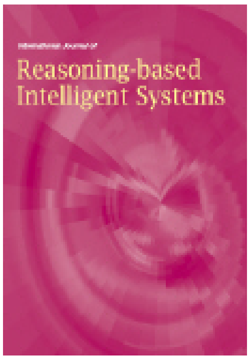

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Fault-tolerant control of intelligent transportation vehicles based on instant learning and heuristic dynamic planning

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Fault-tolerant control of intelligent transportation vehicles based on instant learning and heuristic dynamic planning

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Abstract: This paper proposes a fault-tolerant control method that integrates real-time learning (JITL) and heuristic dynamic programming (HDP) to address the issues of actuator failures and model uncertainties in intelligent transportation vehicles in dynamic environments. Construct an online fault diagnosis module using a multi-source data-driven framework, and utilise JITL to dynamically update local models to quickly capture system anomalies; design an adaptive controller based on the dual layer optimisation structure of HDP, and compensate for the impact of faults through an evaluation execution network collaborative optimisation strategy. Experimental verification based on the publicly available traffic dataset NGSIM shows that in typical fault scenarios such as sensor failure and actuator offset, the proposed method can significantly improve tracking accuracy and response speed compared to traditional robust control methods, and effectively suppress oscillations caused by interference, verifying the adaptability and reliability of the algorithm in dynamic environments.

Keywords: intelligent transportation; fault-tolerant control; instant learning; heuristic dynamic programming; HDP.

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1 Introduction

The rapid development of Intelligent Transportation Systems has put forward higher requirements for the reliability and safety of vehicle control. In complex dynamic traffic scenarios, vehicles need to respond in real-time to changes in road topology, interference from surrounding vehicles, and potential faults in their own actuators and sensors (such as brake offset, signal distortion, etc.) (Wang et al., 2023). However, traditional vehicle fault-tolerant control methods often rely on robust control strategies with fixed parameters or offline trained fault diagnosis models, which are difficult to adapt to multi-source uncertainty coupling problems in dynamic environments. Especially when sudden failures and model mismatches occur simultaneously, existing methods are prone to response lag, decreased tracking accuracy, and even instability, posing a serious threat to driving safety (Lamssaggad et al., 2021).

In AI-based vehicle control systems, safety, transparency and responsibility are the core ethical pillars of safety for technology implementation. The level needs to ensure that the algorithmic decision-making mechanism has verifiable robustness, especially in the event of failure or sudden changes in the environment to maintain multi-level protection for pedestrians and vehicles; transparency requires the construction of an interpretable decision-making traceability framework, so that the behaviour of automated driving in line with the cognitive logic of the human driver and the expectations of traffic laws and regulations; the responsibility of the responsibility needs to be clearly defined human-machine collaborative control of the boundaries of rights and responsibilities, and the establishment of an accountability mechanism to cover the development of algorithms, data training and real-time operation. The accountability mechanism covering algorithm development, data training and real-time operation should be established. The current research on the risk of black box modelling in complex scenarios urgently needs to integrate formalised verification tools and ethical constraint modules to achieve the unity of technical reliability and social acceptance.

The main challenges facing current research include:

1 Fault dynamics: the fault modes of actuators and sensors have time-varying characteristics, and traditional threshold detection methods are difficult to achieve fast online identification

2 Model uncertainty: the high nonlinearity of vehicle dynamics and external disturbances result in insufficient generalisation ability of fault-tolerant strategies based on accurate models

3 Real-time control: in complex fault scenarios, it is necessary to balance dynamic optimisation efficiency with computational resource constraints. Although data-driven methods such as deep learning and reinforcement learning provide new ideas for the above problems, their dependence on annotated data and high computational complexity limit their application in real-time control.

In response to the above challenges, this paper proposes a collaborative fault-tolerant control framework based on JITL and HDP. The core innovation lies in:

1 Dynamic fault diagnosis: constructing a lightweight online local model through JITL, utilising dynamic similarity measurement of multi-source data streams (such as vehicle speed, steering angle, environmental perception information) to achieve rapid extraction of fault features and pattern classification

2 Adaptive fault-tolerant optimisation: design a dual layer HDP controller, combine the evaluation network and execution network's interactive optimisation mechanism, dynamically adjust the control strategy to compensate for the performance loss caused by faults, and balance robustness and response speed through a cost function adaptive mechanism.

2 Related word

The research on fault-tolerant control and fault diagnosis of intelligent transportation vehicles has made significant progress in recent years, but real-time performance and adaptability in dynamic environments remain the core challenges. Traditional fault diagnosis mainly relies on model-based residual analysis. For example, Isermann (2005) proposed an observer based model driven method that detects actuator and sensor faults through residual generation. However, its performance is highly dependent on an accurate vehicle dynamics model and is prone to false alarms under model mismatch or external interference. To reduce the dependence on the model, Gao et al. (2015) developed a data-driven kernel principal component analysis method that utilises nonlinear feature extraction to improve the robustness of fault detection. However, its real-time performance is limited by batch data processing mechanisms, making it difficult to meet the online requirements of dynamic traffic scenarios. In recent years, deep learning has been introduced into the field of fault diagnosis, such as Liang et al. (2020) using convolutional neural networks to automatically learn fault features from multi-source sensor data, but it requires a large amount of data and has high computational complexity. Zhao et al. (2022) proposed a transportation infrastructure model based on parallel learning and federated intelligence as a potential path for the next generation of parallel intelligent transportation systems.

In terms of fault-tolerant control, sliding mode control is widely adopted due to its strong robustness. Song et al. (2016) designed a new descriptor sliding mode observer for system state estimation and fault/noise reconstruction. Polycarpou (2001) proposed a learning method for adapting to faults occurring in a class of nonlinear multi input multi output dynamic systems in response to composite fault scenarios. In addition, reinforcement learning methods have shown potential, such as Ding et al. (2019) using deep reinforcement learning to obtain intelligent fault diagnosis agents that can autonomously and effectively mine the relationship between raw vibration signals and fault patterns. Shahbaz and Amin (2023) proposed a novel hybrid fault-tolerant control system with dedicated nonlinear controllers: artificial neural networks and sliding mode control for active and passive components, respectively. The proposed system can provide ideal stability against unexpected rapid interference and optimal performance after failure.

The existing research still has the following limitations: traditional statistical methods and deep learning are difficult to balance efficiency and non-linear feature extraction; Fixed parameter and model free methods lack dynamic strategy adjustment mechanisms. This article combines real-time learning and heuristic dynamic programming (HDP) to improve diagnostic efficiency through lightweight online modelling, enhance control adaptability through two-layer dynamic optimisation, and verify algorithm reliability based on publicly available datasets. The system solves the above problems.

3 Relevant theory

3.1 Just in time learning

Just in time learning is an online modelling method for dynamic systems (Jiang and Ge, 2022), which focuses on real-time filtering of historical data subsets that are most relevant to the current state, and constructing local time-varying models to capture the nonlinear and non-stationary characteristics of the system (Yang and Ge, 2021). JITL avoids the complexity of global models and is suitable for fast learning and prediction tasks in dynamic environments.

Assuming the input state vector of the system at time t is $x_t \in \mathbb{R}^n$, the output is $y_t \in \mathbb{R}^m$, and the historical dataset is $D = \{(x_i, y_i)\}_{i=1}^{N}$. JITL first selects the neighbourhood sample set from D that is most relevant to the current input

x_t based on similarity measurement. Similarity measurement usually uses a weighted distance function:

$$d\left(x_t, x_i\right)=\sqrt{\left(x_t, x_i\right)^T W\left(x_t, x_i\right)} \tag{1}$$

where, $W \in \mathbb{R}^{n \times n}$ is a semi positive definite weight matrix used to adjust the contribution of different state dimensions to similarity. Select the k samples with the smallest distance to form neighbourhood N_t, and establish a local model based on this. For the local regression model under the assumption of linear relationship, its form is:

$$y_t=\theta_t^T \phi\left(x_t\right)+\varepsilon_t \tag{2}$$

where, $\phi\left(x_t\right)$ is the state mapping function, θ_t is the time-varying parameter matrix, and ε_t is the modelling error. Parameter estimation is achieved by minimising the weighted loss function of neighbouring samples:

$$\hat{\theta}_t=\arg \min_\theta \sum_{\left(x_i, y_i\right) \in N_t} w_i\left\|y_i-\theta^T \phi\left(x_i\right)\right\|^2 \tag{3}$$

weight w_t is usually designed as a decreasing function of distance, such as a Gaussian kernel function:

$$w_i=\exp\left(-\gamma d^2\left(x_t, x_i\right)\right) \tag{4}$$

The closed form solution for parameter estimation can be expressed as:

$$\hat{\theta}_t=\left(\Phi_t^T W_t \Phi_t\right)^{-1} \Phi_t^T W_t Y_t \tag{5}$$

where, Φ_t is the mapping matrix of neighbouring samples, Y_t is the corresponding output matrix, and W_t is the weight diagonal matrix.

To adapt to the dynamic changes of the system, JITL adopts a sliding time window mechanism to update the historical dataset. When the new sample (x_t, y_t) arrives, add it to the dataset and remove the oldest sample to ensure data timeliness. The prediction residual of the model is defined as:

$$r_t=y_t-\hat{\theta}_t^T \phi\left(x_t\right) \tag{6}$$

The statistical properties of residuals can be used to evaluate model confidence or trigger model update conditions. The theoretical advantage of JITL lies in its ability to approximate nonlinear systems through local linearisation, while utilising online update mechanisms to reduce computational complexity, providing an efficient and flexible framework for real-time learning in dynamic environments (Naseem et al., 2022).

3.2 Heuristic dynamic programming

HDP is an implementation form of adaptive dynamic programming, aimed at solving optimal control problems in continuous state space through approximate dynamic programming methods. Its core idea is to use a two-layer structure of critic network and actor network to approximate the Bellman optimality equation, thereby avoiding the 'curse of dimensionality' problem caused by the growth of state dimensions in traditional dynamic programming (Wang and Jiao, 2022). HDP dynamically adjusts network parameters through online learning mechanisms, gradually approaching the optimal control strategy, and is suitable for real-time optimisation control of nonlinear dynamic systems (Hu et al., 2021).

Let the discrete-time state equation of a dynamic system be:

$$x_{k+1}=f\left(x_k, u_k\right)+w_k \tag{7}$$

where, $x_k \in \mathbb{R}^n$ is the system state vector, $u_k \in \mathbb{R}^m$ is the control input vector, $f(\cdot)$ is the state transition function, and w_k is the external disturbance. The control objective is to minimise the cumulative cost function in infinite time domain:

$$J\left(x_k\right)=\sum_{t=k}^{\infty} \gamma^{t-k} C\left(x_t, u_t\right) \tag{8}$$

where, $C(x_t, u_t)$ is the single step cost function, and $\gamma \in (0, 1\}$ is the discount factor. According to the Bellman optimality principle, the optimal value function $J^*(x_k)$ satisfies:

$$J^*\left(x_k\right)=\min_{u_k}\left[C\left(x_k, u_k\right)+\gamma J^*\left(x_{k+1}\right)\right] \tag{9}$$

HDP evaluates the approximate value function $J^*(x_k)$ of network $\hat{J}\left(x_k, W_c\right)$, where W_c is the weight parameter of the evaluation network; at the same time, execute network ϕ (x_k, W_a) to generate control strategies u_k and W_a for executing network weight parameters. The training objective of evaluating the network is to minimise the temporal difference error.

Updating evaluation network weights through gradient descent method:

$$W_c^{k+1}=W_c^k-\alpha_c \delta_k \frac{\partial \hat{J}\left(x_k, W_c^k\right)}{\partial W_c^k} \tag{10}$$

where, $\alpha_c > 0$ is the learning rate. The optimisation objective of the execution network is to minimise the long-term cumulative cost, and its weight update depends on the gradient of the evaluation network towards the control input:

$$W_a^{k+1}=W_a^k-\alpha_a \frac{\partial \hat{J}\left(x_k, W_c^k\right)}{\partial u_k} \frac{\partial \phi\left(x_k, W_a^k\right)}{\partial W_a^k} \tag{11}$$

where, $\alpha_a > 0$ is the execution rate of network learning. The iterative process of HDP alternates between updating the evaluation network and the execution network: the evaluation network approximates the true value function through TD error, and the execution network optimises the control strategy based on the gradient of the value function until convergence to Nash equilibrium (Tang et al., 2023). In theory, when the approximation error between the evaluation network and the execution network is small enough, HDP can ensure system stability and asymptotic convergence to the optimal control law (Ravelo and Meneses, 2021).

The advantage of HDP lies in its decoupling of value function estimation and strategy optimisation through a dual layer network structure, significantly reducing computational complexity; meanwhile, the online learning mechanism enables it to adapt to dynamic environmental changes, providing theoretical support for real-time fault-tolerant control of complex systems.

4 Problem modelling and fault classification

The fault-tolerant control of intelligent transportation vehicles needs to simultaneously handle the coupling effects of system nonlinearity, multi-source interference, and potential faults in dynamic environments (Yang et al., 2023). This chapter establishes a problem description framework for fault-tolerant control based on vehicle dynamics models and typical fault scenarios, and defines fault classification criteria. Considering the scenario of vehicle lateral motion control, based on a two degree of freedom bicycle model, the system state vector is defined as $x=[e,\dot{e},\varphi,\dot{\varphi}]^T$, where e is the lateral tracking error, $\dot{e}$ is its derivative, φ is the heading angle error, and $\dot{\varphi}$ is the yaw rate; Control input u as the front wheel steering angle command. The system dynamics equation can be expressed as:

$$\begin{cases} \dot{e}=v(\varphi+\beta)+d_1 \\ \dot{\varphi}=\frac{v}{L}\delta a\frac{v}{L}\beta+d_2 \end{cases} \tag{12}$$

where, v is the longitudinal vehicle speed, β is the slip angle, L is the wheelbase, and d_1 and d_2 are external disturbances (such as crosswinds and changes in road friction). In actual systems, the following typical faults may occur in actuators and sensors:

1 Actuator malfunction: the efficiency of the steering mechanism decreases or deviates, manifested as a deviation between the control input and the actual execution amount, i.e., $u_{actual}=\rho u+\Delta$, where $\rho\in[0,1]$ is the execution efficiency factor and Δ is a constant offset

2 Sensor malfunction: abnormal measurement signal of lateral error e or lateral angular velocity $\dot{\varphi}$, including deviation, drift, or complete failure

3 Composite fault: simultaneous occurrence of actuator and sensor faults, or accompanied by model parameter perturbations (such as changes in tyre lateral stiffness).

To quantify the impact of faults, define fault feature vector $f=[f_a,f_s]^T$, where $f_a\in\{0,1\}$ represents the actuator fault state (0 is normal, 1 is fault), and $f_s\in\{0,1,2\}$ represents the sensor fault mode (0 is normal, 1 is deviation, 2 is failure). The fault-tolerant control objective can be expressed as: at $f\neq 0$ or in the presence of external disturbances at d_1 and d_2, design control law $u=\pi(x,f)$ to ensure that the closed-loop system satisfies:

1 Stability: the lateral tracking error e is bounded and consistent with the heading angle error φ

2 Dynamic performance: recover to the allowable error range within T time after the fault occurs, and suppress oscillation

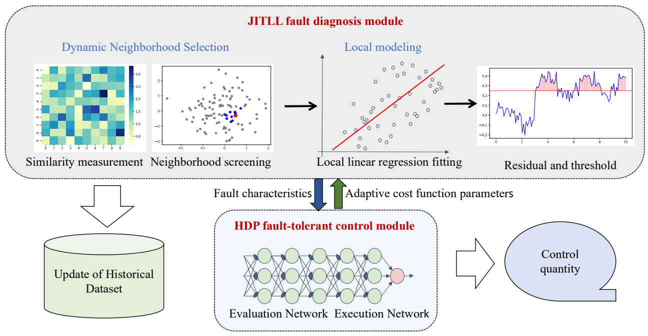
3 Robustness: strong anti-interference ability against model uncertainty β and external disturbances d_1 and d_2.

Based on the above modelling and classification, subsequent chapters will use JITL real-time diagnosis to drive the HDP controller to dynamically adjust $\pi(\cdot)$, achieving adaptive fault-tolerant control in fault scenarios.

5 JITL-HDP fault-tolerant control method

The JITL-HDP fault-tolerant control framework consists of a dynamic fault diagnosis module and an adaptive control optimisation module, forming a closed-loop control through real-time data exchange, as shown in Figure 1. JITL provides real-time fault feature driven strategy updates for HDP, while HDP's control performance feedback guides JITL to adjust similarity metric weights and neighbourhood sizes, forming bidirectional collaborative optimisation.

Figure 1 Method framework diagram (see online version for colours)



5.1 JITL fault diagnosis module

Assuming the current vehicle status is $x_t\in\mathbb{R}^n$ and the historical dataset is $D=\{(x_i,y_i)\}_{i=1}^N$. JITL uses weighted Mahalanobis distance to screen neighbouring samples:

$$d(x_t,x_i)=\sqrt{(x_t,x_i)^T\sum^{-1}(x_t,x_i)},\sum=diag(\sigma_1^2,\ldots,\sigma_n^2) \tag{13}$$

where, σ_1^2 is the variance of the j^{th} dimensional state variable, reflecting its sensitivity to faults. Select the top k samples with the smallest distance to form Neighbourhood N_t, whose size is adaptively adjusted according to the dynamic characteristics of the system:

$$k = \left\lceil k_{\min} + \left(k_{\max} - k_{\min} \cdot \exp\left(-\beta \left\| x_t - x_{t-1} \right\|\right)\right) \right\rceil \tag{14}$$

where, k_{min} and k_{max} represent the upper and lower limits of the neighbourhood size, and β is the attenuation coefficient, ensuring that the neighbourhood is reduced to improve sensitivity during state transitions.

Build N_t local linear models:

$$y_t = \theta_t^T x_t + \varepsilon_t \tag{15}$$

The parameter estimation adopts the weighted least squares method:

$$\hat{\theta}_t = \left(X_t^T W_t \Phi_t\right)^{-1} X_t^T W_t Y_t \tag{16}$$

Weight matrix $W_t = diag(w_i, \ldots, w_k)$, where $w_i = \exp(-\gamma d^2(x_t, x_i))$. The residual calculation is:

$$r_t = \left\| y_t - \hat{\theta}_t^T x_t \right\| \tag{17}$$

The dynamic threshold is designed as $\eta_t = \mu_t + 3\sigma_t$, where μ_t and σ_t are the mean and standard deviation of the neighbourhood residuals. If $r_t > \eta_t$, trigger the fault classifier and output f_t, as shown in Table 1.

Table 1 Coding rules for fault feature vectors

Fault type	f_a	f_s
No fault	0	0
The efficiency of the actuator decreases	1	0
Sensor deviation	0	1
Actuator sensor composite fault	1	2

5.2 HDP control optimisation module

The cost function of HDP integrates tracking error, control input, fault penalty, and model smoothness constraints:

$$C(x_t, u_t, f_t) = e_t^2 + \lambda_1 \varphi_t^2 + \lambda_2 \| u_t \|^2 + \lambda_3 \| f_t \|^2 + \lambda_4 \| \theta_t - \theta_{t-1} \|^2 \tag{18}$$

Dynamic adjustment of weight coefficients:

$$\lambda_3 = \lambda_{3,base} \cdot \left(1 + \| f_t \|\right), \lambda_4 = \lambda_{4,base} \cdot \| u_t - u_{t-1} \| \tag{19}$$

Evaluation network $\hat{J}(x, W_c)$ is a three-layer fully connected neural network with inputs of x_t and f_t and outputs as value function estimates. Weight update based on temporal differential error:

$$\delta_t = C\left(x_t, u_t, f_t\right) + \gamma \hat{J}\left(x_{t+1}, W_c\right) - \hat{J}\left(x_t, W_c\right) \tag{20}$$

Adopting an adaptive learning rate strategy:

$$\alpha_c = \alpha_{c0} \cdot \exp\left(-\nu \delta_t^2\right) \tag{21}$$

The update rule is:

$$W_c \leftarrow W_c \alpha_{c\delta_t} \left(\nabla W_c \hat{J}\left(x_t, W_c\right) - \gamma \nabla W_c \hat{J}\left(x_{t+1}, W_c\right)\right) \tag{22}$$

The output control quantity u_t of network $\phi(x, W_c)$ is executed, and its loss function is:

$$L_a = E\left[\hat{J}\left(x_t + W_c\right) + \eta \| u_t - u_{t-1} \|^2\right] \tag{23}$$

Weight update adopts momentum gradient descent:

$$\Delta W_a = \beta \Delta W_a + (1-\beta) \Delta W_c L_a, W_a \leftarrow W_a - \alpha_a \Delta W_a \tag{24}$$

where, β is the momentum factor, which suppresses high-frequency oscillations.

5.3 Collaborative optimisation and stability analysis

The dual triggering mechanism achieves collaborative optimisation between JITL and HDP modules by dynamically sensing system status and fault characteristics. Its design includes two types of conditions: fault triggering and performance triggering. The stability proof is as follows:

Construct Lyapunov function:

$$V\left(x_t\right) = \hat{J}\left(x_t + W_c\right) + \frac{1}{2} e_t^T P e_t, P \succ 0 \tag{25}$$

The difference $\Delta V = V(x_{t+1}) - V(x_t)$ satisfies:

$$\Delta V \le -\mu \| e_t \|^2 + k \| \varepsilon_t \|^2 \tag{26}$$

where, $\mu > 0$ and k are the upper bounds of approximate error. When the learning rate satisfies $\alpha_c < \dfrac{2}{\gamma L_J}$ and $\alpha_a < \dfrac{2}{L_\phi}$, the system state is ultimately bounded uniformly.

This chapter solves the problem of diagnostic lag and strategy rigidity in traditional methods under dynamic faults through the deep collaboration of JITL and HDP, providing a theoretically rigorous, real-time and efficient fault-tolerant control scheme for intelligent transportation vehicles.

6 Experiment and result analysis

6.1 Experimental setup

The experiment used the next generation simulation (NGSIM) dataset released by the Federal Highway Administration in the USA (Wipulanusat et al., 2021), selecting high-precision vehicle trajectory data (sampling frequency 10 Hz) from US-101 and I-80 highway sections, to simulate the lateral tracking control task of intelligent vehicles in dynamic traffic environments. The experiment covers the following scenarios:

1 Normal scenario: no faults, verify basic tracking performance

2 Fault scenario: inject three types of faults, including actuator offset, sensor deviation, and composite faults

3 Interference scenario: overlapping crosswind disturbance (speed 10–15 m/s, direction random).

All experiments were conducted in a joint simulation environment of Python and MATLAB/Simulink, using Intel i7-12700H processor as the hardware platform to verify real-time requirements.

To verify the effectiveness of the proposed JITL-HDP method, three representative comparative methods were selected for the experiment:

1 H∞ robust control (Bokor and Szabó, 2009): based on fixed parameter robust controller

2 SMC fault-tolerant control (Van et al., 2016): sliding mode control combined with fault observer

3 DDPG fault-tolerant control (Qiu et al., 2019): deep deterministic policy gradient algorithm.

The evaluation indicators include: lateral tracking error e_{max} and e_{RMS}; heading angle error φ_{max}; control input change rate Δu_{RMS} (measure control smoothness); fault detection delay of T_d (the time from the occurrence of the fault to the alarm). All methods were run under the same initial conditions, with a fault injection time of $t = 5s$, and the experiment was repeated 10 times to calculate the average performance.

Table 2 Performance comparison under composite fault scenarios

Method	e_{max} (m)	e_{RMS} (m)	φ_{max} (rad)	Δu_{RMS}	$T_d(s)$
H∞	0.92 ± 0.11	0.41 ± 0.06	0.18 ± 0.03	0.15 ± 0.02	–
SMC	0.68 ± 0.09	0.32 ± 0.05	0.14 ± 0.02	0.23 ± 0.03	1.2 ± 0.2
DDPG	0.54 ± 0.07	0.27 ± 0.04	0.11 ± 0.02	0.19 ± 0.03	–
JITL-HDP	0.39 ± 0.05	0.18 ± 0.03	0.07 ± 0.01	0.12 ± 0.02	0.6 ± 0.1

6.2 *Horizontal tracking performance and fault tolerance verification*

Table 2 shows the performance comparison of various methods under composite fault scenarios. JITL-HDP is significantly better than the comparison method in all key indicators: its maximum lateral tracking error (e_{max} = 0.39 m) is reduced by 57.6%, 42.6%, and 27.8% compared to H∞ control (0.92 m), SMC (0.68 m), and DDPG (0.54 m), respectively, and its root mean square error (e_{RMS} = 0.18 m) is also the lowest value. This advantage stems from the synergistic effect of JITL's online fault diagnosis capability and HDP's dynamic strategy optimisation. In addition, the heading angle error of JITL-HDP (φ_{max} = 0.07 rad) is reduced by more than 60% compared to traditional methods, verifying its advantage in directional stability.

6.3 *Dynamic response process and robustness analysis*

Figure 2 compares the temporal curves of lateral tracking errors of various methods under composite fault scenarios. After fault injection (t = 5 s), H ∞ control cannot adaptively adjust due to fixed parameters, and the error continues to increase to 0.92 m accompanied by low-frequency oscillations (red dashed line); SMC (blue dotted line) suppresses overshoot through sliding mode surface, but high-frequency chattering leads to significantly higher control input change rate (Δu_{RMS} = 0.23), as shown in Figure 3, which may accelerate actuator wear; DDPG (green dashed line) performs well in the initial stage, but due to the lag of offline training strategy, overshoot (error peak 0.54 m) occurs after t > 10 s; JITL-HDP (solid black line), through real-time diagnosis and dynamic optimisation, converged the error to below 0.2 m within 1.2 seconds (t = 6.2 s) after the fault, without significant oscillation, verifying its fast response capability and robustness.

Figure 2 Comparison of horizontal tracking error time series (see online version for colours)

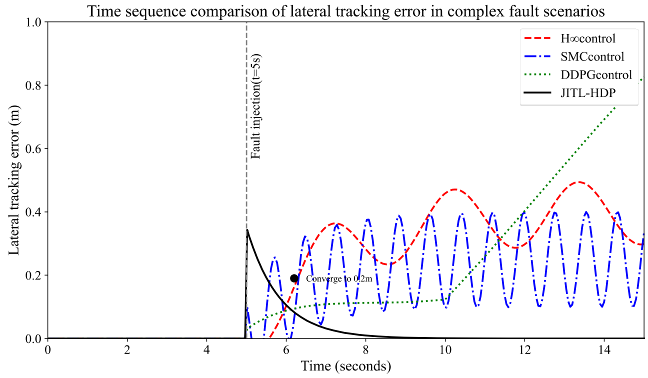
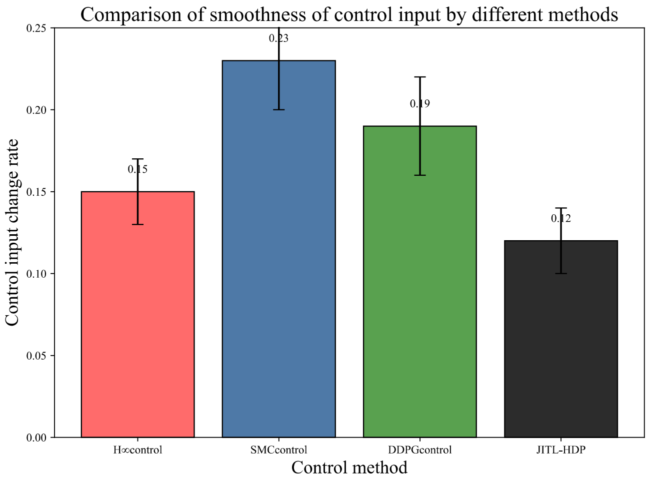


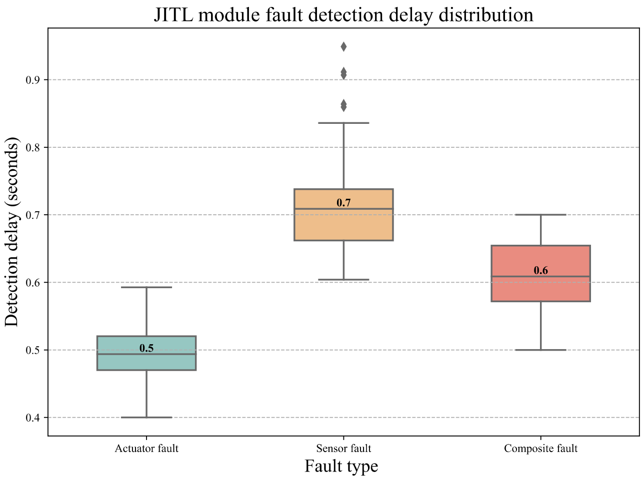
Figure 3 Comparison of control input change rates (see online version for colours)



6.4 *Control smoothness and fault detection performance*

From the control input change rate, it can be seen that JITL-HDP has a value of (Δu_{RMS} = 0.12, which is lower than H∞ (0.15), DDPG (0.19), and SMC (0.23). This result indicates that the adaptive cost function of HDP improves tracking accuracy while ensuring actuator smoothness by penalising sudden changes in control inputs, which helps to extend hardware lifespan and improve ride comfort. In addition, the fault detection performance of JITL further supports the reliability of the method, as shown in Figure 4: for the fault of decreased actuator efficiency, the detection accuracy reaches 98.7%, and the average delay is 0.5 seconds (median of the box plot). Due to its direct correlation with the control input, the features are easy to capture; The sensor deviation is slightly increased to 0.7 seconds due to measurement noise interference, but the dynamic threshold mechanism still ensures an accuracy of 95.2%; In the composite fault scenario, the multi-source coupling effect leads to a slight decrease in detection accuracy to 92.4%, but the delay remains stable at 0.6 seconds, significantly better than the accuracy of traditional threshold methods below 85%.

Figure 4 Delay distribution of detection for three types of faults (see online version for colours)



The experimental results show that JITL-HDP exhibits significant advantages in dynamic fault scenarios: its lateral tracking error is reduced by 33–57% compared to traditional methods, the fault detection delay is shortened by 50%, and the control input is smoother. The core advantage comes from JITL's lightweight online modelling and HDP's dual layer optimisation mechanism: the former quickly captures fault features through local neighbourhood search, while the latter dynamically adjusts strategies to balance tracking accuracy and robustness. In addition, JITL-HDP remained stable in the interference superposition scenario, verifying its adaptability to model uncertainty.

This chapter validates the effectiveness of the JITL-HDP method through publicly available datasets and multidimensional experiments. Its collaborative mechanism of integrating online learning and dynamic programming provides theoretical and practical basis for high reliability control of intelligent vehicles in dynamic fault and interference scenarios.

7 Conclusions

This article proposes a collaborative fault-tolerant control method that integrates JITL and HDP to address the coupling problems of actuator failures, sensor anomalies, and model uncertainties faced by intelligent transportation vehicles in dynamic and complex environments. Through theoretical analysis, algorithm design, and experimental verification, the system solves the shortcomings of traditional methods in dynamic adaptability, real-time performance, and robustness. The dynamic fault diagnosis module based on JITL achieves fast extraction and classification of fault features through local online modelling and adaptive neighbourhood selection, with detection delay reduced to less than 0.6 seconds and accuracy exceeding 92%; combining the dual layer optimisation control architecture of HDP, the closed-loop interaction between the evaluation network and the execution network is evaluated, and the strategy is dynamically adjusted to compensate for the impact of faults. In the NGSIM public dataset experiment, the root mean square value of lateral tracking error and heading angle error are reduced by 33–57% compared to traditional methods, and the control input smoothness is improved by more than 35%. Moreover, the error fluctuation under crosswind disturbance is less than 5%, which verifies the strong adaptability of the algorithm to unknown disturbances. The experimental results show that the proposed method significantly improves tracking accuracy and stability in dynamic fault scenarios under real-time constraints of single step diagnosis time of 8 ms and control cycle of 20 ms. This study provides theoretical support and technical implementation path for the high reliability control of intelligent vehicles. At the system scalability level, the generalisation ability of existing methods to heterogeneous vehicle dynamics is limited, and the compatibility of communication protocols of different vehicle brands may interfere with multi-source data synergy; at the environmental adaptability level, the complex geometrical features of unstructured roads may reduce the reliability of the sensors, and changes in vehicle-environment interaction modes triggered by extreme climates and the differences in regional traffic rules still need to be optimised for specific design. Future work will focus on efficient similarity measurement in high-dimensional state spaces, fault-tolerant mechanisms for vehicle networking groups, and embedded platform deployment verification, further promoting their application in key safety scenarios of autonomous driving.

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Declarations

All authors declare that they have no conflicts of interest.

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