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Vehicle Reidentification as Method for Deriving Travel Time and Travel Time Distributions

Investigation

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Vehicle reidentification was investigated as a method for deriving travel time and travel time distributions with loop and video detectors. Vehicle reidentification is the process of tracking vehicles anonymously from site to site to produce 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. Findings from the investigation included (*a*) results from a platoon reidentification algorithm that improved upon a previous individual vehicle reidentification algorithm, (*b*) sensitivity analysis on the effect of time windows in deriving travel times, and (*c*) derivation and goodness of fit of travel time distributions using vehicle reidentification. Arterial data from Southern California were used in testing the algorithm's performance. Test results showed that the algorithm can reidentify vehicles with an accuracy of greater than 95.9% with 92.4% of total vehicles; can calculate individual travel times with approximately 1% mean error with the most effective time window; and can derive travel time distributions that fit actual distributions at a 99% confidence level.

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

The practical traffic applications of vehicle reidentification are many. The derivation of section travel times is useful to transportation engineers for the purposes of traffic operations, planning, and control. The method of floating car studies is comparatively more labor-intensive and produces only mean or median travel times instead of travel time distributions. Accurate travel times can be instrumental in feedback control, vehicle routing, traffic assignment, estimation of dynamic origin–destination demand, 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 performance of transportation systems. For example, in the Minnesota ramp-metering study, travel time reliability was a performance criterion in addition to travel time and traffic volume (*1*). Rickman et al. (*2*) point to the use of travel time distribution for quantifying traffic signalization service. Bates et al. (*3*) mention that median and travel time distribution are better measures than the mean. From the traveler's perspective, because it decreases anxiety or stress caused by uncertainty, a reduction in variability is often just as valuable as a reduction in mean travel time. Bates et al. point to the notion of disutility of arriving at a destination earlier or later than desired. 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 and Fu (*6*) highlight the difference between minimum travel time paths and paths of optimal reliability of travel time in simulation. Dandy and McBean (*7*) mention that studies on travel time distribution can help improve discrete choice modeling in route selection, since travelers are more concerned with maximum likelihood of travel time than with the average travel time. Wakabayashi and Iida (*8*) discuss the application of travel time variability in road network management and construction. Cohen and Southworth (*9*) note the importance of considering travel time variability in the derivation of traveler cost functions.

RELEVANT LITERATURE

Although few surveillance systems highlight their ability to produce travel time distributions, a number of existing technologies have the potential to produce accurate travel time distributions. One class of techniques uses point measures and stochastic traffic flow modeling. An 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

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are compared for a match with signatures from a downstream station. 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 the matching of license plates (*15*). Examples of video reidentification include the use of color (*16*) and video signature vectors (*17*). Other detector technologies used for vehicle reidentification include laser profiles (*18*), weigh-in-motion axle profiles (*19*), and ultrasonic detectors (*20*).

Some in-vehicle technologies could also be employed to derive travel time distributions (*21–23*). So-called toll tags or advanced vehicle identification is one example. This system requires that vehicles have a toll tag or transceiver to communicate with the readers at points on the transportation network. A drawback of this system is that toll tags currently have a limited market share; thus, only a subset of vehicles is 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 the Geographic Positioning System (GPS) or with cellular telephones. This system is also accurate and allows almost a continuous tracking of vehicles, but it is also dependent upon consumer acceptance. These two systems in use in the private sector can augment the information obtained from the public sector.

DATA

The traffic data used for this experiment were collected on June 30, 1998, in Irvine, California. The data site consisted of two detector stations bounding a two-lane section of Alton Parkway within the intersections of Telemetry and Jenner Streets. Each detector station had double inductive loops in a speed-trap configuration, 3M Canoga detector cards, and video detectors. The data collected from the loops and video were time-synchronized so that the inductive signature and the video image from the same vehicle could 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 was 130 m (425 ft). The inductive loops were standard 1.83- × 1.83-m (6- × 6-ft) rectangular loops commonly used by many transportation agencies. The video camera was a consumer-grade Hi-8mm camcorder. The data were collected during the morning peak between approximately 8:00 and 9:30 a.m. at the downstream station. This data set contained 581 vehicle pairs or 1,162 vehicles. The time-consuming nature of ground truthing (verification) makes the formation of large data sets very difficult. Ground truthing requires that a researcher 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 to obtain travel times. The set of more than 500 samples seems to be large compared with floating car runs of 20 samples, but this is necessary because the goal is to derive travel time distributions and not only mean travel time. The first 200 vehicle pairs were 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, with a 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 that show significant positive skewness for 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.

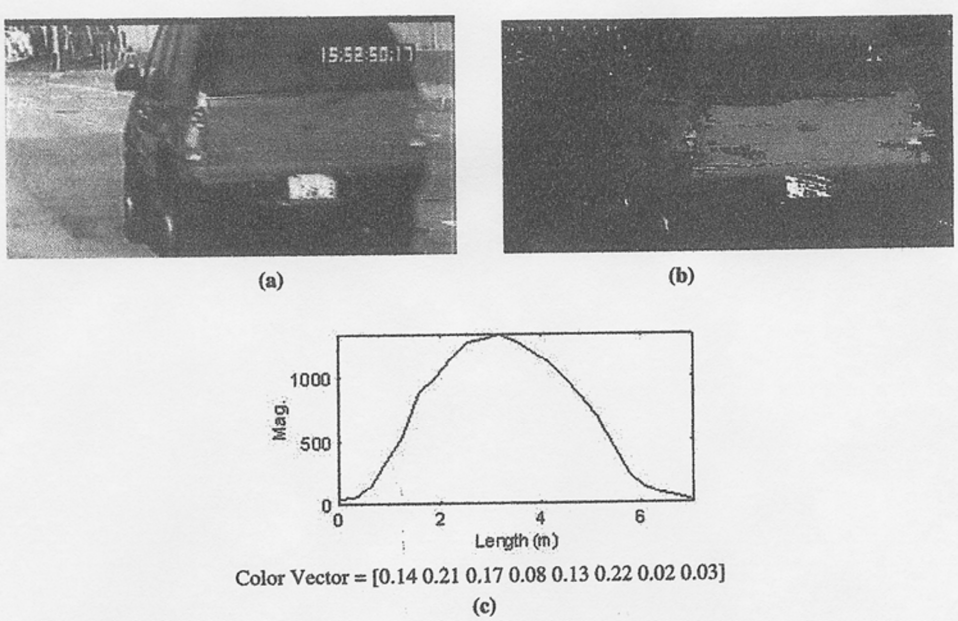

FIGURE 1 Example of features extracted from (*a*) inductive and (*b*) video detectors and (*c*) the extracted color feature.

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

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 takes as an assumption 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. Feature extraction encompasses so-called direct methods and parametric methods. Since the reidentification system must be implemented in the field, many real-life constraints limit the algorithm. The trade-offs between accuracy, computational intensity, and information bandwidth must be carefully weighed.

Feature extraction seeks to extract those salient components of vehicle images that would sufficiently differentiate vehicles. To avoid redundancy, features obtained from the vehicle images must 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 vehicle images. Direct feature extraction methods were employed for this research, since parametric estimation involves the assumption of a specific model structure and requires 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 multiobjective optimization approach was used in the platoon vehicle reidentification algorithm, because it allows incorporation of objectives associated with different features. A sequential multiobjective optimization approach, called lexicographical optimization (LO), was used for the following reasons (*24*):

1. LO enables objectives with different units to be placed at different priority levels.

2. 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. The multiobjective approach 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*).

An overview of the platoon vehicle reidentification algorithm follows. The algorithm starts by selecting a platoon detected at the downstream site. A list of upstream candidate platoons is generated subject to a time window objective that eliminates platoons that do not pass 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 (L1) classifier 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. This effectively eliminates 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 distributions 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 vehicles 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 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 is the downstream feature and f_d^j is the downstream feature 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 LO 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 $>L_t$ (the lower bounds) and $<U_t$ (the upper bounds). The time window objective is

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

The goal value, z_1, is defined by U_t and L_t as

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

and

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

where

$t_{\min}$ = minimum vehicle traversal time based on the training set,
$t_{\max}$ = maximum vehicle traversal times based on the training set,
t_{ld} = travel time for the last vehicle from the downstream platoon, and
t_{fd} = travel time of the first vehicle from the downstream platoon.

Each feasible upstream vehicle will need to have a travel time $>L_t$ and $<U_t$. If N_v is the number of feasible upstream vehicles and N_f is 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 8 consecutive upstream platoons of 3 vehicles need to be examined. Then, the platoon comparison must be performed eight 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, which results in small feature distances. As the platoon is composed of individual vehicles, the feature distances are summed 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 = weight applied to the vehicle signature distance $D(s_u, s_d)$,
w_c = weight applied to the color information feature distance $D(c_u, c_d)$,
w_v = weight applied to velocity feature distance $D(v_u, v_d)$,
w_m = weight applied to the maximum inductive amplitude feature distance $D(m_u, m_d)$,
w_l = weight applied to the electronic length feature distance $D(l_u, l_d)$,
w_p = weight applied to the platoon traversal time feature distance $d(p_u, p_d)$,
$_u$ = upstream,
$_d$ = downstream, and
$_j$ = the jth vehicle in the platoon.

Note that the platoon traversal time feature applies to the entire platoon and not to any individual vehicle. The linear weights add up to 1 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 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 four standard deviations, then the vehicle would be traveling at approximately 212 ft/s (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

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

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 $u_t = \bar{t} + 2s$. Because the travel time distribution is skewed compared with the speed distribution (see Table 1), the second way of using the mean and standard deviation of speed is, in this case for example,

$$l_t = \bar{s} - 2s \qquad u_t = \bar{s} + 2s$$

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 for 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 combinatorial and the solution becomes more computationally intensive. Third, on certain short stretches of roadway, lane changes are infrequent. The test data used are from such a site, and the number of lane changes amounted to only 2% of the traffic.

RESULTS

One goal of this research was 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 those of the previous algorithm. Column 1 lists the different time windows used for extracting a subset of the total number of vehicles for reidentification. The details of the time window were discussed in the section on methodology. The first four time windows, Rows 1 through 4, use the standard deviation, s, of travel times. For example, the time window in Row 1 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 5 through 8, 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 2 and 6 show the reidentification accuracy (rate) for the two algorithms. Columns 3 and 7 show the percentage of vehicles that are excluded by the time window. Columns 4 and 5 and 8 and 9 show values related to the accuracy of the travel time derived with the reidentification algorithms. Columns 5 and 9 show the variance of the percent travel time error. The vari-

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

ance is important to examine, because it indicates the consistency of the derived travel times over a range of values. The results in Column 9 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 with 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 percentage of error. Table 2 also shows encouraging results for deriving travel times with the platoon reidentification algorithm. 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 more than 90% of the vehicles are still used in deriving travel times.

The trade-off 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 narrows and the percentage of vehicles 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 is decreased from ±3.5 standard deviations to ±3 standard deviations before the accuracy increases again with a time window of ±2 standard deviations. To summarize, the narrowing of the time window can exclude outliers that are most often erroneous reidentifications; however, this is not universal, as shown in one of the four cases.

Another goal of this research was to investigate the capability of the reidentification algorithm in deriving travel time distributions. This can be accomplished qualitatively by visually comparing the plots of the derived and actual travel time distributions. Figure 2 shows an example of travel time distribution plots with a time window of mean speed ±2 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 by the chi-square test and the Kolmogorov–Smirnov (K) test (*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 = observed or derived frequency,
f_t = theoretical or actual frequency, and
I = 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

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

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

The following hypothesis is tested using the aforementioned statistics:

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

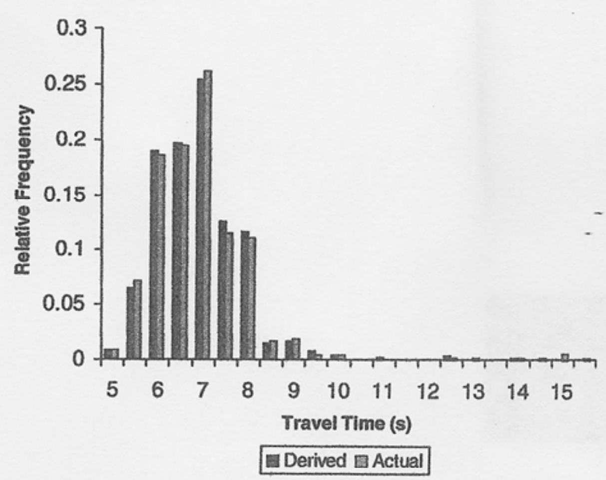

FIGURE 2 Example of derived and actual travel time distributions.

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

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 eight cases are shown related to the different time windows employed. For the chi-square test, the results from Rows 1 to 7 show that the null hypothesis cannot be rejected, which indicates 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-s intervals that resulted after application of the time window. For the K test, the null hypothesis is rejected in none of the cases, which indicates a good fit for all cases. Even though there are some differences in the results from the chi-square and K tests, the results show statistically that, with platoon reidentification, it is possible to derive travel time distributions that fit actual distributions well.

CONCLUSIONS

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.

Although all time windows produced promising results of >90% reidentification accuracy and travel time error of <4%, the narrower time windows such as $\bar{v} \pm 2s$ produced the best results while still retaining a significant percentage of vehicles used (95.85%). The narrower time windows also produced travel time distributions that best fit the actual distribution.

The length of the test segment was too short for collecting useful trip time, and it did not span an intersection to allow for the derivation of intersection control delays. However, the 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 capability of the algorithm to accurately reidentify vehicles, a closed segment was investigated to control for vehicles that 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.

Many research issues related to the development of platoon reidentification are yet unresolved. The current algorithm should be generalized for the case in which lane changing is considered. The ability to transfer the algorithm to different sites should also be assessed. This will necessitate data collection from more traffic sites. However, such an effort is a long-term process, since implementing field instrumentation takes time and developing ground truth data is extremely labor-intensive. It will also be desirable to collect incident travel times because the variability in travel time under incidents is of great interest to drivers and public agencies.

Further examination of the application of travel time distributions in different transportation areas would also be useful. One such area is performance evaluation of transportation systems. This can involve not only variability of travel time but also 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 as speed difference is used. Also, there are many opportunities to use travel time distributions to improve modeling and simulation of traffic route choice, travel cost functions, and driver behavior.

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REFERENCES

1. Twin Cities Ramp Meter Evaluation. Cambridge Systematics, Cambridge, Mass., 2000.
2. Rickman, T. D., M. E. Hallenbeck, and M. Schroeder. Improved Method for Collecting Travel Time Information. In *Transportation Research Record 1271*, TRB, National Research Council, Washington, D.C., 1990, pp. 79–88.
3. Bates, J., J. Polak, P. Jones, and A. Cook. The Valuation of Reliability for Personal Travel. *Transportation Research Part E,* Vol. 37, 2001, pp. 191–229.
4. Eisele, W., and L. Rilett. Estimating Corridor Travel Time Mean, Variance, and Covariance with Intelligent Transportation Systems Link Travel Time Data. Presented to the 81st Annual Meeting of the Transportation Research Board, Washington, D.C., 2002.
5. Taylor, M. Dense Network Traffic Models, Travel Time Reliability, and Traffic Management. I: General Introduction. *Journal of Advanced Transportation,* Vol. 33, No. 2, 1999, pp. 218–233.
6. Hellinga, B., and L. Fu. Route Selection Considering Travel Time Variability. *Proc., 6th World Congress on Intelligent Transport Systems,* Toronto, Ontario, Canada, 1999.
7. Dandy, G., and E. McBean. Variability of Individual Travel Time Components. *ASCE Journal of Transportation Engineering,* Vol. 110, No. 3, 1984, pp. 340–356.

8. Wakabayashi, H., and Y. Iida. Improvement of Terminal Reliability and Travel Time Reliability Under Traffic Management. *Proc., Pacific Rim TransTech Conference,* Seattle, Wash., 1993.
9. Cohen, H., and F. Southworth. On the Measurement and Valuation of Travel Time Variability Due to Incidents on Freeways. *Journal of Transportation and Statistics,* Dec. 1999.
10. Dailey, D. Travel Time Estimation Using Cross-Correlation Techniques. *Transportation Research Part B,* Vol. 27B, No. 2, 1993, pp. 97–107.
11. Petty, K. Accurate Estimation of Travel Times from Single Loop Detectors. Presented to the 76th Annual Meeting of the Transportation Research Board, Washington, D.C., 1997.
12. Kuhne, R. First Experiences with Real-Time Motorway Control Using Section-Related Data Collection. *Proc., International Federation of Automatic Control Transportation Systems Congress,* Tianjin, China, Oct. 1994.
13. Coifman, B. Vehicle Reidentification and Travel Time Measurement in Real Time on Freeways Using Existing Loop Detector Infrastructure. In *Transportation Research Record 1643,* TRB, National Research Council, Washington, D.C., 1998, pp. 181–191.
14. Sun, C., S. G. Ritchie, K. Tsai, and R. Jayakrishnan. Use of Vehicle Signature Analysis and Lexicographic Optimization for Vehicle Reidentification on Freeways. *Transportation Research Part C,* Vol. 7, 1999, pp. 167–185.
15. Turner, S., W. Eisele, R. Benz, and D. Holdener. *Travel Time Data Collection Handbook.* FHWA-PL-98-035. Texas Transportation Institute, A&M University, College Station; FHWA, U.S. Department of Transportation, 1998.
16. Zeng, N., and J. Crisman. Vehicle Matching Using Color. *Proc., IEEE Conference on Intelligent Transportation Systems.* Boston, Mass., Nov. 9–12, 1998, pp. 206–211.
17. MacCarley, C. A., and B. Hemme. Computer Vision Detection System for Network Model Validation. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1771,* TRB, National Research Council, Washington, D.C., 2001, pp. 28–37.
18. Kreeger, K., and R. McConnell. Structural Range Image Target Matching for Automated Link Travel Time Computation. *Proc., 3rd Annual World Congress on Intelligent Transportation Systems,* Orlando, Fla., Oct. 1996.
19. Christiansen, I., and L. Hauer. Probing for Travel Time. *Traffic Technology International,* Aug.–Sept., 1996, pp. 41–44.
20. Yokota, T., T. Inoue, Y. Kobayashi, and K. Takagi. Travel Time Measuring System Based on Platoon Matching: A Field Study. *Proc., Intelligent Transportation Systems America Annual Meeting.* Houston, Tex., April 1996.
21. Yim, Y., and R. Cayford. Investigation of Vehicles as Probes Using Global Positioning System and Cellular Phone Tracking: Field Operations Test. Working Paper. UCB-ITS-PWP-2001-9. Partners for Advanced Transit and Highways, Richmond, Calif., 2001.
22. Sano, Y., S. Furukawa, F. Takamura, and K. Yamana. Travel-Time Measuring System for Efficient Traffic Information Service. *Hitachi Review,* Vol. 49, No. 3, 2000.
23. Brown, W., and E. Jacobson. HOV Evaluation and Monitoring—Phase IV. Annual Data Report. WA-RD 414.2. Washington State Transportation Commission, Olympia, 1998.
24. Steuer, R. *Multiple Criteria Optimization: Theory, Computation, and Application.* John Wiley and Sons, New York, 1986.
25. Pareto, V. *Manuale di Economia Politica* (in Italian). Societa Editrice Libraria, Milano, Italy, 1906; A. S. Schwier (translator). *Manual of Political Economy,* Macmillan, New York, 1971.
26. Ben-Horim, M., and H. Levy. *Statistics: Decisions and Applications in Business and Economics,* 2nd ed. Random House, New York, 1984.
27. Bradley, J. *Distribution-Free Statistical Tests.* Prentice-Hall, Englewood Cliffs, N.J., 1968.

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