Cost-Effective System for Rural Roadway Traffic, Surface Conditions and Weather Conditions Monitoring

FINAL PROJECT REPORT

by

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16. Abstract

This report presents the Mobile Unit for Sensing Traffic (MUST) project, which addresses the critical need for comprehensive traffic data in tribal and rural areas that often suffer from disproportionately high rates of traffic incidents due to limited infrastructure and resources. By implementing a low-cost, user-friendly data collection system, the MUST project aimed to provide real-time traffic information to significantly enhance traffic safety. The pilot installation in Yakama Nation, Washington, at a high-traffic intersection known for frequent accidents, marks a crucial step in this initiative. Collaboration with the Yakama Nation's Tribal Traffic Safety Coordinator and Yakama Power ensured the successful installation and operation of the sensor on a strategically selected telephone pole. Equipped with advanced machine learning technology, the MUST system collects detailed data on traffic flow, road surface conditions, and environmental factors such as temperature and humidity, visualized through a sophisticated dashboard for real-time monitoring and data-driven decision-making. This system allows for the identification of high-risk areas and the implementation of targeted safety measures, such as improved signage and road maintenance, while addressing specific concerns like pedestrian safety, visibility issues due to heavy fog, and speeding. By providing a robust dataset previously unavailable, the MUST project supports the Yakama Nation's efforts to understand and mitigate traffic safety issues, ultimately enhancing the overall safety and quality of life for the community. This pilot project serves as a model for other tribal and rural areas looking to leverage advanced technology to improve their transportation safety infrastructure.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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EXECUTIVE SUMMARY

This project addresses the critical need for comprehensive traffic data in tribal and rural areas, which often suffer from disproportionately high rates of traffic incidents due to limited infrastructure and resources. By implementing a low-cost, user-friendly data collection system, this project aimed to provide real-time traffic information that can significantly enhance traffic safety. The pilot installation in Yakama Nation, Washington, represents a crucial step in this initiative. The chosen location, an intersection at Larue Road and Highway 97 in Toppenish, is known for its high traffic volume and frequent accidents, making it an ideal candidate for the deployment of the MUST (Mobile Unit for Sensing Traffic) sensor. This project involved close collaboration with the Yakama Nation's Tribal Traffic Safety Coordinator and Yakama Power, ensuring the successful installation and operation of the sensor on a strategically selected telephone pole.

The MUST system, equipped with advanced machine learning technology, provides detailed data on traffic flow, road surface conditions, and environmental factors such as temperature and humidity. This data is visualized and managed through a sophisticated dashboard, enabling real-time monitoring and data-driven decision-making. The real-time insights offered by the MUST system allow for the identification of high-risk areas and the implementation of targeted safety measures, such as improved signage and road maintenance. Moreover, the continuous data collection helps address specific safety concerns, including pedestrian safety, visibility issues due to heavy fog, and driver behavior problems like speeding. By providing a robust dataset that was previously unavailable, the MUST project supports the Yakama Nation’s goal of understanding and mitigating traffic safety issues, ultimately enhancing the overall safety and quality of life for the community. This pilot project serves as a model for other tribal and rural areas seeking to leverage advanced technology to improve their transportation safety infrastructure.

CHAPTER 1. INTRODUCTION

1.1. Research Background

Tribal and rural areas often face significant challenges in terms of traffic safety due to a distinct lack of data available for use by practitioners. This gap in data collection and analysis hampers the ability of engineers and traffic safety officials to effectively monitor and address traffic safety issues. To bridge this gap, our project aims to implement a low-cost and user-friendly data collection system known as the Mobile Unit for Sensing Traffic (MUST). This innovative solution is designed to provide comprehensive and real-time traffic data, thereby enhancing traffic safety in these underserved areas.

Tribal and rural areas in the United States face unique challenges in terms of transportation safety. According to the Federal Highway Administration, traffic fatalities are disproportionately higher in rural areas compared to urban areas, and tribal lands often experience even higher rates (Federal, 2023). This is largely due to several factors including limited infrastructure, a lack of funding for road improvements, and inadequate data for traffic management and safety planning. These challenges are compounded by the vast and remote nature of many tribal lands, making it difficult to monitor and address safety concerns effectively.

The transportation safety issues in tribal areas are multi-faceted. A 2019 report by the National Highway Traffic Safety Administration (NHTSA) highlights that American Indians and Alaska Natives (AI/AN) have a motor vehicle death rate that is three times higher than the national average (National, 2020). Several contributing factors include:

- Roadway Conditions: Many roads in tribal areas are unpaved, poorly maintained, and lack basic safety features such as proper signage, lighting, and guardrails.
- Driver Behavior: Issues such as impaired driving, not using seat belts, and speeding are prevalent in many tribal areas.
- Emergency Response: The remote locations of many tribal communities result in longer response times for emergency services, exacerbating the severity of accidents.
- Funding and Resources: Tribes often lack the financial resources and technical expertise needed to implement comprehensive transportation safety programs.

In response to these challenges, federal initiatives such as the Tribal Transportation Program (TTP) and the Tribal Transportation Safety Fund (TTSF) have been established to provide funding and support for improving transportation infrastructure and safety in tribal areas. However, the lack of reliable and detailed traffic data remains a significant barrier to the effective implementation of safety measures.

1.2. Research Objectives

The primary objective of the Mobile Unit for Sensing Traffic (MUST) project is to enhance traffic safety in tribal and rural areas by developing and deploying a cost-effective, user-friendly data collection system capable of providing real-time, comprehensive traffic information. This project specifically aimed to address the significant gap in traffic data that hampers the ability of transportation planners and safety officials in these regions to monitor, analyze, and improve road safety conditions effectively.

Key to achieving this objective is the implementation of the MUST system, which utilizes advanced machine learning technology to gather detailed data on various traffic parameters, including vehicle counts, traffic flow, road surface conditions, and environmental factors such as humidity and temperature. The system’s deployment at a high-risk intersection in Yakama Nation, Washington, serves as a pilot to demonstrate its effectiveness and scalability for broader applications in similar regions.

The project also aimed to develop a sophisticated dashboard for data visualization and management, ensuring that the collected data is accessible and actionable for engineers, safety officials, and community members. By providing real-time insights into traffic conditions, the dashboard supports data-driven decision-making processes, enabling the identification of high-risk areas and the implementation of targeted safety interventions.

Another critical aspect of this research is to assess the impact of the MUST system on improving traffic safety outcomes in the Yakama Nation. This includes evaluating the effectiveness of the system in reducing traffic incidents, enhancing pedestrian safety, and mitigating the risks associated with adverse weather conditions and driver behavior issues. Additionally, the project seeks to explore the potential for integrating technologies and methodologies from related National Cooperative Highway Research Program (NCHRP) projects to further enhance the system’s capabilities.

Overall, the MUST project aimed to provide a scalable, effective solution for traffic data collection and safety improvement in tribal and rural areas, thereby contributing to the broader goal of reducing traffic-related fatalities and injuries in these underserved communities.

CHAPTER 2. LITERATURE REVIEW

2.1. Cooperative and Comprehensive Multi-Task Surveillance Sensing and Interaction System Empowered by Edge Artificial Intelligence

2.1.1. Historical Background

Roadside sensing systems have long been implemented for traffic monitoring, control, and enforcement. These systems historically relied on centralized traffic management centers (TMCs) to coordinate resources and manage data from various sensing technologies, such as inductive loops, magnetometers, microwave radars, LiDAR, ultrasound, and video detection systems (El Faouzi et al., 2011; Djahel et al., 2014).

2.1.2. Advantages and Challenges of TMC-Based Systems

TMCs aggregate and process data from diverse sources, enabling more accurate decision-making and enhanced services. However, they face challenges such as high overheads, delays caused by data transmission, and difficulties integrating heterogeneous data. The large volume of data from various sensors can overwhelm TMCs, making it hard to meet the ultra-fast response time requirements of advanced ITS applications (El Faouzi et al., 2011; Zhou et al., 2021).

2.1.3. Edge Computing Integration

Edge computing offers significant benefits for ITS, including low latency, high computational efficiency, reduced bandwidth usage, and enhanced privacy. By processing data locally, edge computing reduces the load on central servers and enables faster response times. This approach is particularly valuable for real-time applications such as connected and autonomous vehicles, real-time traffic surveillance, and short-term traffic prediction (Zhou et al., 2021; Ferdowsi et al., 2019).

2.1.4. Limitations of Current Systems

Despite the advantages of edge computing, resource constraints on edge devices pose a challenge, especially when deploying computationally intensive AI models. To address this, techniques such as deep neural network compression are employed to optimize performance on edge devices (Han et al., 2015).

2.1.5. Cooperative Perception

Most current roadside sensing systems deploy sensors for individual tasks, leading to inefficiencies. Cooperative perception, which involves fusing information from multiple sensors, can enhance accuracy and perception range. Research has explored multi-agent cooperative perception among connected vehicles and infrastructure-based cooperative perception using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication (Chen et al., 2017; Tsukada et al., 2020).

To address these challenges, the project proposed the COCO SENSOR system, which integrates edge computing and cooperative perception to create a comprehensive and efficient roadside sensing system. The system is designed to process data locally, share sensing results among different components, and reduce data redundancy, ultimately enhancing the effectiveness of ITS applications.

2.2. Machine Learning based Pedestrian Safety Analysis

It can be noted that most of the literature relies on traditional statistical modeling approaches to address pedestrian safety issues. Nevertheless, with the recent advent of Machine Learning, some researchers have started applying these latest approaches to this type of problem. In 2018, Ding developed a study to examine built environmental effects on the frequency of crashes involving automobiles and pedestrians by applying Multiple Additive Poisson Regression Trees (MAPRT), a Machine Learning approach based on decision trees. Using data from Seattle, Washington, the study helped to detect non-linear relationships between the built environment and pedestrian collisions frequency, confronting the linearity assumption frequently used in studies that use statistical models (Ma, 2021). Das applied in 2020 distinct Machine Learning techniques to classify pedestrian collision types (intended vs. untended, pedestrian at fault vs. motorist at fault) using pedestrian crashing data from two locations in Texas (Wang, 2021).These reference studies were essential for the development of our methodology applied specifically to fatal collisions, an unprecedented approach so far.

2.3. State of the Art and the Practice

Recognizing the needs to improve pedestrian safety and reduce pedestrian injury and fatality, the Federal Highway Administration (FHWA) published a guide documented scalable risk assessment methods for pedestrians and bicyclists (Tsukada, 2020). The guide provides guidance on the steps to estimate the exposure to risk of pedestrian and bicyclists, including determining uses of risk values, selecting geographic scale, selecting risk definition, selecting exposure measure, selecting analytical method to estimate exposure, using analytic method to estimate selected exposure measure, and calculating risk values.

In addition, the FHWA developed the guidebook summarizing the data-driven approaches for identifying high-risk location for pedestrian (Liu, 2024). However, despite the intention of the guidebooks to make general approaches that could suit most agencies with different analysis capabilities and resources. Through the research team's communication with tribal leaders and agencies, it is necessary to recognize that most agencies in the RITI communities do not have the practice to collect and manage pedestrian safety related data and lack the guidance of doing so. Without the practice of collecting necessary data and developing data-driven solutions, it is not easy for RITI communities to follow the approaches of such guidebooks. Besides, the uniqueness of roadway geometrics and operational characteristics, traffic characteristics, environmental conditions, and cultural and human behavior characteristics of RITI communities deserve unique data collection and assessment approaches in order to obtain accurate risk assessment results. These guidebooks are based on the classical Empirical Bayes safety performance function based approaches, while studies have suggested that machine learning based approaches could provide more insights from the multi-source pedestrian safety data (He 2011, Ma 2021, Tan 2008, Zhu 2015), as introduced in the previous section.

CHAPTER 3. MAIN PROJECT AND CORRESPONDING TECHNOLOGY DEVELOPMENT

3.1. Main Project

The Yakama Nation, located in south-central Washington, is one of the largest Native American tribes in the Pacific Northwest. The tribe's reservation spans over 1.3 million acres, encompassing a diverse landscape that includes agricultural lands, forests, and urban areas. The Yakama Nation faces numerous transportation safety challenges, particularly at key intersections and roadways that experience high traffic volumes and frequent incidents.

One of the most dangerous intersections on the Yakama Nation is at Larue Road and Highway 97 in Toppenish, WA. This intersection has been the site of numerous accidents, many of which involve semi-trucks and agricultural vehicles, both of which are common in the area due to its agricultural economy. Additionally, pedestrian safety is a significant concern, as many community members rely on walking for their daily activities.

Other notable safety concerns in the Yakama Nation include:

- Visibility Issues: The area is prone to heavy fog and low visibility, especially during the colder months, which increases the risk of accidents.
- Human Behavior: Speeding and failure to stop at stop signs are common issues, contributing to the high rate of traffic incidents.
- Road Surface Conditions: The roads are often in poor condition, with issues such as potholes and uneven surfaces that can be hazardous for drivers.

Given these challenges, there is a pressing need for a robust and effective data collection system that can provide real-time insights into traffic conditions and help inform safety interventions. The implementation of the MUST is aimed at addressing these needs by providing the Yakama Nation with a comprehensive tool for monitoring and improving transportation safety.

As part of our initial implementation, we chose to install the MUST sensor in Yakama Nation, a region that exemplifies the data challenges faced by many tribal areas. Our team has been in close contact with the Tribal Traffic Safety Coordinator, whose support has been instrumental in facilitating connections with other key entities required for the successful installation of the sensor. One of the critical partners in this effort has been Yakama Power, which assisted in identifying a suitable telephone pole for mounting the MUST sensor.

The installation site selected was an intersection at Larue Road and Highway 97 in Toppenish, WA. This location is known to be one of the most dangerous intersections in the area, making it an ideal candidate for the implementation of our sensor technology. By providing a robust dataset on this high-risk intersection, the Yakama Nation will be able to achieve a level of detail in traffic monitoring that was previously unattainable using classical methods. This data will be crucial for understanding and addressing the specific safety issues faced by the community.

To complement the sensor installation, our team has developed a sophisticated dashboard tailored for the MUST system. This dashboard is designed to provide real-time data visualization and management, making it easier for engineers and traffic safety officials to monitor and analyze traffic conditions. The dashboard is equipped to work seamlessly with the MUST sensor, which utilizes advanced machine learning technology to sense traffic flow, road surface conditions, and ambient data such as humidity and temperature.

The data collected by the MUST sensor can be visualized and managed through the dashboard, providing users with a comprehensive view of traffic conditions in real-time. This capability is particularly beneficial during colder months when road conditions can deteriorate rapidly, posing significant risks to travelers. By having access to real-time data, engineers can make informed decisions to improve safety measures and travelers can plan their routes more effectively.

3.1.1. Ongoing Data Collection and Analysis

Following the successful installation of the MUST sensor, our team has been actively collecting vital traffic data to support the implementation of targeted safety countermeasures. The data collection efforts focus on several key areas, including:

- Semi-trucks and Agricultural Vehicles: Monitoring the movement and behavior of large vehicles that are prevalent in the region.
- Pedestrian Safety: Collecting data on pedestrian traffic to identify high-risk areas and improve crosswalks and other pedestrian facilities.
- Heavy Fog and Low Visibility: Capturing environmental data to understand how adverse weather conditions impact traffic safety.
- Human Behavior: Analyzing driver behavior, such as speeding and failure to stop at stop signs, to identify patterns and implement corrective measures.

The ongoing data collection efforts are crucial for developing a comprehensive understanding of traffic conditions and safety issues in Yakama Nation. By continuously monitoring these variables, we can provide valuable insights that will inform the design and implementation of effective safety interventions.

3.1.2. Integration with NCHRP Projects

In addition to the core functionalities of the MUST system, we are also incorporating technologies and methodologies developed from our National Cooperative Highway Research Program (NCHRP) projects. These advanced technologies enhance the capabilities of the MUST system, enabling more accurate and detailed data collection and analysis. By leveraging the insights gained from NCHRP projects, we can further improve the effectiveness of the MUST system in addressing traffic safety issues in tribal and rural areas.

3.1.3. Benefits of the MUST System

The implementation of the MUST system in Yakama Nation offers numerous benefits to both engineers and travelers. Some of the key advantages include:

- Real-Time Traffic Information: Providing up-to-date information on traffic conditions, allowing travelers to make informed decisions about their routes.
- Traffic Counts and Road Surface Conditions: Offering detailed data on traffic volume and road conditions, which are essential for planning maintenance and improvement projects.
- Enhanced Safety During Adverse Weather: Monitoring environmental conditions to help travelers navigate safely during periods of heavy fog, low visibility, or other adverse weather conditions.
- Support for Engineering Improvements: Providing engineers with the data needed to design and implement effective safety interventions, ultimately reducing the risk of traffic incidents.

3.2. Cooperative and Comprehensive Multi-Task Surveillance Sensing and Interaction System Empowered by Edge Artificial Intelligence

3.2.1. Introduction

Modern transportation systems face significant challenges, including traffic congestion, accidents, and fatalities often caused by poor visibility and adverse road conditions. Over the past decade, advancements in sensing technologies have led to the integration of various sensors into intelligent transportation systems (ITS). These sensors, combined with advanced data processing algorithms and communication systems, have been applied to numerous transportation applications, significantly enhancing traffic safety, mobility, and environmental sustainability (Greer et al., 2018; El Faouzi et al., 2011).

Despite the potential of these technologies to revolutionize transportation systems, they introduce new challenges such as redundant sensors, high maintenance costs, and data explosion (Liu et al., 2023). Traditional ITS solutions often prioritize technological advancements over practical user needs, resulting in complex systems that do not fully address real-world problems faced by road users and traffic managers. This focus on cutting-edge technologies at the expense of user needs can lead to bloated and redundant sensing systems (Greer et al., 2018; El Faouzi et al., 2011).

To address these challenges, the concept of "Sensing as a Service" (SaaS) is proposed. SaaS aims to develop a user-oriented sensing system that effectively meets the core demands of traffic agencies. This concept is implemented in the Cooperative and Comprehensive Smart Edge Node for Sensing and OpeRation (COCO SENSOR) system. COCO SENSOR is designed to address key practical applications, including real-time vehicle counting and recognition, road-surface-condition classification, visibility estimation, and live communication among traffic controllers and road users

The COCO SENSOR system architecture is composed of four levels (see Figure 3-1):

- **Application Level**: Determines the needs of different users in various application scenarios, focusing on traffic status for transportation agencies and real-time safety warnings for road users.
- **Sensing Technologies Level**: Utilizes parallel computing to efficiently perform multiple sensing tasks to meet the needs defined at the application level.
- **Data Level**: Identifies the necessary data to support the sensing technologies.
- **Sensor Level**: Involves the sensors used to provide data inputs to the system.

These levels are interconnected through local and global communication systems, enabling comprehensive data collection and processing.

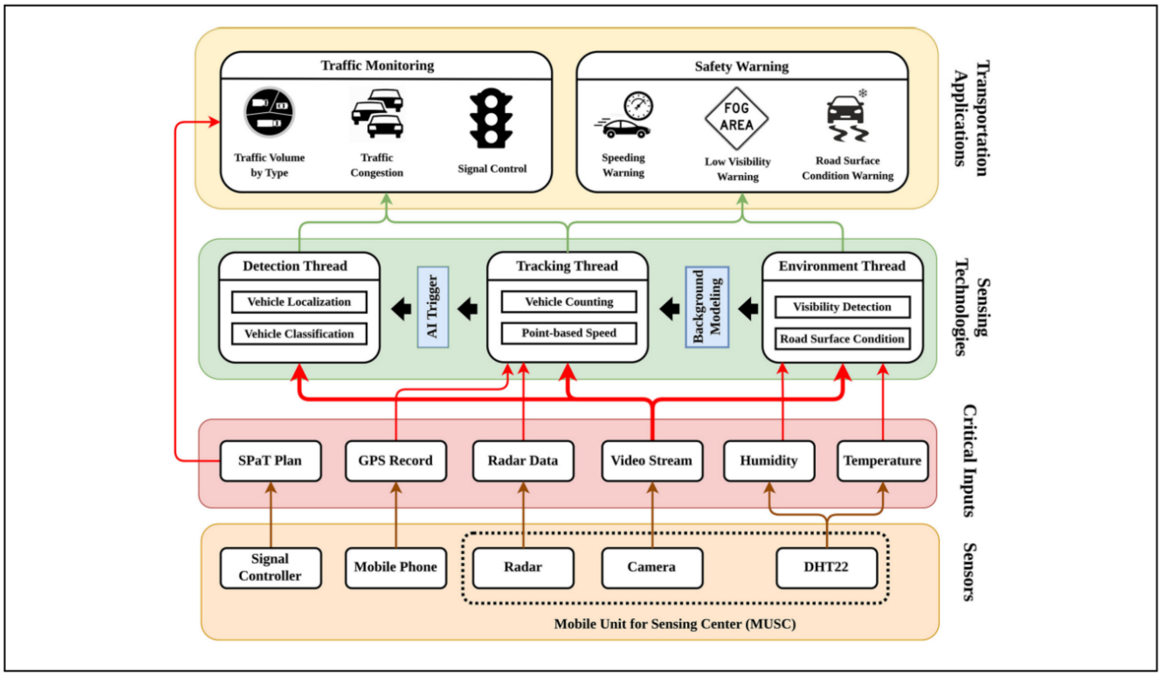

Figure 3-1 COCO SENSOR system architecture illustration (Liu et al., 2023)

One of the primary challenges in modern ITS is data explosion, where the vast amount of multi-source data generated from various sensors overwhelms data centers. Estimates suggest that all data centers globally can only handle approximately 20ZB, while approximately 850ZB were generated daily in 2021. To address this, COCO SENSOR integrates edge computing, processing raw data close to where it is generated. This approach significantly reduces the computational load on central servers, minimizes data transmission latency, and enhances the system's responsiveness (Zhou et al., 2019).

The COCO SENSOR system introduces a cooperative sensing mechanism that connects all the sensors in the system and shares the sensing results with all required users. This approach overcomes the inefficiencies of uncooperative sensing systems, which often lead to redundant data generation, increased costs, and decreased efficiency. Cooperative sensing ensures a comprehensive view of the traffic environment, enhancing perception accuracy and reliability (Chen et al., 2017; Tsukada et al., 2020).

To efficiently utilize limited computational resources on edge devices, COCO SENSOR employs parallel computation through three independent threads dedicated to environment sensing, vehicle tracking, and object detection. This parallelism enables the system to manage multiple sensing tasks simultaneously, ensuring efficient resource allocation and enhanced system robustness in real-world applications.

3.2.2. *Methodology*

The COCO SENSOR system employs advanced multi-task sensing technologies, parallel computing, and cooperative sensing mechanisms to address practical transportation applications. The architecture of the system is designed to maximize efficiency and accuracy while operating within the constraints of edge computing devices.

As shown in Figure 3-2. The COCO SENSOR system architecture is divided into three parallel threads to handle different sensing tasks: the environment thread, the tracking thread, and the object-detection thread. This division ensures efficient resource allocation and robust performance in real-world applications.

The environment thread is responsible for visibility detection and road-surface-condition classification. It includes the following processes:

- **Image Dehaze and Visibility Detection:** The dehaze algorithm estimates and removes haze from the input video stream, enhancing visibility and producing haze-free video.
- **Road-Mask Extraction:** The method integrates contour detection and motion detection to generate road masks. Contour detection uses the Canny edge-detection algorithm (Canny, 1986) to identify object contours, while motion detection tracks moving objects to extract regions of interest. These methods are combined using the cosine similarity method to enhance accuracy.

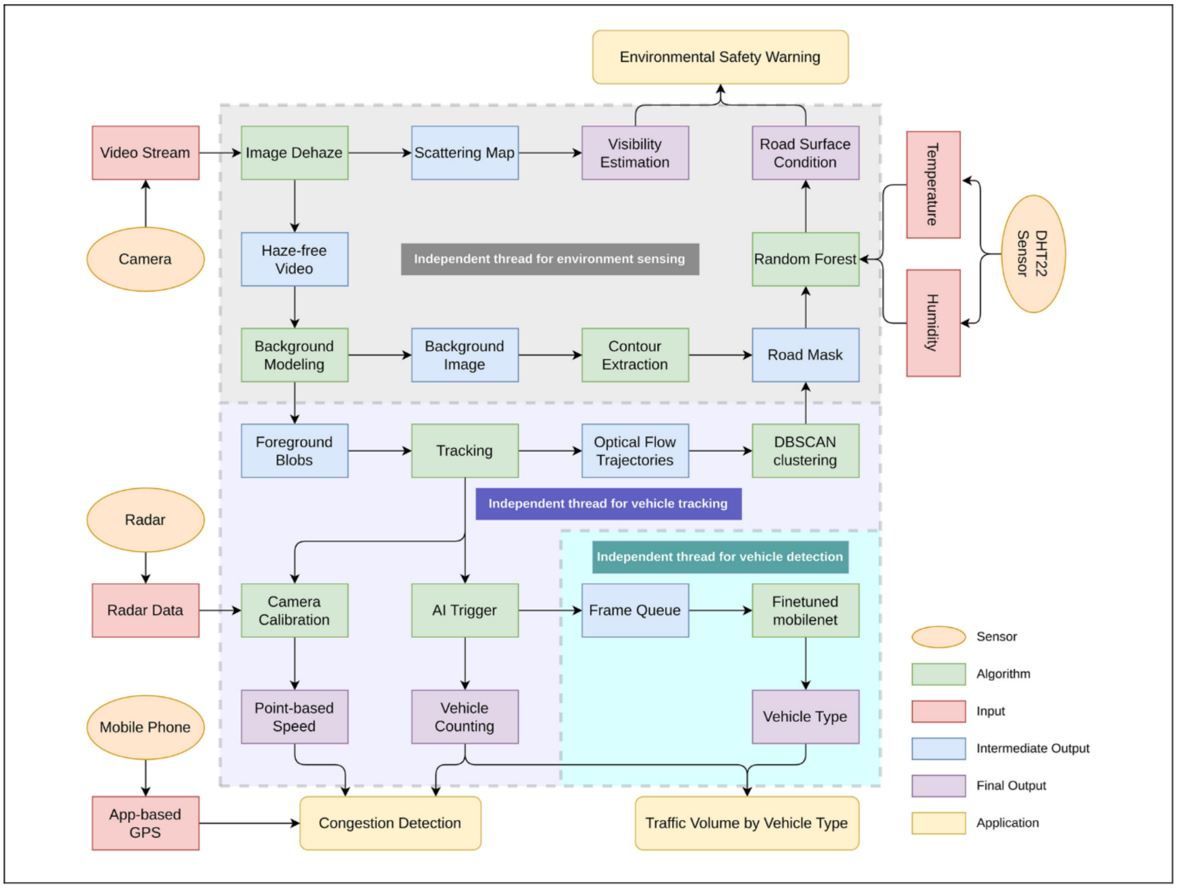

Figure 3-2 Sensing technologies architecture

The tracking thread connects different sensing tasks and manages data flow within the system. It includes:

- **Vehicle Tracking and Traffic Volume Counting:** Background modeling and the SORT algorithm track moving objects in the region of interest, extracting and storing information in a global variable queue *QQ*Q. The MobileNet V2 classifier then classifies road users and counts traffic volume by vehicle type (Sandler et al., 2018)

- **Radar Cooperative Camera Calibration:** To address the challenges of speed measurement, COCO SENSOR integrates radar sensors with cameras for calibration. This method converts 2D image coordinates to 3D real-world coordinates, enabling accurate lane-based speed measurement without the need for physical calibration objects in the roadway.

The object-detection thread processes selected video frames to detect and classify objects. It includes:

Object Detection Model: The MobileNet V2 and SSD models are used for object detection on limited IoT devices, pre-trained with the COCO dataset and fine-tuned with the MIO-TCD dataset for specific transportation-agent detection.

The COCO SENSOR system includes a sophisticated communication system designed to synchronize information among COCO SENSOR units, signal controllers, and user devices through Wi-Fi or cellular networks. This system is essential for real-time data dissemination and interaction, ensuring that traffic information and warnings are efficiently communicated to the relevant parties.

The communication system of COCO SENSOR can be divided into two main parts:

Interaction with Signal Controllers: The communication between COCO SENSOR and the signal controllers is facilitated through either a cable connection or a local wireless network. The system captures real-time signal phase and timing (SPaT) information from the controllers using the National Transportation Communications for ITS Protocol (NTCIP) standard. This information is then stored in a buffer and can be accessed by the COCO SENSOR system for further processing.

Interaction with User Devices: The system broadcasts SPaT information and sensing data to user devices, such as cell phones and wearable devices, using the COCO cooperative user application. This application enables users to receive real-time traffic updates and safety warnings. Additionally, COCO SENSOR integrates an independent thread for handling requests and messages generated by roadway users, such as crossing requests or accident notifications.

The communication algorithms are designed to handle various types of data interactions:

Data Transmission: The system transmits pedestrian information and receives waiting time data for each phase from the signal controller. This data exchange ensures that both the COCO SENSOR system and the signal controller are synchronized, providing accurate and timely traffic management information.

Data Broadcasting: The SPaT and sensing data are broadcast to user devices, enabling real-time updates on traffic conditions. This broadcasting mechanism ensures that users receive the most current information, improving situational awareness and safety.

User Requests and Messages: The system is capable of processing user-generated requests and messages. For instance, if a user sends a crossing request or reports an accident, the system can handle these inputs and respond appropriately, enhancing the overall interactivity and responsiveness of the traffic management system.

Figure 3-3 illustrates the detailed communication scheme, highlighting the synchronization between COCO SENSOR units, signal controllers, and user devices.

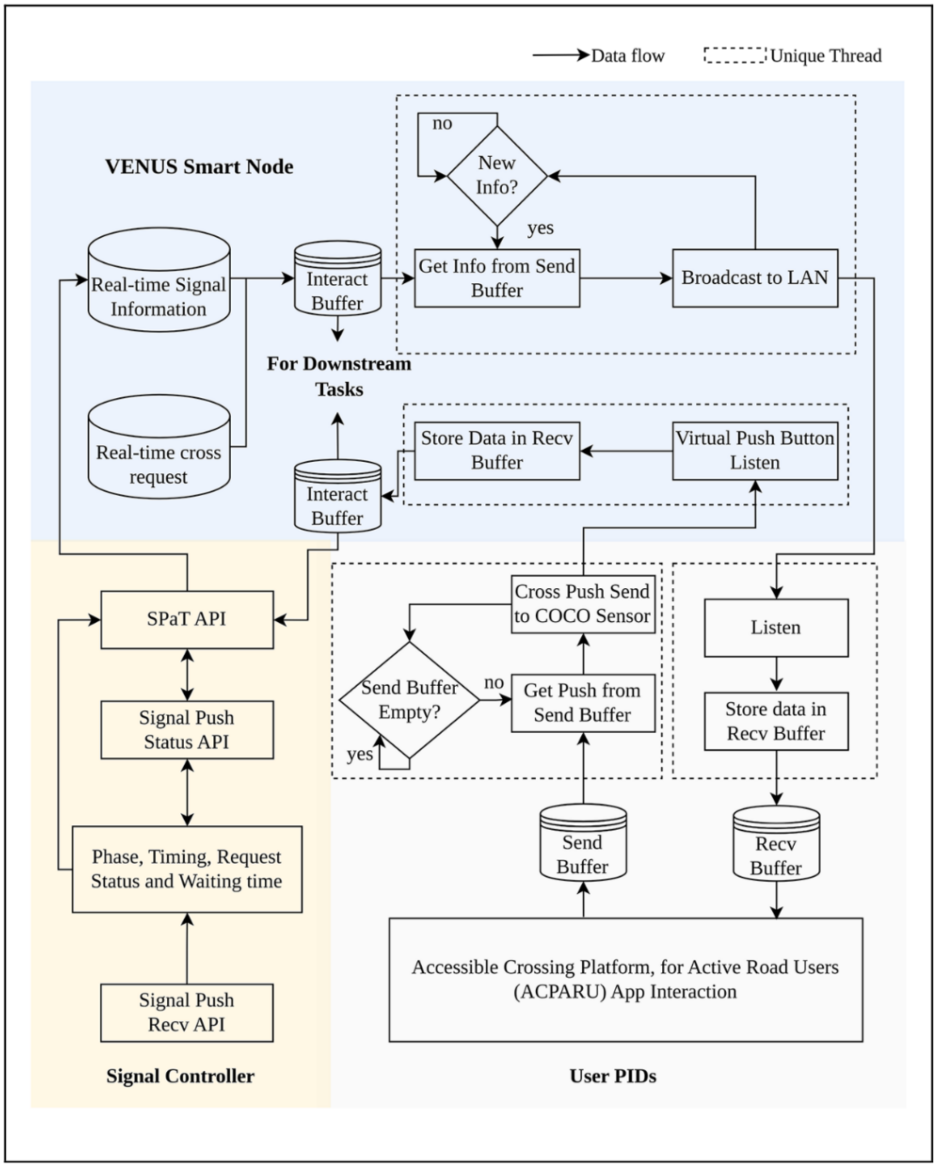

Figure 3-3 The communication workflow

3.2.3. Experiments

The COCO SENSOR system was implemented on Raspberry Pi 4 for multi-task sensing. Raspberry Pi 4, a cost-effective and easily operable edge device, was chosen due to its suitability for large-scale deployments in transportation systems despite its limited hardware capabilities (e.g., absence of a GPU for video processing). Other hardware components included the DHT22 environment sensor, PTZ camera, radar sensor, communication kit, and a protective shell. A test vehicle, a cell phone with the COCO SENSOR application, a portable radar gun, and a laptop were also used in the evaluation.

To validate the performance of environment sensing, the team utilized public weather data from WSDOT weather stations near the testbeds as ground-truth data, which included real-time weather and visibility conditions. The overall accuracy of visibility detection reached 92.15% (with a 10% threshold). As shown in Table 3-1, the system demonstrated higher accuracy in better visibility conditions, while performance decreased in extreme conditions like thick fog or snowstorms.

Table 3-1 Visibility Estimation Performance

Threshold	$\pm$ 5%	$\pm$ 10%	$\pm$ 20%
$V_s < 500$m	85.29%	89.14%	93.18%
$500\text{m} \leqslant V_s < 1000$m	88.17%	90.25%	95.42%
$1000\text{m} \leqslant V_s < 2000$m	90.36%	93.22%	97.03%
$V_s \geqslant 2000$m	91.23%	95.78%	98.75%
Overall	89.27%	92.15%	96.61%

The vehicle tracking and classification system utilized background modeling and the SORT algorithm to track moving objects. The MobileNet V2 classifier was employed for road-user classification and traffic volume counting by vehicle type. The system demonstrated lane-scale vehicle counting with high accuracy in various traffic scenarios. For object detection, the MobileNet V2 and SSD models were used, pre-trained with the COCO dataset and fine-tuned with the MIO-TCD dataset for specific transportation-agent detection. The object-detection results showed high accuracy for buses (96%) and cyclists (95%).

The system integrated radar sensors with cameras for calibration to convert 2D image coordinates to 3D real-world coordinates, enabling accurate lane-based speed measurement. The method was validated with a portable radar gun, showing an average error within ±10%.

The performance of COCO SENSOR's edge adaptation was evaluated using three different system architectures: sequential logic flow, parallel computing without AI trigger, and COCO SENSOR with parallel computing and AI trigger. The results demonstrated significant improvements in processing speed and efficiency with COCO SENSOR, as shown in Table 3-2.

Table 3-2 Processing Efficiency Evaluation

Structures	Sequential architecture	Parallel architecture	COCO SENSOR
Processing speed (fps)	1.3	3.2	11.3
CPU memory usage (%)	34%	65%	82%
Power consumption (W)	2.2	4.1	5.6
Efficiency (fps/W)	0.591	0.780	2.018

3.2.4. Conclusion

This technology presents the concept of "Sensing as a Service" (SaaS) and its implementation in the COCO SENSOR system for practical transportation applications. The COCO SENSOR system introduces a cooperative sensing mechanism and parallel computation to enhance perception accuracy and efficiency with limited computational resources on edge devices. The system was tested in real-world environments in collaboration with WSDOT and the City of Bellevue, demonstrating high accuracy in various practical applications such as traffic-volume counting by vehicle type, traffic-status detection, road-visibility estimation, and road-surface-condition classification.

3.3. Real-Time Multi-Task Environmental Perception System for Traffic Safety Empowered by Edge Artificial Intelligence

3.3.1. Introduction

Weather conditions significantly impact roadway users, and sudden changes can be difficult to forecast, leading to serious safety concerns. Meteorological forecasts are only about 80% accurate within seven days (Rose et al., 2017). Low visibility, often caused by fog, dust, or smoke, is a major driving hazard. Additionally, road surfaces covered by snow, water, or ice reduce tire friction and increase braking distance, commonly causing fatal car crashes. These hazardous conditions often occur simultaneously during extreme weather, creating severe safety risks. Current sensing technologies and methods aid in traffic environment sensing but fall short in improving traffic safety due to three main reasons:

- Single-task Focus of Environmental Sensors and Algorithms: Environmental sensors and algorithms typically address only one task. Most technologies target specific sensing tasks, such as visibility meters for visibility estimation, thermal cameras for image de-haze, and friction sensors for road surface condition detection. However, improving traffic safety involves multiple environmental factors, necessitating a multi-task sensing system for comprehensive environmental monitoring.

- Limitations of Centralized Processing Architecture: Traditional centralized processing systems fail to meet latency and reliability requirements. These systems transmit raw data to a central server for processing, resulting in delays and low reliability. Environment perception, critical for traffic safety, requires real-time performance. In rural areas, such as mountain roads, frequent weather changes demand timely alerts for drivers before entering hazardous regions. Centralized systems cannot provide these timely services due to communication and processing delays, limiting their effectiveness in weather-oriented traffic safety.
- Discriminatory Access to Safety Information: Access to safety information is often inequitable for low-income groups and rural areas. Disparities in data acquisition lead to inadequate and unaffordable traffic data for these populations. Advanced onboard sensors, like LiDAR, thermal cameras, and tire friction sensors, are prohibitively expensive for low-income users. The data they collect primarily benefit the vehicles equipped with them, raising safety and equity concerns for other road users. Public data, like those from weather stations, are insufficient; they lack critical information such as road surface conditions and are updated at five-minute intervals. Moreover, weather stations cover limited areas and are costly to expand, particularly in regions like Washington State.

This study proposes an Edge-based Multi-task Safety-oriented Environmental (Edge-MuSE) sensing system, utilizing monocular cameras to address weather-related traffic safety issues. Edge-MuSE is an integrated environment sensing system performing four sub-sensing tasks using video inputs. Firstly, Edge-MuSE provides visibility estimation based on image or video data captured by the camera sensors. Secondly, it removes haze from the original images or videos and reconstructs a clear vision for transportation agents. Thirdly, Edge-MuSE extracts road segments from the de-hazed images or videos by integrating road contour and optical traffic flow data. Finally, the system investigates multiple features, including dark channel value, intensity, color attenuation, and hue disparity, to classify road surfaces into four categories: dry, wet, snow-covered, and icy. All sensing tasks in the Edge-MuSE system are deployed on edge devices. These devices transmit perception results to users through cost-effective, intensive, and reliable local communication protocols with low latency. Over the past decade, advancements in Internet of Things (IoT) technologies (Wang et al., 2021) have enabled raw data streaming and post-processing on edge nodes, enhancing cybersecurity and reducing the computational load on central processors. However, achieving efficient and reliable multi-task sensing on edge devices remains challenging. To address these challenges, the study optimizes the Edge-MuSE structure for edge computing architecture from two perspectives. The sensing tasks are optimized for edge computing to balance accuracy and efficiency. Additionally, Edge-MuSE employs multiple threads for parallel computing, maximizing the utilization of computational resources.

3.3.2. Methodology

A multi-task sensing technology was used in Edge-MuSE. Weather-oriented traffic safety challenges are influenced by various environmental factors such as road surface conditions and visibility. Compared to single-task sensing, multi-task sensing methods can integrate diverse sensing results for comprehensive environmental perception. Additionally, multi-task sensing methods can reduce system costs and computation loads by maximizing resource utilization. In the study, Edge-MuSE uses video data as the sole input, which helps reduce costs and computation loads by avoiding the need to integrate different environmental sensors.

The architecture of the multi-sensing technologies used for traffic environment perception is shown in Figure 3-4. The sensing technologies are divided into three modules: 1) image de-haze; 2) road segmentation and visibility estimation; 3) road surface condition classification. These three steps are identified by different background colors in Figure 1. The following subsections introduce the details of these three modules.

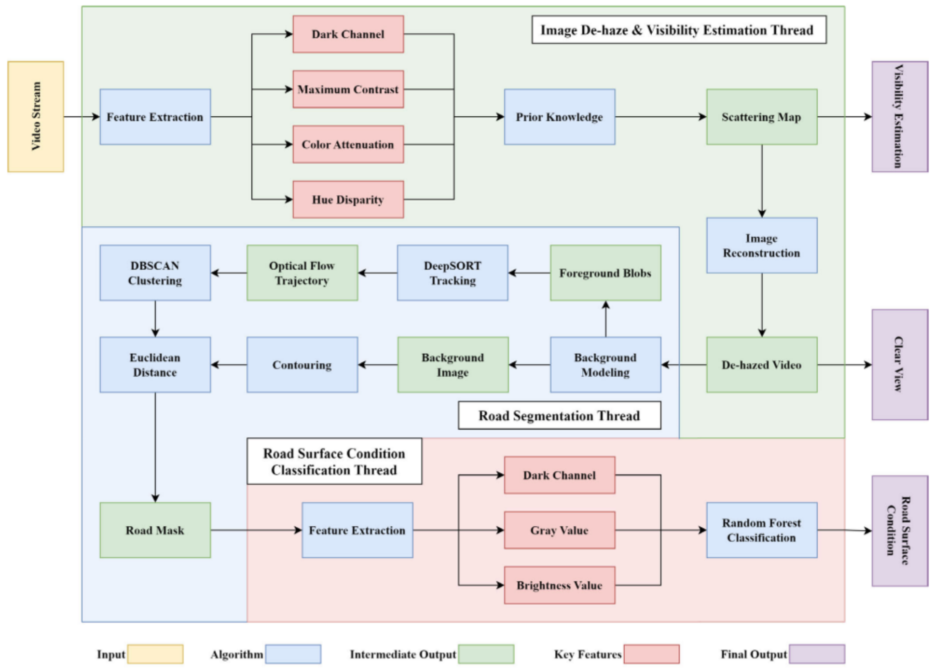

Figure 3-4 Architecture of Edge-MuSE (Liu, et al., 2024)

3.3.3. Image De-Haze & Visibility Estimation

The primary objective of this step is to estimate the scattering effects caused by particles in the raw video inputs. To accomplish this, the study introduces an innovative feature extraction network designed to capture four critical features of the image data: Dark Channel, Maximum Contrast, Color Attenuation, and Hue Disparity. These features are then used to create a scattering map, which is mapped onto the image coordinates. This scattering map is subsequently utilized to estimate visibility and reconstruct a haze-free image.

Based on empirical observations, existing image dehazing methods have proposed various critical metrics and prior knowledge for scattering map estimation. The study leverages four well-established metrics for haze effects estimation:

- Dark Channel: Defined as the minimum value among all pixel colors within a local patch, the dark channel prior (He, et al, 2011) suggests that in haze-free patches, at least one-color channel exhibits a very low intensity, close to zero. Conversely, the presence of haze significantly increases the minimum dark channel value in the patch, making it a reliable indicator for haze removal.

- Maximum Contrast: Haze tends to reduce the contrast of images. According to Reference (Tan, 2008), maximum contrast serves as a measure to remove haze. Applying maximum contrast within a local patch and extending it to neighboring areas can enhance the visibility of the image.
- Color Attenuation: This metric is defined as the difference between the brightness and saturation of a pixel. Color attenuation prior (Zhu, et al., 2015) indicates that haze leads to a sharp decrease in saturation and an increase in brightness. The difference between these two values serves as a useful indicator for generating the scattering map.
- Hue Disparity: Introduced by (Ancuti, et al., 2010) for haze removal, hue disparity is the absolute difference between the original image and its semi-inverse. In haze-free scenarios, there are significant hue differences between these values. The presence of haze reduces this difference, making hue disparity an effective measure for haze detection.

3.3.4. Multi-Scale Feature Extraction Module

The study designs an innovative feature extraction module that integrates four critical metrics to create a comprehensive haze removal algorithm. The module's structure is visualized in Figure 3-5, and the feature extraction process is detailed across four primary steps:

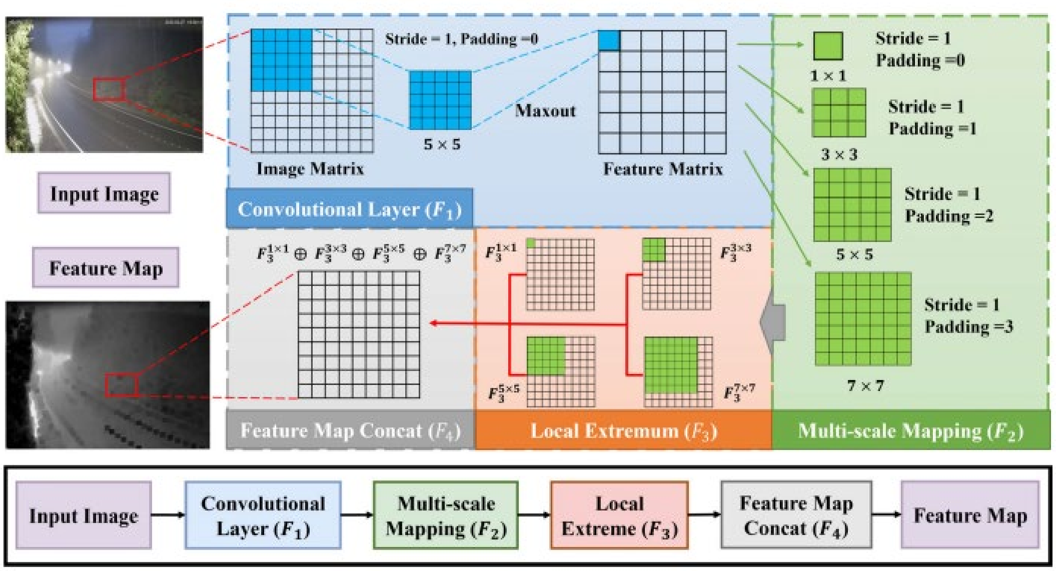

Figure 3-5 Multi-scale feature extraction module structure

- Convolutional Layer: A 5x5 filter is applied to the input image matrix to perform the convolutional operation with a stride of one and zero padding. Inspired by the work cited in (Cai, et al., 2016), the Maxout activation function (Goodfellow, et al., 2013) is used for non-linear mapping. This setup allows for the extraction of essential image features, where the filter design is particularly tailored for capturing these critical features as shown in Figure 3. For instance, an "opposite filter" is used to extract the dark channel feature by identifying the minimum value across three channels at each pixel, while a "round filter" captures visual contrasts by analyzing intensity differences.

- Multi-Scale Mapping Layer: This layer employs filters of varying kernel sizes (1x1, 3x3, 5x5, 7x7) to capture both local and global features. The differing scales help the model to interpret features at multiple levels of detail, which is significant for effective haze removal. This design follows the findings of studies (Tang, et al., 2014) emphasizing the impact of multi-scale features.
- Local Extremum Layer: Here, a spatial integration process takes place, where max pooling is applied within a 12x12 neighborhood centered on each pixel. This method helps to maintain resolution while overcoming local sensitivity and capturing prominent features across the patch.
- Concatenation Layer: The final layer integrates the multi-scale feature maps by averaging them. This concatenated output combines the distinct feature maps into a unified representation of critical features.

To complete the process, the study introduces a scattering map that combines these extracted feature maps based on prior knowledge. For example, the dark channel feature map is normalized to identify haze-free regions where at least one channel shows minimal intensity. The final scattering map is an average of the feature maps related to each critical metric, providing a comprehensive assessment of haze across the image. This methodology allows for a precise and nuanced removal of haze, leveraging both local and global image features.

3.3.5. De-Hazed Image Reconstruction

The estimated scattering map $t(x)$ is used to reconstruct the real scene $J(x)$, which is the haze-free image. The reconstruction process involves several key steps. Firstly, the scattering map $t(x)$ serves as the input for reconstructing the clear image $J(x)$. The haze-free image $J(x)$ is computed using a specific formula that considers the input image $I(x)$, the scattering map $t(x)$, and the atmospheric light A.

The formula can be represented as: $J(x) = \frac{I(x)}{t(x)} - \frac{A}{t(x)}$. The atmospheric light A is estimated through the pixels where the depth d approaches infinity, typically identified as the sky in the image. The scattering map $t(x)$ inferred from the feature extraction module provides depth information. Pixels where $t(x)$ approaches zero are considered sky pixels, and their intensity is used to determine the atmospheric light A. Using these estimated values, the methodology reconstructs a clear, haze-free image $J(x)$ from the original hazy input $I(x)$.

The final step of the methodology involves estimating the visibility based on the extracted scattering map $\mathrm{t(x)}$. In the study, visibility is defined as the distance at which an object or light can be clearly observed, measured by visual contrast $\mathrm{C_v}$. Visual contrast C_v is the relative difference between the light intensity of the background and the object. According to the Beer-Lambert law (Swinehart, 1962), the visual contrast $\mathrm{C_v(d)}$ can be represented as an exponential function of distance d:

$$C_v(d) = \exp(-\gamma d)$$

Here, γ is the contrast attenuation coefficient that describes the decrease in visual contrast with increasing distance d. Based on standards from the International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) (Clearman, 2010), the minimum contrast detectable by the human eye is 2%. Using ground truth visibility data $\mathrm{d_0}$ from weather stations, γ can be calculated as:

$$\gamma = -\frac{\ln\left(\mathrm{C_{T_v}}\right)}{\mathrm{d_0}}$$

where $\mathrm{C_{T_v}}$ is the visual contrast threshold (i.e., 0.02).

Similarly, we can use the median value $\mathrm{t_m}$ of a local patch Ω in the scattering map $\mathrm{t(x)}$ to represent the scattering effects in the view. Based on the definition of the scattering map, the scattering coefficient β can be represented as:

$$\beta = -\frac{\ln\left(\mathrm{Med}_{x\in\Omega}\left(t(x)\right)\right)}{d_0}$$

To map the scattering map $t(x)$ to the contrast map $C_v(x)$ for visibility estimation, it is necessary to establish a function f between the coefficients β and γ:

$$\gamma = \mathrm{f}(\beta)$$

In this process, ground-truth visibility data is used as the training dataset to minimize the loss function, defined as the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\big(\gamma - f(\beta)\big)^2$$

By minimizing this MSE, the relationship between the scattering map and the visibility can be accurately modeled, allowing for effective visibility estimation based on the scattering map.

3.3.6. Road Segmentation

In the Edge-MuSE system, road segmentation is crucial for determining the sensing region, significantly impacting the final detection accuracy. To ensure accurate road segmentation, Edge-MuSE integrates two algorithms: road contour detection and vehicle motion. The structure of the Road Segmentation Thread is marked with a blue background in Figure 3-4. Each algorithm has its strengths and weaknesses. Contour detection can be applied in all scenarios for rapid road segmentation but has relatively low accuracy due to various environmental factors. Optical flow methods achieve high accuracy in road segmentation based on vehicle trajectory accumulation but can be time-consuming in low traffic volume scenarios, like rural areas. Additionally, certain road parts, such as shoulders and work zones, may be excluded from the estimated road mask due to limited vehicle coverage. Therefore, Edge-MuSE combines these methods using Euclidean distance (Danielsson, 1980) for accurate and efficient road segmentation.

The input data for this thread should be the processed de-hazed video data. Initially, a background modeling algorithm is applied to the video data for background subtraction. This step separates moving objects (foreground blobs) like vehicles from static objects (background images) like roadways, eliminating interference between them in subsequent steps. Road contour detection uses the background image as input, while the vehicle motion detection method uses the foreground blobs.

1) Contour Detection:

Pre-processing: Erosion and dilation operations are performed to smooth object contours, break narrow necks, eliminate thin protrusions, bridge narrow discontinuities, eliminate small holes, and fill breaks in contour lines.

Image Filtering: The first step of the Canny algorithm is to smooth the image using a Gaussian function to remove noise.

$$G(x, y) = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)/(2\pi\sigma^2)$$

Image Gradient Calculation: The magnitude and direction of the image gradient are calculated. The partial derivatives in the X and Y directions are approximated, and the gradient magnitude and direction are determined.

$$E_x[i,j] = \frac{(I[i+1,j] - I[i,j] + I[i+1,j+1] - I[i,j+1])}{2}$$

$$E_y[i,j] = \frac{(I[i,j+1] - I[i,j] + I[i+1,j+1] - I[i+1,j])}{2}$$

$$|M(i,j)| = \sqrt{E_x[i,j]^2 + E_y[i,j]^2}$$

$$\theta(i,j) = \arctan\left(\frac{E_y[i,j]}{E_x[i,j]}\right)$$

Contour detection is flexible but can be influenced by real-world factors like illumination, leading to false positives and negatives. To address these challenges, Edge-MuSE introduces vehicle motion detection methods.

2) Optical Flow Detection:

Pre-processing: The foreground blob consists of moving pixels, but static pixels can also be detected due to factors like camera shake. This step aims to handle false positives and negatives using the Canny algorithm for contour detection. Regions enclosed by contours are used to filter target objects like vehicles, pedestrians, and cyclists.

Optical Flow Extraction: Edge-MuSE uses the Simple Online and Realtime Tracking algorithm (SORT) (Bewley, et al., 2016) to track objects and extract optical flow. A lower bound threshold is set to filter optical flow, and marked pixels are represented by a feature vector $\vartheta = [x, y, d, v]$, where (x, y) is the object location, d is the moving direction, and v is the vehicle speed.

Road Segmentation: Over time T, marked pixels accumulate and cover major traffic areas. For high traffic volumes, T can be a few minutes, while for low-density rural roadways, a larger T is needed to extract all target regions.

By integrating these methods, Edge-MuSE ensures accurate and efficient road segmentation, crucial for reliable sensing region determination and improved detection accuracy.

3.3.7. Road Surface Condition Classification

The third thread of Edge-MuSE is Road Surface Classification. This thread uses the road mask extracted from the background images as input. The feature extraction module is then applied to the road mask for feature extraction, with a structure similar to the one used for the scattering map. However, unlike haze removal, road surface condition detection focuses more on the light reflection properties of the pavement. As a result, the key features used in the module are dark channel value, gray value, and brightness value, which help classify the light reflection status on the road surface. Based on this status, the road surface condition can be categorized into four classes:

- **Dry:** In dry conditions, light reflection on the road surface is diffused, allowing light from all parts of the road to reflect into the camera. This results in image features like gray value, dark channel, and brightness being distributed evenly (low standard deviation) across the road. This is the most common road surface condition.
- **Wet:** In wet conditions, water on the road creates a flat surface where specular reflection occurs. This causes sharp spikes in feature values (e.g., dark channel, intensity, brightness) in specific areas, while nearly no light reflects in other road segments, leading to a wide range distribution (large standard deviation) in the feature values.
- **Snowy:** Similar to dry conditions, light reflection on a snowy road surface is diffuse. However, white snow reflects more light into the camera than dry pavement, resulting in evenly distributed but relatively higher feature values compared to dry conditions.
- **Icy:** Like wet conditions, light reflection on icy pavement is specular. However, due to the mixing of ice with snow and dirt from passing vehicles, the reflection is closer to diffuse than purely specular. This results in low-light regions where all three feature maps (dark channel, gray value, brightness) exhibit diffuse reflection characteristics.

The extracted feature maps provide reliable inputs for road surface condition classification. In Edge-MuSE, these inputs are fed into multiple classification methods, including Random Forest (RF), K-Nearest Neighbors (KNN), Support-Vector Machine (SVM), and Naive Bayes (NB). Among these, Random Forest (RF) performs the best and is therefore deployed in Edge-MuSE for practical classification of road surface conditions.

3.3.8. System Structure for Edge-Adaptation

Edge-MuSE is a comprehensive traffic environment sensing system deployed on edge devices. The advantages of using edge devices can be summarized in the following three points. Firstly, edge-based systems relocate computation loads from central servers to the edge, reducing the time latency caused by high computation demands on the server side. Secondly, transmitting only the sensing results instead of the raw data to the server side reduces time latency and communication costs. Additionally, the sensing results produced by edge devices can be disseminated to users via local networks, ensuring lower response times. Finally, privacy-sensitive information can be filtered by edge devices before transmission to the server, enhancing privacy protection and cybersecurity.

However, running a multi-task sensing system effectively on edge devices remains a significant challenge due to their limited computing capabilities. This section introduces a systematic design for adapting to edge devices. Many factors could become bottlenecks and decrease processing speed on edge devices. The proposed systematic design carefully balances these factors and optimizes the entire system by optimizing data stream on edge.

To optimize the data stream, Edge-MuSE separates the algorithm into five parallel threads, each running independently in predefined memory spaces. These threads interact through data storage and retrieval in five predefined caches, increasing the system's robustness and efficiency on edge devices. Figure 3-6 illustrates the data stream, with each thread detailed below.

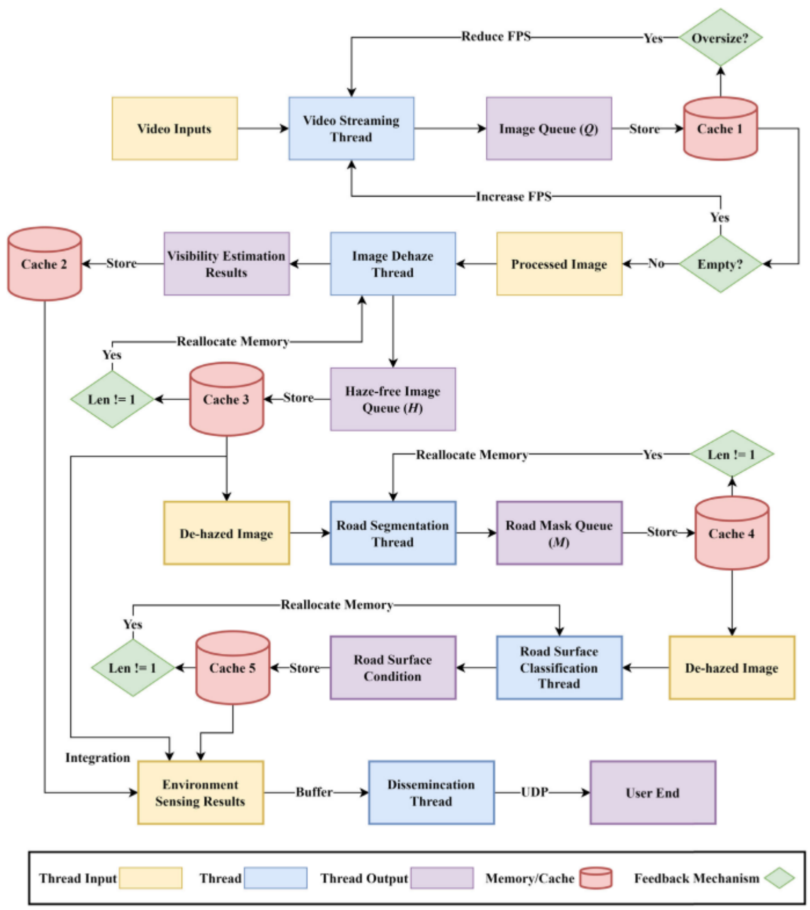

Figure 3-6 Data streaming optimization on edge

Video Streaming Thread: This thread captures video data from camera sensors and pre-processes it. Since different camera sensors have varying characteristics, this thread standardizes the input video data to a uniform size and frame rate (FPS) for further processing. It also filters out broken images from the raw data. The thread's input is raw video data, and the output is a filtered and standardized image queue with stable FPS, stored in Cache 1. A feedback mechanism checks Cache 1's occupancy status and adjusts the video streaming thread's computation resources accordingly.

Image De-haze Thread: This thread estimates and removes haze from the images. It takes the image queue from Cache 1 as input and produces two outputs: a haze-free image queue and visibility estimation results. The visibility estimation results are stored in Cache 2 for dissemination, while the haze-free image queue is stored in Cache 3 for further processing. A feedback mechanism in Cache 3 adjusts the memory allocation of the thread to control processing speed.

Road Segmentation Thread: This thread extracts the road mask from the haze-free image queue in Cache 3. For accurate background modeling and optical flow extraction, the batch size is set to 16. The output road mask is stored in Cache 4 and updated with each iteration. The previous road mask in Cache 4 serves as one of the inputs to the road segmentation thread to enhance accuracy.

Road Surface Condition Classification Thread: This thread classifies the road surface condition into four categories based on the feature extraction module. The input is the latest road mask stored in Cache 4, and the output road surface condition results are stored in Cache 5. A feedback mechanism adjusts the computation resource allocation as needed.

Dissemination Thread: This thread inputs the de-hazed image queue from Cache 2, visibility estimation results from Cache 3, and road surface condition classification results from Cache 5. Edge-MuSE uses User Datagram Protocol (UDP) and local network sockets to transmit data to road users and traffic management agencies for information dissemination.

The feedback mechanism is designed to adjust the distribution of computation resources automatically, based on the occupancy status of the five cache spaces. By frequently detecting whether a cache is overflowing or empty, the mechanism reallocates the computation resources of the upstream thread to decrease or increase its processing speed as needed.

CHAPTER 4. CONCLUSION

The implementation of the Mobile Unit for Sensing Traffic (MUST) in Yakama Nation represents a significant step forward in addressing the traffic safety challenges faced by tribal and rural areas. By providing a low-cost, user-friendly, and highly effective data collection system, the MUST project aims to fill the data gap that has long hindered traffic safety efforts in these regions. The successful installation of the MUST sensor and the development of a comprehensive data visualization and management dashboard demonstrate the potential of this technology to transform traffic safety practices.

As we continue to collect and analyze data, we are committed to working closely with the Yakama Nation and other stakeholders to ensure that the insights gained from this project lead to meaningful improvements in traffic safety. Our ultimate goal is to create a safer and more efficient transportation system for all members of the community, leveraging the power of advanced technology and data-driven decision-making to achieve this vision.

Through ongoing collaboration, innovation, and dedication, we believe that the MUST project will serve as a model for other tribal and rural areas seeking to enhance their traffic safety capabilities. We look forward to sharing our findings and continuing to make a positive impact on the safety and well-being of communities across the country.

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