

Article

A Hierarchical Shared Steering Control Strategy Based on Driver States

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Abstract

Continuous shared control provides an effective approach for intelligent vehicles to balance driving autonomy and system safety boundaries in complex human–machine interaction scenarios. However, existing shared control methods fail to dynamically adapt to the complex and time-varying states of the driver. To address this limitation, a hierarchical shared steering control strategy based on driver states is proposed in this paper. First, an in-vehicle eye tracker is utilized to collect data, and recognition features are extracted based on real-world datasets. Subsequently, a CNN-TCN deep learning algorithm is employed to train a model for identifying five-dimensional driver states. To mitigate excessive intervention and driving experience degradation caused by model misclassifications, a total probability weighting mechanism is developed. This mechanism integrates the real-time confidence distribution output by the neural network with the established baseline safety weights for each driving state, enabling the dynamic and continuous computation of the initial machine control authority. Furthermore, to eliminate high-frequency confidence spikes at the state perception end, a weight-smoothing strategy is designed using an adaptive nonlinear tracking differentiator based on Active Disturbance Rejection Control (ADRC). An autonomous driving controller is then constructed using the Linear Quadratic Regulator (LQR) method to ensure vehicle stability. Finally, Hardware-in-the-Loop (HIL) experiments conducted on a human–machine driving platform with hardware feedback verify the feasibility and superiority of the proposed method.

Keywords: CNN-TCN; driver state recognition; shared control; Linear Quadratic Regulator (LQR)



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1. Introduction

With the rapid development of artificial intelligence, high-definition sensors, and in-vehicle computing power, autonomous driving has been widely recognized as the core direction for the future evolution of intelligent transportation and vehicle engineering [1]. However, constrained by extremely variable weather conditions, complex scenarios, and irreconcilable ethical dilemmas, the engineering deployment of fully autonomous driving in the short term still faces tremendous challenges [2]. Therefore, continuous shared control technology is widely regarded by both academia and industry as the most safe and effective transitional solution for the current stage and a considerable period in the future [3,4]. In continuous shared control systems, shared steering control directly determines the safety of the driving trajectory and the comfort of human–machine interaction by dynamically adjusting the degree of synergy between the human driver and the automated controller [5].

Nevertheless, how to achieve a continuous and smooth transition of control authority between the human and the machine based on real-time changes in the driver's physiological and behavioral states, while ensuring precise trajectory tracking of the underlying vehicle, remains a highly challenging core issue in current shared steering control systems [6,7].

To achieve a reasonable allocation of human-centric intelligent control authority, the co-driving system must first possess the capability for real-time perception and precise recognition of the driver's current physiological state and operational behavior [8]. Many scholars have conducted in-depth research on abnormal states such as fatigue and distraction during driving using various driver behavior models and Driver Monitoring Systems (DMSs) [9,10]. Traditional recognition methods mostly rely on static thresholds or simple rule-based judgments, making it difficult to accurately portray the complex, continuous, and time-varying nonlinear evolutionary process of human drivers from awake to fatigued, and from normal to distracted [11]. In recent years, the rise of deep learning technology has provided powerful tools for processing multi-source heterogeneous time-series behavioral features [12]. Networks such as One-Dimensional Convolutional Neural Networks (1D-CNN) and Long Short-Term Memory (LSTM) have been widely applied to capture the spatiotemporal coupling features of driving data [13,14]. However, traditional recurrent networks still suffer from limitations such as low parallel computation efficiency and difficulties in capturing long-range temporal dependencies when processing long sequences. In contrast, Temporal Convolutional Networks (TCNs), by introducing causal and dilated convolution structures, exhibit a stronger ability to extract long-sequence behavioral features while maintaining the advantage of full-lifecycle parallel computation [15].

Although deep learning-based state recognition models can accurately identify states, existing strategies still face dual challenges due to environmental influences. First, traditional strategies mostly rely on a single classification result for absolute authority allocation, ignoring the uncertainty of the perception model under complex driving conditions; once a state misclassification occurs, it is highly prone to trigger unintended excessive interventions and human-machine conflicts [16]. Second, existing shared control strategies lack effective constraints on high-frequency chattering noise in perception data [17,18]. During frame-by-frame time-series inference by deep neural networks, due to the uncertainty of decision boundaries and disturbances from input noise, the output Softmax posterior probabilities naturally exhibit unavoidable high-frequency jumps and confidence spike phenomena along the time axis [19,20]. According to the transmission mechanism of system dynamics, if this noisy initial control authority is directly applied to the human-machine steering angle synthesis equation, its transient severe steps in the perception dimension will be propagated unhindered to the actuators, leading to severe high-frequency mechanical oscillations of the steering wheel [21,22]. This not only severely damages the driver's operational comfort and cooperative trust but may also induce destabilizing chattering in chassis lateral dynamics during high-speed driving. Therefore, determining how to cut off the dynamic transmission of high-frequency confidence noise from the perception end to the control end while maintaining high perception responsiveness, thereby achieving an overshoot-free and chattering-free smooth transition of authority, is the key to enhancing the robustness of human-machine cooperative steering.

At the lower-level control execution end, the automated controller must continuously maintain extremely high trajectory tracking accuracy and vehicle lateral stability during the transient process of dynamic authority handovers [23]. Currently, theoretical methods such as Model Predictive Control (MPC), Active Disturbance Rejection Control (ADRC), and Linear Quadratic Regulator (LQR) have been successfully applied to vehicle lateral tracking tasks [24,25]. Among them, the LQR algorithm has become the mainstream solution for intelligent vehicle chassis steer-by-wire control due to its advantages of low

computational power consumption, ease of hardware-embedded deployment, and high efficiency in closed-loop optimal computation [26–29].

In light of this, this paper proposes a hierarchical shared steering control strategy framework that integrates data-driven perception with mechanism-based feedback control. The upper-level architecture deeply mines multi-dimensional time-series features through CNN-TCN and calculates the initial machine authority via total probability weighting. To eliminate self-excited oscillations caused by confidence jumps, the concept of the tracking differentiator from ADRC theory is introduced, and an Adaptive Nonlinear Tracking Differentiator (ANTD) is designed to strictly smooth the control authority transfer rate in the time domain. The lower level relies on a 2-DOF vehicle error state-space model to construct an LQR optimal state feedback controller, generating the ideal machine steering angle.

The main contributions of this paper are as follows:

1. To guarantee the driving experience while improving and ensuring vehicle stability, a shared steering control framework based on driver states is established. A driver state recognition model is constructed using CNN-TCN, achieving high-precision real-time recognition of five categories of driver states. Furthermore, control authority weights are smoothly allocated through the five-dimensional driver states.
2. Addressing the issue where misclassifications from a single recognition result easily trigger unintended excessive system interventions, a dynamic human–machine control authority allocation mechanism is proposed based on total probability weighting theory. This method deeply integrates the real-time Softmax posterior probabilities output by the neural network, transforming hard-threshold takeovers into confidence-based continuous weighting, effectively accommodating the uncertainty of the recognition model in complex scenarios.
3. Based on the concept of Active Disturbance Rejection Control (ADRC), an adaptive nonlinear tracking differentiator is designed, which effectively smooths weight changes. Meanwhile, Hardware-in-the-Loop (HIL) experiments conducted on a human–machine driving platform equipped with real actuators and physical feedback verify the effectiveness of the proposed hierarchical shared control strategy in actively adapting to driver states and enhancing the driving experience.

The remainder of this paper is organized as follows. Section 2 introduces the vehicle system dynamics modeling and the driver state recognition model. Section 3 describes the proposed shared steering control strategy. Section 4 introduces the employed LQR control algorithm. Section 5 conducts simulation and HIL experiments and discusses the experimental results. Section 6 concludes the entire paper.

2. Vehicle System Dynamics Model and Driver State Recognition Model

This section establishes a standard 2-degree-of-freedom (2-DOF) vehicle lateral dynamics model and designs a data-driven driver state recognition model. Section 2.1 establishes the vehicle dynamics model, and Section 2.2 designs the CNN-TCN-based driver state recognition model.

2.1. Vehicle System Dynamics Modeling

In this paper, the lateral dynamics are described using a well-established 2-degree-of-freedom (2-DOF) vehicle model, which captures the fundamental coupling relationship between lateral motion (characterized by the sideslip angle β) and yaw motion (characterized by the yaw rate $\dot{\psi}$) [30]. As shown in Figure 1, the equations for the lateral and yaw motions of the vehicle can be expressed as

$$m(\dot{v}_y + V_x \dot{\psi}) = F_{yf} + F_{yr} \quad (1)$$

$$I_z \ddot{\psi} = l_f F_{yf} - l_r F_{yr} \quad (2)$$

where m is the vehicle mass; I_z is the yaw moment of inertia around the center of gravity (CG); v_y is the vehicle lateral velocity; $\dot{\psi}$ and $\ddot{\psi}$ are the yaw rate and yaw acceleration, respectively; l_f and l_r are the distances from the vehicle CG to the front and rear axles, respectively; and F_{yf} and F_{yr} are the lateral forces acting on the front and rear tires, respectively.

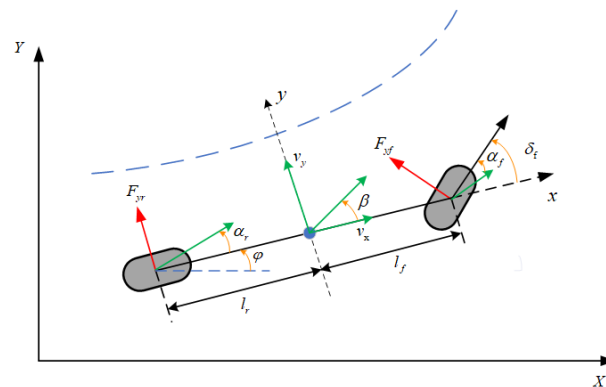


Figure 1. 2-DOF vehicle dynamics model.

Under the small-angle assumption, the tire lateral forces can be approximated as linear:

$$F_{yf} = 2C_{\alpha f} \alpha_f = C_f \left(\delta_f - \frac{v_y + l_f \dot{\psi}}{V_x} \right) \quad (3)$$

$$F_{yr} = 2C_{\alpha r} \alpha_r = C_r \left(\frac{l_r \dot{\psi} - v_y}{V_x} \right) \quad (4)$$

where C_f and C_r are the equivalent total cornering stiffnesses of the front and rear axles, respectively; α_f and α_r are the slip angles of the front and rear tires; δ_f is the front wheel steering angle input.

Substituting the expressions for the tire slip angles into the fundamental dynamics equations yields the expanded vehicle dynamics differential equations:

$$\dot{v}_y = -\frac{C_f + C_r}{mV_x} v_y + \left(\frac{l_r C_r - l_f C_f}{mV_x} - V_x \right) \dot{\psi} + \frac{C_f}{m} \delta_f \quad (5)$$

$$\ddot{\psi} = \frac{l_r C_r - l_f C_f}{I_z V_x} v_y - \frac{l_f^2 C_f + l_r^2 C_r}{I_z V_x} \dot{\psi} + \frac{l_f C_f}{I_z} \delta_f \quad (6)$$

To construct a stable trajectory tracking closed-loop system, an error model must also be established. The lateral distance error e_1 is defined as the geometric distance from the current vehicle CG position to the closest projection point on the reference path, and the heading error e_2 is the difference between the actual vehicle heading angle ψ and the tangent azimuth ψ_r of the reference path:

$$e_2 = \psi - \psi_r \quad (7)$$

$$\dot{e}_1 = v_y + V_x e_2 \quad (8)$$

Substituting these into the above dynamics equations, and under the condition that the rate of change of the reference path curvature is relatively small, the equations can be reorganized as

$$\ddot{e}_1 = -\frac{C_f + C_r}{mV_x} \dot{e}_1 + \frac{C_f + C_r}{m} e_2 + \frac{l_r C_r - l_f C_f}{mV_x} \dot{e}_2 + \frac{C_f}{m} \delta_f \quad (9)$$

$$\ddot{e}_2 = \frac{l_r C_r - l_f C_f}{I_z V_x} \dot{e}_1 + \frac{l_f C_f - l_r C_r}{I_z} \dot{e}_2 - \frac{l_f^2 C_f + l_r^2 C_r}{I_z V_x} \dot{e}_2 + \frac{l_f C_f}{I_z} \delta_f \quad (10)$$

To avoid the linear dependence problem existing in some higher-order models and to construct a strict state space suitable for modern control design, this paper selects the full state feedback vector $X = [e_1, \dot{e}_1, e_2, \dot{e}_2]^T$ to construct a four-dimensional state vector. The control input variable is $u = \delta_f$. The standard form of the linear time-invariant (LTI) continuous state-space model is constructed as

$$\dot{X} = AX + Bu \quad (11)$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{C_f + C_r}{m V_x} & \frac{C_f + C_r}{m} & \frac{l_r C_r - l_f C_f}{m V_x} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{l_r C_r - l_f C_f}{I_z V_x} & \frac{l_f C_f - l_r C_r}{I_z} & -\frac{l_f^2 C_f + l_r^2 C_r}{I_z V_x} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ \frac{C_f}{m} \\ 0 \\ \frac{l_f C_f}{I_z} \end{bmatrix} \quad (12)$$

2.2. Driver State Recognition Model

To achieve a reasonable allocation of vehicle control authority between the human and the machine, the system first needs to accurately and in real-time perceive the driver's current cognitive and operational states. This paper proposes a driver state recognition model integrating a Convolutional Neural Network (CNN) and a Temporal Convolutional Network (TCN) to achieve feature extraction and accurate classification of five categories of driver state sequences.

Specifically, the driver's eye and facial features $P(k)$ collected by the eye-tracker sensor are first subjected to Min-Max normalization to eliminate dimensional differences before being input into the CNN-TCN model. This model can effectively learn cross-dimensional local spatial features and long-range temporal dependencies from driving behavior sequences, thereby outputting a preliminary probability distribution covering five states: awake, normal, mind wandering, distracted, and fatigued. This significantly improves the robustness of the overall system. The final recognition accuracy of the CNN-TCN model is 95.3%, and the Macro-F1 score is 94.91%.

The classification performance is shown in Figure 2. As illustrated in Figure 2a, a large number of incorrect predictions are concentrated in the mind wandering (Category 2) section. This is because, as an implicit cognitive state, its external behavioral manifestations are often relatively weak, and it shares a high degree of intersection and overlap in vehicle dynamic features with states such as awake (Category 3) or early fatigue (Category 1). This makes the model highly prone to cross-misclassification during time-series inference. Figure 2b,c display the confusion matrices of the CNN-TCN model and the CNN-LSTM model, respectively. The recognition of fatigue and mind wandering states is improved compared to the CNN-LSTM model. Especially for the mind wandering state, which features hidden characteristics and is highly prone to misclassification, the recognition accuracy of the proposed CNN-TCN model reaches 95%, representing a significant improvement of 8% over the traditional CNN-LSTM model. This fully verifies its superiority in complex state classification.

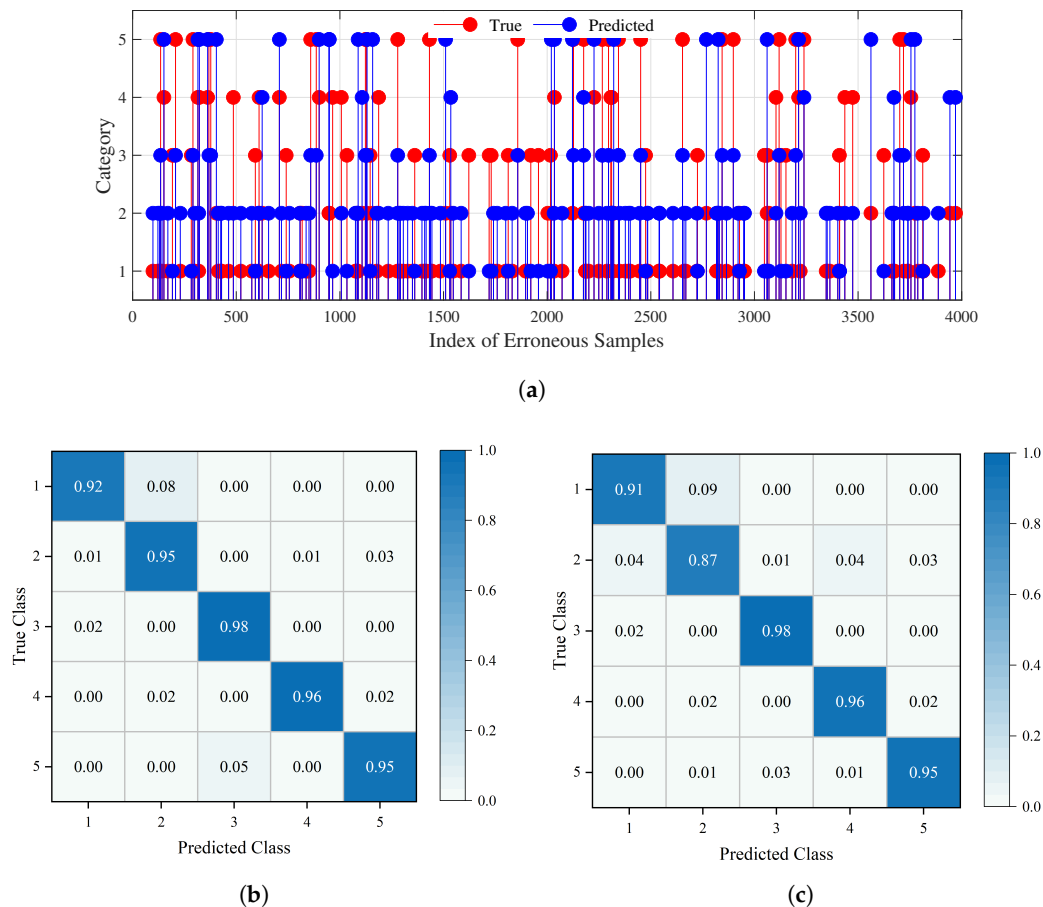


Figure 2. Classification performance diagrams. (a) Analysis of erroneous samples. (b) CNN-TCN confusion matrix. (c) CNN-LSTM confusion matrix.

3. Upper-Level Shared Steering Control Strategy Framework

This section designs a shared control framework based on driver states, and devises a weight-smoothing strategy based on the adaptive nonlinear tracking differentiator from Active Disturbance Rejection Control (ADRC). Section 3.1 establishes the overall system architecture and elucidates the shared weight allocation mechanism. Section 3.2 proposes the authority allocation mechanism based on driver states. Section 3.3 designs the weight-smoothing mechanism with an adaptive risk-anticipating tracking differentiator.

3.1. Design Architecture

The architecture of the proposed shared steering control strategy, as shown in Figure 3, includes two main components: the control authority allocation module and the weight smoothing module. The control authority allocation module consists of the driver state recognition module and the control authority calculation module. The control entities include the driver and the autonomous driving controller. The driver generates the human steering angle δ_h based on brain decision-making, and the controller obtains the optimal steering strategy through model design, outputting the ideal control steering angle δ_m in complex scenarios. These two steering angles are combined to generate the final front wheel steering angle based on the shared control strategy, thereby achieving cooperative vehicle control through human-machine interaction.

Table 1. Baseline weights.

State	Weight
Awake	0.1
Normal	0.3
Mind wandering	0.6
Distracted	0.7
Fatigued	0.9

First, the control authority coefficients of the machine controller (bottom layer of the system) and the human driver are defined to satisfy the convex combination constraints:

$$\alpha_m(t) + \alpha_h(t) = 1 \quad (13)$$

$$\text{s.t. } 0 \leq \alpha_m(t) \leq 1, \quad 0 \leq \alpha_h(t) \leq 1 \quad (14)$$

where $\alpha_m(t)$ is the control authority of the machine system, i.e., the takeover weight; $\alpha_h(t)$ is the control authority of the human driver. When $\alpha_m(t) \rightarrow 0$, the system degrades to the traditional human driving mode; when $\alpha_m(t) \rightarrow 1$, the system transitions into a fully autonomous driving mode. To finely characterize the control requirements under different states, the baseline takeover weight vector of the machine system corresponding to various discrete states is set as

$$W_{base} = [w_1, w_2, w_3, w_4, w_5]^T \quad (15)$$

where w_i ($i = 1, 2, \dots, 5$) strictly correspond to the safety threshold weights under the five states. The specific quantitative boundaries are shown in Table 1. To eliminate the control discontinuity of the system caused by hard-threshold switching, this paper fully activates the Softmax posterior probability output features of the aforementioned CNN-TCN deep neural network. Let the current frame's normalized probability distribution vector output by the classification network at time t be

$$P(t) = [p_1(t), p_2(t), p_3(t), p_4(t), p_5(t)]^T \quad (16)$$

$$\text{s.t. } \sum_{i=1}^5 p_i(t) = 1, \quad p_i(t) \in [0, 1] \quad (17)$$

By introducing the total probability weight synthesis operator, the inner product computation is performed between the discrete expert-experience weight space and the continuous Bayesian posterior probability space, yielding the analytical expression of the comprehensive initial takeover weight for the machine system at time t :

$$\alpha_{base}(t) = P(t)^T \cdot W_{base} = \sum_{i=1}^5 p_i(t) \cdot w_i \quad (18)$$

The vehicle's front wheel steering angle δ_f is a combination of the driver's intended front wheel steering angle δ_h and the optimal expected front wheel steering angle δ_m solved by the controller, which can be expressed by the following mathematical formula:

$$\delta_f(t) = (1 - \alpha_{base}(t))\delta_h(t) + \alpha_{base}(t)\delta_m(t) \quad (19)$$

To deeply investigate the control authority sensitivity diffusion effect brought by perception-end disturbances, the partial derivative of the joint control equation with respect

to the i -th state probability $p_i(t)$ is calculated, yielding the analytical formula of the system state disturbance transmission matrix:

$$\frac{\partial \delta_f(t)}{\partial p_i(t)} = (\delta_m(t) - \delta_h(t)) \cdot w_i \quad (20)$$

In actual driving environments, due to sensor noise and the inherent classification uncertainty of the deep learning model during frame-by-frame inference, the state probability vector $P(t)$ is highly prone to high-frequency jumps along the time axis. According to the formula derivation, this transient severe chattering in the perception dimension will be unrestrictedly amplified by the disturbance transmission matrix and directly propagated to the actuator. Therefore, a weight-smoothing strategy is strictly required.

3.3. Weight Smoothing Strategy

In the aforementioned authority allocation strategy, although the initial machine takeover weight $\alpha_{base}(t)$ calculated using the total probability weight synthesis operator can closely track changes in the driver's state macroscopically, it exhibits severe non-stationary high-frequency confidence spikes at the micro-time scale. If directly applied to the reconstruction of the shared control front wheel steering angle, it will trigger severe chattering of the actuator.

To resolve this issue and smooth the control weights, this paper introduces the Tracking Differentiator (TD) from Active Disturbance Rejection Control (ADRC). Utilizing its transient profile generation mechanism, it cuts off high-frequency noise transmission while achieving a time-domain smooth transition of the controller's takeover weight. Furthermore, considering the requirement for safety boundary response speed when the driver's state undergoes sudden mutations, this paper improves the traditional TD with adaptive time-varying parameters, constructing an adaptive nonlinear tracking differentiator with risk-anticipating characteristics.

A standard second-order nonlinear tracking differentiator constructs a nonlinear feedback system with critical damping, which can achieve high-fidelity, overshoot-free time-optimal tracking of the target signal while suppressing noise input. It can be expressed as

$$\begin{cases} \dot{v}_1(t) = v_2(t) \\ \dot{v}_2(t) = -R \cdot \text{sign}\left(v_1(t) - v(t) + \frac{v_2(t)|v_2(t)|}{2R}\right) \end{cases} \quad (21)$$

where $v(t)$ is the original input signal containing noise, which in this paper corresponds to the initial machine weight $\alpha_{base}(t)$; $v_1(t)$ is the smoothed machine takeover weight $\alpha_{smooth}(t)$; $v_2(t)$ is the time-domain rate of change of the weight; $\text{sign}(\cdot)$ is the standard sign function; and R is the speed factor, which determines the tracking response rate of the differentiator to the input signal.

In traditional TD design, R is usually fixed as a constant. However, in shared control scenarios, the dynamic switching of control authority must simultaneously balance driving compliance and danger intervention timeliness. Based on these requirements, this paper introduces a state change rate adaptive correction operator, formulating $R(t)$ into a nonlinear mapping function that dynamically reconstructs the evolution rate of the initial weight:

$$R(t) = R_0 + \eta \left| \text{LPF}\left(\frac{d\alpha_{base}(t)}{dt}\right) \right|^\gamma \quad (22)$$

where R_0 is the base tracking rate constant; and η and γ are adaptive adjustment coefficients used to adjust the sensitivity of the control authority to the degree of danger of state mutations. Furthermore, $\text{LPF}(\cdot)$ denotes a standard first-order low-pass filter. Because the

initial weight $\alpha_{base}(t)$ derived from the deep learning model inevitably contains high-frequency prediction jitter, direct numerical differentiation would severely amplify the noise. Applying this low-pass filter to the derivative signal is a crucial step to prevent severe fluctuations in $R(t)$ and guarantee the robust stability of the adaptive law.

Remark 1 (Proof of Stability and Boundedness for $R(t)$). *To strictly prove the stability of $R(t)$, we define the input signal as $u(t) = \frac{d\alpha_{base}(t)}{dt}$. Since the network inputs and logits evolve continuously with bounded rates over the considered operating domain, and the Softmax function has a bounded Jacobian, $\dot{\alpha}_{base}(t)$ is bounded. Let $x_f(t)$ denote the internal state of the standard first-order low-pass filter. Its dynamic equation is given by*

$$\dot{x}_f(t) = -\frac{1}{\tau}x_f(t) + \frac{1}{\tau}u(t) \quad (23)$$

where $\tau > 0$ represents the filter time constant. Therefore, Equation (22) is practically equivalent to $R(t) = R_0 + \eta|x_f(t)|^\gamma$.

Consider the Lyapunov candidate function $V = \frac{1}{2}x_f^2(t)$. Taking its time derivative yields $\dot{V} = x_f(t)\dot{x}_f(t) = -\frac{1}{\tau}x_f^2(t) + \frac{1}{\tau}x_f(t)u(t)$. Since $x_f(t)u(t) \leq |x_f(t)||u(t)|$, and combined with the constraint $|u(t)| \leq \bar{u}$, we obtain:

$$\dot{V} \leq -\frac{1}{\tau}|x_f(t)|^2 + \frac{1}{\tau}|x_f(t)|\bar{u} \quad (24)$$

$$\dot{V} \leq -\frac{1}{\tau}|x_f(t)|(|x_f(t)| - \bar{u}) \quad (25)$$

According to the theorem of Uniform Ultimate Boundedness (UUB) in Lyapunov theory, to guarantee that the system energy strictly monotonically decreases ($\dot{V} < 0$), it only requires the condition $|x_f(t)| > \bar{u}$ to be satisfied. This ensures that the filter state $x_f(t)$ is uniformly ultimately bounded. Furthermore, considering that the engineering implementation of the standard low-pass filter possesses zero initial conditions, the state $x_f(t)$ will always be strictly constrained within the boundary $\bar{u}$ throughout the entire transient and steady-state processes. Thus, $R(t)$ remains within a positive bounded range:

$$R_0 \leq R(t) \leq R_0 + \eta\bar{u}^\gamma \quad (26)$$

In summary, $R(t)$ remains strictly bounded and positive throughout the entire operating process. According to the Lyapunov uniform ultimate boundedness theorem, this result establishes the boundedness of the adaptive parameter $R(t)$ and excludes the possibility of parameter divergence.

To achieve absolutely smooth and chattering-free tracking in the discrete domain, the discrete time-optimal control synthesis function must be adopted. Specifically, this study utilizes the classic discrete *fhan* function proposed in Prof. Jingqing Han's foundational literature on Active Disturbance Rejection Control (ADRC) [31]. Based on this, the adaptive nonlinear tracking differentiator can be expressed as

$$\begin{cases} v_1(k+1) = v_1(k) + h \cdot v_2(k) \\ v_2(k+1) = v_2(k) + h \cdot \text{fhan}(v_1(k) - \alpha_{base}(k), v_2(k), R(k), h) \end{cases} \quad (27)$$

To eliminate limit cycle tangential steps, the following piecewise analytical structure is constructed:

$$a = \begin{cases} x_2 + \frac{a_0-d}{2} \cdot \text{sign}(y), & |y| > d_0 \\ x_2 + \frac{y}{h}, & |y| \leq d_0 \end{cases} \quad (28)$$

where $d = R \cdot h$; $d_0 = h \cdot d = R \cdot h^2$; $y = x_1 + h \cdot x_2$; $a_0 = \sqrt{d^2 + 8R|y|}$.

Based on the analytical partition of the above spatial state trajectory, the time-optimal feedback control law is expressed as

$$f_{han}(x_1, x_2, R, h) = -R \cdot \begin{cases} \text{sign}(a), & |a| > d \\ \frac{a}{d}, & |a| \leq d \end{cases} \quad (29)$$

The piecewise operator in Equation (25) is designed to provide a continuous transition within the boundary layer $|a| \leq d$, while maintaining the time-optimal switching behavior outside the boundary layer. Through the mapping of the mathematical structure described above, the system chattering and overshoot caused by discrete differences can be significantly reduced.

4. Lower-Level Controller Design

In the shared steering system, when the driver is unable to safely complete the driving task, the autonomous driving controller is required to assist in tracking the target path. In this section, the implementation of the autonomous driving controller adopts the Linear Quadratic Regulator (LQR) method [32] to enhance the generalization capability in complex scenarios. Section 4.1 conducts the trajectory tracking controller design, Section 4.2 details the design of the performance index function and weight matrices, and Section 4.3 synthesizes the optimal feedback gain and the expected steering angle.

4.1. Trajectory Tracking Controller Design

First, based on the 2-DOF vehicle dynamics model, the error dynamic state-space equation of the vehicle-road system is derived as follows:

$$\dot{X}(t) = AX(t) + Bu(t) \quad (30)$$

where the full state feedback vector $X(t) = [e_1(t), \dot{e}_1(t), e_2(t), \dot{e}_2(t)]^T$ contains the lateral and heading deviation information between the vehicle and the reference path; the system control input $u(t) = \delta_m(t)$ is the expected machine front wheel steering angle output by the lower-level controller; and the system state matrix A and the input matrix B encapsulate the inherent dynamic parameters of the vehicle.

The core design objective of the lower-level controller is as follows: given the initial state, to design an optimal state feedback control law $u(t) = -KX(t)$ such that the lateral distance error e_1 and heading error e_2 can converge to zero rapidly and smoothly, while avoiding severe high-frequency movements of the steering wheel.

4.2. Design of Performance Index Function and Weight Matrices

To seek the optimal solution between tracking accuracy and driving smoothness, this paper introduces the Linear Quadratic Regulator (LQR) algorithm. An infinite-horizon continuous-time quadratic performance index function J is constructed:

$$J = \int_0^\infty [X^T(t)QX(t) + u^T(t)Ru(t)]dt \quad (31)$$

where $Q \in \mathbb{R}^{4 \times 4}$ is a positive semi-definite state error weighting matrix, used to penalize the degree of deviation of the system state from the equilibrium point; $R \in \mathbb{R}^{1 \times 1}$ is a positive definite control input weighting scalar, used to penalize severe actions of the actuator. To ensure scientific reproducibility, the specific numerical values of the weighting matrices

implemented in HIL experiments are explicitly strictly set as $Q = \text{diag}([230, 10, 1, 1])$ and $R = [120]$.

4.3. Synthesis of Optimal Feedback Gain and Expected Steering Angle

To obtain the global minimum of the performance index J , solving for the optimal feedback control law is equivalent to solving the Continuous Algebraic Riccati Equation (CARE):

$$A^T P + PA - PBR^{-1}B^T P + Q = 0 \quad (32)$$

Through numerical calculation using the control algorithm program developed in this paper, the equation can yield a unique symmetric positive definite matrix solution $P \in \mathbb{R}^{4 \times 4}$. After obtaining matrix P , the optimal full state feedback gain matrix $K \in \mathbb{R}^{1 \times 4}$ of the lower-level system can be obtained as

$$K = R^{-1}B^T P = [K_1 \quad K_2 \quad K_3 \quad K_4] \quad (33)$$

Based on the obtained value of K , the expected steering angle of the optimal controller $\delta_m(t)$ is calculated:

$$\delta_m(t) = -KX(t) = -(K_1 e_1(t) + K_2 \dot{e}_1(t) + K_3 e_2(t) + K_4 \dot{e}_2(t)) \quad (34)$$

Through this control law, the ideal control variable $\delta_m(t)$ that guarantees stable vehicle tracking can be calculated in real-time. Subsequently, it is weightedly combined with the control authority $\alpha_{smooth}(t)$ and the driver's intended steering angle $\delta_h(t)$ in the aforementioned shared control framework, ultimately completing the dynamic closed-loop of the human-machine shared control system.

5. Experiments and Results Analysis

In this section, a sinusoidal (Sin) road driving scenario is selected to simulate and evaluate the performance of the designed controller, and the vehicle parameters are shown in Table 2. The CarSim(2019)-MATLAB/Simulink(2021b) co-simulation platform is adopted to verify the human-machine shared control framework, ensuring human-machine interaction performance and vehicle stability. Furthermore, Hardware-in-the-Loop (HIL) experiments are conducted to verify the feasibility of real-time application. As shown in Figure 4, the integrated driving simulator is equipped with a real vehicle steering wheel and actuators, which can provide authentic physical feedback during driving tasks.



Figure 4. Experimental setup.

To verify the superiority of the proposed algorithm, different comparative algorithms are developed for comparison. The algorithm proposed in this paper is abbreviated as ANTD, and the coordination method adopting an equal weight distribution is abbreviated as Controller2. Furthermore, comparisons are conducted under both benign and fatigued

driving states with and without controller assistance. The benign state without controller assistance is abbreviated as NON-1, and the fatigued state without controller assistance is abbreviated as NON-2.

Table 2. Vehicle model parameters.

Symbol	Description	Value [unit]
m	Vehicle mass	1412 [kg]
l_f	Distance from CG to front axle	1.015 [m]
l_r	Distance from CG to rear axle	1.895 [m]
C_f	Front tire cornering stiffness	52,000 [N/rad]
I_z	Vehicle yaw moment of inertia	1536.7 [kg·m ²]
C_r	Rear tire cornering stiffness	34,500 [N/rad]

5.1. Simulation Experiment Comparison and Analysis

The target longitudinal velocity is set to a constant value of 90 km/h. For the completeness of the simulation models, the initial state variables are explicitly defined. The vehicle starts from a steady state accurately aligned with the reference path; thus, the initial full state feedback vector is set as $X(0) = [0, 0, 0, 0]^T$. The vehicle dynamic responses are shown in Figure 5. As can be seen from Figure 5a,b, the proposed controller is significantly superior to Controller2 in terms of the stability of the vehicle center of gravity (CG) sideslip angle and yaw rate. The control performance of Controller2 is relatively poor, exhibiting obvious overshoot. Continuous high-frequency chattering occurs, especially when the driver is in a fatigued state. The results indicate that after introducing the driver state-based weight coordination strategy, the vehicle driving stability can be significantly improved. The heading error and lateral error are shown in Figure 5c,d. Controller2 only yields small errors when the driver is in awake and normal states; however, under adverse states such as fatigue, the errors increase significantly, resulting in unsatisfactory tracking performance. Figure 5e displays the weight variation of the ANTD. It can be clearly observed that as the state changes, the weight rapidly and smoothly tracks the target value. The minor ripples in the figure objectively reflect the uncertainty of the driver state recognition model in state identification. Such dynamic fine-tuning of weights within a local narrow range ensures the driver's driving experience. However, since vehicle safety is of paramount importance, weight fluctuations are strictly constrained. Thus, while guaranteeing the overall safety of the vehicle, the driving experience is also preserved. To further quantitatively evaluate the transient tracking performance during the critical fatigue-induced abrupt changes observed in Figure 5d, the most significant point of abrupt authority transition is isolated and analyzed. As shown in Table 3, standard control performance metrics are extracted based on the lateral tracking error. Compared to the baseline controller, the proposed ANTD strategy substantially reduces the maximum overshoot (from 0.39 m to 0.16 m) and achieves a faster rise time, rigorously proving its superior disturbance rejection capability and rapid transient stabilization even under extreme driver state fluctuations.

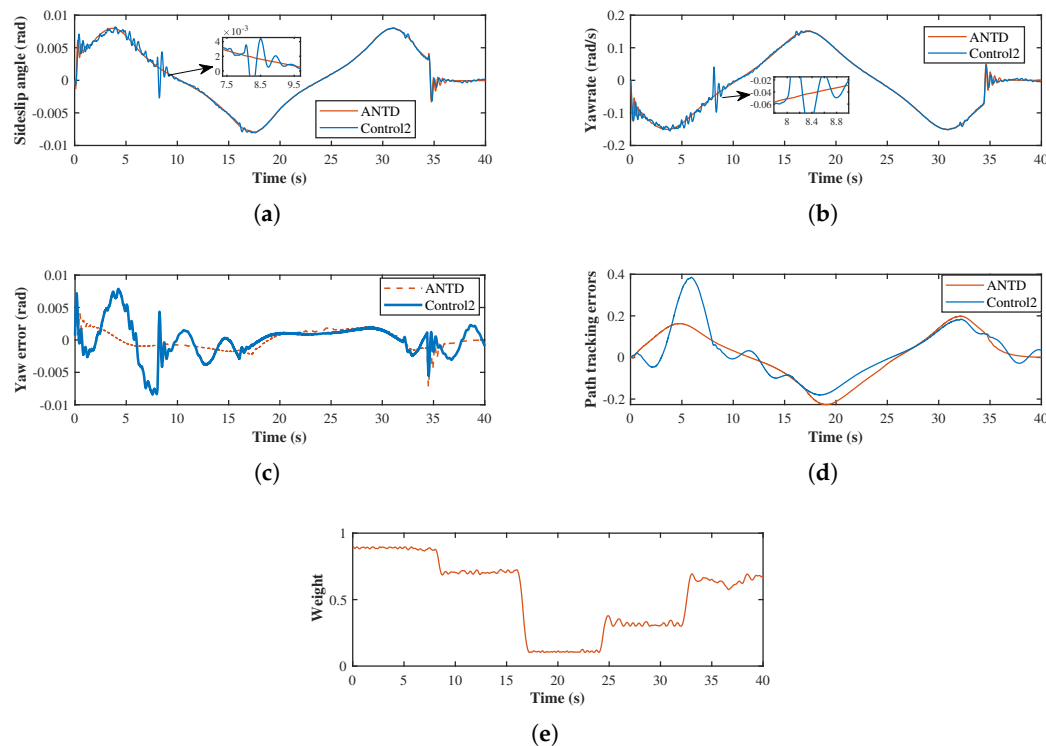


Figure 5. Vehicle dynamic responses. (a) Sideslip angle. (b) Yaw rate. (c) Heading error. (d) Lateral error. (e) Weight variation.

Table 3. Control Performance Metrics.

	Control2	ANTD
Overshoot [m]	0.39	0.16
Rise Time [s]	3.43	2.24
Settling Time [s]	5.89	6.67
Steady State Error [m]	0.0314	0.0016

5.2. HIL Experiment Comparison and Analysis

To further verify the effectiveness of the proposed controller, this section embeds the designed controller into a Hardware-in-the-Loop (HIL) testing platform for experimental validation. In the HIL experimental platform, although vehicle simulation software is used to replace the real vehicle, both the lower-level control system and the actuator hardware genuinely participate in the closed-loop operation. Therefore, this technology is widely applied in reliability testing in the fields of vehicle dynamics control and autonomous driving.

Consistent with the pure software simulation, the initial state variables in the HIL experimental model are identically configured to ensure comparative rigor. The initial longitudinal velocity is maintained at 90 km/h, and the vehicle initiates from a steady zero-error state, i.e., the initial state vector is set as $X(0) = [0, 0, 0, 0]^T$. The vehicle dynamic responses are shown in Figure 6. As shown in Figure 6a,b, it can be seen that when a driver in a fatigued state controls the vehicle, the sideslip angle and yaw rate experience extreme fluctuations, proving that the vehicle has become unstable. Conversely, with the introduction of auxiliary control (ANTD), the values tend to stabilize. To intuitively demonstrate the dynamic changes of these extreme fluctuations, localized zoomed-in views are incorporated into the figures. As clearly revealed in the magnified insets, the NON-2 controller exhibits dangerous high-frequency chattering and sharp transient spikes within a very narrow

time window. In stark contrast, the proposed ANT-D strategy responds instantaneously to smooth the dynamic responses and rapidly suppress the transient overshoot, further verifying its robust suppression capability against severe perturbations. Figure 6c,d show the heading error and lateral error, further proving that without active assistance, a driver in a fatigued state cannot accomplish stable vehicle control. To quantitatively demonstrate the tracking accuracy under the driver's fatigue state, global tracking error metrics are evaluated according to the lateral displacement. Under the NON-2, the global Root Mean Square Error (RMSE) and the maximum absolute error reach 0.4549 m and 0.9819 m, respectively. In contrast, the proposed ANT-D strategy substantially reduces the global RMSE to 0.1531 m and limits the maximum error to 0.2591 m. This statistical error comparison compellingly proves that ANT-D can effectively guarantee continuous tracking precision and correct the vehicle's trajectory under extreme adverse driving states.

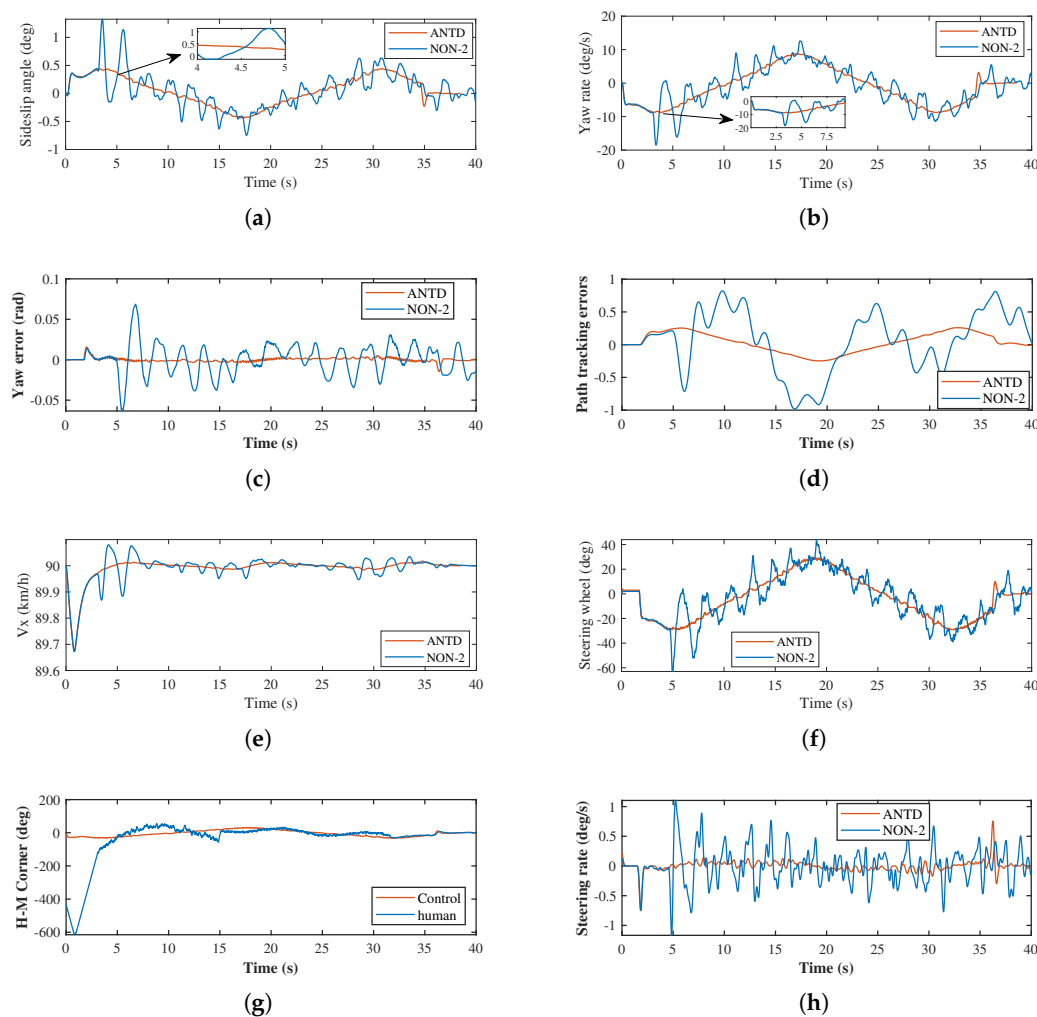


Figure 6. Vehicle dynamic responses under fatigue state. (a) Sideslip angle. (b) Yaw rate. (c) Heading error. (d) Lateral error. (e) Velocity variation. (f) Steering wheel angle. (g) Human–machine steering angle. (h) Steering wheel angle rate.

Figure 6e,f display the velocity variation and steering wheel angle variation, demonstrating that even when the driver is in an adverse state like fatigue, the proposed controller can still guarantee the stable operation of the system. Furthermore, Figure 6g,h provide an in-depth analysis of the human–machine physical conflicts under this extreme fatigue scenario. Figure 6g reveals the significantly divergent steering intentions between the human driver and the machine controller. Notably, an extreme initial steering input (approaching

-600°) generated by the human driver is observed during the experiment. This represents a worst-case boundary condition, emulating the erroneous panic reaction of a fatigued driver abruptly awakening. Despite such severe human perturbations, the control system consistently outputs stable and reasonable steering commands to continuously correct the vehicle's trajectory. Figure 6h compares the steering wheel angle rates. Without auxiliary control (NON-2), the steering rate exhibits severe, high-frequency sawtooth fluctuations. Conversely, the proposed ANTD strategy fundamentally suppresses these transient spikes and significantly attenuates the amplitude of the steering rate. This result compellingly demonstrates that the proposed algorithm effectively balances driving smoothness and ride comfort.

Figure 7 presents the vehicle dynamic responses under a normal driving state, comparing the scenarios of control solely by the human driver and the presence of auxiliary control (ANTD). Figure 7a,b show the sideslip angle and yaw rate of the vehicle. It is evident that the vehicle with auxiliary control exhibits smaller fluctuation amplitudes, indicating a further improvement in vehicle stability. Similarly, to intuitively observe the transient dynamics, localized zoomed-in views are provided in the figures. As revealed in the magnified insets, even under the normal awake state, the NON-1 controller still exhibits noticeable high-frequency chattering within a narrow time window, which is primarily caused by the driver's continuous minor steering corrections or neuromuscular jitters. Conversely, the proposed ANTD strategy effectively filters out these high-frequency noises and seamlessly smooths the dynamic responses without hindering the driver's primary control intention, verifying its excellent capability in dynamic refinement and comfort enhancement. Figure 7c,d display the heading error and lateral error of the vehicle. The values under ANTD control are smaller than those under sole human driving, proving that the proposed method can effectively enhance the driver's driving capability. Furthermore, a quantitative global error analysis is also conducted for the awake state. The lateral RMSE is reduced from 0.1759 m (NON-1) to 0.1688 m (ANTD), and the maximum tracking error is decreased from 0.3732 m to 0.2862 m. This explicitly indicates that even under normal driving conditions, the ANTD strategy can still actively filter out minor neuromuscular jitters, optimizing the tracking trajectory and seamlessly enhancing the overall path-tracking accuracy.

Figure 7e,f present the comparison of velocity variation and steering wheel angle. It can be observed that the overall output of ANTD tends to be a smoother output, thereby improving the driver's comfort. Furthermore, Figure 7g,h investigate the human-machine interaction characteristics under the awake state. In contrast to the severe physical conflicts observed in the fatigue scenario, Figure 7g demonstrates a high degree of consistency between the steering intentions of the human driver and the machine controller. Their tracking trajectories closely align within the normal driving amplitude (approximately [Value]), exhibiting a harmonious cooperative driving mode. Nevertheless, human drivers inevitably generate slight neuromuscular jitters and minor steering corrections during normal manual operations. The comparison of the steering wheel angle rates in Figure 7h clearly quantifies this phenomenon. Under the unassisted scenario (NON-1), the steering rate still exhibits noticeable high-frequency minor fluctuations. With the implementation of the ANTD strategy, these high-frequency transient jitters are significantly smoothed out, thereby further optimizing driving smoothness. Ultimately, the comparative results from Figures 6 and 7 verify that the proposed method can actively adapt to the driver's real-time state and provide appropriate assistance.

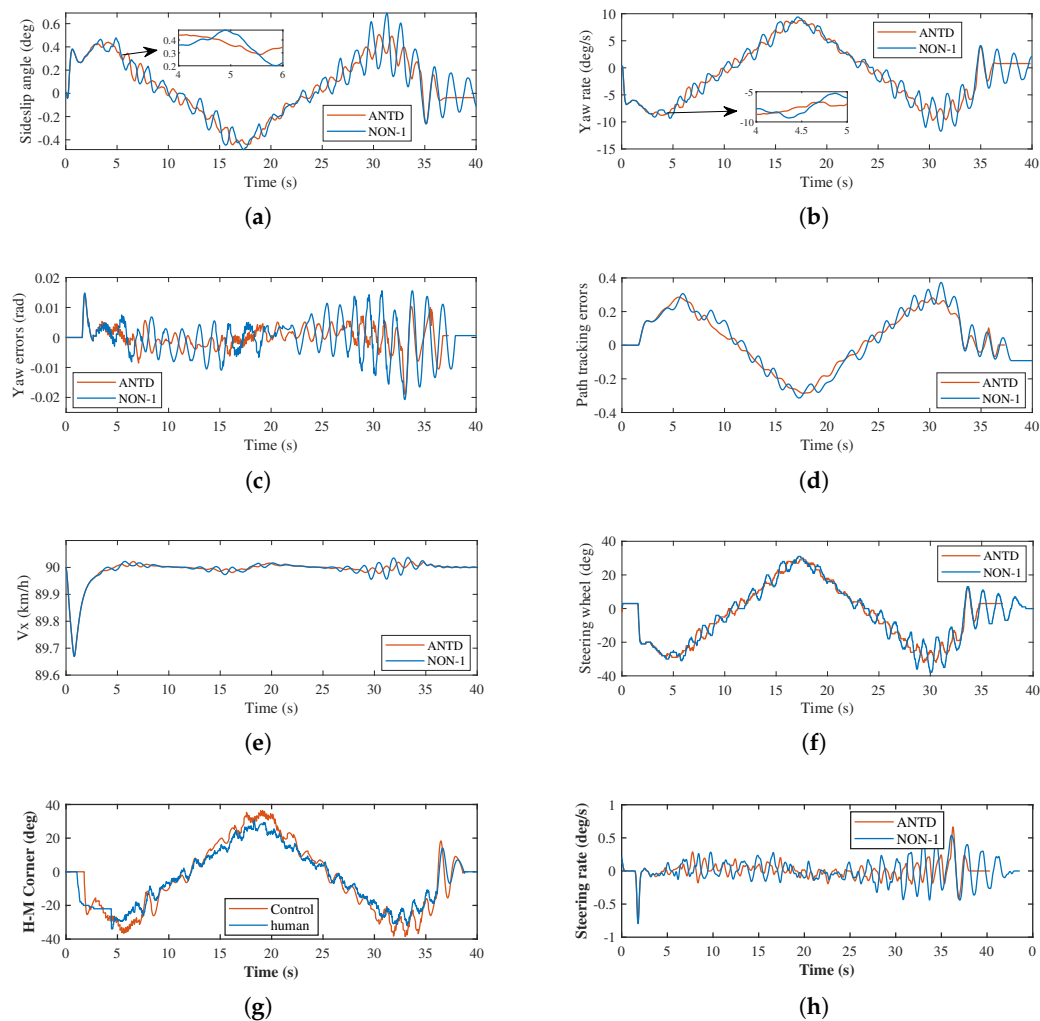


Figure 7. Vehicle dynamic responses under awake state. (a) Sideslip angle. (b) Yaw rate. (c) Heading error. (d) Lateral error. (e) Velocity variation. (f) Steering wheel angle. (g) Human–machine steering angle. (h) Steering wheel angle rate.

6. Conclusions

In this paper, the proposed hierarchical shared steering control strategy adjusts the degree of cooperation between the human and the controller. Specifically, a data-driven model integrating a Convolutional Neural Network and a Temporal Convolutional Network (CNN-TCN) is constructed to achieve high-precision, real-time recognition of driving states under multi-dimensional vehicle sequences. Addressing the control step jump problem caused by state confidence fluctuations, a weight-smoothing mechanism based on an Adaptive Nonlinear Tracking Differentiator (ANTD) is innovatively designed. Combined with the lower-level Linear Quadratic Regulator (LQR), an optimal trajectory tracking closed-loop is constructed. Simulation and Hardware-in-the-Loop (HIL) experiments demonstrate that the proposed strategy achieves effective human–machine cooperation in complex driving environments, reduces the operational burden, and simultaneously maintains reliable path tracking performance.

In the future, the impact of complex road environmental risks on steering behavior will become an important focus. In shared steering control systems, developing controllers with human-like characteristics is equally crucial to minimize discomfort during controller intervention and provide personalized driving assistance. Furthermore, such controllers

should be capable of continuously learning driving behavior preferences to achieve self-evolving human–machine cooperation.

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