Continuous Monitoring of a Signalized Intersection Using Unmanned Aerial Vehicles*

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***Abstract*— The use of drones offers an innovative traffic data collection technique that allows to capture very detailed and accurate vehicle trajectories. However, deploying them for an entire day would be prohibitively expensive due to the limitations of their batteries. In this paper we show how commercial, low-cost drones can be used to monitor traffic during a full day in an efficient way throughout the day. More specifically, we provide a case study of a signalized intersection in the city of Manchester, UK, where traffic streams were recorded during both the morning and afternoon peak hours. Using advanced computer vision techniques, we extract vehicle trajectories that enable us to conduct an in-depth analysis of the intersection. Our analysis includes a comprehensive traffic assessment of the intersection for a complete day with traffic metrics such as OD, turning ratios, fundamental diagrams, and shockwaves.**

I. Introduction

Unmanned aerial vehicles (UAVs), or more commonly referred to as drones, have caught the eye of traffic engineers to collect traffic data in the last years. There are several reasons for such an interest: drones have become a useful, rapid, and reliable data collection methodology due to the recent improvements in computer vision (CV) algorithms that allow to extract trajectories from video sources [1]. Therefore, it is no surprise that the traffic research community has turned into the use of drones to develop new datasets comprising vehicle trajectories in different environments [2]–[5]. Although some concerns about safety or privacy have been raised, the numerous case studies using drones for traffic monitoring purposes show that the technical challenges can be overcome and that the possibilities this technology offers are of great interest to traffic researchers and practitioners [6], [7].

Compared to traditional traffic data collection methodologies, drones offer a versatile and accurate methodology to collect traffic data that can be useful for many traffic applications: flow analysis, safety, vehicular emissions, etc. These analyses are possible due to the extraction of trajectories using CV techniques at a very high frequency. However, due to the limited battery of drones, most of the traffic data recorded with drones focus on a specific time (e.g., only morning peak hour). For example, the only signalized intersection in [5] is recorded during 60 minutes, and the data in [4] corresponds only to the morning peak hour. Thus, these experiments do not allow to have a continuous understanding of the traffic situation during a whole day.

In this paper, we show that it is possible to monitor the traffic at a signalized intersection using commercial drones for a whole day. While tethered drones have been used for similar purposes, they can significantly increase cost or limitations in the spatial coverage. For that reason, an experiment using four drones was conducted in the city center of Manchester, UK, to cover five critical signalized intersections. The experiment lasted four days and drones recorded traffic streams during morning and afternoon peak hours. Using the intersection between Chapel Street and Trinity Way, located in the Salford district in the heart of Manchester, we report continuous traffic metrics during a whole day, including turning ratios, flows, and fundamental diagrams. Specifically, we show how short videos of 3 to 4 minutes of duration are enough to provide continuous monitoring of the traffic.

This paper discusses the whole process to monitor and analyze a signalized intersection using drones and is structured as follows: section II offers the related work concerning the monitoring of signalized intersections and the use of drones in traffic monitoring, section III describes the experiment and its design, section IV outlines the methodologies to obtain traffic metrics from drone video sources and section V shows the results. Lastly, section VI provides a short conclusion and suggestions for future work.

II. Related Work

There are numerous ways to collect traffic data to monitor traffic at intersections. While traditional data collection methods like loop detectors and manual counts are still being used due to their simplicity, they cannot adapt to the needs of smart cities. Moreover, manual counts are prone to human errors and loop detectors aggregate data in a way that limits an in-depth analysis of the traffic from different points of view. Fixed cameras have also become a popular methodology to monitor traffic, and with the use of intelligent cameras, real-time monitoring is possible. However, the installation of fixed cameras is expensive and blind spots are common due to the limited field of view. Other data collection techniques include GPS data from smartphones [8] or connected vehicle data [9]. Such methods are becoming redundant as they offer reduced flexibility to adapt to the flexible and multimodal approaches that can actively promote sustainability.

That is why drones offer a pioneering and reliable methodology to study any intersection -signalized or not- from various traffic perspectives: traffic flow, safety, multimodality, or emissions. In [10] authors use the critical points methodology to analyze shockwaves and traffic states

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at a 4-leg signalized intersection. However, the available data was only a 15-minute video recording at 80m height. Likewise, the authors in [11] use data from drones near a signalized intersection to study PTW driving behavior. Similarly, [12] focused on drones to study traffic safety at a signalized intersection using 1-hour UAV recording in the morning peak hour. It is worth mentioning that UAVs have also been tested to study urban roundabouts or unsignalized intersections [13], [14]. In both cases, the critical gap to enter the roundabout or cross the intersection is one of the main research topics.

In recent years, CV tools such as object detection and object tracking have become increasingly popular for trajectory extraction from drone video data in transportation research. These tools enable researchers to automatically detect and track moving objects such as vehicles, pedestrians, and cyclists, and extract their trajectories over time. Although classical CV methods like background subtraction and optical flow have been widely applied in the past [13], [15], they manifest significant limitations when dealing with complex scenes or occlusions, thus constraining their applicability. To address these limitations, deep learning-based methods have been developed, such as variants of YOLO, e.g., YOLOv5 in [3], and region proposal networks like Faster R-CNN in [5] and computationally-intensive Mask R-CNN in [16]. More recent advancements in this field encompass the utilization of CNNs for precise traffic analysis through non-calibrated drone footage [17], and the introduction of the Butterfly detector, designed for robust detection of small vehicles in aerial images and accurate traffic flow estimation [18]. Linear Kalman filtering for prediction and the Hungarian algorithm for data association are common methods that have been considered for vehicle tracking in [3], [5], [19], although other techniques such as channel and spatial reliability tracker and optical-flow tracking have also been employed in [13], [15]. These CV tools, combined with drone technology, allow researchers to collect trajectory data for applications like traffic flow analysis, driver behavior modeling, and pedestrian safety assessment.

All the aforementioned cases and the recent advances in CV techniques showcase the convenience of drones to extract traffic information from a signalized intersection. However, due to the limited battery of drones, few trajectories have been used in related literature. With the collection of trajectories throughout a whole day we intend to extract traffic metrics and to identify patterns that until now have not been recognized using drones.

III. The Experiment

During the last day of October and the first days of November 2022, an experiment using four drones was conducted in the city of Manchester, UK, to record traffic streams at five critical intersections. Specifically, the drones flew from 2022-10-31 until 2022-11-04.

The experiment took place during the morning peak hour (7:00-11:00) and the afternoon (14:00-17:00) for four days. Professional pilots were hired to fly the drones (DJI MINI3 with 4K (3840 × 2160 pixels) camera recording at 29.97fps) at an altitude of 120m using bird-eye view. Four drones were used to cover different parts of five intersections in different time intervals adapting to the varying traffic conditions. Additionally, one of the particularities of the experiment is that the drones would change their exact position and orientation in each flight, before hovering over the significant part of the intersection.

Since the goal of the experiment was to monitor traffic during a very long duration, the limited battery of the drones played a key role in the design of the experiment. Indeed, existing papers offer studies with a short time duration due to the limited battery of drones. In order to obtain continuous recording, the pilots carefully landed the drones each time the battery reached a minimum safety level, changed the batteries, and started a new flight. For that purpose, each pilot had access to plenty of batteries. The time after the morning session, when traffic conditions were smooth, was also used to recharge all the batteries.

In this paper, we provide a case study of the intersection between Chapel Street and Trinity Way (Fig. 1), one of the busiest in Manchester's city center, in the Salford district. The intersection features traffic lights in each leg, pedestrian crossings, bike lanes, segregated turning lanes and several bus lines drive through it. It constitutes, thus, a perfect case study for multimodality. The details about the experiment and the videos from this intersection can be found in Table I. The videos extend from 07:00 to almost 11:00 and from 14:00 to 17:00, and our results were extracted from November 3rd, 2022.

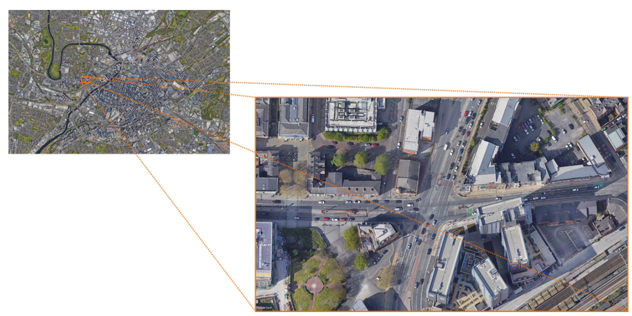

Figure 1. Location of the intersection between Chapel Street and Trinity Way

TABLE I. Experiment Details

	Morning (AM)	Afternoon (PM)
Start Time	07:00:00	14:00:00
End Time	10:50:00	17:00:00
Number of videos	21	19
Avg. video duration [min]	3.77	3.78
Total recording time [min]	79.05	71.7

IV. Methodology

Due to the limited battery of drones each battery lasted between 15 to 20 minutes in total, depending on the atmospheric conditions. Given that the drones were recording different parts, the videos were cut through the identification of the frame numbers where the drones were hovering based on the information from the flight's logs.

A. Computer Vision

In this work, the computer vision pipeline aims at extracting high-quality vehicle trajectories from raw drone videos using a series of tasks. These tasks can be divided into three main steps: video stabilization, object detection, and object tracking, which together enable accurate detection and tracking of vehicles within the analyzed video. Specifically, the pipeline first stabilizes the video footage to reduce motion jitters, identifies and localizes vehicles in each frame, and tracks their movement across multiple frames to generate trajectories in image coordinates. These steps are detailed next.

The aim of the video stabilization step is to ensure that the pixel coordinates of static objects in the drone scene remain constant during the recorded hovering period. This process allowed us to mitigate shakiness and other unintended movements in the video footage caused by external factors such as wind or unintentional pilot control inputs. In this work, the video stabilization was achieved by warping all frames to a reference frame using the Adobe After Effects tool.

In this work, we adopted the YOLOv5 [20] object detection model and, after experimenting with various architectures, selected the YOLOv5s-7.0 model for its optimal balance between accuracy and speed. Enhancements for tiny object detection were implemented through an extra P2/4 output layer and a K-means-based auto-anchor feature for optimal anchor box-sizing. The multi-stage training approach utilized COCO pre-trained weights, followed by large-scale dataset training and fine-tuning on a subset with higher-quality labels. This large-scale dataset includes approximately 30,000 images from six public (e.g., VisDrone, UAVDT, etc.) and two in-house pseudo-labeled drone datasets, filtered and pre-processed to mimic a 120m bird-eye view in Manchester.

Efforts to consolidate class labels resulted in three vehicle classes: car (including vans), bus, and truck, although motorcycles, pedestrians, and bicycles were trained but not used during inference. The training process involved various data augmentation techniques and extensive hyperparameter tuning, culminating in the selection of the fine-tuned model with the highest mAP@.5 test score. These measures reflect a comprehensive effort to align the model with specific project requirements, including considerations for altitude, angle, resolution, illumination, and quality, all crucial to the success of the detection task.

To assign unique IDs to each vehicle in the scene and track their movements across the video frames is the task of a multi-object tracking (MOT) algorithm. MOT allows for consistent identification and tracking of vehicles, even when they are temporarily occluded, and provides valuable information about their behavior and interactions with other vehicles. To solve the MOT problem, we investigated several algorithms that fit our purpose. We tested pure motion-model-based (SORT, OC-SORT, ByteTrack) as well as hybrid (motion and appearance-model-based) approaches such as (DeepSORT, StrongSORT, StrongSORT++). Finally, we chose the Observation-Centric Simple Online and Realtime Tracking (OC-SORT) [21] algorithm. OC-SORT is a pure motion-based MOT algorithm. It is simple, yet real-time and robust to occlusions and non-linear motion. It is designed by recognizing and fixing limitations in the Kalman filter and SORT [22]. Moreover, in our case, we utilized OC-SORT, a motion-based algorithm that has proven to be both fast and robust against partial occlusions and non-linear motion, minimizing split trajectories due to sporadic miss-detections from obstructions such as trees or traffic light poles.

The output of the detection and tracking pipeline is illustrated in Fig. 2. Each vehicle is assigned a unique vehicle ID, a vehicle class label, a confidence score, and a bounding box. To differentiate between various vehicle classes, different colors are employed. Additionally, the trailing tail behind the moving vehicles serves to illustrate their motion.

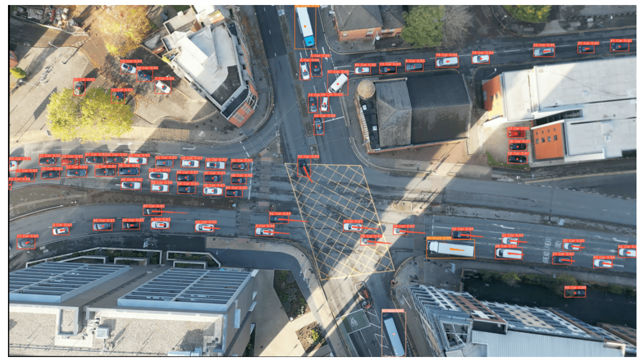

Figure 2. Illustration of the detection and tracking pipeline

B. Extraction of Trajectories

This section concerns the processing of the output of the detection and tracking pipeline described above, which includes a set of vehicle trajectories, each vehicle being identified with a bounding box in pixel coordinates. We choose to represent each vehicle as a single point, which corresponds to the center of the bounding box at each timestep.

The methodology described hereafter relies on the extraction of ground control points (GCPs) and the use of homography matrices. Since the drone was located in different parts of the junction depending on the traffic interest, the use of the same GCPs for all videos is not applicable. However, with the help of CV techniques, it is possible to extract GCPs for just the first video and then compute a homography matrix for each new video. The methodology can be summarized into the following steps:

1. Extraction of GCPs (pixel-UTM coordinates) for the first frame of the first stabilized video with QGIS Georeferencer. This frame is nicknamed as the *georeferenced frame*.
2. For each new stabilized video, computation of the homography matrix between the video's first frame and the georeferenced frame. Transformation of video pixel coordinates to georeferenced pixel coordinates.
3. Linear regression using GCPs to transform georeferenced pixel coordinates into raw UTM coordinates.

Once all the trajectories have been georeferenced and described in raw UTM coordinates, the next step is to smooth the path to avoid unrealistic shifts due to the high data frequency (30Hz) and to compute speed and acceleration profiles. For this, we use a linear Kalman filter with a constant acceleration model. The output of the Kalman filter includes the smoothed trajectory in UTM coordinates as well as the speed and acceleration profiles for each vehicle. Finally, UTM coordinates are transformed into WGS84 coordinates. Additionally, each trajectory is identified with the original video file, a unique track ID and the type of vehicle. To illustrate the methodology described in this section, Fig. 3 shows the georeferenced trajectories in WGS84 coordinates.

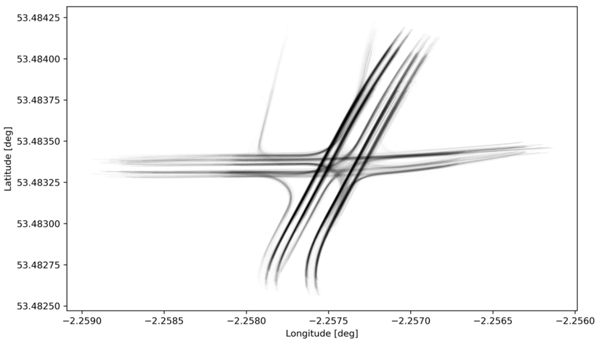

Figure 3. Georeferenced trajectories

C. *Traffic analysis*

In order to analyze the intersection, we install "virtual loop detectors" at the stop lines of the four legs and we divide each leg into an entry and exit area using 60m-long polygons (Fig. 4). We also consider the central part where vehicles cross as a stand-alone area. While the central part and the stop lines are recorded in every video, the recorded length of each leg depends on the position of the drone during the flight. That is why each polygon is cut according to the limits of each video.

Figure 4. Division of the intersection for the analysis

By checking the polygons crossed for each trajectory we obtain OD information, and we compute turning ratios for each leg. Then, using Edie's definition (Equation (1), where M is the total number of vehicles, L_n is the network length, and TD_i and TT_i are the travelled distance and travelled time of vehicle i during the aggregation time ΔT) we also compute flow and accumulation in each polygon throughout the day. While different time aggregations were examined, we choose 20s for the rest of the paper.

$$q = \frac{\sum_{i=1}^{M} TD_i}{L_n \Delta T}, \quad k = \frac{\sum_{i=1}^{M} TT_i}{L_n \Delta T} \tag{1}$$

Finally, the identification of shockwaves follows a similar approach to [23]: we find the critical points of long stops and cluster the stopping and starting points into cycles. We classify datapoints as stopped or moving with a speed threshold of 3.6km/h. The datapoints where the status changes from stopped to moving or vice versa are considered critical points. Next, we check the stopping time between two critical points. It is assumed that the stopped duration of vehicles due to a traffic signal is bigger than in stop-and-go situations and the closer the vehicle is to the stop line the longer the stopped time [23]. By setting a minimum stop duration of 20 seconds we identify the critical points that belong to the formation and dissipation of queues due to a red traffic light. Each critical point contains the distance to the stop line and the timestamp.

Once the stopping and the starting critical points belonging to the queue of a red light have been identified, we cluster them into cycles. For that reason, we use DBSCAN clustering, an unsupervised clustering method to cluster stopping points and starting points into shockwaves. We scale the distance to the stop line to a [0, 1] range and we transform the time dimension into seconds. The goal with the scaling is to emphasize groups that are close in time rather than close in distance. After a sensitivity analysis on the parameters, we use *eps*=10 and *min_samples*=3. With a linear regression of the points belonging to the same shockwave we obtain the shockwave speed. Finally, it must be mentioned that shockwaves can be obtained for a specific lane, and therefore we use the methodology in [24] to identify lanes from trajectories.

V. Results

Using the data from a full day (2022-11-03) we show the evolution of traffic metrics throughout the day in the form of OD and turning ratios, fundamental diagrams, and shockwaves.

A. *OD and Turning Ratios*

Given that each trajectory includes a vehicle type label we compute the origin-destination of each type of vehicle for both the morning and afternoon sessions. In Fig. 5 we observe that the north-south axis is the most used among cars and buses while trucks mostly use the east-west axis. No substantial differences are observed between the morning and afternoon sessions although the south to north movement seems to get even more predominant with time.

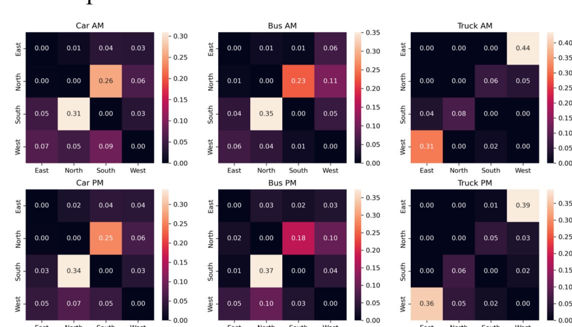

Figure 5. OD matrices

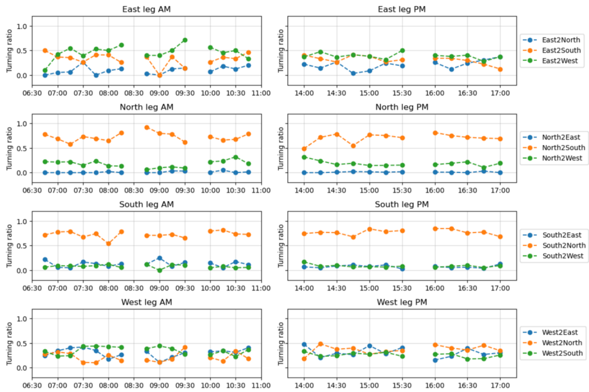

Figure 6. Evolution of turning ratios

Similar to the OD matrices of Fig. 5, the turning ratios express how many vehicles split in each direction in a certain leg (Fig. 6). Using a time aggregation of 15min, Fig. 6 shows indeed that the north-south axis is prioritized during the whole day as the movements north to south and south to north have always turning ratios close to 0.8. The turning ratios in the east and west legs are more balanced.

B. Fundamental Diagrams

Fundamental diagrams (FDs) provide a rapid visualization of the traffic situation. With Edie's definitions and a time aggregation of 20 seconds, we compute the FDs for the entries and the exits in the four legs. Since all the data is time-referenced, we provide FDs with a time component in the colormap.

In Fig. 7 we show the fundamental diagrams for the north and south entries and exits during the morning peak hour. Congestion is heavily observed except in the north exit, where the vehicles drive at their desired speed as the next junction is quite far away. It is also seen that around 10:00 the north entry and the south exit are less congested as the peak hour ends. On the other hand, the south entry is heavily congested even around 10:00.

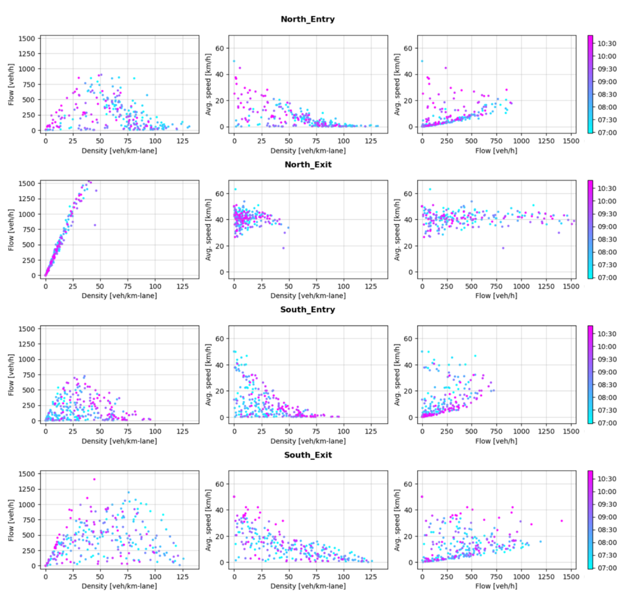

Figure 7. Fundamental diagrams for north and south legs in the morning

C. Shockwaves

With the methodology described in section IV, we can detect shockwaves and their speed. We focus on the north to south movement since it is widely recorded by the drone in all the flights throughout the day and it is proven to be a predominant movement. In Fig. 8 we show an example of the shockwaves that have been identified due to the red light in two consecutive flights in the morning (the gap between 07:51 and 07:56 corresponds to a period where the drone was not recording). The figure also highlights that the position of the drone was changing at every flight: in the flight from 07:45 to 07:51 the drone covered only about 40m of the north leg while in the following video, the drone covered up to 60m before the stop line.

By extending the identification of shockwaves to the whole day, we can check the speed evolution of stopping and starting shockwaves due to the red light (Fig. 9). According to traffic flow theory the starting shockwave is faster than the queue creation, which is empirically verified. It is also seen that the formation and dissipation of queues is faster in the morning than in the afternoon.

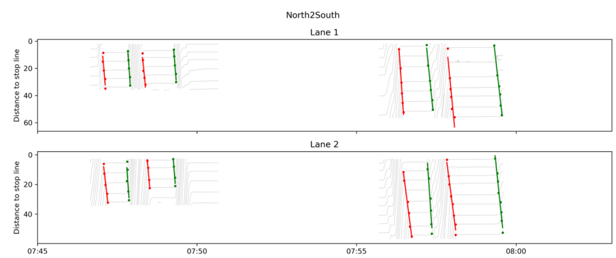

Figure 8. Example of shockwave in the north to south movement

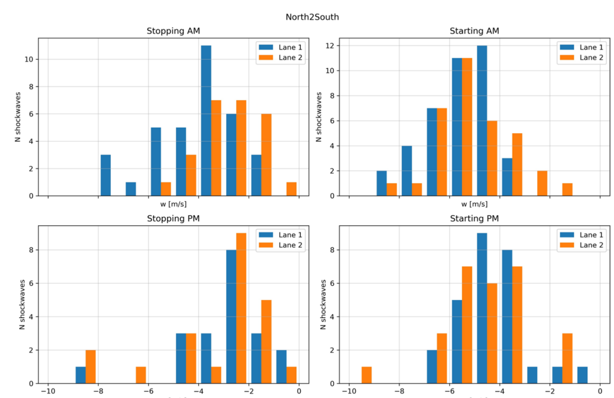

Figure 9. Histograms of shockwaves' speed in the morning and afternoon

VI. Conclusion

In this paper we have demonstrated how drones can serve as a valuable tool to monitor signalized intersections during the whole day. While the main drawback for continuous monitoring of traffic with drones is their limited battery, we have shown that brief recording periods of approximately 4 minutes over a day were sufficient to extract significant traffic metrics like OD, turning ratios, evolution of traffic flow or shockwave analysis to examine how congestion propagates. As a result, the use of small videos significantly reduces the need for batteries or tethered drones, facilitating the design of drone operations to record continuous traffic data.

Moreover, we have shown in this paper a complete methodology of the process to derive traffic metrics using drones at a signalized intersection. Specifically, we have developed a detailed pipeline to extract trajectories from drone videos: detection and tracking algorithm, georegistration of trajectories, extraction of motion metrics, and traffic analysis.

Finally, future research should attempt to optimize the choice of intervals and examine more traffic parameters (journey times, safety metrics, etc.). In addition, the introduction of more vehicle types in the vehicle detection algorithm could strengthen the analysis by elevating it to a multimodal analysis. For example, experiments in other locations where PTWs or bikes are popular could represent an opportunity to study how these modes of transport use the infrastructure and their interactions.

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