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Corridor-Wide Surveillance Using Unmanned Aircraft Systems

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16. Abstract

In the second phase of the project, the research team continued traffic data collection with unmanned aerial systems (UAS) and dual sensors (RGB and thermal cameras) for roadways under normal operational condition and during incident clearance. The research team conducted a thorough literature review of incident detection methods. Based on the review outcomes, the research team extracted traffic features from learning the video data and trained several learning models for identifying non-congestion conditions caused by incidents. This method was tested on a two-minute video with data captured by a drone at a location at which traffic was passing through an incident site. The results show that some machine learning models (support vector machine, K nearest neighbor, and random forest) performed very well in F1 scoring.

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UAV, unmanned aircraft system, drones, traffic, transportation, incident management, UAS applications, object detection algorithm, experimental design

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Abbreviations and Acronyms

APID	All Purpose Incident Detection
ARIMA	Auto Regressive Integrated Moving Average
CNN	Convolutional Neural Network
DELM	Deep Extreme Learning Machine
DES	Double Exponential Smoothing
DTW	Dynamic Time Warping
FDOT	Florida Department of Transportation
GAN	Generative Adversarial Network
HIOCC	High Occupancy
ILD	Inductive Loop Detectors
LSTM	Long Short-Term Memory
MOT	Maintenance of Traffic
MLP	Multilayer Perceptron
RGB	Red Green Blue
SSID	Single-Station Incident Detection
SND	Standard Normal Deviation
SIS	Strategic Intermodal System
SVM	Support Vector Machine
TMC	Traffic Management Center
USF	University of South Florida
UAS	Unmanned Aerial Systems
UAV	Unmanned Aerial Vehicle
YOLO	You Only Look Once

Executive Summary

Phase II of this project focuses on applying machine learning algorithms to videos collected with an unmanned aerial systems (UAS) platform to automatically detect traffic congestion due to incidents. Incident detection methods can be categorized based on the sensing systems used to collect traffic data. They can be classified as point/link-based models and video-based models. Point-based models are fed by data collected from fixed detectors such as inductive loop detectors (ILD), magnetometers and magnetic detectors, microwave radar, infrared, and ultrasonic sensors, whereas link-based models use individual vehicles operating in traffic as probe vehicles. Video-based models apply computer vision techniques to extract traffic data from videos, and incident detection is conducted based on these extracted traffic features. Incident detection algorithms can also be categorized as microscopic and macroscopic. Microscopic algorithms are trajectory-based, with trajectory data required to model driving behavior. The macroscopic approach uses point-based detector data sources such as volume, speed, occupancy, kinetic energy, and their variations. In this project, for real-time incident detection that can help expedite incident clearance, the research team chose to develop the macroscopic approach for incident detection.

Specifically, the research team improved the object detection deep learning model in Phase I so that the model can detect slow-moving or even stopped vehicles in images. Furthermore, based on a thorough literature review, the research team extracted traffic features from learning the video data and trained several learning models for identifying non-congestion conditions caused by incidents. This method was tested on a two-minute video with data captured by a drone at a location at which traffic was passing through an incident site. The results show that some machine learning models (support vector machine, K nearest neighbor, random forest) performed very well in F1 scoring. However, models were trained on one incident data sample; thus, the generalization of these models needs to be validated with more available data in different configurations. In addition, the case study data sample covered only a small part of downstream traffic. To capture the spatial and temporal differences between downstream and upstream traffic caused by an incident, future data should cover more downstream traffic than the data currently used. Finally, compared with Red-Green-Blue (RGB) video data, an alternative data source, infrared data, has the advantage of protecting privacy. More studies can be conducted to explore its performance in automated incident detection.

Chapter 1. Introduction

Unmanned aerial vehicles (UAVs) provide a platform that can carry cameras and sensors for collecting real-time traffic information, especially for corridors under congested conditions, when traditional loop detectors do not work properly and where there is a lack of other means of traffic monitoring. As an alternative, Road Rangers continuously patrol the roadways monitoring for traffic crashes and stranded motorists and then respond to those incidents. Continuously patrolling along roadways is costly and workforce consuming. With the proliferation of UAVs and their ease of use, their effectiveness was investigated for enhancing traffic monitoring and applying advanced learning methodologies to detect non-recurrent congestion caused by incidents.

Video for traffic monitoring has been used for a number of years. Traffic Management Centers (TMCs) currently use stationary closed-circuit television (CCTV) cameras to monitor traffic conditions. However, these video streams are mostly used for verification of conditions once they are identified via other data streams and are limited to a few camera views at a time. TMCs have limited video wall space and cannot actively monitor all video streams from the CCTV network. There is a need for automated video detection of incidents to help TMC staff identify and verify incidents more quickly and accurately.

Research Objectives

The research objectives of this study included the following:

- Conduct experiments to collect traffic data during incidents on freeway corridors.
- Train machine learning models to determine traffic conditions (e.g., congested and non-congested).
- Further train learning models to identify traffic congestion due to incidents.
- Provide outcomes in traffic engineering terms that can be used by a TMC.

Contributions to Research

The efforts of the team on this research project build upon existing video detection and machine learning algorithms to enhance the field in traffic monitoring. The team used existing algorithms but customized them to work using video from UAVs. This differs from existing video detection methods where the video is usually collected on the ground or via stationary CCTV cameras.

Organization of Report

This report is organized as follows: Chapter 2 provides a summary literature review of incident detection methods. Chapter 3 describes the research approach, including an overview of the training and testing of the You Only Look Once (YOLO) model for object detection, incident detection framework, traffic feature extraction, and training the learning model for incident detection. Chapter 4 describes the process of collecting traffic data with drones and dual cameras (RGB and thermal) during several incidents. Chapter 5 discusses the outcomes of incident detection using sample incident data, concludes the Phase II study, and presents the Phase III research plan.

Chapter 2. Literature Review

Phase II of this project focuses on applying machine learning algorithms to videos collected with the UAS platform to automatically detect traffic congestion due to incidents. This section reviews literature related to incident detection methods.

Incident detection methods can be categorized based on the sensing systems used to collect traffic data. They can be classified as point/link-based models and video-based models. Point-based models are fed by data collected from fixed detectors such as ILD, magnetometers and magnetic detectors, microwave radar, infrared, and ultrasonic sensors, whereas link-based models use individual vehicles operating in traffic as probe vehicles. Video-based models apply computer vision techniques to extract traffic data from videos, and incident detection is conducted based on these extracted traffic features. Incident detection algorithms can be categorized as microscopic and macroscopic.

Microscopic algorithms are trajectory based, with trajectory data required to model driving behavior. Although the microscopic approach may provide faster traffic condition detection and lower false alarm rates, trajectory data are not widely available, and modeling driving behavior is challenging, as drivers consider not only the vehicles in front of them but also the traffic stream ahead (Motamed, 2016). The macroscopic approach uses point-based detector data sources such as volume, speed, occupancy, and kinetic energy:

- **Volume –** number of vehicles passing through a point on a highway during a specific interval.
- **Speed –** average speed of vehicles passing through a point over a specific time interval.
- **Occupancy –** (1) for a point-based detector, proportion of time that a detector is occupied by a vehicle in a specific time interval; (2) for a video camera, number of instantaneous space occupancies in a specific time interval.
- **Kinetic energy –** computed from volume and speed measurements.

As an incident occurs, occupancy increases, volume and speed decrease upstream, and occupancy and volume decrease downstream (Shang, Feng, and Gao, 2021). These differences in upstream and downstream traffic features have been the basis of classical automated incident detection algorithms, comparing detected traffic measurements with the thresholds set for each traffic metric to determine if there is an incident. For instance, the widely used California algorithm uses the spatial difference between upstream and downstream occupancy, the relative spatial difference in occupancy, and the relative temporal difference in downstream occupancy as the traffic features (Payne and Tignor, 1978). The algorithm is executed in a sequence of steps as a decision tree to detect the occurrence of an incident. In addition to these three traffic features used in the California algorithm, the All Purpose Incident Detection (APID) algorithm includes downstream occupancy and relative temporal difference in speed in traffic features (Masters, Lam, and Wong, 1991). This type of algorithm is also called a pattern recognition–based algorithm. In Persaud and Hall (1989), an alternative approach was provided to incident detection on freeways, the Catastrophe Theory model, which can fit the data better than conventional models in the transitions to and from congested operations upstream of incidents.

Another category of incident detection algorithms is statistical algorithms, which perform better than pattern recognition–based algorithms. They use statistical models to predict traffic features and compare the difference between predicted and actual values with preset thresholds to determine the occurrence of an incident. Statistical algorithms include the High Occupancy (HIOCC) algorithm (Steed and Clowes, 1989), the Auto Regressive Integrated Moving Average (ARIMA) algorithm (Ahmed and Cook, 1982), the Standard Normal Deviation (SND) algorithm (Dudek, Messer, and Nuckles, 1974), the Double Exponential Smoothing (DES) algorithm (Cook and Cleveland, 1974), the Filtering algorithm (Chassiakos and Stephanedes, 1993), the Bayesian algorithm (Levin and Krause, 1978), and the Single-Station Incident Detection (SSID) algorithm (Antoniades and Stephanedes, 1996). Although these recognition-based and statistical algorithms are simple in theory and easy to implement, a major drawback is their limitation in dealing with non-linear data (e.g., stop-and-go traffic). On the other hand, machine learning algorithms are capable of learning complex problems and achieving better detection performance.

Machine learning algorithms learn historical incident data collected from upstream and downstream of an incident location and solve incident detection as a classification problem (Yuan and Cheu, 2003) by a Support Vector Machine (SVM). In California, the algorithms were trained with simulated incident data and real I-880 freeway data, and the detection performance was as good as the Multilayer Perceptron (MLP) neural network. A decision tree learning was applied in Chen and Wang (2009) to conduct freeway automated incident detection by using simulated traffic data containing volume, speed, time headway, and occupancy. The experimental results showed that decision trees were competitive with MLP. Nearest neighbor, random forest, neural networks, and Naïve Bayes have also been applied in automated incident detection (Cheng, Lin, Liu, and Gu, 2010; Jiang and Deng, 2020; Liu, Chen, and Zhao, 2014; Ozbayoglu, Kucukayan, and Dogdu, 2016).

As more traffic data are accessible, deep learning has been developing rapidly in recent years for incident detection, among which are Convolutional Neural Networks (CNNs), fuzzy deep learning, and Deep Extreme Learning Machine (DELM) (El Hatri and Boumhidi, 2018; Huang, Wang, and Sharma, 2020; Wang, Zhu, Shen, and Liu, 2018; Zhu, Guo, Krishnan, and Polak, 2018). Video data are often used in deep learning, and spatial-temporal traffic features are extracted for the deep learning model to learn.

A hybrid approach that combines two or more algorithms has also been used in automated incident detection. Wang, Ngan, and Yung (2015) used an adaptive boosting classifier to detect traffic abnormality and further identified categories of abnormality by using SVM. Time series Dynamic Time Warping (DTW) and k-nearest neighbor were also combined with SVM in Motamed (2016) and Xiao (2019). In Shang, Feng, and Gao (2021), a hybrid model using random forest and Long Short-Term Memory (LSTM) was proposed, and researchers in Li, Lin, Du, Yang, and Ran (2022) proposed a deep learning model using Generative Adversarial Network (GAN).

Based on findings from the literature review, the research team decided to apply several learning algorithms to address automated incident detection for this study.

Chapter 3. Research Approach

The research approach used to enhance the algorithm developed in Phase I and to achieve automated processing and identification of traffic incidents is depicted in Figure 1.

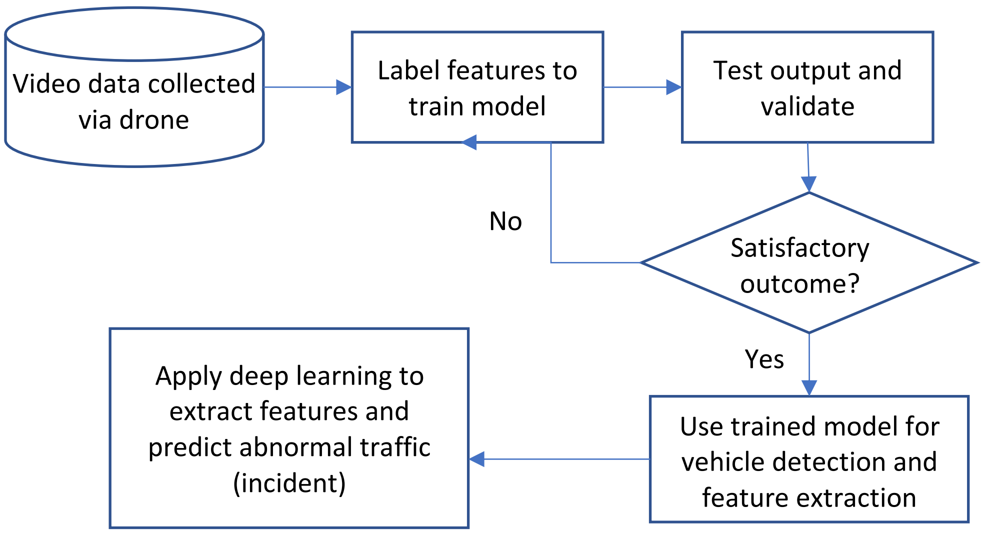

Figure 1. Applying learning methods to UAS collected traffic data for automatic incident detection.

Training and Testing of YOLO Model for Object Detection

Object detection is a classification problem. The research team used the YOLO (You Only Look Once) version 4 model to process video collected via the UAV platform. YOLO is an object recognition model that can predict up to 9,000 classes of objects and can recognize multiple objects from one image to create a bounding box around the object. YOLO version 4 was developed by Bochkovskiy, Wang, and Liao (2020) and is composed of (a) CSPDarknet53 as the backbone, which enhances the learning capability of the Convolutional Neural Network (CNN); (b) a spatial pyramid pooling additional module, which increases the reception field; (c) a PANet path aggregation neck; and (d) YOLO v3 as the head. Although YOLO version 5 is available to use, there are a few reasons behind selecting YOLO version 4. YOLO v5 was released just two months after the release of YOLO v4. Even though YOLO v5 is publicly available, there are no papers published by the author to accompany the release. The release of YOLO v5 created a controversy and started a lot of debates in the machine learning research community. Even though it was said that YOLO v5 was extremely fast and light weight compared to YOLO v4 and the accuracy was on par with YOLO v4, nobody was sure about these statements. Apart from this, a comparison between YOLO v3, YOLO v4, and YOLO v5 done by Nepal and Eslamiat (2022) on images extracted by UAVs indicates that the accuracy of YOLO v4 is higher than the other two versions.

To detect vehicles with a moving background, the deep learning state-of-art YOLO v4 model was trained on images extracted from videos recorded via UAVs. Two types of images were used in this process: (1) RGB filter (standard vision) and (2) infrared (thermal) filter. For each type of image, 90 images were labeled and used as the training set. Labeling is one of the most important steps in supervised machine learning (Pokhrel, 2020); the model must be taught different images annotated as vehicles for the machine to classify them correctly. In other words, annotation/labels on each image help the machine train itself to classify between different objects. As the number of labeled images to train the machine increases, the accuracy of the machine to classify the images also increases and the error rate (of misclassification) decreases. Figure 2 and Figure 3 show labeled RGB and thermal images.

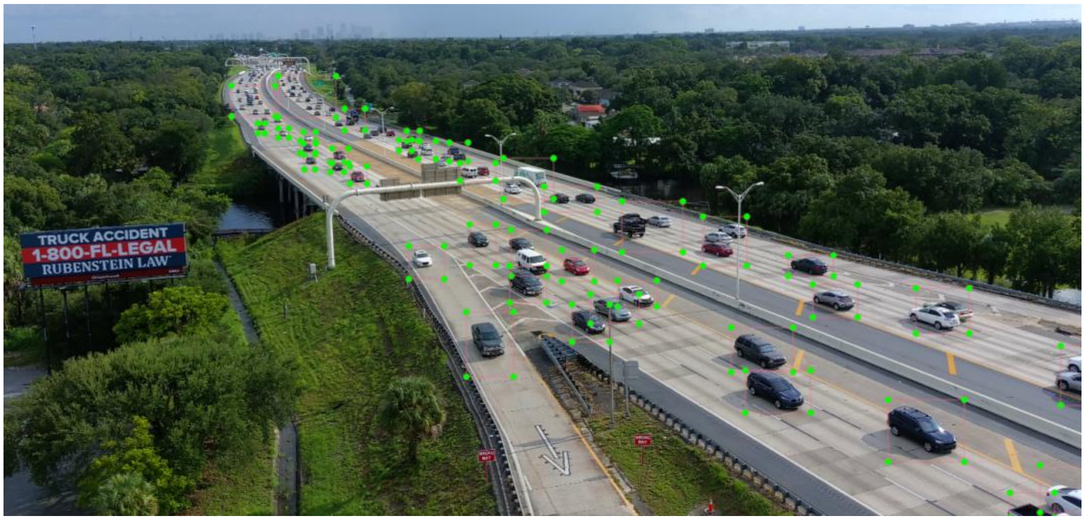

Figure 2. Labeled RGB image.

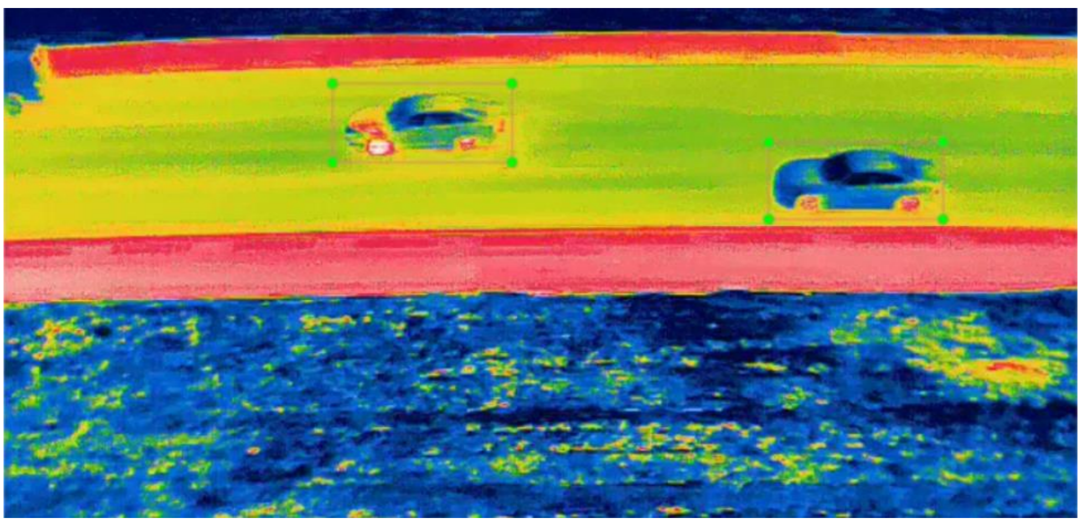

Figure 3. Labeled infrared image.

After training, the learning model is applied to unlabeled images to detect the desired objects. At the early stage of this research while testing videos experiencing heavy traffic due to incidents, the trained learning model was not able to detect very slowly moving or stopped vehicles in the images. Figure 4 shows the learning outcome of one such situation. Many slowly moving and stopped vehicles in the image were not detected.

Figure 4. Undetected stopped vehicles after model training.

To overcome this issue, more images were labeled, from 90 to 250, and the model was retrained. In addition, the width and height in the configuration file were changed from 416×416 to 608×608 pixels. Increasing the size of configuration file could help the model learn better from the training images. The images used for training the model had a high-quality resolution of 4K (3840×2160). Trial-and-error was used to determine the best width and height. A combination smaller than 608×608 did not work well for detecting vehicles but combinations larger than 608×608 caused overfitting issues. Overfitting (Bochkovskiy et al., 2020; IBM Cloud Education, 2021) is a very common issue of machine learning or deep learning models, wherein the model fails to filter noise or random fluctuations in the training and starts detecting noise along with the objects. Thus, 608×608 was selected as the final resolution of images. Figure 5 shows the same images as those in Figure 4 but with all vehicles detected after retraining the learning model. The outcomes of object detection were then used in deep learning models for automated incident detection, as described in the following section.

Figure 5. Detected vehicles after model retraining.

Automated Incident Detection Framework

The trained YOLO v4 deep learning model was first applied to detect vehicles on the collected video data in which there was an incident occurring on the freeway. Traffic flow features (density, median speed, max speed, and standard deviation speed from both directions) were extracted from the video data. Density—the number of vehicles per lane per frame and median, max, and standard deviation speeds—was calculated based on all vehicles in one frame in pixels per frame. In the next step and based on the extracted features, traffic features were generated in a form that could be fed into the machine learning model for training. The model was trained as a binary classification model. After the model training was completed, the abnormality of the traffic caused by an incident was predicted. Figure 6 shows a flow of the applied framework for incident detection.

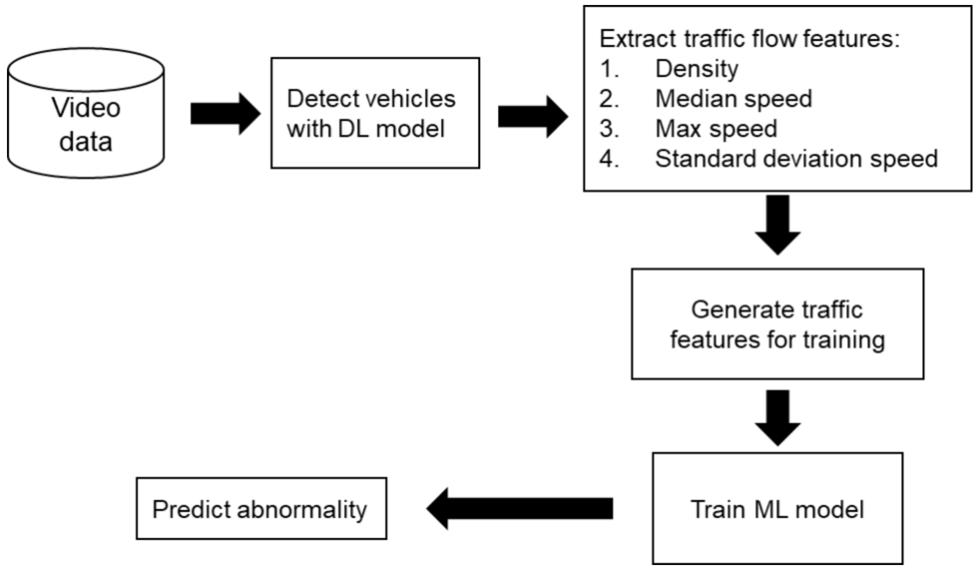

Figure 6. Framework of automated incident detection.

Traffic Flow Feature Extraction

The deep learning model detects vehicles as confined bounding boxes, with coordinates of the box vertices in a frame. The Lucas-Kanade optical flow tracker (Bouguet, 2001) was applied to track the bounding box vertex between two consecutive frames. Those points are iteratively tracked; thus, the motion of a vehicle can be recorded. Vehicle speed was calculated according to its movement between frames. In the data collected, the drone camera was facing the roadway at an azimuth angle of 90 degrees to the road, which captured both directions of traffic. To distinguish traffic direction, the actual vehicle speed on the highway must be known. If the drone is static, vehicle speeds obtained by the previous method can be used to determine whether each vehicle is moving to the right or left of the frame. If the vehicle speed on x-axis is greater than zero, then it is moving to the right; otherwise, it is moving to the left. When the drone flies along a roadway, the vehicle speeds extracted from the video are the combination of the actual vehicle speed and the drone speed (or background speed). The background speed must be subtracted from the vehicle speed to obtain the actual vehicle speed on the road. Similarly, the Lucas-Kanade optical flow tracker is applied to the background to estimate the background speed in a unit of pixel per frame, and the background is manually selected by mouse-clicking on the frame. The steps followed for the extraction process are shown in Figure 7.

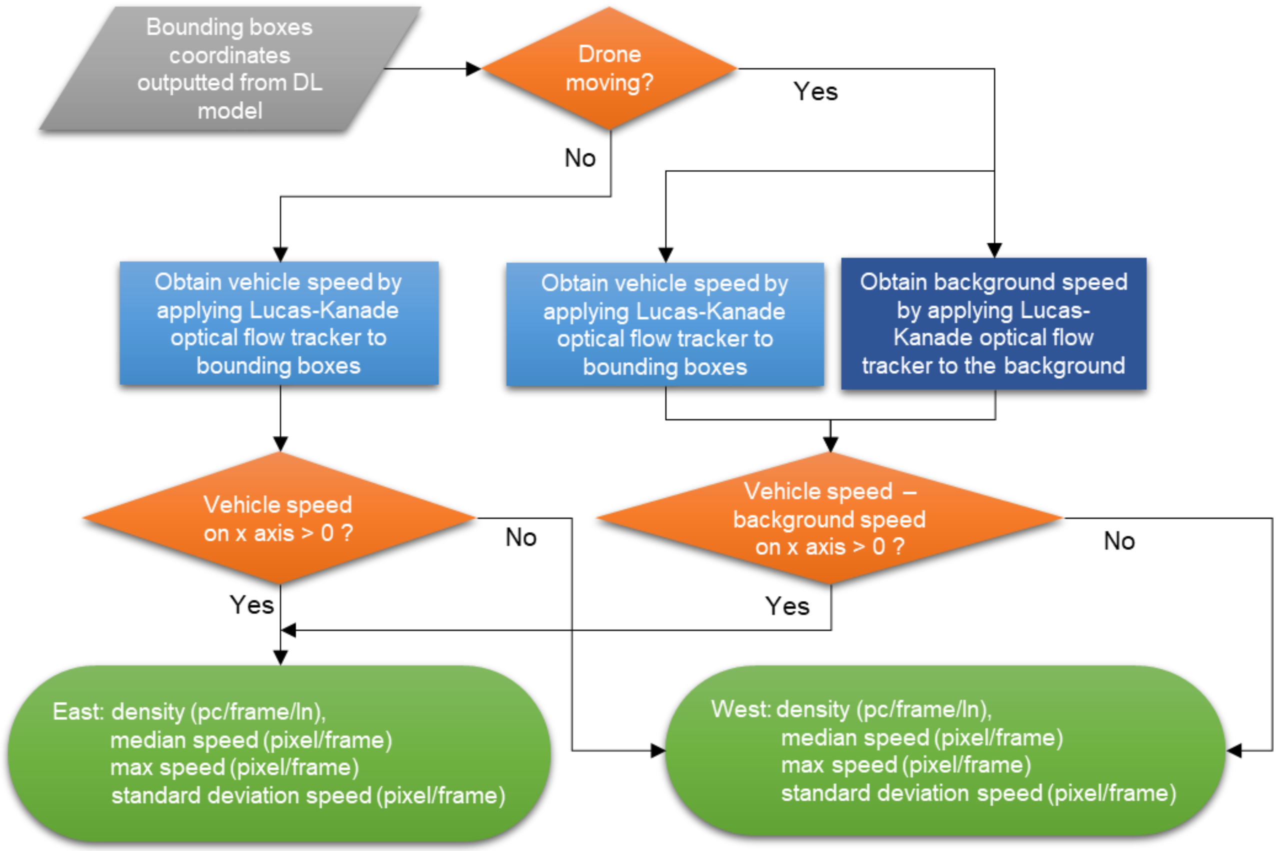

Figure 7. Steps for extracting traffic flow features.

Figure 8 is a snapshot of the background speed estimation process, where red points are the selected background points, and the motion vectors of these points are shown in green lines following the red dots. It should be noted that as long as the drone's speed, height above the ground, and azimuth angle are the same, the background speed needs to be detected only once and the identical background speed can be used for all images.

Figure 9 shows the detected vehicles in green bounding boxes and motion vectors of vehicles in blue lines. The traffic flow features (eastbound traffic)—density, median, max, and standard deviation speeds—are displayed at the top of the frame.

Figure 8. Motion vector background selected points.

Figure 9. Extracted traffic flow features.

Feature Generation and Machine Learning Model Training

Traffic features used further in matching learning training for incident detection include the four extracted traffic flow features of density, median speed, max speed, and speed S.D. and their spatial-temporal differences. For example, Density(t) – Density(t-30) represents the difference between the density at time t and 30 seconds earlier. As the drone is moving along the roadway, this difference incorporates both temporal and spatial differences. After normalizing these features, they are fed into five different machine learning classifiers for training, as shown in Figure 10. Once the model is trained, it can be used to detect traffic abnormalities caused by an incident.

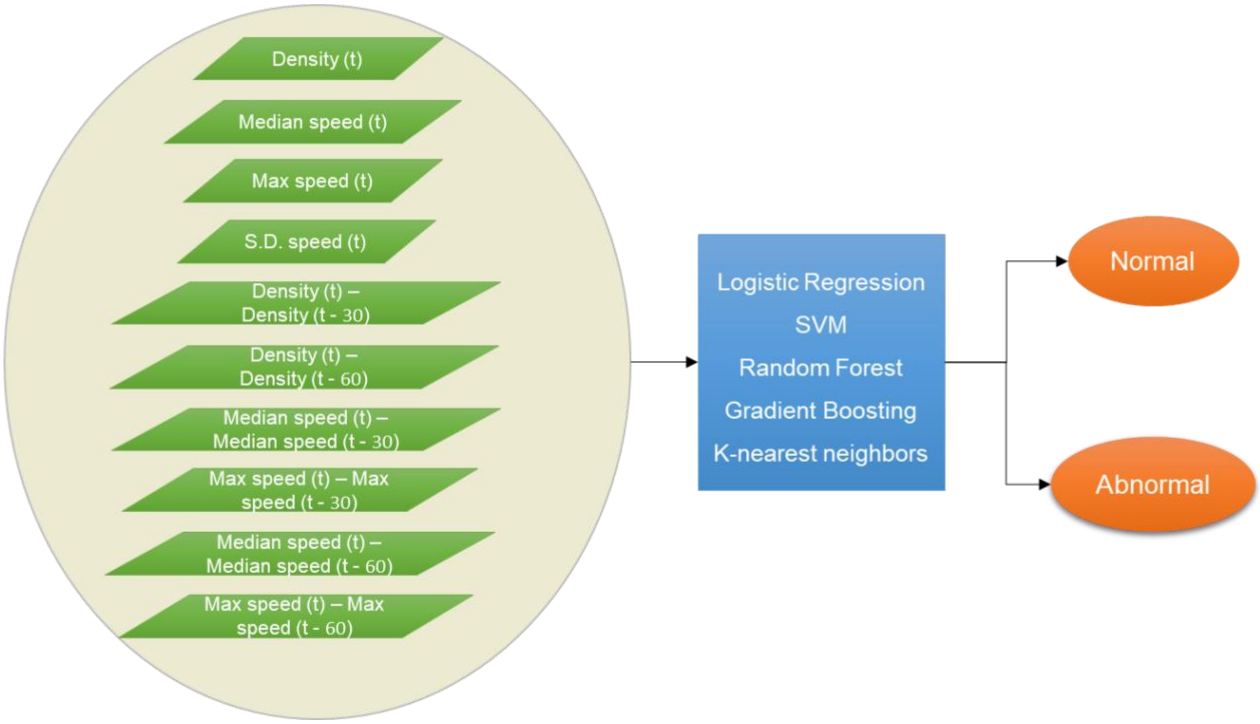

Figure 10. Features used for training machine learning models.

Chapter 4. Data Collection

Coordination between the University of South Florida (USF) and the Florida Department of Transportation (FDOT) allowed the remote drone pilot to ride along with FDOT Road Rangers to capture video data of incidents or crashes. The remote pilot scheduled ride-along times with Road Rangers through the TMC at FDOT District 7 headquarters. Road Rangers patrol almost all the Strategic Intermodal System (SIS) facilities in Florida, including interstate highways and most major highways and freeways. They provide incident management response services and are often the first to arrive at the scene of an incident or crash to set up Maintenance of Traffic (MOT) measures. They also provide limited no-cost motorist assistance such as tire changes, gas refills, and quick mechanical fixes. Whether a major crash or a car out of gas on the shoulder of a roadway, a Road Ranger will likely be the first on the scene.

Data Collection Locations

The location of the first incident observed with a Road Ranger was on the off ramp of I-75 Northbound to SR-60, as shown in Figure 11. A dump truck had overturned, spilling dirt into all lanes and blocking two of the three travel lanes, leaving only the inside lane open. This major incident took multiple hours to clear before traffic was returned to normal. The drone was flown over the grass median between the interstate and the ramp to avoid flying over traffic.

Figure 11. Location of first observed incident and congested lanes.

The second (later) incident involved a four-door pickup truck towing a concrete-filled trailer that jackknifed, spilling concrete into all lanes of roadway, as shown in Figure 12. The incident occurred on I-275 just north of E Bearss Ave. The truck rolled off the roadway, and the trailer was staged in the median. Considered a major incident that took multiple hours to clear, the inside and entrance ramp lane were closed during incident clearance.

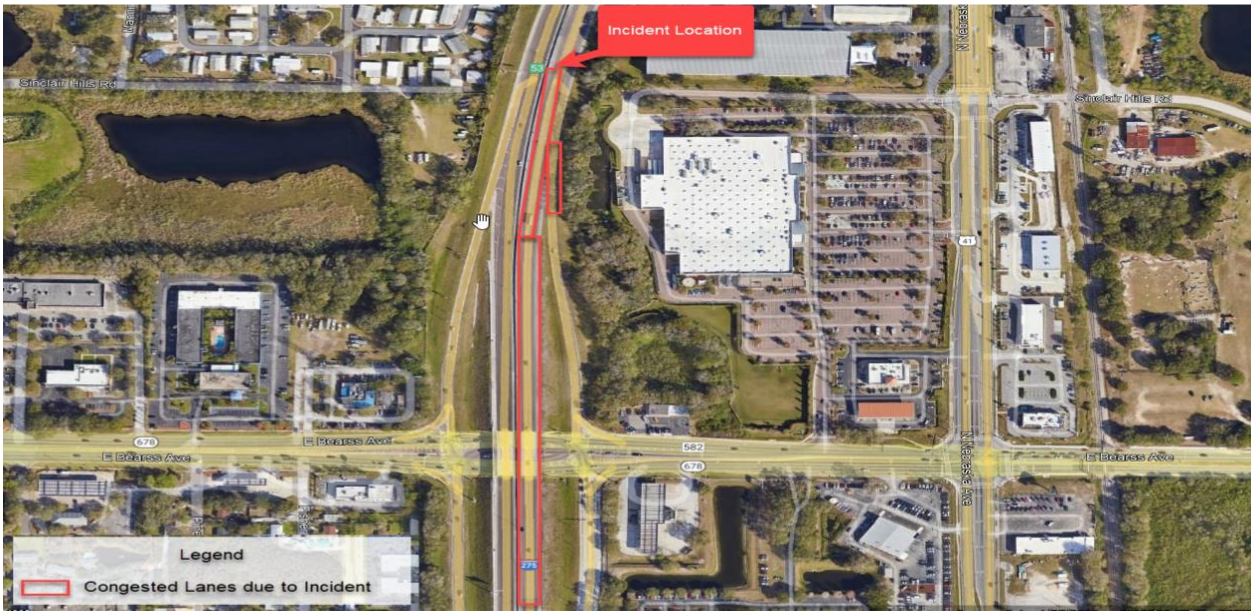

Figure 12. Location of second incident and congested lanes.

The next three incidents were recorded on the same day and were considered minor incidents. The third incident was located on I-75 Southbound in the exit lanes to Exit 274 to I-275, as shown in Figure 13. This incident involved a disabled commercial semitruck on the shoulder; the lanes leading to the I-275 exit ramp were blocked for only 100 feet, and minimal congestion occurred due to the incident.

Figure 13. Location of third incident without congested lanes.

The fourth incident occurred on I-275 Southbound, south of SR-580 (E Busch Blvd), as shown in Figure 14. It was a minor “fender bender” that was relocated to the inside shoulder and caused minimal to no congestion.

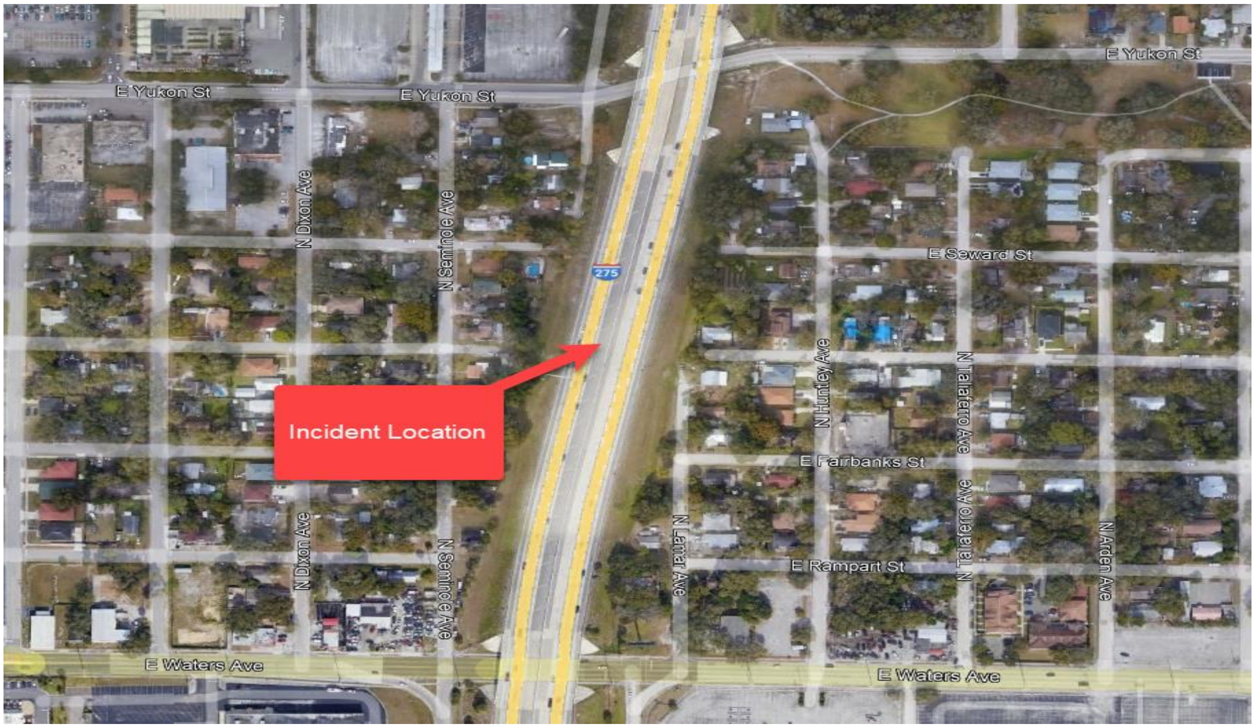

Figure 14. Location of fourth incident moved to inside shoulder on I-275 without congestion.

The last (fifth) incident captured was on I-275 Northbound, south of E Hillsborough Ave, as shown in Figure 15. The UAV pilot asked the Road Ranger to stop well before the location of the incident to capture the congestion queue forming. For this reason, the cause and type of crash are unknown. Heavier congestion occurred due to this being a recurring congested section of I-275. The congestion did not last long so it was assumed to be a minor incident.

Figure 15. Location of fifth incident on I-275 Northbound.

The dataset used for the case study was a two-minute video clip filmed by a drone at a speed of 5 mph and 300 feet above the ground with an azimuth angle of 90 degrees on I-275. Two lanes were closed near the incident location (incident #2, Figure 12). Part of the clip (38 seconds) that covered the upstream and downstream of the incident location was labeled “abnormal” traffic. Traffic flow features were extracted from the video for every fifth frame; thus, there were 190 frames with 10 features labeled as abnormal traffic. A second two-minute free-flow video was used as the “normal” traffic filmed by the same drone, with the same configuration in speed, height, and azimuth angle.

After the features were generated for both normal and abnormal traffic samples, they were used to train five machine learning models. Given the small number of samples, rather than partitioning the data into training, validation, and test sets, which would drastically reduce the number of samples used for learning, k-fold cross-validation was used. The training dataset was split into k smaller sets named

$f_1, f_2, \ldots f_k$. The model was trained using k-1 of the folds (f_2 to f_k) as training data and was tested on the remaining fold f_1. This process was iterated until the model was tested on all the folds.

The performance measure reported by k-fold cross-validation was the average of the values computed in the loop. The test results (Table 1) show that SVM performed best among the five models, with an F1 score of 0.981, whereas logistic regression had the worst performance, with an F1 of 0.784.

Table 1. Machine Learning Models Test Results on F1 Score

Model	F1 Score (SD)	Hyperparameters
SVM	0.981 (+/-0.047)	Regularization: 10; Kernel: radial basis function kernel
K nearest neighbor	0.971 (+/-0.07)	Leaf size: 15; Number of neighbors: 5; Weights: uniform
Random forest	0.942 (+/-0.075)	Max depth: 4; Number of trees: 50
Gradient boosting	0.907 (+/-0.099)	Learning rate: 0.1; Max depth: 3; Number of trees: 50
Logistic regression	0.784 (+/-0.014)	Regularization: 10

Chapter 5. Phase II Conclusions and Next Steps for Phase III

The automated incident detection framework proposed in this study consists of deep learning–based vehicle detection, traffic feature extraction and generation, and machine learning–based abnormalities detection. This method was tested on a two-minute video with data captured by a drone at a location at which traffic was passing through an incident site. The results show that some machine learning models (SVM, K nearest neighbor, random forest) performed very well in F1 scoring. However, models were trained on one incident data sample; thus, the generalization of these models needs to be validated with more available data in different configurations. In addition, the case study data sample covered only a small part of downstream traffic. To capture the spatial and temporal differences between downstream and upstream traffic caused by an incident, future data should cover more downstream traffic than the data currently used. Finally, compared with RGB video data, an alternative data source—infrared data—has the advantage of protecting privacy.

During Phase III, the team aims to collect additional incident data both upstream and downstream of the incidents to validate the models and include more spatial and temporal differences in traffic. In addition, the team will explore hybrid machine learning models in Phase III by combining random forest and Long Short-Term Memory (LSTM) or using Generative Adversarial Network (GAN) models.

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