Improving Freeway Traffic Speed Estimation Using High-Resolution Loop Detector Data

Final Report

Prepared by:

Henry X. Liu
Jie Sun

**Department of Civil Engineering
University of Minnesota**

CTS 13-21

Technical Report Documentation Page

1. Report No. CTS 13-21	2.	3. Recipients Accession No.	
4. Title and Subtitle Improving Freeway Traffic Speed Estimation Using High-Resolution Loop Detector Data		5. Report Date April 2013	
		6.	
7. Author(s) Henry X. Liu and Jie Sun		8. Performing Organization Report No.	
9. Performing Organization Name and Address Department of Civil Engineering University of Minnesota 500 Pillsbury Drive Minneapolis, MN 55455		10. Project/Task/Work Unit No. CTS Project #2012048	
		11. Contract (C) or Grant (G) No.	
12. Sponsoring Organization Name and Address Intelligent Transportation Systems Institute Center for Transportation Studies University of Minnesota 200 Transportation and Safety Building 511 Washington Ave. SE Minneapolis, MN 55455		13. Type of Report and Period Covered Final Report	
		14. Sponsoring Agency Code	
15. Supplementary Notes http://www.its.umn.edu/Publications/ResearchReports/			

16. Abstract (Limit: 250 words)

In this project, we developed an innovative methodology to solve a long-standing traffic engineering problem, i.e. measuring traffic speed using data from single inductive loop detectors. Traditionally, traffic speeds are estimated using aggregated detector data with a manually calibrated effective vehicle length. The calibration effort (usually through running probe vehicles), however, is time consuming and costly. Instead of using aggregated data, in this project, our data collection system records every vehicle-detector actuation "event" so that for each vehicle we can identify the time gap and the detector occupation time. With such high-resolution "event-based" data, we devised a method to differentiate regular cars with longer vehicles. The proposed method is based on the observation that longer vehicles will have longer detector occupation time. Therefore, we can identify longer vehicles by detecting the changes of occupation time in a vehicle platoon. The "event-based" detector data can be obtained through the implementation of the SMART-Signal (Systematic Monitoring of Arterial Road Traffic Signals) system, which was developed by the principal investigator and his students in the last five years. The method is tested using the data from Trunk Highway 55, which is a high-speed arterial corridor controlled by coordinated traffic signals. The result shows that the proposed method can correctly identify most of the vehicles passing by inductive loop detectors. The identification of long vehicles will improve the estimation of effective vehicle length on roads. Consequently, speed estimation from the inductive loop detector is improved.

17. Document Analysis/Descriptors Speed measurement, Loop detectors, Speed data, Vehicle classification		18. Availability Statement No restrictions. Document available from: National Technical Information Services, Alexandria, Virginia 22312	
19. Security Class (this report) Unclassified	20. Security Class (this page) Unclassified	21. No. of Pages 27	22. Price

Improving Freeway Traffic Speed Estimation Using High-Resolution Loop Detector Data

Final Report

Prepared by:

Henry X. Liu
Jie Sun

Department of Civil Engineering
University of Minnesota

April 2013

Acknowledgments

Table of Contents

List of Figures

Executive Summary

In this project, we developed an innovative methodology to solve a long-standing traffic engineering problem, i.e. measuring traffic speed using data from single-loop detectors. Traditionally, traffic speeds are estimated using aggregated detector data with a manually calibrated effective vehicle length. The calibration effort (usually through running probe vehicles), however, is time consuming and costly.

Instead of using aggregated data, in this project, our data collection system records every vehicle-detector actuation "event" so that for each vehicle we can identify the time gap and the detector occupation time. The "event-based" detector data can be obtained through the implementation of the SMART-Signal (Systematic Monitoring of Arterial Road Traffic Signals) system, which was developed by the principal investigator and his students in the last five years. With such high-resolution "event-based" data, we devised a method to differentiate regular cars from longer vehicles. The identification of long vehicles is the key to speed estimation using inductive loop detectors, as it will improve the estimation of effective vehicle length on roads, which, in turn, results in more accurate speed estimation from inductive loop detectors.

The proposed method is based on the observation that longer vehicles will have longer detector occupation times. Therefore, we can identify longer vehicles by detecting the changes of occupation times in a vehicle platoon. The vehicles are first put into groups according to the time gap between consecutive vehicles. Then speed relation of vehicles within a group is described by applying Newell's simplified car-following model, which is verified in (Ahn et al, 2004). By assuming all the vehicles are regular cars, estimated occupation times of all vehicles are represented as a function of estimated speed. Then a mathematical program is used to obtain the optimal speed and acceleration rate of the first vehicle in the group by minimizing the summation of differences between estimated occupation times and measured occupation times of all vehicles in the group. The optimal estimated speed of every vehicle can then be calculated according to the speed relation based on the car-following model. The optimal estimated occupation time for each vehicle is calculated from optimal estimated speed by assuming regular vehicle length. If the measured occupation time of a vehicle is significantly longer than its optimal estimated occupation time, that vehicle is identified as a long vehicle. The method is tested using data from Trunk Highway 55, which is a high-speed arterial corridor controlled by coordinated traffic signals. The result shows the proposed method can identify a significant majority of the long vehicles passing by inductive loop detectors.

Chapter 1. Introduction

Inductive loop detectors have been widely deployed in almost all metropolitan areas in the United States. Traditionally, if the aggregated occupancy and flow measurements (say in 30 seconds interval) are available, the space mean traffic speed at the detector location can be estimated by using these measurements together with a manually-calibrated effected vehicle length. Because the effective vehicle length is dependent on the vehicle composition, which may vary at different locations and different times, calibration of this parameter is time consuming and costly. On the other hand, the speed estimation error is linearly proportional to the error of the effective vehicle length; therefore, frequent calibration efforts are required to ensure the accuracy of speed estimation.

Although it is possible to get vehicle class information via technologies such as weigh in motion (WIM) station, piezo sensors, video imaging, or acoustic signal analysis (Jolly, et al. 1996, Nooralahiyan, et al. 1997, Avery, et al. 2004). None of these techniques, however, are as widely deployed as inductive loop detectors (ILDs). With the widespread deployment of ILDs, there will be no or little extra installation cost if IDLs can be used for vehicle classification.

IDLs can be configured in the form of single-loop detector or dual loop detectors. Single-loop detectors are most widely deployed. Dual loop detector consists of two single inductive loop detectors placed closely together and allows direct estimation of vehicle speed and length, which enables length-based vehicle classification (Nihan, et al. 2002, Cheevarunothai, et al. 2007). The deployment of dual detectors is, however, also limited compared with that of single-loop detectors and more costly.

There have been some researches on using vehicle signature for length-based vehicle classification (Oh, et al. 2002, Cheung, et al. 2005). Vehicles are usually classified into more than 3 classes and the accuracy rate is higher than 80%. Although using IDLs, it requires special data acquisition card with high scan rate to obtain vehicle signature, which is expensive.

Researchers have also used aggregated data (e.g. with 30 second interval) from single-loop detector for vehicle classification (Kwon, et al. 2003, Wang and Nihan, 2003, 2004). Kwon et al. (2003) developed a vehicle classification algorithm based on speed correlation between lanes. With assumed existence of a truck-free lane, the speed of that lane can be estimated using the measured volume and occupancy data from a single-loop detector. The estimated speed for the truck-free lane can then be used to derive the effective vehicle length for other lanes based on speed correlation. Wang and Nihan (2003, 2004) classify vehicles by separating time intervals (20 seconds in their case) with long vehicles from those without in a time period (5 minutes in their case), and by assuming constant speed within the time period. Then they use the speed estimated from those car-only intervals, in which vehicle length is known, to derive effective vehicle length and vehicle composition for those intervals with long vehicles. Both approaches described above, however, rely on the assumption that a benchmark, either a truck-free lane or a truck-free time interval, is available so that traffic speed can be estimated using known length of regular cars. It is apparent that such assumptions can be easily violated.

(Coifman and Kim, 2009) is the only exception that uses the "event-based" data from a single-loop detector to identify vehicle length. They study the probability distribution of the detector occupancy time (i.e., the detector on-time actuated by individual vehicles), and classify a vehicle by associating its detector actuation time with that distribution. Since low vehicle speed also creates high actuation time, their method performs poorly during congestion, as reported in their paper.

On contrast to the statistical based method used in (Coifman and Kim, 2009), a method based traffic dynamics is proposed in this report. Newell's simplified car-following theory (Newell, 2002) is used to describe the relation between consecutive vehicles in a platoon. Observed vehicle occupation time is compared with estimated vehicle occupation time. Discrepancy between these two is used to identify long vehicles by comparing the ratio between them with predefined critical length ratio. The proposed method is tested using high-resolution traffic data collected from Trunk Highway 55 in Minnesota and concurrently recorded videos are used for verification.

Our proposed research is based on the high-resolution "event-based" data from single-loop detectors. In the past five years, with the funding from ITS Institute and Minnesota DOT, the PI and his students have developed the SMART-Signal (Systematic Monitoring of Arterial Road Traffic Signals) system to monitor the performance of urban arterials. SMART-Signal offers a viable approach to collect and archive "event-based" traffic flow data (including both vehicle-detector actuation events and signal phase change events) from traffic signal controller cabinets. Using such data, SMART-Signal is capable of measuring arterial signal performance in real-time and fine-tuning traffic signal parameters (Liu and Ma, 2009, Liu, et al. 2009). The SMART-SIGNAL system has been field-tested on several major arterial corridors in the Twin Cities area including TH13 in Burnsville, TH55 in Golden Valley, France Ave. in Bloomington, and Prairie Center Dr. in Eden Prairie. A technology demonstration project for the SMART-Signal system is currently operational with the City of Pasadena in California.

This report is organized as follows. The high-resolution traffic data is briefly explained at first and some initial observations from the field data are offered in Chapter 2. In Chapter 3, the speed relation between consecutive vehicles is described by extending Newell's simplified car-following model (Newell, 2002), and a vehicle classification algorithm is developed by comparing the measured occupation time with the estimated occupation time of each vehicle in Chapter 4. Field test results are shown in the Chapter 5 and concluding remarks are offered in the last chapter.

Chapter 2.   Data Description and Empirical Observations

2.1   Event-Based Data

The Systematic Monitoring of Arterial Road Traffic and Signal system (SMART-Signal) has been developed at University of Minnesota by the PI and his students. The system offers an easily implementable approach to collect high-resolution event-based traffic data. In the SMART-Signal system, every vehicle-detector actuation and every signal phase changes are recognized and recorded as an event. The difference between the arriving times of consecutive vehicles gives the headway for these two vehicles and taking the occupation time out of the headway gives the gap between these two vehicles. It has been shown that the information of individual vehicles allows better estimation of the travel times and queue lengths along signalized arterials (Liu and Ma, 2009, Liu, et al. 2009).

2.2   Field Observation

The motion of a vehicle traveling in a platoon closely following the vehicle in its front can be approximately described by a car-following model. Assuming the vehicles in a platoon have the same acceleration rate (a) when passing by a fixed location, the traffic flow can be in one of three categories based on the value of a. If $a = 0$, it is steady flow; if $a > 0$, it is acceleration flow; if $a < 0$, it is deceleration flow.

As the inductive loop detector gives point measurement of the traffic flow, it is convenient to see how the speed changes when vehicles passing by a detector. In steady flow, acceleration flow and deceleration flow, the speed of vehicles in the traffic keeps about the same, increasing, or decreasing, respectively, when passing by a detector. Free flow traffic is an example of steady flow. Discharging flow when signal turns to green can be seen as an example of acceleration flow. And deceleration flow can be observed where vehicles arrive at an intersection when the signal is red. Despite of different traffic flow patterns, a bump in terms of individual vehicle occupation time can always be observed in event-based data when a long vehicle passes by a detector. Next, three examples from field data corresponding to the three traffic conditions will be given to demonstrate the vehicle occupation time changes (Figures 2.1, 2.2, and 2.3), which represent the key observations for long vehicle identification in the proposed method.

Individual vehicle occupation time is readily available from event-based traffic data. Significant difference in occupation time is caused by either the difference in speed or the length of vehicles. If there is no disturbance in traffic, the speed of vehicles in the traffic flow should be about the same. There will be little difference between individual vehicles if their effective vehicle lengths are similar, since there is little speed variance in steady flow. If a significant occupation time difference is observed in steady flow, it is most likely caused by the difference in vehicle lengths, as it is very unlikely that the speed difference between consecutive vehicles in steady flow is huge.
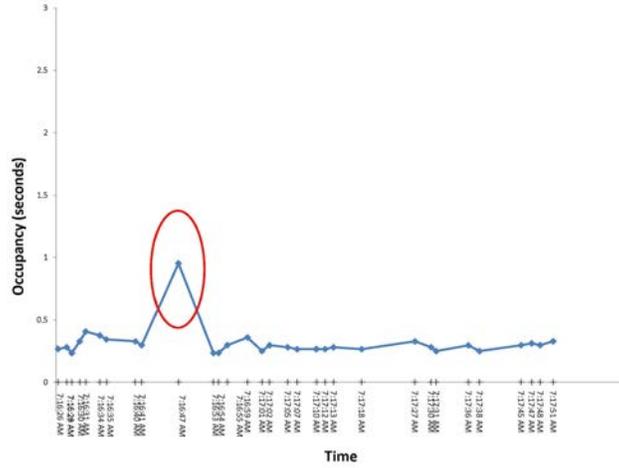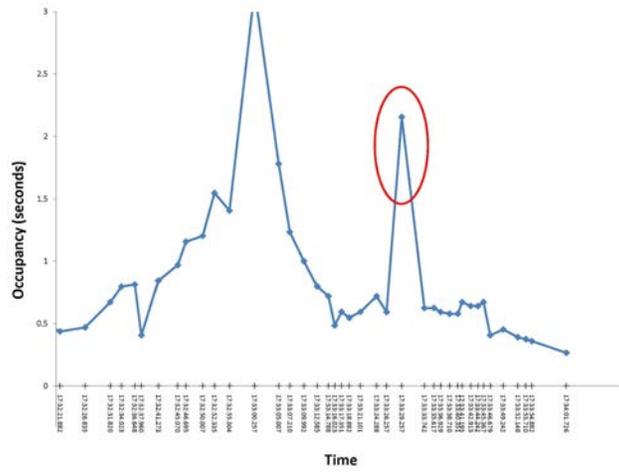
Figure 2.1: Occupation time bump in steady flow.

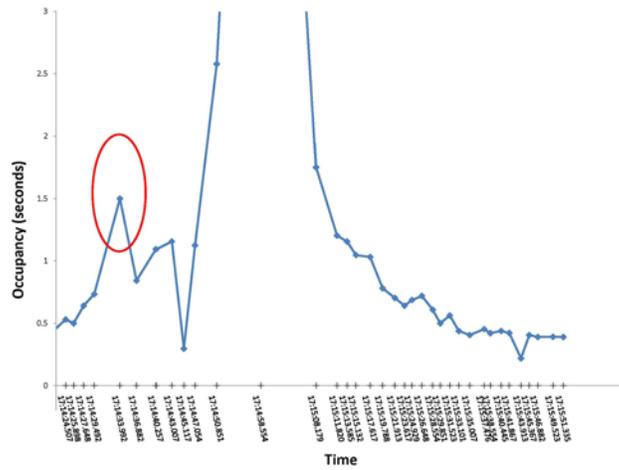**Figure 2.2: Occupation time bump in acceleration flow.**

Figure 2.3: Occupation time bump in deceleration flow.

2.2.1 Steady Flow

Figure 2.1 shows an example of vehicle occupation time bump in steady flow traffic. The data were obtained by the SMART-Signal system at TH-55 on an ordinary weekday. The traffic is not congested at the moment of interest and the traffic is in steady flow. Based on the analysis above, the observed bump in occupation time (circled in red line) indicates a long vehicle. And using video recorded concurrently, it is confirmed that there was a big truck passing by at that time.

2.2.2 Acceleration Flow

When traffic begins to accelerate (e.g. at the start of green), individual vehicle occupation times are supposed to become smaller and smaller, as vehicles accelerate. Even if there are fluctuations in speed and differences in vehicle lengths, the occupation time is not likely to have a dramatic increase like a bump in occupation time. If observed, it indicates a long vehicle in the traffic. An example can be seen in Figure 2.2 and verified against video.

2.2.3 Deceleration Flow

When a vehicle decelerates, the effect will propagate back along the traffic flow. The speeds of consecutive vehicles passing by a detector are expected to decrease gradually. In this situation, an occupation time bump still suggests a long vehicle. (Situations may get complicated when traffic speed becomes lower than 20 *mph* based on empirical observation, as traffic is likely moving in a stop-and-go condition.) Other than that, the occupation time bump usually means a long vehicle passing by. Figure 2.3 demonstrates the occupation time bump caused by a long vehicle in deceleration flow, where occupation times increase gradually. The observation is also verified by video.

2.3 Analysis

The goal of this study is to identify long vehicles (LVs) in traffic. Vehicles, whose lengths are at least as 2 or 3 times as that of a typical passenger car (PC), are regarded as long vehicles in this study. Although long vehicles cause occupation time bump in all traffic conditions, the problem is to quantitatively decide the criteria of long vehicle identification.

Recall that occupation time (*o*) equals effective vehicle length (*l*) divided by vehicle speed (*v*), i.e. $o = l/v$. Single vehicle occupation time is affected by both effective vehicle length and vehicle speed. On the other hand, inductive loop detectors only give measurements of occupation time. For an individual vehicle, it is impossible to tell its effective vehicle length without knowing its speed only based on occupation time or vice versa. However, the speeds of vehicles in a platoon are closely related. If the speed relation between consecutive vehicles can be quantitatively described, the relation of lengths between these vehicles (relative vehicle lengths) can be estimated, although it is still difficult to calculate the absolute vehicle length. Given most vehicles on road are not long vehicles (Kwon, et al. 2003, Wang and Nihan, 2003), long vehicles can be identified by utilizing relative vehicle lengths.

Before developing the length-based vehicle classification algorithm, several assumptions are needed. In this study, it is assumed that: *1)* a vehicle is either close to the vehicle in front and thus following it or is far away from the front vehicle and thus travels at desired speed; *2)* Newell's simplified car following model (Newell, 2002) can be used to describe vehicles' trajectories if they are close.

Chapter 3. Theoretical Foundations of Vehicle Classification

3.1   Newell's Simplified Car Following Model and its Extension

Newell (2002) proposed a simplified car-following model, in which the trajectory of a vehicle is approximately the same as its leading vehicle with a displacement in space d and in time τ (see Figure 3.1). Equation 3.1 describes how the locations of a vehicle and its leading vehicle related. d and τ are assumed to be related to the driving behavior of the following vehicle's driver.
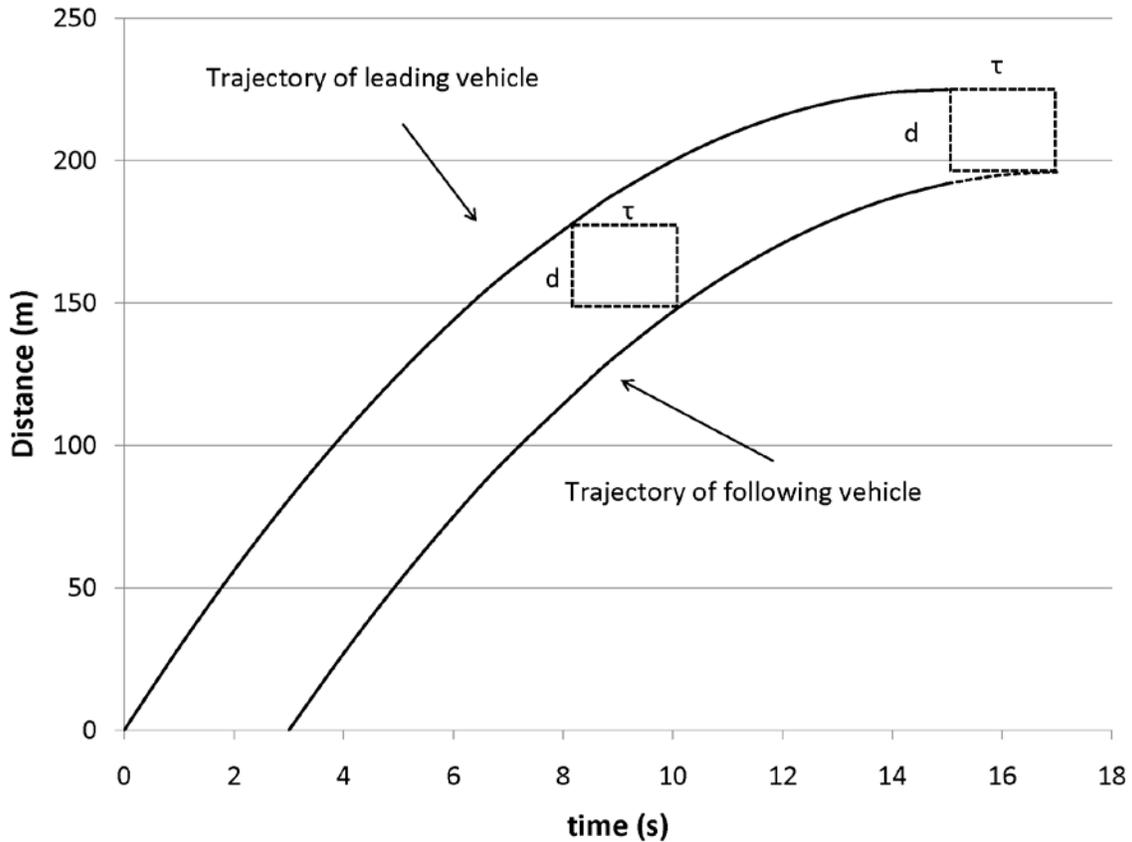
Figure 3.1: Extended simplified car following model.

$$x_n(t + \tau_n) = x_{n-1}(t) - d_n.$$
<div align="right">Equation 3.1</div>

Newell (2002) considers the behavior of the leading vehicle (represented as subscript *n-1*) as given. Assumptions about acceleration rate are needed to specify the behavior of the leading vehicle. In this study, the acceleration rate of the leading vehicle is assumed to be constant, i.e. the leading vehicle is either accelerating or decelerating, according to the same rate. Then, the trajectory of the leading vehicle can be described by Equation 3.2, where a is the speed changing rate and v_{n-1} is the initial speed.

$$x_{n-1} = \frac{a}{2}t^2 + v_{n-1}t \qquad\qquad \text{Equation 3.2}$$

Consequently, the trajectory of the following vehicle can be described by Equation 3.3, which is derived from Equation 3.1 and Equation 3.2. Newell's assumption implies that the speed changing rate of the following vehicle is the same as that of the leading vehicle.

$$x_n = \frac{a}{2}(t - \tau_n)^2 + v_{n-1}(t - \tau_n) - d_n \qquad\qquad \text{Equation 3.3}$$

Assuming the leading vehicle passes by the detector at time zero with initial speed v_{n-1}, the following vehicle will pass by the detector with speed v_n. Let $x_n = 0$ in Equation 3.3 and solve for t, the solutions are

$$t_{1,2}^* = \frac{-(v_{n-1} - a\tau_n) \pm \sqrt{v_{n-1}^2 \mp 2ad_n}}{a} \qquad\qquad \text{Equation 3.4}$$

The speed of the following vehicle, when it passes by the detector, can be calculated by differentiating Equation 3.3 with respect to t, which would be

$$v_n = \sqrt{v_{n-1}^2 + 2ad_n} \qquad\qquad \text{Equation 3.5}$$

Negative speed is ignored as vehicles are moving forward.

3.2   Estimation of Vehicle Occupation Time

Based on the assumptions made at the end of last chapter, a vehicle can be either *1)* far away from its immediate front vehicle, or *2)* following its immediate front vehicle. In the first situation, the vehicle travels at its desired speed (all the vehicles are assumed to have the same desired speed in this study). In the second situation, the trajectory of the vehicle can be described by the extended Newell's car-following model developed above.

High-resolution traffic data include individual vehicle occupation time (detector on-time) and the gap between consecutive vehicles. Assuming a vehicle is not following its immediate leading vehicle if the gap between them is greater than or equal to critical gap ξ, a sequence of vehicles can be divided into groups based on the gaps between consecutive vehicles using ξ. The gaps between vehicles with a group are all smaller than ξ. Vehicles in different groups are not following each other. Vehicles within a group are following the immediate front vehicles in the group and thus their trajectories can be described by the extended Newell's car-following model.

Next, the method to estimate vehicle occupation time will be presented, which is the key step for vehicle classification. Let n denotes the number of vehicles in a group. If $n \leq 2$, the vehicles are assumed to travel at desired speed. When n equals to or is greater than 3, estimated speed of each vehicle within a group is calculated by Equation 3.5, given the speed of the first vehicle v_0, the acceleration rate a, and the space displacement d_n. The space displacement of vehicle trajectory d is vehicle or driver property and direct measurement of d is difficult. For practical application, calibration may be needed. For research purpose in this study, the value of d is estimated to be 24

feet based on the results of other researches (Ahn, et al. 2004, Wang and Coifman, 2005, Chiabaut, et al. 2009). After examining the data, it is found that the car-following model becomes inaccurate when $n > 10$. So n is constrained to be less than 10.

With space displacement d fixed, the speed of vehicles within a group is a function of the leading vehicle speed v_0 and acceleration rate a. Assuming all the vehicles are not long vehicles and their effective lengths are l, the estimated occupation time for ith vehicle is,

$$\hat{o}_i = \frac{l}{\hat{v}_i}$$

Equation 3.6

where $\hat{v}_i$ is the estimated speed of ith vehicle and can be calculated by Equation 3.5.

The mean square error (MSE) of vehicle occupation time is calculated as,

$$MSE(\hat{o}) = \frac{1}{n+1} \sum_{i=0}^{n} (\hat{o}_i - o_i)^2$$

Equation 3.7

where $\hat{o}_i$ is the estimated occupation time and o_i is the measured occupation time of ith vehicle in a group.

For the situation where $n \geq 3$, optimal v_0 and a is obtained from the following minimization program,

$$\min MSE(\hat{o})$$
$$s.t. \quad -10 ft/s^2 < a < 7 ft/s^2$$
$$0 < v_i < 100 mph, i = 0, 1, \dots n$$

Equation 3.8

where a is the acceleration rate of vehicles and v is the speed of all the vehicles in the group.

The constraints are added for the sake of both physical limit of vehicles and algorithm considerations. First, the acceleration rate and speeds of most vehicles won't go beyond the specified range. Second, when there is large change in occupation time, a curve with larger absolute acceleration rate value can usually fit data better. But this large change in occupation time is usually caused by long vehicles rather than unusual vehicle acceleration rate.

With the estimated optimal v_0 and a, estimated speed of each vehicle in a group is calculated using Equation 3.5. Corresponding estimated occupation time is calculated by Equation 3.6, assuming all vehicle effective lengths are l.

Chapter 4.   Vehicle Classification Algorithm

As the proposed method works on vehicle platoons, a pre-defined critical gap (ξ) is used to group the vehicles. In addition, the number of vehicles in a group is constrained to be less than a given number (n_ξ), as it is found out the description of vehicle dynamics by car-following model becomes inaccurate, when the number of vehicles in a group is large. The measured occupation time of each vehicle is compared with its estimated occupation time. If the ratio between these two is greater than or equal to predefined critical ratio (δ), this vehicle is classified as long vehicle. A flowchart of vehicle classification algorithm is presented in Figure 4.1 and explanations are provided below.
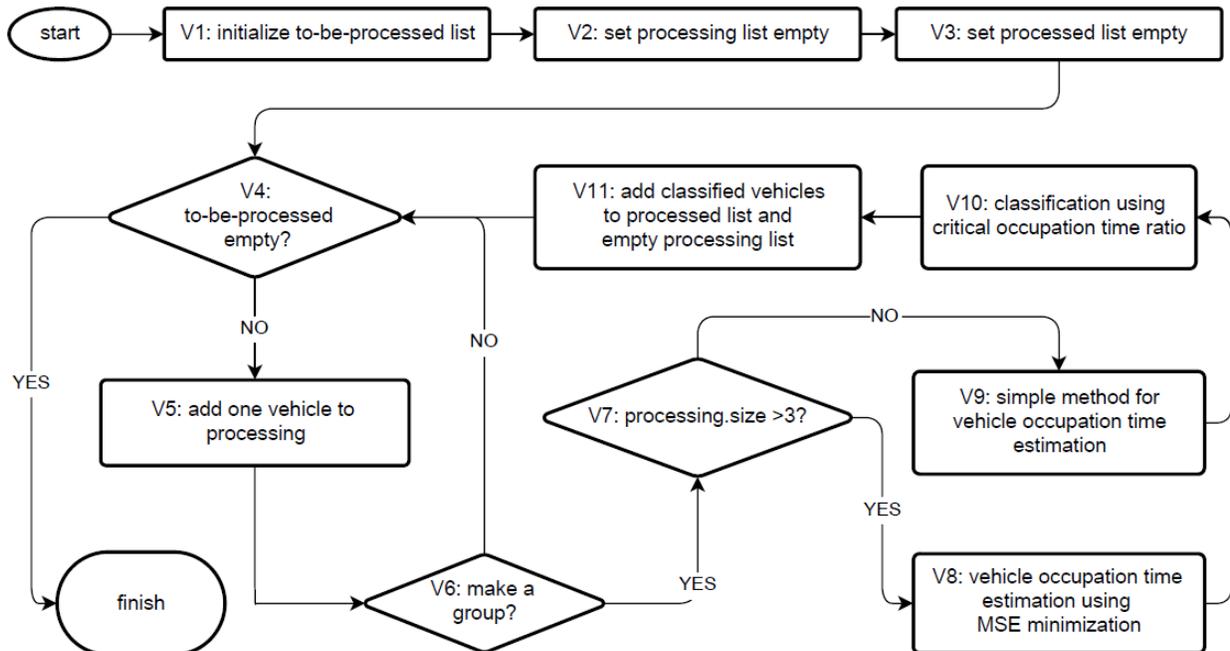
Figure 4.1: Vehicle classification algorithm flowchart.

Algorithm V (vehicle classification)

Data: Individual vehicle occupation time and gap.

Result: A list of long vehicles.

V1. [initialize ***to-be-processed*** list] Each element in the list represents one vehicle with an occupation time and time gap.

V2. [set ***processing*** list empty] *processing* list is a temporary list holding a group of vehicles to be classified.

V3. [set ***processed*** list empty] *processed* list stores vehicle classification results.

V4. [***to-be-processed*** empty?] If yes, finish.

V5. [add one vehicle to *processing*] pop the first vehicle in *to-be-processed* to *processing*.

V6. [make a group?] If current gap is greater than or equal to critical gap (ξ), or number of vehicles in a group is greater than n_ξ, or *to-be-processed* is empty, go to **V7**; otherwise, go to **V4**.

V7. [size of *processing* > 3?] If yes go to **V8**; otherwise, go to **V9**.

V8. [vehicle occupation time estimation using MSE minimization.] Get estimated vehicle occupation times using MSE minimization introduced at the end of last chapter, then go to **V10**.

V9. [simple method for vehicle occupation time estimation] Get estimated vehicle occupation time with desired speed and typical vehicle length.

V10. [classification using critical occupation time ratio] For each vehicle, if the ratio between its measured occupation time and its estimated occupation is greater than or equal to critical ratio, mark it as long vehicle list. Add result to *processed* list.

V11. [add classified vehicles to processed list and empty processing list] save results and go to **V4**.

A special treatment has to be made to the vehicles that have stopped or nearly stopped over the detectors. This can be usually observed at intersections with high traffic volume and the queues build up to the detector location. As inductive loop detector only gives vehicle occupation time, it is necessary to assume that vehicles with extremely large occupation time actually stopped over the detector. In this situation, little information about this vehicle can be extracted from the data. Since the majority of vehicles on the road are not long vehicles, these vehicles with extremely long occupation time are assumed not to be long vehicles.

Chapter 5. Field Test of Vehicle Classification Algorithm

A field test of vehicle classification algorithm was carried out on Trunk Highway 55 (TH-55), which is located at the west of Twin Cities Metropolitan Area. Data were collected by the SMART-Signal system from the 2-mile corridor along TH-55 between Boone Ave N. and TH-100. Detector 3 at Glenwood Ave. is used to collect the data (see Figure 5.1). This is an advanced detector located at 400 *feet* upstream of the stop line. The outer lane is purposefully chosen, as more long vehicles are expected to travel in outer lane. Data from typical weekday morning peak hours (6 am to 9 am on Jun. 3, 2008) are used. Concurrent video was recorded for verification purpose.
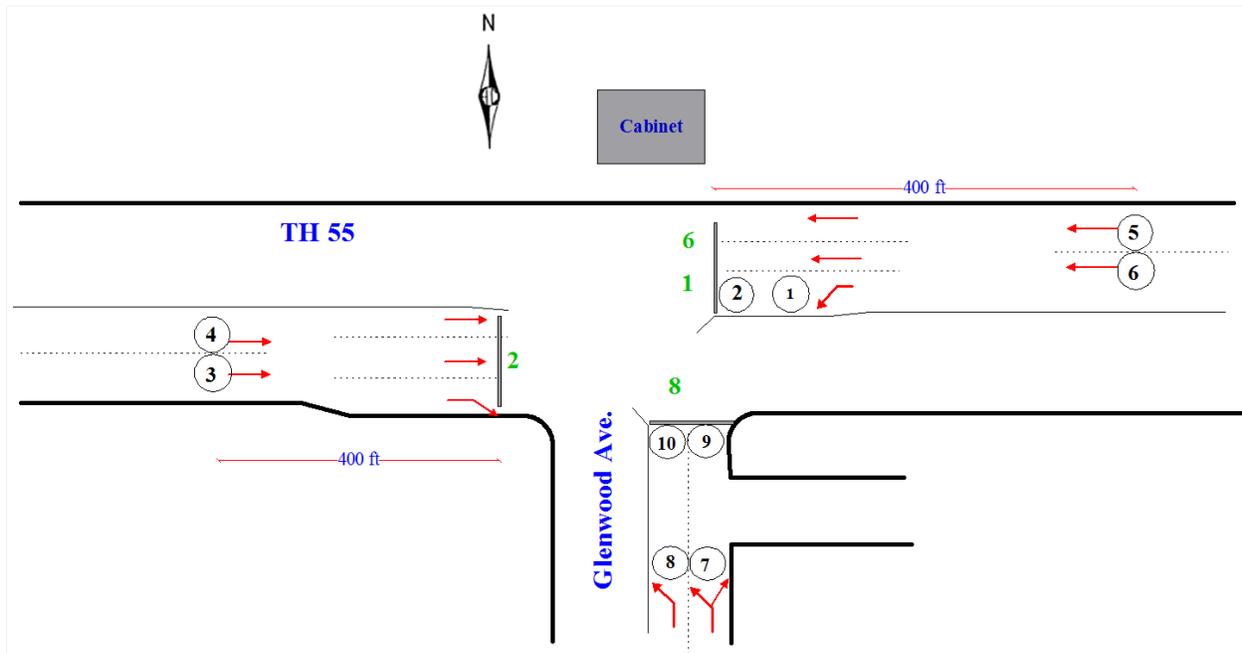

Figure 5.1: Field test site of vehicle classification algorithm.

The outputs of the algorithm will be a list of long vehicles identified by the algorithm. The time when each long vehicle actuates the detector will also be output, which is used to verify the result against concurrently recorded video. The video is manually processed to identify the long vehicles passing by the detector during the test period.

The desired speed of vehicles is assumed to be 50mph The effective vehicle length of a regular car is estimated as 24 *feet* based on the observation of field data. The choice of critical length ratio (δ) is important. The lengths of vehicles on road are not uniformly distributed. For example, Wang and Nihan (2003) has shown that the distribution of vehicle lengths at a typical freeway location on I-5 is bi-normal distribution. The shorter vehicles had a mean length of 18 *ft* with a standard deviation of 3 *ft* and the long vehicles had a mean length of 73.8 *ft* with a standard deviation of 11.8 *ft*. If the critical length ratio is so chosen that it is larger than the value when shorter vehicles travel at slightly lower speed and smaller than the value when long vehicles travel at slightly higher speed, the algorithm will be more robust to the speed variation.

Based on the data from ASSHTO (2004) and field observation, two critical length ratios are used. The first one (δ_1) is chosen to be 1.5625, which means vehicles with effective vehicle length equal to or longer than 37.5 *ft* (24*1.5625) are identified as long vehicles. The second critical length ratio is chosen to be 2.4, which means vehicles with effective vehicle length equal to or longer than 57.6 *ft* (24*2.4) are identified as long vehicles. As mentioned above, space displacement is set to be 24 *feet*. Critical gap (ξ) is determined to be 8 *second* after calibration. The final results are given Figure 5.2. On the left is the test result when critical length ratio is 1.5625 and on the right is the test result when critical length ratio is 2.4. The numbers of correctly classified vehicles are shown in green and the numbers of incorrect classification are given in red.
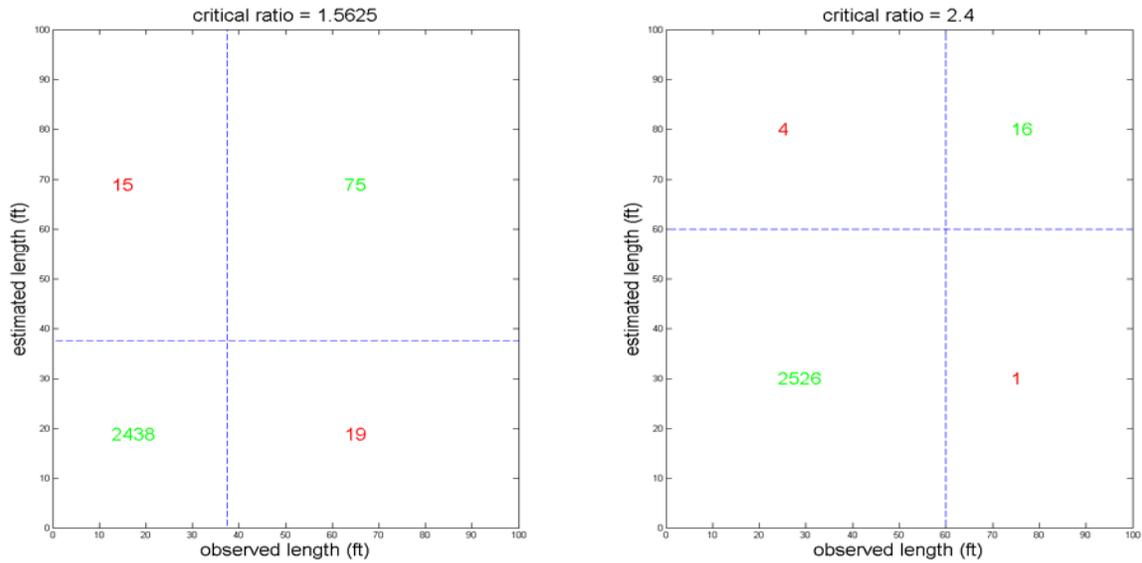

Figure 5.2: Field test results of vehicle classification algorithm.

It can be observed that the long vehicle percentage is very low (around 3%), which agrees with general observation on TH-55. It is interesting to see what the data look like when the algorithm makes right identification and it will be even more interesting to look at the data when the algorithm gives incorrect results. Figure 5.3 and Figure 5.4 are both taken from the test when critical ratio is 1.5625. Vehicles with effective lengths greater than or equal to 37.5 *ft* are considered as long vehicles.
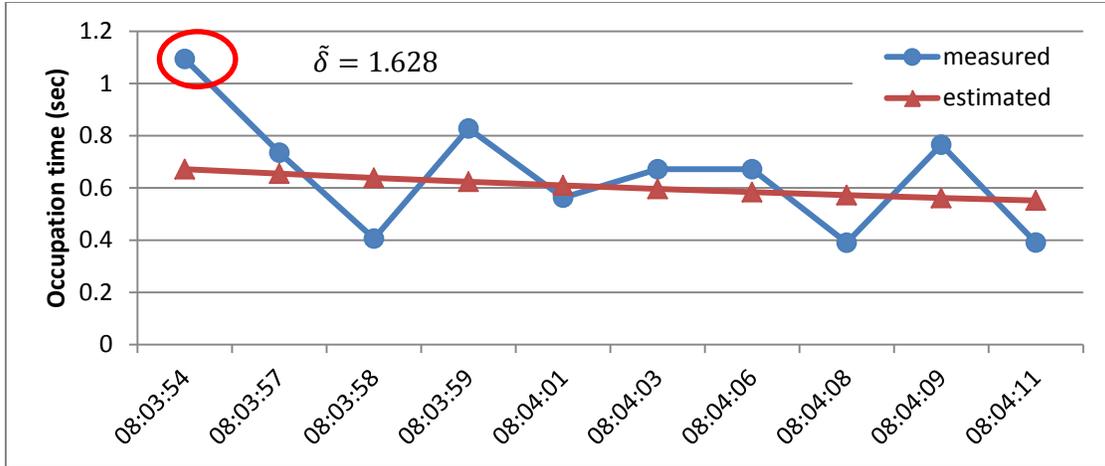
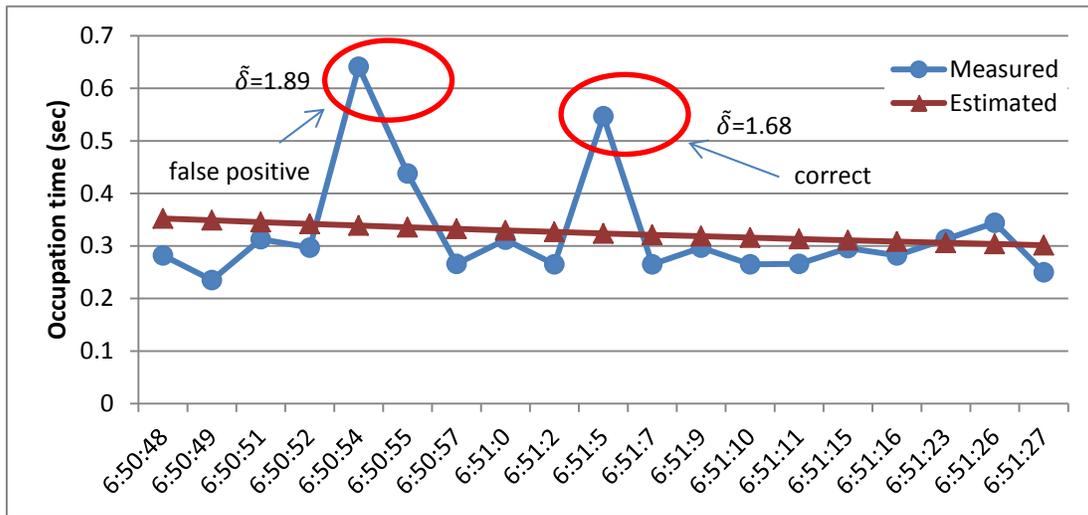**Figure 5.3: Vehicle identification example (1).**

Figure 5.4: Vehicle identification example (2).

Figure 5.3 shows the example when a long vehicle is correctly identified. The long vehicle caused a clear bump in terms of occupation time. The ratio between its measured and estimated occupation time is 1.628. This is greater than the critical length ratio 1.5625, so it is identified as a long vehicle and confirmed by the video observation. Figure 5.4 shows one example of false positive and one example of correct identification. The first occupation time bump is identified by the algorithm as a long vehicle, as its length ratio is 1.89. But from the video, it can be seen what really happened was that the vehicle at the left lane in front of the subject vehicle made a lane change and forced the subject vehicle slow down before it touched the detector. These are the factors not considered in the proposed model, and in fact it might be difficult to consider this kind of factors in a theoretical model. For the second case, the occupation time bump was caused by a school bus. Although it traveled faster than it was supposed to, it is still identified as long vehicle. This is achieved by properly choosing the critical length ratio so that the algorithm is robust to small speed variations.

Chapter 6.   Conclusion

The vehicle occupation time sequence provided by high-resolution traffic data allows the observation of irregularity in occupation time caused by long vehicles. To exploit the irregularity, it is necessary to describe the speed relation between vehicles. This is done by extending Newell's simplified car-following model. The gap data from high-resolution traffic data are used to group vehicles traveling as a platoon, where it is appropriate to describe the speed relation by a car-following model. For each group of vehicles, a minimization program is used to find the best fitted initial speed and acceleration rate. Then by assuming all the vehicles have a typical length, an estimated occupation time is calculated for each vehicle. The estimated occupation time is compared with corresponding measured occupation times. Usually high occupation times are regarded as indications of the presence of long vehicles.

The proposed algorithm is readily applicable to high-resolution traffic data that is obtainable from single-loop detectors, which have been widely deployed in the road system. The additional cost for implementation of such vehicle classification is expected to be low. Some calibration work may be necessary for the parameters used in the algorithm, but additional infrastructure cost is minimal. Although the test data are from signalized arterial roads, the method is also applicable to freeways.

References

[1]   A. Y. Nooralahiyan, M. Dougherty, D. McKeown, and H. R. Kirby, "A field trial of acoustic signature analysis for vehicle classification," *Transportation Research Part C*, vol. 5, no. 3–4, pp. 165–177, 1997.

[2]   M. P. D. Jolly, S. Lakshmanan, and A. K. Jain, "Vehicle segmentation and classification using deformable templates," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 3, pp. 293–308, 1996.

[3]   R. P. Avery, Y. Wang, and G. S. Rutherford, "Length-based vehicle classification using images from uncalibrated video cameras," in *Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems*, Washington, D.C., 4-6 October, 2004, pp. 737–742.

[4]   N. L. Nihan, X. Zhang, Y. Wang, and P. Briglia, *Evaluation of dual-loop data accuracy using video ground truth data*, Washington State Transportation Center; Washington State Department of Transportation; Federal Highway Administration; TransNow, Transportation Northwest. Report WA-RD 535.1, 2002.

[5]   P. Cheevarunothai, Y. Wang, and N. L. Nihan, "Using Dual-Loop Event Data to Enhance Truck Data Accuracy," *Transportation Research Record*, vol. 1993, no. 1, pp. 131–137, 2007.

[6]   S. Oh, S. G. Ritchie, and C. Oh, "Real-time traffic measurement from single-loop inductive signatures," *Transportation Research Record*, vol. 1804, pp. 98–106, 2002.

[7]   S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C. W. Tan, and P. Varaiya, "Traffic measurement and vehicle classification with single magnetic sensor," *Transportation Research Record*, vol. 1917, pp. 173–181, 2005.

[8]   J. Kwon, P. Varaiya, and A. Skabardonis, "Estimation of Truck Traffic Volume from Single-loop Detectors with Lane-to-Lane Speed Correlation," *Transportation Research Record*, vol. 1856, pp. 106–117, 2003.

[9]   Y. Wang and N. L. Nihan, "Can single-loop detectors do the work of dual-loop detectors?" *Journal of Transportation Engineering*, vol. 129, p. 169, 2003.

[10] Y. Wang and N. L. Nihan, "Dynamic Estimation of Freeway Large-Truck Volumes Based on Single-Loop Measurements," *Journal of Intelligent Transportation Systems*, vol. 8, no. 3, pp. 133–142, 2004.

[11] B. Coifman and S. B. Kim, "Speed estimation and length based vehicle classification from freeway single-loop detectors," *Transportation Research Part C*, vol. 17, no. 4, pp. 349–364, 2009.

[12] G. G. Newell, "A simplified car-following theory: a lower order model," *Transportation Research Part B*, vol. 36, pp. 195–205, 2002.

[13] H. X. Liu and W. Ma, "A virtual vehicle probe model for time-dependent travel time estimation on signalized arterials," *Transportation Research Part C: Emerging Technologies*, vol. 17, no. 1, pp. 11–26, 2009.

[14] H. X. Liu, X. Wu, W. Ma, and H. Hu, "Real-time queue length estimation for congested signalized intersections," *Transportation Research Part C: Emerging Technologies*, vol. 17, no. 4, pp. 412–427, 2009.

[15] S. Ahn, M. J. Cassidy, and J. Laval, "Verification of a simplified car-following theory," *Transportation Research Part B: Methodological*, vol. 38, no. 5, pp. 431–440, 2004.

[16] N. Chiabaut, C. Buisson, and L. Leclercq, "Fundamental diagram estimation through passing rate measurements in congestion," *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 2, pp. 355–359, 2009.

[17] C. Wang and B. Coifman, "The study on the effect of lane change maneuvers on a simplified car-following theory," *2005 IEEE Intelligent Transportation Systems, 2005. Proceedings*, pp. 478–483, 2005.

[18] ASSHTO, *A Policy on Geometric Design of Highways and Streets, 5th Edition*. American Assocociation of State Highway and Transportation Officials, Washington, D.C., 2004.