An Investigation in the Use of Vehicle Reidentification for Deriving Travel Time and Travel Time Distributions

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ABSTRACT

This paper presents the results from an investigation in the use of vehicle reidentification for deriving travel time and travel time distributions using loop and video detectors. Vehicle reidentification is the process of tracking vehicles anonymously from site to site thus yielding individual vehicle travel times and overall travel time distribution. Travel time and travel time distribution are measures of the performance and reliability of the transportation system and are useful in many transportation applications such as planning, operations, and control. This paper will present the following findings: 1) the results from a platoon reidentification algorithm that improved upon a previous individual vehicle reidentification algorithm, 2) sensitivity analysis on the effect of time windows in deriving travel times, and 3) the derivation and goodness-of-fit of travel time distributions using vehicle reidentification. Arterial data from Southern California are used in testing the algorithm performance. The test results show that the algorithm can reidentify vehicles with an accuracy of over 95.9% when using 92.4% of total vehicles, calculate individual travel times with approximately 1% mean error using the most effective time window and derive travel time distributions that fit actual distributions at a 99% confidence level.

INTRODUCTION

One motivation for performing vehicle reidentification is to address the need for section measures of traffic performance as opposed to point measures. As the names imply, point measures are those obtained at a particular point on the roadway while section measures are those obtained for an entire section of roadway. Point measures such as speed, flow and occupancy are measured over the distance of a traffic detector's field-of-view, which is around 2m (6.6ft) in the case of an octagonal loop. Traffic engineers and travelers on the other hand, require information about entire sections of roadways. It is true that under certain traffic conditions, point measures can approximate section measures. However in general, the use of point measure surrogates for section measures can lead to inaccuracies. The direct measurement of section travel times can avoid the inaccuracies involved with estimating section travel times using point speeds.

The practical traffic applications of vehicle reidentification are many. The derivation of section travel times is useful to transportation engineers for the purpose of traffic operations, planning, and control. The method of floating car studies is comparatively more labor intensive and only produces mean or median travel times instead of travel time distributions. Accurate travel times can be instrumental in feedback control, vehicle routing, traffic assignment, dynamic origin/destination demand estimation, and traveler information systems.

The usefulness of travel time distributions has been discussed by many for different applications in transportation. Travel time distribution or variability has been used in measuring the performance of transportation systems. For example in the Minnesota ramp metering study, travel time reliability is used as a performance criterion in addition to travel time and traffic volume (1). Rickman points to the use travel time distribution for quantifying traffic signalization service (2). Bates mentions that median and travel time distribution are better measures than the mean (3). From the traveler's perspective many times a reduction in variability is just as valuable as the reduction in the mean travel time since it reduces anxiety or stress caused by uncertainty. Bates points to the

notion of disutility from arriving at a destination earlier or later than desired. The placement of confidence intervals around mean travel times improves the information for travelers (4). Travel time distributions are also valuable in simulation and modeling of networks (5). Hellinga highlights the difference between minimum travel time paths and paths of optimal travel time reliability in simulation (6). Dandy mentions that studies on travel time distribution can help improve discrete choice modeling in route selection since travelers are more concerned with maximum likelihood travel time rather than the average (7). Wakabayashi discusses the application of travel time variability in road network management and construction (8). Cohen mentions the importance of considering travel time variability in the derivation of traveler cost functions (9).

RELEVANT LITERATURE

Even though few surveillance systems highlight the fact that they are able to produce travel time distributions, there are a number of existing technologies that have the potential to produce accurate travel time distributions. One class of techniques uses point measures and stochastic traffic flow modeling. One such example is Dailey's use of cross-correlation for measuring the propagation time of traffic (10). Another is Petty's use of the assumption that upstream and downstream travel times have the same probability distribution (11). Another class of techniques for obtaining travel times involves vehicle reidentification or the matching of vehicle signatures that come from locations along road sections. In other words, detector signatures from an upstream station are compared with the signatures from a downstream station for a match. Some algorithms match individual inductive loop signatures or lengths from vehicles by correlating such signatures from two contiguous sites (12)-(14). One traditional method of vehicle reidentification is license plate matching (15). Some examples of video reidentification include the use of color (16) and video signature vectors (17). Other detector technologies that have been used for vehicle reidentification including laser profiles (18), weigh-in-motion axle profiles (WIM) (19), and ultrasonic detectors (20).

There are some in-vehicle technologies that could be employed to derive travel time distributions (21)-(23). One is the use of so-called toll tags or AVI (Advanced Vehicle Identification). This system requires vehicles to have a toll tag or transceiver to communicate with the readers at points on the transportation network. A drawback to this system is that toll tags currently have a limited market share thus only a subset of vehicles are detected. An advantage of this system is that the accuracy in identification is high since each toll tag transmits a unique identification number. Another system is the use of probe vehicles often equipped with GPS and/or cellular telephones. This system is also accurate and allows almost a continuous tracking of vehicles. However, this system is also dependent upon consumer acceptance. The two aforementioned systems in use in the private sector can augment the information obtained by the public sector.

DATA

The traffic data used for this experiment are collected on June 30, 1998 in Irvine, California. The data site consists of two detector stations bounding a two-lane section of Alton Parkway within the intersections of Telemetry and Jenner streets. Each detector station has double inductive loops in a speed trap configuration, 3M Canoga detector cards, and video detectors. The data collected from the loops and video are time synchronized so that the inductive signature and the video image from the same vehicle can be identified. Figure 1 shows an example of the field data that was collected including the inductive signature, original video image, background subtracted image, and the extracted color feature. The distance between the two detector stations is 130m (425 ft). The inductive loops are standard 1.83mX1.83m (6ftX6ft) rectangular loops that are commonly used by many transportation agencies. The video camera used was a consumer grade Hi-8mm camcorder. The data are collected during the morning peak between approximately 8:00am and 9:30am at the downstream station. This dataset contains 581 vehicle pairs or 1162 vehicles. The time consuming nature of ground truthing makes the formation of large data sets very difficult. This process requires a researcher to identify an upstream vehicle on a monitor, search and find the corresponding downstream vehicle on another monitor, and record the time stamp of the vehicles at both locations in order to obtain travel times. The set of over 500 samples seem to be large compared to floating car runs of 20 samples, but this is necessary since the goal is to derive travel time distributions and not just the mean travel time. The first 200 vehicle pairs are used for training and the rest for testing.

Table 1 shows the characteristics of the actual travel time and speed distributions of the field data. A high skewness value implies that the distribution is not symmetrical. The kurtosis value represents the "fatness" of the

tails of the distribution. The information in Table 1 explains the reasons for using both travel time and speed time windows as presented in the results section. The table shows that the travel time distribution is relatively skewed while the speed distribution is not. The right tail of the travel time distribution which corresponds to the slower travel times is relatively fat (large kurtosis value). The mean and the median travel times are not the same for the travel time or the speed distributions which shows that neither distribution is normal. This is consistent with data from other research which show significant positive skewness for the travel time distribution (7). Other research also points to normal distributions as inappropriate but suggests that log-normal or gamma distributions might be better for characterizing travel time distributions.

METHODOLOGY

Instead of treating vehicles as individual images, traffic flow considerations can be used to further constrain the vehicle reidentification problem. The proposed platoon algorithm uses the fact that vehicles tend to travel in groups or platoons. Platoon in this context refers to a group of vehicles in chronological sequence in close proximity to each other. This is a more general formulation than the previous individual reidentification since the size limits of vehicle platoons are individual vehicles in the least congested case and all existing vehicles in the extremely congested case. By comparing multiple vehicles instead of individual vehicles, the algorithm performance should be improved while individual vehicle matches are still maintained.

An intrinsic step in the algorithm formulation of the vehicle reidentification problem is the process of feature extraction. Traditionally, vehicle reidentification or more generally system identification is split into two separate components: feature extraction and classification. Within feature extraction, there are so-called direct methods and also parametric methods. Since the reidentification system needs to be field implementable, there are many "real-life" constraints that limit the algorithm. The various trade offs between accuracy, computational intensity, and information bandwidth are carefully weighed.

Feature extraction seeks to extract the salient components of vehicle images that would sufficiently differentiate vehicles. In order to avoid redundancy, features obtained from the vehicle images need to contain different information. This is similar to the process of deriving a basis in linear algebra or finding the principal components in data analysis. In a likewise fashion, the goal here is to find an orthogonal set of vectors that would span the space of possible vehicles images. Direct feature extraction methods have been employed for this research since parametric estimation involves the assumption of a specific model structure and require more computation. The features used in the algorithm include inductive signature, color, velocity, inductive amplitude (proportional to the suspension height), electronic length (similar to physical length), and platoon travel time or the headway between the first and last vehicles of the platoon.

Once the salient features from various detectors images are extracted, they are combined in the platoon vehicle reidentification algorithm which performs the identification or classification. In other words, the algorithm performs the vehicle reidentification and matches the images produced by the same vehicle along various points on the roadway. A multi-objective optimization approach is used in the platoon vehicle reidentification algorithm because it allows the incorporation of various objectives associated with the different features. A sequential multi-objective optimization approach called lexicographical optimization (LO) is used for the following reasons (24). First, LO enables objectives with different units to be placed at different priority levels. Second, LO progressively reduces the feasible set from level to level thus improving computational efficiency. The separation into multiple optimization levels allows sensitivity analysis to be conducted at every level. Multi-objective has the notion of Pareto optimality which is defined as “a certain position when it is impossible to find a way of moving from that position very slightly in such a manner that the ophelimity enjoyed by each of the individuals of the collectivity increases or decreases” (25).

The following paragraph gives an overview of the platoon vehicle reidentification algorithm. The algorithm starts by selecting a platoon detected at the downstream site. A list of upstream candidate platoons are generated subject to a time window objective that eliminates platoons that are not within a reasonable time frame. In other words, candidate vehicles that travel at excessive or unreasonably low speeds are eliminated from candidate platoons. Each upstream platoon is then compared with the downstream platoon. A minimum absolute distance classifier (L1) is used as the objective in determining the “best match”. The classifier uses the feature vectors described previously. An individual vehicle time window objective is used in the end to exclude vehicles with unreasonable travel times effectively eliminating outliers in the data set. The trade off in this final objective

involves an improvement in the fit in the majority of the travel time distribution at the cost of the edges of the distribution. Because there is a one-to-one correspondence between the individual vehicles of the upstream and downstream platoons, the results from this algorithm yield individual vehicle reidentifications. Therefore individual vehicle are tracked from point to point and vehicle travel times are measured.

The minimum absolute distance measure (L1) between an upstream feature f_u and downstream feature f_d is given by

$$d(f_u, f_d) = \sum_{i=1}^{q} | f_u(i) - f_d(i) |$$

where i denotes the ith component of the feature vector and q is the vector dimension. If the number of components of the signatures is different for different vehicles, then the feature vector with fewer components is padded before taking the L1 distance. If the size of the platoon is denoted as N_p, the L1 distance for the overall platoon, D, is

$$D(f_u, f_d) = \sum_{j=1}^{N_p} d(f_u^j, f_d^j)$$

where f_u^j and f_d^j are the upstream and downstream features for vehicle j. The optimum number of vehicles in a platoon is determined by the platoon size that achieves the highest reidentification accuracy using the training set. For this data set, the optimal platoon size is three.

The first level of the lexicographic optimization is formulated as a time window objective in the fashion of a goal criterion. Goal programming is useful in establishing target or threshold values. Stated verbally this objective has the goal of retaining vehicles whose upstream and downstream travel times are greater than L_t and less than U_t. The time window objective is

$$f_1 = goal\{D(t_u, t_d) = z_1\}, (z_1 \in [L_t, U_t])$$

The goal value z_1 is defined by upper and lower bounds U_t and L_t and defined as

$U_t = t_{ld} - t_{min}$

and

$L_t = t_{fd} - t_{max}$

where t_{min} and t_{max} are the minimum and maximum vehicle traversal times based on the training set, t_{ld} is the travel time for the last vehicle from the downstream platoon and t_{fd} is the travel time of the first vehicle from the downstream platoon. Each feasible upstream vehicle will need to have a travel time that is greater than L_t and less than U_t. If the number of feasible upstream vehicles is defined as N_v and N_f is defined as the number of feasible upstream platoons then $N_f = N_v - N_p + 1$. For example, if N_v=10 and N_p=3, then there would be 8 consecutive upstream platoons of 3 vehicles that need to be examined. Then, the platoon comparison needs to be performed 8 times to find the upstream platoon that best matches the downstream platoon.

The second level objective involves the comparison of feasible candidate upstream platoons with the downstream platoon. How closely two platoons are matched to each other is defined by a linear program which is a weighted-average of feature distances. If two images are produced from the same vehicle, then the features from the images should not differ significantly resulting in small feature distances. As the platoon is composed of individual vehicles the feature distances are summed up to obtain an overall platoon distance. The second level objective is formulated as

$$f_2 = \min\{w_s\ D(s_u, s_d) + w_c\ D(c_u, c_d) + w_v\ D(v_u, v_d) + w_m\ D(m_u, m_d) + w_l\ D(l_u, l_d) + w_p\ d(p_u, p_d)\}$$

where w_s is the weight applied to the vehicle signature distance $D(s_u, s_d)$, w_c is the weight applied to the color information feature distance $D(c_u, c_d)$, w_v is the weight applied to velocity feature distance $D(v_u, v_d)$, w_m is the weight applied to the maximum inductive amplitude feature distance $D(m_u, m_d)$, w_l is the weight applied to the electronic length feature distance $D(l_u, l_d)$ and w_p is the weight applied to the platoon traversal time feature distance $d(p_u, p_d)$. As before, the subscripts u and d refer to upstream and downstream, respectively. Also, the superscript j refers to the jth vehicle in the platoon. Note that the platoon traversal time feature applies to the entire platoon and not for any individual vehicle. The linear weights add up to one and are determined during training by searching an n-dimensional grid of real numbers and finding the optimum combination that gives the best performance on the training data alone. The upstream platoon that achieves the objective f_2 or the smallest distance is matched to the downstream platoon.

The last level objective involves an individual vehicle time window. This objective is used in order to eliminate vehicles that travel at unreasonable speeds for the segment in question. For example, if the vehicle had a travel time of the mean travel time minus 4 standard deviations, then the vehicle would be traveling at approximately 212 fps (144 mph). Effectively, this objective helps to eliminate some vehicles that were erroneously reidentified as a travel time sample. The individual time window objective is

$$f_3 = goal\left\{d\left(t_u^j, t_d^j\right) = z_2\right\}, \left(z_2 \in \left[l_t, u_t\right]\right)$$

The goal value z_2 is defined by lower and upper bounds l_t and u_t and defined in two ways. One way is to use the mean travel time $\bar{t}$ and form the limits of the time window by adding and subtracting multiples of the sample standard deviation of the travel time, s. For example, if a four standard deviation range is desired, then $l_t = \bar{t} - 2s$ and $u_t = \bar{t} + 2s$. Due to the fact that the travel time distribution is skewed compared to the speed distribution (see Table 1), a second way of using the mean and standard deviation of speed is also used. In this case, for example, $l_t = \bar{s} - 2s$ and $u_t = \bar{s} + 2s$, where $\bar{s}$ is the mean speed and s is the sample standard deviation of speed.

In this initial development of the platoon reidentification algorithm, the two lanes of traffic were treated separately. This is due to several reasons. First, this is a simpler case upon which more complicated scenarios such as overtaking can be added. Second, if vehicles are not required to be sequential in a platoon, then the problem becomes a combinatorial problem and the solution becomes more computationally intensive. Third, on certain short stretches of roadway, lane changes are infrequent. The test data used is from such a site and the number of lane changes amounted to only 2% of the traffic.

RESULTS

One of the goals of this research is to improve upon a previous algorithm for vehicle reidentification that used individual vehicle reidentification (14). Table 2 compares the results of the new platoon algorithm with the previous algorithm. Column one lists the different time windows used for extracting a subset of the total number of vehicles for reidentification. The details of the time window are discussed in the methodology section. The first four time windows, rows one through four, use the standard deviation, s, of travel times. For example, the time window in row one has the lower limit of mean travel time minus two standard deviations and the higher limit of mean travel time plus two standard deviations. The next four time windows, rows five through eight, use the standard deviation of speeds translated into equivalent travel times. Because of the inverse relationship between speed and travel time, the time windows using speed are skewed toward the right of the mean when translated into equivalent travel times. Columns two and six show the reidentification accuracy (rate) for the two algorithms. Columns three and seven show the percentage of vehicles that are excluded using the time window. Columns four, five, eight, and nine show values related to the accuracy of the travel time derived using the reidentification algorithms. Columns five and nine show the variance of the percent travel time error. The variance is important to examine because it gives an indication as to the consistency of the derived travel times over a range of values. The results in column nine show that the travel time errors do not fluctuate widely but are consistent among the derived travel times of individual vehicles.

The results show that the reidentification algorithm using the platoon reidentification algorithm is superior in all aspects to the individual vehicle reidentification algorithm. This is true in the reidentification accuracy, the mean percent error for travel time, and the variance of the percent error. Table 2 also shows encouraging results for the use of the platoon reidentification algorithm for deriving travel times. In the best case, the reidentification accuracy is close to 96%, the mean travel time error is approximately 1% and the variance in the travel time error is 0.36% while over 90% of the vehicles are still used in deriving travel times.

The trade offs in the use of individual vehicle time windows is between accuracy and the percentage of vehicles used in reidentification. In three of the four sets of cases, as the time window become narrower and as the percentage of vehicle used decreases the reidentification accuracy increases. The exception is the platoon reidentification with a time window using travel time. In this case, the reidentification accuracy decreases as the time window was decreased from +/- 3.5 standard deviations to +/- 3 standard deviations before the accuracy increased again with a time window of +/- 2 standard deviations. To summarize, the narrowing of time window can exclude outliers that are most often erroneous reidentifications, however this is not universal as is shown in one of the four cases.

One of the goals of this research is to investigate the ability of the reidentification algorithm for deriving travel time distributions. A qualitative way of accomplishing this is by visually comparing the plots of the derived and actual travel time distributions. Figure 2 shows an example of travel time distribution plots using a time window of mean speed +/- two standard deviations. From the plot, the two distributions look very similar.

Two quantitative ways of evaluating the performance of the reidentification in deriving travel time distributions are chi-square and Kolmogorov-Smirnov (K) tests (26). These tests measure the goodness-of-fit between observed distributions and expected distributions. The two tests operate on slightly different principles. The chi-square test assesses how closely the derived frequency distribution represents the actual distribution by classifying data into *I* distinct intervals and summing the results of comparison between each travel time interval. The chi-square test statistic is

$$\chi^2 = \sum_{i=1}^{I} \frac{(f_o - f_t)^2}{f_t}$$

where f_o is the observed or derived frequency, f_t is the theoretical or actual frequency, and I is the number of travel time intervals. The statistic has I-1 degrees of freedom (DF). The Kolmogorov-Smirnov is a statistic based on the maximum deviation between two cumulative relative frequencies over the entire range of the variable and depends on the sample size N. It is expressed as

$$D(N) = \max\left|E(x) - O(x)\right|$$

where $E(x)$ is the expected (actual) cumulative frequency distribution and $O(x)$ is the observed (derived). Briefly, some trade-offs between chi-square and K test include K test's more moderate assumptions about random sampling and sample size, its use of ungrouped data, and efficiency; while chi-square does not require that the hypothesized population be specified in advanced, it's values can be meaningfully added, and it can be easily applied to discrete populations. See (27) for more discussions on the relative merits of chi-square and K test as well as discussions on other maximum deviation tests such as Cramer-von Mises.

The following hypothesis is tested using the aforementioned statistics:

H_o: The frequency distribution of the derived and actual travel times are the same.

The results from testing the frequency distribution generated by the platoon reidentification algorithm at 99% confidence level are shown in Table 3. Similar to Table 2, values for 8 cases are shown related to the different time windows that are employed. In terms of the chi-square test, the results from rows 1-7 show that the null hypothesis can not be rejected indicating a good fit. Even in the case of row 8 where the null hypothesis is rejected, the test statistic is very close to the chi-square value at a 99% confidence level. The number of intervals chosen in the chi-square test is a function of the number of 0.5 second intervals that resulted after the application of the time window. In terms of the K test, the null hypothesis is rejected in none of the cases indicating a good fit for all cases. Even though there are some differences in the results from the chi-square and K tests, the results have shown statistically that it is possible to derive travel time distributions that fit actual distributions well using platoon reidentification.

CONCLUSION

The use of the platoon reidentification algorithm is shown to be superior to the individual vehicle reidentification algorithm. However, the optimal static size of the platoon or a criterion for establishing dynamic platoon sizes should be further investigated for different traffic flow conditions and facilities. The platoon behavior between freeways and arterials should necessitate different platoon sizes in the algorithm.

Even though every time window produced promising results of over 90% reidentification accuracy and travel time error of less than 4%, the narrower time windows such as $\bar{v} \pm 2s$ produced the best results while still retaining a significant amount of vehicles used (95.85%). The narrower time windows also produced travel time distributions that fit the actual distribution the best.

The length of the test segment was too short for the collection of useful trip time, and it did not span an intersection to allow for the derivation of intersection control delays. However, this section was useful in proving the feasibility of vehicle reidentification and derivation of travel time distribution which are precursors to the derivation of trip travel times and trip reliability. To validate the ability of the algorithm to reidentify vehicles accurately, a closed segment is investigated in order to control for vehicles which do not appear at both upstream and downstream stations. In the future, data should be collected from longer segments such as freeway corridors and arterial segments that span intersections.

There are many research issues related to the development of the platoon reidentification that are yet unresolved. The current algorithm should be generalized for the case where lane changing is considered. There is also need for assessing the transferability of the algorithm to different sites. This will necessitate the collection of data from more traffic sites. However, such an effort is a long term process, since implementing field instrumentation takes time and ground truth data development is extremely labor intensive. In addition, incident travel times will be desirable to collect since the variability in travel time under incidents is of great interest to drivers and public agencies.

It is desirable to further examine the application of travel time distributions in different transportation areas. One such area is its use in performance evaluation of transportation systems. This can involve more than just variability of travel time and include assessment of the shapes of the distributions. For example a peaked distribution seems to be more desirable than a relatively uniform distribution. Travel time distributions can be used in safety applications similar to the use of speed difference. Also, there are many opportunities where travel time distributions can be used for improving modeling and simulation of traffic in terms of route choice, travel cost functions, and driver behavior.

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TABLES

TABLE 1 Comparison of Travel Time and Speed Distributions

distribution	mean	median	variance	skewness	kurtosis	range
travel time	6.73 s	6.94 s	1.18	2.59	14.17	11.02 s
speed	19.72 m/s 64.72 fps 44.13 mph	18.67 m/s 61.26 fps 41.77 mph	6.47	-0.19	1.03	17.99 m/s 59.05 fps 40.26 mph

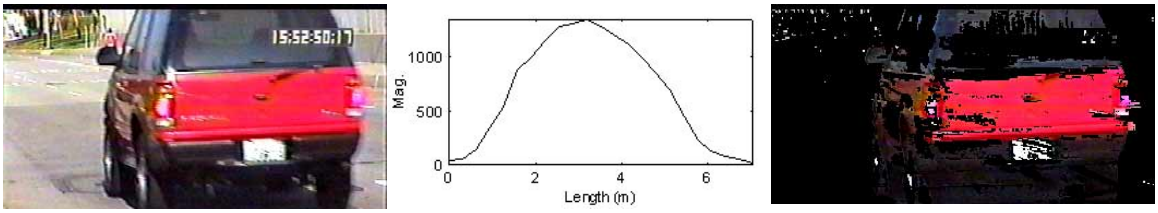
TABLE 2 Individual Versus Platoon Algorithm Results

	Individual				Platoon			
Time Window	Reid Rate	% Veh's	Mean % Error	Var % Error	Reid Rate	% Veh's	Mean % Error	Var % Error
$\bar{t} \pm 2s$	89.04	98.63	0.0311	0.0104	94.23	95.85	0.0155	0.0054
$\bar{t} \pm 3s$	87.39	99.31	0.0394	0.0142	93.11	97.75	0.0212	0.0082
$\bar{t} \pm 3.5s$	86.53	99.31	0.0430	0.0159	93.49	98.10	0.0186	0.0069
$\bar{t} \pm 4s$	85.03	99.66	0.0580	0.0282	92.31	98.79	0.0277	0.0145
$\bar{v} \pm 2s$	90.65	97.26	0.0258	0.0086	95.89	92.40	0.0104	0.0036
$\bar{v} \pm 3s$	87.80	98.46	0.0495	0.0290	94.12	96.89	0.0204	0.0116
$\bar{v} \pm 3.5s$	86.23	99.66	0.0567	0.0329	93.71	98.79	0.0227	0.0143
$\bar{v} \pm 4s$	85.57	99.83	0.0750	0.0598	93.06	99.48	0.0356	0.0334

TABLE 3 Goodness-of-fit Test for Derived Travel Time Distribution

Time Window	% Veh Used	calc. chi-square	DF	Chi-square 99%	calc. K	N	K 99%
$\bar{t} \pm 2s$	95.85	5.01	8	20.1	0.0216	555	0.0680
$\bar{t} \pm 3s$	97.74	11.72	10	23.2	0.0177	566	0.0677
$\bar{t} \pm 3.5s$	98.10	14.31	11	24.7	0.0229	568	0.0677
$\bar{t} \pm 4s$	98.79	18.34	9	21.7	0.0297	572	0.0676
$\bar{v} \pm 2s$	92.40	2.61	6	16.8	0.0187	535	0.0685
$\bar{v} \pm 3s$	96.89	21.67	10	23.2	0.0321	561	0.0680
$\bar{v} \pm 3.5s$	98.79	18.61	10	23.2	0.0332	572	0.0676
$\bar{v} \pm 4s$	99.48	27.79	11	24.7	0.0436	576	0.0676

FIGURES



Color Vector = [0.14 0.21 0.17 0.08 0.13 0.22 0.02 0.03]

FIGURE 1 Example of features extracted from inductive and video detectors.

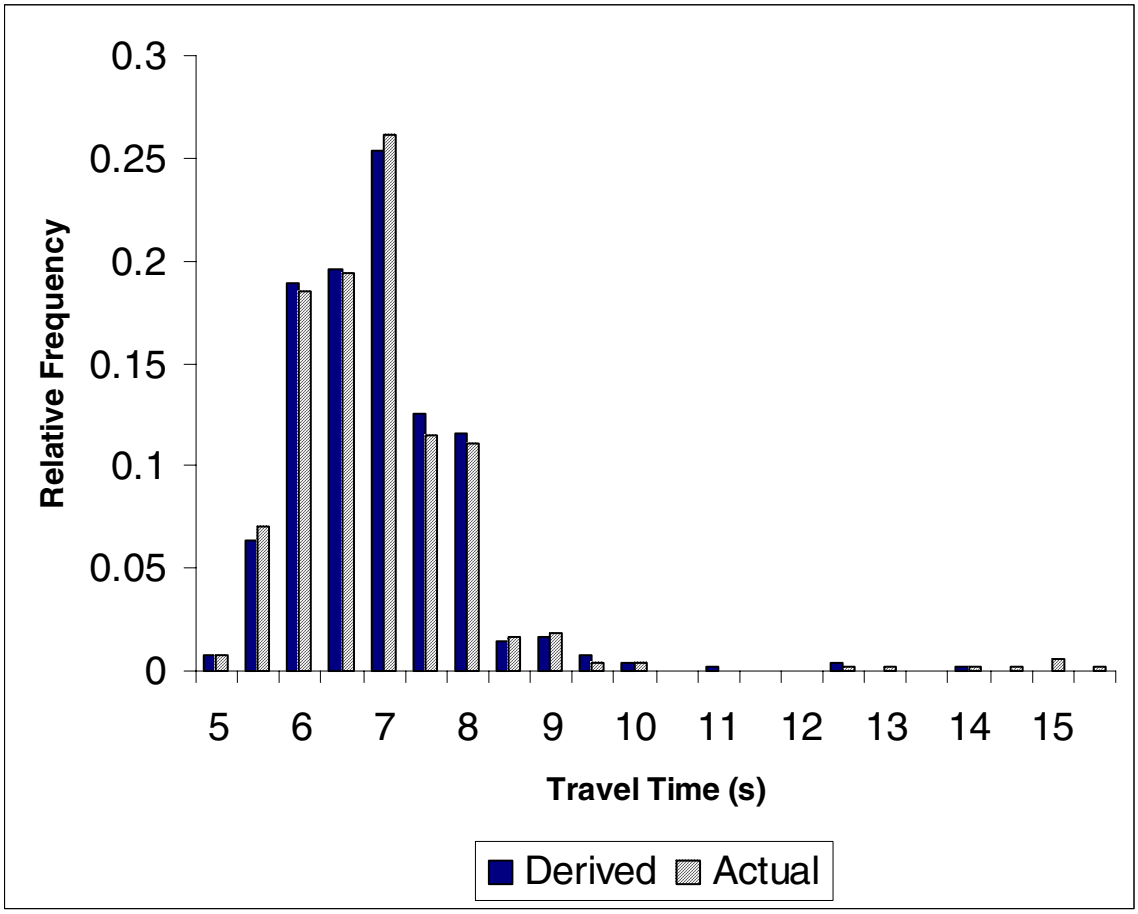


FIGURE 2 Example of derived and actual travel time distributions.