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# Developing a Traffic Safety Diagnostics System for Unmanned Aerial Vehicles UsingDeep Learning Algorithms

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# DEVELOPING A TRAFFIC SAFETY DIAGNOSTICS SYSTEM FOR UNMANNED AERIAL VEHICLES USING DEEP LEARNING ALGORITHMS

by

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# ABSTRACT

This thesis presents an automated traffic safety diagnostics solution using deep learning techniques to process traffic videos by Unmanned Aerial Vehicle (UAV). Mask R-CNN is employed to better detect vehicles in UAV videos after video stabilization. The vehicle trajectories are generated when tracking the detected vehicle by Channel and Spatial Reliability Tracking (CSRT) algorithm. During the detection process, missing vehicles could be tracked by the process of identifying stopped vehicles and comparing Intersect of Union (IOU) between the tracking results and the detection results. In addition, rotated bounding rectangles based on the pixel-to-pixel manner masks that are generated by Mask R-CNN detection, which are also introduced to obtain precise vehicle size and location data. Moreover, surrogate safety measures (i.e. post-encroachment time (PET)) are calculated for each conflict event at the pixel level. Therefore, conflicts could be identified through the process of comparing the PET values and the threshold. To be more specific, conflict types that include rear-end, head-on, sideswipe, and angle could be determined. A case study is presented at a typical signalized intersection, the results indicate that the proposed framework could notably improve the accuracy of the output data. Furthermore, by calculating the PET values for each conflict event, an automated traffic safety diagnostic for the studied intersection could be conducted. According to the research, rear-end conflicts are the most prevalent conflict type at the studied location, while one angle collision conflict is identified at the study duration. It is expected that the proposed method could help diagnose the safety problems efficiently with UAVs and appropriate countermeasures could be proposed after then.

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# CHAPTER 1: INTRODUCTION

## 1.1 Background

It is vitally important to collect traffic data before doing traffic safety analysis. When analyzing the traffic conditions for specific areas or road segments, thousands of detectors such as loop detectors or radar sensors located at fixed locations helps the traffic data collections. In addition, the detectors could not monitor most of the detailed driver behaviors, such as lane changing, merging, and interaction between road users in the past years. In 2018, Wu et al. analyzed rear-end crash risk for individual vehicles through a radar sensor on a freeway location (*1*). However, such analysis is still limited to certain locations that have installed detectors. Meanwhile, the detectors could not monitor many detailed driver behaviors, such as lane changing, merging, interaction between road users, etc. Trajectory data could be collected and utilized in traffic safety analysis due to the development of various technologies such as in-vehicle GPS, surveillance cameras, and Unmanned Aerial Vehicle (UAV) in recent years (*2-4*).

In order to determine the relationship between crash risk and driver behavior, some studies utilize in-vehicle devices to collect data and some studies extracted road users' trajectories by surveillance cameras. By reviewing the data from surveillance cameras, the safety conditions for the selected areas can be calculate through surrogate safety measures, such as time-to-collision (TTC), post-encroachment time (PET)) (*5-7*).

## 1.2 Motivations and Objectives

Nevertheless, since the data collection could be conducted for certain road users with the in-vehicle devices or certain locations that have installed certain infrastructure sensors such as radars and cameras. In recent years, the technologies of UAV have been developed, which can attract much attention when collecting the traffic data. Hence, UAVs are now advocated as an alternative data collection method to analyze road users' trajectories and extract traffic flow parameters since researchers could select the locations and views for video recording (*8*).

An automated framework for safety diagnosis utilized Mask R-CNN detection algorithm and Channel and Spatial Reliability Tracking (CSRT) multi-object tracking algorithm for UAV videos is proposed. Accurate trajectory data and vehicle information could be extracted from UAV videos based on the pixel-to-pixel manner predicted masks, which are generated by Mask R-CNN and object tracking process. So that, safety diagnostics based on PET values could be conducted for each pixel in the UAV images.

## 1.3 Study Methodology

The thesis includes three studies: proposed automatic detection and tracking system, system evaluation, and automatic traffic safety diagnostics system.

Proposed automatic detection and tracking system could improve the precise of the output data. Moreover, the output of the framework are trajectories of the vehicles in the UAV video, and the vehicle size data from detection are also archived as one of the outputs.

For system evaluation, the trajectories extracted from the automatic detection and tracking processes are utilized as the input to automatically capture conflicts with the corresponding conflict types between road users.

An automatic traffic safety diagnostics system could extract trajectories and identify conflicts with the corresponding conflict types from UAV videos. PET is employed to identify potential conflicts due to its higher flexibility, which can better detect conflicts during turning movement.

## 1.4 Thesis Structure

The rest of the thesis is organized as follow: Chapter 2 provides a brief review of early studies; Chapter 3 elaborates the methodology; Chapter 4 reports methodology, and the results of the data collection and findings from the results; Finally, a summary is presented in Chapter 5.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Unmanned Aerial Vehicle (UAV)

Several studies have been conducted UAVs, in order to obtain traffic parameters through detecting and tracking road users' positions and movements from UAV videos. Since UAVs flying above the roadways, so that they usually collect the top views of vehicles. So that, vehicle locations could be directly obtained and plotted on a 2D map based on detection and tracking results without considering the impact of depth of field like in-vehicle or conventional surveillance cameras. Most of the previous studies focused on obtaining traffic flow data. In details, the data includes speed, volume, and density from UAV videos. For example, Ke et al. proposed a framework for traffic flow parameters estimation based on UAV videos through ensemble classifier (Haar cascade + convolutional neural network) and optical flow, and UAV videos from a freeway segment was utilized to test the system performance (*8*). Zhao et al. collected speed, density, and volume data for uninterrupted flow corridors based on an aerial camera array mounted on an airplane (*9*). Yamazki et al. extracted vehicle speeds based on detecting vehicles from two consecutive digital aerial images (*10*). Meanwhile, some studies utilized UAV videos to investigated traffic safety related issues, such as incident detection. In 2014, Liu et al. used UAV to detect traffic incidents for low-volume roads (*11*). In 2015, Lee et al. proved the applicability of using UAV to conduct real-time incident monitoring through pilot tests (*12*). Even though some studies have been conducted to evaluate traffic safety situations using UAV *(2,3)*, to the authors' best knowledge, few studies have been conducted to propose methods to specifically diagnose traffic safety conditions based on UAV videos other than incident detection. Although UAV videos with high resolution and frame frequency could capture adequate ground details and vehicles' movements, most of the current studies focus on calculating the traffic flow characteristic and aggregating the data into certain time intervals.

## 2.2 Surrogate Safety

Surrogate safety measures are widely employed for safety diagnostics using trajectory data to describe the safety situations for a certain time and spatial range. Among the previous studies, TTC and PET are two of the most prevalent measures to evaluate road safety conditions. In 2018, Essa et al. employed TTC as the rear-end conflict indicator and developed conflict-based safety performance functions (SPFs) for signalized intersections based on surveillance cameras at 6 signalized intersections (*13*). Guo et al. evaluated the effects of right-turn treatments effect on right-turn-on-red conflicts using TTC (*14*). Meanwhile, PET is preferred when turning or crossing movements are included. Fu et al. investigated pedestrian safety at unsignalized crossing by calculating surrogate safety measures including PET from videos (*7*). Moreover, TTC requires continuous calculation for each conflict event, which would return a set of values for each conflict. However, only one PET value is calculated and returned for each conflict event. Thus, PET is much simpler and faster to compute, which would be beneficial when evaluating safety situations between multiple road users within an area.

## 2.3 Detection and Tracking

Detection and tracking of road users are one of the central applications in computer vision studies (*15*). Thus, in recent years, it has attracted more attention to solve video-based detection and tracking issues for both automated driving applications and road monitoring applications. Some car manufactures integrate cameras with Lidars in automated vehicles to obtain depth information and determine the boundaries of surrounding vehicles using sensor fusion technology. The improvement of vehicle boundary detection would be beneficial for real-time safety estimation including calculating TTC between the automated vehicles and their surrounding road users to avoid potential collisions. As for vision-based detection, the conventional vehicle detection methods (e.g. background subtraction, optical flow) tend to only work under simple traffic scenes such as uninterrupted traffic flow and have limitations to detect the precise locations of vehicles from UAV images. Meanwhile, the results could be sensitive to the environment like vehicle color, vehicle orientation, shadows, background motion, intricate ground conditions (*16; 17*). Moreover, these methods may have difficulties to detect and track slow-moving or stopped vehicles. Thus, these methods could not be employed to analyze congested area or intersections. In recent years, multiple Regional-CNN (R-CNN) detection methods have been proposed based on deep learning approaches, which include R-CNN, fast R-CNN, and faster R-CNN. These methods have been applied for vehicle detection and have shown better performance than conventional approaches (*16; 18; 19*).

## 2.4 Summary

In summary, to the authors' best knowledge, no existing automated detection and tracking system has been proposed for pixel-to-pixel manner safety diagnostics based on UAV videos. Meanwhile, vehicles' turning movements have not been considered for vehicle detection and tracking with computer vision technologies. In this study, the authors propose a framework for extracting vehicles' trajectories and conducting safety diagnostics automatically. Then, a case study was conducted at a typical signalized intersection.

# CHAPTER 3: METHODOLOGY

## 3.1 Mask R-CNN Object Detection

Mask R-CNN is used for vehicle detection in this research, which predicts segmentation mask in a pixel-to-pixel manner (*20*). The pixel-to-pixel manner mask would be beneficial to obtain precise location of vehicles in UAV images. Mask R-CNN algorithm could provide both classification and masks as output. Meanwhile, since Mask R-CNN could generate precise masks for detected objects, rotated bounding rectangles can be obtained from the masks, which provide an alternative method to obtain vehicle sizes and more precise locations. The rotated bounding rectangles for the detected objects can be generated based on the mask as the smallest rectangle that could cover the predicted mask (*21*). Since the straight bounding rectangles of the vehicles from detection would not be rotated to align with the vehicles moving direction. Thus, the results of vehicle sizes tend to be larger when vehicles are on a curve or turn at an intersection. Figure 1 illustrates an example of the differences between the detected object's mask, straight bounding rectangle, and rotated bounding rectangle. The area within the green line is the masked area of the detected object. The red rectangle is the rotated bounding rectangle of the predicted mask, while the yellow area is the straight bounding rectangle. As shown in the figure below, the area covered by the straight bounding rectangle tends to be larger when the vehicle is conducting turning movement.

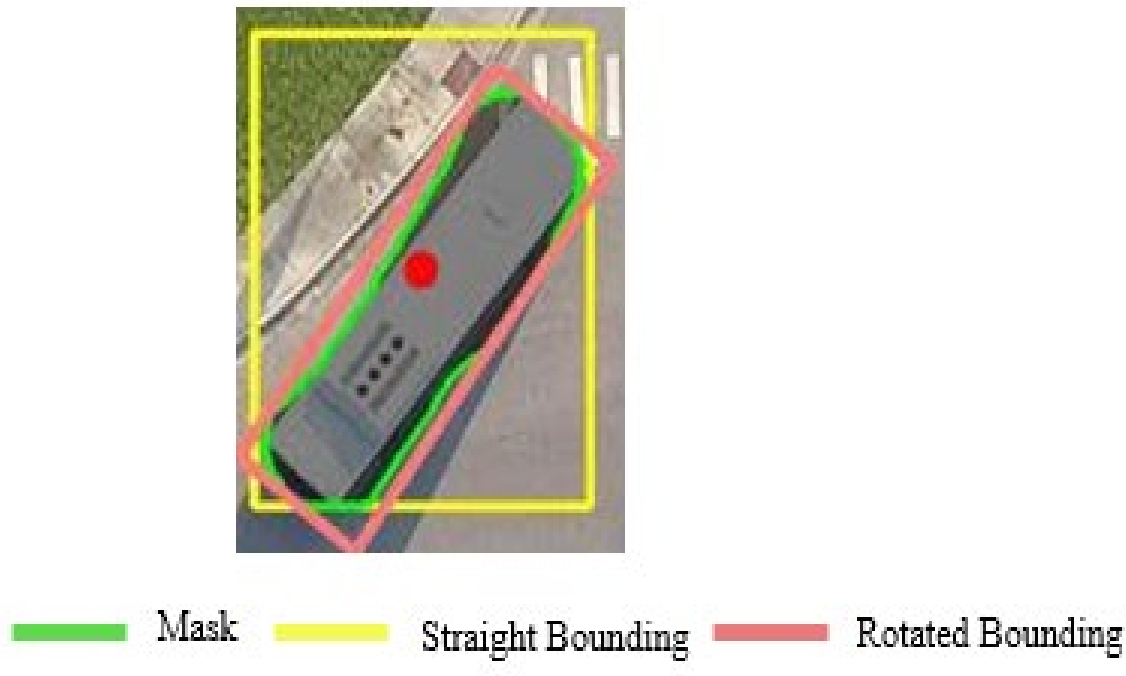



**Figure 1. Differences between mask, straight bounding box, and rotated bounding box**

The first step of detection is to collect sample library for vehicle images from UAV videos. In this study, over 10,000 vehicle samples were manually collected from multiple UAV videos (1 image per 10 seconds) from different locations. Thus, each sample includes one vehicles without duplicated samples (*17*). Three indicators are chosen to evaluate the detection accuracy, which include correctness, completeness, and quality.

$$correctness = \frac{TP}{TP + \mathrm{FP}}$$

$$completeness = \frac{TP}{TP + \mathrm{FN}}$$

$$quality = \frac{TP}{TP + FP + \mathrm{FN}}$$

where, True Positive (TP) means the number of vehicles that detected correctly; False Positive (FP) means the number wrongly detected vehicles; False Negative (FN) means the number of missing vehicles. Over 2,000 samples with different vehicle images were utilized to test the performance of training results. The performance of the detection algorithm is as follows: The correctness of the sample is 98%; The completeness is 77%; The quality of the samples is 76%. It is worth noting that since detection will run multiple times during the detection & tracking process to find the untracked vehicles, the performance is expected to be better when processing continuous video images. Moreover, in order to illustrate the differences between rotated bounding rectangles and straight bounding rectangles. Intersection of Union ($IOU_{gt}$) are calculated based on the following equation:

$$IOU_{gt} = \frac{DetectionResult \cap GroudTruth}{DetectionResult \cup GroudTruth}$$

For all the detected vehicles, the average IOU for rotated bounding rectangle area is 0.81, while the average IOU for straight bounding rectangle area is 0.62. Meanwhile, based on the results of paired t-test, there is a significant difference in IOU values between the rotated and straight bounding rectangle area (*p-value*<0.01). The results indicate that the rotated bounding rectangle could provide more precise data for the locations of the detected objects.

## 3.2 Vehicle Tracking Method

Chanel and Spatial Reliability Tracking (CSRT) is used for tracking the object that are detected based on Mask R-CNN algorithm (*22*), which provides high accuracy but lower speed based on two standard features (i.e. HoGs, Colornames) (*23, 24*). One of the challenges for vehicle tracking is that vehicles may lose tracking due to the influence of shadows, light conditions, etc. Since the accuracy of the vehicle trajectories has a significant impact when calculating surrogate safety measures and plays an importation role in safety analysis, this study proposes the following step to detect lost vehicles while tracking:

Step 0: Identify vehicle speed=0 at frame j;

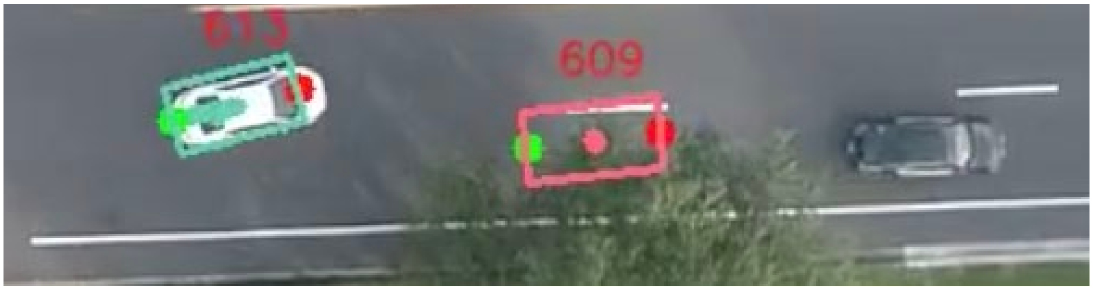
Step 1: Conduct detection for frame j;

Step 2: Calculate the intersection-over-union for tracking and detection areas based on the following equation.

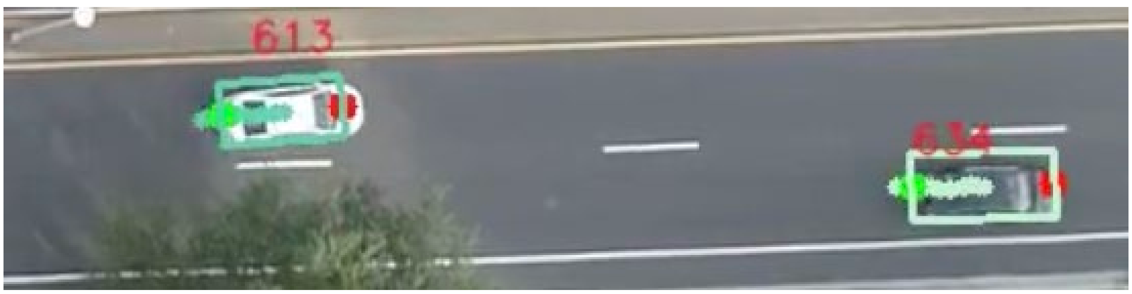
$$IOU_{DT} = \frac{DetectionResult \cap TrackingResults}{DetectionResult \cup TrackingResults}$$

Step 3: if $IOU_{DT}$<threshold, find a lost vehicle and start tracking for the lost vehicle. The threshold that we employed in this study is 0.5.

Meanwhile, vehicles' moving directions can be extracted based on the difference in locations from two consecutive frames. Thus, vehicles' bounding rectangles are rotated according to the moving direction to obtain more precise information of vehicles' occupied locations. Figure 2 (a) shows an example of a vehicle (#609) lost tracking when approaching a tree shadow area. The speed of the vehicle would be 0 after lost tracking. Thus, detection was conducted at that frame in order to find and continue tracking the lost vehicle. As it is shown in Figure 2(b), the lost vehicle is detected and tracked again as vehicle #634. Then, by comparing the lost time and location of vehicle #609 and the detected time and location of vehicle #634, vehicle #609 and vehicle #634 could be identified as the same vehicle.




(a) Lost tracking




(b) Track the lost vehicle

**Figure 2. An example of find lost vehicle during tracking**

3.3 Conflict Identification

Figure 4 shows the flowchart of conflict and conflict type identification. In order to calculate PET values, a vehicle occupancy table needs to be generated, which include the timestamps that each part of each vehicle (front, middle, rear) that arrive and leave each pixel that the vehicle has occupied in the video. Then, PET values could be calculated by comparing the timestamps for two consecutive vehicles at each pixel. The PET is calculated as time difference between the first vehicle leaving the pixel and the time that the second vehicle arrives at the pixel. Conflicts could be identified by filtering out the events that have PET less than the threshold. In this study, a sensitivity analysis was conducted for different thresholds. In order to find the precise locations and time of the identified conflicts, the earliest arrival time and pixel of the second vehicle are utilized as the corresponding conflict point and conflict time.

Then, moving direction of the vehicles, Intersect of Pixels (IOP), and vehicle occupancy table are utilized to identify conflict types (i.e., head on, angle, rear-end, sideswipe). IOP is defined as the percentage of the pixels that have been occupied by both vehicles before the conflict event happens over the pixels that have been occupied by either vehicle. The value is employed to identify if the second vehicle is following the first vehicle, which could be used to determine if the conflict is rear-end collision conflict or not. If the angle between the two vehicles' moving direction is between 0 degree and 45 degree or between 315 degree and 360 degree, and the IOP is less than or equals to the threshold, the conflict is identified as a rear-end conflict; If the angle is between 0 degree and 45 degree or between 315 degree and 360 degree, and the IOP is greater than the threshold, the conflict would be sideswipe conflict; Meanwhile, if the angle is between 135 degree and 225 degree and the conflict parts are not the front parts of the vehicles, the conflict would also be identified as sideswipe conflict; If the angle is between 135 degree and 225 degree and the conflict parts are the front parts of the vehicles, the conflict would be a head-on conflict; Otherwise, the conflict would be identified as an angle conflict.

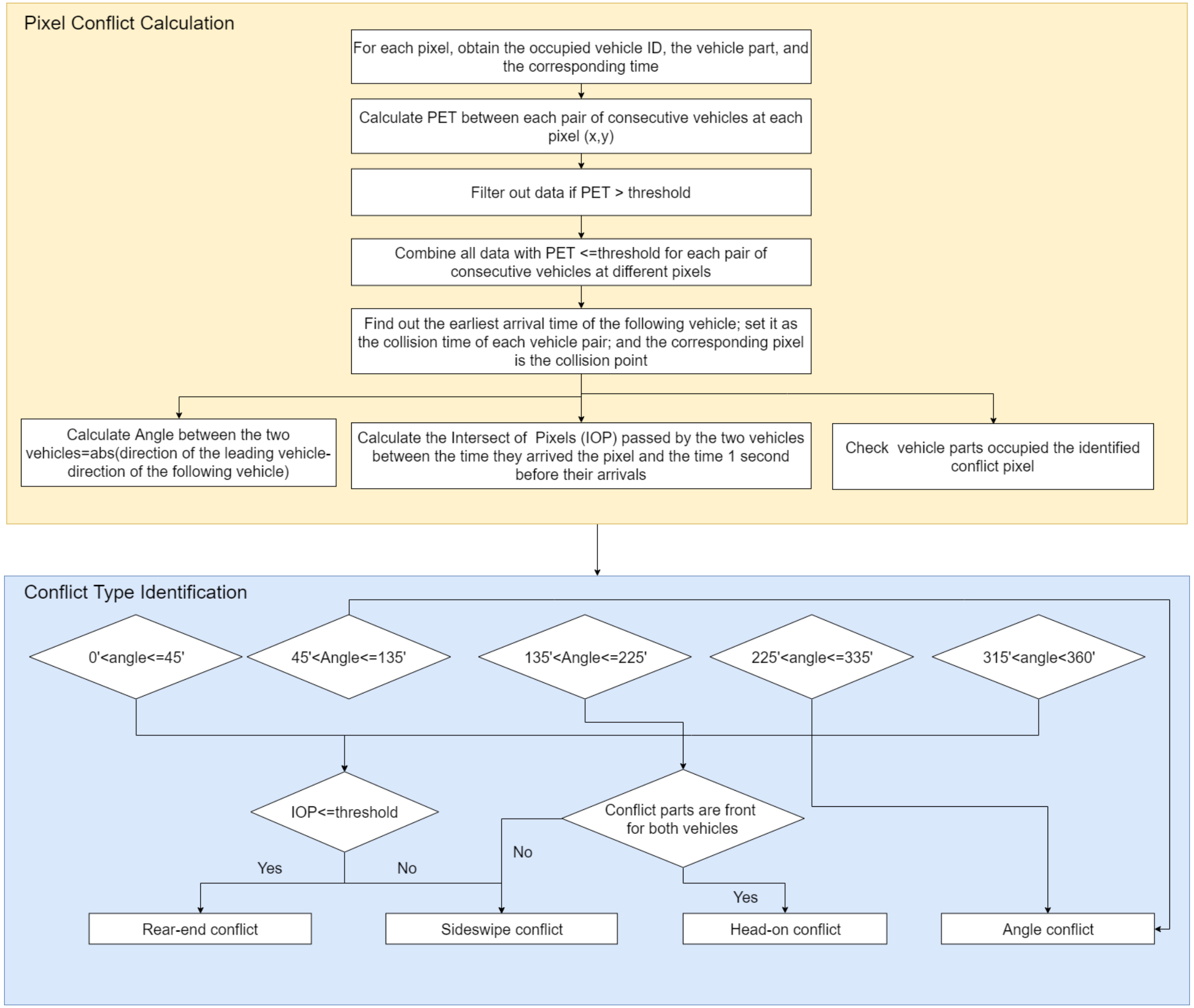



**Figure 3. Conflict identification**

# CHAPTER 4: FIELD SURVEY

## 4.1 UAV Data

To validate the proposed conflict diagnose framework, data collection was conducted on October 8$^{th}$, 2018 from 8:30 AM to 8:50 AM at a typical 4-leg intersection at the University of Central Florida (UCF). A DJI Phantom 4 UAV was utilized to collect the data, and the video was captured by an optical camera with 1920 ×1080 resolution.

## 4.2 Running Environment

Mask R-CNN detection was conducted at intervals of 0.5 seconds by Keras (*28*). Meanwhile, the position of the vehicles was tracked at intervals of every $\frac{1}{15}$ second (15 frames per second mode) by OpenCV. All experiments are conducted using Python implementation on a desktop computer with Intel i9-7980XE (18 cores and 36 threads) @ 4.2Hz, 64 GB DDr4 (3200MHz) memory and two Nvidia 2080ti GPUs.

## 4.3 Detection and Tracking Performance

In total, 1,588 vehicles were detected and tracked based on the UAV video. The accuracy of the proposed algorithm was evaluated based on IOU values. For each type of movement (i.e. left turn, right turn, straight), 20 vehicles were randomly selected from the UAV video. IOU values were calculated at the movement duration for each vehicle based on the outputs and the ground truths that were collected manually. Totally 3,541 video images were collected to calculate the IOU for the selected vehicles. Higher IOU values indicate higher accuracy of the detection and tracking results. Moreover, simple Mask R-CNN detection with CSRT tracker was conducted in order to compare with the performance of the proposed algorithm. As shown in Table 1, the proposed algorithm could significantly improve the performance for all type of movements, especially for turning movements (i.e. left turn, right turn). Also, the straight movements have the best performance for both methods.

**Table 1. Comparison of Average IOUs**

| | Simple Mask R-CNN detection and CSRT tracker | Proposed Algorithm |
|---|---|---|
| Left Turn | 0.42 | 0.78 |
| Right Turn | 0.38 | 0.70 |
| Straight | 0.80 | 0.85 |
| Average | 0.53 | 0.76 |

4.4 PET Diagnostics

In order to calculate the PET values for each pixel data, vehicles' occupancy table for each pixel was generated based on the vehicles' trajectories. A table with 68,211,472 observations were generated, which includes arrival and leave timestamps for every pixel of each part of the vehicles, and PET values were calculated based on the table. The PET values were calculated between two consecutive vehicles that have occupied the same pixels in the video, and one value is returned for each conflict with the corresponding conflict location at the pixel level. The conflict events with the corresponding locations of the identified potential conflicts were obtained based on the PET values. Moreover, heatmap could be generated based on the locations of the conflict events to investigate the spatial distribution of the conflicts.

Figure **4**(a) shows the conflict heatmap that were identified based on vehicles' trajectories where PET values are less than 1.5 s. As it is shown in the figure, the right-turning lane of the northbound has the highest risk. The results are expected as the right-turning vehicles have more frequently stop-and-go behavior in order to yield to vehicles from the other directions and lead to higher rear-end collision risk. Since the data collection was conduct at a typical morning peak duration, many vehicles turn right at the northbound to enter the UCF campus area.

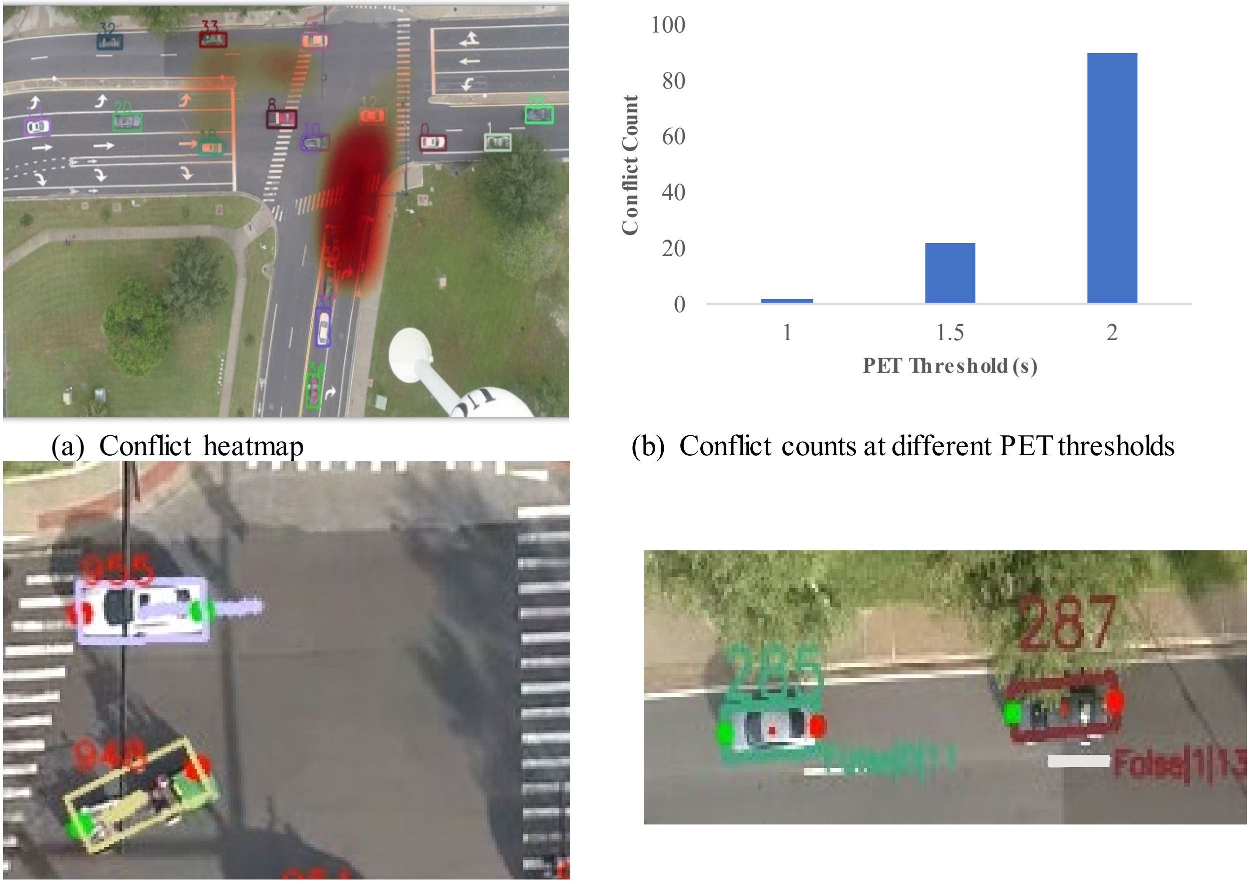
Figure **4** (b) displays the number of conflicts based on different PET thresholds. Different PET values could be employed to determine conflict risk levels, while smaller PET values indicate higher risk (*29; 30*). Significant difference could be observed for the number of conflicts with the increase of PET thresholds. If the PET threshold is 1 s, only 2 conflicts were identified as high-risk conflicts. When the threshold increases to 1.5 s, the conflict count increased to 22. Moreover, the number of conflicts increases to 90 when the PET threshold increases to 2 s.

From the UAV video, most of the identified conflicts are rear-end collision conflicts, only 1 angle collision conflict was identified with PET value equal to 1.7 s.

Figure **4** (c) shows an example of angle collision conflict, where a left-turning vehicle (vehicle #948) has a potential conflict with the straight moving vehicle (vehicle #955).

Figure **4** (d) provides an example of rear-end collision conflict between vehicles #285 and #287 which is due to relatively small headway.

Based on the diagnosis results, countermeasures such as adding a dynamic message sign or beacon could be implemented at the upstream of the northbound approach to reduce the right-turn conflicts.




(a) Conflict heatmap

(b) Conflict counts at different PET thresholds

(c) An example of angle collision conflict

(d) An example of rear-end collision conflict

**Figure 4. Safety diagnostics**

# CHAPTER 5: CONCLUSION

This research proposes an automated framework for safety diagnosis utilizing Mask R-CNN detection algorithm and Channel and Spatial Reliability Tracking (CSRT) multi-object tracking algorithm for UAV videos. A case study was conducted at a typical signalized intersection at UCF. The case study has validated the feasibility of investigating safety situation from UAV videos based on surrogate safety measures (i.e. PET). It also demonstrated that the proposed methods of using computer vision techniques to automatically extract vehicles' trajectories and identify conflicts from UAV videos have better performance in terms of data accuracy, especially for turning vehicles (i.e., right turning, left turning). To the best of the authors' knowledge, this is the first study that proposes a framework to automatically identify conflict types from video-based trajectory data without using other types of data (e.g., road geometry, lane configuration). Sensitivity analysis for PET threshold was conduct in the study. The results of the identified conflicts indicate that rear-end conflicts is the most prevalent type of conflicts for the studied intersection, while only one angle collision conflict was identified between a left-turning vehicle and a through vehicle. Moreover, the right-turning lane at the northbound was found to have the highest risk where many vehicles turn right to enter the UCF campus and frequently stop-and-go behavior were present in order to yield to the vehicles from other directions.

In the future, different type of objects (e.g. truck, bus) could be detected with enriched UAV datasets for detection. Also, other surrogate safety measures (e.g. TTC) could be utilized to further explore the safety conditions of the study area. In addition, the data obtained from the UAV datasets can be served as a good validation dataset for the safety risk-related analysis, as an alternative augmentation to traditional data source such as Bluetooth and crash data (*25, 26, 27, 28, 29; 30*); as well as a good dataset for CAV applications and prototype (*31, 32,33, 34; 35; 36*).

# REFERENCES

1. Wu, Y., M. Abdel-Aty, Q. Cai, J. Lee, and J. Park. Developing an algorithm to assess the rear-end collision risk under fog conditions using real-time data. *Transportation Research Part C: Emerging Technologies*, Vol. 87, 2018, pp. 11-25.
2. Gu, X., M. Abdel-Aty, Q. Xiang, Q. Cai, J. J. Yuan, and Prevention. Utilizing UAV video data for in-depth analysis of drivers' crash risk at interchange merging areas. *Accident Analysis & Prevention*, Vol. 123, 2019, pp. 159-169.
3. Xing, L., J. He, M. Abdel-Aty, Q. Cai, Y. Li, O. Zheng. Examining traffic conflicts of up stream toll plaza area using vehicles' trajectory data. *Accident Analysis & Prevention*, Vol. 125, 2019, pp. 174-187.
4. Ahmed, M. M., and A. Ghasemzadeh. The impacts of heavy rain on speed and headway behaviors: an investigation using the SHRP2 naturalistic driving study data. *Transportation research part C: emerging technologies*, Vol. 91, 2018, pp. 371-384.
5. Sayed, T., K. Ismail, M. H. Zaki, and J. Autey. Feasibility of computer vision-based safety evaluations: Case study of a signalized right-turn safety treatment. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2280, No. 1, 2012, pp. 18-27.
6. Zaki, M. H., T. Sayed, A. Tageldin, and M. Hussein. Application of computer vision to diagnosis of pedestrian safety issues. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2393, No. 1, 2013, pp. 7
7. Fu, T., L. Miranda-Moreno, and N. Saunier. Pedestrian crosswalk safety at nonsignalized crossings during nighttime: use of thermal video data and surrogate safety measures. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2586, No. 1, 2016, pp. 90-99.

8. Ke, R., Z. Li, J. Tang, Z. Pan, and Y. Wang. Real-time traffic flow parameter estimation from UAV video based on ensemble classifier and optical flow. *IEEE Transactions on Intelligent Transportation Systems*, No. 99, 2018, pp. 1-11.
9. Zhao, X., D. Dawson, W. A. Sarasua, and S. Birchfield. Automated traffic surveillance system with aerial camera arrays imagery: Macroscopic data collection with vehicle tracking. *Journal of Computing in Civil Engineering*, Vol. 31, No. 3, 2016, p. 04016072.
10. Yamazaki, F., W. Liu, and T. Vu. Vehicle extraction and speed detection from digital aerial images.In IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium, No. 3, IEEE, 2008. pp. III-1334-III-1337.
11. Liu, X., Z. Peng, H. Hou, and L. Wang. Simulation and evaluation of using unmanned aerial vehicle to detect low-volume road traffic incident. Presented at Transportation Research Board 94th Annual Meeting, 2015.
12. Lee, J., Z. Zhong, K. Kim, B. Dimitrijevic, B. Du, and S. Gutesa. Examining the Applicability of Small Quadcopter Drone for Traffic Surveillance and Roadway Incident Monitoring. Marine Transportation. Presented at 94rd Annual Meeting of the Transportation Research Board, Washington, D.C., 2015
13. Essa, M., and T. Sayed. Traffic conflict models to evaluate the safety of signalized intersections at the cycle level. *Transportation research part C: emerging technologies*, Vol. 89, 2018, pp. 289-302.
14. Guo, Y., P. Liu, Y. Wu, J. Chen, and Security. Evaluating how right-turn treatments affect right-turn-on-red conflicts at signalized intersections. *Journal of Transportation Safety & Security*, 2018, pp. 1-22.
15. Sayed, T., M. H. Zaki, and J. Autey. Automated safety diagnosis of vehicle–bicycle interactions using computer vision analysis. *Safety science*, Vol. 59, 2013, pp. 163-172.

16. Kim, E., H. Park, S.-W. Ham, S. Kho, and D.-K. Kim. Extracting Vehicle Trajectories Using Unmanned Aerial Vehicles in Congested Traffic Conditions. *Journal of Advanced Transportation*, Vol. 2019, 2019.

17. Xu, Y., G. Yu, X. Wu, Y. Wang, and Y. Ma. An enhanced viola-jones vehicle detection method from unmanned aerial vehicles imagery. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 18, No. 7, 2016, pp. 1845-1856.

18. Tang, T., S. Zhou, Z. Deng, H. Zou, and L. Lei. Vehicle detection in aerial images based on region convolutional neural networks and hard negative example mining. *Sensors*, Vol. 17, No. 2, 2017, p. 336.

19. Xu, Y., G. Yu, Y. Wang, X. Wu, and Y. Ma. Car detection from low-altitude UAV imagery with the faster R-CNN. *Journal of Advanced Transportation*, Vol. 2017, 2017.

20. He, K., G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn.In Proceedings of the IEEE international conference on computer vision, 2017. pp. 2961-2969.

21. OpenCV. Contour Features. https://docs.opencv.org/3.4.2/dd/d49/tutorial_py_contour_features.html. Accessed July 29, 2019.

22. Lukezic, A., T. Vojir, L. ˇCehovin Zajc, J. Matas, and M. Kristan. Discriminative correlation filter with channel and spatial reliability. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017. pp. 6309-6318.

23. Mallick, S. Object Tracking using OpenCV (C++/Python). https://www.learnopencv.com/object-tracking-using-opencv-cpp-python/2019, Accessed July 20, 2019.

24. Yuan, J. and Abdel-Aty, M., 2018. Approach-level real-time crash risk analysis for signalized intersections. Accident Analysis & Prevention, 119, pp.274-289.

25. Wu, Y., Abdel-Aty, M., Ding, Y., Jia, B., Shi, Q. and Yan, X., 2018. Comparison of proposed countermeasures for dilemma zone at signalized intersections based on cellular automata simulations. Accident Analysis & Prevention, 116, pp.69-78.

26. Cai, Q., Abdel-Aty, M., Sun, Y., Lee, J. and Yuan, J., 2019. Applying a deep learning approach for transportation safety planning by using high-resolution transportation and land use data. Transportation Research Part A: Policy and Practice, 127, pp.71-85.

27. Yuan, J., Abdel-Aty, M., Wang, L., Lee, J., Yu, R. and Wang, X., 2018. Utilizing bluetooth and adaptive signal control data for real-time safety analysis on urban arterials. Transportation research part C: emerging technologies, 97, pp.114-127.

28. Zhang, J., Yan, X., An, M. and Sun, L., 2017. The impact of beijing subway's new fare policy on riders' attitude, travel pattern and demand. Sustainability, 9(5), p.689.

29. Yue, L., Abdel-Aty, M., Lee, J. and Farid, A., 2019. Effects of signalization at rural intersections considering the elderly driving population. Transportation research record, 2673(2), pp.743-757.

30. Wang, X., Yuan, J., Schultz, G.G. and Fang, S., 2018. Investigating the safety impact of roadway network features of suburban arterials in Shanghai. Accident Analysis & Prevention, 113, pp.137-148.

31. Chen, D., Yan, X., Liu, F., Liu, X., Wang, L. and Zhang, J., 2019. Evaluating and diagnosing road intersection operation performance using floating car data. Sensors, 19(10), p.2256.

32. Yue, L., Abdel-Aty, M., Wu, Y. and Wang, L., 2018. Assessment of the safety benefits of vehicles' advanced driver assistance, connectivity and low level automation systems. Accident Analysis & Prevention, 117, pp.55-64.

33. Yue, L., Abdel-Aty, M.A., Wu, Y. and Farid, A., 2019. The Practical Effectiveness of Advanced Driver Assistance Systems at Different Roadway Facilities: System Limitation, Adoption, and Usage. IEEE Transactions on Intelligent Transportation Systems.

34. Zheng, O. and ElAarag, H., 2018, April. Simultaneous locallzation and mapping using UAVs equipped with inexpensive sensors. In Proceedings of the Communications and Networking Symposium (p. 1). Society for Computer Simulation International.

35. Cai, Q., Abdel-Aty, M. and Lee, J., 2017. Macro-level vulnerable road users crash analysis: a Bayesian joint modeling approach of frequency and proportion. Accident Analysis & Prevention, 107, pp.11-19.

36. Wu, Y., Abdel-Aty, M., Zheng, O., Cai, Q. and Yue, L., 2019. Developing a Crash Warning System for the Bike Lane Area at Intersections with Connected Vehicle Technology. Transportation Research Record, 2673(4), pp. 47-58.