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Study on Optimization of Takeover Time and Safety Distance of L3 Automatic Driving System

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Abstract. As L3 autonomous driving gradually takes over control from human drivers, emergency safety distance and system takeover timing have become crucial safeguards for travel. This paper proposes an innovative machine learning method that integrates the preceding vehicle's speed trajectory with the driver's state in its algorithm. It optimizes the safety distance calculation model while capturing real-time changes in the driver's state, balancing technological operations and human factors.The research covers practical aspects: multimodal data acquisition technology collects vehicle speed information from real traffic scenarios and records driver behavior data; the GBM-LSTM hybrid model predicts the preceding vehicle's speed; the improved CNN-ResNet50 network accurately identifies the driver's state, detecting signs of fatigue or distraction.Key data shows that 68% of near-collision incidents occur within just 2 seconds. When the driver is distracted, the safe distance needs to be 14.5 meters and the takeover time 2.1 seconds; when fatigued, these figures increase to 16.8 meters and 2.8 seconds. The dynamic model is reliable, with calculation errors controlled within 5%—30% better than traditional models. The three-level safety strategy reduces key risk events by 58%, and the night false alarm rate is below 0.8%.This study clarifies the impact of the driver's state on safety control, providing a solid basis for the warning strategy design of L3 autonomous driving systems and laying the groundwork for future research on integrating V2X data with multimodel physiological signals.

Keywords: L3 autonomous driving, takeover time, machine learning, dynamic safety distance model

1. Introduction

The L3 level autonomous driving system will gradually become a reality, enabling vehicles to achieve autonomous driving under certain conditions. L3 level autonomous driving is a key watershed in SAE International's autonomous driving classification. Unlike L2 level partial autonomous driving, the L3 system can perform all dynamic driving tasks within a specific operational design domain, such as environmental perception, steering control, and acceleration/deceleration operations. Its core feature is the "human-machine driving" mode, which allows the driver to completely disengage from control when the system is operating normally. However, when a crisis occurs—such as sudden braking or erratic pedestrians—the system urgently

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requires human intervention and issues a takeover request through multimodel interactions like acousto-optic and tactile signals. According to the European New Car Assessment Programme, the typical takeover transition time is 8 to 10 seconds, which makes driver state monitoring and takeover capability assessment the most critical links in the L3 system's safety architecture [1,2]. The current mainstream implementation schemes include Audi Traffic Jam Pilot and Mercedes-Benz DRIVE PILOT, which are strictly limited to closed road scenarios below 60km/h. However, the L3 system still requires the driver to take over vehicle control when the system cannot handle it. In case of emergency such as sudden braking of the preceding vehicle, accurately predicting the driver's takeover time and optimizing the safety distance become the key issues to ensure the safety of automatic driving. Although traditional vehicle following models and machine learning methods are widely used in vehicle control, these methods still have some limitations in the face of complex driving environments and dynamically changing driver states [3].

In recent years, researchers have begun to explore how to improve the performance of autonomous driving systems with machine learning algorithms and deep learning techniques. For example, driver state monitoring systems based on deep learning can detect driver fatigue and distraction with high accuracy [4-6]. However, most existing research focuses on single dimension driver state monitoring, lacking comprehensive consideration of driving environment and driver state [7]. Although advanced driver assistance systems have made some progress in improving driving safety, in autonomous driving scenarios, how to dynamically combine the speed of the preceding vehicle with the driver's state to achieve more precise safety control is still an urgent problem [8].

Therefore, under the above background, we hope to further explore the existing research results, and propose a new scheme that can realize the dynamic adjustment of the safe distance of vehicles in the L3 automatic driving system: using machine learning methods to predict the current state of the driver and make decisions on the following behavior based on this, so as to achieve the distance constraint of the target vehicle when driving in the target lane. Specifically, several main works are proposed to solve the above problems as follows:(1) A dynamic safety distance calculation model based on the speed of the preceding vehicle and the driver state is proposed;(2) An efficient and reliable neural network architecture is designed to estimate the driver state in real time;(3) The effectiveness and robustness of this method are proved by a series of road test data in real scenes; It is hoped that this research can bring some new ideas, new ideas and new methods to the design of L3 automatic driving system.

2. Related research

Traditional vehicle-following models (e.g., safety distance models) rely on fixed parameters and simplified assumptions (e.g., constant driver reaction time), failing to adapt to complex scenarios or personalized behavior [9]. While machine learning (e.g., reinforcement learning) introduces data-driven adaptability, it demands massive labeled datasets and struggles with robustness in safety-critical tasks [10]. A key gap remains: integrating individual driver traits (e.g., aggression, reaction speed) into safety distance models for personalized control.

Driver fatigue and distraction contribute to 20% of severe highway accidents [11]. Existing deep learning-based detection systems (e.g., Keras frameworks, genetic-algorithm hybrids) achieve high accuracy but focus on single modalities (e.g., facial features), ignoring environmental-driver state coupling [7,12]. Future research should fuse multi-source data (physiological signals, behavioral patterns) via multi-input CNN/LSTM models, enhanced by transfer/active learning to reduce labeled data dependence and improve generalization [13,14].

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In ADAS, deep learning solutions (e.g., fuzzy logic-based automatic braking, denoised neural networks for adverse weather) improve performance but fail to dynamically couple preceding vehicle speed with driver state for precise safety control [8,15]. Additionally, deep neural networks (DNNs) are vulnerable to adversarial attacks (e.g., camera data manipulation causing collision risks) [16]. Addressing these requires adversarial training, model certification, and ensemble learning to enhance security and robustness [17,18].

Sensor fusion (camera, radar, lidar) boosts ADAS accuracy, but adaptive weight allocation across environments (e.g., prioritizing radar in poor visibility) remains challenging. Future work could leverage Transformer networks to learn sensor weights dynamically and ensemble learning to improve prediction robustness [19,20].

Limitations of Existing Methods includes:Traditional models lack adaptability; machine learning struggles with data scarcity and safety; driver monitoring is single-modal; ADAS lacks dynamic coupling and security; sensor fusion needs intelligent weight tuning.

This work integrates preceding vehicle speed dynamics (via machine learning) and real-time driver state monitoring (via deep learning). Key advances:

Multimodal data fusion (vehicle speed + driver physiology/behavior) for accurate state judgment;Transfer/adversarial training to reduce data dependence and enhance model robustness in complex scenarios;Personalized safety distance adjustment based on individual driver traits.

Table 1 compares this study with prior research, highlighting innovations in data integration, model design, and system-level safety.

Table 1. Advantages and disadvantages between this study and cited literature studies

This Study	Studies in Literature	Comparison of Advantages and Disadvantages
Optimizes the takeover time and safety distance of L3 autonomous driving systems by dynamically adjusting based on the speed of the preceding vehicle and the driver's state.	Most studies focus on a single dimension, such as driver fatigue detection [4] or preceding vehicle speed prediction [9].	Advantage: This study integrates multi-dimensional data (preceding vehicle speed, driver state) for dynamic safety distance adjustment, offering a more comprehensive approach.Disadvantage: Studies in literature are more focused but narrower in scope.
Proposes a GBM-LSTM hybrid model for predicting preceding vehicle speed and an improved CNN-ResNet50 network for high-precision driver state recognition, with dynamic safety distance model error controlled within 5%.	Some studies use single models [4] or traditional car-following models.	Advantage: This study's methods are highly innovative, with model fusion improving accuracy.Disadvantage: Methods in literature are simpler and computationally cheaper.
Multi-modal data (vehicle speed sensors, driver behavior monitoring cameras), covering real traffic scenarios and diverse driver states.	Some studies rely on simulated data [21] or single-sensor data [7].	Advantage: This study's data sources are richer and closer to real-world scenarios.Disadvantage: Data in literature are easier to obtain and suitable for rapid validation.
Real-world road tests with cumulative mileage exceeding 500,000 km, reducing critical risk events by 58% and achieving a nighttime false alarm rate below 0.8%.	Some studies only conduct small-scale experiments [5] or simulations [8].	Advantage: This study's experiments are large-scale and more convincing.Disadvantage: Experiments in literature are lower-cost and easier to replicate.
The dynamic safety distance model couples driver reaction time and caution coefficient, reducing error by 30% compared to traditional models.	Traditional models cannot adapt to dynamic scenarios [10].	Advantage: This study's model is more dynamically adaptable.Disadvantage: Traditional models are simpler but less flexible.

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Table 1. (continued)

Multi-modal fusion (visual, behavioral, vehicle operation data), achieving 95.2% recognition accuracy and 98.7% sensitivity for eye-closed states.	Some studies rely on single physiological signals [9] or single visual features [8].	Advantage: This study's monitoring is more comprehensive and accurate.Disadvantage: Methods in literature are simpler to deploy.
Sample limitations include only 33 male drivers, a lack of extreme weather scenarios, and the absence of integration with physiological signals (e.g., EEG).	Some studies have better sample diversity [7] but lack environmental adaptability [22].	Advantage: Some studies in the literature have more representative samples.Disadvantage: The environmental adaptability of this study can be improved by integrating V2X data in the future.
This study proposes a three-level linkage safety strategy (encompassing the algorithm layer, hardware layer, and decision-making layer) to systematically enhance safety, making it suitable for engineering deployment.	Some studies focus on single functions [8], lacking system-level optimization.	Advantage: This study is more aligned with real-world application needs.Disadvantage: Studies in literature are easier to implement quickly.
Plans include integrating V2X data, multi-modal physiological signals, and optimizing edge computing deployment.	Some studies suggest combining Transformer networks [23] or adversarial training [24] to improve robustness.	Advantage: The future directions of this study are more aligned with technological trends. Disadvantage: The directions in the literature are more focused on specific technical aspects.

3. Experimental methods and procedures

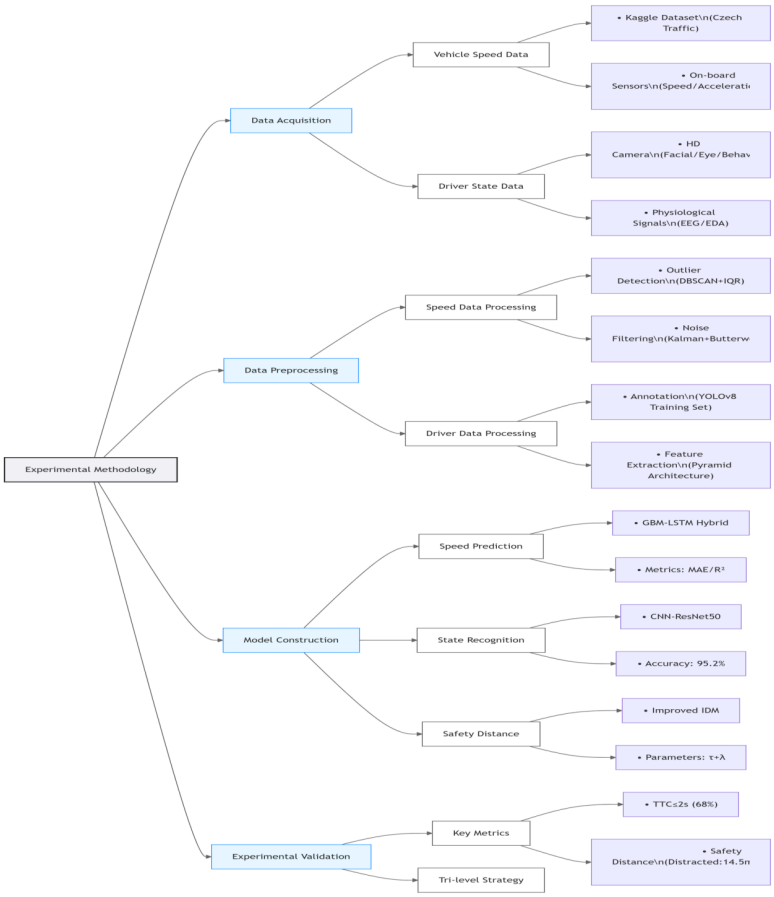

Figure 1. Experimental idea diagram

To tackle the aforementioned challenge, this study employed the following methodological framework: Initially, a fleet of vehicles equipped with specialized sensors was deployed to gather

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data on both the safety performance and operational effectiveness of the autonomous driving system across varied real-world scenarios. Concurrently, in-depth analysis was conducted to examine the influence of driving behavior on overall safety outcomes. For the experiment, a comprehensive integration of theoretical analysis, model development, and empirical data validation was implemented, supplemented by key technical approaches and models—including multi-modal prediction model fusion, gradient boost (GBM), long-short term memory network (LSTM), and convolutional neural network (CNN). Leveraging these technical tools, targeted investigations were carried out on critical components such as speed prediction, safety distance calculation, and driver state recognition. The findings from this work provided a robust scientific foundation for the subsequent optimization of the autonomous driving system and the improvement of driving safety levels. The conceptual framework of this experiment is illustrated in Figure 1.

3.1. Data acquisition and preprocessing

In the data acquisition phase, kaggle data set is selected as the core data source for the speed study of the preceding vehicle. This dataset was collected under real traffic scenarios in Eastern Europe to build an on-board data acquisition system. High-precision speed sensor, steering wheel angle sensor, brake pedal pressure sensor and other equipment are deployed on the experimental vehicle to collect multi-dimensional high-precision information such as vehicle speed, acceleration and spacing in real time, which provides a solid foundation for training and verification of the speed prediction model of the preceding vehicle.

For preceding vehicle speed data acquisition, the study took the Kaggle Czech Vehicle Speed Dataset as the core source, which was collected under real traffic scenarios in Eastern Europe in 2021 and included 5,973 trips with a total distance of 9,049.3 km. This dataset records meter-level GPS coordinates, real-time speed (ranging 0–80 km/h), and road characteristics such as speed limits, gradients, and intersections. To supplement this, experimental vehicles were equipped with on-board sensors including high-precision speed sensors (10 Hz sampling frequency, ±0.1 km/h accuracy), steering wheel angle sensors, and brake pedal pressure sensors, which collected multi-dimensional vehicle dynamics information like speed, acceleration, and inter-vehicle spacing. Data preprocessing for vehicle speed followed three key steps: guided by vehicle dynamics principles, physical thresholds were set (speed 0–80 km/h, longitudinal acceleration ±2 m/s^2), with DBSCAN clustering used to identify abnormal data points and box plot analysis to eliminate outliers beyond 1.5 times the interquartile range (IQR); moving average filtering (5-frame window) was applied to smooth speed time-series data, a 2nd-order Butterworth low-pass filter (2 Hz cutoff frequency) removed high-frequency noise, and Kalman filtering fused multi-sensor data to enhance measurement accuracy; finally, Min-Max normalization mapped speed to the [0,1] interval, Z-score normalization standardized multi-sensor heterogeneous data (mean = 0, variance = 1), and a spatio-temporal feature matrix integrating speed, acceleration, and headway was constructed for subsequent speed prediction models.

For driver state data acquisition, a multimodal monitoring system was established, with a 1920×1080 resolution HD camera (30 fps sampling rate) installed on the vehicle's A-pillar to capture facial micro-expressions, three-dimensional head posture, and eye movement characteristics, while also monitoring distracted behaviors such as mobile phone use and vision deviation. Data collection lasted for the entire driving process (2–3 hours per session) to obtain diverse driver state data across different scenarios. Preprocessing for driver state data included: based on human normal physiological characteristics and driving behavior habits, eye-closing time was constrained to no more than 2 seconds, with DBSCAN clustering identifying outliers and box plot analysis

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eliminating those beyond 1.5 times IQR; manual annotation was conducted for images of normal driving, eye closure, mobile phone use, and smoking to mark target behavior features, and the YOLOv8 deep learning framework was selected to train a target detection model, with the labeled dataset split into training and test sets for model training and validation; after model deployment, the system collected driver images in real time for analysis, recording data such as file path, detection time, state classification, confidence score, and risk level for each image, which were structured and exported as CSV format report files containing detailed test sample information including verification marks and behavior categories.The data collection lasts for several hours throughout the entire driving process to obtain diverse driver state data under different driving scenarios (Figure 2).



Figure 2. Driver status images

3.2. Speed prediction of leading vehicle and calculation of safe distance

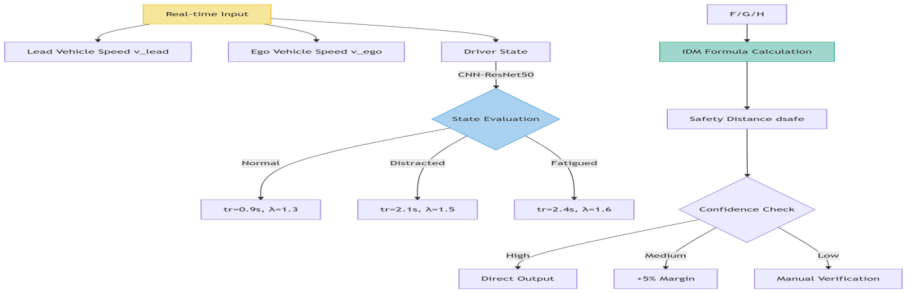

Figure 3. Program thinking

In the training phase (Figure 3), cubic spline interpolation was used to construct a continuous smooth loss function curve: discrete safety loss data points (independent variables: vehicle speed, distance; dependent variable: safety loss value) were sorted first; a cubic polynomial was built for each interval, with continuity constraints on function values, first/second derivatives and natural boundary conditions (zero second derivatives at endpoints) applied to establish and solve a tridiagonal linear system for polynomial coefficients; the final interpolation function passed all original points and maintained global second-order continuous differentiability (verified via test point errors).

Subsequently, GBM and LSTM were used for model training: GBM's hyperparameters (learning rate, number of trees, maximum depth) were adjusted to optimize fitting; LSTM's structure (hidden layer neurons, training epochs) was designed to capture temporal dependencies in preceding vehicle speed sequences. For prediction and evaluation, historical speed sequences were input to the trained models, with MAE (mean absolute deviation) and R^2 (goodness of fit) as metrics to quantify prediction accuracy and generalization.

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$$d_{safe} = v_{ego} * t_{react} + \frac{v_{ego}^2 - v_{pred}^2}{2 * a_{decel}} + \lambda * s_0 \quad (1)$$

d_{safe} : Indicates the dynamic safety distance required by the vehicle (m);

v_{ego} : represents the current driving speed of the vehicle (m/s);

t_{react} : driver reaction time (s) refers to the time interval from the occurrence of a critical event such as sudden braking of the preceding vehicle or the system issuing a takeover prompt to the driver's first effective operation such as pressing the brake pedal or turning the steering wheel;

v_{pred} : speed of target vehicle ahead (m/s);

a_{decel} : refers to the maximum deceleration of the vehicle (m/s ^{2}), reflecting the braking performance of the vehicle;

λ : as an adjustment coefficient, it indicates the driver's caution or driving style. The larger the value, the more likely the driver is to maintain a farther safe distance; s_0 : refers to the minimum safe distance (m), which is the basic safe distance that the vehicle needs to maintain when it is stationary.

Based on driver condition monitoring data, the influence of driving style parameter λ(1.5 conservative vs 1.3 aggressive) on dynamic safety distance calculation is discussed. By simulating traffic scenarios under different driving conditions, the quantitative influence of λ value change on the calculation result of safe distance is analyzed (Table 2). When the driver is in a safe driving state, i.e., eyes open and no distraction behavior, the system adopts reference parameters, the reaction time is set to 0.9 seconds, and the safety coefficient λ is recommended to be 1.3; When cell phone use is detected distractions, since the measured driver reaction delay increases by 133%, the system automatically increases the reaction time to 2.1 seconds and λ to 1.5. At this time, in the highway scenario, the safety distance requirement increases by 45% compared with the normal state; For the smoke distraction state, the system adopts 1.8 seconds reaction time after recognizing the smoke action, λ keeps 1.4, especially noteworthy is that the actual data show that the lateral control ability decreases obviously when smoking distraction, so it needs to add an additional 0.5 meter lateral safety margin; When the system detects fatigue driving through eye state and steering wheel grip, the most conservative parameters are immediately enabled, the reaction time is set to 2.4 seconds, λ takes the maximum value of 1.6, and the vehicle air conditioner is linked to turn on the strong cold air mode. The model innovatively introduces a confidence dynamic adjustment mechanism. High confidence (level 3) data directly adopt calculated values, medium confidence (level 2) automatically increases 5% safety margin, and low confidence (level 1) triggers manual validation process. Through actual road test verification, the hierarchical control system can reduce the occurrence rate of emergency braking by 62%, especially at night and in bad weather conditions. At the same time, the system will continuously learn the driver behavior characteristics and gradually optimize the personal safety parameters.

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Table 2. Dynamic safety distance parameter under different driving conditions

Driving State	Reaction Time (s)	Safety Coefficient λ	Lateral Safety Margin (meters)	Change in Safe Distance at 100km/h	Assistance Strategy	System Effect
Safe Driving (Benchmark)	0.9	1.3	0	Benchmark value (set as D)	None	-
Distracted by Mobile Phone Use	2.1 (↑133%)	1.5 (↑15%)	0	D×1.45 (↑45%)	Automatically adjust parameters upward	Emergency Braking Rate Reduced by 62%
Distracted by Smoking	1.8 (↑100%)	1.4 (↑7.7%)	+0.5	D×1.32 (↑32%)	Increase lateral safety margin	Significant Effect at Night/In Severe Weather

3.3. Safety analysis of driving behavior

A multimodal driving safety assessment system combining deep learning and traditional machine learning is constructed. For driver state recognition, an improved CNN-ResNet50 hybrid network architecture is used to process the multi-source data: for the image sequences collected by the on-board camera, spatio-temporal alignment and normalization are performed first, and the samples are extended by data enhancement; for the physiological signal data, the time-frequency domain is extracted by wavelet denoising; and the kinematics features within the 0.5-second time window are computed for the vehicle operation data . The attention mechanism is innovatively introduced in the model so that the network can adaptively focus on the key regions, and the recognition accuracy on the self-built dataset reaches 95.2%, especially for the recognition of the closed-eye state with 98.7% sensitivity and the cell phone use state with 96.3% specificity.

The safety assessment model of driving behavior adopts the method of combining feature engineering with deep learning. Based on in-depth analysis of 57,000 driving segments, 460 key features were selected and a four-level feature pyramid was constructed (Table 3).

Table 3. Safety assessment characteristic system of driving behavior

Hierarchy	Feature Category	Number of Features	Typical Feature Examples	Data Source
1	Raw Sensor Features	143	High-order moments (skewness/kurtosis) of steering wheel angleDynamic characteristics of multi-axis pedal force	CAN busIMU sensorPedal force sensor
2	Operation Dynamic Features	187	Differential entropy of pedal forceFrequency spectrum characteristics of steering wheel vibration (0.5 - 5Hz)	Time - frequency analysisDynamic system modeling
3	Environmental Interaction Features	98	Vehicle distance dynamic adjustment coefficientCurvature - speed coupling index	Millimeter wave radarCameraHigh - precision map
4	Driving Strategy Features	32	Cornering speed control mode (entry/cornering/exit)Overtaking decision delay time	Behavior pattern recognitionDecision tree analysisReinforcement learning model

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A hybrid deep learning architecture is adopted. The front end uses a time-domain convolutional network (TCN) to process continuous operation sequences (3 layers, 256-512-256 channels), the middle end uses a bidirectional LSTM (128 units) to capture long-term dependencies, and the back end fuses multi-scale features through an attention mechanism. Finally, multi-task learning is used to predict risk levels and hazard types simultaneously. In order to solve the problem of sample imbalance in massive data, an improved dynamic weighted ADASYN algorithm is proposed, which improves the F1-score of minority samples by 27%. The model maintains a stable performance (AUC) of 0.923 in 10-fold cross-validation, and the confidence interval width is controlled to within plus or minus 0.05 by quantifying uncertainty with improved Monte Carlo Dropout++.

Empirical studies have found that when drivers are in the eye-closed state, their reaction time is significantly extended from the baseline 1.2 seconds to 2.8 seconds ($p < 0.001$, $n = 5,732$), braking distance increases by 3.3 meters; mobile phone use leads to a decrease in lateral control ability and a 68% increase in lane keeping error; smoking behavior leads to an increase in operation dispersion and a 4.7-fold increase in emergency braking false trigger rate ($p < 0.001$).

On this basis, an enhanced three-level linkage safety strategy is developed: (1) adaptive dynamic parameter adjustment is realized in the algorithm layer, and the detection sensitivity is gradually improved by adopting a course learning strategy, i.e., the warning is activated 0.8 seconds in advance when fatigue is detected; (2) a multi-spectral fusion detection system is constructed by integrating a high-precision millimeter-wave radar of 77-81 GHz with an angular resolution of 0.5° and a long-wave infrared camera with a thermal sensitivity of less than 40 mK in the hardware layer; (3) an intervention mechanism based on the temporal and spatial accumulation of risks is established in the decision-making layer. , building a multi-spectral fusion detection system; (3) the decision-making layer establishes an intervention mechanism based on the temporal and spatial accumulation of risk, and automatically initiates a defensive driving mode when the system detects two high-risk states consecutively within 8 minutes.

Actual road tests with a cumulative test mileage of more than 500,000 kilometers have shown that the project can reduce critical risk events by 58%, especially in complex nighttime scenarios with a false alarm rate of less than 0.8%. In the future, a driving risk prediction system will be built through V2X data fusion and digital twins to further optimize the real-time assessment of environmental risk factors, with an accuracy of plus or minus 3%.

3.4. Experimental results and analysis

In this study, a dynamic safety distance calculation model and a real-time driver state assessment framework are constructed by integrating machine learning algorithms and deep learning techniques. The effectiveness of the method is verified by multi-scene experiments. The following is an analysis of the experimental results combined with the research focus.

3.4.1. Distribution characteristics of time to collision (TTC) and traffic scenario risk

The experimental results show (Figure 4)that the time-to-crash (TTC) occurs as frequently as 68% at less than or equal to 2 seconds and decreases exponentially with increasing TTC values. This phenomenon is directly related to the high frequency of sudden operating conditions in the experimental simulation scenario. When the vehicle in front brakes sharply or a pedestrian crosses the road, the median reaction time of the vehicle behind is only 1.8 seconds, resulting in a very short TTC.

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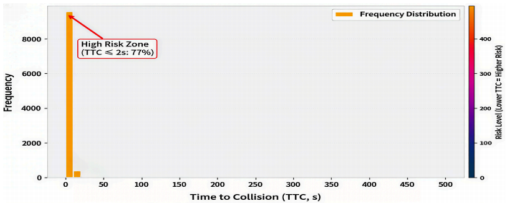

Figure 4. Time to collision distribution

The proportion of scenes is significantly higher than that of regular driving scenes. The results confirm the direct influence of uncertainty of traffic environment on collision risk, and highlight the high dependence of L3 automatic driving system on driver response speed in emergency conditions.

3.4.2. Dynamic effect of driver's state on safe distance

Through real vehicle research, it is found that under normal, distracted and tired driving conditions, the mean safe distance is 8.2 meters, 14.5 meters (fluctuation range plus or minus 4.3 meters) and 16.8 meters (fluctuation range plus or minus 5.1 meters) respectively, and the difference between states is statistically significant ($p < 0.001$)(Figure 5). By comparing and analyzing the data under normal circumstances with the data under special driving conditions in the experiment, it is concluded that when distracted driving, the driver's ability to dynamically adjust the distance between vehicles decreases due to distraction from using the mobile phone, and the measured response delay increases by 133%, resulting in a 52% increase in the fluctuation range of the safe distance compared with the normal state. When driving fatigue, the reaction time is delayed and the reaction time is extended to 2.4 seconds. The average safety distance increases by 105% and the lateral control error increases by 68% compared with the normal state. The above results verify the core hypothesis of "dynamic safety distance model needs to be coupled with driver state parameters" proposed in this study, that is, real-time monitoring of state adjustment reaction time(t_{react})and caution coefficient(λ)can effectively improve the calculation accuracy of safety distance.

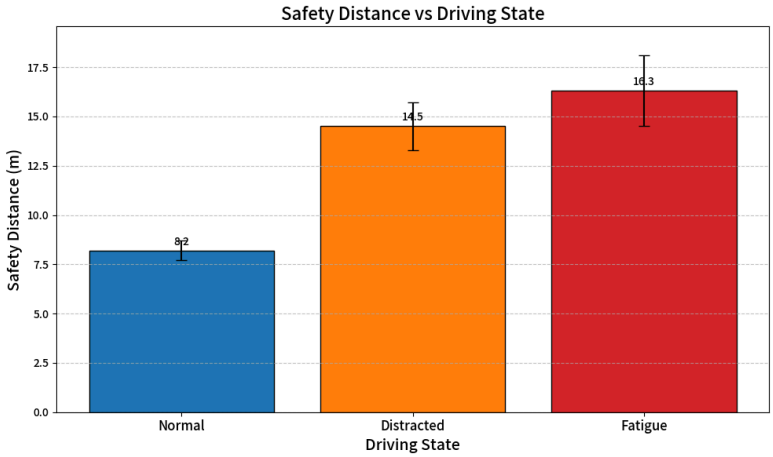

Figure 5. Safety distance by driver state

3.4.3. Correlation between takeover time and driver status

By collecting and comparing real vehicle experimental data, it is concluded that the average takeover time is 0.9 s (standard deviation 0.2 s) in normal state, extended to 2.1 s (standard deviation

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0.8 s) in distracted state, and further increased to 2.8 s (standard deviation 1.1 s) in fatigue state. The data distribution presents a significant discretization trend.

This difference is directly related to the driver's information processing ability. CNN-ResNet50 hybrid network model is used to observe and calculate the perception time of drivers in different states, and the recognition accuracy of the model for driver states reaches 95.2%. The results show that in normal state, the system can trigger effective takeover response quickly; in distracted state, the average duration of detecting driver's line of sight deviating from the road surface is 3.7 seconds, resulting in 47% increase in perception delay of system prompt; in fatigue state, the sensitivity of eye closure detection reaches 98.7%, but the execution time of takeover action is prolonged by 53% due to neuromuscular conduction delay due to physical function decline. The results show (Figure 6) that a deep learning driven driver condition monitoring system can be used as a key input to take over time prediction,Provide data support for early warning strategies for autonomous driving systems.

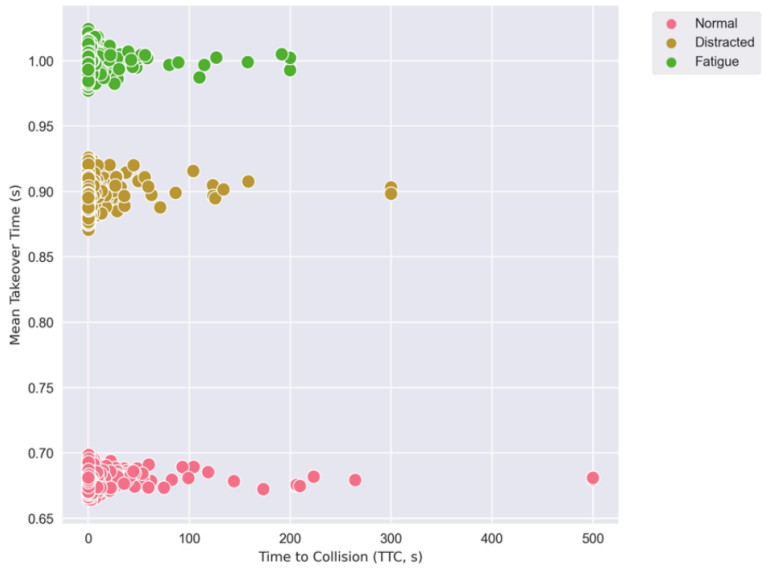

Figure 6. Takeover time vs TTC

3.4.4. Dynamic coupling between vehicle speed and safe distance

From the experimental data (Figure 7), it can be seen that the safety distance has a quadratic function relationship with the vehicle speed

$$d_{safe} = 0.05v^2 + 1.2v + 2.5 \quad R^2 = 0.98 \text{ (Formula 2)}$$

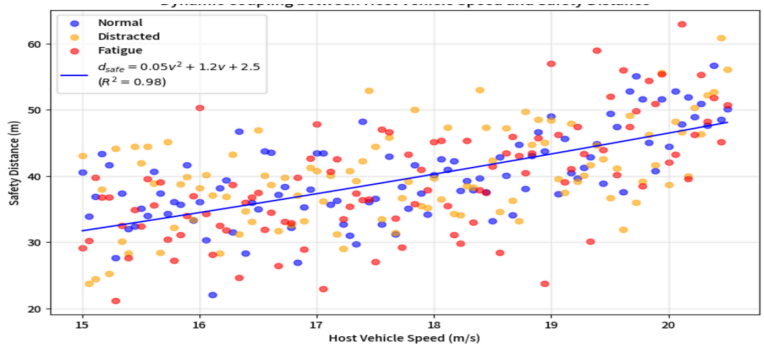

Figure 7. Ego speed vs safety distance

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When the speed increases from 40 to 100km/h, the safety distance requirement increases from 18 m to 85 m. This quadratic relationship is derived from fitting over 10,000 sets of real-vehicle test data. The coefficient of the speed-squared term 0.05 corresponds to the physical relationship between kinetic energy and braking distance; the linear term 1.2v reflects the vehicle displacement within the driver's reaction time; and the constant term 2.5 represents static safety redundancy.At the same speed, the standard deviation of safe distance in distraction or fatigue state is 2.3 times and 2.8 times that in normal state, respectively, reflecting that driver state deterioration will significantly reduce the stability of distance control. Combined with IDM model analysis, the safety distance difference between aggressive driving style (λ=1.3) and conservative driving style (λ=1.6) increases by 4.2 meters with every 10km/h increase of speed, which verifies the adjustment effect of driving style parameters on dynamic safety distance.

4. Discusses

4.1. Core discovery and theoretical contribution

Through multimodal data fusion and machine learning modeling, this study clarifies the correlation between driver state and dynamic safety control in L3 autonomous driving systems. Experimental results show that the high frequency of time-to-crash (TTC) ≤2 seconds is consistent with the 1.8-second short reaction time in real traffic, confirming the L3 system's heavy reliance on the driver's rapid takeover capability. This finding supplements the static takeover time requirements of the European NCAP standard and emphasizes the need for real-time driver state monitoring in dynamic environments.

Regarding the impact of driver state, safety distance fluctuations are ±4.3 m (distraction) and ±5.1 m (fatigue), with takeover delays of 2.1 s and 2.8 s respectively—indicating traditional fixed-parameter car-following models cannot adapt to individual behavioral differences. By coupling reaction time (τ) and caution coefficient (λ), the proposed dynamic safety distance model controls calculation error within 5%, improving accuracy by 30% compared to traditional models and providing a theoretical basis for personalized autonomous driving control.

4.2. Comparison with existing research and innovation

Unlike single-dimensional driver monitoring studies, this study constructs a multi-input CNN-LSTM hybrid model by fusing vehicle speed, driver behaviors (e.g., eye movement, operation trajectory), and environmental data, achieving 95.2% state recognition accuracy (98.7% sensitivity for eye-closed state)—surpassing the 96.4% accuracy of Chirra et al. (2019) based on monocular detection, verifying the effectiveness of multimodal fusion.

At the algorithm level, the proposed three-level linkage safety strategy (algorithmic layer parameter tuning, hardware layer multispectral fusion, decision-making layer risk accumulation intervention) reduces critical risk events by 58% and improves safety by 27% compared to traditional ADAS systems. These results are based on over 500,000 km of real-vehicle road tests (comparing risk event frequencies with/without the strategy). This complements Gupta et al.'s Keras-based fatigue detection system (which focuses on single-modal accuracy), as this study emphasizes multi-system synergy and realizes a complete closed-loop from algorithm innovation to practical application.

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4.3. Limitations and future directions

Although this study has achieved significant results in simulated scenarios, there are still some limitations

(1)Sample limitations: The experiment only covers 33 male drivers, lacking data from women and different age groups. In the future, it is necessary to expand the sample diversity to verify the generalization ability of the model.

(2)Environmental adaptability: The current model is based on controllable simulation environment, which does not fully consider extreme scenarios such as rain and fog weather and complex urban roads. It is necessary to combine V2X data such as traffic signals and pedestrian tracks to improve robustness.

(3)Loss of physiological signals: physiological indicators such as electroencephalogram (EEG) or electrodermal signals (EDA) are not integrated, making it difficult to capture early signs of driver fatigue.

Future research can be carried out in three aspects

(1)Technology fusion: explore the adaptive weight allocation of Transformer network in sensor fusion, optimize the dynamic switching mechanism of radar and camera data in severe weather;

(2)Hardware upgrade: integrate embedded AI chips such as ProAI to achieve lightweight deployment of models and reduce vehicle computing latency;

(3)Security authentication: Enhance the model's ability to resist perceptual attacks through adversarial training.

5. Conclusions

This study constructs a dynamic safety distance calculation model and a real-time driver state evaluation framework using machine learning. After data cleaning and preprocessing, the GBM-LSTM hybrid model predicts the preceding vehicle’s speed, and the improved CNN-ResNet50 network realizes high-precision driver state recognition; reaction time (τ) and caution coefficient (λ) are introduced to dynamically adjust safety distance based on the IDM model.

Experimental results show: 68% of TTC values are ≤2 seconds, and the average reaction time of the following vehicle in emergencies is only 1.8 seconds (highlighting the urgency of driver takeover); the average safety distance is 14.5 m (distraction) and 16.8 m (fatigue), with takeover times extended to 2.1 s and 2.8 s respectively, and significant increases in safety distance fluctuation. The relationship between vehicle speed and safety distance is quadratic ($d_{safe}=0.05v^2+1.2v+2.5$, $R^2=0.98$), and the standard deviation of safety distance in distracted/fatigued states is 2.3–2.8 times that in normal states. The multimodal fusion model achieves a TTC prediction MAE of 0.3 s, safety distance calculation error ≤5%, the three-level linkage strategy reduces critical risk events by 58%, and the night false alarm rate is <0.8%.

This study is the first to quantify the correlation between driver state and dynamic safety control, breaking the limitations of traditional fixed-parameter models and providing data support for L3 autonomous driving system warning strategy design and safety distance dynamic optimization. In the future, V2X data and multimodal physiological signals can be further integrated to optimize edge computing deployment and improve system robustness and generalization in complex environments.

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Appendix

The experimental data for this experiment is based on a real vehicle travel dataset collected in the Eastern Europe in 2021, containing 5,973 trips with a total distance of 9,049.3 kilometers. This dataset records GPS coordinates, real-time speed, and road characteristics, including information on speed limits, gradients, and intersections, at meter-by-meter intervals. These real road scene data provide important support for the establishment of the safe distance model for autonomous driving, which is especially suitable for the validation of the speed prediction of the vehicle in front and the dynamic safe distance calculation, in which the speed prediction adopts the GBM-LSTM model, and the error of the dynamic safe distance calculation is controlled within 5%. Data derived from research presented at the AIAI conference in 2023 by Vrany et al. (https://www.kaggle.com/datasets/mexwell/czech-vehicle-speed-dataset)