2018

DOCTORAL DISSERTATION

Development and Deployment of an Unmanned Aerial Vehicle-based Traffic Analysis System

Muhammad Arsalan Khan

Promoter: Prof. Dr. Geert Wets

Co-Promoters: Prof. Dr. Davy Janssens

Prof. Dr. Ir. Tom Bellemans

DEDICATION

Dedicated to my Parents with love and eternal appreciation.

Acknowledgements

This thesis is the outcome of three years (2015-2018) of research with the Transportation Research Institute (IMOB) at Hasselt University, Belgium. After completing this thesis, I am indebted to a great number of people who generously offered support, inspiration, advise, and encouragement throughout my PhD study.

After thanking Allah Almighty, I would like to thank a few people without whom this thesis would not have been possible. First of all, I am deeply grateful to my promoter Prof. Dr. Geert wets and co-promoters Prof. Dr. Davy Janssens and Prof. Dr. Ir Tom Bellemans for their guidance and insight. I am grateful to them for giving me the opportunity to join the research team at IMOB in Hasselt University. The success of this project was in a large part due to their constant encouragement. These people were always present to help me with my research whenever I needed them. Working with them was a steep learning curve for me as they did not only polish my research skills but also gave me an insight into the dimensions of the real world mobility issues.

Apart from the internal committee members, I am also thankful to the international jury members of my doctoral committee: Prof. Dr. Yassine Ruichek (UTBM, France) and Prof. Dr. Afzal Ahmed (NED University, Pakistan), for their positive feedback and constructive comments on my dissertation. I would like to specially thank Prof. Dr. Yassine Ruichek who guided me in the initial phase of my PhD regarding the development of vehicle detection and tracking algorithm. My research stay at UTBM, Belfort (France) set me out on achieving the desired goals of this research.

The gratitude also goes to Higher Education Commission (HEC)-Pakistan for providing me with financial supports to carry out this research. Getting an MS-leading-to-PhD scholarship from HEC was a life changing opportunity for me. Moreover, special regards must also be given to IMOB for providing a positive research environment with all the state-of-the-art facilities.

I would like to express my appreciation to all the colleagues in IMOB. I would especially like to mention Wim Ectors. His critical reviews played an important part in the success of this research. Moreover, I would like to thank all the IMOB staff who helped me in administrative procedures. I am also deeply grateful to all the friends I made in Hasselt during my 5-year stay. Their support and companionship did not let me feel home-sick.

Finally, last but not the least, my deepest gratitude goes to my parents to whom I have dedicated this thesis dissertation. Their unconditional support, prayers and encouragement is the influencing factor that made me complete my PhD in 3 years. Moreover, I would like to thank my sisters for their continuous support as well.

As it is famously said that journey is more important than the destination. So, In the end, I would like to thank everyone who was there to support me during the ups and downs of this journey. Each one of you has a special place in my heart.

Thank you!

Muhammad Arsalan Khan

October, 2018

Executive Summary

In order to tackle the increasing traffic challenges and to achieve the goal of sustainable transportation, various policies have to be devised and implemented. In this regard, it is critical to analyze traffic patterns and travel behaviour via traffic models and simulations. The traffic data serves as a foundation for the development and calibration of such models and simulations. Naturally, this also magnifies the importance of traffic data collection methods as well as the equipment used. However, it is not easy to collect traffic data for large spans of roadway networks as most of the data collection methods require a large fixed infrastructure or are labor intensive. It is important to maintain a balance between the costs and quality of the collected data. Over the years, several types of data collection methodologies and equipment have been employed. However, each method and equipment comes with its own set of drawbacks and limitations. Traditional equipment such as manual counts, fixed camera, inductive loops etc. provide point data only, hence they are not applicable for covering large sections of the network. Other advanced equipment e.g. vehicle to infrastructure (V2I), probe vehicle with GPS, smartphone technologies etc., produce big datasets and are intrusive in nature. Additionally, the use of satellites and manned aircrafts to collect dynamic traffic data, is often very expensive. Therefore, there is a need for a data collection methodology that combines all the good features of the existing apparatus and minimizes the effects of the drawbacks. This leads to the use of Unmanned Aerial Vehicles (UAVs) for traffic data collection.

Unmanned aerial vehicles or drones are considered to be one of the most impactful and multi-dimensional emerging technologies of the modern era. The UAV technology is swiftly making its presence felt in multiple fields of life varying from commercial tasks such as parcel delivery, sports coverage etc. to research applications like surveying of inaccessible areas and crop fields. UAVs are also being increasingly used in the transportation field to monitor and analyze the traffic flow as well as safety conditions, particularly in emergency situations. UAVs provide a dynamic and a bird-eye view of the traffic network, and can be utilized for example by traffic planners and management centers to determine the state of the traffic flow and manage congestion problems. This also provides a cheap alternative to fixed camera systems and sensors infrastructure, as they are flexible and can be deployed anywhere (mobile). The mobility and flexibility are the key assets of this technology.

The objective of this research is to demonstrate the traffic data collection and analysis applications of small *UAVs* by presenting specific frameworks for the conduction of UAV-based traffic studies. This research presents various

frameworks and methodologies in order to effectively use the data acquired via small UAVs for traffic flow analysis. The ultimate goal is to develop a complete package that allows a small UAV-based traffic study for multiple traffic related applications, particularly focusing on traffic flow analysis for various types of infrastructural elements. The emphasis is also on the extraction of useful traffic information in a short period of time, hence the automated processing and analysis of UAV videos. The nature of this research is highly applied and practical, aiming to improve the existing data collection and analysis procedures. In this regard, a number of contributions are made in each of the chapters of this dissertation:

Chapter 1 gives the introduction of this 3-year PhD research. This chapter formulates the problem to be addressed and outlines the research questions. Moreover, the contributions and objectives of the research are also described.

Chapter 2 presents a universal guiding framework for the conduction of a UAV-based traffic study. The concept of utilizing small UAVs for traffic-related applications is addressed in detail. In order to streamline the whole process, a detailed framework is proposed that covers all the aspects of using UAVs for traffic data collection and analytical purposes; ranging from ensuring a safe and efficient UAV flight execution to the analysis steps that follow the execution of a UAV flight. The framework is classified into the following seven components: (i) scope definition, (ii) flight planning, (iii) flight implementation, (iv) data acquisition, (v) data processing and analysis, (vi) data interpretation and (vii) optimized traffic application. It provides a comprehensive guideline and gives an overview of the management in the context of the hardware and the software entities involved in the process. In this chapter, an extensive yet systematic review of the existing traffic-related UAV studies is presented by molding them in a step-by-step framework.

Chapter 3 proposes a detailed methodological framework for automated UAV video processing. The main objective is to efficiently process the traffic data acquired via UAVs; ensuring the data is converted into useful and reliable traffic information. The proposed framework consists of five components, namely: preprocessing, stabilization, geo-registration, vehicle detection and tracking, and trajectory management. After all these sub-processes, the trajectories of multiple vehicles at a particular road segment are extracted, which can then be used either to extract various traffic parameters or to analyze traffic flow and safety situations. This chapter also gives a brief comparison of existing UAV studies based on either manual or semiautomatic processing techniques. However, the main focus is on the description of the proposed automated framework. In the end, the proposed framework is validated with the help of a field experiment conducted in the city of Sint-Truiden, Belgium. This data is processed and analyzed as per the modules of the framework, resulting in a series of vehicle trajectories.

Chapter 4 evaluates the performance of the proposed UAV based traffic analysis system with a special emphasis on the vehicle detection and tracking module. The main objective is to determine the level of accuracy of the generated vehicle detection and trajectory data. A certain level of accuracy is critical to ensure the collected data is converted into useful and reliable traffic information. The UAV video processing and analysis framework, initially presented in chapter 3 has been further optimized. In order to evaluate the accuracy of the system, the outputs from the vehicle detection and tracking system have been compared with the ground-truth data. Various measures of performance have been calculated for different UAV-based traffic videos. The results show that the overall accuracy of the system lies above 90%. Moreover, the sensitivity of UAV flight altitude to the overall preciseness of the outputs is also evaluated. The comparison shows that a higher altitude level provides more precise results. The results are presented in tabular as well as graphical format.

Chapter 5 explores the applications of data collected via small UAVs, for an in-depth traffic flow analysis at a signalized 4-legged intersection. The analysis is basically a practical extension of the outputs generated from the previously proposed detailed methodological framework for automated UAV video processing. In this chapter, the main emphasis is on the comprehensive analysis of vehicle trajectories extracted via UAV-based video processing framework. An analytical methodology is presented for: (i) the automatic identification of flow states and shockwaves based on processed UAV trajectories, and (ii) the subsequent extraction of various traffic parameters and performance indicators in order to study flow conditions at a signalized intersection. The experimental data to analyze traffic flow conditions was obtained in the city of Sint-Truiden, Belgium. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted-flow conditions at a signalized four-legged intersection using UAV-acquired data.

Chapter 6 authenticates the application of small multirotor UAVs for traffic data collection and subsequent analysis of traffic streams at urban roundabouts. This chapter presents an analytical methodology to evaluate the performance of roundabouts by extracting various parameters and performance indicators. The performance evaluation methodology is based on: (i) determining traffic volume via Origin-Destination matrices between legs, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The overall analytical process is principally based on the previously proposed automated UAV video-processing framework for the extraction of vehicle trajectories. The extracted trajectories are further employed to extract useful traffic information. The experimental data to analyse roundabout traffic flow conditions was obtained in the city of Sint-Truiden (Belgium). The study depicts the overall applicability of the UAV-based traffic analysis system.

Chapter 7 further extends the traffic data collection applications of UAVs to mixed traffic situations in developing countries. The objective is to validate the applications of UAV video processing and analysis framework in a more challenging traffic scenario. In order to demonstrate the traffic analysis process, a case study based on data collected in Pakistan, is presented in this chapter. Traffic data has been collected via a small UAV for an urban roundabout and a T-intersection in Rawalpindi/Islamabad (Pakistan). The overall analytical methodology is based on the previously proposed UAV-based traffic analysis framework. The extraction of various traffic parameters and measures of performance help in highlighting the usefulness of UAVs for traffic analysis. The developing countries generally lack even in the basic infrastructure required for traffic monitoring and data collection. In this scenario, UAVs can serve as a useful apparatus for traffic data collection in developing countries. The results of the analysis at two study locations reflect the overall driving attitude and lack of implementation of traffic rules in developing countries, resulting in high congestion levels and serious safety concerns.

Chapter 8 explores a new application of the traffic data collected via small UAVs. The chapter presents a methodology to utilize the UAV-based traffic data for the development as well as for the calibration of microsimulation models. The main objective is to examine the feasibility of microsimulation model development from UAV-based traffic data. For this purpose, two case studies comprising of a roundabout and a signalized intersection, have been presented based on the data collected via UAVs in Sint-Truiden, Belgium. The base models are developed using PTV VISSIM. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework, are utilized for the microsimulation model development and calibration. The calibration process is based on various measures of effectiveness and validation parameters. Acceptable calibration targets have been defined for both roundabout and signalized intersection models. The results show that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implies that UAVs can become a useful source of traffic data for the development and calibration of microsimulation models.

Chapter 9 concludes the dissertation with a discussion of main findings of this research work. The chapter also discusses the limitations and challenges attached with the use of UAVs for traffic data collection. Apart from it, the chapter ends with some recommendations and an insight into the future research avenues.

Beknopte Samenvatting

Om de toenemende verkeersproblemen aan te pakken en tot een duurzaam vervoer te komen moeten verschillende beleidsmaatregelen ontwikkeld en geïmplementeerd worden. Daarom is de analyse van verkeerspatronen en verplaatsingsgedrag door middel van verkeersmodellen en simulaties van cruciaal belang. Verkeersgegevens dienen als basis voor de ontwikkeling en kalibratie van dergelijke modellen en simulaties. Hierdoor stijgt uiteraard het belang van de methoden voor datacollectie van verkeersgegevens en de gebruikte instrumenten. Het is echter niet gemakkelijk om verkeersgegevens te verzamelen voor omvangrijke delen van het wegennet aangezien de meesten van de methoden voor datacollectie een grote vaste infrastructuur vereisen of arbeidsintensief zijn. Het is belangrijk om een evenwicht te bewaren tussen de kosten en de kwaliteit van de verzamelde gegevens. Er werden in de loop der jaren verschillende methoden en instrumenten gebruikt voor het verzamelen van gegevens. Echter, bij elke methode of bij elk instrument zijn er specifieke nadelen en beperkingen. De traditionele instrumenten zoals visuele tellingen, vaste camera's, inductielussen etc. leveren enkel gegevens op van een bepaald locatie. Deze kunnen niet gebruikt worden voor metingen van grote delen van het netwerk. Andere geavanceerde instrumenten, zoals voertuig-infrastructuursystemen (V2I), meetvoertuigen uitgerust met GPS, smartphonetechnologieën enz., leveren grote datasets op maar zijn opdringerig van aard. Bovendien is het gebruik van satellieten en bemande vliegtuigen om dynamische verkeersgegevens te verzamelen vaak erg duur. Daarom is er behoefte aan een datacollectiemethode die alle goede eigenschappen van de bestaande instrumenten combineert en de gevolgen van de nadelen minimaliseert. Dit leidt ons naar het gebruik van onbemande luchtvoertuigen (UAV's) voor het verzamelen van verkeersgegevens.

Onbemande luchtvoertuigen of drones worden beschouwd als een van de meest impactvolle en multidimensionale opkomende technologieën van de moderne tijd. De aanwezigheid van de UAV-technologie is meer en meer voelbaar in verschillende domeinen, variërend van commercieel gebruik zoals het leveren van pakjes of het verslaan van sportwedstrijden tot onderzoekstoepassingen zoals het overzien van ontoegankelijke gebieden en akkers. UAV's worden ook steeds vaker gebruikt in het domein van transport om de verkeersstroom en veiligheidsomstandigheden te controleren en te analyseren, met name in noodsituaties. UAV's bieden een dynamisch en vogelperspectiefzicht van het verkeersnetwerk, en kunnen ingezet worden door bijvoorbeeld verkeersplanners en verkeerscentra om de status van de verkeersstroom te beoordelen en congestieproblemen te beheren. Het is eveneens een goedkoop alternatief voor

vaste camerasystemen en sensorinfrastructuur, omdat ze flexibel zijn en overal ingezet kunnen worden (mobiel). De mobiliteit en flexibiliteit zijn de belangrijkste troeven van deze technologie.

Het doel van dit onderzoek is om de verkeersdatacollectie en analysetoepassingen van kleine UAV's aan te tonen door het presenteren van specifieke frameworks voor het uitvoeren van UAV-gebaseerde verkeersstudies. Dit onderzoek bevat verschillende frameworks en methodologieën zodat er efficiënt gebruik gemaakt kan worden van de gegevens die verkregen werden via kleine UAV's voor de analyse van de verkeersstroom. Het uiteindelijke doel is de ontwikkeling van een volledig softwarepakket waarmee verkeersstudies door kleine UAV's kunnen worden uitgevoerd voor meerdere verkeerstoepassingen, in het bijzonder voor de analyse van de verkeersstroom voor diverse infrastructurele elementen. De nadruk ligt ook op het verkrijgen van nuttige verkeersinformatie in een korte periode, vandaar de geautomatiseerde verwerking en analyse van UAV-video's. Dit onderzoek is zeer toegepast en praktisch van aard, en is gericht op het verbeteren van de bestaande datacollectie en analyseprocedures. Hiertoe worden er een aantal bijdragen gedaan in elk van de hoofdstukken van dit proefschrift:

Hoofdstuk 1 vertegenwoordigt de inleiding van dit 3-jarig doctoraatsonderzoek. Dit hoofdstuk formuleert het probleem dat aangepakt moet worden en schetst de onderzoeksvragen. Bovendien worden ook de bijdragen en doelstellingen van het onderzoek beschreven.

Hoofdstuk 2 introduceert een universeel framework voor het uitvoeren van verkeersstudies op basis van UAV's. Het gebruik van kleine UAV's voor verkeersgerelateerde toepassingen wordt in detail besproken. Om het hele proces te stroomlijnen, wordt er een gedetailleerd framework voorgesteld dat alle aspecten van het gebruik van UAV's voor het verzamelen van verkeersgegevens en voor analytische doeleinden bevat; gaande van het uitvoeren van een veilige en efficiënte UAV-vlucht tot de er op volgende analysestappen. Het framework bevat de volgende zeven componenten: (i) het vastleggen van de doelstellingen, (II) vluchtplanning, (III) uitvoering van de vlucht, (IV) gegevensverwerving, (v) gegevensverwerking en -analyse, (VI) gegevensinterpretatie en (VII) geoptimaliseerd verkeerstoepassing. Het biedt uitgebreide richtlijnen en geeft een overzicht van het beheer van zowel de hardware als de software die betrokken zijn bij het proces. Dit hoofdstuk bevat een uitgebreide maar systematische bespreking van de bestaande verkeersgerelateerde UAV-studies door deze in een stappenplan te gieten.

Hoofdstuk 3 introduceert een gedetailleerd methodologisch framework voor een geautomatiseerde UAV-videoverwerking. Het belangrijkste doel is een efficiënte verwerking van de verkeersgegevens die via UAV’s verkregen worden. Hierbij dienen de gegevens omgezet te worden in nuttige en betrouwbare verkeersinformatie. Het voorgestelde framework bestaat uit vijf componenten, namelijk: voorbewerking, stabilisatie, geo-registratie, voertuigdetectie en -tracking en trajectmanagement. Na het doorlopen van al deze deelprocessen worden de trajecten van meerdere voertuigen in een bepaald wegsegment geëxtraheerd. Deze kunnen vervolgens gebruikt worden om verschillende verkeersparameters te extraheren of om de verkeersstroom en veiligheidssituaties te analyseren. In dit hoofdstuk wordt er ook een korte vergelijking gegeven van de bestaande UAV-studies op basis van hetzij handmatige of semiautomatische verwerkingstechnieken. De nadruk ligt echter vooral op de beschrijving van het voorgestelde geautomatiseerde framework. Uiteindelijk wordt het voorgestelde framework gevalideerd aan de hand van een veldonderzoek uitgevoerd in de stad Sint-Truiden, België. Deze gegevens worden verwerkt en geanalyseerd volgens de modules van het framework, resulterend in een reeks van voertuigtrajecten.

Hoofdstuk 4 evalueert de prestaties van het voorgestelde UAV-gebaseerde verkeersanalysesysteem met een speciale aandacht voor de voertuigdetectie en -trackingmodule. De belangrijkste doelstelling is het beoordelen van de nauwkeurigheid van de gegenereerde voertuigdetectie en trajectgegevens. Een zekere mate van nauwkeurigheid is van cruciaal belang om ervoor te zorgen dat de verzamelde gegevens omgezet worden in nuttige en betrouwbare verkeersinformatie. Het UAV-videoverwerkings- en analyse framework, dat reeds in hoofdstuk 3 voorgesteld werd, wordt verder geoptimaliseerd. Om de nauwkeurigheid van het systeem te evalueren, werd de output van het voertuigdetectie en -trackingsysteem vergeleken met de werkelijke toestand. Verschillende prestatieniveaus werden gevonden voor verschillende UAV-gebaseerde verkeersvideo's. De resultaten tonen aan dat de algemene nauwkeurigheid van het systeem boven 90% ligt. Bovendien werd ook de gevoeligheid van de UAV-vluchthoogte t.o.v. de algemene nauwkeurigheid van de output geëvalueerd. De vergelijking toont aan dat een hogere vluchthoogte preciezere resultaten oplevert. De resultaten worden zowel in tabelvorm als grafisch weergegeven.

Hoofdstuk 5 onderzoekt de toepassingen van gegevens die verzameld werden door middel van kleine UAV's voor een diepgaande verkeersstroomanalyse op een 4-takskruispunt met verkeerslichten. De analyse is in feite een praktische uitbreiding van de output die gegenereerd werd door het eerder voorgestelde gedetailleerde methodologisch framework voor geautomatiseerde UAV-videoverwerking. In dit hoofdstuk ligt de belangrijkste nadruk op een omvattende analyse van voertuigtrajecten die geëxtraheerd werden via het UAV-gebaseerde videoverwerking framework. Er wordt een analytische methodologie voorgesteld voor: (i) de automatische identificatie van verkeersstromen en -schokgolven op basis van verwerkte UAV-trajecten, en (II) de daaropvolgende extractie van verschillende verkeersparameters en prestatie-indicatoren om de verkeersstromen op kruispunten met verkeerslichten te bestuderen. De experimentele data voor het analyseren van de verkeersstromen werd verkregen in de stad Sint-Truiden, België. Het genereren van vereenvoudigde trajecten, verkeersschokgolven en het fundamenteel diagram helpt bij het analyseren van de onderbroken doorstroming op een 4-takskruispunt met verkeerslichten met behulp van UAV-verworven gegevens.

Hoofdstuk 6 staaft de toepassing van kleine multirotor UAV's voor het verzamelen van verkeersgegevens en de daaropvolgende analyse van verkeersstromen op stedelijke rotondes. Dit hoofdstuk bevat een analytische methodologie om rotondes te evalueren door verschillende parameters en prestatie-indicatoren te extraheren. De methodologie voor de evaluatie van rotondes is gebaseerd op: (i) het bepalen van het verkeersvolume op basis van herkomst-en-bestemmingsmatrices tussen de afritten en (II) het analyseren van het gedrag van de bestuurders op basis van de analyse van de aanvaarde volgafstand. Het algemene analytische proces is hoofzakelijk gebaseerd op het eerder voorgestelde geautomatiseerde UAV-videoverwerking framework voor de extractie van voertuigtrajecten. De geëxtraheerde trajecten worden vervolgens gebruikt om nuttige verkeersinformatie eruit te halen. De experimentele gegevens voor het analyseren van de verkeersstroomvoorwaarden bij rotondes werden verkregen in de stad Sint-Truiden (België). De studie bevestigt de algemene toepasbaarheid van een UAV-gebaseerd verkeersanalysesysteem.

Hoofdstuk 7 behandelt de verdere datacollectietoepassingen van UAV's voor gemengde verkeerssituaties in ontwikkelingslanden. Het doel is om de toepassing van een UAV-videoverwerkings en –analyse framework te valideren in een complexere verkeerssituatie. Om het verkeersanalyseproces te tonen worden er in dit hoofdstuk twee case studies gepresenteerd die gebaseerd zijn op gegevens die in Pakistan werden verzameld. Er werden verkeersgegevens verzameld via een kleine UAV bij een stedelijke rotonde en een T-kruispunt in Rawalpindi/Islamabad (Pakistan). De algemene analytische methodologie is gebaseerd op het eerder voorgestelde UAV-gebaseerde verkeersanalyse framework. De extractie van diverse verkeersparameters en de beoordelingscriteria benadrukken het nut van UAV's voor verkeersanalyse. Ontwikkelingslanden beschikken over het algemeen zelfs niet over de basisinfrastructuur die nodig is voor verkeersbewaking en gegevensverzameling. In dit scenario kunnen UAV's een nuttig instrument zijn voor het verzamelen van verkeersgegevens in ontwikkelingslanden. De resultaten van de analyse op twee locaties weerspiegelen het algemeen rijgedrag en het gebrek aan de implementatie van verkeersregels in ontwikkelingslanden, wat resulteert in hoge congestieniveaus en ernstige veiligheidsproblemen.

Hoofdstuk 8 onderzoekt een nieuwe toepassing van de verkeersgegevens die verzameld werden door middel van kleine UAV's. Dit hoofdstuk introduceert een methodologie om gebruik te maken van de UAV-gebaseerde verkeersgegevens voor de ontwikkeling en de kalibratie van microsimulatiemodellen. Het belangrijkste doel is de haalbaarheid te bepalen van de ontwikkeling van microsimulatiemodellen op basis van UAV-gebaseerde verkeersgegevens. Hiertoe worden twee case studies voorgesteld, bestaande uit een rotonde en een kruispunt met verkeerslichten waarvoor de gegevens verzameld werden door middel van UAV's in Sint-Truiden, België. De basismodellen werden ontwikkeld aan de hand van PTV VISSIM. De vormgeving van de weg en de verkeersparameter die uit de UAV-video's geëxtraheerd werden door middel van het eerder voorgestelde UAV-videoverwerkings en –analyse framework worden gebruikt voor de ontwikkeling en kalibratie van het microsimulatiemodel. Het kalibratieproces is gebaseerd op verschillende effectiviteits- en validatieparameters. Er werden aanvaardbare kalibratie doelstellingen gedefinieerd voor modellen van zowel rotondes als van kruispunten met verkeerslichten. De resultaten tonen aan dat de microsimulatiemodellen gekalibreerd kunnen worden door verkeersgegevens die verzameld werden door middel van kleine UAV's. De studie impliceert dat UAV's een nuttige bron van verkeersgegevens kunnen worden bij de ontwikkeling en kalibratie van microsimulatiemodellen.

Hoofdstuk 9 sluit het proefschrift af met een bespreking van de belangrijkste bevindingen van dit onderzoek. In dit hoofdstuk worden ook de beperkingen en uitdagingen besproken die verbonden zijn aan het gebruik van UAV's voor het verzamelen van verkeersgegevens. Het hoofdstuk eindigt met enkele aanbevelingen en een blik op toekomstige onderzoeksmogelijkheden.

Contents

List of Figures

List of Tables

Acronyms

UAV	Unmanned Aerial Vehicle
UAS	Unmanned Aerial System
sUAV	Small Unmanned Aerial Vehicles
FFTT	Free-Flow Travel Time
GIS	Geographic Information Systems
QGIS	Quantum GIS
GPS	Global Positioning System
GUI	Graphical User Interface
ITS	Intelligent Transportation Systems
V2I	Vehicle-to-Infrastructure
GCP	Ground Control Point
FAA	Federal Aviation Agency
FHWA	Federal Highway Association
HCM	Highway Capacity Manual
HSM	Highway Safety Manual
CV	Computer Vision
HD	High Definition
CPU	Central Processing Unit
HP	Hewlett Packard
TTC	Time to collision
TRB	Transportation Research Board
PET	Post Encroachment Time
MOP	Measures of Performance
MOE	Measures of Effectiveness
LOS	Level of Service

IMOB	Instituut voor MOBiliteit (IMOB)
OD	Origin-Destination
OSM	OpenStreetMap
RSA	Reduced Speed Area
TAZ	Traffic Analysis Zone
TDM	Transportation Demand Management
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error

Chapter 1

Introduction

1.1 Overview

This research is aimed to explore the practical applications of small Unmanned Aerial Vehicles (sUAVs) for traffic data collection and analysis. The research covers all the aspects necessary for conducting a UAV-based traffic study; starting from the initial UAV flight planning stage to the analysis and interpretation of the collected data. Different frameworks, algorithms and analytical methodologies are presented in the following 7 chapters of this dissertation. This chapter describes the background or perspective of this research and also outlines the research questions. The chapter concludes with an overview of the subsequent chapters of this dissertation.

The rest of this chapter is as follows. Section 1.2 provides the background of the research. Section 1.3 describes the motivation for the research. Section 1.4 of this chapter presents the problem description and enlists the research questions. Section 1.5 presents the resulting research objectives and contributions pursued in this thesis. Section 1.6 provides the research approach and finally the thesis outline is presented in section 1.7.

1.2 Background

Over the last few decades, urbanization rates have increased rapidly. A very high percentage of population has migrated towards urban metropolitans in order to improve their overall living standards. According to United Nations, the total urban population increased from 30% in 1950 to 54% in 2014. By 2050, the world population is projected to reach 10 billion out of which 66% shall be dwelling in cities (United Nations, 2015). In Europe, 73% of the population is already living in urban areas (United Nations, 2015). Similarly, it has been estimated that the population of the current four largest cities of Australia will be equal to its present total population by 2050 and the countries like USA, China and India are also reported to witness an increase of 33%, 38% and 96% respectively in their major cities (Stevenson et al., 2016). While the urban area quadrupled in the time period between 1970-2000, it has increased at a twice rate as compared to the population in the past few years. This situation has given birth to a variety of immense challenges like traffic congestion, unemployment, and a scarcity of public facilities (Wu et al., 2015).

The need to travel has always been considered as a necessity for human society. This need has only increased with the soaring growth of urbanization trend; thereby resulting in high motorization rates and excessive traffic volumes. This trend has caused a major strain on the existing infrastructure. The management of transportation operations has become one of the most critical challenges faced by local as well as regional governments all over the world. According to the World Bank's report, it is estimated that transportation contributes almost 20% to the total gross national product (GNP) of each country in the world. In most of the developing countries, the contribution of transportation in the gross domestic product (GDP) is 6% to 12% (Senguttavan, 2006). Since, the transportation sector acts as a backbone for any country's economy and overall progress, therefore it is pivotal for transport planners and governments to devise well-planned transportation policies.

Traditionally, transport planners and governments focused on the expansion of existing infrastructure in order to accommodate for the increasing travel demands. With the passage of time, it was realized that the expansion policy is not sustainable and cannot cope with the worsening situation. In this scenario, transportation planners and managers have to devise ways to make the transportation system more sustainable and efficient[38]. The characteristics of the sustainable transport system include accessibility, safety, affordability and being environmental friendly (Gilbert et al., 2003; Shiftan & Kaplan, 2003). On the other hand, the rapid expansion of cities has led to an increase in vehicle ownership. It is expected that by the year 2020, the number of automobiles in the world would be doubled (Litman, 2003). The rapid increase in vehicle ownership led to many transport related problems which included traffic congestion, traffic accident and environmental pollution (Banister, 2002). In order to handle this situation and to achieve the target of sustainable transportation, an integration of urban and transportation policy is necessary that could withstand all the immense global challenges. Moreover, the efficient use of existing networks can only be ensured by monitoring and analyzing traffic streams dynamically, especially in emergency situations or other events. This leads to the employment of state-of-the-art intelligent traffic information systems.

The efficient operational management of the network requires an accurate, timely and quick inflow of traffic data. Urban planning in general and traffic modelling in particular is highly dependent on the available traffic data. The quality of traffic data determines the performance of traffic models. Therefore, traffic data collection is termed as the primary step towards making informed decisions and devising traffic policies that ensure an efficient operation of the network. However, it is not easy to collect the traffic data for large spans of roadway networks as most of the data collection methods require a large fixed infrastructure or are labor intensive (Coifman et al., 2006).

The traffic data collection methods have evolved with the passage of time. The traditional methods e.g. manual counts, induction loops, fixed video camera systems etc. have been used abundantly to collect accurate traffic data for a number of years. Moreover, advanced ITS technologies e.g. vehicle-to-infrastructure (V2I), probe vehicles with GPS and other smartphone sensor technologies are also being used for traffic data collection. Another alternative for traffic data collection is the aerial photography or remote sensing. The characteristics such as flexibility, wide field-of-view and quick deployment make this technology extremely useful for dynamic traffic data collection. However, the use of satellites and manned aircrafts for dynamic traffic data collection may prove to be too costly. Recently, unmanned aerial systems in the traffic monitoring, management, and control are starting to take center stage (Kanistras et al., 2015; Puri, 2005).

Unmanned aerial vehicles or drones are considered to be one of the most impactful and multi-dimensional emerging technologies of the modern era. The UAV technology is swiftly making its presence felt in multiple fields of life varying from commercial tasks such as parcel delivery, sports coverage etc. to research applications like surveying of inaccessible areas and crop fields. The drones are also being used in transportation field to monitor the traffic flow and safety conditions, particularly in emergency situations (Kanistras et al., 2015; Khan et al., 2017; Puri, 2005).

UAVs are basically aircrafts that fly without carrying a human pilot. They can either be piloted remotely or fly autonomously, but fly without direct human input (McCormack & Trepanier, 2008). There are several types of unmanned aerial vehicles depending upon their use, size, range and capabilities. UAVs can broadly be classified into two categories;(i) fixed wing and (ii) rotary-wing UAVs. Traditionally, only fixed-wing UAVs were used for traffic data collection purposes. Recently, small multi-rotor UAVs with dimensions less than 2 meters, altitude less than 1 kilometer and weight less than 10 kilograms (US Army, 2010), have been employed for traffic-related applications. These applications are, however currently very limited and are still in the research stages; mainly due to the hardware and legal limitations. Nevertheless, this technology is progressing rapidly and can be safely termed as a future-proof technology.

The objective of this research is *to demonstrate the traffic data collection and analysis applications of small UAVs* by presenting specific frameworks for the conduction of UAV-based traffic studies. This research presents various frameworks and methodologies in order to effectively use the data acquired via small UAVs for traffic flow analysis. The ultimate goal is to develop a complete package that allows a small UAV-based traffic study for multiple traffic related applications, particularly focusing on traffic flow analysis for various types of infrastructural elements. The emphasis is also on the extraction of useful traffic information in a short period of time, hence the automated processing and analysis of UAV videos. The nature of this research is highly applied and practical, aiming to improve the existing data collection and analysis procedures.

1.3 Motivation

The aspects of traffic patterns and travel behaviour can be investigated via traffic models and simulations. The traffic data serves as a foundation for the development and calibration of such models and simulations. Naturally, this also magnifies the importance of traffic data collection methods as well as the equipment used. As mentioned earlier, various types of equipment have been used to collect traffic data over the years. However, each method and equipment comes with a set of its own drawbacks and limitations. Therefore, it becomes vital to select the equipment that is most appropriate for a given study. The scope and the area of study must be carefully studied before making the choice of data collection method and equipment. The traditional and widely used methods e.g. manual counts, induction loops, fixed video camera systems etc., have certain drawbacks as well. Since, such equipment yield point data with generally no useful data about traffic flows over a large section of the network (Puri, 2005), a high density of sensors or manual deployments are required to cover the entire network or study area. The point data cannot be used to monitor the densities as well as process of accumulation and dissipation of queues at the intersections. However, it is not feasible to cover the entire network with fixed sensors or deployed personnel, therefore certain 'hidden points' exist in the network (Barmpounakis et al., 2016; Puri, 2005). The transport planners and managers cannot make informed decisions based on such datasets as the actual root cause of congestion or a particular behavioral pattern may remain unknown. On the other hand, advanced traffic data collection methods based on ITS technologies e.g. vehicle-to-infrastructure (V2I), probe vehicles with GPS and other smartphone sensor technologies, are effective, However, these technologies produce large datasets which are not easy to process especially in a short time span (Vlahogianni, 2015) and with limited computational power. Additionally, such technologies may turn out to be intrusive in nature as the actual behaviour of the travelers might be influenced since they already know they are being observed (Barmpounakis et al., 2016; Salvo et al., 2014). Another alternative for traffic data collection, the aerial photography or remote sensing have highly valued characteristics such as flexibility, wide field-of-view and quick deployment. In addition, this is a non-intrusive technology yielding unbiased datasets. However, it is quite expensive to collect data using satellites or manned aircrafts for a particular study. Therefore, it is evident that there is a need for a budget-friendly and flexible technology that provides traffic data relevant both in time and space. In this scenario, unmanned aerial systems have the capability to fill the loopholes left by other type of data collection apparatus.

The UAV-based data collection systems have the potential for traffic and driving-behavior monitoring due to their mobility, large field of view, and capability of following vehicles (Kanistras et al., 2015). UAVs provide a dynamic and a bird-eye view of the traffic network, and can be utilized for example by traffic planners and management centers to determine the state of the traffic flow and manage congestion problems. This also provides a cheap alternative to fixed cameras and sensors infrastructure as they are flexible and can be deployed anywhere (mobile). The mobility and flexibility are the key assets of this technology (Khan et al., 2017).

UAVs already are starting to take center stage for traffic monitoring, management, and control operations (Kanistras et al., 2015; Puri, 2005). UAVs are being increasingly used in the transportation field to monitor and analyze the traffic flow as well as safety conditions, particularly in emergency situations (Kanistras et al., 2015; Khan et al., 2017; Puri, 2005). Over the years, this non-intrusive technology has improved rapidly and is now capable of providing high resolution data (both in space and time) that can be used effectively for detailed traffic analysis e.g. for extracting vehicle trajectories and estimating traffic parameters. Due to all these characteristics, this technology can complement and in specific cases even replace the traditional traffic monitoring equipment (fixed camera installations, pneumatic vehicle detectors etc.). The real time traffic data transmission with a relatively low cost as compared to other ITS sensor technologies makes this technology even more worthwhile. UAVs can be particularly useful for data collection at sub-urban or such areas in the network where there is no or very limited fixed sensor/camera infrastructure.

In the start of this PhD research project (October-2015), a significant gap was observed in the existing literature regarding the use of small rotary-wing UAVs (sUAV) for traffic related applications. Moreover, most of the existing studies employing sUAVs for traffic-related applications, focused on manual or semi-automatic processing of the collected data; thereby significantly increasing the processing time. Therefore, there was a need for a system that generates useful traffic information in a short period of time. As this is a recent technology and the actual applications, particularly for traffic data collection have not yet fully developed (Barmpounakis et al., 2016; Puri, 2005), therefore, it was identified that there is a need for presenting detailed methodological frameworks that serve as a guide for not only a safe and efficient execution of UAV-based traffic study but also for the processing and analysis steps that follow the execution of a UAV flight. With the significant increase in the number of UAV studies expected in the coming years, such analytical studies based on systematic frameworks could become a useful resource for practitioners and researchers alike. This also implies the practical and applied nature of this research.

1.4 Problem Description & Research Questions

This dissertation is centered around the applicability of small UAVs for traffic survey and analytical studies. However, there are certain limitations and challenges attached with this technology. These limitations vary from hardware aspects to safety, legal and privacy issues. The limited battery times and extreme weather conditions also cause hindrance in the applications of this technology. Moreover, the initial literature survey indicated that there was a lack of existing literature that particularly focuses on using the small rotary-wing type UAV-acquired data for traffic analysis purposes. Therefore, in this scenario, the main problem identified was the lack of proper methodological frameworks that cover all the aspects of conducting a UAV-based traffic study; ranging from the initial flight planning stage to the detailed traffic analysis of the collected data. It was important to outline as well as demonstrate all the steps necessary for efficient utilization of rich UAV data with the help of case studies. Additionally, it was critical to reduce the data processing times in comparison to the manual or semi-automatic techniques.

The research gaps identified in the previous section can be formulated into a set of various research questions and sub-questions that need to be addressed in a scientific manner. For this purpose, this dissertation is revolved around the following research questions:

1. Can the small UAV technology be used effectively for traffic studies and what are the challenges or limitations?
2. How can the small UAVs be employed to conduct traffic-related studies and how to efficiently process the collected data?
3. How can the data collected via UAVs be used for traffic flow analysis of different types of infrastructural elements and for varying traffic situations? What are the limitations or remaining challenges in this context?

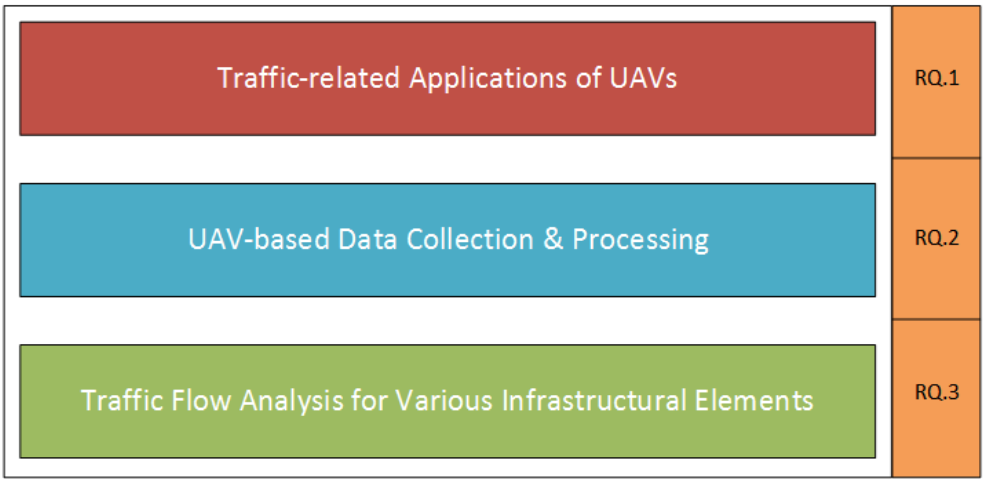


Figure 1.1: Illustration of the defined research questions

1.5 Objectives & Contributions

The motivation to address the gaps or shortcomings in the applied use of small UAVs for traffic analysis applications leads to the core of this thesis dissertation. In order to highlight the potential advantages and benefits of using small UAVs for traffic data collection and analysis, this dissertation makes the following contributions:

Contribution 1: Proposing a universal guiding framework for the employment of any UAV for traffic-related studies. The proposed systematic framework encompasses all the aspects involved in conducting a UAV-based traffic monitoring and analysis study. This framework is transferrable and independent of regional constraints or limitations, hence serving as a universal guide for the utilization of UAVs in any part of the world.

Contribution 2: Development of a methodological framework for UAV video processing and analysis. It is critical to efficiently utilize the traffic data by generating an accurate and timely set of output data. The proposed detailed framework streamlines all the video processing and analysis steps in a systematic manner. Using various tools, techniques and algorithms, this framework can be used to convert the UAV video data into useful traffic information. However, the framework is not limited to certain tools or software, as it puts forward the general modules involved in the whole process of conducting a UAV-based traffic study.

Contribution 3: Description of methodologies to conduct in-depth traffic flow analysis based on UAV data. With the help of case studies, various traffic situations have been analyzed. Moreover, a list of performance measures to analyze different types of infrastructural elements, using limited UAV data, is presented.

The main objective of this research is to demonstrate the applications of small UAVs for traffic analysis and monitoring. Another aspect of the research is to extract useful traffic information from the collected UAV data, in a short period of time. In this regard, minimization of processing times is dependent on the number of automated processes and on the available computational power. In order to achieve the desired objectives, the research will focus on defining frameworks for an efficient UAV-based traffic data collection, processing and analysis.

This dissertation is divided into 8 core chapters with each chapter having its own set of objectives and contributions. Overall, the initial chapters present the frameworks for the utilization of UAVs for traffic-related studies, while the later chapters focus more on the traffic analysis methodologies and case studies.

1.6 Approach

As mentioned earlier, the initial research problem to be addressed was to identify and define a systematic approach for developing a UAV-based traffic analysis and monitoring system. For this purpose, a guiding framework is presented, which incorporates all the steps necessary for successfully conducting a UAV-based traffic analysis study. Additionally, another framework is proposed to streamline the UAV video processing and analysis procedure. This framework covers all the steps in order to efficiently process the UAV traffic video data and extract useful traffic information from the collected data.

Since one of the objectives of this research is to minimize the time required to process and analyze the UAV-based traffic video data, it was important to opt for the methods that provide quick as well as accurate outputs. A special consideration was given to minimize the manual operations. For this purpose, the proposed framework for the processing and analysis of the UAV data was based primarily on automated tools and techniques.

Most of the existing UAV-based traffic studies employed manual or semi-automatic approaches in order to extract detections and tracks of the object or vehicles of interest. This approach requires manual operations, hence higher processing times. On the other hand, the process of automatic detection and extraction of vehicle trajectories has its own complications and challenges. In this research, however, the automatic approach was selected for the processing of UAV traffic videos. A set of algorithms was developed in C++ (OpenCV library) which will be elaborated in detail in the following chapters. In contrast to the commercial automated video processing systems (e.g. Data from sky etc.), the emphasis was on extracting useful traffic information in a short period of time; eventually leading to the real-time processing of the UAV videos in future research. For this purpose, the employed algorithms were selected on the basis of minimal processing times and computational requirements. A balance was maintained between the accuracy and processing time of the developed automated vehicle detection and tracking system.

After the automated vehicle detection and tracking process, the outputs are further used for detailed traffic analysis. The traffic analysis approach is dependent on the scope and objectives of the study. In this research, the main focus is on the traffic flow analysis. Various approaches or methodologies have been employed for various infrastructural elements such as signalized intersections, roundabouts etc. For signalized intersections, the simplified trajectory approach has been used, for example to study shockwaves, queue lengths etc. Furthermore traffic volume and gap acceptance modelling approach has been used for roundabout flow analysis. Similar approach is also used to analyze mixed traffic conditions in the scenario of developing countries, specifically Pakistan. Moreover, the integration of UAV-based traffic data with microsimulation modelling approach has also been investigated.

1.7 Thesis Outline

This dissertation is divided into several chapters based on the theme of conducted UAV-based studies. Overall, the research can be classified in 2 parts as per the contributions made. The first part *(Chapters 2, 3 and 4)* consists of the proposed frameworks for: (i) the conduction of UAV-based traffic studies, and (ii) the efficient processing and analysis of the collected UAV data. A special consideration is also given to the automatic vehicle detection and tracking mechanism. The second part *(Chapters 5,6,7 and 8)* focuses more on the traffic flow analysis of the data collected via small UAVs. Table 1.1 gives an overview of the key topics covered in each of the following chapters of this dissertation. Similarly, Table 1.2 shows how the components of developed frameworks and analytical mechanisms are integrated in each chapter. It provides a synthetic view of the contributions over the different chapters.

Table 1.1: Key topics covered in each chapter

Chapters	**Ch.2**	**Ch.3**	**Ch.4**	**Ch.5**	**Ch.6**	**Ch.7**	**Ch.8**
UAV-based Traffic Framework							
UAV Video Processing & Analysis Framework							
Traffic Analysis							
Signalized Intersection							
Roundabout Analysis							
Mixed Traffic- Pakistan							
Microsimulation Applications							

Legend			
Main Focus (Major)		**Further Applications (Minor)**	

Table 1.2: Checklist of the contributions of each chapter

Features	Ch.2	Ch.3	Ch.4	Ch.5	Ch.6	Ch.7	Ch.8
UAV-based Traffic Study Framework							
Data Collection	√	√	-	√	√	√	√
Data Processing	√	√	-	√	√	√	√
Video Processing & Analysis Framework							
Video Processing	-	√	√	√	√	√	-
Trajectory Extraction	-	√	√	√	√	√	-
Signalized Intersection Traffic Analysis							
Simplified Trajectories	-	-	-	√	-	-	-
Flow State Identification	-	-	-	√	-	-	-
Shockwave Analysis	-	-	-	√	-	-	-
OD Matrices	-	-	-	√	-	-	√
Roundabout Traffic Analysis							
OD Matrices	-	-	-	-	√	√	√
Critical Gap Analysis	-	-	-	-	√	√	√
Waiting Times	-	-	-	-	√	√	-
Mixed Traffic Analysis - Pakistan							
OD Matrices	-	-	-	-	-	√	-
Critical Gap Analysis	-	-	-	-	-	√	-
Turning movement behaviour	-	-	-	-	-	√	-
Microsimulation							
Base Model Development	-	-	-	-	-	-	√
Calibration & Validation	-	-	-	-	-	-	√

UAVs							
Argus One	-	√	√	√	√	-	√
DJI Phantom 4 Pro	-	-	√	-	-	√	-
Dataset used							
Sint-Truiden, Belgium	-	√	√	√	√	-	√
Rawalpindi/Islamabad, Pakistan	-	-	√	-	-	√	-
Tools used							
C++	-	√	√	√	√	√	√
Microsoft-Excel	-	√	√	√	√	√	√
MATLAB	-	√	√	√	√	√	√
PTV VISSIM	-	-	-	-	-	-	√

Chapter 1 gives the introduction of this 3-year PhD research. This chapter formulates the problem to be addressed and outlines the research questions. Moreover, the contributions and objectives of the research are also described.

Chapter 2 presents a universal guiding framework for the conduction of a UAV-based traffic study. The concept of utilizing small UAVs for traffic-related applications is addressed in detail. In order to streamline the whole process, a detailed framework is proposed that covers all the aspects of using UAVs for traffic data collection and analytical purposes; ranging from ensuring a safe and efficient UAV flight execution to the analysis steps that follow the execution of a UAV flight. The framework is classified into the following seven components: (i) scope definition, (ii) flight planning, (iii) flight implementation, (iv) data acquisition, (v) data processing and analysis, (vi) data interpretation and (vii) optimized traffic application. It provides a comprehensive guideline and gives an overview of the management in the context of the hardware and the software entities involved in the process. In this chapter, an extensive yet systematic review of the existing traffic-related UAV studies is presented by molding them in a step-by-step framework.

Chapter 3 proposes a detailed methodological framework for automated UAV video processing. The main objective is to efficiently process the traffic data acquired via UAVs; ensuring the data is converted into useful and reliable traffic information. The proposed framework consists of five components, namely:

preprocessing, stabilization, geo-registration, vehicle detection and tracking, and trajectory management. After all these sub-processes, the trajectories of multiple vehicles at a particular road segment are extracted, which can then be used either to extract various traffic parameters or to analyze traffic flow and safety situations. This chapter also gives a brief comparison of existing UAV studies based on either manual or semiautomatic processing techniques. However, the main focus is on the description of the proposed automated framework. In the end, the proposed framework is validated with the help of a field experiment conducted in the city of Sint-Truiden, Belgium. This data is processed and analyzed as per the modules of the framework, resulting in a series of vehicle trajectories.

Chapter 4 evaluates the performance of the proposed UAV based traffic analysis system with a special emphasis on the vehicle detection and tracking module. The main objective is to determine the level of accuracy of the generated vehicle detection and trajectory data. A certain level of accuracy is critical to ensure the collected data is converted into useful and reliable traffic information. The UAV video processing and analysis framework, initially presented in chapter 3 has been further optimized. In order to evaluate the accuracy of the system, the outputs from the vehicle detection and tracking system have been compared with the ground-truth data. Various measures of performance have been calculated for different UAV-based traffic videos. The results show that the overall accuracy of the system lies above 90%. Moreover, the sensitivity of UAV flight altitude to the overall preciseness of the outputs is also evaluated. The comparison shows that a higher altitude level provides more precise results. The results are presented in tabular as well as graphical format.

Chapter 5 explores the applications of data collected via small UAVs, for an in-depth traffic flow analysis at a signalized 4-legged intersection. The analysis is basically a practical extension of the outputs generated from the previously proposed detailed methodological framework for automated UAV video processing. In this chapter, the main emphasis is on the comprehensive analysis of vehicle trajectories extracted via UAV-based video processing framework. An analytical methodology is presented for: (i) the automatic identification of flow states and shockwaves based on processed UAV trajectories, and (ii) the subsequent extraction of various traffic parameters and performance indicators in order to study flow conditions at a signalized intersection. The experimental data to analyze traffic flow conditions was obtained in the city of Sint-Truiden, Belgium. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted-flow conditions at a signalized four-legged intersection using UAV-acquired data.

Chapter 6 authenticates the application of small multirotor UAVs for traffic data collection and subsequent analysis of traffic streams at urban roundabouts. This chapter presents an analytical methodology to evaluate the performance of roundabouts by extracting various parameters and performance indicators. The performance evaluation methodology is based on: (i) determining traffic volume via Origin-Destination matrices between legs, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The overall analytical process is principally based on the previously proposed automated UAV video-processing framework for the extraction of vehicle trajectories. The extracted trajectories are further employed to extract useful traffic information. The experimental data to analyse roundabout traffic flow conditions was obtained in the city of Sint-Truiden (Belgium). The study depicts the overall applicability of the UAV-based traffic analysis system.

Chapter 7 further extends the traffic data collection applications of UAVs to mixed traffic situations in developing countries. The objective is to validate the applications of UAV video processing and analysis framework in a more challenging traffic scenario. In order to demonstrate the traffic analysis process, a case study based on data collected in Pakistan, is presented in this chapter. Traffic data has been collected via a small UAV for an urban roundabout and a T-intersection in Rawalpindi/Islamabad (Pakistan). The overall analytical methodology is based on the previously proposed UAV-based traffic analysis framework. The extraction of various traffic parameters and measures of performance help in highlighting the usefulness of UAVs for traffic analysis. The developing countries generally lack even in the basic infrastructure required for traffic monitoring and data collection. In this scenario, UAVs can serve as a useful apparatus for traffic data collection in developing countries. The results of the analysis at two study locations reflect the overall driving attitude and lack of implementation of traffic rules in developing countries, resulting in high congestion levels and serious safety concerns.

Chapter 8 explores a new application of the traffic data collected via small UAVs. The chapter presents a methodology to utilize the UAV-based traffic data for the development as well as for the calibration of microsimulation models. The main objective is to examine the feasibility of microsimulation model development from UAV-based traffic data. For this purpose, two case studies comprising of a roundabout and a signalized intersection, have been presented based on the data collected via UAVs in Sint-Truiden, Belgium. The base models are developed using PTV VISSIM. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework (Khan et al., 2017), are utilized for the microsimulation model development and calibration. The calibration process is based on various measures of effectiveness and validation parameters. Acceptable calibration targets have been defined for both roundabout and signalized intersection models. The results show that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implies that UAVs can become a useful source of traffic data for the development and calibration of microsimulation models.

Chapter 9 concludes the dissertation with a discussion of main findings of this research work. The chapter also discusses the limitations and challenges attached with the use of UAVs for traffic data collection. Apart from it, the chapter ends with some recommendations and an insight into the future research possibilities.

1.8 References

Banister, D. (2002). Transport Planning,. London: Abingdon/Oxford: Routledge.

Barmpounakis, E. N., Vlahogianni, E. I., & Golias, J. C. (2016). 16-3429: Extracting Kinematic Characteristics from Unmanned Aerial Vehicles.

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. IEE Proceedings - Intelligent Transport Systems, 153(1), 11. https://doi.org/10.1049/ip-its:20055014

Gilbert, R., Irwin, N., Hollingworth, B., & Blais, P. (2003). Sustainable Transportation Performance Indicators (STPI). Presented at the TRB 2003.

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. Handbook of Unmanned Aerial Vehicles, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. Transportation Research Procedia, 22, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Litman, T. (2003). Sustainable Urban Transport: A Sourcebook for Policy-makers in Developing Countries. Module 2b: Mobility Management. GTZ Transport and Mobility Group.

McCormack, E. ., & Trepanier, T. (2008). The use of small unmanned aircraft by the Washington State Department of Transportation. Washington State Department of Transportation.

Puri, A. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. Department of Computer Science and Engineering, University of South Florida,. https://doi.org/10.1.1.108.8384

Salvo, G., Caruso, L., & Scordo, A. (2014). Urban Traffic Analysis through an UAV. Procedia - Social and Behavioral Sciences, 111, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

Senguttavan, P. . (2006). Fundamentals of Air transport management. Excel Books.

Shiftan, Y., & Kaplan, S. (2003). SCENARIO BUILDING AS A TOOL FOR PLANNING A SUSTAINABLE TRANSPORTATION SYSTEM. Transportation Research Part D: Transport and Environment, 8(5), 323–342.

Stevenson, M., Thompson, J., de Sa, T. H., Ewing, R., Mohan, D., McClure, R., … Woodcock, J. (2016). Land-use, transport and population health: estimating the health benefits of compact cities. Lancet (London, England), 388(10062), 2925–2935. https://doi.org/10.1016/S0140-6736(16)30067-8

United Nations, Department of Economic and Social Affairs, Population Division. (2015). World Urbanization Prospects: The 2014 Revision (No. (ST/ESA/SER.A/366)).

US Army, U. A. S. C. O. E. F. R. A. (2010). U.S. Army Unmanned Aircraft Systems Roadmap 2010-2035: Eyes of the Army (Technical Report No. ADA518437).

Vlahogianni, E. I. (2015). Computational Intelligence and Optimization for Transportation Big Data: Challenges and Opportunities. In Engineering and Applied Sciences Optimization: Volume 1. Springer International Publishing.

Wu, W. ., Zhao, S. ., & Zhu, C. (2015). A Comparative Study of Urban Expansion in Beijing, Tianjin and Shijiazhuang over the Past Three Decades. Landscape and Urban Planning, 134, 93–106.

Chapter 2

Universal Guiding Framework Based on Literature Survey

This chapter consists of following peer-reviewed conference paper:

Khan, M.A.; Ectors, W.; Bellemans, T.; Janssens, D.; Wets, G. UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. *Transp. Res. Procedia* **2017**, *22*, 541–550.

2.1 Overview

This chapter presents a universal guiding framework for the conduction of a UAV-based traffic study. The concept of utilizing small UAVs for traffic-related applications is addressed in detail. In order to streamline the whole process, a detailed framework is proposed that covers all the aspects of using UAVs for traffic data collection and analytical purposes; ranging from ensuring a safe and efficient UAV flight execution to the analysis steps that follow the execution of a UAV flight. The framework is classified into the following seven components: (i) scope definition, (ii) flight planning, (iii) flight implementation, (iv) data acquisition, (v) data processing and analysis, (vi) data interpretation and (vii) optimized traffic application. It provides a comprehensive guideline and gives an overview of the management in the context of the hardware and the software entities involved in the process. In this chapter, an extensive yet systematic review of the existing traffic-related UAV studies is presented by molding them in a step-by-step framework.

2.2 Abstract

The Unmanned Aerial Vehicles (UAVs) commonly also known as drones are considered as one of the most dynamic and multi-dimensional emerging technologies of the modern era. Recently, this technology has found multiple applications in the transportation field as well; ranging from the traffic surveillance

applications to the traffic network analysis for the overall improvement of the traffic flow and safety conditions. However, in order to conduct a UAV-based traffic study, an extremely diligent planning and execution is required followed by an optimal data analysis and interpretation procedure. This paper presents a universal guiding framework for ensuring a safe and efficient execution of a UAV-based study. It also explores the analysis steps that follow the execution of a drone flight. The framework based on the existing studies, is classified into the following seven components: (i) scope definition, (ii) flight planning, (iii) flight implementation, (iv) data acquisition, (v) data processing and analysis, (vi) data interpretation and (vii) optimized traffic application. The proposed framework provides a comprehensive guideline for an efficient conduction and completion of a drone-based traffic study. It gives an overview of the management in the context of the hardware and the software entities involved in the process. In this paper, an extensive yet systematic review of the existing traffic-related UAV studies is presented by molding them in a step-by-step framework. With the significant increase in the number of UAV studies expected in the coming years, this literature review could become a useful resource for future researchers. The future research will mainly focus on the practical applications of the proposed guiding framework of the UAV-based traffic monitoring and analysis study.

2.3 Introduction

The continuous increase in number of motorized vehicles and the ever-increasing travel demands call for innovative and effective measures to be taken to tackle the challenges of high traffic volumes and congestion levels. With the limited yet expensive infrastructural expansion alternatives, the transportation managers are only 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 the traffic streams, particularly in emergency situations.

The efficient operational management of the network requires an accurate, timely and quick inflow of traffic data. Traffic data collection and its subsequent analysis has also been a critical element for the development and improvement of the macroscopic as well as the microscopic traffic simulation models. However, it is not easy to collect the traffic data for large spans of roadway networks as most of the data collection methods require a large fixed infrastructure or are labor intensive (Coifman et al., 2006).

Over the years, the methods of collecting useful traffic data have evolved with the advancement in technology. The 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; however, the data collected is only measured at a particular point with generally no useful data about traffic flows over space (Puri,2005). This results in a number of hidden points as a high density of detectors are required to cover the whole network (Barmpounakis et al., 2016a; Coifman et al., 2006). In such a dataset, the real root cause of the traffic congestion or any other incident remains unknown. Manual detections are made by the specially deployed personnel if some traffic information is required beyond the range of the installed cameras or sensors.

Apart from such traditional equipment, advanced ITS technologies such as vehicle-to-infrastructure(V2I), probe vehicles with GPS and other smartphone sensor technologies resulting in "big datasets" are also being used. However, such data is not always easily converted to useful traffic data (Vlahogianni, 2015). Also, the use of GPS technology might not be correct for studying the driver behavior since the drivers know they are being monitored (Barmpounakis et al., 2016; Salvo et al., 2014b).

The technological advances have recently enabled an alternative to an inflexible fixed network of sensors or the labor intensive and potentially slow deployment of personnel (Coifman *et al*.,2006). The complex traffic situations can be fully observed with the help of wide field-of-view and non-intrusive sensors and cameras mounted on airborne systems. Initially, satellites and manned aircrafts were used for traffic surveillance purposes, but a number of quality, cost and safety issues have proven these methods to be inefficient. Recently, unmanned aerial systems in the traffic monitoring, management, and control are starting to take center stage (Kanistras *et al*.,2013; Puri, 2005).

The Unmanned Aerial Vehicles (UAVs) commonly also known as drones are considered to be one of the most dynamic and multi-dimensional technologies of the modern era. This technology is swiftly strengthening its presence in multiple fields of the human life, varying from commercial tasks such as parcel delivery, sports coverage etc. to research applications e.g. survey of inaccessible areas and crop fields. UAVs are predicted to be the most dynamic growth sector of the world aerospace market this decade (PR Newswire, 2011).

As mentioned by Kanistras *et al*. (2013) and Puri (2005), the UAVs recently are being used in the transportation field to monitor and analyze the traffic flow and safety conditions. These airborne imaging systems are mobile and most importantly provide high resolution traffic data relevant in both time and space (Puri,2005). The UAVs cover a large area in short times with an extreme low cost. The lower cost can also be achieved, since all the equipment is reusable to a different point of interest (Barmpounakis *et al*., 2016).

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 (Barmpounakis *et al*,2016; Puri,2005). The actual applications of this technology are currently limited in numbers but are still in the research stages. Nevertheless, this technology is progressing rapidly and can be safely termed as a future-proof technology with the widespread commercial availability and decreasing costs. It is forecasted by the aviation authority that 30,000 drones could be over U.S. skies by 2020, implying new and improved applications of the technology.

However, the use of drone technology in traffic related studies involves a high level of planning and management precision. With an introduction of state laws regarding the use of UAVs, an extremely diligent planning and execution of a UAV flight is required as the consequences of a mismanaged execution could be pretty severe. For this purpose, we aim to propose a universal framework that serves as a guide for not only 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. In this paper, we re-organize the existing UAV-based traffic studies into a step-by-step framework. Such a detailed framework may prove to be helpful for various traffic related UAV studies such as traffic surveillance, network traffic analysis and behavioural studies. It may also serve as a foundation for more advanced studies involving swarms of UAVs. Up till now, there have been general survey studies (Puri,2005; Kanistras *et al*,2013) regarding the research applications of UAVs in the field of transportation, but there has been no such detailed framework based on the existing literature.

This paper is organized as follows: first of all, the relevant survey studies that have been carried out regarding the applications of UAVs in traffic field are briefly discussed in section 2.4. This is followed by a detailed description of the proposed framework (section 2.5). Finally, the section 2.6 comprises of the brief discussion of the framework along with the conclusions and the proposed future developments of the framework.

2.4 Related Work

As mentioned earlier that the UAVs are increasingly being employed for multiple purposes. According to the literature, the UAVs are widely being researched for traffic surveillance and network evaluation applications (Coifman,2006; Puri *et al*.,2007; Heintz *et al*.,2007, etc.). Various types of UAVS are being used or tested to measure traffic related data at several universities (Puri,2005). A few literature survey studies have been conducted to summarize the research work carried out around the world regarding UAV-based traffic applications.

Puri (2005) discusses and summarizes the research carried out all over the world until 2005 in the domain of UAV based traffic surveillance and analysis. The author initially covers some of the research work on-going at various universities such as University of Florida, Ohio State University, Linköping University, Georgia tech etc. This is followed by a systematic categorization of the relevant research based on the research objective, methodology, platform used and the place of research. Also, the author mentions a number of advantages along with the barriers that the UAVs have to overcome in order to be successfully employed for civil applications like traffic monitoring and surveillance operations. Similarly, Kanistras *et al*.(2013) adopt the same approach as Puri (2005) by conducting a literature survey of the applications of the unmanned aerial vehicles for traffic monitoring and management. However, the authors only focus on the research that has been carried out in this perspective within a specified period i.e. between 2005 and 2012. The relevant research conducted during this period is also systematically arranged as per the approach employed in the previous research of Puri.

Some researchers have tried to propose a workflow or an outline for the conduction of the UAV based studies. Eisenbeiss (2009) proposes a workflow for UAV photogrammetric studies particularly for archeological and environmental applications. The author enlists and discusses the different modules of the proposed workflow i.e. flight planning, image acquisition and processing of UAV images. A particular focus is on the improvement of the UAV flight planning and control systems, eventually ensuring the quality of the acquired data. On the other hand, Zheng *et al*. (2015) develop a UAV system specifically for driving-behavior monitoring to prevent accidents. Based on an application-specific outline or workflow, the authors propose a methodology for real-time vehicle tracking using image processing, and vehicle risk modelling through statistical analysis. The main focus of this particular work, however is on the evaluation of the drivers' behavior and the development of a risk analysis model.

2.5 Framework

In this paper, we re-organize the existing UAV-based traffic studies and the available software platforms into a step-by-step framework. This framework categorizes the whole process into a number of stages, resulting in a systematic and efficient conduction of any drone-based study. The framework based on the existing studies, is classified into the following seven components: (i) scope definition, (ii) flight planning, (iii) flight implementation, (iv) data acquisition, (v) data processing and analysis, (vi) data interpretation and (vii) optimized traffic application. Figure 2.1 below illustrates the steps involved in conducting a drone or a UAV platform based traffic related study. We discuss each step on the basis of the existing relevant studies with a particular focus on the studies that employ small, low altitude (<150m) multirotor UAVs for the traffic related applications. Also, a special consideration is given to the data analysis techniques that have been used to detect and track different vehicles in the existing relevant studies.

Figure 2.1 below illustrates the steps involved in conducting a drone or a UAV platform based traffic related study. As the figure suggests that the whole process can be divided into two main blocks i.e. the drone block and the processing(software) block. The output of the scope definition step is fed consequently into the two blocks as shown below:

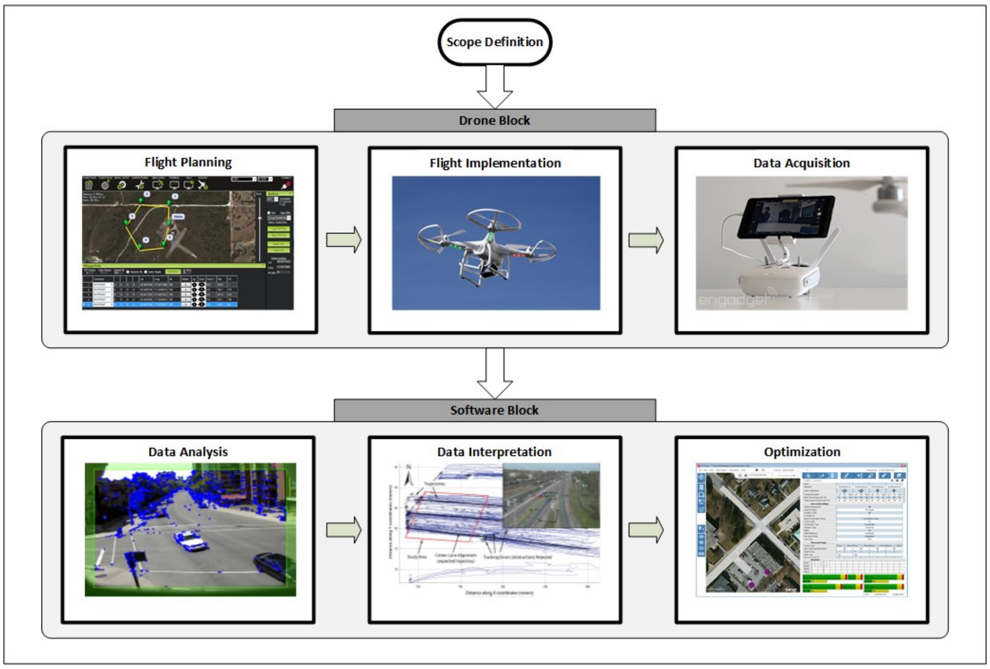


Figure 2.1: The proposed framework for UAV-based traffic study

2.5.1 Scope Definition

The first module of our proposed framework involves the definition of the scope of the study to be conducted. This is a critical step in any project as all the latter steps are dependent on it. Therefore, a clear problem statement with fixed and definite project objectives must be defined during this step. As mentioned by Eisenbeiss (2009), the attributes of the workflow modules are generated in the first module in which the project parameters like object type, output data, camera sensor, type of model helicopter and flight restrictions are designated. These parameters can vary from one application to another. Based on the literature review of project scope development (AASHTO,2010), we present a 3-step process in the context of a UAV based traffic study as shown in the figure 2.2:

Figure 2.2: The scope definition module

First of all, the main objectives of the study are defined and a specific focus is established with respect to the expected results of the study. The objectives of the project may include an implementation of a traffic policy program to improve traffic flow or to reduce the traffic conflicts. This can be achieved with the help of the drivers' lane change behaviors and traffic pattern studies e.g. Salvo *et al*. (2014b) use a UAV video to analyze the gap-acceptance in an urban intersection. After the establishment of the objective, the network elements to be monitored and analyzed are selected. This can be an intersection, a roadway segment, a ramp or a combination of them. In the Performance measures step, the parameters to be determined for the study are selected such as traffic volume, pedestrian volume, number of lane changes, vehicle classification, velocities, acceleration/deceleration, number of conflicts etc. The type of traffic parameters to be derived from the UAV videos also define the type of UAV flight to be conducted e.g. Barmpounakis *et al.* (2016) extract the vehicle trajectories across the different legs of the intersection by just making the UAV hover (constant altitude, zero velocity) above an intersection.

2.5.2 Flight Planning Stage

The Flight Planning Stage involves the preparation for the implementation of the actual UAV flight for the collection of the required data. With the significant increase in the number of UAVs, state laws are now being formulated and implemented all over the world to avoid major mishaps. In this situation, the UAV flight planning step has become even more important. This implies that an in-depth flight planning, based on the project parameters or scope is essential (Eisenbeiss,2009). Based on the literature survey of the traffic related UAV studies, the whole process of the UAV flight planning may be classified into three main categories; safety, environment and route planning aspects, as shown in the figure 2.3.

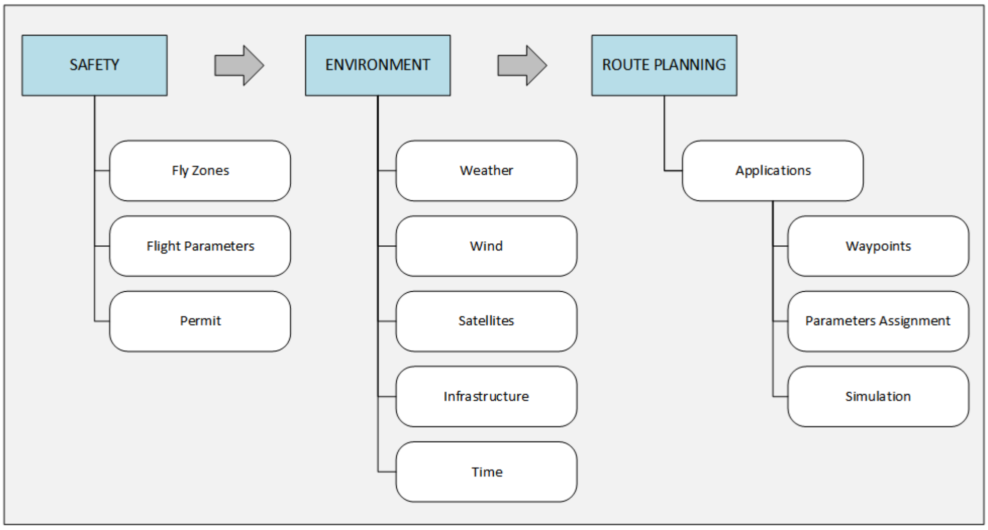


Figure 2.3: The flight planning steps

These three categories include all the aspects that are critical for ensuring a successful UAV flight operation. First of all, the flying zone category of the study area must be evaluated with the help of the local flying zone maps. Also, a safe distance has to be maintained from the active airfields and from other sensitive installments. Based on the relevant flying zone, safety thresholds and other project characteristics, the flight parameters may be selected during the flight planning process (Eisenbeiss,2009). This is followed by an acquisition of a flight permit from the concerned department. This process has become easier with the development of UAV flight management platforms which automate a number of steps involved in ensuring safety and attaining flight permits. Idronect and Unifly UTMS are examples of such platforms from Belgium.

The location characteristics i.e. infrastructural environment and extents of the built-up area in the study zone must also be considered in quest for an optimal set of flight parameters. Apart from the spatial planning for the UAV flight, a temporal planning is also necessary. This requires a special deliberation towards the weather and wind conditions in the area of study along with the optimal selection for the time of the day. For example, Salvo *et al*. (2014[1]) conduct their UAV flight at noon as the shadows are minimal during this time of the day, ultimately resulting in an easier and higher quality analysis of the videos. Also, the interference effects of electromagnetic emissions (Yochim, 2010) and the status of GPS satellites especially in case of an automated UAV flight must also be considered during the planning phase.

With the advancement in the technology, UAV flight planning tools have been developed that enable a more systematic and automated flight operation. Using such tools, the users can mark the waypoints along the desired path. The users can plan and upload the exact route of the flight to the UAV for an automated flight. Mission Planner and UgCS ground station are examples of such softwares. However, a backup certified pilot in line of sight (LOS) is compulsory even for automated UAV flights in the civilian domain due to security and insurance constraints. (Eisenbeiss,2009).

2.5.3 Flight Implementation Stage

During the flight implementation Stage, the UAV actually flies over an area of interest as per the planned flight path/route. This flight is conducted based on the parameters decided during the flight planning stage. The flight depending upon the user's preference and flying expertise, is controlled either manually via the radio controller or automatically via the auto-pilot function. This step in conjunction with the flight planning step requires a number of safety and legal issues to be carefully addressed as mentioned in the previous step.

During the UAV flight implementation, it also has to be made certain that the captured video is not shaky or wobbly. While minor stability issues can be handled during the pre-processing stages, the camera platform has to be stable enough to achieve a high quality video. For this purpose, most UAVs hold a gimbal (3-axis) which allows the rotation of the camera about a single axis only (Barmpounakis *et al*,2016). The gimbal has its own motion sensors (similar to those that hold the UAV stable) and small motors. It keeps the motion of the camera independent (within certain limits) from the motions of the UAV (motions from tilting to move forward or sideways, or when hit by a gust of wind). The camera operator is able to aim the camera at will (overriding the 'lock' of the camera position relative to the environment). We discuss some individual flight implementation standards adopted by the researchers in their traffic-related UAV studies as following:

Barmpounakis *et al.* (2016) conduct a UAV flight over a low-volume intersection in the university area. The UAV was hovered at a particular point from where all the legs of the intersection were clearly visible as shown in the figure 2.4. The flight attained a maximum height of 70m and the authors were able to record a 14-minute video excluding the take-off, landing and the time to reach the recording point. The authors particularly selected a site where no alternate sufficiently high position was available in the surroundings to have a complete overview of the intersection. The flight was planned to be executed on a sunny day with moderate wind speed. Also, it was particularly made sure that the flight is conducted during the noon hours so that the effect of shadows is minimal, thereby ensuring an efficient detection of vehicles during the analysis stage.

Figure 2.4: View of the intersection from a UAV (Source: Barmpounakis et al., 2016)

Similarly, Salvo *et al.* (2014a) implement their UAV flight for the collection of traffic data over a road segment in the suburbs of Palermo City, Italy. The authors after a thorough planning process conducted the UAV flight and were able to collect a 15 minute video with 10 frames per second in HD quality (1280x720). A series of flights were conducted to acquire the desired video length due to the technical limitations of the hardware. Also, the flights were conducted during the noon hours in order to minimize the effects of the shadows of the objects. Salvo *et al*. (2014b) in their another, study conduct the UAV flight over the intersection in the vicinity of the university. The authors conducted 5 flights over the area under observation at an altitude of 60m and acquired a total of 20 minute HD quality video. The UAV was hovered (zero speed, constant altitude) at 5 different points during the series of flights.

Zheng *et al.* (2015) employed a different approach to validate their driver-behaviour monitoring study. To counter the safety restrictions imposed by Federal Aviation Authority (FAA) and local law enforcement agencies, the authors used 2 types of methods for controlled testing of their methodology. A test track with RC cars instead of real cars was set up to evaluate a UAV-based traffic study. Apart from this, the experiment was also conducted in the university grounds in controlled conditions.

2.5.4 Data Acquisition

The acquisition of data from the UAV is also a critical step of the proposed framework and is largely dependent on the scope of the study. The data that has to be acquired from the UAV includes the high quality UAV recorded video footage of the region of interest along any other data from sensors (infrared, thermal, ultrasonic etc.) mounted on the UAV. In some cases, the flight telemetry data (altitude, horizontal speed, vertical speed along with the position and the orientation data) is also acquired from the UAV in order to calibrate the recorded video. As indicated by Cramer (2001), the integration of position and orientation data generated by the navigation unit of the UAV leads to a reduction of the number of physical control points that are required for the orientation and calibration of the UAV videos. Overall, the scope specific data is acquired from the UAV and is then further treated and processed during the later stages of the framework.

The data acquisition can be real-time or offline depending upon the requirements of the project. Most of the studies mentioned up till now in this paper such as (Salvo *et al*,2014a; Salvo *et al*,2014b; Barmpounakis *et al*,2016 etc.) employ an offline processing approach in which the video data is acquired and processed after the completion of the UAV flight. However, some studies such as (Zheng *et al*, 2015; Sekmen *et al*,2009 etc.) employ a real-time data acquisition and processing techniques. Zheng *et al*. (2015) propose a methodology for a real time vehicle tracking system in order to monitor and study the drivers' behaviour to prevent accidents and promote highway safety. The proposed system is based on the live transmission of the UAV video to the ground station computer on which a near real-time image processing is conducted followed by a statistical analysis for vehicle risk modelling. (Luo et al,2011; Sekmen et al, 2009) are other such studies which employ a real time data acquisition and processing approach. The authors present an airborne traffic surveillance system to detect and track multiple moving objects in real-time.

2.5.5 Data Processing & Analysis

Video Analytics have attracted significant attention mainly because they enable researchers to easily collect detailed trajectory data and at the same time have a visual observation of the phenomenon (Barmpounakis *et al*., 2016). A lot of research has been carried out for fixed camera video analysis systems such as (Micchalopoulos,1991; Cao *et al*.,2007; Wang *et al*.,2008). However, the analysis of a traffic stream from a video recorded via an unstable aerial platform i.e. a UAV is a relatively new topic. This process is more complex as compared to the analysis of a moving traffic stream from a stationary or fixed camera system.

Multiple approaches have been employed in the existing literature for the processing and analysis of the UAV-based traffic data. These approaches can be broadly classified into two categories:

3.5.1 Semi-Automated Video Analysis: The semi-automated video processing and analysis approach has been employed in a number of traffic related UAV studies. Such an approach is easy to set up and ensures a high level of accuracy and reliability. Also, no complex image processing algorithms are required which implies that far less computational power is needed. On the other hand, this approach is more laborious and generally requires more manpower as it generally involves the establishment of some physical ground control points (GCPs) or have certain lengths accurately measured on the site in order to calibrate the UAV images. 'Tracker' is an open source video analysis and modelling tool (Brown, 2007, 2008, 2009, 2010) which is commonly used for feature tracking in semi-automatic analysis studies. This software makes use of the stabilized and calibrated video to speed up the tracking process and produce more consistent data by eliminating the need for marking each frame (Barmpounakis *et al*, 2016). A few studies that utilize a semi-automatic video analysis approach are (Salvo et al, 2014a; Salvo et al,2014b; Barmpounakis *et al*, 2016).

3.5.2 Automated Video Analysis: An automated analysis of the UAV acquired traffic data involves a series of advanced image processing filters and techniques in order to detect and track the relevant road users. The automated video analysis is gaining popularity especially for the real-time traffic monitoring and tracking applications. Although such an approach is quick and requires minimal manpower, it still has some limitations. Generally, the accuracy of such systems fluctuates dramatically with changes in conditions such as light, climate etc. Additionally, the automated system requires a high computational power and is difficult to initially set up as it involves complex algorithms for each sub-task of the analysis. Some studies that propose an automated video analysis include (Zheng *et al*,2015; Apeltauer *et al*,2015; Oh *et al*, 2014; Azevedo *et al*, 2014, Luo *et al*,2011; Sekmen *et al,*2009). The authors attempt to make use of fast and robust object detection and tracking techniques for the processing of UAV videos.

However, for both the approaches, the basic workflow remains the same as illustrated in the figure 2.5. The analysis of the UAV-based traffic footage involves some pre-processing and stabilization procedures. These are necessary in order to make the video ready for the actual analyses steps. After the Geo-Referencing or calibration of the images to the real world coordinate system, the detection and tracking of different road users is carried out either automatically or semi-automatically as discussed earlier.

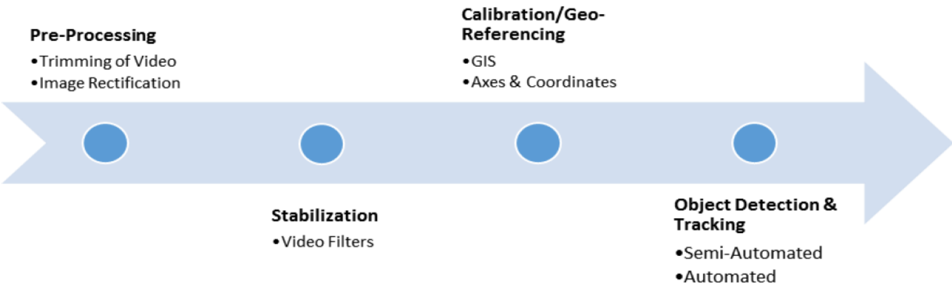
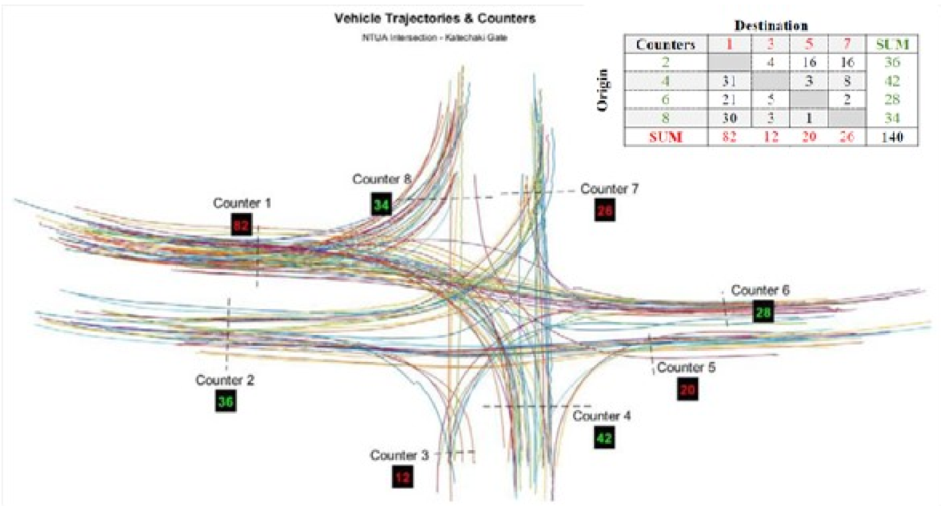


Figure 2.5: The data processing steps

2.5.6 Data Interpretation

The interpretation of the processed video data is the next step in the framework. The interpretation is done with the help of different types of graphs and charts that are generated as an output of the data analysis procedures. This step too, along with the preceding steps of the proposed framework, is directly dependent on the scope of the study. The trajectories of the vehicles or other road users extracted during the analysis part are displayed in x-y planar graphs to understand the behaviour and trend of the road users. Similarly, such trajectories are also represented graphically to illustrate the traffic movement across the intersection as depicted by Barmpounakis *et al*. (2016) in figure 2.6.



Counters	1	3	5	7	SUM
2		4	16	16	36
4	31		3	8	42
6	21	5		2	28
8	30	3	1		34
SUM	82	12	20	26	140

Figure 2.6: Graphical representation of vehicle trajectories for a given intersection (Source: Barmpounakis et al., 2016)

The authors (Barmpounakis *et al*,2016) especially focus on the unusual trajectories that may compromise the traffic safety situation. This is also followed by the construction of OD matrices in order to quantify the traffic volume for each leg of the intersection. Similarly, other authors such as Salvo *et al*. (2014a) determine the traffic kinematic parameters i.e. flow and density during the analysis phase of the study. These parameters are then compared with the flow and density values determined via theoretical macro-simulation models i.e. Greenshields, Greenberg, Underwood models etc.

2.5.7 Optimized Traffic Application

The optimized conclusion of the traffic study in accordance with its scope is the final step in our proposed UAV-based traffic analysis framework. The study-specific traffic parameters determined during the analysis and interpretation steps are employed to improve the existing traffic models which ultimately help in solving the real-world traffic situations. This application dependent optimization may include a number of traffic related objectives such as traffic signal optimization, observation of drivers' behaviours, lane change manoeuvres etc. Moreover, a real-time information system can optimize the traffic operation by sending alerts to the concerned departments in case of incidents and emergencies (Barmpounakis *et al*,2016).

Salvo *et al*. (2014a) conclude their study by comparing the traffic parameters obtained via the analysis of the UAV-acquired video with the traffic parameters obtained via macro-simulation models. Similarly Salvo *et al*. (2014b) attempt to determine the gap acceptance of all vehicles that try to enter the principle traffic stream at an intersection by using a UAV-acquired video dataset. Additionally, Barmpounakis *et al*. (2016) try to optimize the traffic safety and flow conditions by understanding the road user behavior in intersections by observing unusual trajectories and behavior.

2.6 Discussion & Conclusions

This paper presents an extensive yet systematic review of the existing traffic-related UAV studies by moulding them in a step-by-step framework. Up till now, there have been general survey studies (Puri,2005; Kanistras *et al*,2013) regarding the research applications of UAVs in the field of transportation, but there has been no such detailed framework based on the existing literature.

With the passage of time, the UAV technology is rapidly being accepted as a very useful and dynamic technology, particularly for the collection of detailed and accurate traffic data. This relatively low cost technology provides high resolution video data while covering a larger area. The mobility and flexibility of the system further increases the worth of this technology. However, despite of a number of advantages, UAVs still have some significant concerns and limitations that need to be addressed. The technical limitations i.e. limited battery time, weather constraints along with the safety and privacy concerns are the biggest hindrances in making this technology more effective. Although, high-end technology could be used to increase the battery life, this however exponentially increases the cost of ownership. Therefore, the current low cost technology can be utilized most effectively by combining it with the other traffic data collection apparatus.

The UAVs can be used to collect data beyond the range of fixed sensors in order to get a detailed and accurate data over space and time. This can particularly be useful in areas where the fixed sensor infrastructure is either not available or is financially not feasible to install a high density of sensors along the area. Moreover, the management of traffic incidents can also be improved drastically with the help of such technology. Therefore, it can be concluded that advancement in technology, effective regulations and systematic frameworks will result in a safer and more efficient usage of the UAVs, particularly for the traffic applications.

With the significant increase in the number of UAVs, state laws are now being formulated and implemented all over the world to avoid major mishaps. In this situation, there is a dire need for a systematic and detailed step-by-step framework for the conduction of UAV flights. Apart from it, the proposed framework may prove to be helpful for various traffic related UAV studies such as traffic surveillance, network traffic analysis and behavioural studies. The development of such a framework may optimize the usage of limited UAV flight time, thereby resulting in an efficient conduction of the traffic study. Additionally, it may also serve as a foundation for more advanced studies involving the swarms of UAVs. Overall, the proposed framework serves as a comprehensive guide for the conduction of a UAV-based traffic study. The steps involved in the process outline all the hardware as well as software ingredients that are essential to ensure a safe and efficient operation, management and control of a UAV-based traffic study.

The future research will mainly focus on the implementation of the proposed framework in a real-world situation to observe and analyse traffic streams in Belgium. A particular focus will also be on the scenario evaluations, in terms of feasibility measures and cost-benefit analysis, in comparison to other existing technologies.

2.7 References

AASHTO. (2010). Highway Safety Manual (1st ed.)American Association of State Highway and Transportation Officials, Washington, D.C., USA

Apeltauer, J., Babinec, A., Herman, D. and Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. In ISPRS Archives. Munich: TUM.

Azevedo, C.L., Cardoso, J.L., Ben-Akiva, M., Costeira, J.P., & Marques, M. (2014). Automatic Vehicle Trajectory Extraction by Aerial Remote Sensing, Procedia - Social and Behavioral Sciences, Volume 111, pp 849-858.

Barmpounakis, E.N., Vlahogianni, E.I., & Golias, J.C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. Proceedings of the 95th Annual Meeting of the Transportation Research Board.

Brown, D. (2007). Combining computational physics with video analysis in Tracker. Paper presented at the American Association of Physics Teachers AAPT Summer Meeting, Greensboro

Brown, D. (2008). Video Modeling: Combining Dynamic Model Simulations with Traditional Video Analysis. Paper presented at the American Association of Physics Teachers AAPT Summer Meeting, Edmonton.

Brown, D. (2009). Video Modeling with Tracker. Paper presented at the American Association of Physics Teachers AAPT Summer Meeting, Ann Arbor.

Brown, D. (2010). Tracker Introduction to Video Modeling (AAPT 2010). Portland Oregon

Cao, M., Vu, A., & Barth, M. (2007). A novel omnidirectional vision sensing technique for traffic surveillance. IEEE Intelligent Transportation Systems Conference, pp. 678-683.

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M. and Y. Ji. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. IEEE Proceedings –Intelligent Transport Systems, vol. 153, no. 1, pp. 11-20.

Coifman, B., McCord, M., Mishalani, R., Redmill, K. (2004). Surface Transportation Surveillance from Unmanned Aerial Vehicles. Proc. of the 83rd Annual Meeting of the Transportation Research Board.

Cramer, M. (2001). Genauigkeitsuntersuchungen zur GPS/INS-Integration in der Aerophotogrammetrie, Deutsche Geodätische Kommission, München, p. 122.

Eisenbeiss, H. (2009). UAV Photogrammetry. DISS. ETH NO. 18515, doi:10.3929/ethz-a-005939264. and Institute of Geodesy and Photogrammetry, ETH Zurich, Switzerland, Mitteilungen Nr.105, p. 235.

Heintz, F., Rudol, P., & Doherty, P. (2007). From images to traffic behaviour - a UAV tracking and monitoring application. 10th IEEE International Conference on Information Fusion.

Kanistras, K. (2013). A survey of unmanned aerial vehicles (UAVs) for traffic monitoring. 2013 Int. Conf. Unmanned Aircraft Systems (ICUAS), pp. 221–234.

Luo, X., Wu, Y., Huang, Y., & Zhang, J. (2011). Vehicle flow detection in real-time airborne traffic surveillance system. Transactions of the Institute of Measurement & Control,33(7), 880-897.

Micchalopoulos, P. G. (1991). Vehicle detection through video image processing AUTOSCOPE System [J]. IEEE Transaction on Vehicular Technology, 40 (1), pp. 21 - 29.

Oh, H., Kim, S., Shin, H.S., Tsourdas, A., & White, B.A. (2014). Behaviour recognition of ground vehicle using airborne monitoring of unmanned aerial vehicles. International Journal of Systems Science, 45 (12), pp. 2499 - 2514.

PR Newswire. (2011). "Teal Group Predicts Worldwide UAV Market Will Total $89 Billion in Its 2012 UAV Market Profile and Forecast," PRNewswire press release, April 11, 2012. http://www. prnewswire.com/news-releases/teal-grouppredicts-worldwide-uav-market-will-total-89-billion-in-its-2012-uav-market-profileand-forecast-147008115.html

Puri, A. (2005) A Survey of Unmanned Aerial Vehicles (UAV) for Traffic Surveillance, Department of Computer Science and Engineering, University of South Florida.

Puri, A., Valavanis, K.P., & Kontitsis, M. (2007). Statistical profile generation for traffic monitoring using real-time UAV based video data. IEEE Mediterranean Conference on Control & Automation, pp. 1–6.

Salvo, G., Caruso, L., & Scordo, A. (2014a). Urban traffic analysis through an UAV. Procedia - Social and Behavioural Sciences, 111, pp. 1083 – 1091.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. Recent Advances in Civil Engineering and Mechanics, pp. 199-205.

Sekmen, A., Yao, F., & Malkani, M. (2009;2008;). Smart video surveillance for airborne platforms. Robotica, 27(5), pp. 749-761.

Vlahogianni, E. I. (2015). Computational Intelligence and Optimization for Transportation Big Data: Challenges and Opportunities. Springer International Publishing.

Wang, G., Xiao D., & Gu, J. Review on Vehicle Detection Based on Video for Traffic Surveillance. Proceedings of the IEEE International Conference on Automation and Logistics, pp. 2961 - 2966.

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In G. V. Duffy (Ed.), Digital Human Modeling. Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health: 6th International Conference, DHM 2015, Proceedings, Part II (pp. 305–312).

Yochim, J.A. (2010). The Vulnerabilities of Unmanned Aircraft System Common Data Links to Electronic Attack. M.M.A.S. Thesis, Fort Leavenworth, Kansas.

Chapter 3

Methodological Framework for Automated Multivehicle Trajectory Extraction

This chapter consists of following peer-reviewed journal paper (published):

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Record: Journal of the Transportation Research Board **(IF:0.695)**, 32(0), 1–15. doi: 10.3141/2626-04

Based on the following peer-reviewed conference paper:

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Board, 96th Annual Meeting, Washington D.C, USA.

3.1 Overview

This chapter proposes a detailed methodological framework for automated UAV video processing. The main objective is to efficiently process the traffic data acquired via UAVs; ensuring the data is converted into useful and reliable traffic information. The proposed framework consists of five components, namely: preprocessing, stabilization, geo-registration, vehicle detection and tracking, and trajectory management. After all these sub-processes, the trajectories of multiple vehicles at a particular road segment are extracted, which can then be used either to extract various traffic parameters or to analyze traffic flow and safety situations. This chapter also gives a brief comparison of existing UAV studies based on either manual or semiautomatic processing techniques. However, the main focus is on the description of the proposed automated framework. In the end, the proposed framework is validated with the help of a field experiment conducted in the city of Sint-Truiden, Belgium. This data is processed and analyzed as per the modules of the framework, resulting in a series of vehicle trajectories.

3.2 Abstract

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, geo-registration, 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.

3.3 Introduction

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 (Coifman et al., 2006).

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 (Puri, 2005). 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 (Barmpounakis et al., 2016; Coifman et al., 2006). 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 (Vlahogianni, 2015). Also, the use of GPS technology might not be applicable for studying driver behavior because drivers know they are being monitored (Barmpounakis et al., 2016; Salvo et al., 2014a).

Technological advances have recently provided an alternative to an inflexible fixed network of sensors or the labor-intensive and potentially slow deployment of personnel (Coifman et al., 2006). 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 (Hoogendoorn et al., 2003). 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 (Kanistras et al., 2015; Puri, 2005).

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 predicted to be the most dynamic growth sector within aviation in the coming years (Schaufele, 2015).

UAVs have been used in the transportation field to monitor and analyze traffic flow and safety conditions (Kanistras et al., 2015; Anuj Puri, 2005). These airborne imaging systems are mobile and, more importantly, provide high resolution traffic data relevant in both time and space (Anuj Puri, 2005). 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 (Kanistras et al., 2015; Puri, 2005). 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 lbs.) could be over U.S. skies by 2020, implying new and improved applications of the technology (Schaufele, 2015).

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 (Khan et al., 2017).

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.

3.4 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 (Coifman et al., 2006; Heintz et al., 2007; Puri et al., 2007). Different types of UAVS are being used or tested to measure traffic related data at several universities (Puri, 2005). 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 (Kanistras et al., 2015; Puri, 2005). 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 (Kanistras et al., 2015; Puri, 2005).

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 (Khan et al., 2017). 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. (2015) developed a UAV system specifically focused on monitoring driving behavior to prevent accidents. 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. (2014b) analyzed the gap acceptance of vehicles entering a major road in an urban intersection with the help of UAV videos. The same authors also used UAV-acquired traffic videos to determine various traffic parameters (e.g., flow and velocity) and compare them with theoretical macro-simulation models (Salvo et al., 2014a). Barmpounakis et al. (2016) conducted a UAV-based traffic experiment over a low-volume intersection to extract various kinematic parameters, including the estimation of vehicle trajectories. All the studies mentioned above employed either manual or semiautomatic processing methods; other studies have proposed automated video analysis methods (Apeltauer et al., 2015; Gao et al., 2014; Oh et al., 2014; Sekmen et al., 2009; Zheng et al., 2015). 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 (Calabrese et al., 2013; Gurusinghe et al., 2002; Iqbal et al., 2014; Punzo & Simonelli., 2005). 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 (Guido et al., 2014; Jutaek et al., 2009; Li et al., 2014; St-Aubin et al., 2013). An extensive trajectory data set using Next Generation Simulation has also been developed using video analytic techniques (Kim et al., 2005). However, all this research has used fixed camera videos. Some researchers have attempted to employ UAV videos to extract vehicle trajectories (Apeltauer et al., 2015; Barmpounakis et al., 2016; Gao et al., 2014; Rajamohan & Rajan, 2013). Gao et al. (2014) 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.

3.5 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, geo-registration, vehicle detection and tracking, and trajectory management. Figure 3.1 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.

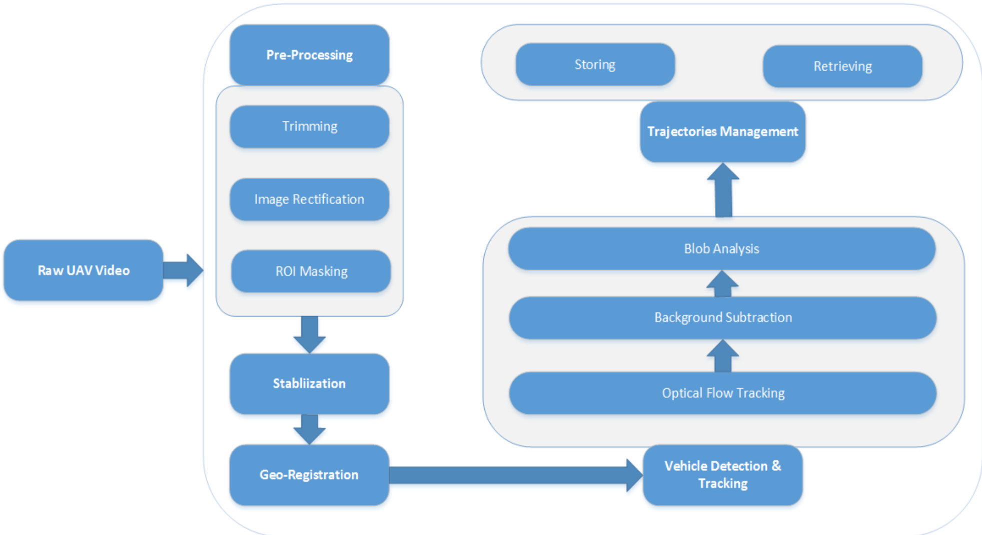


Figure 3.1: The proposed framework for the automated UAV video processing and analysis

3.5.1 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 sub-steps 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.

3.5.2 Stabilization

UAVs have advanced significantly over the last few years. State-of-the-art hardware parts, including three-axis camera-mount gimbal, 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 post-recording 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 (Barmpounakis et al., 2016). 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 3.2, 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 $3 \cdot 3$ 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.

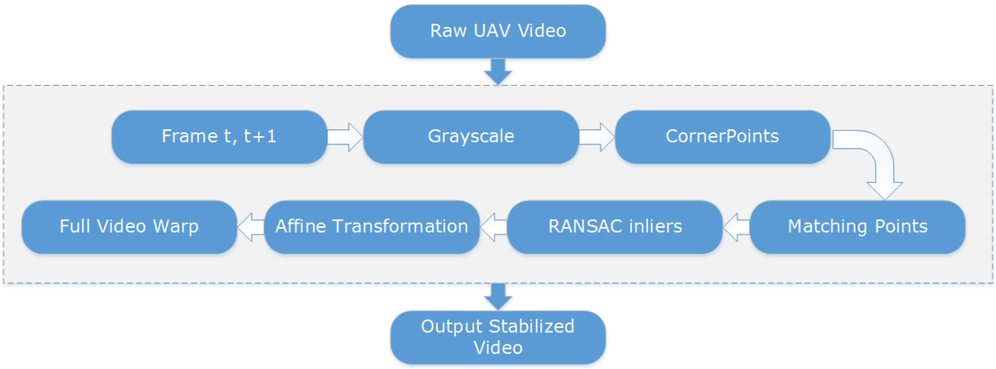


Figure 3.2: The schematic diagram of the UAV video stabilization process

3.5.3 Geo-registration

Geo-registration 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 geo-register the UAV-acquired mono-vision 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:

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

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

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

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

3.5.4 Vehicle Detection and Tracking

After geo-referencing 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 (Khan et al., 2017). Semiautomatic techniques produce accurate results, but they are laborious and require certain steps to be performed manually (Barmpounakis et al., 2016; Salvo et al., 2014a, 2014b). 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 (Lucas & Kanade, 1981; Tomasi & Kanade, 1991). 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 3.3 shows a simplified schematic diagram for the vehicle detection and tracking process.

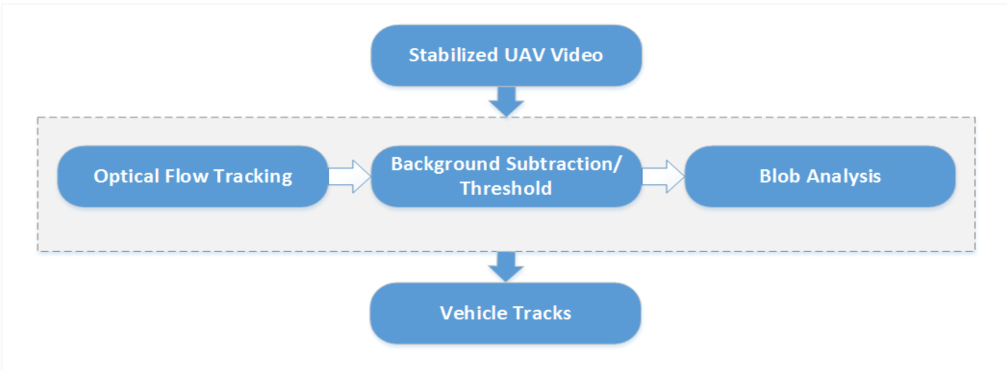


Figure 3.3: The schematic diagram of the vehicle detection and tracking process

3.5.5 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).

3.6 Experiments & Results

To test the proposed framework for the automated traffic analysis via a UAV-acquired footage, a series of flights were conducted over an urban intersection near the city of Sint-Truiden in Belgium. The equipment used for the flights was the Argus-One (from Argus-Vision) which is a high-end octocopter UAV, capable of a 9 minute flight while carrying 3 kilograms of weight. Panasonic Lumix GH4 DSLM camera was attached with the UAV to obtain a high resolution (4K Resolution@ 25fps) traffic footage. In addition to this, a live-feed transmission (first-person-view) system was also attached with the UAV for real-time monitoring of the camera angles. This particular UAV requires simultaneous operation by the pilot and the camera operator. Despite of a relatively lower flight time, this particular UAV was employed as it provides a high quality and stable video data which was necessary to initially develop and test the proposed methodology. Figure 3.4 below shows the Argus-one UAV in standby mode and in flight respectively.

Figure 3.4: The argus-one UAV; ready for take-off (left-side) and in-flight (right-side)

The experiment was conducted on a Friday afternoon (16:30 to 18:00 hours) to capture the evening rush hour. The weather was mostly clear while the wind level was gentle as well (18km/hour, Beaufort scale 3). The location as shown in Figure 3.5 is an intersection joining the national highways N80 and N718 with speed limits of 120km/hour and 90km/hour respectively. The selected 4- legged intersection for the experiment leads from the city of Hasselt into the center and suburbs of Sint-Truiden, with 2 lanes in each direction. The UAV was hovered (constant altitude, zero velocity) above the intersection at the heights of 80m and 60m.Due to the availability of backup battery packs, a series of flights were conducted, resulting in a 14-minute useful traffic video after excluding the take-off and landing maneuvers.

Figure 3.5: The studied 4-leg intersection; Google earth satellite image (left-side) and image from the UAV (right-side)

As mentioned earlier, a combination of various softwares 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 the results generation was done on an Intel ® Core ™ i5-4210M CPU@2.60GHz, with 4GB RAM and Windows 8.1 (64 bits). The UAV video was stabilized according to the proposed methodology explained in the previous sections. The images were then scaled as per actual distances and a Cartesian coordinate axis was assigned having 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 3.6 depicts the trajectories of 2 sample vehicles and their corresponding velocity profiles. In addition, the figures 3.6(c) and (f) illustrate the space-time diagrams of platoon of vehicles while approaching and crossing the intersection at different times during the UAV flights.

A number of interpretations can be made from the trajectories and velocity profiles illustrated in Figure 3.6. It can be observed from graphs in Figure 3.6(b) and (c) that all the vehicles in the Platoon-1 including the sample vehicle-1, show an increasing speed trend which implies that the traffic signal just turned green at the instant. Initially, the sample vehicle moved slowly while approaching the center of the intersection as it was moving in a group of vehicles (platoon-1) with small headways. As the vehicle entered and crossed the intersection, the velocity kept on increasing uniformly. The mean velocity of the sample vehicle while approaching and maneuvering through the intersection was measured to be 26 km/hour with a maximum of 32 km/hour (Figure 3.6(b)). As the accuracy of the calibration process was ensured by several measurements at site and then verification with Google Maps, therefore the values estimated did not have significant errors.

Similarly, another group of vehicles (platoon-2) approaching and crossing the intersection under observation was also analyzed. The graphs in the Figure 3.6(d), (e) and (f) illustrate the drivers' behavior while approaching a signalized intersection. It is clearly evident from the trajectories that the each driver decelerated in his own particular manner in order to stop at the traffic signal. Some trajectories show a smooth transition to a stationary position (e.g. car 7) while others have a steep curve (car 1) implying a strong deceleration (Figure 3.6(f)). Additionally, the behavior of a right-turning vehicle (car 8) can also be observed. The slope of the car 8's trajectory suggests that the vehicle had to reduce its speed in order to safely execute the turning maneuver. Such diagrams can be also effectively used to monitor and study the unusual trajectories leading to traffic incidents.

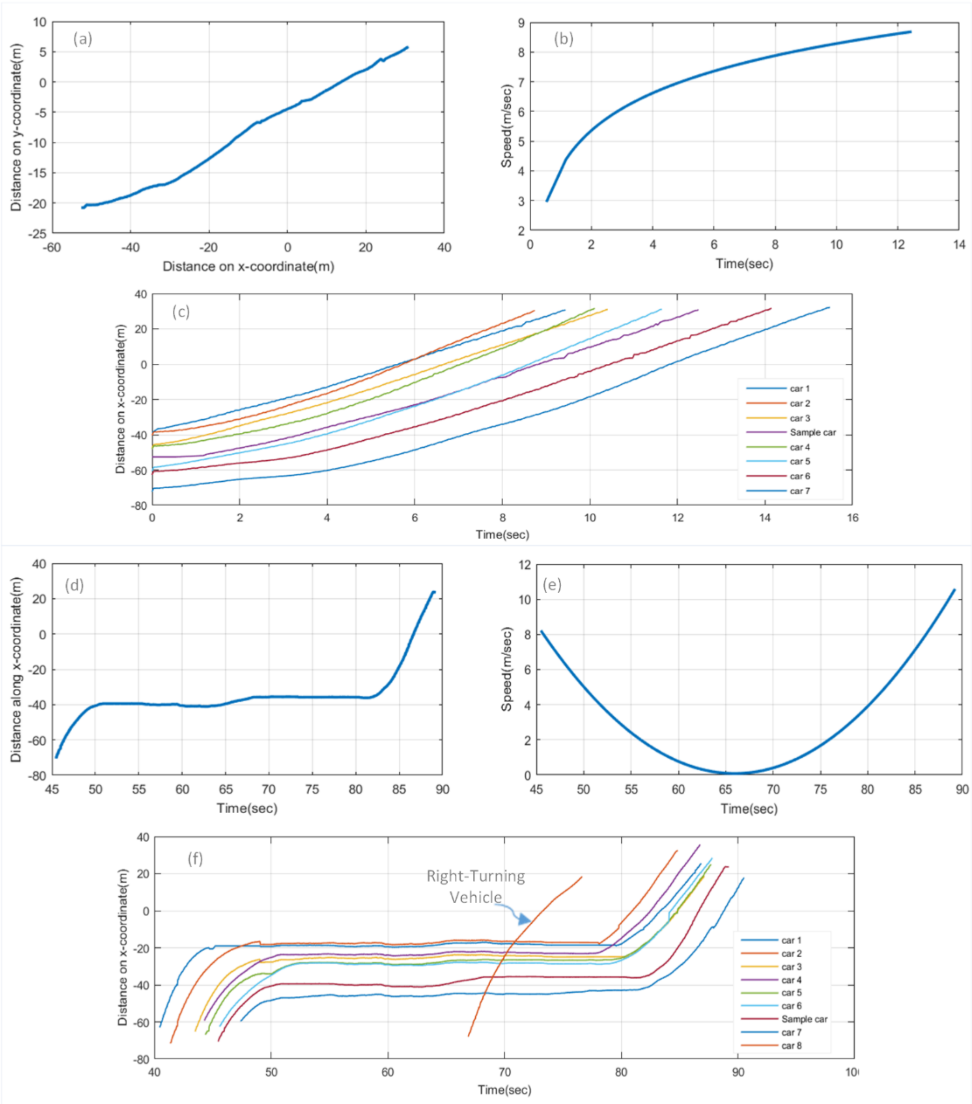


Figure 3.6: The automatically extracted trajectories (a) Trajectory of Sample Vehicle-1 along x-y axis, (b) Speed profile of sample vehicle-1, (c) x-t trajectories of platoon-1, (d) Trajectory of sample vehicle-2 along x-t axes, (e) Speed profile of sample vehicle

3.7 Discussion & 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. For this purpose, the employed algorithms were selected on the basis of minimal processing times and computational requirements. A balance was maintained between the accuracy and processing time of the developed automated vehicle detection and tracking system.

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.

3.8 References

Apeltauer, J., Babinec, A., Herman, D., & Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-3/W2, 9–15.

Barmpounakis, E. N., Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In Transportation Research Board 95th Annual Meeting (p. 16).

Calabrese, F., Diao, M., Lorenzo, G. D., Ferreira, J., & Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation Research Part C: Emerging Technologies, 26, 301–313.

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. IEE Proceedings - Intelligent Transport Systems, 153(1), 11. https://doi.org/10.1049/ip-its:20055014

Gao, H., Kong, S. L., Zhou, S., Lv, F., & Chen, Q. (2014). Automatic Extraction of Multi-Vehicle Trajectory Based on Traffic Videotaping from Quadcopter Model. Applied Mechanics and Materials, 552, 232–239.

Guido, G., Alessandro, V., Frank, S., Vittorio, A., & Vincenzo, G. (2014). Vehicle Tracking System Based on Videotaping Data. Procedia - Social and Behavioral Sciences, 111, 1123–32.

Gurusinghe, G., Nakatsuji, T., Azuta, Y., Ranjitkar, P., & Tanaboriboon., Y. (2002). Multiple Car-Following Data with Real-Time Kinematic Global Positioning System. Transportation Research Record: Journal of the Transportation Research Board, 1802(1), 166–180.

Heintz, F., Rudol, P., & Doherty, P. (2007). From images to traffic behavior - A UAV tracking and monitoring application. FUSION 2007 - 2007 10th International Conference on Information Fusion. https://doi.org/10.1109/ICIF.2007.4408103

Hoogendoorn, S., Van Zuylen, H., Schreuder, M., Gorte, B., & Vosselman, G. (2003). Microscopic Traffic Data Collection by Remote Sensing. Transportation Research Record: Journal of the Transportation Research Board, 1855, 121–128. https://doi.org/10.3141/1855-15

Iqbal, M. S., Choudhury, C. F., Wang, P., & González, M. C. (2014). Development of origin-destination matrices using mobile phone call data. Transportation Research Part C: Emerging Technologies, 40, 63–74.

Jutaek, O., Joonyoung, M., Myungseob, K., & Hanseon, C. Z. (2009). Development of an Automatic Traffic Conflict Detection System Based on Image Tracking Technology. Transportation Research Record: Journal of the Transportation Research Board, 2129, 45–54.

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. Handbook of Unmanned Aerial Vehicles, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. Transportation Research Procedia, 22, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Kim, Z., Gomes, G., Hranac, R., & Skabardonis., A. (2005). A Machine Vision System for Generating Vehicle Trajectories over Extended Freeway Segments. In 12th World Congress on Intelligent Transportation Systems.

Li, J., Hajimirsadeghi, H., Zaki, M., Mori, G., & Sayed, T. (2014). Computer Vision Techniques to Collect Helmet-Wearing Data on Cyclists. Transportation Research Record: Journal of the Transportation Research Board, 2468, 1–10.

Lucas, B. ., & Kanade, T. (1981). An Iterative Image Registration Technique with an Application to Stereo Vision. In Proceedings of the International Joint Conference on Artificial Intelligence (pp. 674–679). Vancouver, Canada.

Oh, H., Kim, S., Shin, H. S., Tsourdas, A., & White, B. . (2014). Behaviour recognition of ground vehicle using airborne monitoring of unmanned aerial vehicles. Vehicles. International Journal of Systems Science, 45(12), 2499–2514.

Punzo, V., & Simonelli., F. (2005). Analysis and Comparison of Microscopic Traffic Flow Models with Real Traffic. Transportation Research Record: Journal of the Transportation Research Board, 1934, 53–63.

Puri, A, Valavanis, K. ., & Kontitsis, M. (2007). Statistical profile generation for traffic monitoring using real-time UAV based video data. IEEE Mediterranean Conference on Control & Automation.

Puri, Anuj. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. Department of Computer Science and Engineering, University of South Florida,. https://doi.org/10.1.1.108.8384

Rajamohan, D., & Rajan, K. S. (2013). Extracting Road Features From Aerial Videos of Small Unmanned Aerial Vehicles, XL(October), 5–8.

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. Recent Advances in Civil Engineering and Mechanics, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. Procedia - Social and Behavioral Sciences, 111, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

Schaufele, R. D. J. (2015). FAA Aerospace Forecast: Fiscal Years 2016-2036. https://doi.org/10.1017/CBO9781107415324.004

Sekmen, A., Yao, F., & Malkani, M. (2009). Smart video surveillance for airborne platforms. Robotica, 27(5), 749–761.

St-Aubin, P., Saunier, N., & Miranda-Moreno, L.F., Ismail, K. (2013). Use of computer vision data for detailed driver behavior analysis and trajectory interpretation at roundabouts. Transportation Research Record: Journal of the Transportation Research Board, 2389, 65–77.

Tomasi, C., & Kanade, T. (1991). Detection and Tracking of Point Features (Technical Report No. CMU-CS-91-132). Pittsburgh: School of Computer Science, Carnegie Mellon University.

Vlahogianni, E. I. (2015). Computational Intelligence and Optimization for Transportation Big Data: Challenges and Opportunities. In Engineering and Applied Sciences Optimization: Volume 1. Springer International Publishing.

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In G. V. Duffy (Ed.), Digital Human Modeling: Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health: 6th International Conference (pp. 305–312).

Chapter 4

An Evaluation of the Accuracy of Vehicle Detection & Tracking System

This chapter consists of following paper:

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: An Evaluation of the Accuracy of Vehicle Detection & Tracking Process. (In-Review).

4.1 Overview

This chapter evaluates the performance of the proposed UAV based traffic analysis system with a special emphasis on the vehicle detection and tracking module. The main objective is to determine the level of accuracy of the generated vehicle detection and trajectory data. A certain level of accuracy is critical to ensure the collected data is converted into useful and reliable traffic information. The UAV video processing and analysis framework, initially presented in chapter 3 has been further optimized. In order to evaluate the accuracy of the system, the outputs from the vehicle detection and tracking system have been compared with the ground-truth data. Various measures of performance have been calculated for different UAV-based traffic videos. The results show that the overall accuracy of the system lies above 90%. Moreover, the sensitivity of UAV flight altitude to the overall preciseness of the outputs is also evaluated. The comparison shows that a higher altitude level provides more precise results. The results are presented in tabular as well as graphical format.

4.2 Abstract

Object Detection and tracking is a widely-researched topic in image processing and computer vision field. The applications of this technology are also extended to the field of traffic and transportation e.g. for the detection of vehicles, measurement of speed, license plate recognition etc. However, these applications are heavily dependent on the employed data collection methodology. Traditionally, fixed camera systems have been used to collect traffic data for video analytics. Recently, Unmanned Aerial Vehicles (UAVs) commonly referred to as drones have also been used for traffic data collection and analysis. However, the use of this technology still needs to be streamlined and optimized. For this purpose, the authors previously proposed a detailed UAV video processing framework for the extraction of multi-vehicle trajectories at a particular road segment. The proposed methodological framework was validated based on the collected experimental dataset. In this paper, however, the main focus is on the evaluation of the performance of the proposed UAV based traffic analysis system with a special emphasis on the vehicle detection and tracking module. In order to evaluate the accuracy of the system, the outputs from the vehicle detection and tracking system have been compared with the ground-truth data. Various measures of performance have been calculated for different UAV-based traffic videos. The results show that the overall accuracy of the system lies above 90%. Moreover, the sensitivity of UAV flight altitude to the overall preciseness of the outputs is also evaluated. The comparison shows that a higher altitude level provides more precise results. The future work will mainly focus on making the system more consistent and robust in all types of conditions.

Keywords: UAVs, Drones, Traffic Applications, Traffic Analysis, Video Analytics, Trajectories

4.3 Background

Traffic analysis and behaviour modelling are the key attributes in transportation planning and management. Over the years, various sources have been used to gather useful traffic information. One of the widely used methods has been the video analytics. This method including the object detection, classification and tracking has been widely-researched in image processing and computer vision field. This method has attracted significant attention mainly because it provides rich data that cannot only be used to easily collect detailed trajectory data but also to maintain a visual observation of the phenomenon (Barmpounakis et al., 2016).

Traditionally, fixed camera systems have been used to collect traffic data for video analytics. A lot of research has been carried out for fixed camera video analysis systems such as (Cao et al., 2007; Micchalopoulos, 1991; Wang et al., 2008). Researchers have applied image-processing techniques to fixed-camera traffic videos to extract and analyze trajectory data (Guido et al., 2014; Jutaek et al., 2009; Li et al., 2014; St-Aubin et al., 2013). An extensive trajectory data set using Next Generation Simulation has also been developed using video analytic techniques (Kim et al., 2005). However, the fixed camera systems have their own limitations such as camera angle and the creation of a number of hidden points resulting in an inability to extract the detailed trajectories of the vehicles. To tackle these issues, some authors made use of satellites and manned aircrafts for traffic monitoring (Hinz et al., 2006; Lenhart et al., 2008), but the costs and limited availability of these airborne instruments proved to be significant drawbacks. Recently, UAVs have been increasingly used for traffic monitoring and analysis purposes (Kanistras et al., 2015; Puri, 2005). The analysis of a traffic stream from a video recorded via an unstable aerial platform, i.e. a UAV, is a relatively new topic. This process is more complex as compared to the analysis of a moving traffic stream from a stationary or fixed camera system. This is mainly due to the sensitivity of the UAV platform to the environmental and wind conditions.

UAVs are increasingly being employed for multiple purposes. According to the literature, UAVs are being widely researched for traffic surveillance and network evaluation applications (Coifman et al., 2006; Heintz et al., 2007; Puri et al., 2007). Different types of UAVS are being used or tested to measure traffic related data at several universities (Puri, 2005). 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 (Kanistras et al., 2015; Puri, 2005). 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 (Kanistras et al., 2015; Puri, 2005). Some researchers have attempted to employ UAV videos to extract vehicle trajectories (Apeltauer et al., 2015; Barmpounakis et al., 2016; Gao et al., 2014; Rajamohan & Rajan, 2013). As this is a recent technology and the actual applications, particularly for traffic data collection, have not yet fully developed (Kanistras et al., 2015; Puri, 2005), some considerable concerns and limitations still exist, such as limited battery time, safety concerns, etc. In order to streamline the processes involved in the application of UAV technology in traffic analysis, a universal guiding framework was proposed in (Khan et al., 2017a).

The processing and analysis of the UAV-acquired traffic video is a challenging task, particularly a manual vehicle annotation in aerial images involves a tremendous effort (Apeltauer et al., 2015). For this purpose, multiple approaches have been employed in the existing literature for the processing and analysis of the UAV-based traffic data. These approaches can be broadly classified into two categories; (i) semi-automatic, and (ii) fully automatic approach, as explained in detail:

i) Semi-Automated Video Analysis: The semi-automated video processing and analysis approach requires a manual object identification by the analyst for a series of frames. A number of existing UAV-based traffic studies are based on this processing technique (Barmpounakis et al., 2016; Salvo et al., 2014b, 2014a). This technique provides a higher level of accuracy and requires less setup time and computation power. However, this processing approach is more time-consuming and laborious. Various softwares are available that enable the users to semi-automatically identify and track various objects. 'Tracker' is an open source video analysis and modelling tool which is commonly used for feature tracking in semi-automatic analysis studies (Brown, 2009). This software makes use of the stabilized and calibrated video to speed up the tracking process and produce more consistent data by eliminating the need for marking each frame (Barmpounakis et al., 2016).

ii) Automated Video Analysis: The automated video processing approach is based on advanced image processing filters and techniques in order to make relevant detections over a series of frames. In the last few years, this approach has been widely adopted, especially in cases where minimal processing times are desired, e.g. in real-time traffic monitoring and tracking applications. Some studies that propose an automated video analysis approach for UAV videos have been conducted by Apeltauer et al. (2015), Lima et al. (2014), Zheng et al., (2015) etc. Additionally, a detailed methodological framework for the automated UAV traffic video processing and vehicle trajectory extraction has been presented by Khan et al., (2017b) in their previous research. The authors make use of different object detection and tracking techniques for the processing of UAV videos. Overall, the automated approach provides useful traffic information in a short period of time requiring minimal labor. However, some limitations and challenges are also attached with this approach. The robustness of automated systems is the key issue. The performance may fluctuate with variations in site conditions. Traffic intensity, weather, lighting conditions etc. influence the overall accuracy of the system. Minor adjustments have to be made in order to achieve the desired level of accuracy. Apart from this, another limitation of automated processing approach is the required computational power. As the system is based on complex image processing algorithms, therefore a certain level of processing power is required.

In this paper, the main focus is on the evaluation of performance of the proposed UAV based traffic analysis system with a special emphasis on the vehicle detection and tracking module. Various criteria for the performance and accuracy evaluation have been presented in order to estimate the reliability and robustness of the developed system. The measures of performance have been calculated for different traffic videos acquired via UAVs. A statistical comparison between the automated detections and manual observations (ground truth) has also been made. This comparison study can help in maintaining an essential balance between the level of accuracy and the processing time. Additionally, the effect of UAV flight altitude on the overall precision of the system is also evaluated. With the increase in number of UAV-based traffic studies, the detailed evaluation results presented in this paper can serve as a reference for future researchers to further optimize the developed algorithms.

This paper is organized as follows: first of all, an overview of the previously proposed UAV video processing and analysis framework is given. This is followed by a detailed description of the vehicle detection and tracking module. All the algorithms employed in this module are explained briefly. The succeeding section presents the performance evaluation of the vehicle detection and tracking process. Different datasets are employed to determine the accuracy of the system. Finally, the paper concludes with a brief discussion regarding the overall performance and limitations of the system. This section also gives an outline for the proposed future developments of the framework.

4.4 UAV Video Processing Framework

In order to extract useful traffic information from traffic videos acquired via small UAVs, Khan et al. (2017b) presented a detailed methodological framework. The proposed framework streamlined and described all the requisite steps for ensuring an efficient processing of the UAV-based traffic data. The framework is categorized into five modules, i.e.: (i) pre-processing, (ii) stabilization, (iii) geo-registration, (iv) vehicle detection and tracking, and (v) trajectory management. Moreover, certain additions have been made in the original framework in order to further optimize the final output. Figure 4.1 illustrates the components of the UAV-based traffic video data processing framework.

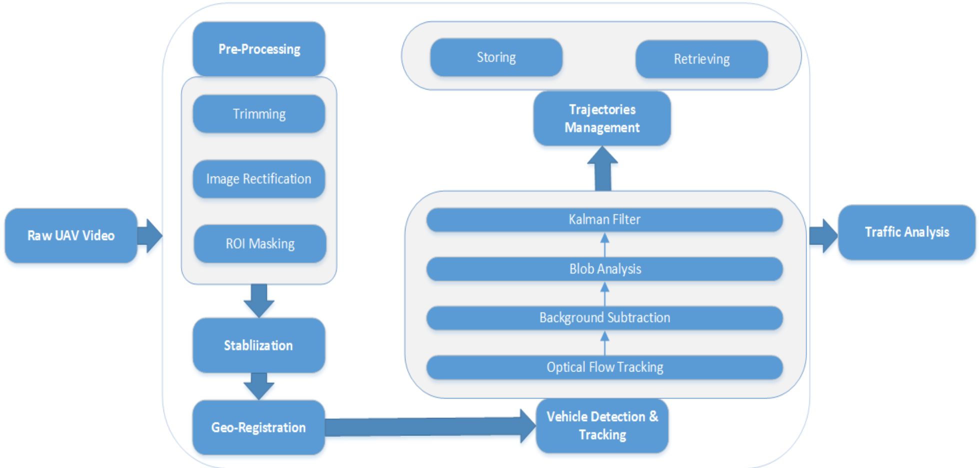


Figure 4.4.1: The proposed framework for the automated UAV video processing and analysis

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 this section, a brief overview of the different modules of UAV-based processing and analysis framework, is presented whereas the detailed description has been given in (Khan et al., 2017b).

The first step towards the extraction of useful information from the UAV-based traffic videos, is to pre-process the data. The UAV videos are prepared for the actual processing and analysis steps by removing or minimizing the undesirable aspects of the recorded video e.g., lens distortion effect, ascending/descending of UAV, etc. The pre-processing step is important as it maximizes the efficiency of the whole system by increasing the processing speed. After preprocessing , the next steps are to stabilize and calibrate the traffic videos obtained via small UAVs. The stabilization process is necessary particularly for UAV videos as there might be a certain level of shakiness in the collected video data. The stabilization filters and algorithms can help in reducing the effects of undesired UAV movements. This stabilized video data is then calibrated and geo-referenced. The collected UAV images are assigned a coordinate system according to a specific scale. Further, the UAV acquired mono-vision 2D image coordinates can be converted into a real-world coordinate system by using a 3x3 homography transformation matrix. This matrix is obtained after point correspondence between the UAV-acquired image and a referenced map. This transformation increases the applicability of the output traffic data The details of the process are given in (Khan et al., 2017b).

The geo-referencing or calibration process is then followed by the vehicle detection and tracking process. This process is the most critical as the overall performance of the whole system is heavily dependent on it. In order to obtain a reliable set of detections and tracks, the geo-referenced or calibrated images are used as an input for the automatic detection and tracking module, which constitutes a number of sub-modules, as indicated in Figure 4.1. The details of this process are given in the following section. The outputs from the vehicle detection and tracking module have to be handled systematically in order to use them effectively for further traffic analysis. For this purpose, an output file in .txt format is generated. This file includes all the relevant spatial and temporal data of vehicles moving across the region of interest (ROI). The output data can then be sorted and post-processed in order to estimate various measures of performance, thereby helping in analyzing the actual traffic situation.

4.5 Vehicle Detection and Tracking

As mentioned earlier, the main focus of this paper is on the vehicle detection and tracking module. As automated vehicle detection and tracking is the most critical and complicated step of the proposed framework, therefore a special consideration is given to analyze and evaluate the performance of the developed algorithm. 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. In this regard, the efficiency and accuracy of this process is critical for extracting a reliable and consistent set of trajectory data.

The automatic detection and tracking of vehicles 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++. Figure 4.2 shows a simplified schematic diagram for the vehicle detection and tracking process.

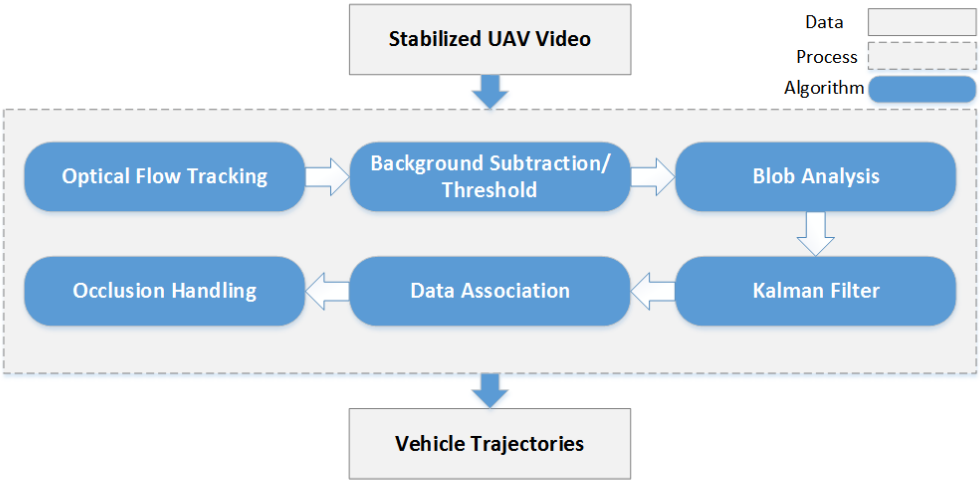


Figure 4.2: The schematic diagram of the vehicle detection and tracking process

As shown in figure 4.2, the stabilized UAV video is used as input into the system. First, the input video is passed through the optical flow–tracking algorithm, in which the direction and speed of the moving pixels are estimated from one frame to another by using the concept of weighted least squares (Lucas & Kanade, 1981; Tomasi & Kanade, 1991). The Lucas–Kanade optical flow algorithm tracks the corner points of all the significant features throughout the video. The output of the optical flow process is then used as an input for the background subtraction algorithm. 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 are separated from the background, the filtered neighboring moving pixels (blobs) and their contours in the foreground, are identified as vehicles and tracked through each frame. Further, the Kalman filter algorithm helps in achieving a smooth tracking data. Finally, the data association module helps in assigning detections to their relevant tracks over a series of frames. A particular consideration is given in the algorithm to counter the inaccuracies caused by losing and reinitializing tracks. For this purpose, the occlusion handling module deals with the missed detections and lost tracks which can occur due to various reasons. The following sub-sections describe each algorithm involved in the vehicle detection and tracking process, in detail:

4.5.1. Optical Flow

Optical flow estimates the direction and speed of the moving pixels from one frame to another. As defined by Aslani & Mahdavi-Nasab (2013), optical flow describes the direction and time pixels in a time sequence of two consequent images. A two dimensional velocity vector, carrying direction and the velocity of motion is assigned to the moving pixels. The patterns of motion caused by movement of objects or camera over a series of frames can be identified via optical flow fields (Royden & Moore, 2012). These 2-dimensional vector fields contain displacement vectors which indicate the movement of points over different frames.

The optical flow mechanism is based on a number of assumptions. The most significant assumptions are regarding the pixel intensities or brightness and the nature of motion of neighboring pixels. It is assumed that the brightness remains constant over the frames and there is no random movement of surrounding pixels. Based on these assumptions, the optical flow field is estimated. Consider a pixel $I(x,y,t)$ in the initial frame that moves by distance (dx,dy) in next frame taken after dt time. This can be represented as:

$$I\ (x, y, t) = I\ (x + dx, y + dy, t + dt) \qquad (1)$$

Approximating the right-hand side with Taylor series leads to the following equations:

$$\frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt} + \frac{\partial f}{\partial t}\frac{dt}{dt} = 0 \qquad (2)$$

$$f_x u + \ f_y v + \ f_t = 0 \qquad (3)$$

The above equation 3 is the Optical Flow equation. The functions f_x and f_y are the changes in position of the object while f_t is the change in time. However, the velocity components u and v remain unknown in this equation. The two unknowns cannot be solved through one equation. Therefore, in order to solve for u and v, various approaches have been developed over the years. The widely used approaches are: (i) Horn–Schunck (HS), and (ii) Lucas–Kanade (LK) methods (Aslani & Mahdavi-Nasab, 2013). Horn–Schunck algorithm is a dense optical flow method that estimates the complete velocity field based on a differential technique (Zainuddin et al., 2015). The horn-Schunk algorithm assumes a constant pixel intensity (brightness) all over the image. The process can be divided into two parts. In the first part, the partial derivatives are estimated whereas in the second part, the sum of the errors are minimized iteratively. This results in the motion vector of all the pixels. On the other hand, Lucas–Kanade method employs a sparse optical flow methodology. It uses the concept of weighted least squares (Lucas & Kanade, 1981; Tomasi & Kanade, 1991) to estimate the unknowns in the optical flow equation. As compared to Horn-Schunck algorithm, Lucas-Kanade algorithm is computationally more efficient. HS algorithm estimates the complete optical flow solution through various iterations, hence requiring more computational power and processing time. This issues can be tackled by the Lucas-Kanade algorithm, which assumes a constant motion in a local patch of pixels under consideration. Only the points in the selected neighborhood are tracked over different frames and are eventually used to determine the local flow vector (u, v) with the help of least squares criterion (Lucas & Kanade, 1981) as shown in the following equation 4.

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum_i f{x_i}^2 & \sum_i fx_i fy_i \\ \sum_i fx_i fy_i & \sum_i f{y_i}^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i fx_i ft_i \\ -\sum_i fy_i ft_i \end{bmatrix} \tag{4}$$

In the developed vehicle detection and tracking algorithm, Lucas-Kanade optical flow has been employed due to its high efficiency in terms of processing times and computational requirements.

4.5.2. Background Subtraction

Background subtraction is a widely used mechanism for object detection (McIvor, 2000). The objects of interest are isolated from the objects in the background. This technique has also been applied in various traffic surveillance systems (Gupte, 2002; SenChing et al., 2004). The basic principle of background subtraction method is to use a background model as a reference to identify the moving objects in the foreground. The current frame is subtracted from the reference background frame, hence leading to the detection of the object.

The background subtraction method can be categorized into two approaches: (i) Recursive algorithm, and (ii) Non-Recursive Algorithm (Abdul Malik et al., 2013). Recursive algorithm is based on a single background model that is updated on each frame whereas a non-recursive technique estimates the background by using a sliding-window approach. The Recursive technique is commonly used as they are computationally more efficient as compared to Non-Recursive technique. However, the issue of error propagation can affect the performance of recursive algorithm. Approximate median, adaptive background, Gaussian of mixture etc. are some of the background subtraction algorithms based on Recursive techniques.

The accuracy of the background subtraction method depends on the background model. Overall, this method is simple to execute, and accurately detects the objects in foreground, however the results are sensitive to various factors including the motion of the camera and occlusion conditions. Another issue might be due to the presence of slow moving objects which might be treated as background objects by simple background subtraction algorithms. These issues can be better handled by using Mixture of Gaussian background modelling algorithm (Stauffer & Grimson, 1999). This algorithm models each pixel as a mixture of Gaussians, and accordingly assigns it either to background or foreground model based on the weights.

In the developed algorithm for vehicle detection and tracking, the output images from the Lucas-Kanade optical flow algorithm are used as an input for the background subtraction. As mentioned earlier, the combination of optical flow and background subtraction methods increase the performance of the system by reducing the number of false and missed detections. In the developed algorithm, Mixture of Gaussians background subtraction method has been employed to differentiate moving vehicles from the background.

4.5.3. Contour Blob Analysis

The developed vehicle detection module which includes a combination of Lucas-Kanade optical flow and mixture of Gaussians background subtraction algorithms, results in a binary threshold image. This image consists of black and white pixels, where white pixels represent objects detected in the foreground. However, this binary state data has to be processed in order to extract useful information from it. The detected pixels have to be identified as vehicles, based on various conditions and thresholds. For this purpose, the contour blob tracking method is used.

In contouring method, the edges of the foreground object are marked (Shapiro & Stockman, 2001). This edge information can be used to cluster neighboring foreground pixels. These neighboring pixels (also termed as blobs) represent the size and position of a certain vehicle in a particular frame. The contour or blob area can be used as an indicator of the vehicle's size. It can also be used as a condition for the selection of only relevant objects or vehicles of interest. Accordingly, the spatial information can be used to determine the object's center point, and also to draw the bounding box around it. The bounding box and its center point can then be used for tracking the object over a series of frames. OpenCV provides a set of useful functions to extract all the information from binary images via contouring and blob analysis.

4.5.4. Kalman Filter

Kalman filter is a widely used algorithm for point tracking and for obtaining a smooth trajectory data. This algorithm helps in removing the noise in final data that might be caused due to random detections, occlusions etc. The Kalman filtering algorithm also known as linear quadratic estimation (LQE), estimates the different states of any process. It is based on the Optimal Recursive Data Processing Algorithm. The measurement data including the statistical noise and other inaccuracies, observed over a specific time period is used to predict the unknown variables. As this prediction is based on a joint probability distribution of the measurements, therefore the estimated variable values are more accurate as compared to values based on single measurement data (Welch & Bishop, 1995).

Similarly, the Kalman filter can also be defined as "a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process in several aspects: it supports estimations of past, present, and even future states, and it can do the same even when the precise nature of the modelled system is unknown" (Welch & Bishop, 1995). It is important to mention that the Kalman filter estimates the state of a linear system where the state is assumed to be distributed by a Gaussian. The Kalman filter equations can be divided into two categories: prediction and measurement. The prediction step is responsible for predicting the new state of the linear system by projecting the present state and noise estimates (Salarpour et al., 2011). Moreover, the measurement step updates the state of the system. As a result of this recursive algorithm, the Kalman filter always produces optimal outputs. The equations for the filter are given as:

$$\bar{X}^t = DX^{t-1} + W \tag{5}$$

$$\bar{\Sigma}^t = D\bar{\Sigma}^{t-1}D^T + Q^t \tag{6}$$

Where $\bar{X}^t$ and $\bar{\Sigma}^t$ are the state and the covariance predictions at time t. D is the state transition matrix which defines the relation between the state variables at time t and t − 1. Q is the covariance of the noise W.

$$X^t = \bar{X}^t + K^t[\, Z^t - M\bar{X}^t] \tag{7}$$

M is the measurement matrix, K is the Kalman gain. Note that the updated state, is still distributed by a Gaussian.

4.5.5. Data Association (Overlap Ratio Method)

Data association process plays an important role in the extraction of a useful vehicle trajectory data. This process is critical to ensure that the detections over a series of frames are assigned to the correct vehicle tracks. The bounding box overlap ratio method has been used to check the association of Ids to the vehicle detection data. Table 4.1 shows the framework of the algorithm. The main idea of this method is to compare the bounding box of the detected vehicle in a specific frame with the detected bounding boxes in the successive frames. The threshold range ($Threshold_{min}$ and $Threshold_{max}$) for the overlap ratio is specified. If a series of detections lie within the specified range, an Id is assigned to the detections. Additionally, it is also important to cater for random assignment of IDs, which might occur due to various reasons. Therefore, the algorithm incorporates certain checks for this purpose. Before assigning an Id to a detection, it is verified that the similar detection occurs in the defined minimum frames $F_{min.}$ Similarly, the maximum frame checking range F_{max} is also defined in order to keep a check on the inactive tracks (tracks with no recent matched detections).

Table 4.1: The work flow/pseudo-code for the data association process

```
Input:   Vehicle Detection Data P_i=1…n (x_i, y_i, t_i, F_i)
Output:  Processed Trajectory Data Traj_Id=1..n ← P_j=1…n (x_j, y_j, t_j, Id_j)

BEGIN
READ Vehicle Detection Data P_i=1…n (x_i, y_i, t_i, F_i)
FOR Detection P_i = 1  to n
|   FOR Frame F_i = F_i+1 to n
|   |   //Check for contour area
|   |   IF Contour Area within Specified Range
|   |   |   //Overlap Ratio
|   |   |   IF Threshold_min <= (P_i / (P_i+1)) <= Threshold_max
|   |   |   |   IF F_i >= F_min (3 or 5 frames)
|   |   |   |   |   IF F_i <= F_max (50 frames)
|   |   |   |   |   |   SET Id_j
|   |   |   |   |   |   OUTPUT P_j (x_j, y_j, t_j, Id_j)
|   |   |   |   |   |   SET Traj_j=1..n = P_j
|   |   |   |   |   ENDIF
|   |   |   |   ENDIF
|   |   |   ENDIF
|   |   ENDIF
|   ENDFOR
|   COMPUTE Id_j = Id_j + 1
ENDFOR
STORE Trajectory Data Traj_Id=1..n
END
```

4.5.6. Occlusion Handling

Different types of occlusions can occur in a traffic video stream. In some cases, for example, the vehicles can be partially or completely hidden behind stationary road-side objects or between other vehicles in close proximity. Other than that lighting conditions and shadows can also create hindrance in proper detection and tracking of the objects of interest. Therefore, it is critical to handle the occlusions in an effective manner. For this purpose, a specific sets of conditions have been incorporated in the vehicle detection and tracking system in order to make it more reliable and robust. The following figure (Figure 4.3) shows the work flow diagram of the occlusion handler module of the vehicle detection and tracking system.

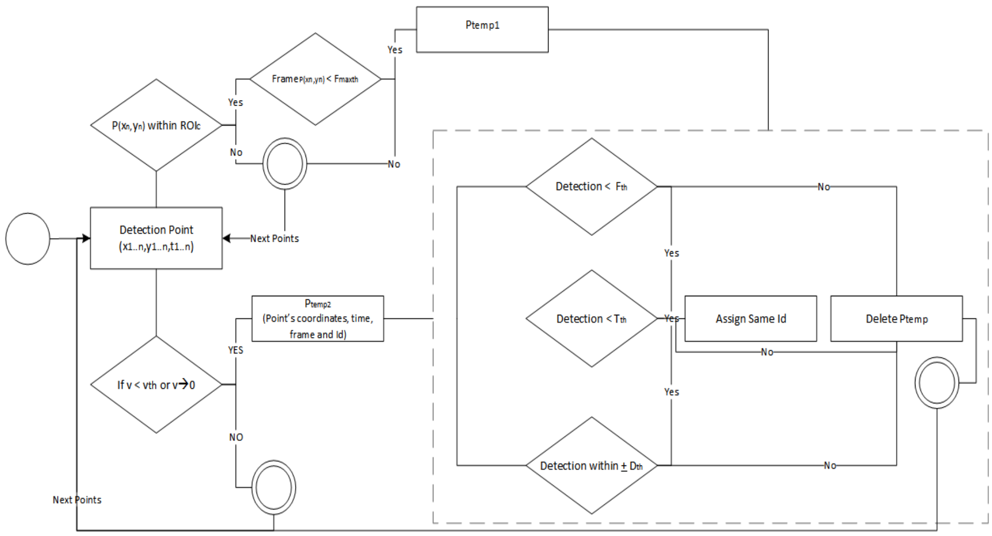


Figure 4.3: The work flow diagram of the occlusion handling process

It is evident from Figure 4.3 that various conditions have to be applied in order to extract a reliable set of trajectory data. The basic purpose of the occlusion handling process is to cater for random outputs that might occur due to varying road environment and traffic situations. Overall, the occlusion handler module is divided into 2 parts. The first part deals with the random loss of trajectories due to occlusion between vehicles or stationary objects. In order to deal with this randomness, the last detected coordinate points of a particular trajectory are compared with the boundaries of the region of interest (ROI). A centered ROI ($ROI_{c\,=}$ 80% of ROI) is used as the boundary for comparison. If the trajectory is lost inside this region, the last coordinates are saved in a temporary vector (P_{temp1}). These points are then compared with the next detections. If a series of detections are found which fulfill the specified criteria, then these detections are merged with the trajectory that was lost randomly and the same Id is assigned to them. The specified criteria is based on a set of thresholds for frames, time and distance. The matched detections have to be: (i) inside the frame threshold (F_{th}) e.g. the maximum difference between the last coordinate and the potential matching coordinate cannot be greater than 50 frames , (ii) less than the threshold for time (T_{th}),and (iii) within the specified threshold for distance (D_{th}). On the other hand, the second part of the occlusion handling process deals with the go-stop-go scenario. This can occur at intersections where vehicles come to a stationary position and then start moving again. In this scenario, there can be a possible loss of detections and tracking. In order to cater for this type of trajectory loss, speed measurements have been used as an indicator. If the speed of a specific vehicle tends to zero or any other specified threshold value (V_{th}), the last detected coordinate points are stored in a temporary vector (P_{temp2}). These coordinates are then used for comparison with the next detections. The same criteria as used in the first part of occlusion handling process, is used for this part as well. If a new detection matches the specified criteria, it is termed as the continuation of the lost trajectory.

4.6 Experiments & Results

As mentioned earlier, the proposed UAV video processing and analysis framework provides an in-depth description of the processes involved in the conduction of UAV-based traffic analysis studies. However, it is critical to demonstrate the applicability as well as evaluate the performance of the proposed framework, particularly the vehicle detection and tracking algorithm. For this purpose, this section focuses on presenting the performance results of the vehicle detection and tracking process. Different datasets have been employed to determine the accuracy and processing times of the system. Various measures of performance have been calculated in this regard.

4.6.1 Case Studies/Datasets

In order to estimate the performance of the developed vehicle detection and tracking algorithm, it is important to obtain UAV-based experimental datasets. These datasets can then be used as a reference to evaluate the system performance. For this purpose, a series of UAV flights were conducted to obtain traffic data at various locations. In this paper, 2 sets of experimental data have been used. Traffic flow has been observed via UAVs at a signalized intersection and an urban roundabout as shown in the images in Figure 4.4. The details of these experiments can be found in the in the following chapters of this dissertation.

Figure 4.4 shows the data collection sites in Sint-Truiden, Belgium. As evident from the images that the UAV flights were conducted at an angle from the center of intersection. This was due to Belgian legal constraints which prohibit the flying of UAVs directly above the population or traffic. It can also be seen that the nature of traffic and the level of occlusions vary for different sites and types of intersections. All these factors have an influence on the performance of the vehicle detection and tracking system.

Figure 4.4: The data collection sites: UAV view of the roundabout (left-side); UAV view of the signalized intersection (right-side).

4.6.2 Performance Evaluation

The proposed framework for the extraction of vehicle trajectories using the UAV based video footage ensures an efficient utilization of the collected traffic data. However, it is important to objectify the performance of the developed algorithm, especially the vehicle detection and tracking module. For this purpose, this sub-section presents a methodology to estimate various measures of performance. Most of the indicators have been extracted by comparing the automated extracted data with the ground truth data.

Ground truth data is widely used in the fields of image processing and computer vision in order to validate the accuracy and precision of the developed systems. Ground truth data basically represents the actual set of measurements or detections in the region of interest. The datasets usually contains information regarding the object's actual position, state, time, frame etc. (Glowacz et al., 2015). This data is mostly generated manually by annotating the collected video data. This process can be extremely cumbersome and time-consuming. Lately, many tools have been developed to simplify the process. In this study, a modeling tool named 'Tracker' (Brown, 2009) has been used to manually annotate the collected UAV-based traffic videos. The generated ground truth data is then used for the evaluation of the developed framework.

As stated earlier, various measures of performances (MOP) can be estimated in order to quantify the performance of the vehicle detection and tracking algorithm. For evaluating the vehicle detection performance, various indicators e.g. correctness, completeness, quality etc. can be extracted for different experimental UAV videos. These indicators are calculated based on the number of true positives (TP), false positives (FP) and false negatives (FN). True positives are the correct detections of a particular vehicle or any object of interest, whereas false positives are the incorrect or undesired detections made by the vehicle detection algorithm. This may occur due to various reasons, as discussed in the later sections. Similarly, false negatives are the detections that are missed by the detector. These terms can be used to compare the ground truth data with the automatic detections; thereby resulting in various measures of performance. Based on these terms, the following can be calculated as:

$$Correctness = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{7}$$

$$Completeness = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{8}$$

$$Quality = \frac{True\ Positives}{True\ Positives + False\ Negatives + False\ Positives} \tag{9}$$

Tables 4.2 and 4.3 show the vehicle detection results for the roundabout and signalized intersection UAV videos, respectively. 10 random samples of 100 frames each have been selected from the 2 video datasets in order to evaluate the vehicle detection performance of the developed algorithm. It is evident for the 2 tables that the performance at roundabout location was less as compared to the signalized intersection. This was due to the presence of large number of occlusions. Overall, it can be stated that the performance of the system lies above 90%. This is a reasonably good detection performance, keeping in mind the general instability of the UAV platform and the nature of the developed algorithm, which is to maintain a balance between accuracy and processing times and computational power.

Table 4.2: The measures of performance for vehicle detection evaluation at Roundabout location

	Frames	GT Detections	False Positives	False Negatives	True Positives	Correctness %	Completeness%	Quality%
1	100	158	0	12	146	100.00	92.41	92.41
2	100	227	0	7	220	100.00	96.92	96.92
3	100	182	21	15	167	88.83	91.76	82.27
4	100	157	7	2	155	95.68	98.73	94.51
5	100	185	5	16	169	97.13	91.35	88.95
6	100	80	13	0	80	86.02	100.00	86.02
7	100	135	2	2	133	98.52	98.52	97.08
8	100	153	9	3	150	94.34	98.04	92.59
9	100	169	11	4	165	93.75	97.63	91.67
10	100	129	8	1	128	94.12	99.22	93.43
					Average	94.84	96.46	91.58

Table 4.3: The measures of performance for vehicle detection evaluation at Signalized-Intersection

	Frames	GT Detections	False Positives	False Negatives	True Positives	Correctness %	Completeness%	Quality%
1	100	174	0	4	170	100.00	97.70	97.70
2	100	150	11	0	150	93.17	100.00	93.17
3	100	64	4	5	59	93.65	92.19	86.76
4	100	41	3	0	44	93.62	100.00	93.62
5	100	53	0	6	47	100.00	88.68	88.68
6	100	91	7	8	83	92.22	91.21	84.69
7	100	113	4	9	104	96.30	92.04	88.89
8	100	141	2	7	134	98.53	95.04	93.71
9	100	86	1	3	83	98.81	96.51	95.40
10	100	66	3	7	59	95.16	89.39	85.51
					Average	96.15	94.28	90.81

Additionally, other statistical indicators like co-efficient of determination (R-squared), Root mean square error (RMSE), mean absolute error (MAE) etc. can also be used to evaluate the vehicle detection results. Figure 4.5 consists of scattered plots for the ground truth and automatic detection data. The R-squared values reflect the level of closeness of data to the regression line. In this case, this indicates the overall difference between the ground-truth and automatic detections. It is evident from figure 4.5 (a) and (b) that R-squared values for roundabout and signalized-intersection data are 98.19% and 99.31% respectively. Figure 4.5(c) shows the combined evaluation of both the datasets. This gives an overall R-squared value of 99.16% for the developed system.

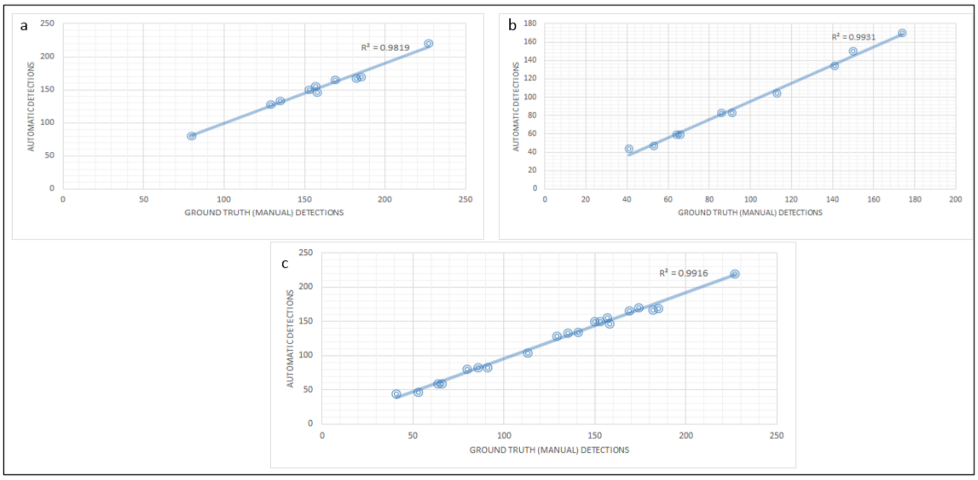


Figure 4.5: R-squared measure of performance for vehicle detection evaluation: (a) for roundabout; (b) for signalized intersection; (c) combined overall evaluation

Apart from the determination of performance parameters for the developed vehicle detection system, it is also important to evaluate the sensitivity of different UAV flight-related attributes for traffic data collection. In this regard, the altitude at which the UAV flight is conducted, plays a significant role. The altitude has to be optimal in order to ensure efficient UAV operation as well as providing the maximum coverage for the area under observation. Since, the UAV videos were recorded at an angle from the intersection, the altitude or the height factor becomes even more important.

In order to determine the most suitable level of UAV flight altitude for traffic data collection, the experimental UAV flights were conducted at 2 altitude levels i.e. 80m and 60m for each location. The traffic data collected from both observed locations in Sint-Truiden (Belgium) was used for testing the UAV altitude sensitivity. For both sets of data and altitude levels, a stationary object e.g. road marking, lamp post, sign post etc., was tracked over a number of randomly-selected frames. The coordinates of the reference object were then compared with the actual ground-truth coordinates of the object, which were recorded on site with the help of GPS receiver. The variation in the location of the referenced stationary object as viewed from the UAV perspective, reflects the sensitivity of the UAV flight altitude. The box charts in Figures 4.6 and 4.7 show the extent of variation in x and y coordinates (longitudes and latitudes) of the marked stationary object. The charts show that for both locations, the x and y coordinates are closer to the actual ground-truth value for 80meter altitude level. This indicates that the errors are magnified at lower UAV altitude. Even a slight UAV movement or vibration due to winds and other factors, may cause higher errors in measurement at lower altitudes as compared to higher altitudes. Also, the higher UAV altitude provides a better viewing angle by reducing the obliqueness in the captured frames as well as minimizing the level of occlusions that might occur due to nearby trees and other objects. The effects of shadows also decrease at higher altitudes. Therefore, all these factors imply that the higher altitude level i.e. 80m provides more precise and consistent data. The effect of errors (due to wind, vibration, shadows etc.) reduce with the increased altitude. However, an optimal flight altitude has to be selected by maintaining a balance between the advantages and disadvantages of a particular altitude level. The greater height may provide large area coverage and consistent measurements, while at the same time, the pixel density of the objects of interest may reduce drastically. Therefore, the UAV flight altitude has to be selected keeping in mind the project requirements and the local regulations (e.g. the maximum height allowed for small UAVs in Belgium is 90m). Overall, it can be concluded that the accuracy and preciseness of the object detection and tracking process is sensitive to the UAV flight altitude.

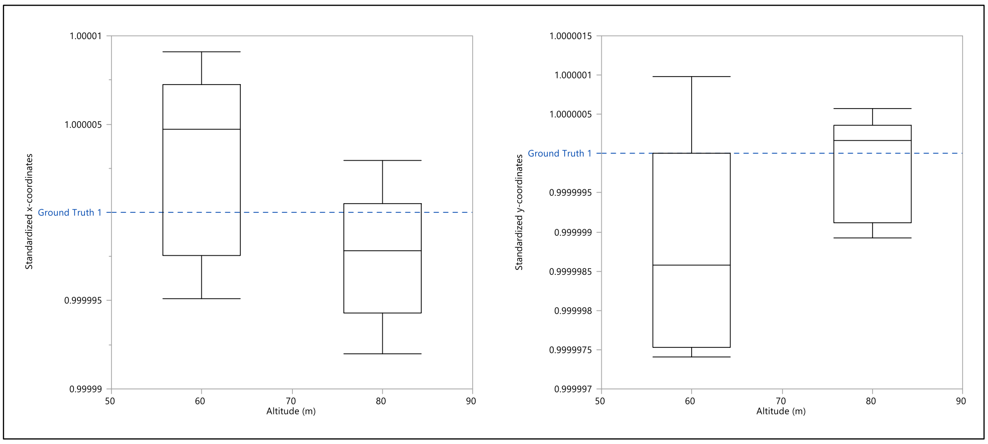


Figure 4.6: Evaluation of the effect of flight altitude on the object coordinates (roundabout)

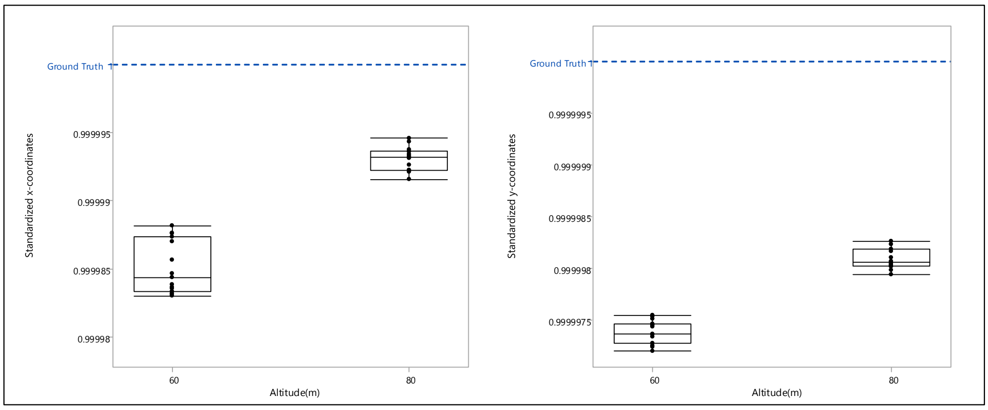


Figure 4.7: Evaluation of the effect of flight altitude on the object coordinates (signal intersection)

4.7 Discussion & Conclusion

The small multi-rotor unmanned aerial vehicles have been demonstrated to be applicable for traffic data collection purposes. In this regard, the previously proposed guiding framework streamlines all the necessary steps for the conduction of a UAV-based traffic study, whereas the UAV-based traffic processing and analysis framework further elaborates the methodology in detail (Khan et al., 2017a, 2017b). As mentioned earlier, the main objective of the proposed UAV-based traffic analysis system is to efficiently utilize the traffic data obtained via UAVs to extract useful traffic information. However, it is critical to evaluate the performance of the proposed framework, especially the vehicle detection and tracking algorithm. A certain level of accuracy is critical to ensure the collected data is converted into useful and reliable traffic information. For this purpose, this paper evaluates the performance of the proposed system with a special emphasis on the vehicle detection and tracking module.

In order to evaluate the accuracy of the developed system, various measures of performance have been calculated for different UAV-based traffic videos. The outputs from the vehicle detection and tracking system have been compared with the ground-truth data. Performance indicators i.e. correctness, completeness and quality have been estimated using the concept of true positives, false positives and false negatives. The results of the performance analysis conducted on 2 UAV-based experimental datasets indicated an overall accuracy level of more than 90%. Furthermore, the R-squared values of more than 98% also reflected the consistency between the automatic and ground-truth detections. It is also important to mention that the level of accuracy directly influences the processing times as well. This is due to the fact that less accurate detections and tracks need more post-processing and manual checks (Apeltauer et al., 2015). On the other hand, the processing or computation times are greatly dependent on the type of algorithms selected for the vehicle detection and tracking process. The semi-automatic techniques or automated algorithms requiring extensive pre-trained datasets, are not useful in cases where least processing times are highly desired. Therefore, it is critical to design a system that maintains a balance between the accuracy and the processing times. In this regard, the developed system performed well as the algorithms were selected keeping in mind the respective processing times and required computational power.

Additionally, the sensitivity of UAV flight altitude on the preciseness of the generated outputs has also been tested. For this purpose, the experimental dataset with 2 different altitude levels was used to verify the significance of the UAV altitude. The results showed that the outputs are more consistent when the UAV flies at an altitude of 80 meters as compared to 60 meters. The results also showed that the errors due to slight UAV movement are magnified at lower altitudes. Hence, indicating that the effects of errors (due to wind, vibration, shadows etc.) are sensitive to the UAV flight altitude. Since, the UAV videos were recorded at an angle form the intersection, the height factor becomes even more important. The objects can be observed better from a greater height due to reduced obliqueness (better angle) and less occlusions. Overall, it can be concluded that the accuracy and preciseness of the object detection and tracking process is sensitive to the UAV flight altitude.

Although, the small multi-rotor UAVs have been shown to be effective for traffic-related studies, still the current technology has some limitations. Flight duration, safety, legal issues etc. are some of the challenges faced in the applications of UAV technology. The flight time of UAVs depends on internal, as well as external, factors. Internal factors include the size, payload, battery type, etc., whereas the external factors consist of weather conditions, wind conditions, status of GPS satellites, etc. Apart from limited flight times, the legal considerations, including the safety and privacy concerns, also limit the use of UAVs for practical applications. Nevertheless, all these concerns will eventually fade away with the development of more reliable and robust technology in the coming years.

Future research will mainly focus on further optimization of the developed system and the respective algorithms. Although, the current systems gives good results, still there is a need to make the system more consistent and efficient. The system should be able to achieve the highest accuracy level for all types of conditions while keeping the post-processing times at minimal levels. For this purpose, various approaches for further automation of the system, will be explored. This optimization may eventually lead to the real-time analysis of the data streamed via UAVs. Furthermore, the aspects of processing and analyzing traffic data from drones flying parallel to the direction of traffic, will also be investigated.

4.8 References

Abdul Malik, A., Khalil, A., & Khan, H. U. (2013). Object Detection and Tracking using Background Subtraction and Connected Component Labeling. ..*International Journal of Computer Applications*, *75*(13).

Apeltauer, J., Babinec, A., Herman, D., & Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-3/W2*, 9–15.

Aslani, S., & Mahdavi-Nasab, H. (2013). Optical Flow Based Moving Object Detection and Tracking for Traffic Surveillance. *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering*, *7*(9), 1253–1256.

Barmpounakis, E. N., Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In *Transportation Research Board 95th Annual Meeting* (p. 16).

Brown, D. (2009). Video Modeling with Tracker. Presented at the the American Association of Physics Teachers AAPT Summer Meeting, Ann Arbor.

C. Stauffer, & W. E. L. Grimson. (1999). Adaptive background mixture models for real-time tracking. In *Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149)* (Vol. 2, pp. 1-252 Vol. 2). https://doi.org/10.1109/CVPR.1999.784637

Cao, M., Vu, A., & Barth, M. (2007). A novel omnidirectional vision sensing technique for traffic surveillance. In *IEEE Intelligent Transportation Systems Conference* (pp. 678-683.).

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. *IEE Proceedings - Intelligent Transport Systems*, *153*(1), 11. https://doi.org/10.1049/ip-its:20055014

Gao, H., Kong, S. L., Zhou, S., Lv, F., & Chen, Q. (2014). Automatic Extraction of Multi-Vehicle Trajectory Based on Traffic Videotaping from Quadcopter Model. *Applied Mechanics and Materials*, *552*, 232–239.

Glowacz, S. B. A., Mikrut, J. K. Z., & Pawlik, P. (2015). GROUND TRUTH GENERATING TOOL FOR TRAFFIC VIDEO DETECTOR. *Image Processing & Communications, V*, *20*(2), 17–28.

Guido, G., Alessandro, V., Frank, S., Vittorio, A., & Vincenzo, G. (2014). Vehicle Tracking System Based on Videotaping Data. *Procedia - Social and Behavioral Sciences*, *111*, 1123–32.

Gupte, S. (2002). Detection and Classification of Vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *3*(1), 37–47.

Heintz, F., Rudol, P., & Doherty, P. (2007). From images to traffic behavior - A UAV tracking and monitoring application. *FUSION 2007 - 2007 10th International Conference on Information Fusion*. https://doi.org/10.1109/ICIF.2007.4408103

Hinz, S., Bamler, R., & Stilla, U. (2006). Airborne and space-borne traffic monitoring. *Journal of Photogrammetry and Remote Sensing*, *61*.

Jutaek, O., Joonyoung, M., Myungseob, K., & Hanseon, C. Z. (2009). Development of an Automatic Traffic Conflict Detection System Based on Image Tracking Technology. *Transportation Research Record: Journal of the Transportation Research Board*, *2129*, 45–54.

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. *Handbook of Unmanned Aerial Vehicles*, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017a). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. *Transportation Research Procedia*, *22*, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017b). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. *Transportation Research Record: Journal of the Transportation Research Board*, *32*(0), 1–15. http://dx.doi.org/10.3141/2626-04

Kim, Z., Gomes, G., Hranac, R., & Skabardonis., A. (2005). A Machine Vision System for Generating Vehicle Trajectories over Extended Freeway Segments. In *12th World Congress on Intelligent Transportation Systems*.

Lenhart, D., Hinz, S., Leitloff, J., & Stilla, U. (2008). Automatic traffic monitoring based on aerial image sequences. *Pattern Recognition and Image Analysis*, *18*(3), 400–405.

Li, J., Hajimirsadeghi, H., Zaki, M., Mori, G., & Sayed, T. (2014). Computer Vision Techniques to Collect Helmet-Wearing Data on Cyclists. *Transportation Research Record: Journal of the Transportation Research Board*, *2468*, 1–10.

Lima, C., Cardoso, J. L., Ben-akiva, M., Costeira, J. P., & Marques, M. (2014). Automatic vehicle trajectory extraction by aerial remote sensing. *Procedia - Social and Behavioral Sciences*, *111*, 849–858. https://doi.org/10.1016/j.sbspro.2014.01.119

Lucas, B. ., & Kanade, T. (1981). An Iterative Image Registration Technique with an Application to Stereo Vision. In *Proceedings of the International Joint Conference on Artificial Intelligence* (pp. 674–679). Vancouver, Canada.

McIvor, A. M. (2000). Background subtraction techniques. In *Proceedings of Image and Vision Computing*.

Micchalopoulos, P. G. (1991). Vehicle detection through video image processing AUTOSCOPE System. *IEEE Transaction on Vehicular Technology*, *40*(1), 21–29.

Puri, A, Valavanis, K. ., & Kontitsis, M. (2007). Statistical profile generation for traffic monitoring using real-time UAV based video data. *IEEE Mediterranean Conference on Control & Automation*.

Puri, Anuj. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. *Department of Computer Science and Engineering, University of South Florida,*. https://doi.org/10.1.1.108.8384

Rajamohan, D., & Rajan, K. S. (2013). Extracting Road Features From Aerial Videos of Small Unmanned Aerial Vehicles, *XL*(October), 5–8.

Royden, C. S., & Moore, K. D. (2012). Use of speed cues in the detection of moving objects by moving observers. *Vision Reseacrh*, *59*, 17–24.

Salarpour, A., Salarpour, A., Fathi, M., & Dezfoulian, M. (2011). VEHICLE TRACKING USING KALMAN FILTER AND FEATURES. *Signal & Image Processing : An International Journal (SIPIJ)*, *2*(2).

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. *Recent Advances in Civil Engineering and Mechanics*, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. *Procedia - Social and Behavioral Sciences*, *111*, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

SenChing, S., Cheung, S., & Kamath, C. (2004). Robust techniques for background subtraction in urban traffic video. In *Proceedings of the video communication and image processing*. San Jose, CA.

Shapiro, L. G., & Stockman, G. C. (2001). *Computer Vision*. New Jersey: PrenticeHall.

St-Aubin, P., Saunier, N., & Miranda-Moreno, L.F., Ismail, K. (2013). Use of computer vision data for detailed driver behavior analysis and trajectory interpretation at roundabouts. *Transportation Research Record: Journal of the Transportation Research Board*, *2389*, 65–77.

Tomasi, C., & Kanade, T. (1991). *Detection and Tracking of Point Features* (Technical Report No. CMU-CS-91-132). Pittsburgh: School of Computer Science, Carnegie Mellon University.

Wang, G., Xiao, D., & Gu, J. (2008). Review on Vehicle Detection Based on Video for Traffic Surveillance. In *Proceedings of the IEEE International Conference on Automation and Logistics* (pp. 2961-2966.).

Welch, G., & Bishop, G. (1995). *An Introduction to the Kalman Filter* (No. TR95-041). Chapel Hill: University of North Carolina,Department of Computer Science.

Zainuddin, N., Ramli, S., Tan Zizi, T., Hasbullah, N. A., Mohd Hanafi, M., Wahab, N. A., & Ibrahim, N. (2015). Horn Schunck Algorithm for Facial Expression Change Detection Classification. *International Journal for Information Security Research (IJISR)*, *5*(3).

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In *G. V. Duffy (Ed.), Digital Human Modeling: Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health: 6th International Conference* (pp. 305–312).

Chapter 5

UAV–Based Traffic Analysis: Signalized Intersections

This chapter consists of following peer-reviewed journal paper (published):

Khan, M.A.; Ectors, W.; Bellemans, T.; Janssens, D.; Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: A Case Study for Shockwave Identification and Flow Parameters Estimation at Signalized Intersections. Remote Sensing **(IF:3.406)**, 10, 458. doi:10.3390/rs10030458

5.1 Overview

This chapter explores the applications of data collected via small UAVs, for an in-depth traffic flow analysis at a signalized 4-legged intersection. The analysis is basically a practical extension of the outputs generated from the previously proposed detailed methodological framework for automated UAV video processing. In this chapter, the main emphasis is on the comprehensive analysis of vehicle trajectories extracted via UAV-based video processing framework. An analytical methodology is presented for: (i) the automatic identification of flow states and shockwaves based on processed UAV trajectories, and (ii) the subsequent extraction of various traffic parameters and performance indicators in order to study flow conditions at a signalized intersection. The experimental data to analyze traffic flow conditions was obtained in the city of Sint-Truiden, Belgium. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted-flow conditions at a signalized four-legged intersection using UAV-acquired data.

5.2 Abstract

Owing to their dynamic and multidisciplinary characteristics, Unmanned Aerial Vehicles (UAVs), or drones, have become increasingly popular. However, the civil applications of this technology, particularly for traffic data collection and analysis, still need to be thoroughly explored. For this purpose, the authors previously proposed a detailed methodological framework for the automated UAV video processing in order to extract multi-vehicle trajectories at a particular road segment. In this paper, however, the main emphasis is on the comprehensive analysis of vehicle trajectories extracted via a UAV-based video processing framework. An analytical methodology is presented for: (i) the automatic identification of flow states and shockwaves based on processed UAV trajectories, and (ii) the subsequent extraction of various traffic parameters and performance indicators in order to study flow conditions at a signalized intersection. The experimental data to analyze traffic flow conditions was obtained in the city of Sint-Truiden, Belgium. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted-flow conditions at a signalized four-legged intersection using UAV-acquired data. The analysis conducted on such data may serve as a benchmark for the actual traffic-specific applications of the UAV-acquired data. The results reflect the value of flexibility and bird-eye view provided by UAV videos; thereby depicting the overall applicability of the UAV-based traffic analysis system. The future research will mainly focus on further extensions of UAV-based traffic applications.

Keywords: drones; UAVs; traffic data; traffic data collection; traffic flow analysis; vehicle trajectories; shockwave analysis

5.3 Introduction

The management of ever increasing traffic volumes and congestion levels is one of the most critical challenges faced by modern human society. This problem further magnifies particularly at urban intersections. Moreover, there are only limited viable options available for the expansion of existing infrastructure. Therefore, transport managers are bound to employ "soft measures or policies" in order to ensure smooth and efficient traffic operations. For this purpose, it has become critical to monitor and analyze the state of traffic flow at urban and suburban intersections. However, this requires an accurate, dynamic, and quick inflow of traffic data (Khan et al., 2017b).

The collection of detailed traffic data with traditional equipment, like manual counters, induction loops, fixed video camera systems, etc., is an expensive and difficult process as it either requires a large amount of installed sensors/equipment or a high number of deployed staff in order to cover the entire network (Coifman et al., 2006). Such data cannot be used to estimate the densities, as well as other more complex traffic flow phenomenon, such as the process of accumulation and dissipation of queues at the intersections. Additionally, as it is not practically possible to cover the entire network with fixed sensors or deployed staff, therefore, certain 'hidden points' emerge in the network (Barmpounakis et al., 2016; Puri, 2005). On the other hand, advanced ITS data collection technologies e.g., vehicle-to-infrastructure (V2I), floating cars (probe vehicles with GPS) and other smartphone sensor technologies have also been employed in recent years. These technologies provide detailed and dynamic traffic data, however, they result in large datasets which are difficult to handle, especially in a short time span (Vlahogianni, 2015). Additionally, such technologies might influence the actual behavior of the travelers since they already know they are being observed (Barmpounakis et al., 2016; Salvo et al., 2014a). Another alternative for traffic data collection is the aerial photography or remote sensing. Satellites and manned aircrafts have been used over the years for dynamic traffic data collection. These technologies provide wide field-of-view and unbiased data, however cost and deployment issues restrict their practical employment. Recently, unmanned aerial systems have started to take the center stage for traffic monitoring, management, and control (Kanistras et al., 2015; Puri, 2005).

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are being used in the transportation field to monitor and analyze the traffic flow and safety conditions (Kanistras et al., 2015; Puri, 2005). Traditionally, only fixed-wing UAVs were employed for traffic monitoring purposes, however, in recent years the small rotary-wing type UAVs have also been used for traffic-related applications (Lee et al., 2015). This non-intrusive and low-cost technology has improved rapidly and is now capable of providing high-resolution data (both in space and time) that can be used to extract vehicle trajectories and estimate traffic parameters. The UAVs can be particularly useful for data collection at sub-urban or such areas in the network where the installation of fixed sensor infrastructure is not viable. Mobility and flexibility are the key assets of this technology (Khan et al., 2017a). As this is a recent technology and the actual applications, particularly for traffic data collection, have not yet fully developed (Barmpounakis et al., 2016; Puri, 2005), some considerable concerns and limitations still exist, such as limited battery time, safety concerns, etc. In order to streamline the processes involved in the application of UAV technology in traffic analysis, a universal guiding framework was proposed in (Khan et al., 2017a). Additionally, a detailed methodological framework for the automated UAV traffic video processing and vehicle trajectory extraction has been presented in (Khan et al., 2017b). This paper is a detailed application and pilot study of the methodology presented by authors in (Khan et al., 2017b).

In this paper, the main focus is on the traffic flow analysis of vehicle trajectories acquired via small rotary-wing UAV footage. The experimental data to analyze traffic flow conditions at a signalized intersection was obtained in the city of Sint-Truiden, Belgium. With the help of a case study, this paper attempts to evaluate the performance of the presented analytical methodology at a signalized intersection using UAV-acquired trajectory data. An analytical methodology is presented for: (i) the automatic identification of shockwaves based on processed trajectories and, (ii) the subsequent extraction of various traffic parameters and performance indicators in order to study flow conditions at a signalized intersection. The paper constitutes an in-depth flow analysis of traffic streams crossing a signalized four-legged intersection. Firstly, the trajectories are processed based on the critical point approach. These processed trajectories are then employed for shockwave analysis and queue estimation at the signalized intersection. This type of analysis conducted on UAV-based data may serve as a benchmark for further research into practical applications of UAV-based traffic analysis systems. With the significant increase in the number of UAV-based traffic studies expected in the coming years, such analytical studies based on an automated systematic framework could become a useful resource for practitioners and researchers alike.

This paper is organized as follows: first of all, the relevant UAV-based traffic analysis studies are discussed concisely. The methodology section consists of a brief description of the UAV video processing and trajectory extraction framework along with the presentation of the signalized intersection flow analysis methodology. In the next section, a case study is presented to support the proposed methodology. This includes the vehicle trajectory extraction and the subsequent traffic flow analysis. Finally, the paper is briefly concluded along with some critical discussion regarding the use of UAVs for traffic data collection, analytical applications of the framework, and proposed future developments.

5.4 Related Work

According to the literature, various applications of UAVs for traffic monitoring and analysis are currently being researched (Coifman et al., 2006; Heintz et al., 2007; Puri et al., 2007). Various researchers summarized the current research trends around the world regarding the use of UAVs for traffic surveillance and analysis applications (Barmpounakis et al., 2017; Colomina & Molina, 2014; Kanistras et al., 2015; Puri, 2005).

Numerous UAV-based studies specifically for traffic analysis have been conducted in the past few years. These studies can be broadly classified into two types depending on the video processing technique, i.e., (i) manual or semi-automatic studies and (ii) automatic studies. Studies employing the semi-automatic approach have shown high accuracy, but are laborious as vehicles have to be detected and then manually tracked for a number of frames (Barmpounakis et al., 2016; Salvo et al., 2014b; Salvo et al., 2014a). In (Salvo et al., 2014a), authors make use of UAV traffic footage of a stop-controlled intersection to study the drivers' behavior. The authors determine the gap-acceptance and waiting time of vehicles while entering a major road in an urban stop-sign controlled intersection. The same authors in (Salvo et al., 2014b) have also attempted to determine various traffic parameters (flow, velocity, etc.) from UAV-acquired video data. The authors further compare the calculated values with the theoretical macro-simulation models. Similarly, the authors in (Barmpounakis et al., 2016) have used UAVs to conduct an experiment over an intersection and then using the semi-automated approach extract the vehicle trajectories and consequently determine various traffic parameters. As stated earlier, the semi-automatic approach requires a great deal of time for processing while, on the other hand, the automatic approach promises a quick processing and analysis procedure, ultimately leading to the real-time analysis of the UAV acquired data. Recently, the number of studies based on the automated approach have increased (Apeltauer et al., 2015; Gao et al., 2014; Khan et al., 2017b; Oh et al., 2014; Zheng et al., 2015). The authors have been attempting to extract various traffic parameters and vehicle trajectories in an automatic environment by using state-of–the art object detection and tracking algorithms.

A great deal of research has been conducted to analyze traffic flow at signalized intersections using data acquired from different sources. This also includes the shockwave and queue analysis based on the traffic video data (Chai et al., 2013; Hourdos & Zitzow, 2014; Morris & Shirazi, 2017). Additionally, a number of studies have employed vehicle trajectories from the NGSIM data for shockwave analysis and queue estimation (Cheng et al., 2010; Cheng et al., 2011; Izadpanah et al., 2009; Lu & Skabardonis, 2007). All these studies have devised and demonstrated various ways to evaluate the performance of signalized intersections. However, all of the existing studies mentioned up until now have been principally based on the fixed video camera systems. Only a couple of studies have been found in the existing literature that have employed UAV-based traffic data in order to analyze the traffic safety and flow conditions specifically for a signalized intersection. In (Chen et al., 2017), the authors analyze the traffic safety conditions at an urban signalized intersection using data acquired via a small quadcopter UAV. The authors focus on the pedestrian-vehicle conflicts and estimate different parameters, e.g., time-to-collision (TTC) and post-encroachment time (PET), as safety performance measures. On the other hand, authors in (Cheng et al., 2013) present a computational model based on the famous traffic wave theory in order to determine the velocity of stop-start waves at an urban intersection. The authors have employed the UAV-acquired traffic data to validate the proposed model. However, the paper is focused mainly on the derivation and validation of the model equations.

5.5 Methodology

This paper is principally based on the vehicle trajectories extracted via the UAV-based video processing and vehicle trajectory extraction framework originally presented in (Khan et al., 2017b). The extracted trajectories are further analyzed based on the proposed analytical methodology. This section consists of a brief description of the UAV based trajectory extraction framework, which is then followed by an explanation of the signalized intersection flow analysis process.

5.5.1 UAV Video Processing Framework.

The authors in (Khan et al., 2017b) proposed a detailed UAV-based traffic video processing framework in order to automatically extract multi-vehicle trajectories for an area of interest. The framework consisted of an in-depth description of the steps involved in the systematic and efficient processing of the UAV-based traffic data. The whole process as categorized in the framework included five modules: (i) pre-processing, (ii) stabilization, (iii) geo-registration, (iv) vehicle detection and tracking, and (v) trajectory management. Moreover, certain additions have been made in the framework recently in order to further optimize the final trajectories. Figure 5.1 illustrates the components of the UAV-based traffic video data processing framework.

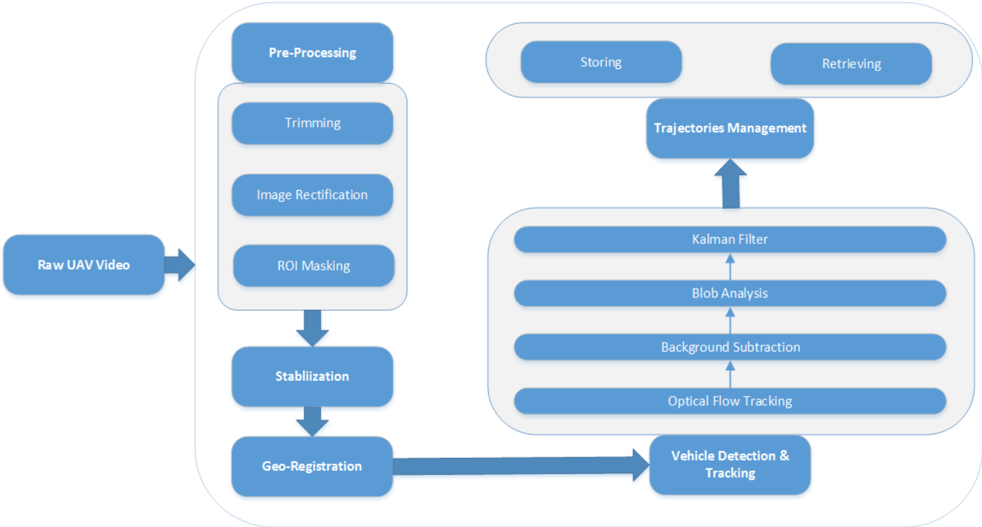


Figure 5.1: The automated UAV video processing and analysis framework with some modifications.

The different modules of the proposed framework are elaborated in detail in (Khan et al., 2017b). However, in this paper the different stages are discussed briefly so as to give an overview of the UAV video processing and analysis.

Firstly, the traffic videos acquired via UAVs are pre-processed. The main target of the step is to prepare the UAV video for the actual processing and analysis steps by removing or minimizing the undesirable aspects of the recorded video e.g., fish-eye effect, ascending/descending of UAV, etc. The pre-processing step ensures an optimal usage of the computational power, hence, increasing the processing speed. This step is followed by the video stabilization and geo-registration of the UAV-acquired videos. Since a slight camera vibration can induce undesired movement in captured images, the stabilization step is critical to minimize the level of instability or shakiness in UAV videos. Once the UAV videos are stabilized, the efficiency of all other modules of the framework, especially the vehicle detection and tracking process, significantly improves. Further, the geo-registration process ensures an efficient calibration and conversion of the UAV acquired mono-vision 2D image coordinates into a real-world coordinate system. This is done in order to enhance the applicability of the extracted vehicle trajectory data. For this purpose, the UAV image is firstly calibrated according to the real-world distances and assigned a coordinate system. These image coordinates can then be converted to real-world coordinates based on a 3×3 homography matrix, which is computed after comparing the extracted frames with the referenced map. The details of the process are given in (Khan et al., 2017b). In a nutshell, this process enables the user to integrate the geo-referenced calibrated trajectories with any GIS application, thereby assisting in an actual-scale visualization and estimation of various traffic parameters.

Once the UAV images are geo-referenced or calibrated to a specific coordinate system, the next step is the automatic detection and tracking of multiple road users. The efficiency and accuracy of this process is critical in order to obtain a reliable and consistent set of trajectory data. The stabilized and calibrated UAV videos are fed into the detection and tracking module which constitutes a number of sub-modules, as indicated in Figure 5.1. The vehicles in motion are detected and tracked by a series of algorithms implemented using the OpenCV library in C++. First of all, the optical flow tracking and background subtraction algorithms identify the pixels that are in motion. These moving pixels representing the vehicles are then tracked over a series of frames with the help of blob tracking. Finally, the Kalman filter algorithm helps in achieving a smooth tracking data, thereby resulting in fewer outliers and consequently lesser post-processing or noise removal.

A proper management system for the handling of extracted vehicle trajectories is critical to efficiently deal with data extracted during the vehicle detection and tracking process. The data has to be easily accessible so that it can be effectively used for further traffic analysis. For this purpose, a text file is generated which contains all the extracted coordinates of the vehicles detected and tracked in the area of interest. Such a data file allows the analyst to conveniently sort and post-process the data in order to extract various traffic parameters and create different types of graphical displays and illustrations of the vehicle trajectory data.

5.5.2 Signalized-Intersection Flow Analysis Methodology

The vehicle trajectories extracted via UAV based traffic data collection process can be employed for various traffic related applications. This paper presents an analytical methodology specifically aimed for a systematic traffic flow analysis at signalized intersections. The proposed methodology streamlines the steps involved in the efficient employment of the extracted vehicle trajectory data in order to analyze the flow at signalized intersections. The methodology as shown in Figure 5.2 consists basically of four modules: (i) the automated simplified trajectories extraction module, (ii) the automated shockwave identification module, (iii) the traffic parameters estimation module, and (iv) the performance indicators' estimation module.

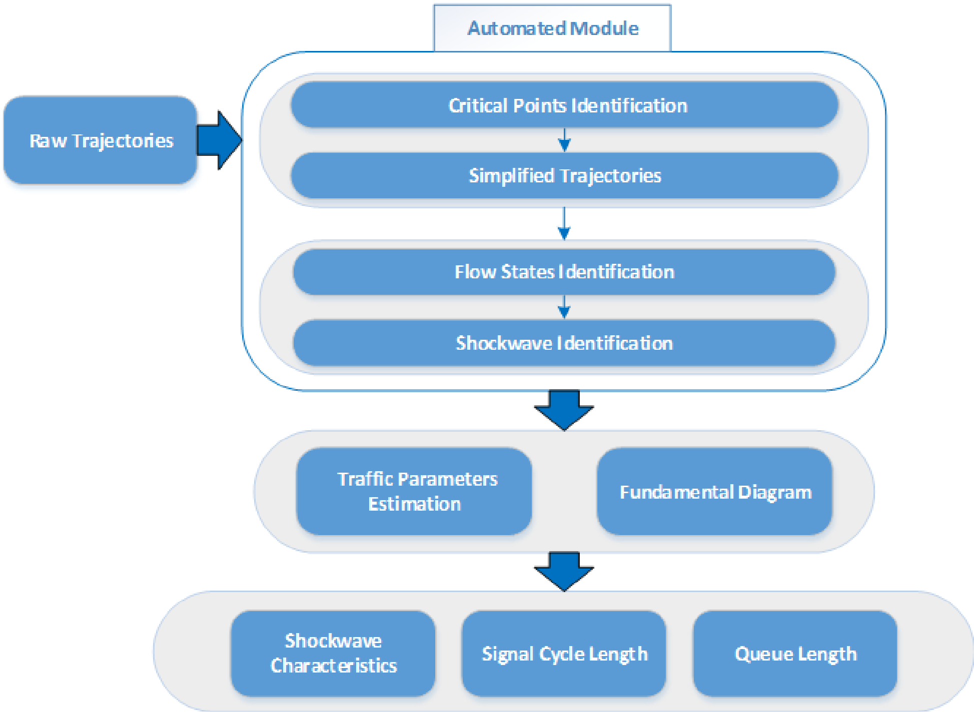


Figure 5.2: The proposed methodology for the extraction of signalized intersection traffic flow parameters.

First of all, the extracted vehicle trajectories are fed as an input into the automated simplified trajectories extraction module. The raw trajectories are processed in order to simplify the visualization of the transformation of traffic flow at a signalized intersection. For this purpose, the 'critical point' concept presented by Cheng et al. (2010) is employed with some modifications. The critical point is defined as that point in a vehicle trajectory after which the motion of vehicle changes significantly, e.g., a critical point may be detected on a vehicle trajectory before it starts accelerating or decelerating. Based on this approach, the critical points are identified on the vehicle trajectories which represent the major or definitive changes in the motion of vehicles along the road. The critical point approach does not only help in simplifying the further analysis of trajectories, but also increases the efficiency of the system by reducing the amount of data to be processed and analyzed. The logic of the critical point extraction and traffic flow state identification algorithm is illustrated in Figure 5.3, where x_i is any point on the trajectory at time t_i with velocity v_i and acceleration a_i. The critical points (CPs) are generated by comparing trajectory points with certain threshold values for velocity and acceleration. In order to minimize the chances of false CP detection, the succeeding 'n' (usually 5 or 10) number of acceleration values are checked.

Moreover, the stopping velocity threshold v_s (normally less than 5 km/h) is compared with the velocity v_{cp} at the critical point. This assists in identifying the true traffic flow regime. Depending on the type of condition it satisfies, the vehicle trajectories can be classified into various regimes, i.e., uniform motion, accelerated/decelerated motion or stationary regime. It is worth mentioning here that the proposed approach is, numerically, very efficient to compute, thereby having an advantage over the more complex approaches (e.g., piece-wise linear regression methods), particularly for cases requiring a quick processing and analysis system.

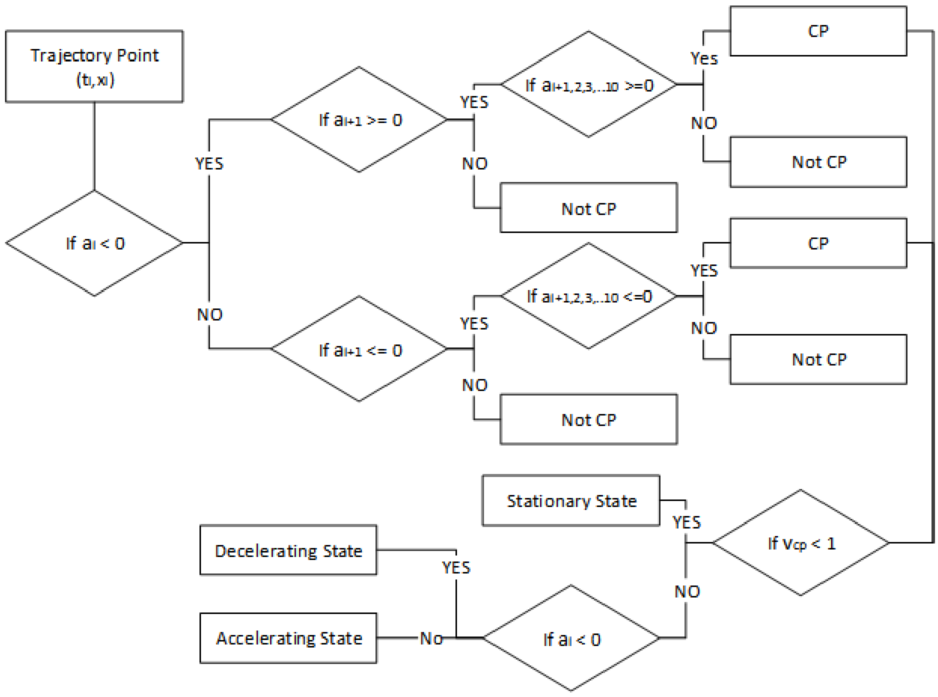


Figure 5.3: The critical point (CP) extraction and traffic flow state identification algorithm.

The resulting simplified trajectories of multiple vehicles can then be utilized efficiently for the identification of different shockwaves that are generated within the proximity of a signalized intersection. The critical points of a series of trajectories are grouped together in order to identify shockwaves. Moreover, the processed vehicle trajectories can also be used to estimate various traffic flow parameters, e.g., density, flow, speed, etc., for each flow regime. These parameters can then be used to develop the speed-flow-density fundamental diagrams which further assist in determining the unknown parameters.

A number of performance indicators can also be extracted to evaluate the performance of the traffic infrastructure under consideration. The combination of space-time and fundamental diagrams is essential for determining the characteristics of traffic flow at the intersection in detail. These diagrams can be used effectively not only to study the signal cycle lengths, but also to determine the speed of generation and dissipation of shockwaves. Additionally, the extracted parameters and the shockwave speeds can also be used for detailed queue analysis at an intersection or any other interrupted flow situation. All these parameters and performance indicators have been estimated and described in detail in the next section with the help of a case study.

5.6 Case Study

In this section, a detailed case study is presented in order to validate and demonstrate the practicality of the UAV-based traffic data collection, processing and analytical methodology. The data collection experiment is followed by the automated extraction of the vehicle trajectories which are then further employed for detailed traffic flow analysis. The following sub-sections present an in-depth description of the whole experiment and the analytical process:

5.6.1 Experiment Specifications

In order to obtain an experimental dataset, UAV flights were conducted in the suburbs of the city of Sint-Truiden, Belgium. A four-legged sub-urban signalized intersection was selected as the area under observation. The location as shown in Figure 5.4 is a linking junction between the Belgian national highways N80 (speed limit: 120 km/h) and N718 (speed limit: 90 km/h), with two lanes in either direction. The specified four-legged intersection primarily handles the traffic leading to and from the city of Hasselt into the center and suburbs of Sint-Truiden. A detailed flight planning process was carried out before the actual conduction of the flights. This included the operational, as well as safety and legal considerations. The UAV flights were conducted in order to capture the Friday evening rush hour (16:30 to 18:00 h). Importantly, the weather and wind conditions were perfect for the UAV flights, i.e., mostly clear skies with gentle wind levels (18 km/h, Beaufort scale 3).

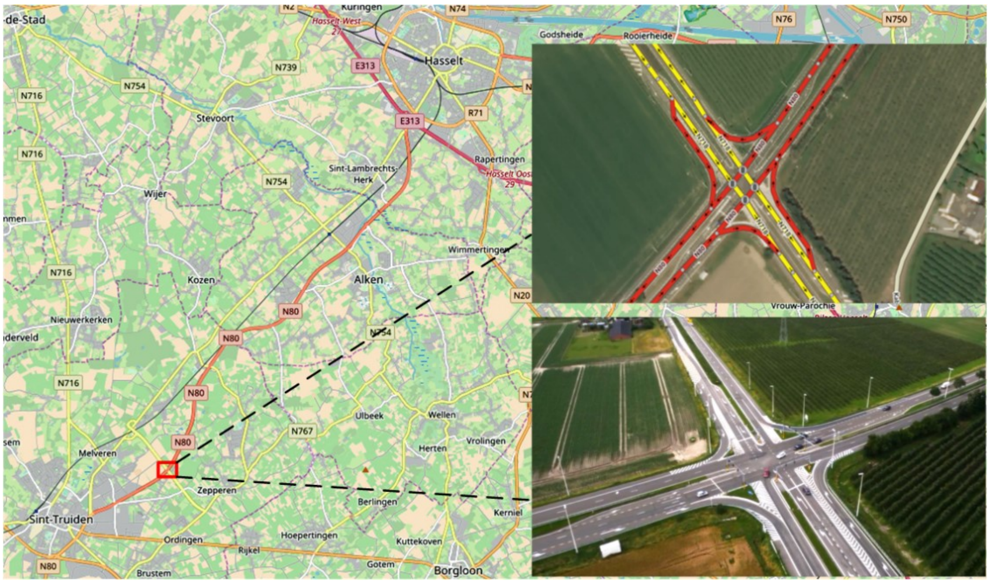


Figure 5.4: Location map of the observed area, along with the satellite and UAV images of the studied intersection (shown in the inset).

A high-end custom-built octocopter UAV, i.e., Argus-One (from Argus-Vision) with an attached Panasonic Lumix GH4 DSLM camera (Panasonic Corporation: Kadoma, Osaka, Japan) was employed for a series of UAV flights. The equipment used for this experiment belonged to a UAV-imaging company named Argus-Vision, registered in Tongeren, Belgium. Table 5.1 lists the detailed technical specifications of the equipment used. The equipment as shown in Figure 5.5 provides stable and high-resolution (4K@25 fps) video data with nearly 10–12 min of flight time. Importantly, the 4K video from this camera does not contain any fish-eye effects (curvature, wide field of view). Additionally, an attached live-feed transmission system allowed to optimize the camera angles for the best view of the intersection during the flight. The UAV was hovered (constant altitude, zero velocity) over the intersection at the altitudes of 80 m and 60 m above ground level. After the conduction of a series of flights over the intersection, the recorded video was trimmed in order to remove insignificant parts of the video which included, e.g., the take-off and landing maneuvers of the UAV. Eventually, a nearly 15-min useful traffic video with 22,649 frames was attained after the pre-processing or trimming step. It is also worth-mentioning that the UAV camera covered approximately 0.07 km^2 of intersection area from an 80 m height.

Table 5.1: Technical specifications of Argus-one UAV and the attached camera.

UAV		**Camera**	
Technical Features		**Technical Features**	
Body	Carbon fiber	Camera	Panasonic Lumix GH4 DSLM
Dimensions	1200 mm × 1000 mm × 600 mm	Body Type	SLR-style mirrorless
Number of Rotors	8	Weight	560 g
Battery	16,000 mAH Lipo Battery	Mega Pixels	16 MP
Flight Time	Around 12 min	Video Resolution	4K (3840 × 2160 pixels)
Payload	0–3 kg	Frame Rate	25 fps
GPS	DJI A2 GPS-Compass Pro		
Range	1200 m		
Speed	0–80 km/h		

Figure 5.5: The Argus-one UAV: (left) take-off position, and (right) in-flight.

5.6.2 Vehicle Trajectories

The extraction of vehicle trajectories crossing the intersection under observation was done using the proposed UAV video processing framework. Specifically, the developed computer vision algorithm, as described in the vehicle detection and tracking module of the framework, was utilized for this purpose. All the processing and analysis was done on an HP (Hewlett Packard Enterprise: Palo Alto, CA, USA) Probook 650 G1 machine, having an Intel® Core™ i5-4210M (2.60 GHz) processor with 4-GB RAM and Windows 8.1 (64 bits). It is important to mention that UAV-acquired images were calibrated and a Cartesian coordinate axis was assigned, with the center of the intersection designated as an origin.

Figure 5.6 consists of various graphs depicting a selected set of extracted vehicle trajectories. These trajectories and speed profiles can be used to make a number of interpretations regarding the drivers; behavior, and overall traffic flow. Figures 5.6a and 5.6b depict the trajectory of a sample vehicle along with its corresponding speed profile. Figure 5.6a reflects that the sample car initially came to rest upon reaching the queue at the signalized intersection, however it moved after a few seconds in order to reduce the queue spacing or the headway. Figure 5.6b includes the instantaneous speed accompanied by the running average and smoothed function speed curves. Running or moving averages help in illustrating the trend of instantaneous speed over time as shown in Figure 5.6b. An interval of 50 frames, implying a 2-s time window, was used to determine the running average speed of the sample vehicle. Similarly, smoothed curve is also used to demonstrate the overall speed trend. The smoothed curve is basically a second-degree (quadratic) polynomial regression curve fit. These curves make the interpretation of instantaneous speed data more efficient. In addition, Figure 5.6c shows the trajectories of a platoon of vehicles on a space-time diagram while Figure 5.6d illustrates a sample set of extracted trajectories overlaid on the UAV-acquired image.

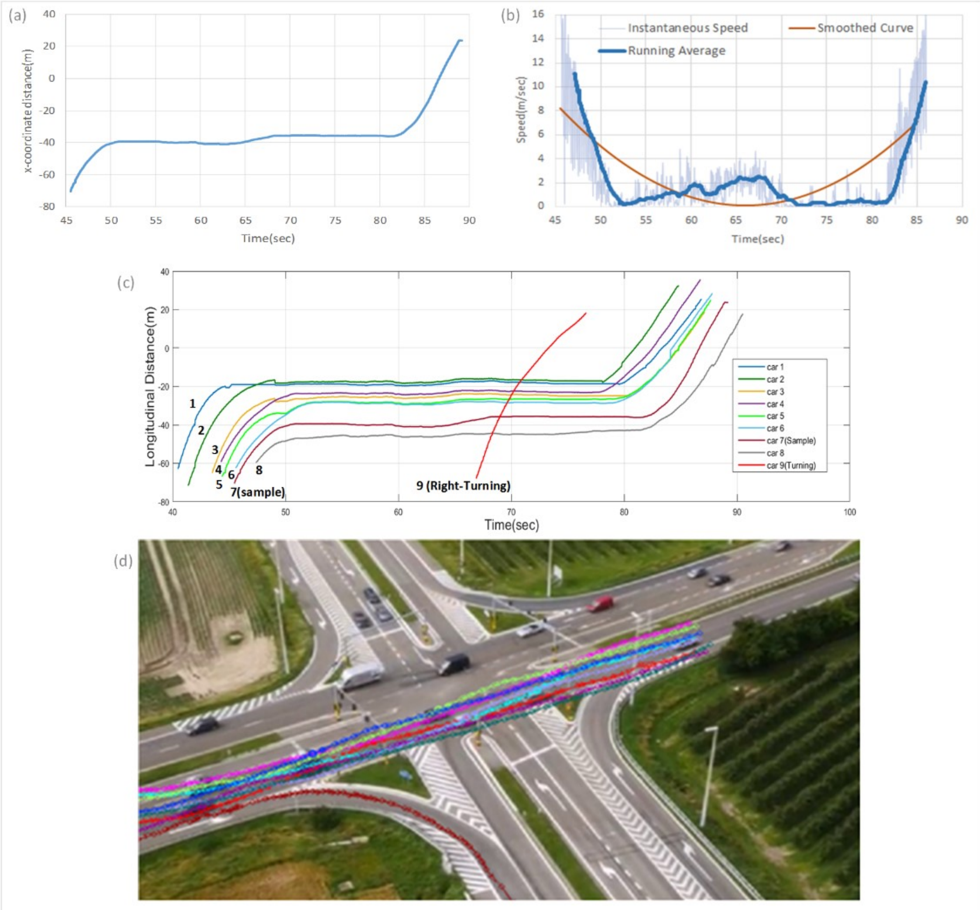


Figure 5.6: (a) The space-time diagram of the trajectory of a sample vehicle; (b) the speed profile of the sample vehicle; (c) the space-time diagram of extracted trajectories (labelled with assigned number) of a group of vehicles; and (d) an illustration of extra

The drivers' behavior while approaching a signalized intersection can be observed from graph in Figure 5.6c. It can be inferred from vehicle trajectories that each individual driver has its own specific braking behavior in order to halt at the traffic signal. Some drivers decelerate smoothly to a stationary position, e.g., car 8 in Figure 5.6c. On the other hand, some drivers have the tendency of decelerating strongly as indicated by the steep curve of car 1's trajectory (Figure 5.6c). The average speed of the sample vehicle (car 7) based on the smoothing function was measured to be 29.52 km/h (8.2 m/s) and 24.48 km/h (6.8 m/s), respectively, for the intersection arrival and departure maneuvers (Figure 5.6b).

Apart from the observation of through traffic, the space-time diagrams can also be used to study the behavior of turning vehicles. In this regard, Figure 5.6c indicates the movement of a right-turning vehicle (car 9). The changing slope of car 9's trajectory suggests that the vehicle completed the turning maneuver safely by adjusting its speed slightly. All these examples show that the trajectory data can be effectively used to study and analyze the traffic flow, as well as safety conditions on a specific intersection.

In addition to the extracted trajectories, the UAV-based traffic video data was also used to generate origin-destination matrix for the signalized intersection. The volume and direction of the traffic approaching and crossing the intersection is a good indicator of the level of service. The Origin-Destination matrices are commonly used tools for planning and studying various road infrastructural elements. These matrices help in quantifying and analyzing traffic movement through each leg of the intersection. In order to determine the traffic volume, a virtual counter was placed on each leg of the intersection. These virtual counters provide an accurate sum of vehicles entering or leaving the roundabout. Figure 5.7 shows the counters and OD matrices for the study area. As indicated in Figure 5.7, maximum traffic flows from Sint-Truiden towards the city of Hasselt (counter 1)

15-min Interval		Destination				
	Counters	2	3	6	7	Total
Origin	1	242	0	2	11	255
	4	0	172	5	28	205
	5	9	3	0	8	20
	8	17	7	5	0	29
	Total	268	182	12	47	*509*

Figure 5.7: Traffic counts based on Origin-Destination matrix

It is important to mention here that the precision of all these calculations is highly dependent on the calibration of the extracted frames. Therefore, a two-step calibration process was conducted in order to ensure high accuracy and minimal errors. This involved several on-site measurements followed by a point correspondence step. In this step, the on-site measurements were verified with the referenced maps. Various prominent stationary objects visible in the UAV image were matched with their coordinates and distances on a referenced satellite image. All this helped in the extraction of an accurate trajectory dataset, ultimately leading to a precise calculation of other traffic parameters, as well.

Moreover, the accuracy of the estimated speed was also verified with the ground-truth speed of the sample vehicle (car 7) during different flow states. This was done by calculating the mean absolute percentage error (MAPE) as shown in Equation (1). The ground-truth speed, as given in Equation (2), was determined by observing the number of frames (N_f) taken by the vehicle to travel between two points of known distance (d). In order to determine time (t) for speed estimation, the number of frames were divided by the frames per second (fps) of the UAV video The ground-truth speed was evaluated for both the intersection arrival and departure phases. Eventually, the mean absolute percentage error was found out to be 5.85%. This shows a good level of accuracy especially for an oblique angled UAV video.

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}}\sum\nolimits_{1,\ldots,\mathrm{N}} \frac{\text{GROUND TRUTH} - \text{ESTIMATION}}{\text{GROUND TRUTH}} \times 100\% \tag{1}$$

$$\text{GROUND TRUTH SPEED} = \frac{d}{t} = \frac{d}{N_f / fps} \tag{2}$$

5.6.3 Traffic Flow Analysis

As mentioned earlier, the extracted vehicle trajectories can be used for various types of traffic analyses, e.g., traffic safety analysis, drivers' behavior analysis, traffic flow analysis, etc. In this paper, however, the focus has been on the traffic flow analysis. Therefore, in this regard, the shockwave analysis can be of particular interest especially for signalized intersections where the vehicle flow is distinctively transformed from one state to another.

The set of trajectories as shown in Figure 5.6c can be processed based on the critical point concept presented in previous section. Figure 5.7 shows the transformation of vehicle trajectories into simplified trajectories, which are then used for further traffic analysis.

Figure 5.8a demonstrates the extracted critical points on a sample trajectory while Figure 5.8b shows the resulting simplified trajectory. This process results in a series of simplified trajectories with distinct flow states. Figure 5.8c shows the space-time diagram of the processed trajectories of the vehicles while approaching, waiting, and eventually crossing the signalized intersection. It can be deduced from the figure that the motion of vehicles have basically three types of flow states, i.e., (A) the free-flowing state before reaching the signal, (B) the formation of queue during the red phase of the signal (stationary state), and (C) the dissipation flow state during the green phase of the signal cycle. These changes in flow states at a signalized intersection result in the generation of backward shockwaves as indicated in Figure 5.8c. Moreover, the signal cycle length can also be determined from such space-time shockwave diagrams. In this particular case, it can be observed that the signalized intersection had a 40-s red phase interval while the green phase interval was of approximately 40 s as well. These estimated times were also verified with the site observation and video recordings. It is clearly evident from Figure 5.8c that simplified trajectories make the analysis and interpretation of traffic flow much simpler, thereby assisting in an efficient estimation of various traffic parameters and performance indicators. Additionally, Figure 5.8d illustrates the positioning of the three traffic flow states, i.e., A, B, and C on the UAV-acquired image of the intersection. It is important to emphasize that the areas of these flow states (specifically A and B) can vary, depending on various factors such as the traffic volume and the length of traffic signal cycle.

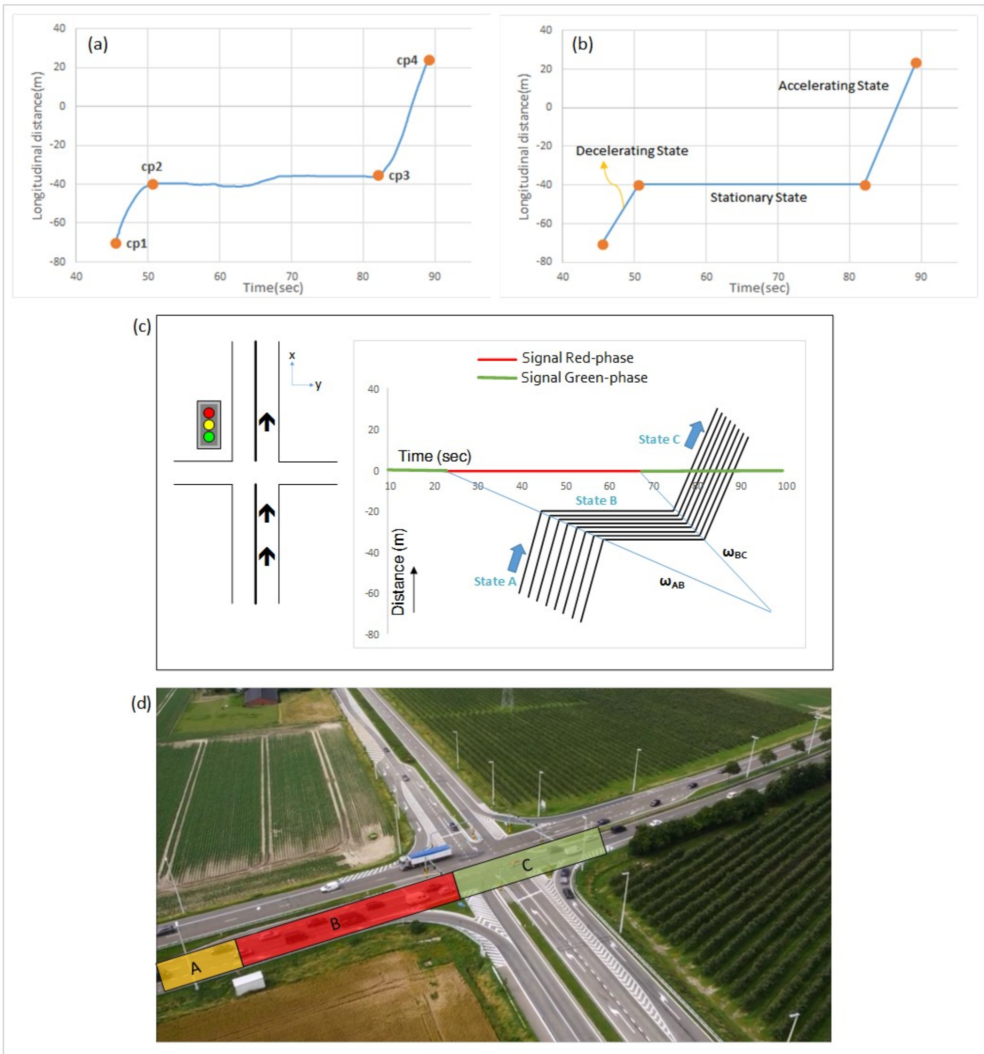
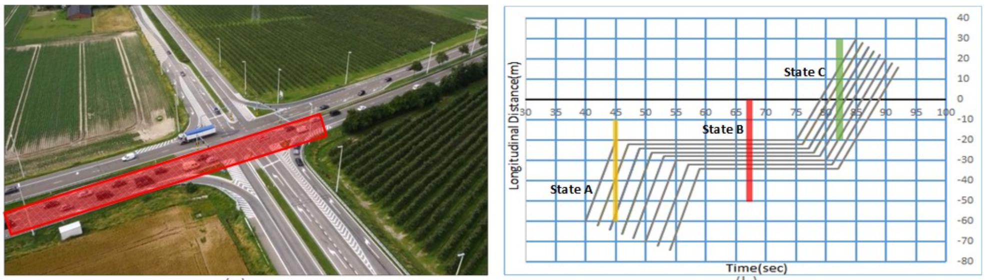


Figure 5.8: (a) Extracted critical points (CP) on vehicle trajectory; (b) simplified trajectories with identified traffic states; (c) the generated shockwaves and signal cycle length; and (d) an illustration of various traffic states on the UAV-acquired image

The space-time diagram shown in Figure 5.8c can also be used to produce a flow-density fundamental diagram. The flows, densities and speeds for different traffic states, i.e., A, B, and C can be inferred from the trajectory data obtained through UAV-based traffic videos. Figure 5.9a highlights the overall grid-area used for density estimation at the signalized intersection, whereas Figure 5.9b demonstrates the specific strips of area on the space-time diagram that are utilized for density estimation of the three traffic states.



(a) (b)

Figure 5.9: (a) Highlighted area for density estimation; and (b) density estimation for various traffic states

Table 5.2 below shows the values of the traffic parameters i.e., flow, speed, and density for each of the three states. It is worth mentioning here that the density for state B represents the jam density (k_j) while the flow during state C is the maximum flow rate (q_{max}). Additionally, the calculated values of k_j and q_{max} can be verified with the default values given for the type of infrastructure and prevailing traffic conditions in the Highway Capacity Manual-HCM (Transportation Research Board, 2010). The estimated values generally lie on the higher side of the default values provided in HCM (default q_{max} = 1750 to 1900 vehicles/hour, default queue spacing for k_j = 25feet). All these parameters cannot only be used to link the space-time diagram with the fundamental diagram, but also can be used for further analysis, including the determination of shockwave speeds and queue lengths.

Table 5.2: The estimated traffic parameters for each traffic state

Traffic State	**Flow *q* (veh/h/lane)**	**Speed *v* (km/h)**	**Density *k* (veh/km/lane)**
A	1200	30	40
B	0	0	160 (k_j)
C	1920 (q_{max})	24	80

Figure 5.10 represents the flow-density fundamental diagram along with the shockwaves and speeds of the vehicles in each traffic state. The speed of the shockwaves can be determined using the Equations (3) and (4). The computed values are −10 km/h and −24 km/h for the accumulating wave (AB) and the dissipating wave (BC), respectively. The negative sign reflects the direction of the propagation of the waves, i.e., backwards:

$$\omega_{AB} = \frac{q_A}{k_A - k_j} \tag{3}$$

$$\omega_{BC} = \frac{q_{max}}{k_C - k_j} \tag{4}$$

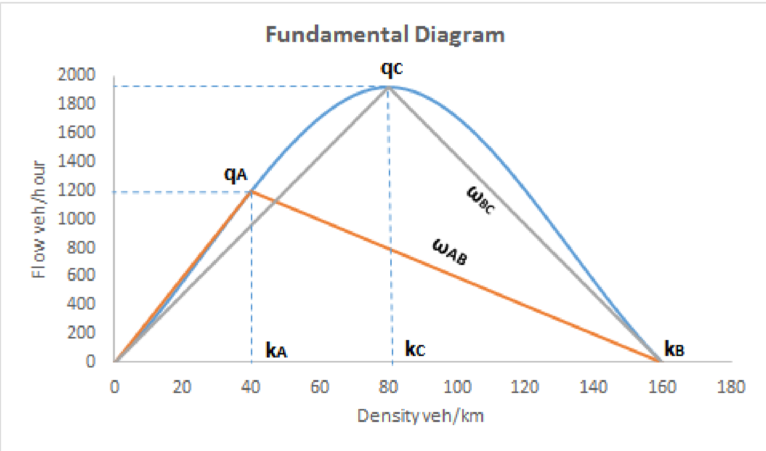


Figure 5.10: Density-flow fundamental diagram with shockwaves

Moreover, other performance indicators for the signalized intersection can be estimated based on the available data. An example of this performance measure can be the maximum queue length which can be used to verify that the end of the queue does not influence the flow on a neighboring intersection. Equation (5) can be used to determine the maximum queue length (Q_M), where γ is the duration of the red-phase of the signal. The maximum queue length turns out to be 190.47 meters with a 40 s red phase:

$$Q_M = \frac{\gamma}{3600} \times \frac{\omega_{BC} \times \omega_{AB}}{\omega_{BC} - \omega_{AB}} \tag{5}$$

Similarly, Equation (6) helps in calculating the time (T_M) required for the complete dissipation of queue after the signal turns green. Substituting the calculated shockwave speeds and the red-phase duration, i.e., 40 s into the equation, the dissipation time is calculated to be 28.57 s. This value can also be verified with the shockwave diagram in Figure 5.8c, where the point of the intersection of shockwaves represents the queue dissipation time:

$$T_M = \gamma \times \frac{\omega_{AB}}{\omega_{BC} - \omega_{AB}} \tag{6}$$

Additionally, the accuracy of the values calculated for various performance indicators can be verified by measuring the mean absolute percentage error (MAPE). The estimated quantity can be compared with the observed ground truth value as shown in Equation (1). A mean error of 7.5% was calculated in the estimation of the maximum queue length in the above example. The ground truth queue length was calculated by multiplying the number of vehicles in the queue by the minimum headway distance (normally 25 feet (~7.6 m)).

5.7 Discussion

As mentioned earlier, UAVs or drones, have several potential applications for traffic analysis and management. Therefore, there is a need to streamline the complete process and conduct validation studies. Accordingly, this paper has aimed to demonstrate the real-life application of the UAVs for traffic analysis, particularly in the scenario of signalized intersection flow analysis. The overall analytical process is principally based on vehicle trajectories extracted via a previously-proposed automated UAV video processing framework (Khan et al., 2017b). Based on these vehicle trajectories, the signalized intersection traffic flow analysis has been conducted for a sub-urban 4-legged intersection, situated in Sint-Truiden, Belgium. The proposed methodological analysis conducted on such experimental data may serve as a proof-of-concept for the actual traffic-specific applications of the UAV-acquired data. Such studies can be of particular interest not only for researchers, but also for practitioners and traffic experts responsible for transport planning and management operations. Furthermore, this study can also lead to the integration of UAV-based traffic data with the more conventional traffic data collected via fixed cameras, loop detectors, etc. The UAV data can provide an additional dimension to the existing traditional data sources.

The UAV-acquired intersection traffic data was used to estimate various traffic parameters. These include the speed, flow, density, shockwaves, signal cycle length, queue lengths, queue dissipation time etc. Importantly, the values of estimated traffic parameters were found to be in accordance with the ground-truth values as well as with the values found in the literature for signalized intersections. The ground truth values were calculated manually based on the recorded videos and site observations. The estimated and the ground-truth values were then used to evaluate the mean absolute percentage error (MAPE). The mean error for the speed of the sample vehicle was approximately 5% while the error for the estimated queue length was approximately 7.5%. Additionally, the values of flow and density were also verified with the default values provided in the Highway Capacity Manual for the specific type of infrastructure and prevailing traffic conditions. The estimated values were generally on the higher side but with no major errors. In future, the estimates can be improved by considering more heterogeneous data as well as accurate classification of vehicles.

Although, vehicle trajectories and the corresponding traffic parameters were extracted successfully using the UAV-acquired data, there are still some limitations attached with the automated UAV video processing. Various types of errors can occur in vehicle detection and tracking due to different reasons such as partial occlusions, shadows, objects in close proximity, false detections, etc. Therefore, the resulting trajectories may contain some noise and errors which have to be dealt-with accordingly. Additionally, some limitations regarding the current UAV technology also exist. These include the limited flight time of small UAVs, along with some other concerns regarding the safety of flight operations. The flight time of UAVs depends on internal, as well as external, factors. Internal factors include the size, payload, battery type, etc., whereas the external factors consist of weather conditions, wind conditions, status of GPS satellites, etc. Apart from limited flight times, the legal considerations, including the safety and privacy concerns, also limit the use of UAVs for practical applications. In particular, the current Belgian law restricts the small UAVs to fly directly above vehicles and population. Therefore, in this study, the UAV was hovered at an oblique angle to the intersection traffic, thereby compromising the accuracy of extracted trajectories, as well as complicating the overall video processing. Nevertheless, all these concerns will eventually fade away with the development of more reliable and robust technology in the coming years.

5.8 Conclusions

In this paper, the main focus has been on the traffic flow analysis of the extracted vehicle trajectories. For this purpose, an analytical methodology has been presented for analyzing traffic flow conditions at a signalized intersection. In order to validate the methodology, an experimental UAV-based dataset was collected at a sub-urban four-legged signalized intersection. A dataset of vehicle trajectories was extracted and illustrated graphically in the form of space-time diagrams.

These extracted trajectories were then employed for further traffic flow analyses relevant for the signalized intersection traffic. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted flow conditions at the signalized intersection. Importantly, the values of the estimated traffic parameters did not have significant errors. The results of the analysis reflect the value of the flexibility and birds-eye view provided by UAV videos, thereby depicting the overall applicability of the UAV-based traffic analysis system. However, the factors affecting the robustness of the system have to be addressed in the future research in order to further optimize the use of UAVs for traffic data collection. Apart from it, the future research will also be focused on further improving and extending the traffic-related UAV applications. In future, detailed datasets have to be collected in order to incorporate for heterogeneity in traffic flow. Various flights need to be conducted over different times of the day and also different days in the week to collect heterogeneous data. Various approaches for further automation and optimization of vehicle trajectories' analysis, including the 'critical point' approach, will be explored in more detail. Additionally, the prospects of real-time processing and analysis of traffic data obtained via UAVs will also be inspected.

5.9 References

Apeltauer, J., Babinec, A., Herman, D., & Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-3/W2, 9–15.

Barmpounakis, E N, Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In Transportation Research Board 95th Annual Meeting (p. 16).

Barmpounakis, Emmanouil N, Vlahogianni, E. I., & Golias, J. C. (2017). Unmanned Aerial Aircraft Systems for transportation engineering : Current practice and future challenges. International Journal of Transportation Science and Technology, 5(3), 111–122. https://doi.org/10.1016/j.ijtst.2017.02.001

Chai, Q., Cheng, C., Liu, C., & Chen, H. (2013). Vehicle Queue Length Measurement Based on a Modified Local Variance and LBP. In Emerging Intelligent Computing Technology and Applications. ICIC 2013. Springer, Berlin, Heidelberg.

Chen, P., Zeng, W., Yu, G., & Wang, Y. (2017). Surrogate Safety Analysis of Pedestrian-Vehicle Conflict at Intersections Using Unmanned Aerial Vehicle Videos. Journal of Advanced Transportation, 2017, 12.

Cheng, K., Chang, Y., & Peng, Z. (2013). A Computational Model for Stop-Start Wave Propagation Velocity Estimation Based on Unmanned Aerial Vehicle. In Transportation Research Board 89th Annual Meeting (p. 13).

Cheng, Y., Qin, X., Jin, J., & Ran, B. (2010). An Exploratory Shockwave Approach for Signalized Intersection Performance Measurements Using Probe Trajectories. In Transportation Research Board 89th Annual Meeting (pp. 1–23).

Cheng, Y., Qin, X., Jin, J., Ran, B., & Anderson, J. (2011). Cycle-by-Cycle Queue Length Estimation for Signalized Intersections Using Sampled Trajectory Data. Transportation Research Record: Journal of the Transportation Research Board, 2257, 87–94. https://doi.org/10.3141/2257-10

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. IEE Proceedings - Intelligent Transport Systems, 153(1), 11. https://doi.org/10.1049/ip-its:20055014

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing : A review. ISPRS Journal of Photogrammetry and Remote Sensing, 92, 79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013

Gao, H., Kong, S. L., Zhou, S., Lv, F., & Chen, Q. (2014). Automatic Extraction of Multi-Vehicle Trajectory Based on Traffic Videotaping from Quadcopter Model. Applied Mechanics and Materials, 552, 232–239. https://doi.org/10.4028/www.scientific.net/AMM.552.232

Heintz, F., Rudol, P., & Doherty, P. (2007). From images to traffic behavior - A UAV tracking and monitoring application. FUSION 2007 - 2007 10th International Conference on Information Fusion. https://doi.org/10.1109/ICIF.2007.4408103

Hourdos, J., & Zitzow, S. (2014). Investigation of the Impact the I-94 ATM System has on the Safety of the I-94 Commons High Crash Area.

Izadpanah, P., Hellinga, B., & Fu, L. (2009). Automatic Traffic Shockwave Identification Using Vehicles ’ Trajectories. In Transportation Research Board 88th Annual Meeting (p. 14).

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. Handbook of Unmanned Aerial Vehicles, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017a). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. Transportation Research Procedia, 22, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017b). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Record: Journal of the Transportation Research Board, 32(0), 1–15. http://dx.doi.org/10.3141/2626-04

Lee, J., Zhong, Z., Kim, K., Dimitrijevic, B., Du, B., & Gutesa, S. (2015). Examining The Applicability Of Small Quadcopter Drone For Traffic Surveillance And Roadway Incident Monitoring. In Transportation Research Board 94th Annual Meeting,Washington D.C.

Lu, X., & Skabardonis, A. (2007). Freeway Traffic Shockwave Analysis: Exploring NGSIM Trajectory Data. In Transportation Research Board 86th Annual Meeting (p. 19).

Morris, B. T., & Shirazi, M. S. (2017). Intersection Monitoring Using Computer Vision Techniques for Capacity, Delay, and Safety Analysis. In Computer Vision and Imaging in Intelligent Transportation Systems In Communications in Computer and Information Science, vol 375. Springer (pp. 163–193). https://doi.org/10.1002/9781118971666.ch7

Oh, H., Kim, S., Shin, H. S., Tsourdas, A., & White, B. . (2014). Behaviour recognition of ground vehicle using airborne monitoring of unmanned aerial vehicles. Vehicles. International Journal of Systems Science, 45(12), 2499–2514.

Puri, A, Valavanis, K. ., & Kontitsis, M. (2007). Statistical profile generation for traffic monitoring using real-time UAV based video data. IEEE Mediterranean Conference on Control & Automation.

Puri, Anuj. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. Department of Computer Science and Engineering, University of South Florida,. https://doi.org/10.1.1.108.8384

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. Recent Advances in Civil Engineering and Mechanics, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. Procedia - Social and Behavioral Sciences, 111, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

Transportation Research Board. (2010). HCM 2010 : Highway Capacity Manual. Washington, D.C.

Vlahogianni, E. I. (2015). Computational Intelligence and Optimization for Transportation Big Data: Challenges and Opportunities. In Engineering and Applied Sciences Optimization: Volume 1. Springer International Publishing.

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In G. V. Duffy (Ed.), Digital Human Modeling: Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health: 6th International Conference (pp. 305–312).

Chapter 6

UAV–Based Traffic Analysis: Roundabouts

This chapter consists of following peer-reviewed paper:

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts, Procedia Computer Science, 130, 636-643, Ambient Systems, Networks and Technologies (ANT) 2018, Porto, Portugal. doi.org/10.1016/j.procs.2018.04.114.

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts. IEEE ITSM. (Conference Extension: In-Review)

6.1 Overview

This chapter authenticates the application of small multirotor UAVs for traffic data collection and subsequent analysis of traffic streams at urban roundabouts. This chapter presents an analytical methodology to evaluate the performance of roundabouts by extracting various parameters and performance indicators. The performance evaluation methodology is based on: (i) determining traffic volume via OD matrices for each leg, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The overall analytical process is principally based on the previously proposed automated UAV video-processing framework for the extraction of vehicle trajectories. The extracted trajectories are further employed to extract useful traffic information. The experimental data to analyse roundabout traffic flow conditions was obtained in the city of Sint-Truiden (Belgium). The study depicts the overall applicability of the UAV-based traffic analysis system.

6.2 Abstract

Recently, multirotor Unmanned Aerial Vehicles(UAVs) or drones have become increasingly popular for a vast variety of civil applications. Efficient traffic data collection and extraction of various flow parameters are some of the futuristic applications of this technology. However, such applications still need to be streamlined and thoroughly explored for varying traffic and infrastructural conditions. In this paper, the focus is on the authentication of the application of small multirotor UAVs for traffic data collection and subsequent analysis of traffic streams at urban roundabouts. This paper presents an analytical methodology to evaluate the performance of roundabouts by extracting various parameters and performance indicators. The performance evaluation methodology is based on: (i) determining traffic volume via OD matrices for each leg, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The overall analytical process is principally based on the authors' previously proposed automated UAV video-processing framework for the extraction of vehicle trajectories. The extracted trajectories are further employed to extract useful traffic information. The experimental data to analyse roundabout traffic flow conditions was obtained in the city of Sint-Truiden (Belgium). The results reflect the value of flexibility and bird-eye view provided by UAV videos; thereby depicting the overall applicability of the UAV-based traffic analysis system. With the significant increase in the usage of UAVs expected in the coming years, such studies could become a useful resource for practitioners as well as future researchers. The future research will mainly focus on further extensions of the UAV-based traffic applications.

Keywords: Unmanned Aerial Vehicles(UAV);Drones;Traffic Data Collection;Traffic Analysis; Roundabout Traffic;Vehicle Trajectories

6.3 Introduction

The efficient management and control of ever-increasing traffic volumes and congestion levels, has become one of the most critical challenges faced by municipalities and governments all over the world. This problem further magnifies particularly at urban intersections where a high number of conflict points emerge, leading to road safety as well as capacity issues. In this regard, roundabouts provide an efficient alternative for managing traffic at at-grade intersections (Mahesh & Rastogi, 2016; St-Aubin et al., 2013). Roundabouts are basically circular intersections with specific design and traffic flow priorities. The circulating traffic is given priority over the approaching traffic, hence ensuring a smooth and safe flow of traffic. Based on these priority rules, the roundabouts can also be termed as a series of T-junctions which have their own drawbacks (Fisk, 1991). Therefore, it is critical to analyze and evaluate the roundabout performance, particularly in urban environments, in order to ensure smooth traffic operation. However, for this purpose, an accurate, dynamic and quickly generated traffic data is required (Khan et al., 2017b).

The collection of traffic data is usually an expensive and cumbersome process, depending majorly on the employed method and the required level of detail. In the past decades, the majority of the traffic data collection has been done using the traditional sources e.g. manual counters and observers, induction loops, stationary video recorders etc. However, these equipment produce extremely limited ‘point’ data which cannot be used to estimate complex traffic flow phenomenon such as the process of accumulation and dissipation of queues. In addition to this, the emergence of hidden points in the study area further limits the scope of the study (Barmpounakis et al. 2016; Puri, 2005). Particular, fixed video camera-based studies face a huge problem of occlusion in which the objects of interest are hidden either partially or completely behind other objects e.g. trees, trucks etc. Although, this problem can be solved technically by increasing the number of cameras/sensors or manual observations (Coifman et al., 2006), the increased expenses and workforce deem it practically unfeasible. On the other hand, advanced ITS data collection technologies e.g. vehicle-to-infrastructure (V2I), probe vehicles with GPS and other smartphone sensor technologies have also been employed in recent years. These technologies provide detailed and dynamic traffic data, however they result in big datasets which are difficult to handle especially in a short time span (Vlahogianni, 2015). Additionally, such technologies might influence the actual behavior of the travelers since they already know they are being observed (Barmpounakis et al., 2016; Salvo et al., 2014a). Another alternative for traffic data collection is the aerial photography or remote sensing. Satellites and manned aircrafts have been used over the years for dynamic traffic data collection. These technologies provide wide field-of-view and unbiased data, however cost and deployment issues restrict their practical employment. Recently, unmanned aerial systems (UAS) have started to gain popularity for traffic monitoring, management, and control purposes (Kanistras et al., 2015; Puri, 2005).

Small Unmanned Aerial Vehicles (UAVs), commonly termed as drones have become popular for a large variety of civil applications, ranging from survey of crop fields to parcel delivery applications (Colomina & Molina, 2014; Khan et al., 2017a). In the past few years, this technology has also been identified to be useful in various transport management and planning applications.. UAVs are being used to observe, analyze and evaluate the traffic flow as well as safety conditions

(Barmpounakis et al., 2017; Kanistras et al., 2015; Puri, 2005). Traditionally, only the fixed-wing UAVs were employed for traffic monitoring purposes, however, in recent years the small rotary-wing type UAVs have also been used for traffic-related applications (Lee et al., 2015). This non-intrusive and low-cost technology has improved rapidly and is now capable of providing high-resolution data (both in space and time) that can be used to extract vehicle trajectories and estimate traffic parameters. The UAVs can be particularly useful for data collection at sub-urban or such areas in the network where the installation of fixed sensor infrastructure is not viable. The key characteristics of this technology are its flexibility and the bird-eye view of the area of interest (Khan et al., 2017a). However, this is a recent technology and the actual applications, particularly for traffic data collection have not yet fully developed (Barmpounakis et al., 2016; Puri, 2005). Therefore, there are some concerns and restrictions attached to this technology as well, such as limited battery time, safety concerns etc. All these concerns have to be coped with in the coming years. In order to streamline the processes involved in the application of UAV technology in traffic analysis, a universal guiding framework was proposed by Khan et al. (2017a). Additionally, a detailed methodological framework for the automated UAV video processing and vehicle trajectory extraction has been presented by Khan et al. (2017b).

In this paper, the emphasis is on the traffic flow analysis of vehicle trajectories extracted via small rotary-wing UAV footage. The experimental data to analyze traffic flow conditions was obtained over an urban compact roundabout situated in the city of Sint-Truiden (Belgium). This paper presents an analytical methodology to evaluate the performance of a roundabout by extracting various parameters and performance indicators. The performance evaluation methodology is based on: (i) determining traffic volume via OD matrices for each leg, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The paper constitutes of an in-depth analysis of the roundabout traffic streams. In the coming years, the use of UAVs is expected to rise significantly. In this scenario, such analytical studies based on an automated systematic framework could serve as a reference for practitioners and researchers alike.

This paper is structured as follows: firstly, the existing literature is discussed concisely. The methodology section consists of a brief description of the UAV video processing and trajectory extraction framework along with the presentation of the roundabout flow analysis methodology. In the next section, a Belgian case study is presented to support the proposed methodology. This includes applications of extracted vehicle trajectories for traffic flow analysis. Lastly, a brief conclusion along with some discussions regarding the limitations and planned future works is presented.

6.4 Related Work

As found in the existing literature, UAVs are being researched upon for a wide range of applications, including traffic management, monitoring and analysis. Various researchers summarized the current research trends around the world regarding the use of UAVs for traffic surveillance and analysis applications (Barmpounakis et al., 2017; Colomina & Molina, 2014; Kanistras et al., 2015; Puri, 2005).

Numerous UAV-based studies specifically for traffic analysis have been conducted in the previous few years. These studies can be classified based on 2 factors i.e. (i) type of equipment used, and (ii) type of video processing technique used. In the early years, mostly fixed-wing UAVs were used for traffic-related applications[7] whereas recently, many researchers have employed small multirotor UAVs for their experiments (Barmpounakis et al., 2016; Khan et al., 2017b; Lee et al., 2015; Salvo et al., 2014b). Similarly, studies depending on the video processing technique can be broadly classified into 2 types i.e. (i) Manual or Semi-Automatic studies and (ii) Automatic studies. Studies employing the semi-automatic approach are highly accurate, but are time-consuming and laborious as the object has to be detected and tracked manually for a number of frames (Barmpounakis et al., 2016; Salvo et al., 2014a; Salvo et al., 2014b). On the other hand, the automatic approach promises a quick processing and analysis procedure; ultimately leading to the real-time analysis of the UAV acquired data. Recently, the number of studies based on automated approach have increased (Apeltauer et al., 2015; Gao et al., 2014; Khan et al., 2017b; Oh et al., 2014; Zheng et al., 2015). The authors have been attempting to extract various traffic parameters and vehicle trajectories in an automatic environment by using state-of-the-art object detection and tracking algorithms.

A lot of research has been conducted to analyze roundabout traffic flow using data acquired from different sources. St-Aubin et al. (2013) employed traffic data from a fixed video camera system to analyze driver behavior at roundabouts in Canada. The authors extracted various traffic parameters by interpreting vehicle trajectories. Similarly, Mussone et al. (2011) have attempted to analyze roundabout performance by applying image processing techniques on fixed video camera data. All these studies have devised and demonstrated various ways to evaluate the performance of roundabouts. However, all of the existing studies mentioned up till now have been principally based on the fixed video camera systems, which generally produce data with high occlusion rate. Recently, few researchers have employed UAV-acquired data to conduct roundabout traffic flow and safety analyses studies. Salvo et al. (2014a) have analyzed driving behavior using UAV videos at an urban roundabout in Italy. The authors conducted a gap-acceptance analysis for vehicles entering the roundabout. Similarly, same authors (Salvo et al., 2014b) have also conducted gap-acceptance analysis for an urban intersection using UAV data. Additionally, Guido et al. (2017) and Apeltauer et al. (2015) have evaluated the accuracy of roundabout traffic data obtained via UAVs.

6.5 UAV Video Processing and Analysis Framework

The traffic video data obtained via UAV has to be efficiently processed in order to conduct the desired traffic analysis on it. For this purpose, a UAV video processing and traffic analysis framework is presented which consists of an in-depth description of the steps involved in the systematic usage of the UAV-based traffic data. The UAV video processing framework for the automatic extraction of multi-vehicle trajectories has been presented in detail by Khan et al. (2017b). The processing framework is categorized into five modules i.e.: (i) pre-processing, (ii) stabilization, (iii) geo-registration, (iv) vehicle detection and tracking, and (v) trajectory management. The processing module is then followed by the traffic analysis module in which the trajectory dataset is used as an input. Figure 6.1 illustrates the components of the UAV based traffic video data processing and traffic analysis framework. All the modules of this framework are elaborated in detail in the previous research (Khan et al., 2017b). However, in this paper, only an overview of the UAV video processing framework is included.

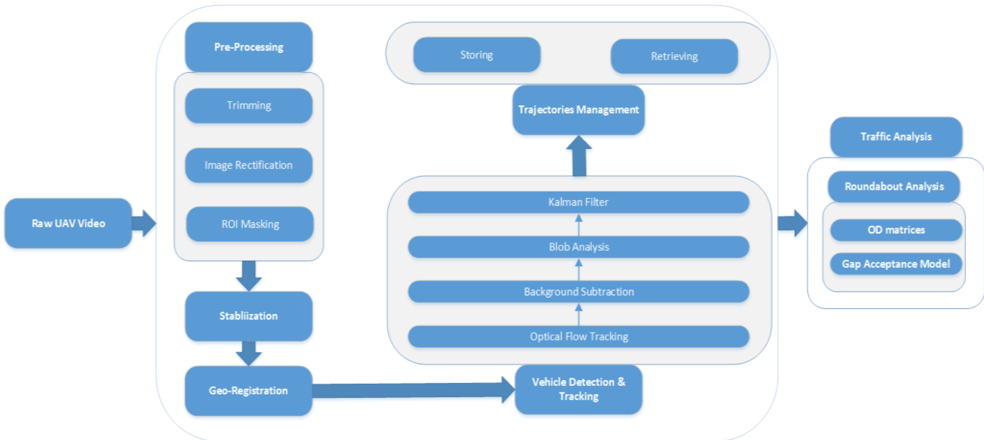


Figure 6.1: The UAV video processing and traffic analysis framework

Firstly, the UAV videos are preprocessed by removing or minimizing the undesirable aspects of the recorded video. This step is followed by the video stabilization and geo-registration of the UAV-acquired traffic videos. The stabilization step is critical to minimize the level of instability or shakiness in UAV videos, as even a slight vibration of the camera can affect the accuracy of the extracted data. Further, the geo-registration or geo-referencing process ensures an efficient conversion of the UAV acquired mono-vision 2D image coordinates into a real-world coordinate system in order to enhance the applicability of the extracted vehicle trajectory data. Once the UAV images are geo-referenced or calibrated to a specific coordinate system, the next step is the automatic detection and tracking of vehicles of interest. The efficiency and accuracy of this process is critical in order to obtain a reliable and consistent set of trajectory data. The stabilized and calibrated UAV videos are fed into the detection and tracking module which constitutes of a number of sub-modules as indicated in Figure 6.1. The vehicles in motion are detected and tracked via a series of algorithms implemented in C++ (OpenCV library). Moreover, the extracted trajectory dataset is stored and managed in order to utilize it efficiently for further traffic analysis. The processing of UAV videos is then followed by the traffic analysis module in which the resulting trajectories are employed to extract useful traffic information. In this paper, the capacity and flow analysis of roundabout traffic is conducted by estimating various parameters and performance indicators. More specifically, the UAV-acquired traffic data is utilized to generate OD matrices for different legs of the roundabout by placing virtual counters for each entry and exit point. The algorithm for these virtual counters is implemented in visual C++ and the computer vision library OpenCV. Additionally, the waiting times and critical gaps for the vehicles entering the roundabout are also calculated. The following sections will elaborate the detailed analytical process via a case study.

6.6 Case Study

As mentioned earlier as well, the main aim of this paper is to demonstrate the potential applications of UAVs or drones for traffic analysis and management, particularly in the scenario of urban roundabout flow analysis. In this section, a detailed case study is presented in order to validate the practicality of the UAV-based traffic data collection, processing and analytical framework. The data collected via UAV flights is used for analyzing traffic volume and capacity by generating origin-destination(OD) matrices. Additionally, the extracted data is also used to analyze drivers' behavior via gap-acceptance study. The following sub-sections present an in-depth description of the whole experiment and the analytical process:

6.6.1 Experiment Specifications

In order to obtain an experimental dataset for the validation of the proposed analytical framework, a series of UAV flights were conducted in the urban commercial area of the city of Sint-Truiden (Belgium). An urban compact roundabout was selected as the area under observation. The location as shown in Figure 6.2 is a busy urban commercial area, having a football stadium and rail-station in the vicinity. The selected roundabout consists of single-lane approaches from each side, whereas one leg also has a right turning lane just before the roundabout in order to minimize the traffic flowing into the roundabout. A detailed flight planning process was carried out before the actual conduction of the flights. The UAV flights were conducted in order to capture the early-evening rush hour on a Friday afternoon (15:00 to 16:30 hours). Importantly, the weather and wind conditions were perfect for the UAV flights i.e. mostly clear skies with gentle wind level (18km/hour, Beaufort scale 3).

Figure 6.2: The UAV view of the studied roundabout (left-side); and Google Earth satellite image of the roundabout(right-side)

A series of UAV flights were conducted using a custom-built high-end octocopter UAV i.e. Argus-One (from Argus-Vision) with an attached Panasonic Lumix GH4 DSLM camera. The main focus for the experiment was to obtain a high-quality experimental data with a minimal setup time. The equipment as shown in Figure 6.3 has a relatively low flight time of around 10 minutes, but provides an extremely stable and high resolution (4K@25fps) video data. Additionally, an attached live-feed transmission system allowed to optimize the camera angles for the best view of the roundabout area during the flight. The UAV was hovered i.e. maintaining a constant altitude with zero velocity, over the study area at 80m and 60m heights. The series of UAV flights resulted in a nearly 15-minute useful traffic video after trimming the take-off and landing maneuvers of the UAV. It is also important to mention here that the analysis of UAV traffic videos was done on an Intel® Core™ i5-4210M CPU at 2.60 GHz, with 4-GB RAM.

Figure 6.3: The Argus-one UAV: (left) take-off position, and (right) in-flight.

6.6.2 Roundabout Traffic Analysis

The UAV traffic video data can be employed to extract useful traffic information required for analyzing traffic flow. This paper presents an analytical approach, specifically aimed to evaluate the performance of an urban roundabout. The performance evaluation methodology is based on: (i) quantifying traffic volume via OD matrices for each leg, and (ii) analyzing capacity and drivers' behavior via gap-acceptance analysis.

The volume of the traffic flowing through the roundabout is a good indicator of the performance of a roundabout. The Origin-Destination matrices are commonly used tools for planning and studying various road infrastructural elements, particularly roundabouts. These matrices help in quantifying and analyzing traffic movement through each leg of the roundabout. In order to determine the traffic volume, a virtual counter is placed on each leg of the roundabout. These virtual counters provide an accurate sum of vehicles entering or leaving the roundabout. Figure 6.4 shows the counters and OD matrices for the study area. As indicated in Figure 6.4, maximum traffic originates from the main city(counter 7) and flows majorly into surrounding shopping and residential area(counter 4). It is also worth mentioning that the automatic traffic counts were verified by manual counts and only a minor error of 2.26% was detected. The errors mainly occurred in case of vehicles partially occluded by close-by trees.

		Destination				
	Counters	2	4	6	8	Total
Origin	1	25	27	20	0	72
	3	0	7	26	12	45
	5	1	4	33	36	74
	7	19	61	0	19	99
	Total	45	99	79	67	290

Figure 6.4: Position of virtual counters at roundabout approaches; and the Origin-Destination(OD) matrix for the roundabout traffic

Apart from traffic counts, the analyses of capacity and actual drivers' behavior are important aspects employed for traffic modeling and management. Various measures of effectiveness(MOEs) e.g. waiting time, queue lengths, gap acceptance/rejection are used to evaluate the infrastructure performance and determine level-of-service. Gap-acceptance model is commonly used not only to estimate the capacity but also to study drivers' behavior while merging or crossing another traffic stream. The primary parameter used in gap acceptance modeling is the critical gap. The critical gap is defined as the minimum time gap between consecutive vehicles circulating inside the roundabout that allow waiting vehicles on an approach to enter the roundabout (Özuysal et al., 2009). The follow-up headway is defined as the time between the vehicles using the same major-street headway under the queuing on the roundabout entry (Macioszek, 2018).The average range of critical gap and follow-up-time is taken as 4.1 to 4.6 sec and 2.6 to 3.1 sec (approximately 60% of the critical gap) respectively in the HCM 2000 (Transportation Research Board, 2000). The estimation of the critical gap is done using Modified Raff's method (Brilon et al., 1999; Mensah et al., 2010), which utilizes both the accepted and rejected gaps. Table 6.1 shows the number of gaps accepted or rejected by merging drivers for each time gap level.

Table 6.1: Number of gaps accepted and rejected according to different time gap intervals (seconds)

Time Gap (seconds)	Number of Accepted Gaps	Number of Rejected Gaps
< 1	0	4
1-2	1	15
2-3	4	19
3-4	5	2
4-5	7	0

As evident from data in Table 6.1, the number of gaps accepted and rejected are inversely proportional to each other. According to modified Raff's method, the critical gap can be calculated by determining the intersection point of the gap accepted and rejected plots. Figure 6.5 illustrates the critical gap estimation approach and highlights the intersection point of the plots as the critical gap. The value of the critical gap for the experimental data is found to be approximately 3.83 seconds. This value is slightly less than the HCM 2000 and HCM 2010 specified average value of 4.1 seconds, reflecting the general driving attitude and also the level of service of the roundabout.

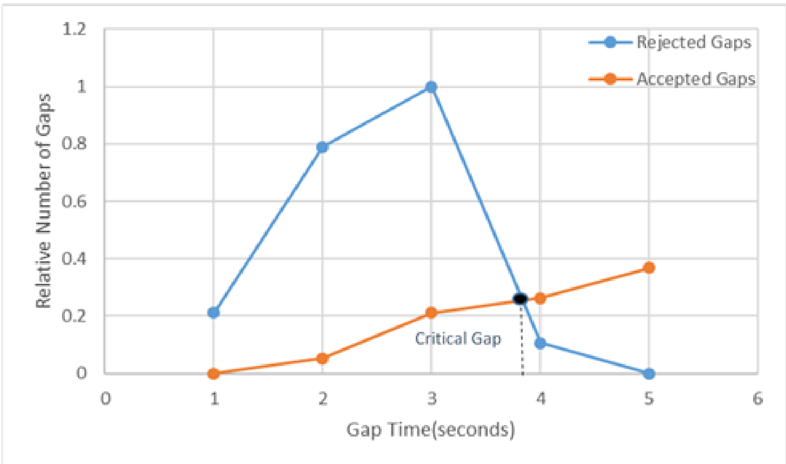


Figure 6.5: The critical gap estimation based on the plots of accepted and rejected gaps

As stated earlier, the estimated critical gap and follow-up headway can be used to determine the capacity of a roundabout. The capacity of a roundabout gives an overview of the performance of the infrastructure. According to Highway Capacity

Manual (Transportation Research Board, 2010), the capacity of a roundabout can be calculated as:

$$q_{e,max} = Ae^{-Bq_c} \tag{1}$$

where:

$q_{e,max}$ = Capacity of critical lane (veh/h)

$A = \frac{3600}{t_f}$

$B = \frac{(0.5(t_c - t_f))}{3600}$

t_c = Critical Gap

t_f = Follow-up headway

$q_c = v_c$ = Conflicting flow (veh/h)

As evident from equation(1), the capacity of a roundabout is dependent on conflicting flow, critical gap and follow-up headway. Conflicting flow is the number of vehicles circulating inside the roundabout at a particular time interval. The conflicting flow was calculated to be 672 vehicles/hour respectively. Using the estimated values of critical gap and follow-up headway, the capacity of the roundabout was found out to be 1357 vehicles/hour. The estimated capacity can be further utilized to determine the level of service of a particular roundabout. Similarly, other parameters e.g. waiting time, queue lengths etc. may also be estimated using the traffic data acquired via UAVs.

6.7 Discussion & Conclusion

In this paper, a case study has been presented in order to validate the applications of UAVs for traffic analysis, particularly in the scenario of roundabout flow analysis. A framework is presented for processing as well as analysis of traffic data acquired via small UAV. The vehicle trajectories are extracted based on previously proposed automated UAV video processing framework (Khan et al., 2017b). In addition to this, a methodology to employ the resulting trajectories for roundabout traffic flow analysis is proposed in this paper. The roundabout performance evaluation methodology is based on: (i) determining traffic volume via OD matrices for each leg, and (ii) analyzing level-of-service and drivers' behavior via gap-acceptance analysis. Based on the collected experimental data, a number of performance indicators were estimated. The generation of OD matrices and the estimation of critical gap parameter help in analyzing the interrupted flow conditions at an urban single-lane roundabout. The results of the analysis reflect the value of the flexibility and the bird-eye view provided by the UAV videos. Additionally, the proposed methodological analysis conducted on such experimental data may serve as a proof-of-concept for the actual traffic-specific applications of the UAV-acquired data. Such studies can be of particular interest not only for researchers but also for practitioners and traffic experts responsible for transport planning and management operations.

Further improvements to the UAV-based traffic monitoring and analysis system will be made in the future work. Although, UAVs have been demonstrated to be highly effective in traffic applications, still there are some limitations attached with the current technology. This includes factors ranging from hardware and software to legal aspects, such as the limited flight time of small UAVs along with some other concerns regarding the safety of flight operations. Additionally, some limitations also exist for the automated processing of the UAV videos. Depending on various reasons, false or missed detection errors can occur. All these factors need to be addressed in the future research in order to further optimize the use of UAVs for traffic data collection. Apart from it, the future research will also be focused on conducting a more detailed and comprehensive roundabout traffic analysis. The collection of larger datasets will also be necessary in order to increase the acceptability of UAVs for actual traffic studies. Additionally, the prospects of real-time processing of UAV data will also be explored.

6.8 References

Apeltauer, J., Babinec, A., Herman, D., & Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-3/W2, 9–15.

Barmpounakis, E N, Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In Transportation Research Board 95th Annual Meeting (p. 16).

Barmpounakis, Emmanouil N, Vlahogianni, E. I., & Golias, J. C. (2017). Unmanned Aerial Aircraft Systems for transportation engineering : Current practice and future challenges. International Journal of Transportation Science and Technology, 5(3), 111–122. https://doi.org/10.1016/j.ijtst.2017.02.001

Brilon, W., Koenig, R., & Troutbeck, R. J. (1999). Useful Estimation Procedures for Critical Gaps. Transportation Research, Part A, 33(3), 161–186.

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. IEEE Proceedings - Intelligent Transport Systems, 153(1), 11. https://doi.org/10.1049/ip-its:20055014

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing : A review. ISPRS Journal of Photogrammetry and Remote Sensing, 92, 79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013

Fisk, C. S. (1991). Traffic Performance Analysis At Roundabouts. Transpn. Res., 25B, 89–102.

Gao, H., Kong, S. L., Zhou, S., Lv, F., & Chen, Q. (2014). Automatic Extraction of Multi-Vehicle Trajectory Based on Traffic Videotaping from Quadcopter Model. Applied Mechanics and Materials, 552, 232–239.

Guido, G., Gallelli, V., Rogano, D., & Vitale, A. (2017). Evaluating the accuracy of vehicle tracking data obtained from Unmanned Aerial Vehicles. International Journal of Transportation Science and Technology, 5(3), 136–151. https://doi.org/10.1016/j.ijtst.2016.12.001

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. Handbook of Unmanned Aerial Vehicles, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017a). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature

Survey. Transportation Research Procedia, 22, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017b). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Record: Journal of the Transportation Research Board, 32(0), 1–15. http://dx.doi.org/10.3141/2626-04

Lee, J., Zhong, Z., Kim, K., Dimitrijevic, B., Du, B., & Gutesa, S. (2015). Examining The Applicability Of Small Quadcopter Drone For Traffic Surveillance And Roadway Incident Monitoring. In Transportation Research Board 94th Annual Meeting,Washington D.C.

M. Özuysal, Çalışkanelli, S. P., Tanyel, S., & Baran, T. (2009). Capacity prediction for traffic circles: applicability of ANN. Proceedings of the Institution of Civil Engineers - Transport, 162(4), 195–206.

Mahesh, S., & Rastogi, R. (2016). An approach for the estimation of entry flows on roundabouts. Transportation Research Procedia, 17, 52–62. https://doi.org/10.1016/j.trpro.2016.11.060

Mensah, S., Eshragh, S., & Faghri, A. (2010). A critical Gap Analysis for Modern Roundabouts. In Transportation Research Board 89th Annual Meeting.

Mussone, L., Matteucci, M., Bassani, M., & Rizzi, D. (2011). Traffic Analysis in Roundabout Intersections by Image Processing. IFAC Proceedings Volumes (Vol. 44). IFAC. https://doi.org/10.3182/20110828-6-IT-1002.02626

Oh, H., Kim, S., Shin, H. S., Tsourdas, A., & White, B. . (2014). Behaviour recognition of ground vehicle using airborne monitoring of unmanned aerial vehicles. Vehicles. International Journal of Systems Science, 45(12), 2499–2514.

Puri, A. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. Department of Computer Science and Engineering, University of South Florida,. https://doi.org/10.1.1.108.8384

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. Recent Advances in Civil Engineering and Mechanics, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. Procedia - Social and Behavioral Sciences, 111, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

St-Aubin, P., Saunier, N., & Miranda-Moreno, L.F., Ismail, K. (2013). Use of computer vision data for detailed driver behavior analysis and trajectory interpretation at roundabouts. Transportation Research Record: Journal of the Transportation Research Board, 2389, 65–77.

Transportation Research Board. (2000). HCM 2000 : Highway Capacity Manual. Washington, D.C.

Transportation Research Board. (2010). HCM 2010 : Highway Capacity Manual. Washington, D.C.

Vlahogianni, E. I. (2015). Computational Intelligence and Optimization for Transportation Big Data: Challenges and Opportunities. In Engineering and Applied Sciences Optimization: Volume 1. Springer International Publishing.

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In G. V. Duffy (Ed.), Digital Human Modeling: Applications in Health, Safety, Ergonomics and Risk Management: Ergonomics and Health: 6th International Conference (pp. 305–312).

Chapter 7

UAV–Based Traffic Analysis: Applications in Developing Countries (Pakistan)

This chapter consists of following paper:

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Mixed Traffic Conditions in Developing Countries (Pakistan), (In-Review).

7.1 Overview

This chapter further extends the traffic data collection applications of UAVs to mixed traffic situations in developing countries. The objective is to validate the applications of UAV video processing and analysis framework in a more challenging traffic scenario. In order to demonstrate the traffic analysis process, a case study based on data collected in Pakistan, is presented in this chapter. Traffic data has been collected via a small UAV for an urban roundabout and a T-intersection in Rawalpindi/Islamabad (Pakistan). The overall analytical methodology is based on the previously proposed UAV-based traffic analysis framework. The extraction of various traffic parameters and measures of performance help in highlighting the usefulness of UAVs for traffic analysis. The developing countries generally lack even in the basic infrastructure required for traffic monitoring and data collection. In this scenario, UAVs can serve as a useful apparatus for traffic data collection in developing countries. The results of the analysis at two study locations reflect the overall driving attitude and lack of implementation of traffic rules in developing countries, resulting in high congestion levels and serious safety concerns.

7.2 Abstract

The ever-growing levels of motorization rates and travel demands pose a critical challenge for transport managers, planners and governments in developed as well as developing countries. The mixed traffic conditions worsen off the situation even further in developing countries. The management and analysis of such high density mixed traffic is a challenge on its own. This calls for embracing a variety of state-of-the-art ITS technologies. Although, such technologies are becoming common rapidly in developed world, a lot of technologies still need to be introduced and applied practically in developing countries. The developing countries generally lack even in the basic infrastructure required for traffic monitoring and data collection. In this scenario, the Unmanned Aerial Vehicles (UAVs) commonly referred to as drones, can become a useful source of traffic data in such regions. This flexible and easy-to-deploy technology can yield data rich in both time and space. In order to demonstrate the applications of UAVs for traffic data collection specifically in developing countries, a case study based on data collected in Pakistan, is presented in this paper. Traffic data has been collected via a small UAV for an urban roundabout and a T-intersection in Rawalpindi/Islamabad (Pakistan). The overall analytical methodology is based on the previously proposed UAV-based traffic analysis framework (Khan et al., 2017b). The extraction of various traffic parameters such as OD matrices, critical gaps, average waiting times etc., help in highlighting the usefulness of UAVs for traffic analysis. The results of the analysis reflect the overall driving behavior and lack of implementation of traffic rules in developing countries. The future research will be focused on presenting and analyzing a larger-scale case study in a more complicated traffic environment.

Keywords: UAVs, Drones, Traffic Analysis, OD matrix, Critical Gaps, Image Processing, Developing Countries, Pakistan

7.3 Introduction

Since the last quarter of previous century, rapid urbanization has taken place in most of the cities around the world. The cities have grown at an enormous rate with a high percentage of population migrating towards urban metropolitans in order to improve their overall living standards. According to United Nations, the total urban population increased from 30% in 1950 to 54% in 2014. By 2050, the world population is projected to reach 10 billion out of which 66% shall be dwelling in cities (United Nations, 2015). This has given birth to a variety of immense challenges like traffic congestion, unemployment, and a scarcity of public facilities (Wu et al., 2015). In conjunction with the soaring urbanization rates, the trend of using motorized vehicles have also increased significantly. This trend has caused a major strain on the existing infrastructure. The situation gets even more intense in low-income and developing countries where the existing infrastructure and facilities are not capable of handling the exceeding demands. Additionally, the mixed traffic and various other factors such as insufficient regulations, minimal law enforcement, rash behaviour etc., further complicate the situation. All these factors necessitate the integration of various policy measures and state-of-the-art ITS technologies, in order to ensure an effective management of existing infrastructure. However, the analysis of high density mixed traffic is a challenging task, especially in the situation where there is very limited availability of traffic data.

Urban planning in general and traffic modelling in particular is highly dependent on the available traffic data. The quality of traffic data determines the performance of traffic models. Therefore, traffic data collection is termed as the primary step towards making informed decisions and devising traffic policies that ensure an efficient operation of the network. Traditionally, the data collection methodology in developing countries has been mostly based on manual observations. In recent years, fixed camera systems and induction loops have been installed at specific sites. Additionally, satellite and aerial imageries have also been used to collect data for analysis of particular areas. However, this data is usually not up-to-date and is quite expensive to collect updated data for a particular study. It is obvious that there is a significant technology gap between developed and developing countries. The governments have invested very little in developing data collection infrastructure. Therefore, in this scenario, there is a need for a budget-friendly and flexible technology that provides data relevant both in time and space.

Unmanned Aerial Vehicles (UAVs) commonly referred as drones, are already being used to monitor and collect traffic data in developed countries (Kanistras et al., 2015; Khan et al., 2017a; Puri, 2005). In the early years, only fixed-wing UAVs were used for traffic monitoring, however with the advancement of technology, the small rotary-wing type UAVs have become reliable and are being used abundantly for various applications. This non-intrusive, low-cost and easy-to-deploy technology can yield high-resolution rich traffic data. UAVs have the potential to become a useful source of traffic data, particularly in regions where there is no or very limited fixed sensor/camera infrastructure. As this is a recent technology and the actual applications, particularly for traffic data collection, have not yet fully developed (Barmpounakis et al., 2016; Puri, 2005), some considerable concerns and limitations still exist, such as limited battery time, safety concerns, etc. In order to streamline the processes involved in the application of UAV technology in traffic analysis, a universal guiding framework was proposed by Khan et al. (2017a). Additionally, a detailed methodological framework for the automated UAV traffic video processing and vehicle trajectory extraction has been presented in (Khan et al., 2017b). This paper presents a detailed application of the methodology presented by authors in (Khan et al., 2017b).

The principle aim of this paper is to demonstrate the applications of small UAVs for traffic data collection, specifically in developing countries where there is minimal data collection infrastructure available. For this purpose, a series of experimental UAV flights were conducted in the city of Rawalpindi/Islamabad, Pakistan. Traffic data has been collected via a small UAV for an urban roundabout and a T-intersection. With the help of two case studies, this paper attempts to evaluate the usefulness of UAVs as a mean of collecting valuable traffic data in developing countries. Based on our previously proposed UAV video processing and analysis framework, the collected traffic data is utilized to analyze the prevailing traffic conditions and to extract useful traffic information. This type of analysis conducted on UAV-based data may serve as a benchmark for further research into practical applications of UAV-based traffic analysis systems. With the significant increase in the number of UAV-based traffic studies expected in the coming years, such analytical studies based on an automated systematic framework could become a useful resource for practitioners and researchers alike.

This paper is structured as follows: firstly, the related work regarding the use of UAVs for traffic data collection specifically in developing countries, is discussed. This is followed by a brief description of the UAV-based traffic analysis framework. The next section contains a case study which is based on the traffic data collected in a Pakistani city using a small UAV. This section also elaborates the vehicle trajectory extraction process followed by a detailed traffic analysis. In the end, the paper is briefly concluded along with some critical discussion regarding the use of UAVs for traffic data collection, analytical applications of the framework, and proposed future developments.

7.4 Related Work

The number of UAV-based traffic analysis studies have increased during the last decade. Various literature survey studies (Barmpounakis et al., 2017; Colomina & Molina, 2014; Kanistras et al., 2015; Puri, 2005) have summarized these applications in a systematic manner. Overall, the UAV-based traffic–related studies can be categorized on the basis of 2 factors i.e. (i) type of UAV used, and (ii) type of video analysis technique used. Traditionally, fixed-wing UAVs were used commonly for traffic-related applications (Coifman et al., 2006) whereas in the last few years, the focus has shifted towards small multirotor UAVs (Barmpounakis et al., 2016; Khan et al., 2017b; Lee et al., 2015; Salvo et al., 2014b). On the other hand, the existing research can also be classified into 2 types, based on the video processing technique, i.e. (i) manual or semi-Automatic processing and (ii) automatic processing studies. The semi-automatic approach yields accurate results, but is time-consuming and laborious as the object has to be detected and tracked manually for a number of frames (Barmpounakis et al., 2016; Salvo et al., 2014b; Salvo et al., 2014a). Moreover, the studies based on automated processing approach consist of a quick processing and analysis procedure; ultimately leading to the real-time analysis of the UAV acquired data. Recently, the number of studies based on automated approach have increased (Apeltauer et al., 2015; Gao et al., 2014; Khan et al., 2017b; Oh et al., 2014; Zheng et al., 2015). The researchers have employed various state-of-the-art object detection and tracking algorithms in order to extract useful traffic information from the UAV-based traffic videos.

Various studies focusing on the analysis of roundabout traffic flow have been conducted over the years. Most of these studies have utilized traffic data acquired from traditional sources such as fixed camera systems. St-Aubin et al. (2013) employed traffic data from a fixed video camera system to analyze driver behavior at roundabouts in Canada. The authors extracted various traffic parameters by interpreting vehicle trajectories. Similarly, Mussone et al. (2011) have attempted to analyze roundabout performance by applying image processing techniques on fixed video camera data. Mahesh et al. (2016) examined the relation between entry and circulating roundabout flows in the scenario of a developing country i.e. India. In this regard, the authors estimated critical gaps for roundabouts. Additionally, Polus & Shmuel (1999) calculated critical gaps for roundabouts in 2 Israeli cities. All these studies have devised and demonstrated various ways to evaluate the performance of roundabouts. However, all of the existing studies mentioned up till now have been principally based on the fixed video camera systems, which generally produce data with high occlusion rate. Recently, few researchers have employed UAV-acquired data to conduct roundabout traffic flow and safety analyses studies. Khan et al. (2018) analyzed the performance of an urban roundabout by extracting the critical gaps. Salvo et al. (2014b) have analyzed driving behavior using UAV videos at an urban roundabout in Italy. The authors conducted a gap-acceptance analysis for vehicles entering the roundabout. Additionally, researchers have evaluated the accuracy of roundabout traffic data obtained via UAVs (Apeltauer et al., 2015; Guido et al., 2017).

Like roundabouts, various studies have also been conducted around the world for the analysis of unsignalized stop-controlled three-leg intersections(T-intersections). Various researchers have estimated parameters like average waiting times, critical gaps, queue lengths etc. in order to determine the level of service of the infrastructure (Fitzpatrick, 1991; Rodriguez, 2006; Salvo et al., 2014a). However, only a handful of studies have been conducted to analyze critical gaps and waiting times for vehicles approaching an un-signalized T-intersection in the scenario of developing countries. Dutta & Ahmed (2017) have conducted gap-acceptance analysis on 3 different uncontrolled T-intersections in Indian cities. The authors have focused on classifying the driving behaviour in heterogeneous traffic conditions. The study is based on data from fixed camera systems. However, no study employing the traffic data acquired via UAVs has been found.

7.5 UAV Video Processing & Analysis Framework

The UAV video processing and analysis framework streamlines all the steps necessary to produce useful traffic information form the collected data. The framework for the automatic extraction of multi-vehicle trajectories has been presented in detail by Khan et al. The processing framework is categorized into five modules i.e.: (i) pre-processing, (ii) stabilization, (iii) geo-registration, (iv) vehicle detection and tracking, and (v) trajectory management. The outputs generated from the processing modules i.e. the vehicle detections and trajectories, are used as an input for the traffic analysis module. The traffic analysis module differs with the scope and objectives of the study. Figure 1 illustrates the components of the UAV based traffic video data processing and traffic analysis framework. A detailed account of all the components and modules of this framework is given in the previous research. However, in this paper, only an overview of the UAV video processing framework is included with more focus on the analysis part.

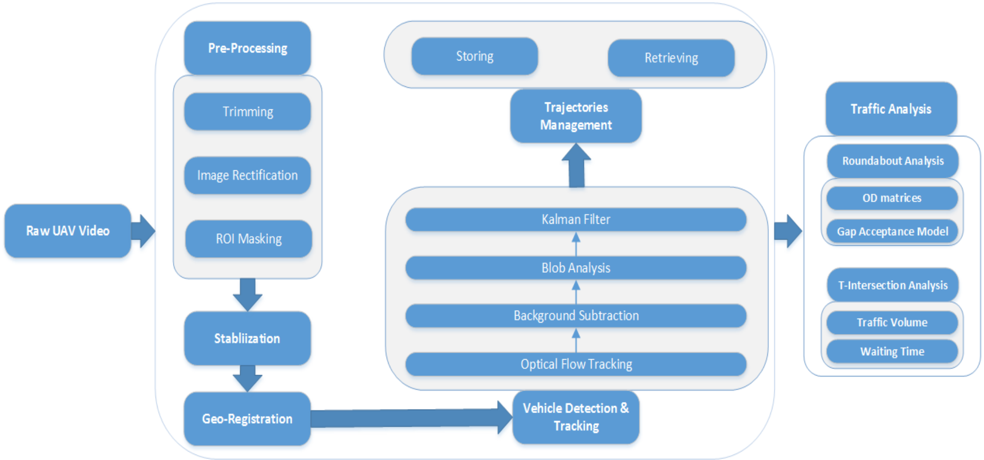


Figure 7.1: The UAV video processing and traffic analysis framework

The analysis of the UAV-based traffic footage involves some general pre-processing and stabilization procedures, mainly due to the instability and other limitations of the UAV platform. First of all, the recorded video is trimmed in order to retrieve only the useful part of the traffic video; the take-off, landing and other insignificant parts of the video are omitted. This is followed by the application of stabilization filters. The video is passed through some filters to eliminate or reduce the shakiness of the camera. Alternatively, a stationary object could be tracked through the entire video to stabilize the video by compensating for the minor movements. All these pre-processing and stabilization sub-tasks are necessary in order to make the video ready for the actual processing and analyses steps. Further, the geo-registration or geo-referencing process ensures an efficient conversion of the UAV acquired mono-vision 2D image coordinates into a real-world coordinate system in order to enhance the applicability of the extracted vehicle trajectory data. After the Geo-Referencing or calibration of the UAV images to a coordinate system, the detection and tracking of different road users is carried out with the help of the developed algorithm, implemented in C++ (OpenCV library). The vehicle detection and tracking algorithm consists of a number of sub-modules as illustrated in Figure 7.1. The efficiency and accuracy of this process plays a pivotal role in the overall accuracy of the study. The stabilized and calibrated UAV videos are fed into the detection and tracking module, and the outputs are stored accordingly in order to employ them further for traffic analysis.

The traffic analysis module utilizes the processed UAV video data to extract and estimate various traffic parameters and measures of performance. As explained before, this paper revolves around the analysis of traffic flow in the scenario of a developing country. The flow of traffic at a roundabout and at a T-intersection with merging/diverging traffic, is analyzed in order to demonstrate the applications of the collected data. Apart from the video processing module, Figure 7.1 also shows the overall traffic analysis module along with the specified sub-modules for different traffic flows. In both cases i.e. roundabout and T-intersection, traffic volume is an important parameter to be determined. For the roundabout traffic, origin-destination matrices are produced to quantify the traffic flowing through the roundabout. The approach for estimating traffic volume or counts is based on the detection of vehicles. This is done by placing virtual counters for each entry and exit point of the roundabout. The algorithm for these virtual counters is implemented in visual C++ and the computer vision library OpenCV. Additionally, further analysis consists of the calculation of critical gaps and average waiting times for the vehicles entering the roundabout and entering the major road (merging traffic) respectively. The details of the analytical process along with a case study, are given in the following sections.

7.6 Case Studies

As stated previously, the main aim of this paper is to validate the applicability of UAVs or drones for traffic analysis and management, particularly in developing countries with high density mixed traffic conditions. For this purpose, two detailed case studies are presented in this section. The whole experiment is centered around the UAV-based traffic data collection, processing and analytical framework. The section is divided into 2 sub-sections; the first sub-section describes the details of the data collection experiment, whereas the following sub-section contains the processing and analysis of the collected data. This data is then used for extracting vehicle trajectories and estimating various traffic parameters. The outputs can be used to determine the performance of a particular type of infrastructure and also to analyze the overall driving attitude/behaviour prevailing in the area of study.

7.6.1 Experiment Specifications

In order to develop case studies regarding the applications of UAVs for traffic analysis in developing countries, a data collection experiment was setup in Pakistan. A series of UAV flights were conducted over 2 sites in the urban city of Rawalpindi/Islamabad. Pakistan is a developing country with a population of over 200 million. Just like other developing countries, there is a sharp increase in urbanization and motorization rates over the last few decades. The two twin cities, Rawalpindi and Islamabad have also followed the similar trend, hence resulting in an increase of over two times in their population and the metropolitan area in a period of two decades (Pakistan Bureau of Statistics, 2017).

A couple of sites for the data collection experiment, were selected after careful considerations. All the privacy, safety and security concerns were thoroughly deliberated. The necessary permits were obtained from the concerned authorities. Location 1 as shown in Figure 7.2 comprises of a busy multi-lane roundabout. The selected roundabout provides an access to the surrounding residential as well as commercial areas. Additionally, it also handles the traffic crossing the area in order to approach the Islamabad Highway. On the other hand, Location 2 as shown in Figure 7.3 includes a T-intersection between a segment of Grand Trunk (G.T.) Road and the main entrance of a Housing/Commercial Society. As it is evident for pictures in Figure 7.3, the observed road segment is extremely busy as it handles local as well as highway traffic. There is also a school on the opposite side of the housing society's main gate. All these factors affect the movement of turning vehicles that are trying to enter the housing society.

Figure 7.2: The studied roundabout at Location 1; image from the UAV (left-side); Google earth satellite image (right-side)

Figure 7.3: The studied T-intersection at Location 2; image from the UAV (left-side); Google earth satellite image (right-side)

The selection of UAV equipment is also an important aspect while demonstrating the applications of small UAVs. It is critical to maintain a balance between costs and video quality. Hence, DJI's Phantom 4 Pro was employed to collect the traffic data. Phantom 4 Pro is a high-quality and reliable quadcopter UAV with a flying time of around 30 minutes. This UAV comes with a 20 megapixel camera, capable of recording a high resolution video i.e. 4K Resolution@ 25fps. Moreover, a user-friendly remote control system and smartphone application makes the UAV operation much simpler. The live-feed transmission (first-person-view) system helps in selecting the best camera angles of the study area. This particular UAV is an ideal option for conducting experimental studies as it provides a high quality and stable video data, required to demonstrate and validate the traffic-related UAV applications. Figure 7.4 below shows the Phantom 4 Pro UAV while taking-off and in flight respectively. The UAV flights were conducted on a Tuesday afternoon (16th January, 13:00 to 15:30 hours) to capture the working/school day afternoon rush hour. The weather was clear while the wind level was extremely mild as well (1-2 km/hour, Beaufort scale 1). The UAV was hovered (constant altitude, zero velocity) above the observed locations at the heights of 200 meters and 150 meters respectively. These heights provided coverage of the entire intersection as well as the connecting links. After a series of flights were conducted, a nearly 30-minute useful traffic video was obtained after excluding the take-off, landing and camera adjustment maneuvers.

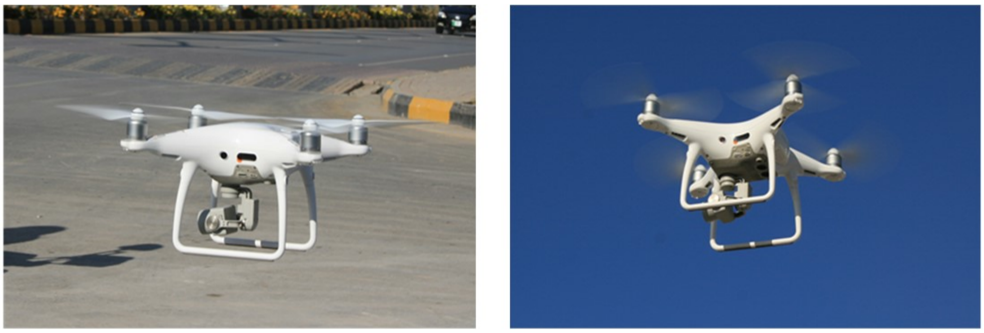


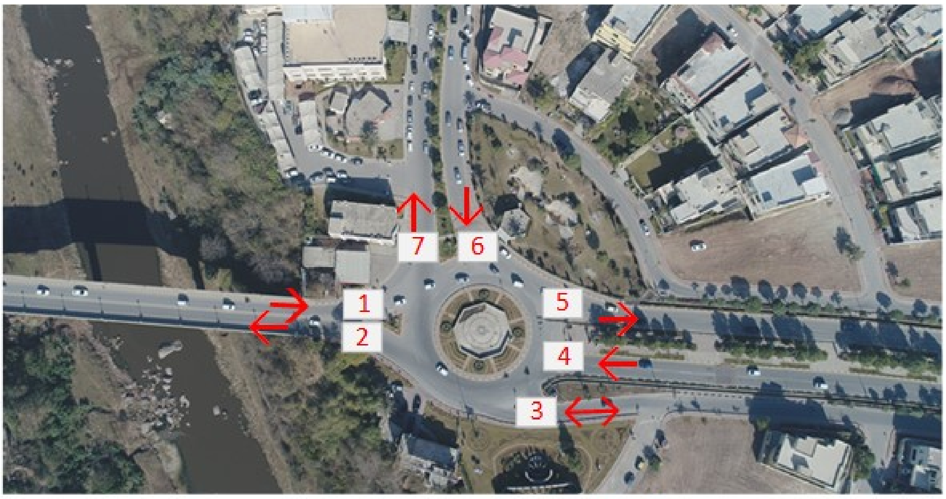
Figure 7.4: The Phantom4 Pro UAV; taking-off (left-side) and in-flight (right-side)

7.6.2 Traffic Analysis

In order to extract useful traffic information from the collected data, the UAV video processing and analysis framework was utilized. As per the modules of the framework, UAV data from the two selected study locations was pre-processed, stabilized and geo-referenced as well. The details of these processes can be found in (Khan et al., 2017). The next step was to analyze the traffic flow conditions by extracting road users' space-time information and estimating the suitable traffic parameters for each location. The UAV video processing and the results generation was done on an Intel ® Core ™ i5-4210M CPU@2.60GHz, with 4GB RAM and Windows 8.1 (64 bits).

The traffic analysis methodology for *Location 1's roundabout* is based on: (i) the determination of traffic volume via origin-destination matrix for each roundabout approach, and (ii) the estimation of critical gaps to analyze the driving attitude and the overall performance of the roundabout. On the other hand, the analytical methodology for *Location 2's T-junction* includes: (i) the quantification of merging, diverging and through traffic, and (ii) the estimation of waiting times for merging traffic. Additionally, the analysis points out some serious traffic safety issues or conflicts observed during the process at both locations.

With regards to *Location 1*, firstly the number of vehicles approaching and crossing the roundabout, is estimated with the help of an origin-destination matrix. The determination of traffic volume provides a good overview of the level of service and overall performance of a roundabout. For this purpose, the origin-destination (OD) matrices are widely used to analyze traffic counts across different approaches of various types of infrastructural elements, particularly roundabouts. In order to create OD matrix for the roundabout at *Location 1*, the developed algorithm was employed. The traffic count was made by placing a virtual counter at each approach of the roundabout. These virtual counters provide an accurate sum of vehicles entering or leaving the roundabout. It is worth mentioning here that the OD matrix did not account for motor bikes, however their influence was incorporated in the overall flow analysis of the system. The estimated parameters such as critical gaps and average waiting times were affected by the presence of motor bikes. Figure 7.5 displays the virtual counters at each leg, along with the estimated OD matrix for the roundabout under study for a period of 5 minutes and 27 seconds. The figure also illustrates the direction of traffic, hence identifying the traffic originating and terminating approaches. It is obvious from OD matrix that the roundabout legs, numbered 6 and 7, are the busiest originating and terminating approaches respectively. The maximum traffic originates to and from the direction of Bahria Town Corporate Office. This approach links the traffic to the main residential and commercial areas inside Bahria Town, while also providing an access to the crossing traffic between Islamabad Highway and other surrounding residential schemes. It is also worth mentioning that the automatic traffic counts were verified by manual counts and only a negligible amount of error was detected, specifically in case of vehicles partially covered by shadows.



		Destination				
	Counters	2	3	5	7	Total
Origin	1	1	11	32	53	97
	3	15	0	1	16	32
	4	23	0	1	35	59
	6	39	10	53	12	114
	Total	78	21	87	116	302

Figure 7.5: Traffic counts based on origin-destination matrix, at roundabout location.

In addition to traffic counts, the collected UAV video data can be used to estimate other traffic indicators such as waiting times, queue lengths etc. As proposed in previous research (Khan et al., 2018), the data can also be used to develop gap acceptance models in order to analyze the driving behavior and also the overall performance of the roundabout. In this paper, similar methodology is re-applied to the scenario of roundabout traffic in a developing country. Modified Raff's method (Brilon et al., 1999; Mensah et al., 2010) has been used to estimate the critical gap which is the minimum time gap between circulating traffic that allows the approaching vehicle to merge into the roundabout traffic stream (Özuysal et al., 2009). The critical gap value for the roundabout approach number 4 (Figure 7.6) has been estimated as various conflicts were observed at this approach. The graph in Figure 7.6 illustrates the number of gaps accepted and rejected by the approaching drivers for each time gap interval. The gap acceptance and rejection are inversely proportional to each other while the intersection point of the two plots represent the critical gap. For the experimental Pakistani case, the intersection point or the critical gap is found to be approximately around 3 seconds. It is also important to mention that the Highway Capacity Manual

(Transportation Research Board, 2000) provided typical average value of critical gap is 4.1 to 4.6 seconds. Therefore, it is obvious that the estimated critical gap is significantly less than the HCM typical value. This highlights the driving attitudes and the overall performance of the infrastructure, particularly at the observed locations and generally in developing nations. The mixed traffic scenario further intensifies the traffic situation. Additionally, the values of critical gap can also be compared with the values estimated in existing roundabout studies, mostly based on data collected via fixed cameras or other traditional equipment. Mahesh et al. (20) estimated the critical gap values of 2.43 and 2.51 seconds for 2 urban roundabouts in the scenario of another developing country i.e. India. Similarly, critical gaps for roundabouts in 2 Israeli cities were calculated (Polus & Shmuel, 1999). The estimated values were 4.1 and 4.2 seconds. Moreover, the critical gap in (Khan et al., 2018) was found out to be 3.83 seconds for a single-lane urban roundabout in Belgium. The comparison of all these values highlights the fact that estimated critical gap value is in proportion with the values provided in the existing literature. The proposed UAV-based methodology can be effectively used for the estimation of such parameters.

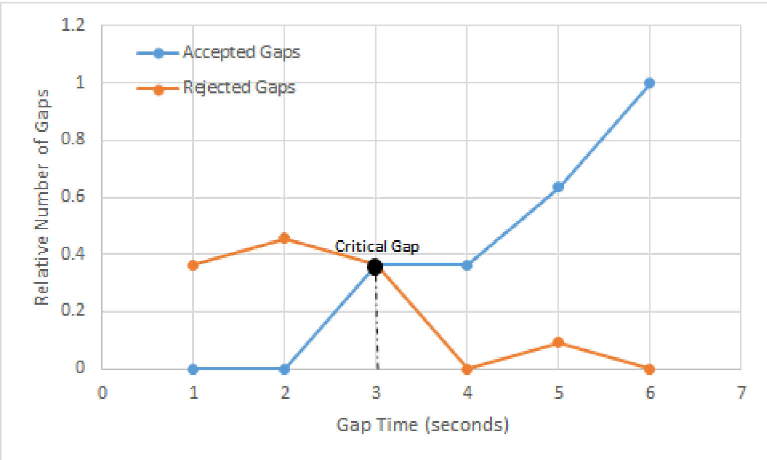
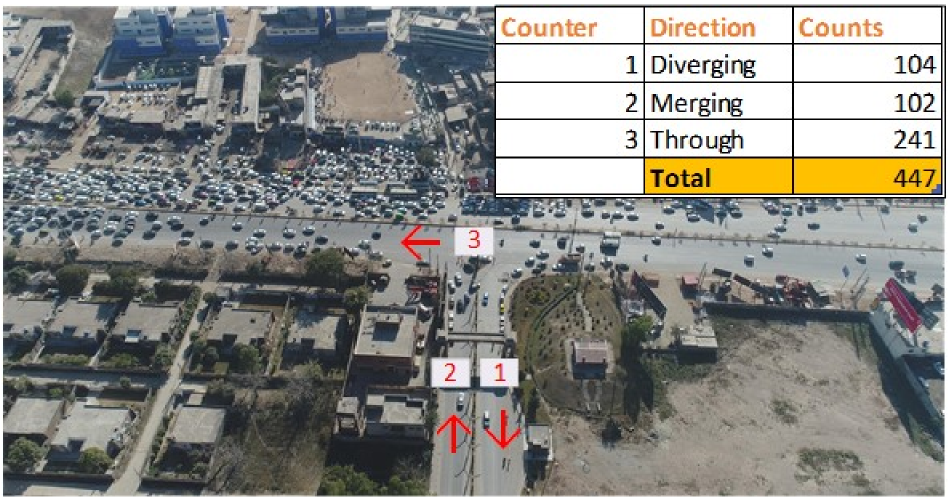


Figure 7.6: The critical gap estimation based on the plots of accepted and rejected gaps

As explained before, Location 2 comprises of the main entrance/exit community gate and a busy highway with some commercial and educational activities in the vicinity. This forms a T-intersection at this site, with vehicles merging and diverging with the through traffic. Similar to Location 1 analysis, the first part of the analytical process is to estimate the traffic movement across the area of interest. For this purpose, the traffic counts are made for the merging (exiting from gate), diverging (entering the gate) and through Highway traffic. The virtual counters are placed at 3 positions as shown in Figure 7.7. This results in the quantification of traffic in each direction. Figure 7.7 shows the total counts for the observed time period of 5 minutes and 27 seconds. The table in Figure 7.7 indicates the traffic volume at the studied T-intersection. It can be seen that the amount of vehicles merging and diverging are almost equal while a large number of vehicles travel straight on the Highway (major road).



Counter	Direction	Counts
1	Diverging	104
2	Merging	102
3	Through	241
	Total	**447**

Figure 7.7: Traffic counts at Location 2’s T-intersection.

Furthermore, the merging/diverging behaviour of the turning traffic is also an important aspect that influences the overall traffic flow state. For this purpose, the collected UAV-based traffic data at Location 2, is employed to extract the waiting times of the merging traffic that tries to enter the traffic stream at major road. The bar chart in Figure 7.8 shows the waiting times of vehicle over a 5-minute time interval. The estimated average waiting time shown as blue dashed-line, turns out to be 22.57 seconds. This value reflects a certain level of congestion at the major road during the observed time period. It was identified through the video analysis that the Highway (major road) faced a significant amount of congestion and blockage during the afternoon rush hour, mainly due to the nearby school’s off-time. This affected the merging traffic as well, hence the higher waiting times. According to the Highway Capacity Manual (Transportation Research Board, 2000), the average waiting time of 22.57 seconds indicates a level of service (LOS) D at the intersection. Therefore, the intersection requires some improvement measures, particularly during the rush hours. In this scenario, alternatives' analysis with the help of microsimulation models can assist in providing a long-term solution for the problem.

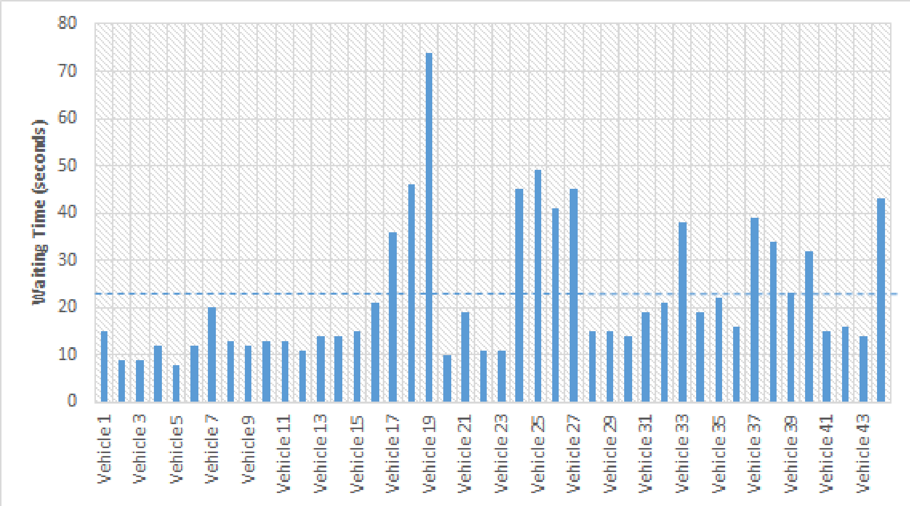


Figure 7.8: Waiting times for merging traffic on the major road.

Apart from the traffic flow analysis, several serious traffic safety issues were also observed visually at both locations. Vehicles traveling in the wrong direction in order to make shortcuts, random behaviour of crossing pedestrians, illegal parking are some of the observed traffic issues that influence not only the traffic flow but also the safety of the people involved. This also reflects the lack of implementation of traffic laws as well as the general attitude and the level of awareness of public.

The identification of these issues is the first step towards the rectification of the problem. Further detailed analysis and behavioral studies are required in order to understand the situation comprehensively.

7.7 Discussion & Conclusion

This paper presents a systematic approach, specifically aimed to study and analyze traffic environment in high density mixed traffic situations in developing countries. For this purpose, an experimental UAV-based traffic dataset has been collected in an urban city of Rawalpindi/ Islamabad, Pakistan. The collected UAV data has been processed and analyzed based on the proposed framework. The processed data i.e. the vehicle detections and tracks, are extracted based on the improved version of the previously proposed UAV video processing and analysis framework (Khan et al., 2017b). Moreover, an analytical methodology to utilize outputs from the processing modules, is also presented in this paper.

The proposed methodology focuses on analyzing traffic flow state for different infrastructural elements. On this basis, the traffic analysis methodology is divide into 2 parts, i.e. (i) roundabout analysis, and (ii) T-intersection analysis. The roundabout traffic flow analysis is based on: (i) the determination of traffic volume via origin-destination matrix for each roundabout approach, and (ii) the estimation of critical gaps to analyze the driving attitude and the overall performance of the roundabout. On the other hand, the traffic flow analysis of T-intersection includes: (i) the quantification of traffic in each direction (merging, diverging and through), and (ii) the estimation of waiting times for merging traffic. The proposed methodology is demonstrated and validated with the help of two case studies. Based on the collected experimental data, a number of performance indicators were estimated. Overall, the determination of traffic volume and other parameters help in analyzing and interpreting the interrupted flow conditions. The comparison of the estimated parameters with the typical values provided in Highway Capacity Manual and also with the existing literature, concludes that the proposed UAV-based methodology can be effectively used for the estimation of various parameters. The UAV technology can be employed for data collection, specifically in the scenario of developing countries where there are very limited sources of traffic data collection. In this regard, the mobility and the bird-eye view provided by the UAV videos make this technology even more attractive. Additionally, the proposed methodological analysis conducted on such experimental data may serve as a benchmark or proof-of-concept for the actual traffic-specific applications of the UAV-acquired data in developing countries. Such studies can be of particular interest not only for researchers but also for practitioners and traffic experts responsible for transport planning and management operations.

Further improvements to the UAV-based traffic monitoring and analysis system will be made in the future work. Although, UAVs have been demonstrated to be highly effective in traffic applications, still there are some limitations attached with the current technology. This includes factors ranging from hardware and software to legal aspects, such as the limited flight time of small UAVs along with some other concerns regarding the safety of flight operations. Additionally, some limitations also exist for the automated processing of UAV videos, especially for the cases of developing countries with a high density mixed traffic and unexpected driver behaviour. Errors such as wrong or lost detections can occur due to multiple reasons. As compared to the Belgian case studies, the developed vehicle detection algorithm resulted in a much higher error rate in the Pakistani case, thereby resulting in high post-processing time. It is also worth mentioning that the automatic traffic counts were verified by manual counts. In case of roundabout (Location 1), only a negligible amount of error was detected. This was mainly due to vehicles that were partially covered by shadows. On the other hand, the congested state and high traffic density at T-intersection (Location 2) posed a challenge for the developed vehicle detection algorithm. A certain level of post-processing was conducted in order to cater for the errors and to achieve the desired accuracy standards. All these factors need to be addressed in the future research in order to reduce the processing times and further optimize the use of UAVs for traffic data collection. Apart from it, the classification of road users must also be incorporated in future, especially for mixed traffic environments. The future research will also be focused on presenting more complicated case studies with a more detailed and comprehensive analysis of various infrastructural elements. Additionally, the prospects of microsimulation modelling in the scenario of developing countries, will also be explored.

7.8 References

Apeltauer, J., Babinec, A., Herman, D., & Apeltauer, T. (2015). Automatic Vehicle Trajectory Extraction for Traffic Analysis from Aerial Video Data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-3/W2*, 9–15.

Barmpounakis, E N, Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In *Transportation Research Board 95th Annual Meeting* (p. 16).

Barmpounakis, Emmanouil N, Vlahogianni, E. I., & Golias, J. C. (2017). Unmanned Aerial Aircraft Systems for transportation engineering : Current practice and future challenges. *International Journal of Transportation Science and Technology*, *5*(3), 111–122. https://doi.org/10.1016/j.ijtst.2017.02.001

Brilon, W., Koenig, R., & Troutbeck, R. J. (1999). Useful Estimation Procedures for Critical Gaps. *Transportation Research, Part A*, *33*(3), 161–186.

Coifman, B., McCord, M., Mishalani, R. G., Iswalt, M., & Ji, Y. (2006). Roadway traffic monitoring from an unmanned aerial vehicle. *IEE Proceedings - Intelligent Transport Systems*, *153*(1), 11. https://doi.org/10.1049/ip-its:20055014

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing : A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *92*, 79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013

Dutta, M., & Ahmed, M. A. (2017). Gap acceptance behavior of drivers at uncontrolled T-intersections under mixed traffic conditions. *Journal of Modern Transportation*, *26*(2), 119–132. https://doi.org/10.1007/s40534-017-0151-9

Fitzpatrick, K. (1991). Gaps Accepted at Stop-Controlled Intersections. *Transportation Research Record*, *1303*, 103–112.

Gao, H., Kong, S. L., Zhou, S., Lv, F., & Chen, Q. (2014). Automatic Extraction of Multi-Vehicle Trajectory Based on Traffic Videotaping from Quadcopter Model. *Applied Mechanics and Materials*, *552*, 232–239.

Guido, G., Gallelli, V., Rogano, D., & Vitale, A. (2017). Evaluating the accuracy of vehicle tracking data obtained from Unmanned Aerial Vehicles. *International Journal of Transportation Science and Technology*, *5*(3), 136–151. https://doi.org/10.1016/j.ijtst.2016.12.001

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2015). Survey of unmanned aerial vehicles (uavs) for traffic monitoring. *Handbook of Unmanned Aerial Vehicles*, (October 2015), 2643–2666. https://doi.org/10.1007/978-90-481-9707-1_122

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017a). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. *Transportation Research Procedia*, *22*, 541–550. https://doi.org/10.1016/j.trpro.2017.03.043

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017b). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. *Transportation Research Record: Journal of the Transportation Research Board*, *32*(0), 1–15. http://dx.doi.org/10.3141/2626-04

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y., Yasar, A.-H., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts. *Procedia Computer Science*, *130*, 636–643. https://doi.org/10.1016/j.procs.2018.04.114

Lee, J., Zhong, Z., Kim, K., Dimitrijevic, B., Du, B., & Gutesa, S. (2015). Examining The Applicability Of Small Quadcopter Drone For Traffic Surveillance And Roadway Incident Monitoring. In *Transportation Research Board 94th Annual Meeting,Washington D.C*.

M. Özuysal, Çalışkanelli, S. P., Tanyel, S., & Baran, T. (2009). Capacity prediction for traffic circles: applicability of ANN. *Proceedings of the Institution of Civil Engineers - Transport*, *162*(4), 195–206.

Mahesh, S., Ahmed, A., & Rastogi, R. (2016). An approach for the estimation of entry flows on roundabouts. *Transportation Research Procedia*, *17*, 52–62. https://doi.org/10.1016/j.trpro.2016.11.060

Mensah, S., Eshragh, S., & Faghri, A. (2010). A critical Gap Analysis for Modern Roundabouts. In *Transportation Research Board 89th Annual Meeting*.

Mussone, L., Matteucci, M., Bassani, M., & Rizzi, D. (2011). *Traffic Analysis in Roundabout Intersections by Image Processing*. *IFAC Proceedings Volumes* (Vol. 44). IFAC. https://doi.org/10.3182/20110828-6-IT-1002.02626

Oh, H., Kim, S., Shin, H. S., Tsourdas, A., & White, B. . (2014). Behaviour recognition of ground vehicle using airborne monitoring of unmanned aerial vehicles. *Vehicles. International Journal of Systems Science*, *45*(12), 2499–2514.

Pakistan Bureau of Statistics. (2017). *6th Population & Housing Census 2017*.

Polus, A., & Shmuel, S. (1999). Entry Capacity at Roundabouts and Impact of Waiting Times. *Road and Transport Research*, *8*(3), 43–54.

Puri, A. (2005). A Survey of Unmanned Aerial Vehicles(UAV) for Traffic Surveillance. *Department of Computer Science and Engineering, University of South Florida,*. https://doi.org/10.1.1.108.8384

Rodriguez, J. J. R. (2006). *Gap Acceptance Studies and Critical Gap Times forTwo-Way Stop Controlled Intersections in the Mayaguez Area.* (Master Thesis). University of Puerto Rico, Mayaguez, Puerto Rico.

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. *Recent Advances in Civil Engineering and Mechanics*, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. *Procedia - Social and Behavioral Sciences*, *111*, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

St-Aubin, P., Saunier, N., & Miranda-Moreno, L.F., Ismail, K. (2013). Use of computer vision data for detailed driver behavior analysis and trajectory interpretation at roundabouts. *Transportation Research Record: Journal of the Transportation Research Board*, *2389*, 65–77.

Transportation Research Board. (2000). *HCM 2000 : Highway Capacity Manual.* Washington, D.C.: Transportation Research Board.

United Nations, Department of Economic and Social Affairs, Population Division. (2015). *World Urbanization Prospects: The 2014 Revision* (No. (ST/ESA/SER.A/366)).

Wu, W. ., Zhao, S. ., & Zhu, C. (2015). A Comparative Study of Urban Expansion in Beijing, Tianjin and Shijiazhuang over the Past Three Decades. *Landscape and Urban Planning, 134*, 93–106.

Zheng, C., Breton, A., Iqbal, W., Sadiq, I., Elsayed, E., & Li, K. (2015). Driving-Behavior Monitoring Using an Unmanned Aircraft System (UAS). In *G. V. Duffy*

(Ed.), Digital Human Modeling: Applications in HSE and Risk Management: Ergonomics and Health: 6th International Conference (pp. 305–312).

Chapter 8

UAV–Based Traffic Analysis: Development and Calibration of Microsimulation Models

This chapter consists of following paper:

Khan, M. A., Raza, M. M., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: Development and Calibration of Microsimulation Models, Transportation. (In-Review).

8.1 Overview

This chapter explores a new application of the traffic data collected via small UAVs. The chapter presents a methodology to utilize the UAV-based traffic data for the development as well as for the calibration of microsimulation models. The main objective is to examine the feasibility of microsimulation model development from UAV-based traffic data. For this purpose, two case studies comprising of a roundabout and a signalized intersection, have been presented based on the data collected via UAVs in Sint-Truiden, Belgium. The base models are developed using PTV VISSIM. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework (Khan et al., 2017b), are utilized for the microsimulation model development and calibration. The calibration process is based on various measures of effectiveness and validation parameters. Acceptable calibration targets have been defined for both roundabout and signalized intersection models. The results show that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implies that UAVs can become a useful source of traffic data for the development and calibration of microsimulation models.

8.2 Abstract

Microsimulation modelling has been widely used in recent years for transportation planning and traffic engineering. Generally, microsimulation model development requires extensive data with high level of detail. Therefore, it is not easy to collect traffic data for microsimulation modelling. Over the years, several data collection techniques have been employed for collecting inputs for microsimulation models. In the recent years, Unmanned aerial vehicles (UAVs) have also been employed for traffic data collection. However, the UAV acquired traffic data has not yet been employed for microsimulation modelling. This paper aims to demonstrate and validate the applications of traffic data collected via small UAVs for the development and calibration of microsimulation models. For this purpose, two case studies comprising of a roundabout and a signalized intersection, have been presented based on the data collected via UAVs in Sint-Truiden, Belgium. The base model for the 2 sites has been developed by using PTV VISSIM. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework (Khan et al., 2017b), are utilized for the microsimulation model development and calibration. Using the UAV-based data, the model is calibrated by selecting various parameters and measures of effectiveness (MOEs). Acceptable calibration targets have been defined for both roundabout and signalized intersection models. The results show that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implies that UAVs can become a useful source of traffic data for the development as well as calibration of the microsimulation models. Such studies can become a pioneer in establishing the practical applications of UAVs for microsimulation studies. It can serve as a reference for future studies. The future research will be consisting of a more in-depth analysis of the simulation parameters and measures of effectiveness.

8.3 Introduction

Increasing traffic demands and congestion levels have become one of the most critical challenges faced by concerned authorities and governments all over the world. The rising motorization levels have further magnified the challenges. In order to achieve the goals of sustainability, various policy measures have to be devised. The transport planners and managers have to balance the traffic demand and supply in order to ensure smooth and efficient traffic operations. For this purpose, it is necessary to analyze existing traffic trends and network performance. Analytical modeling can help in analyzing the current traffic situation as well as projecting the future demands. The traffic analytical models can be generally categorized into 3 types, i.e. macroscopic, mesoscopic and microscopic models. The macroscopic modeling, though effective for large networks, doesn't include details of traffic behavior. However, microsimulation models have the ability to model individual traffic behaviour in a stochastic environment. Subsequently, they require more computation time and effort to simulate the actual traffic conditions. The intention of managing bigger networks with comparatively less computational times has directed to the evolution of another approach of traffic simulation i.e. mesoscopic approach. Nevertheless, this approach is not much precise in the illustration of traffic behavior. However, microsimulation traffic modelling or simulated traffic models have now been mainly used as a technique to study traffic-engineering and transport-planning situations (Khan et al., 2017a).

In recent years, a lot of efforts have been made for development of microsimulation models. Microsimulation has been used in different areas of research such as evaluating redistribution policy (Bourguignon & Spadaro, 2006), social welfare programs (Citro & Hanushek, 1994), evaluating public policies (Spadaro & Fundación BBV, 2007) and evaluating alternative health care strategies financing strategies (Hennessy et al., 2015). The major expansion is being observed in the use of microsimulation model for traffic engineering and planning practices (Dowling et al., 2004).

In developing a microsimulation model, data requirements are similar in scope as data required in conventional mesoscopic or macroscopic models, however, it is more intensive in detail. Whereas, specification of local parameters controlling the microscopic lane changing, car-following and gap acceptance models is another major additional element in model development process (Halcrow & TRL, 2006). The required data for developing a microsimulation model includes link-node diagram, geometry data (no. of lanes, lane width, curvature etc.), traffic control data, traffic demand data, driver's behavior data and simulation run control data. Over the years, several techniques have been employed for traffic data collection. The most commonly used methods for data collection include manual observations, fixed camera-based data collection, probe vehicles and aerial photographs.

With the passage of time, many technological advancements have been observed in the data collection process. In the recent years, Unmanned aerial vehicles (UAVs) have also been employed for traffic data collection. Traditionally, fixed-wing UAVs were used for traffic data collection, but lately the trend has shifted towards the small multirotor UAVs. This is due to improved technology as well as wide commercial availability. As compared to traditional data sources e.g. manual collections, fixed video cameras etc., UAVs are flexible and provide a wide coverage of the area of interest (Kanistras et al., 2013; Puri, 2005). Also, other aerial equipment such as satellites and piloted aircrafts have been proven to be inefficient due to several issues regarding quality, cost and safety.

Since, the UAV acquired traffic data has not yet been employed for microsimulation modelling, this paper is focused on demonstrating the applicability of UAV based traffic data for the development and calibration of microsimulation models. For this purpose, two case studies have been developed based on the data acquired via UAVs for signalized intersection and roundabout. The UAV-based traffic data has been collected in the city of Sint-Truiden, Belgium. The base model for the 2 sites has been developed by using PTV VISSIM. Using the UAV-based data, the model is calibrated by selecting various parameters and measures of effectiveness (MOEs). Acceptable calibration targets have been defined for both roundabout and signalized intersection models. The results show that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implies that UAVs can become a useful source of traffic data for the development as well as calibration of the microsimulation models. Such studies can become a pioneer in establishing the practical applications of UAVs for microsimulation studies. The study can be valuable for transport planners, researchers and policy makers.

This paper is organized as follows: first of all, an overview of the existing microsimulation studies and the employed data collection methodologies is given. This is followed by a description of the proposed methodology for the utilization of UAV-based traffic data for microsimulation modelling. The succeeding section presents a couple of case studies in order to demonstrate and validate the simulation modelling applications of UAV-based traffic data. The models for a roundabout and a signalized intersection are developed and calibrated. Finally, the paper concludes with a brief discussion regarding the whole process. This section also gives an outline for the proposed future research.

8.4 Related Work

As mentioned earlier, a detailed dataset is required for the development of microsimulation models. Over the years, different data collection methods have been used to develop and calibrate microsimulation models. Many studies have been conducted regarding data collection methods for traffic simulation. Vehicle trajectory data provide detail information that can be utilized to model car-following, gap-acceptance and lane changing behaviors. According to Alexiadis (2006), video based data collection has become more prominent for transportation researchers in recent years. In 2001, efforts were made to collect vehicle trajectory data for microsimulation modelling in Columbus, Ohio. A team was designed which used mobile, pole-mounted camera system to collect data (Skabardonis, 2005). Similarly, Ardö et al. (2012) conducted a study employing automated video analysis to acquire vehicle trajectory data, as a cost effective traffic data solution. Mathew & Radhakrishnan (2010) used video data for calibration of model. Whereas, probe vehicle method has also been used for this purpose (Ben-Akiva et al., 2002; Fellendorf & Vortisch, 2001). In another study, Ben-Akiva et al. (2002) used detector data and aerial photographs for collecting data.

Researches have endeavored to employ microscopic trajectory data in calibration process to enhance the credibility and reliability of traditional traffic simulation calibration process. For instance, Brockfeld et al. (2004) aligned several car following models utilizing information offered by ten test vehicles outfitted with Global Positioning System (GPS). Lu et al. (2016) used video-based method for calibration of car-following models in VISSIM. Similarly, Fellendorf & Vortisch (2001) performed microscopic calibration in VISSIM. A procedure was proposed to calibrate commercial motor vehicle distribution using CORSIM by Schultz & Rilett (2005). Likewise, Ben-Akiva et al. (2002) used MITSIMLab for calibration of microscopic model by using optimization techniques. Moreover, Sheu & Ritchie (2001) presented a stochastic traffic model, calibrated by using video data of two-lane road. However, all the mentioned existing studies have employed either fixed camera videos or other traditional equipment to collect data for their simulation experiments.

UAVs have been used for various purposes such as remote sensing and mapping (Everaerts, 2008), contemporary conflicts (Kreps & Kaag, 2012), geo-rectified mosaics (Turner et al., 2012), as well as monitoring soil erosion (d'Oleire-Oltmanns et al., 2012). Several traffic related studies have also been conducted using unmanned aerial vehicles (Barmpounakis et al., 2016; Khan et al., 2017b, 2018a, 2018b; Salvo et al., 2014b, 2014a). All these researchers acquired traffic flow data by means of unmanned aerial vehicles. Moreover, (Khan et al., 2017a) states that UAVs are considered to be most dynamic and multidimensional evolving technologies of modern era. The bird-eye view data enables the researchers to study correlation between flow, speed and density.

8.5 Methodology

The main focus of this paper is to demonstrate and validate the applications of UAV-based traffic data for microsimulation modelling and calibration. After detailed literature review, it was found that the UAV-based traffic data has not yet been employed for the development and calibration of microsimulation models. Therefore, there is a need to examine the feasibility of using traffic data obtained via UAVs for model development. For this purpose, a methodology has been proposed that streamlines the processes involved in utilizing the UAV-based traffic data for microsimulation modelling. Overall, the methodology is based on the general microsimulation modelling approach, however certain modifications are made to cater for the UAV data. Figure 8.1 illustrates the proposed methodology for the integration of UAV-based traffic data with microsimulation modelling.

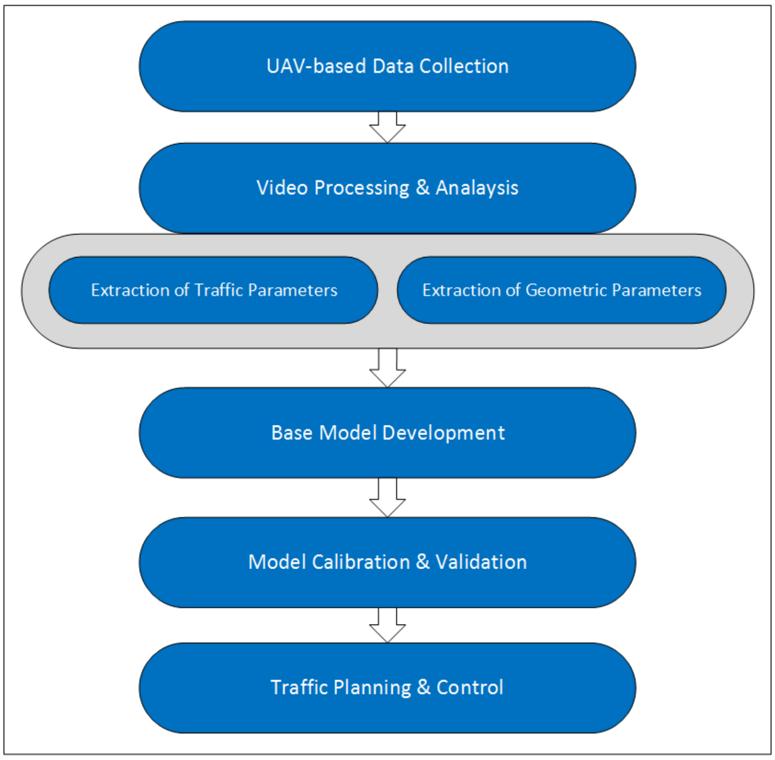


Figure 8.1 UAV-based microsimulation modelling and calibration framework

Firstly, the traffic data for the study area is collected via an unmanned aerial vehicle (UAV). This data is used to extract traffic parameters and geometric information. The previously proposed UAV-based video processing and vehicle trajectory extraction framework (Khan et al., 2017b) is used for this purpose. The extracted traffic information is then as an input for base model development. Various features and attributes of the study area are added during this process. The base model is then calibrated in order to make it as close to reality as possible. For this purpose, various parameters are altered and checked against the defined criteria. If the selected measures of effectiveness fall within the calibration targets, the model is said to be calibrated and replicates the real-life traffic situation. The calibrated model can be utilized for various traffic planning and control related projects. The proposed methodology is validated with the help of case studies in the following sections.

8.6 Case Study

The main objective of this paper is to demonstrate the potential applications of small UAVs for microscopic traffic model development and calibration. In this regard, two case studies are presented to validate the proposed methodology for employing UAV-based traffic data. The data acquired via small UAV is utilized for base model development as well as for the calibration and validation of the developed model. The following sub-sections describe the whole experiment in detail.

8.6.1 UAV-based Data Collection & Processing

To obtain an experimental dataset for the validation of the proposed framework for microsimulation model development and calibration, a series of UAV flights were conducted in the city of Sint-Truiden (Belgium). Two sites were selected in order to collect traffic data via small UAVs. The first site consisted of an urban roundabout as shown in figure 8.2. The selected roundabout is situated in a busy urban commercial area, having a football stadium and rail-station in the vicinity. The roundabout consists of single-lane approaches from each side, whereas one leg also has a right turning lane just before the roundabout in order to minimize the traffic flowing into the roundabout. On the other hand, the second site comprised of a four-legged suburban signalized intersection. The selected intersection as shown in figure 8.2, is a linking junction between the Belgian national highways N80 (speed limit: 120 km/h) and N718 (speed limit: 90 km/h), with two lanes in either direction. The specified four-legged intersection primarily handles the traffic leading to and from the city of Hasselt into the center and suburbs of Sint-Truiden.

Figure 8.2 The data collection sites: UAV view of the roundabout (left-side); UAV view of the signalized intersection (right-side).

A detailed flight planning process was carried out before the actual conduction of the flights. The UAV flights were conducted in order to capture the early-evening rush hour on a Friday afternoon. Importantly, the weather and wind conditions were perfect for the UAV flights i.e. mostly clear skies with gentle wind level (18km/hour, Beaufort scale 3). The Argus-One (from Argus-Vision) UAV, as shown in figure 8.3, was hovered i.e. maintaining a constant altitude with zero velocity, over the study area at 80m and 60m heights. The series of UAV flights resulted in a nearly 30-minute useful traffic video after trimming the take-off and landing maneuvers of the UAV.

Figure 8.3 The Argus-one UAV: (left) take-off position, and (right) in-flight

In order to extract various traffic parameters, the previously proposed UAV-based video processing and analysis framework was employed (Khan et al., 2017b). The collected UAV traffic data was processed and useful traffic information was obtained through the UAV videos. The extracted parameters were then used as an input for the development and calibration of microsimulation models for both case studies. It is also important to mention here that the analysis of UAV traffic videos was done on an Intel® Core™ i5-4210M CPU at 2.60 GHz, with 4-GB RAM.

8.6.2 Roundabout Model

8.6.2.1 Base model development

The base model development is the first and the foremost step for conducting a microsimulation study. For this purpose, a study area is defined for which the base model must be developed. The software used for base model development and this research is PTV VISSIM 8.0. To develop a base model, geometric data of the study area is required. The UAV-acquired imagery is useful for extracting the geometric data as well. This includes the number of lanes, pedestrian crossings, prominent permanent features etc. Using this information, the link-node diagram for the roundabout was developed as shown in figure 8.4. This is followed by vehicle inputs and routing procedure. In this step, vehicle volumes were assigned from each entry link. The observed volume data that was extracted via UAV traffic video processing and analysis framework (Khan et al., 2017b), was used as an input for the roundabout model.

Figure 8.4 Base model for the studied roundabout (VISSIM)

After the development of basic link-node diagram and assignment of traffic volumes, the next step is to make the model as close to reality as possible. For this purpose, priority rules and reduced speed areas were assigned to specific areas in and around the studied area. The priority rule helps in defining the vehicle crossing behavior, depending on minimum gap time and minimum headway. The default values for priority rules in VISSIM are; gap time = 3.0 sec and minimum headway = 5.0 m. Similarly, reduced speed areas (RSA) are used to replicate the actual conditions while approaching a junction or conflicting area. The speed of the vehicles are automatically reduced as per the defined desired speed (PTV VISSIM, 2011). The length of reduced speed areas used in this model was 5m, the desired speed distribution in these areas for cars was 30km/h and deceleration rate used was 2m/s² by default.

Data collection points are used to collect traffic data at any specified point. This can be helpful in estimating various traffic parameters e.g. speed, total queue, type of vehicle, acceleration, headway, vehicle length etc. However, these points are most important in roundabout as this feature helps in calculating the critical gap and follow-up headway for vehicles. Figure 8.5 below is showing the placement of data collection points on entry link and roundabout.

Figure 8.5 Data collection points on roundabout base model

In order to cater for the stochastic nature of microsimulation models, the developed base model has to be simulated for a number of runs. Therefore, it is critical to evaluate optimal number of simulations runs to get desired level of accuracy in the model. It is almost impossible to know about exact number of model runs in advance that are needed to get the desired value. Dowling et al. (2004) stated that an analyst can estimate the required number of simulations run to obtain valid result after performing few models runs. They have formulated an equation to compute the minimum required simulations run.

$$CI_{1-\alpha\,\%} = 2 * t_{(1-\alpha\,/\,2), N-1} \frac{s}{\sqrt{N}} \qquad (1)$$

where:

$CI_{1-\alpha\,\%}$ = (1-alpha) % confidence interval for the true mean, where alpha equals the probability of the true mean not lying within the confidence interval

$t_{(1-\alpha\,/\,2), N-1}$ = Student's t-statistic for the probability of a two-sided error summing to alpha with N-1 degrees of freedom, where N equals the number of repetitions

s = standard deviation of the model results

N = number of iterations

For this research, the above-mentioned equation was used to find out the optimal number of simulations run. For a 95% confidence interval, the optimal number of runs was calculated to be 20. Therefore, the base model had to be simulated 20 times for each setting, in order to achieve reliable outputs.

8.6.2.2 Model Calibration & Validation

Developing a good base model does not guarantee that the model will predict traffic performance correctly, therefore, calibration of working model is required. It is basically an adjustment of parameters used in model to replicate local driver's behavior to improve the model. It is necessary because no single model can be accurate for all traffic conditions. As Dowling et al. (2004) mentioned "The objective of calibration is to improve the ability of the model to accurately reproduce local traffic conditions". Every microsimulation software has its own set of parameters for calibrating the model to local conditions.

After the base model was finalized, a number of simulation runs were conducted based on the following parameter settings: simulation period of 1800 sec (30 minutes) at a resolution of 10-time steps per simulation second, keeping simulation speed at maximum. A warm-up time of 300 seconds (5 min) was included in each run to allow traffic to stabilize before collecting data between 300 sec and 1800 sec (25 minutes). The input vehicle flow, assuming the peak hour, was converted from 5-min to 30-min data. In order to calibrate the developed base model, the values of 3 parameters were altered with 20 simulation runs on each setting, resulting in total 460 simulation runs for roundabout.

In the existing literature, it was found that the capacity is an important and commonly used measure of effectiveness, particularly for roundabouts. The capacity of a roundabout gives an overview of the performance of the infrastructure. According to Highway Capacity Manual (Transportation Research Board, 2010), the capacity of a roundabout can be calculated as

$$q_{e,max} = Ae^{-Bq_c} \tag{2}$$

where:

$q_{e,max}$ = Capacity of critical lane (pcu/h)

$A = \frac{3600}{t_f}$

$B = \frac{(0.5(t_c - t_f))}{3600}$

t_c = Critical Gap

t_f = Follow-up headway

$q_c = v_c$ = Conflicting flow (veh/h)

As evident from equation(2), the capacity of a roundabout is dependent on conflicting flow, critical gap and follow-up headway. Conflicting flow is the number of vehicles circulating inside the roundabout at a particular time interval. Critical gap is defined as the minimum time between vehicles of major stream in which vehicle of minor stream can make a maneuver (Amin & Maurya, 2015). It can also be defined as minimum time in a circulating flow that allows intersection entry for one vehicle (Mahesh et al., 2016). However, in literature follow-up headway is defined as the time between the vehicles using the same major-street headway under the queuing on the roundabout entry (Macioszek, 2018). Brilon et al. (1999) highlighted that the estimation of critical gap is not an easy task as it cannot be measured directly. The only thing known is that the individual critical gap is larger than the rejected gap and shorter than the accepted gap.

Although, there are several methods available for the estimation of critical gaps and follow-up headways, however, in this research, critical gaps were estimated by using Raff's method. Raff explained that a critical gap is the time at the sum of cumulative number of accepted and rejected gaps (Amin & Maurya, 2015). To estimate the critical gap and follow-up headway, data collections points were marked as shown in figure in base model development section and timestamps difference between the points was used to calculate gaps. These calculated gaps were indexed chronologically. The characteristics of accepted gaps and rejected gaps were computed to find the estimates of critical gap. The critical gaps and follow-up headways were calculated for different values of various simulation parameters (minimum gap setting, deceleration rate and safety distance) and for each simulation run. The calculated values were compared with the observed values for critical gap, follow-up headway and conflicting flow. The observed values were 3.83 sec, 2.3 sec and 672 vehicles/hour respectively. The comparison showed that the parameter of minimum gap setting in priority rules was the best fit with the observed values at minimum gap of 4.5 sec. The simulated values of critical gap, follow-up headway and conflicting flow for this parameter setting were 3.7 sec, 2.331 sec and 572 vehicles/h respectively.

By putting these values in the above-mentioned equations, both the observed and simulated capacities were calculated as given in the table 8.1 below:

Table 8.1 Comparison of observed and simulated capacity

	Critical Gap (t_c)	**Follow-up Headway (t_f)**	**Conflicting flow (q_c)**	**Capacity ($q_{e,max} = Ae^{-Bq_c}$)**
Observed	3.83	2.3	672	1357
Simulated	3.7	2.331	572	1385

As evident from Table 8.1, the observed and simulated capacity of the roundabout are in close range. The mean absolute percentage error (MAPE) for the roundabout capacity was found to be 1.99%. This shows that the simulated model is close to reality. However, it is necessary to meet the calibration target for other measures of effectiveness as well as stated by (Dowling et al., 2004) that the calibration needs to be multi-faceted and iterative process. Though, the aim of calibration is to match the simulated outputs with observed values, there is a practical limit to the time and effort made to achieve close fit. There are several criteria and measures described in literature for calibration acceptance targets but for this research two targets were selected as calibration targets; difference between observed and simulated volume counts and GEH statistics.

In achieving these targets, the simulated link volumes from various experiments with changed behavior parameters, were best-fitted with the observed link volumes. A comparison was made between observed and simulated volumes as shown in tables 8.2, 8.3 and 8.4. Maryland Department of Transportation State Highway Administration (MDOT SHWA, 2017) has published guidelines for VISSIM modelling and mentioned that the percentage difference between observed and simulated volume must not exceed 10% and GEH statistic must be <5. The GEH statistics was calculated as:

$$GEH = \sqrt{\frac{(E-V)^2}{(E+V)/_2}} \qquad (3)$$

where:

E = Estimated model volume

V = Field count

The following tables show the difference among observed and simulated volumes, and the calculated GEH statistics value for different parameter settings:

Table 8.2 Observed vs simulated volume having minimum gap settings of 3 sec

Segment	**Volume Calibration (Min Gap 3 sec)**					
	Observed Volume (Vehicles)	Simulated Volume (Vehicles)	Difference (%age)	Difference < 10%?	GEH	GEH < 5?
Link 1	444	444.365	0.08	Yes	0.017	Yes
Link 3	594	524.66	-11.67	No	2.931	Yes
Link 7	432	434.2	0.51	Yes	0.105	Yes
Link 9	270	258.785	-4.15	Yes	0.689	Yes
Link 20	672	621.165	-7.56	Yes	1.999	Yes

Table 8.3 Observed vs simulated volume having deceleration of 2.5m/sec²

Segment	**Volume Calibration (Decel 2.5m/sec²)**					
	Observed Volume (Vehicles)	Simulated Volume (Vehicles)	Difference (%age)	Difference < 10%?	GEH	GEH < 5?
Link 1	444	444.22	0.05	Yes	0.010	Yes
Link 3	594	529.09	-10.93	No	2.739	Yes
Link 7	432	431.51	-0.11	Yes	0.023	Yes
Link 9	270	259.69	-3.82	Yes	0.633	Yes
Link 20	672	620.38	-7.68	Yes	2.030	Yes

Table 8.4 Observed vs simulated volume having additive and multiplicative safety distance value as 3

Segment	Volume Calibration (add 3 & multi 3)					
	Observed Volume (Vehicles)	Simulated Volume (Vehicles)	Difference (%age)	Difference < 10%?	GEH	GEH < 5?
Link 1	444	444.09	0.02	Yes	0.004	Yes
Link 3	594	524.56	-11.69	No	2.936	Yes
Link 7	432	430.795	-0.28	Yes	0.058	Yes
Link 9	270	254.27	-5.83	Yes	0.971	Yes
Link 20	672	617.105	-8.17	Yes	2.162	Yes

It is observed from above tables that GEH statistics for each link and volume is <5, which means one of the calibration targets achieved. However, the difference percentage of one link in each case is more than 10% but less than 15%. This is also an acceptable limit according to Wisconsin Department of Transport in which it is stated that the difference in observed and simulated volume of individual links must not exceed 15% (Jobanputra & Vanderschuren, 2012). Moreover, the graphs in figure 8.6 show the best-fit lines between the observed and simulated countsfor above mentioned tables. The R-squared values for all the cases is above 97% which indicates that the data does not have large variations.

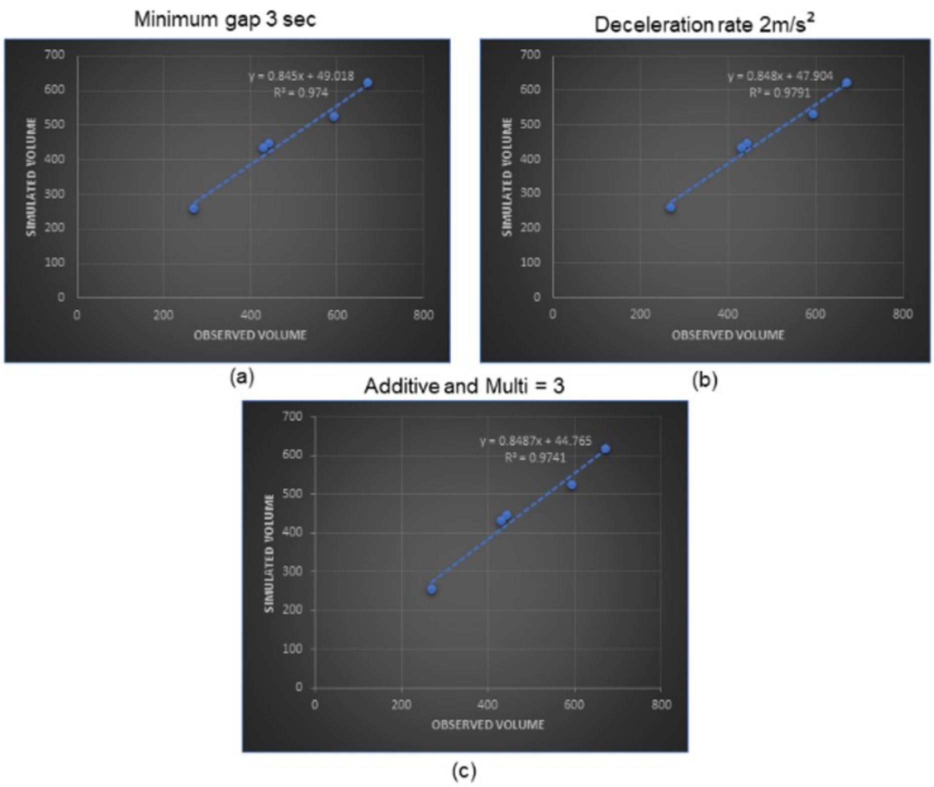


Figure 8.6 Relationship between observed and simulated volumes

8.6.3 Intersection Model

8.6.3.1 Base model development

Like roundabout, the base model of signalized intersection was finalized, and simulation parameters were set as discussed in previous section for simulation. For signalized intersection, the signal controllers were added in the base model. Figure 8.7 shows the base model for the studied signalized intersection. The signal timings obtained from the UAV-based traffic videos were used as an input to the model. Apart from this, queue counters and vehicle travel time detectors were also placed. The figure shows the base model for the studied intersection. A simulation period of 1800 sec (30 minutes) with a warm-up time of 300 seconds (5 min) was selected for the experimental simulations. The input vehicle flow, assuming the peak hour, was converted from 15-min to 30-min data as mentioned earlier. The number of optimal runs were determined at 95% confidence interval. As a result, 25 simulations were conducted for the signalized intersection model.

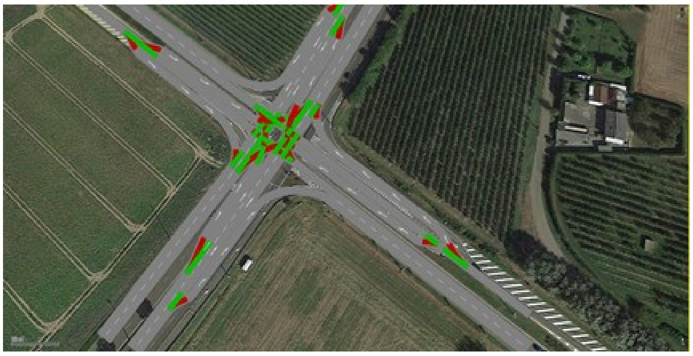


Figure 8.7 Base model for the studied signalized intersection (VISSIM)

8.6.3.2 Model Calibration & Validation

As discussed for the roundabout case, the main objective of model calibration is to achieve the best possible match of simulated values and field measurements of performance. As mentioned earlier in section 2, that there is no universal rule or any accepted procedure for model calibration and validation. However, the responsibility lies with modeler to implement such procedure that can provide appropriate level of confidence in achieving model results. The calibration goals for signalized intersection require to meet the following criteria for model estimates vs observed values:

- Link volumes, speed and travel times must not exceed 10% difference with observed values
- GEH statistics for link volumes must be less than 5
- Mean absolute percentage error (MAPE) should be less than 5%

The signalized intersection in this research is a 4-leg junction comprising two major roads (Link 5 & Link 10) and 2 minor roads (Link 1 & Link 3). Apparently, the huge amount of traffic flow was found on major roads. In contrast to this, very small amount flow was observed on minor roads. As mentioned earlier in this section that total 25 simulation runs were carried out. The simulated flow for all entry vehicles was calculated. Initially, the calibration showed 3 out of 4 links within the acceptable calibration goals except Link 5. It was observed through UAV-based traffic videos that Link 5 carried more heavy traffic as compared to other links. Therefore, a factor of 1.25 was assumed to cater the flow of heavy traffic. This resulted in achieving the desired calibration goals. Again, simulation runs were performed to check the output. The following table 8.5 shows the results for the volume calibration of the signalized intersection:

Table 8.5 Volume calibration (field count vs simulated count)

Segment	Volume Calibration					
	Count Volume (Vehicles)	Simulated Volume (Vehicles)	Difference (%age)	Difference < 10%?	GEH	GEH < 5?
Link 1	58	59.30	2.24	Yes	0.17	Yes
Link 5	510	512.00	0.39	Yes	0.09	Yes
Link 10	410	410.61	0.15	Yes	0.03	Yes
Link 13	40	39.32	-1.70	Yes	0.11	Yes
Total Flow	1018	1021.23	0.32	Yes	0.10	Yes

It is evident from the above table that the difference percentage between observed and simulated volume is way less than 10% for each link which is an acceptable calibration target. Similarly, the GEH statistics also found to be less than 5 for each individual link, indicates that the volume calibration is achieved. Moreover, in the last row of table, total flow was calculated for both observed and simulated volumes and both difference percentage and GEH statistics values are less than 10% and 5 respectively. Figure 8.8 shows the linear relationship between both volumes and most important the value of R^2 is computed as 1, which means that data is best fitted in the regression.

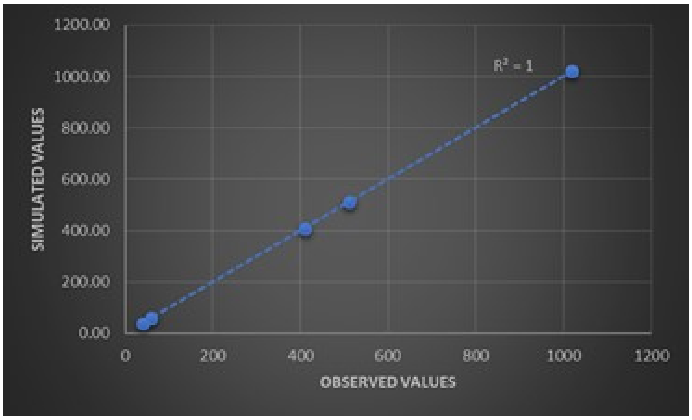


Figure 8.8 Observed vs simulated for volume calibration

As mentioned earlier, in this section that the signalized intersection is a 4-leg junction and it was observed that the maximum flow is at one leg (Link 5) of the junction. Therefore, for experimental purposes, only the critical approach is considered for travel time and speed calibration. For 25 simulations runs, the table 8.6 shows the average observed and simulated travel time for vehicles travelling through Link 5.

Table 8.6 Observed vs simulated travel time

Segment	Travel Time Calibration					
	Observed Travel Time (sec)	Simulated Travel Time (sec)	Differenc e < 10%?	Difference < 10%?	RMSE (sec)	MAPE (%)
Link 5	27.55	26.39	4.23	Yes	1.48	4.23

The above table indicates the difference percentage between observed and simulated travel time, which is less than 10%. This is within the defined level of calibration targets. Moreover, root mean square error and mean absolute percentage error were calculated for travel time and these are also in acceptable limits for calibration. Figure 8.9 shows the box plot of observed and simulated travel times and it can be seen that the observed travel time falls in between mean value and upper limit value of simulated value.

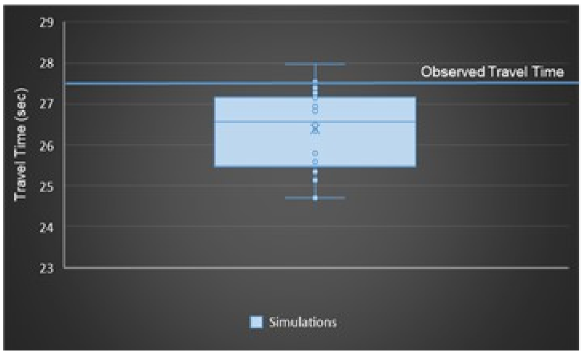


Figure 8.9 Box-plot of observed and simulated travel time

Similarly, another measure of effectiveness i.e. speed was used for model calibration of signalized intersection. Again, the speed for the approach with the maximum volume was calibrated. The segment was divided into two sections; (i) approaching to signal (Link 5), and (ii) after the signal (Link 8). The individual effect of both links was found to be more than 15%. However, by taking an average of both, as they combined to make a complete travel section of vehicles approaching and crossing the signal, the difference in percentage was found to be less than 10% and the mean absolute percentage error was also less than 5% as shown in table 8.7. Therefore, it was assumed that the acceptable calibration target was achieved.

Table 8.7 Observed vs simulated speed

Segment	**Speed Calibration**				
	Observed Speed (km/hour)	Simulated Speed (km/hour)	Difference (%age)	Difference < 10%?	MAPE (%)
Link 5	24	19.70	-17.92	No	17.92
Link 8	30	35.04	16.80	No	16.80
Link 5 + Link 8	27	27.37	1.37	Yes	1.37

8.7 Discussion & Conclusion

This paper aims to demonstrate and validate the applications of traffic data collected via small UAVs for the development and calibration of microsimulation models. The main objective was to examine the feasibility of microsimulation model development from UAV-based traffic data. For this purpose, two case studies comprising of a roundabout and a signalized intersection, have been presented based on the data collected via UAVs in Sint-Truiden, Belgium. Based on the literature study, it was concluded that the microsimulation models require extensive input characteristics to develop and calibrate a model. Also, it was found that there is no universal rule for model calibration and the overall modelling process is dependent on project requirements and modeler's judgement in order to achieve the desired level of confidence.

Over the years, several data collection techniques have been employed for collecting inputs for microsimulation models. However, no existing research was found that employed UAV-based traffic data for microsimulation modelling. Therefore, the general microsimulation modelling and calibration methodology was adopted in order to incorporate the traffic information extracted from UAV collected data. The data required for the simulation was acquired by using unmanned aerial vehicle (UAV) for two different case studies; a roundabout and a signalized intersection in Belgium. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework (Khan et al., 2017b), were utilized for the microsimulation model development and calibration. To develop a base model of case studies, PTV VISSIM was selected as it provides a high level of detail with multiple features. An optimal number of simulation runs were conducted in order to achieve desired confidence level.

The calibration process was based on various measures of effectiveness and validation parameters. In case of roundabout, capacity was used as a measure of effectiveness. In order of calculate capacity, critical gaps and follow-up headways were estimated for different behavior parameter settings. The critical gaps were estimated based on accepted and rejected gaps by using the Raff's method. The comparison of simulated and observed critical gaps helped in calibrating the model. The minimum gap setting of 4.5 seconds resulted in an error of 1.99% in the simulated and observed capacities. Apart from capacity, the entry volumes were also calibrated and validated. The calibration targets were defined and analysis was performed to check the percentage difference that must not exceed 10% and GEH statistics must be less than 5. When the results were compared and GEH statistics was calculated, the model showed coherence among observed and simulated results. It was detected that difference between observed flow count and simulated count was less than 10% and GEH statistics was also found to be less than 5.

Similarly, in case of intersection, the vehicle flows, travel time and speed were taken as calibration goals to observe the difference between field counts and simulated counts. In this research, the calibration criteria was set at maximum 10% difference. However, in other researches or guidelines, difference within 15% and 20% are also considered to be good fit for the model. Like, previous case GEH statistics was also taken as calibration target. The simulation runs computed for this case was 23 but 25 simulation runs were performed. The base model needed only a few minor modifications in order to get the acceptable volume calibration results. Moreover, observed travel time and speed were also compared with simulated values. The root mean square error and mean absolute percentage error was calculated and was found to be in acceptable limits.

After all the calibration and validation procedure, it can be concluded that traffic data obtained via UAVs can be used to develop and calibrate the microsimulation models. This also shows another application of the traffic parameters extracted via previously proposed UAV video processing and analysis framework. The UAVs provide data that contains useful information both in time and space domains. It can be confidently stated that in the coming year, UAVs will become a cheap and efficient alternative to traditional data collection equipment. The bird-eye view data provided by a single UAV can compete with the data obtained from a number of installed fixed cameras and sensors. Additionally, this research is the first step towards the usage of UAV data for microsimulation model development and calibration. It can serve as a reference for future studies.

Even though model development and calibration were successfully performed, but still there are many more aspects that can be further investigated and improved. The current research was solely focused to examine the feasibility of UAV data for microsimulation model development and calibration. However, the future research will be consisting of a more in-depth analysis of the simulation parameters and measures of effectiveness. Moreover, various datasets will be used in future to further explore the practical applications of UAVs for microsimulation model development and calibration. These datasets may be from developing countries where modeling of intersection or roundabout can be more complex in nature.

8.8 References

Alexiadis, V. (2006). Video-Based Vehicle Trajectory Data Collection. Transportation Research Board 86th Annual Meeting, Washington D.C.

Amin, H. J., & Maurya, A. K. (2015). A review of critical gap estimation approaches at uncontrolled intersection in case of heterogeneous traffic conditions. *Journal of Transport Literature*, *9*(3), 5–9. https://doi.org/10.1590/2238-1031.jtl.v9n3a1

Ardö, H. akan, Nilsson, M., Laureshyn, A., & Persson, A. (2012). Enhancements of traffic micro simulation models using video analysis. In *The 17th European Conference on Mathematics for Industry*.

Barmpounakis, E. N., Vlahogianni, E. I., & Golias, J. C. (2016). Extracting Kinematic Characteristics from Unmanned Aerial Vehicles. In *Transportation Research Board 95th Annual Meeting* (p. 16).

Ben-Akiva, M., Davol, A., Toledo, T., Koutsopoulos, H. N., Burghout, W., Andréasson, I., … Lundin, C. (2002). Calibration and evaluation of MITSIMLab in Stockholm. In *81st Transportation Research Board Meeting*.

Bourguignon, F., & Spadaro, A. (2006). Microsimulation as a tool for evaluating redistribution policies. *The Journal of Economic Inequality*, *4*(1), 77–106. https://doi.org/10.1007/s10888-005-9012-6

Brilon, W., Koenig, R., & Troutbeck, R. J. (1999). Useful Estimation Procedures for Critical Gaps. *Transportation Research, Part A*, *33*(3), 161–186.

Brockfeld, E., Kühne, R., & Wagner, P. (2004). Calibration and Validation of Microscopic Traffic Flow Models. *Transportation Research Record: Journal of the Transportation Research Board*, *1876*, 62–70. https://doi.org/10.3141/1876-07

Citro, C. F., & Hanushek, E. A. (1994). Estimating the Effects of Proposed Legislation: The Case for Model Validation. *Chance*, *7*(2), 31–40.

d'Oleire-Oltmanns, S., Marzolff, I., Peter, D. K., & Ries, B. J. (2012). Unmanned Aerial Vehicle (UAV) for Monitoring Soil Erosion in Morocco. *Remote Sensing*, *4*(11). https://doi.org/10.3390/rs4113390

Dowling, R., Skabardonis, A., & Alexiadis, V. (2004). *Traffic Analysis Toolbox: Guidelines for applying traffic microsimulation modeling software*. Federal Highway Administration, Research, Development, and Technology.

Everaerts, J. (2008). THE USE OF UNMANNED AERIAL VEHICLES (UAVS) FOR REMOTE SENSING AND MAPPING. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *Vol. XXXVII.*(Part B1), 6.

Fellendorf, M., & Vortisch, P. (2001). VALIDATION OF THE MICROSCOPIC TRAFFIC FLOW MODEL VISSIM IN DIFFERENT REAL-WORLD SITUATIONS. Presented at the Transportation Research Board 80th Annual Meeting. Retrieved from https://trid.trb.org/view/689890

Halcrow, & TRL. (2006). Traffic Microsimulation Modelling. The Institution of Highways & Transportation 6 Endsleigh Street, London. Retrieved from file:///C:/Users/Mubeen%20Raza/Downloads/traffic_microsimulation_modelling.pdf

Hennessy, D. A., Flanagan, W. M., Tanuseputro, P., Bennett, C., Tuna, M., Kopec, J., … Manuel, D. G. (2015). The Population Health Model (POHEM): an overview of rationale, methods and applications. *Population Health Metrics*, *13*(1), 24. https://doi.org/10.1186/s12963-015-0057-x

Jobanputra, R., & Vanderschuren, M. (2012). Calibration and Validation of a microsimulation model for local arterial in Cape Town.

Kanistras, K., Martins, G., Rutherford, M. J., & Valavanis, K. P. (2013). A survey of unmanned aerial vehicles (UAVs) for traffic monitoring. In *2013 International Conference on Unmanned Aircraft Systems (ICUAS)* (pp. 221–234). https://doi.org/10.1109/ICUAS.2013.6564694

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017a). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. *Transportation Research Procedia*, *22*, 541–550.

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017b). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. *Transportation Research Record: Journal of the Transportation Research Board*, *32*(0), 1–15. http://dx.doi.org/10.3141/2626-04

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: A Case Study for Shockwave Identification and Flow Parameters Estimation at Signalized Intersections. *Remote Sensing*, *10*(3), 458. https://doi.org/10.3390/rs10030458

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y., Yasar, A.-H., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts. *Procedia Computer Science*, *130*, 636–643. https://doi.org/10.1016/j.procs.2018.04.114

Kreps, S., & Kaag, J. (2012). The Use of Unmanned Aerial Vehicles in Contemporary Conflict: A Legal and Ethical Analysis. *Polity*, *44*(2), 260–285. https://doi.org/10.1057/pol.2012.2

Lu, Z., Fu, T., Fu, L., Shiravi, S., & Jiang, C. (2016). A video-based approach to calibrating car-following parameters in VISSIM for urban traffic. *International Journal of Transportation Science and Technology*, *5*(1), 1–9. https://doi.org/10.1016/j.ijtst.2016.06.001

Macioszek, E. (2018). The Comparison of Models for Follow-up Headway at Roundabouts. In E. Macioszek & G. Sierpiński (Eds.), *Recent Advances in Traffic Engineering for Transport Networks and Systems* (Vol. 21, pp. 16–26). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-64084-6_2

Mahesh, S., Ahmed, A., & Rastogi, R. (2016). An approach for the estimation of entry flows on roundabouts. *Transportation Research Procedia*, *17*, 52–62. https://doi.org/10.1016/j.trpro.2016.11.060

Mathew, T. V., & Radhakrishnan, P. (2010). Calibration of microsimulation models for nonlane-based heterogeneous traffic at signalized intersections. *Journal of Urban Planning and Development*, *136*(1), 59–66.

MDOT SHWA, M. D. of T. S. H. A. (2017). *VISSIM Modeling Guidance*.

PTV VISSIM. (2011). *VISSIM Manual* (No. 5.30-05).

Puri, A. (2005). A survey of unmanned aerial vehicles (UAV) for traffic surveillance. *Department of Computer Science and Engineering, University of South Florida*, 1–29.

Salvo, G., Caruso, L., & Scordo, A. (2014a). Gap acceptance analysis in an urban intersection through a video acquired by an UAV. *Recent Advances in Civil Engineering and Mechanics*, 199–205.

Salvo, G., Caruso, L., & Scordo, A. (2014b). Urban Traffic Analysis through an UAV. *Procedia - Social and Behavioral Sciences*, *111*, 1083–1091. https://doi.org/10.1016/j.sbspro.2014.01.143

Schultz, G., & Rilett, L. (2005). Calibration of Distributions of Commercial Motor Vehicles in CORSIM. *Transportation Research Record: Journal of the Transportation Research Board*, *1934*, 246–255. https://doi.org/10.3141/1934-26

Sheu, J.-B., & Ritchie, S. G. (2001). Stochastic modeling and real-time prediction of vehicular lane-changing behavior. *Transportation Research Part B: Methodological*, *35*(7), 695–716. https://doi.org/10.1016/S0191-2615(00)00015-1

Skabardonis, A. (2005). *Estimating and Validating Models of Microscopic Driver Behavior with Video Data* (Institute of Transportation Studies, Research Reports, Working Papers, Proceedings No. qt48s0p5gb). Institute of Transportation

Studies, UC Berkeley. Retrieved from https://ideas.repec.org/p/cdl/itsrrp/qt48s0p5gb.html

Spadaro, A., & Fundación BBV. (2007). *Microsimulation as a tool for the evaluation of public policies: methods and applications*. Bilbao: Fundación BBVA.

Transportation Research Board. (2010). *HCM 2010 : Highway Capacity Manual.* Washington, D.C.: Transportation Research Board.

Turner, D., Lucieer, A., & Watson, C. (2012). An Automated Technique for Generating Georectified Mosaics from Ultra-High Resolution Unmanned Aerial Vehicle (UAV) Imagery, Based on Structure from Motion (SfM) Point Clouds. *Remote Sensing*, *4*(5). https://doi.org/10.3390/rs4051392

Chapter 9

Conclusions & Recommendations

Motivated by the limitations of the traditional traffic data collection equipment and existing gaps or shortcomings in the applied use of small UAVs for traffic analysis, an unmanned aerial vehicle-based traffic analysis system has been developed in order to streamline the processes involved in the data collection, processing and analysis. One of the major contribution of this research is the presentation and description of 2 frameworks: (i) a universal guiding framework for the employment of UAVs for traffic-related studies , and (ii) a methodological framework for the processing of UAV videos. The proposed frameworks have been validated with the help of various case studies. The other contribution is the conduction of an in-depth traffic analysis on the collected experimental UAV data. Various types of infrastructural elements such as roundabout, signalized intersection, unsignalized T-intersection etc. have been analyzed. Additionally, the UAV-based traffic data is also utilized for the development and calibration of microsimulation models.

As mentioned in the introduction (chapter 1), the study of traffic demands and travel behaviour is necessary in order to devise policies and measures for an efficient management of the network. In this regard, the traffic data plays a significant role for the development and calibration of various models and simulations. However, the collection of traffic data is not straight-forward and has been termed as a challenging task by experts. It is critical to maintain a balance between the costs and the quality of the data obtained. For this purpose, this research has aimed to demonstrate the applications of small rotary-winged UAVs for traffic data collection. UAVs provide a dynamic and bird-eye view of the traffic network, and can be utilized for example by traffic planners and management centers to determine the state of the traffic flow and manage congestion problems. This technology provides a cheap alternative to fixed cameras and sensors infrastructure as they are flexible and can be deployed anywhere (mobile). The mobility and flexibility are the key assets of this technology.

In order to demonstrate the traffic data collection and analysis applications of small UAVs, this research presented various frameworks and methodologies in order to effectively use the data acquired via small UAVs for traffic flow analysis. Firstly, chapter 2 presented a universal guiding framework for the conduction of UAV-based traffic study. The detailed framework covered all the aspects of using UAVs for traffic data collection and analytical purposes; ranging from ensuring a safe and efficient UAV flight execution to the analysis steps that follow the execution of a UAV flight. It provided a comprehensive guideline and gave an overview of the management in the context of the hardware and the software entities involved in the process. This was followed by another framework that was focused on efficient processing of the UAV traffic data. The objective was to ensure that the UAV data is converted into useful and reliable traffic information in a short period of time. A balance had to be maintained between the accuracy and processing time of the developed automated system. Chapter 3 described this methodological framework for automated UAV video processing. The main output of this framework was a series of trajectories of multiple vehicles at a particular road segment This chapter also gave a brief comparison of existing UAV studies based on either manual or semiautomatic processing techniques. The proposed framework was validated with the help of a field experiment conducted in the city of Sint-Truiden, Belgium. The data was processed and analyzed as per the modules of the framework, resulting in a series of vehicle trajectories. Chapter 4 evaluated the accuracy and the overall performance of the developed vehicle detection and tracking system.

In order to evaluate the accuracy of the developed system, various measures of performance were calculated for different UAV-based traffic videos. The outputs from the vehicle detection and tracking system were compared with the ground-truth data. Performance indicators i.e. correctness, completeness and quality were estimated using the concept of true positives, false positives and false negatives. The results of the performance analysis conducted on 2 UAV-based experimental datasets indicated an overall accuracy level of more than 90%. Furthermore, the R-squared values of more than 98% also reflected the consistency between the automatic and ground-truth detections. It is also important to mention that the level of accuracy directly influences the processing times as well. This is due to the fact that less accurate detections and tracks need more post-processing and manual checks (Apeltauer et al., 2015). On the other hand, the processing or computation times are greatly dependent on the type of algorithms selected for the vehicle detection and tracking process. The semi-automatic techniques or such automated algorithms that require extensive pre-trained datasets, are not useful in cases where least processing times are highly desired. Therefore, it was critical to design a system that maintained a balance between the accuracy and the processing times. In this regard, the developed system performed well as the algorithms were selected on the basis of minimal processing times and computational requirements. Additionally, the sensitivity of UAV flight altitude on the preciseness of the generated outputs was also tested. For this purpose, the experimental dataset with 2 different altitude levels was used to verify the significance of the UAV altitude. The results showed that the outputs are more consistent when the UAV flies at an altitude of 80 meters as compared to 60 meters. The results also showed that the errors due to slight UAV movement are magnified at lower altitudes. Hence, indicating that the effects of errors (due to wind, vibration, shadows etc.) are sensitive to the UAV flight altitude. Moreover, the objects can be observed better from a greater height due to reduced obliqueness (better angle) and less occlusions . Overall, it can be concluded that the accuracy and preciseness of the object detection and tracking process is sensitive to the UAV flight altitude.

After presenting the frameworks for UAV-based data collection and processing, the next task was to propose analytical methodologies focusing on the utilization of UAV-based traffic data for traffic flow analysis. For this purpose, the collected experimental datasets were used to conduct analysis for various types of infrastructural elements i.e. signalized intersections, roundabouts, T-intersections etc. The emphasis was also on the extraction of useful traffic information in a short period of time. Firstly, Chapter 5 explored the applications of data collected via small UAVs, for an in-depth traffic flow analysis at a signalized 4-legged intersection. The analysis was basically a practical extension of the outputs generated from the UAV video processing framework. The generation of simplified trajectories, shockwaves, and fundamental diagrams help in analyzing the interrupted-flow conditions at a signalized four-legged intersection using UAV-acquired data. The estimated parameters were found to be highly accurate after comparing them with the ground truth values. Similarly, chapter 6 focused on authenticating the application of small multirotor UAVs for traffic data collection and subsequent analysis of traffic streams at urban roundabouts. This chapter presented an analytical methodology to evaluate the performance of roundabouts by extracting various parameters and performance indicators. The performance evaluation methodology was based on: (i) determining traffic volume via OD matrices for each leg, and (ii) analyzing drivers' behavior via gap-acceptance analysis. The study depicted the overall applicability of the UAV-based traffic analysis system. Furthermore, Chapter 7 further extended the traffic data collection applications of UAVs to mixed traffic situations in developing countries. In order to demonstrate the traffic analysis process, a case study based on data collected in Pakistan, was presented in this chapter. The extraction of various traffic parameters and measures of performance helped in highlighting the usefulness of UAVs for traffic analysis. The developing countries generally lack even in the basic infrastructure required for traffic monitoring and data collection.

In this scenario, UAVs can become a useful apparatus for traffic data collection in such regions. The results of the analysis at two study locations reflected the overall driving attitude and lack of implementation of traffic rules in developing countries, resulting in high congestion levels and serious safety concerns.

Apart from traffic flow analysis, the UAV-based traffic data was also used to demonstrate the applications for microsimulation modelling. Chapter 8 presented a methodology to utilize the UAV-based traffic data for the development as well as for the calibration of microsimulation models. The main objective was to examine the feasibility of microsimulation model development from UAV-based traffic data. For this purpose, two case studies comprising of a roundabout and a signalized intersection, were presented based on the data collected via UAVs in Sint-Truiden, Belgium. The base models were developed using PTV VISSIM. The road geometry data and traffic parameters extracted from the UAV videos via previously proposed UAV video processing and analysis framework (Khan et al., 2017b), were utilized for the microsimulation model development and calibration. The calibration process was based on various measures of effectiveness and validation parameters e.g. link volume, capacity, critical gaps etc. Acceptable calibration targets were defined for both roundabout and signalized intersection models. The results showed that the microsimulation models can be calibrated through traffic data collected via small UAVs. The study implied that UAVs can become a useful source of traffic data for the development and calibration of microsimulation models.

Although, UAVs have been demonstrated to be highly effective in traffic applications, still there are some limitations attached with the current technology. This includes factors ranging from hardware and software to legal aspects, such as the limited flight time of small UAVs along with some other concerns regarding the safety of flight operations. The flight time of UAVs depends on internal, as well as external, factors. Internal factors include the size, payload, battery type, etc., whereas the external factors consist of weather conditions, wind conditions, status of GPS satellites, etc. Apart from limited flight times, the legal considerations, including the safety and privacy concerns, also limit the use of UAVs for practical applications. In particular, the current Belgian law restricts the small UAVs to fly directly above vehicles and population. Therefore, the UAV has to be hovered at an oblique angle to the traffic, thereby compromising the accuracy of extracted trajectories, as well as complicating the overall video processing. Nevertheless, all these concerns will eventually fade away with the development of more reliable and robust technology in the coming years. Additionally, some limitations also exist for the automated processing of the UAV videos. Various types of errors can occur in vehicle detection and tracking due to different reasons such as partial occlusions, shadows, objects in close proximity, false detections, etc. Therefore, the resulting trajectories may contain some noise and errors which have to be dealt-with accordingly.

This research is one of the pioneer studies that have employed the UAV-based traffic data for detailed traffic analysis. Although, various frameworks and several case studies to demonstrate the applications of UAVs, have been presented in this research work, still there are many aspects that can be improved and upgraded in the future research. Future research shall mainly focus on further optimization of the processing and analysis procedures by following the rapidly evolving field of video processing and employing improved state-of-the-art tools and technology. The hardware and software improvements might make the system more robust in all types of extreme conditions as well. The existing limitations of UAVs are bound to shrink in the coming years, hence increasing the overall efficiency of the data processing and analysis system. Additionally, the future research might lead to the real-time processing and analysis of the data transmitted directly by the UAV. This aspect has been kept in consideration in the current research work as well by developing the system capable of providing results in a short period of time. Apart from the technological aspects, future research shall also focus on studying the acceptability of general public and transportation professionals towards the use of UAVs. The results of such studies can help in spreading awareness as well as serving as a guideline for governments and policy makers.

As mentioned before, the UAV technology is multi-dimensional and has vast applications. This research may serve as a benchmark for a wide range of future research projects involving the use of UAVs, particularly for traffic and transportation applications. However, the proposed frameworks can be improved in future research by incorporating rapidly improving tools and technologies. Road user classification can be termed as the immediate step that should be incorporated in the future extension. Additionally, machine learning algorithms can also be tested for their efficiency. The traffic analysis applications presented in this research can be extended by conducting more detailed analyses and by focusing on more complex traffic situations. In addition, the collection of larger datasets will also be necessary in order to increase the acceptability of UAVs for actual traffic studies. Prospects of utilizing a swarm of UAVs can also be explored in future for the purpose of collecting uninterrupted data for longer durations and also for covering larger areas simultaneously. Apart from the specific traffic flow analysis extensions, the existing research can be extended in various different directions. Some of the potential future projects that can be linked to this research are:

1. The development of UAV-based parking management system: The developed UAV video processing and analysis framework may be modified in future for parking space management and analysis. UAVs have the capability to be used to monitor the state of parking infrastructure. The UAV's bird-eye view data can be accordingly used for analysis and modelling; thereby assisting in efficient operations and management.
2. Traffic safety studies based on data acquired via UAVs: The UAV-based traffic data may be used to analyze traffic safety situation at a particular location. Specifically. the black spots in the network can be identified and studied in more detail using the UAV data. The frameworks proposed in this research may be extended in order extract safety-related parameters. The wide field-of-view provided by UAV videos provides another aspect to such studies by providing rich data that can be used to identify the source of conflicts. Apart from this, the UAVs may be used to study safety issues faced by pedestrians as well as cyclists. UAVs can play an important role by making the networks safer for non-motorized vehicles.
3. UAV-based measurement of environmental pollutants: The UAV technology may be used in future to identify areas with higher pollution emission, hence various measures can be introduced to promote the use of sustainable transportation modes. The universal guiding framework for conducting UAV-based studies may prove to be helpful for these applications.
4. Real-time traffic updates: The UAVs may be used to transmit real-time status of the network directly to vehicles. This can provide a new dimension to the existing Advanced Traveler Information Systems, thereby helping in smooth network operations. With a drastic increase in the use of commercial UAVs expected in the coming years, this application has the potential to become a reality. The traffic management centers can make use of the collected data for traffic flow and safety analysis. In this scenario, the proposed frameworks may prove to be highly useful.
5. Special Event/Incident flow management: This technology can also become useful in monitoring and analyzing the traffic situation in the scenario of special events or an unexpected incident. The future research can focus on real-time data transmission from UAV to Traffic management center, which can then utilize the data accordingly.

Appendix A

Curriculum Vitae

Muhammad Arsalan Khan

Researcher & PhD Student
Transportation Research Institute (IMOB)
Hasselt University, Campus Diepenbeek
Wetenschapspark 5 bus 6,
BE-3590 Diepenbeek Belgium

Contact Details

Tel. 1: +32 471 59 21 71 (Belgium)
Tel. 2: +92 345 5197097 (Pakistan)
Email 1: muhammadarsalan.khan@uhasselt.be
Email 2: arsalankhan.7@live.com
Current Address: 24 Steenblookstraat, 3590 Diepenbeek,Belgium
Permanent Address: 235-B, Street 9, Phase 3, Bahria Town, Rawalpindi,Pakistan

Personal Details

Place of birth	Rawalpindi, Pakistan
Date of birth	1990-March-02
Nationality	Pakistani

Educational Background

- **2013-2015** **Masters in Transportation Sciences (HEC-Funded)**
  Hasselt University, Belgium
  Grade: Distinction Cum Laude
  Thesis Title: Activity Based Models: Agent Negotiation to Cooperate for Carpooling
  Supervisor: Prof. Dr. ir. Tom Bellemans

- **2008-2012** **Bachelors in Civil Engineering**
  National University of Science and Technology (NUST), Pakistan
  Cumulative GPA : 3.32/4.0 (83%)
  Dissertation Project: Slope Stability Study in DHA-I Islamabad

- **2006 - 2008** **HSSC (Higher Secondary School Certificate)**
  FBISE, Pakistan
  Hamza Army Public College, Rawalpindi, Pakistan
  Obtained A Grade

- **2004 – 2006** **SSC (Secondary School Certificate)**
  FBISE, Pakistan
  OPF Boys College , H-8/4 , Islamabad, Pakistan
  Obtained A+ grade.

Work Experience

- Graduate Researcher in **IMOB, Belgium** (Transportation Research Institute, Hasselt University) **October 2015-Till date:** Responsible for conducting research, supervising master thesis and teaching of masters courses
- Paid Internship in **IMOB, Belgium** (Transportation Research Institute, Hasselt University) **July-August 2015**: Processed and analyzed surrogate traffic safety video data
- Paid Internship in **IMOB, Belgium** (Transportation Research Institute, Hasselt University) **March-July 2014**: Assisted a driving simulator research study followed by compilation and analysis of the data on MATLAB.

- Worked as infrastructure design engineer in **Bahria Town, Pakistan** Design wing (Asia's largest real-estate developers) **July2012-August2013** : Responsible for designing of all infrastructural elements(Geometric design, Pavement design, Drainage, Sewerage, Water Supply) in coordination with town planners; also responsible for supervising of site inspectors/construction managers to ensure proper site work as per the issued drawings.
- Internship in **FWO, Pakistan** (Frontier Works Organization) **July-August 2010**: Carried out survey on different types of equipment for layout of roads and learnt to read and execute site/shop drawings.
- Internship in **Bahria Town, Pakistan** (Planning and design wing) **August-September 2011**: Got hands-on experience on different infrastructure design softwares and got acquainted with AASHTO and other design criteria.

Publications

- **Journals:**
  - **Khan, M.A.;** Ectors, W.; Bellemans, T.; Janssens, D.; Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: A Case Study for Shockwave Identification and Flow Parameters Estimation at Signalized Intersections. Remote Sensing **(IF:3.406)**, 10, 458. doi:10.3390/rs10030458
  - **Khan, M. A.**, Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Record: Journal of the Transportation Research Board **(IF:0.695)**, 32(0), 1–15. doi: 10.3141/2626-04
- **Conferences:**
  - **Khan, M. A.**, Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts, Procedia Computer Science, 130, 636-643, Ambient Systems, Networks and Technologies (ANT) 2018, Porto, Portugal. doi.org/10.1016/j.procs.2018.04.114.
  - **Khan, M. A.**, Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Board, 96th Annual Meeting, Washington D.C, USA.
  - **Khan, M. A.**, Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on

Literature Survey. Transportation Research Procedia, 22, 541–550. doi: 10.1016/j.trpro.2017.03.043

- Zubair, M.U., **Khan, M.A.,** Akhtar, K**.** (2016). Stabilizing a Failed Slope in Islamabad. 2nd International Conference on Emerging Trends in Engineering, Management and Sciences (ICETEMS-2016), Peshawar, Pakistan.
- Hussain I., Knapen L. & **Khan M.A.** (2015) Agent-based Negotiation Model for Long-term Carpooling: A Flexible Mechanism for Trip Departure Times. 21st International Conference on Urban Transport and Environment, Valencia, Spain.

Computer skills

- **Engineering Softwares** Paramics Discovery; VISSIM; Synchro; ArcGIS; QGIS; AutoCAD; EaglePoint; T-Analyst; ETABS; SAP2000; Surfer; Grapher; Rocscience Slide; Clara-w; NDsoft; HY-8; Bentley SewerCad; Autodesk Storm and Sanitary Analysis.
- **Project Management** PrimaVera P6; Microsoft Project.
- **Programming Languages** Visual C++, OpenCV (C++ & Python), MS .NET Framework, MATLAB, GW-BASIC.
- **Statistical Softwares** R; SAS; SPSS; JMP.
- **General Softwares** MS Office (Ms Word, Ms Excel, Ms Powerpoint), Microsoft Visio, Adobe Photoshop & Illustrator; Image and video editing Tools.

Short courses and projects

- Attended EIT Labs Summer School 2014 at Eurecom, France.

- Prepared and presented a business model for “Green Logistics Alliance: Individual CO2-equivalent metrics for Green Logistics” during the Summer School.
- Designed and coordinated Infrastructure projects (Geometric design, Pavement design, Drainage, Sewerage and Water Supply) in Bahria Town.
- Completed a certified course on Primavera P6.
- Attended and presented a research paper in Ambient Systems, Networks & Technology (ANT) Conference-2018 in Porto, Portugal.
- Attended and presented a research paper in Euro Working Group on Transportation(EWGT) Conference-2016 in Istanbul, Turkey.
- Attended International Workshop on Managing Hydrological Extremes and Geo-hazards
- Attended International conference on Earthquake engineering and Seismology

Achievements and Activities

- HEC-Pakistan scholarship holder for masters leading to PhD.
- Scored 81 marks with a Percentile of 99.57% in NTS GAT (Graduate Assessment Test) General.
- Merit-based Scholarship holder during bachelors.
- Bachelor’s Final year project shortlisted for Rector’s Gold Medal Award.
- Received Cash prize from DHA as a token of appreciation for final year project.
- PEC Registered Engineer
- Student Membership of ASCE (American Society of Civil Engineers).
- Student Membership of ACI (American Concrete Institute).
- Volunteer of Pakistan Red Crescent Society.
- 2nd runners up in SYTEC bridge-modeling competition held at NUST, Islamabad.

Language proficiency

- English (Excellent)
- Urdu (Excellent)
- Dutch (Beginner)

Appendix B

Publications

Journals:

Published

Khan, M.A.; Ectors, W.; Bellemans, T.; Janssens, D.; Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: A Case Study for Shockwave Identification and Flow Parameters Estimation at Signalized Intersections. Remote Sensing (IF:3.244), 10, 458. doi:10.3390/rs10030458

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Record: Journal of the Transportation Research Board (IF:0.592), 32(0), 1–15. doi: 10.3141/2626-04

In-Review

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Mixed Traffic Conditions in Developing Countries (Pakistan).

Khan, M. A., Raza, M. M., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: Development and Calibration of Microsimulation Models.

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-Based Traffic Analysis: An Evaluation of the Accuracy of Vehicle Detection & Tracking Process.

Conferences:

Khan, M. A., Ectors, W., Bellemans, T., Ruichek, Y,, Yasar, AH,, Janssens, D., & Wets, G. (2018). Unmanned Aerial Vehicle-based Traffic Analysis: A Case Study to Analyze Traffic Streams at Urban Roundabouts, Procedia Computer Science, 130, 636-643, Ambient Systems, Networks and Technologies (ANT) 2018, Porto, Portugal. doi.org/10.1016/j.procs.2018.04.114.

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle-Based Traffic Analysis: A Methodological Framework for Automated Multi-Vehicle Trajectory Extraction. Transportation Research Board, 96th Annual Meeting, Washington D.C, USA.

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). UAV-Based Traffic Analysis: A Universal Guiding Framework Based on Literature Survey. Transportation Research Procedia, 22, 541–550. doi: 10.1016/j.trpro.2017.03.043

Zubair, M.U., Khan, M.A., Akhtar, K. (2016). Stabilizing a Failed Slope in Islamabad. 2nd International Conference on Emerging Trends in Engineering, Management and Sciences (ICETEMS-2016), Peshawar, Pakistan.

Zubair, M.U., Gabriel, H., Thaheem, M.J., Khan, M.A. (2016). Comparison of causes of Disputes in the Published Literature and the Construction industry of Pakistan. 2nd International Conference on Emerging Trends in Engineering, Management and Sciences (ICETEMS-2016), Peshawar, Pakistan.

Hussain I., Knapen L. & Khan M.A. (2015) Agent-based Negotiation Model for Long-term Carpooling: A Flexible Mechanism for Trip Departure Times. 21st International Conference on Urban Transport and Environment, Valencia, Spain.