Design of a Deep Learning-Based Intelligent Driving Decision System for Vehicle Engineering and Adaptability Verification in Complex Road Conditions

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ABSTRACT To address the limitations of conventional intelligent driving decision systems, including insufficient real-time performance, low decision accuracy, and weak adaptability under complex road conditions, this study proposes a deep learning-based intelligent driving decision framework with enhanced multi-source electromagnetic sensing and environmental perception capabilities. Considering the increasing importance of millimeter-wave radar and heterogeneous sensor fusion in intelligent transportation systems, a multi-source data fusion module integrating cameras, LiDAR, millimeter-wave radar, and vehicle status information is first established, where adaptive Kalman filtering is employed to improve data reliability and suppress noise interference. Subsequently, a hybrid decision architecture combining an improved Deep Q-Network (DQN) and a Transformer encoder is developed. Dual Q-learning and prioritized experience replay optimize sequential driving decisions, while the Transformer captures global contextual features of complex road environments, enabling effective integration of local behavioral optimization and holistic situational awareness. Finally, a comprehensive validation framework covering extreme weather, special traffic scenarios, and sudden obstacles is constructed to evaluate system robustness. Experimental results based on the nuScenes dataset and real-vehicle tests demonstrate that the proposed system achieves a decision response time below 80 ms and an average decision accuracy of 92.7% under complex road conditions, outperforming conventional rule-based and single deep learning approaches by 10.6%–28.4%. The proposed framework provides reliable decision support for intelligent vehicles and offers valuable references for electromagnetic sensing, multi-source information fusion, and wireless perception systems in advanced autonomous driving applications.

INDEX TERMS deep learning, intelligent driving, multi-source sensor fusion, millimeter-wave radar, electromagnetic sensing

I. INTRODUCTION

A. RESEARCH BACKGROUND

With the rapid advancement of artificial intelligence, big data, and sensor technologies, intelligent driving has become the core development direction for the global automotive industry, propelling vehicle engineering toward an era defined by "electrification, intelligence, connectivity, and sharing," a paradigm shift similarly influencing the industry's integration of these technologies for automated and smart manufacturing [1]. As the "brain" of intelligent vehicles, the autonomous driving decision-making system analyzes road conditions, assesses traffic situations, and formulates driving strategies, directly determining the safety, reliability, and comfort of autonomous driving [2]. According to the World Health Organization (WHO), over 1.35 million people die annually in traffic accidents worldwide, with 90% of these fatalities stemming from human errors such as misjudgment and delayed reactions [3]. The application of autonomous driving decision-making systems can effectively reduce human interference and enhance traffic safety.

However, real-world driving environments are complex and dynamic, encompassing extreme weather (rain, fog, snow), special traffic scenarios (congested intersections, road construction, unprotected left turns), and sudden risks (sudden pedestrian intrusion, abrupt vehicle deceleration), imposing stringent demands on the system's adaptability and robustness [4]. Traditional intelligent driving decision methods primarily rely on rule-based logic and simple machine learning models. Rule-based approaches suffer from poor scalability and struggle to cover all complex scenarios, while single machine learning models exhibit insufficient environmental feature extraction capabilities and weak generalization, resulting in low decision accuracy and poor real-time performance under complex road conditions [5].

Deep learning possesses powerful feature extraction and nonlinear fitting capabilities, enabling effective discovery of underlying patterns in multi-source sensor data and offering a new technical pathway for solving complex intelligent driving decision problems [6]. By integrating deep learning algorithms such as reinforcement learning and Transformers, decision systems can achieve adaptive learning of driving behaviors and precise perception of complex environments, enhancing adaptability to challenging road conditions. Therefore, conducting research on the design of vehicle engineering intelligent driving decision systems based on deep learning and verifying their adaptability to complex road conditions holds significant theoretical value and engineering application implications for advancing the industrialization of intelligent driving technology, much like the rigorous adaptive control required for managing the high-speed and complex dynamics of automated weaving machinery.

B. CURRENT RESEARCH STATUS AT HOME AND ABROAD

1) Overseas Research on Intelligent Driving Decision Technologies

International research on intelligent driving decision-making began earlier and has developed a relatively mature technical framework. Tesla's Autopilot system employs a decision-making framework combining rule-based and deep learning approaches, utilizing computer vision technology based on cameras to perceive the environment and implement functions such as adaptive cruise control and lane keeping [7]. Waymo centers its decision-making system around LiDAR as the primary sensor, integrating deep learning algorithms to construct high-precision maps for decision support, achieving Level 4 autonomous driving in specific areas [8]. In academic research, Mnih et al. [9] proposed the Deep Q-Network (DQN) algorithm, integrating deep learning with Q-learning to achieve optimal decisions for complex sequential tasks, laying the foundation for reinforcement learning applications in intelligent driving decision-making. Lillicrap et al. [10] introduced the Deep Deterministic Policy Gradient (DDPG) algorithm to address decision-making in continuous action spaces, applied to intelligent vehicle speed control and path planning. Vaswani et al. [11] proposed the Transformer model, utilizing self-attention mechanisms to extract global features, which has been widely adopted in intelligent driving environment perception and decision-making. However, foreign research often focuses on single-scenario optimization, with insufficient comprehensive validation of adaptability to complex road conditions.

2) Domestic Research on Intelligent Driving Decision-Making Technologies

Domestic research on intelligent driving decision-making has advanced rapidly, with major automakers and research institutions undertaking extensive work. BAIC Group's Arcfox Alpha-S HI Edition, equipped with Huawei's intelligent driving system, employs a hybrid rule-based and deep learning decision-making approach to achieve autonomous driving on urban roads [12]. BYD's DiPilot system integrates multi-source sensor data, using deep learning algorithms to optimize decision logic for tasks such as following distance and lane changes [13].

C. RESEARCH SCOPE AND TECHNICAL APPROACH

1) Research Scope

1. Multi-source sensor data fusion module design: Integrate camera, LiDAR, millimeter-wave radar, and vehicle status data. Develop Adaptive Kalman Filter (AKF) preprocessing algorithms to address data noise and heterogeneity issues;

2. Construction of Hybrid Deep Learning Decision Models: Implement driving behavior sequence decisions based on an enhanced DQN network; introduce a Transformer encoder to extract global environmental features, establishing a "local optimization-global perception" integrated decision framework;

3. Development of Adaptive Validation Framework for Complex Road Conditions: Design three validation scenarios–extreme weather, special traffic conditions, and sudden risks–to evaluate system performance using public datasets and real-vehicle testing.

2) Technical Approach

The technical approach comprises three stages: data layer, model layer, and validation layer. The data layer handles multi-source sensor data acquisition, preprocessing, and fusion. The model layer constructs an improved DQN-Transformer hybrid decision model, optimizing parameters through training. The validation layer designs multi-dimensional complex road scenarios, conducts simulations and real-vehicle testing, and evaluates system decision accuracy, real-time performance, and adaptability.

II. THEORETICAL FOUNDATIONS

A. MULTI-SOURCE SENSOR DATA FUSION TECHNOLOGY

1) Sensor Data Types and Characteristics

Common sensors in intelligent driving systems include cameras, LiDAR, millimeter-wave radar, and vehicle status sensors. The characteristics of each sensor type are summarized in Table 1 [14].

TABLE 1. Characteristics of Commonly Used Sensors in Intelligent Driving

Sensor Type	Core Advantages	Main Limitations	Application Scenarios
Camera	Rich image information, low cost	Susceptible to lighting, low ranging accuracy	Traffic sign recognition, lane line detection
LiDAR (Laser Radar)	High ranging accuracy, strong anti-interference	High cost, sparse point cloud data	Obstacle detection, environment modeling
Millimeter-Wave Radar	Strong penetration, adapts to harsh weather	Low resolution, susceptible to electromagnetic interference	Following distance detection, speed measurement
Vehicle State Sensor	High real-time performance, reliable data	Only reflects the vehicle's own state	Vehicle speed, steering angle, acceleration monitoring

2) Core Data Fusion Algorithms

Multi-source data fusion enhances data reliability and integrity by integrating information from different sensors. Common fusion algorithms include Kalman filtering, Bayesian estimation, and D-S evidence theory. This paper employs Adaptive Kalman Filtering (AKF), which adapts to data noise variations by dynamically adjusting filtering gains in real time [15]. Its core formula is as follows:

State Prediction Equation:

$$x_{k|k-1} = Ax_{k-1|k-1} + Bu_{k|k-1} \tag{1}$$

Covariance Prediction Equation:

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{2}$$

Filter Gain Update Equation:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R_k)^{-1} \tag{3}$$

where $x_{k|k-1}$ is the state prediction at time k, A is the state transition matrix, B is the control input matrix, $u_{k|k-1}$ is the control input, $P_{k|k-1}$ is the predicted covariance matrix, Q is the process noise covariance, K_k is the filter gain, H is the observation matrix, R_k is the adaptive observation noise covariance, z_k is the observation value, and I is the identity matrix [16-18].

B. CORE DEEP LEARNING ALGORITHMS

The Transformer leverages self-attention mechanisms to effectively extract global contextual features, with its core architecture comprising an encoder and decoder [19]. The self-attention mechanism computes similarity weights by calculating the similarity between query (Q), key (K), and value (V) vectors, as follows:

Self-Attention Calculation:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Multi-head Attention Calculation:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(head_1, head_2, \ldots, head_h)W \tag{5}$$

$$head_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{6}$$

where d_k denotes the dimension of the Q/K vector, h represents the number of attention heads, and QW_i^Q, KW_i^K, VW_i^V are trainable weight matrices. This paper introduces a Transformer encoder to extract global features from the road environment, aiding DQN in achieving more precise behavioral decisions [20-21]. The core requirement of this study is to extract global contextual features of the road environment (e.g., lane line distribution, global obstacle position relationships), which does not require the sequence generation function of the decoder. The Transformer encoder can fully capture global spatial correlation features through the self-attention mechanism, while the decoder's cross-attention mechanism is designed for "input-output" sequence mapping, which is irrelevant to the feature extraction target of this study. Omitting the decoder can simplify the model structure and improve real-time performance (reducing computational complexity by approximately 15%).

III. INTELLIGENT DRIVING DECISION SYSTEM DESIGN

A. OVERALL SYSTEM ARCHITECTURE

The intelligent driving decision system adopts a four-layer architecture: "Data Input Layer - Data Fusion Layer - Feature Extraction Layer - Decision Output Layer." The data input layer collects multi-source sensor data; the data fusion layer preprocesses and fuses data via adaptive Kalman filtering; the feature extraction layer utilizes a Transformer encoder to extract global environmental features; the decision output layer generates driving decision commands (accelerate, decelerate, steer, brake) based on an improved DQN network [22].

B. CORE MODULE DESIGN

1) Multi-source Data Fusion Module

1. Data Preprocessing: Performs noise reduction and distortion correction on camera images; downsamples and performs ground segmentation on LiDAR point clouds; filters and denoises millimeter-wave radar data.

2. Adaptive Kalman Filter Fusion: Inputs preprocessed multi-source data into the AKF model to fuse obstacle positions, velocities, lane line information, and vehicle state in real time, outputting a unified environmental state vector.

2) Hybrid Decision Module

Constructs an "Enhanced DQN+Transformer" hybrid decision model with the following workflow:

1. State Modeling: Fuses global features extracted by the Transformer with real-time vehicle states (speed, steering angle) to build the decision state space S;

2. Action Space Definition: Defines a discrete driving action set A = {accelerate, maintain speed, decelerate, turn left, turn right, brake};

3. Reward Function Design: Design a reward function integrating safety, comfort, and efficiency:

4. Model Training: Dual Q-learning with priority experience replay was employed to optimize the training process. The experience replay pool capacity was set to 100,000, with a batch size of 64, learning rate of 0.001, and discount factor γ of 0.95 [23-26].

5. Feature Dimension Mapping: The global feature output by the Transformer encoder is 1024-dimensional, which is compressed and mapped through two fully connected layers–reducing from 1024D to 256D in the first layer and further to 64D in the second layer.

6. Feature Fusion: The 64D global features are concatenated with the 16D vehicle state features (speed, steering angle, etc.) to form an 80D fused state vector, serving as the input state space S of DQN.

7. Feature Normalization: The concatenated features are standardized through the LayerNorm layer to ensure consistent numerical scales between global features and vehicle state features, avoiding model training imbalance.

IV. ADAPTABILITY VERIFICATION SYSTEM FOR COMPLEX ROAD CONDITIONS

A. VERIFICATION SCENARIO DESIGN

1) Extreme Weather Scenarios

Includes rainy conditions (rainfall 5–20 mm/h), foggy conditions (visibility 50–200 m), and snowy conditions (snow depth 5–15 cm), simulating scenarios with sensor interference and reduced road surface friction coefficients [27].

2) Special Traffic Scenarios

Includes congested intersections (vehicle density $\geq$8 vehicles/100m), road construction zones (lane-occupying works $\geq$20m), unprotected left turns (no signal control), and roundabout navigation. These simulate scenarios with complex traffic participant behavior and dynamic road structures [28].

3) Sudden Hazard Scenarios

Includes sudden pedestrian intrusion (crossing speed $\geq$5 m/s), abrupt vehicle deceleration (leading vehicle deceleration acceleration $\geq$-5 m/s^2), and falling objects (sudden road obstacles $\geq$30 cm diameter), simulating scenarios requiring rapid response within short timeframes [29].

B. EXPERIMENTAL ENVIRONMENT AND DATASET

1) Simulation Environment

A simulation platform was constructed using MATLAB/Simulink and Prescan, configured with sensor models (camera resolution 1920×1080, LiDAR point cloud density 100,000 points/second, millimeter-wave radar range 0.5–200m). Vehicle parameters referenced a compact sedan (wheelbase 2700 mm, maximum speed 180 km/h, maximum acceleration 3 m/s^2) [30].

2) Real-Vehicle Experimental Environment

The real-vehicle platform is based on a smart modified vehicle equipped with a multi-source sensor suite, computing platform (NVIDIA Jetson AGX Orin), and CAN bus communication modules. Test sites include urban roads, highways, and closed test tracks.

3) Datasets

The experiment utilized the public nuScenes dataset and a proprietary dataset: nuScenes contains multi-source sensor data from 1,000 scenarios, including rainy conditions and traffic congestion; the proprietary dataset was collected via the test vehicle, encompassing 200 hours of complex road condition data annotated with obstacles, traffic lights, lane markings, and other information.

C. COMPARISON MODELS AND EXPERIMENTAL SETUP

1) Comparison Model Selection

Four mainstream intelligent driving decision models were selected for comparison:

1. Rule-Based Model: Decision logic designed based on expert experience;
2. Traditional DQN Model: Unoptimized Deep Q-Network;
3. CNN+LSTM Model: Fusion of Convolutional Neural Network and Long Short-Term Memory Network;
4. Single Transformer Model: Decision model based solely on the Transformer architecture.

2) Experimental Parameter Settings

Core parameters for simulation and real-vehicle experiments are shown in Table 2.

TABLE 2. Experimental Parameter Settings

Parameter Type	Parameter Value
Decision Cycle	100ms
Sensor Sampling Frequency	Camera 30fps, LiDAR 10Hz, Millimeter-Wave Radar 20Hz
Training Epochs	500 rounds
Simulation Scenarios	300 pieces
Real-Vehicle Test Mileage	500km
Proportion of Complex Road Conditions	60%

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. DECISION ACCURACY ANALYSIS

The decision accuracy comparison of different models under complex road conditions is shown in Table 3.

TABLE 3. Comparison of Decision Accuracy in Complex Road Conditions (%)

Model	Extreme Weather	Special Traffic Scenarios	Sudden Risk Scenarios	Average Accuracy
Rule-Based Model	72.3	75.6	68.9	72.1
Traditional DQN Model	78.5	81.2	76.3	78.7
CNN+LSTM Model	82.4	84.7	80.5	82.5
Single Transformer Model	83.6	86.1	81.8	83.8
Proposed Model	90.5	94.2	93.4	92.7

As shown in Table 3, our model achieves significantly higher decision accuracy than the comparison models across various complex scenarios, with an average accuracy of 92.7%. This represents a 20.6% improvement over rule-based models and a 14.0% improvement over traditional DQN models. This superior performance stems from our model's integration of the Transformer's global feature extraction capabilities with the sequence decision optimization of the improved DQN, enabling it to accurately capture the interrelated information and dynamic changes within complex environments.

B. REAL-TIME ANALYSIS

The decision response times of different models are compared as shown in Table 4.

TABLE 4. Decision Response Time Comparison (ms)

Model	Average Response Time (ms)	Maximum Response Time (ms)	Minimum Response Time (ms)
Rule-Based Model	45	85	28
Traditional DQN Model	92	156	68
CNN+LSTM Model	83	132	59
Single Transformer Model	78	125	55
Proposed Model	62	78	47

The average decision response time of this model is 62ms, with a maximum response time below 80ms, meeting the real-time requirements for intelligent driving ($\leq$100ms). Despite incorporating a dual-model architecture, real-time performance is ensured through lightweight design techniques (such as optimizing Transformer encoder layers and pruning DQN network parameters), achieving a 30.4% reduction in response time compared to traditional DQN models.

C. ADAPTABILITY ANALYSIS

Figure 2 compares the decision stability rates of various models under complex road conditions. Our model demonstrates strong adaptability with stability rates exceeding 90% in scenarios such as rain/fog, congestion, and sudden risks. In contrast, comparison models exhibit significant stability declines under extreme weather and sudden risk scenarios, with rule-based models being most affected by scene changes.

Real-vehicle testing results indicate that over 500km of testing mileage, the proposed model exhibited no safety issues such as collisions or misjudgments. It demonstrated adaptive adjustment of following distance in rainy and slippery conditions, with a braking response time under sudden pedestrian emergence scenarios below 0.3 seconds, meeting practical driving requirements.

D. ABLATION STUDY ANALYSIS

To validate the effectiveness of each optimization module, ablation experiments were conducted, with results presented in Table 5.

TABLE 5. Melting Experiment Results (Average Accuracy %)

Model Configuration	Experimental Result (%)	Performance Drop Rate
Proposed Complete Model	92.7	-
Without Transformer Module	85.3	7.4%
Without Double Q-Learning Optimization	88.6	4.1%
Without Prioritized Experience Replay	89.2	3.5%

Dissolution experiments demonstrate that the Transformer module delivers the most significant performance enhancement, with its global feature extraction capability serving as the core guarantee for adaptability to complex road conditions. Dual-Q learning and priority experience replay optimization effectively improve decision accuracy and training efficiency.

VI. CONCLUSIONS AND OUTLOOK

A. RESEARCH FINDINGS

This study addresses core challenges in intelligent driving decision systems–insufficient real-time performance, low decision accuracy, and weak adaptability under complex road conditions–by designing a deep learning-based vehicle engineering intelligent driving decision system and validating its adaptability in complex scenarios, echoing the need for comparable robustness and speed in quality control systems for high-volume, variable production. By constructing a multi-source sensor data fusion module and employing adaptive Kalman filtering to integrate heterogeneous data from cameras, LiDARs, and other sensors, the research effectively reduces noise interference and enhances environmental perception reliability. An innovative hybrid decision model combining DQN and Transformer was designed. Dual-Q learning and prioritized experience replay optimized DQN's sequential decision capabilities, while the Transformer encoder extracted global environmental context features, achieving deep synergy between localized driving behavior optimization and holistic situational awareness. A three-dimensional validation framework covering extreme weather, special traffic scenarios, and sudden risks was established. System performance was comprehensively validated through simulation and real-vehicle testing. Experimental results demonstrate that the system's decision response time remains consistently below 80ms. achieving an average decision accuracy of 92.7% in complex road conditions. This represents improvements of 20.6% and 8.9%–14.0% over traditional rule-based models and single deep learning models, respectively. The system demonstrates excellent adaptability and robustness in scenarios such as rain, fog, congestion, and sudden obstacles. It provides safe and reliable decision support for intelligent driving, laying a solid foundation for the engineering application of intelligent driving technologies in vehicle engineering.

B. FUTURE OUTLOOK

Future research may deepen and expand in three directions: First, introduce a hybrid training mechanism combining reinforcement learning and supervised learning with transfer learning techniques to enhance the model's generalization capability in small-sample and rare complex scenarios. Second, integrate vehicle-to-infrastructure (V2X) data with high-definition map information to expand the spatio-temporal scope of environmental perception and optimize decision prediction accuracy in special traffic scenarios. Third, conducting real-world vehicle testing over longer distances (tens of thousands of kilometers) and more complex real-world road conditions. This should incorporate user experience feedback to iteratively refine reward functions and decision logic, while exploring the application of multi-objective optimization algorithms to balance safety, comfort, and economy. These efforts will propel the system toward more efficient and safer engineering implementation.

AUTHOR CONTRIBUTIONS

Conceptualization – He Hao, Yongcheng Ling, Ying Wang and Feifei Yu; methodology – He Hao, Yongcheng Ling, Ying Wang and Feifei Yu; investigation – He Hao, Ying Wang and Feifei Yu; writing-original draft preparation – He Hao, Yongcheng Ling, Ying Wang and Feifei Yu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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