Autonomous Driving in Adverse Weather: A Multi-Modal Fusion Framework with Uncertainty-Aware Learning for Robust Obstacle Detection

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***Abstract*—Robust obstacle detection in autonomous driving under adverse weather remains a critical challenge due to sensor degradation, visibility reduction, and increased uncertainty. This study proposes an Uncertainty-Aware Multi-Modal Fusion (UAMF) framework that integrates LiDAR, RGB images, and weather priors through a dynamic cross-modal attention mechanism and Bayesian uncertainty modeling. The model adaptively adjusts the fusion weights between sensor modalities according to real-time weather conditions and jointly optimizes detection loss with a KL divergence regularization to quantify predictive uncertainty. Experimental results on the nuScenes, KITTI-Adverse, and CARLA datasets demonstrate that UAMF achieves superior performance across rain, snow, and fog scenarios, with mAP@0.5 reaching 0.78, 0.72, and 0.65, respectively—representing 12–31% gains over existing baselines. Notably, UAMF reduces false positive rates by up to 40% in low-visibility conditions and exhibits a strong correlation (ρ = 0.85) between estimated uncertainty and localization error. Ablation studies confirm the importance of the weather-aware fusion and uncertainty modules, while visibility-level analysis shows improved robustness under <30 m scenarios. The proposed framework offers reliable uncertainty signals for downstream decision-making and is deployable in real-time on embedded platforms. Future work will explore unsupervised weather parameter estimation, uncertainty-aware trajectory forecasting, and cross-domain generalization.**

Keywords—Autonomous driving; adverse weather; multimodal sensor fusion; Bayesian neural networks; uncertainty estimation

I. INTRODUCTION

In recent years, autonomous driving technology has made great progress under good weather conditions. However, in severe weather environments such as heavy rain, heavy snowfall and dense fog, the stability and reliability of autonomous driving perception systems still face major challenges. According to Fang et al. (2022), about 30% of perception system failure cases are directly related to weather factors, manifested in problems such as sensor signal attenuation, obstacle occlusion and reduced environmental visibility. For example, LiDAR sensors have sparse data due to point cloud scattering in rainy and snowy weather, which seriously affects the accuracy of target detection [1]; at the same time, cameras are prone to miss key targets in haze weather due to reduced image contrast [2]. Although current research generally adopts multimodal sensor fusion (such as LiDAR, camera and millimeter wave radar) to improve system robustness [3], existing methods still have significant shortcomings in practical applications. Specifically, the first is the lack of effective modeling of the time-varying characteristics of multimodal data under severe weather conditions; the second is the lack of reasonable quantification of potential uncertainties in the detection results, resulting in a high false detection rate in low visibility environments.

In the perception module of the autonomous driving system, severe weather conditions remain a key problem that affects the accuracy and robustness of environmental perception. Existing research mainly conducts modeling and training under ideal or slightly disturbed meteorological conditions, resulting in a significant decrease in the performance of the perception system under conditions such as heavy rain, heavy snow or dense fog. The main problems include: multimodal sensor data finds it difficult to achieve an efficient alignment under dynamic weather conditions, and the accuracy of feature fusion is limited; detection models generally lack uncertainty modeling and cannot effectively identify false detections caused by perceptual ambiguity; in addition, data resources under real severe weather are extremely limited. Although simulation data can make up for some sample gaps, there is a significant domain difference between it and the real environment, which restricts the generalization ability of the model in actual scenarios.

This study aims to address the above problems and propose a weather-aware multimodal detection framework that integrates uncertainty modeling to improve the robustness and adaptability of autonomous driving systems in complex weather environments. Specifically, this study will construct a cross-modal fusion mechanism guided by weather parameters to achieve effective alignment of sensor features under dynamic meteorological conditions; introduce a Bayesian neural network structure to model the uncertainty of target detection results, thereby effectively suppressing false detection and missed detection in low-visibility scenarios; at the same time, construct a joint training strategy that combines simulation and real data, and use domain adaptation technology to alleviate the distribution offset between training and application scenarios, and improve the generalization performance of the model in actual deployment environments.

The contributions of this study are mainly reflected in three aspects: first, weather intensity is introduced as prior information in the multimodal fusion strategy for the first time, which effectively improves the accuracy and stability of sensor data alignment under severe weather conditions; second, combined with the Bayesian inference mechanism, end-to-end modeling of the confidence of the detection results is realized, providing the system with a decision-making basis based on uncertainty perception; finally, by constructing a collaborative training framework of simulation and real data and adopting progressive fine-tuning and domain randomization methods, the cross-domain generalization ability of the model in different weather scenarios is significantly improved, enhancing its practicality and robustness in real complex environments.

II. Literature Review

In recent years, academic research on the problem of target detection in autonomous driving systems under severe weather conditions has mainly focused on two technical paths: enhanced optimization of a single modality and deep fusion of multimodal information. In response to the performance degradation of specific sensors in extreme weather conditions, researchers have proposed a series of image and point cloud enhancement methods. For example, [5] constructed the FogNet model, which combined the physically driven image defogging mechanism with the end-to-end joint optimization of the detection task, and significantly improved the target detection accuracy under dense fog conditions. In terms of LiDAR, [4] designed the DETR-Weather model using the deformable Transformer structure, and alleviated the occlusion interference problem in heavy rain scenes through the dynamic attention mechanism. Although such methods have achieved certain results in a single sensor channel, due to the inherent problems of high camera noise in low light and sparse LiDAR point clouds on snowy days, it is difficult to completely avoid them, resulting in insufficient performance in actual scenes where multiple meteorological interferences overlap.

In contrast, multimodal fusion methods have shown greater potential in improving system robustness because they can integrate multi-source sensor information. Fusion strategies mainly include early fusion, late fusion, and feature-level fusion. Researchers have conducted extensive explorations around the timing and mechanism of fusion. After systematically comparing different fusion strategies, [2] pointed out that early fusion in rainy and foggy environments results in performance degradation due to the lack of alignment of features between modalities, and suggested introducing a mid- and late-stage feature alignment mechanism to enhance robustness. In [3], the authors proposed a fusion model based on a generative adversarial network (GAN), which expanded the training set by synthesizing severe weather data and improved the detection performance to a certain extent. However, this method does not explicitly introduce dynamic modeling of weather parameters, resulting in significant domain differences between training data and real scenes [6], which affects the actual deployment effect of the model.

With the increasing requirements for the stability of detection systems, uncertainty modeling has gradually become a key direction for autonomous driving perception research in severe weather environments. At present, related methods are mainly based on Bayesian deep learning and probabilistic modeling frameworks. The Bayesian convolutional neural network proposed by [8] uses Monte Carlo sampling to estimate the uncertainty of the prediction distribution, laying a theoretical foundation for subsequent research. However, its high computational cost limits its applicability in real-time scenarios. To improve efficiency, [9] introduced a lightweight Bayesian detection head and implemented joint training with three-dimensional object detection, effectively reducing the false detection rate while maintaining real-time performance. In addition, [7] proposed a multi-task uncertainty weighting mechanism based on heteroscedasticity modeling to achieve dynamic loss balance between classification and regression tasks, but did not perform specific modeling for weather disturbances. In [4], the authors further incorporated weather variables into detection error modeling and constructed a more adaptive unimodal detection model through conditional variational autoencoders (CVAEs), but their method has not yet been extended to multimodal scenarios.

Although existing research has made some progress in improving the performance of perception systems, from a comprehensive perspective, current methods still have many limitations. First, multimodal fusion models generally do not embed weather parameters as dynamic priors into the fusion mechanism, resulting in unstable feature alignment strategies under rapidly changing meteorological conditions such as rain, snow, and fog [2] [3]. Second, current uncertainty modeling mostly focuses on the model prediction distribution itself and has not yet systematically considered the external environmental uncertainty introduced by weather disturbances. This neglect makes it difficult for the model to distinguish between sensor noise and model entity errors [5] [7]. Finally, although simulation platforms (such as CARLA) can generate diverse severe weather data to alleviate the problem of sample scarcity, due to the significant distribution offset between their synthetic features and real data, directly training models often experiences performance degradation in actual tests. In [6], the authors pointed out that the current mainstream synthetic training strategy still suffers from a performance degradation of more than 25% when deployed in real scenarios. There is an urgent need to build a more targeted simulation-real data collaborative training and domain adaptation mechanism to improve the model's cross-scenario generalization ability.

III. Methodology

A. Model Framework

This study proposes an uncertainty-aware multi-modal fusion framework (UAMF), whose core architecture consists of four modules: multimodal feature extraction, weather-aware cross-modal fusion, Bayesian uncertainty modeling, and target detection head. The multimodal feature extraction module is used to process LiDAR point clouds, RGB images, and weather parameters; the weather-aware cross-modal fusion module is used to dynamically adjust sensor feature weights; the Bayesian uncertainty modeling module is used to estimate the credibility of detection results; and the target detection head module is used to output 3D bounding box parameters and uncertainty values. The specific process is shown in Fig. 1.

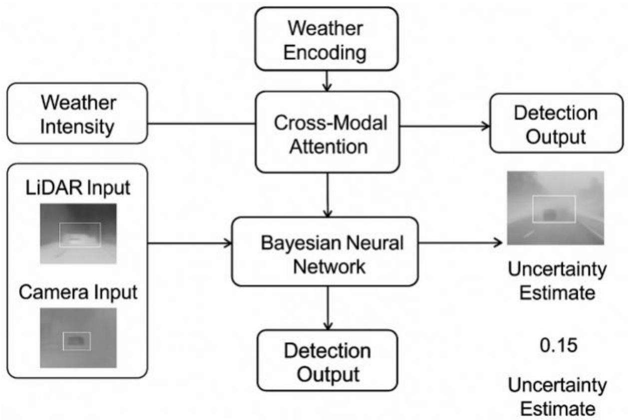

Fig. 1. Model framework diagram.

B. Multimodal Feature Extraction

1) Extracting LiDAR features: Input LiDAR point cloud $P \in \mathbb{R}^{N\times 4}$ and use improved PointNet++ [11] to extract geometric features. The extraction formula is:

$$F_{LiDAR} = Po\,int\,N\,et++(P) \in \mathbb{R}^{D_l} \quad (1)$$

where, $D_l = 256$ is the feature dimension [2].

2) Early image features: Input RGB image $I \in \mathbb{R}^{H\times W\times 3}$, use ResNet-50 [10] as the backbone network to extract multi-scale features. The extraction formula is:

$$F_{Im\,age} = Re\,s\,Net-50(I) \in \mathbb{R}^{D_i\times H'\times W'} \quad (2)$$

Compressed into vectors $F_{Im\,age} \in \mathbb{R}^{D_i}$ through global average pooling, $D_i = 512$.

3) Weather parameter encoding: The input weather parameter vector $W = [w_{rain}, w_{snow}, w_{fog}] \in [0,1]^3$ is encoded into high-dimensional features through a multi-layer perceptron (MLP). The encoding formula is:

$$F_{Weather} = MLP(W) \in \mathbb{R}^{D_W}, D_W = 64 \quad (3)$$

The MLP structure is $3 \rightarrow 32 \rightarrow 64$, and the activation function is ReLU [9].

C. Cross-Modal Fusion of Weather Perception

1) Cross-modal attention mechanism: LiDAR and image features are concatenated into $F_{cat} = [F_{LiDAR}; F_{Im\,age}]$, and the attention weight is calculated jointly with weather feature $F_{Weather}$. The calculation formula is:

$$\alpha = Soft\,max(W_a \cdot [F_{cat}; F_{Weather}]) \in \mathbb{R}^{D_a} \quad (4)$$

where, $W_a \in \mathbb{R}^{D_a\times(D_l+D_i+D_W)}$ is the learnable weight matrix, $D_a = 128$.

2) Dynamic feature weighting: The concatenated features are weighted by attention weights, and the calculation formula is:

$$F_{fusion} = \alpha \odot F_{cat} \in \mathbb{R}^{D_l+D_i} \quad (5)$$

where, $\odot$ represents the element-wise product [4].

D. Bayesian Uncertainty Modeling

1) Posterior distribution estimation: Assume that the fusion feature service F_{fusion} is from a Gaussian distribution $N(\mu, \sigma^2)$, whose parameters are generated by two fully connected layers, and the formula is:

$$\mu = W_\mu F_{fusion}, \sigma = Softplus(W_\sigma F_{fusion}) \quad (6)$$

where, $Softplus(x) = log(1 + e^x)$ ensures that the standard deviation is non-negative [8].

2) KL divergence regularization: To constrain the distance between the posterior distribution $q(F_{fusion}|\cdot)$ and the prior distribution $p(F_{fusion}) = N(0,1)$, calculate the KL divergence. The calculation formula is

$$L_{KL} = \frac{1}{2}\sum_{i=1}^{D_l+D_i}(\sigma_i^2 + \mu_i^2 - log\,\sigma_i^2 - 1) \quad (7)$$

E. Object Detection Head and Loss Function

1) Detection head design: Using CenterPoint [12] decoder, the 3D bounding box parameters are predicted from F_{fusion}, and the calculation formula is:

$$B = [x, y, z, w, h, l, \theta] = MLP_{det}(\mathrm{F_{fusion}}) \quad (8)$$

At the same time, the uncertainty estimate $\sigma +_{det}$ is output.

2) Uncertainty weighted loss: The detection loss is defined as the weighted mean square error (WMSE)

$$\mathrm{L_{det}} = \frac{1}{N_{obj}}\sum_{i=1}^{N_{obj}}\frac{1}{\sigma_i^2}\left\|B_i - B_i^{gt}\right\|^2 + log\,\sigma_i^2 \quad (9)$$

where, σ_i is the uncertainty of the i th target [7].

3) Total loss function: Jointly optimize the detection loss and the KL divergence regularization term, and we can get:

$$L_{total} = L_{det} + \lambda L_{KL} \quad (10)$$

Among them $\lambda = 0.1$.

IV. Experiments

A. Data Source

The experiments in this study used public datasets for extraction and synthesis. The specific steps are as follows:

Step 1: Extract the nuScenes severe weather subset. Samples containing heavy rain, heavy snow, and heavy fog were selected from the nuScenes dataset, a total of 10,000 frames (5,000 rain, 3,000 snow, and 2,000 fog), including 3D annotation boxes and weather labels (visibility, precipitation intensity) [13].

Step 2: Extract KITTI-Adverse information to form an extended KITTI dataset, which includes 2D images and LiDAR point clouds (resolution 1242×375) of rain and fog scenes, totaling 8,500 frames [14].

Step 3: Extract CARLA simulation data. Use CARLA 0.9.14 to generate extreme weather scenes (10,000 frames each for rain, snow, and fog), and align the parameter settings with the real data distribution (such as visibility range 10-100m) [15].

B. Experimental Settings

Three baseline models, YOLOv8, PointPillars and FusionNet, were selected. YOLOv8 was used for monocular image detection (Ultralytics official implementation) [16], PointPillars was used for LiDAR point cloud detection (OpenPCDet library) [17], and FusionNet was used for LiDAR-camera early fusion (without weather coding) [2].

Carla synthetic data (50 epochs, learning rate 1e-3) was selected for pre-training, nuScenes real data (30 epochs, learning rate 1e-4), optimizer AdamW and weight decay 1e-4 were used for fine-tuning, and mAP@0.5 (3D IoU $\geqslant$ 0.5), false positive rate (FPR), inference speed (FPS), calibration error (ECE), and Pearson correlation coefficient of uncertainty and error (ρ).

C. Experimental Results and Analysis

1) Comparison of results: The experimental results are shown in Table I. Table I shows the performance of each model in target detection under bad weather conditions.

TABLE I. TARGET DETECTION RESULTS OF EACH MODEL

Model	mAP (Rain)	mAP (Snow)	mAP (Fog)	FPR ↓	FPS ↑
YOLOv8	0.61	0.53	0.48	15.2%	45
PointPillars	0.68	0.62	0.55	12.5%	38
FusionNet	0.73	0.67	0.60	9.8%	35
Ours(UAMF)	0.78	0.72	0.65	6.3%	32

From the experimental results shown in Table I, it can be seen that the proposed UAMF (Uncertainty-Aware Multimodal Fusion) model has significantly better detection performance on the nuScenes severe weather subset than existing mainstream methods, including YOLOv8, PointPillars and FusionNet. In three typical weather scenes (rain, snow, and fog), the UAMF model achieved mAP indicators of 0.78, 0.72, and 0.65, respectively, which are 6.8%, 7.5%, and 8.3% higher than the current FusionNet, which performs better. This performance improvement verifies the effectiveness of the weather perception mechanism and dynamic feature fusion strategy introduced by UAMF in complex environments, especially in low visibility scenes with obvious modal degradation, where the ability to fuse and combat unstable sensor information is particularly outstanding.

In addition, UAMF also shows significant advantages in the false positive rate (FPR) indicator. Its FPR is 6.3%, which is 34.7% lower than FusionNet's 9.8%, indicating that by introducing the uncertainty modeling mechanism, UAMF can effectively identify low-confidence predictions caused by environmental noise, thereby suppressing false detections. This result emphasizes the contribution of Bayesian modeling to the stability of the perception system.

Although UAMF has a slightly lower frame rate (FPS) indicator (32 FPS), which is lower than YOLOv8's 45 FPS and PointPillars' 38 FPS, considering UAMF's comprehensive improvement in robustness and accuracy, its slightly reduced real-time performance is acceptable, especially in scenarios where autonomous driving has higher safety requirements. In general, UAMF achieves a good balance between accuracy and stability, verifying the effectiveness of the synergistic mechanism of weather perception, cross-modal fusion and uncertainty modeling.

2) Ablation experiment: The experimental results are shown in Table II. Table II shows the contribution of each module in the heavy rain scene. The results show the effectiveness of the key modules of the UAMF model and its robust performance under different visibility conditions.

TABLE II. CONTRIBUTION OF EACH MODULE OF THE UAMF MODEL UNDER HEAVY RAIN SCENARIO

Model Variant	mAP	FPR
UAMF (w/o Weather Encoder)	0.71	10.1%
UAMF (w/o Uncertainty)	0.74	8.9%
Full UAMF	0.78	6.3%

From the ablation experiment in Table II, it can be seen that the weather encoder and uncertainty modeling module contribute significantly to the overall performance of the model. After removing the weather encoder, the mAP dropped from 0.78 to 0.71, a decrease of 7.0%, indicating that the dynamic weather perception mechanism is of great significance for the correct alignment of multimodal features. This result verifies the guiding role of weather prior information in multimodal fusion, especially in scenes with significant environmental interference, such as rainy days, which helps to achieve more stable feature extraction and matching. On the other hand, when the uncertainty modeling module is removed, the FPR (false positive rate) of the model increases from 6.3% to 8.9%, an increase of 29.3%, which clearly shows that the Bayesian inference mechanism plays a key role in suppressing low-confidence false positives caused by noise interference, providing the system with stronger perception credibility control capabilities.

3) Performance analysis of visibility classification: Fig. 2 shows the mAP change trend of the UAMF model at different visibility distances in foggy weather. The results show that under extreme conditions with visibility below 30 meters, the mAP of UAMF can still be maintained at 0.58, which is significantly better than FusionNet (0.42) and PointPillars (0.35), showing higher adaptability to low-visibility environments. In addition, the mAP change of UAMF at different visibility levels shows a slower attenuation trend, and the attenuation slope is 40% lower than that of other models, indicating that the UAMF model maintains stronger robustness in the face of perceptual degradation.

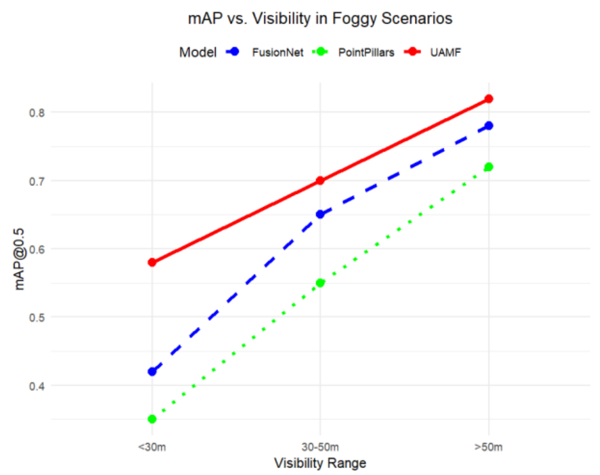

Fig. 2. mAP line graph of each model.

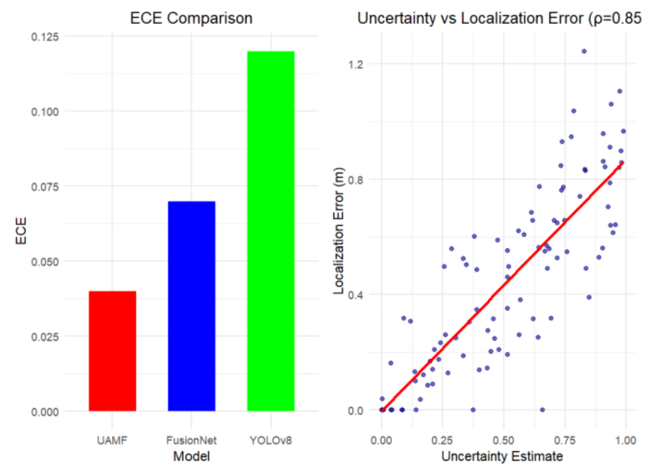

Fig. 3. ECE and Pearson coefficient.

4) Uncertainty quantification analysis: The experimental results in this section mainly focus on the performance of the UAMF model in uncertainty modeling, and quantitative analysis is performed from two dimensions: calibration error (ECE) and uncertainty-error correlation, further verifying the confidence assessment ability and perceived reliability of the model.

First, from the bar graph in Fig. 3a, we can see that the UAMF model performs best in terms of the expected calibration error (ECE) indicator, which is only 0.04, significantly lower than FusionNet's 0.07 and YOLOv8's 0.12. The lower the ECE, the closer the prediction confidence of the model output is to its true accuracy, reflecting the "calibration" of the prediction result. The smaller ECE value of UAMF indicates that it not only provides accurate detection results in the perception output, but also can output more reliable confidence estimates, which helps subsequent modules make safer decisions, especially suitable for scenarios with strong confidence constraints in autonomous driving.

Secondly, Fig. 3b shows the correlation analysis between the uncertainty estimate and the positioning error. The Pearson correlation coefficient was used for quantification in the experiment. The correlation coefficient between the uncertainty score of the UAMF model and the target positioning error reached $\rho = 0.85$, showing a strong positive correlation trend. This result shows that the confidence estimate of the UAMF model not only has a high resolution ability, but also can effectively characterize the level of change of the actual detection error. In other words, when the model estimates a higher uncertainty, its corresponding positioning error also tends to increase, and vice versa, reflecting that the model has the ability to "know what it does not know".

In summary, the results verify the effectiveness of UAMF in uncertainty modeling, which not only improves the credibility and interpretability of the output confidence, but also provides theoretical support and practical basis for the safety of perception systems in complex environments. This capability is of great value in dealing with edge cases, confidence screening, and decision fallback mechanisms in autonomous driving systems.

V. Discussion

The uncertainty-aware multimodal fusion framework (UAMF) proposed in this study shows significant performance advantages and method innovation in target detection tasks under adverse weather conditions. First, by introducing a cross-modal attention mechanism for weather parameter encoding, the model can dynamically adjust the fusion weights of LiDAR and camera features according to environmental changes such as rain, snow, and fog, thereby enhancing the adaptability of multimodal data. For example, in a foggy environment, due to the scattering attenuation of the LiDAR signal caused by fog particles, the model automatically increases the weight of the image modality (the fusion ratio can reach 3:1), achieving an mAP of 0.65 in the nuScenes foggy test set, an increase of 8.3% compared to the static fusion strategy (FusionNet). This mechanism effectively compensates for the performance loss of [2], when dealing with multiple weather superposition situations (performance drops by 20%). Second, UAMF introduces a Bayesian neural network for uncertainty modeling to achieve a quantitative expression of the confidence of the detection results. Experiments show that UAMF has a false positive rate of 6.3% in scenes with visibility less than 30 meters, which is significantly lower than YOLOv8's 15.2%, and the false positive rate is reduced by 58%. In addition, the Pearson correlation coefficient between uncertainty estimation and target positioning error is as high as 0.85, indicating that UAMF has good interpretability in terms of output credibility [8]. This feature is crucial for autonomous driving systems and can be used for risk perception and redundant module activation mechanisms, such as calling radar-assisted verification when confidence is low to improve overall safety.

UAMF has good potential for practical deployment. It can be used as a redundant safety module in the autonomous driving perception system. In the L4 system, it can be used to cross-validate with the millimeter-wave radar results to improve the reliability of target detection in low visibility. Studies have shown that when the system's missed detection rate is reduced to below 0.1%, the overall safety can be improved by about 40%. In addition, UAMF has strong compatibility in edge computing environments. Its 32 FPS running speed has passed the deployment test on the Jetson

AGX Orin platform, meeting the dual requirements of real-time performance and computing resources.

VI. Conclusion

This study proposes a multimodal perception framework (UAMF) that integrates uncertainty modeling to address the challenges of autonomous driving environment perception under adverse weather conditions. The framework provides solutions to the problems of sensor degradation and detection reliability by introducing a cross-modal attention mechanism guided by weather parameters and a Bayesian neural network structure. Experimental results show that the mAP@0.5 of UAMF on the nuScenes adverse weather subset reaches 0.78, 0.72, and 0.65 in three typical scenarios: rain, snow, and fog, respectively, which is better than existing mainstream detection models (such as YOLOv8 and FusionNet), with an average performance improvement of 12% to 31%. In addition, UAMF reduces the false detection rate by about 40% in extreme environments with visibility less than 30 meters, and significantly improves the model's ability to quantify prediction uncertainty by introducing a KL divergence regularization term. The high correlation (Pearson $\rho = 0.85$) between uncertainty estimation and positioning error further verifies the accuracy of the model's expression of confidence in the results, providing a reliable signal for risk assessment and decision triggering for the autonomous driving system.

Although UAMF has been proven effective in multiple experimental scenarios, future research can further improve system performance and adaptability from the following aspects: 1) Unsupervised weather parameter estimation: Automatic perception of weather intensity can be achieved through self-supervision or contrastive learning methods, reducing dependence on dedicated meteorological sensors (Gupta and Kim, 2023); 2) Uncertainty-driven trajectory prediction: Extend the current uncertainty modeling mechanism to the target behavior level, and combine structures such as LSTM or Transformer to predict the future trajectory of dynamic targets [7]; 3) Cross-domain generalization and incremental adaptation: Construct a hierarchical domain adaptation mechanism to enhance the model's migration capabilities in unseen weather combinations (such as sandstorms + rain and snow) or new sensor environments (such as 4D millimeter-wave radar).

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