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ABSTRACT

One of the fundamental requirements to facilitate implementation of any Advanced Transportation Management and Information System (ATMIS) is the development of a real-time traffic surveillance system to produce reliable and accurate traffic performance measures. This study presents a new framework for anonymous vehicle tracking that is capable of tracing individual vehicles by utilizing vehicle features. The core part of the proposed vehicle tracking method is a vehicle reidentification algorithm for signalized intersections based on inductive vehicle signatures, which consists of two major components: search space reduction and probabilistic pattern recognition. Not only real-time intersection performance but also intersection Origin-Destination (OD) information can be obtained as basic outputs of the algorithm. A systematic simulation investigation of the performance and feasibility of anonymous vehicle tracking on signalized arterials using the Paramics simulation model is performed. Extensive research experience with vehicle reidentification techniques on single roadway segments is used to investigate the performance obtainable from tracking individual vehicles across multiple detector stations. The findings of this study serve as a logical and necessary precursor to possible field implementation of vehicle reidentification techniques. The proposed anonymous vehicle tracking methodology utilizing existing traffic surveillance infrastructure would be an invaluable tool for operating agencies in support of various ATMIS strategies including congestion monitoring, adaptive traffic control, system evaluation, and provision of real-time traveler information.

1. Introduction

One of the fundamental requirements to facilitate implementation of any Advanced Transportation Management and Information System (ATMIS) is the development of a real-time traffic surveillance system that is capable of producing reliable and accurate traffic performance measures. Although various ATMIS are now widely under development, the limitations, and often large errors, inherent in present traffic surveillance systems greatly diminishes the ability of operating agencies to effectively control and manage public highway systems, and to provide useful, timely and accurate information to highway users.

New types of travel data, in real-time, are essential for effective implementation of ATMIS. To address this need, there has recently been substantial interest in the United States and Europe, and particularly in California, in implementing vehicle reidentification systems. Initially this interest has focused on using the extensive existing inductive loop infrastructure, and ultimately using emerging technologies such as video and laser detectors, the Global Positioning System (GPS) of satellites, and on-board vehicle sensors and wireless communications. Regardless of the technologies used, real-time travel time and origin-destination (OD) information have been identified as particularly important outputs of such systems. In addition, relatively inexpensive, anonymous vehicle tracking systems, without potential privacy concerns (as exist with tagged automatic vehicle identification systems) are preferred. This study presents a new framework for anonymous vehicle tracking that is capable of tracing individual vehicles by utilizing vehicle features. By using non-obtrusive and anonymous tracking methods,

individual vehicles can be identified and correlated over numerous identification stations, and very specific real-time data can be obtained for each tracked vehicle.

The core part of the proposed vehicle tracking method is a vehicle reidentification algorithm for signalized intersections that is based on inductive vehicle signatures. The new vehicle reidentification system consists of two major components, search space reduction and probabilistic pattern recognition, and is presented in this study. This approach has yielded very accurate real-time section travel time, speed, delay, level of service, density, vehicle classification and origin destination information from either double or single loop detector stations. The algorithm has also been implemented in the field at a major intersection in the city of Irvine and real-time performance information provided to operators at the city's traffic management center. Although the potential for extension of this approach to network applications is very high, further feasibility study is necessary before investing in network-wide implementation.

The insights obtained by the authors in previous research with single roadway segments have been used as input to investigate the performance obtainable from tracking individual vehicles across multiple detector stations through an arterial to obtain real-time traffic information. The Paramics (PARALLEL MICROSOPIC SIMULATION) microscopic traffic simulation model (1) is employed to evaluate and analyze the framework for anonymous vehicle tracking on signalized arterials. The findings of this study serve as a logical and necessary precursor to possible field implementation of vehicle reidentification techniques for transportation systems analysis.

The following section of this paper introduces the framework for the proposed anonymous vehicle tracking system based on tracing individual vehicles at signalized intersections. The methodology on how to generate synthetic vehicle signatures, which is used for the vehicle tracking simulation, is presented in the third section. Then, the simulation experiment using Paramics is conducted and the results are discussed. Finally, the conclusions are presented.

2. Anonymous vehicle tracking based on vehicle reidentification

Anonymous vehicle tracking is defined as tracing individual vehicles on transportation networks based on correlating the vehicle features obtained from different detection stations. Recently, sensor technologies have advanced to the degree where individual vehicle features are obtainable. The vehicle features contain a valuable set of information that enables us to identify the characteristics of individual vehicles such as length, width, height, and color. Examples include use of existing loop detectors with high speed scanning detector cards to generate inductive signatures (2-6), laser-based detection systems (7) providing vehicle length, and video-based vehicle signature generation (8) using video image processing technology. The proposed vehicle tracking method utilizes vehicle feature vectors extracted from inductive vehicle signatures.

2-1 Advanced loop detector technologies and inductive vehicle signatures

Conventional detector cards used with inductive loop detectors are usually bivalent in nature, where the detector card output is either "0" or "1" depending on vehicle presence. However, detector card technology has advanced to the degree where now the inductance change over the loop due to the vehicle's passage is obtainable. In particular, high scan rate detectors can sample these inductance changes and produce a waveform or "vehicle signature." Figure 1 shows the examples of the vehicle signatures with the 7 millisecond scan rate generated from the different types of vehicles. The vertical axis is proportional to the change in inductance, and the horizontal axis is time.

The vehicle inductive signatures represent the physical characteristics or features of the vehicles such as vehicle length, weight, and shape etc. Each piece of information embedded in the signature can be extracted and included in an individual vehicle feature vector. Moreover, vehicle lane information, vehicle speed, signal phase information, and vehicle arrival time can also be recorded for individual vehicle and included in the feature vector.

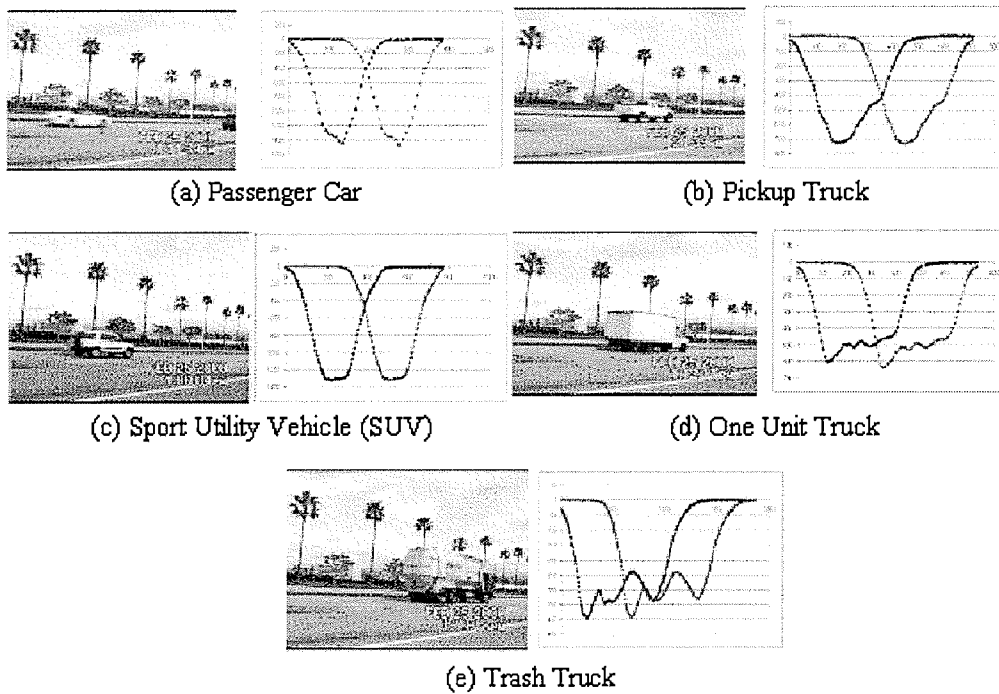


Figure 1 Vehicle inductive signatures

A raw vehicle signature is normalized by two procedures in order to be used in the vehicle reidentification algorithm. First, the magnitude of the vehicle signature, shown in Figure 2, is divided by its maximum magnitude to purge the variations by different detector locations. Second, the time the vehicle is present on the loop detectors is transformed to vehicle length by multiplying by the speed of the vehicle. The major role of the second step of the normalization procedure is to exclude the effects of the vehicle speed. Equally Spaced Interpolations (ESIs) representing the shape of the normalized vehicle signature are then extracted. ESIs include invaluable information about vehicle characteristics for each individual vehicle.

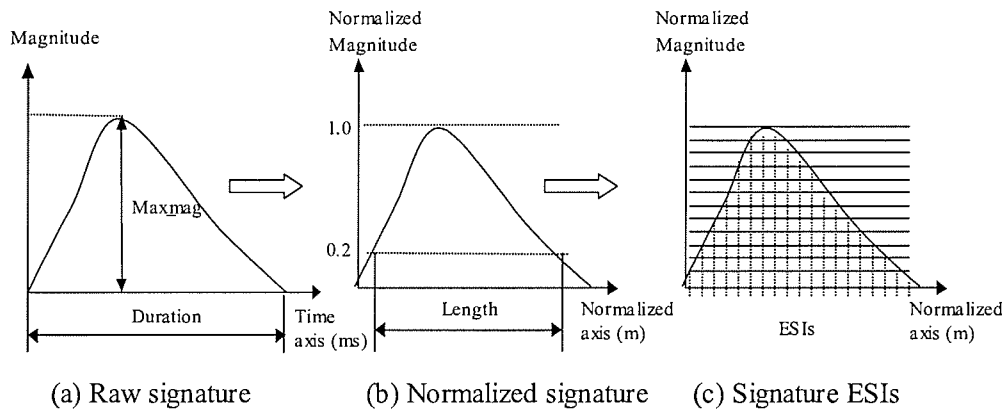


Figure 2 Vehicle signature normalization

2-2 Inductive-signature-based vehicle reidentification at signalized intersections

The fundamental idea of vehicle reidentification based on inductive signatures is to match a given downstream vehicle signature with an upstream vehicle signature from amongst a set of candidate upstream vehicle signatures. Applying the concept of the lexicographic method developed by Sun et al (3) for freeway applications, vehicle reidentification was formulated as a five-level optimization problem. Minimizing mismatches between feature vector pairs denotes the “optimization” on any given objective. Unlike the freeway case, the intersection traffic flow is interrupted by vehicle-actuated signal control, resulting in highly variable travel times. Each downstream station also has three different upstream stations, which makes the vehicle reidentification much more challenging. As far as we know, there has been no attempt to date to trace individual vehicles with anonymous tracking methods in signalized networks, even though transportation problems such as congestion and safety in signalized networks are more significant in some cases.

In on-going research by the authors, a real-time traffic surveillance system based on vehicle reidentification technology that utilizes vehicle inductive signatures is operating at the intersection of Alton Parkway and Irvine Center Drive in the City of Irvine, California. The present system yields valuable real-time traffic information obtained by matching vehicle signatures from upstream and downstream detector stations. Real-time performance information from the intersection has been provided to operators at the city’s traffic management center. The present intersection vehicle reidentification system has yielded real-time intersection travel time, speed, delay, level of service, vehicle classification and localized origin destination information, from either double or single loop detector stations (many other performance measures can also be derived).

The vehicle reidentification algorithm for signalized intersections developed by the authors consists of two main procedures involving search space reduction and probabilistic pattern recognition. In order to attain faster algorithm running times and enhance tracking performance, search space reduction is an essential element of the algorithm. In this paper, the main framework of the vehicle reidentification algorithm for signalized intersections is presented. Further details about the algorithm are discussed elsewhere (9-10).

1) Spatial-temporal search space reduction

Intersections on a signalized network are interrupted by signal control, resulting in highly variable travel times. Each downstream station also has three different upstream stations. The first step of the algorithm is to reduce the spatial search space, which identifies the upstream origin of each vehicle. The next step of the search space reduction is temporal search space reduction, which establishes a lower and upper bound for feasible travel time, called a ‘time window’. If a large time window is applied to cover many vehicles, the required capability of the algorithm to match the corresponding vehicle signature increases and the computational burden and false-tracking rate increases as well. On the other hand, with a small time window, the algorithm can find the corresponding vehicle efficiently (if it is there), but the vehicle may not exist in the time window. Therefore, setting the proper time window is an important component for tracking performance. Signal phase information and travel time estimates, which are functions of traffic and signal conditions, are used to set time windows dynamically.

2) Probabilistic pattern recognition

Vehicle feature matching corresponds to an object identification problem within the candidate sets, which is the task of determining that two observed vehicles are in fact the same vehicle. Because feature vector matching between each vehicle is a highly complex process, neural networks that have a capability to learn complex non-linear patterns and trends are expected to produce improved matching performance. The matching algorithm should also be capable of producing a probabilistic estimate of the reliability associated with a vehicle match.

The Probabilistic Neural Network (PNN) proposed originally by Specht (11), which is a neural network implementation of the well-established multivariate Bayesian classifier using Parzen estimators, is used to solve the probabilistic pattern recognition problem for inductive vehicle signature matching. An example of Parzen estimator for the Probability Density Function (PDF) can be expressed as follows if a global single smoothing parameter and a bell-shaped Gaussian function are applied:

$$f(X) = \frac{1}{(2\pi)^{p/2} n \sigma^p} \sum_{i=1}^n \exp\left(-\frac{\|X - X_i\|^2}{2\sigma^2}\right)$$

where X and X_i are the vectors of input variables and the i th training vector, respectively; σ is the smoothing parameter that represents the standard deviation around the mean of the input variables; and p represents the dimensionality of input feature space.

Figure 3 shows the PNN network architecture for this study. The PNN consists of four layers involving an input layer, pattern layer, summation layer, and output layer. The number of nodes in the input layer represents the number of vehicle signature feature vectors that are used for pattern recognition. The pattern layer is established to hold one node for each training case. The summation layer consists of two nodes representing each pattern class and it calculates PDFs for each class. The output layer has just one node determining the class of pattern for given input feature vectors. That is, the output layer mechanizes the Bayesian decision strategy for classifying input patterns to corresponding classes.

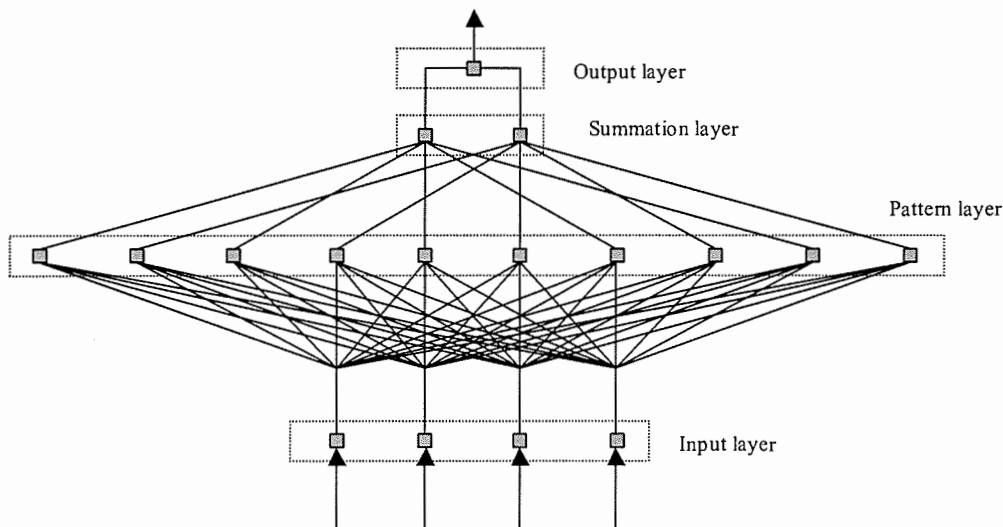


Figure 3 Probabilistic Neural Network (PNN) diagram

Each input pattern in the training dataset is directly used for the connection weights. Therefore, adjusting the connection weights using the generalized delta rule as with back-propagation neural networks is not required. This feature makes training much faster and the PNN more attractive compared to back-propagation networks (12). In addition, the PNN allows users to add new training data readily without necessitating retraining of the network.

The original version of the PNN by Specht used a global single smoothing parameter, which is applied to all the pattern units without any consideration of the effects of each training pattern on kernel shape. On the other hand, Adaptive PNN (APNN) utilizes various smoothing parameters for reflecting the characteristics of each training vector in computing probability density functions for each class. Since the smoothing parameters are the most significant parameters affecting the classification performance of the PNN, an effective method for optimizing smoothing parameters is required. Genetic Algorithms (GA) and Self-Organizing Maps (SOM) were employed to obtain the optimal set of smoothing parameters. SOM was used for clustering training patterns into similar ones, and then smoothing parameters representing each cluster were optimized by GA. Further details about the development of the proposed probabilistic pattern recognizer based on the PNN is given in Oh et al (10). Figure 4 depicts the vehicle reidentification algorithm for signalized intersections.

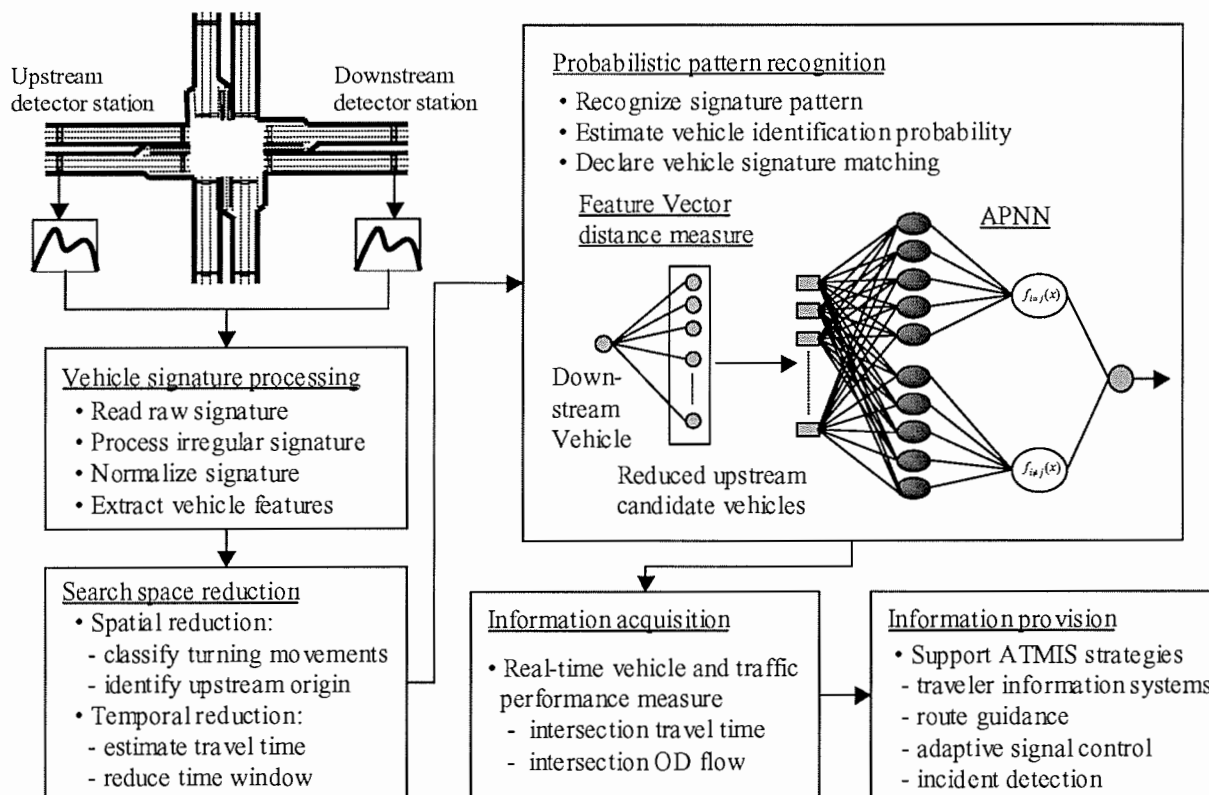


Figure 4 Vehicle reidentification algorithm for signalized intersections

Currently, the actual implementation of the algorithm at the intersection of Alton Parkway and Irvine Center Drive in the City of Irvine, California has yielded excellent results. For example, average real-time intersection delay has been estimated with errors of less than 10%, with aggregation periods of up to 15 minutes.

2-2 Anonymous vehicle tracking

The literature on vehicle tracking can be grouped into several categories based on the technologies used, such as GPS, vehicle tag-based Automatic Vehicle Identification (AVI), and Video Image Processing (VIP). GPS is a potentially valuable tool for traffic surveillance due to its capability of providing positioning data for individual vehicles (13-16). The major limitations of GPS though are currently minimal fleet penetration, varying accuracies, and signal loss in urban areas due to tall buildings, tunnels, and trees etc. The most widely-used AVI technologies are based on license plate identification and the use of transponder tags (17-18). A number of studies have utilized VIP methods for localized vehicle tracking in a lab environment (19-23). However, video sensors are not yet widely deployed and often involve relatively high initial costs with reliabilities that are yet to be proven. In addition, public perceptions of significant privacy concerns remain for many GPS, AVI and VIP systems.

Consequently, a non-intrusive and anonymous vehicle tracking surveillance technology that could utilize vehicle features from the existing infrastructure would be highly advantageous for assessing real-time performance of transportation systems. The proposed method makes use of inductive vehicle signatures produced by advanced high-speed scanning loop detector cards, but it can be adapted to other detectors, for example laser-based or video-based detection systems, by substituting different input feature vectors. The proposed anonymous vehicle tracking method aims to identify and correlate individual vehicles' features throughout a transportation network. In other words, features of individual vehicles are successively traced over numerous detection stations.

Path-based traffic information from anonymous vehicle tracking based on multiple section vehicle reidentification is obtained as follows. Individual vehicles pass the detector stations in each section, and the vehicle features including detector station ID and detection time are collected. The vehicle information is stored in a database, and is later used for matching corresponding downstream vehicles. The vehicle reidentification algorithm matches a given downstream vehicle with one of the upstream candidate vehicles that has the most similar vehicle features. Link-based traffic information for any given section can be therefore obtained at this stage. The vehicle path information is then updated by adding the downstream station ID and detection time. The path information for individual vehicles is stored in the database. Once the vehicle passing a pre-defined destination detector station is matched with the corresponding upstream vehicle, the recorded path information is queried to obtain the vehicle's path and its travel time by tracing station IDs and their detection times. The proposed framework for vehicle tracking is presented in Figure 5.

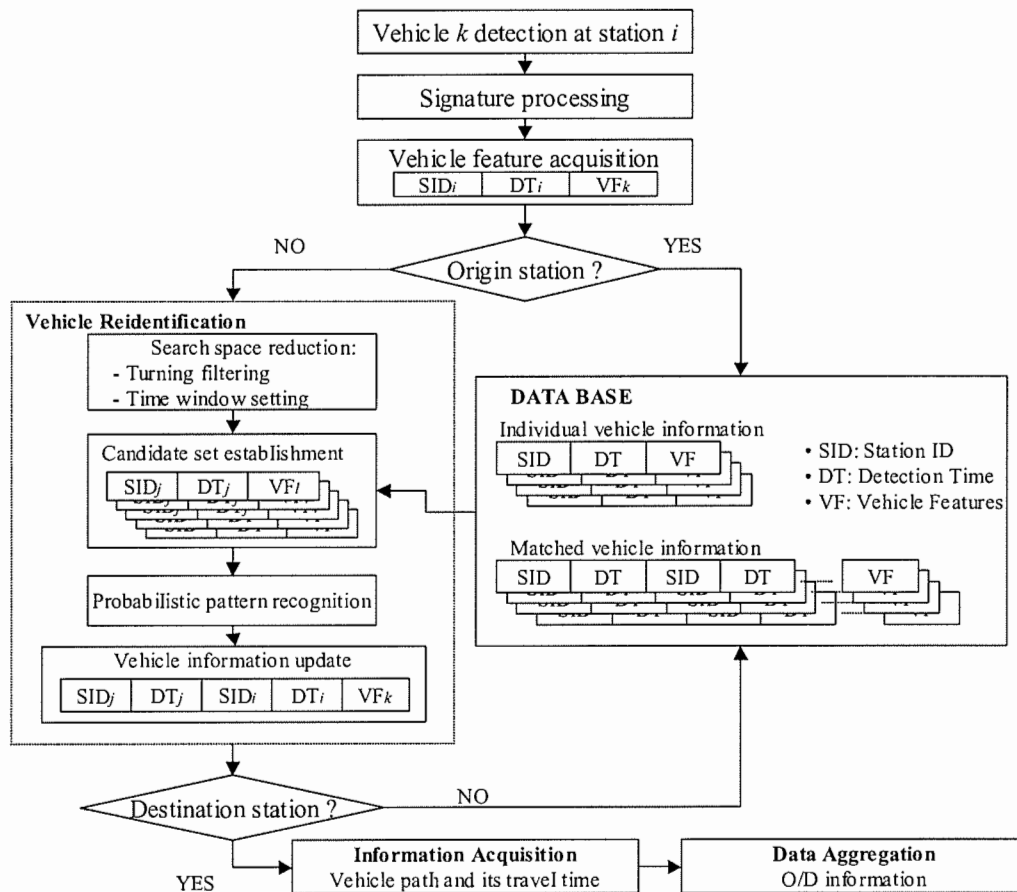


Figure 5 The proposed vehicle tracking framework

The proposed vehicle tracking framework is investigated in this paper using Paramics. To date, various simulation models have been used for evaluating ATMIS strategies. Traffic simulation models can be broadly classified into two groups such as microscopic, and macroscopic models. As recently developed ATMIS strategies often require the observation of very detailed levels of traffic phenomenon such as individual vehicle movements, the microscopic simulation model is suited for such needs, although model validation and calibration issues still need to be solved. Many studies have used microscopic simulation models for evaluating dynamic traffic assignment, route guidance, signal control, incident detection, and ramp control strategies. However, the traffic surveillance system, which is a core part of such strategies, has not been evaluated under the simulation environment. One of the invaluable features of this study is to present a methodology on how to use microscopic simulation models for evaluating traffic

surveillance system. The proposed simulation framework could be of great value for testing and performance comparison of traffic surveillance algorithms.

3. Synthetic vehicle signature generation

This section focuses on the methodology to generate synthetic vehicle signatures that are used for the vehicle tracking simulation. Prior to implementing the proposed vehicle tracking technique in the real world, the feasibility of the application of the vehicle reidentification algorithm to signalized arterials needs to be evaluated and analyzed. Microscopic simulation is an essential tool to investigate the practicality of newly developed ATMISS strategies in the laboratory. Therefore, in order to perform the simulation investigation of the proposed vehicle tracking technique, first we should be able to obtain the inputs of the vehicle reidentification algorithm, that is, vehicle feature vectors extracted from inductive vehicle signatures, as discussed above. The statistical investigation of the repeatability and variability of specific features between upstream and downstream detector stations was performed by extensive data analysis using vehicle signatures collected on Alton Parkway in the City of Irvine.

The proposed vehicle reidentification algorithm utilizes the differences in vehicle feature vectors, called 'feature distance', as inputs to the algorithm. Therefore, if signature variations that result in wide distance between up and downstream vehicle features do not exist, the algorithm would be capable of producing perfect vehicle signature matching. However, we usually are not able to obtain such accurate vehicle signatures from different detection stations. It is because the exogenous effects of environmental elements on the shape of vehicle signatures, such as the entrance angle of a vehicle into the inductive field, physical loop installation, and roadway geometry etc, exist in practice. Hence, in order to generate synthetic vehicle signatures, the signature shape error should be identified first.

The processed upstream and down stream vehicle signatures were compared with video ground-truth data to identify signature data from the same vehicle. ESIs of the matched vehicle signatures were extracted and feature distances were computed. Therefore, given upstream signatures and downstream signatures for vehicle type i , S_{up}^i and S_{down}^i , the signature error can be described by $S_{up}^i = S_{down}^i + \epsilon_i$. Errors close to zero explain that two signatures for the same vehicle observed from different detection stations are exactly the same.

Efforts to find out the error distribution discussed above were performed with actual vehicle signatures. Basically, a unique vehicle signature is observed from each individual vehicle. However, to estimate each single error distribution for each individual vehicle is impractical. A clustering technique was employed to overcome this limitation based on the assumption that vehicles in the same cluster would generate similar vehicle signatures and the generated signatures would be differentiable from those of other vehicles in different clusters.

We clustered the vehicle signatures of our dataset based on their similarities. This clustering should meet two requirements: homogeneity of vehicle signatures within the same categories, i.e. data that belong to the same category should be as similar as possible, and heterogeneity of vehicle signatures between categories, i.e. data belonging to different categories should be as different as possible. For clustering analysis, the ESI differences extracted from individual vehicles passing between upstream and downstream detectors were used. The total number of vehicle signatures used for clustering was 1,819. The number of clusters corresponds to the number of vehicle types specified in Paramics. However, how many clusters to use is an issue because the number of clusters for actual vehicle signatures can affect the performance of the vehicle reidentification algorithm. To determine a reasonable number of vehicle clusters, we selected a number of clusters that was able to reproduce the actual performance of vehicle reidentification, which we have obtained from the field. So far, the vehicle reidentification performance has reached around 70 ~ 80% of correct matching rate based on both intersection (10) and freeway experiments (3). We have also found that 50 clusters can reproduce this actual performance of vehicle reidentification.

Mean vectors and covariance matrices for each cluster of vehicle signatures were estimated assuming that feature vectors were normally distributed. Then random error vectors from the estimated multivariate normal distributions were applied to generate synthetic vehicle signatures in simulating the proposed vehicle tracking method.

A Self-Organizing Map (SOM) was applied to cluster the vehicle signature data in this study. The SOM developed by Kohonen (24) is two-layer neural network that falls into the category of unsupervised learning methodology for clustering and dimension reduction. An advantage of SOM over other clustering algorithms is its ability to visualize high dimensional data using a two-dimensional grid while preserving similarity between data points as much as possible. The observations are automatically organized into a meaningful two-dimensional order in which similar ones are closer to each other in the grid than the more dissimilar ones. In this sense the SOM can be regarded as a multivariate clustering algorithm to seek clusters in the data.

Each node of the SOM contains a weight vector, which is equal to the dimension of the feature vectors. Originally, the weight vectors are initialized to random values. During the training, the weight vectors are modified based on the input feature vectors.

As a result of this learning algorithm, the clusters corresponding to characteristic features are formed onto the map automatically. Although SOM identifies a winning neuron based on the same method as employed by traditional competitive learning, it differs from competitive learning in that all neurons within a certain neighborhood of the winning neuron are adjusted instead of adjusting only the winning neurons. After the map has been organized, the clusters can be labeled, which corresponds to a physical interpretation of the formed clusters.

4. Simulation experiment

To demonstrate the potential feasibility of the proposed vehicle tracking system in terms of deriving real-time performance measures, a microscopic traffic simulation model was used. Paramics (PARAllel MICROscopic Simulation) was used to gather the sample data. Paramics is a suite of high-performance software tools for microscopic traffic simulation. The movement and behavior of individual vehicles is modeled in detail for the duration of their entire trip. One of the nice features of Paramics is that it can be customized. Access is available through a functional interface or Application Programming Interface (API). APIs allow additional functionality by adding more external modeling routines. This is an essential feature of Paramics that allows the implementation of various ATMS application algorithms.

The test arterial that was modeled by Paramics has five signalized intersections, including the intersection of Alton and Irvine Center Drive (ICD) in Irvine where the vehicle reidentification system has been implemented, operated by actuated signal control as shown in Figure 6. The test network is one part of a corridor network that has been studied by the ATMS Testbed laboratory in the Institute of Transportation Studies at the University of California, Irvine. The testbed network includes three freeway sections and adjacent surface streets in the City of Irvine. Paramics has been calibrated for this network (25-26). The calibrated parameters in Paramics include mean target headway, driver reaction time, route choice parameters, and demand matrix etc.

Two data sets using Paramics were generated, representing congested and uncongested traffic conditions. Congested traffic conditions result in individual cycle failures on the simulation network. Using the Highway Capacity Manual (27) Level Of Service (LOS) criteria, congested and uncongested traffic conditions can therefore be categorized into LOS 'A - C' and 'D-F' respectively.

In Paramics, users can define not only vehicle types but also the proportions of such vehicle types in traffic streams. In addition, the physical characteristics of each vehicle including length, height, width, maximum speed, acceleration and deceleration can also be specified. Based on the analysis of vehicle signatures discussed in the previous section, we pre-defined vehicle types and vehicle proportions in Paramics prior to running the simulation.

One of the major elements affecting vehicle tracing performance is the capability of the sensor technologies used. Sensor technology can be evaluated by repeatability, which means that the sensor should be able to generate the same output at any location. The actual vehicle signatures used in this study for producing synthetic vehicle signatures were collected with 7 millisecond scan rate detector cards. However, because loop detector technology to generate more accurate and unique vehicle signatures with faster scan rates has been developed and tested in practice, it is expected that we would be able to obtain higher quality vehicle signatures in the future. Once such data can be gathered from the field, more fine-tuned error distributions, which are used for generating synthetic vehicle signatures, would be obtainable. Investigations of the vehicle tracking performance with high-quality data will be needed, considering real-world implementation of the proposed vehicle tracking system. The variances of vehicle

signature error distributions are therefore treated as variables for evaluating the capability of the sensor technology in this simulation study.

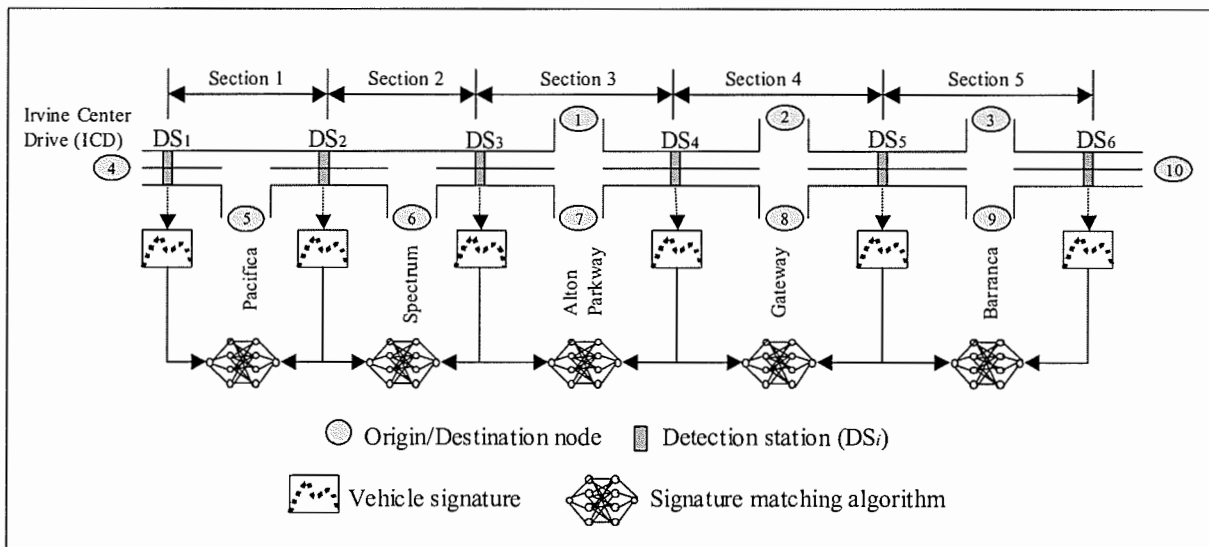


Figure 6 Test arterial

The concept of anonymous vehicle tracking based on vehicle reidentification introduced in the previous section was implemented for successive through-movements passing through detection station 1 (DS₁) ~ detection station 6 (DS₆) as shown in Figure 6. The synthetic vehicle signatures for each individual vehicle were utilized as inputs for the vehicle reidentification algorithm. The through-movement vehicles coming from DS₁ via DS₂ ~ DS₅, and passing over DS₆, were traced by the proposed anonymous vehicle tracking method when the vehicles were detected at DS₆.

5. Simulation results and discussion

As a performance measure for the algorithm evaluation, the Correct Tracking Rate (CTR), which is the percentage of individual vehicles that the algorithm is able to trace correctly, was used. CTR was computed based on vehicles traveling from DS₁ to DS₆, and for the different levels of variance of the vehicle signature error distribution, as shown in Table 1. The variance of error distribution based on the actual vehicle signatures (σ^2), and reduced variances ($\sigma^2 / 2, \sigma^2 / 4$) represent the current and improved capabilities of the loop detector technology, respectively.

Table 1 Correct Tracking Rate (CTR) of vehicles under different conditions

Variance of error distribution	Traffic Conditions	
	Uncongested	Congested
σ^2	31.0 % (140/451)	18.5 % (122/659)
$\sigma^2 / 2$	41.2 % (186/451)	27.9 % (184/659)
$\sigma^2 / 4$	65.4 % (295/451)	38.4 % (253/659)

The most valuable feature of this study is to investigate how to produce useful real-time traffic information via the anonymous vehicle tracking method. This method can produce not only link travel time but also path travel time. Although real-time network traffic management strategies including dynamic traffic assignment, route guidance etc., require accurate path travel time, most studies use the simple addition of travel times estimated from each link based on existing surveillance capabilities as the path travel time, which can be inaccurate. In this study, a Mean Absolute Percentage Error (MAPE) was calculated by comparing with the case of 100% correct vehicle tracking.

$$MAPE(\%) = \frac{\sum_{n=1}^N \left[\left| \frac{TTime_{obs,n} - TTime_{est,n}}{TTime_{obs,n}} \right| \times 100 \right]}{N}$$

where,

$TTime_{obs,n}$: Observed path travel time at time step n (100% correct matching)

$TTime_{est,n}$: Estimated path travel time at time step n (reidentified vehicle matching)

N : Total number of time steps

Table 2 Path travel time errors (MAPE) under different conditions

Variance of vehicle signature error distribution	Traffic conditions	Path travel time aggregation interval			
		1 cycle	5 min	10 min	15 min
σ^2	Uncongested	38.19 %	21.66 %	15.49 %	12.67 %
	Congested	40.78 %	27.27 %	19.73 %	14.58 %
$\sigma^2 / 2$	Uncongested	24.49 %	14.25 %	13.62 %	8.56 %
	Congested	31.56 %	24.41 %	18.83 %	14.73 %
$\sigma^2 / 4$	Uncongested	18.31 %	9.53 %	7.61 %	4.71 %
	Congested	23.25 %	19.14 %	16.33 %	11.58 %

The travel time evaluations presented in Tables 2 were obtained by comparing 'true' travel time from ground-truthing data, which was obtained by matching the unique identification numbers for each individual vehicle at each detection station in the simulation model, and 'estimated' travel time from vehicle tracking based on vehicle reidentification and considering various data aggregation intervals. The major findings from the simulation experiment are summarized as follows:

- (1) In case of σ^2 , which is based on the actual error distributions of vehicle signatures, the path travel time estimates show the potential feasibility of the proposed vehicle tracking algorithm. For an aggregation interval of 15 minutes, path travel time errors less than 15% were achieved under both uncongested and congested traffic conditions.
- (2) For the purpose of investigating the proposed vehicle tracking system with reduced variances of the vehicle signature error distributions, $\sigma^2 / 2$ and $\sigma^2 / 4$ were applied. As expected, the performances were better than those of the case of σ^2 . Path travel time errors under 15% were achieved for 5 min., 10 min., and 15 min. aggregation intervals under uncongested traffic conditions with $\sigma^2 / 2$. In case of applying $\sigma^2 / 4$, the proposed vehicle tracking method was capable of generating less than 10 % path travel time errors for 5 min., 10 min., and 15 min. aggregation intervals under uncongested traffic conditions, and less than 20% path travel time error under congested traffic conditions for the same aggregation intervals.
- (3) The aggregation interval is an important issue for designing real-time traffic information. As shown in the evaluation results, different aggregation intervals produce different accuracies. In addition, shorter

aggregation intervals have bigger travel time variations than those of the longer intervals. Therefore, the use of the successive averages of travel times would be a possible way in order to reduce the travel time variations. Identifying optimal travel time aggregation intervals for generating useful traffic information accounting for the real-time performance of transportation systems would be an important issue in the field of traffic surveillance and information systems.

6. Conclusions

Research in Intelligent Transportation Systems (ITS) addresses various transportation needs such as efficiency, safety, environmental protection, mobility, and economic viability. Different agencies on different levels try to utilize ITS for improving the transportation system. These agencies range from day-to-day operators and managers of the transportation system to long term designers and planners of the transportation infrastructure. In order to fully exploit the advantages of ITS strategies, accurate and appropriate data need to be collected from the transportation network. Therefore it is vital to develop advanced surveillance systems that can properly support the objectives of ITS. Vehicle tracking appears to be a suitable technology for developing such traffic surveillance systems, which allows us to obtain sophisticated traffic parameters such as path-based traffic information in real time.

Although a variety of sensor technologies have been developed and tested for tracing individual vehicles on transportation networks, the proposed anonymous vehicle tracking system utilizing vehicle feature vectors is preferred since it uses existing field equipment and is free from the privacy concerns. Use of existing loop infrastructure makes the proposed system more attractive in terms of immediate field implementation. Field investigation of the vehicle reidentification system for a single roadway intersection in the City of Irvine, California, has shown the potential for extension to multiple section implementations.

This study has presented a framework for studying the feasibility of an anonymous vehicle tracking system for real-time arterial traffic surveillance. The potential feasibility of such an approach was demonstrated by simulation experiments for a signalized arterial operated by actuated traffic signal controls. Synthetic vehicle signatures were generated to evaluate the proposed tracking algorithm under the simulation environment. The Paramics microscopic simulation model was used to investigate the proposed vehicle tracking algorithm. The findings of this study can serve as a logical and necessary precursor to possible field implementation of the proposed system in an arterial network. It is believed that the proposed method for evaluating a traffic surveillance system using microscopic simulation in this study can offer a valuable tool to operating agencies interested in real-time congestion monitoring, traveler information, control, and system evaluation.

References

1. *PARAMICS User Guides Version 3.0*. Quadstone LTD., Edinburgh, UK, 2000.
2. Ritchie, S.G., and C. Sun. *Section Related Measures of Traffic System Performance: Final Report*. California PATH Research Report UCB-ITS-PRR-98-33. 1998.
3. Sun, C., S.G. Ritchie, W. 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.
4. Sun, C., and S.G. Ritchie. Individual Vehicle Speed Estimation Using Single Loop Inductive Waveforms. *Journal of Transportation Engineering*, American Society of Civil Engineers, Vol. 125, No. 6, 1999, pp 531-538.
5. Oh, C., and S.G. Ritchie. Real-time inductive-signature-based level of service for signalized intersections. Paper presented at 81st Transportation research Board Annual Meeting, Washington D.C. 2002.
6. Oh, S., S.G. Ritchie, and C. Oh. Real-Time Traffic Measurement from Single Loop Inductive Signatures. Paper presented to the Transportation Research Board Annual Meeting, Washington D.C. 2002.
7. Larson, J.E. et al. *A real-time laser-based prototype detection system for measurement of delineation of moving vehicles*. MOU 263 Working paper to California PATH, University of California, Davis, 1998.
8. MacCarley, C.A. *Video-based vehicle signature analysis and tracking system phase 2: algorithm development and preliminary testing*. MOU 350 Final Report to California PATH, California Polytechnique State University, San Luis Obispo. 2001.

9. Ritchie, S.G. et al. *Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies*. MOU 3008 Draft Final Report to California PATH, Institute of Transportation Studies, University of California, Irvine, 2001.
10. Oh, C., S.G. Ritchie, S. Park. Development a real-time probabilistic vehicle reidentification algorithm for signalized intersections. *ITS Working paper*, Institute of Transportation Studies, University of California, Irvine, 2002.
11. Specht, D.F. Probabilistic neural networks and general regression neural networks. In: Chen, C.H. (Ed.), *Fuzzy logic and neural network handbook*. 1996.
12. Wasserman, P.D. *Advanced Methods in Neural Computing*. Van Nostrand Reinhold, New York, 1993
13. Kim, J., and J. Oh. A land vehicle tracking algorithm using stand-alone GPS. *Control Engineering Practice*. Vol. 8, 2000, pp 1189-1196.
14. Taylor, S. , and J. Green, and A. Richardson. Applying vehicle tracking and palmtop technology to urban freight. *Working Paper* (Institute of Transportation Studies (Australia)), No. ITS-WP-98-23, 1998.
15. Vlcek, C., P. McLain, and M. Murphy. GPS/dead reckoning for vehicle tracking in the "urban canyon" environment. *Proceedings of the IEEE-IEE Vehicle Navigation and Information Systems Conference*, 1993, pp 461, A34-A37.
16. Hossfeld, B. GPS for vehicle tracking. *GPS world*. Vol. 2 (9), 1991, pp 44-46.
17. Asakura, Y., E. Hato, and M. Kashiwadani. Origin-destination matrices estimation model using automatic vehicle identification data and its application to the Han-Shin expressway network. *Transportation* 27,2000, pp.419-438, 2000.
18. Dixon, M., and L.R. Rilett. Real-time origin-destination estimation using automatic vehicle identification data. *Transportation Research Board Annual Meeting*, Washington, D.C., 2000.
19. Groen, F.C.A. et al. Real-time vehicle tracking in image sequences. *IEEE Instrumentation and Measurement Technology Conference. Proceedings*. Vol.3, 2001, pp 2049-2054.
20. Leuck, H., and H.H. Nagel. Automatic differentiation facilitates OF-integration into steering-angle-based road vehicle tracking. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition. Proceedings*. Vol. 2, 1999, pp 360-365.
21. Coifman, B., D. Beymer, P. Mclauchlan, and J. Malik. A real-time computer vision system for vehicle tracking and traffic surveillance. *Transportation Research Part C*, Vol. 7, 1998, pp 271-288.
22. Fujii, A. et al. Vehicle tracking system using DCT for image extraction," *World Congress on Intelligent Transport Systems, (4th : 1997 : Berlin, Germany)*. *Proceedings : mobility for everybody*, 1997.
23. Bullock, D. Vehicle tracking using radial basis function neural networks," *International Symposium on Automotive Technology & Automation (29th : 1996 : Florence, Italy)*. *Proceedings of the Conference on Supercomputer Applications in the Transportation Industries*, 1996, pp 211-218.
24. Kohonen, T. *Self-Organizing Maps*. Springer, Berlin, 2001.
25. Lee, D-H, X. Yang, and P. Chandrasekar. Parameter calibration for PARAMICS using genetic algorithm. 80th Annual Meeting Preprint CD-ROM, Transportation Research Board, January 7-11, 2001, Washington D.C.
26. Chu, L., H.X. Liu, W. Recker, and S. Hague. Evaluation of effectiveness of potential ATMIS strategies using microscopic simulation. *ITS Working paper*, Institute of Transportation Studies, University of California, Irvine, 2002.
27. Special report 209: *Highway Capacity Manual*. TRB, National Research Council, Washington, D.C. 2000.