Dual-Loop Length-Based Vehicle Classification Models against Synchronized and Stop-and-Go Traffic Flows

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By

Qingyi Ai
Ph.D. Candidate
Advanced Research in Transportation Engineering and Systems Laboratory
School of Advance Structures
College of Engineering and Applied Science
735 Engineering Research Center
University of Cincinnati
Cincinnati, OH 45221-0071
Tel: (513) 708-8928; E-mail: aiqi@email.uc.edu

Faculty Advisor:
Heng Wei, Ph.D., P.E.
Associate Professor, Director of
Advanced Research in Transportation Engineering and Systems Laboratory
School of Advance Structures
College of Engineering and Applied Science
792 Rhodes Hall
University of Cincinnati
Cincinnati, Ohio 45221-0071
Tel: (513) 556-3781; Email: heng.wei@uc.edu

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ABSTRACT

The accurate measurement of vehicle speed and classification is a highly valued factor in traffic operation and management, validation of travel demand models, freight studies, and even emission impact analysis of traffic operation. The capability of measuring vehicle lengths makes dual-loop detectors a potential real-time data source for speed and vehicle classifications. However, the existing dual-loop length-based vehicle classification model has been well evaluated against free traffic but not suitable for non-free traffic conditions (such as synchronized and stop-and-go congestion states). This paper presents an innovative approach to evaluate dual-loop length-based vehicle classification models against concurrent ground-truth video vehicle trajectory data at the selected dual-loop traffic monitoring stations. The software VEVID (Vehicle Video-Capture Data Collector) is used to extract high-resolution vehicle trajectory data from the videotapes. Meanwhile, a probe vehicle equipped with a Global Positioning System (GPS) traveler data logger is applied to collect traffic pattern data for validating parameters involved in the new vehicle classification models. As a result, new dual-loop length-based vehicle classification models are developed against the synchronized and stop-and-go traffic flows, namely, VC-Sync model and VC-Stog model. Comparing to the obtained ground-truth data, the sample results show that the error of the estimated length by the VC-Sync model is reduced to 8.5% compared to 35.2% produced by the existing model, and the error of the VC-Stog model is reduced to 27.7% compared to 210% generated by the existing model.

INTRODUCTION

Inductive loops are increasingly used specifically for traffic monitoring at highway traffic data collection sites. Single loop and dual-loop are two major types of inductive loop detectors. While lots of efforts have been reported on estimating vehicle speed and vehicle length by using single loop data [1-3], the configuration of the single loop disenables accurate estimate of vehicle speed and classification. The accurate measurement of vehicle speed and classification is a highly valued factor in validations of travel demand models and freight studies, as well as emission impact analysis of traffic operation. Also, the detector data need to be sufficiently accurate since any errors will propagate to decision-making and traffic control actions. Many studies have proven that the vehicle speed can be estimated accurately by using dual-loop data under light traffic (or free traffic flow) 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 classifications. However, the existing dual-loop length-based vehicle classification models produce high and unstable errors 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 congestion; but quantification of such contributing factors remains unclear.

The dual-loop detector consists of two single loop detectors which are placed apart with a very short distance (e.g. 20 ft in Ohio), as shown by Figure 1. The dual-loop detector is also called "speed trap" by someone. The current dual-loop model for estimating vehicle length is theoretically fitting to the case as vehicles run over the detection area at a constant speed [4]. This has been well validated only against light traffic but is unsuitable to non–free traffic flows, in particular the stop-and-go situation.

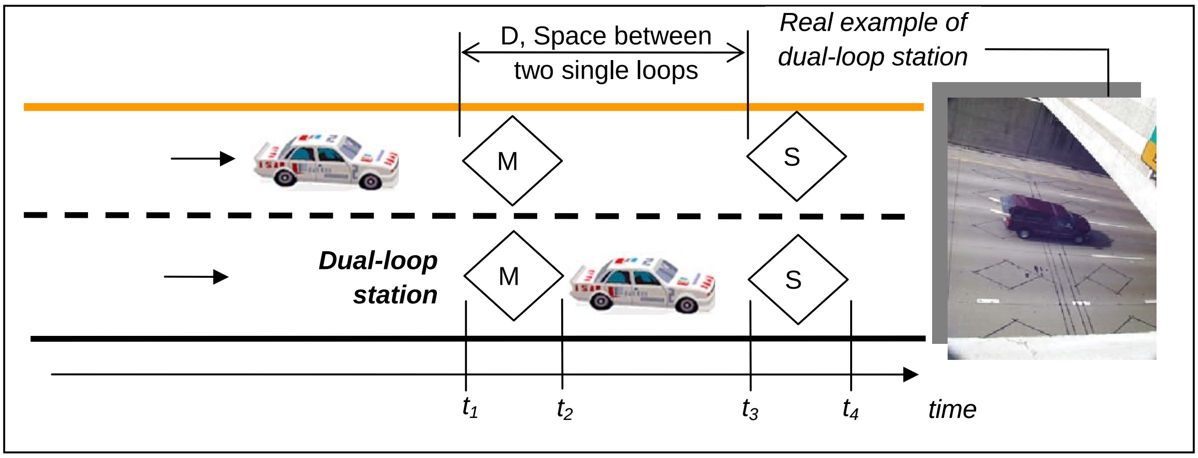

Figure 1. Sketch of Dual-loop Detector Station

The existing dual-loop length-based vehicle classification model is expressed as follows [4]:

$$speed = \frac{D}{t} \tag{1}$$

$$vehicel\_length = speed \times \frac{OnT_1 + OnT_2}{2} - loop\_length \tag{2}$$

Where, 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), as illustrated by Figure 1. Other parameters are denoted as the following:

D = distance between two single loops in the dual-loop station (ft);

$t = t_3 - t_1$;

$OnT_1 = t_2 - t_1$; and

$OnT_2 = t_4 - t_3$.

Kerner et al. defined traffic flows in three categories: free flow, synchronized flow, and stop-and-go flow [5, 6], as shown by Figure 2. The free flow has high travel speed and low traffic volume and density. The synchronized flow is viewed as a kind of congested traffic, which has relative low speed and high volume and density. The speed of the synchronized traffic stream fluctuates frequently but its average speed remains a relatively stable trend. The stop-and-go traffic flow is the very congested traffic condition, which has very low speed, low volume and high density. The vehicle speed not only fluctuates frequently, but also stops from time to time. Thus, within the synchronized and stop-and-go traffic flows there is a high probability that vehicles run over the upstream and downstream loops at different speeds and acceleration or deceleration may exist as running over the dual-loop station. Within the stop-and-go traffic flow some vehicles may experience multiple stops within the detection area.

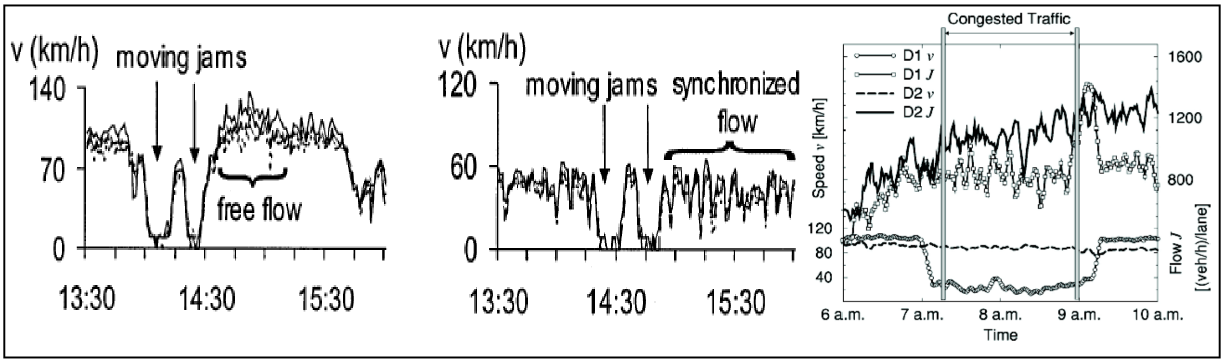

Figure 2. Demonstrations of Three Traffic Patterns [5, 6]

The Ohio Department of Transportation (ODOT) length-based classification scheme for dual-loop detectors was designed to be capable of classifying vehicles into three bins (or called 3-bin scheme): vehicle length <= 28 ft (Bin 1), vehicle length <=46 ft (Bin 2), and vehicle length >46 ft (Bin 3) [7]. Meanwhile, The Washington State Department of Transportation (WSDOT) length-based classification scheme for dual-loop detectors can classify vehicles into four bins (or 4-bin scheme): vehicle length <= 26 ft (Bin 1), vehicle length <=39 ft (Bin 2), vehicle length <=65 ft (Bin 3), and vehicle length >65 ft (Bin 4) [4, 8]. Nihan et al. found that during both off-peak hours and peak hours “dual-loop detectors often mistakenly assign Bin 3 vehicles to Bin 4, but reverse assignments (Bin 4 vehicles to Bin 3) do not occur”, and “dual-loop detectors have difficulties distinguishing Bin 2 vehicles from Bin 3 vehicles. They sometimes assign Bin 2 vehicles to Bin 3”. For off-peak hour traffic, observed misclassification errors for truck ranges from 30 to 41 percent.

Event dual-loop data are usually applied to traffic analysis in order to obtain accurate travel features of individual vehicles traveling over the loop [4, 7-11]. The event loop data is referred to a kind of high-resolution data of the detected individual vehicles, such as the timestamps of vehicle arriving and leaving the loop. Meanwhile, it has been proven that vehicle trajectory data extracted from video files is a reliable ground-truth data source for the length-based vehicle classification [4, 12]. In the study presented in this paper, the video-capture-based approach is proposed to extract the ground-truth trajectory data from videos by using the software, VEVID (Vehicle Video-Capture Data Collector). VEVID was originally developed by the author's advisor and then upgraded by him along with other members at the Advanced Research in Transportation Engineering and System (ART-Engines) Laboratory at The University of Cincinnati [13, 14]. The ground-truth trajectory data includes the timestamps, speed and length of the vehicle running over the loops. Accordingly, the proposed evaluation approach is also termed as VEVID-based approach.

At the same time, the concurrent event dual-loop data is collected. The video ground-truth trajectory data is then used to evaluate the existing dual-loop model against different traffic states. The results indicate that the existing model is unreliable to estimate vehicle length under synchronized and stop-and-go traffic conditions. In this study, a new length-based vehicle classification model, named as VC-Sync model, is developed for synchronized traffic flows, and a new set of models named, as VC-Stog model, is developed for the stop-and-go traffic condition. The study also indicates that under synchronized traffic the error of the vehicle lengths estimated by the VC-Sync model is reduced to 8.5% compared to the error of 35.2% by the existing model. Under the stop-and-go traffic the error of the VC-Stog model is 27.7% compared to the error of 210% produced by the existing model. For the 3-bin scheme, the VC-Sync model increases the correction rate of the vehicle classification from 86% to 99% for Bin 1, and from 33% to 100% for Bin 2. For the 4-bin scheme, the correction rate of Bin 1 is increased from 83% to 99%, and that of Bin 4 is increased from 66% to 97%. The VC-Stog model increases the correction rate of Bin 1 from 43% to 92%, and Bin 3 from 85% to 91% in the case of the 3-bin scheme. For the 4-bin scheme, the correction rate is increased from 43% to 92% for Bin 1.

This paper is organized as follows: the developed methodology will be firstly introduced following the introduction. Then, data collection, vehicle classification modeling which includes evaluation of the existing model and development of new models against non-free traffic flows, as well as relevant results analysis are presented, respectively. Finally, the conclusions are presented.

METHODOLOGY FOR EVALUATING DUAL-LOOP MODELS WITH VEVID DATA

This study is to evaluate the dual-loop length-based vehicle classification models against concurred ground-truth video event vehicle trajectory data at the selected dual-loop detector stations that are in good working condition in reoccurring congestion areas. The software VEVID had been developed to extract accurate trajectory data [13], and the accuracy of its outputs has been improved [14]. In this study, traffic video data is collected in field and video event vehicle trajectory data is extracted with VEVID. With availability of both dual-loop and VEVID-based vehicle event trajectory data, the errors and possible causes in estimating length-based vehicle classifications by dual-loop data could be effectively investigated against the congested conditions, i.e., synchronized and stop-and-go states. In addition, Global Positioning System (GPS) data is collected to provide supplementary data for identifying features of traffic flows under stop-and-go condition. New models for synchronized and stop-and-go traffic flows are then developed. Figure 3 illustrates the framework for evaluating dual-loop vehicle classification models with VEVID-based trajectory data. More details about main components involved in the framework and their applications are presented in the following sections.

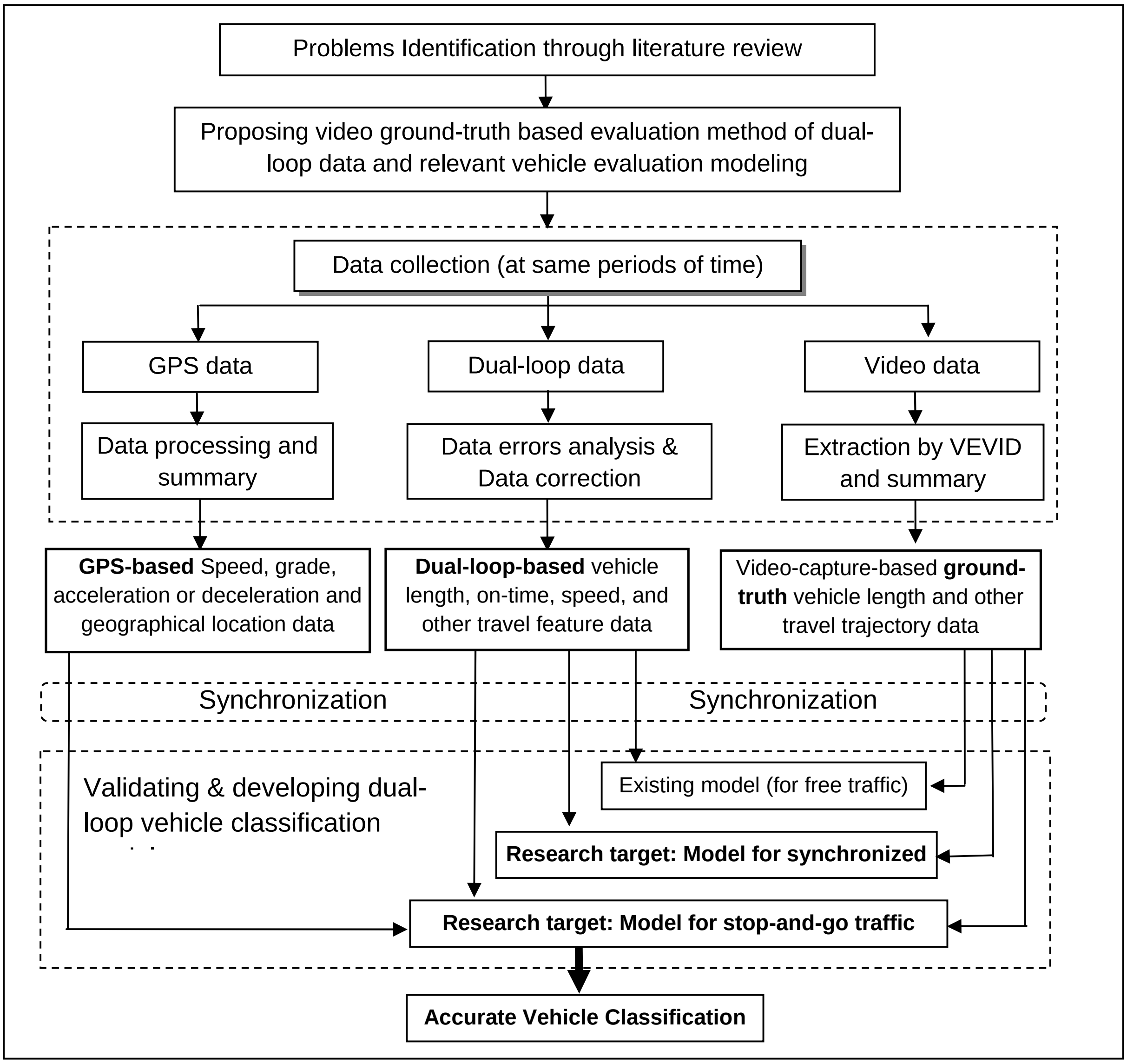

Figure 3. Framework of Evaluating Dual-loop Data Based Vehicle Classification Models

DATA COLLECTION

Ground-truth VEVID-based Trajectory Data

Two loop stations, numbered as V1002 and V1003, in Columbus, Ohio were selected as the study sites (see Figure 4). Three-day videotaping of the traffic running over the two loop stations were completed from July 14, 2009 to July 16, 2009. (see Figure 5). Totally 26 hours of traffic video data were collected, including light traffic and congestion traffic flows (i.e., synchronized traffic and stop-and-go traffic).

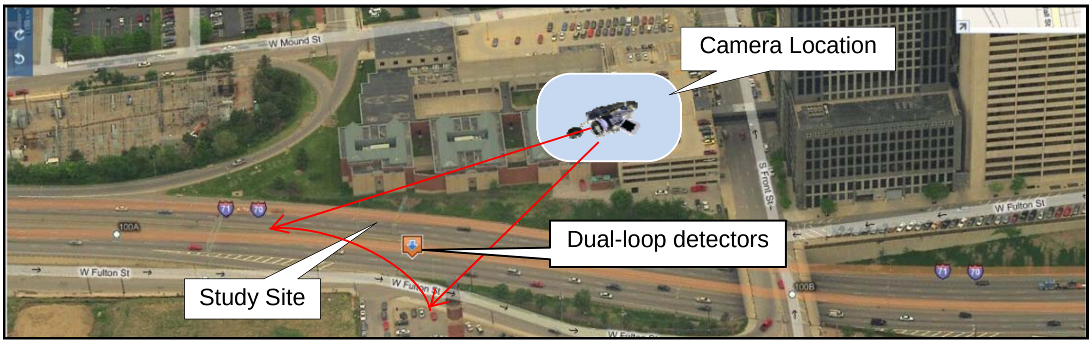

Figure 4. Loop Station V1002 on I-70/71 in Downtown Columbus, OH

Figure 5. Videotaping at the Selected Dual-loop Station

The vehicle trajectory ground-truth data was extracted using VEVID, and the extracted data are used in the calibration and validation of the developed vehicle classification models. Table 1 shows examples of the sample data extracted by VEVID. Figure 6 shows a snapshot of VEVID interface as the vehicle trajectory is being extracted.

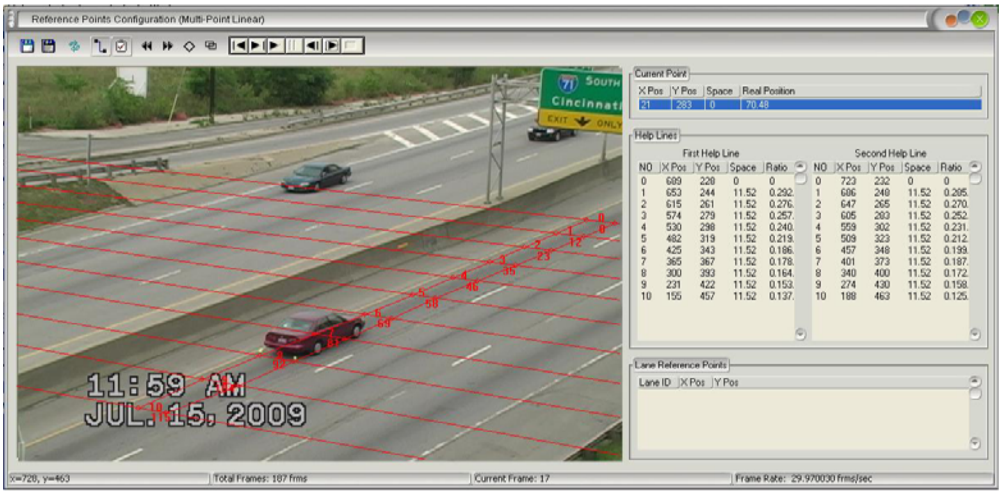

Figure 6. Extracting Trajectory Data Using VEVID

Table 1. Sample Data Extracted from Video using VEVID

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

Event Dual-loop Data

The concurrent dual-loop vehicle event data at the selected stations is obtained from the Traffic Management Center of Ohio Department of Transportation (ODOT) in Columbus, Ohio. The dual-loop vehicle event data records the timestamps of entering and leaving each loop for each detected vehicle. The timestamp with status value of “1” indicates the time when a vehicle enters the loop, and the timestamp with the status value of “0” is the time when the vehicle leaves the loop. Table 2 illustrates exemplary samples of the dual-loop vehicle event data.

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

M loop (Upstream)		S loop (Downstream)	
Status	Timestamp	Status	Timestamp
1	3522267	1	3523667
0	3524341	0	3524489
1	3524504	1	3524652
0	3524675	0	3524795
1	3524817	1	3524919
0	3525598	0	3525914

GPS Data Collection

GPS data can reflect vehicles’ speeds and changes of speeds during a very short period of time along a stretch of the roadway. It can be hence used to reveal the traffic features under stop-and go traffic flow. A GPS travel data logger is equipped in a testing car, and this car runs along a freeway segment of I-70/71 which covers the two selected study sites. The GPS travel data logger enables accurate recording of travel speed at one second interval. Statistical analysis of the obtained GPS data results in the estimates of the following parameters: (1) the average acceleration or deceleration rate of vehicle; and (2) the average minimum speed. These parameters will be used to quantify some variables involved in the developed vehicle classification models under the stop-and-go traffic condition.

VEHICLE CLASSIFICATION MODELING

Three sets of dual-loop data are used in the case study to evaluate the vehicle classification models. They include: 902 samples with free flow traffic, 147 samples with synchronized traffic, and 61 samples with stop-and-go traffic. The concurrent ground-truth video data is aligned with the above dual-loop data samples.

Existing Vehicle Classification Model under Free Flow Traffic

T-test is used to compare the ground-truth vehicle length data with the vehicle lengths estimated by using existing models based on the concurrent loop data. The hypothesis is set up assuming that the two variables have the same mean but different variations. According to the T-test result, the *t value* = 0.7734, which is less than the *critical t value* = 1.96 with confidence level of 95%. So the hypothesis can be accepted that the two variables have the same mean value. In other words, the result confirms that the existing model is suitable for free flow condition.

Vehicle Classification Model under Synchronized Traffic (VC-Sync model)

Under the synchronized condition, 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. Based on related literature review [15-18] and verification with the collected data, a speed threshold for discerning the free flow traffic and the synchronized traffic is 45 mile per hour in this study. As mentioned earlier, the vehicles possibly run over the upstream and downstream loops at different speeds within the synchronized traffic flows. Acceleration or deceleration may play an influential role in measuring the vehicle length. In the proposed **V**ehicle **C**lassification Model under **S**ynchronized Traffic (VC-Sync model), vehicles' acceleration or deceleration is therefore considered as one of contributing factors. If a vehicle passes the dual-loop detectors area at a stable acceleration or deceleration rate (without a stop), the VC-Sync model is expressed by the following equations:

$$L_s + L_v = v_0 \cdot OnT_1 + \frac{1}{2}a(OnT_1)^2 \tag{3}$$

$$L_s + L_v = v_t \cdot OnT_2 + \frac{1}{2}a(OnT_2)^2 \tag{4}$$

$$v_t = v_0 + at \tag{5}$$

$$\frac{v_0 + v_t}{2} = \frac{D}{t} \tag{6}$$

Where,

L_V = length of the detected vehicle (ft);
L_S = length of each single loop within the dual-loop (ft);
v_o = speed of the vehicle entering the upstream loop (M loop) (ft/s);
v_t = speed of the vehicle entering the downstream loop (S loop) (ft/s);
a = vehicle acceleration (ft/s^2); and
D, t, OnT_1, and OnT_2 are the same as defined earlier in the paper (see Figure 1).

Figure 7 shows the results in comparing the sample vehicle lengths that are estimated by the existing model and by the VC-Sync model, respectively. Compared to the ground-truth data, the error of the existing model is 35.2%, and the error of the VC-Sync model is 8.5%. This result indicates that the developed VC-Sync model greatly improves the accuracy of vehicle classification under the synchronized flow condition.

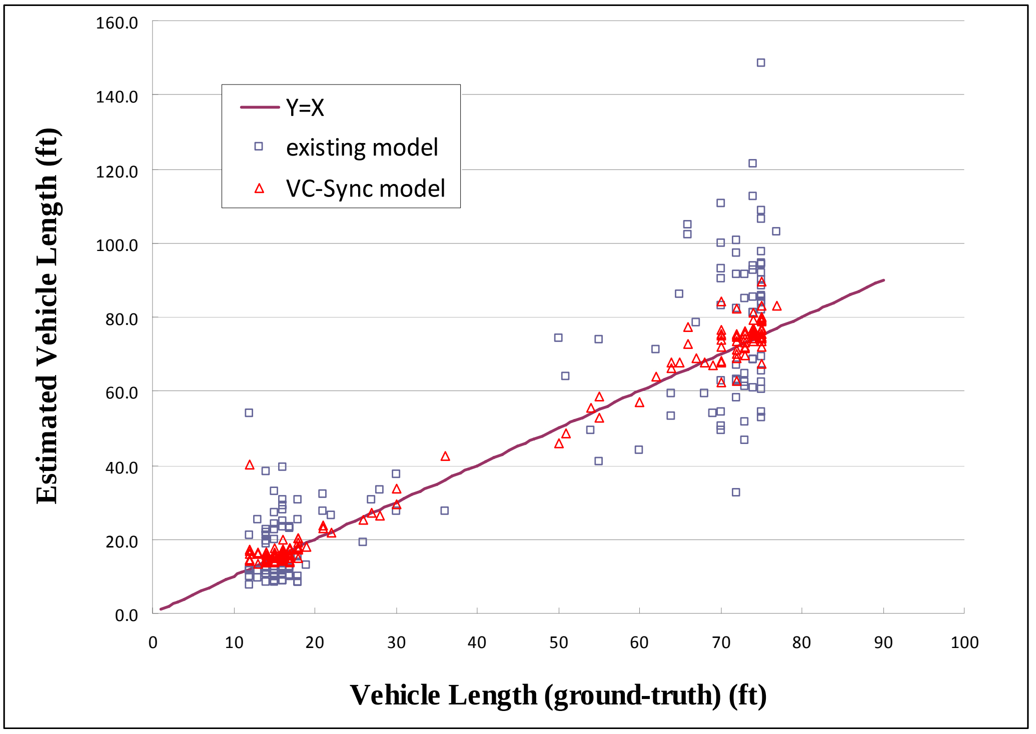

Figure 7. Estimated Vehicle Lengths under Synchronized Traffic

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

By Ground-truth Data		**By Dual-loop Data** (note: *correct identification)				
Bins	**# of Vehicles**	**Bin type identified by vehicle length**	**# of vehicles by existing model**	**%**	**# of vehicles by VC-Sync model**	**%**
Bin 1	73	**Bin 1*	*63*	*86%*	*72*	*99%*
		Bin 2	9	12%	1	1%
		Bin 3	1	1%	0	0
Bin 2	3	Bin 1	2	67%	0	0
		**Bin 2*	*1*	*33%*	*3*	*100%*
		Bin 3	0	0	0	0
Bin 3	71	Bin 1	0	0	0	0
		Bin 2	3	4%	1	1%
		**Bin 3*	*68*	*96%*	*70*	*99%*

Table 3 shows the comparison of the outcomes resulted from the existing model and VC-Sync model based on 3-bin and 4-bin schemes. As mentioned earlier, the 3-bin scheme is currently used by ODOT and the 4-bin scheme is used by WSDOT. As shown in Table 3, the existing model results in 13% of vehicles of Bin 1 which are misidentified as vehicles of Bin 2 and Bin 3. 67% of vehicles of Bin 2 are mistaken as vehicles of Bin 1. The accuracy for Bin 3 is good (97%). When the VC-Sync model is used, the accuracy of Bin 2 has been improved to 100% while there is only 1% vehicle of Bin 1 which is misidentified as Bin 2. For 4-bin scheme, VC-Sync model has resulted in a significant improvement in the accuracy of vehicle classification. As shown in Table 4, the accuracy for Bin 1 has been improved from 83% to 99%, and that for Bin 4 has been improved from 66% to 97%.

Table 4. Vehicle Assignment during Synchronized Traffic (4-Bins Scheme)

By Ground-truth Data		**By Dual-loop Data** (note: *correct identification)				
Bins	**# of Vehicles**	**Bin type identified by vehicle length**	**# of vehicles by existing model**	**%**	**# of vehicles by VC-Sync model**	**%**
Bin 1	71	**Bin 1*	*59*	*83%*	*70*	*99%*
		Bin 2	11	15%	0	0%
		Bin 3	1	1%	1	1%
		Bin 4	0	0%	0	0%
Bin 2	5	Bin 1	0	0%	0	0%
		**Bin 2*	*5*	*100%*	*4*	*80%*
		Bin 3	0	0%	1	20%
		Bin 4	0	0%	0	0%
Bin 3	10	Bin 1	0	0%	0	0%
		Bin 2	0	0%	0	0%
		**Bin 3*	*6*	*60%*	*7*	*70%*
		Bin 4	4	40%	3	30%
Bin 4	61	Bin 1	0	0%	0	0%
		Bin 2	1	2%	0	0%
		Bin 3	20	33%	2	3%
		**Bin 4*	*40*	*66%*	*59*	*97%*

Vehicle Classification Model under Stop-and-Go Traffic (VC-Stog model)

Under the stop-and-go traffic state, vehicles will stop within the detection area frequently for at least one time. Based on collected data and related literature review [5, 6, and 19], a speed threshold of 15 mile per hour is determined to identify the synchronized and the stop-and-go flows. The **V**ehicle **C**lassification under **S**top-and-**G**o (VC-Stog) model is developed to estimate vehicle length under the stop-and-go traffic condition. To facilitate the modeling, eight scenarios are developed depending on the stopping locations of the detected vehicles within the detection area, and then different sub-models are developed compatible with those scenarios (Figure 8) as detailed as follows:

Scenario 1: the vehicle runs across the loops without stop;
Scenario 2: the vehicle stops only on the M loop;
Scenario 3: the vehicle stops only on the S loop;
Scenario 4: the vehicle stops only on both the M and S loops;
Scenario 5: the vehicle stops on M loop and then move on, then stop on S loop;
Scenario 6: the vehicle stops only on the M loop, and then stops on both the M and S loops;
Scenario 7: the vehicle stops on both of the M and S loops, and then stops only on S loop; and
Scenario 8: the vehicle stops only on the M loop and then stops on both of the M and S loop, and finally stops only on the S loop.

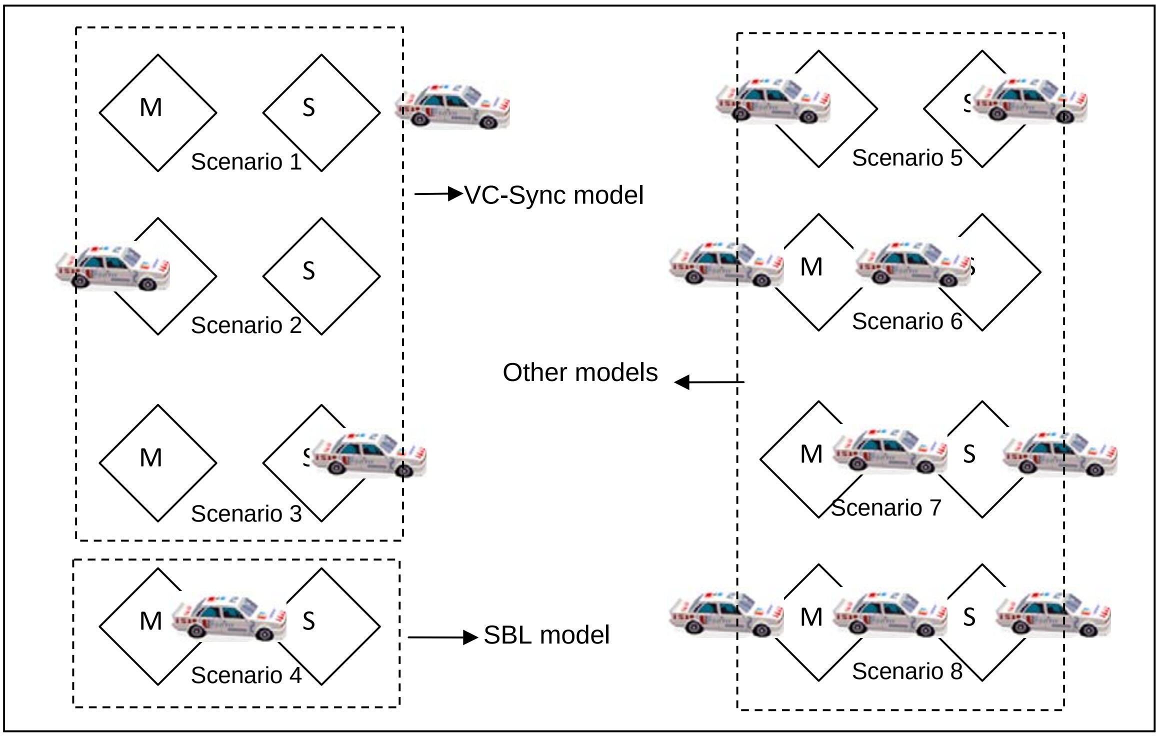

Figure 8. Different Scenarios of Vehicle Stopping on Loops under Stop-and-go Flow

Accordingly, the VC-Stog model is comprised of several sub-models which deal with different scenarios. For Scenario 1, the vehicle does not stop, so it can be treated against synchronized traffic and the VC-Sync model is applied to it. Based on the theoretical calculation, Scenarios 2 approximately equals to the situation that the vehicle just stops at the front edge of M loop and then leaves the detection area without stopping. Similarly, Scenarios 3 is close to the situation that the vehicle just stops at the rear edge of S loop. Thus, the VC-Sync model is also suitable to Scenarios 2 and 3. A **S**top-on-**B**oth-**L**oops-only (SBL) model is developed for Scenario 4. For Scenario 4 it is assumed that the vehicle stops in the middle between the two loops. After stopping a period of t_s it starts to move again with the acceleration rate a, and then leaves the loop station area. The SBL model is expressed by the following equations:

$$t_{dec} = \frac{\frac{1}{2}(L_v + D + L_s)}{\frac{D}{t} \cdot f_1} \tag{7}$$

$$t_{acc} = f_2 \frac{\sqrt{a(L_v - D + L_s)}}{a} \tag{8}$$

$$t_s = t_2 - t_3 - \frac{L_v - D + L_s}{f_3 \cdot v_{\min}} \tag{9}$$

$$OnT_1 = t_{dec} + t_{acc} + t_s \tag{10}$$

Where,

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

t_{acc} = time period from a vehicle starting to move to leaving the M loop (s);
v_{min} = the minimum speed which can maintain a vehicle running without stop (ft/s);
f_1, f_2, *and* f_3 = adjusting factors for different vehicle types; and
D, t, t_2, t_3, OnT_1, and OnT_2 = *as the* same as defined previously.

In order to estimate vehicle lengths by this SBL model, it is necessary to determine the vehicle's acceleration rate and deceleration rate and how long the vehicle stopped on both of the loops. As mentioned above, the GPS data can reflect vehicles' speeds and changes of speeds during very short period of time along a stretch of road, so in order to quantify these parameters, the GPS data gained within stop-and-go traffic flows is employed to set up the acceleration rate a via statistical analysis. The minimum speed v_{min} is defined as the speed that a vehicle can maintain during the course of the "go" state in the stop-and-go stream.

Scenarios 5, 6, 7, and 8 are more complicated. Each of these scenarios can be considered as the combination of 2 or more scenarios of scenarios 1-4. The models for scenario 5, 6, 7, and 8 will be developed in the future research plan.

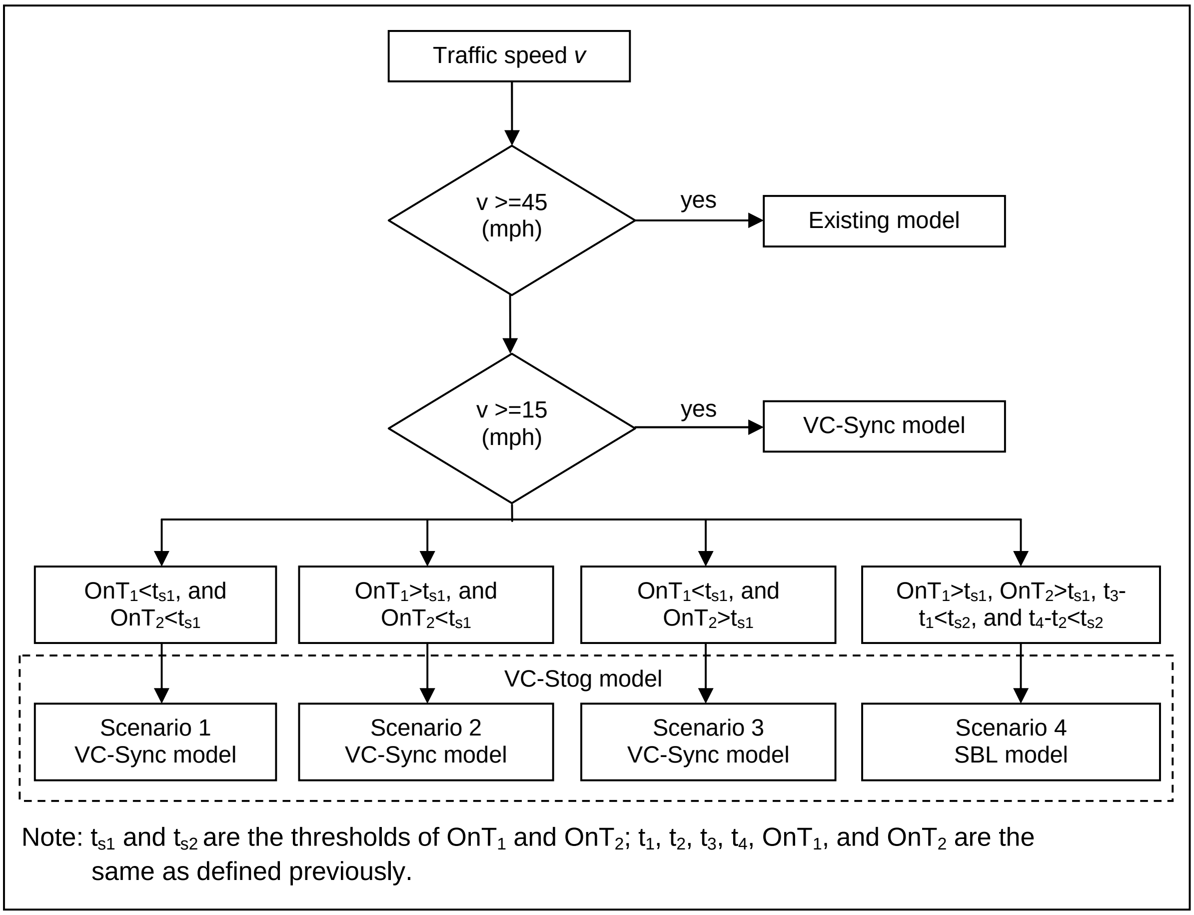

Figure 9. A Flowchart for Identifying Traffic States and Vehicle Stopping Status

Figure 9 is a flowchart for identifying which scenario a vehicle falls in. The thresholds of on-times on both upstream and downstream loops can be determined based on collected dual-loop data. Based on the statistical analysis of dual-loop data under stop-and-go traffic, t_{s1} and t_{s2}

are determined as: t_{s1} = 4.1s, and t_{s2} = 3.0s. Among the 61 sample vehicles with stop-and-go traffic, there are 35 sample vehicles falling into the Scenario 4 and 26 sample vehicles in the Scenarios 2 and 3. Among the 35 sample vehicles, 25 sample vehicles are used to calibrate the SBL model. The rest of the 10 sample vehicles are used to validate the SBL model. Using the GPS data and the model calibration, the factors involved in the SBL model are determined as follows:

- The average vehicle acceleration rate and deceleration rate are determined as 2.5 ft/s^2 and 3.0 ft/s^2, respectively.
- The minimum speed v_{min} is determined as 7 ft/s (4.77 miles/hour).

Figure 10 shows the estimated the lengths of stop-and-go vehicles 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 210%, while the relative error of those resulted from the VC-Stog model is 27.7%. Although the error of 27.7% remains unsatisfactory, a significant improvement has been achieved comparing to the error of 210% by the existing model.

Similarly, 3-bin and 4-bin schemes are investigated using the outcomes resulted from the existing model and VC-Stog model, respectively. Table 5 shows the result for 3-bin scheme. 58% vehicles of Bin 1 are misidentified as Bin 2 or Bin 3 by the existing model, and 15% vehicles of Bin 3 are mistaken as Bin 1 or Bin 2. With use of the VC-Stog model (VC-Sync model + SBL model), the accuracies for vehicles of Bin 1 and Bin 3 have been improved to 92% and 91%, respectively. For 4-bin scheme result as shown in Table 6, the accuracy for Bin 1 has been improved from 43% to 92%. However, it is not good for vehicles of Bin 3 and Bin 4. This implies a problem that will be addressed in the future research.

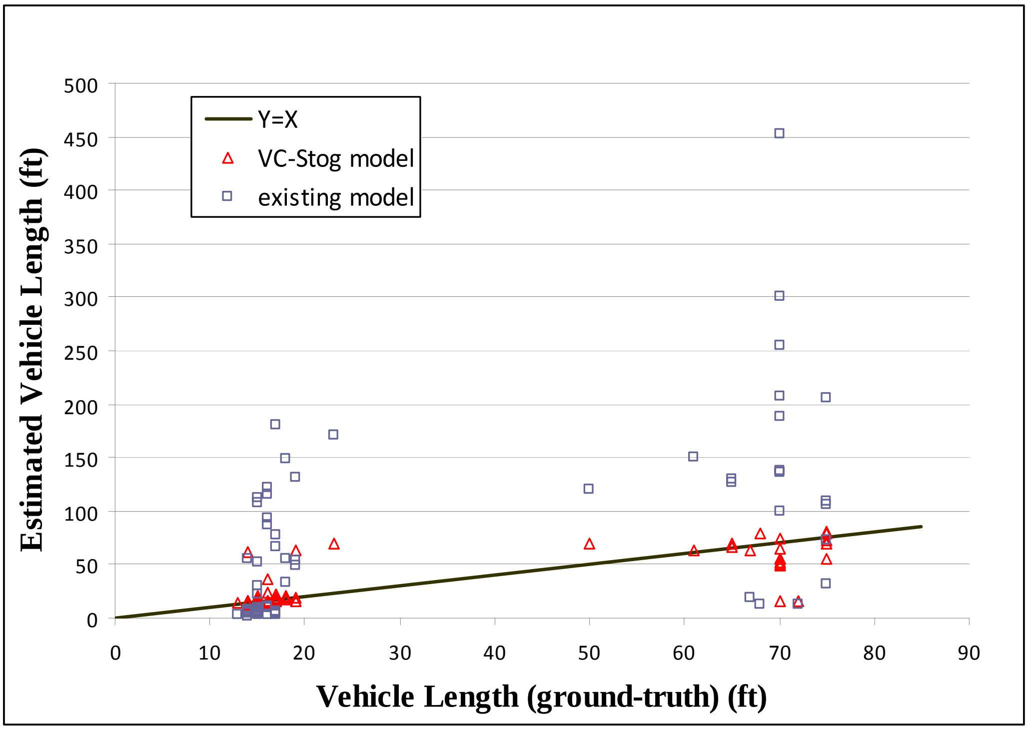

Figure 10. Estimated Vehicle Lengths under Stop-and-go Traffic

Table 5. Vehicle Assignment during Stop-and-go Traffic (3-Bin Scheme)

By Ground-truth Data		**By Dual-loop Data** (note: *correct identification)				
Bins	**# of Vehicles**	**Bin type identified by vehicle length**	**# of vehicles by existing model**	**%**	**# of vehicles by VC-Stog model**	**%**
Bin 1	39	**Bin 1*	*17*	*43%*	*36*	*92%*
		Bin 2	4	11%	0	0%
		Bin 3	18	47%	3	8%
Bin 2	0	Bin 1	0	N/A	0	N/A
		**Bin 2*	*0*	*N/A*	*0*	*N/A*
		Bin 3	0	N/A	0	N/A
Bin 3	22	Bin 1	2	11%	2	9%
		Bin 2	1	4%	0	0%
		**Bin 3*	*19*	*85%*	*20*	*91%*

Table 6. Vehicle Assignment during Stop-and-go Traffic (4-Bin Scheme)

By Ground-truth Data		**By Dual-loop Data** (note: *correct identification)				
Bins	**# of Vehicles**	**Bin type identified by vehicle length**	**# of vehicles by existing model**	**%**	**# of vehicles by VC-Stog model**	**%**
Bin 1	39	**Bin 1*	*17*	*43%*	*36*	*92%*
		Bin 2	4	9%	0	0%
		Bin 3	6	15%	2	5%
		Bin 4	13	34%	1	3%
Bin 2	0	Bin 1	0	N/A	0	N/A
		**Bin 2*	*0*	*N/A*	*0*	*N/A*
		Bin 3	0	N/A	0	N/A
		Bin 4	0	N/A	0	N/A
Bin 3	4	Bin 1	0	0%	0	0%
		Bin 2	0	0%	0	0%
		**Bin 3*	*0*	*0%*	*1*	*25%*
		Bin 4	4	100%	3	75%
Bin 4	16	Bin 1	2	11%	2	13%
		Bin 2	0	0%	0	0%
		Bin 3	2	11%	8	50%
		**Bin 4*	*12*	*78%*	*6*	*38%*

CONCLUSIONS

In this study, the dual-loop length-based vehicle classification models have been evaluated against the ground-truth vehicle trajectory data extracted from video. Different traffic conditions have been investigated: free flow, synchronized flow, and stop-and-go flow. It has been proved that the existing model has much larger error under both synchronized and stop-and-go traffic conditions. In the new developed models against synchronized traffic and stop-and-go traffic, the impact of traffic flow characteristics is properly considered: 1) relative stable accelerations or decelerations are observed for individual vehicles within the synchronized traffic, so the acceleration or deceleration rate is incorporated into the VC-Sync model; and 2) eight scenarios are defined depending on the vehicle's stopping locations within the detection area as the stop-and-go traffic occurs, and the VC-Stog model is developed based on those assumed scenarios. The sample study results indicate that the VC-Sync model and VC-Stog model significantly increase the accuracy of the vehicle classification against synchronized and stop-and-go traffic flows. However, more samples are needed for the future research, especially the cases under stop-and-go traffic conditions. Despite a total of 26 hours of traffic video data, the sampling size for stop-and-go traffic is likely insufficient. Nevertheless, the results are exciting. The innovation of the proposed VEVID-based approach has been fully exhibited and the significant increase of vehicle classification accuracy has demonstrated the advantages of the VC-Sync and VC-Stog models over the existing model under non-free traffic conditions. The author has developed a plan for further collecting more sample data to complete the research on VC-Stog modeling for Scenarios 5 through 8. Finally, VEVID-based approach plays a critical role in extracting the ground-truth vehicle event trajectory data. It would be difficult or even impossible to conduct this research without use of VEVID.

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