basic shared steering control model is introduced, and then we explore the evolution mechanism of trust in human-vehicle system and build a quantitative trust dynamics model in the scenario of trajectory tracking.

A shared control model [28], [29] is built in this paper and represent as

$$\delta_f = \alpha\delta_d + (1-\alpha)\delta_v, \tag{7}$$

where, $\alpha \in [0,1]$ is the control authority of human driver; δ_d, δ_v indicate the steering angles of the driver and vehicle; δ_f is the final control input to the vehicle system.

Remark 1: Note that in this paper, the autonomous vehicle is assumed to possess the capability for independent steering control input. However, it is essential to emphasize that the operation of the driver is considered to be more reliable and safe than that of the automation [30]. In this paper, the human driver represented by preview model and intelligent vehicle calculate their optimal steering control input independently.

Trust is regarded as objective reliability of autonomous driving system, which depends on the actual performance of the shared steering control system, related to the operational deviations of human-vehicle co-driving system (named as "error" later). The authors of [15] present a method for evaluating trust in human-ACC system. However, this model is limited to longitudinal control and does not address human-machine collaborative steering. Therefore, this paper develops a quantitative model of trust and its dynamics specifically for human-vehicle shared steering control. The evaluated error during the co-driving process is defined as

$$\begin{aligned} E(t) &= E_1(t) + E_2(t) \\ &= 0.1\{[\dot{y}_v(t) - \dot{y}_d(t)]^2 + [\dot{\varphi}_v(t) - \dot{\varphi}_d(t)]^2\} \\ &\quad - 0.2e^{-\|y(t)-y_t(t)\|}, \end{aligned} \tag{8}$$

where, $\dot{y}_v(t)$ and $\dot{y}_d(t)$ are lateral velocity of vehicle and driver's expectation; and $\dot{\varphi}_v(t), \dot{\varphi}_d(t)$ are the yaw rate; $y(t)$ is the real lateral displacement while $y_t(t)$ is the target lateral position of human driver. It can be found that, the difference between driving expectations of driver and machine as well as the actual tracking performance of system are both considered in the evaluation of error.

Hence, the performance level of the human-vehicle collaboration is defined by

$$P(t) = 1 - tanh(E(t)), \tag{9}$$

where, a hyperbolic tangent function is used to organize the value of performance $P(t)$ into range $[0,1]$. Sequentially, trust can be described in a form of state equation as

$$\dot{T}(t) = -\lambda T(t) + u_T(t), \tag{10}$$

where, $T(t)$ is the real-time trust level; λ is a positive constant which describes the descent rate of trust with $\begin{cases} SS: & \lambda = \lambda_1 \\ NSS: & \lambda = \lambda_2 \end{cases}$; the parameters are chosen as $\lambda_1 = 4 \times 10^{-4}, \lambda_2 = 2 \times 10^{-3}$ in this paper to regulate the changing range of trust level; *SS* indicates the steady state of lateral trajectory tracking(i.e., $y(t) - y_t(t) = 0$); $u_T(t)$ is the input used to update the dynamic trust state, which is defined as

$$u_T(t) = \begin{cases} SS: & 0, \\ NSS: & \begin{cases} \kappa_1 P(t), & P(t) > P_{thr} \\ -\kappa_2\|\delta_d(t) - \delta_v(t)\|, & P(t) \le P_{thr} \end{cases} \end{cases} \tag{11}$$

where, $P_{thr} = 0.86$ is the threshold of performance level; $\kappa_1 = 5 \times 10^{-2}, \kappa_2 = 6 \times 10^{-3}$ are constant parameters.

Remark 2: As shown in Equations (10) and (11), when the vehicle system tracks the desired trajectory well (i.e., in SS), the trust level will decrease slowly at a low rate, since the driving environment is not urgent. When the vehicle system is in NSS and requires continuous adjustment of the driving operations, the trust level will either increase or decrease depending on the changes in the overall performance of shared control system.

III. Trust-based MFADP Steering Controller

In this section, a model-free ADP controller is designed to solve the optimal steering control policy. Moreover, a trust-based MFADP controller is established which can adjust its control policy based on real-time trust level for better driving performance and less human-vehicle conflicts.

A. MFADP-based Steering Controller

A model-free adaptive dynamic programming method is proposed to address optimal steering control problem.

Generally, for the vehicle dynamics established in (2), it is widely accepted to find a feedback control as

$$u = -K\boldsymbol{x}, \tag{12}$$

The feedback gain K in (12) is obtained to realize optimal control where the following cost function is minimized.

$$J = \int_0^\infty \left(\boldsymbol{x}^T Q\boldsymbol{x} + u^T Ru\right) dt, \tag{13}$$

where, Q, R are state weighting matrix and control weighting matrix, respectively. In the case that the parameters A and B in the system model are already known precisely, the feedback control problem can be addressed directly by solving the Algebraic Riccati Equation(ARE) as follows.

$$\begin{cases} A^T P^* + PA + Q - P^* BR^{-1} B^T P^* = 0, \\ K^* = R^{-1} B^T P^*, \end{cases} \tag{14}$$

where, P^* is a real symmetric, positive definite matrix which is the solution of ARE; $K^*$is the optimal feedback gain.

Nevertheless, in many steering control conditions and complex scenarios, A and B cannot be measured exactly due to the uncertainty and unsteady disturbance. To this end, model-free data-driven approach is used in this paper without the reliance on knowledge of the specific parameters of system model.

In the perspective of online iteration, a control policy with noise is considered as:

$$u = -K_k \boldsymbol{x} + e, \tag{15}$$

where, K_k is the feedback control gain in iteration; e is the artificial exploration noise selected to be a sinusoidal signal with $e = 2\sin(100t)$. Then the online policy iteration equation is obtained

$$\begin{cases} K_k = R^{-1} B^T P_{k-1}, \\ \boldsymbol{x}^T(t+\delta t) P_k \boldsymbol{x}(t+\delta t) - \boldsymbol{x}^T(t) P_k \boldsymbol{x}(t) \\ \qquad -2\int_t^{t+\delta t} e^T R K_{k+1} \boldsymbol{x} d\tau \\ \qquad = -\int_t^{t+\delta t} \boldsymbol{x}^T (Q + K_k^T R K_k) \boldsymbol{x} d\tau, \end{cases} \tag{16}$$

where, P_k is the real symmetric positive definite solution of Lyapunov equation $A_k^T P_k + P_k A_k + Q + K_k^T R K_k = 0$ with $A_k = A - BK_k$. In this case, P_k and the feedback gain K_{k+1} can be solved by online iterations when A, B in the system model are unknown.

Off-policy learning method is then applied to find the optimal control in this paper. From (16), with an initialized arbitrary control $u = u_0$, we can transform the equation into the form of kronecker product with

$$\begin{cases} \boldsymbol{x}^T Q_k \boldsymbol{x} = \left(\boldsymbol{x}^T \otimes \boldsymbol{x}^T\right) vec(Q_k), \\ (u + K_k \boldsymbol{x})^T R K_{k+1} \boldsymbol{x} \\ \qquad = [\left(\boldsymbol{x}^T \otimes \boldsymbol{x}^T\right)\left(I_n \otimes K_k^T R\right) \\ \qquad\quad + \left(\boldsymbol{x}^T \otimes u_0^T\right)(I_n \otimes R)] K_{k+1}, \end{cases} \tag{17}$$

where, $Q_k = Q + K_k^T R K_k$. Organizing the parameters and variables, we have

$$\tilde{\Theta}_k \begin{bmatrix} vec(P_k) \\ vec(K_{k+1}) \end{bmatrix} = \tilde{\Xi}_k, \tag{18}$$

$$\tilde{\Theta}_k = \begin{bmatrix} \delta_{xx} \\ -2\left[I_{xx}\left(I_n \otimes K_k^T R\right) + I_{xu}(I_n \otimes R)\right] \end{bmatrix}^T, \tag{19}$$

$$\tilde{\Xi}_k = -I_{xx} vec(Q_k), \tag{20}$$

where $vec(\cdot)$ is defined as a vector in $\mathbb{R}^{mn}$ by stacking the columns of a matrix in $\mathbb{R}^{n \times m}$; δ_{xx}, I_{xx} and I_{xu} are matrices used to record state information for iterations. For any positive integer l and time constants $0 < t_1 < t_2 < \cdots < t_l$, we have

$$\begin{cases} \delta_{xx} = \left[x \otimes x|_{t_0}^{t_1}, x \otimes x|_{t_1}^{t_2}, \cdots, x \otimes x|_{t_{l-1}}^{t_l} \right]^T, \\ I_{xx} = \left[\int_{t_1}^{t_2} x \otimes x d\tau, \int_{t_2}^{t_3} x \otimes x d\tau, \cdots, \int_{t_{l-1}}^{l} x \otimes x d\tau \right]^T, \\ I_{xu} = \left[\int_{t_1}^{t_2} x \otimes u d\tau, \int_{t_2}^{t_3} x \otimes u d\tau, \cdots, \int_{t_{l-1}}^{l} x \otimes u d\tau \right]^T. \end{cases} \tag{21}$$

Hence, $\tilde{\Theta}_k, \tilde{\Xi}_k$ are derived by measuring system states and inputs at multiple time ranges as well as combining with parameter values at current iteration step. The optimal steering control is realized using MFADP.

B. Trust-based Steering Control Model

This section establishes a novel steering control model based on established trust dynamics.

In the steering controller using MFADP, the value of state weighting matrix Q is very crucial in the calculation of the feedback gain. Inspired by [31], the value of Q could be dynamically adjusted. In our work, we consider that parameter Q will be influenced by quantitative trust in the real time, which will further affect the control policy. The adjustment mechanism of Q is described by

$$Q = Q_v + [1 - T(t)](Q_d - Q_v), \tag{22}$$

where, Q_v and Q_d are the weighting matrices of automation and human driver. In this case, the parameters are given by $Q_d = diag(5,5,0,0)$ and $Q_v = diag(0,0,5,5)$ such that the control weightings for distinct state variables are different to emulate the steering characteristics of human driver and intelligent controller. Then the trust-based SCM can be established as Algorithm I.

Algorithm 1: Trust-based model free ADP control

Data: initial feedback gain K_0, set the weighting matrices Q_d and Q_v, Set $\varepsilon > 0$ as a small threshold.

$k \leftarrow 0$;
Get the real-time trust level $T(t)$;
$Q \leftarrow Q_v + [1 - T(t)](Q_d - Q_v)$;
Set $t = t_1 := 0$;
repeat
  $u \leftarrow -K_0 \boldsymbol{x} + e$;
  Compute matrices δ_{xx}, I_{xx} and I_{xu} from (21);
until *full rank condition of* $\tilde{\Theta}_k$ *is satisfied*;
Compute P_k and K_{k+1} from (18) with $k = 0$;
repeat
  $k \leftarrow k + 1$;
  Update P_k and K_{k+1} from $\tilde{\Theta}_k \begin{bmatrix} vec(P_k) \\ vec(K_{k+1}) \end{bmatrix} = \tilde{\Xi}_k$;
until $|P_k - P_{k-1} \leq \varepsilon|, k \geq 1$;

Result: Optimal control policy $u = -K_k \boldsymbol{x}$.

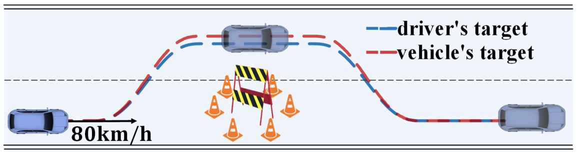

Fig. 2. Driving scenario of double lane change.

TABLE I
PARAMETERS OF VEHICLE MODEL

Parameters	Value	Parameters	Value
m	1412kg	l_f	1.015m
I_z	$1536.7\text{kg}\cdot\text{m}^2$	l_r	1.895m
C_f	-112600N/rad	C_r	-94548N/rad

Specifically, when the value of trust is low, the automated vehicle would focus on deviation of lateral position and yaw angle, updating its control policy to follow driver's expectation to increasing the performance and trust. Conversely, if the trust is high, the vehicle applies steering strategy with a weighing matrix close to Q_v. The optimal control policy is solved based on updated weighing matrix using MFADP.

IV. SIMULATION STUDIES AND ANALYSIS

High-fidelity Carsim-Simulink simulations are used to verify the effectiveness of trust model for human-vehicle cooperation as well as the trust-based steering control. We choose a driving scenario of double lane change for human-vehicle collaborative trajectory tracking as shown in Fig.2. And the longitudinal velocity of vehicle in the simulation is controlled to be a constant value of $v_x = 80\text{km/h}$.

Remark 3: To validate the proposed trust-based human-machine co-driving strategy, the human driver and automation are considered to have different driving expectations. In the lane-changing scenario, the automated system prioritizes safety by maintaining maximum distance from obstacles, which may increase the consumption of time and energy. In contrast, experienced drivers can optimize the efficiency while ensuring safety by following a more suitable trajectory. As shown in Fig.2, the blue line represents the driver's expected trajectory, while the red line indicates a more conservative path preferred by the automated system.

Based on the designed scenario, high-fidelity Carsim-Simulink co-simulations are conducted to validate the proposed framework with parameters listed in Table I. The time period of simulation is 15s, and the time step is 0.01s. In this section, traditional shared control model (abbreviated as "Tra-SCM") and the proposed trust-based shared control model ("Trust-SCM") are tested and evaluated, the control authority is allocated using numerical function method with same parameters referring to [32]. But the "Tra-SCM" uses the controller with constant matrix Q, while "Trust-SCM" applies trust-based MFADP controller for the automation.

The results of trajectory tracking with different shared control methods are represent in Fig.3. Under "Tra-SCM", the actual trajectory has a larger deviation from the human driver's expectation. In contrast, the tracking performance of "Trust-SCM" is significantly better than the "Tra-SCM" which indicates that utilizing trust-based MFADP controller, thereby adaptively adjusting control strategies according to the trust level, can enhance the performance of human-vehicle collaborative driving.

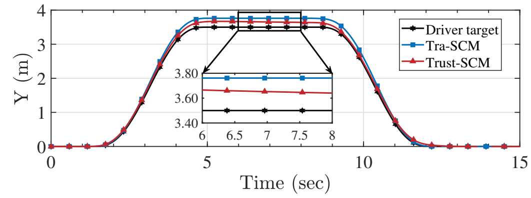

Fig. 3. Trajectory tracking profiles.

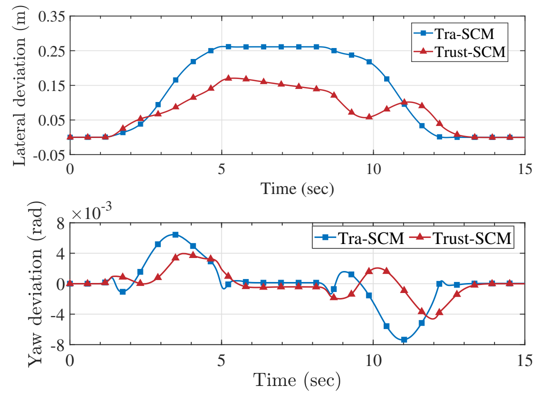

Fig. 4. Profiles of tracking deviation e_y, e_φ.

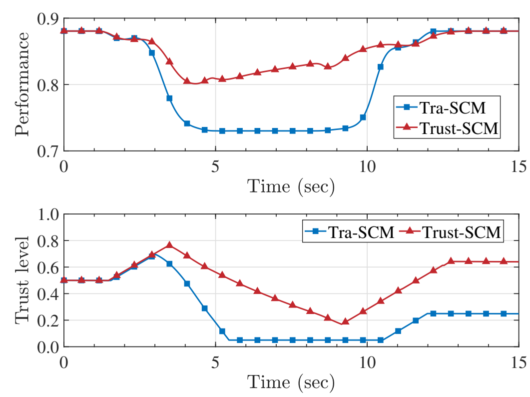

Fig. 5. Profiles of performance and Trust.

Fig.4 shows the deviations of lateral displacement and yaw angle. It is evident that the average tracking error under "Trust-SCM" is significantly smaller than that of "Tra-SCM" during the steering processes. Meanwhile, a less value of e_φ is can also be found in "Trust-SCM", which indicates better trajectory tracking performance.

Moreover, it is evident that both the performance of co-driving system and the trust level under "Trust-SCM" takes higher average level than "Tra-SCM" from Fig. 5. This implies that real-time adjustment of control strategies based on trust can effectively improve the performance of collaborative driving and reduce conflicts.

V. Conclusion

The major contribution of this work is proposing a novel quantitative trust dynamic model for human-vehicle shared steering control for the first time, considering the deviations between human and automation expectations. Additionally, the paper designs a trust-based model-free adaptive dynamic programming controller that can adaptively adjust the control weight matrix based on the real-time trust level. Validation through high-fidelity Carsim-Simulink co-simulations confirms the increase in trust level and reduction in driver workload using the proposed trust-based human-vehicle co-driving system. Future research will focus on trust-based authority allocation strategies for human-vehicle cooperative driving and game theory-based shared steering control.

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