Dynamic Estimation of Freeway Large-Truck Volumes Based on Single-Loop Measurements

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Abstract

Because of heavy weights and large turning radii, large truck (LT) movements have very different characteristics than those of smaller vehicles, such as passenger cars. This difference makes collection of LT volume data very important for accurate analysis of traffic stream characteristics in transportation planning and engineering. Since LT travel patterns are seasonal, data obtained by surveys conducted for a short period of time every one to three years may not be adequate for safety planning, traffic management, and infrastructure maintenance. Therefore, the ability to collect such data continuously via loop detectors is highly desirable. In this paper, an algorithm for estimating LT volumes using only single-loop outputs is presented. LT volumes estimated by the proposed algorithm were compared with those observed by dual-loop detectors, and the two LT volume series fit each other very well, especially when traffic volume was low.

Key words: large trucks, single-loop detectors, pattern discrimination, nearest neighbor, traffic-volume estimation.

INTRODUCTION

Large truck (LT) movements have very different characteristics than those of smaller vehicles, such as passenger cars, due to their size as well as weight carried. An LT is defined in this paper as any truck that is longer than 11.89m (39 feet). The characteristics associated with LT movements require special attention in transportation planning and management, and many studies have been conducted to address specific problems caused by LTs. For example, Hutchinson (1990) studied the influences of LT characteristics on highway design and concluded that many procedures used for infrastructure design should be revised since the characteristics of many of the LT types using the highway system are incompatible with a variety of the assumptions underlying highway infrastructure design methods. Garber and Joshua (1989) analyzed LT-involved accidents in Virginia and determined that highway alignment is a predominant factor influencing the occurrence of crashes resulting from driver errors. As the presence of large and/or low-performance vehicles in the traffic stream reduces the total number of vehicles that can use the highway (Cunagin and Messer, 1983), the Highway Capacity Manual explicitly stipulates that passenger-car equivalents under different conditions should be used for highway design (Transportation Research Board, 1998).

Therefore, LT volume data are essential for many purposes. Transportation planners require such data for route planning and traffic assignment; highway engineers need the data for road geometric and structural designs; and traffic managers need the data for traffic control and operation. Traditionally, such volume data are obtained by surveys. Due to their high cost, traffic volume surveys are normally conducted periodically (every 1 to 5 years) at some "typical" locations for limited data collection durations. Though the survey-obtained data may be good for planning and design purposes, it is obviously too rough for dynamic traffic control and management as truck volume patterns vary with time (Hallenbeck, 1993). To meet the requirements of modern traffic control and advanced traffic management systems (ATMS), new techniques have been developed and are being applied to collect real-time LT volume data. As an example, Nihan *et al.* (1995) used the Mobilizer image processing system to collect volume data for different vehicle categories. Though the results of applying this type of vehicle classification procedure were favorable, there are still some feasibility problems with site application, as the system requires detailed calibration information and a good video perspective for satisfactory results. Such conditions are generally difficult to obtain. Another technique more widely applied is dual-loop detection which involves measurements using two consecutive loops placed several meters apart. Since a dual-loop detector (also called a speed trap or a double loop detector) is capable of measuring vehicle length, all the measured vehicles can be classified by their lengths. Dual-loop-measured vehicle lengths can also be used for vehicle identification purposes (Coifman, 1998). However, dual-loop detectors are not as widely available as single-loop detectors due to the costs. Obtaining LT volume information from single-loop measurements is, therefore, highly desirable. 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 detectors cannot produce. This may hinder the application of this method.

Since most single-loop detectors are known to measure only gross volume and lane-occupancy directly, further efforts are needed to extract the desired vehicle length information from single-loop outputs (volume and lane occupancy). In this paper, an algorithm that uses pattern discrimination and nearest-neighbor (NN) methods for LT volume estimation from single-loop measurements is described. Features of vehicle-length distribution for the selected site are addressed first, followed by the presentation of a pattern discrimination algorithm for separating intervals with possible LTs from those without. Then a NN method for LT volume estimation for those intervals with possible LTs is described. The estimated LT volumes are compared with those measured by dual-loop detectors and estimation errors are analyzed. In the last section, conclusions of this study are summarized.

FEATURES OF VEHICLE-LENGTH DISTRIBUTION

Study Data

All data used for this study were obtained from the loop detection system of the Washington State Department of Transportation (WSDOT). The WSDOT has a network of traffic counters embedded in the roadway infrastructure. These counters are 6 feet (1.83m) wide square-loops of copper wire connected to cabinets located beside the roads (Ishimaru and Hallenbeck, 1999). Such counter stations are deployed about every half-mile on mainline lanes and ramps of freeways and state highways in the central Puget Sound region.

Most stations have only single-loop detectors that measure volume and lane-occupancy in real time. Some stations are equipped with dual-loop detectors and are capable of measuring traffic speeds and vehicle lengths in addition to volumes and lane-occupancies. Loop measurements are aggregated into 20-second intervals and transmitted to the WSDOT Traffic Systems Management Center (TSMC) for processing and archiving. Station ES-163R, located under NE 130th Street's over-bridge of southbound I-5, is equipped with both single-loop detectors and dual-loop detectors. As shown in Figure 1, at this station on southbound I-5, there are five lanes, one HOV lane and four general-purpose (GP) lanes. The third general-purpose lane from the right was chosen for this study. Two single-loop detectors that form the dual loop are *ES-163R: MMS___3* and *ES-163R: MMS__S3*. Measurements of *ES-163R: MMS___3* were used as input for LT volume estimation. Dual-loop (*ES-163R: MMS__T3*) measurements were used to calculate vehicle length statistics and to verify the results produced by the proposed algorithm using single-loop measurements.

FIGURE 1. Snapshot of southbound I-5 at NE 130th Street.

Vehicle Classification Categories

Dual loops in the WSDOT freeway detection system classify vehicles into four bins according to their lengths. Because of variations in the lengths of vehicles within specific FHWA vehicle classes, the four WSDOT length-based vehicle classes do not directly relate to the 13 FHWA vehicle classes (Hallenbeck, 1993). The four length-based vehicle categories are described in Table 1.

TABLE 1. Four Length-Based Vehicle Categories Used by the WSDOT

As an LT is defined as a vehicle longer than 11.89m, its volume corresponds to the summed volume of Bin3 and Bin4. For convenience, SV (short vehicle) is used to represent vehicles assigned to Bin1 or Bin2 in this paper.

Vehicle-Length Distribution

Since knowledge of vehicle-length distribution features is essential for choosing appropriate algorithms for vehicle classification, individual vehicle-length data are desired for analysis. Though the WSDOT dual-loop detectors measure vehicle lengths individually, the data are aggregated into 20-second intervals for output. This makes the individual vehicle-length measurements unavailable when more than one vehicle is detected per interval. Hence, to obtain specific vehicle length data, interval measurements with only one vehicle detected per interval were analyzed. This was, obviously, time-consuming work, so a computer program to extract such data was developed. To guarantee a large sample population, 14 days of data (from May 3 to May 16, 1999) were employed. In this 14-day data sample, 5045 20-second intervals were found to contain only 1 vehicle and 4915 of them were qualified for this study (all error-flagged measurements were excluded).

Figure 2 shows the frequency distribution of the observed vehicle lengths (measurements taken for intervals with only one vehicle detected). If the probability of a vehicle being uniquely detected by a dual-loop detector during any 20-second interval is identical across bins, the sample vehicle-length distribution shown in Figure 2 represents the real vehicle-length distribution at the study site. Obviously, there are two peaks in the figure, one at about 5.2m, and the other at about 23.5m. The fact that vehicle lengths concentrate at two different levels indicates that vehicles can be naturally divided into two classes, corresponding to the SV class and the LT class, according to their lengths.

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

Figures 3(a) and 3(b) show length distributions for the SV class and the LT class, respectively, together with their associated normal distribution curves. It can be seen that the normal distribution curve fits the count histogram very well for both classes. Descriptive statistics of the SVs and LTs are given in Table 2. The standard deviation of SV lengths is 0.87 m (2.86 ft), about one fourth that of LT lengths. This indicates a high concentration of SV lengths, and this feature is to be used for LT volume estimation later.

FIGURE 3. Vehicle length distributions with normal distribution curves

TABLE 2. Descriptive Statistics of Dual-Loop Measured Vehicle Lengths

METHODOLOTY FOR THIS STUDY

Since traffic flow contains a mixture of SVs and LTs, single-loop measurements are typically the integrated results of the two types of vehicles. However, the two types of vehicles have very different length and weight characteristics. The length difference can serve as a theoretical basis for estimating the volumes of SVs and LTs based on single-loop measured volumes and occupancies. In this study, a two-step algorithm is developed to estimate LT volumes. The first step in the proposed algorithm is to separate interval measurements with possible LTs from those without LTs. Then, for the measurements with possible LTs, the nearest neighbor (NN) decision rule is applied as the second step to extract LT volumes out from single-loop outputs. Details of the algorithm are described below.

Vehicle Length Difference (LT vs SV)

As shown in Table 2, the mean length of LTs is over three times longer than that of SVs. Hence the presence of LTs in any 20-second interval significantly increases the average vehicle-length for the interval. When the average vehicle-length for an interval reaches some critical level, the existence of LTs in the interval may be inferred. Wang and Nihan (2002) used this feature to exclude single-loop measurements with long vehicles from speed estimations and the calculated speeds were very close to those observed by dual loops.

Two Fundamental Assumptions

Though vehicle length is not directly measurable by single loops, it may be estimated by models that use the single-loop measurements. Wang and Nihan (2000) used a log-linear regression model to estimate mean effective vehicle length (EVL, defined as the average length of vehicles plus the single-loop length) for each interval using only single-loop outputs. They applied the estimated mean EVLs for speed estimation, and obtained favorable results. In this paper, it is also needed to represent mean EVL by single-loop measurements, but instead of using regression, a pattern discrimination method is employed to determine their relationship. The method is based on the following two fundamental assumptions:

(1) For each study period that contains m ($m > 2$) intervals, vehicle speeds can be considered constant; and

(2) There are at least two intervals that have no LTs present in each period.

Please note that, in this paper, the 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.

Relationship between Mean EVL and Occupancy

The basic relationship between mean EVL and occupancy is shown in Equation (1).

$$l_i = O_i \cdot s_i \cdot T \tag{1}$$

Where i = vehicle index;

l_i = EVL of the i^{th} vehicle;

s_i = speed of the i^{th} vehicle;

O_i = percentage of time loop is occupied by the i^{th} vehicle in the interval;

T = time length of each interval (In this study T = 20 seconds).

Since vehicle speeds are assumed constant within each period, the average EVL for period j can be obtained as follows:

$$\bar{l}(j) = \frac{O(j) \cdot s(j) \cdot T}{N(j)} \tag{2}$$

Where j = period index;

$\bar{l}$ = mean EVL of all the vehicles in the period;

s = constant speed of the period;

N = volume of the period; and

O = summation of measured interval-based occupancies for the period, i.e. $O = \sum_{i=1}^{N} O_i$.

Since T is a known constant, and O and N can be straightforwardly calculated from single-loop outputs, the only problem in obtaining $\bar{l}$ is the unknown variable s. To solve this problem, the following pattern discrimination algorithm is adopted to get rid of the unknown variable s in the calculation.

Screening out Interval Measurements without LTs

First, a suitable period length (some multiple of interval length) needs to be determined - that is, to choose the appropriate *m* value for the analysis that maximally meets the two assumptions. For meeting assumption one, it is better to choose *m* as small as possible. However, if *m* is too small, assumption two may be easily violated. To meet assumption two, *m* should be reasonably large. Thus the selection of *m* is a trade-off between the two assumptions and depends on traffic conditions of the specific site. In this study, *m = 15* was selected based on preliminary calculation results (m = 9 and m = 12 were also tried, but the results were less favorable). That is, the period length of 5 min was chosen for this study and, for any time period *j*, 15 sets of interval measurements (lane occupancy and volume) were available.

Given *m=15*, 46 out of 288 periods had a maximum speed change larger than 15% of the period mean speed, and 19 of the 46 periods had a maximal speed change of more than 20%. Since the effects of speed variation on estimation results are not obvious, further study is needed to clarify how much variation of speed is acceptable for the proposed algorithm. As for the chance of violating assumption two, it should be very low based on the observed data. Assume that LT arrivals follow Poisson process. Then, the probability of violating assumption two can be straightforwardly calculated. For the study data, the average LT arrival rate was 0.4745 vehicles per 20-sec interval. Then the probability that a period would violate assumption two was 0.0082. Based on the calculated probability, 2.36 out of 288 periods were expected to violate assumption two, and this was very close to the actual number of 2 periods.

Sorting the interval measurements in ascending order of average occupancy per vehicle results in

$$\frac{O_1(j)}{N_1(j)} \le \frac{O_2(j)}{N_2(j)} \le \cdots \le \frac{O_m(j)}{N_m(j)} \tag{3}$$

Based on assumption two, there should be at least two sets of non-zero interval measurements of volume and occupancy for intervals without LTs. These two smallest non-zero measurement sets, ($O_p(j)$, $N_p(j)$) and ($O_{p+1}(j)$, $N_{p+1}(j)$), where p $\in$ [*1*, *m-1*], are used to calculate the occupancy sum ($O_{sv}(j)$) and the volume sum ($N_{sv}(j)$) of the corresponding two intervals with the smallest average occupancy per vehicle.

$$O_{sv}(j) = O_p(j) + O_{p+1}(j) \tag{4}$$

$$N_{sv}(j) = N_p(j) + N_{p+1}(j) \tag{5}$$

Then, based on Equation (2), $O_{sv}(j)$ and $N_{sv}(j)$ can be used to calculate $\bar{l}_{sv}(j)$, the "ruler" for measuring the rest of non-zero measurements, as shown in Equation (6). The reason for using two non-zero interval measurements instead of one for $\bar{l}_{sv}(j)$ calculation was to reduce the possible effect of data errors.

$$\bar{l}_{sv}(j) = \frac{O_{sv}(j) \cdot s(j) \cdot T}{N_{sv}(j)} \tag{6}$$

Since SV lengths vary only slightly, $\bar{l}_{sv}(j)$ can be regarded as a known variable being equal to the mean EVL for all SVs. Then, Equation (7) can be used to calculate mean EVLs of the remaining intervals (*p+2*, *p+3*, …, *m*), if any, for period *j*.

$$\bar{l}_k(j) = \frac{O_k(j)}{N_k(j)} \cdot \frac{N_{sv}(j)}{O_{sv}(j)} \cdot \bar{l}_{sv} \qquad \textit{for } k = p\text{+}2,\ldots, m \tag{7}$$

Where *k* is the interval index.

As shown in Figures 3(a) and 3(b), length distributions for SV and LT are very close to their corresponding normal distributions. The Kolmogrov-Smirnov Z statistics for SV and LT lengths were 11.415 and 2.211, respectively, indicating that both SV and LT lengths were normally distributed at 0.01 significance levels according to our sample data. Hence SV lengths are assumed to follow the $N(\mu_{sv},\ \sigma_{sv}^2)$ distribution, and LT lengths to follow the $N(\mu_{lt},\ \sigma_{lt}^2)$ distribution, where μ_{sv} and σ_{sv}^2 are the mean and variance of SV lengths, and μ_{lt} and σ_{lt}^2 are the mean and variance of LT lengths. If there are $n_{ksv}(j)$ SVs detected for interval *k* of period *j*, then the mean SV length follows the $N(\mu_{sv},\ \sigma_{sv}^2 / n_{ksv}(j))$ distribution. Since there are normally several SVs per interval, the mean vehicle length for the interval should be very close to μ_{sv} if no LT is present. However, if an LT appears in an interval, the mean vehicle length can increase significantly. Thus, a critical value of mean EVL, $\bar{l}_{kc}(j)$, for interval *k*, is required to identify whether the interval contains possible LTs. Based on trial and error, Equation (8) was employed to calculate the critical values of mean EVLs for separating intervals with only SVs from intervals with possible LTs.

$$\bar{l}_{kc}(j) = \frac{(N_k(j)-1)\cdot \mu_{sv} + \mu_{lt} - \sigma_{lt}}{N_k(j)} + l_{loop} \tag{8}$$

Where l_{loop} is loop length and l_{loop} = 1.83 meters (6 feet) for WSDOT's loop detectors. Using the values shown in Table 2, $\bar{l}_{kc}(j)$ can be calculated in real time for interval *k*.

The mean EVL for each interval, $\bar{l}_k(j)$, calculated by Equation (7) will be compared with the chosen critical value, $\bar{l}_{kc}(j)$, calculated by Equation (8). If $\bar{l}_k(j) > \bar{l}_{kc}(j)$, interval *k* will be identified as one which may contain LTs, and the measurements will be processed further to calculate the LT volume. Otherwise, the interval measurements will be used to update $O_{sv}(j)$ and $N_{sv}(j)$ by Equations (9) and (10) in order to reduce the effects of random errors on the calculation.

$$O_{sv}(j) = O_{sv}(j) + O_k(j) \tag{9}$$

$$N_{sv}(j) = N_{sv}(j) + N_k(j) \tag{10}$$

When Equations (9) and (10) have been used for all qualified intervals, $O_{sv}(j)$ and $N_{sv}(j)$ will be the occupancy and volume for intervals with only SVs for period *j*.

LT Volume Estimation

For the intervals identified as intervals that may contain LTs, the nearest neighbor (NN) decision rule is applied to determine the number of LTs within each interval. The NN theory is typically employed to assign an unclassified sample to the nearest classification category. To find the nearest neighbor, the distance or similarity between the current sample and each of the existing categories needs to be calculated. There are many different ways, such as the fuzzy K-nearest neighbor algorithm (Keller *et al.*, 1985), conditional Bayes risk (Cover and Hart, 1967), and the distance-weighted k-NN rule (Dudani, 1976), to determine the appropriate category to which the sample belongs.

In this study, the unclassified sample interval is assigned to a vehicle composition category based on its single-loop measurements (interval lane-occupancy and volume). The predefined categories are possible compositions of SVs and LTs, and the number of predefined categories depends on total volume of the interval and possible maximal LT volume. According to previous observations, the maximal LT volume per interval is 7. Then for any interval k of period j, there should be no more than 8 possible vehicle compositions, corresponding to LT numbers from 0 to 7 respectively. If $N_k(j) < 7$, there are $N_k(j) + 1$ categories identified by LT numbers from 0 to $N_k(j)$. For example, if only 3 vehicles are detected in the interval (i.e. $N_k(j) = 3$), the following four predefined categories are available to assign to, (3 SVs, 0 LT), (2 SVs, 1 LT), (1 SVs, 2 LTs) and (0 SVs, 3 LTs).

Since LT length and SV length were assumed to follow the $N(\mu_{lt},\ \sigma_{lt}^2)$ and the $N(\mu_{sv},\ \sigma_{sv}^2)$ distributions, respectively, and the LT number and SV number are independent variables, the mean vehicle-length distribution for a category with x LTs should follow the $N(\mu_{kx}(j),\ \sigma_{kx}^2(j))$, where

$$\mu_{kx}(j) = \frac{(N_k(j) - x)\mu_{sv} + x\mu_{lt}}{N_k(j)} \tag{11}$$

$$\sigma_{kx}^2(j) = \frac{(N_k(j) - x)\sigma_{sv}^2 + x\sigma_{lt}^2}{N_k^2(j)} \tag{12}$$

Then the distance between the sample interval and the category with *x* LTs can be calculated by Equation (13).

$$d_{kx}(j) = \left| \frac{\bar{l}_k(j) - l_{loop} - \mu_{kx}(j)}{\sigma_{kx}(j)} \right| \qquad \text{for } x = 0, 1, ..., \min(N_k(j), 7) \tag{13}$$

Equation (13) actually 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 $d_{kx}(j)$, the greater the probability that the current interval's vehicle composition belongs to category *x*. If

$$d_{kn}(j) \le d_{kx}(j) \qquad \text{for } x = 0, 1, ..., \min(N_k(j), 7) \tag{14}$$

then this unclassified sample interval is allocated to category *n*, and the LT volume is automatically determined correspondingly.

ESTIMATION RESULTS AND DISCUSSION

Based on the methodology presented, a computer program was developed to implement the entire procedure from loading data to printing out the estimated LT volumes. All the information required to set up the parameters for the program is loop length, mean and variance of SV lengths, and mean and variance of LT lengths. For the current study, data from the third GP lane of Station ES-163R on southbound I-5 was used. Statistics on dual-loop measured SV lengths and LT lengths are given in Table 2.

The period length was chosen to be 5 minutes, and there were 15 20-second intervals per period. The program, therefore, processed 15 sets of interval measurements each time, estimated LT volumes for each time interval, and output aggregated LT volumes for each period. Input data were 24-hour single-loop measurements, dated Thursday, May 13, 1999. Figure 4 shows the comparison between the LT volumes observed by the dual loop and those estimated by the proposed algorithm using single-loop measurements for each time period. In general, the two curves fit well, especially during nighttime and early morning stretches. The correlation coefficient between the two time series is 0.83, showing that they are well synchronized. Comparisons of the two LT volumes are summarized in Table 3.

FIGURE 4. Comparison of dual-loop observed LT volumes and those estimated by the proposed algorithm.

TABLE 3. Comparisons between the Observed LT Volumes and Estimated LT Volumes

As the dual-loop observed 24-hour volume of 28,060 is smaller than the single-loop observed volume of 28,302, the difference in sums in Table 3 may be exaggerated. In fact, the two single loops that form the dual loop, ES-163R: MMS___3 and ES-163R: MMS__S3, observed almost the same volume – 28,302 and 28,325, respectively. Thus, the dual loop probably discarded some vehicles from its volume count. This happens when the dual loop flags an error in the length or speed calculation and drops the detected vehicle from calculation. LTs are judged to be the most likely vehicles to activate such flags. If LTs have a higher probability of causing dual-loop malfunctions, and hence are discarded, the difference between the estimated LT volume and ground truth data should be even smaller than that shown in Table 3. However, further study is needed to verify this. Video ground truth data could aid such verification and provide closer evaluation results.

FIGURE 5. LT volume estimation error and total vehicle volume curves.

Figure 5 shows the estimation error (denoted by ε defined as the estimated LT volume minus the dual-loop observed LT volume) and single-loop-observed total vehicle volume for each time period. Statistics for estimation errors are summarized in Table 4. Due to the fluctuation of traffic volumes and the tiny difference in segmentation time between single-loop and dual-loop detectors, the variation of the error curve within a small range should be normal. In Figure 5, however, while estimation errors are very close to 0 under low volume (less than 100veh/5min, or 1200vph) conditions, the proposed algorithm overestimates LT volumes when traffic volume is heavy (over 150veh/5min or 1800vph). This is probably due to the fact that when traffic volume is heavy, speed is very unstable, and the uniform speed assumption is seriously violated. The lengthened occupancies caused by slower speeds were attributed to longer vehicle lengths and, therefore, LT volumes were overestimated. On the other hand, there were two periods, one at 9:45am and the other at 2:30pm, with LT volumes significantly underestimated by the algorithm. By checking the dual-loop measurements of the periods, the underestimations were found caused by violations of the second assumption, i.e., there was no interval or only one interval was LT-free for each of the two periods. Under such cases, the algorithm will mistakenly regard occupancy for intervals with LTs as SV occupancy, and hence real vehicle lengths will be shortened correspondingly in the calculation. However, the probability of such violations can be very rare if period length is properly chosen.

TABLE 4. Statistics of Estimation Errors

In general, the proposed algorithm works better under un-congested conditions as shown by the statistics in Table 4. When traffic volume is heavy, estimation errors may be enlarged. For the studied data, relative estimation errors shown in the bottom row of Table 4 were within 8% even for conditions with high traffic volume. This indicates that the proposed algorithm works reasonably well under low, moderate, and reasonably high, yet still stable, traffic conditions. However, if traffic is under stop-and-go conditions, the algorithm will not be applicable due to the serious violations of its fundamental assumptions.

CONCLUSION

LT volume data are important for many purposes in transportation planning and engineering. As LT travel patterns are season-dependent, data obtained by surveys conducted for a short period of time every one to three years may not be sufficient for adequate safety planning, traffic management and infrastructure maintenance. Though dual-loop detectors provide comparatively reliable real-time measurements of volume for each classification, they are still not as commonly available as single-loop detectors. Therefore, making single loops capable of providing LT volume data is a very significant goal for practice as well as for research and development of ATMS systems.

In this paper, an algorithm to estimate LT volume using only single-loop outputs was presented. A computer program that implements the algorithm was developed in this study. To run the program, a few parameters, i.e., single-loop length, mean and variance of SV length, and mean and variance of LT length, need to be identified. The program takes in single-loop measurements and outputs LT volume for each time interval. Pattern discrimination was used to separate intervals with possible LTs from those without LTs. For the intervals with possible LTs, the NN decision rule was applied to the interval's characteristics (as measured by single-loop data), to assign it to one of the predefined vehicle composition categories. Once the nearest category is identified, LT volume is automatically estimated.

The LT volumes estimated by the proposed algorithm were compared to those observed by dual-loop detectors. The two LT volume series fit very well, especially when traffic volume was low. If single-loop data are input in real time, the program will give real-time LT volumes. This will be very valuable for dynamic traffic control and management.

Possible estimation errors in using the algorithm were also discussed. To avoid overestimation and underestimation of the LT volumes, two fundamental assumptions, i.e., uniform speed within each period, and at least two intervals per period have no LTs present, must be met. Under the current status, the program is not capable of checking the satisfaction of the two fundamental assumptions automatically. Also, quantitative effects of the violations of the two fundamental assumptions on the estimation results are unclear. Future research will specifically address these problems and widely check the transferability of the algorithm to other sites in order to make the proposed method more complete and robust.

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List of Figures:

Figure1

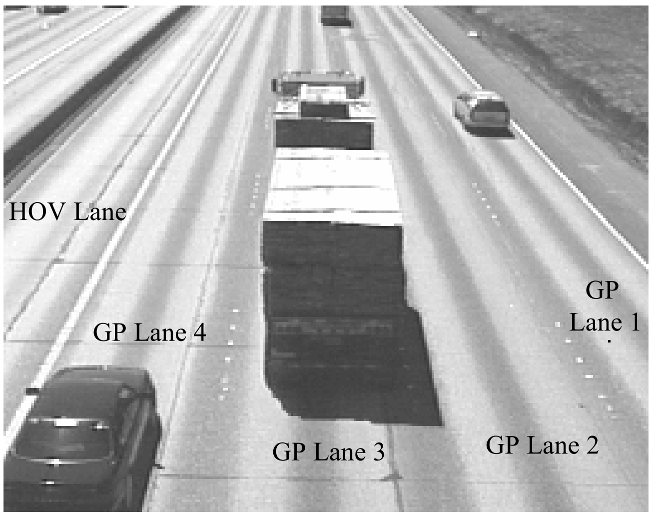


Figure 2

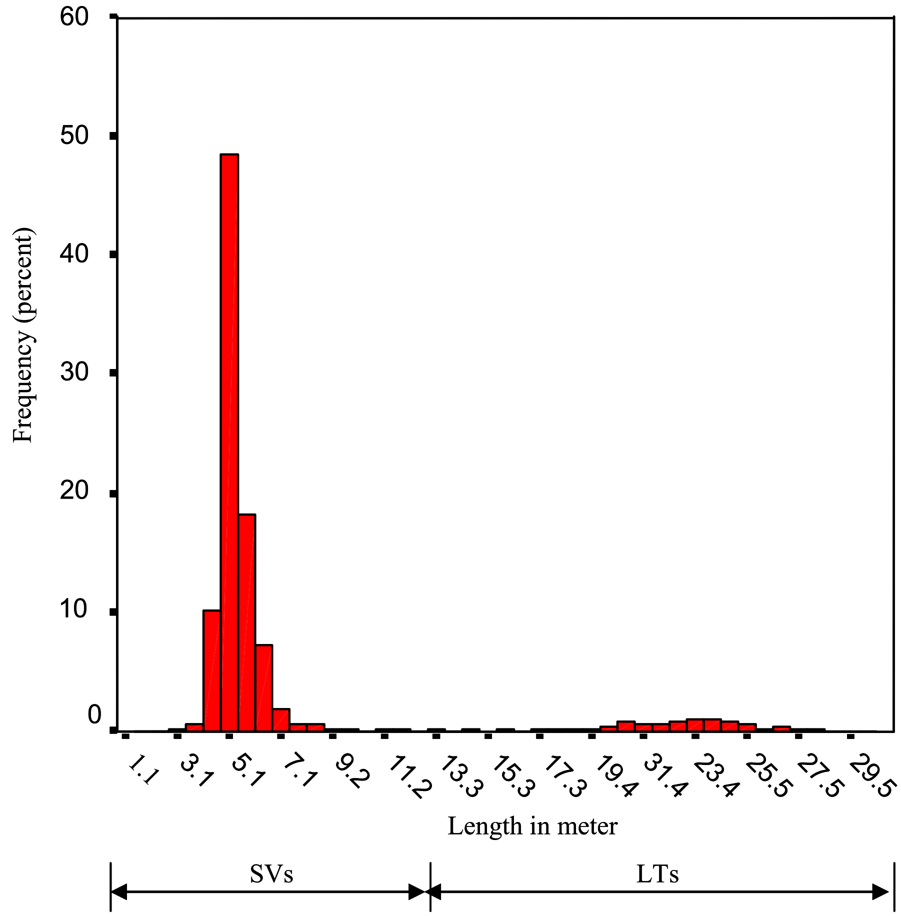
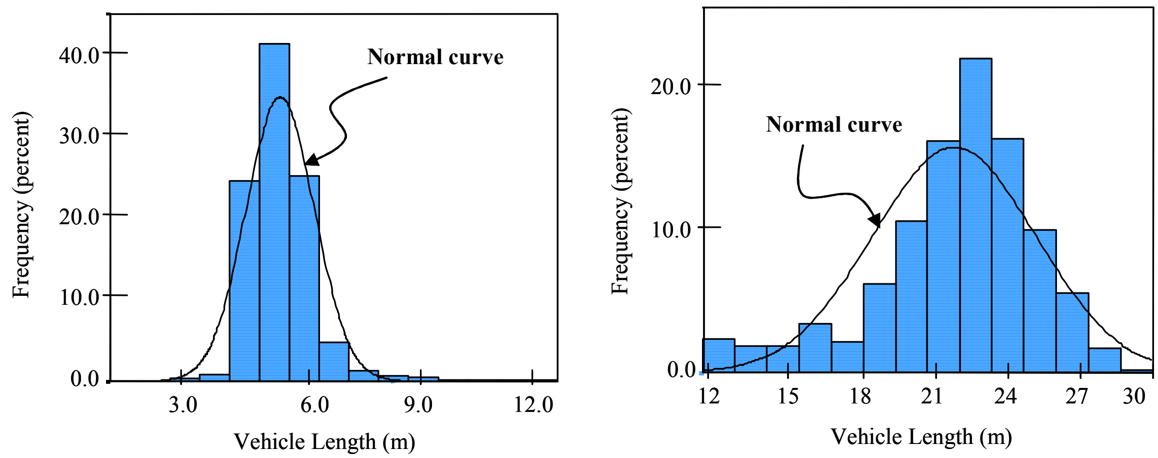

60
50
40
30
20
10
0
Frequency (percent)
1.1
3.1
5.1
7.1
9.2
11.2
13.3
15.3
17.3
19.4
31.4
23.4
25.5
27.5
29.5
Length in meter
SVs
LTs

Figure 3



(a) SV Class (b) LT Class

Figure 4

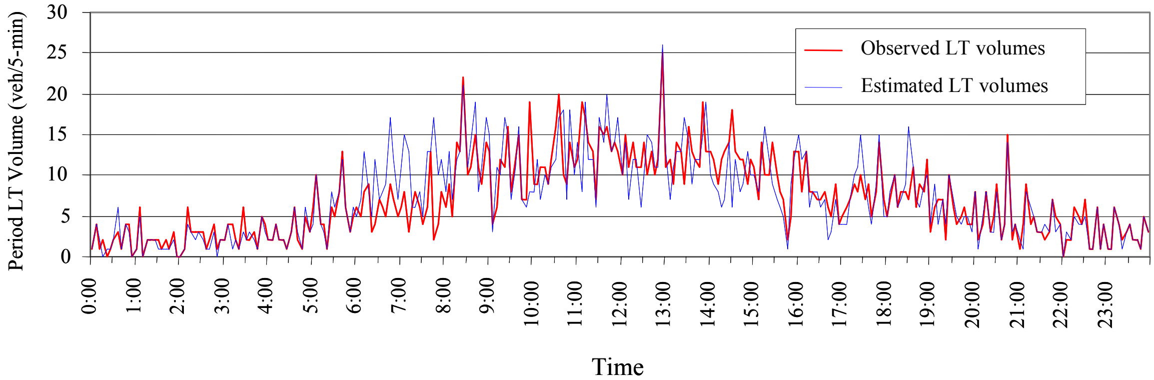
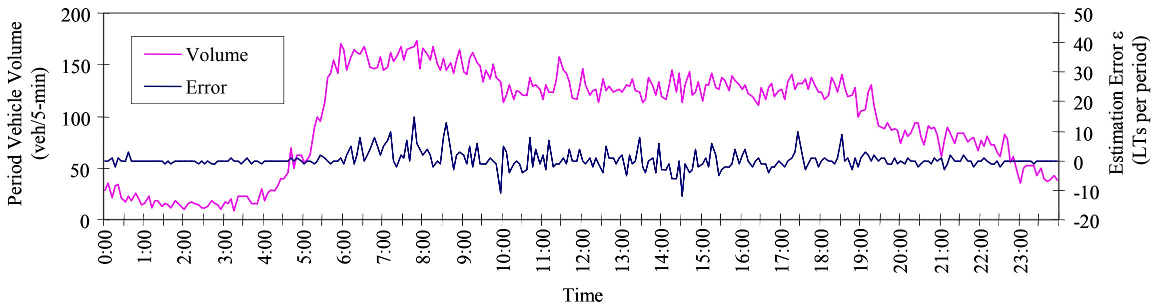

Period LT Volume (veh/5-min)
30
25
20
15
10
5
0
Observed LT volumes
Estimated LT volumes
0:00
1:00
2:00
3:00
4:00
5:00
6:00
7:00
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
17:00
18:00
19:00
20:00
21:00
22:00
23:00
Time

Figure 5


Period Vehicle Volume
(veh/5-min)
200
150
100
50
0
Volume
Error
50
40
30
20
10
0
-10
-20
Estimation Error ε
(LTs per period)
0:00
1:00
2:00
3:00
4:00
5:00
6:00
7:00
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
17:00
18:00
19:00
20:00
21:00
22:00
23:00
Time

List of Tables:

Table1

TABLE 1. Four Length-Based Vehicle Categories Used by the WSDOT

Classes	Range of length (meter)	Vehicle types
Bin1	Less than 7.92	Cars, pickups, and short single-unit trucks
Bin2	From 7.93 to 11.89	Cars and trucks pulling trailers, long single-unit trucks
Bin3	From 11.90 to 19.81	Combination trucks
Bin4	Longer than 19,82	Multi-trailer trucks

Table 2

TABLE 2. Descriptive Statistics of Dual-Loop Measured Vehicle Lengths

Class	Number of Cases	Mean	Std Deviation	Minimum	Maximum
SV (Bin1 + Bin2)	4443	5.48m	0.87m	1.83m	11.89m
LT (Bin3 + Bin4)	472	22.50m	3.59m	12.19m	30.17m

Table 3

TABLE 3. Comparisons between the Observed LT Volumes and Estimated LT Volumes

	Minimum	Maximum	Mean	Median	Std Dev.	Sum
Observed 5-min LT Volume	0	25	7.12	6	5.24	2050
Estimated 5-min LT Volume	0	26	7.49	7	4.77	2156

Table 4

TABLE 4. Statistics of Estimation Errors

	Period volume conditions (veh/5min)			
	Less than 50	Between 50 and 100	More than 100	All conditions
Case No.	122	55	166	288
$E(\varepsilon)$ * (veh/5min)	-0.098	-0.146	0.711	0.368
$\sigma(\varepsilon)$ ** (veh/5min)	0.827	1.026	3.742	2.915
E(LTs) (veh/5min)	2.373	4.636	9.855	7.118
$E(\varepsilon)$ / E(LTs)	-0.041	-0.031	0.072	0.052

* $E(\cdot)$ indicates the expectation of the variable in the parentheses.
** $\sigma(\cdot)$ indicates the standard deviation of the variable in the parentheses.

Author biography:

Dr. Yinhai Wang is a Research Assistant Professor of Civil and Environmental Engineering at the University of Washington. He has a Ph.D. in transportation engineering, a master's degree in computer science, another master's degree in construction management, and a bachelor degree in civil engineering. Dr. Wang established the TransNow (Transportation Northwest) ITS Program at the University of Washington and serves as the Program coordinator. Dr. Wang has conducted extensive research in loop data application, traffic accident modeling, image processing, and vehicle tracking.

Nancy L. Nihan is a Professor of Civil and Environmental Engineering at the University of Washington in Seattle and also serves as the Director of Transportation Northwest (TransNow), which is the University Transportation Center for Federal Region 10. Prior to joining the UW, Professor Nihan had a joint appointment with the Department of Systems Engineering and the Center for Urban Studies at the University of Illinois, Chicago Circle Campus. Dr. Nihan's degrees include the B.S.I.E. from the Department of Industrial Engineering, Northwestern University, Evanston Illinois and the Masters and PhD degrees from the Department of Civil Engineering at NU.