Unmanned Aerial Vehicle–Based Traffic Analysis

Methodological Framework for Automated Multivehicle Trajectory Extraction

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Unmanned aerial vehicles (UAVs), commonly referred to as drones, are one of the most dynamic and multidimensional emerging technologies of the modern era. This technology has recently found multiple potential applications within the transportation field, ranging from traffic surveillance applications to traffic network analysis. To conduct a UAV-based traffic study, extremely diligent planning and execution are required followed by an optimal data analysis and interpretation procedure. In this study, however, the main focus was on the processing and analysis of UAV-acquired traffic footage. A detailed methodological framework for automated UAV video processing is proposed to extract the trajectories of multiple vehicles at a particular road segment. Such trajectories can be used either to extract various traffic parameters or to analyze traffic safety situations. The proposed framework, which provides comprehensive guidelines for an efficient processing and analysis of a UAV-based traffic study, comprises five components: preprocessing, stabilization, georegistration, vehicle detection and tracking, and trajectory management. Until recently, most traffic-focused UAV studies have employed either manual or semiautomatic processing techniques. In contrast, this paper presents an in-depth description of the proposed automated framework followed by a description of a field experiment conducted in the city of Sint-Truiden, Belgium. Future research will mainly focus on the extension of the applications of the proposed framework in the context of UAV-based traffic monitoring and analysis.

The continual increase in the number of motorized vehicles and ever-increasing travel demands call for innovative and effective measures to tackle the challenges of high traffic volumes and congestion levels. Because infrastructure expansion alternatives are limited and expensive, transportation managers are left with the option of ensuring an efficient and optimal use of the existing network. For this purpose, state-of-the-art intelligent traffic information systems are employed to monitor and analyze traffic streams, particularly in emergency situations.

The efficient operational management of the network requires an accurate, timely, and quick inflow of traffic data. The collection and analysis of traffic data have also been critical elements for the development and improvement of macroscopic and microscopic traffic simulation models. However, it is not easy to collect traffic data for large spans of roadway networks, as most data collection methods require a large fixed infrastructure or are labor intensive (*1*).

Methods of collecting useful traffic data have evolved with advancements in technology. Induction loops, overhead radar sensors, and fixed video camera systems have been commonly used to monitor traffic status for a number of years. Although such traditional devices provide accurate and useful data, the data collected are only measured at a particular point with generally no useful data about traffic flows over larger areas (*2*). This data collection method results in many points in the network remaining effectively hidden because a high density of detectors would be required to cover the whole network (*1, 3*). In such a data set, the real root cause of traffic congestion or any other incident remains unknown. Manual detection made by specially deployed personnel can be used if some traffic information is required beyond the range of the installed cameras or sensors.

Apart from such traditional equipment, advanced intelligent transportation system technologies such as vehicle-to-infrastructure, probe vehicles with GPS, and smartphone sensor technologies resulting in "big data sets" are being used, especially for the extraction of vehicle trajectories. However, such data are not always easily converted to useful traffic information (*4*). Also, the use of GPS technology might not be applicable for studying driver behavior because drivers know they are being monitored (*3, 5*).

Technological advances have recently provided an alternative to an inflexible fixed network of sensors or the labor-intensive and potentially slow deployment of personnel (*1*). Complex traffic situations can be fully observed with the help of wide field-of-view and nonintrusive sensors and cameras mounted on airborne systems. Initially, satellites and manned aircraft were used for traffic data collection purposes (*6*). However, various quality, cost, and safety issues have proven these methods to be inefficient. Recently, unmanned aerial systems in traffic monitoring, management, and control are starting to take center stage (*2, 7*).

Unmanned aerial vehicles (UAVs), commonly referred to as drones, are one of the most dynamic and multidimensional technologies of the modern era. This technology is swiftly strengthening its presence in multiple applications, varying from commercial tasks (such as parcel delivery and sports coverage) to research applications (such as surveys of inaccessible areas and crop fields). UAVs are

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predicted to be the most dynamic growth sector within aviation in the coming years (*8*).

UAVs have been used in the transportation field to monitor and analyze traffic flow and safety conditions (*2, 7*). These airborne imaging systems are mobile and, more importantly, provide high-resolution traffic data relevant in both time and space (*2*). UAVs, without affecting drivers' behavior, can cover a large area in a short time at a considerably lower cost than alternate solutions. The technology can be particularly useful in areas where the fixed-sensor infrastructure is either not available or installing a high density of sensors is not financially feasible. Mobility and flexibility are the key assets of this technology.

Although attempts to collect traffic information from UAV-based images have been made in the past, their use in traffic studies is still at an early stage (*2, 3*). Only a few applications of this technology have been implemented, and they are still in the research stages. Practically, UAVs still have some significant concerns and limitations that need to be addressed. Technical limitations (e.g., limited battery time and weather constraints) and safety and privacy concerns are the biggest hindrances in making this technology more effective. However, the hardware limitations are expected to be reduced significantly in the coming years as the technology is progressing rapidly. Automated UAV flights and coordinated flights of a swarm of UAVs are already becoming a reality. Therefore, UAVS can be safely termed as a future-proof technology, especially with widespread commercial availability and decreasing costs. It is forecasted that 600,000 commercial small UAVs (weighing between .55 and 55 lb) could be over U.S. skies by 2020, implying new and improved applications of the technology (*8*).

However, the use of drone technology in traffic-related studies involves a high level of planning and management precision (*9*). With the introduction of state laws regarding the use of UAVs, extremely diligent planning and execution of a UAV flight are required as the consequences of a mismanaged execution could be severe. For this purpose, Khan et al. proposed a universal framework that serves as a guide not only for a safe and efficient execution of a UAV-based traffic study, but also for the processing and analysis steps that follow the execution of a UAV flight (*9*).

This paper focuses on the processing and analysis of UAV-acquired traffic footage. A detailed methodological framework for automated UAV video processing is proposed for the extraction of the trajectories of multiple vehicles at a particular road segment. Such trajectories can be used to extract various traffic parameters or to analyze traffic safety situations. Until now, most traffic-focused UAV studies have employed either manual or semiautomatic processing techniques. This paper provides an in-depth description of the proposed automated framework and also describes a field experiment conducted in the city of Sint-Truiden, Belgium. With the significant increase in the number of UAV studies expected in the coming years, this automated systematic framework could become a useful resource for research studies.

This paper is organized as follows. First, previous relevant studies regarding the applications of UAVs in the domain of transportation (traffic) are briefly discussed. This review is followed by a detailed description of the proposed framework. To support the proposed framework, an experiment along with its results are presented. Finally, the paper concludes with some discussion regarding the proposed future developments and applications of the framework.

RELATED WORK

UAVs are increasingly being employed for multiple purposes. According to the literature, UAVs are being widely researched for traffic surveillance and network evaluation applications (*1, 10, 11*). Different types of UAVS are being used or tested to measure traffic-related data at several universities (*2*). Various authors have discussed and summarized the research carried out all over the world in the domain of UAV-based traffic surveillance and analysis, including a systematic categorization of the relevant research based on the research objective, methodology, platform used, and the place of research (*2, 7*). These authors mention various advantages along with the barriers that UAVs must overcome to be successfully employed for civil applications like traffic monitoring and surveillance operations (*2, 7*).

Some researchers have tried to propose a workflow or outline for conducting UAV-based studies. Khan et al. presented a universal guiding framework for ensuring a safe and efficient execution of a traffic-related UAV study (*9*). The authors reorganized the existing UAV-based traffic studies and the available software platforms into a step-by-step framework. The systematic framework included a detailed description of all aspects of conducting an efficient traffic-related UAV study. Similarly, Zheng et al. developed a UAV system specifically focused on monitoring driving behavior to prevent accidents (*12*). Based on an application-specific outline or workflow, the authors proposed a methodology for real-time vehicle tracking by using image processing and vehicle risk modeling through statistical analysis. The main focus of this particular work, however, was on the evaluation of the drivers' behavior by developing a risk analysis model.

Recently, many researchers have attempted to use UAV-acquired traffic videos to conduct traffic analysis studies. Salvo et al. analyzed the gap acceptance of vehicles entering a major road in an urban intersection with the help of UAV videos (*13*). The same authors also used UAV-acquired traffic videos to determine various traffic parameters (e.g., flow and velocity) and compare them with theoretical macrosimulation models (*5*). Barmpounakis et al. conducted a UAV-based traffic experiment over a low-volume intersection to extract various kinematic parameters, including the estimation of vehicle trajectories (*3*). All the studies mentioned above employed either manual or semiautomatic processing methods; other studies have proposed automated video analysis methods (*12, 14–17*). The authors of these studies have attempted to use fast and robust computer vision–based object detection and tracking techniques for the processing of aerial traffic videos.

A lot of research has been conducted for the extraction of vehicle trajectories and their application for traffic analysis purposes. Researchers have employed GPS and smartphone technology to extract vehicle trajectories (*18–21*). Apart from these big data sources, computer vision technology using fixed camera systems has also been researched widely for trajectory extraction and traffic analysis applications. Researchers have applied image-processing techniques to fixed-camera traffic videos to extract and analyze trajectory data (*22–25*). An extensive trajectory data set using Next Generation Simulation has also been developed using video analytic techniques (*26*). However, all this research has used fixed-camera videos. Some researchers have attempted to employ UAV videos to extract vehicle trajectories (*3, 14, 16, 27*). Gao et al. present an especially effective methodology on the automatic extraction of vehicle trajectories, although in their approach the user initially has to manually select the vehicle to be tracked (*16*).

PROPOSED FRAMEWORK

In this section a detailed framework is proposed for the automatic extraction of multivehicle trajectories on a particular stretch of road via UAV-acquired data, and a step-by-step methodology is presented for the optimal application of a UAV in the domain of transportation engineering and management. The framework categorizes the whole process into stages that allow a UAV-based traffic study to be conducted systematically and efficiently. The proposed framework, which is broadly targeted for traffic analysis and surveillance applications, is classified into the following five components: preprocessing, stabilization, georegistration, vehicle detection and tracking, and trajectory management. Figure 1 illustrates the steps involved in the processing and analysis of a drone- or UAV-acquired video for a traffic-related study.

The proposed framework employed a combination of software packages to ensure an optimal processing and analysis of the traffic-related UAV videos. Apart from some video editing tools, the major portion of the implementation was done in MATLAB and C++ (OpenCV library).

In the following subsections, the five elements of the proposed framework are discussed in detail. This discussion is followed by a description of an experiment and its results to demonstrate the applicability and efficiency of the proposed framework.

Preprocessing

The first step of the proposed framework is the preprocessing of the traffic video acquired via a UAV. This step is critical as all the subsequent steps directly depend on it. Various substeps can be included in the preprocessing phase of the proposed framework to prepare the UAV-acquired traffic videos for the actual processing and analysis procedures.

The preprocessing procedure of the UAV videos can be grouped into three categories: video trimming, image rectification, and region-of-interest masking stages. First, the UAV videos are trimmed to extract the useful part of the videos. Trimming is done by excluding the parts of videos that are not useful for the traffic analysis, such as the UAV takeoff and landing portions of the recorded videos. After the useful part of the UAV videos is trimmed or extracted, the next step is image rectification. In this step, special attention is given to the type and quality of the acquired images. The types of image-rectification processes used depend on the type of hardware (i.e., UAV and the camera) employed. Image distortions such as fish-eye and darkened-edges effects caused by the type and settings of lens used are removed or minimized to prepare the video for the processing and analysis phase. The main target of this step is to make every pixel of the image useful for processing.

The third step of the proposed framework's preprocessing phase is the masking of the irrelevant parts of the images. This process is particularly significant for studies that target automatic detection and tracking of vehicles or other road users via computer vision algorithms. Only the regions of interest, such as specific lanes in a particular direction, are kept in focus; all other areas are masked in the frame. Masking makes the image-processing or computer vision algorithms more efficient as they will extract only the required data. In addition, the computational power and processing time are optimized.

Stabilization

UAVs have advanced significantly over the last few years. State-of-the-art hardware parts, including three-axis camera-mount gimbals,

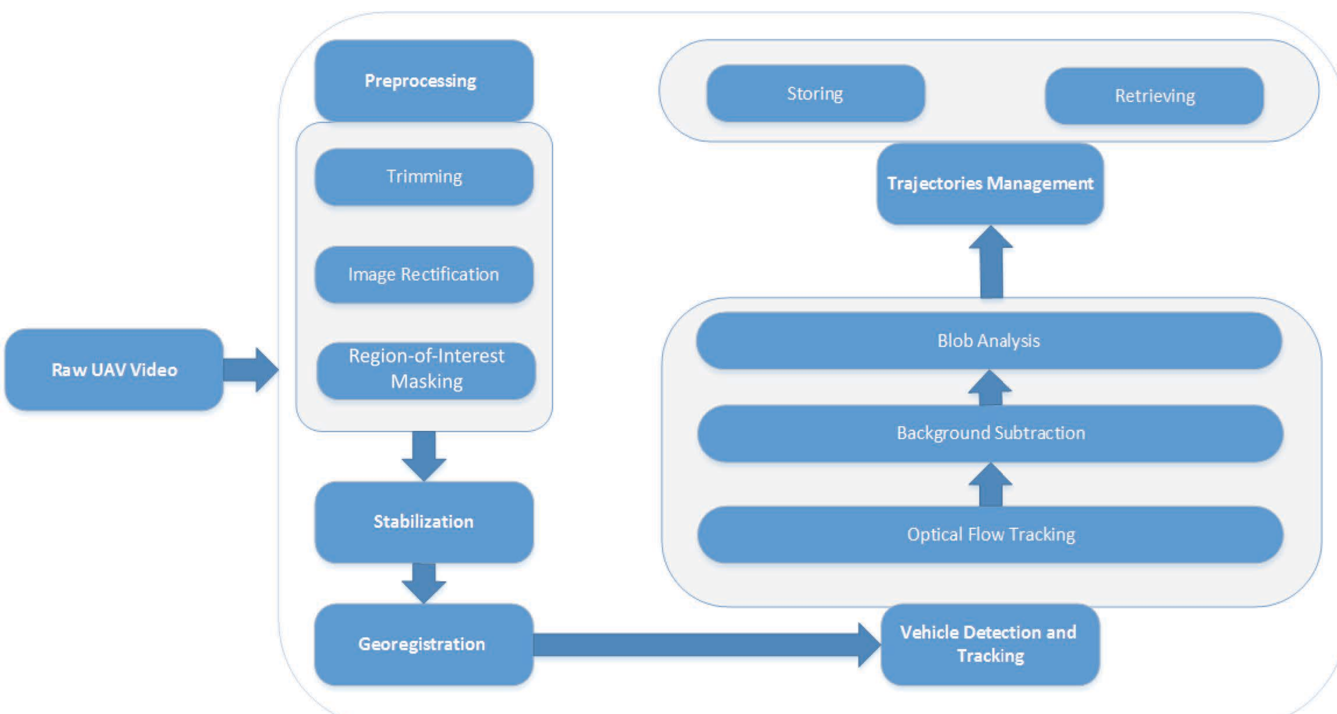

FIGURE 1 Proposed framework for automated UAV video processing and analysis.

have drastically improved the stability of the recorded videos. However, the videos acquired via a UAV or drone still have a certain amount of shakiness because of external factors (such as the pressure applied by wind gusts) or internal factors (such as the vibrations of the platform caused by the rotors and other mechanical parts). A reliable stabilization procedure is necessary to minimize the effects of UAV instability, as even a minor camera vibration can result in major movement in the imagery. The stabilization process also significantly simplifies and improves the efficiency of the subsequent processes of the proposed framework, particularly vehicle detection and tracking.

The use of a three-axis camera-mount gimbal is critical to achieve the maximum possible stability in UAV videos during the flight. These videos are processed during the postrecording phase as well to maximize the level of stability. Various stabilization methods and software are available that can reduce the effects of small camera movements. A simple but laborious method usually employed to ensure stability is tracking an established ground control point, or any other stationary object whose coordinates are known, throughout the length of the recorded video (*3*). This object is then regarded as a reference point, and the difference between the coordinates of this object for consecutive frames is applied to the coordinates of all other objects. This technique—although effective—requires frame-by-frame manual tracking, as well as the prior knowledge of the exact coordinates of the reference object.

This paper, however, specifically focuses on using automated techniques for the processing of UAV-based traffic videos. A point feature-matching approach is employed to counter the instability and shakiness in UAV videos. This MathWork's stabilization approach, as illustrated in Figure 2, first converts two consecutive frames into grayscale to increase the computation speed. Next, the corner points of features in both the images are determined and matched with each other by using the concept of the sum of the squared differences. To maintain a degree of uniqueness in the matching points and to keep only the valid inliers, a random sampling and consensus algorithm is used. These points are then used to compute an affine transformation matrix, which is a 3×3 matrix used to correct the geometric distortions in the image. The affine transformation matrix performs the transformation based on the scale, rotation, and translation parameters. This transformation matrix is then warped to all the frames to remove the distortion caused by the instability of the UAV platform.

Georegistration

Georegistration of the UAV-acquired images involves assigning real-world distances and coordinates to the image coordinates. The pixel coordinates are converted into real-world coordinates to increase the applicability of the produced trajectory data. The georeferenced calibrated trajectories can be directly used and integrated with various geographic information system applications as well. This process also enables the user to visualize and estimate various traffic parameters by generating the data in an actual scale.

To georegister the UAV-acquired monovision two-dimensional (2-D) imagery, various UAV-acquired video frames are used to create a mosaic image using the scale-invariant feature transformation matching algorithm. This image is then assigned a coordinate system (mostly Cartesian) and is calibrated according to a specific scale with the help of any geographic information system tool. This calibration leads to the point correspondence step, in which various points on the calibrated UAV image are compared to the referenced (or Google) map of that particular area. This process results in the generation of two sets of coordinate data: the image coordinates and the corresponding real-world coordinates. The point correspondence data are then processed using the random sampling and consensus algorithm to compute the homography matrix. This 3×3 matrix allows the transformation of a 2-D planar image into three-dimensional coordinates by using the assumptions of a pinhole camera model. This model is based on certain assumptions that enable the projection of a three-dimensional object onto the 2-D image plane. The coefficients of the matrix H can then be used to convert a set of 2-D image coordinates (x_i, y_i) into the real-world coordinates (x_w, y_w, z_w), as shown in the following equations:

$$\begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \tag{1}$$

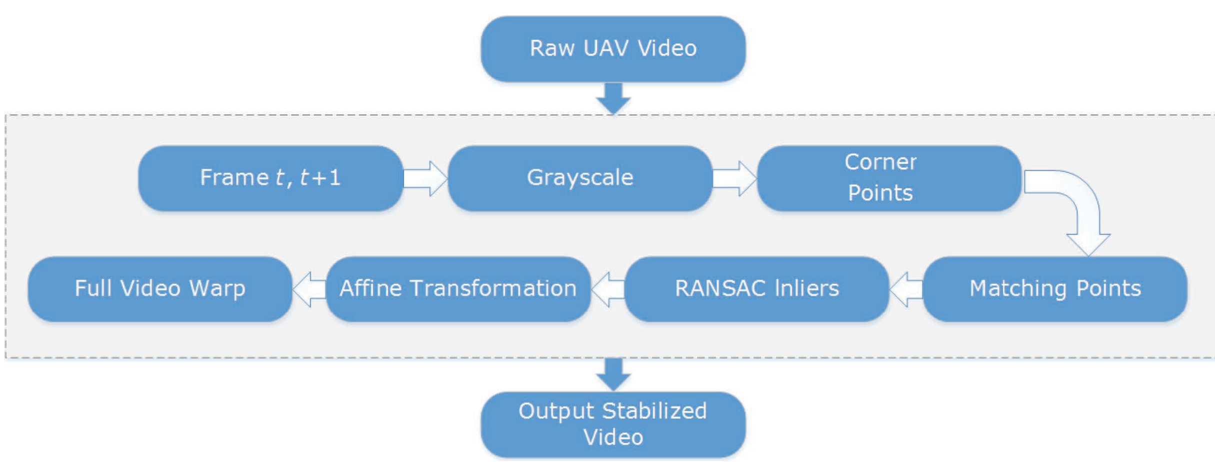

FIGURE 2 Diagram of the UAV video stabilization process.

$$z_w = h_{31}x_i + h_{32}y_i + h_{33} \tag{2}$$

$$x_w = \frac{(h_{11}x_i + h_{12}y_i + h_{13})}{z_w} \tag{3}$$

$$y_w = \frac{(h_{21}x_i + h_{22}y_i + h_{23})}{z_w} \tag{4}$$

Vehicle Detection and Tracking

After georeferencing or calibrating the images to the desired coordinate system, the detection and tracking of different road users is carried out. This process is the pivotal step in any video analytics–based traffic study as the principal results are all based on the efficiency and accuracy of this process. The main aim of any vehicle detection and tracking method is to produce consistent tracks of detected vehicles while minimizing the number of false or missed tracks.

The efficiency of the vehicle detection and tracking depends on the method employed. The vehicle detection and tracking processes used in existing studies can be broadly classified into two categories: semiautomatic and automatic techniques (*9*). Semiautomatic techniques produce accurate results, but they are laborious and require certain steps to be performed manually (*3, 5, 13*). Automatic techniques, though having some limitations, are gaining popularity as they provide quick results with minimum manpower involved.

In the proposed framework, the automatic detection and tracking of vehicles is the most complex step as it involves a series of computer vision algorithms to efficiently detect and track the different types of vehicles on a particular road segment. This process requires a robust and reliable algorithm to produce accurate results. For this purpose, a detection and tracking algorithm was developed using the OpenCV library in C++. The stabilized UAV video was used as input into the system. First, the input video was passed through the optical flow–tracking algorithm, in which the direction and speed of the moving pixels were estimated from one frame to another by using the concept of weighted least squares (*28, 29*). The Lucas–Kanade optical flow algorithm tracked the corner points of all the significant features throughout the video. The output of the optical flow process was then used as an input for the background subtraction algorithm. Background subtraction is a commonly used technique (especially for static videos) in which the moving objects are detected by subtracting the current image from the reference background image. The main reason for implementing optical flow before background subtraction is to improve its accuracy for the UAV videos, which have dynamic backgrounds and some instability. Once the moving objects were separated from the background, the neighboring moving pixels (blobs) in the foreground were identified as vehicles and tracked through each frame. A particular consideration was given in the algorithm to counter the inaccuracies caused by losing and reinitializing tracks. Figure 3 shows a simplified schematic diagram for the vehicle detection and tracking process.

Trajectory Management

The final step of the proposed framework for an optimal processing and analysis of UAV traffic videos is the management of the extracted trajectories of the vehicles of interest. The tracks or trajectories extracted automatically during the vehicle detection and tracking step must be dealt with effectively so they can be stored and then retrieved for further traffic analysis.

In the proposed framework, each coordinate of the vehicle detected and tracked in the area of study is automatically written and saved to a text (.txt) file. This text file—which contains the coordinates of each vehicle for every frame of the UAV video—enables the user to sort and process the data to extract various traffic parameters such as the vehicle's velocity, average velocity, and acceleration and traffic flow. These sorted data can be used to generate various charts and graphic displays of the extracted vehicle trajectories to study drivers' behavior and to track unusual activities (incidents).

EXPERIMENTS AND RESULTS

To test the proposed framework for the automated traffic analysis via UAV-acquired footage, a series of flights was conducted over an urban intersection near the city of Sint-Truiden in Belgium. The equipment used for the flights included the Argus-One (from Argus-Vision), which is a high-end octocopter UAV capable of a 9-min flight while carrying 3 kg of weight. A Panasonic Lumix GH4 digital single-lens mirrorless camera was attached to the UAV to obtain

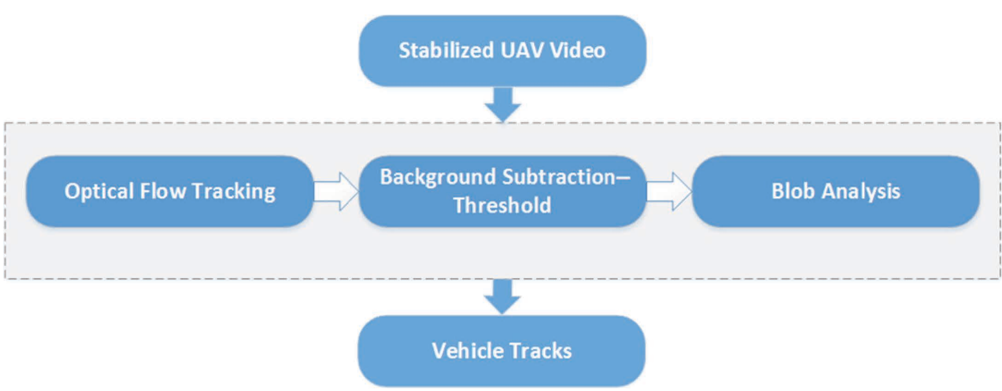

FIGURE 3 Diagram of the vehicle detection and tracking process.

(a) (b)

FIGURE 4 Argus-One UAV (*a*) ready for takeoff and (*b*) in flight.

high-resolution (4-K resolution at 25 fps) traffic footage. A live-feed transmission (first-person-view) system was also attached to the UAV for real-time monitoring of the camera angles. This particular UAV requires simultaneous operation by the pilot and the camera operator. Despite its relatively shorter flight time, this UAV was employed as it provides the high-quality and stable video data that were necessary to initially develop and test the proposed methodology. Figure 4 shows the Argus-One UAV in standby mode and in flight.

The experiment was conducted on a Friday afternoon (16:30 to 18:00 hours) to capture the evening peak hour. The weather was mostly clear, and the wind was gentle (18 km/h, Beaufort scale 3). The location was an intersection joining the national highways N80 and N718 with speed limits of 120 km/h and 90 km/h, respectively (Figure 5). The selected four-leg intersection leads from the city of Hasselt into the center and suburbs of Sint-Truiden, with two lanes in each direction. The UAV was hovered (constant altitude and zero velocity) above the intersection at heights of 80 m and 60 m. The use of backup battery packs allowed a series of flights that resulted in a 14-min useful traffic video after excluding the takeoff and landing maneuvers.

As mentioned above, a combination of various software packages, including MATLAB and C++ (OpenCV library), was used to develop an algorithm for the different steps of the proposed framework. The aim was to make every step of the framework automated with quick outcomes. The UAV video processing and results generation were done on an Intel® Core™ i5-4210M central processing unit at 2.60 GHz, with 4-GB RAM and Windows 8.1 (64 bits). The UAV video was stabilized according to the proposed methodology explained above. The images were then scaled according to actual distances, and a Cartesian coordinate axis was assigned with an origin at the center of the intersection.

The trajectories of multiple vehicles crossing the intersection under observation were extracted using the developed computer vision algorithm. Figure 6 depicts the trajectories of two sample vehicles and their corresponding velocity profiles. Figure 6, *c* and *f,* illustrates the space–time diagrams of platoons of vehicles as they approach and cross the intersection at different times during the UAV flights.

Several interpretations can be made from the trajectories and velocity profiles illustrated in Figure 6. It can be observed from Figure 6, *b* and *c,* that all the vehicles in Platoon-1, including the sample Vehicle-1, showed an increasing speed trend, which implies that the traffic signal turned green at that instant. Initially, the sample vehicle moved slowly while approaching the center of the intersection because it was moving in a group of vehicles (Platoon-1) with small headways. As the vehicle entered and crossed the intersection, its velocity increased uniformly. The mean velocity of the sample vehicle while approaching and maneuvering through the intersection was measured at 26 km/h, with a maximum of 32 km/h (Figure 6*b*). As the accuracy of the calibration process was ensured

(a) (b)

FIGURE 5 Images of the studied four-leg intersection from (*a*) the Google Earth satellite and (*b*) the UAV.

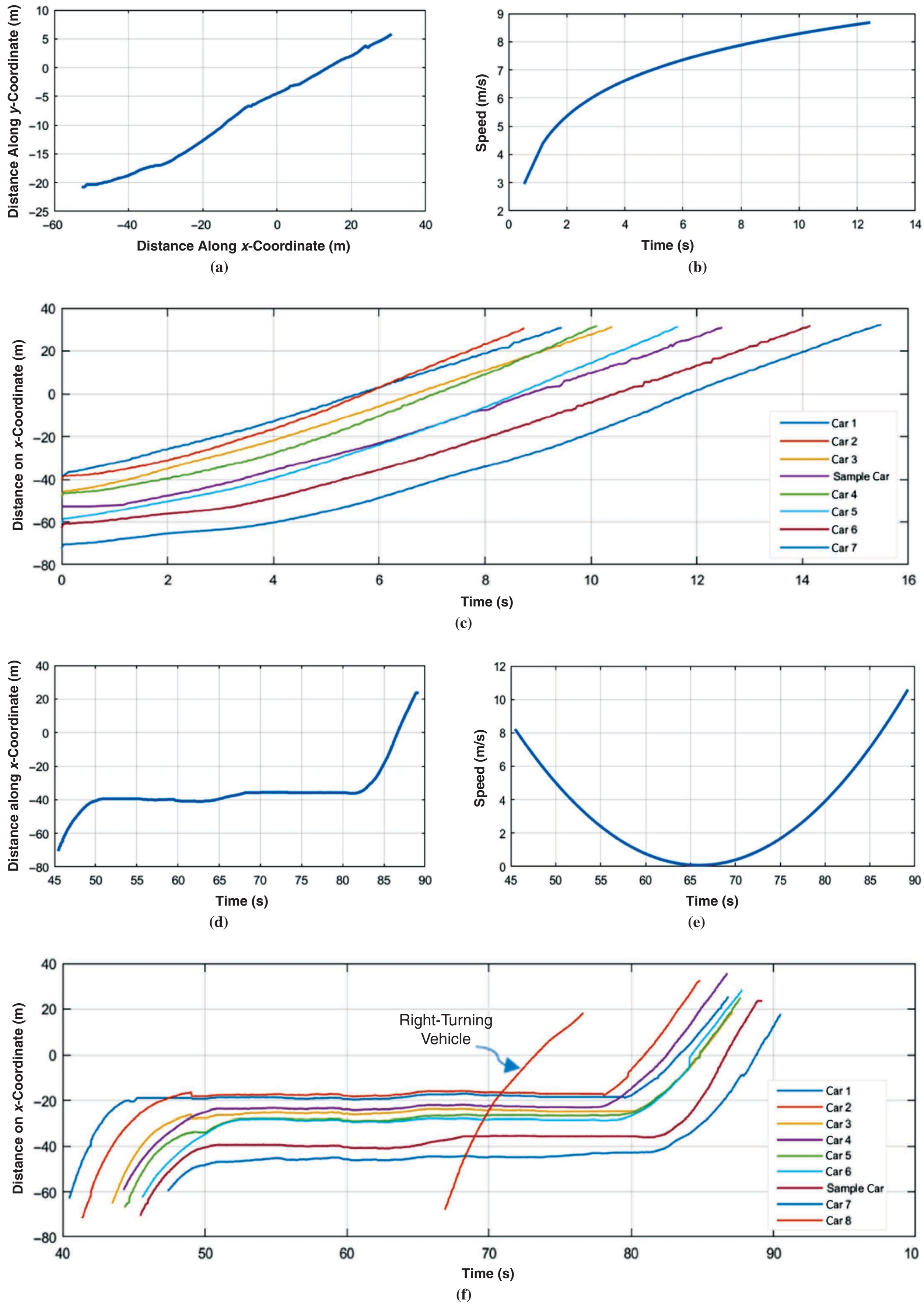

FIGURE 6 (*a*) Trajectory of sample Vehicle-1 along *x*–*y* axes, (*b*) speed profile of sample Vehicle-1, (*c*) space–time trajectories of Platoon-1, (*d*) trajectory of sample Vehicle-2 along space–time axis, (*e*) speed profile of sample Vehicle-2, and (*f*) space–time trajectories of Platoon-2.

by several measurements on site and then verification with Google Maps, the values estimated did not have significant errors.

Another group of vehicles (Platoon-2) approaching and crossing the intersection under observation was also analyzed. Figure 6, *d* through *f,* illustrates the drivers' behavior while approaching a signalized intersection. It is clearly evident from the trajectories that each driver decelerated to stop at the traffic signal. Some trajectories show a smooth transition to a stationary position (e.g., Car 7), and others have a steep curve (Car 1), implying a strong deceleration (Figure 6*f*). The behavior of a right-turning vehicle (Car 8) can also be observed. The slope of Car 8's trajectory suggests that the vehicle had to reduce its speed to safely execute the turning maneuver. Such diagrams can be effectively used to monitor and study the unusual trajectories leading to traffic incidents.

DISCUSSION AND CONCLUSION

This paper presents an extensive and systematic methodological framework for the optimal application of a drone or UAV in the domain of transportation engineering and management. A step-by-step methodology elaborates the processes involved in the automatic extraction of the trajectories of multiple vehicles on a particular stretch of road using UAV-acquired data. Most existing traffic-related UAV studies generally have employed semiautomatic processing and analysis methods; in contrast, the present study emphasizes the automation of all the steps included in the framework. The ultimate goal of this research was to develop a system that produces useful traffic data in a short time.

The proposed framework is supported by a field experiment conducted in the city of Sint-Truiden, Belgium, over an urban intersection. A series of trajectories was extracted and graphed by using the proposed methodological framework. The results generated depict the overall applicability of the system. Such a systematic framework may prove to be helpful for future traffic-related UAV studies as well by streamlining the processes involved. It may also serve as a comprehensive guide for the automated and quick extraction of multivehicle trajectories from UAV-acquired data.

Although the methodology employed and the results generated showed a reasonably good performance, the vehicle detection and tracking algorithms need to be more robust and accurate in all types of conditions. Fully automated vehicle detection and tracking, although ideal for real-time applications, have limitations as well. Errors can arise for various reasons, such as partial occlusions, objects in close proximity, and false detections; and a certain amount of noise appears in the produced data that must be dealt with. The video stabilization process plays an important role in improving the overall efficiency of the detection and tracking system.

Future research will mainly focus on the extension of the applications of the proposed framework within the context of UAV-based traffic monitoring and analysis. More specific and detailed UAV-based traffic-oriented studies will be carried out, and the proposed framework will be extended to implement real-time processing and analysis of UAV-acquired data.

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