

Can Single-Loop Detectors Do the Work of Dual-Loop Detectors?

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Abstract: Real-time speed and vehicle-classification data are important inputs for modern freeway traffic control and management systems. However, these data are not directly measurable by single-loop detectors. Although dual-loop detectors provide speeds and classified vehicle volumes, there are too few of them on our current freeway systems to meet the practical ATMS (Advanced Traffic Management System) needs, and the cost of upgrading from a single-loop detector to a dual-loop detector is high. This makes it extremely desirable to develop appropriate algorithms to make single-loop detectors capable of performing the tasks of double loops. This paper presents just such an algorithm, i.e., one that uses single-loop measurements to provide accurate speed and vehicle-classification estimates. There are three steps in the algorithm: (1) to separate intervals with long vehicles (LVs) from those without; (2) to use measurements of intervals without LVs for speed estimation; and (3) to identify LV volumes for the intervals with LVs using the estimated speed. Preliminary tests for both spatial transferability and temporal transferability of the algorithm were performed, and the results were encouraging.

DOI: 10.1061/(ASCE)0733-947X(2003)129:2(169)

CE Database keywords: Traffic control; Traffic volume; Traffic speed; Traffic surveillance.

Introduction

Real-time traffic data are essential for modern traffic control and management systems, and inductance-loop detectors are valuable sources of such data. Since its introduction in the early 1960s, the inductance loop detector has become the most popular form of detection systems (ITE 1998). Many freeway networks have deployed single-loop detectors for collecting volume (the number of vehicles passing per unit time) and lane occupancy (the fraction of some total time interval that a loop is occupied by vehicles) data. These data have been valuable sources for transportation planning and traffic control. However, recent developments in advanced traffic management systems (ATMS) require accurate speed and vehicle-classification data, which are not directly measurable by single-loop detectors. To obtain such speed and vehicle-classification data, dual-loop detectors are typically employed.

A dual-loop detector is formed by two consecutive single-loop detectors several meters apart. Since a dual-loop detector is capable of recording the time used for a vehicle to traverse from the first loop to the second loop and the distance between the two loops is predetermined, a dual-loop detector can calculate traffic speed fairly accurately based on such information. By applying

the calculated speed from the dual-loops and the single-loop measured lane occupancies, the length of a vehicle can be estimated and the vehicle can be assigned to a certain class based on its length. In short, dual-loop detectors distinguish themselves from single-loop detectors by giving speed and vehicle-classification data.

Though dual-loop detectors are ideal for collecting speed and vehicle-classification data, there are too few of them on our current freeway systems to meet practical ATMS needs, and the cost of upgrading from a single-loop detector to a dual-loop detector is high. According to the experience of the Washington State Department of Transportation (WSDOT), the cost for upgrading from a single-loop detector to a dual-loop detector ranges from \$3,250 to \$5,750 (includes \$750 direct cost for loop placement and \$2,500–\$5,000 indirect cost caused by lane closure). Hence, dual-loop detectors are far less widely deployed than single-loop detectors. Making existing single-loop detectors capable of providing better speed and vehicle-classification data is of practical significance for traffic researchers.

Previous Work

Most studies of single-loop data application have focused on freeway speed estimation. The methodologies applied can be basically divided into two types according to whether Athol's speed estimation formula (Athol 1965), as shown in Eq. (1), is employed:

$$\bar{s}(i) = \frac{N(i)}{T \cdot O(i) \cdot g} \quad (1)$$

where i =time interval index; \bar{s} =space-mean speed for each interval; N =volume (vehicles per interval); O =percentage of time loop is occupied by vehicles per interval (lane occupancy); T =time length per interval; and g =speed estimation parameter.

The first type of research is based on Eq. (1), and improvements are mainly in the method of choosing appropriate g values.

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Note. Discussion open until August 1, 2003. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on December 21, 2000; approved on November 29, 2001. This paper is part of the *Journal of Transportation Engineering*, Vol. 129, No. 2, March 1, 2003. ©ASCE, ISSN 0733-947X/2003/2-169-176/\$18.00.

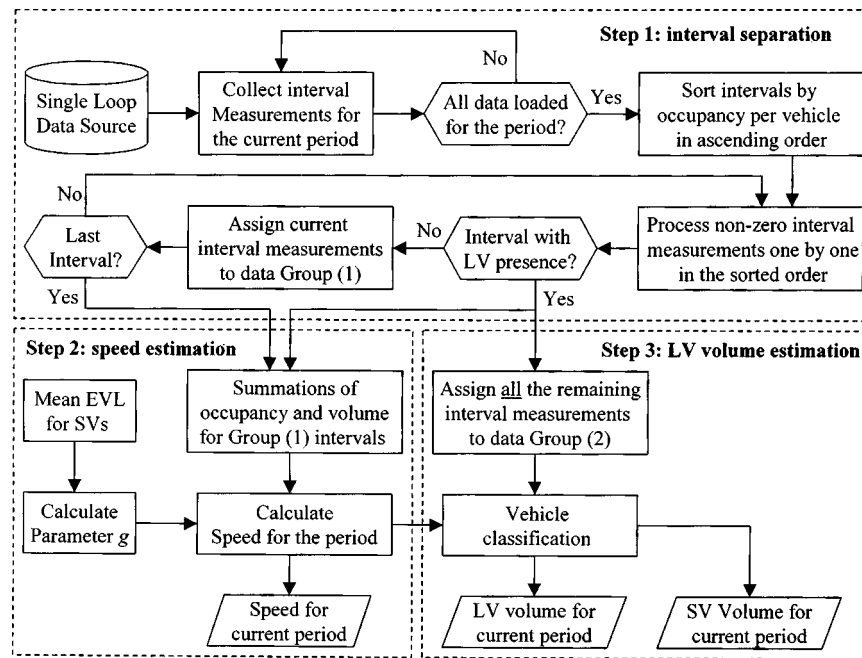


Fig. 1. Flow chart of proposed algorithm

In practice, g has been assumed to be a constant value, determined by the average effective vehicle lengths (EVLs) of the traffic stream. For example, WSDOT uses $g = 2.4$ (Ishimaru and Hallenbeck 1999) and the Chicago Traffic Systems Center takes $g = 1.90$ (Aredonk 1996). In reality, however, g varies as the average EVL changes with vehicle composition, which typically varies over time. Wang and Nihan (2000) studied the relationship between lane occupancy and speed and concluded that, for accurate speed estimation, g could be considered constant only when all vehicle lengths were approximately equal. They suggested that the value of the speed estimation parameter, g , should be updated periodically in response to changing traffic compositions to avoid biased estimations; that is, the speed estimation parameter for interval i , $g(i)$, should be determined by the mean of EVLs for the interval, $\bar{l}(i)$, as shown in Eq. (2):

$$g(i) = \frac{1}{\bar{l}(i)} \quad (2)$$

Hall and Persaud (1989) also demonstrated that g was not a constant using site data collected from several stations and found that g varied with lane occupancy.

The second type of research uses methods other than Eq. (1) for speed estimation. Pushkar et al. (1994) developed a cusp catastrophe theory model to estimate speed. The comparison of the estimation results between their model and Eq. (1) indicated that the cusp catastrophe theory model gave more accurate results. Dailey (1999) considered random errors in the measurements and used a Kalman filter for speed estimation. The estimated average speeds per interval were basically consistent with the observed average speeds, but the estimated variance over the entire study phase was significantly smaller than the observed variance.

Few studies were found to address the vehicle-classification issue with single-loop detectors. Sun et al. (1999) used waveforms to extract vehicle lengths for vehicle reidentification, and their algorithm was found robust under various traffic conditions. However, their algorithm requires a single-loop detector to output waveforms, which the majority of the existing single-loop detec-

tors cannot produce. This may seriously hinder the application of this method. Wang and Nihan (2000) built a log-linear model to estimate mean EVL using statistical moments of occupancy and volume. This estimated mean EVL gave one potential means of classifying vehicles with single-loop data. In a more recent study, Wang and Nihan (2001) developed an improved algorithm for vehicle classification with single-loop measurements that involved a different approach. Computer software was developed and copyrighted based on the algorithm. The vehicle-class volumes estimated by the algorithm were close to those measured by dual-loop detectors.

Methodology

Scheme

The target of this study is to develop an algorithm that makes single-loop detectors capable of doing what dual-loop detectors do. The algorithm should take in single-loop measurements and produce reasonable speed and vehicle-classification data. Accurate speed data is the key, because once speed is known, vehicle length can be straightforwardly calculated.

Vehicles are divided into two classes for this study: short vehicles (SVs) with lengths ≤ 11.89 m and long vehicles (LVs) with lengths > 11.89 m. This corresponds to Bins 1 and 2 and Bins 3 and 4 for the WSDOT classification system [see Wang and Nihan (2001) for details].

The methodology for the current study is based on the findings of two previous studies by Wang and Nihan (2001, 2002). A flow chart of the procedure is shown in Fig. 1. The algorithm contains three steps: (1) to separate time intervals with LVs from those without (marked as "interval separation" in Fig. 1); (2) to use measurements of intervals without LVs (where average vehicle-length can be closely approximated) for speed estimation (noted as "speed estimation" in Fig. 1); and (3) to determine the LV volume of the period based on this estimated speed (labeled "LV volume estimation" in Fig. 1). Please note that, in this paper, the

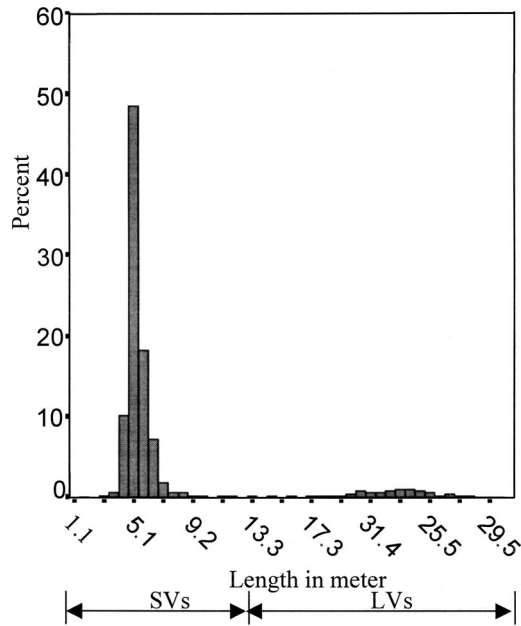


Fig. 2. Length distribution of vehicles on southbound I-5

terms “period” and “interval” are used with significant distinction. An interval indicates the duration of a single volume or occupancy measurement and is predetermined by the loop detection system (in this study, it was 20 seconds, determined by the WSDOT loop detection system). A period represents multiple intervals and is determined by the requirements of the proposed algorithm.

The algorithm processes all interval measurements for a given analysis period simultaneously in order to utilize the relative relationships among intervals for interval separation. The methodology for speed estimation is still based on Eq. (1). However, instead of updating g periodically, the proposed algorithm uses a constant g (based on SV data) and forces the input data to meet the uniform vehicle-length assumption for Eq. (1) by screening out measurements for intervals with LVs. With this estimated speed, the mean EVL for an interval can be calculated and the vehicle composition for the interval can be identified using the Nearest Neighbor (NN) decision rule.

Separating Intervals With LVs from Those Without

The frequency distribution of vehicle lengths observed by a dual-loop detector (ES-163R:MMS__T3 in the WSDOT loop detection system) at southbound I-5 is shown in Fig. 2. Two peaks were obvious in the plot: one at about 5 m, representing the concentration of SV lengths, and the other at about 23 m, representing that for LVs. The fact that the first peak is much higher than the second peak indicates a good concentration of SVs with similar lengths. The standard deviation of vehicle-lengths for SVs is only 0.87 m, about 16% of that for both SVs and LVs observed. This feature guarantees a reasonable satisfaction with the uniform vehicle-length assumption when the traffic flow contains only SVs.

However, a typical traffic stream contains both SVs and LVs. Since an LV’s length is usually several times longer than that of an SV, the mix of SVs and LVs seriously breaks the uniform vehicle-length assumption for speed estimation underlying Eq. (1). Consequently, we need to separate intervals with LVs from

those without. To do so, all interval measurements for a time period must be inspected simultaneously. Relative relationships among the single-loop measurements can be used for the separation purpose, provided that the following two fundamental assumptions hold:

1. For each time period that contains $m(m > 2)$ intervals, vehicle speeds are constant; and
2. Of the m intervals in a period, at least two contain and only contain SVs.

The first assumption makes occupancy proportional to EVL within each period, and the second assumption can be used to calibrate the ratio between occupancy and EVL, since SV lengths are approximately uniform. Here, two interval-measurement sets are used for calibration in order to reduce the possible effects of segmentation error, which refers to the misassignment of a vehicle’s scan count number when the vehicle is right over the loop at the segmentation time (beginning of a new interval), with single-loop data.

For satisfying assumption 1, the period length should be as short as possible, but if the period length is too short, assumption 2 can be easily violated, and vice versa. Thus, the determination of period length is a tradeoff between the two assumptions. There should be some mechanism for making the tradeoff, and research is currently underway to address this specific issue. In this study, interval length was 20 s (determined by the WSDOT loop detection system) and period length was selected to be 5 min, an appropriate value proved by previous studies (Wang and Nihan 2001, 2002). Correspondingly, the m value was determined to be 15.

For any time period, there may be intervals with zero vehicles. These must be removed before beginning the algorithm. Thus, for any time period j , if there are p zero measurement sets, the rest $m - p$ nonzero measurement sets can be sorted in ascending order of average occupancy per vehicle as follows:

$$0 < \frac{O_{p+1}(j)}{N_{p+1}(j)} \leq \frac{O_{p+2}(j)}{N_{p+2}(j)} \leq \dots \leq \frac{O_m(j)}{N_m(j)} \quad \text{for } 0 \leq p \leq m - 2 \quad (3)$$

Based on assumption 2, measurement sets $[O_{p+1}(j), N_{p+1}(j)]$ and $[O_{p+2}(j), N_{p+2}(j)]$ should correspond to intervals with only SVs. Since SV lengths vary narrowly, the mean EVL for these first two intervals can be approximated by the observed mean EVL for all SVs; that is

$$\bar{l}_{sv} = \frac{O_{sv}(j)}{N_{sv}(j)} \cdot \bar{s}(j) \quad (4)$$

where sv = subscript for short vehicles; and \bar{l}_{sv} = observed mean EVL for SVs;

$$O_{sv}(j) = O_{p+1}(j) + O_{p+2}(j) \quad (5)$$

$$N_{sv}(j) = N_{p+1}(j) + N_{p+2}(j) \quad (6)$$

Then, the mean EVL for any interval k of period j and \bar{l}_{sv} has the following relationship:

$$\frac{\bar{l}_k(j)}{\bar{l}_{sv}} = \frac{O_k(j)}{N_k(j)} \cdot \frac{N_{sv}(j)}{O_{sv}(j)} \quad (7)$$

where k = interval index; \bar{l}_k = mean EVL for interval k ; N_k = volume for interval k ; and O_k = occupancy for interval k .

By comparing the length ratio calculated by Eq. (7) with some critical value, intervals with SVs only can be separated from those

with possible LVs. The critical value, $\alpha_k(j)$, for interval k can be determined by Eq. (8) based on trial and error:

$$\alpha_k(j) = \frac{\bar{l}_{lv} \cdot \sigma_{lv} + (N_k(j) - 1) \cdot \bar{l}_{sv}}{N_k(j) \cdot \bar{l}_{sv}} \quad (8)$$

where α =minimum length ratio for an interval to contain LVs; \bar{l}_{lv} =observed mean EVL for LVs; and σ_{lv} =observed standard deviation for LV length.

For the sorted sequence of nonzero measurements, if

$$\frac{\bar{l}_q(j)}{\bar{l}_{sv}} \geq \alpha_q(j) \quad \text{for } p+2 < q \leq m \quad (9)$$

then the intervals with possible LVs can be distinguished and, correspondingly, the sequence can be divided into the following two groups:

1. $\{(O_{p+1}, N_{p+1}), (O_{p+2}, N_{p+2}), \dots, (O_{q-1}, N_{q-1})\}$; and
2. $\{(O_q, N_q), (O_{q+1}, N_{q+1}), \dots, (O_m, N_m)\}$.

Group 1 data are measurements for intervals with SVs only, and they are used for speed estimation. Group 2 data correspond to intervals with possible LVs. With the estimated speeds based on group 1 data, group 2 data are employed for LV volume estimation.

Speed Estimation

To maximally reduce estimation bias, all qualified measurement intervals (group 1) are used to calculate speed of the period as shown in Eqs. (10)–(12):

$$O_{sv}(j) = \sum_{b=p+1}^{q-1} O_b(j) \quad (10)$$

$$N_{sv}(j) = \sum_{b=p+1}^{q-1} N_b(j) \quad (11)$$

$$\bar{s}(j) = \frac{N_{sv}(j)}{O_{sv}(j) \cdot g} \quad (12)$$

Due to the sensitivity difference among single-loop detectors, a vehicle moving at a constant speed may have different occupancy measurements at different stations. For eliminating such effects, a correction coefficient is introduced, as shown in Eq. (13), when calculating g :

$$g = \frac{1}{\beta \bar{l}_{sv}} \quad (13)$$

where β =loop sensitivity correction coefficient, which needs to be calibrated before applying the algorithm.

A simple but effective way for calibrating β is based on nighttime speed. Traffic speed at midnight is generally consistent at each station. For example, from 12:00 am to 4:00 am on May 13, 1999, double loop ES-163R:MMS__T3 observed 659 valid interval speeds. The mean of the observed speeds was 105.56 km/h and the standard deviation was 7.45 km/h, or about 7% of the mean. This feature of speed is consistent day by day. Therefore, by observing midnight speeds at the station, β can be calibrated through Eq. (14):

$$\beta = \frac{\bar{s}_{ob} \cdot C}{\sum_{h=1}^C \frac{N_{sv}(h)}{O_{sv}(h)} \cdot \bar{l}_{sv}} \quad (14)$$

Table 1. Descriptive Statistics of SV and LV Lengths

Class	Number of cases	Mean (m)	Standard deviation (m)	Minimum (m)	Maximum (m)
SV (Bin 1+Bin 2)	4,443	5.48	0.87	1.83	11.89
LV (Bin 3+Bin 4)	472	22.50	3.59	12.19	30.18

where C =number of nighttime intervals involved for calibrating β ; h =index of the selected nighttime intervals; and \bar{s}_{ob} =observed space mean speed of the nighttime intervals.

A simple way to obtain \bar{s}_{ob} is through radar guns. Omitting the tiny speed variation when traversing a loop, \bar{s}_{ob} can be calculated as the harmonic mean of the observed spot speeds of vehicles by radar guns. Once β is calibrated, the algorithm is ready to provide dynamic space-mean speed estimation for any time period.

Vehicle Classification

As mentioned previously, vehicles are divided into SV and LV classes according to their lengths. Descriptive statistics for SV and LV lengths, based on the single-vehicle lengths observed by dual-loop detector ES-163R:MMS__3 from May 3 to May 16, 1999, are summarized in Table 1. Frequency distributions of SV lengths and LV lengths are shown in Figs. 3 and 4, respectively. Associated normal-distribution curves are given in each figure as well, and each curve is seen to fit the length distribution histogram very well for both classes. The Kolmogrov-Smirnov Z statistics for SV and LV lengths were 11.415 and 2.211, respectively, indicating that both SV and LV lengths are normally distributed at 0.01 significance levels. Therefore, SV lengths are assumed to follow the $N(\mu_{sv}, \sigma_{sv}^2)$ distribution, and LV lengths to follow the $N(\mu_{lv}, \sigma_{lv}^2)$ distribution, where μ_{sv} and σ_{sv}^2 =mean and variance of SV lengths; and μ_{lv} and σ_{lv}^2 =mean and variance of LV lengths.

With the normal distribution assumptions, SV volume and LV volume can be estimated by applying the NN decision rule. The NN theory is typically employed to assign an unclassified sample to the nearest classification category. Distance between the current sample and each of the existing categories needs to be calculated for comparison, and the current sample is assigned to the category with the smallest distance from it.

The predefined categories developed in this way are possible unique compositions of SVs and LVs, and the number of pre-

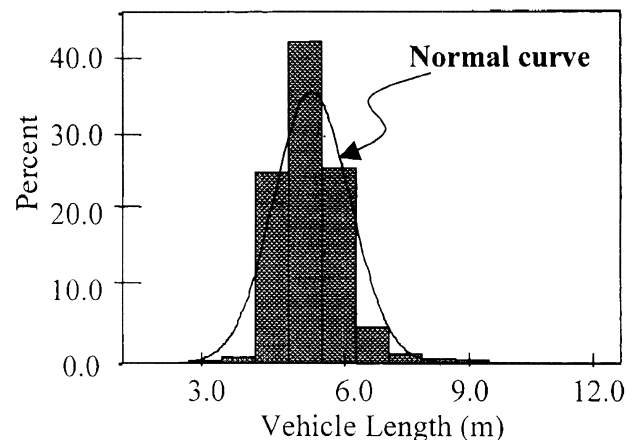


Fig. 3. SV length distribution with normal curve

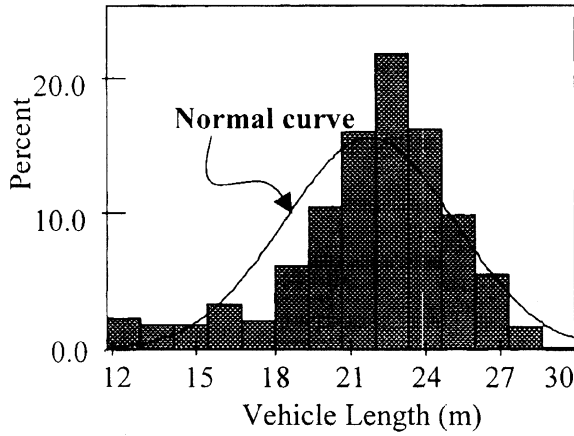


Fig. 4. LV length distribution with normal curve

defined categories depends on the total volume and the possible maximal LV volume for the interval. According to previous observations, the maximal LV volume per interval for the study stations was 7. Then, for any interval k of period j , there should be no more than eight possible vehicle compositions, corresponding to LV numbers from 0 to 7, respectively. If $N_k(j) < 7$, there are $N_k(j) + 1$ categories with LV numbers from 0 to $N_k(j)$. For example, if only three vehicles are detected in the interval [i.e., $N_k(j) = 3$], then we have the following four predefined categories that can be assigned to: (3 SVs, 0 LV), (2 SVs, 1 LV), (1 SVs, 2 LVs), and (0 SVs, 3 LVs).

With the single-loop sensitivity correction coefficient and the estimated period speed, the mean EVL for any interval k of period j can be calculated by Eq. (15):

$$\bar{l}_k(j) = \frac{O_k(j) \cdot \bar{s}(j)}{N_k(j) \cdot \beta} \quad (15)$$

Then the vehicle combination represented by $\bar{l}_k(j)$ is the unknown sample that needs to be identified. Existing categories are combinations with $0, 1, \dots, \min[7, N_k(j)]$ LVs. Since LV lengths and SV lengths are assumed to follow the $N(\mu_{lv}, \sigma_{lv}^2)$ and the $N(\mu_{sv}, \sigma_{sv}^2)$ distributions, respectively, and the LV number and SV number are independent variables, the distribution of the mean vehicle length for a category with x LVs [where $0 \leq x \leq \min(7, N_k(j))$] can be determined as $N[\mu_{kx}(j), \sigma_{kx}^2(j)]$, where

$$\mu_{kx}(j) = \frac{[N_k(j) - x]\mu_{sv} + x\mu_{lv}}{N_k(j)} \quad (16)$$

$$\sigma_{kx}^2(j) = \frac{[N_k(j) - x]\sigma_{sv}^2 + x\sigma_{lv}^2}{N_k(j)} \quad (17)$$

Then the distance between the unknown sample and the category with x LVs can be calculated by

Table 2. Selected Loop Detectors for Example Study

Station code	Location	Lane number (from right)	Dual-loop code ^a	Single-loop code ^a
ES-211D	NB I-5 and 140th St. SW	2	_MN_T2	_MN__2
ES-210D	NB I-5 and 148th St. SW	2	_MS_T2	_MS__2
ES-209D	SB I-5 and 156th St. SW	2	_MN_T2	_MN__2
ES-163R	SB I-5 and NE 130th St.	3	_MS_T3	MMS__3

^aWSDOT uses exactly seven characters as loop code to indicate its location and purpose.

$$d_{kx}(j) = \left| \frac{\bar{l}_k(j) - l_{loop} - \mu_{kx}(j)}{\sigma_{kx}(j)} \right| \quad \text{for } x = 0, 1, \dots, \min[N_k(j), 7] \quad (18)$$

where l_{loop} represents loop length.

Eq. (18) transforms variable $\bar{l}_k(j) - l_{loop}$ (mean vehicle length) into a standardized variable [variable that follows the $N(0,1)$ distribution] $d_{kx}(j)$, which represents the distance to the origin. The smaller the $d_{kx}(j)$ is, the greater the probability that the current interval's vehicle composition belongs to category x . If

$$d_{kn}(j) \leq d_{kx}(j) \quad \text{for } x = 0, 1, \dots, \min[N_k(j), 7] \quad (19)$$

then we can allocate this unclassified sample to category n , and the LV volume and SV volume can be automatically determined correspondingly.

Estimation Results and Discussion

To verify the effectiveness of the proposed algorithm, four stations with dual-loop detectors on I-5 in Seattle were chosen for this study. Single-loop measured interval volumes and occupancies for one general-purpose lane of each selected station were used for speed estimation and vehicle classification. Dual-loop measured speeds and bin volumes were employed to check the results. The selected loop detectors are described in Table 2.

To check the spatial transferability of the proposed algorithm, 24-h data were collected from all the listed detectors on May 13, 1999 (Thursday). For the station at SB I-5 and NE 130th St. (ES-163D), an additional 3 days' data, from May 14 to May 16, 1999, were collected for examining the temporal transferability of the algorithm. Estimation error, a statistic defined as the estimated value minus the observed value for each period, was adopted for result comparisons. Means and standard deviations of the estimation errors for the 24-h study duration of each selected station are given in Table 3.

For speed estimation, the entire day's mean of the estimation errors for any station was close to 0 while standard deviations were smaller than 6.2 km/h. These figures indicate that, for all four stations, the proposed algorithm produced favorable speed

Table 3. Statistics of Estimation Errors for Different Seattle Freeway Locations

Estimation error	ES-211D		ES-210D		ES-209D		ES-163R	
	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume
Mean	-0.756	0.066	-0.632	0.570	-0.718	-0.038	-0.631	-0.031
Standard deviation	6.151	2.940	5.380	3.220	5.436	3.380	5.583	2.760

Table 4. Statistics of Estimation Errors for Different Days, Same Location

Estimation error	May 13 (Thursday)		May 14 (Friday)		May 15 (Saturday)		May 16 (Sunday)	
	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume	Speed (km/h)	Period LV volume
Mean	-0.631	-0.031	0.248	0.003	0.365	-0.180	0.591	0.024
Standard deviation	5.583	2.760	5.728	3.040	3.549	1.300	3.399	1.240

estimations. The estimation accuracy was much higher than that realized by just using Eq. (1) [interested readers are referred to Wang and Nihan (2002) for comparison results].

Although the means of the estimation errors for LV volumes were very small for all four stations, the standard deviations of these errors, which ranged from 2.76 to 3.38, seemed too large, based on the observation that most of the 5-min periods contained less than six LVs. However, since there is always a time lag between dual-loop and single-loop detectors, the difference between the estimated LV volumes and the dual-loop observed LV volumes might be exaggerated. By integrating LV volumes into longer time periods, such time-lag effects can be reduced.

Comparisons of estimation results for different days for station ES-163R are described in Table 4. The statistics of estimation errors were roughly consistent with those in Table 3, except that the standard deviations of the estimation errors for May 15 (Saturday) and 16 (Sunday) were much lower than those for May 13 (Thursday) and 14 (Friday). This was most likely due to the difference in traffic flow levels between weekday and weekend.

Besides the uniform feature of SV lengths, the effectiveness of the proposed algorithm depends largely on how well the two fundamental assumptions can be met. If assumption one is violated, larger occupancies due to low speeds will be mistakenly attributed to longer vehicle length and, hence, LV volumes will be overestimated, and, because corresponding low-speed samples will be cut in the speed estimation, estimated space-mean speeds will be higher than ground-truth speed. On the other hand, violations to assumption two will underestimate both speed and LV volume. This is because, under such circumstances, the algorithm erroneously regards occupancies for intervals with LVs as SV occupancies, and this makes the vehicle lengths shortened in the calculation. Using this “ruler” to determine single-loop measurements will inevitably result in lower speed and fewer identified LVs. Both of the violations are likely to happen when traffic volumes are very high. For example, during morning or evening peak hours, traffic volumes may exceed road capacity and cause serious speed changes that violate assumption one. Simultaneously, high interval volumes also increase the probability of an interval containing at least one LV and reduce, correspondingly,

the probability that a period satisfies assumption two. Therefore, the algorithm may produce larger estimation errors under truly congested conditions.

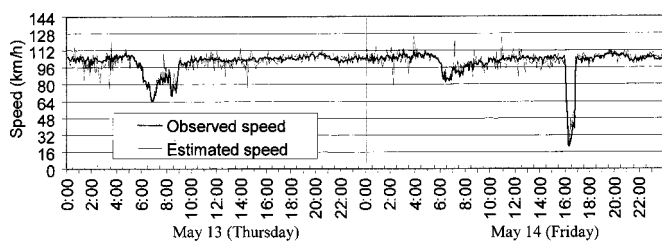
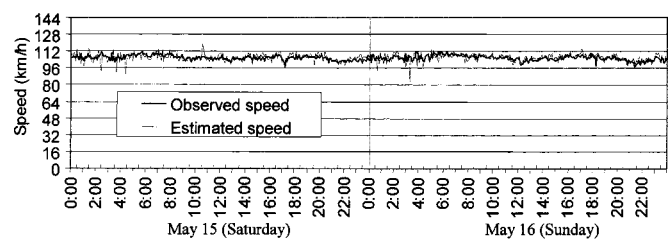
In Figs. 5 and 6, the observed-speed and estimated-speed curves at ES-163R:MMS__3 are plotted for weekdays and weekends, respectively. On weekdays, speed dropped significantly during peak hours. But for weekends, no abrupt speed changes were found, although the average daily volume for weekends was only slightly lower than that for weekdays. This was due to the fact that weekend traffic volumes are generally less concentrated than those for weekdays. Highly concentrated traffic during peak hours caused noticeable violations to the two fundamental assumptions and resulted in larger estimation errors for weekdays than for weekends, as shown in Table 4.

Though the estimation error was larger under serious traffic congestions, Figs. 5 and 6 show that the estimated speeds and the observed speeds were very well synchronized over all time. Comparisons between the estimated speeds and observed speeds across locations led to the same conclusion, and these facts indicate the robustness of the algorithm for speed estimation.

For comparison purposes, estimation results for period LV volumes were aggregated into hourly LV volumes. The four-day comparison results for ES-163R:MMS__3 are illustrated in Fig. 7. Obviously, the discrepancies between the two curves increased at congested periods, such as from 6:00 to 8:00 am on May 13, and decreased under uncongested conditions at night or on weekends. In general, the estimated LV-volume curve was basically consistent with the observed curve. The maximum relative estimation error for daily LV volume for the four days was 7.12%. This indicates that the estimated LV volumes were good enough for planning purposes. Comparisons among the four stations are shown in Fig. 8. The consistency between the two curves for each location shows that the proposed algorithm works stably and effectively in LV volume estimations across locations as well as over time.

Conclusion

Real-time traffic-speed information is essential for ATMS. Additionally, LV volume data are desirable for transportation planning

**Fig. 5.** Comparisons between observed speeds and estimated speeds for weekdays**Fig. 6.** Comparisons between observed speeds and estimated speeds for weekends

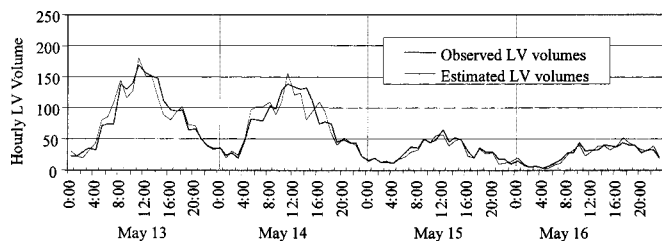


Fig. 7. Comparisons between observed hourly LV volumes and estimated LV volumes for different days

and engineering purposes. However, speed and LV volume data are not directly available from the single-loop detectors that are widely deployed in current networks. To obtain these data, another single-loop detector is generally required to upgrade a single-loop detector to a dual-loop detector. The cost for such an upgrade is high. Hence, making single-loop detectors capable of producing useful speed and LV volume data is economically desirable.

This study described an algorithm that makes single-loop detectors capable of doing the work of dual-loop detectors based on two fundamental assumptions: constant average speed for each time period and at least two intervals containing only SVs in each period. Pattern discrimination was used to separate intervals with possible LVs from those without. For the intervals without LVs, single-loop measurements were employed for speed estimation. With the estimated speed, the remaining measurements were further processed to identify LV volumes. The NN decision rule was applied to assign the vehicle composition of an interval to one of the predefined vehicle composition categories. Once the nearest category was identified, the LV volume and SV volume of the interval were automatically estimated.

Twenty-four hour data from four locations were collected on Seattle's I-5 freeway for checking spatial transferability of the algorithm. For station ES-163R, an additional 3 days of data were collected for the purpose of testing the temporal transferability. Comparisons between estimated results and dual-loop observed results for different locations and different days found that the algorithm consistently provided reasonable estimations of period mean speeds and LV volumes. The accuracy of the algorithm depends largely on how well the two fundamental assumptions are met. Violations to the first assumption make the algorithm overestimate speed and LV volume, while breaking the second assumption results in lower speed and LV volume estimations. When traffic volume is very high, the probability for violating the assumptions is high. Hence, the algorithm should work better

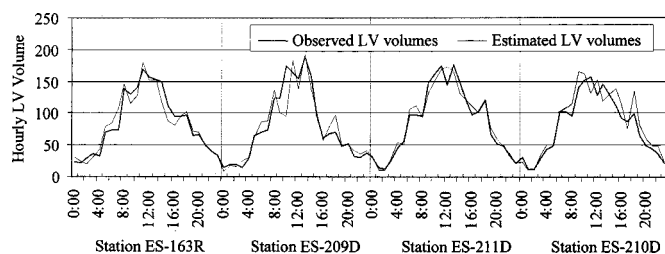


Fig. 8. Comparisons between observed hourly LV volumes and estimated LV volumes for different stations

under less congested conditions, although it also worked reasonably well during peak hours for the selected locations at the selected time.

Before applying the algorithm to a new location, the value of the loop-sensitivity-correction coefficient (β) needs to be determined. Nighttime mean speed is the only variable needed for setting β value correctly. Since nighttime traffic speed is normally very consistent on freeways, it should not be too difficult to obtain. Therefore, the proposed algorithm should be easy to apply in practice.

Although the algorithm performed reasonably well at the selected sites and days, future research is needed to handle the conditions when one or both of the assumptions are violated in order to reduce estimation errors. Also, since choosing the appropriate value of m is important, guiding rules on m selection need to be clarified through further research. The proposed algorithm will be more robust and accurate when the violation circumstances are properly addressed.

Acknowledgments

The writers express their deep appreciation to Mark Morse and Mark Hallenbeck of WSDOT for their kind help in understanding the WSDOT loop data extraction algorithms, data format, and detector installation costs.

Notation

The following symbols are used in this paper:

- C = number of nighttime intervals involved for calibrating β ;
- d = distance between known and unknown categories;
- g = speed estimation parameter;
- h, i = interval indices;
- j = period index;
- l = loop length;
- \bar{l} = effective vehicle length;
- m = number of intervals per period;
- N = vehicle volume;
- O = occupancy;
- \bar{s} = space-mean speed;
- T = time length per interval;
- x = number of LVs in interval;
- α = minimum length ratio for interval to contain LVs;
- β = loop sensitivity correction coefficient;
- μ = mean of normal-distributed vehicle lengths; and
- σ = standard deviation of normal-distributed vehicle lengths.

Subscripts

- b, k, p, q = interval indices;
- loop = refers to loop;
- lv = refers to long vehicles;
- n, x = category indices;
- ob = refers to observed; and
- sv = refers to short vehicles.

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