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Review A Summary On: Modern Vehicle Safety Technology In Hazy Conditions

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ABSTRACT: This paper discusses the range of advanced techniques aimed at enhancing object detection in challenging conditions such as fog, haze, adverse weather, and dense traffic environments. Key contributions include perspective-based obstacle detection, which utilizes scale maps to encode the apparent size of objects, incorporating perspective information in both training and detection phases for improved performance. For adverse weather detection, an energy-based framework for detecting outliers in LiDAR data is introduced, robustly identifying adverse weather effects while performing simultaneous outlier detection and semantic segmentation.

In winter conditions, SIWNet, a deep learning model with uncertainty estimation, is proposed to predict road surface friction from images, enhancing safety. Traffic surveillance improvements include the application of bounding ellipses to CenterNet and SpotNet models, outperforming traditional bounding box methods in vehicle detection from aerial imagery. Additionally, R-YOLOv5 is presented for rotational object detection in drone images, incorporating angle prediction and various feature enhancement techniques for high-accuracy, real-time vehicle detection. Obstacle detection in foggy weather is enhanced by combining GCANet defogging with YOLOv5, improving detection by fusing edge and convolution features. A smart traffic monitoring system is also proposed, utilizing CNNs for vehicle detection and classification from aerial imagery, employing customized pyramid pooling and advanced tracking techniques. Lastly, improved detection in hazy weather is achieved by enhancing YOLOv3 with ResNet, DenseNet, and attention modules, along with the introduction of focal loss for better accuracy. These methods collectively advance the accuracy, efficiency, and robustness of vehicle detection systems, demonstrating significant progress in autonomous driving and smart traffic monitoring.

KEYWORDS: Vehicle detection, Fog, Haze, Adverse weather, Traffic environments, Perspective-based obstacle detection, LiDAR, Outlier detection, Semantic segmentation, Winter road surface condition, SIWNet Bounding ellipses, CenterNet, SpotNet, Rotational object detection, R-YOLOv5, GCANet, defogging, YOLOv5, Smart traffic monitoring, CNN, Pyramid pooling, Kalman filter, Kernelized filter, Feature enhancement, Focal loss

INTRODUCTION:

The rapid evolution of vehicle safety technology has revolutionized the way we approach driving, particularly in challenging conditions like fog. Traditional vehicle systems relied heavily on a single type of sensor for object detection, which often resulted in limitations under varying weather and lighting conditions. However, the advent of multi-sensor fusion systems has dramatically improved real-time object tracking capabilities on the roads. These systems leverage a combination of cameras and radar to provide accurate and reliable data, essential for safe driving.

Cameras play a crucial role by capturing high-resolution visual information, including color and texture details, which are vital for identifying objects and discerning road conditions. Radar, on the other hand, offers robust detection capabilities by measuring the range, velocity, and direction of objects, maintaining performance across diverse weather conditions. The integration of these technologies compensates for the individual limitations of each sensor, resulting in a more effective and comprehensive detection system. Beyond vehicular applications, autonomous robots across various industries are enhancing operational efficiency and reducing costs. These robots rely on advanced detection systems to navigate and perform tasks autonomously. However, adverse weather conditions, such as fog, pose significant challenges in obstacle detection. Researchers have addressed this issue by simulating foggy conditions in clear-weather scenarios to create better training data for improved object detection algorithms. Additionally, vehicle detection systems face difficulties in low-light and glare situations, where traditional cameras may fail. The implementation of thermal infrared imaging has shown promise in improving detection accuracy under such conditions.6

This review paper aims to explore the integration and performance of these advanced sensor technologies, with a focus on their application in enhancing safety, efficiency, and reliability in adverse weather conditions. The comprehensive analysis of multi-sensor fusion technologies underscores their potential to transform autonomous driving and object detection systems, ensuring safer and more efficient operations in various scenarios.

LITERATURE REVIEW:

"Perspective aware road obstacle detection." By Lis, Krzysztof, Sina Honari, Pascal Fua, and Mathieu Salzmann proposes an innovative method for road obstacle detection by incorporating perspective information. Central to this method is the use of a scale map that adjusts the apparent size of obstacles based on their distance from the camera. This approach corrects for perspective distortion, where distant objects appear smaller than those that are closer. By integrating the scale map, the method enhances the synthesis of training data, allowing for more accurate learning and better generalization in real-world scenarios.

One significant advantage of this technique is its ability to reduce false positives, minimizing the chances of misidentifying non-obstacles as obstacles. The experiments and evaluations presented in the paper demonstrate that this method outperforms current state-of-the-art obstacle detection methods, achieving higher accuracy and reliability. This advancement holds considerable promise for applications in autonomous driving and advanced driver-assistance systems (ADAS), enhancing the safety and efficiency of vehicle navigation in complex environments.

Existing methods overlook the size and scene geometry of objects, leading to inaccurate obstacle detection. Additionally, generating synthetic anomalies by altering the semantic class yields limited performance improvements. The proposed method addresses these issues by using a scale map to adjust for the apparent size of obstacles based on their distance, enhancing detection accuracy and reducing false positives.

“Energy-based Detection of Adverse Weather Effects in LiDAR Data” By Piroli, Aldi, Vinzenz Dallabetta, Johannes Kopp, Marc Walessa, Daniel Meissner, and Klaus Dietmayer proposes a novel energy-based framework for identifying adverse weather effects in LiDAR data by treating it as an outlier detection problem. This approach assigns low energy scores to inliers (normal data) and high energy scores to outliers (anomalies), thereby enhancing the system's robustness against previously unseen weather conditions. This method improves the reliability and accuracy of interpreting LiDAR data in challenging weather scenarios, ensuring better performance even in adverse weather.

LiDAR sensors face decreased reliability under adverse weather conditions, which can severely affect their performance. Furthermore, such weather introduces unwanted noise into the measurements, complicating the interpretation of LiDAR data.[4] These challenges underscore the necessity for advanced detection frameworks, like the proposed energy-based approach, to enhance the robustness and accuracy of LiDAR systems in adverse weather scenarios.

“Lightweight Regression Model with Prediction Interval Estimation for Computer Vision-based Winter Road Surface Condition Monitoring” By Ojala, Risto, and Alvari Seppänen introduces SIWNet, a lightweight deep learning regression model designed to estimate winter road surface friction using camera images. This model incorporates a prediction interval mechanism to quantify uncertainty, which enhances its robustness and facilitates practical deployment in automated driving applications. However, the paper does not specifically address a lightweight regression model with prediction interval estimation for monitoring winter road surface conditions using computer vision. Instead, it emphasizes methods for assessing road surface conditions in areas lacking sufficient coverage.

The paper identifies several limitations, including the lack of detailed analysis of contact methods and the constraints of limited vehicle on-board computational resources. Additionally, it addresses the challenge of accurately assessing road surface conditions during winter and the significant impact of these conditions on vehicle friction.[7] These factors highlight the need for advanced methods to improve the accuracy and efficiency of winter road surface condition monitoring.

"Non-anchor-based vehicle detection for traffic surveillance using bounding ellipses" by Yu, Byeonghyeop, Johyun Shin, Gyeongjun Kim, Seungbin Roh, and Keemin Sohn introduces a groundbreaking vehicle detection model that utilizes bounding ellipses rather than traditional anchors. This non-anchor-based approach, implemented in CenterNet and SpotNet, eliminates the need for non-max suppression, which in turn improves detection accuracy.[8] The results demonstrate that this method outperforms conventional anchor-based models such as YOLO4 and SSD, marking a significant step forward in vehicle detection technology.

CenterNet and SpotNet are limited by slower detection speeds and the impact of a heavier backbone on processing speed. Additionally, bounding boxes can create large empty spaces when objects are not aligned parallel to the axes.[8] These factors highlight challenges that need addressing for optimizing detection performance.

"R-YOLOv5: A Lightweight Rotational Object Detection Algorithm for Real-Time Detection of Vehicles in Dense Scenes" by Li, Zhengwei, Chengxin Pang, Chenhang Dong, and Xinhua Zeng introduces R-YOLOv5, a lightweight rotational object detection algorithm tailored for real-time vehicle detection in densely populated scenes. It demonstrates impressive performance, achieving an accuracy of 84.91% on the Drone-Vehicle dataset and 90.23% on the UCAS-AOD dataset. [9] Notably, R-YOLOv5 operates with a minimal parameter count of just 2.02 million, highlighting its efficiency and effectiveness in detecting vehicles in challenging environments.

Traditional algorithms often overlook the diversity in vehicle scales found in drone images, which can lead to inaccuracies in detection. Additionally, these methods typically lack information regarding the rotation angles of detected vehicles. These shortcomings highlight the need for more advanced detection algorithms that can accommodate variations in vehicle scale and provide detailed information on rotation angles for improved accuracy in drone-based vehicle detection.

"Research on Driving Obstacle Detection Technology in Foggy Weather Based on GCANet and Feature Fusion Training" by Liu, Zhaohui, Shiji Zhao, and Xiao Wang proposes a **method for detecting driving obstacles in foggy** weather by integrating the GCANet defogging algorithm with a training approach that combines edge and convolution features. This innovative technique significantly enhances detection performance, achieving a 12% improvement in mean Average Precision (mAP) and a 9% increase in recall compared to conventional methods.[10] This combined approach demonstrates the potential for more reliable obstacle detection in foggy conditions, contributing to safer driving experiences.

In foggy weather, the quality of images can degrade significantly, making it challenging to accurately detect driving obstacles. Moreover, defogging techniques may lead to a loss of crucial information, further complicating obstacle detection. These challenges emphasize the need for advanced methods like the proposed integration of the GCANet defogging algorithm with edge and convolution feature fusion, which aims to improve detection performance and ensure safer driving under foggy conditions.

"Vehicle detection method with low-carbon technology in haze weather based on deep neural network" by Tao, Ning, Jia Xiangkun, Duan Xiaodong, Song Jinmiao, and Liang Ranran introduces enhancements to the YOLOv3 algorithm aimed at improving vehicle detection in hazy conditions. These improvements include the integration of DenseNet for more effective feature extraction, an attention module to focus on latent information, and the use of focal loss to increase accuracy.[13] As a result, the enhanced algorithm achieves a recognition accuracy of 75%, demonstrating its effectiveness in challenging visibility conditions.

The model faces limitations in its deployment to edge devices, as its complexity and resource requirements exceed the capabilities of these devices. Additionally, there is a scarcity of publicly available datasets specifically designed for detecting foggy weather conditions. These constraints highlight the need for further advancements and the development of more accessible datasets to improve the model's

Year	Publisher	Title	Authors	Results
2024	IEEE	**"Lightweight Regression Model with Prediction Interval Estimation for Computer Vision-based Winter Road Surface Condition Monitoring."**	Ojala, Risto, and Alvari Seppänen	SIWNet w/o sigmoid **0.099(MAE) 0.151(RMSE)** EfficientNet-B0 w/o sigmoid **0.289(MAE) 0.309(RMSE)**
2023	IEEE	**"Perspective aware road obstacle detection."**	Lis, Krzysztof, Sina Honari, Pascal Fua, and Mathieu Salzmann	Image warping: **45.2 ± 0.5 (F1) 65.5 ± 0.7(AuPRC)** for Road Obstacles No perspective channel: **52.5 ± 6.7 (F1) 70.6 ± 1.0(AuPRC)** for Road Obstacles Ours (perspective-aware): **67.1 ± 1.7 (F1) 75.2 ± 0.1(AuPRC)** for Road Obstacles
2023	IEEE	**"Energy-based detection of adverse weather effects in lidar data."**	Piroli, Aldi, Vinzenz Dallabetta, Johannes Kopp, Marc Walessa, Daniel Meissner, and Klaus Dietmayer	Particle-UNet **97.62(AUROC),97.09(AUPR),9.82(PPR95)** Particle-VoxelNet **98.51(AUROC),98.35(AUPR),2.19(PPR95)**
2023	IEEE	**"R-YOLOv5: A lightweight rotational object detection algorithm for real-time detection of vehicles in dense scenes."**	Li, Zhengwei, Chengxin Pang, Chenhang Dong, and Xinhua Zeng.	R-YOLOv5 CSPDarkNet5 **:88.92(Car AP) 13.2(Parameter) 26(Model size) 46.4(FPS)**
2023	Sensors	**"Research on driving obstacle detection technology in foggy weather based on GCANet and feature fusion training."**	Liu, Zhaohui, Shiji Zhao, and Xiao Wang	GCA Net + Edge and convolution feature fusion training: Single Image Defogging Time(s):**0.10-0.11** Single Image Detection Time(s):**0.008-0.023**
2023	IEEE	**"Smart traffic monitoring through pyramid pooling vehicle detection and filter-based tracking on aerial images."**	Rafique, Adnan Ahmed, Amal Al-Rasheed, Amel Ksibi, Manel Ayadi, Ahmad Jalal, Khaled Alnowaiser, Hossam Meshref, Mohammad Shorfuzzaman, Munkhjargal Gochoo, and Jeongmin Park.	Proposed Model :Accuracy-**92.22%** Darknet: Accuracy **-90.51%** A VDNet: Accuracy- **56.24%**
2022	International Journal of Low-Carbon Technologies	**"Vehicle detection method with low-carbon technology in haze weather based on deep neural network."**	Tao, Ning, Jia Xiangkun, Duan Xiaodong, Song Jinmiao, and Liang Ranran.	YOLO: **mAP/% 68.7** FD-YOLO: **mAP/%75**
2021	IEEE	**"Non-anchor-based vehicle detection for traffic surveillance using bounding ellipses."**	Yu, Byeonghyeop, Johyun Shin, Gyeongjun Kim, Seungbin Roh, and Keemin Sohn.	Baseline model **0.873(Box) 0.848(Ellipse) 0.865(OBB)** Label smoothing **0.866(Box) 0.853(Ellipse) 0.887(OBB)**

applicability and performance in real-world scenarios.

CONCLUSION:

In this comprehensive review, we delve into recent advancements in road condition monitoring, vehicle detection, and obstacle detection, particularly in challenging scenarios such as adverse weather and cluttered environments. The SIWNet model enhances winter road condition monitoring, improving automated driving reliability across all weather conditions by utilizing uncertainty quantification and requiring minimal computational resources. This advancement supports the robustness of automated vehicle functionalities. The R-YOLOv5 model enhances drone-based vehicle detection by incorporating rotation angle prediction, Swin Transformer blocks, and adaptive spatial feature fusion. This results in high accuracy and real-time performance, making it suitable for drone platforms. Combining GCANet defogging with edge and convolution feature fusion improves obstacle detection in foggy weather. This method shows significant improvements in precision, recall, and mAP compared to conventional methods.

A new traffic monitoring system using customized pyramid pooling modules effectively segments and classifies vehicles in aerial images, validated on multiple datasets. This approach provides significant advancements in traffic monitoring and smart surveillance systems. Future research should address the scarcity of real foggy weather datasets by simulating realistic conditions using atmospheric scattering models and image depth estimation. Moreover, optimizing models through pruning, quantization, or applying lightweight networks can ensure deployment on edge devices while maintaining accuracy. Enhancing vehicle tracking with end-to-end deep learning methods will further improve traffic monitoring and surveillance, addressing challenges like occlusions and diverse backgrounds.

These innovations contribute to more reliable and robust automated driving and traffic monitoring solutions, paving the way for safe and effective deployment in real-world scenarios.

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