

UCI-ITS-TS-WP-02-15

# **Anonymous Vehicle Tracking for Real-Time Traffic Surveillance**

UCI-ITS-TS-WP-02-15

Cheol Oh  
Stephen G. Ritchie

Department of Civil and Environmental Engineering and  
Institute of Transportation Studies  
University of California, Irvine  
cheolo@uci.edu, sritchie@uci.edu

August 2002

Institute of Transportation Studies  
University of California, Irvine  
Irvine, CA 92697-3600, U.S.A.  
<http://www.its.uci.edu>

## **Anonymous Vehicle Tracking for Real-time Traffic Surveillance**

**Cheol Oh**

([cheolo@uci.edu](mailto:cheolo@uci.edu))

**Stephen G. Ritchie**

([sritchie@uci.edu](mailto:sritchie@uci.edu))

Department of Civil and Environmental Engineering and  
Institute of Transportation Studies  
523 Social Science Tower  
University of California  
Irvine, CA 92697-3600  
USA  
Voice: (949) 824-5623  
Fax: (949) 824-8385

**Submitted for presentation and publication  
at the 82nd Annual meeting of the Transportation Research Board  
January 12-16, 2003, Washington D.C.**

# Anonymous Vehicle Tracking for Real-time Traffic Surveillance

Cheol Oh and Stephen G. Ritchie

Department of Civil and Environmental Engineering and  
Institute of Transportation Studies  
University of California, Irvine

## ABSTRACT

One of the fundamental requirements of facilitating the implementation of any Advanced Transportation Management and Information System (ATMIS) is the development of real-time traffic surveillance systems that are capable of producing reliable and accurate traffic performance measures. This study presents a new methodology for evaluating traffic surveillance systems using microscopic simulation model. A systematic simulation investigation of the performance and feasibility of anonymous vehicle tracking on arterials using the Paramics simulation model is performed. Previous 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 to obtain real-time path flow information such as travel time and volume. The findings of this study serve as a logical and necessary precursor to possible field implementation of vehicle reidentification techniques. In addition, it is believed that the methodology in this study, attempting to evaluate a traffic surveillance system based on the microscopic traffic simulation, will be an invaluable tool for investigating and comparing the performances of newly developed traffic surveillance systems.

## 1. Introduction

One of the fundamental requirements of facilitating the implementation of any Advanced Transportation Management and Information System (ATMIS) is the development of real-time traffic surveillance systems that are 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. In the past, such data were extremely difficult to obtain. 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 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 tracking systems, without potential privacy concerns (as exist with tagged automatic vehicle identification systems) are preferred.

A general vehicle reidentification system using inductive loop signatures to uniquely but anonymously track individual vehicles, has been formulated and tested in recent years at the University of California, Irvine. 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 results have been reported by Ritchie and Sun (1), Sun et al (2), Sun and Ritchie (3), Oh and Ritchie (4) and Oh et al (5).

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 algorithms have also been implemented in the field at a major intersection in 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 findings of this study serve as a logical and necessary precursor to possible field implementation of vehicle reidentification techniques for transportation systems analysis.

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 would be greatly used for testing and performance comparison of traffic surveillance algorithms.

The main purpose of this study is to evaluate and analyze the feasibility of the application of vehicle reidentification technique to signalized arterials using the Paramics (PARALLEL MICROSOPIC SIMULATION) microscopic traffic simulation model. The second section of this paper introduces the framework for the proposed anonymous vehicle tracking system based on tracing individual vehicles at signalized intersections. The characteristics of inductive vehicle signatures and the methodology for generating synthetic vehicle signatures are presented in the third and fourth sections, respectively. 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**

Recently, sensor technologies have advanced to the degree where individual vehicle features are obtainable. Examples include use of existing loop detectors with high speed scanning detector cards to generate inductive signatures (1) – (5), laser-based detection systems (6) providing vehicle length, and video-based vehicle signature generation (7) using video image processing technology. 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. Moreover, vehicle lane information, vehicle speed, signal phase information, and vehicle arrival time can also be obtained and considered as vehicle features. Therefore, anonymous vehicle tracking can be defined as tracing individual vehicles on transportation networks based on correlating the vehicle features obtained from different detection stations.

### **2-1 Inductive-signature-based vehicle reidentification at signalized intersections**

The basic 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 (2) 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, no one has attempted 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 (AP) and Irvine Center Drive (ICD) 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 object identification. 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 by (8-9).

### **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 (10), which is a neural network implementation of the well-established multivariate Bayesian classifier using Parzen estimators, is used to solve probabilistic pattern recognition problem for inductive vehicle signature matching. 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) represents that various smoothing parameters are employed for reflecting the characteristic of each training vector in computing probability density functions for each class. In this research, a new architecture of PNN has been developed by embedding a Self-Organizing Map (SOM) and Genetic Algorithm (GA) onto the BPNN in order to implement APNN. Figure 1 depicts the vehicle reidentification algorithm for signalized intersections.

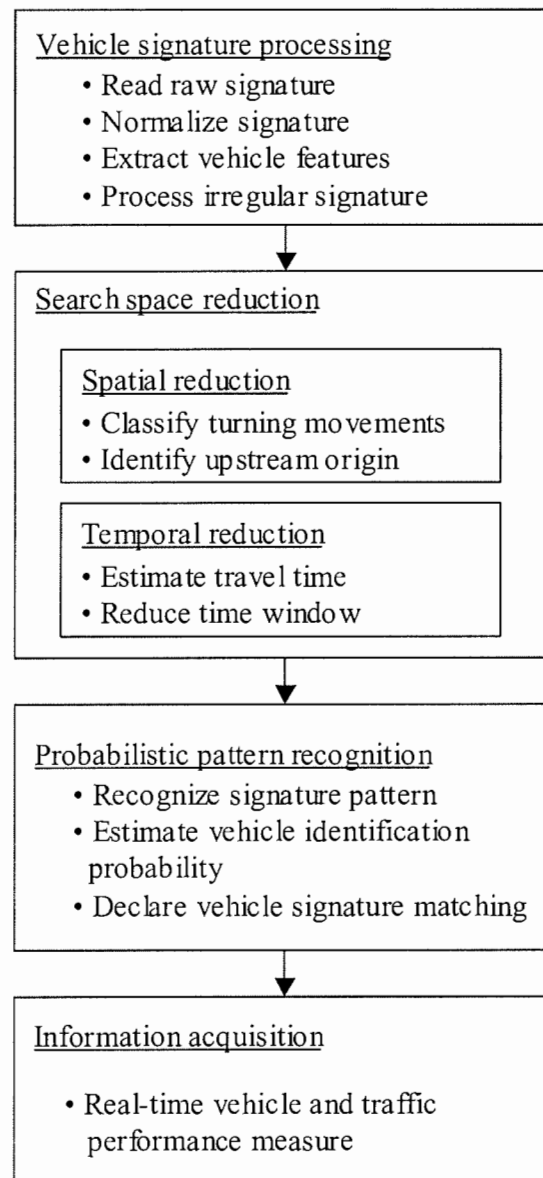


Figure 1 Vehicle reidentification algorithm for signalized intersections

Currently, the actual implementation of the algorithm at the intersection of AP and ICD 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 basic concept of vehicle tracking proposed in this study consists of sequential search space reductions. Firstly, origin and destination stations are pre-determined in order to define the search space. When individual vehicles pass the downstream detection stations, the vehicle features including detection time and location are recorded. Then the algorithm establishes the candidate set of upstream vehicle features that potentially would be matched. Then the

most similar feature vector among the candidates is identified, a match is declared and vehicle path history is updated. After conducting the matching procedure for vehicle features, the algorithm investigates if the identified detection station is the given destination station. Once the station is identified as the destination, vehicle information is acquired by recording the vehicle history. To produce real-time OD-based traffic information, individual vehicles information is aggregated based on a given aggregation interval. The proposed framework for vehicle tracking is presented in Figure 2.

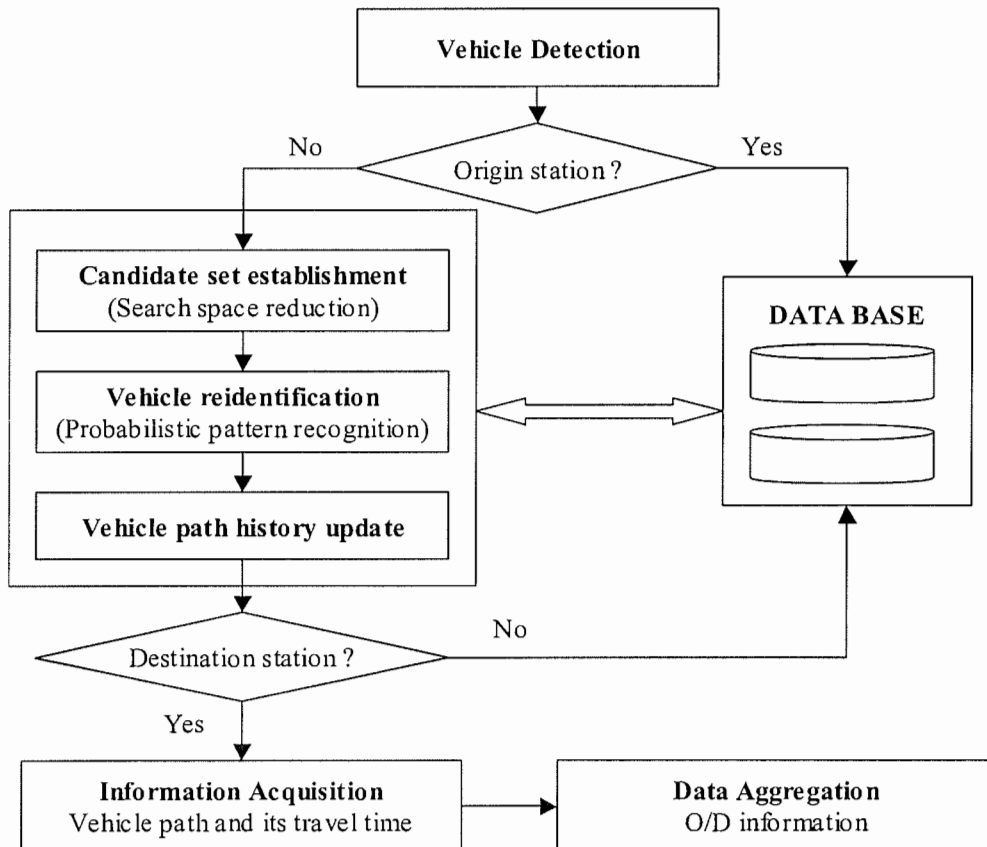


Figure 2 The proposed vehicle tracking framework

### 3. Characteristics of 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 3 shows the examples of the vehicle signatures with the 7 milli-second 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 signatures contain a valuable set of information representing the physical characteristics of the vehicles such as vehicle length, weight, and shape etc. Each piece of information embedded in the signature can be extracted into individual feature vectors. Moreover, vehicle lane information, vehicle speed, signal phase information, and vehicle arrival time are recorded for individual vehicle and can also be considered as feature vectors.

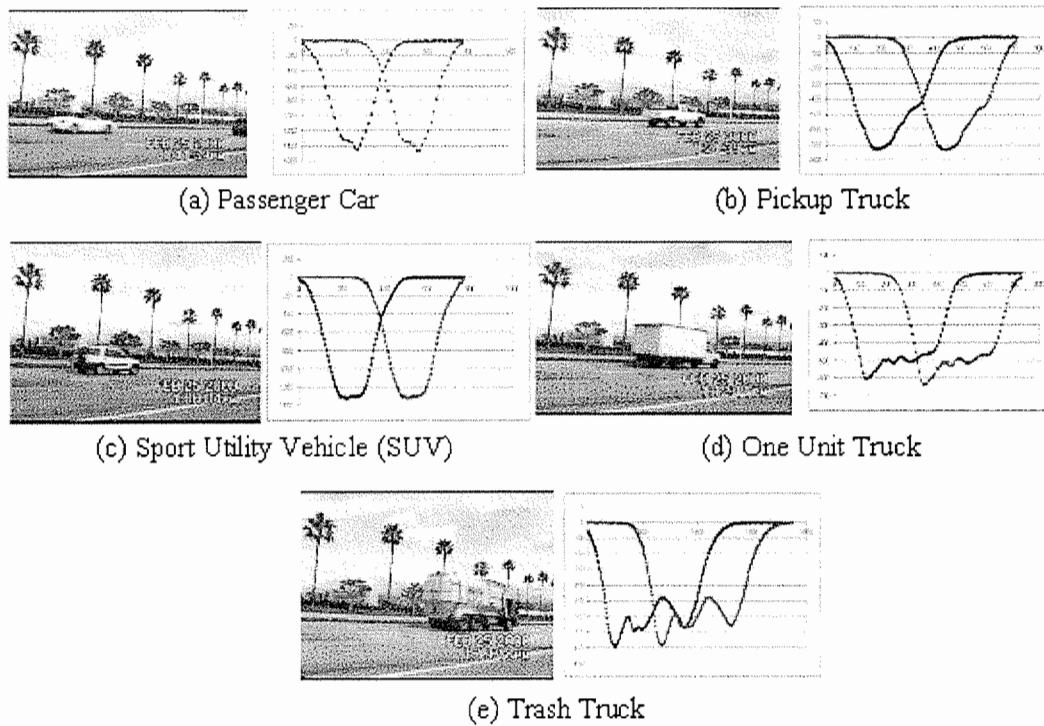


Figure 3 Vehicle inductive signatures

Raw vehicle signature is normalized by two procedures in order to be used as input vectors of the vehicle reidentification algorithm. First, the magnitude of vehicle signature, y-axis in Figure 4, is divided by its maximum magnitude to purge the variations by different detector locations. Second, x-axis representing the time while vehicle is present on the loop detectors is transformed to vehicle length by multiplying 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. A methodology to generate synthetic ESIs of the vehicle signatures is presented in the following section.

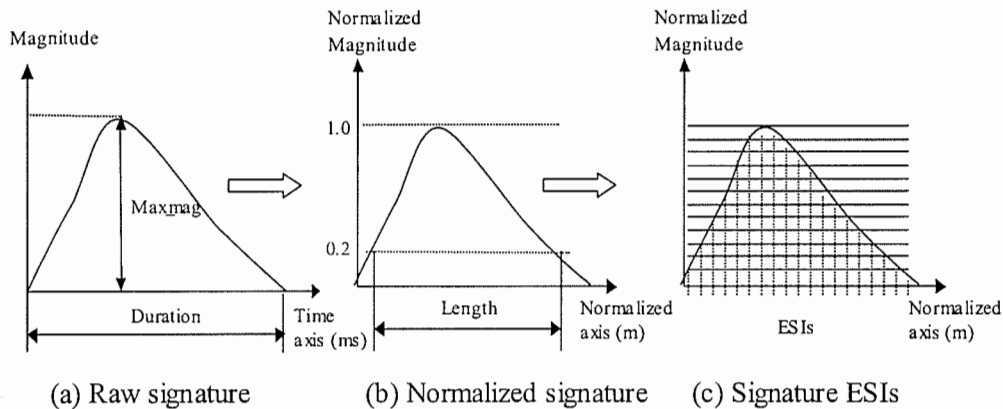


Figure 4 Feature vector extraction from vehicle signature

#### 4. Synthetic vehicle signature generation

The main purpose of this study is to evaluate and analyze the feasibility of the application of vehicle reidentification algorithm to signalized arterials using microscopic simulation environments. To accomplish this, we should be able to obtain the inputs of 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 were 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 for 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 can not 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 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 check whether two processed signature data would be observed 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

$S_{up}^i = S_{down}^i + \varepsilon_i$ . Errors close to zero explain that two signatures for the same vehicle observed from different detection stations are the exactly 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 impossible. Therefore, 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 ESIs 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. Error distributions for each clustered vehicle signature was then estimated. It was assumed that each feature vector is normally distributed. Figure 5 shows the summarized procedure for generating synthetic vehicle signatures.

Our basic idea for vehicle reidentification using vehicle features is that each individual vehicle generates a unique feature that is obviously differentiable from that of other vehicles. Therefore, the number of clusters for actual vehicle signatures would greatly affect the performance of vehicle reidentification algorithm. To determine a reasonable number of vehicle clusters, we selected the number of clusters that is able to produce 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 (9) and freeway experiments (2). It has been identified that 50 clusters can reproduce the actual performance of vehicle reidentification.

Self-Organizing Map (SOM) was applied to cluster vehicle signature data in this study. The SOM developed by Kohonen (11) 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 according to the following two steps.

#### Step1: Search winning node

When each input  $x$  is entered into the Kohonen layer, the neurons compute the input intensity  $I_j = D(\underline{w}_j, \underline{x})$ , where  $D(\underline{w}_j, \underline{x})$  is a distance measurement function, in which Euclidean distance is commonly used. After each neuron calculates its  $I_j$ , a 'competition' occurs to find the neuron called 'winner' with the smallest  $I_j$ .

#### Step2: Update weight

When the winning neuron  $c$  is determined, the weight vectors  $w$  are updated according to the following rule:

$$\underline{w}_j^{new} = \begin{cases} \underline{w}_j^{old} + \alpha[\underline{x} - \underline{w}_j^{old}], & j \in N_c \\ \underline{w}_j^{old}, & \text{otherwise} \end{cases}$$

Here  $N_c$  is the neighborhood of the winner node  $c$ , and  $\alpha$  is the learning coefficient. Both are decreasing with time during the training. Step 1 and 2 are repeated until the map has converged, which may be tested using average quantization error of training 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 is corresponding to a physical interpretation of the formed clusters.

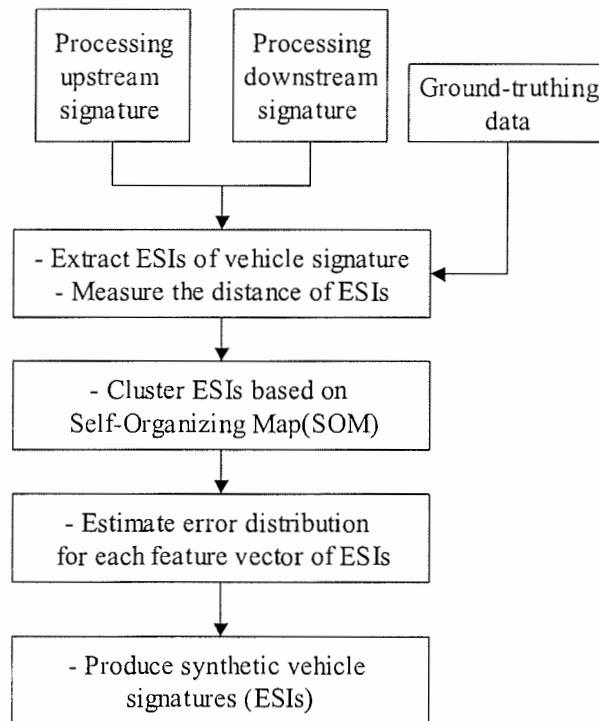


Figure 5 Procedure for the generation of synthetic vehicle signature

## 5. 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 MICROSOPIC 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 are 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 allowed the implementation of the various ATMIS application algorithms. The test arterial that was modeled by Paramics has three 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.

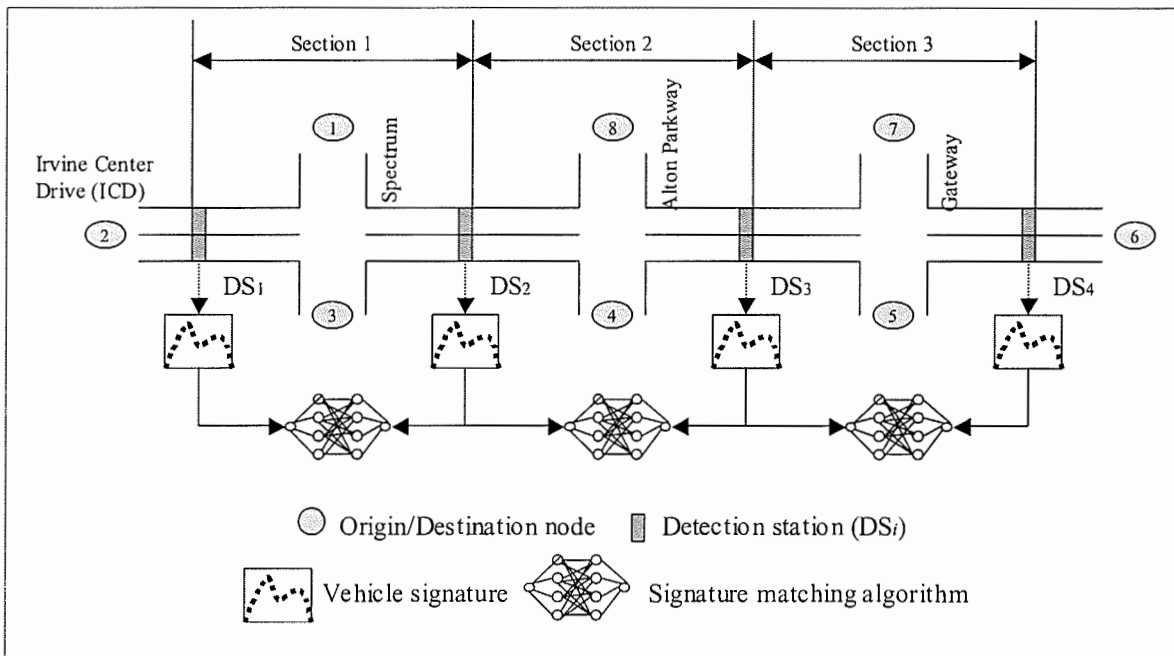


Figure 6 Test arterial

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 (12) 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 simulation.

One of the major elements affecting the tracing performance is the capability of sensor technologies. Sensor technology is 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 the 7 milli-second scan rate detector cards. However, since loop detector technology to generate more accurate and unique vehicle signatures with higher scan rate has been developed and tested in practice, it is expected that we would be able to obtain higher quality vehicle signatures. 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 treated as variables for evaluating the capability of the sensor technology in this simulation study.

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 (DS<sub>1</sub>) ~ detection station 4 (DS<sub>4</sub>) 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 DS<sub>1</sub> via DS<sub>2</sub> and DS<sub>3</sub>, and passing over DS<sub>4</sub>, were traced by the proposed anonymous vehicle tracking method when the vehicles were detected at DS<sub>4</sub>.

## 6. Simulation results and discussions

As a performance measure for the algorithm evaluation, Correct Tracing 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 DS<sub>1</sub> to DS<sub>4</sub>, and presented with the different levels of the variances of vehicle signature error distribution as shown in Table 1. The variance of error distribution based on the actual vehicle signatures ( $\sigma^2$ ), and reduced variances ( $\sigma^2 / 2$ ,  $\sigma^2 / 4$ ) represent the current and improved capabilities of the loop detector technology.

Table 1 Vehicle tracking performance

CTR (%)		Traffic Conditions	
		Uncongested	Congested
Variance of error distribution	$\sigma^2$	45.0 % (197/438)	31.7 % (194/612)
	$\sigma^2 / 2$	57.8 % (253/438)	43.4 % (265/612)
	$\sigma^2 / 4$	80.1 % (351/438)	52.6 % (322/612)

The most valuable feature of this study is to investigate how to produce the useful real-time traffic information via anonymous vehicle tracking method. The proposed anonymous vehicle tracking 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., requires the 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 is inaccurate. The path travel time obtained by the proposed method presented in Table 2. 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 step

Table 2 Travel time analysis

MAPE (%)		Travel time aggregation interval			
		1 cycle	5 min	10 min	15 min
$\sigma^2$	Uncongested	28.69	15.17	12.28	8.69
	Congested	34.49	21.72	16.03	13.43
$\sigma^2 / 2$	Uncongested	19.65	12.81	10.56	7.20
	Congested	24.11	18.22	15.39	12.67
$\sigma^2 / 4$	Uncongested	14.37	7.42	6.03	2.94
	Congested	20.02	14.27	13.50	9.58

Travel time accuracies for path travel times are presented in Table 2 in terms of the MAPE. 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  $\sigma^2$  which is based on the given 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, less than 10% MAPEs for path travel times were achieved under congested traffic conditions and less than 15% for congested traffic conditions.
- (2) For the purpose of investigating the proposed vehicle tracking system with small variances of the vehicle signature error distributions,  $\sigma^2 / 2$  and  $\sigma^2 / 4$  were applied. The performances were better than those of the case of  $\sigma^2$ . Less than 15 % MAPEs were achieved for 5 min., 10 min., and 15 min. aggregation intervals under uncongested traffic conditions with  $\sigma^2 / 2$ . In addition, for the same aggregation intervals, less than 10 % and 15% MAPEs were obtained for uncongested and congested traffic conditions, respectively, after applying  $\sigma^2 / 4$ .
- (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 levels of accuracies. Shorter aggregation interval involving 1 cycle would be more desirable for the purpose of real-time traffic control such as adaptive signal coordination strategies based on the estimated path travel time. On the other hand, 5 min. or 10 min. intervals would be better for use in traveler information systems. It is because shorter aggregation intervals have bigger travel time variations than those of the longer intervals. To reduce the travel time variations, the use of the successive averages of travel times on the time horizon would be a possible way.

## 7. Conclusions

Although a variety of traffic surveillance systems have been developed and tested for tracing individual vehicles on transportation networks, the proposed anonymous vehicle tracking system is preferred since it is relatively inexpensive and free from the privacy concerns. Use of existing loop infrastructures makes the proposed system more attractive in terms of the immediate field implementation. Field investigation of the vehicle reidentification system for single roadway segment in the City of Irvine, California, has showed 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 system. 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. 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 on an arterial street. It is believed that the proposed method for evaluating 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. 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.
2. 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.
3. 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.
4. Oh, C., and S.G. Ritchie. Real-time inductive-signature-based level of service for signalized intersections. Paper presented at 81<sup>st</sup> Transportation research Board Annual Meeting. Washington D.C. 2002.
5. 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.
6. 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.
7. 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.
8. 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.
9. Oh, C., S.G. Ritchie, Park, S. Development a real-time probabilistic vehicle reidentification algorithm for signalized intersections. Draft Paper for *Transportation Research, Part C*. 2002.
10. Specht, D.F. Probabilistic neural networks and general regression neural networks. In: Chen, C.H. (Ed.), *Fuzzy logic and neural network handbook*. 1996.
11. Kohonen, T. *Self-Organizing Maps*. Springer, Berlin, 2001.
12. Special report 209: *Highway Capacity Manual*. TRB, National Research Council, Washington, D.C. 2000.