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POLICY BRIEF

# Corridor-Wide Surveillance Using Unmanned Aircraft Systems

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**BACKGROUND AND OBJECTIVES**

Phase II of this project focused on applying machine learning (ML) 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. The objectives of the project included:

- 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 Traffic Management Center.

**METHODOLOGY**

The main objective was to provide the outcome in traffic engineering terms that can be used by the TMC, the team needed to translate the traffic congestion recorded into Level of Service (LOS), and traffic density, or occupancy. The team enhanced the algorithm developed in Phase I by following a specific framework and pieces of algorithm to perform different tasks as described here:

1) Training and testing of You Only Look Once (YOLO) model for object detection, which included training YOLO v4 on videos collected via the UAS in the Tampa Bay area. The model was trained on detecting vehicles of varied sizes using both the Red-Green-Blue (RGB) video and the infrared (thermal) video. The model was then tested on untrained video to establish accuracy and was tuned to detect moving vehicles in the videos.
2) The algorithm was then expanded to extract traffic features from the video to establish parameters for traffic monitoring. Vehicle speed including median speed, max speed, and standard deviation of speed were calculated. Traffic density was then calculated based on the road segment available in the video.

To train, test and validate algorithms, data were collected using the UAS in both RGB and infrared videos. Coordination between the University of South Florida (USF) and the Florida Department of Transportation (FDOT) District 7 allowed the remote drone pilot to ride along with FDOT Road Rangers to capture video data of incidents or crashes. Data were collected during five incidents for both upstream and downstream of the incident with limitations when the UAS could not cross over roadways.

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## RESEARCH FINDINGS

This second phase of the project provided an opportunity for the team to enhance the algorithm, which was broken into steps in the previous phase. The team collected more real-time videos of incidents and trained the ML model to detect vehicles with high accuracy. Also, the team tested different algorithms to compare and identify which had the highest accuracy. Among the five models tested, the support vector machine (SVM) model performed best.

The test results presented in Table 1 show the SVM's best performance 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 |

## POLICY AND PRACTICE RECOMMENDATIONS

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 particular 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.