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Reliability-Aware Lane Detection for Autonomous Driving in Complex Nighttime Environments

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Abstract: To address the challenges of unstable lane line segmentation, incomplete structural representation, and insufficient reliability in complex nighttime traffic environments due to low illumination, glare, road surface reflection, and local occlusion, a reliability modeling method for lane line detection in autonomous driving scenarios is proposed. This method is based on semantic segmentation, integrating lane region identification and prediction reliability representation into a unified framework. It enhances effective semantic representation in nighttime road scenes through feature encoding and context aggregation. Based on this, a lane segmentation branch and a reliability learning branch are constructed to generate pixel-level lane responses and corresponding confidence information, respectively. To improve the continuous representation of slender lane structures in complex backgrounds, structural consistency constraints are further introduced to mitigate the adverse effects of boundary ambiguity, local missing values, and spurious response interference. Simultaneously, a confidence modulation mechanism is designed to guide the optimization of the segmentation results, ensuring that the final output maintains lane region discrimination capability while more effectively suppressing uncertain responses in nighttime scenes. Experimental results compare and analyze typical semantic segmentation models, demonstrating that the proposed method achieves superior overall performance in complex nighttime traffic environments, exhibiting outstanding performance in lane region identification accuracy, structural integrity, and result stability. Related research provides a technical approach for nighttime autonomous driving lane line perception that balances semantic representation and reliable modeling.

Keywords: Nighttime road scene; lane line semantic segmentation; reliability learning; confidence modulation

1. Introduction

As autonomous driving technology continues to evolve towards higher levels of perception and decision-making capabilities, lane detection, as a fundamental component of road scene understanding, directly impacts the stability of vehicle lateral control, path planning, and driving safety[1]. In real-world road environments, lane lines not only serve to indicate road boundaries and express traffic rules but also provide autonomous driving systems with continuous, structured, and highly constraining spatial prior information[2,3]. Especially in urban arterial roads, expressways, tunnel entrances and exits, and areas where multiple road types intersect, lane line information is often crucial for ensuring vehicles maintain correct driving trajectories, identifying passable areas, and constraining dangerous maneuvers. Therefore, conducting reliability modeling research for lane detection in complex scenarios not only has significant theoretical value but also clear engineering application implications[4].

Compared to daytime environments, visual degradation is more pronounced in complex nighttime traffic environments. Scene perception faces multiple adverse factors such as low illumination, localized overexposure, headlight glare, road surface reflections, shadow occlusion, and rain/fog interference, making issues like blurred lane line boundaries, weakened texture information, and unstable category features more prominent. Under these conditions, traditional detection approaches based on clear edges, color contrast, or local texture consistency are prone to missed detections, false detections, and continuity interruptions, thus affecting the downstream decision-making system's stable understanding of the road structure. More importantly, the nighttime traffic environment is characterized by high dynamism, numerous target interferences, and rapid risk accumulation[5]. If lane detection results lack reliability constraints, perception errors may be continuously amplified during trajectory control. Table 1 summarizes the main challenges of lane detection in complex nighttime traffic environments and their potential impact on autonomous driving systems. This further illustrates that reliability modeling is not merely an additional modification to the detection results, but a crucial component in improving system safety and robustness.

Table 1: Major Challenges in Lane Detection Under Complex Nighttime Traffic Environments and Their Impacts

Typical Factor	Scene Manifestation	Impact on Lane Detection	Potential Impact on Autonomous Driving Systems
Low illumination	Overall reduction in road texture and	Weakened edge responses and difficulty	Unstable lateral localization and increased

Typical Factor	Scene Manifestation	Impact on Lane Detection	Potential Impact on Autonomous Driving Systems
	lane marking brightness	in feature extraction	path tracking errors
Headlight glare	Strong light interference caused by oncoming headlights and streetlights	Local overexposure and loss of lane marking details	Biased drivable area judgment and short term control anomalies
Road surface reflection	Specular reflection caused by wet roads or highly reflective materials	Enhanced pseudo lane lines and suppression of true markings	Higher false detection rate and distorted decision constraints
Occlusion interference	Lane markings occluded by vehicles, pedestrians, or roadside facilities	Interrupted lane continuity and missing structural information	Discontinuous trajectory prediction and disturbed lane change judgment
Scene complexity	Coexistence of curves, intersections, ramps, and construction areas	Large geometric variation and complex topological relationships	Increased difficulty in road understanding and accelerated risk accumulation

From a research and development perspective, the core issue of lane detection at night is no longer limited to whether lane lines can be detected at all, but rather whether the detection results possess interpretable, quantifiable, and transferable reliability. Autonomous driving systems operate on real open roads, not static environments under ideal imaging conditions. Therefore, relying solely on deterministic results from a single visual output is insufficient to meet the requirements of perception stability and risk controllability in high-safety scenarios. The introduction of reliability modeling enables lane detection to move beyond simple result generation to a unified modeling of result quality assessment, risk identification, and state constraints, thereby establishing a more robust information transmission mechanism between the perception module and the decision-making and control module. Based on this approach, researching the reliability of lane detection in complex nighttime traffic environments helps to drive the evolution of autonomous driving perception systems from a high-precision orientation to a high-reliability orientation.

From an application value perspective, research on reliability modeling for autonomous driving lane detection in complex nighttime traffic environments is of great significance for improving the continuous operation capability of intelligent vehicles in real-world scenarios. On the one hand, this direction can enhance the system's robust acquisition of road structure information under visual degradation conditions, providing vehicles with more stable lateral control basis and reducing operational risks caused by instantaneous perception fluctuations. On the other hand, reliability modeling can provide the system with more granular confidence expressions and risk warning mechanisms, enabling the autonomous driving platform to have stronger adaptive adjustment capabilities when facing uncertain scenarios, thereby improving the overall safety redundancy level. Furthermore, this research not only serves the nighttime autonomous driving scenario itself, but also provides a reference theoretical foundation and methodological support for general visual perception research under low visibility weather, complex road structures, and multi-source interference conditions.

2. Related work

In recent years, lane detection research has mainly focused on three directions: enhancing feature representation capabilities, structural constraint modeling, and improving adaptability to complex scenes. Early methods relied heavily on edge, color, and geometric priors for explicit lane line extraction. While these methods performed well on regular roads and under stable lighting conditions, they often lacked robustness in scenarios with texture degradation, enhanced background interference, and significant lane marking wear. With the development of deep learning technology, lane detection methods based on convolutional neural networks have gradually become mainstream. Their core idea is to achieve joint modeling of fine-grained boundary information and high-level semantic information through multi-layer feature extraction, thereby improving the ability to recognize curved lanes, occluded lanes, and slender targets in complex backgrounds[6]. Building on this, some studies have further introduced attention mechanisms, multi-scale feature fusion, and contextual aggregation strategies to enhance the model's ability to collaboratively perceive local details and global road structure, driving the transformation of lane detection from being driven by shallow visual cues to being driven by deep semantic understanding.

At the task modeling level, related research has gradually expanded from traditional detection or regression paradigms to pixel-level modeling methods based on semantic segmentation. Compared to methods that only output lane parameters or key point locations, semantic segmentation methods can more meticulously depict the spatial distribution, boundary morphology, and continuous structure of lane line regions, thus exhibiting stronger expressive advantages in complex road topologies and multi-interference contexts[7]. Meanwhile, addressing performance degradation in nighttime scenes, low-visibility environments, and dynamic traffic interference conditions, existing research has begun to focus on the impact of uneven illumination, reflection artifacts, target occlusion, and visual noise on segmentation results, and has attempted to improve model stability from the perspectives of feature enhancement, uncertainty estimation, and structural consistency constraints. However, current work as a whole still focuses more on detection accuracy itself. Further in-depth research is needed on the reliability characterization of lane line segmentation results in complex nighttime traffic environments, their risk perception capabilities, and their coupling relationship with the safety requirements of autonomous driving. This provides a clear entry point for subsequent reliability modeling research.

3. Datasets

3.1 Dataset

This paper selects BDD100K as the research dataset. This dataset is a publicly available open-source data resource for autonomous driving scenarios, covering urban roads, highways, and various traffic scenarios. It includes images from different time periods, such as daytime, nighttime, and dawn/dusk, effectively reflecting the visual characteristics of real road environments, including lighting changes, traffic flow interference, and scene complexity. More importantly, BDD100K provides lane markings and drivable area annotations closely related to road structure understanding. The lane marking task has a pixel-level annotation foundation, which can be used for lane line semantic perception and structure extraction research. Therefore, its data attributes are highly consistent with the theme of reliable modeling of lane line detection in complex nighttime traffic environments.

From the perspective of task adaptability, BDD100K has advantages such as open access, diverse scenarios, a complete annotation system, and widespread research use, providing reliable data support for nighttime lane line semantic segmentation research. Its data includes typical challenging factors such as nighttime road images, vehicle headlight interference, road surface reflection, occlusion, and complex road topology, which is beneficial for characterizing the visual degradation features and structural uncertainties of lane line regions in complex nighttime traffic environments. Meanwhile, BDD100K has formed a relatively mature ecosystem of open benchmarks and tools, which facilitates model building, result comparison and reliability analysis under unified data conditions. Therefore, it is reasonable and feasible to use it as the data basis for this paper. An example of its dataset is shown in Figure 1.

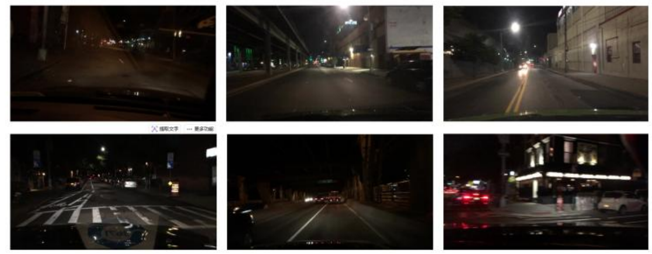

Figure 1. Dataset Example

4. Method

To improve the trustworthiness of lane perception in complex nighttime traffic scenes, the proposed method formulates lane detection as a reliability-aware semantic segmentation problem in which pixel-level classification and confidence modeling are optimized in a unified framework. This paper presents the overall model architecture, as shown in Figure 2.

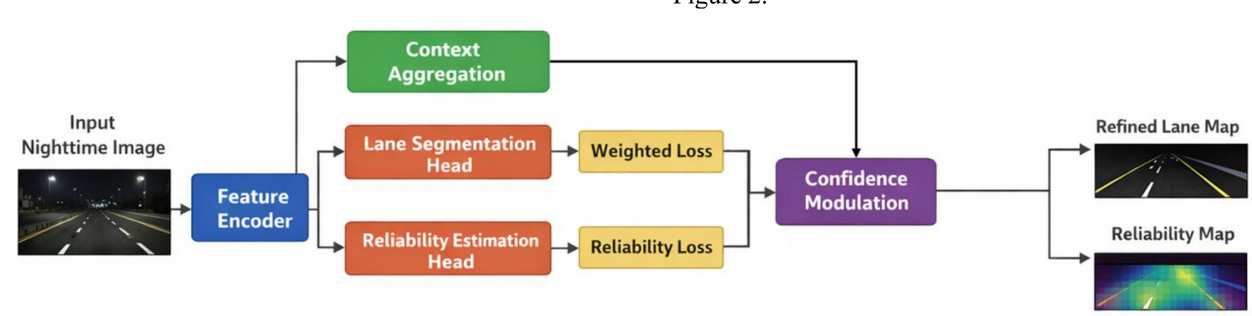

Figure 2. Overall model architecture

Given an input nighttime road image $\boldsymbol{I} \in \mathbb{R}^{H\times W\times 3}$, a feature encoder first extracts hierarchical representations that preserve both local lane boundaries and global road topology, while a context aggregation module enhances the response to weak and discontinuous lane markings under glare, reflection, and occlusion. On this basis, the network predicts a dense lane probability map $\boldsymbol{P} \in [0,1]^{H\times W}$ together with a reliability field $\boldsymbol{R} \in [0,1]^{H\times W}$, where $\boldsymbol{P}$ describes the semantic likelihood of lane pixels and $\boldsymbol{R}$ characterizes the confidence of the corresponding prediction under degraded visual conditions. Such a design is meaningful because nighttime scenes often contain ambiguous structures that may appear lane-like in local regions but become inconsistent when viewed from a broader spatial context, so the model must learn not only where the lane exists but also how credible the decision is. Formally, the overall mapping process is defined as:

$$(\boldsymbol{P},\boldsymbol{R}) = \Phi(\boldsymbol{I};\Theta)$$

where $\Phi(\cdot)$ denotes the reliability-aware segmentation network parameterized by Θ. Since lane markings in night scenes usually occupy only a small portion of the image and exhibit thin elongated geometry, a weighted binary cross-entropy term is introduced to strengthen supervision on difficult foreground pixels, which can be written as:

$$\mathcal{L}_{seg} = -\frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W}\left[\alpha y_{ij} log p_{ij} + (1-y_{ij}) log(1-p_{ij})\right]$$

where $y_{ij} \in \{0,1\}$ is the ground-truth label at pixel (i,j), p_{ij} is the predicted lane probability, and α controls the contribution of sparse lane regions. Beyond pixel classification, structural continuity is essential because fragmented responses can easily propagate instability to downstream path planning, thus a spatial smoothness regularization term is imposed on the predicted lane field as:

$$\mathcal{C}_{str} = \frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W}\left(|p_{i+1,j} - p_{ij}| + |p_{i,j+1} - p_{ij}|\right)$$

thereby encouraging adjacent pixels along the road surface to maintain coherent segmentation responses. Meanwhile, reliability learning is guided by the intuition that high-confidence predictions should correspond to low segmentation uncertainty, so an uncertainty proxy is constructed from the probability entropy and then converted into a supervision target for confidence estimation through:

$$u_{ij} = - p_{ij} log p_{ij} - (1 - p_{ij}) log (1 - p_{ij})$$

which makes uncertain pixels naturally receive larger entropy values in ambiguous nighttime regions.

A dedicated reliability branch is further introduced to suppress unstable responses caused by headlight flare, reflective pavement, and partial occlusion, and its objective is to make the estimated confidence map consistent with the inverse uncertainty distribution produced by the segmentation branch. Rather than treating confidence as an auxiliary score detached from perception, the method embeds it into the optimization process so that unreliable pixels can be explicitly recognized during training. For this purpose, the reliability supervision loss is expressed as:

$$\mathcal{C}_{rel} = \frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W}\left(r_{ij} - exp(-u_{ij})\right)^{2}$$

where r_{ij} is the predicted reliability value and $exp(-u_{ij})$ serves as a soft target that assigns lower confidence to high-entropy locations. This formulation is important because nighttime lane regions often suffer from nonuniform illumination, and a purely deterministic segmentation output cannot fully reveal whether the extracted structure is stable enough to support autonomous driving decisions.

To further couple semantic prediction with reliability perception, the final lane response is refined by confidence-aware modulation so that pixels with high lane probability but low reliability are adaptively suppressed before subsequent interpretation. In this way, the model avoids overtrusting visually confusing regions that resemble lane markings only in appearance but lack stable contextual support. The refined response is defined as:

$$\widehat{p}_{ij} = p_{ij} \cdot r_{ij}$$

which enables the final output $\widehat{p}_{ij}$ to reflect both semantic evidence and credibility strength at each pixel. Such a mechanism is especially beneficial in nighttime road scenes because strong reflections or overexposed light sources may locally produce high activation values, whereas the estimated reliability can counterbalance these misleading cues and preserve the robustness of the lane structure representation.

Finally, the complete optimization objective combines segmentation accuracy, structural consistency, and reliability alignment in a unified learning framework, allowing the network to jointly model lane existence and prediction trustworthiness instead of optimizing the two aspects independently. By integrating these complementary constraints, the method aims to produce lane maps that are not only spatially precise but also more compatible with safety-oriented autonomous driving perception. The total loss is formulated as:

$$\mathcal{C} = \lambda_1\mathcal{C}_{seg} + \lambda_2\mathcal{C}_{str} + \lambda_3\mathcal{C}_{rel}$$

where λ_1, λ_2, and λ_3 balance the contributions of semantic discrimination, topology preservation, and confidence calibration, respectively. Through this design, the proposed reliability modeling strategy provides a principled way to address the intrinsic uncertainty of lane segmentation in complex nighttime traffic environments and establishes a more dependable perception foundation for subsequent autonomous driving modules.

5. Experimental Results and Analysis

This paper first presents the experimental results compared with other models, as shown in Table 2.

Table 2: Experimental results compared with other models

Method	mPrecision	IoU	F1	mAcc
Unet[8]	86.21	78.46	82.08	88.14
nn-Unet[9]	87.35	79.92	83.31	89.06
Segforemer[10]	88.04	80.57	84.02	89.68
PSPNet[11]	86.97	79.11	82.84	88.73
FCN[12]	84.76	76.35	80.34	86.91
Deeplabv3+[13]	88.63	81.24	84.76	90.12
SegMan[14]	89.18	82.03	85.41	90.57
Ours	91.42	84.68	87.73	92.36

Overall, the proposed algorithm demonstrates stronger lane line recognition capabilities and more stable pixel-level segmentation quality in complex nighttime traffic environments. This method more effectively characterizes the continuous boundaries of slender lane structures while maintaining high region discrimination accuracy under complex background interference, indicating that the constructed reliability modeling mechanism has good adaptability to weak textures, low illumination, and local distortion scenarios. Since nighttime road images are often accompanied by uneven illumination, road surface reflections, and occlusion interference, traditional segmentation networks are prone to generating erroneous responses in local areas. However, the proposed method establishes a closer connection between semantic representation and reliable perception, thus achieving more robust lane region representation.

The algorithm not only improves the recognition accuracy of lane line foreground regions but also enhances the overall segmentation results in terms of structural integrity and spatial consistency. This shows that the method can more accurately distinguish between real lane lines and interfering textures in complex nighttime road scenes, thereby reducing the risk of misjudgment caused by false edges and blurred regions. At the same time, the model exhibits better recovery capabilities for problems such as local lane line loss, blurred boundaries, and impaired continuity, making the output results more consistent with the actual needs of autonomous driving systems for road structure stability perception. Overall, the algorithm proposed in this paper has strong robustness and practical value, providing more reliable methodological support for lane detection tasks in nighttime autonomous driving. Furthermore, the ablation experiment results are presented in this paper, as shown in Table 3.

Table 3: Ablation test results

Ablation Setting	mPrecision	IoU	F1	mAcc
w/o Structural Consistency Loss	89.47	82.41	85.73	90.88
w/o Reliability Learning Branch	89.12	81.96	85.28	90.43
w/o Confidence Modulation	90.03	83.14	86.19	91.27
Full Model	91.42	84.68	87.73	92.36

The ablation results show that the proposed complete model achieves superior overall performance in complex nighttime traffic environments, indicating that each key component of the method contributes to the quality of lane detection. Structural consistency constraints enhance the continuous representation of lane regions, enabling the model to maintain good spatial integrity even under complex road boundaries and local missing conditions. The reliability learning branch improves the ability to identify uncertain regions, helping to reduce erroneous responses caused by glare, reflection, and occlusion. The confidence modulation mechanism further strengthens the credible representation of the segmentation results, making the final output more consistent with the real road structure. Overall, the proposed algorithm demonstrates strong advantages in semantic segmentation accuracy, region discrimination stability, and result reliability, indicating that the constructed reliability modeling framework can effectively improve the practical application value of nighttime lane detection tasks. This paper also provides qualitative detection results, as shown in Figure 3.

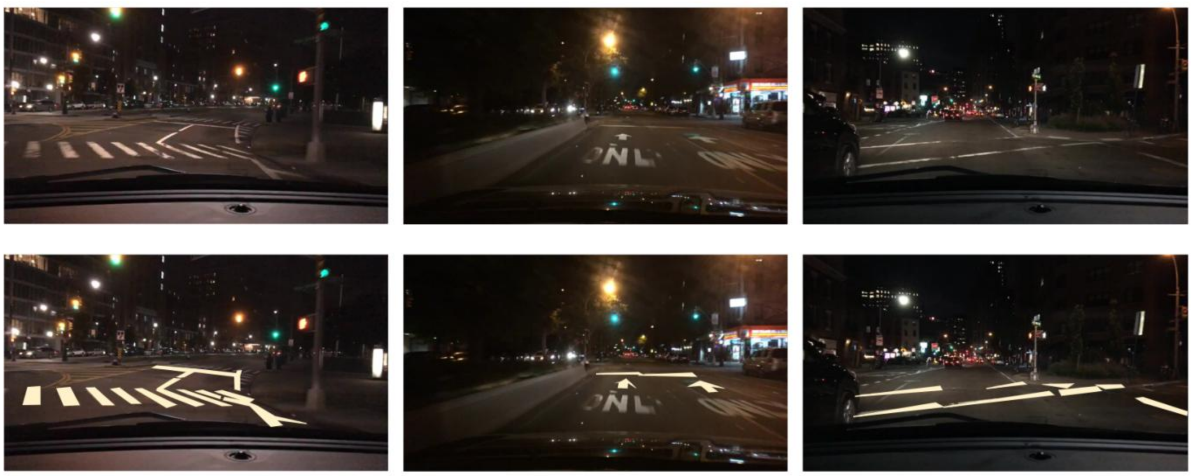

Figure 3. Qualitative test results

The proposed algorithm can accurately identify key lane line regions in complex nighttime traffic scenarios, and the overall segmentation results maintain a high degree of consistency with the real road structure. Even under conditions of low lighting, significant road surface reflection, and complex backgrounds, the model can still preserve the main outline and extension direction of lane lines well, indicating its strong perception capability for weakly textured targets at night. For curved areas, intersecting guide lines, and road structures with multiple lines appearing simultaneously, the proposed method also demonstrates good region differentiation, making the output results clearer and more readable.

The proposed algorithm not only effectively extracts the main lane boundaries but also maintains the continuity and structural integrity of the segmented regions to a certain extent, thereby reducing the impact of local missing parts and incorrect connections in complex scenes. This indicates that the constructed reliability modeling mechanism has a good suppression effect on uncertain interference in nighttime environments, enabling the model to output relatively stable lane representation results even when facing glare, occlusion, and blurred textures. Overall, the proposed algorithm has good scene adaptability and practical application potential, and can provide more reliable road perception support for nighttime autonomous driving systems.

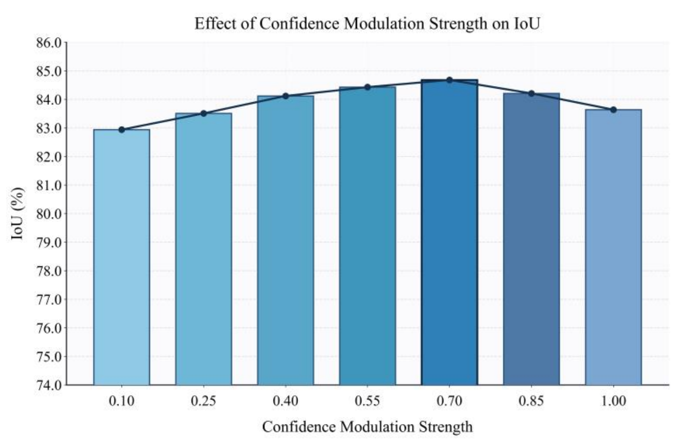

Figure 4. The impact of confidence modulation strength parameter sensitivity on IoU

As shown in Figure 4, the proposed algorithm maintains good lane segmentation capabilities despite variations in the confidence modulation intensity parameter, demonstrating the strong stability of the constructed reliability modeling framework. A reasonable confidence modulation mechanism effectively coordinates the relationship between semantic prediction and reliable representation, enabling the model to more accurately preserve the real lane structure in complex nighttime traffic scenarios and reduce erroneous responses caused by illumination disturbances, road surface reflections, and local blurring. This indicates that the proposed method has good adaptability when dealing with uncertain regions, providing a more robust pixel-level representation of lane line regions.

Furthermore, the setting of the confidence modulation intensity parameter plays a crucial role in the final lane line output quality, and the proposed algorithm exhibits good overall performance with the support of this mechanism. This result shows that the proposed method not only focuses on the semantic recognition of lane line regions but also emphasizes the reliability of the prediction results, thus making the output results more in line with the actual needs of nighttime autonomous driving scenarios in terms of boundary integrity, regional consistency, and structural clarity. Overall, the proposed algorithm effectively leverages the role of the confidence modulation module, providing more reliable methodological support for lane line detection in complex nighttime traffic environments.

6. Conclusion

This paper addresses the reliability issues in lane detection for autonomous driving systems operating in complex nighttime traffic environments. Factors such as low illumination, headlight glare, road surface reflection, occlusion interference, and complex road topology can easily lead to unstable lane line semantic representation, impaired boundary continuity, and insufficient prediction reliability. To address these problems, a lane line semantic segmentation method oriented towards reliability modeling is constructed. This research extends the lane detection task from simply focusing on pixel classification accuracy to jointly characterizing the reliability of prediction results and structural stability. This enables the model to not only identify key lane regions in the road but also to more effectively constrain and represent uncertain information in complex nighttime scenes. This approach shifts nighttime lane detection from a traditional result-oriented approach to a safety- and reliability-oriented one, which is significant for improving the perception robustness of autonomous driving systems in real-world road environments.

From a methodological perspective, the proposed model integrates lane semantic segmentation, structural consistency constraints, reliability learning, and confidence modulation mechanisms within a unified framework, creating a closer connection between pixel-level recognition of lane line regions and reliable prediction modeling. By introducing structural continuity constraints during segmentation, the model's ability to recover slender targets, blurred boundaries, and locally missing regions can be enhanced, thereby improving the spatial integrity representation of lane lines in complex backgrounds at night. Simultaneously, the reliability learning branch and confidence modulation mechanism further strengthen the model's ability to identify and suppress uncertain regions, ensuring that the final output maintains high clarity and interpretability even when faced with complex interferences such as glare, reflection, and occlusion. Overall, the reliability modeling strategy constructed in this paper provides a technical path that better meets the safety requirements of autonomous driving in nighttime traffic scenarios, and also offers new insights into the research of reliable perception problems in semantic segmentation tasks.

From an application perspective, this research not only has practical significance for the task of lane line detection in nighttime autonomous driving, but also provides valuable support for the engineering deployment of intelligent driving perception systems. In actual road operation, lane line detection results often directly participate in key aspects such as lateral control, path planning, drivable area judgment, and risk warning; therefore, their stability and reliability have a fundamental impact on the overall safety of the system. This paper's method, by strengthening the joint modeling of lane structure and prediction reliability in complex nighttime scenes, helps improve the continuous perception and decision support capabilities of autonomous vehicles in real-world open environments. Furthermore, this research has significant reference value for nighttime assisted driving, intelligent cruise control, unmanned delivery vehicles, road monitoring systems, and machine vision applications in low-visibility traffic scenarios, providing a theoretical foundation and methodological support for visual perception research under complex lighting conditions in related fields.

Future research can be further deepened in several directions. First, combining temporal information with multi-frame scene association modeling can further enhance the model's dynamic perception capability of continuous road structures, extending lane line reliability expression from single-frame static judgment to spatiotemporal consistency analysis. Second, the synergistic fusion with depth information, LiDAR information, or infrared imaging information can be explored to improve the model's perception robustness under extreme low light, inclement weather, and complex occlusion conditions, thereby further expanding the applicability of the method in real-world autonomous driving systems. In addition, research can be conducted on lightweight deployment, online reliability assessment, and scene adaptive learning to meet the comprehensive requirements of in-vehicle platforms for real-time performance, stability, and transferability. As autonomous driving technology continues to develop towards higher safety, higher reliability, and stronger generalization, research on lane detection reliability modeling for complex nighttime traffic environments will have more prominent theoretical significance and application prospects, and is expected to play a more important supporting role in intelligent transportation systems and future smart mobility systems.

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