I, Qingyi Ai, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Civil Engineering.

It is entitled:
Length-Based Vehicle Classification Using Dual-loop Data under Congested Traffic Conditions

Student’s name: Qingyi Ai

This work and its defense approved by:

Committee chair: Heng Wei, Ph.D.
Committee member: Changjoo Kim, Ph.D.
Committee member: Herbert Bill, Ph.D.
Committee member: Anant Kukrety, Ph.D.
Length-Based Vehicle Classification Using Dual-loop Data
under Congested Traffic Conditions

A dissertation submitted to the
Graduate School of the University of Cincinnati
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in the Department of Civil and Architectural Engineering and Construction Management
of the College of Engineering and Applied Science
October 2013
By
Qingyi Ai

B.S. Huazhong University of Science & Technology, Wuhan, China 1998
M.S. Beijing University of Technology, Beijing, China 2006

Committee members:

Dr. Heng Wei (Chair)

Dr. Anant R. Kukreti

Dr. Herbert L. Bill

Dr. Changjoo Kim
ABSTRACT

The accurate measurement of vehicle classification is a highly valued factor in traffic operation and management, validations of travel demand models, freight studies, and even emission impact analysis of traffic operation. Inductive loops are increasingly used specifically for traffic monitoring at highway traffic data collection sites. Many studies have proven that the vehicle speed can be estimated accurately by using dual-loop data under free traffic condition, and then vehicle lengths can be estimated accurately. The capability of measuring vehicle lengths makes dual-loop detectors a potential real-time data source for vehicle classification. However, the existing dual-loop length-based vehicle classification model was developed with an assumption that the difference of a vehicle’s speed on the first and the second single loop is not significant. Under congested traffic flows, vehicles’ speeds change frequently and even fiercely, and the assumption cannot be met any more. The outputs of the existing models have a high error rate under non-free traffic conditions (such as synchronized and stop-and-go congestion states). The errors may be contributed by the complex characteristics of traffic flows under congestion; but quantification of such contributing factors remains unclear.

In this study, the dual-loop data and vehicle classification models were evaluated with concurred video ground-truth data. The mechanism of the length-based vehicle classification and relevant traffic flow characteristics were tried to be revealed. In order to obtain the ground-truth vehicle event data, the software VEVID (Vehicle Video-Capture Data Collector) was used to extract high-resolution vehicle trajectory data from the videotapes. This vehicle trajectory data was used to identify the errors and reasons of the vehicle classifications resulted from the existing dual-loop model. Meanwhile, a probe vehicle equipped with a Global Positioning System (GPS) data logger was used to set up reference points for VEVID and to collect traffic
profile data under varied traffic flow states for developing the new model under stop-and-go traffic flow. The research has proven inability of the existing vehicle classification model in producing satisfactory estimates of vehicle lengths under congestion, i.e., synchronized or stop-and-go traffic states. The Vehicle Classification under Synchronized Traffic Model (VC-Sync model) was developed to estimate vehicle lengths against the synchronized traffic flow and the Vehicle Classification under Stop-and-Go Model (VC-Stog model) was developed to estimate vehicle lengths against the stop-and-go traffic flow. Compare to the existing models, under the congested traffic flows, the newly developed models have improved the accuracy of vehicle length estimation significantly.

The contribution of this research is reflected in the following aspects: 1) An innovative VEVID-based approach is developed for evaluating the concurred dual-loop data and resulted vehicle classification and relevant traffic flow characteristics against video-based ground-truth vehicle event trajectory data, which is difficult to conduct with traditional approaches; 2) Innovative vehicle classification models for both synchronized traffic and stop-and-go traffic states are developed through such an evaluation process; 3) The algorithms for processing the dual-loop vehicle event raw data have been improved by considering the influence of traffic flow characteristics; 4) A GPS-based approach is developed for setting up the reference points in field in conjunction with application of VEVID, which is proven a safety and efficient approach compared to traditional manual approaches. And the GPS-based travel profile data is greatly helpful in developing the new models.
ACKNOWLEDGEMENT

First, I would like to express my gratefulness to my advisor, Dr. Heng Wei for his guidance and great support on my research. Without his insight, instructions and patience, it is impossible for me to establish the methodology of my research and to conduct my research successfully. During my Ph.D. study at the University of Cincinnati, Dr. Wei was always around me giving me invaluable guidance and suggestions both on my research and career development.

I would like to thank Dr. Anant R. Kukreti, Dr. Herbert L. Bill, and Dr. Changjoo Kim for their valuable suggestions on my research and their service on my dissertation committee despite their busy schedules.

This research was partially based on the project *Optimal Loop Placement and Models for Length-based Vehicle Classification and Stop-and-Go Traffic*, which was funded by the Ohio Transportation Consortium (OTC).

Also, I would like to thank Dr. Ben Coifman at the Ohio State University for providing the event dual-loop data, which is playing a vital important role in my research.

Many thanks to Mr. Sudhir Reddy Itekyala, M.S. student in our transportation study lab at the University of Cincinnati for his assistance in data collection, data extraction, and modeling when we were working together on the OTC project. Special gratitude goes to Dr. Zhixia Li, for his timely update of the VEVID software. The video-based ground-truth vehicle trajectory data could not be extracted without his great efforts. I have many thanks to other colleagues in the lab for their big helps on various aspects as needed by my research activities.

Finally, I would like to thank my parents, my wife and my lovely daughter, for their support and patience.
CONTENTS

ABSTRACT .................................................................................................................................. II
ACKNOWLEDGEMENT ........................................................................................................... V
LIST OF ACRONYMS ............................................................................................................... XI
LIST OF ABBREVIATIONS ................................................................................................... XII
CHAPTER 1: INTRODUCTION ................................................................................................ 1
  1.1 BACKGROUND .................................................................................................................. 1
  1.2 IDENTIFIED PROBLEMS ................................................................................................. 6
  1.3 GOAL AND OBJECTIVES .................................................................................................. 6
CHAPTER 2: LITERATURE REVIEW .................................................................................... 8
  2.1 INDUCTIVE LOOP DETECTORS ....................................................................................... 8
  2.2 DUAL-LOOP DATA PROBLEMS .................................................................................... 10
  2.3 LENGTH-BASED VEHICLE CLASSIFICATION USING INDUCTIVE LOOP DATA ........... 11
  2.4 VEHICLE BINS ................................................................................................................ 12
  2.5 DIFFERENT TRAFFIC FLOW STATES ............................................................................ 13
  2.6 THRESHOLDS FOR DISTINGUISHING TRAFFIC STATES ............................................. 15
CHAPTER 3: METHODOLOGY ............................................................................................. 19
CHAPTER 4: DATA COLLECTION AND DATA PROCESSING ....................................... 22
  4.1 STUDY SITES .................................................................................................................. 22
  4.2 VIDEO DATA COLLECTION ........................................................................................... 25
  4.3 EVENT DUAL-LOOP DATA COLLECTION ..................................................................... 27
CHAPTER 5: TRAFFIC FLOW PHASES IDENTIFICATION ............................... 43

5.1 FREE FLOW IDENTIFICATION ................................................................. 44
5.2 SYNCHRONIZED TRAFFIC FLOW IDENTIFICATION ............................. 47
5.3 STOP-AND-GO TRAFFIC IDENTIFICATION ............................................. 48

CHAPTER 6: LENGTH-BASED VEHICLE CLASSIFICATION MODELS .......... 50

6.1 EVALUATING THE EXISTING VEHICLE CLASSIFICATION MODEL ........ 50
6.2 DEVELOPING NEW VEHICLE CLASSIFICATION MODEL UNDER SYNCHRONIZED FLOW ........... 53
6.3 DEVELOPING NEW VEHICLE CLASSIFICATION MODEL UNDER STOP-AND-GO TRAFFIC ....... 58
   6.3.1 Scenarios of Vehicle Stopping Status ....................................................... 58
   6.3.2 Scenario Identification ............................................................................. 63
   6.3.3 Developing Length-based Vehicle Classification against the Stop-and-Go Traffic ...... 64

CHAPTER 7: CONCLUSIONS ........................................................................... 71

REFERENCES ................................................................................................. 74
LIST OF TABLES:

TABLE 1. SUMMARY OF THRESHOLDS OF TRAFFIC STATES USED IN PREVIOUS STUDIES ............. 17
TABLE 2. EXEMPLARY SAMPLE OF THE EVENT DUAL-LOOP DATA ........................................ 28
TABLE 3. EXEMPLARY SAMPLE OF GPS DATA ........................................................................ 29
TABLE 4. SAMPLE DATA EXTRACTED FROM VIDEO USING VEVID ..................................... 35
TABLE 5. TIMESTAMPS OF THE M LOOP AND THE S LOOP ................................................. 39
TABLE 6. T-TEST RESULTS FOR THE FREE FLOW TRAFFIC .............................................. 51
TABLE 7. T-TEST RESULTS FOR THE SYNCHRONIZED TRAFFIC FLOW ............................. 53
TABLE 8. T-TEST RESULTS FOR VC-SYNC MODEL UNDER SYNCHRONIZED FLOW .......... 56
TABLE 9. VEHICLE ASSIGNMENT DURING SYNCHRONIZED TRAFFIC (3-BIN SCHEME) .... 56
TABLE 10. VEHICLE ASSIGNMENT DURING SYNCHRONIZED TRAFFIC (4-BINS SCHEME) ... 57
TABLE 11. LIST OF PERCENTAGE OF VEHICLE STOPPING STATUS ................................. 62
TABLE 12. T-TEST RESULTS FOR OUTPUT FROM VC-SYNC MODEL FOR SCENARIO 2 AND 3 66
TABLE 13. VEHICLE ASSIGNMENT DURING STOP-AND-GO TRAFFIC (3-BIN SCHEME) ..... 70
LIST OF FIGURES:

FIGURE 1. OVERVIEW OF DUAL-LOOP DETECTOR STATION .............................................................. 2
FIGURE 2. DEMONSTRATIONS OF THREE TRAFFIC PHASES (KERNER, ET AL. 1998 AND 2004) ....... 5
FIGURE 3. DUAL-LOOP DETECTORS INSTALLED IN PAVEMENT (KLEIN ET AL. 2006) ....................... 8
FIGURE 4. COMPONENTS OF AN INDUCTIVE DETECTOR (NEUDORFF ET AL. 2003) ......................... 9
FIGURE 5. A DUAL-LOOP DETECTOR INSTALLED IN HIGHWAY PAVEMENT ................................ 10
FIGURE 7. FRAMEWORK OF EVALUATING DUAL-LOOP DATA BASED VEHICLE CLASSIFICATION ...
...................................................................................................................................... 21
FIGURE 8. LOOP STATION V1002 ON I-70/71 AT WEST MOUND STREET ...................................... 23
FIGURE 9. LOOP STATION V1003 ON I-70/71 AT SOUTH FOURTH STREET ...................................... 23
FIGURE 10. VIDEOTAPING AT THE SELECTED DUAL-LOOP STATION ........................................... 24
FIGURE 11. SHOOTING TRAFFIC AT TWO DIFFERENT DUAL-LOOP STATIONS ....................... 24
FIGURE 12. STUDY SITE AT WILLIAMS AVE & I-71 IN CINCINNATI ............................................. 25
FIGURE 13. VIDEOTAPING TRAFFIC AT WILLIAMS AVE & I-71 IN CINCINNATI ............................ 25
FIGURE 14. ILLUSTRATION OF VIDEO DATA COLLECTION AT A SELECTED STUDY SITE ......... 26
FIGURE 15. THE GPS DATA LOGGER AND THE INTERFACE OF ITS SOFTWARE ......................... 29
FIGURE 16. SETTING UP REFERENCE POINTS MANUALLY (DISTANCE BETWEEN POINTS: 20FT) .... 32
FIGURE 17. PROCEDURE FOR SETTING REFERENCE POINTS USING VPC-GPS APPROACH ......... 33
FIGURE 18. REFERENCE POINTS SET IN VEVID USING VPC-GPS APPROACH .............................. 34
FIGURE 19. ALGORITHM FOR REMOVING ERRORS FROM ORIGINAL EVENT LOOP DATA ....... 40
FIGURE 20. SKETCH OF DUAL-LOOP SENSITIVITY ANALYSIS ................................................... 42
FIGURE 21. THE FLOWCHART OF SENSITIVITY ANALYSIS .............................................................. 42
FIGURE 22. SPEED DISTRIBUTION IN EB LANE 3 ............................................................................ 45
FIGURE 23. OCCUPANCY DISTRIBUTION IN EB LANE 3 ......................................................... 45
FIGURE 24. RELATIONSHIP BETWEEN VOLUME AND OCCUPANCY IN EB LANE 3 .............. 45
FIGURE 25. SPEED DISTRIBUTIONS IN DIFFERENT LANES .............................................................. 47
FIGURE 26. A FLOWCHART OF IDENTIFYING TRAFFIC STATES ......................................................... 49
FIGURE 27. VALIDATE THE EXISTING MODEL UNDER FREE FLOW TRAFFIC ............................ 51
FIGURE 28. OUTPUT OF THE EXISTING MODEL UNDER SYNCHRONIZED TRAFFIC FLOW .......... 52
FIGURE 29. ESTIMATED VEHICLE LENGTHS UNDER SYNCHRONIZED TRAFFIC ....................... 55
FIGURE 30. OUTPUT OF THE EXISTING MODEL UNDER STOP-AND-GO TRAFFIC FLOW ............ 59
FIGURE 31. DIFFERENT SCENARIOS OF VEHICLE STOPPING ON DUAL-LOOPS UNDER STOP-AND-GO
FLOW ...................................................................................................................................... 61
FIGURE 32. DISTRIBUTION OF VEHICLE STOPPING STATUS IN CONGESTED TRAFFIC .............. 62
FIGURE 33. FLOW CHART OF SCENARIOS IDENTIFICATION ............................................................. 64
FIGURE 34. OUTPUT OF VC-SYNC MODEL FOR SCENARIO 2 AND 3 ........................................... 65
FIGURE 35. ESTIMATED VEHICLE LENGTHS UNDER STOP-AND-GO TRAFFIC ........................... 68
# LIST OF ACRONYMS

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVI</td>
<td>Audio Video Interleave</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>ODOT</td>
<td>Ohio Department of Transportation</td>
</tr>
<tr>
<td>SBL</td>
<td>Stop-on-Both-Loops-only</td>
</tr>
<tr>
<td>TMC</td>
<td>Transportation Management Center</td>
</tr>
<tr>
<td>VC-Stog</td>
<td>Vehicle Classification under Stop-and-Go</td>
</tr>
<tr>
<td>VC-Sync</td>
<td>Vehicle Classification under Synchronized Traffic</td>
</tr>
<tr>
<td>VEVID</td>
<td>Vehicle Video-Capture Data Collector</td>
</tr>
<tr>
<td>WSDOT</td>
<td>Washington State Department of Transportation</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>------------------------------</td>
</tr>
<tr>
<td>d</td>
<td>day</td>
</tr>
<tr>
<td>fps</td>
<td>frames per second</td>
</tr>
<tr>
<td>ft</td>
<td>feet</td>
</tr>
<tr>
<td>ft/s</td>
<td>feet per second</td>
</tr>
<tr>
<td>ft/s²</td>
<td>feet per square second</td>
</tr>
<tr>
<td>hr</td>
<td>hour</td>
</tr>
<tr>
<td>ln</td>
<td>lane</td>
</tr>
<tr>
<td>m</td>
<td>meter</td>
</tr>
<tr>
<td>min</td>
<td>minute</td>
</tr>
<tr>
<td>mph</td>
<td>miles per hour</td>
</tr>
<tr>
<td>s</td>
<td>second</td>
</tr>
<tr>
<td>veh</td>
<td>vehicle</td>
</tr>
<tr>
<td>veh/hr/ln</td>
<td>vehicles per hour per lane</td>
</tr>
</tbody>
</table>
CHAPTER 1: INTRODUCTION

1.1 Background

Traffic monitoring sensors have been widely used on both highways and local roads to monitor the traffic flow conditions within the road network and obtain traffic parameters. The data captured from these sensors can be used in traffic operation and management as well as other fields in Traffic/Transportation Engineering. Traffic monitoring sensors include radars, cameras, and loop detectors, etc. The inductive loop detector is one of the most widely used traffic sensors, and most States in the United States use inductive loops as the primary and permanent traffic data collection stations and use pneumatic tubes for short term data collection (Fekpe et al., 2004). They are installed in highways by being embedded in the pavement. A loop detector will detect a vehicle’s present when the vehicle is running across it on the road surface. There are two major types of inductive loop detectors that have been widely used: single loop detector and dual-loop detector. It can be understood easily from their names that a single loop detector includes only one loop and a dual-loop detector is made up of two single loops serially in one lane.

The procedure classifying vehicles into different bins is called vehicle classification. Usually, vehicles are classified according to their lengths or number of axles they have, and vehicle classification based on vehicles’ lengths is called length-based vehicle classification. Due to the structure of the single loop detector, the single loop is only capable of counting vehicles and is not able to measure traffic speed and thereby the vehicle lengths cannot be estimated based on its data. Although in previous studies a lot of effort has been reported to estimate vehicle speed and length by employing single loop detector data (Coifman et al. 2008, Zhang et al. 2008, and Zhu et al. 2010), the structure of the single loop limits the accuracy of estimation of
vehicle speed and length. However, the accurate measurement of vehicle speed and classification has vital importance because vehicle speed and classification are highly valued factors which play important roles in validation of travel demand models and freight studies, as well as emission impact analysis of traffic operation. On the other hand, the data extracted from loop detectors has to be sufficiently accurate since any errors will propagate to decision-making and traffic control actions.

**Figure 1. Overview of Dual-loop Detector Station**

The dual-loop detector consists of two single loop detectors which are placed serially within a lane with a very short distance (e.g. 20 ft or 6 m). This special structure of dual-loop detector enables it to measure traffic speed, therefore sometimes it is also called “speed trap”. The structure of the dual-loop detector is illustrated by Figure 1. Event dual-loop data is the raw data obtained from the dual-loop detector station without being aggregated. This data set is a type of high resolution data source which contains the records of the timestamp when a detected vehicle entering and leaving each single loop. Since the distance between the single loops is fixed, the vehicle speed can be calculated by the time stamps that are detected as the vehicle passes over the upstream and downstream loops, and consequently the vehicle length can be
estimated. So the capability of measuring vehicle lengths makes the dual-loop detector a potential real-time data source for length-based vehicle classification. The existing models of length-based vehicle classification using dual-loop detector data are described as follows (Nihan et al., 2006):

\[
speed = \frac{D}{t} \quad \text{(1)}
\]

\[
\text{vehicle\_length} = speed \times \frac{OnT_1 + OnT_2}{2} - \text{loop\_length} \quad \text{(2)}
\]

Where,

\( D \) = distance between two loops (ft)

\( t = t_3-t_1 \)

\( OnT_1 = t_2-t_1 \)

\( OnT_2 = t_4-t_3 \)

\( t_1, t_2, t_3, \) and \( t_4 \) are timestamps when a vehicle enters or leaves the upstream loop (M loop) or downstream loop (S loop) (See Figure 1).

This existing model is based on the assumption that vehicles run across the dual-loop detection area at a constant speed. The model has been validated only against light traffic as vehicles under light traffic condition may operate at a relatively high and stable speed.

As the event dual-loop data is high resolution data which includes individual vehicle’s information, it is usually applied in traffic analysis in order to obtain accurate travel features of individual vehicles traveling over the loop (Chen et al., 1987, Turner et al., 2000, Coifman 2004a, Nihan et al., 2002 and 2006, and Cheevarunothai et al., 2005). The traffic parameters, such as traffic volume, speed, and occupancy or density can be extracted or calculated from the event dual-loop detector data.
Although the dual-loop data can be used to perform the length-based vehicle classification, previous researchers have found that the accuracy is not always reliable. There are some errors reported in dual-loop detector data due to loop sensitivity, data communication problems, crosstalk between adjacent lanes, and even vehicle lane-changing behaviors, etc. (Chen et al. 1987, Nihan et al. 2002 and 2006, Cheeverunothai et al. 2006). When the traffic flow is congested, a vehicle’s travel time trapped on the upstream loop is often much different from the time on the downstream loop due to unstable flow movement during the congested traffic conditions. This phenomenon is a traffic cause to the errors of the modeled speeds and vehicle lengths by using Equation (1) and (2). To filter off the “bad” loop data, traditional method for screening the dual-loop detector data is to check the difference between the time periods that the detected vehicle spent on the upstream loop and the downstream loop (Nihan et al., 2006). If the difference is less than a certain threshold value, the loop data is considered good to use; otherwise, it will be abandoned. Therefore many datasets which are detected under congestions are supposed to be discarded in practice. It has been found that around 80% of the dual-loop detectors undercounted traffic significantly due to such a screening process.

However, this model is not suitable for other congested traffic conditions, especially for the stop-and-go traffic condition. Considering the features of vehicles movement in different conditions, Kerner et al. (1998 and 2004) defined traffic flows in three categories: free flow, synchronized flow, and stop-and-go flow (or moving jams), as shown by Figure 2. According to the descriptions, the different traffic phases have different traffic characteristics. The free flow can maintain stable and high traffic speed and low volume and density. In this circumstance, a vehicle can do maneuvers relatively freely and is not restricted by other vehicles surrounding it. The synchronized flow is a certain stage of congested traffic, which has relative low speed and
high volume and density compared to free traffic flow. Within synchronized traffic flow, the traffic speed is not stable and fluctuates frequently as vehicles have to adjust the headways between each other by accelerating or decelerating from time to time. The traffic phase of stop-and-go is referred to the very congested traffic condition, which has very low speed, low volume and high density. The traffic speed may drop to extremely low and some vehicles may even have to stop for a short period of time. The stop-and-go traffic phase is a very special traffic situation with very unstable traffic flow features.

![Figure 2. Demonstrations of Three Traffic Phases (Kerner, et al. 1998 and 2004).](image)

According to Kerner’s Three Phases Theory, during uncongested traffic flow, it is reasonable that vehicle speeds are regarded as constant. However, during congested traffic, especially stop-and-go traffic, vehicle speeds are unstable most of the time and are not considered constant any more. The assumption is not met under this circumstance. When the existing model is used to estimate vehicle lengths, the accelerations and decelerations of vehicles will distort the outputs of the model. Accuracy of vehicle classification drops greatly under very congested traffic (Fekpe et al., 2004). It is reported that observed errors in truck misclassification ranged from 30 to 41 percent for off-peak hours, and from 33 to 55 percent for peak hours (Nihan et al. 2006). So far, there is no a new set of length-based vehicle classification model using dual-loop detector data have been reported in previous studies to estimate accurate vehicle lengths under congested traffic states.
1.2 Identified Problems

According to literature reviews, the problems which exist in dual-loop detector data and the length-based vehicle classification model are summarized as follows:

1) The algorithm of screening dual-loop detector data may remove those data points which actually are good.
2) The existing dual-loop length-based vehicle classification models produce high errors under non-free traffic conditions, especially under stop-and-go traffic flow.
3) Errors mentioned in 2) may be contributed by the complex characteristics of traffic flows under congestion; but quantification of such contributing factors remains unclear.
4) The characteristics of different traffic phases have not been appropriately considered in the existing length-based vehicle classification model using dual-loop detector data.

1.3 Goal and Objectives

Based on the identified problems in previous section, the goal of this research is to develop improved or new length-based vehicle classification models using dual-loop detector data against congestion traffic. To fulfill the goal, the following objectives have to be achieved:

1) Identifying dual-loop detector data errors accurately. These errors include loop sensitivity, missing data, outliers, etc. The causes of these errors are also to be investigated. Improved algorithms are to be developed to remove those identified errors and avoid undercounting the traffic under congested traffic.
2) Evaluating the existing dual-loop length-based vehicle classification model against ground-truth data under non-free flow traffic phases.
3) Investigating the characteristics of different traffic phases. Improved algorithms are to be developed to identify the three traffic phases based on traffic parameters extracted from dual-loop detector data.

4) Developing the improved or new dual-loop length-based vehicle classification model under synchronized traffic.

5) Developing the improved or new dual-loop length-based vehicle classification model under stop-and-go traffic.
CHAPTER 2: LITERATURE REVIEW

2.1 Inductive loop detectors

An inductive-loop station is usually made up of four parts: wire loops, lead-in wires, lead-in cables, a pull box, and a controller (Figure 4). Inductive-loop detectors are installed in a roadway by being embedded in the pavement (Figure 3). Inductive-loop detectors have been widely used in both urban and rural roadway systems to collect traffic information. The cost of inductive-loop detectors is one of the lowest among all traffic monitoring sensors (Klein et al., 2006). The highway traffic monitoring systems in most states utilize inductive-loop detectors for permanent data collection stations and the pneumatic tubes for short term data collection (Fekpe et al., 2004).

![Figure 3. Dual-loop Detectors Installed in Pavement (Klein et al. 2006)](image)

A loop detector senses the presence of a conductive metal object by inducing currents in the object, which reduce the loop inductance (Klein 2006). An oscillator and amplifiers in a loop system that excite the embedded wire loop and support other functions such as the selection of loop sensitivity and pulse or presence mode operation to detect vehicles that pass over the detection area of the loop (Neudorff 2003).
Figure 4. Components of an Inductive Detector (Neudorff et al. 2003)

Usually, the wire loop is excited with a signal ranging in frequency from 10 kHz to 200 kHz and functions as an inductive element in conjunction with the electronics unit. When a vehicle enters the loop, the loop’s inductance is decreased, and consequently the oscillation frequency is increased, which causes the electronics unit to send a pulse to the controller. This pulse is recorded and indicates that a vehicle has been detected (Neudorff 2003). The basic information can be obtained from inductive loop detectors are vehicle count, occupancy, and timestamp.

The shape of an inductive loop detector may be a rectangle, diamond, or circle. There are two main types of inductive loop detectors which are widely used: single loop and dual-loop. A typical single loop detector is illustrated by Figure 5. The shape and size of a single loop detector change according to its different applications. The most common size is 6 feet by 6 feet. A dual-loop detector consists of two single loops which are placed at a very close distance (the common distance is 20ft). These two consecutive single loops are installed in one lane. Usually, the upstream loop is called “M” loop and the downstream loop is called “S” loop (Figure 5).
2.2 Dual-loop Data Problems

Previous studies revealed that the existing problems in dual-loop data were caused by many reasons. Zhang (2003) analyzed the causes for the incorrect sensitivity levels of a dual-loop detector. Nihan (2006) and Cheevarunothai (2006) proved that incorrect sensitivity is due to factors of maker-specific standards and road materials, which means it is difficult to keep detectors’ sensitivity at an appropriate level. An algorithm was proposed by Cheevarunothai (2006) which aimed to remove the sensitivity discrepancy between two single loops of a dual-loop station and to keep the sensitivities to an appropriate level. Besides data errors caused by the loop sensitivity problem, there are still errors which exist in loop data caused by other factors. Under light traffic, the contributing factors to the data errors have been fully studied and algorithms for removing errors in the collected data have been developed; however, the traffic-related contributing factors have not been fully revealed (Coifman 1999 and Nihan 1997). Nihan et al. (2002) proposed a method for eliminating data errors in current practice. According to this method, if the occupancy difference between the first and second single loop detectors within a dual-loop station is found beyond 10 percent, or if the second single loop detector does not detect a vehicle in a reasonable amount of time, this data sample will be discarded as an “error”. However, during very congested traffic, especially stop-and-go traffic, it happens frequently that
the occupancy difference between the first and second loops is larger than 10 percent, or the second single loop detector does not detect a vehicle in an extended period of time. So this method would flag many real vehicle samples as errors and then lots of valuable samples may be mistakenly discarded. As a result, traffic flow under the congested state would be greatly undercounted, and the accuracy of vehicle classification would be very low.

2.3 Length-Based Vehicle Classification Using Inductive Loop Data

There are two types of inductive loop detectors that are used nowadays: single loop detector and dual-loop detector. The length-based vehicle classification can be based on the data from either of these two types of loop detectors. According to single loop models, vehicle speed cannot be obtained from single data, and consequently, it is impossible to estimated vehicle lengths. However, some models have been proposed by some researchers (Coifman 2008, Kwon 2003, and Zhang 2008) in previous studies. In order to obtain vehicle speed, Coifman (2008) adopted median speed, instead of the usual mean speed adopted by many other researchers. Coifman then proposed an algorithm to estimate vehicle length using median speed and on-time. The accuracy of vehicle length estimation was therefore improved to some extent. Kwon (2003) proposed an algorithm to the mean effective vehicle length using single loop data for multi-lane freeways. However, this algorithm is limited to the assumption that there is a truck-free lane on the freeway and vehicle speeds over different lanes tend to have very small speeds variances. Due to the structure of single loop detector, the models for estimating vehicle speed and length using single loop data are still not able to provide very accurate results, especially under congested traffic. As the structure of dual-loop detector enables researchers to calculate vehicle speed accurately, the vehicle lengths can be estimated accurately. It is has been proven that the
estimation of the vehicle speed and length using the dual-loop data is more accurate than that using the single loop data (Nihan 2006 and Viti 2008).

2.4 Vehicle Bins

According to the Ohio Department of Transportation (ODOT) length-based classification scheme (3-bin scheme), vehicles can be classified into three bins: small vehicle with vehicle length $\leq 28$ ft (Bin 1), median vehicle with length $\leq 46$ ft (Bin 2), and large vehicle with length $>46$ ft (Bin 3) (Coifman 2004). The Washington State Department of Transportation (WSDOT) adopts a 4-bin scheme for length-based classification using dual-loop detectors: vehicle length $\leq 26$ ft (Bin 1), vehicle length $\leq 39$ ft (Bin 2), vehicle length $\leq 65$ ft (Bin 3), and vehicle length $>65$ ft (Bin 4) (Nihan et al. 2002 and 2006). Nihan et al. found that large vehicles are often wrongly classified under both off-peak and peak hours. They discovered that during both off-peak and peak hours Bin 3 vehicles were often assigned to Bin 4. Sometimes Bin 4 vehicles were not assigned to Bin 3. In addition, Bin 2 vehicles were sometimes assigned to Bin 3. For trucks classification during off-peak hours, the misclassification rate ranged from 30 to 41 percent.

There are two types of dual-loop data used in traffic engineering: event loop data and aggregated loop data. The event loop data is a type of raw data recording each event happened to the loop detector. In this case, an event means a vehicle running across the detector and being detected by the loop. So event loop data contains information of each detected individual vehicle. The aggregated data is aggregated from the event data for a certain time interval (usually 20 seconds). Obviously, the aggregated data will remove much useful information. So the event loop data is a type of high-resolution data that includes detailed individual vehicle information, such as the timestamps of a vehicle arriving or leaving the loops. The features of event dual-loop
data usually enable the event data to be used in traffic analysis to obtain accurate vehicle information, such as vehicle length, traffic count, speed, occupancy, and time headway (Chen et al. 1987, Turner et al. 2000, Coifman 2004a, Cheevarunothai et al. 2005, and Nihan et al. 2002, 2006). Meanwhile, Nihan et al. (2002 and 2006) and Coifman et al. (2004a and 2004b) proved that vehicle trajectory data extracted from video footage is a reliable data source which can play as the ground-truth data for length-based vehicle classification. Wei et al. (2005) developed the software VEVID (Vehicle Video-Capture Data Collector) to extract accurate vehicle trajectory data from video footage. The accuracy of the VEVID’s outputs has been proven by the previous study (Wei, 2008).

2.5 Different Traffic Flow States

Greenshields (1935) assumed that the relationship between speed and density is linear and then proposed his famous traffic flow model which is made up of relationships between the parameters of flow, speed, and density. Similarly, Greenberg (1959) proposed a traffic flow model assuming that speed and density fits a logarithmic curve, and Underwood (1961) proposed a traffic flow model assuming that speed and density fits an exponential curve. Those three models are all one-regime models, which means traffic flow is described by only one function under both free flow and congested flow conditions. However, nowadays more and more studies support that the relationships between traffic volume, speed, and density are different under different traffic conditions (i.e. free flow traffic, congested traffic, and even extremely congested traffic). Consequently, multiple-regime models have been proposed by many researchers. Edie (1961) proposed his two-regime linear model for two states of traffic flow: uncongested traffic flow and congested traffic flow. In fact, Edie’s model is a combination of the Underwood’s model for uncongested traffic and the Greenberg’s model under congested traffic. Koshi (1983)
proposed a model to describe the traffic flow-density relationship using a reverse lambda-shaped curve. May (1990) also proposed a two-regime model to describe the relationship between the traffic volume and concentration. It was found that the models did not fit the data very well at capacity and the models were hard to be generalized. A ‘V’ shaped curve was proposed by Hall (1986) to represent the flow-occupancy relationship under uncongested and congested traffic, respectively. Meanwhile, some researchers tried to use three-regime models to interpret traffic flow under different conditions. Polus et al. (2002) categorized traffic flow into three states: free flow, dense flow, and unstable flow. They defined the traffic breakdown as the change from the dense flow to the unstable flow, and the traffic state of stop-and-go was considered as an extreme situation of the unstable traffic. Kerner (1998) tried to reveal the mechanism of how unstable traffic flow happened, especially the stop-and-go phenomenon. Neubert (1999) used the time headway distribution and the headway dependence of the velocity to identify the difference between the free flow state and the congested flow state. Helbing (1999) used the phase diagram to describe the different traffic states. By using the phase diagram, the congested traffic was categorized into four states: homogeneous congested traffic, oscillatory congested traffic, triggered stop-and-go traffic, and moving localized cluster. Kerner et al. (1994 and 1998) proposed a three-phase traffic flow theory and defined traffic flows into three categories: free flow, synchronized flow, and stop-and-go flow, as shown by Figure 6.

According to Kerner’s theory, the free flow traffic has the feature of high travel speed and low traffic volume and density. The synchronized traffic flow can be considered as a type of congested traffic, which has lower speed and higher volume and density than those of the free flow. Under synchronized traffic flow, vehicles have to accelerate or decelerate frequently, which causes the speed of the synchronized traffic flow to fluctuate frequently. However, the
average speed is maintained at a relatively stable level, as illustrated by Figure 6. The stop-and-go traffic flow is considered as a very unstable traffic status caused by very congested conditions. The features of the stop-and-go traffic are very low speed and volume, as well as very large density. The average speed is much lower than that of the synchronized traffic with vehicles stopping from time to time. So, under synchronized traffic, vehicles have high chances of running over the upstream and downstream loops at different speeds. The situation becomes more complicated under the stop-and-go traffic flow as some vehicles may stop one or more times over the detection area.


2.6 Thresholds for Distinguishing Traffic States

Athol (1965) found that the uncongested traffic flow and congested traffic flow would transit to each other at the point when the traffic volume is lower than capacity. Athol suggested that the onset of traffic congestion could be identified by using both volume and occupancy. Non-free traffic flow is an unstable flow, and some researchers named it as oscillatory traffic pattern. Zhang et al. (2009) studied features of the traffic oscillation: the occurrence of oscillation, the offset of the oscillation patterns in different lanes, the period of oscillation, and the oscillation amplitude under different situations. In their study, the jam density was set as 240 veh/mile/ln, and the jam speed was set as 50 miles/hour, and the wave speed was set as 10
miles/hour. Lorenz et al. (2001) proposed a definition of traffic breakdown that when the average speed of all lanes on a highway segment decreased to below 60 miles/hour for at least a 15-minute period. And then in 2003, Elefteriadou et al. changed the speed threshold as of below 50 miles/hour for at least a 15-minute time period. However, other studies indicated that only using the speed is not sufficient to ensure the identification of traffic congestion. Congestion may not be detected by using the speed-based algorithm only, and “perhaps the optimal speed thresholds are different above a certain occupancy threshold” (Wieczorek et al. 2010). Kerner (2004) proposed a fuzzy logic method to identify traffic flow phases. Kerner used traffic flow rates and traffic speed as the parameters in traffic flow identification. The flow rate was classified into “low” and “high”, and speed was classified into “low”, “medium”, and “high. Then the classification of the traffic phases is based on a comparison of measured flow rates and vehicle speeds in different traffic states and a fuzzy inference system is used to perform the classification. Habib-Mattar et al. (2009) found that the unstable flow occurred when the speed dropped to below 60 km/h for at least 5 minutes and density increased firstly and then became greater than 40 veh/km/lane. Their proposed a model composed of an exponential model, a logistic model, and a weighting function. This proposed model can trace the changes of traffic density to identify the traffic breakdown. This model is shown as follows:

\[ H = DE(t) \times (1 - W(t)) + DL(t) \times W(t) \]  \hspace{1cm} (3)

\[ DE(t) = \alpha E \times e^{(\beta_E \times t)} \]  \hspace{1cm} (4)

\[ DL(t) = \frac{L_{max}}{1 + e^{(\alpha_L + \beta_L \times t)}} \]  \hspace{1cm} (5)

\[ W(t) = \frac{1}{1 + e^{(\alpha_W + \beta_W \times t)}} \]  \hspace{1cm} (6)

Where,
\(DE(t)\) = density in time \(t\) in the exponential model (veh/km);
\(t\) = time from midnight (sec);
\(\alpha_E, \beta_E\) = parameters of the exponential model;
\(DL(t)\) = density at time \(t\) in the logistic model (veh/km);
\(L_{max}\) = average value of density in the unstable flow (veh/km);
\(\alpha_L, \beta_L\) = parameters of the logistic model;
\(W(t)\) = weighting function; and
\(\alpha_W, \beta_W\) = parameters of the weighting function.

### Table 1. Summary of Thresholds of Traffic States Used in Previous Studies

<table>
<thead>
<tr>
<th>Researchers &amp; Year</th>
<th>Speed</th>
<th>Volume</th>
<th>Density or Occupancy</th>
<th>Others</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Athol (1965)</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td>To identify congested and uncongested traffic</td>
</tr>
<tr>
<td>Zhang et al. (2009)</td>
<td>50 mph</td>
<td></td>
<td>Jam density = 240 veh/mile/lane</td>
<td>Wave speed=10mph</td>
<td>To identify oscillatory traffic pattern</td>
</tr>
<tr>
<td>Habib-Mattar et al. (2009)</td>
<td>&lt; 37 mph for at least a 5-minute period</td>
<td>64 veh/mile/lane</td>
<td></td>
<td></td>
<td>To identify the unstable flow</td>
</tr>
<tr>
<td>Elefteriadou et al. (2003)</td>
<td>&lt; 50 mph for at least a 15-minute period</td>
<td></td>
<td></td>
<td></td>
<td>To identify traffic breakdown</td>
</tr>
<tr>
<td>Chow et al. (2010)</td>
<td>Speed drop &gt;5mph during 5-minute period</td>
<td></td>
<td></td>
<td></td>
<td>Traffic transition may happen</td>
</tr>
<tr>
<td>Kerner (2004)</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td>A fuzzy logic model is used to identify traffic transition</td>
</tr>
</tbody>
</table>

Besides the model described above, Habib-Mattar et al. (2009) also proposed using traffic speed as the threshold for identifying the traffic breakdown for different types of freeway segments. The speed thresholds are site-specific, which are dependent upon the geometry and other traffic features of the study site. In order to identify traffic transitions, Chow et al. (2010)
adopted speed drop as a criteria. They proposed that the traffic system was considered to become unstable when the drop of speed was larger than 5 mph within 5 minutes, and then the traffic was going to transit from the current state to another state. The thresholds adopted by previous researchers for identifying the traffic states are summarized in Table 1.
CHAPTER 3: METHODOLOGY

It has been proven that vehicle trajectory data extracted from video is a reliable data source, and it can be used to evaluate the concurrent dual-loop detector data and the existing vehicle classification models. In this study, freeway segments with dual-loop detector stations were selected as the study sites. The dual-loop data was collected at the study sites, and the concurrent video data was collected by videotaping the traffic over the detection areas using erected video cameras nearby. Meanwhile, a probe vehicle equipped with a Global Positioning System (GPS) data logger traveled back and forth in the traffic within a freeway segment in which the study sites were included. The GPS data logger is able to record the probe vehicle’s speed, acceleration or deceleration, and locations at an updating time interval of one second. At first, the probe vehicle traveled through the study area back and forth for several times, at a constant speed with its cruise control function on. Then, the probe vehicle traveled in a way of following the traffic flow, which means trying to maintain the average speed of the traffic flow, the GPS data logger can be considered to record the average speed, acceleration, and deceleration of the traffic flow. This probe vehicle collected the GPS data under different traffic conditions, by which way the parameters of traffic characteristics of different traffic states were collected.

After the field data collection, the video tapes were digitalized and stored in computer hard drives. Then the software VEVID was employed to extract the vehicle trajectory data, such as vehicle speeds, vehicle lengths, and timestamps of each vehicle when it is entering and leaving each single loop detector. By comparing the event dual-loop data to the corresponding VEVID-based vehicle trajectory data which was used as the ground-truth data in this research, the errors of dual-loop data could be identified. A new algorithm for processing the concurrent
dual-loop data was developed to identify and remove data errors caused by vehicle lane-changing behaviors and communication problems during data transmission. Then the processed dual-loop data was applied to the existing length-based vehicle classification model to estimate vehicles. The output was evaluated against the concurrent ground-truth data extracted from video by VEVID. The errors and possible causes were effectively investigated against three traffic conditions, namely, free, synchronized, and stop-and-go states. The evaluation result inspired the development of new models for congested traffic flows.

The GPS data, which was collected during the probe vehicle running across the study area at a constant, was used to set up reference points in VEVID. The GPS data which was collected when the probe vehicle was operated to follow the traffic flow, is of the supplementary aligned with video and dual-loop data to reveal the pattern characteristics of different traffic states, which are helpful to the development of new length-based vehicle classification models under congested traffic.

Before the improved vehicle classification models were established against different traffic conditions, a traffic state identification model was needed to be developed. The traffic flow parameters, i.e., speed, volume, and density (occupancy) was derived from the collected dual-loop data and was used to develop the traffic state identification model. As the synchronized traffic flow and stop-and-go traffic flow have different characteristics of the vehicle movement, the vehicle classification models were developed under the two traffic states, respectively. The developed vehicle classification models were evaluated against the ground-true data extracted from the traffic video. Figure 7 illustrates the framework guided for this evaluation.
Figure 7. Framework of Evaluating Dual-loop Data Based Vehicle Classification Models
CHAPTER 4: DATA COLLECTION AND DATA PROCESSING

As the first step of this research, field data collection was conducted. There were four types of data to be collected: the traffic video data at the study sites, the concurrent dual-loop data, the GPS data, and dimensions of the dual-loop detectors. Digital camcorders were set up on an elevated platform near the selected detector stations to videotape the traffic over the detection areas. The concurrent dual-loop data and the dimensions of the dual-loop detectors are collected from the traffic management center of the Ohio Department of Transportation. Meanwhile, the GPS data was collected with the GPS travel data logger equipped on the probe car, which were used to set up reference points in VEVID and to extract traffic characteristics under different traffic situations.

4.1 Study Sites

The eligible study sites for this research should meet the following requirements:

- A dual-loop station has been installed and in good working condition;
- Recurring traffic congestion exists at the study site and all traffic flow states can be found from free flow to extremely congested, namely, stop-and-go traffic flow;
- The event (raw) dual-loop data can be obtained; and
- The dual-loop detectors embedded in pavement are clearly visible at a nearby elevated place where camcorders can be placed to videotape the traffic flow over the detection area.

Two dual-loop stations located on I-70/71 in Columbus, OH were eventually selected as the study sites. In the loop detector system which is operated by Ohio Department of Transportation, these two dual-loop stations are named as V1002 and V1003, respectively. Traffic Management Center (TMC) at ODOT operates those detector stations and provided the
corresponding raw loop detector data for this research. The V1002 station is located on I-70/71 at South Front Street in downtown Columbus, which has 6 dual-loop detectors in both directions. The V1003 station is located on I-70/71 at South Fourth Street, which has 3 dual-loop detectors in the westbound, and it is about 0.8 mile away from the V1002 station (Figure 8 and Figure 9). The Franklin County Juvenile Parking Garage is located at the southern side of I-70/71, which is very close to the V1002 station. The dual-loop station is clearly visible from the top floor of the parking garage, on which a video camera was placed to videotape the traffic over the station. The Columbus Africentric High School is located along I-70/71, which is close to the V1003 station. A video camera was placed at a parking lot of the school to film the traffic flow over the detection area of this station. The configuration of dual-loop detectors at each station is illustrated by Figure 10 and Figure 11.

![Figure 8. Loop Station V1002 on I-70/71 at West Mound Street](image)

![Figure 9. Loop Station V1003 on I-70/71 at South Fourth Street](image)
Besides the two study sites described above, another study site was also selected at the Exit 6 on I-71, which is located at Williams Ave at I-71 in Cincinnati, OH (Figure 13 and Figure 13). Recurrent congestion has been identified at this site and video cameras were set up on the overpass of Williams Ave to videotape the traffic flows on I-71. However, there is no dual-loop detectors installed at this site. But the video footage about congested traffic collected here is still an important supplement to this research. How to utilize the video data collected at this site will be described in Chapter 6.
4.2 Video Data Collection

As described in Section 4.1, video cameras were placed at elevated places near the study sites to videotape traffic running over the detection areas. In order to measure vehicles’ lengths...
and speeds in the traffic video, a reference point system was needed to be set up in the field within the shooting scope. The reference point system enables the software VEVID to measure distance in the video, which consequently enables researchers to obtain vehicles’ speeds and lengths. For the sake of safety, a new approach has been invented to set up reference points in the field, avoiding the need for staff to work along two sides of the highway. This new approach will be elaborated in the next chapter.

**Figure 14. Illustration of Video Data Collection at a Selected Study Site**

The videotaping periods covered morning peak hours, evening peak hours, and off peak hours. There was three-day traffic video collected at the study sites V1002 and V1003 from July 14, 2009 to July 16, 2009. The total length of the traffic video footage was 26 hours, with coverage of different traffic flows, from light traffic to congestion traffic flows (i.e., synchronized traffic and stop-and-go traffic). At another study site on I-71 at Williams Ave in Cincinnati, eight hours long video footage of stop-and-go traffic for 2 days was collected from July 7, 2010 to July 8, 2010. Figure 14 illustrates the camera configuration for the video data collection.
4.3 Event Dual-loop Data Collection

The concurrent dual-loop detector data was obtained from the TMC at ODOT. This data is in a format of raw data, also known as event data. The raw data is a kind of high resolution data, which records the timestamps of each vehicle entering and leaving each single loop. Timestamps are a sequence of numbers, which denotes the time at which a certain event occurred. In this study, the event is a vehicle entering or leaving a single loop. Timestamps in the raw data are presented in a consistent format, which makes it easy to compare different records and track progress over time. The scanning frequency of the dual-loop detectors at the study sites is 60 Hz, which means that occupied status of a loop are automatically updated 60 times per second. There is an exemplary sample of the event data illustrated in Table 2. The timestamp with status value of “1” indicates the moment when a vehicle is to enter the single loop, and the timestamp with the status value of “0” is the moment when the vehicle is to leave the single loop. So timestamps in this table record the moments at which vehicles are detected by a single loop, which make up of the event dual-loop data by combining the data of the two single loops together. The timestamps in this dataset are not recorded as the common used time format of [hh]:[mm]:[ss], but in a format of the ordinary number, as shown in Table 2. The following procedure shows how this time system is established and how to convert a timestamp into a readable time format:

1) In the dual-loop detector clock system, 1/60 second is used as the basic time unit.

2) Midnight (00:00:00) is defined as the start point of the day: 0;

3) For instance, if a vehicle is detected at the time of 13:09:31, then:

   \[\text{timestamp} = 13 \times 60 \times 60 + 9 \times 60 + 31 = 2842260.\]

On the other hand, if a timestamp of a detected vehicle is 3116160, then:
hh = INT(3116160/(60*60*60)) = 14;
mm = INT((3116160-hh*60*60*60)/3600) = 25;
ss = INT((3116160 - hh*60*60*60 - mm*60*60)/60) = 36;

Therefore, the corresponding event happened at 14:25:36.

Table 2. Exemplary Sample of the Event Dual-loop Data

<table>
<thead>
<tr>
<th>M loop (Upstream)</th>
<th>S loop (Downstream)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Status</td>
<td>Timestamp</td>
</tr>
<tr>
<td>-------</td>
<td>-----------</td>
</tr>
<tr>
<td>1</td>
<td>3522267</td>
</tr>
<tr>
<td>0</td>
<td>3524341</td>
</tr>
<tr>
<td>1</td>
<td>3524504</td>
</tr>
<tr>
<td>0</td>
<td>3524675</td>
</tr>
<tr>
<td>1</td>
<td>3524817</td>
</tr>
<tr>
<td>0</td>
<td>3525598</td>
</tr>
<tr>
<td>1</td>
<td>3536773</td>
</tr>
<tr>
<td>0</td>
<td>3629086</td>
</tr>
</tbody>
</table>

4.4 GPS Data Collection

When a GPS device is mounted to a vehicle, the vehicle’s position can be traced at a certain time interval during its traveling. Consequently, the vehicle’s speed and even the change of speed for each time interval can be obtained. This information is very useful in revealing traffic characteristics of congested flows, especially stop-and-go flows. In this study, the QSTARZ™ BT-Q1200 Ultra GPS Travel Recorder was adopted as the data logger to collect GPS data. The GPS travel data logger was equipped in a probe car, and this car was running to and fro along freeway segments of I-71 which cover the selected study sites. This GPS travel data logger is able to update the travel information at a time interval of one second, which means the probe vehicle’s speed and location information can be collected every one second. The software TravelRecorderV4, which comes with the GPS data logger, enables the speed of the probe vehicle to be displayed along the study highway route. Figure 15 illustrates the GPS data logger and a sample data diagram along a sample highway route. The GPS data can be exported
into an Excel file for further analysis, which includes the probe vehicle’s speed, location, and altitude for each time interval. Sample data exported from TravelRecorderV4 to Excel is shown in Table 3.

Table 3. Exemplary Sample of GPS Data

<table>
<thead>
<tr>
<th>Index</th>
<th>Date</th>
<th>Time</th>
<th>Latitude</th>
<th>N/S</th>
<th>Longitude</th>
<th>E/W</th>
<th>Altitude</th>
<th>Speed (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6/18/2009</td>
<td>9:11:20</td>
<td>39.153718</td>
<td>N</td>
<td>84.538517</td>
<td>W</td>
<td>121.0784</td>
<td>34.31250</td>
</tr>
</tbody>
</table>

Figure 15. The GPS Data Logger and the Interface of Its Software

Some traffic parameters of stop-and-go traffic flow are required by the proposed vehicle.
classification models which will be described in the following sections. The parameters represent characteristics of very congested traffic, and they are: range of acceleration or deceleration rate, and average minimum speed to maintain a vehicle’s moving. These parameters can be derived from the statistical analysis of the collected GPS data.

The data accuracy of the GPS data logger could directly affect the reliability of the derived parameters. According to the QSTARZ™ BT-Q1200 Ultra GPS Travel Recorder’s manual, the accuracy of location positioning is within 10 ft and the error of velocity measuring is less than ±0.33 ft/s. Acceleration is calculated based on the change of two consecutive speeds over the time interval. Thus, the error of acceleration is less \((0.33 + 0.33) \text{ft/s}/1\text{s}=0.66\text{ft/s}^2\). In this study, such accuracy is good enough for the purpose of quantifying traffic characteristics.

4.5 Video Trajectory Data Extraction

4.5.1 Introduction of VEVID

The ground-truth data used in this study is the vehicle trajectory data extracted from the traffic video of the study sites. The software VEVID was employed to extract the ground-truth vehicle trajectory data from videos. VEVID was originally developed by Dr. Heng Wei in the Advanced Research in Transportation Engineering and System (ART-Engines) Laboratory at The University of Cincinnati (Wei et al., 2005). Then it has been upgraded by both him and his PhD student, Dr. Zhixia Li. This software requires an AVI file as its input video file, and it can automatically identify the video’s frame rate set up in the AVI file. So the time interval of two consecutive frames is determined. A coordination system is built up in VEVID based on the reference points set up in the field during the time of videotaping, which enables the position of a vehicle in one video frame to be measured easily and accurately. Then the distance a vehicle travels between two consecutive frames can be determined by calculating the vehicle’s position
change from one frame to the immediately next frame. Consequently, vehicle trajectory data, such as speed, acceleration or deceleration, and length of vehicles can be calculated and stored via VEVID.

4.5.2 Setting up Reference Points in Field

A coordination system is built up in VEVID based on the reference points set up in the field during the time of videotaping, which enables the real position of a vehicle to be measured in video. In VEVID, when two points are clicked on the monitor screen, an embedded algorithm will calculate the real distance between these two points. However, the reference points system is required to be set up in advance within VEVID before this algorithm can be used. The traditional way to set up the reference points in field is manually marking the points on the surface of the sidewalk along both sides of the roadway (Figure 16). In the field, the staff mark points along both sides of the road with red traffic cones or something else that can be easily identified in the video. Usually the distance between two marked points is 20ft. This method works very well in local streets, as the traffic speed in the street is not high and staff can work safely on sidewalk; however, it will not work when it is applied to freeway cases. Freeway traffic has a high volume and high speed. Moreover, there is not sidewalk on which staff can work. So a new method of setting up reference points in the field is necessary, which will be convenient and have no safety concern for staff.

Therefore, a new approach using GPS data loggers was applied to create the reference points using a special car which was driven through the study area, and there was no need for staffs to physically stay in field. In this new approach, a GPS-equipped probe vehicle with the aid of cruise control function was used to help with setting up reference points in field. When this probe vehicle was driving through the study area, the car’s cruise control function was set
on, which ensures the car to be traveling at a constant speed (e.g. 60mph). Meanwhile, the in-vehicle GPS data logger was recording the speed of the car at each location and the probe vehicle was also videotaped by the camera which was filming the traffic over the study site. Finally, a video segment that records the process of marking the reference points in field was played in VEVID to set up the reference points system, or called the coordination system. This approach is illustrated by Figure 17 to show how the reference points are set up in the field.

![Figure 16. Setting up Reference Points Manually (Distance between points: 20ft)](image)

In VEVID, video-capture and linear perspective drawing techniques are used to determine the real distance based on the reference points from the video frames. The speed data of the probe vehicle recorded by the GPS data logger was used to determine the reference spacing intervals. The frame rate of video in this study is 30 frames per second, which means the time interval between two consecutive frames is 1/30s. If the speed of the probe car is 60mph, i.e. 88ft/s, the real distance the car traveled from the first frame to the second one will be 88/30 = 2.93 ft. In this way, a real-distance coordinate system is registered in VEVID. Since Video-capture and Perspective drawing techniques, Cruise control function, and GPS-based Probe
technology constitute such a systematic approach, this new approach of setting up reference points in VEVID is named as the VPC-GPS approach. In the field, while the video camera was shooting the traffic, the probe car would be driving through the shooting range. The GPS Travel Data Logger in the vehicle was used to accurately measure and record the speed, S (ft/s). In VEVID, the desired video frame rate F (frames/s) can be selected, and the travel time between two consecutive frames t equals 1/F. So the travel distance between two consecutive frames is: D (ft) = S × t. The procedure of setting up reference points in the interface of VEVID is illustrated in Figure 17.

**Figure 17. Procedure for Setting Reference Points using VPC-GPS Approach**
4.5.3 Extracting Vehicle Trajectory Data from Video

Once the reference point system is set up and registered in VEVID, the vehicle trajectory data can be obtained from any traffic video via VEVID by clicking the selected vehicle on a computer screen. Firstly, a distinguishing point of a vehicle is selected. Usually, this point is the contact point of the rear (or front) tire on pavement. Then this point is clicked on the first selected video frame and then on the second selected video frame. The location difference of the distinguished points (i.e. the clicked points) on two frames is the distance the vehicle travels during the time between those frames. As the frame rate is constant once it is selected, the time interval between any two consecutive frames is fixed. So the time between any two frames can be easily determined. In this way, the speed and other travel parameters of the studied vehicle can be calculated by an embedded program in VEVID. For an instance, at the 200th frame, the position of the distinguished point is 60ft. After 5 frames, namely at 206th frame, the position of the same point is 72ft. So the vehicle traveled 12ft during the time of 5 frames (5/30=1/6s), and its speed is (72-60)/(1/6) = 72 ft/s, or 49.1mph. The length of a vehicle can be measured in...
VEVID by clicking the vehicle’s rear bumper and front bumper on the same frame, respectively. The real position difference between these two points is the length of this vehicle. Table 4 shows exemplary extracted trajectory data obtained from traffic video by VEVID.

<table>
<thead>
<tr>
<th>Vehicle No.</th>
<th>Speed on M loop (mph)</th>
<th>Speed on S loop (mph)</th>
<th>On_time 1 (M loop) (sec)</th>
<th>On_time 2 (S loop) (sec)</th>
<th>Vehicle Length (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.24</td>
<td>17.74</td>
<td>0.6333</td>
<td>0.7000</td>
<td>8.7</td>
</tr>
<tr>
<td>2</td>
<td>18.06</td>
<td>15.36</td>
<td>1.1000</td>
<td>1.2667</td>
<td>18.1</td>
</tr>
<tr>
<td>3</td>
<td>16.14</td>
<td>13.96</td>
<td>1.1333</td>
<td>1.2667</td>
<td>16.1</td>
</tr>
<tr>
<td>4</td>
<td>14.83</td>
<td>12.69</td>
<td>1.1333</td>
<td>1.3333</td>
<td>13.7</td>
</tr>
<tr>
<td>5</td>
<td>13.85</td>
<td>12.32</td>
<td>1.2667</td>
<td>1.4667</td>
<td>15.8</td>
</tr>
<tr>
<td>6</td>
<td>11.36</td>
<td>9.92</td>
<td>1.5333</td>
<td>1.6333</td>
<td>17.1</td>
</tr>
<tr>
<td>7</td>
<td>10.26</td>
<td>9.54</td>
<td>1.6000</td>
<td>1.7667</td>
<td>14.8</td>
</tr>
<tr>
<td>8</td>
<td>12.92</td>
<td>8.37</td>
<td>2.0000</td>
<td>2.1667</td>
<td>17.0</td>
</tr>
<tr>
<td>9</td>
<td>8.99</td>
<td>8.62</td>
<td>2.2000</td>
<td>2.4333</td>
<td>19.4</td>
</tr>
<tr>
<td>10</td>
<td>9.75</td>
<td>8.74</td>
<td>1.8333</td>
<td>2.0000</td>
<td>13.6</td>
</tr>
</tbody>
</table>

Note: M loop: Upstream loop; S loop: Downstream loop.

Each detected vehicle has its timestamps recorded in the dual-loop detector data. The concurrent video footage has timestamps displayed, too. So a vehicle detected by the dual-loop detector can be identified in the concurrent video by matching its timestamps from the video and loop detector, respectively. Then by clicking a distinguishing point on this vehicle in the same and different frames in VEVID, its length, speed, and on-times can be extracted. Thus, the vehicle’s loop data and its corresponding ground-truth data are ready for use. Each selected vehicle would be processed in VEVID as described above to be identified in the video and to extract its ground-truth data. At the two study sites in Columbus, 813 vehicle samples under the free flow traffic, 194 vehicle samples under the synchronized traffic, and 61 vehicle samples under the stop-and-go traffic, have been extracted from the video. The study site in Cincinnati contributes 112 vehicle samples under stop-and-go traffic.
4.6 Dual-loop Data Processing

4.6.1 Existing Problems in Event Dual-loop Data

In this study, the original event dual-loop data was obtained with the help of the TMC at ODOT. The data was directly downloaded from the dual-loop station controllers without any aggregation or processing treatment. It is very possible that this event data has errors caused by factors such as vehicles’ lane changing or other communication problems. As the data from upstream loop (M loop in Figure 1) is combined with its corresponding downstream loop (S loop in Figure 1) to form a dual-loop data record, even a single error which exists in the data set will cause a mismatch of all data records. Therefore, these errors have to be identified and eliminated before any evaluation is conducted. The vehicle’s lane-changing behavior may result in missing data either from the upstream loop or the downstream loop. When a vehicle is making a lane-changing maneuver within a certain range of the dual-loop detector, it may just pass over the upstream loop and comes into an adjacent lane before entering the downstream loop of the current lane; or it may come from another lane and directly runs over the downstream loop of the current lane without entering the upstream loop. As introduced previously, for the normal event dual-loop data a timestamp of “1” status (occupied) is always followed by a timestamp of “0” status (not occupied) (see Table 5). Communication problems may cause fake timestamps in the dual-loop data set. When communication problems happen, some errors will be found like a timestamp of “1” status followed by another timestamp of “1” status, or a timestamp of “0” status followed by another timestamp of “0” status. Like the errors caused by lane-changing behaviors, these communication errors also can lead to mismatch of the records from the M loop and the S loop. For instance, at the V1002 loop station, the total number of 24-hour records of the M loop in a lane is 347639, while those of the corresponding S loop in this lane is 346749. So
there are 890 counts difference. This difference may be caused by either vehicle lane-changing or communication problems. A dual-loop data record is made up of a record from the M loop and another record from the corresponding S loop. If there are no lane-changing or communication problems, the total counts of the M loop should be the same as those of the S loop. When they have a difference, it is impossible to determine which pair of the data points represents a certain vehicle running over the detection area. Such errors have to be identified and removed from the dual-loop detector data.

The traditional method for eliminating data errors under congested traffic is: if the occupancy difference between the first and second single loop detectors within a dual-loop station is found beyond 10 percent, or if the second single loop detector does not detect a vehicle in a reasonable amount of time, this data sample will be discarded as an “error” (Nihan et al., 2002). However, during very congested traffic, especially stop-and-go traffic, it happens frequently that the occupancy difference between the first and second loops is larger than 10 percent, or the second single loop detector does not detect a vehicle in an extended period of time. So this method is very likely to flag and remove many real vehicle samples as errors. So traffic counts under the congested state would be greatly underestimated, and the accuracy of vehicle classification would be decreased. The algorithm described avoids this problem and tries to keep all possible good data samples under congested traffic.

The processed dual-loop detector data then was validated against the concurrent video data in VEVID. Each vehicle’s on-times from the dual-loop data were compared with its on-times extracted from the concurrent video. As a result, the errors caused by vehicle land-changing and communication problems have been identified and removed successfully; most of the real and good vehicle samples under stop-and-go traffic have been retained, and the dual-
loop data under stop-and-go traffic is still accurate after those errors being removed.

4.6.2 An Error Elimination Algorithm for Original Event Dual-loop Data

An algorithm was developed to identify and eliminate the errors discussed in the previous section. This algorithm is made up of three parts: (1) identify and remove the communication problems; (2) identify and remove the errors caused by vehicles’ lane-changing happened on the S loop; and (3) identify and remove the errors caused by vehicles’ lane-changing happened on the M loop. The whole procedure is described in details as follows:

Step 1: Identify and remove communication errors. A data point will be recorded only when a vehicle is detected by the loop. So in a data set, the first record must be a timestamp of “1”. If the first record is a timestamp of “0”, it must be an error and should be removed until the first timestamp of “1” appears. For the rest of the records in the data set, the normal event dual-loop data points are records with a timestamp of “1” status followed by a timestamp of “0” status. If the second timestamp is not a “0” status, this record will be removed until a “0” status appears. This “0” status should be followed by another “1” status. This procedure is repeated until all data points in the data set are checked and corrected.

Step 2: Identify and remove errors caused by a vehicle coming from an adjacent lane and driving onto the S loop without running over the M loop. In this algorithm, T_u represents a timestamp of the M loop and T_d is a timestamp of the S loop (Table 5). So T_u(i) and T_d(i) represent the timestamps for the i^{th} vehicle entering the M loop and leaving the M loop, respectively. Similarly, T_d1(i) and T_d2(i) represent the timestamps for the i^{th} vehicle entering the S loop and leaving the S loop, respectively. When T_d(i) is found to be less than T_u(i), it means that the event of
the vehicle entering the S loop happened before the event of the same vehicle entering the M loop. Since it will not happen that the vehicle would arrive at the S loop first, the vehicle must come from an adjacent lane and went over the S loop directly without entering the M loop. So, this timestamp $T_{d1}(i)$ does not have a corresponding $T_{u1}(i)$ aligned with it to form a dual-loop data point, and it will be removed from the data set. This step is repeated until all data points of lane-changing in the data set are identified and removed.

<table>
<thead>
<tr>
<th>Table 5. Timestamps of the M Loop and the S loop</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>M loop (Upstream)</strong></td>
</tr>
<tr>
<td>Status</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>...</td>
</tr>
</tbody>
</table>

Step 3: Identify and remove errors caused by a vehicle leaving from the M loop for an adjacent lane without entering the S loop. In Table 5, when $T_{u1}(i+1)$ is less than $T_{d1}(i+1)$ and $T_{u1}(i+1)- T_{d1}(i)$ is less than $T_{u1}(i)- T_{d1}(i)$, it means that $T_{d1}(i)$ happened much closer to $T_{u1}(i+1)$ than $T_{u1}(i)$ did, which indicates that $T_{u1}(i+1)$, instead of $T_{u1}(i)$, and $T_{d1}(i)$ are more likely a data pair representing the same vehicle. So the timestamp $T_{u1}(i)$ and $T_{u2}(i)$ can be identified as the timestamps for a vehicle entering the M loop and leaving for an adjacent lane before it reached the S loop. As a result, the timestamp $T_{u1}(i)$ and $T_{u2}(i)$ will be removed from the data set.

In order to describe the algorithm more clearly, especially Step 2 and Step 3, a flowchart
is illustrated by Figure 19. This flowchart focuses on identifying and eliminating the errors caused by vehicles’ lane-changing behaviors. Computer programming code based on this algorithm was compiled in MatLab to process the original event dual-loop data. The output of this programming code has been verified against the ground truth data extracted from the video data by VEVID.

![Figure 19. Algorithm for Removing Errors from Original Event Loop Data](image)

4.6.3 Dual-Loop Sensitivity Analysis

Cheevarunothai et al. (2006) found that one factor affecting dual-loop data quality is the inappropriate sensitivity level. The loop sensitivity problems can be classified into two categories: one is sensitivity discrepancies between the upstream loop and the downstream loop,
and the other is unsuitable sensitivity levels of both the M and S loops. According to Cheevarunothai’s study, a sensitivity problem will be considered in existence when the on-time differences are greater than $\pm 10$ percent comparing to concurrent ground truth data. When a loop detector is identified with a sensitivity problem, it means that its effective detection area is not the same as its physical area. The effective detection area is defined as the virtual dimension of the loop detector. The virtual dimension may be bigger or smaller than the physical dimension. For instance, the physical length of the M loop is 8.5ft. When its sensitivity is higher than the normal level, its virtual length may be as long as 11ft. In this study, the criteria used by Cheevarunothai et al. are adopted to identify a sensitivity problem. If a sensitivity problem is determined, its virtual dimension of the loop detector will be calculated by comparing to the concurrent ground truth data, as illustrated by Figure 20.

Considering the features of free flow traffic, where vehicles are traveling at a relatively high speed, and speed changes within short distance (such as the length of detection area of a dual-loop detector) are very small or even zero. So theoretically, under free flow traffic, a vehicle’s on-times of the M loop and the S loop can be assumed the same, and it is more true to smaller vehicles. A set of event dual-loop data of small vehicles (vehicle length < 26 ft) under free traffic flow is applied for sensitivity analysis. The on-times ($OnT_1$ and $OnT_2$) and travel time ($t$) from the M loop to the S loop are derived from the data set. Then these calculated parameters based on loop data are compared with the concurrent ground-truth data extracted by VEVID. The flowchart of sensitivity analysis is shown by Figure 21, which demonstrates the algorithm for identifying and analyzing the dual-loop sensitivity levels. The calculated virtual dimensions will be used as the real size of the detector dimensions in the following vehicle classification modeling.
Figure 20. Sketch of Dual-loop Sensitivity Analysis

Figure 21. The Flowchart of Sensitivity Analysis

Notes:
1. OnT₁, OnT₂, and v are on-times and the vehicle’s speed extracted by VEVID;
2. tᵣ is the travel time from the M loop to the S loop, which is extracted by VEVID;
3. Lᵥ and Lᵥ are the virtual lengths of the M loop and the S loop, respectively;
4. Dᵥ is the virtual distance of the two single loops; and
5. OnT₁, OnT₂, and t are defined as before.
CHAPTER 5: TRAFFIC FLOW PHASES IDENTIFICATION

According to the literature review, the existing length-based vehicle classification model is working well under free flow traffic, but it produces many errors under congested traffic flows, especially under stop-and-go traffic. So the goal of this study is to develop vehicle classification models under congested traffic flows. Congested traffic flows consist of synchronized and stop-and-go flow, so different models are needed for different traffic flows due to their different traffic characteristics. In this case, a traffic flow phase identification model is expected to identify the traffic flow before a suitable vehicle classification model is applied. So whether varied traffic flows can be identified correctly will influence the correct application of the length-based vehicle classification models.

Previous studies have indicated that it is not reliable to identify different traffic states only using one traffic parameter, such as speed or volume. So the heuristic approach with a combination of two or three primary variables is adopted to develop the algorithm for identifying the traffic states. The primary parameters, such as density, volume, and speed, can be obtained directly from the dual-loop data.

Several traffic flow parameters have been used to describe the traffic characteristics, including volume (or vehicle count), speed, and density (or occupancy). The vehicle count, speed and occupancy can be derived directly from the loop data, and density can only be estimated based on other variables. In light of previous studies, among those discussed variables, vehicle speed and occupancy are considered as stronger indicators in traffic states identification. The relationship of traffic speed vs. time, occupancy vs. time, and volume vs. occupancy are illustrated by Figure 22, 23, and 24. The data used in these diagrams is part of collected event dual-loop data from the study site, which has been aggregated by a time interval of 20 seconds.
Based on the statistical analysis of the aggregated data, comparing to the concurrent video in which the traffic states can be observed, models of identifying three traffic states, namely, free flow, synchronized flow, and stop-and-go flow, are developed. In the following sections, the models of identifying each traffic state are described in details.

5.1 Free Flow Identification

According to Kerner’s three-phase theory and other previous studies, the free flow traffic has a relatively high and stable average speed, low volume and low density or occupancy. Previous studies also have proven that the average free flow speed is not a constant for all roadways. In fact, the free flow speeds are often varying in different roadways and even different lanes on the same roadway segment. The results in this study have proven it. The speed distributions during a same period of time for two different lanes, lane 2 and lane 3 at the dual-loop station V1002, are illustrated by Figure 25. In the distribution diagrams, it can be easily identified that the average free flow speed for lane 2 is about 65mph and that for lane 3 is about 55mph. So it is not reliable to identify the free flow traffic by giving a threshold value of average speed. However, statistical analysis shows that the observed difference of average speeds of two consecutive time intervals within the same lane is usually limited within a certain small range. In this study, the range is within 10mph with standard deviation of 7 mph over every 5 minutes. The model of identifying the free flow traffic is described as follows:
Figure 22. Speed Distribution in EB Lane 3

Figure 23. Occupancy Distribution in EB Lane 3

Figure 24. Relationship between Volume and Occupancy in EB Lane 3
if $\bar{v}(t) - \bar{v}(t + 1) \leq \Delta v$ \hspace{1cm} (7)

and

$var(v) < v^*$ \hspace{1cm} (8)

is true, then the traffic flow during the time interval $t$ is free flow.

Where,

$t$ is a period of time and in this study $t=5 \text{ min}$;

$\bar{v}(t)$ (mph) is the average speed in time interval $t$;

$\bar{v}(t + 1)$ (mph) is the average speed in the successive time interval $t+1$;

$var(v)$ is the variation of all vehicles’ speed during time interval $t$; and

$\Delta v$ and $v^*$ are predefined threshold of spot speed difference and predefined threshold of the speed variation range in successive time intervals, respectively. Based on the statistical analysis of the collected dual-loop data set, $\Delta v$ is determined as 10 mph and $v^*$ is determined as 49 mph$^2$ (or the standard deviation is 7 mph).
5.2 Synchronized traffic flow identification

Comparing to the free flow, the synchronized traffic flow has the following characteristics: the traffic speed is relatively low and the speed is not stable and is fluctuating frequently. For example, the average speed of the synchronized traffic flow may be 40 mph, and vehicles in the traffic stream have to accelerate or decelerate from time to time. Meanwhile, the traffic volume at this state begins to increase and is larger than that of the free flow. However, although the occupancy at this state is slightly increased, it still remains stable and a significant increase cannot be identified. So the synchronized traffic flow can be identified in terms of changes of occupancy over a period of time and the occupancy variance. The model for
identifying the synchronized traffic is described as follows:

When $\bar{v}(t) - \bar{v}(t + 1) \leq \Delta v$, and $\text{var}(v) \leq v^*$ are not satisfied,

If $\bar{occ}(t) - \bar{occ}(t + 1) \leq \Delta occ$

and

$\bar{occ}(t) < occ^*$

is true, then the traffic flow is identified as the synchronized traffic flow.

Where,

- $t$ is a period of time (5 minutes in this study);
- $\bar{occ}(t)$ is the average occupancy during time interval $t$;
- $\bar{occ}(t + 1)$ is the average occupancy in the successive time interval $t+1$; and

$\Delta occ$, and $occ^*$ are the predefined occupancy bandwidth and the maximum average occupancy during the time interval $t$, respectively.

In this study, in light of the statistical analysis on the collected data, the thresholds of $\Delta occ$ is defined as 0.3, and $occ^*$ is 0.35, respectively.

5.3 Stop-and-go traffic identification

If the traffic flow does not belong to the free flow or synchronized traffic, it will be considered as stop-and-go traffic. Under stop-and-go traffic, the traffic speed is extremely low (vehicles have to make a stop from time to time), and the occupancy is very high while volume is at a low level. The model for identifying the stop-and-go traffic is described as the following:

If $\bar{v}(t) - \bar{v}(t + 1) \leq \Delta v$ and $\text{var}(v) < v^*$, and

$\bar{occ}(t) - \bar{occ}(t + 1) \leq \Delta occ$ and $\bar{occ}(t) < occ^*$

is false, then the traffic flow will be identified as the stop-and-go traffic flow.
The models described above are integrated into a flowchart shown by Figure 26, which can be used to identify the three different traffic states using dual-loop detector data.

Figure 26. A Flowchart of Identifying Traffic States
CHAPTER 6: LENGTH-BASED VEHICLE CLASSIFICATION MODELS

6.1 Evaluating the Existing Vehicle Classification Model

Three dual-loop data sets for three traffic states were employed to evaluate the existing length-based vehicle classification model. These data sets have been processed by the data processing algorithm described in Chapter 4, so the data used in this chapter is the corrected data based on the original dual-loop data. The extracted data from the study sites in Columbus include 813 vehicle samples under the free flow traffic, 194 vehicle samples under the synchronized traffic, and 61 vehicle samples under the stop-and-go traffic. As the supplementary data set, the study site in Cincinnati contributes 112 vehicle samples under stop-and-go traffic.

The existing length-based vehicle classification model has been described in Chapter 1 (Equation (1) and (2)). It is based on the assumption that the vehicle travels across the dual-loop at a constant speed without acceleration or deceleration, or the change of speed is small enough to be ignored.

The data set of the free flow was applied to the existing model to estimate the length of the individual vehicle. The ground truth data, vehicle lengths extracted from the concurrent video, was employed to validate the output of the existing model. A t-test was adopted to examine if there is any significant difference between the estimated vehicle lengths and the real ones. The hypothesis was set up by assuming that the two variables have the same mean with different variances. According to the t-test results, the t value is 0.9565, which is less than 1.96, the critical value at the 95% confidence level. The hypothesis can be accepted and so the two variables are considered having the same mean values (Table 6). This result proves that the existing model is working very well against the free flow traffic.
Figure 27. Validate the Existing Model under Free Flow Traffic

Table 6. T-test Results for the Free Flow Traffic

<table>
<thead>
<tr>
<th>t-Test: Two-Sample Assuming Unequal Variances</th>
<th>Estimated Lengths from the Existing model</th>
<th>Ground-Truth Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>19.83056578</td>
<td>19.15835178</td>
</tr>
<tr>
<td>Variance</td>
<td>207.5216172</td>
<td>194.0063158</td>
</tr>
<tr>
<td>Observations</td>
<td>813</td>
<td>813</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>1622</td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>0.956521958</td>
<td>0.169475568</td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>1.645793605</td>
<td>0.338951136</td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.961427617</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) two-tail</td>
<td>1.961427617</td>
<td></td>
</tr>
</tbody>
</table>

The dual-loop data under the synchronized traffic flow was applied to the existing vehicle classification model. Similarly, the estimated vehicle lengths from the existing model were compared with the real lengths extracted from the concurrent traffic video. The results are
illustrated by Figure 28. It is obvious that for all vehicle types, the existing model produce more errors under the synchronized traffic, especially for large size vehicles.

Another t-test was applied to examine if there is any significant difference between the estimated vehicle lengths and the real ones under synchronized traffic flow. The hypothesis was set up by assuming that the two variables have the same mean with different variances. The results are listed in Table 7. The $t$ value is 1.8905, which is larger than the critical value at the 95% confidence level, 1.96. So the hypothesis is rejected and the two variables are considered having different mean values. This result indicates that the existing model is not suitable for synchronized traffic flow anymore. The relative error rate was also calculated to quantify the errors produced by the existing model. Under synchronized traffic flow, the relative error rate is 33.5%, which is very large. So updated vehicle classification models are to be developed to estimate vehicles lengths under synchronized traffic flow.
### Table 7. T-test Results for the Synchronized Traffic Flow

<table>
<thead>
<tr>
<th>t-Test: Two-Sample Assuming Unequal Variances</th>
<th>Estimated Lengths from the Existing model</th>
<th>Ground-Truth Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>50.67745655</td>
<td>44.81443299</td>
</tr>
<tr>
<td>Variance</td>
<td>1128.526666</td>
<td>737.3643502</td>
</tr>
<tr>
<td>Observations</td>
<td>194</td>
<td>194</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>1.890511691</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>0.029735365</td>
<td></td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.648982315</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) two-tail</td>
<td>0.059470731</td>
<td></td>
</tr>
<tr>
<td>t Critical two-tail</td>
<td>1.966396196</td>
<td></td>
</tr>
</tbody>
</table>

6.2 Developing New Vehicle Classification Model under Synchronized Flow

The characteristics of the vehicle movement under synchronized traffic flow are different from those under the free traffic flow or stop-and-go traffic flow. Under the synchronized traffic flow condition, the density of traffic is higher than that of the free flow, the interaction between vehicles has been increased and vehicles are not able to perform maneuvers very freely. As a result, the travel speed of the traffic flow is lower than that of the free flow, and higher than that of the stop-and-go flow. The thresholds of identifying the synchronized traffic flow have been discussed in previous sections. As discussed earlier, under the synchronized traffic, it is very possible that a vehicle will run over the upstream and downstream loops at different speeds as it may increase or decrease its speed after leaving the upstream loop. Under this circumstance, the assumption for the existing model does not work anymore, and the vehicle’s acceleration or deceleration begins to play an influential role in measuring the vehicle length. It is the vehicle’s acceleration or deceleration that distorts the estimation of the existing model. A new model is proposed to estimate vehicle lengths under the synchronized traffic flow, which is named as the
Vehicle Classification under Synchronized Traffic Model (VC-Sync model). In the new model, a vehicle’s acceleration or deceleration is considered as one of contributing factors. It is assumed that a vehicle passes the dual-loop detection area at a constant acceleration rate \( a \) (\( a \) can be positive or negative depending on the vehicle’s accelerating or decelerating movement) without a stop, and the movement of the vehicle passing over the dual-loop detection area can be described by the equations as follows:

\[
L_s + L_v = v_0 \cdot OnT_1 + \frac{1}{2} a(OnT_1)^2
\]

(11)

\[
L_s + L_v = v_1 \cdot OnT_2 + \frac{1}{2} a(OnT_2)^2
\]

(12)

\[
v_i = v_0 + at
\]

(13)

\[
\frac{v_0 + v_1}{2} = \frac{D}{t}
\]

(14)

The estimated vehicle length can be deduced based on the four equations above, and the VC-Sync model is expressed as the following equations:

\[
L_v = v_0 \cdot OnT_1 + \frac{1}{2} a(OnT_1)^2 - L_s
\]

(15)

\[
v_0 = \frac{D}{t} - \frac{a \cdot t}{2}
\]

(16)

\[
a = \frac{D}{t} \left[ \frac{2 \cdot (OnT_1 - OnT_2)}{(OnT_2)^2 - (OnT_1)^2 + (OnT_1 + OnT_2) \cdot t} \right]
\]

(17)

Where,
\( L_v \) = length of the detected vehicle (ft); 

\( L_s \) = length of each single loop which makes up a dual-loop detector (ft); 

\( v_o \) = speed of the vehicle at the moment it is to enter the upstream loop (M loop) (ft/s); 

\( a \) = vehicle acceleration (ft/s^2); and \( D, t, OnT_1, \) and \( OnT_2 \) are the same as defined earlier in Chapter 1 (see Figure 1).

![Synchronized Traffic](image)

**Figure 29. Estimated Vehicle Lengths under Synchronized Traffic**

The dual-loop data for the synchronized traffic flow was applied to the proposed VC-Sync model to estimate the length of vehicles. The output of the model is shown by Figure 29. The vehicle lengths estimated by the existing model are also illustrated by Figure 29 to compare the difference between the results from the two models. It is obvious that the outputs from the VC-Sync model have been improved significantly. Compared to the ground-truth data, the error rate of the existing model is 33.5%, while that of the VC-Sync model has decreased to 6.7%. Again a t-test was conducted to the estimation of the VC-Sync model and the ground-truth data (Table 8). The \( t \) value is 0.2359, which is less than the critical value at the 95% confidence level,
1.96. So the hypothesis is accepted and the two variables are considered having the same mean. The results indicate that the developed VC-Sync model has greatly improved the accuracy of length-based vehicle classification under the synchronized flow condition.

Table 8. T-test Results for VC-Sync Model under Synchronized Flow

<table>
<thead>
<tr>
<th>t-Test: Two-Sample Assuming Unequal Variances</th>
<th>Estimated Lengths from VC-Sync model</th>
<th>Ground-Truth Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>45.47293</td>
<td>44.81443</td>
</tr>
<tr>
<td>Variance</td>
<td>774.5289</td>
<td>737.3644</td>
</tr>
<tr>
<td>Observations</td>
<td>194</td>
<td>194</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>386</td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>0.235883</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>0.406824</td>
<td></td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.648811</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) two-tail</td>
<td>0.813649</td>
<td></td>
</tr>
<tr>
<td>t Critical two-tail</td>
<td>1.966129</td>
<td></td>
</tr>
</tbody>
</table>

Table 9. Vehicle Assignment during Synchronized Traffic (3-Bin Scheme)

<table>
<thead>
<tr>
<th>By Ground-truth Data</th>
<th>By Dual-loop Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bins</td>
<td>Bin type identified by vehicle length</td>
</tr>
<tr>
<td>Bin 1</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Bin 2</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Bin 3</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 10. Vehicle Assignment during Synchronized Traffic (4-Bins Scheme)

<table>
<thead>
<tr>
<th>Bins</th>
<th># of Vehicles</th>
<th>By Ground-truth Data</th>
<th>By Dual-loop Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Bin type identified by vehicle length</td>
<td># of vehicles by existing model</td>
</tr>
<tr>
<td>Bin 1</td>
<td>85</td>
<td>Bin 1</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 4</td>
<td>1</td>
</tr>
<tr>
<td>Bin 2</td>
<td>9</td>
<td>Bin 1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 4</td>
<td>0</td>
</tr>
<tr>
<td>Bin 3</td>
<td>14</td>
<td>Bin 1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 4</td>
<td>6</td>
</tr>
<tr>
<td>Bin 4</td>
<td>86</td>
<td>Bin 1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 4</td>
<td>64</td>
</tr>
</tbody>
</table>

ODOT classifies vehicles by their lengths into 3 bins: Bin 1 for small vehicle (vehicle length <= 28 ft), Bin 2 for median vehicle (28 ft < vehicle length <= 46 ft), and Bin 3 for large vehicle (vehicle length > 46 ft). WSDOT uses a 4-bin scheme to classify vehicle into 4 bins: Bin 1 for vehicle length <= 26 ft, Bin 2 for vehicle length >26 ft and vehicle length <= 39 ft, Bin 3 for vehicle length >39 ft and vehicle length <= 65 ft, and Bin 4 for vehicle length > 65 ft.

Outputs from the existing model and the VC-Sync model were compared to each other and the results are shown in Table 9 and Table 10, using 3-bin and 4-bin schemes, respectively. The number of vehicles in the column of “By Ground Truth Data” is assigned into different bins according to the vehicles’ real lengths. Under the column of “By Dual-loop Data”, the vehicles...
are assigned into different bins according to their estimated lengths from existing model and VC-Sync model, respectively. As shown in Table 9, the existing model results in 14.9% of vehicles of Bin 1 which are misidentified as vehicles of Bin 2 and Bin 3. For Bin 2, there is 28.6% of vehicles of Bin 2 are mistaken as vehicles of Bin 1. For Bin 3, the accuracy is pretty good, which is as high as 97%. When the VC-Sync model is applied, the accuracy for all bins has been improved. There are 85.1% of vehicles identified as Bin 1 when the existing model is used, and the identification rate is improved to 98.9% after the new model being applied. The accuracy of Bin 2 is improved to 100%. When the 4-bin scheme is applied, VC-Sync model also has resulted in a significant improvement in the accuracy of vehicle classification. The comparison of estimated vehicles lengths estimated from the existing model against the VC-Sync model is shown in Table 10. The accuracy for Bin 1 has been improved from 82.4% to 100%, and that for Bin2 and Bin 3 have been improved from 66.7% to 88.9% and from 57.1% to 85.7%, respectively. Meanwhile, for Bin 4, the accuracy has been improved from 74.4% to 94.2%.

6.3 Developing New Vehicle Classification Model under Stop-and-go Traffic

6.3.1 Scenarios of Vehicle Stopping Status

The characteristics of vehicles’ movement under stop-and-go traffic flow are very different from those under free flow traffic or synchronized traffic. Vehicles are operating at a high, relatively constant speed under the free flow traffic, and the free flow traffic will transit to the synchronized traffic flow when the traffic speed drops significantly. The synchronized traffic flow has a low speed with frequently acceleration or deceleration involved. The traffic will change into stop-and-go traffic when the traffic speed becomes very slow, with more frequently acceleration or deceleration involved, and from time to time, vehicles have to come to a stop and then start to move again. Under the stop-and-go traffic state, a vehicle may stops within the
detection area for at least one time. The existing vehicle classification model produced more errors under the stop-and-go traffic, especially for large vehicles (See Figure 30), and the relative error rate is 235%. It is the vehicle movement under stop-and-go traffic, including vehicles’ acceleration or deceleration, and vehicles’ stopping on loops, that distorts the estimation of the existing model. The assumption of the existing model cannot be met anymore in this situation and an updated length-based vehicle classification model has to be developed to improve the accuracy of vehicle length estimation under the stop-and-go traffic.

![Figure 30. Output of the Existing Model under Stop-and-Go Traffic Flow](image)

**Stop-and-go Traffic**

The thresholds for identifying the stop-and-go traffic flow have been discussed in Section 3.5.3. In this section, a new length-based vehicle classification model will be proposed to estimate the vehicle length under the stop-and-go traffic condition. The **Vehicle Classification under Stop-and-Go Model** (VC-Stog model) is developed to estimate vehicle lengths under the stop-and-go traffic condition fully considering the characteristics of vehicles’ movement under this traffic condition. Based on the observation of stop-and-go traffic flow both in the field and in the traffic video, there are quite a few situations will happen when a vehicle is driving through the dual-loop detection area. The vehicle may go through the dual-loop without a stop, or it may
stop on the upstream loop and then start to move through the whole detection area without another stop. It is also very likely that the vehicle will stop on the downstream loop or on both loops without another stop. There are also chances that the vehicle may stop within the detection area for a few times, although the probability is pretty low. So the situations for a vehicle running across the dual-loop detection area may be very complicated. To simplify the situations and to facilitate the modeling, eight possible scenarios are developed depending on the stopping locations of the detected vehicle within the detection area, as shown by Figure 31. For each scenario, a sub-model would be developed to estimate the vehicle length. The eight scenarios are listed and explained below.

**Scenario 1:** the vehicle drives across the dual-loop detection area without a stop;

**Scenario 2:** the vehicle stops ONLY on the M loop and then leaves the dual-loop detection area without another stop;

**Scenario 3:** the vehicle runs across the M loop and stops ONLY on the S loop;

**Scenario 4:** the vehicle comes into the dual-loop detection area and stops ONLY on BOTH the M and S loops, and leaves the detection area without another stop;

**Scenario 5:** the vehicle stops on the M loop and then move on, and then stops on the S loop and finally leaves the detection area without another stop;

**Scenario 6:** the vehicle stops firstly on the M loop and then stops on both the M and S loops and finally leaves the detection area;

**Scenario 7:** the vehicle stops firstly on both of the M and S loops, and then stops only on S loop; and
Scenario 8: the vehicle stops firstly only on the M loop and then stops on both of the M and S loop, and finally stops only on the S loop. Eventually the vehicle leaves the dual-loop detection area without another stop.

Based on the collected ground-truth data, a statistical analysis is conducted to find the percentage of vehicle stopping locations under the stop-and-go traffic flow. In this analysis, the data is for vehicles which stop within the dual-loop detection area for one or more times. So Scenario 1 is not included in it. According to the analysis results, Scenario 2 and 3 take the highest percentages among the 7 scenarios, which are 29.8% and 36.9%, respectively. Scenario 4 and 5 take the percentage of 14.2% and 12.8%, respectively, which are lower than those of Scenario 2 and 3. It is obviously that the probabilities of Scenario 6, 7, and 8 happening are much lower comparing to other scenarios, which are 2.8%, 2.1%, and 1.4%. The results are illustrated by Table 11 and Figure 32.

![Figure 31. Different Scenarios of Vehicle Stopping on Dual-loops under Stop-and-go Flow](image-url)
Scenario 6, 7 and 8 only take the total percentage of $2.8\% + 2.1\% + 1.4\% = 6.3\%$, which is very low. On the other hand, these three scenarios represent very complicated vehicle movement combinations under the stop-and-go traffic. It is even harder to model these movements for the vehicle classification modeling.

### Table 11. List of Percentage of Vehicle Stopping Status

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Stopping Status</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 2</td>
<td>M</td>
<td>29.8</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>S</td>
<td>36.9</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>M+S</td>
<td>14.2</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>M, S</td>
<td>12.8</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>M, M+S</td>
<td>2.8</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>M+S, S</td>
<td>2.1</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>M, M+S, S</td>
<td>1.4</td>
</tr>
</tbody>
</table>

**Figure 32. Distribution of Vehicle Stopping Status in Congested Traffic**

Although Scenario 5 takes a percentage of 12.8% among all scenarios, it condition is much more complicated than those of Scenario 2, 3, and 4, as it is involved in 2 stops within the
detection area. Due to the limitation of the data sample size, this scenario will not be studied in this research and will be further analyzed in the future. So in this study, only Scenario 1 to 4 will be modeled and Scenario 5 to 8 will not be analyzed to develop their corresponding sub-models.

6.3.2 Scenario Identification

Before the VC-Stog model is applied to a certain scenario, the scenario has to be identified based on the characteristics of vehicle movement. In order to identify different scenarios, an algorithm was developed using variables of On-times and difference of On-times.

In this algorithm, \( t_{s1} \) is defined as the threshold of \( \text{OnT}_1 \) and \( \text{OnT}_2 \), and \( t_{s2} \) is defined as the threshold of differences between timestamps of the M and S loop. For a vehicle operating under stop-and-go traffic condition:

1. If both of \( \text{OnT}_1 \) and \( \text{OnT}_2 \) are less than \( t_{s1} \), it indicates that the vehicle did not make a stop within the dual-loop detection area, which means this vehicle falls into Scenario 1.
2. If \( \text{OnT}_1 \) is larger than \( t_{s1} \), and \( \text{OnT}_2 \) is less than \( t_{s1} \), it indicates that the vehicle spent much longer time on the upstream loop, and this vehicle will be identified into Scenario 2.
3. If \( \text{OnT}_1 \) is less than \( t_{s1} \), and \( \text{OnT}_2 \) is larger than \( t_{s1} \), it indicates that the vehicle spent much longer time on the downstream loop, and this vehicle will be identified into Scenario 3.
4. If both of \( \text{OnT}_1 \) and \( \text{OnT}_2 \) are larger than \( t_{s1} \), and \( t_3-t_1 \leq t_{s2} \) and \( t_4-t_2 \leq t_{s2} \) (\( t_1, t_2, t_3, \) and \( t_4 \), are the same as defined previously), the vehicle can be identified as falling into Scenario 4.
The flow chart of identifying different scenarios is illustrated by Figure 33. Based on the statistical analysis on the dual-loop data under stop-and-go traffic, the thresholds are determined as: $t_{s1} = 4.1s$, and $t_{s2} = 3.0s$.

### Figure 33. Flow Chart of Scenarios Identification

6.3.3 Developing Length-based Vehicle Classification against the Stop-and-Go Traffic

The VC-Stog model is comprised of several sub-modes for different scenarios.

For Scenario 1, the detected vehicle does not stop over the dual-loop detector. In this circumstance, during the time period the vehicle spent on the dual-loop detector, the characteristics of its movement are the same as those under the synchronized traffic condition: at a slow speed and an acceleration or deceleration may be involved. So the VC-Sync model is still suitable for vehicles under this condition.

Scenarios 2 is approximately equivalent to the situation in which a vehicle just stops at the front edge of the upstream loop and then goes across the detection area without a stop. This

Note: 1. $t_{s1}$ is the threshold of $OnT_1$ and $OnT_2$, and $t_{s2}$ is the threshold of timestamp differences; $t_1$, $t_2$, $t_3$, $t_4$, $OnT_1$, and $OnT_2$ are the same as defined previously.

2. In this study, $t_{s1}$ and $t_{s2}$ are determined as 4.1s and 3.0s, respectively.
situation can be considered that a vehicle under synchronized traffic is driving through the
detection area with acceleration and an initial speed of zero. Similarly, Scenario 3 is
approximately equivalent to the situation in which a vehicle just stops at the end edge of the
downstream loop and then goes across the detection area without a stop. This situation can be
considered that a vehicle under synchronized traffic is driving through the detection area with
deceleration and a final speed of zero. The dual-loop data of vehicles in Scenario 2 and 3 was
applied to the VC-Sync model the estimate vehicle lengths. The output is illustrated by Figure 34.

![VC-Sync Model for Scenario 2 and 3](image)

**Figure 34. Output of VC-Sync Model for Scenario 2 and 3**

A t-test was used to examine if the estimated the vehicle lengths from the VC-sync model
for Scenario 2 and 3 have the same mean as the ground-truth data (Table 12). The $t$ value is
0.7977, which is less than the critical $t$ value of 1.96. The hypnosis is acceptable and they have
the same mean. So the VC-Sync model is still suitable for vehicles falling into Scenario 2 and 3.
Table 12. T-test Results for Output from VC-Sync Model for Scenario 2 and 3

<table>
<thead>
<tr>
<th>t-Test: Two-Sample Assuming Unequal Variances</th>
<th>Estimated Lengths from VC-Sync model</th>
<th>Ground-Truth Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>18.73622047</td>
<td>17.51517848</td>
</tr>
<tr>
<td>Variance</td>
<td>170.3669316</td>
<td>127.2127122</td>
</tr>
<tr>
<td>Observations</td>
<td>127</td>
<td>127</td>
</tr>
<tr>
<td>Hypothesized Mean Difference</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>df</td>
<td>247</td>
<td></td>
</tr>
<tr>
<td>t Stat</td>
<td>0.797683941</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) one-tail</td>
<td>0.212910057</td>
<td></td>
</tr>
<tr>
<td>t Critical one-tail</td>
<td>1.651046077</td>
<td></td>
</tr>
<tr>
<td>P(T&lt;=t) two-tail</td>
<td>0.425820115</td>
<td></td>
</tr>
<tr>
<td>t Critical two-tail</td>
<td>1.969614755</td>
<td></td>
</tr>
</tbody>
</table>

A **Stop-on-Both-Loops-only** (SBL) model was developed to estimate the vehicle lengths under Scenario 4. For simplicity, it is assumed that the detected vehicle stops right in the middle of the two single loops, which means the center of the vehicle is right above the mid-point between the two single loops. After stopping for a period of time \( t_s \) it starts to move again with an acceleration rate \( a \), and then leaves the dual-loop detection area. The SBL model is expressed by the following equations:

\[
L_v = f_1 \cdot t_{\text{dec}} \cdot D \cdot \frac{1}{t} + \frac{1}{2} f_2 \cdot a \cdot t_{\text{acc}}^2 - L_s
\]  

(18)

\[
t_{\text{dec}} + t_{\text{acc}} = O_n T_1 - t_s
\]  

(19)

\[
t_s = t_2 - t_3 - f_3 \frac{t_{\text{acc}}^2}{v_{\text{min}}}
\]  

(20)

Where,

\( L_v \) = length of vehicle (ft);

\( L_s \) = length of each single loop (ft);
\( t_{\text{dec}} \) = time period from a vehicle entering the M loop to its stop (s);

\( t_{\text{acc}} \) = time period from a vehicle starting to move to leaving the M loop (s);

\( a \) = the average acceleration rate of vehicles when they start to move under stop-and-go traffic (ft/s\(^2\));

\( t_s \) = time period for a vehicle to stop on both loops (s);

\( v_{\text{min}} \) = the average minimum speed which can maintain a vehicle running without stop (ft/s);

\( f_1, f_2, \text{ and } f_3 \) = adjusting factors for different vehicle types (in this study, \( f_1 = f_2 = f_3 = 1 \));

\( D, t, t_2, t_3, OnT_1, \text{ and } OnT_2 \) = as the same as defined previously.

When this SBL model is applied to estimate vehicle lengths, it is necessary to determine the vehicle’s acceleration rate (\( a \)) and the time period for the vehicle to stop on both of the loops (\( t_s \)). The acceleration rate \( a \) of a detected vehicle cannot be derived from its corresponding dual-loop data. The GPS data collected by GPS data loggers can be used to reveal the vehicle’s speeds and changes of speed over a very short time interval. According to the principle of Kinematics, the change of speeds during a unit time is defined as acceleration. So a vehicle’s acceleration can be obtained by calculating the change of speeds extracted from the GPS data.

To obtain these parameters, a GPS data logger was amounted on a probe car, which was operated by our research staff. With the GPS data logger being turned on, the probe car was operating within the concurrent traffic flow on a segment of highway, and the dual-loop detector stations are located within this highway segment. The probe car was running at an average speed of the traffic flow, which means it has to follow the traffic flow, not to be faster or slower. The
The total length of this highway segment is around 2 miles. The probe vehicle traveled along this road segment from one end to the other, and then made a U turn to repeat the process. Eventually, there were 4-5 round trips that were made for the stop-and-go traffic condition each day. This collected GPS data within stop-and-go traffic flows was employed to set up the general acceleration rate $a$ through the statistical analysis. A variable is also defined as the average minimum speed $v_{min}$. It is the average lowest speed that a vehicle can maintain during the course of the “go” state in the stop-and-go stream.

Combining the data from GPS data loggers and the model calibration, the factors involved in the SBL model are determined as follows:

- The average vehicle acceleration rate is determined as 2.5 ft/s$^2$.
- The average minimum speed $v_{min}$ is determined as 7 ft/s (4.77 miles/hour).

Figure 35 shows the estimated lengths of stop-and-go vehicles for Scenario 2, 3, and 4 by using the existing model and the VC-Stog model (i.e. VC-Sync model + SBL model),
respectively. Compared to the ground-truth data, the relative error of the estimated vehicle lengths resulted from the existing model is 235%, while the relative error of those resulted from the VC-Stog model has been reduced to 17.1%. As illustrated by Figure 35, when the existing model is applied, it produces high errors for all vehicle types: small vehicles, median vehicles, and large vehicles. When the VC-Stog model is applied, the estimation error for small vehicles is much lower. However, those for median vehicles and large vehicles are still rather high. Considering the modeling procedure, it looks reasonable and it can be explained as follows:

(1) The VC-Stog model is made up of the VC-Sync model and the SBL model. Comparing SBL model, the VC-Sync model has simpler assumption and less factors. Theoretically it is easily understood that the accuracy of the VC-Sync model is higher than that of the SBL model. The small vehicles have an average length of about 16 ft, while those of median and large vehicles are much longer, especially the large vehicles often with a length of 55-70 ft. So larger vehicles have a higher probability of falling into Scenario 4 than small vehicles do and more small vehicles fall into Scenario 2 and 3. As the VC-Sync model is applied to Scenario 2 and 3, the estimated results have higher accuracy.

(2) The average length of large vehicles is much longer than that of small vehicles. The total period of time that large vehicles spend on the dual-loop detection area is usually much longer than that of small vehicles. From the SBL model, it can be found that the longer $OnT_1$, $OnT_2$, and the $t_s$, the higher error might be produced.

The estimated vehicle lengths from the VC-Stog model under the stop-and-go traffic flow were analyzed by using the 3-bin scheme. The output from the existing model is also listed to compare to these results. Table 13 shows the analysis results for the 3-bin scheme. By the existing model, there are 49.2% vehicles of Bin 1 which are misidentified as Bin 2 or Bin 3;
there are 14.7% vehicles of Bin 3 are mistaken as Bin 1 or Bin 2. When the VC-Stog model,
which is made up of the VC-Sync model and the SBL model, is applied, the accuracies for
vehicles of Bin 1 and Bin 3 have been improved to 96.9% and 95.1%, respectively.

<table>
<thead>
<tr>
<th>Bins</th>
<th># of Vehicles</th>
<th>By Ground-truth Data</th>
<th>By Dual-Loop Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Bin type identified by vehicle length</td>
<td># of vehicles by existing model</td>
</tr>
<tr>
<td>Bin 1</td>
<td>130</td>
<td>Bin 1</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>56</td>
</tr>
<tr>
<td>Bin 2</td>
<td>2</td>
<td>Bin 1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>2</td>
</tr>
<tr>
<td>Bin 3</td>
<td>41</td>
<td>Bin 1</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bin 3</td>
<td>35</td>
</tr>
</tbody>
</table>
CHAPTER 7: CONCLUSIONS

Dual-loop detector is a widely used traffic monitoring sensor for highway system operation and management and traffic data collection. Traffic flow parameters, such as speed, volume, and occupancy, can be obtained from the dual-loop detector data, and traffic speeds and vehicle lengths can be calculated based on these parameters. Vehicle classification data plays a very important role in many fields of transportation engineering, such as travel demand forecasting, pavement design, and even traffic related air quality study. The dual-loop detector data has been a main data source for length-based vehicle classification. However, it has been reported that the existing length-based vehicle classification model produces high errors during congested traffic due to the complicated characteristics of traffic flows. In this study, the traffic video and the concurrent event dual-loop data are collected at the dual-loop detector stations, and the vehicle trajectory data was extracted from the collected concurrent video using the software VEVID. An algorithm is proposed to screen the original event dual-loop data by identifying different types of errors and removing them. The characteristics of different traffic flow phases have been studied and an algorithm for identifying traffic flow phases is proposed to identify the free flow, synchronized flow, and stop-and-go flow by using traffic parameters from the dual-loop detector data. In order to improve the accuracy of the length-based vehicle classification model using the dual-loop detector data, two length-based vehicle classification models are developed for the synchronized traffic flow and the stop-and-go traffic flow, respectively. The achievements in this study can be summarized as follows:

1. An innovative VEVID-based approach is developed for evaluating the concurred dual-loop data and validating the outcomes from the new vehicle classification models against video-based ground-truth vehicle event trajectory data. With traditional investigation
methods, it is very difficult to obtain the ground truth data which can be used to validate the loop detector data or the estimated vehicle length for each individual vehicle.

2. The algorithm for processing the dual-loop detector data has been improved by considering the influence of traffic flow characteristics. The errors caused by communication problems and vehicle lane changing, can be identified and removed. As the traffic flow characteristics have been fully considered, the problem of undercounting traffic caused by the traditional data screening methods has been corrected.

3. A GPS-based approach is developed for setting up the reference points in field, and those points can be used to set up reference system in the software VEVID, which is proven a very safe and efficient approach compared to the traditional manual method. The reference distance required by VEVID can be obtained by videotaping a probe car equipped with a GPS data logger which travels through the studied highway segment at a constant speed. So the reference points can be determined in VEVID and research staffs do not have to place physical reference points in field. In addition, the GPS-based travel profile data is greatly helpful in developing the new length-based vehicle classification model under stop-and-go traffic flow.

4. An algorithm for identifying different traffic phases has been developed. Traffic speed and occupancy are employed to identify the free flow traffic, synchronized traffic, and stop-and-go traffic flow. This algorithm helps select the corresponding length-based vehicle classification model for different traffic states.

5. Innovative vehicle classification models for both synchronized traffic and stop-and-go traffic states are developed by fully considering the characteristics of the different traffic states. For the synchronized traffic flow, the possible acceleration or deceleration
behaviors have been considered in the VC-Sync model to eliminate the distortion caused by them in the existing model. The relative error has been reduced from 33.5% of the existing model to 6.7% of the VC-Sync model. For the stop-and-go traffic condition, as vehicles may stop from time to time within the detection area, the stopping status has been simplified into eight scenarios. Sub-models are developed for each scenario to estimate the vehicle lengths. The relative error has been reduced from 235% of the existing model to 17.1% of the VC-Stog model.
REFERENCES


