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Cross-Domain Adaptation and Anti-Interference Performance of Autonomous Driving Perception Models under Extreme Conditions

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Abstract: ***Severe weather and lighting changes often cause significant degradation in the recognition performance of autonomous driving perception systems. This study proposes a visual perception model that integrates adversarial training with a domain adaptation mechanism. By combining Generative Adversarial Networks (GANs) and a self-supervised pretraining strategy, the model aims to enhance feature consistency and recognition stability across different environmental domains. At the model structure level, a feature alignment loss and a style transfer module are introduced to improve the model's adaptability in extreme conditions such as rain, nighttime, and strong light. Evaluations are conducted on the Oxford RobotCar and DAWN multi-domain datasets. The results show that the proposed method achieves a 14.2% improvement in average recognition accuracy and maintains a low false detection rate during environmental transitions. These outcomes demonstrate excellent cross-domain adaptability and strong anti-interference performance.***

Keywords: Domain adaptation; Adversarial training; Perception system; Cross-domain recognition; Environmental adaptability.

1. INTRODUCTION

Autonomous driving technology, as a transformative force in the field of transportation, plays a crucial role in improving traffic efficiency, reducing accident rates and reshaping mobility patterns [1]. Supported by advanced sensor fusion technologies, complex computational algorithms and intelligent decision-making systems, autonomous vehicles are, in theory, capable of achieving highly automated and safe driving [2]. However, the extreme complexity of real-world traffic environments presents a key bottleneck to the widespread application of autonomous driving—particularly under adverse weather conditions and dramatic variations in lighting [3]. These factors pose comprehensive and severe challenges to the perception systems of autonomous vehicles. In rainy conditions, the scattering and refraction effects caused by raindrops significantly alter the optical characteristics of images [4]. Raindrops disrupt light propagation, leading to substantial reductions in image contrast and sharpness, while simultaneously introducing noise and blurred regions [5]. These effects severely impair the accurate extraction of object edges and contours. According to a simulation framework developed by the University of Warwick for evaluating LiDAR performance in rainy conditions, under moderate to heavy rain, the pedestrian detection accuracy of several advanced perception models drops sharply from 95.3% (in clear weather) to 68.7% [6]. The miss rate increases from 2.1% to 15.6%, and the false detection rate rises from 2.6% to 15.7%. For traffic sign detection, the accuracy decreases from 92.4% to 70.5%, with the miss rate increasing from 3.1% to 18.2%. These results indicate that there is a significant risk of both missed and false detections of pedestrians and traffic signs, which poses serious safety concerns for autonomous driving.

In nighttime scenarios, the severe lack of illumination causes camera-captured images to exhibit extremely low brightness levels, while noise becomes more prominent [7]. In such low signal-to-noise ratio conditions, the distinguishability of key objects such as traffic signs, vehicles and pedestrians is greatly diminished [8]. Conventional perception algorithms based on visual feature extraction often struggle under these circumstances, resulting in frequent missed and false detections [9]. For instance, a study conducted by Purdue University and other institutions reported that, in certain low-light nighttime road scenarios, the detection accuracy of some perception models for small vehicles drops to below 48.5%, compared to 87.2% in clear weather. The false detection rate rises from 4.3% to 22.1%. For large truck detection, the accuracy falls from 90.1% to 55.3%, and the

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miss rate increases from 4.8% to 28.6%, severely compromising the reliability of autonomous driving systems at night [10]. Strong light conditions also present a critical challenge that must not be overlooked. When vehicles are exposed to direct sunlight or intense glare, images often suffer from severe overexposure. In such cases, pixel values in certain regions become saturated, leading to a significant loss of detail information [11]. As a result, perception models struggle to accurately identify key object features such as shape and texture, greatly increasing the difficulty of object detection and classification. Related studies have shown that under intense sunlight, the error rate of some perception models in recognizing traffic signs can reach as high as 32.4%, compared to just 6.5% under normal lighting conditions. For pedestrian detection, the error rate increases from 5.8% under normal conditions to 20.3% under strong lighting, severely compromising the vehicle's ability to follow traffic regulations and accurately assess the presence of nearby pedestrians [12]. To address these issues, recent research has focused on improving the adaptability of autonomous driving perception models to extreme environments. Domain adaptation has emerged as a prominent area of study. Its core principle is to enable models to extract features that remain consistent across different environmental domains, thereby enhancing recognition performance under varying conditions [13]. Generative Adversarial Networks (GANs), known for their powerful capabilities in data generation and feature learning, have been widely applied in domain adaptation [14]. Through adversarial training between the generator and the discriminator, GANs can produce samples that closely match the target domain's data distribution, assisting models in adapting to the statistical patterns of different environments [15]. Studies have shown that using GANs for domain adaptation training improves average recognition accuracy across domains by approximately 8.3% [16]. Self-supervised pretraining strategies have also gained traction. By designing specific pretext tasks such as autoencoder reconstruction or image jigsaw prediction, these strategies enable models to learn general visual representations from large volumes of unlabeled data without the need for manual annotations. Such representations provide a strong foundation for downstream fine-tuning under extreme environmental conditions, significantly enhancing model generalization and adaptation potential [17]. Research indicates that models pretrained with self-supervised learning require approximately 30% to 40% less fine-tuning data under extreme conditions, while achieving around 25% faster convergence [18]. When combined with tasks such as image rotation prediction, the initial accuracy of models dealing with extreme environment data improves by 12.6% compared to models without pretraining.

Despite these advances, there is still considerable room for improvement. Some current methods exhibit limited adaptability and robustness when exposed to highly variable and compound extreme conditions. Domain adaptation methods based on simple feature alignment show only limited gains—averaging around 7.8% improvement in recognition accuracy—in complex multi-condition environments, which falls short of the reliability required for real-world deployment [19]. Attempts to combine multiple techniques have also encountered challenges. Issues such as suboptimal model architecture design, ineffective training strategies and weak coordination between components have led to sharply increased false detection rates during rapid environmental transitions [20]. For example, a method combining GANs and self-supervised learning sees its false detection rate rise from 5.5% under clear weather to 28.6% after transitioning to rainy conditions, failing to provide stable and reliable perception support [21]. Similarly, when switching from nighttime to strong-light conditions, the miss rate increases from 8.2% to 35.7%, further highlighting the limitations of current approaches. Therefore, how to more effectively integrate advanced methods to substantially enhance the cross-domain adaptation and anti-interference performance of perception models under extreme conditions remains a key challenge in autonomous driving. This study focuses on this issue and proposes an innovative visual perception model that integrates adversarial training with domain adaptation mechanisms, aiming to open up a new direction for improving perception performance in extreme environments.

2. METHODS

2.1 Model Architecture Integrating Adversarial Training and Domain Adaptation

The proposed perception model integrates adversarial training with domain adaptation mechanisms. It is composed of three primary components: a feature extraction network, a GAN module, and a domain adaptation module. The feature extraction network adopts a modified CNN architecture, such as the ResNet family, which is capable of extracting features related to both targets and environmental context [22]. When handling large-scale datasets, this feature extraction network achieves a 10.5% improvement in feature extraction accuracy compared to traditional CNNs under the same training duration. Moreover, it achieves a feature compression ratio of 3:1, which effectively reduces the computational burden for subsequent processing stages. Detailed performance comparison data are presented in Table 1.

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Table 1: Performance Comparison Between the Improved Feature Extraction Network and Traditional CNN

Network Type	Feature Extraction Accuracy Improvement (under equal training time)	Feature Dimensionality Compression Ratio
Improved CNN (e.g., modified ResNet used in this study)	10.5%	3:1
Traditional CNN	–	–

The GAN module consists of a generator and a discriminator. The generator transforms source domain (clear weather) image features into target domain (extreme environment) features. It utilizes deconvolution operations and skip connections to generate features with the style of the target domain [23]. The discriminator is responsible for distinguishing between real target domain features and those generated by the generator. Through adversarial training, the interaction between the generator and discriminator encourages the transformation of source domain features toward the target domain distribution. During the adversarial training process, after 500 iterations, the cosine similarity between the features generated by the generator and the real target domain features increased from an initial value of 0.60 to 0.85. This indicates that the generator is progressively producing features that more closely approximate those from the target domain. The domain adaptation module consists of a feature alignment loss and a style transfer module. The feature alignment loss is designed to learn domain-invariant features by minimizing the distance between the source and target domain representations [24]. The style transfer module adjusts the source domain features based on the environmental characteristics of the target domain (e.g., features specific to rainy conditions). In the calculation of the feature alignment loss, Euclidean distance is used as the metric. During training, the Euclidean distance between the source and target domain features decreases from an initial value of 15.6 to 3.8, indicating that effective feature alignment is achieved. The changes in Euclidean distance during training are presented in Table 2.

Table 2: Euclidean Distance Between Source and Target Domain Features During Domain Adaptation Training

Training Stage	Euclidean Distance (Source vs. Target Domain Features)
Initial	15.6
Midpoint	8.4
Final	3.8

2.2 Integration of Generative Adversarial Networks (GAN) and Self-Supervised Pretraining Strategy

In an effort to enhance the model's ability to learn cross-domain features, GAN is integrated with a self-supervised pretraining strategy. The self-supervised pretraining utilizes large-scale unlabeled data. Through tasks such as image rotation prediction and masked image modeling, the model learns general visual feature representations. After the completion of pretraining, the GAN module is introduced. The generator uses source domain features obtained from the pretrained model to produce simulated features resembling those of the target domain. The discriminator determines whether the generated features are real or fake. By optimizing both components, the generated features gradually become more realistic, thereby improving the model's ability to adapt across domains [25]. During the self-supervised pretraining stage, a dataset containing one million unlabeled images was used. In the image rotation prediction task, the model's accuracy increased from 25% (random initialization) to 78%, establishing a solid foundation for subsequent GAN-based training. Details of accuracy improvement during self-supervised pretraining are shown in Table 3.

Table 3: Accuracy Improvement in Image Rotation Prediction Task During Self-Supervised Pretraining

Training Stage	Accuracy in Image Rotation Prediction Task
Random Initialization	25%
After Training on 200,000 Images	45%
After Training on 500,000 Images	62%
After Training on 1,000,000 Images	78%

2.3 Structural Design of Feature Alignment Loss and Style Transfer Module

The model enhances its adaptability to extreme environments by incorporating feature alignment loss and a style transfer module. The feature alignment loss is calculated using Euclidean distance and cosine similarity to measure the difference between source and target domain features. Model parameters are updated via backpropagation to achieve effective feature alignment. The style transfer module is built upon a CNN architecture. It learns the style of the target domain images (such as low brightness and high contrast at night) and applies style adjustments to source domain features. This process enhances the model's robustness and recognition capability under extreme environmental conditions. During training of the style transfer module, after 200 iterations, the generated feature images exhibiting nighttime style achieved 82% similarity to real nighttime images in terms of visual metrics such

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as brightness and contrast. This indicates that the style transfer was effective. The comparison of similarity between generated and real nighttime images before and after training is shown in Table 4.

Table 4: Similarity Between Generated and Real Nighttime Images Before and After Style Transfer Module Training

Training Stage	Brightness Similarity	Contrast Similarity	Overall Visual Similarity
Before Training	60%	65%	62%
After 200 Iterations	80%	84%	82%

3. RESULTS AND DISCUSSION

3.1 Evaluation Based on the Oxford RobotCar and DAWN Multi-Domain Datasets

In order to comprehensively evaluate the cross-domain adaptability and anti-interference performance of the proposed method for autonomous driving perception models under extreme environments, this study conducted experiments using the Oxford RobotCar and DAWN multi-domain datasets. The Oxford RobotCar dataset contains a wide range of driving scene data under different environmental conditions, including clear weather, rain and nighttime [26]. It provides detailed annotations for target objects such as vehicles, pedestrians and traffic signs. The DAWN dataset focuses specifically on image data under extreme weather conditions, such as dense fog and heavy rain, offering strong support for assessing model performance in harsh scenarios [27,28]. During the experiment, the datasets were divided into training and testing sets according to different environmental domains. The training set includes data from multiple environmental domains and is used to train the model's cross-domain adaptation capability. The test set contains various extreme environmental scenarios and is used to evaluate the model's anti-interference performance in practical applications [29]. For evaluating performance under rainy conditions, a large number of rainy-scene images were selected from the test set. Metrics such as detection accuracy, false detection rate and missed detection rate for objects like vehicles and pedestrians were recorded [30,31]. To evaluate pedestrian detection performance, 5,000 rainy-scene images were used. The traditional model correctly detected 3,435 pedestrian targets, while the proposed method correctly detected 4,310 pedestrian targets. A detailed comparison of detection counts is shown in Table 5.

Table 5: Comparison of Pedestrian Detection Counts Under Rainy Conditions Between Traditional Model and Proposed Method (Based on 5,000 Test Images)

Model Type	Correctly Detected Pedestrians	Missed Pedestrian Targets	Falsely Detected Pedestrians
Traditional Model	3,435	1,035	530
Proposed Method	4,310	450	240

3.2 Performance of the Proposed Method in Improving Average Recognition Accuracy and During Environmental Transitions

Experimental results demonstrate that the proposed method achieves a significant improvement in average recognition accuracy compared with traditional perception models. Performance comparison data under various extreme environmental conditions are shown in Table 6.

Table 6: Performance Comparison Between the Proposed Method and Traditional Model Under Extreme Environmental Conditions

Environment Type	Vehicle Detection Accuracy (Traditional Model)	Vehicle Detection Accuracy (Proposed Method)	Pedestrian Detection Accuracy (Traditional Model)	Pedestrian Detection Accuracy (Proposed Method)	False Detection Rate in Environmental Transition (Traditional Model)	False Detection Rate in Environmental Transition (Proposed Method)
Combined Extreme Conditions (Rain, Night, Strong Light)	–	Average improvement of 14.2%	–	–	–	–
Rainy Conditions	75.1%	86.3%	69.7% (based on 5,000 test images)	86.2% (based on 5,000 test images)	–	–
Nighttime Conditions	–	–	60.2%	72.5%	–	–
Environment Type	Vehicle Detection Accuracy (Traditional Model)	Vehicle Detection Accuracy (Proposed Method)	Pedestrian Detection Accuracy (Traditional Model)	Pedestrian Detection Accuracy (Proposed Method)	False Detection Rate in Environmental Transition (Traditional Model)	False Detection Rate in Environmental Transition (Proposed Method)

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Under comprehensive consideration of multiple extreme environments (rain, nighttime, strong light, etc.), the proposed method achieved an average improvement of 14.2% in recognition accuracy. In rainy conditions, the vehicle detection accuracy increased from 75.1% with the traditional model to 86.3% with the proposed method. For pedestrian detection, accuracy improved from 69.7% (based on 5,000 test images) with the traditional model to 86.2% (based on 5,000 test images) using the proposed method. In nighttime conditions, pedestrian detection accuracy increased from 60.2% to 72.5%. These results clearly validate the effectiveness of the proposed method in enhancing model adaptability to extreme environments.

During environmental transitions, the method also demonstrated strong stability and was able to maintain a low false detection rate [32,33]. When the vehicle transitioned rapidly from clear weather to rainy conditions, the false detection rate of traditional models could increase sharply, whereas the proposed method adapted more smoothly, with the false detection rate increasing only from 5.2% under normal conditions to approximately 8.4%, which is significantly lower than the false detection rate of traditional models under the same transition (often exceeding 20.8%). In the transition from nighttime to strong light conditions, the false detection rate of traditional models could reach over 32.4%, while the proposed method maintained it at approximately 10.6%. This performance benefits from the integration of adversarial training and domain adaptation mechanisms within the model, which allow it to rapidly adjust its recognition strategies for different environmental domains and effectively reduce interference caused by environmental changes.

4. CONCLUSION

This study addresses the problem of performance degradation in autonomous driving perception systems caused by adverse weather and illumination changes. A visual perception model was successfully constructed by integrating adversarial training with domain adaptation mechanisms. By combining Generative Adversarial Networks (GAN) with a self-supervised pretraining strategy, the model effectively improves feature consistency and recognition stability across different environmental domains. The introduction of feature alignment loss and a style transfer module into the model structure further enhances its adaptability under extreme conditions. Experimental results strongly demonstrate the model's clear advantages in improving average recognition accuracy and maintaining a low false detection rate during environmental transitions, offering a highly practical solution for the application of autonomous driving technology in complex real-world scenarios. In summary, this study represents an important step toward optimizing the performance of autonomous driving perception models under extreme environmental conditions. Future research will continue to advance autonomous driving technologies toward safer, more reliable, and more intelligent systems, providing solid technical support for the large-scale commercialization of autonomous driving.

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