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16. ABSTRACT

This report details the development and evaluation of an innovative component in a traffic management system that can enhance road safety during severe weather conditions. Severe weather conditions, such as dense fog, heavy rain, and snow, significantly hinder road safety by reducing visibility and increasing the risk of collisions, particularly for emergency vehicles like tow trucks and snowplows. These vehicles play a critical role in maintaining roadway accessibility during adverse weather, but their effectiveness is limited by the challenges of obstacle detection in low-visibility environments. Current driver assistance technologies, including optical cameras, LiDAR, and radar systems, face significant limitations in such conditions due to interference from weather elements. Infrared (IR) cameras, which detect thermal radiation rather than relying on visible light or laser reflections, offer a promising alternative for improving situational awareness and obstacle detection during adverse weather. This research evaluates the effectiveness of commercial off-the-shelf (COTS) IR camera systems in enhancing driver safety and operational efficiency for snowplows and tow trucks during severe weather. Controlled and real-world testing, along with driver surveys, were conducted to assess the performance of IR-based Advanced Driver Assistance Systems (ADAS) in detecting obstacles, such as pedestrians, animals, and vehicles, under low-visibility conditions. The findings provide insights into the viability of thermal imaging technology for emergency fleet operations, informing policymakers and transportation departments on this technology's potential to enhance roadway safety and efficiency during extreme weather scenarios.

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Evaluation of Commercial Forward-Looking Infrared Driver Assistance Technology for use in Emergency Tow Trucks and Snowplow

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Executive Summary

In our collaborative study with the California Department of Transportation (Caltrans), our research explored the use of commercial off-the-shelf (COTS) infrared (IR) camera systems to improve safety and operational efficiency for emergency vehicles in low-visibility conditions. This effort focused on snowplows and tow trucks operating under severe weather, leveraging IR-based Advanced Driver Assistance Systems (ADAS) to detect obstacles, such as pedestrians, animals, and other vehicles.

Field tests were conducted to evaluate the performance of IR cameras in controlled and real-world scenarios. These tests highlighted the capability of IR technology to maintain reliable obstacle detection and situational awareness in dense fog, heavy snowfall, and rain environments where traditional optical cameras and LiDAR often fail. The results demonstrated that IR cameras effectively detect obstacles obscured by adverse weather, enhancing operator awareness and response times during emergency and snow-clearing operations.

Collected data and surveys were also used to identify optimal IR camera placements on emergency vehicles, ensuring comprehensive coverage while maintaining system cost-effectiveness. Initial findings suggest that IR cameras can seamlessly integrate with existing fleet systems, offering a scalable solution for improving road safety in harsh weather conditions.

The next phase of this research will focus on pilot field deployment to measure the direct impact of IR camera systems on emergency response efficiency and collision rates, refining the approach to better serve transportation departments and policymakers seeking to enhance roadway safety during extreme weather scenarios.

Major Results and Recommendations

Our comprehensive research explored the use of IR camera systems in emergency vehicles, like snowplows and tow trucks, highlighting their potential to enhance safety and operational efficiency in severe weather conditions. Field tests confirmed that IR cameras, unlike traditional optical cameras, remain effective under low visibility caused by dense fog, and rain. This reliability is critical for emergency vehicles operating in such environments where traditional systems are often inadequate. Moreover, integrating these IR cameras into existing vehicle systems has proven to be cost-effective and scalable, suggesting this approach is a viable option for widespread adoption across transportation fleets.

While the results advocate for the adoption of IR camera systems due to their superior performance in adverse weather, it is also recommended to continue exploring this technology further. Strategic placement of IR cameras on vehicles can maximize coverage and effectiveness, significantly enhancing driver situational awareness. Additionally, expanding testing to include more diverse weather scenarios could help in understanding the system's full range of capabilities and limitations. Emphasizing ease of integration and maintaining a focus on cost-effectiveness will facilitate smoother adoption and operation of IR cameras. Ensuring continuous updates and support for these systems will also be crucial to keep up with technological advancements and maintain their reliability in the field. This balanced approach allows for a flexible adoption strategy tailored to specific operational needs and technological developments.

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Acronyms and Abbreviations

Acronym	Definition
AHMCT	Advanced Highway Maintenance and Construction Technology Research Center
AV	Autonomous Vehicle
AI	Artificial Intelligence
ADAS	Advanced Driver Assistance Systems
Caltrans	California Department of Transportation
DOT	Department of Transportation
COTS	Commercial off the Shelf
DRISI	Caltrans Division of Research, Innovation and System Information
IR	Infrared

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Chapter 1 Introduction

Problem

Severe weather conditions, such as dense fog, heavy rain, and snow, pose significant challenges to road safety, particularly for emergency and maintenance vehicles like snowplows and tow trucks [1]. Reduced visibility during such conditions hampers the ability of operators to detect obstacles, navigate safely, and respond to hazards, increasing the risk of collisions and delays during emergency response [2]. Existing driver assistance technologies, including optical cameras and LiDAR, are limited in their performance under low-visibility scenarios, leaving critical gaps in road safety [3]. The increasing frequency of extreme weather events due to climate change underscores the urgency for innovative solutions to enhance the safety and efficiency of these vehicles [4].

Objectives

The primary objective of this research was to evaluate the effectiveness of commercial off-the-shelf (COTS) infrared (IR) camera systems as a solution for driver assistance in low-visibility conditions. Specifically, the study aimed to:

1. Assess the ability of IR-based Advanced Driver Assistance Systems (ADAS) to detect obstacles such as pedestrians, animals, and vehicles under severe weather conditions.
2. Analyze the operational efficiency and safety improvements achieved by integrating IR cameras into snowplows and tow trucks.
3. Provide insights for policymakers and transportation departments regarding the adoption and deployment of IR camera technology across emergency fleets.

Scope

This study focused on evaluating IR camera technology as a viable solution for enhancing driver assistance under severe weather conditions. The scope included:

- The performance of IR cameras in detecting obstacles during dense fog, heavy snowfall, and rain.
- Application of IR technology in emergency and maintenance vehicles, such as snowplows and tow trucks.

- Controlled and real-world testing environments to simulate operational conditions.
- Surveys and feedback from vehicle operators to gauge the practical utility of IR systems.

The study does not cover the broader economic implications or provide a cost-benefit analysis of widespread IR camera deployment, focusing instead on technical feasibility and safety improvements.

Background

Current driver assistance technologies, such as optical cameras, LiDAR, and radar systems, enhance safety by detecting obstacles, providing collision warnings, and supporting navigation. However, these technologies face significant limitations when weather is severe. In particular,

- Optical cameras struggle with reduced visibility due to weather interference like fog and snow.
- LiDAR systems experience signal scattering from rain or snow, compromising accuracy and reliability.
- Radar-based systems are robust but have difficulty detecting smaller or non-metallic objects and are vulnerable to sensor obstruction from ice or dirt.

IR cameras, which detect thermal radiation rather than relying on visible light or laser reflections, offer a promising alternative. With the ability to "see" through dense fog, rain, and snow, IR cameras provide reliable obstacle detection under conditions that hinder conventional systems. This capability makes them particularly suited for emergency vehicles operating in high-risk, low-visibility environments.

Research Methodology

The study employed a multi-faceted approach to evaluate the effectiveness of IR camera systems:

1. Controlled Testing
    - Simulated low-visibility conditions, including fog chambers, were used to test IR cameras' obstacle detection capabilities.
    - Key metrics, such as detection range and accuracy, were measured.
2. Real-World Trials
    - IR cameras were installed on snowplows in District 3, located in South Lake Tahoe, and tow trucks in District 4, located in the Bay Area, that then operated during actual severe weather conditions.

- Data on obstacle detection and operator feedback were collected to assess real-world performance.

3. Driver Surveys

    - Surveys and interviews with vehicle operators from Districts 3 and 4 were conducted to understand the usability and practical benefits of IR camera systems.
    - Feedback on system integration, reliability, and situational awareness was analyzed.

4. Comparative Analysis

    - The performance of IR cameras was compared to existing driver assistance technologies to highlight their advantages and limitations.

The study comprehensively assesses IR camera systems for enhancing safety and efficiency in low-visibility conditions by combining technical evaluations with operator insights.

Chapter 2 Methodology

To incorporate the IR camera into the vehicle system to assist drivers, we adopted a simplified approach that leveraged the existing visual framework drivers were familiar with, such as front or backup cameras commonly observed in cars. The IR camera presents its environmental view on a monitor inside the vehicle, allowing the driver to refer to the feed in low-visibility conditions, particularly when traveling at slower speeds. The IR cameras were mounted on top of the vehicle cap near the driver's side using strong magnets as shown in Figure 2.1. The IR cameras must not be placed inside the vehicle cap behind normal optical glass since normal glass blocks IR radiation. This approach reduces the need for specialized training and simplified installation, significantly lowering the cost of retrofitting older fleet vehicles, which is especially valuable for departments of transportation where many fleet vehicles may be aging and in need of modernized, but affordable, safety enhancements.

The IR camera feed is further processed by a machine learning algorithm that automatically detects objects within the camera's field of view. The system can then overlay visible bounding boxes around detected objects, presenting enhanced visual information to the driver. This system helps drivers notice obstacles faster in challenging conditions.

Figure 2.1: Installed IR cameras on a Caltrans vehicle

Camera Selection

To identify the most suitable IR cameras for our study, we thoroughly reviewed commercially available options, focusing on two primary criteria: technical specifications and cost. Our goal was to select cameras that provide high performance in terms of image resolution, frame rate, and connectivity to analog or digital monitors while also being cost-effective for deployment in vehicle fleets. Based on these criteria, we evaluated two candidates, FLIR and InfiRay. The detailed specifications of the cameras are presented in Chapter 3.

Experimental Evaluations

We designed a series of controlled and field experiments to evaluate the effectiveness of the selected IR cameras under low-visibility conditions. These experiments assessed the cameras' technical performance and gathered user feedback on their practicality in real-world scenarios.

First, we conducted controlled environment tests where we synthetically introduced low-visibility conditions, such as fog and darkness, to simulate the challenging environments tow truck and snowplow drivers often face. These experiments allowed us to collect data for both qualitative and quantitative analysis, focusing on the cameras' ability to detect obstacles and provide clear visual feedback under such conditions. Field tests were also carried out in natural fog to validate the results under real-world conditions. Through these evaluations, we compared the performance of the two selected cameras—the FLIR ADK and the InfiRay (Xsafe-II M6S).

In addition to the technical evaluations, we sought feedback from tow truck and snowplow drivers to understand their experiences with the IR camera systems. Driver trainings were conducted for tow truck and snowplow drivers after vehicles were retrofit with the IR cameras. Vehicles retrofitted with the IR cameras were deployed in field conditions, and drivers were surveyed to assess their perception of the cameras' utility, particularly regarding safety improvements and ease of use in low-visibility scenarios. Unlike the controlled experiments, the primary objective in this task was to evaluate the overall usefulness of IR camera technology rather than compare the two specific models.

We will discuss these evaluations in detail in the following chapters, focusing on the technical assessment and user feedback from the field.

Chapter 3 Commercial Off the Shelf Camera System Selection

In this project, three cameras are used. Two IR cameras (InfiRay and FLIR) and one regular RGB camera (CAM-720). Since the IR camera's video feed is not easily interpretable by human eyes, CAM-720 is used as a reference during studies. The CAM-720 will not be part of the final installed hardware in the vehicles. Two different IR cameras were selected: InfiRay and FLIR. The infiRary camera has an onboard object detector. The FLIR does not have any onboard processor, and it only consists of an IR camera. The following sections provide detailed information about the selected IR cameras.

InfiRay

Product Introduction: The InfiRay (Xsafe-II M6S) Automotive Infrared Camera is a miniaturized, automotive-grade product tailored to meet the demands of the automotive industry. It is designed for versatility and serves applications in before-market assembly, commercial vehicle after-market assembly, autonomous driving, and low-speed unmanned vehicles. Its robust design and advanced IR capabilities make it an excellent choice for enhancing safety and operational efficiency.

Figure 3.1: InfiRay (Xsafe-II M6S) Automotive Infrared Camera

Sensor Capabilities: The Infiray camera boasts a resolution of 640×512 pixels and operates in the 8 to 14 μm infrared band, delivering high-quality thermal imaging. With a wide field-of-view (FOV) of 48.7°, it provides comprehensive coverage for diverse applications. Its advanced features include automatic defrost, ensuring optimal functionality in temperatures below 7°C, and scene-based non-uniformity correction (NUC) for improved image accuracy. The camera operates efficiently under extreme conditions with a temperature range of -40°C to 85°C and an IP69K ingress protection rating for superior durability.

Performance and Integration: The InfiRay is equipped with a Fakra interface and supports external synchronization, facilitating seamless integration with automotive systems. It operates on a 12V DC power supply and consumes less than 5W, even with automatic defrost enabled, making it an energy-efficient solution. Compact and lightweight, the M6 has dimensions of 36mm x 36mm x 62mm and weighs approximately 90g, ensuring easy installation in space-constrained environments.

Applications: The InfiRay is ideal for autonomous driving, ADAS, and special-purpose vehicles. Its automotive-grade design, combined with exceptional imaging and durability, ensures reliable performance in a variety of automotive scenarios.

FLIR

Product Introduction: The FLIR Automotive Development Kit (ADK) is a next-generation thermal vision solution designed for ADAS and autonomous vehicles (AV) development. With its compact, rugged design and plug-and-play integration, the FLIR ADK enhances safety and decision-making in diverse driving environments. Equipped with the proven Boson™ thermal sensor, it provides reliable detection and classification capabilities, making it a critical component for modern automotive systems.

Figure 3.2: FLIR IR camera

Sensor Capabilities: The FLIR ADK is equipped with a 640 × 512 resolution uncooled VOx microbolometer sensor featuring a pixel pitch of 12 μm, operating within the long-wave infrared (LWIR) spectrum (8 to 14 μm). It offers various horizontal field-of-view (HFOV) options, including 24°, 32°, 50°, and 75°, to meet diverse operational needs. With thermal sensitivity of less than 50 mK and solar protection to prevent sensor damage, it guarantees optimal imaging performance in challenging conditions. The device accommodates selectable frame rates of 30 Hz, 60 Hz, and an optional 9 Hz mode for versatile data acquisition.

Performance and Integration: The FLIR ADK is designed for seamless integration with automotive systems, offering USB 2.0, GMSL, Ethernet, and FPD-Link interfaces. It supports software-selectable 16-bit raw or 8-bit compressed data formats and is compatible with NVIDIA®, Linux®, Windows®, ROS, and ADTF platforms. The camera requires 5V DC or 24V DC power with an optional heated window for all-weather operation, consuming up to 12W. Its compact dimensions (35mm x 40mm x 47mm) and lightweight design (100g) make it suitable for space-constrained installations.

Applications: The FLIR ADK enhances safety by reliably detecting pedestrians and other obstacles in cluttered environments. It is particularly effective in adverse lighting and weather conditions, such as fog, smoke, and headlight glare, making it an essential tool for ADAS and AV systems. The camera integrates effortlessly into existing platforms, allowing developers to quickly collect thermal data and implement classification analytics using the free FLIR Thermal Starter Dataset.

Comparison

InfiRay includes onboard object detection that comes packaged with the camera. Additionally, we connected the FLIR to an NVIDIA Orion via a USB port and used our preferred object detector to identify various objects. This set-up will be discussed in detail in the following chapters.

The NVIDIA Jetson Nano

The NVIDIA Jetson Nano, Figure 3.3, is a compact, energy-efficient computing platform designed for artificial intelligence (AI) and machine learning applications in edge devices. It offers powerful GPU capabilities suitable for running deep learning models in real time while maintaining a low power footprint. Due to its dedicated GPU, the Jetson Nano provides significantly better performance for AI workloads than platforms like the Raspberry Pi, making it an ideal choice for embedded systems in which computational resources are constrained.

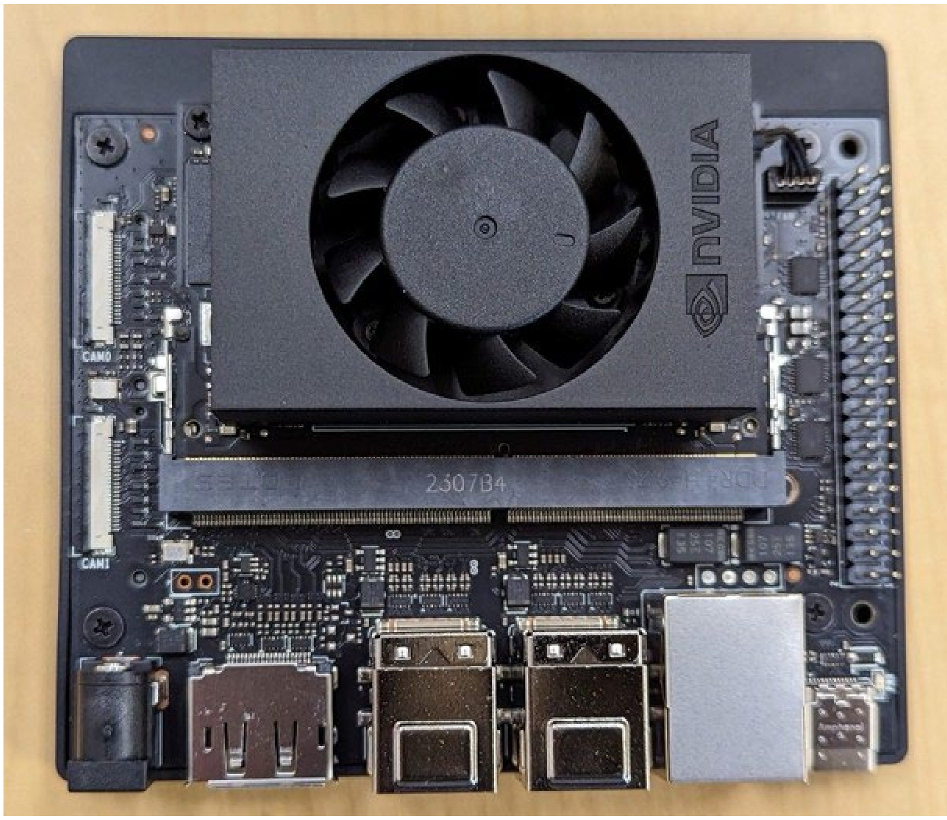

Figure 3.3: NVIDIA Jetson Orion

Chapter 4 Object Detection

The InfiRay camera features an onboard object detector that is pre-programmed into the device, and users can only use InfiRay's updates for the camera. In contrast, the FLIR camera outputs raw video format, allowing for the use of customized object detection algorithms. We employ a state-of-the-art deep learning-based method for processing the raw video. The FLIR camera was connected to an NVIDIA Orion via a USB port, and our preferred object detector was utilized to identify various objects. This testing approach is discussed in detail in the following sections.

Dataset

We utilized the Teledyne FLIR Thermal Dataset, which provides fully annotated thermal and visible spectrum frames captured from over-the-hood driving scenes to develop our object detection system. The dataset contains a total of 26,442 fully annotated frames with 520,000 bounding box annotations across 15 different object categories. For our application, we selected the most relevant object classes: `['person', 'bike', 'car', 'motor', 'bus', 'train', 'truck', 'dog', 'deer', 'other vehicle']`, while removing all unrelated categories to streamline training and improve detection accuracy.

You Only Look Once (YOLOv7)

The You Only Look Once (YOLOv7) model was selected for its state-of-the-art performance in real-time object detection at the time of implementation [5]. YOLOv7 offers balanced architecture designed to deliver high detection accuracy while maintaining efficiency, making it suitable for real-time object detection on resource-constrained environments. Of the variants of YOLOv7 available, we initially implemented YOLOv7-tiny. This variant is the most lightweight and designed for environments with limited computational resources. This model was trained on our customized IR dataset and evaluated on both validation data and our in-house recorded dataset, demonstrating robust accuracy. However, achieving real-time performance on the low-power NVIDIA Jetson Nano required further optimization. YOLOv7-tiny was implemented with FLIR cameras.

Enhancing Real-Time Performance on Jetson Nano

To overcome the inference speed limitations of the NVIDIA Jetson Nano and to meet real-time application requirements, we implemented and evaluated the following optimization techniques:

Model scaling: The model size was optimized to align with the computational constraints of the Jetson Nano by carefully adjusting its structural parameters. This optimization process involved reducing both the depth and the width of the network, thereby decreasing the number of layers and neurons per layer. By doing so, we were able to significantly reduce the computational complexity, ensuring efficient processing on the Jetson Nano's limited hardware resources.

Quantization: Applied post-training quantization to reduce numerical precision in the model's weights and activations, significantly decreasing computational overhead while maintaining acceptable accuracy.

Inference acceleration: NVIDIA TensorRT, a deep learning inference optimizer was employed to enhance throughput and reduce latency during model inference. TensorRT involves optimization techniques, such as layer fusion and GPU specific kernel tuning. These optimizations significantly improved fps for the FLIR camera.

These optimization techniques collectively improved the FLIR system's performance, achieving real-time processing requirements while accuracy remained at acceptable levels for the target application.

Extension to Jetson Orin Nano

Building on the success of our optimization efforts with the Jetson Nano, we expanded our experiments to its successor, the NVIDIA Jetson Orin Nano. This hardware provided enhanced computational power, allowing for improved real-time inference and greater scalability. Taking advantage of the increased computational resources, we deployed the full YOLOv7 model instead of the YOLOv7-tiny previously implemented on the Jetson Nano. This transition resulted in significantly better detection accuracy and robustness. To further optimize real-time performance, we applied the same optimization techniques, including model scaling, quantization, and inference acceleration, with NVIDIA TensorRT. The YOLOv7 optimized model deployed on the Jetson Orin Nano achieved over 60fps in inference speed, meeting the real-time application requirements.

Table 4.1: Overall performance of Milesight

Board	**YOLOv7-tiny**	**YOLOv7-tiny-optimized**	**YOLOv7**	**YOLOv7-optimized**
Jetson Nano	7.5fps	13 fps	1.2 fps	-
w/ TensorRT	13 fps	**24 fps (deployed on Jetson Nano)**	3 fps	-
Jetson Orin Nano	38 fps	47 fps	12.5 fps	34 fps
w/ TensorRT	-	90 fps	30 fps	**62 fps (deployed on Jetson Orin nano)**

Chapter 5 Field Tests and Results

Test setup

A test bench, as shown in Figure 5.1, was prepared for data gathering and hardware evaluation. The test bench allowed researchers to place the three cameras, FLIR, InfiRay, and CAM-720, side-by-side to expose them to the same lightning and weather conditions. The test bench was installed on an SUV, which drove in various places and conditions, including the city, the road, at night, during the day, and in fog. A regular RGB camera (CAM-720) with night vision was included in the setup as a reference. We drove more than 1,000 miles to collect data, and the final dataset includes around 200 miles of severe weather conditions.

Figure 5.1: Camera setup including FLIR, InfiRay, and CAM-720

We present some sample data collected in various conditions. The data collection route is shown in Figure 5.2. Most of the fog data was collected around San Francisco and Pacifica, CA. The data were collected at all times of the day to create a balanced dataset that included as many environmental variations as possible. We also tested the IR cameras in simulated super-dense fog and report on these results in the following sections. Please note, all CAM-720 frame samples are mirrored. This mirroring does not affect the interpretation, detection, or final system setup.

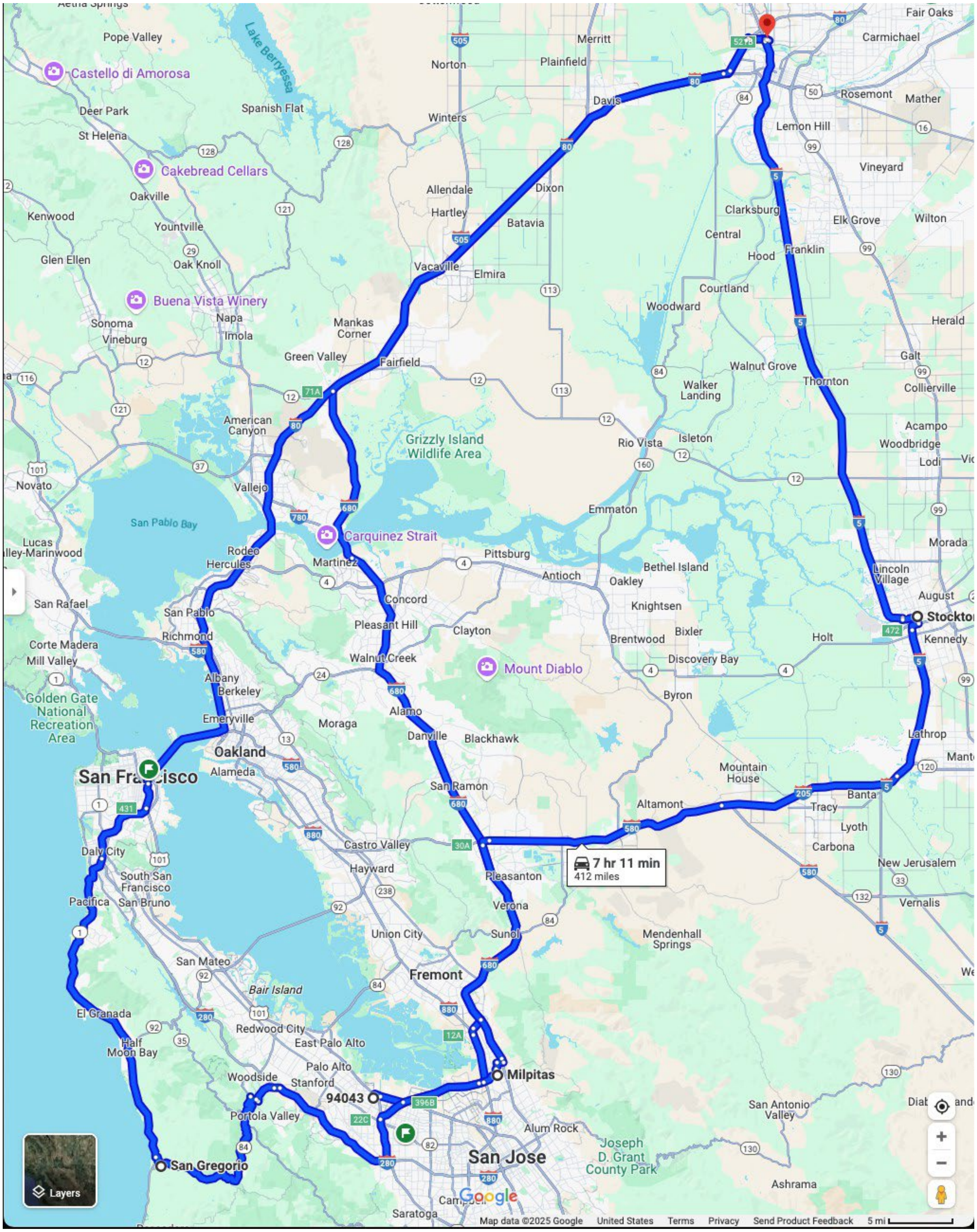

Figure 5.2: Data collection route map. Map image courtesy of Google Maps

Clear Day

These data were collected to evaluate the performance of cameras under normal visibility conditions. The vehicle speed ranged from 0 to 70 mph. Data were also gathered at various times, including early morning, noon, and afternoon, and other factors, such as sun glare, were also considered.

CAM-720 Sample

The CAM-720 operates well during the day as shown in Figure 5.3.

Figure 5.3: Sample frame from CAM-720 during daylight

FLIR IR Camera Sample

Figure 5.4 shows the same frame captured by the FLIR camera at the same timestamp. The red brackets indicate detected vehicles, and the green brackets represent detected pedestrians.

Figure 5.4: FLIR sample frame during daylight

InfiRay IR Camera Sample

Figure 5.5 shows the same frame captured by the InfiRay camera at the same timestamp. In Figure 5.5, the detected objects are boxed. As mentioned, the InfiRay has an onboard object detector.

Figure 5.5: InfiRay sample frame during daylight

Clear Night

These data were collected to evaluate the performance of the cameras under typical nighttime visibility conditions. The vehicle speed ranged from 0 mph to 70 mph. Data were also collected at various times and conditions, such as with or without streetlights and with oncoming traffic. Additionally, the cameras feature night vision, resulting in images appearing in black and white for improved visibility.

CAM-720 Sample

The CAM-720 performs well at night as shown in Figures 5.6 and 5.7. The CAM-720 night vision feature activates automatically in low-light conditions for better visibility. However, while the RGB camera includes this functionality, we found that it is ineffective during severe weather conditions.

Figure 5.6: Sample frame from CAM-720 at night with night vision on

Figure 5.7: Sample frame from CAM-720 at night with night vision off

FLIR IR Camera Sample

Figure 5.8 displays the same frame captured by the FLIR camera at the identical timestamp. The red brackets show detected vehicles. While in Figure 5.6, the glare from the headlights of oncoming traffic significantly impacts visibility with CAM-720, this effect is not noticeable in the FLIR frame as the object detector successfully identifies the approaching vehicles. Figure 5.8 shows the FLIR performance during traveling at 65 mph, and Figure 5.9 depicts the camera's performance while the vehicle is stationary.

Figure 5.8: FLIR sample frame at night with night vision on

Figure 5.9: FLIR sample frame at night with night vision off

InfiRay IR Camera Sample

Figure 5.10 shows the same frame captured by the InfiRay camera at the same timestamp. The box indicates the detected vehicles. While, as seen in Figure 5.6, the glare from the headlights of the oncoming traffic dramatically affects the visibility of the CAM-720, this effect is not visible in the InfiRay frame. Instead, the object detector detects the oncoming vehicles. Figure 5.10 shows the InfiRay performance during traveling at 65 mph, and Figure 5.11 depicts the performance while the vehicle is stationary.

Figure 5.10: InfiRay sample frame at night with night vision on

Figure 5.11: InfiRay sample frame at night with night vision off

Foggy Day

These data were collected to evaluate the performance of cameras in foggy weather with low visibility. The vehicle speed ranged from 0 mph to 55 mph. Data were also collected at various times and conditions.

CAM-720 Sample

The CAM-720 performs poorly in foggy conditions as shown in Figures 5.12 and 5.13. The image appears blurry, and with heavier fog and rain, detecting objects in the frame becomes impossible to distinguish. As seen in Figure 5.13, since the cameras are mounted outside the vehicle and due to the fog and humidity, water droplets form on the camera lens, significantly reducing visibility.

Figure 5.12: Sample frame from CAM-720 during daytime fog

Figure 5.13: Sample frame from CAM-720 during daytime fog at low speed

FLIR IR Camera Sample

Under foggy conditions, the IR camera performs normally as shown in Figures 5.14 and 5.15. The fog, humidity, and water droplets do not affect the performance of the FLIR camera. As shown in both figures, the camera remains able to detect vehicles on the road.

Figure 5.14: FLIR sample frame during daytime fog

Figure 5.15: FLIR sample frame during daytime fog at low speed

InfiRay IR Camera Sample

Like the FLIR camera, the InfiRay operates effectively under foggy weather conditions. The camera can detect vehicles on the road when it is stationary and while moving at 35 mph (Figures 5.16 and 5.17).

Figure 5.16: InfiRay sample frame during daytime fog

Figure 5.17: InfiRay sample frame in fog during daytime at low speed

Foggy Night

These data were collected to evaluate the performance of the cameras in foggy weather with low visibility and at nighttime. The vehicle speed ranged from 0 mph to 50 mph.

CAM-720 Sample

The CAM-720 performs poorly as shown in Figures 5.18 to 5.20. The images appear blurry, and detecting objects in the frame becomes impossible in heavier fog and rain. Additionally, light scattering worsens due to droplets on the camera lens. Figure 5.18 presents a sample from the CAM-720 on a foggy night. Furthermore, Figures 5.19 and 5.20 demonstrate that the light from oncoming traffic makes it impossible to detect any objects in the frame.

Figure 5.18: Sample frame from CAM-720 in fog at night with night vision off

Figure 5.19: Sample frame from CAM-720 in fog at night with night vision on

Figure 5.20: Sample frame from CAM-720 in fog at night with night vision on with multiple vehicles on the road

FLIR IR Camera Sample

The FLIR camera performs normally as shown in Figures 5.21 to 5.23. Fog, humidity, and water droplets do not affect the performance of the FLIR camera. As shown in all selected frames, the camera can detect vehicles on the road whether they are in the same lane, oncoming, or from the side.

Figure 5.21: FLIR sample frame in fog at night

Figure 5.22: FLIR sample frame in fog at night with night vision on

Figure 5.23: FLIR sample frame in fog at night with multiple vehicles on the road

InfiRay IR Camera Sample

The InfiRay camera also performs normally (Figures 5.24 to 5.26). On foggy nights, it may lose some objects, which, overall, does not indicate that it is underperforming compared to the FLIR. In the next chapter, we will compare these two IR cameras in depth.

Figure 5.24: InfiRay sample frame in fog at night

Figure 5.25: InfiRay sample frame in fog at night with night vision on

Figure 5.26: InfiRay sample frame in fog at night with multiple vehicles on the road

Artificial Fog

To test the performance and effectiveness of the camera setup, AHMCT researchers performed an adverse weather test using artificial fog created by a fog machine placed inside a 10 X 20 ft tent. The fog density was monitored and recorded at all stages. During all stages, the performance of the InfiRay and FLIR cameras remained consistent. When conditions varied from clear to very dense fog, the camera view on FLIR and InfiRay remained able to distinguish objects and humans in the scene. The YOLO-based object detector was also successfully tested. The figures in the following sections are screenshots from the dense fog situation. Although nothing is visible in the RGB image, the scene is clearly visible on both FLIR and InfiRay cameras, and objects, including the parked vehicle and human, are detected in the background.

CAM-720 Sample

The CAM-720 works fine when the fog is not dense, but it fails as soon as the fog density increases (Figures 5.27 and 5.28).

Figure 5.27: Sample frame from CAM-720 with light artificial fog

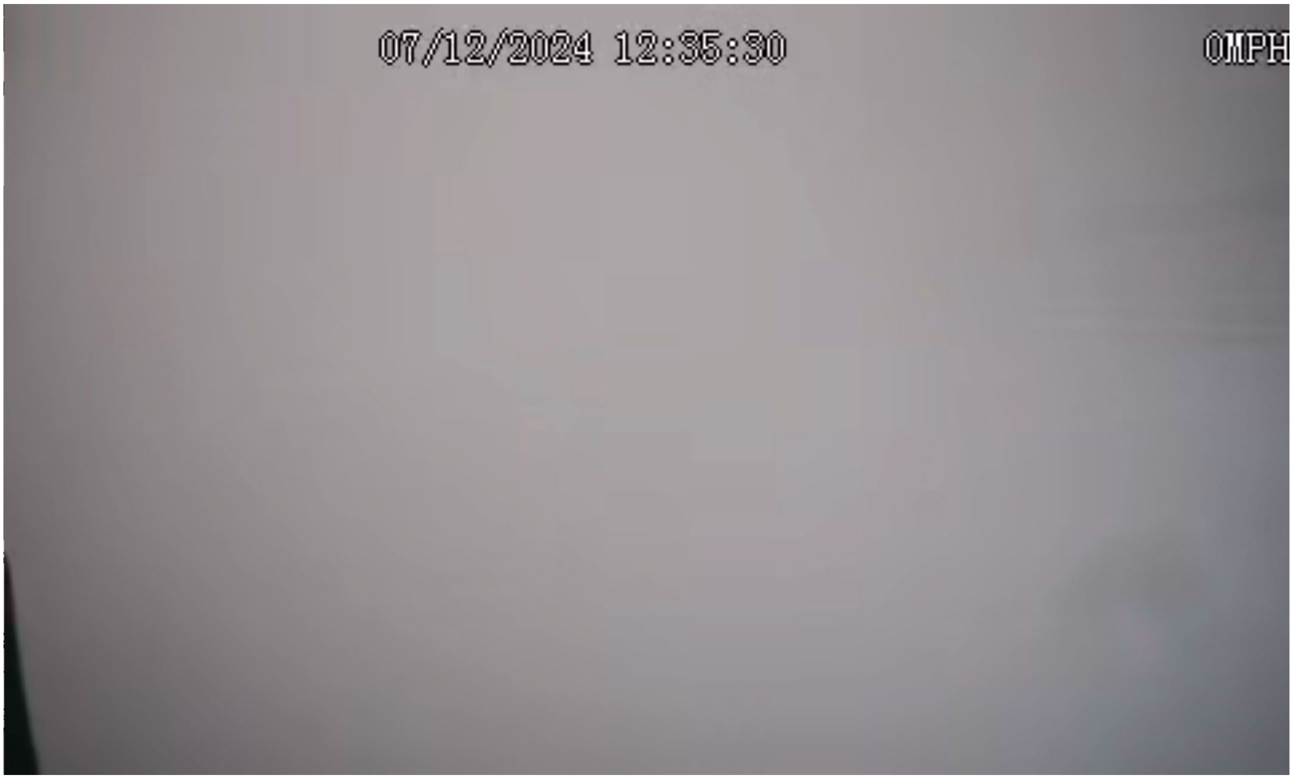

Figure 5.28: Sample frame from CAM-720 with dense artificial fog

FLIR IR Camera Sample

As shown in Figures 5.29 and 5.30, the FLIR camera works normally, even in very dense fog.

Figure 5.29: FLIR sample frame with light artificial fog

Figure 5.30: FLIR sample frame with dense artificial fog

InfiRay IR Camera Sample

As shown in Figures 5.31 and 5.32, the InfiRay camera works normally, even in very dense fog.

Figure 5.31: InfiRay sample frame with light artificial fog

Figure 5.32: InfiRay sample frame with dense artificial fog

Results:

This section analyzes object detection performance using IR and regular RGB cameras under various environmental conditions. The analysis is based on the Final Label Summary data, which categorizes InfiRay, FLIR, and CAM-720 detections across different scenarios: Cloud-Day, Day, Foggy-Day, Foggy-Night, and Night. The objective was to assess detection accuracy and missed detections, providing insights for improving ADAS performance in challenging visibility conditions.

Table 5.1: Camera performance for object detection in normal weather conditions

Item Detected	FLIR-Day	InfiRay-Day	CAM-Day	FLIR-Cloudy Day	InfiRay-Cloudy Day	CAM-Cloudy Day	FLIR-Night	InfiRay-Night	CAM-Night
Detected Vehicles	1132	695	324	1772	1362	1333	2945	1293	447
Vehicles	1410	1436	1255	2255	1563	2063	4009	3277	1451
Detected Bicyclists	4	4	0	0	0	0	0	0	0
Bicyclists	5	4	4	0	0	0	0	0	0
Detected Pedestrian	0	0	4	0	0	4	4	2	3
Pedestrian	0	0	0	0	0	0	4	3	2
Detected Animal	0	0	0	0	0	0	0	2	0
Animal	0	0	0	0	0	0	0	2	0

The numbers in Table 5.1 were pulled from randomly selected frames during daylight, clear night, and cloudy day for all three cameras: InfiRay, FLIR, and CAM-720. The dataset includes object detection counts for various sensors and environmental conditions. Total Images analyzed:

- Day: 1,200 images (400 per camera)

- Night: 3,000 images (1,000 per camera)
- Foggy-Day: 900 images (300 per camera)

Table 5.2: Camera performance for object detection in severe weather conditions

Item Detected	FLIR-Foggy Day	InfiRay-Foggy Day	CAM-Foggy Day	FLIR-Foggy Night	InfiRay-Foggy Night	CAM-Foggy Night
Detected Vehicles	624	478	432	2435	1567	665
Vehicles	872	819	1060	3131	2946	2059
Detected Bicyclists	1	1	0	6	3	6
Bicyclists	1	1	1	7	5	0
Detected Pedestrian	34	43	3	69	46	10
Pedestrian	82	82	83	88	72	24
Detected Animal	0	0	0	0	0	0
Animal	0	0	0	0	1	1

The numbers in Table 5.2 were pulled from randomly selected frames during foggy day and foggy night. The dataset includes object detection counts for various sensors and environmental conditions. Total Images analyzed:

- Foggy-Day: 1500 images (500 per camera)
- Foggy-Night: 4500 images (1500 per camera)

The objects in Tables 5.1 and 5.2 include vehicles, pedestrians, animals, and bicyclists. As previously mentioned, the InfiRay and FLIR cameras have object detection enabled while recording. The onboard object detector results for InfiRay camera and customized object detector for FLIR are reported in both tables for different weather conditions.

Discussion

Referring to Table 5.1, the number of annotated vehicles for each camera is presented during clear daylight. The number of vehicles that are visible by human eyes for annotation in the extracted frames from the FLIR camera is 1,410, and for the InfiRay is 1,436, which is almost in the same range. But for the CAM-720, the number is dropped to 1,255. It may be counter-intuitive that vehicles are more visible with an infrared camera than a CAM-720 in the daylight. However when considering different contributing factors, like direct sunlight in the camera lens, there might have been imbalance in the image brightness, thereby resulting in poor performance of the CAM-720. Direct sunlight does not affect visibility of objects for IR cameras. Comparing data from the IR cameras in both Table 5.1 and 5.2, we see that FLIR has a slightly better performance in terms of image quality. More objects are visible in FLIR images. Both IR cameras outperform the CAM-720, especially for pedestrian detection during foggy nights.

Comparing the performance of the object detection algorithms applied for both IR cameras indicates the FLIR performs better. For example, under the daylight condition, 1,132 vehicles were detected by FLIR camera while the onboard object detector on the InifiRay camera detected 695 vehicles. The number of vehicles annotated by humans for FLIR is 1,410 and 1,436 for InfiRay. This difference translates to almost 80% true positive for FLIR and 48% true positive rate for InfiRay. FLIR also has the advantage of utilizing a state-of-the-art object detector that could be improved and customized in the future. Table 5.3 compares some advantages and disadvantages of the FLIR and InfiRay cameras.

Table 5.3: Infrared camera comparison

IR Camera	Advantages	Disadvantages
FLIR	Image quality, customizable object detector	Needs extra hardware for operating (NVIDIA Orion)
InfiRay	Onboard object detector	Not able to customize object detector

Chapter 6 Survey Results

A survey was conducted among tow track and snowplow drivers in both Districts 3 and 4. The results of the survey are presented in Table 6.1. The survey evaluates the performance and usability of an IR camera system across various conditions, as reported by six operators. The analysis includes feedback on usability during rain, fog, and nighttime as well as ratings for overall satisfaction, safety improvement, display quality, and system reliability. Below are the key findings:

1. Usability Across Conditions:
   - Operators rated the system highly usable at night (average: 3.62/5) and during fog (average: 3.62/5).
   - Usability in rain received slightly lower ratings (average: 3.2/5).

2. Overall Satisfaction and Safety Improvement:
   - Overall satisfaction averaged 3.25 on a 5-point scale, showcasing strong approval of the system's performance.
   - Safety improvement was rated slightly lower at 2.75 on a 5-point scale, suggesting the system positively impacts safety but could benefit from further enhancements.

3. Display Quality and System Reliability:
   - Display quality received an average rating of 3.5 on a 5-point scale, indicating clarity and effectiveness in visual representation.
   - System reliability was rated at 2.87 on a 5-point scale on average, reflecting dependable operation with minor potential improvements.

4. Beneficial Situations:
   - Operators highlighted the system's effectiveness in low-visibility scenarios, such as nighttime operations, poor lighting, and challenging weather conditions.

5. Challenges Faced:
   - Common challenges included screen quality due to the lack of an auto brightness feature, which was later addressed by updating the monitors to ones that were capable of auto brightness.

6. Suggestions for Improvement:
   - Respondents suggested relocation, screen quality improvement.

Table 6.1: Survey Responses from Districts 3 and 4 Operators

Respondent ID	Role	Tried on Caltrans Vehicle	Usefulness : Rain	Usefulness : Fog	Usefulness : Night	Overall Satisfaction	Safety Improvement	Displa y Quality	System Reliabilit y	Beneficial Situations	Challenges Faced	Other Suggestions
1	Operator	Yes	5	5	5	4	4	5	4	It is only good for nighttime driving	None	None
2	Operator	Yes	1	1	1	1	1	1	1	Camera is a distraction for operators	It's useless in the work we do	Remove from wrecker
3	Operator	Yes	3	3	3	3	2	3	2	Low visibility. Night driving. Heavy fog.	None	None
4	Operator	Yes	4	3	4	4	4	5	4	One Situation it helped was in seeing homeless and pedestrians on the roadways/streets and sidewalks before you physically see them	It was a little distracting also while parking I would look up at the IR screen instead of the reverse camera	It does not pick up motorcycle riders
5	Operator	Yes	1	4	4	3	3	4	3	Nighttime	Hard to see in rain	Needs to be clearer in the rain
6	Operator	Yes	4	5	5	5	3	4	4	Nighttime	None	None
7	Operator	Yes	4	4	4	2	2	3	3	Inclement weather and nighttime	Location of the unit	Better location of the unit
8	Operator	Yes	4	4	3	4	3	3	2	In low light and rain	The image is blurry and slow to react	Brightness adjustment and different color image
			Min: 1 Max: 5	Min: 1 Max: 5	Min: 1 Max: 5	Min: 1 Max: 5	Min: 1 Max: 5	Min: 1 Max: 5	Min: 1 Max: 5			
Average			**3.5**	**3.625**	**3.625**	**3.25**	**2.75**	**3.5**	**2.875**	**Nighttime**	**Location and screen quality improvement**	**Location and screen quality improvement**

Chapter 7 Conclusions and Future Research

This study demonstrates the potential of IR camera systems to enhance driver assistance and safety for emergency and maintenance vehicles under severe weather conditions. Through a combination of controlled and real-world testing, IR cameras were shown to be reliable in detecting obstacles, such as pedestrians, vehicles, and animals, even in environments where traditional driver assistance technologies, like optical cameras and LiDAR, fail. The survey results from vehicle operators further affirm the practical utility of these systems, particularly in low-visibility conditions, such as fog, rain, and nighttime operations.

The findings highlight the advantages of integrating COTS IR camera systems into existing fleet vehicles. The ability of IR cameras to seamlessly integrate with current fleet setups, coupled with cost-effective implementation strategies, makes them an accessible and scalable solution for transportation departments. While minor improvements, such as display quality and system reliability, were suggested, the overall operator feedback indicates strong satisfaction with the technology and its positive impact on safety and operational efficiency, especially during severe weather conditions like fog and rain.

Future research should focus on the large-scale deployment of IR camera systems across diverse operational environments to validate these findings and quantify the reduction in collision rates and response times. Efforts to enhance user experience, including optimizing screen quality and addressing operator suggestions, could further improve the technology's effectiveness. These next steps will solidify the role of IR cameras as a critical component of ADAS, ensuring safer and more efficient roadway operations during extreme weather conditions.

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