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Safe Reinforcement Learning Strategies with Interpretable Decision-Making for Autonomous Driving in Uncertain Traffic Conditions

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Abstract: ***The study focuses on improving the safety and interpretability of reinforcement learning in autonomous driving under uncertain traffic conditions. A decision-making model is developed using the Soft Actor-Critic algorithm, with an added module to estimate uncertainty and detect risky situations in real time. To make the system's behavior more understandable, a state–action salience mapping is designed to show which inputs have the greatest effect on each decision. The model is tested in simulation environments involving sudden pedestrian crossings, lane changes by other vehicles, and complex traffic flows. Results show that the method reduces the accident rate by 23.5% compared with standard approaches, while also making it easier for users to follow the reasoning behind the system's actions. These findings suggest that combining risk detection with simple visual explanation tools can help reinforcement learning models perform more reliably and transparently in real-world traffic.***

Keywords: Reinforcement Learning; Safety Strategy; Bayesian Modeling; Interpretability; Autonomous Driving Decision.

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1. Introduction

In the current era of rapid technological progress, continuous innovations in artificial intelligence (AI) and sensor technologies have laid a solid foundation for the steady transition of autonomous driving from theoretical research to practical application [1]. According to data from the Society of Automotive Engineers (SAE), by the end of 2024, more than 5 million vehicles equipped with various levels of autonomous driving capabilities had been deployed globally and this number is increasing at an annual rate of approximately 30% [2]. Many technology enterprises and automobile manufacturers have actively engaged in the development of autonomous driving technologies [3]. The industry has evolved from early-stage driver assistance functions, such as Adaptive Cruise Control (ACC) and Automatic Parking, toward highly automated and even fully autonomous systems [4]. The future of autonomous driving is promising, with the potential to significantly improve traffic efficiency and alleviate urban congestion. Relevant studies show that in large cities experiencing severe traffic congestion, the implementation of high-level autonomous driving could increase roadway throughput by 20%–30%, potentially reducing annual economic losses caused by traffic delays by several hundred billion yuan [5]. At the same time, autonomous driving could dramatically reduce traffic accidents caused by human error, offering unprecedented convenience and safety for public travel [6]. Data indicate that approximately 1.35 million people die in traffic accidents globally each year, with more than 90% of these accidents attributed to human-related factors [7]. If autonomous driving systems can reliably replace human drivers, they could generate profound and positive societal impacts.

However, real-world traffic environments are highly complex and uncertain. Participants include motor vehicles, non-motorized vehicles and pedestrians, all exhibiting highly diverse and random behavioral patterns [8]. According to investigations by traffic behavior research institutions, in urban road environments, about 50 out of every 1,000 vehicles display irregular driving behaviors each day, such as sudden lane changes or emergency braking [9]. In certain congested areas, up to 20% of non-motorized vehicles illegally move between motor vehicle and bicycle lanes. In some older city districts, the rate of pedestrian violations—such as crossing against red lights or not using designated crosswalks—can reach 15%. Road infrastructure also varies across cities and regions [10]. There are narrow and winding alleyways as well as complex multi-level traffic interchanges. Additionally, differences in traffic sign placement and lane markings further increase the difficulty of autonomous system decision-making. Environmental conditions are also subject to frequent changes [11]. There are considerable differences in lighting between day and night and weather variations—such as sunny, rainy, or snowy conditions—affect visibility and road surface friction [12]. For example, on rainy days, road friction can decrease by 30%–40% compared to dry conditions, posing a serious challenge to the perception and decision-making capabilities of autonomous systems [13].

Traditional rule-based autonomous driving approaches feature relatively clear logical structures and can function effectively in simple and well-structured traffic scenarios [14]. For example, on highways with low vehicle density and clearly marked lanes, such systems can maintain safe following distances and comply with speed limits based on predefined rules [15]. However, when confronted with the complexity and variability of real-world traffic environments, their limitations become evident. Rules are inherently limited in scope and cannot comprehensively address all possible situations. When encountering rare or unexpected events, the system often struggles to make reasonable decisions, leading to ineffective or incorrect responses. Studies have shown that in complex urban traffic environments, rule-based autonomous systems exhibit decision failure rates as high as 40% when dealing with abnormal conditions. The emergence of data-driven techniques such as deep learning and reinforcement learning has injected new vitality into the field of autonomous driving. Deep learning, with its strong feature extraction capabilities, enables large-scale analysis and learning of traffic scene data, leading to significant progress in the perception layer [16]. It allows more accurate detection of traffic signs, vehicles, and pedestrians. Under ideal conditions, traffic sign recognition based on deep learning can achieve accuracy rates above 95%. Reinforcement learning, by contrast, allows an agent to learn optimal behavior through trial-and-error interactions with the environment to maximize long-term cumulative rewards [17]. Theoretically, this provides a feasible solution for autonomous systems to adapt to dynamic and complex traffic conditions. However, both deep learning and reinforcement learning are essentially black-box models. The internal structure of deep learning models—comprising intricate parameter settings and multi-layered networks—makes it difficult to interpret their decision-making processes [18]. As a result, the reasoning behind decisions in specific scenarios is often unclear. Reinforcement learning also faces challenges under uncertain conditions. It is sensitive to environmental noise, reward design, and other external factors, which can lead to instability during training and unreliable decisions. Research has shown that in simulated complex traffic scenarios, the decision reliability of reinforcement learning alone is only about 60%.

Safety is the fundamental prerequisite for the widespread application of autonomous driving technology [19]. Any minor safety risk can lead to serious accidents in real-world traffic, resulting in significant loss of life and property. Statistical data indicate that traffic-related injuries and fatalities remain high each year, with human error accounting for a substantial proportion [20]. If autonomous systems can safely and reliably replace human drivers, the potential social benefits would be considerable and far-reaching. At the same time, interpretability is equally critical for the large-scale adoption of autonomous driving. From the user's perspective, people are often hesitant to trust their safety to a system whose decision logic they cannot comprehend. Only when users can clearly understand the basis for system decisions—especially in key situations such as emergency braking or evasive maneuvers—can trust in the system be truly established. From a regulatory standpoint, interpretability is essential for authorities to understand the system’s decision-making processes, enabling the development of rational and effective policies to guide and supervise technological deployment. Furthermore, during system development and testing, interpretability assists researchers in pinpointing issues efficiently, refining algorithms, and improving overall system performance. In recent years, reinforcement learning has been widely applied in the field of autonomous driving decision-making. Many studies have attempted to use reinforcement learning algorithms to train autonomous vehicles to generate decision strategies under different traffic scenarios, such as navigating intersections or driving through roundabouts. However, as discussed earlier, reinforcement learning has inherent limitations in handling uncertainty. Bayesian methods, as a powerful tool for dealing with uncertainty, provide probabilistic modeling of model parameters. This allows for quantitative analysis of uncertainty and offers more reliable support for prediction outcomes. In autonomous driving systems, Bayesian approaches can be used to model the uncertainty in sensor data, thereby enabling more accurate perception of the surrounding environment

[21]. Meanwhile, with the continued development of research in interpretable artificial intelligence, a series of interpretability techniques have emerged. These include attention-based visualization methods and inherently interpretable models such as decision trees. Incorporating such techniques into reinforcement learning is expected to enhance the transparency of the decision-making strategies, making them easier to understand and verify.

Based on the above research background, this paper proposes a strategy generation framework that combines Bayesian uncertainty modeling with an explainable reinforcement learning mechanism. The goal is to comprehensively enhance the safety and interpretability of autonomous driving systems under uncertain traffic scenarios. By conducting detailed analysis and precise modeling of complex traffic situations, reinforcement learning is used to train efficient decision strategies suitable for different contexts. Bayesian methods are applied to quantitatively assess uncertainty, and interpretable models are designed to clearly reveal the decision-making basis. This integrated approach aims to realize safe, transparent, and reliable autonomous driving decisions, thereby addressing key technical bottlenecks in practical deployment.

2. Methods

2.1 Reinforcement Learning Framework Integrated with Bayesian Uncertainty Modeling

This study adopts the Soft Actor-Critic (SAC) algorithm to construct the fundamental reinforcement learning framework. In autonomous driving scenarios, the policy network $\pi_\theta(a|s)$ outputs an action a based on the current state s, where θ denotes the parameters of the policy. Two value networks, $Q_{\phi_1}(s,a)$ and $Q_{\phi_2}(s,a)$, are used to evaluate the value of the state–action pair, with ϕ_1 and ϕ_2 representing their respective parameters.

The network parameters are updated by optimizing the following loss functions:

$$L_\theta = \mathbb{E}_{s\sim\mathcal{D},a\sim\pi_\theta}[\log\pi_\theta(a|s) - \alpha Q_{\min}(s,a)]$$

$$L_{\phi_i} = \mathbb{E}_{s\sim\mathcal{D},a\sim\pi_\theta}[(Q_{\phi_i}(s,a) - (r(s,a) + \gamma\mathbb{E}_{s'\sim\mathcal{P}}[V_\psi(s')]))^2], (i = 1,2)$$

$$L_\psi = \mathbb{E}_{s\sim\mathcal{D}}[(V_\psi(s) - \mathbb{E}_{a\sim\pi_\theta}[Q_{\min}(s,a) - \alpha\log\pi_\theta(a|s)])^2]$$

Here, $\mathcal{D}$ represents the experience replay buffer, r(s,a) is the immediate reward, γ is the discount factor, and α is the coefficient used to balance the reward and entropy terms. The function $Q_{\min}(s,a) = \min\{Q_{\phi_1}(s,a), Q_{\phi_2}(s,a)\}$ is used to compute the minimum of the two value estimates. The state value function is denoted as $V_\psi(s)$, where ψ denotes its parameters. In addition, Bayesian methods are used to model the policy network parameters θ, which are assumed to follow a prior distribution $p(\theta)$. After observing the dataset $\mathcal{D}$, the posterior distribution is calculated according to Bayes' theorem:

$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta)p(\theta)}{\int p(\mathcal{D}|\theta)p(\theta)d\theta}$$

Since computing the exact posterior distribution is intractable, variational inference is adopted to approximate it. A variational distribution $q_\phi(\theta)$ is introduced to approximate the true posterior by minimizing the Kullback–Leibler divergence $D_{KL}(q_\phi(\theta)||p(\theta|\mathcal{D}))$ [22]. This is achieved by optimizing the evidence lower bound (ELBO):

$$\mathcal{L}(\phi) = \mathbb{E}_{q_\phi(\theta)}[\log p(\mathcal{D}|\theta)] - D_{KL}(q_\phi(\theta)||p(\theta))$$

The parameter ϕ is updated accordingly. In practical implementation, Monte Carlo sampling is performed to draw parameter samples $q_\phi(\theta)$ from the variational distribution θ_i. These samples are then used to generate different policies for evaluating uncertainty.

2.2 Confidence Evaluation Module for Identifying High-Risk States

To accurately determine high-risk states, a confidence evaluation module is designed. Given a state s, N parameter samples $\{\theta_1, \theta_2, \cdots, \theta_N\}$ are drawn from the variational distribution $q_\phi(\theta)$. Based on these samples, a corresponding action set $\{a_1, a_2, \cdots, a_N\}$ is generated, where each action $a_i \sim \pi_{\theta_i}(a|s)$. The confidence level is quantified by calculating the action variance $\sigma^2(s)$ as follows:

$$\sigma^2(s) = \frac{1}{N-1}\sum_{i=1}^{N}(a_i - \overline{a})^2$$

Here, $\overline{a} = \frac{1}{N}\sum_{i=1}^{N} a_i$ A larger variance indicates a higher level of uncertainty and risk. When the confidence level is lower than a predefined threshold τ, the state is identified as a high-risk state, and corresponding safety measures—such as deceleration or evasive actions—are taken.

2.3 Design of the State–Action Salience Mapping Model

To improve the interpretability of the policy, a state–action salience mapping model is designed. Based on the gradient backpropagation algorithm, the gradient of the action with respect to the state is calculated $\nabla_s a$. For each state dimension s_j, the salience score $S(s_j)$ is defined as:

$$S(s_j) = \left|\frac{\partial a}{\partial s_j}\right|$$

The salience scores for all state dimensions are normalized to clarify the relative importance of each dimension. These normalized values are then projected onto the original state space to generate salience maps. Such maps visually highlight the key factors influencing decision-making under different states, and help users better understand the rationale behind the decisions.

3. Results and Discussion

3.1 Experimental Setup

This study conducts experiments using the CARLA autonomous driving simulation platform.

CARLA provides a highly realistic urban traffic environment that includes a wide range of road types, various traffic participants and dynamically changing environmental factors [23]. In the simulation environment, several complex and uncertain traffic scenarios are carefully designed. These include irregular pedestrian crossings, vehicle cut-ins and mixed traffic flows involving cars, motorcycles, and bicycles. To simulate different weather and lighting conditions, the environment is configured with diverse settings to better reflect real-world traffic situations. To rigorously verify the performance improvements of the proposed method in uncertain traffic scenarios—including safety, interpretability and driving efficiency—we systematically select several representative baseline algorithms. These algorithms include traditional rule-based methods and classical reinforcement learning approaches, both of which are widely used. This selection enables a comprehensive assessment of the proposed method's features and advantages from multiple perspectives, as summarized in Table 1.

Table 1: Characteristics of the Comparison Algorithms

Algorithm	Decision Basis	Advantages	Limitations
Traditional Rule-Based Method	Based on predefined driving rules, such as maintaining safe distance and following traffic signals	Can maintain basic driving order in regular and structured scenarios	Difficult to cover all traffic situations; high decision error rate in special cases
Plain SAC Algorithm	Soft Actor-Critic algorithm without additional mechanisms; outputs actions based on the current state	Serves as a fundamental reinforcement learning algorithm with general applicability	Lacks capability in handling uncertainty and providing interpretability
Deep Q-Network (DQN) Method	Selects optimal actions by learning state–action value functions	A classical reinforcement learning method with practical applications in some scenarios	Shows limited decision reliability in complex environments

To accurately evaluate the performance of different algorithms in autonomous driving scenarios, a set of comprehensive and targeted evaluation metrics is adopted. Accident Rate, This metric is calculated by dividing the number of collisions or similar incidents by the total number of simulation scenarios. It directly reflects the safety level of the autonomous driving system. As a core evaluation metric, it is closely related to the protection of life and property. Average Driving Speed, This refers to the average speed of the vehicle throughout the entire driving process. It is used to measure the system's driving efficiency under the condition of ensuring safety. Balancing safety and efficiency is a key factor in the real-world application of autonomous driving [24].

Interpretability Score, this score is determined by manually evaluating the clarity and comprehensibility of the state–action salience mapping visualizations. A scoring system ranging from 0 to 10 is used, where a higher score indicates stronger interpretability. Interpretability is crucial for enhancing user trust, facilitating regulatory oversight, and supporting system debugging.

3.2 Safety Comparison

The method proposed in this study, which integrates Bayesian uncertainty modeling and an explainable reinforcement learning mechanism (hereafter referred to as the proposed method), exhibits significantly lower accident rates than all baseline algorithms across all predefined scenarios [25]. Specifically, in the irregular pedestrian crossing scenario, the accident rate of the proposed method is 5.5%, whereas the rate reaches 28% for the traditional rule-based method, 18% for the plain SAC algorithm, and 22% for the DQN method. In the vehicle cut-in scenario and the mixed traffic flow scenario, the proposed method also demonstrates excellent performance, with accident rates reduced to 7% and 9%, respectively, representing clear improvements over the other algorithms. Across all scenarios, the proposed method achieves a 23.5% reduction in accident rate compared to the traditional rule-based method, a 10.5% reduction compared to the plain SAC algorithm, and a 13.5% reduction compared to the DQN method. These results clearly demonstrate that the proposed method, by introducing Bayesian uncertainty modeling, can more accurately assess risks in traffic environments and adopt safer decision strategies, thereby effectively reducing the occurrence of accidents [26].

Table 2: Average Driving Speeds of Different Algorithms

Traffic Scenario	Proposed Method	Traditional Rule-Based Method	Plain SAC Algorithm	DQN Method
Irregular Pedestrian Crossing	32 km/h	34 km/h	33 km/h	28 km/h
Vehicle Cut-in	33 km/h	35 km/h	34 km/h	30 km/h
Mixed Traffic Flow	35 km/h	38 km/h	36 km/h	30 km/h

The data in the table clearly indicate that the proposed method ensures high safety without a significant loss in driving efficiency. In various traffic scenarios, the average driving speed of the proposed method is close to that of the plain SAC algorithm, slightly lower than that of the traditional rule-based method, but significantly higher than that of the DQN method [27,28]. This confirms that the proposed method can maintain a relatively high level of driving efficiency while addressing uncertainty and ensuring safety, demonstrating strong practical application value.

The comparison of interpretability scores shows that the proposed method achieves a score of 8, which is significantly higher than the other baseline algorithms. The traditional rule-based method, due to its relatively simple and direct decision-making rules, receives a score of 4. The plain SAC algorithm and the DQN method, limited by their black-box model characteristics, perform poorly in interpretability, scoring 3 and 2, respectively. By employing the state–action salience mapping model, the proposed method is able to clearly present the decision basis of the autonomous driving system under different states. This allows users to intuitively understand how decisions are made, significantly enhancing the interpretability of the system. This improvement in interpretability is of great importance for increasing user trust, facilitating system debugging, and supporting algorithm optimization. From the perspective of user acceptance, high interpretability enables users to better understand how autonomous vehicles behave in various situations, reducing fear and uncertainty toward opaque decisions and thereby increasing their willingness to adopt autonomous driving technologies [29]. During the system debugging process, developers can use the salience maps to quickly locate the cause of abnormal decisions, enabling precise tuning of algorithm parameters and improving overall system performance. For regulatory authorities, a transparent decision logic makes it easier to formulate reasonable regulatory standards and policies, thereby promoting the orderly development of autonomous driving technologies [30,31]. Compared with the traditional rule-based method, the proposed method not only provides explanations for standard decisions, but also offers insights into the rationale behind decisions in complex scenarios, overcoming the limitations of single-scenario applicability in traditional approaches. In contrast to black-box models such as SAC and DQN, the proposed method transforms obscure and hard-to-interpret decision processes into visual and understandable forms [32]. This compensates for the lack of transparency in black-box models and provides a solid foundation for the widespread application of autonomous driving systems in complex real-world environments.

3.3 Discussion

Based on the experimental results, the proposed reinforcement learning framework that integrates Bayesian uncertainty modeling achieves clear and effective outcomes. The framework effectively handles uncertainty in traffic scenarios by identifying high-risk states through the confidence evaluation module and taking timely countermeasures [33]. This significantly enhances the safety of the autonomous driving system. In complex traffic environments, the proposed method shows a notable reduction in accident rates compared with traditional methods and other reinforcement learning algorithms, providing a more reliable safety guarantee for practical applications. At the same time, under the condition of ensuring safety, the method maintains a good balance in driving efficiency. Although the average driving speed in some scenarios is slightly lower than that of the traditional rule-based method, it is close to that of the plain reinforcement learning algorithms, indicating strong overall performance. In addition, the state–action salience mapping model provides a direct explanation of the decision-making process. The high interpretability score demonstrates its effectiveness, which contributes to improving user acceptance and trust, and facilitates system optimization and adjustment. However, the framework still has certain limitations. In terms of computational resources, Bayesian uncertainty modeling and repeated Monte Carlo sampling impose relatively high requirements on computing performance, which limits its application in low-end in-vehicle systems [34]. Moreover, in extremely complex combinations of traffic scenarios, the clarity of interpretation provided by the current state–action salience mapping model may be reduced. It is necessary to further optimize the model structure and algorithm to improve robustness and scalability. Future research can focus on optimizing the algorithmic process to reduce computational cost and on exploring more efficient uncertainty quantification methods and interpretability techniques [35,36]. This will help autonomous driving systems achieve a better balance among safety, interpretability and computational efficiency and promote their transition toward practical large-scale deployment.

4. Conclusion

This study explores a reinforcement learning framework that combines Bayesian-based uncertainty modeling with an interpretable decision mechanism, aiming to improve the safety and transparency of autonomous driving systems in complex and uncertain traffic environments. Through probabilistic analysis, the proposed approach estimates uncertainty in decision-making and identifies high-risk traffic states, allowing the system to take appropriate safety actions. In parallel, the designed state–action salience mapping enhances interpretability by visually illustrating the decision rationale in a structured and explainable manner. Experiments conducted in the CARLA simulation environment show that the proposed method reduces the frequency of accidents compared to both traditional rule-based systems and conventional reinforcement learning algorithms. While there is a marginal reduction in average driving speed relative to the rule-based baseline, the method maintains stable performance and ensures consistent safety benefits. In terms of interpretability, the visual clarity provided by the salience mapping contributes meaningfully to user understanding and supports debugging and system refinement efforts. Nevertheless, the method’s reliance on Bayesian inference and repeated sampling increases the computational burden, which may limit deployment on low-power hardware platforms. In addition, under highly entangled or edge-case traffic scenarios, the effectiveness of visual interpretability may decrease, indicating room for structural optimization. In summary, the proposed method offers a feasible route toward safer and more interpretable autonomous driving decisions. Future research may focus on improving computational efficiency and refining interpretability under extreme conditions to facilitate real-world implementation at scale.

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